DISSERTATION

MANAGING DEVELOPING LANDSCAPES FOR STORMWATER, WATER YIELD, AND ECOSYSTEM SERVICES WITH DATA-DRIVEN APPROACHES

Submitted by

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In partial fulfillment of the requirements

For the Degree of Doctor of Philosophy

Colorado State University

Fort Collins, Colorado

Fall 2022

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ABSTRACT

MANAGING DEVELOPING LANDSCAPES FOR STORMWATER, WATER YIELD, AND ECOSYSTEM SERVICES WITH DATA-DRIVEN APPROACHES

Urban population growth and land conversion are placing immense pressures on natural and anthropogenic systems. Urbanization is drastically altering catchment hydrology and producing detrimental impacts on streams, waterbodies, ecosystems, and watersheds. Increasing emissions of carbon and other greenhouse gases are driving global climate change, and higher value urban and industrial water uses are removing water from irrigated agriculture, which is essential for feeding the world's population. Being able to make informed decisions about managing these challenges is critical for planetary health.

The overall objective of this dissertation was to enable better decisions regarding urban stormwater management, land use of dried agricultural land, and water management of land use-land cover development. To meet this objective four primary questions corresponding to the four chapters were addressed:

Question 1: How can we advance the practice of stormwater management via information sharing and cross-jurisdiction communication?

Question 2: What variables explain the variation in selection of stormwater management approaches in various physiographic, climatic, socioeconomic, and federal regulatory settings?

Question 3: How can more informed decisions, regarding land use and ecosystem services, be made in the face of drying agricultural land as water is transferred to urban and industrial uses?

Question 4: How do various land use-land cover scenarios impact water yield in diverse physiographic and climatic settings?

To address question 1, stormwater control measure (SCM) inventories were gathered from 23 United States cities and compiled into a publicly available dataset. Classification of SCMs were explored and suggestions were made about how cities should address asset management in the context of stormwater and SCMs. Data that would be beneficial to understanding the hydrologic and water quality impacts of SCMs and how they vary across spatial scales and regions was highlighted and a call to better record information regarding SCM networks, and not just single SCMs was made.

The data gathered for answering question 1 was further used to address the second question. Data regarding physiography, climate, socioeconomics, and federal regulations were gathered to understand how those factors have shaped SCM inventories in the United States. Despite climate clearly being an important driver of stormwater management, the assemblages of SCMs present in city inventories were better explained by physiographic constraints, such as slope, depth to water table, and imperviousness, federal regulations related to the Clean Water Act, and socioeconomic variables such as population density and housing age – a proxy for development age. While stormwater decisions are generally made locally, data suggested that federal regulations have impacted those local decisions. Furthermore, this work contextualized the SCM inventories of 23 United States cities such that other cities can better understand the settings in which cities are managing stormwater so that they can identify cities with more advanced stormwater experience from which to learn.

To address question 3, a thorough literature review regarding spatially explicit assessment and valuation of ecosystem services was performed. Literature review was guided by the need for policy makers and environmental managers that are interested in ecosystem services to be able to make easy, cheap, and good-enough valuations of various scenarios so that informed decisions can be made. The work was highly motivated by the current situation in the South Platte River Basin of Colorado, where water rights are being purchased from agricultural irrigators and transferred to municipal uses. This process leaves what has been irrigated land permanently dried. Understanding how to best manage that land for local and global benefits is of interest to local policy makers. Special attention and effort were placed on providing background information regarding climate-related ecosystem services (i.e., carbon sequestration) and payments for ecosystem services in general. Important considerations such as understanding who pays for ecosystem services, who gets paid, and how that dynamic will affect economic inequality were highlighted. A pre- and post-processor application was developed to enable easy application of the COMET-Planner tool to scenarios of drying agriculture being transferred to more natural land cover. Using Monte Carlo simulations with distributions of valuation variables identified in literature, the application produces stochastic estimates of the return on investment in the case of irrigated agricultural land drying to more natural grass cover. The application was applied to three areas of the South Platte River basin illustrating its utility.

Lastly, national datasets of climate, hydrologically relevant land use, water use, and physiographic data were used to address question 4. Using 2,913 catchments of varying sizes and degrees of development from across the contiguous United States, three data-driven predictive models were applied to nine ecoregions, as well as to reference catchments only, to non-reference catchments only, and to all catchments at once to predict mean annual, annual, and monthly water yield. Models performed best on catchments in the eastern half of the country. Performance in the western half of the country was mixed, with catchments along the west coast performing adequately, but catchments throughout the mountain west performing inconsistently, ranging from poor to good. Climate variables were shown to be the most impactful in terms of predicting water yield with the relative impact of climate variables increasing as the timescale became finer. Physiographic variables were the next most impactful variable type. Anthropogenic alterations to water resources and land displayed varying levels of importance and varied across timescales, but especially across regions. Results suggest that anthropogenic activities have varying effects depending on the climatic and physiographic setting in which they occur. It was also shown that many anthropogenic variables play moderate roles in predicting water yield across scales and if well performing models of water yield are to be developed in heavily impacted catchments, they will require high-dimensional models that include timeseries data for anthropogenic variables such as dam and reservoir management and water use.

ACKNOWLEDGEMENTS

Reflecting upon my journey to completing this dissertation and degree I am overwhelmed with the number of people for whom I am thankful. Dr. Aditi Bhaskar, my advisor, gave me the opportunity to pursue my PhD and for that, I am forever grateful. Her guidance was invaluable and instrumental to my success. Thank you Nicole Opalinski, Noelle Fillo, Katie Knight, Stacy Wilson, Abdullah Al Fatta, Dixie Poteet, Nick Guthro, and Jorge 'Santi' Nunez, for sitting through hours of my practice presentations and for sweetening the experience of graduate school. There are too many individuals in the Department of Civil and Environmental Engineering to acknowledge independently. Thank you to the faculty and staff for all that you do to improve the student experience and to ensure the department maintains its amazing reputation.

Thank you to my beautiful wife Jamie Lynn. I am excited to graduate, but you are easily the best thing to happen to me this year, or in my life. Thank you for enduring the PhD journey with me, supporting me in so many ways, and for being such an inspiration to me. I love you. To all my family, old and new, thank you for the endless and unconditional support. Knowing I have you, even when you are far away, makes all challenges seem smaller.

The data used in Chapters 1 and 2 was voluntarily shared by many city employees and could not have been completed without their assistance. Thank you to Dr. Margaret Garcia who provided a dry well inventory for Phoenix, AZ and Constance Kim, Connor Williams, and Wyatt Young for their efforts on the analyses in Chapters 1 and 2. This dissertation was partially supported by the USDA National Institute of Food and Agriculture, Hatch project 1015939 and this material is based upon work supported by the National Science Foundation under Grant No.'s 1444758, 1828902, 1444755, and 2045340. Any use of trade, firm, or product names is for descriptive purposes only and does not imply endorsement by the U.S. Government. Any opinions, findings, conclusions, or recommendations expressed in this material are those of the author's and do not necessarily reflect the views of the National Science Foundation.

Chapter 4 utilized the Summit supercomputer, which is supported by the National Science Foundation (awards ACI-1532235 and ACI-1532236), the University of Colorado Boulder, and Colorado State University. The Summit supercomputer is a joint effort of the University of Colorado Boulder and Colorado State University.

DEDICATION

I dedicate this dissertation to those that are no longer with us; Dr. Jorge Ramirez, Dr. Andrè Dozier, Dr. Tom Meixner. Each of these individuals was an inspiration, leaving the world better than they found it, and strengthening the hope I have for the world. “Hope is not optimism, which expects things to turn out well, but something rooted in the conviction that there is good worth working for.” – Seamus Heaney, as tweeted by Tom Meixner eight days before his murder. May we all leave the world with more hope than when we came into it.

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INTRODUCTION

Globally, urban population is expected to grow from roughly 4.2 billion people in 2018 to about 6.6 billion in 2050; a 57% increase (United Nations and Social Affairs 2018). Growing urban populations will place immense pressure on urban centers to develop more land and secure water resources (Angel et al. 2005; Artmann et al. 2019; Bibri et al. 2020; Dozier et al. 2017; Elmqvist et al. 2013; Payne et al. 2014; Watson and Davies 2011). Development patterns vary but can be broadly characterized as either outward expansion (e.g., sprawl) or infill, where already developed areas are reimagined so that population density can be increased (Angel et al. 2005; Artmann et al. 2019; Schneider and Woodcock 2008). Despite the form of urban development, hydrology and ecosystem services are inevitably altered (Elmqvist et al. 2013 Haase and Nuissl 2007; Leopold 1968; Poff et al. 2006; Walsh et al. 2005).

Recent iterations of urban stormwater management attempt to mitigate the numerous negative impacts of urbanization on stream and catchment health (Poff et al. 1997; Walsh et al. 2005) by managing hydrology at site and catchment scales (Chocat et al. 2001; Delleur 2003; Roy et al. 2008). Emphasis has shifted from end-of-pipe solutions towards implementation of smaller stormwater control measures (SCMs) that are implemented throughout the catchment to control runoff near the source (Askarizadeh et al. 2015; WEF and ASCE-EWRI 2012). As this transition has occurred, adoption and innovation has largely occurred at the city scale. This has created an obstacle for communication (Fletcher et al. 2015) and a lack of knowledge about how federal regulations requiring management of stormwater interact with city-scale physical, climatic, and socioeconomic factors to shape stormwater management approaches in different cities. To understand how those factors interact to drive adoption of different stormwater management approaches, cross-city comparisons are necessary. However, data about SCMs is typically held at the city level making comparisons of approaches in different cities difficult. Existing cross-city comparisons only include two to three cities at a time (Hale 2016; McPhillips and Matsler 2018) and those cities are often in similar physical, climatic, and socioeconomic settings. There is a need for increased data sharing about local stormwater approaches and more standardized SCM terminology and/or record keeping to help with communication, assist in developing more standard procedures and designs (Marsalek 2013; Minton 2007; Taira et al. 2018), and to enable cross-city comparisons (Hale 2016). Chapters 1 and 2 address this need.

The subsequent work moves from management of stormwater specifically, to more general management of land development and two associated ecosystem services. Being able to make informed policy decisions will be critical to manage the challenges presented by the continued development of land (Angel et al. 2005; Artmann et al. 2019; Bibri et al. 2020) and transfer of water resources out of irrigated agriculture to urban and industrial uses (Dozier et al. 2017; Flörke et al. 2018; Rosegrant and Ringler 1998). Inclusion of ecosystem services in trade-off analysis is becoming increasingly popular when making such decisions (Elmqvist et al. 2013; Fürst et al. 2017; Tallis et al. 2011). Two ecosystem services of interest are carbon sequestration (Bagstad et al. 2013; Clerici et al. 2019; Kovacs et al. 2013; Krkoška lorencová et al. 2016) and water yield (i.e., how much water is leaving a catchment via streamflow over a given amount of time; Lang et al. 2017; Li et al. 2021; Tallis et al. 2011). Chapters 3 and 4 address these ecosystem services, respectively. While these needs are global, Chapter 3 uses the South Platte River Basin in Colorado as a case study. There the Colorado Water Conservation Board (CWCB) is actively engaged in decision-making as irrigated agriculture is being dried to other land uses (Colorado Water Conservation Board 2015). They are particularly interested in understanding how different uses of the dried agricultural land may assist in our fight against climate change by sequestering and storing carbon (addressed in Chapter 3).

There have been extensive efforts to develop general modelling approaches to predicting water yield in reference catchments (i.e., minimal human impacts), but approaches that include anthropogenically altered catchments are rare (Hrachowitz et al. 2013; Kratzert et al. 2019a; Razavi and

Coulibaly 2013; Visessri and McIntyre 2016). A modelling approach that can identify drivers of water yield in altered catchments, as well as predict water yield in such catchments, would be of great benefit in land-use planning. To improve our understanding of the effects of anthropogenic activities on water yield (addressed in Chapter 4), 2,913 catchments across the contiguous United States were used to develop statistical and machine learning models that predict water yield. Mean-annual, annual, and monthly water yield were predicted in reference and non-reference catchments. Shapley Additive Explanations (Lundberg et al. 2020; Lundberg and Lee 2017; Shapley 1953) were used to investigate the impact of many variables that potentially affect water yield.

This dissertation is organized as follows:

<u>Chapter 1 – A Call to Record Stormwater Control Functions and To Share Network Data</u>: To address the need for information sharing about stormwater management and the need for easier communication between cities, and between cities and researchers, the following question was addressed:

How can we advance the practice of stormwater management via information sharing and cross-jurisdiction communication?

<u>Chapter 2 – Understanding What Physical, Climatic, Socioeconomic, and/or Regulatory Factors Are Driving Selection of Stormwater Controls in United States Cities</u>: To better understand what is driving (or constraining) the selection of SCMs in different cities, and to contextualize the SCM inventories of 23 United States cities so that other cities can better understand the settings in which cities are managing stormwater and the approaches taken in those settings, Chapter 2 addresses:

What variables explain the variation in selection of stormwater management approaches in various physiographic, climatic, socioeconomic, and federal regulatory settings?

<u>Chapter 3 – Estimating Carbon Sequestration Under Various Land-Use Scenarios of Dried Agricultural Land in the South Platte River Basin</u>: To enable easier assessment of tradeoffs of potential uses of dried

agricultural land to assist stakeholders in making informed land development and policy decisions the two following subobjectives were addressed:

1. Identify needs, traits, and options with respect to policy relevant valuation of ecosystem services.
2. Identify and apply an appropriate methodology for valuating carbon related ecosystem services in the case of irrigated agriculture drying to more natural land cover in the South Platte River Basin of Colorado.

Chapter 4 – Predicting Monthly, Annual, and Mean Annual Water Yield in Response to Mixed Land Use-Land Cover Scenarios and Understanding Drivers of Water Yield: To enable easier assessment of the impacts of different land use-land cover scenarios on water yield, to gain insight about drivers of water yield and how spatial and temporal scales affect those drivers, and to identify appropriate methodology for predicting water yield in highly impacted catchments the following question is addressed:

How do various land use-land cover scenarios impact water yield in diverse physiographic and climatic conditions?

CHAPTER 1: A CALL TO RECORD STORMWATER CONTROL FUNCTIONS AND TO SHARE NETWORK DATA[1]

Introduction

Urban stormwater is an ongoing contributor to the degradation of the health of many watersheds and water bodies. In the United States, federal regulations (e.g., Clean Water Act) require monitoring and reporting of relevant water quality metrics in regulated waterbodies to ensure standards are being met, but decisions about how to manage urban stormwater are left up to state or other local agencies. While this allows for local adaptation and innovation, it has also led to isolated holding of implemented stormwater control data at the city level and inconsistent terminology surrounding stormwater control measures (SCMs) between cities and regions (Fletcher et al. 2015; Minton 2000, 2007; WEF and ASCE-EWRI 2012). Particularly at this time when the types of SCMs are shifting to include smaller, distributed SCMs (Chocat et al. 2001; Delleur 2003; Roy et al. 2008; WEF and ASCE-EWRI 2012), the isolated management of SCM inventories is a significant missed opportunity to

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[1] Published in the Journal of Sustainable Water in the Built Environment: https://doi.org/10.1061/JSWBAY.0000971
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improve stormwater management through information sharing between cities, agencies, and researchers (Marsalek 2013; Minton 2000; Taira et al. 2018).

As an increasing number of regulated cities look for solutions to protect environmental resources while fulfilling their regulatory obligations, sharing of reliable information is imperative, particularly for small and mid-size communities that may lack the resources needed to adequately address these issues. Sharing of SCM inventories would allow cities wishing to pursue newer approaches to stormwater management to gain insight from cities that have already tried them. Sharing of SCM inventories could also enable cross-watershed comparisons to help isolate and understand the effects of different SCM approaches at the city or catchment scale (Bell et al. 2016; Hale 2016; Hopkins et al. 2020; Jefferson et al. 2017; Marsalek 2013). Furthermore, sharing of SCM inventories could move terminology and record keeping practices towards a more universally interpretable format that conveys details about SCM form and function (Minton 2000; WEF and ASCE-EWRI 2012), which would lead to more consistent sets of design criteria (Minton 2007), and help practitioners select appropriate SCMs and SCM systems to meet specific objectives (Taira et al. 2018; WEF and ASCE-EWRI 2012).

Here, our overall objective was to address the isolated management of implemented SCM inventory data, with the hope of improving the communication, decision-making, and evaluation of stormwater management across cities. Our overall objective includes two research questions: 1. Are cities across the United States or within states using comparable SCM nomenclature?; 2. Is it feasible to develop an SCM nomenclature that efficiently and effectively communicates SCM function?

To meet our overall objective of addressing the need for better SCM information sharing (Driscoll et al. 2015; Taira et al. 2018) and to answer our research questions required access to SCM inventories from many cities, but such a database does not currently exist. So, first we collected SCM inventories from several cities (e.g., geospatial data; Choat et al. 2021). Then, we explored SCM terminology in the city inventories and considered function-based nomenclature to address the ability to efficiently and effectively communicate SCM functions (Bell et al. 2019; Fletcher et al. 2015; McPhillips and Matsler 2018; Minton 2000, 2007). We used an existing nomenclature (WEF and ASCE-EWRI 2012) and k-means clustering to see if SCMs cluster differently based the functions of quantity control, pollutant control, biological, or other unit processes.

SCM Inventories and Data Sharing

Background on SCM Network Data Sharing

Efforts to identify challenges in stormwater management often identify the lack of data sharing as an impediment. For example, nearly all cities implementing new SCM types, sometimes collectively known as green infrastructure (GI), agreed that communication of knowledge from other cities implementing GI is critical to the development of a GI program (Driscoll et al. 2015). Also, a team of transportation drainage experts highlighted the importance of developing and sharing information and being clear about definitions for a robust approach to GI implementation (Taira et al. 2018).

Efforts to share information about SCMs are ongoing, such as the International Stormwater BMP database (Clary et al. 2002, 2020), but these efforts are focused on the performance of individual SCMs (i.e., site-scale), as opposed to city-scale SCM networks. To achieve all desired outcomes, stormwater management should be designed and applied across site-level and watershed scales (Roy et al. 2008; Taira et al. 2018; WEF and ASCE-EWRI 2012). Information on existing SCMs at the watershed scale would help advance stormwater management to meet watershed goals. Furthermore, to understand ecosystem services provided by SCMs and responses in physical and biological integrity to urbanization, it is essential to understand the integrated effects of stormwater (e.g., SCM) networks (Hopkins et al. 2015; Parr et al. 2016; Vogel et al. 2015).

Background on SCM Terminology

When SCM data are available, comparisons between cities are frequently burdened by inconsistent and vague terminology (Bell et al. 2019; Fletcher et al. 2015; McPhillips and Matsler 2018; Minton 2000; Prudencio and Null 2018). Much of the inconsistency can be attributed to an evolution of SCM terms over time and by region, where particular terms may be used in a city or region because they have been designated or defined by the regional regulatory agency (Fletcher et al. 2015). There have been calls for a simplified SCM nomenclature based on either function (Minton 2000; Shrestha and Brodie 2011; WEF and ASCE-EWRI 2012) or form (i.e., construction materials, SCM sizes, and contributing areas) (Bell et al. 2019). Shrestha and Brodie (2011) developed a formal nomenclature focused on physical treatment systems capable of receiving and treating high and variable flow rates and effective at removing suspended solids to a non-potable water quality. Despite their narrow focus on specific SCM types, the proposed nomenclature, including two primary treatment mechanisms and up to four sublevels, quickly became complex.

Others have proposed simpler function- or process-based nomenclature. Minton (2007) proposed a naming framework that attempted to reduce the number of names used for SCMs that provide the same or similar functions. Minton identified a hierarchy of considerations for naming SCMs. The base consideration was what principles an SCM is based on (e.g., chemistry of precipitation and sorption of pollutants), followed by unit processes (e.g., sedimentation, filtration, or etc.), unit operations (i.e., the “box” in which unit operations occur or SCM form), and systems (i.e., one or more unit operations). Based on those considerations, Minton (2007) then placed SCMs into subfamilies and families (i.e., groups of systems with common key characteristics) which were to be used as SCM names. Minton proposed five families of SCMs including *basins, swales, filters, infiltrators, and screens.*

The Water Environment Federation (WEF) and American Society of Civil Engineers’ Environmental and Water Resources Institute (ASCE-EWRI) built heavily on Minton’s work in WEF

Manual of Practice No. 23 and ASCE Manuals and Reports on Engineering Practice No. 87 (2012). Similar to Minton, they produced a nomenclature for SCMs based on the processes provided by them, where SCMs were grouped based on similar quantity control, pollutant control, biological, and other unit processes (Table 1.1; WEF and ASCE-EWRI 2012). They provided a coarse nomenclature with five groups (MOP-coarse) and a finer nomenclature with 21 groups (MOP-fine). Their MOP-coarse nomenclature consisted of *basins, swales and strips, filters, infiltrators,* and *gross-pollutant traps,* nearly identical to the five families of SCMs identified by Minton (2007).

Table 1.1. Nomenclature and associated unit processes. Modified from Table 4.2 (WEF and ASCE-EWRI 2012).

		Quantity control						Pollutant control								Biological				Other			
MOP-Coarse	MOP-Fine	Peak flow attenuation	Runoff volume reduction	Infiltration	Dispersion	ET	Runoff collection usage	Sedimentation	Flotation	Laminar separation	Swirl concentration	Sorption	Precipitation	Coagulation	Filtration	Plant metabolism	Nitrification denitrification	Sulfate reduction	Organic compound degradation	Pathogen dieoff	Temperature reduction	Disinfection	Screening
Basins	Wet basins	x	x			x	x	x	x			x				x	x	x	x	x		x	x
	Wetlands	x	x			x	x	x	x			x				x	x	x	x	x		x	
	Dry basins	x	x	x				x															
	Vaults and swirl concentrators	x						x	x		x												
	Oil Water Separators							x	x	x													
	Forebays							x	x														
	Cisterns		x					x															
	Basin Unknown*																						
Swales and Strips	Swales			x	x											x					x		
	Strips			x	x			x								x					x		
Filters	Sand filters	x						x	x						x		x					x	
	Bioretention	x	x	x		x	x	x	x			x	x	x	x	x	x		x		x	x	
	Landscaped roofs	x			x	x						x				x					x		
	Drain inlet inserts							x							x								
	Manufactured filters							x							x								
	Filter Unknown*																						
	Gravel Wetland*																						
Infiltrators	Infiltration Basins	x	x	x				x	x			x	x	x			x		x	x	x	x	
	Infiltration Vaults	x	x	x				x				x	x	x			x		x	x	x	x	x
	Trenches	x	x	x				x				x	x	x			x		x	x	x	x	
	Dry Wells	x	x	x				x				x	x	x			x		x	x	x	x	
	Permeable pavement	x	x	x								x	x	x					x	x	x	x	
	Infiltration Unknown*																						
Gross Pollutant Traps	Screens nets baskets racks																						x
	Hoods								x														
	Gross Pollutant Trap Other*																						
	Gross Pollutant Trap Unknown*																						
Disconnection*	Disconnection*																						
Other*	Other*																						
	Stormwater Conveyance*																						
Unknown*	Unknown*																						

Note: Row headings with an * under MOP-coarse and MOP-fine were added to the original table to allow all listed SCMs to be placed in a category. Reported unit processes (x) are from the original table 4.2 (WEF and ASCE-EWRI, 2012).

Previous efforts (Minton 2000, 2007; Shrestha and Brodie 2011; WEF and ASCE-EWRI 2012) have highlighted the desire for SCM function to be easily communicated. They have also made clear that due to overlapping functions between SCMs, it is virtually impossible to use SCM nomenclature alone to communicate all of the information that may be of interest to professionals, researchers, or others in the field regarding SCMs (Minton 2007; WEF and ASCE-EWRI 2012). Despite the clear challenges created by overlapping SCM functions Minton (2007) expressed hope that his proposed naming convention, which was largely reiterated by WEF and ASCE-EWRI, would be slowly adopted over time by states, provincials, and included in city stormwater manuals. By exploring the SCM inventories we collected, we were able to investigate to what extent these proposed naming frameworks have been integrated into practice by cities.

SCM Inventory Collection

We attempted to gather SCM inventories from 32 cities and 3 counties, but some cities and all counties never responded to our request, some cities did not maintain an SCM inventory, while other cities were unwilling to share their SCM inventories due to security concerns or because their inventories were incomplete. Twenty-three cities shared SCM inventories through personal communication or via their online access portals (Choat et al. 2021). While we would have preferred to have received inventories from more cities, we are only aware of existing SCM database comparison studies that include three or less cities at a time (Hale 2016; McPhillips and Matsler 2018), so having access to SCM inventories from 23 cities was a large improvement. The cities included in our study were from 8 climatic zones (Fig. 1.1; Beck et al. 2018). Nine historically had or currently have combined sewers present, and 15 were MS4 phase I cities with city populations ranging from about 37,000 to over 8 million persons. Seven cities had combined sewers and MS4 phase I permits. We suspected cities in different climates may use different SCM types and that cities with combined sewers or MS4 phase I cities may be more incentivized to record and implement SCMs, so we felt confident that our 23 cities were reasonably representative of diverse stormwater settings found in cities across the United States.

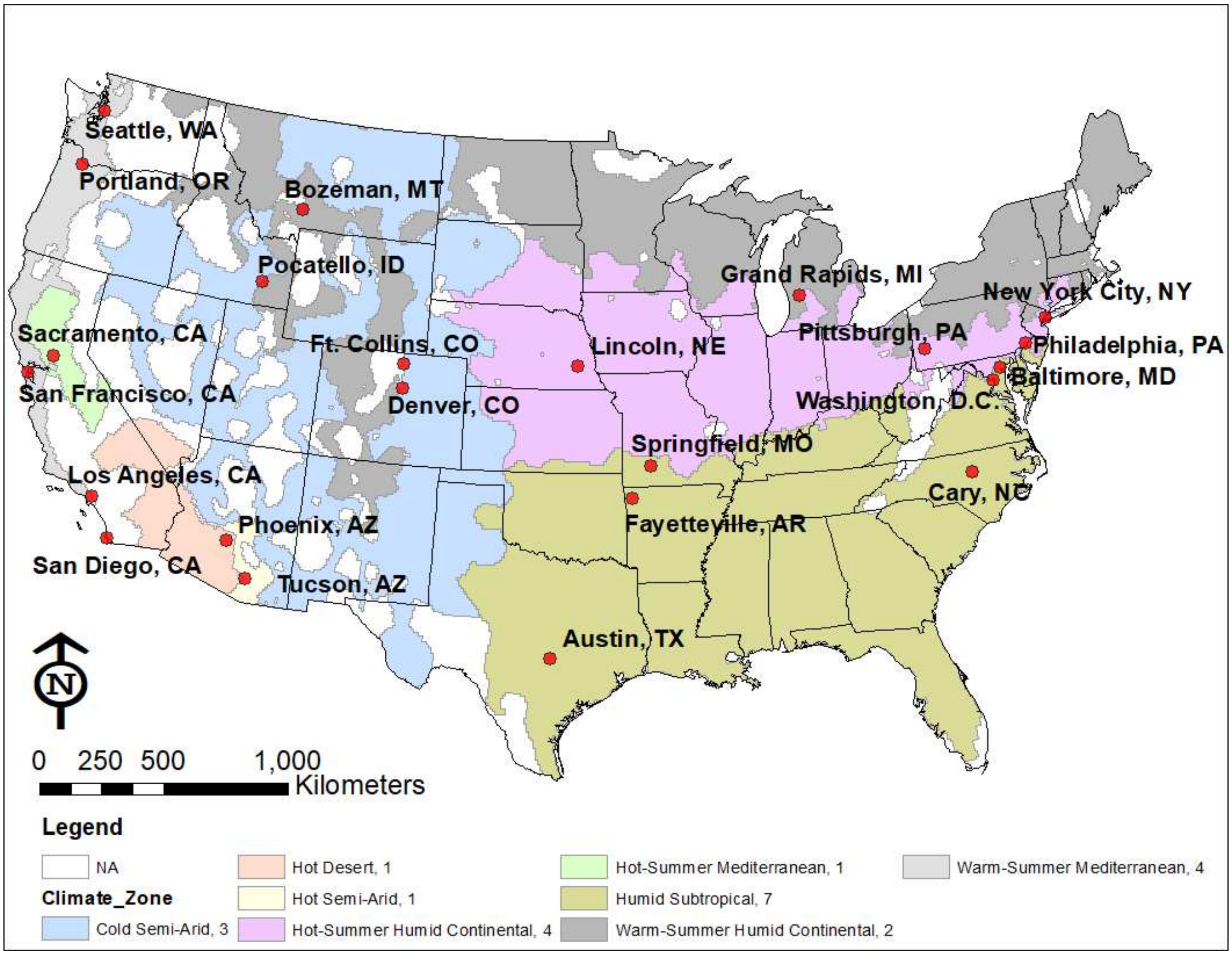

Fig. 1.1. Map of 23 United States cities. Legend defines Köppen climate zones (Beck et al. 2018) and presents how many cities fall within each zone. “NA” represents climate regions that do not contain a studied city.

Of the 23 cities that were able to share their inventories, some had online portals that made downloading inventories easy and others had inventories that they were able to send to us. We already had some of the inventories in our possession from previous efforts (e.g., Hale 2016; McPhillips and Matsler 2018). Most of the inventories we received came as geospatial data while some came as lists of SCMs. We did not utilize the spatial attributes of the inventories in this study, but those datasets are available online (Choat et al. 2021) for the cities that allowed us to share their data.

Analysis of SCM Terms and Types (Question 1)

Despite the relatively small number of SCM groups identified by Minton (2007) and WEF and ASCE-EWRI (2012; i.e., 5 coarse groups or families and ~ 21 fine groups or subfamilies), there were 378 different terms listed by the 23 cities in their SCM inventories (Table 1.2). Although there were many different terms used for SCMs, these had little commonality across cities. The SCM term that appeared in the largest number of SCM inventories was *rain garden* which appeared in 9 of 23 cities. *Bioretention* (Table 1.2), *green roof,* and *unknown* appeared in 8 inventories. The inclusion of the surprisingly common term *unknown* implied these cities were aware of some type of facility but did not know what type of facility it was. The only other term appearing in 7 or more inventories was *dry well*. A full list of terms included in the inventories is listed in Table S1.1 in supplementary material.

Table 1.2. SCM types and terms.

SCM Class (**Coarse**, Fine)	# of Cities Including SCM	# Times Listed in Inventories	Count of Terms	3 Most Common Terms (# cities listing term)
Basin	**22**	**32,438**	**104**	**"Detention Basin", "Rainwater Harvesting", "Detention Pond"**
Dry Basin	17	8,987	30	"Detention Basin" (6), "Detention Pond" (4), "Underground Detention" (4)
Cistern	11	12,294	15	"Rainwater Harvesting" (6), "Cistern" (3), "Rain Barrel" (2)
Vaults Swirl Concentrator	10	7,757	28	"Detention Vault" (2), "Sedimentation Manhole" (1), "Water Quality Vault" (1)
Wet Basin	7	667	9	"Wet Pond" (3), "Water Quality Pond" (1), "Detention Pond-Wet" (1)
Wetland	7	261	6	"Wetland" (2), "Constructed Wetland" (1), "Wetland Pond" (1)
Forebay	3	2,066	5	"Sedimentation" (1), "Sedimentation Only" (1), "Sediment" (1)
Basin Unknown	3	252	3	"Basin" (1), "Storage" (1), "Subsurface Storage System" (1)
Oil Water Separator	3	154	6	"Oil-Grit Separator" (2), "Vortechs" (2), "Stormceptor" (1)
Infiltrator	**22**	**20,451**	**64**	**"Dry Well", "Porous Pavement", "Infiltration Trench"**
Permeable Pavement	16	2,794	22	"Porous Pavement" (6), "Permeable Pavers" (5), "Pervious Pavement" (3)
Infiltration Basin	13	10,919	22	"Retention Basin" (4), "Infiltration Basin" (4), "Retention Pond" (2)
Dry Well	10	2,092	6	"Dry Well" (7), "Infiltration-Dry Well" (1), "Drywell-Aggregate Filled" (1)
Trench	9	4,163	9	"Infiltration Trench" (6), "Soakage Trench" (1), "Trench" (1)
Infiltration Unknown	5	464	3	"Infiltration" (4), "Infiltration BMPs" (1), "Infiltration Basin or Trench" (1)
Infiltration Vault	1	19	2	"Storm Chamber System" (1), "Leaching Tank" (1)
Filter	**20**	**18,767**	**75**	**"Rain Garden", "Bioretention", "Green Roof"**
Bioretention	19	12,495	30	"Rain Garden" (9), "Bioretention" (8), "Planter" (2)
Sand Filter	9	3,104	16	"Sand Filter" (5), "Sand Filtration" (1), "Underground Sandfilter" (1)
Landscaped Roof	9	2,249	8	"Green Roof" (8), "Ecoroof" (1), "Extensive Green Roof" (1)
Filter Unknown	4	402	5	"Filtration Only" (1), "Filtering System" (1), "Underground Filter" (1)
Manufactured Filter	4	388	7	"StormFilter" (2), "Downspout Filter" (2), "Storm Filter-Canister" (1)
Drain Inlet Insert	3	118	7	"Drainage Insert" (1), "Fossil Filter" (1), "Inlet with Insert" (1)
Gravel Wetland	1	2	1	"Submerged Gravel Wetlands" (1)
Other	**18**	**4,597**	**35**	**"Other" (6), "Pond" (2), "Shade Tree" (1)**
Unknown	**16**	**2,977**	**17**	**"Unknown" (8), "Retention" (2), "Filtration System" (2)**
Swales Strips	**15**	**13,052**	**25**	**"Vegetated Swale", "Grass Swale", "Swale"**
Swale	14	9,764	16	"Vegetated Swale" (3), "Grass Swale" (3), "Swale" (2)
Strip	8	3,288	9	"Vegetated Filter Strip" (2), "Swales-Vegetated Filter Strips" (1), "Vegetative Filter Strip" (1)
Gross Pollutant Trap	**11**	**441,288**	**21**	**"Catch Basin", "Inlet", "Drop Inlet"**
Gross Pollutant Trap Unknown	10	419,130	8	"Catch Basin" (6), "Inlet" (4), "Drop Inlet" (2)
Screens Nets Baskets Racks	4	21,938	9	"Trench Drain" (2), "Catch Basin Drain" (1), "Grated Inlet" (1)
Hood	3	56	3	"Snout" (2), "Modified Manhole with Snout" (1), "Mechanical Separation" (1)
Gross Pollutant Trap Other	1	164	1	"Debris Basin" (1)
Stormwater Conveyance	**6**	**5,615**	**19**	**"Culvert" (1), "Storm Water Inlet Drain" (1), "Level Spreader" (1)**
Disconnection	**4**	**477**	**9**	**"Simple Disconnection to a Pervious Area" (1), "Depaving" (1), "Grass" (1)**
None	**4**	**122**	**8**	**"None" (1), "Proposed" (1), "CDA to a Shared BMP" (1)**
Multiple	**1**	**54**	**4**	**"Multiple GI Components" (1), "Dual System" (1), "Aqua-Shield-Filter" (1)**

Note: MOP-coarse SCMs are **bolded** and left-aligned. MOP-fine SCMs are listed under the MOP-coarse SCM terms to which they belong. For both MOP-coarse and MOP-fine, the number of cities including that SCM, the total number of times that SCM was listed, the number of terms used to label that SCM, and the three most common terms listed by cities representing that SCM are presented along with the number of cities including that term in their inventory

Since federal regulation leaves the management of stormwater to state and other local agencies, such as state Departments of Environmental Quality, we evaluated whether SCM terms were similar for cities within the same state. There were four states with multiple cities with inventories: California, Colorado, Pennsylvania, and Arizona. In California, Los Angeles' inventory included 13 terms, Sacramento's included 9, San Diego's included 11, and San Francisco's included 33. Out of those the only common SCM terms used between cities included *vegetated swale* which appeared in Sacramento's and San Diego's inventories and *bioretention* which appeared in San Diego and San Francisco's inventories. In Colorado, Denver's inventory included 17 terms and Fort Collins' included 13. Out of those only *unknown* appeared in both inventories. In Pennsylvania, Philadelphia included 26 terms and Pittsburgh included 13. *Porous pavement, green roof,* and *other* appeared in both inventories, a small number compared to the total number of terms included. The two SCM inventories from Arizona cities had the fewest SCM terms and the most similar SCM terms out of cities in the same state, suggesting Arizona cities are using a simpler and more standardized nomenclature. Phoenix included 8 SCM terms and Tucson included only 4. Three of the four terms included by Tucson also appeared in Phoenix's inventory. Those included *detention basin, retention basin,* and *bioretention.*

It is unclear why the cities in Arizona used similar SCM nomenclature while the other cities from a given state did not. We explored three possible explanations. First, we investigated if the terms appeared in both Arizona inventories simply because there were few terms included and they were rather non-specific, but there was only one other city using all three shared terms (i.e., Washington D.C.). Second, we investigated if it was due to both Arizona cities being younger cities that are implementing SCMs in areas of new growth, whereas many other cities are retroactively implementing SCMs in already developed spaces. The data did not support this though, as Washington D.C. is a much older city. The last possible explanation we explored is that common SCM nomenclature is related to state-wide and/or regional organizations associated with stormwater. We did not identify any statewide associations or agencies in Arizona however, that may be driving more uniform adoption of SCM terms. There it could be that Tucson, being in close proximity to Phoenix (~300 km), has referred to Phoenix when making decisions regarding stormwater. Phoenix established the non-profit organization STORM ("STORM (STormwater Outreach for Regional Municipalities)" n.d.) in 2002 in response to federal regulations. Their focus is on educating the public about protecting the quality of stormwater. It could be that the existence of such programs has led to a more uniform SCM nomenclature regionally. Overall, we found that different SCM terms are used by different cities, and next examine whether a function-based nomenclature might be used to group these unique SCM terms.

Exploring Function-Based Nomenclature (Question 2)

We grouped the terms included in city inventories into broader groups so they can be more easily understood and used for cross-city comparison studies (Choat et al. 2021). We did not use all 378 SCM terms because 35 described types of facilities that were not considered to be SCMs (*other*; e.g., "Green Wall", "Planting Area"), 19 described *stormwater conveyance* (e.g., "Culvert", "Riser") which we did not consider in our subsequent analysis, 17 terms were too vague to properly place under an SCM category (*unknown*; e.g., "Unknown", "Stormwater Treatment System"), and 8 terms described either proposed SCMs or specified that there was no SCM there (*none*; "Proposed", "CDA to a shared BMP"). Another 9 terms described *disconnection* of impervious surfaces (e.g., "Impervious Surface Removal", "Depaving"), but such terms were only reported by 4 cities and there were no two cities reporting the same *disconnection* term. After accounting for terms falling into the o*ther*, *stormwater conveyance*, u*nknown, none, and disconnection* categories, there were 290 terms placed under the WEF-ASCE nomenclature (i.e., MOP-coarse and MOP-fine).

When it was unclear which group an SCM term should be placed in, documentation from the city using that SCM term was referenced, such as web-based sources describing the design of the

SCM. For example, *ROW subsurface pipe-broken stone* was included by New York City, NY. Here, we knew ROW implies it was installed in a right-of-way area, but it was unclear what the function or form of the SCM was. After searching the New York City government websites, we found a document (NYC Environmental Protection n.d.) that makes clear that this SCM term referred to a perforated pipe with broken stone surrounding it which is meant to allow water to infiltrate into the subsurface. So, we placed this SCM term in the *infiltration basin* MOP-fine group and *infiltrator* MOP-coarse group. For proprietary SCMs that were listed we referenced the manufacturers description. In rare cases best judgement was used to place an SCM term, but if there was uncertainty about where to place a it, it was placed in the *unknown* category.

There are many possible ways to group MOP-fine classes into broader SCM groups. One approach is to use the MOP-coarse classes used by WEF and ASCE-EWRI, building on Minton (2007). Other groupings may be possible when focusing on specific functions. For example, do SCM groups based on quantity-focused functions differ from groups based on pollutant-oriented functions? We sought to understand how the WEF and ASCE-EWRI classifications may differ when using different unit processes (i.e., quantity control, pollutant control, biological control, other, and all).

To investigate if we could build on the ASCE-WEF nomenclature so that particular functions of SCMs are directly communicated, we performed a non-hierarchical and unconstrained clustering using k-means partitioning based on each of: overall, water quantity, water quality, biological, and other unit processes provided by each SCM (Table 1.1; Table S1.2). This resulted in a total of seven function-based grouping schemes for SCM terms: the coarse and fine schemes from WEF and ASCE-EWRI (Table 1.1) and five k-means clusters based on unit processes. The vegan package (Oksanen et al. 2019) in the R statistical programming language (R Core Team 2020) contains pre-programmed tools to assist with statistical ecosystem analysis and was used to perform k-means clustering where the simple structure index (Dimitriadou 2017) was used to select the optimal number of clusters, k. Using k-means clustering on binary data (i.e., presence/absence data) essentially uses the number of presence values within each category considered so can sometimes perform poorly using such data. To ensure the resulting clusters were reasonable we inspected them and concluded that they were more similar within clusters than between them which is the purpose of k-means clustering.

There were five groups of SCMs that clustered together regardless of which unit processes (all, quantity, pollutant, biological, or other) were used for clustering (Fig. 1.2; Table S1.2). However, these groups included other SCMs depending on which functions were considered. For example, *infiltrators* always clustered together, but *dry basins* clustered with them based on quantity functions, *bioretention* clustered with them based on pollutant functions, *sand filters* clustered with them based on biological functions, and *wet basins* and *wetlands* clustered with them based on other functions. The SCM classification and nomenclature system differed based on which SCM functions were being considered, indicating little possibility that there could be a universal function-based nomenclature for SCMs that communicates all SCM functions.

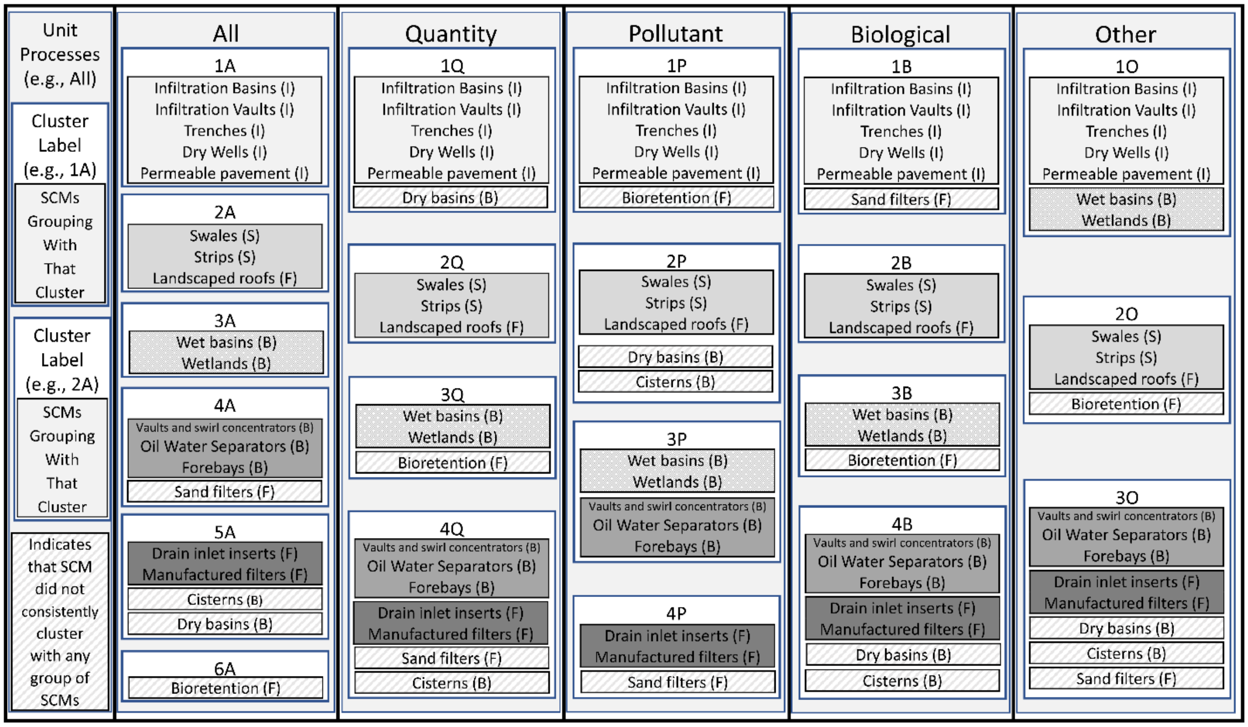

Fig. 1.2. k-means clusters based on unit processes provided. The farthest left column is a legend indicating how to interpret the other columns. Each of the other columns presents the clusters of SCMs resulting from k-means clustering using the unit-processes noted at the top of the column (e.g., 1A). For example, boxes 1A-6A present the 6 clusters of SCMs that resulted when using all unit-processes for clustering. Boxes with the same shades of gray or fill patterns indicate SCMs that grouped together despite which unit-processes were considered. SCMs in boxes by themselves and with gray diagonal lines (e.g., Cisterns) were not consistently grouped with each other or other SCMs. Original MOP-coarse groups are presented in parenthesis next to each SCM term: (I) = Infiltrators, (S) = Swales and Strips, (B) = Basins, and (F) = Filters. Table S1.2 in supplementary material combines Table 1.1 and Fig. 1.2 to easily see which unit processes are provided by SCMs in different clusters.

Why is SCM nomenclature still so heterogeneous between cities?

Despite efforts to develop a simpler and standardized SCM nomenclature (Minton 2007; Shrestha and Brodie 2011; WEF and ASCE-EWRI 2012), the SCM inventories we collected have clearly shown that those efforts have not been widely received or implemented. As Minton pointed out in 2007, the existence of duplicative and overlapping terms is common in the early evolution of new fields. It is with time that consolidation of terms occurs, as duplicative and poorly defined terms are removed from use. Calling stormwater management a new field is far from accurate (National Research Council 2009), but the field is rapidly evolving (WEF and ASCE-EWRI 2012). This rapid evolution is occurring in the absence of regulatory or institutional incentives that would motivate a more standard approach to SCM nomenclature, leaving adaptation and innovation to largely occur at the city level.

Allowing cities, counties, or other jurisdictions to take custom approaches to stormwater management ensures they can implement location-appropriate methods, which in turn can drive more diverse approaches and spur innovation. However, being able to communicate the methodology, successes, and failures of local approaches to other cities is necessary to support broadscale adoption of effective stormwater management. To move towards a more standardized nomenclature we suggest the use of a reference such as WEF's and ASCE-EWRI's manual of practice (2012) which built directly on Minton (2007). For those that do not have access to such resources, the tables and figures presented in this article should serve as a good point of reference. Even if we never achieve a fully standardized nomenclature, the use of common references should at least reduce the number of terms being used over time (Minton 2007).

However, our exploration of WEF and ASCE-EWRI's function based classifications, and how they grouped based on different types of functions, showed that using a name to effectively and efficiently communicate all important details about the form and function of an SCM is not possible. After thoroughly exploring the SCM inventories of 23 United States cities, we suggest a shift towards standardized record keeping. We propose cities have a common subset of fields for SCM function which would enable practitioners and researchers to easily understand the stormwater goals and performance in different cities. Using the fields in Table 1.1, the city can notate which functions are intended to be fulfilled by each SCM by marking presence or absence of that function. Additional information that would benefit future stormwater analysis includes a quantitative estimate of the intended function, such as what portion of the water entering an SCM is designed to be evapotranspired, infiltrated, or used as water supply, SCM footprint, contributing area, treatment depth, date installed, and maintenance regimen. Moving towards a more standard SCM record keeping approach would allow for locally-appropriate approaches to continue while enabling easy cross-boundary communication about the specifics of SCMs being implemented.

Conclusions

Being able to compare and contrast how different cities are facing the common challenge of stormwater management would accelerate the evolution of the field toward effective approaches that result in desired site- and watershed-scale performance. To address the isolated holding of SCM data we collected SCM inventories from 23 United States cities and explored the SCM terminology used across the country and within states. We found that:

1. Cities are not using comparable SCM nomenclature in the United States or within states. A notable exception is that the two SCM inventories we collected from Arizona used several of the same terms with 3 of 4 terms used by Tucson also being used by Phoenix.
2. A function-based nomenclature that efficiently and effectively communicates SCM function is not feasible. For all information about SCM form and/or function to be communicated, a complex nomenclator, similar to efforts by Shrestha and Brodie (2011), would be required and would likely not be adopted. While SCM nomenclature follows a slow evolutionary process towards a more simplified and standardized form, we highly encourage those maintaining SCM inventories to expand them to include information on function needed to understand the intended and observed performance and effectiveness of an SCM or SCM network.

Information sharing is essential for broadscale adoption of effective approaches that meet the multi-dimensional and multi-scale goals now associated with stormwater management (Marsalek 2013; Minton 2000; Taira et al. 2018). We hope that the SCM inventories we have collected (Choat et al. 2021) and our exploration of function-based SCM nomenclature will motivate more robust SCM data collection, record keeping, and information sharing and will enable cross-city comparison studies that are invaluable to hydrology and watershed studies.

Data Availability

Some or all data, models, or code generated or used during the study are available in a repository or online in accordance with funder data retention policies (Database of Implemented Stormwater Controls (DISC); https://tinyurl.com/HUB-DISC). Some or all data, models, or code that support the findings of this study are available from the corresponding author upon reasonable request (SCM data not found in the DISC and code used for analysis).

CHAPTER 2: UNDERSTANDING WHAT PHYSICAL, CLIMATIC, SOCIOECONOMIC, AND/OR REGULATORY FACTORS ARE DRIVING SELECTION OF STORMWATER CONTROLS IN UNITED STATES CITIES[2]

Introduction

Stormwater management is a necessary practice in every city with heightened investment driven by regulatory compliance, increased urbanization, aging infrastructure, and climate change (U.S. EPA 2016). In 2012 the U.S. Environmental Protection Agency (US EPA) estimated that an investment of approximately $19.2 billion in stormwater management was needed to meet national water quality objectives of the Clean Water Act (U.S. EPA 2016). Flood mitigation in urban settings, via water conveyance, has been a primary focus of stormwater management since its first implementation (Chocat et al. 2001; Delleur 2003; National Research Council 2009). Newer types of stormwater infrastructure designed to clean, harvest, infiltrate, detain, or retain storm runoff (referred to here as stormwater control measures; SCMs) have been regulated and implemented in U.S. cities for decades (Eger et al. 2017; National Research Council 2009; Roy et al. 2008). More recently, it has become clear

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[2] This chapter is in preparation for submission to the Journal of Environmental Management
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that to achieve the goals of stormwater management at site- and city-scales, SCM networks must be considered in addition to individual SCMs implemented in isolation . Furthermore, cities wishing to develop their stormwater plans, especially small and midsize cities, can greatly benefit by learning from other cities that already have mature plans (Clary et al. 2002; Driscoll et al. 2015; Taira et al. 2018).

Understanding broad drivers and constraints of city SCM assemblages would enable cities to make more effective city-scale stormwater plans. This is especially true for cities with less mature stormwater programs. As opposed to implementing individual SCMs in a piecemeal way, cities may begin with an understanding of what types of SCM assemblages have been implemented by cities in similar physical, socioeconomic, regulatory, and climatic settings. However, it is not clear if or how federal regulations requiring management of stormwater have interacted with city-scale physical, climatic, and socioeconomic factors to shape current SCM assemblages.

Comparison of stormwater management in multiple cities is required to understand what the strongest drivers and/or constraints of varying stormwater management approaches are. Yet, few cross-city comparisons of stormwater management exist, and those that do only compare a few cities at a time. For example, three cities in similar social and ecological settings in Utah had different designs and densities of implemented SCMs and each city's stormwater infrastructure varied through time on its own trajectory (Hale 2016). While that study only considered storm sewers, detention basins, and canals, McPhillips and Matsler (2018) compared eight types of SCMs. They found that types of SCMs in Portland, OR; Phoenix, AZ; and Baltimore, MD, have become more diverse over time: evolving from SCMs with large footprints and single-purpose functions to more SCMs with smaller footprints and multi-purpose functions. Hale (2016) explicitly highlighted the need for cross-city comparison studies of stormwater infrastructure with large sample sizes in order to understand the factors driving SCM variation between cities.

Although there are no studies statistically analyzing SCMs between many cities (e.g., more than 3), there has been extensive work to identify important considerations when selecting SCM types. A study in the Great Lakes area of the United States interviewed stormwater professionals from across the region (Polich 2017). Those interviews highlighted that local considerations such as topography, soils, and climate as well as citizen awareness were thought to drive stormwater management decisions. Constraints such as tighter rules from state and local regulators, which are often driven by federal regulation, and more expensive land required for larger SCMs also drive the adoption of new SCM technologies (Polich 2017). A panel of experts in the field of stormwater identified that meeting permit compliance in a cost-effective way was the primary driver guiding decision-making for municipal stormwater infrastructure projects (Bell et al. 2019). The potential benefits of SCM networks, however, are now recognized to go beyond permit compliance. The Water Environment Federation and American Society of Civil Engineers (2012) identified, “flood control, stream channel protection, groundwater recharge, water quality improvement, protection of public safety, health, and welfare,” and more as potential SCM benefits. As such, they suggested considerations when selecting SCMs, including physical, construction and maintenance, environmental, social factors, and permitting.

It is known that local stormwater design and criteria manuals have a strong influence on SCM selection at the site scale, but understanding current SCM assemblages using such manuals is challenging. For example, most cities have had manuals evolve over time (McPhillips et al. 2021) so comparisons with current SCM inventories would require a date of SCM installation in order to associate the specific manuals with specific SCMs. This would make it more difficult to obtain a large enough sample size (e.g., enough cities that had SCM inventories with date of SCM installation) to reveal meaningful statistical relationships. There is also the fact that some cities use multiple manuals (McPhillips et al. 2021), as illustrated by the recent work by Grabowski et al. (2022), where they investigated 122 plans in just 20 cities to understand how cities define green infrastructure, a type of infrastructure most frequently associated with stormwater management. Furthermore, it is often difficult to obtain such documents, even in cities with combined sewers (Hopkins et al. 2018). Even if manuals for all cities could be easily obtained, using data directly to reveal statistical relationships between SCM inventories and physical, climatic, socioeconomic, and regulatory variables has greater potential to gain insight to the underlying drivers and constraints of stormwater management – on which, local design and guidance manuals are based.

Important considerations have been identified for the selection of individual SCMs, but it is not clear what factors have actually driven and/or constrained current city-scale SCM assemblages. To compare SCM assemblages and understand drivers of assemblages across cities, our goal was to use the database of implemented stormwater controls (DISC; Choat et al. 2021) to perform a rigorous statistical analysis on SCM assemblages testing a general hypothesis that physical, climatic, socioeconomic, and regulatory attributes of cities are governing their SCM assemblages. This hypothesis is predicated upon the idea that like species, individual SCMs have niche environments in which they will perform optimally, and that like species assemblages, SCM assemblages evolve out of the interplay of environmental drivers and constraints. To meet this research goal, we asked the following questions:

1. How do SCM density and assemblages of SCMs differ among U.S. cities?
2. Which physical, climatic, regulatory, and socioeconomic variables or classes of variables best explain differences in SCM assemblages between cities?
3. Have federal regulatory programs related to the Clean Water Act had quantifiable effects on the SCM inventories of U.S. cities?

Methods

To address our research questions, we first collected stormwater control measure inventories from as many cities as reasonably possible (Choat et al. 2022). After compiling a list of possible explanatory variables based on hypothesized relationships with SCM types and SCM assemblages, we collected and analyzed data representing the possible explanatory variables.

1. Data Collection

We used SCM data from the database of implemented stormwater controls along with data from six additional cities for a total of 23 cities (Fig. 2.1; Choat et al. 2022). All SCM data were received by the authors as spatial data except for dry-wells in Phoenix, AZ, catch basins in New York City, NY, and green roofs, inlets, drains, and catch basins in San Francisco, CA, which came as lists. While we collected data for gross pollutant traps (e.g., catch basins) we did not end up using gross pollutant traps in our analysis, as discussed in more detail below in next section. Choat et al. (2022) used k-means clustering to group SCMs that provide similar processes based on quantity control processes, pollutant control processes, biological processes, other processes, and by considering all four groups of processes, resulting in five classifications of SCMs in addition to a fine and a coarse resolution classification system, for seven total SCM classification systems. Of the 23 cities we collected data for, 15 were MS4 phase I cities, 8 were MS4 phase II cities, 9 had combined sewer systems within their boundaries, and 5 were under consent decrees with the US EPA (i.e., Baltimore, MD, San Diego, CA, San Francisco, CA, Seattle, WA, and Washington D.C.). Of the five cities under a consent decree, all were MS4 Phase I cities and three had combined sewer systems. Eight Köppen climate regions (Beck et al. 2018; Köppen 1923) were represented by the cities with humid-subtropical being the most prominent (7 cities). With the exception of the southeast and north-central parts of the country, most Köppen climate regions of the country were represented.

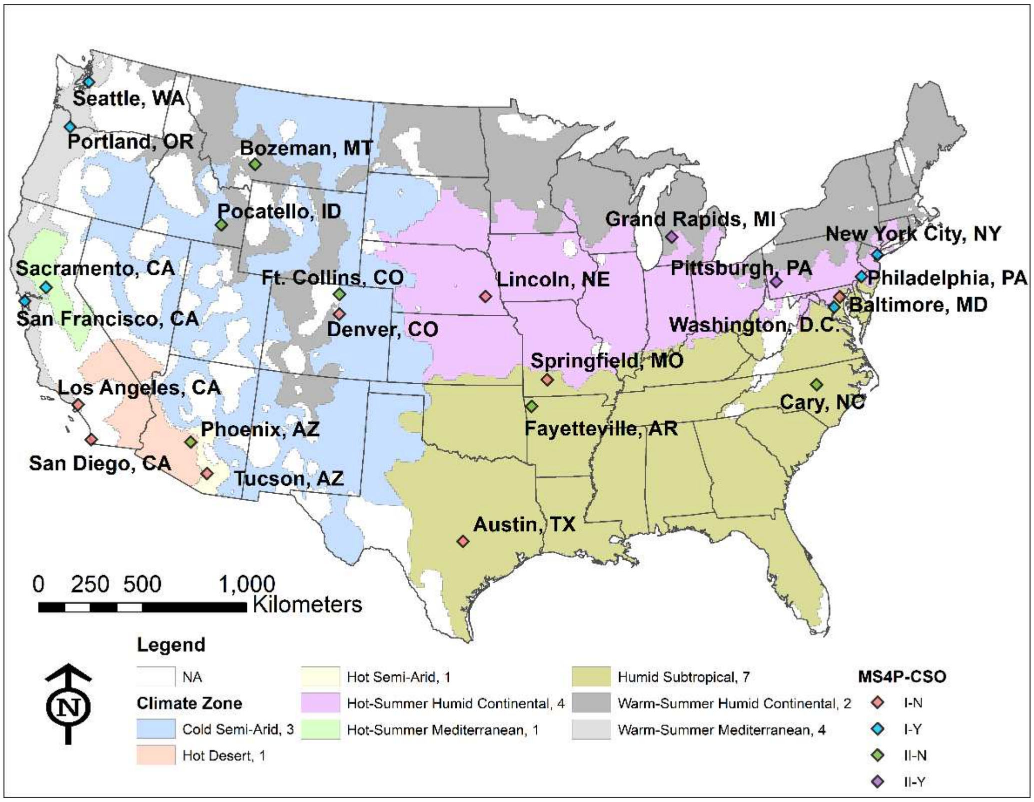

Fig. 2.1. Map of 23 U.S. study cities. Legend defines Köppen climate zones (Beck et al. 2018) and how many cities fall within each zone. "NA" represents climate regions that do not contain a studied city. MS4P-CSO specifies if each city is a MS4 Phase I (I) or Phase II (II) city and if the city has a combined sewer present (Y) or not (N). Colors match those in Fig. 2.2.

Possible explanatory variables that were collected (Table 2.1) included physical, climatic, socioeconomic, and regulatory variables that were hypothesized, based on anecdotal evidence, to either directly affect SCM assemblages or to be indicators of variables that directly affect SCM assemblages. For example, we hypothesized that shallow depth to water table would limit the implementation of infiltration-based SCMs and that older cities would have a less diverse composition of SCMs since available SCMs have become more diverse over time. Examples of indicator variables (Fayers and Hand 2002; Haraldsson 2000) used in this study are median housing age which was used as an indicator of city and infrastructure age, population density which was used as an indicator of development density and type (e.g., compact vs sprawl), and minimum, mean, and maximum depth to water table were used to indicate groundwater conditions throughout each city. The only variables we hypothesized would affect SCM assemblages but that we did not include in our analysis were related to the subsurface and included soil properties and depth to bedrock. Soil variables were not included because there was poor coverage in the study cities from existing national-scale soil databases (e.g., SSURGO; Shuster et al. 2021; Wieczorek 2014). For example, SSURGO's coverage of saturated hydraulic conductivity data ranged from 0% to about 59% of city land area with an average coverage of only 28%. The only datasets of depth to bedrock that we were able to identify have relatively low accuracy and their creators urge caution when applying them (Hengl et al. 2017; Shangguan et al. 2017) so depth to bedrock was also not included in our analysis. Despite the exclusion of these subsurface properties, the analysis presented herein provides useful insights. The processing steps for each explanatory variable and example hypotheses are described in Table S2.1 and the values of the explanatory variables are presented in Table S2.2. All spatial data was converted to the North American Datum 1983 (NAD83) geographic coordinate system and projected to the USA Contiguous Albers Equal Area Conical projected coordinate system. To be consistent between datasets and analyses between cities, all SCM and explanatory variable data were clipped to city boundaries when possible (i.e., lists could not be clipped).

Table 2.1. Explanatory Variables.

Type of Variable	Description	Continuous or Categorical	Data Source
Physical	Impervious Percentage (mean)	Continuous	(Homer et al. 2012)
Physical	Impervious Area	Continuous	(Homer et al. 2012)
Physical	Mean slope in the city based on 3dep	Continuous	(U.S. Geological Survey 2019)
Physical	Standard dev. of slope in the city based on 3dep	Continuous	(U.S. Geological Survey 2019)
Physical	Ratio of total withdrawals as groundwater	Continuous	(Dieter et al. 2018)
Physical	Annual minimum (spatially) depth to water table	Continuous	(Fan et al. 2013)
Physical	Annual maximum (spatially) depth to water table	Continuous	(Fan et al. 2013)
Physical	Annual mean (spatially) depth to water table	Continuous	(Fan et al. 2013)
Climatic	30 Year Average Precipitation (in.)	Continuous	(PRISM Climate Group n.d.)
Climatic	Magnitude of the 2-year, 24-hour precipitation event (in.)	Continuous	(NOAA n.d.)
Climatic	30 Year Average Max Temperatures (Deg. F)	Continuous	(PRISM Climate Group n.d.)
Climatic	30 Year Average Mean Temperatures (Deg. F)	Continuous	(PRISM Climate Group n.d.)
Climatic	30 Year Average Min Temperatures (Deg. F)	Continuous	(PRISM Climate Group n.d.)
Climatic	30 Year Average Max Vapor Pressure Deficit (hPa)	Continuous	(PRISM Climate Group n.d.)
Climatic	30 Year Average Min Vapor Pressure Deficit (hPa)	Continuous	(PRISM Climate Group n.d.)
Climatic	Aridity Index based on Köppen approach [mm/C]	Continuous	(Beck et al. 2018; Köppen 1923; PRISM Climate Group n.d.; Quan et al. 2013)
Socioeconomic	Population Density (person/mi^2)	Continuous	(“U.S. Census Bureau QuickFacts” n.d.)
Socioeconomic	Median Household Income (2013-2017)	Continuous	(“U.S. Census Bureau QuickFacts” n.d.)
Socioeconomic	Median Housing Age (Years)	Continuous	(“Census Reporter” n.d.)
Regulatory	Percent of lentic waterbody area considered impaired (303d)	Continuous	(U.S. EPA n.d.; U.S. Geological Survey n.d.)
Regulatory	Percent of lotic waterbody length considered impaired (303d)	Continuous	(U.S. EPA n.d.; U.S. Geological Survey n.d.)
Regulatory	MS4 Phase (I or II)	Categorical	(“Enforcement and Compliance History Online” n.d.)
Regulatory	Are combined sewers present in the city (Y or N)	Categorical	(“Enforcement and Compliance History Online” n.d.)
Regulatory	Is the city under a consent decree with the USEPA? (Y or N)	Categorical	(U.S. EPA and OECA n.d.)

Note: The type of each variable is noted in the first column (Type of Variable). A brief description of each variable is presented in the second column (Description). If the variable is continuous or categorical is noted in the third row (Continuous or Categorical). The citation for each data source is noted in the fourth column (Data Source).

2. Intercity Stormwater Control Measure (SCM) Comparison and Analysis

To compare SCM assemblages between cities (Question 1), we used the definitions and classification systems identified by the American Society of Civil Engineers (ASCE) and Water Environment Federation (WEF) in the manual of practice *Design of Urban Stormwater Controls* (2012) (referred to here as Manual of Practice (MOP) and built upon by Choat et al. (2022). Those classification systems included what we considered to be a fine resolution classification system (MOP-fine) that contained 27 SCM types and a coarse classification system (MOP-coarse) which contained five SCM types (Table S2.3). Our analyses focused on SCMs falling under the four MOP-coarse categories of basins, swales and strips, filters, and infiltrators. Simple definitions for these SCMs can be misleading by ignoring the diversity of form and functions found within each type (Choat et al. 2022), but for the sake of clarity we provide short definitions in Table 2.2 (WEF and ASCE-EWRI 2012) or see Table S2.3 for a detailed breakdown of the functions provided by the various SCM types. The fifth MOP-coarse category of gross pollutant traps was excluded because they include SCMs such as screens that are simple inline treatment devices with limited functionality other than gross-pollutant removal. They can also be expected to be found in every city yet were only included in eleven cities' inventories. In eight of the eleven cities' inventories in which they were listed, they accounted for greater than 80% of the listed SCMs and in one case as much as 99.5% of all SCMs. Including gross pollutant traps would have greatly skewed our analysis.

Table 2.2. MOP-Coarse SCM definitions.

SCM Type	**Definition** (WEF and ASCE-EWRI 2012)
Basin	Unit operations in which water is detained for a period that varies with the type of basin and the design requirements.
Swales and Strips	Unit operations with the distinct purpose of conveying stormwater from one point to another at very shallow water depths.
Filters	Unit operations where stormwater flows through an engineered porous medium and into an underdrain.
Infiltrators	Unit operations in which a design volume is infiltrated to the native soil to recharge aquifers.

We compared SCM density (total SCM counts per impervious area) and relative SCM abundance (count of each SCM type per total SCM count) under each of the classification systems. An unbiased Shannon diversity index, H', (Bowman et al. 1971; Hutcheson 1970; Shannon 1948) was calculated as a measure of SCM assemblage diversity to better understand which cities listed a greater diversity of SCMs and what was driving that diversity. Adapted to our analysis, H' was a function of the proportion of SCM type i out of all SCMs in a city, (p_i), the number of unique SCM types in that city, (S), and the total number of SCMs in that city, (N), so was a useful measure for understanding city SCM assemblages. The Shannon diversity index was calculated as,

Eq. 1 $$H' = -\sum_{i=1}^{S} p_i ln(p_i) - \frac{S-1}{N} + \frac{1-\sum p_i^{-1}}{12N^2} + \sum \frac{p_i^{-1}-p_i^{-2}}{12N^3}.$$

To address our second research question about which explanatory variables or classes of variables best explain differences in SCM assemblage, we used four statistical approaches. First, to investigate which variables or classes of variables best explain SCM assemblages, where assemblage indicates relative abundance of all SCM types (Question 2), we investigated linear relationships between classes of explanatory variables and groups of response variables using redundancy analysis (RDA) for each of the classification systems, followed by permutation tests for significance. RDA is a constrained ordination technique that combines principal component analysis with multiple linear regression to reveal linear relationships between groups of explanatory and response variables. It is a technique commonly used in ecology to understand species composition in a species assemblage and statistically assess the variation explained by environmental variables (Borcard et al. 2018; Legendre and Birks 2012). Under our general hypothesis that SCM assemblage is governed by external factors (Hale 2016; McPhillips and Matsler 2018), RDA has direct application to analyses of SCM compositions of cities. In our analysis we analyzed individual SCM types (individual species) that make up SCM assemblages (species assemblages) in individual cities (habitats). SCM counts were Hellinger-transformed (square root of relative abundance) such that variables with many zeros or very low counts would be given lower weight (Legendre and Birks 2012). RDA using Hellinger-transformed SCM counts from each of the seven classification systems was applied to compare relative abundance of the different SCMs as opposed to total counts of each SCM.

Combined with RDA, we applied multiple linear regression, a natural extension of RDA, to investigate correlations between Hellinger-transformed SCMs and the explanatory variables remaining in the best RDA models. We used forward selection that maximized $R^2_{adj.}$ while minimizing p-values and identified and removed collinear explanatory variables (variance inflation factor (VIF) > 10). Explanatory variables remaining in the best models produced by RDA that considered only explanatory variables of one class were then included in a final RDA producing final models considering physical, climatic, socioeconomic, and regulatory variables.

Our second statistical approach was specifically for MOP-coarse SCMs. Variation partitioning by subtraction (Borcard et al. 2018) was performed to identify what portion of the variation in SCMs was explained by each class or combination of classes of explanatory variables. The vegan package (Oksanen et al. 2019) in R was used for RDA and variation partitioning.

Our third statistical approach was used to complement findings from RDA and to investigate if any single variable explained the observed differences in SCM assemblages. In this approach, we performed non-parametric tests on the Hellinger-transformed MOP-coarse SCMs and each of the explanatory variables. For the continuous explanatory variables, we applied Spearman's correlation (Spearman 1987) and to further investigate the effects of regulation, we applied the rank sum test (Mann and Whitney 1947; Wilcoxon 1992) to the categorical variables (i.e., combined sewer (CSO) presence, if the city is under a consent decree, and MS4 phase). Non-parametric tests were used because some of the data did not pass tests of normality (Shapiro and Wilk 1965) and/or equal variance (Levene 1961). In our single variate analysis of continuous variables, we included the Shannon diversity index as a response variable.

Lastly, our fourth statistical approach was used for the possibility that some continuous variables may show threshold relationships with the SCM assemblages or certain SCM types. For example, infiltrators may not be implemented below some threshold in depth to water table (DTWT). This is expected to be the case when a single infiltrator is being implemented, and we tested whether such thresholds appear when examining city-scale SCM implementation using summary statistics of the explanatory variable (e.g., mean DTWT over a city). Two approaches were taken to test if such relationships exist. First, segmented regression was performed to test if regression models produced smaller squared residuals with the inclusion of a breakpoint where the data below the breakpoint had its own line of best fit and the data above the breakpoint had its own line of best fit. For any regression models with improved squared residuals, Spearman's rank-order correlation (Spearman 1987) was used to test if statistical correlation existed between the response variables and the explanatory variables falling below the threshold or above the threshold independently. Second, the nonparametric Wilcoxon rank-sum test (Wilcoxon 1992) was used to test for statistical differences in medians in the data below and above a given threshold. To identify statistically significant thresholds, each explanatory variable data point, except for the smallest and largest 5, were tested as thresholds. If more than one statistically significant threshold was identified, only the one producing the smallest p-value was retained.

Results

SCM Assemblages and Density (Question 1)

We counted the number of SCMs per square mile of impervious area in each city to understand how SCM density differed between cities. SCM density varied over orders of magnitude with as little as 0.74 SCMs per square mile of impervious area in Los Angeles, CA and as much as 505 SCMs per square mile of impervious area in Washington D.C. (Fig. 2.2). MS4 Phase I cities and especially those with combined sewers had the greatest SCM densities.

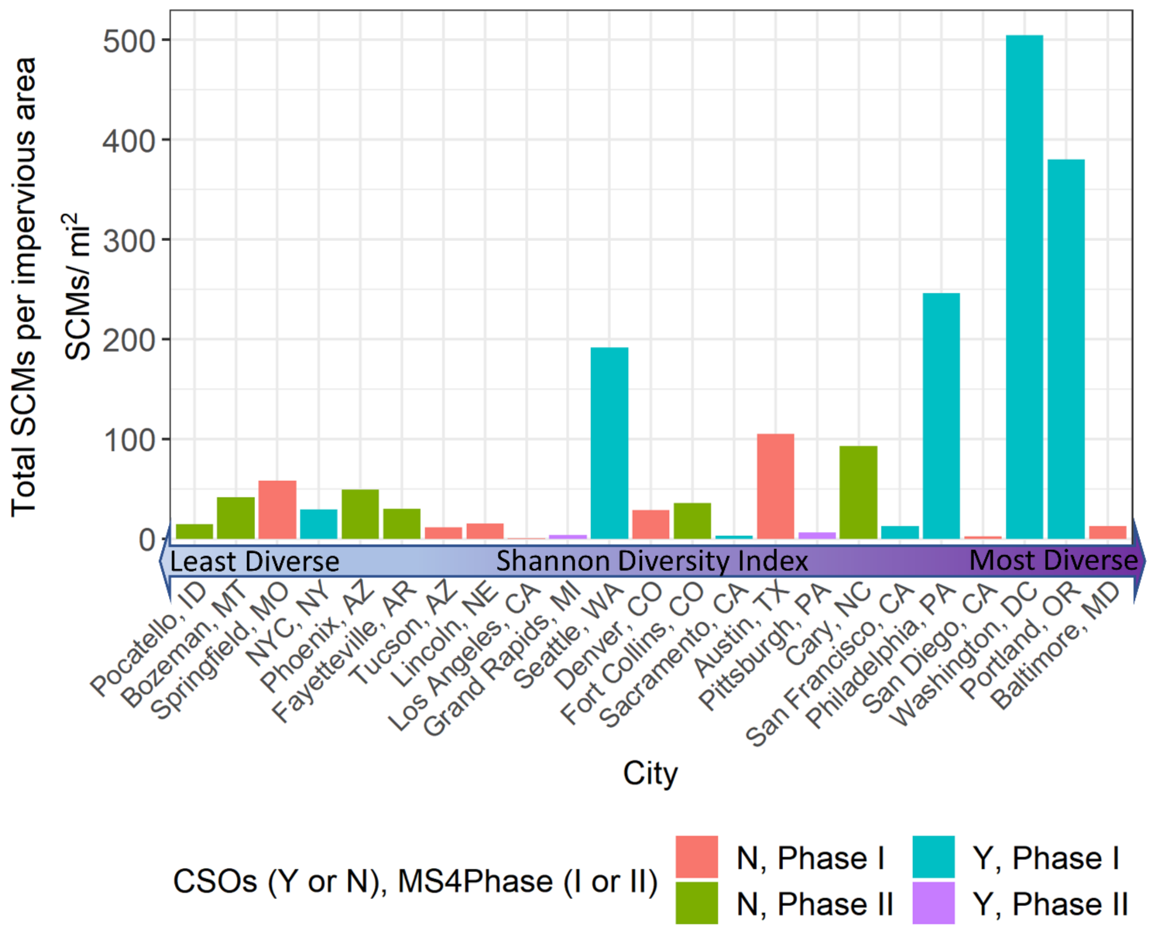

Fig. 2.2. Stormwater control measures (SCMs) per square mile of impervious area. Fill indicates combined sewers overflows (CSOs) as Yes (Y) or No (N) and MS4 phase I vs. II cities. Cities are ordered from least to most diverse from left to right based on Shannon Diversity Index scores of MOP-fine SCMs.

To better understand how SCM assemblages differed between cities, we examined the fraction of total SCM counts as each SCM type in each city (Fig. 2.3) and calculated the Shannon diversity index for MOP-fine SCMs. Diversity in MOP-fine SCMs showed large variability (Fig. 2.3). Pocatello, ID only listed one SCM that was considered in our statistical analysis (infiltration basin) and represented the lowest MOP-fine SCM diversity out of all cities (Fig. 2.3). Baltimore, MD had the highest MOP-fine SCM diversity, listing multiple types of basins, filters, and infiltrators (Fig. 2.3). Overall, basins and infiltrators were common even when MOP-fine SCM diversity was low (left of Fig. 2.3) and swales and strips and filters drove the greater diversity in cities with high diversity (right of Fig. 2.3).

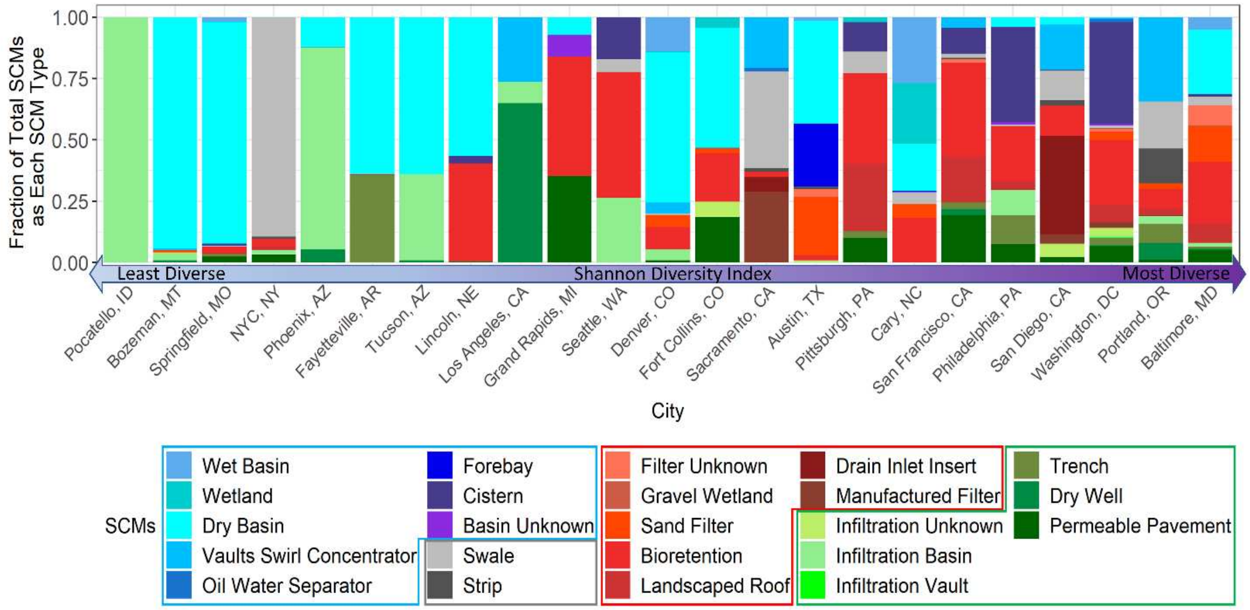

Fig. 2.3. Proportion of Stormwater control measure (SCMs) types as defined by the fine classification system established by the Water Environment Federation and American Society of Civil Engineers ordered from least to most diverse from left to right based on Shannon Diversity Index scores of MOP-fine SCMs. SCMs are color coded to represent MOP-coarse SCMs. (Blue-Purple: Basins, Gray: Swales and Strips, Orange-Brown: Filters, and Light Green-Dark Green: Infiltrators)

Analysis of Explanatory Variables for SCM Assemblages (Questions 2 & 3)

RDA, Multiple Linear Regression, and Variation Partitioning

To better understand which physical, climatic, regulatory, and socioeconomic variables, or classes of variables best explain the SCM assemblages, we first performed multivariate statistical analyses. SCM abundance across cities was best explained by physical or regulatory conditions, or a combination of those variables (Table 2.3). Neither socioeconomic nor, to our surprise, climatic variables were retained in the best models except for median household income (MHI) which remained in one model (Table 2.3). Using the MOP-coarse classification system, the physical explanatory variables that remained after forward selection were impervious percentage, standard deviation of slope, minimum, and maximum depth to water table (Table 2.3). These variables were important in describing relative abundance of basins, filters, and infiltrators.

Table 2.3: Significant RDA results for SCM classifications MOP-Coarse and MOP-Fine with Physical, Climatic, Regulatory, Socioeconomic and All explanatory variables.

Classification system	Explanatory Variable Class	Global $R^2_{adj.}$	p-value	Explanatory Variables	VIF	Response Variables	MLR $R^2_{adj.}$	MLR p-value
MOP-coarse	Physical	0.47	≤ 0.001	Impervious %	1.42	Basins	0.58	≤ 0.001
				St.Dev. Slope	2.84	Filters	0.61	≤ 0.001
				Min. DTWT	1.32	Infiltrators	0.48	≤ 0.01
				Max. DTWT	2.92			
MOP-coarse	Regulatory	0.21	≤ 0.03	Impaired Area %	1.28			
				Impaired Length %	1.82	Filters	0.41	≤ 0.02
				CSO (Y or N)	1.76	Swales and Strips	0.41	≤ 0.02
				CD (Y or N)	1.49			
				MS4Phase (I or II)	1.29			
MOP-coarse	All	0.58	≤ 0.001	Impervious %	1.66			
				St.Dev. Slope	3.47	Swales and Strips	0.55	≤ 0.01
				Min. DTWT	1.42	Infiltrators	0.52	≤ 0.01
				Max. DTWT	4.16	Basins	0.57	≤ 0.01
				Med. Hh Income	1.24	Filters	0.65	≤ 0.001
				Impaired Length %	2.00			
MOP-fine	Physical	0.45	≤ 0.01	Min. DTWT	1.12	Infiltration Basins	0.63	≤ 0.0001
				Max. DTWT	1.45	Dry Wells	0.63	≤ 0.0001
				Mean Slope	1.33			
MOP-fine	All	0.55	≤ 0.001	Min. DTWT	2.00	Infiltration Basins	0.72	≤ 0.0001
				Max. DTWT	1.17	Dry Wells	0.63	≤ 0.0001
				MS4Phase (I or II)	1.86	Permeable Pavement	0.55	≤ 0.01
				Impaired Area %	1.05			
				Impervious %	1.33			

Note: Only models with global $R^2_{adj.}$ values greater than 0.2 are presented. Only response variables with goodness-of-fits (GOFs) greater than 0.4 when considering all RDA axes (i.e., not just the first two) are presented. VIF is the variance inflation factor. MLR $R^2_{adj.}$ is the adjusted GOF which is equivalent to the $R^2_{adj.}$ from multiple linear regression. Associated multiple linear regression p-values are presented as well.

All five regulatory explanatory variables (i.e., percent waterbody length impaired (Impaired Length %), percent waterbody area impaired (Impaired Area %), presence of combined sewers (CSOY or CSON), if the city was under a consent decree (CDY) or not (CDN) and MS4 phase (MS4Phase I or MS4Phase II)) were included in the final RDA model relating regulatory variables with MOP-coarse SCMs (Table 2.3). Filters and swales and strips were the only MOP-coarse SCM types that were explained with these regulatory variables.

Impervious percentage, standard deviation of slope, minimum and maximum depth to water table, median household income, and percent waterbody length impaired remained in the MOP-coarse model considering all explanatory variables (Table 2.3). All four groups of MOP-coarse SCMs including swales and strips, infiltrators, basins, and filters were well explained by those variables suggesting they are important considerations when understanding SCM assemblages in different cities.

Infiltrator composition was the only MOP-fine class of SCMs that was well explained in any RDA model (bottom two rows of Table 2.3). The two RDA models related to MOP-fine infiltrator types and meeting the statistical criteria to be presented were similar to one another. When considering only physical explanatory variables, mean slope and minimum and maximum depths to water table were significant explanatory variables of infiltrator composition with infiltration basins and dry wells being well explained. When all explanatory variables were included, minimum and maximum depths to water table, MS4 phase, percent waterbody area impaired, and impervious percentage remained in the final model. Infiltration basins and dry wells were also well explained by these explanatory variables along with permeable pavement .

To further address explanatory variables, variation partitioning by subtraction was applied such that the variation in listed SCMs explained by each class of explanatory variable was quantified while controlling for the effects of the other classes. Variation partitioning was applied to the explanatory variables in each explanatory variable class (physical, climatic, socioeconomic, and regulatory) remaining after forward selection in RDA (Fig. 2.4). In Fig. 2.4, values within a single class of explanatory variable (e.g., 0.44 within physical under basins) indicate the unique contribution of that explanatory variable class (e.g., physical) to explaining variation in abundance of that SCM group (e.g., basins). Values falling within more than one class of variables (e.g., 0.02 within physical and socioeconomic under basins) highlights the portion of variation in abundance of that SCM group that is explained by a combination of those classes of variables. Larger values in the shared spaces of the Venn diagrams indicate intercorrelation between the variable classes. Since forward selection was applied to individual explanatory variable classes, some collinearity still existed between classes, but it was not large. Some areas of the Venn diagrams are blank because the portion of variation explained is negative, and negative values can be ignored in interpreting the results (Borcard et al. 2018). Therefore, the summation of the values within subsets of the Venn diagrams is greater than the variation explained by the entire model.

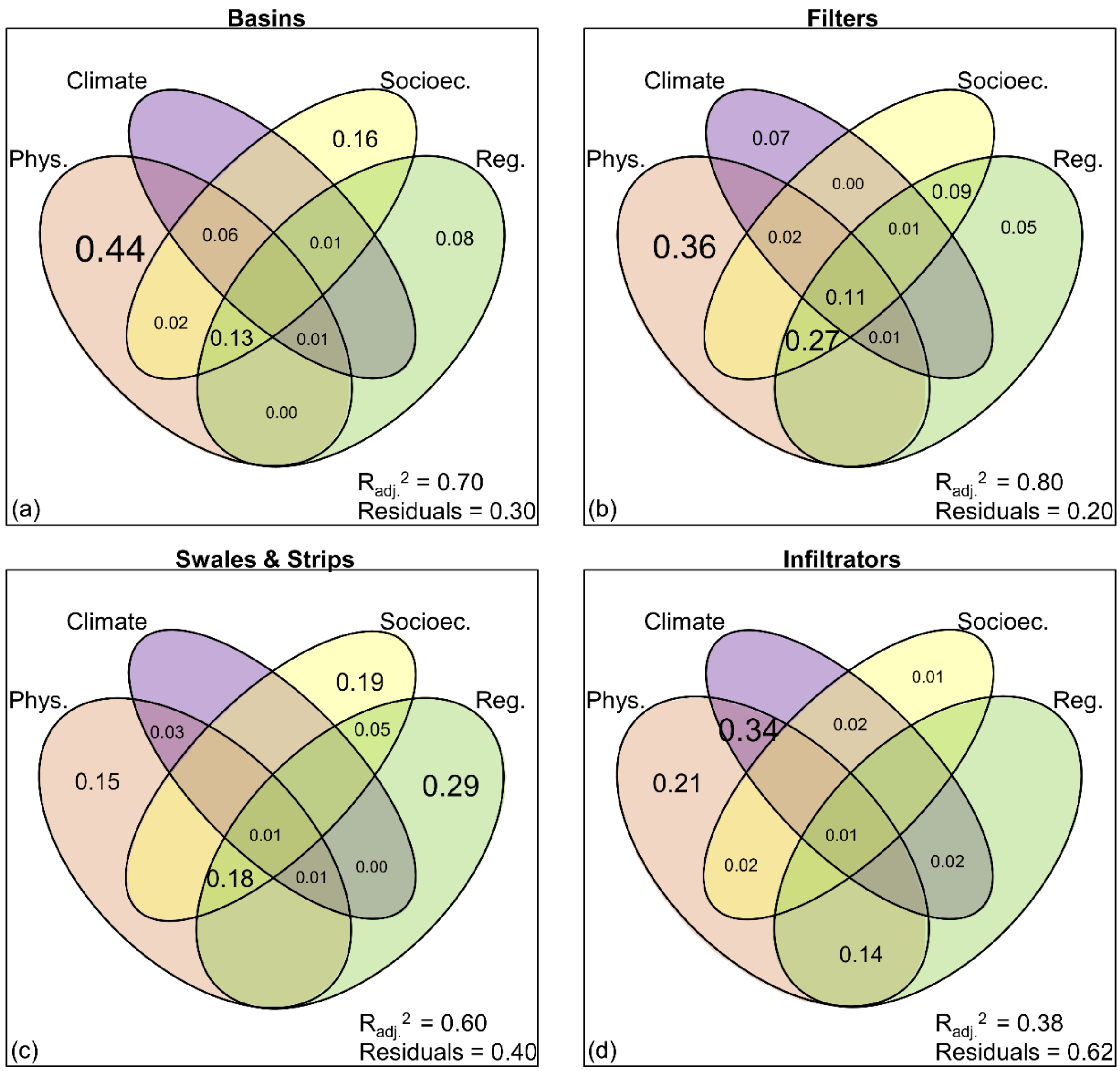

Fig. 2.4: Venn diagrams of variation partitioning for MOP-coarse SCMs. Size of the text of $R^2_{adj.}$ values in each partition are scaled by $R^2_{adj.}$ values. $R^2_{adj.}$ values less than 0 can be ignored in interpreting variation partitioning so values ≤ 0 are not shown. Peach represents physical variables, purple represents climatic variables, yellow represents socioeconomic variables, and green represents regulatory variables. Phys. = physical, Socioec. = socioeconomic, and Reg. = regulatory.

Based on the results from multiple linear regression, we expected physical and regulatory explanatory variables to explain more variation of each MOP-coarse SCM type than climate or socioeconomic variables alone. This general trend was observed (Fig. 2.4). The largest portions of variation explained by climate and socioeconomic variables were explained in combination with physical and/or regulatory variables (e.g., Fig. 2.4d). About 34% of the variation in infiltrators was explained by a combination of physical and climatic variables. However, socioeconomic variables alone did explain notable portions of basins and swales and strips. The bulk of the explained variation in basin implementation (Fig. 2.4a) was described by physical variables such as impervious percentage, slope, and groundwater conditions (Table 2.3). Filters were well explained by all four classes of explanatory variables, with physical variables being the only class of explanatory variables that explained a substantial portion of observed variation on its own (Fig. 2.4b). Swales and strips were not quite as well explained by all classes of explanatory variables (Fig. 2.4c) and infiltrators were the least well explained by the four classes of variables (Fig. 2.4d).

Single Variate Analysis (Questions 2 & 3)

To better understand if any single variable was driving the relative abundance of a given MOP-coarse SCM class, Spearman's correlation was calculated between Hellinger transformed MOP-coarse SCMs and explanatory variables (Fig. 2.5). The variables that showed statistically significant relationships with the Hellinger transformed MOP-coarse SCMs that did not remain in the strongest RDA models were mean depth to water table, 30-year average maximum vapor pressure deficit, median housing age, population, and population density. All of these variables were significantly ($p \leq 0.05$) correlated with at least one other explanatory variable remaining in the final RDA models. Mean depth to water table was correlated with minimum and maximum depth to water table, mean slope, and standard deviation of slope (Fig. S2.1). Older cities (greater median housing age) were positively correlated with population,

population density, and impervious percentage, and were negatively correlated with minimum depth to water table. Impaired area was the only explanatory variable that remained in a final RDA model but was not directly correlated with relative abundance of any MOP-coarse SCM type.

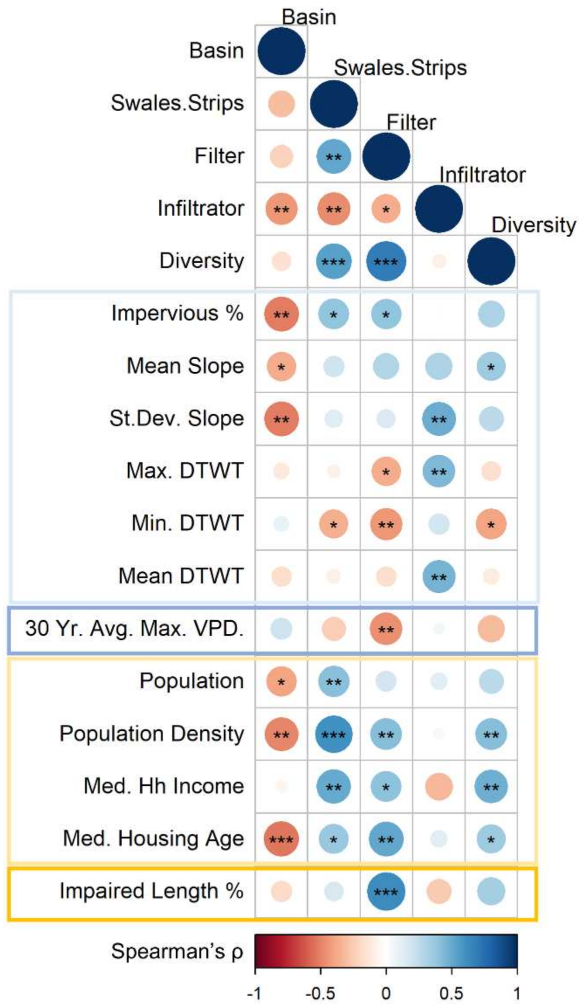

Fig. 2.5: Correlogram of Spearman's correlation coefficients between Hellinger-transformed MOP-coarse SCMs, Shannon diversity index (Diversity) of those SCMs, and explanatory variables. Only explanatory variables that were significantly correlated with at least one SCM are presented. Explanatory variables within the light-blue box are physical explanatory variables, within the dark-blue box are climatic variables, within the light-yellow box are socioeconomic variables, and within the orange box are regulatory variables. Red represents negative correlations and blue represents positive correlations. The size of the circle represents the magnitude of the correlation coefficients (e.g., large dark red circles represent strong negative correlations and large dark blue circles represent strong positive correlations). *'s specify p-values: $*p\leq0.1$, $**p\leq0.05$, $***p\leq0.01$. St.Dev. = Standard deviation, VPD = Vapor pressure deficit, Med. Hh = Median household.

Cities that were not limited by shallow water tables preferred stormwater infiltrators over basins, swales and strips, and filters (Fig. 2.5). Swales and strips and filters were implemented more often in the same cities as one another and their implementation was correlated with the same explanatory variables (Fig. 2.5). Impervious percentage, population, and population density were correlated with one another, but population density had the largest and most statistically significant correlation coefficients with swales and strips and filters. Filters were implemented less frequently when maximum depth to water table was deeper, perhaps due to greater implementation of infiltrators which can provide some degree of filtration. Filters were implemented more frequently with an increasing percentage of regulated waterways considered to be impaired (Fig. 2.5). This can likely be attributed to greater implementation of bioretention facilities, which provide the greatest variety of pollutant control out of any MOP-fine SCM type (WEF and ASCE-EWRI 2012). Also, bioretention facilities were the most commonly listed MOP-fine SCM type considered to be a filter (Choat et al. 2022).

Basins were the most frequently listed MOP-coarse SCM type (Table 2.2 in Choat et al. 2022), but the relative abundance of basins was only positively correlated with one variable, the 2-yr 24-hour design depth, and only when that depth was about 2 inches or greater (Fig. 2.5 and Fig S2). Older cities with greater impervious percentage and population density had smaller relative abundances of basins and implemented more filters and swales and strips. Of all explanatory variables, basins were most strongly and significantly negatively correlated with median housing age followed by imperviousness and standard deviation of slope. Overall diversity of MOP-coarse SCMs was positively correlated with socioeconomic variables of median household income and population density (Fig. 2.5).

Wilcoxon rank-sum analysis of categorical explanatory variables indicated that MS4 phase I cities listed higher rates of swales and strips than MS4 phase II cities ($p \leq 0.1$; Fig. 2.6). Presence of combined sewers and consent decrees led to greater differences in MOP-coarse SCM composition and diversity. In cities with combined sewers, basins ($p \leq 0.05$) were implemented less frequently in favor of swales and strips (p≤0.05) and filters (p≤0.05) leading to greater diversity in cities with combined sewers (p≤0.01). Similar trends were observed in cities that were under a consent decree, except basins did not show a significant relationship and consent decrees were a more significant predictor of the presence of filters (Fig. 2.6).

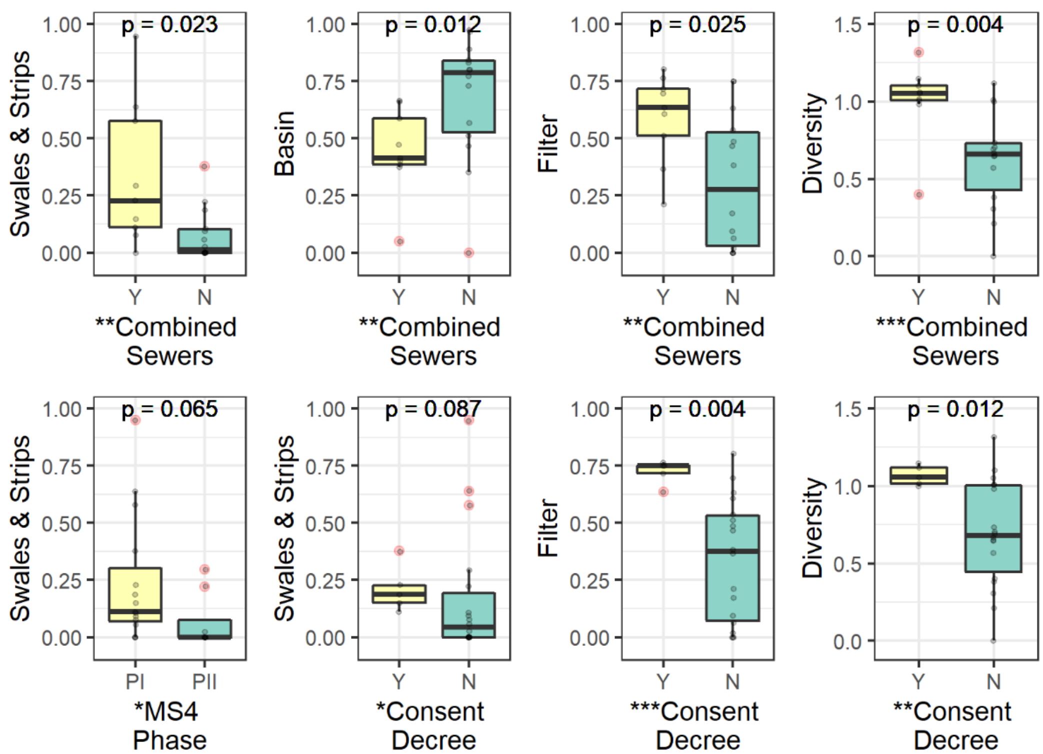

Fig. 2.6: Boxplots from Wilcoxon rank sum test on categorical regulatory explanatory variables and Hellinger-transformed MOP-coarse SCMs and their diversity. Only results with a p-value ≤ 0.1 are presented. Asterisks next to the x-axis labels note whether the results are *p≤0.1, **p≤0.05, or ***p≤0.01 and the p-value is presented at the top of each boxplot. Red dots represent outliers. The middle line of each box represents the median value, the top and bottom lines of the boxes represent the 25% and 75% quantile, and the whiskers extend to the smallest and largest values or no longer than the 25% and 75% quantiles plus 1.5 * the inter-quartile range.

Segmented regression revealed four relationships between SCMs and explanatory variables that had smaller squared residuals with the inclusion of a breakpoint compared to without one (Fig. S2.2). Of those, the only statistically significant Spearman's correlation observed was the increasing proportion of basins with increasing depth of the 2-year 2-hour design storm, and that relationship was the only significant above a breakpoint of 1.97 in. (Table S2.4). Several statistically significant thresholds (22 total; 9 with p≤0.1, 8 with p≤0.05, and 5 with p≤0.01) were identified using the Wilcoxon rank-sum test to test if SCM abundance was different below and above a given threshold (Fig. S2.3). Other than minimum, mean, and maximum depth to water table, all thresholds were identified in climatic variables (e.g., aridity index, temperature, vapor pressure deficit, annual precipitation, and the 2-year 24-hour design storm depth). These results generally suggest that infiltrators are favored over the other three SCM types in more arid (i.e., warmer and drier) climates that have greater depths to water table.

Discussion

SCM density and diversity in the study cities' inventories exhibited large variability between cities (Question 1). SCM density (i.e., SCM counts per impervious area) varied over four orders of magnitude over our 23 study cities (Fig. 2.2). One city only reported one MOP-fine SCM considered in our analysis, some cities reported three or less, while others reported more than ten (Fig. 2.3). These results could reflect record keeping practices of cities or actual SCM implementation or both. In an ideal world these would be the same, however some cities did not keep inventories of all considered SCM types. For example, Fort Collins, CO had a well-organized SCM inventory, but they did not include swales and strips in their inventory. Another example of inconsistent record keeping is that some of the cities' inventories did not include privately owned SCMs while others did. It is also possible that other groups such as counties, departments of transportation, or sewerage districts sometimes have inventories of SCMs, but we were unable to collect such inventories. These limitations create a double zero problem common in species composition data; while presence of an SCM clearly says something, the lack of an SCM is difficult to interpret. We do not know if an SCM that is not listed is simply not included in that city's inventory or if there actually are not any in the city. We addressed the limitation of the double zero problem the same way it is commonly overcome in analyses of species assemblages – by using

Hellinger-transformed SCM counts (Legendre and Birks 2012; Michel et al. 2007) instead of comparing the overall magnitude of SCMs implemented, except for our analysis of SCM density (Fig. 2.2). Despite how representative cities' inventories were of the full array of implemented SCMs, they highlight SCMs that are prioritized within a city.

Of the continuous explanatory variable classes we considered, physical characteristics of cities best explained SCM assemblages (Question 2). Physical explanatory variables as a group were the most important drivers of the composition of MOP-coarse SCM assemblages (Table 2.3) and of relative abundance of individual MOP-coarse SCMs (Fig. 2.4). However, when explanatory variables were considered individually, this was only true for infiltrators (Fig.5). On the other hand, socioeconomic variables of median housing age and population density were most correlated with relative abundance of basins and swales and strips, respectively, and filters were most correlated with the regulatory variable of percentage of regulated waterway length considered impaired (Fig. 2.5). Similarly, based on categorical explanatory variables of MS4 phase, presence of combined sewers, and whether a city was under a consent decree, infiltrators were the only SCM type that were not well explained by any of the three (Fig. 2.6). Identifying the unique contributions of combined sewers and consent decrees is difficult based on these results, but results suggest cities under consent decrees are more likely to choose filters while cities with combined sewers are more likely to choose a diverse array of SCMs. Although our analysis revealed correlations between the single explanatory variables and SCM types, some of the explanatory variables were strongly correlated with each other across classes. For example, cities with combined sewers tend to be older cities (i.e., older median housing age) and older cities had greater impervious percentage and population density, with these relationships being amongst the strongest and most statistically significant of all variables considered (Fig. S2.1). The multivariate analyses did not produce models with strongly correlated explanatory variables though, since such variables produced large variance inflation factors (Table 2.3).

Perhaps the most surprising result from our analysis was the lack of explanatory power of climatic variables. Climatic variables did not remain in any of the strongest RDA models (Table 2.3). Based on variation partitioning (Fig. 2.4) climate variables only showed moderate explanatory power of infiltrators, which was explained in combination with physical explanatory variables, and only average maximum vapor pressure deficit was statistically correlated with any of the Hellinger-transformed MOP-coarse SCM types (i.e., filters; Fig. S2.1). However, our analysis of breakpoints and thresholds in the relationships between explanatory variables and Hellinger transformed SCMs highlighted that climatic variables may be better used as categorical predictors (Fig. S2.3).

Relationship to previous studies

There are no other rigorous statistical or general comparison studies that we are aware of that have compared SCM assemblages between more than three cities. Possible reasons for this are that many cities are still developing and refining their databases to store SCM information, and terminology differences make such comparisons challenging (Choat et al. 2022). Our results are generally supported by McPhillips and Matsler (2018) though, who similarly found that impervious cover, economic activity, and changes to policy over time directly influenced the types and rates of SCMs implementation. On the other hand, Hale (2016) found that the development of stormwater infrastructure was decoupled from impervious cover. However, for Hale's analysis they included conveyance structures, which could have resulted in different conclusions than our study, which excluded traditional conveyance structures. Another important consideration highlighted by Hale was that new infrastructure is directly impacted by already existing infrastructure. This is a possible constraining factor for SCM implementation that we were not able to capture, since we did not consider temporal information on SCM implementation, but could help explain some of the variability in SCM implementation that remained unexplained by our analysis. Our analysis explained variability in SCM implementation to a large extent, but even our strongest metrics suggest we are only able to explain around 70% of the variability in SCM choice. Further work may explore in greater detail the local, regional, and national factors in decisions made in cities and across cities for how selection of SCM types is made.

Implications

Despite significant expenditures by the federal government to help eliminate and/or control nonpoint source pollution, the US EPA found that four of 13 stream and river quality indicators showed statistically significant decreases between 2009 and 2013, with no indicators showing improvement (U.S. EPA 2020). Such data imply that current stormwater management approaches are not adequate to prevent adverse downstream impacts. Results from this work suggest that SCM implementation in the 23 study cities have been influenced by federal regulations related to the Clean Water Act (i.e., regulation of cities with combined sewers, larger cities with municipal separate stormwater and sewer systems, and the utilization of consent decrees for enforcement). For example, cities with combined sewers and/or under consent decrees had greater SCM density and diversity, but it is important to note that neither SCM density nor diversity are measures of effectiveness, but rather useful measures for comparing SCM assemblages across cities. However, there is potential to provide a broader range of functions and system-wide resilience with a more diverse SCM inventory, but there is also the potential for greater maintenance time and workforce training requirements with more SCM types. In addition to federal regulations factors specific to the cities, especially physical and socioeconomic factors, are also important drivers or constraints of SCM composition. While federal regulations are clearly having an influence on stormwater management decisions in cities, this does not mean that the magnitude and type of SCMs implemented is adequate to reach water quality targets in downstream water bodies.

As more SCMs are implemented in the U.S. to meet the goals of the Clean Water Act, knowing how other cities have approached similar problems under similar constraints can help inform cities planning to implement newer approaches to stormwater management. For example, cities looking to develop a stormwater plan can find partner cities in similar settings that have already addressed stormwater challenges from whom to learn. While there are numerous factors to be considered when developing a stormwater plan and selecting SCMs (e.g., construction and maintenance, environmental factors, and permitting; WEF and ASCE-EWRI 2012) this work has provided evidence that important indicators exist that may allow for prediction of SCMs in cities, which has implications for modeling and stormwater network design. Those same indicators may be used to identify good cities to partner with as all cities attempt to deal with the challenge of urban stormwater management. For example, if a city has combined sewers and relatively shallow depths to groundwater (e.g., mean DTWT < ~ 7ft), then that city may consider partnering with Grand Rapids, MI or Sacramento, CA which are under similar constraints. Specifically, our work has shown important indicators of SCM assemblages to be impervious percentage, depth to water table, land surface slope, median household income, regulatory factors (e.g., MS4 Phase, combined sewer presence, and consent decrees), and thresholds in climatic factors (e.g., aridity index, annual precipitation, etc.) are important indicators when identifying partner cities.

Conclusions

If stormwater management is to reach its potential of meeting site-, city-, and watershed-scale goals of not only mitigating the negative effects of urbanization, but also providing additional services that improve the environment and quality of life for all, then challenges need to be explicitly addressed at each scale. Advancing the practice towards that vision will be greatly accelerated if stormwater asset management systems (Green Infrastructure Ontario Coalition et al. 2021) include SCM functions and are made available as suggested by Choat et al. (2022). However, stormwater management is not a one size fits all practice, so even if data is made available, understanding what factors are driving SCM assemblages in different cities will be useful in allowing cities to learn from one another. To advance towards that goal, we performed robust statistical analyses on SCM inventories from 23 U.S. cities to better understand SCM assemblages and what is driving variation in SCM assemblages as we addressed our research questions:

1. How do assemblages of SCMs and SCM density differ among U.S. cities?

SCM assemblages and density varied wildly between cities (Figs. 2 and 3). Some cities listed only one or two SCM types while others listed more than 10 (Fig. 2.3). The four cities reporting the largest SCM density were each MS4 phase I cities with combined sewers (Fig. 2.2). Cities that implemented a low diversity of SCMs tended to be dominated by infiltrators and basins, but as cities implemented a greater diversity of SCMs swales and strips and filters were listed more frequently (Figs. 3 and 5). New York City was the only city to report swales and strips as their dominant MOP-coarse SCM type.

2. Which physical, climatic, regulatory, and socioeconomic variables or classes of variables best explain differences in SCM assemblages between cities?

Physical variables explained the most variability in SCM types. Minimum and maximum depths to the water table remained in all but one redundancy analysis (RDA) model, suggesting depth to water table is an important constraint and indicator of SCM assemblages (Table 2.3). Climatic variables were shown to be better treated as categorical indicator variables, where cities below and above a given threshold implement different SCM types at different rates. The most statistically important socioeconomic indicator variable was median household income since population density and median housing age were highly correlated with impervious percentage. All federal regulatory variables appeared as significant predictors, but the presence of combined sewers and whether a city is under a consent decree or not were shown to be especially important indicators in understanding SCM assemblages.

3. Have federal regulatory programs related to the Clean Water Act had quantifiable effects on the SCM inventories of U.S. cities?

Variables related to federal regulatory programs (i.e., presence of combined sewers, MS4 phase, if city is under an EPA consent decree, percent water body length impaired, and percent water body area impaired) all showed statistically significant relationships with the SCM assemblages. While federal legal processes can take long periods to be implemented, this analysis of 23 SCM inventories suggests that federal regulation has helped to shape the SCM inventories in U.S. cities.

We postulated a general hypothesis that physical, climatic, socioeconomic, and regulatory attributes of cities are governing their SCM assemblages. Our results generally support our hypothesis. In many cases more than half of the variability in SCM assemblages was explained by the explanatory variables we identified. It was surprising to find that climatic variables were perhaps the least important in explaining observed SCM assemblages. Their importance was highlighted however, when they were considered as categorical predictors of individual SCM types.

While one can make assumptions about SCM function based on design, it is critical that future work further explore implications of SCM assemblages on city- and watershed-scale function. The International BMP database (Clary et al. 2002, 2020) is a wonderful resource that has helped aggregate information on function of individual SCM types, but there is still a need to further our understanding of the emergent functions of SCM assemblages, and understand broader suites of functions beyond the core water quantity and quality related functions. This would also help us understand if there is a relationship between greater diversity of SCMs and meeting the more diverse goals now common in stormwater management. Additionally, future qualitative work could further explore the development of SCM design guidelines in cities, which might provide some insight into SCM choices that could not be explained here. An important step towards these goals is the collection and aggregation of SCM assemblage data, such as expanding the database of SCMs used in this study (Choat et al. 2021) to include more cities and inventories from non-city entities.

Data Availability

Some data and code generated or used during the study are available in a repository or online in accordance with funder data retention policies (Databased of Implemented Stormwater Controls; DISC); https://tinyurl.com/HUB-DISC).

CHAPTER 3: ESTIMATING CARBON SEQUESTRATION UNDER VARIOUS LAND-USE SCENARIOS OF DRIED AGRICULTURAL LAND IN THE SOUTH PLATTE RIVER BASIN

InTERFEWS Required Sections

This chapter was developed as a requirement for the InTERFEWS program and the contributions to InTERFEWS requirements are summarized below.

Interdisciplinary Considerations

This report was motivated by an interdisciplinary challenge and utilized an interdisciplinary approach to address that challenge. Broadly, the disciplines important to the review and analysis presented in this report include economics, policy, natural resources and land management, and ecosystem services.

Economic Considerations

Sustaining rural economies in the face of drying irrigated agriculture was a primary motivation for this work. A methodological review and application of benefits transfer and valuation of carbon sequestration was performed. Specific methods for spatially explicit scenario analysis and return on investment from ecosystem services are suggested based on literature review. For example, I suggest caution when applying benefit transfer when needed data is sparce, recommend inclusion of uncertainty when developing or using tools for return on investment from ecosystem services, and estimate return on investment for three scenarios of conversion of irrigated agriculture to more natural land covers in three areas of interest in the South Platte River Basin (SPRB). Those three areas were Greeley's long range expected growth area, Brighton's South Platte River Heritage Corridor, and properties in Weld and Larimer counties that have been purchased by the City of Thornton with the intention of transferring the water from irrigated agricultural to municipal uses. Only application to the Thornton Norther Properties is presented in Chapter 3. For applications in other areas of interest please see Appendix-Chapter 3.

Policy Considerations

As the SPRB experiences rapid land conversion due to the drying of irrigated agricultural land, policy will help shape the outcomes and experiences for agrarian communities. Therefore, this work included multiple policy considerations. A review of payment for ecosystem services schemes with a focus on payments for conservation and payments for carbon sequestration is provided. Valuation of ecosystem services can help prioritize which irrigated land to keep in production and which to target with conservation programs and/or payment for ecosystem services programs, having implications for natural resources and land management related policy.

Systems-Thinking Considerations

The overall motivation for this report originates from a systems-thinking perspective. Specifically, growing urban populations are placing pressure on urban water resources, so municipalities are responding by purchasing agricultural water rights, drying what was irrigated cropland, and transferring the water to urban uses. In response, agrarian economies are likely to be strained due to the loss of substantial acreage of irrigated agriculture. This report addresses one potential response to the economic damage caused by buy-and-dry water transfers – paying landowners for ecosystem services.

Stakeholder Engagement

While this work did not specifically include stakeholder engagement as a method, it was motivated by work with the Colorado Water Conservation Board (who may be considered a stakeholder). The report also poses the question of whether the landowners in the communities in which payment for ecosystem services programs may be implemented have any interest in such programs.

DPSIR

Growing urban populations and reduced commodity prices are *driving* the transfer of water from irrigated agriculture to urban and municipal uses. Cities in the SPRB of Colorado are actively securing water supply to meet the demands of growing urban populations and industry and to ensure those demands can be met well into the future. With limited opportunities to develop new water sources, cities are resorting to the purchase of agricultural water rights with older water rights being in greater demand due to the enhanced security they provide.

Irrigated agriculture has become the cornerstone of many of the rural landscapes and economies of the SPRB. As water is transferred away from irrigated agriculture significant *pressures* are being placed on both the landscapes and economies in the agrarian communities. Land that was once irrigated is being converted to other land uses such as urban development, non-irrigated agriculture, or more natural land cover such as native grasslands. Communities that have come to rely on irrigated agriculture will experience loss or alteration of employment opportunities and the local tax base.

To characterize the situation within the SPRB important *states* to consider include: 1. The SPRB is home to 70% of the Colorado's population, 2. It demands over 2.5 million acre-ft of water for irrigated agriculture annually, 3. There are over 4 million acre-ft of water diverted from surface water sources, for all uses, annually, 4. There are another 500,000 acre-ft of groundwater withdrawn annually, 5. There are only about 1.4 million acre-ft of native water available annually, 6. Due primarily to the purchase of water rights by municipalities from irrigators (i.e., buy-and-dry), a decline of between 131,900 and 174,000 acres of irrigated agriculture is excepted to be dried by 2050 (~15-20%).

While there will be many *impacts* from the buy-and-dry trend in the SPRB, this document focuses on the *impacts* that local communities and economies which have been built around irrigated agriculture will experience as the vital economic driver and core aspect of local culture (i.e., irrigated agriculture) is significantly reduced.

The primary objectives of this document are related to a potential *response* to ease the impacts of buy-and-dry on local economies and communities while also mitigating any negative land use changes that may occur as what has been irrigated agriculture is altered to other land uses.

Intellectual Merit and Broader Impacts

This document is intended to be of practical interest to policy-oriented professionals working in the SPRB, that are also interested in climate, buy-and-dry, and ensuring the agrarian communities in the SPRB do not experience undue harm as water is transferred away from irrigated agriculture. A thorough literature review related to payment for ecosystem services with a focus on climate related ecosystem services is presented. Key points, considerations, and open questions are identified and a framework for policy-relevant and spatially explicit valuation of ecosystem services is discussed. Furthermore, a review of potentially relevant existing web tools is presented as a reference for those seeking easy access to relevant analyses. Finally, a web-tool which extends the COMET-Planner tool is presented with three example areas of interest within the SPRB. The web-tool enables easy estimates of the return on investment from conservation measures present in the COMET-Planner tool, at a property scale resolution. The work presented herein is not extremely novel, but rather, synthesizes and extends existing knowledge for policy-relevant professionals.

Introduction

Growing urban populations are accelerating land-use change (LUC) around the globe, as witnessed in the Front Range of Colorado (Angel et al. 2011; Colorado Water Conservation Board 2015;

United Nations and Social Affairs 2018). In recent history, we have witnessed LUC exacerbating climate change due to disturbed soils, development of greenhouse gas (GHG) producing land uses, and more (Houghton et al. 2012). This trend is a product of our approach to land management, however, and is not a required feature of human progress. Local decisions determine how LUC manifests with significant implications for local livability and the global challenge of climate change.

The South Platte River Basin

Like many semi-arid and arid regions of the world, the substantial gap between the supply and demand of water in the South Platte River Basin (SPRB; Fig. 3.1) is driving competition for water supply between economic sectors. The SPRB is Colorado's most populous, economically diverse, and agriculturally productive basin. It is home to 70% of the state's residents and demands over 2.5 million acre-feet of water for irrigated agriculture annually. Municipal and rural stakeholders are in competition for water resources in the basin as there are only about 1.4 million acre-ft of native water (i.e., sourced from within the basin) available annually while annual water diversions of surface water are around 4 million acre-ft, with groundwater withdrawals accounting for another 500,000 acre-ft of supply.

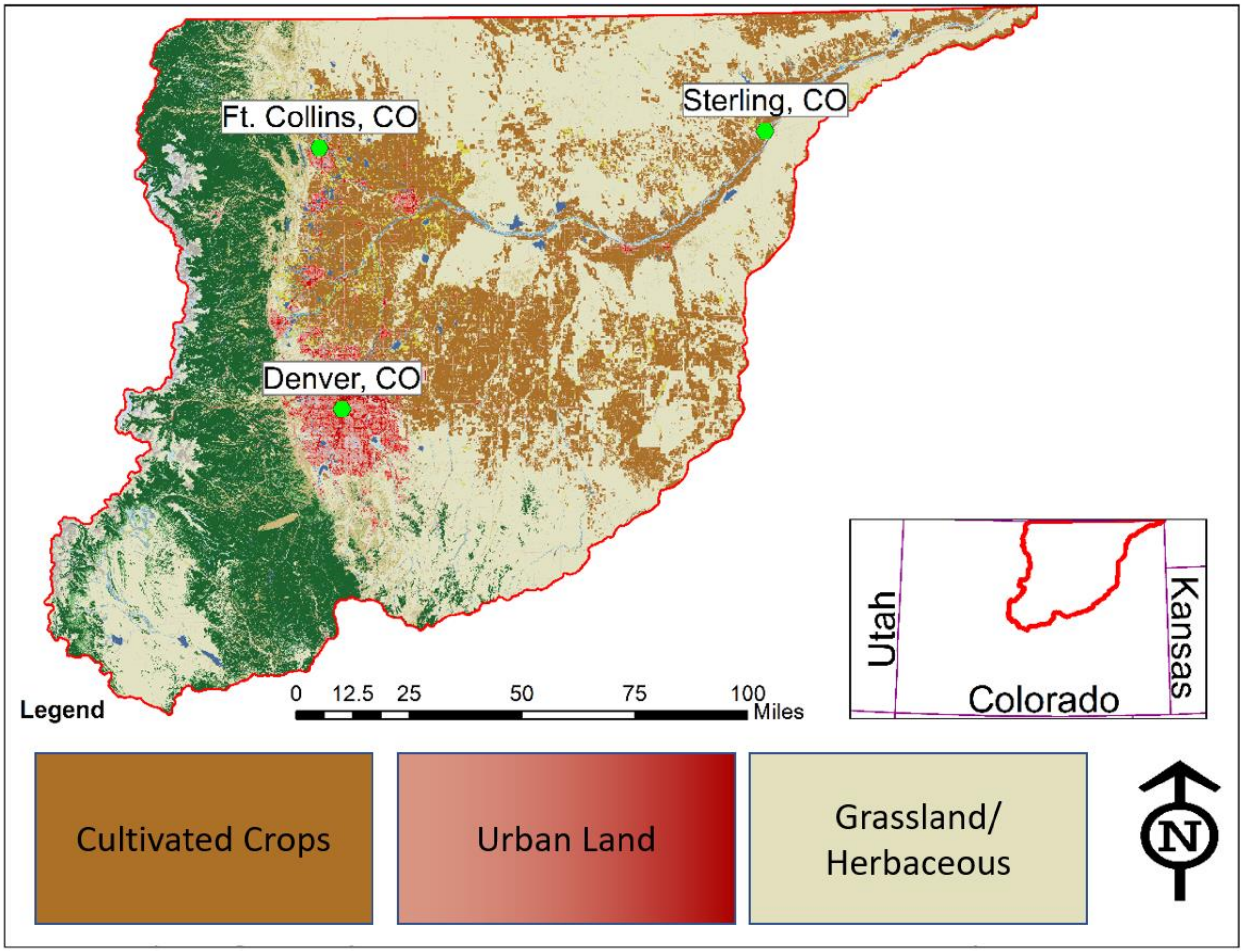

Fig. 3.1: Map of the Colorado portion of the South Platte River Basin highlighting relevant land cover from the 2016 National Land Cover dataset (Homer et al. 2012).

Of heightened interest in the SPRB is the competition between municipal (e.g., industrial and residential) and rural (e.g., irrigated agriculture) water users which has driven the phenomenon known as buy-and-dry. Within the doctrine of prior appropriation, which governs water rights in Colorado, a water user owns the rights to use water for some beneficial use, such as growing crops or an industrial use, but that water user may not use or lease the water for a different use. As the SPRB has witnessed rapid urban and industrial growth it has become common for municipalities to purchase water rights from irrigated agriculture to secure water supply for the near and long-term future of the municipality. While there are ongoing efforts to figure out ways to allow for the transfer of water without permanently drying irrigated agricultural land, the buy-and-dry trend is expected to continue through at least 2050 leading to a decline of between 131,900 and 174,000 acres of irrigated agriculture (Colorado Water Conservation Board 2019).

While direct development of land will account for a significant portion (~6-7%) of the expected loss of irrigated agriculture coming to the SPRB over the coming decades, the primary driver will be buy-and-dry. Although urbanization is relatively compartmentalized spatially, its indirect effects will be experienced throughout the basin. Many rural areas of the basin rely on irrigated agriculture to support their economies. The loss of that economic driver is likely to have significant social, cultural, and economic implications for those agrarian communities as the local tax base, employment opportunities, and general experience of living in an agricultural area are lost or altered. Of growing importance is the question of how to help maintain rural economies in the SPRB that will experience significant declines in irrigated agriculture.

Times of change provide opportunities for innovation, reorientation of goals, and for new approaches to be used to reach those goals. In early 2021, Governor Jared Polis' office in Colorado released a roadmap for the state's goals of reducing greenhouse gas (GHG) production. Within that document several steps and important considerations were highlighted that will enable Colorado to meet its ambitious climate-change goals. Of particular relevance to this work is the key finding that, "protecting, restoring, and enhancing the resilience of Colorado's natural and working lands is critical for sequestering carbon" (Governor Jared Polis' Office 2021). The Colorado Water Plan (Colorado Water Conservation Board 2015) also identified the need for additional incentives to assist basins in implementing agricultural efficiency and conservation practices to support the ecosystem services that agriculture can provide. By paying private landowners or other relevant stakeholders for providing the public good of carbon sequestration by implementing climate-smart strategies on their land, rural economies can gain an additional source of revenue. Owners of land that transition from irrigated agriculture to another land use can maintain some income while those that are fortunate enough to keep their land in production can add the additional income to their portfolio. As such, policy makers in the SPRB are interested in payments for ecosystem services (e.g., carbon sequestration, water purification, pollinator services, etc.) policies that may keep revenue flowing into rural communities in the basin while incentivizing land-use practices that benefit society at large.

The overall objective of this work was to enable easier assessment of the tradeoffs of potential uses of dried agricultural land to assist stakeholders and policymakers in the SPRB with making informed land development decisions. To meet this overall objective, two subobjectives were addressed:

1. Identify needs, traits, and options with respect to policy relevant valuation of ecosystem services
2. Perform valuation of carbon related ecosystem services in the case of irrigated agriculture drying to more natural land cover in the SPRB

To achieve these objectives literature review was first performed, exploratory data analysis with an existing dataset was undertaken to better understand the role of uncertainty in carbon sequestration in agricultural and working lands, and results from literature review were used to identify appropriate methodologies and to apply an appropriate methodology to achieve subobjective 2.

Results

Literature Review

A Need for Scenario Analysis – Land Use-Land Cover, Ecosystem Services, and Return on Investment

As the South Platte River Basin evolves as a socio-hydrological system, policy decisions are being made that will help determine the future economic, environmental, and societal health of the basin. For good decisions to be made, good information must be available. If policy makers and entities that help inform them (e.g., the Colorado Department of Natural Resources or the CWCB) require an expert each time they need to explore the climate change implications of various LULC scenarios, then cost in and of itself may become prohibitive to desired programs (Paustian et al. 2016; Van Hecken and Bastiaensen 2010). What is needed is a robust, yet easy to use tool that does not require expertise. Of particular interest is the ability to explore various LULC scenarios (e.g., Fig. 3.2) to allow for the prioritization of various policies and decisions.

Fig. 3.2: Four different land-use types in the South Platte River Basin. Images captured with Google Earth. (A) Pivot irrigation agriculture, (B) Medium-intensity residential development, (C) Peri-urban low intensity development, (D) High-intensity development. Growing populations in urban areas (B-D) are drying irrigated land (A). What are the implications of different land-use decisions with regards to water management and climate change?

Uncertainty in Estimating Carbon Sequestration and Storage

There is a vast amount of literature related to GHG production, sequestration, and storage. A quick search using the keywords "greenhouse gases" in the Web of Science results in 87,762 results, 31,707 open access articles, 6,352 review articles, and 1,385 highly cited papers (https://www.webofscience.com/wos/woscc/summary/04d67fc8-021b-4fad-8a07-149346d558bb-0df31403/relevance/1). With respect to carbon sequestration and storage, there is a significant focus on soils (e.g., Alexander et al. 2015; Conant et al. 2017; Entry et al. 2007; Kane et al. 2021; Paustian et al. 2016, 2019; Smith et al. 2020) due to a few primary reasons. First, within the top meter of soils globally, there is an estimated stock of around 5,500 – 8,800 Gt CO_2 with the lower range representing about three times the total stock of CO_2 found in vegetation and twice that found in the atmosphere. Second, as a result of cultivation and agricultural management practices, it is estimated soils have lost around 510 – 550 Gt CO_2 since agriculture became popular around 8,000 years ago (Smith et al. 2020). A 2018 systematic literature review concluded that soil carbon sequestration has the potential to sequester about 2 to 5 Gt CO_2 annually (Fuss et al. 2018). Lastly, using soil to sequester carbon can improve soils, make them more resilient to drought and climate change, and improve overall agricultural productivity (Fuss et al. 2018; Kane et al. 2021). Essentially, the literature shows that carbon sequestering agricultural practices are likely good for agricultural production and the fact that they sequester carbon is a bonus. Although we have a decent understanding of large-scale carbon storage in soils, extreme spatial heterogeneity makes it very difficult to generalize carbon storage based on management practice from place to place. Soil carbon storage is location specific, depending on climate, previous and current land-use/management, soils, and other factors (Fig. 3.3; Ramesh et al. 2019).

Conant et al. (2017) performed an extensive literature review to synthesize experiments that have compared soil carbon storage between a control treatment (e.g., traditional irrigated agriculture or an ungrazed grassland) with an 'improved' or experimental treatment (e.g., cropland transitioned to pasture or a grazed grassland). The studies took place over 37 countries representing a wide variety of conditions. They found, "improved grazing management, fertilization, sowing legumes and improved grass species, irrigation, and conversion from cultivation all tend to lead to increased soil C, at rates ranging from 0.105 to more than 1 MgC/ha-yr." To see if we could learn more from the data used in that study, which the authors made publicly available, I performed a brief data analysis. The data included observations from 241 papers, with each study comparing two or more treatments. For example, one study may have compared soil carbon in an irrigated crop plot to the soil carbon in a native grassland. Values related to soil carbon were reported in terms of storage per acre [tC/ha], although, in the related paper the authors present results in terms of carbon sequestration [MgC/ha-yr]. First, I plotted the full range of all observed stored carbon as boxplots (Fig. 3.3 – left) and then plotted the same data except limited to relatively non-humid areas of the USA (Fig. 3.3 – right) which resulted in data from 10 states. Then I plotted the data from the USA with the control treatments and "improved" (i.e., test) treatments split (Fig. 3.4 – left). Last, I plotted boxplots of study-wise differences between the control and "improved" treatments, with positive values representing better performance by the "improved" treatment and negative values representing better performance by the control treatment (Fig. 3.4 – right). Boxplots were used because they allow for an easy comparison between treatments.

The range of values of observed carbon storage per area is larger when studies from around the globe are included (Fig. 3.3 – left) compared to studies from more similar climatic and geographic areas (Fig. 3.3 – right). This is potentially simply due to fewer datapoints being included in the plot presenting observations from non-humid areas of the USA, but the idea that more similar climatic and geographic areas store more similar magnitudes of carbon follows reason (Paustian et al. 2016; Ramesh et al. 2019). In Fig. 3.3 we also observe that for four treatments (e.g., shift from ag. to pasture or modified grazing intensity) the observed carbon storage per area ranged over three orders of magnitude, highlighting the uncertainty in such measurements.

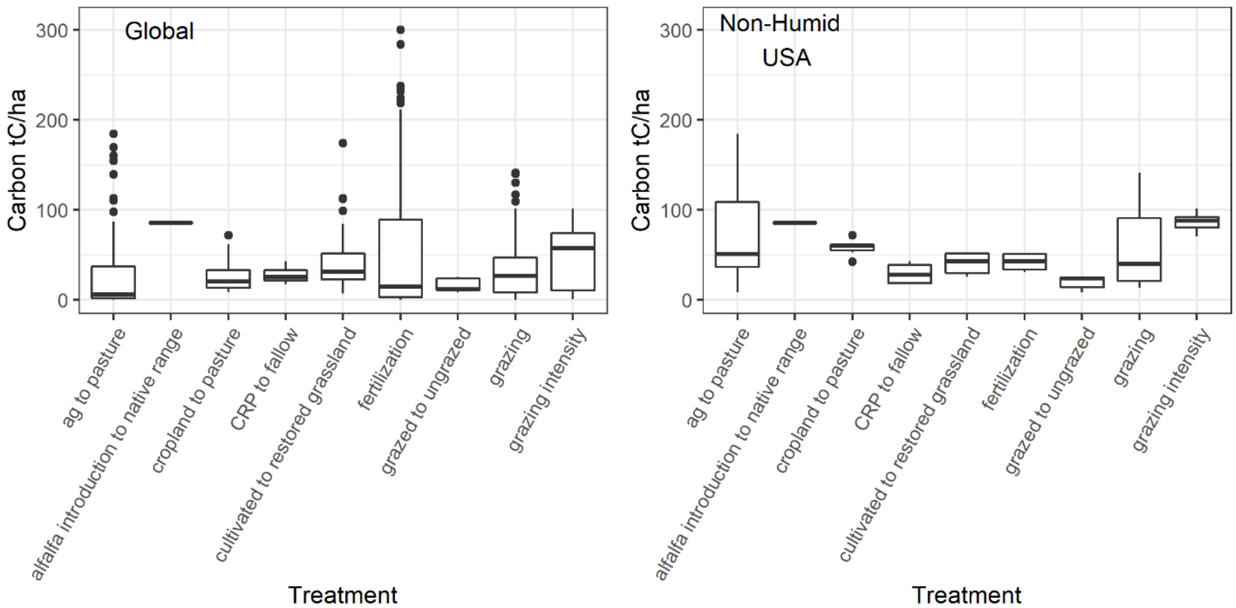

Fig. 3.3. Boxplots presenting carbon storage per area [tC/ha] based on studies around the globe (left) and on studies from the USA with humid regions removed (right). Boxplots represent the 25th and 75th percentiles as the edges of the box, the 50th percentile (median) as the line lying within the box, and the largest and smallest values falling within 1.5 times the interquartile range above the 75th percentile or below the 25th percentile, respectively. (Data from Conant et al. 2017)

Further highlighting the site-specific nature of soil carbon storage, we see that when comparing all control treatments with all "improved" treatments (Fig. 3.4 – left) it is very difficult, if not impossible, to generalize across locations. On the other hand, if we look at the study-wise differences between control and "improved" treatments (Fig. 3.4 – right) the range of observations narrows. For example, values of carbon storage per area (Fig. 3.4 – left) for conversion from *ag to pasture* range from near 0 to about 175 tC/ha. In contrast, looking at the study-wise differences of the same treatment (i.e., *ag to pasture* in Fig. 3.4- right) reveals that lands converted from agriculture to pasture almost always increase in soil carbon storage. Those differences ranged from about 0 to just over 20 tC/ha, which is nearly an order of magnitude smaller than the range observed when looking at carbon stored per area (i.e., 20 tC/ha vs 175 tC/ha). Looking at the study-wise differences between control and "improved" treatments (Fig. 3.4 – right) also shows that many treatments thought to improve (or increase) soil carbon do not always perform as expected. Taking the shift from *cropland to pasture* as an example, we see that sometimes soil carbon is increased and other times it is decreased. This inconsistent behavior is likely due to differences in soils, climates, and/or previous management or land uses (Conant et al. 2017; Olsson et al. 2014; Pouyat et al. 2006; Ramesh et al. 2019). Overall, the data from Conant et al. (2017) show us that the differences in observed soil carbon between locations is greater than the difference between management approaches. This highlights the difficulty in generalizing observations in soil carbon between locations. To minimize uncertainty in scenario analysis it may be better to use relative performance of sequestration instead of an absolute measure.

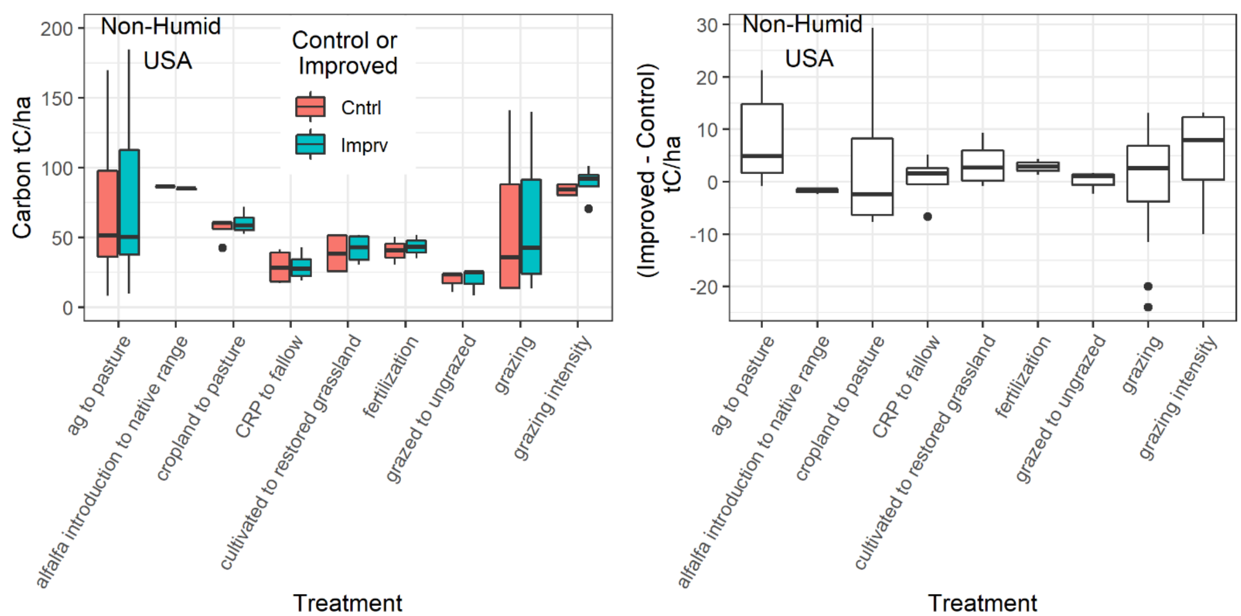

Fig. 3.4. Boxplots comparing the overall observations of carbon per area [tC/ha] between the control and "improved" treatments in all of the reviewed studies (left) and showing the study-wise differences between the control and "improved" treatments (right). Note that CRP = conservation reserve program. (Data from Conant et al. 2017)

Uncertainty in Valuating ROI from Carbon Sequestration and Storage

To assist with policy decisions, quantifying the ROI (return on investment) from carbon sequestration/GHG mitigation is highly desirable. The vast majority of efforts attempting to so consider the ROI to be the social cost of carbon (SCC) avoided. That is to say, if sequestering a ton of carbon today avoids $200 of social damage (e.g., property destruction or loss of national or global GDP) then the ROI of sequestering one ton of carbon is taken to be $200. Quantifying a value for the SCC includes extensive uncertainty and is a highly debated topic (Drupp et al. 2015; Interagency Working Group 2013; Pindyck 2019; Plummer 2009; Ricke et al. 2018). There are many ways to approach to this challenge. The Natural Capital Project's InVEST carbon model takes a simple but well-accepted approach (Sharp et al. 2020) so I use it as an example here.

A Valuation Formulation

Data requirements for valuating carbon storage and sequestration in the InVEST carbon model and many other approaches include price per metric ton of carbon, the market discount in price of carbon, and the annual rate of change in the price of carbon (Sharp et al. 2020). Price per metric ton of carbon is based on the social damage avoided as discussed above. The market discount in price of carbon refers to society's preference for present benefits over future benefits. The annual rate of change in the price of carbon is an input used to capture how the value of carbon sequestration may change over time based on the damages caused by climate change. Setting the annual rate of change to a value greater than 0% means you assume the societal value of carbon sequestered today is greater than the value of carbon sequestered in the future (Sharp et al. 2020). For example, it could be argued that sequestration has greater value now because sequestration of the same amount of carbon now compared to later may have a greater impact on climate change. Discount rates can be considered in different ways with some combining the market discount and annual rate of change for example (Pindyck

2019; Ricke et al. 2018) with others suggesting a dynamic discount rate that changes with time (Ricke et al. 2018). Discounting is consistently shown to be one of the largest sources of the differences in estimates of SCC (Ricke et al. 2018). Both market discount in the price of carbon and the annual rate of change in the price of carbon can be set to 0 in the InVEST model. Ultimately, the value of sequestered carbon over time for a given parcel, $value_{seq_x}$ (i.e., LULC pixel) is calculated as,

$$Eq.1. \quad value_{seq_x} = V \frac{sequest_x}{yr_{future} - yr_{current}} \sum_{t=0}^{yr_{future} - yr_{current} - 1} \frac{1}{\left(1+\frac{r}{100}\right)^t \left(1+\frac{c}{100}\right)^t},$$

where V is the price per metric ton of elemental carbon (not CO_2), $sequest_x$ is the amount of carbon sequestered, yr_{future} and $yr_{current}$ are the future and current years being simulated, respectively, r is the market discount in price of carbon or discount rate [%], t is the time elapsed since the current year being simulated, and c is the annual rate of change (or discount) in the price of carbon time preference [%]. It is important to note that this approach assumes a constant carbon sequestration rate over time but a constant rate is unlikely to be observed in reality (Sharp et al. 2020). Due to this assumption however, this formulation of the value of sequestered carbon lends itself to accepting outputs such as those provided by COMET-Planner (Swan et al. 2018, *seqrate;* e.g., amount of carbon sequestered per year). By simply replacing, $\frac{sequest_x}{yr_{future} - yr_{current}}$, with the carbon sequestration rate provided by COMET-Planner, $seqrate$, we arrive at the following formulation of the value provided by scenario being considered ($value_{seq}$; e.g., conversion of irrigated agriculture to native grassland).

$$Eq.2. \quad value_{seq} = (V * seqrate) \sum_{t=0}^{yr_{future} - yr_{current} - 1} \frac{1}{\left(1+\frac{r}{100}\right)^t \left(1+\frac{c}{100}\right)^t},$$

with t now being the total number of years to be included in the valuation. For example, if we wanted to estimate the value of carbon sequestration provided if 640 acres of land were converted from irrigated agriculture to a native grassland today, we must decide how far into the future we want to assume the constant sequestration reasonably applies. Lands will eventually reach an equilibrium with regard to carbon storage, where the net amount of carbon being sequestered is essentially zero (i.e., the amount being sequestered is equal to the amount being released; Entry et al. 2007).

Review of Valuation Input Variables

Deciding how far into the future to consider when estimating the value from carbon sequestration or GHG mitigation provided by a LULC scenario is not the only complicating factor. Due to sources of uncertainty related to nearly every variable used to quantify the SCC, the resulting uncertainty is extreme. Three variables in particular Ricke et al. (2018) estimated the global social cost of carbon (GSCC) by considering possible socioeconomic pathways (SSP), possible climate futures (i.e., representative concentration pathways-RCP), the potential negative impacts of climate change on the economy (i.e., using damage functions), and various discounting approaches. The resulting estimates of the GSCC are presented in Fig. 3.5 where the extensive uncertainty in the estimates can be clearly seen to range over three, and sometimes four, orders of magnitude (color bars represent the 66% confident intervals).

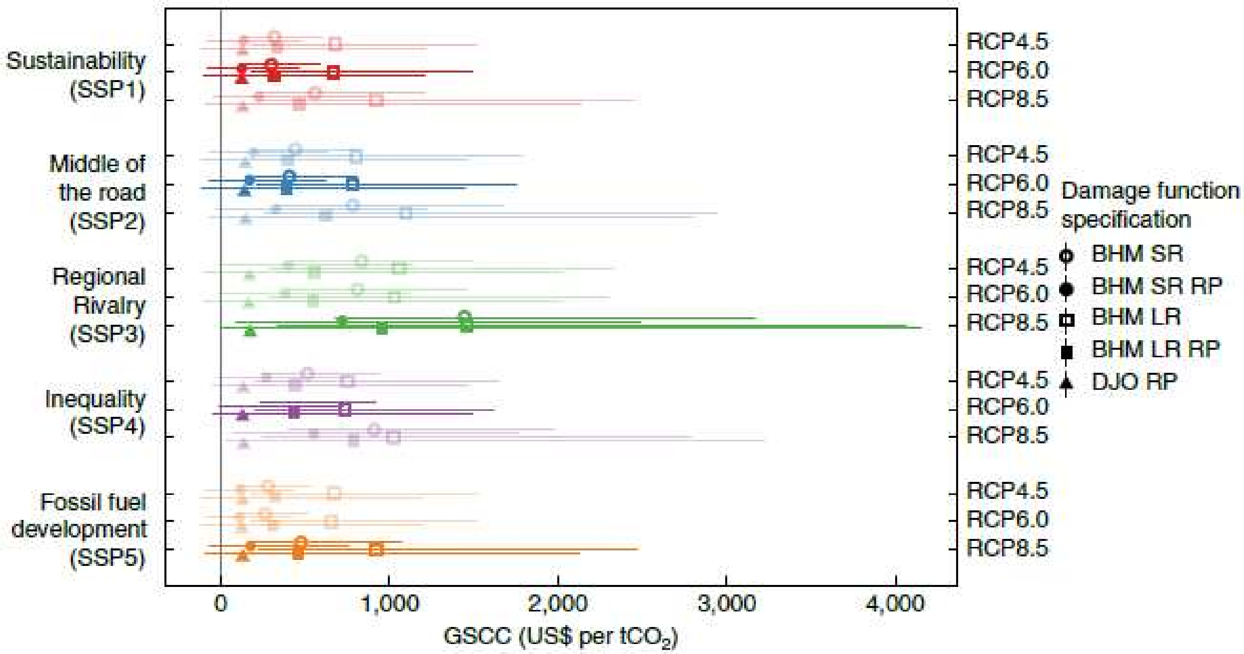

Fig. 3.5. Global SCC in 2020 under various assumptions and scenarios. Median estimates and 16.7% to 83.3% quantile bounds for GSCC under SSPs 1–5, and RCPs 4.5, 6.0 and 8.5. For each SSP, the darker colors indicate the SSP–RCP pairing with a superior consistency. The values displayed assume growth-adjusted discounting with a pure rate of time preference of 2% per year and elasticity of marginal utility substitution (μ) of 1.5. Supplementary Fig. 3.3 in the original document compares these results with fixed discounting (rate of 3%). Colored bars represent the 66% CIs. SSP = socioeconomic pathway scenarios as based on: O'Neill, B. C. et al. A new scenario framework for climate change research: the concept of shared socioeconomic pathways. *Climatic Change* **122**, 387–400 (2013). RCP = Representative Concentration Pathway as accepted by the IPCC. BHM = Burke-Hsiang-Miguel damage function (a model used to estimate social cost of carbon). DJO = Dell-Jones-Olken (another model used to estimate social cost of carbon). This graph and footnote are taken directly from Ricke et al. (2018).

The Interagency Working Group on Social Cost of Greenhouse Gases (IAWG; Interagency Working Group 2013) considered 150,000 estimates from 10,000 simulations for discount rates of 2.5, 3, and 5 percent. Those estimates were based on average SCC values produced by three integrated assessment models and the 95th percentile estimate which assumes an unlikely but highly costly scenario (i.e., close to worst-case scenario). The full distribution of the results for the three discount rates are shown in Fig. 3.6. Average values of the SCC were $12, $42, $62, and $123 for the 5%, 3%, 2.5%, and the close to worst-case scenario, respectively. Like results of Ricke et al. (2018) discussed above, these results also show high uncertainty in estimates of the SCC. The range of values estimated by the IAWG is much narrower than those arrived at by Ricke et al. likely reflecting their lack of consideration of uncertainty related to factors other than discounting.

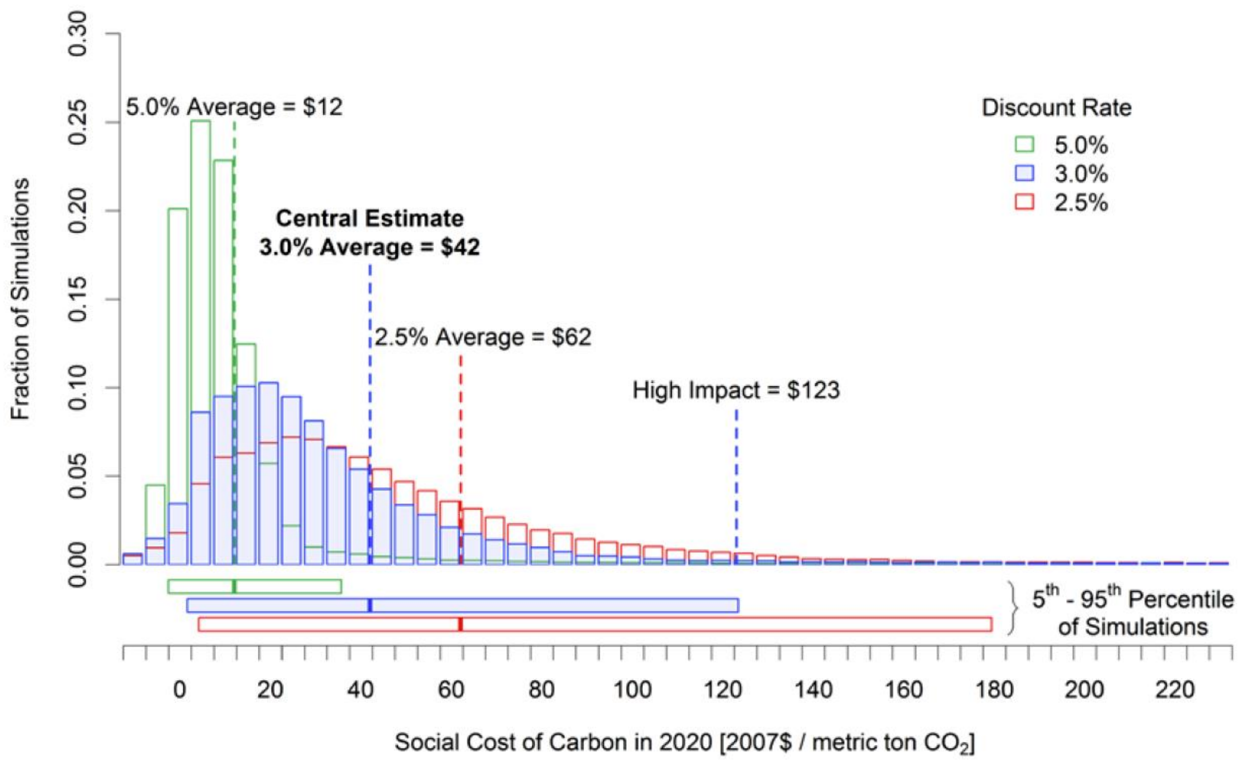

Fig. 3.6. Frequency distribution of SCC estimates for 2020. "Presents the frequency distribution of the SC-CO2 estimates for emissions in 2020 for each of the three discount rates. Each of these distributions represents 150,000 estimates based on 10,000 simulations for each combination of the three models and five socioeconomic and emissions scenarios.16 In general, the distributions are skewed to the right and have long right tails, which tend to be even longer for lower discount rates. To highlight the difference between the impact of the discount rate on the SC-CO2 and other quantified sources of uncertainty, the bars below the frequency distributions provide a symmetric representation of quantified variability in the SC-CO2 estimates conditioned on each discount rate. The full set of SC-CO2 results through 2050 is available on OMB's website. This may be useful to analysts in situations that warrant additional quantitative uncertainty analysis (e.g., as recommended by OMB for rules that exceed $1 billion in annual benefits or costs). See OMB Circular A-4 for guidance and discussion of best practices in conducting uncertainty analysis in RIAs." Based on integrated assessment models (IAMs; DICE, FUND, and PAGE) which are used by the U.S. gov't to estimate the social cost of carbon (CO2). (Interagency Working Group 2013)

Pindyck (2019) took a different approach and surveyed 386 experts including 113 economists and 220 climate scientists with 170 of those experts being from North America, 158 from Europe and 30 from developing countries. The range of SCC values resulting from the expert surveys exhibited large uncertainty and was between that of Ricke et al. (2018) and the IAWG (2013) (about one third of responses were between $0 and $100, several were spread across $100 and $700, and the mean was $291; Fig. 3.7). The primary source of uncertainty though, was related to the potential impacts of climate change and not the discount rate which was held constant at 3% for the survey questions. Also seen in Fig. 3.7 is a gamma function fit to the data as a probability distribution function (pdf; red line) that best fit the responses of all surveyed experts. Using a pdf is one way in which uncertainty may be included in estimates of the SCC and ROI from various LULC decisions. There was a marked difference in the values provided by economists and climate scientists (Fig. 3.8). Climate scientists tended to suggest much higher SCC (average of $316.3) than economists (average of $173.7), but both the averages and distributions of estimates from North America and Europe were very similar with averages of $284.5 and $284.2, respectively.

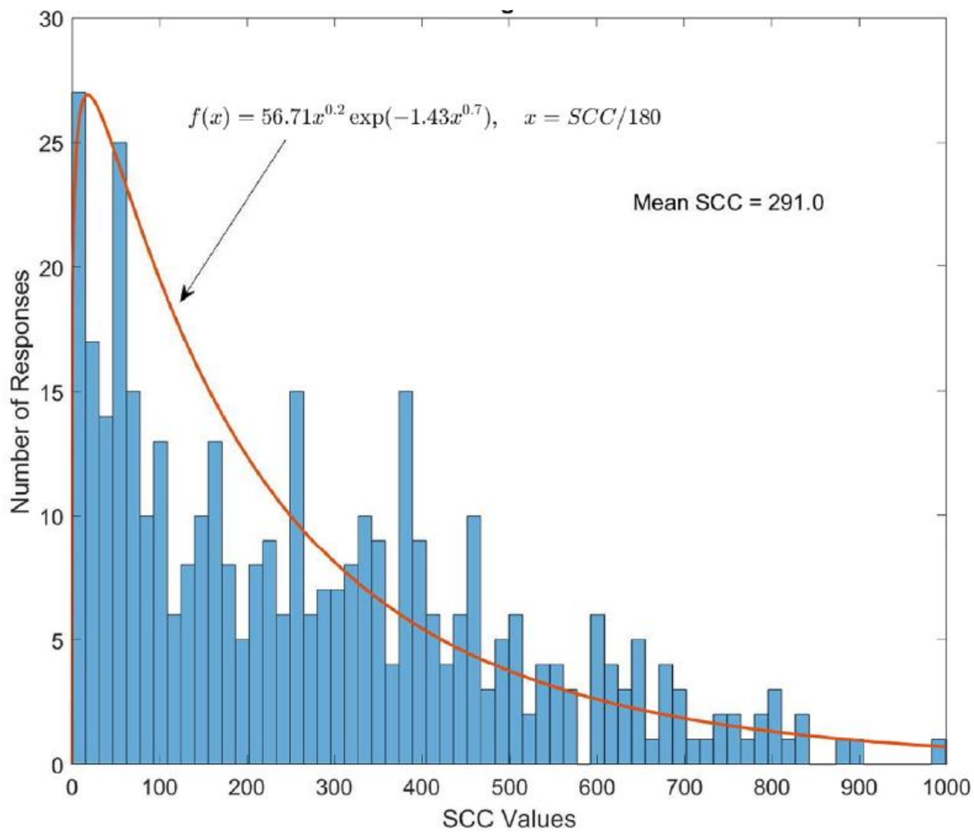

Fig. 3.7. The social cost of carbon based on an expert survey of 386 experts. (Pindyck 2019)

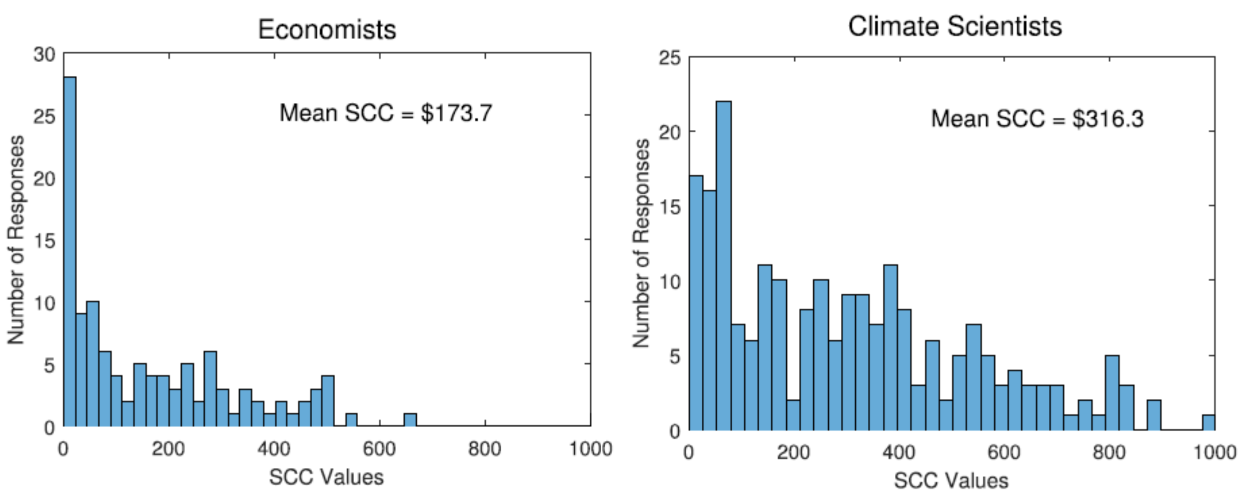

Fig. 3.8. The social cost of carbon based on surveys of economists (left) and climate scientist (right). (Pindyck 2019)

Estimates of the SCC, discount rates, and time preference rates from various scholarly literature are presented in Table 3.1. Estimates of the SCC in the table reflect averages or likely ranges as opposed to the full range of estimates found in each study. The range of the SCC was from $12 to $300. The range of discount rates was 1% to 7% with 2.5, 3, and 5 being the most common. Time preference rate ranged from 0% to 6% with values between 1% and 2% being the most common. Inclusion of the full range of values presented in Table 3.1 when estimating the ROI from climate-related ecosystem services will produce more robust estimates, but the range of estimated values will be larger.

Table 3.1. Estimates of the social cost of carbon (SCC), discount rate, and time preference for estimates of ROI

Notes	Social cost of carbon	Units	Discount Rate [%]	Time Preference [%]	Citation (See articles for their references)
"Conservative estimate"	21	US$/ton CO_2	7	0	Bagstad et al. 2012
"Non-conservative estimate"	85	US$/ton CO_2	1	6	Bagstad et al. 2012
India (66% C.I.)	86 ($49-$157)	US$/ton CO_2	3, 5, and growth adjusted	1, 2	Ricke et al. 2018
U.S.A. (66% C.I.)	48 ($1-$118)	US$/ton CO_2	3, 5, and growth adjusted	1, 2	Ricke et al. 2018
Saudi Arabia (66% C.I.)	47 ($27-$86)	US$/ton CO_2	3, 5, and growth adjusted	1, 2	Ricke et al. 2018
Brazil (66% C.I.)	24 (14–41)	US$/ton CO_2	3, 5, and growth adjusted	1, 2	Ricke et al. 2018
China (66% C.I.)	24 (4–50)	US$/ton CO_2	3, 5, and growth adjusted	1, 2	Ricke et al. 2018
United Arab Emirates (66% C.I.)	24 (14–48)	US$/ton CO_2	3, 5, and growth adjusted	1, 2	Ricke et al. 2018
USEPA estimate	12	US$/ton CO_2	5	1	IAWG 2013
USEPA estimate	42	US$/ton CO_2	3	1	IAWG 2013
USEPA estimate	62	US$/ton CO_2	2.5	1	IAWG 2013
SCC Survey of 386 experts	80 - 300	US$/ton CO_2	NA	NA	Pindyck 2019
SCC Survey w/outliers trimmed	80 - 100	US$/ton CO_2	NA	NA	Pindyck 2019
SCC	121	US$/ton CO_2	2.5	0	Pindyck 2019
SCC	101	US$/ton CO_2	3	0	Pindyck 2019
SCC	81	US$/ton CO_2	4	0	Pindyck 2019
SCC	65	US$/ton CO_2	6	0	Pindyck 2019
Discount rate only	NA	NA	1 - 3 (mean = 2.25, median = 2)	mode = 0, mean = 1.1%, median = 0.5%	Drupp et al. 2015

Development of Shiny Application

Following the important considerations highlighted so far and after investigating many freely available online tools, the COMET-Planner tool (Swan et al. 2018) was identified as the most appropriate and applicable to aiding our valuation of carbon sequestration in the scenario of irrigated agriculture drying to more natural grass cover. It has many of the traits desirable for such analysis: 1. It is relatively easy to use and does not require an expert, 2. It estimates changes, or relative increases in carbon sequestration opposed to estimating values of carbon storage that are attached to some land use, and 3. It makes place-based estimates of the relative change in carbon sequestration (i.e., estimates vary by county). COMET-Planner takes state, county, area (acres), and conservation practice as inputs (Fig. 3.9). Many Natural Resource Conservation Service (NRCS) conservation practices are available to choose from. Three conservation practices were identified as relevant to the scenario of irrigated agricultural drying to more natural land cover: 1. *Forage and Biomass Planting* conservation practice of *Conversion of Annual Cropland to Non-Irrigated Grass/Legume Forage/Biomass Crops*, 2. *Conservation Cover* practice of *Convert Irrigated Cropland to Permanent Unfertilized Grass/Legume Cover*, 3. *Conservation Cover* practice of *Convert Irrigated Cropland to Permanent Unfertilized Grass Cover*. It then outputs the approximate carbon sequestration and greenhouse gas emission reductions (tonnes CO_2 equivalent per year) broken down by contributions from carbon dioxide, nitrous oxide, methane, and total CO_2 equivalents.

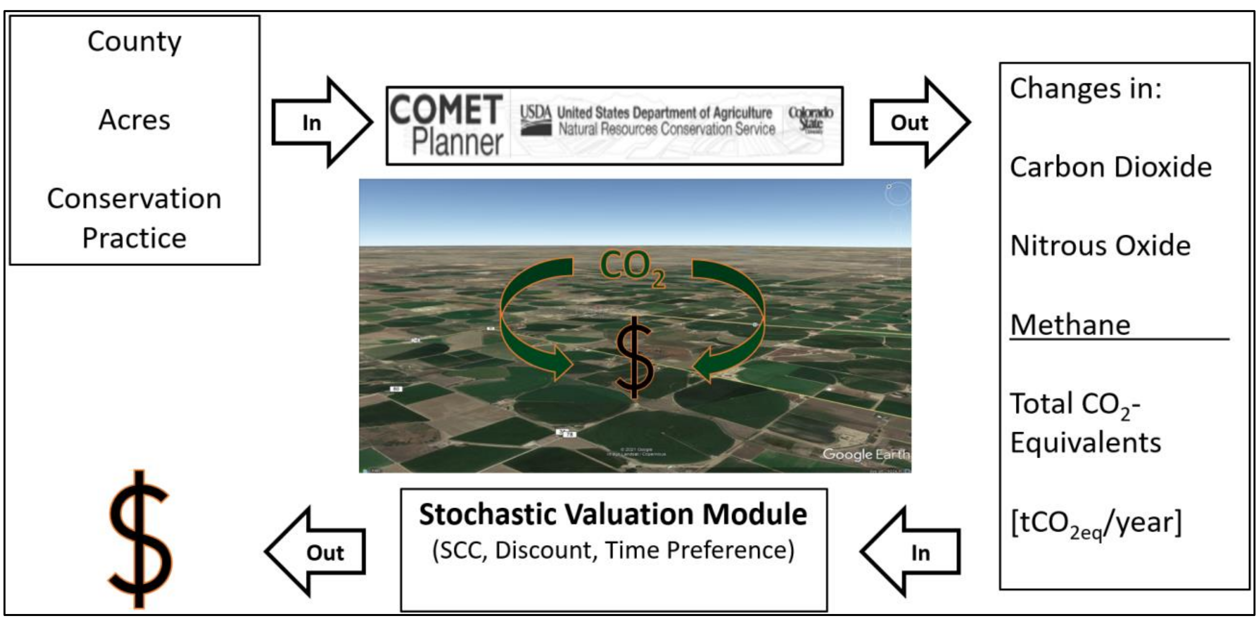

Fig. 3.9. Workflow of Shiny application used for pre- and post-processing data related to the COMET-Planner tool.

To enable policy relevant valuation of the return on investment from climate related ecosystem services, an application was developed (Pre-Post-COMET; https://liminaleng.shinyapps.io/comet_pre_post_app/) for pre- and post-processing of data for use with the COMET-Planner tool. The application was developed using R Shiny (RStudio, Inc 2013). The study area of interest includes properties purchased by the City of Thornton, CO ("Thornton Agricultural Stewardship" n.d.). Thornton purchased the properties with specific intentions of converting the irrigated acres to more natural grass cover and diverting the water from the irrigated land to the city for municipal uses.

First, the application calculates the total acreage of irrigated land by land-owner type (e.g., private, municipal, etc.) within an area of interest as defined by a shapefile (Fig. 3.10). This step produces an acreage to be used as an input to the COMET-Planner tool. Land ownership data (Colorado Natural Heritage Program and the Geospatial Centroid n.d.) and irrigated lands data from 2015 ("Division 1 - South Platte | Colorado's Decision Support Systems" n.d.) were used for identifying land ownership type and irrigated lands. After retrieving estimates of the tonnes of CO_2 equivalents per year from the COMET-Planner tool (Fig. 3.11), those estimates are used as inputs into the next and final step of the Pre-Post-COMET application (Fig. 3.12) - Valuation. The valuation tab allows user specified inputs defining the type of probability distribution to be used for representing the social cost of carbon as a random variable. Normal, log-normal, and uniform distributions are available. Normal and long-normal distributions are defined using mean and standard deviation as input parameters. Uniform distributions are defined by providing the minimum and maximum values. Monte-Carlo simulations are performed by sampling the defined distribution 600 times with random draws without replacement. Values of social cost of carbon below zero were dropped from consideration. Then discount rate and time-preference variables are represented as uniform distributions and are sampled at six equal intervals each. All combinations of the 600 draws from the social cost of carbon distribution, and the six discount rate values and six time-preference values are used to calculate a range of potential return on investment values. Return on investment is calculated using equation 2.

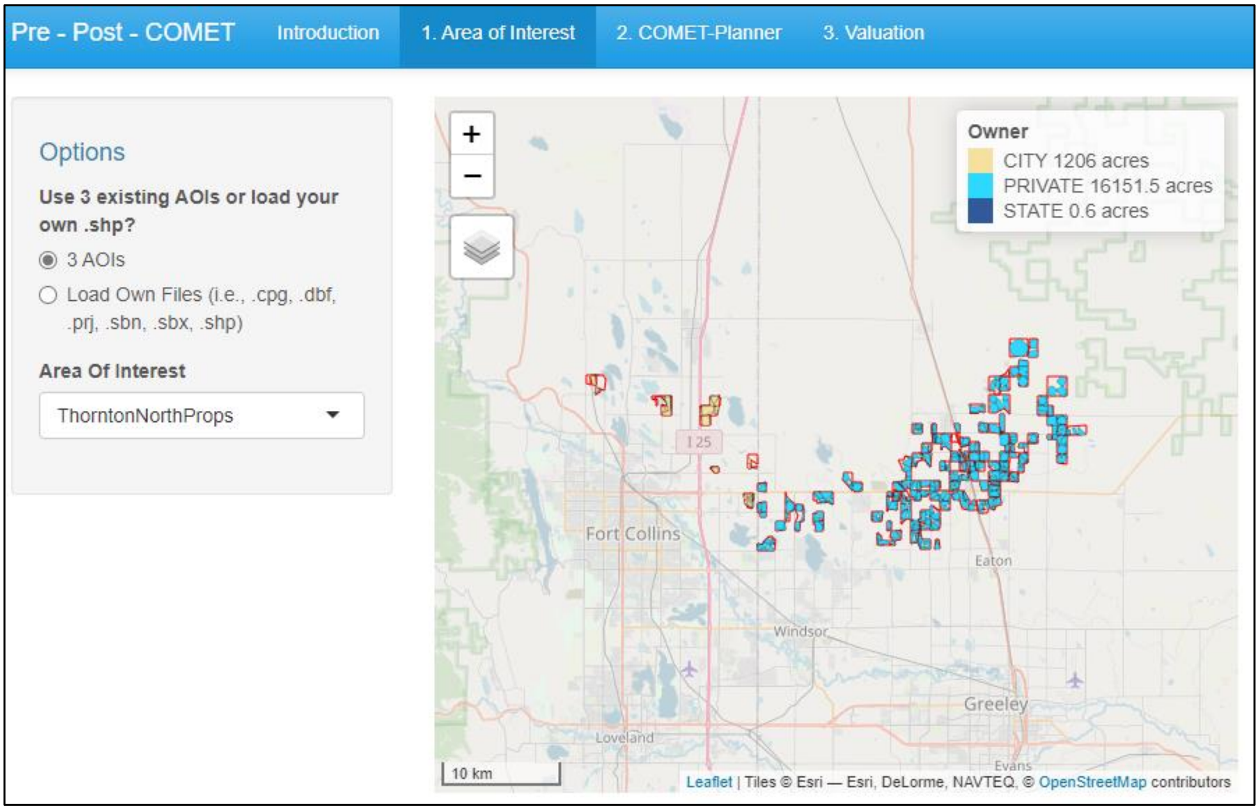

Fig. 3.10. Application of the Pre-Post-COMET application to the Thornton Northern Properties located in Larimer and Weld Counties in the South Platte River Basin, CO. In Step 1, the area of irrigated property within the area is calculated.

Approximate Carbon Sequestration and Greenhouse Gas Emission Reductions*

(tonnes CO_2 equivalent per year)

NRCS Conservation Practices	Acreage	Carbon Dioxide	Nitrous Oxide	Methane	Total CO_2 Equivalent
Conversion of Annual Cropland to Non-Irrigated Grass/Legume Forage/Biomass Crops	17358.1 ac	7,593	2,377	0	9,970
Convert Irrigated Cropland to Permanent Unfertilized Grass/Legume Cover	17358.1 ac	5,039	4,081	0	9,120
Convert Irrigated Cropland to Permanent Unfertilized Grass Cover	17358.1 ac	2,185	4,287	0	6,472

Fig. 3.11. Screenshot of output from COMET-Planner tool.

Fig. 3.12. Valuation tab of Pre-Post-COMET application.

In the example demonstrated in Figures 11-13, it was shown that assuming a normal distribution (mean = 42, St.Dev. = 20; Table 3.1; based on Interagency Working Group 2013), a range of possible discount rates between 2.5 and 5 and time preference values between 1 and 2 (Table 3.1; Interagency Working Group 2013; Pindyck 2019; Ricke et al. 2018), if all of the irrigated land in the Thornton Northern Properties was converted to each of the three conservation practices identified in Figure 12, then over a 20 year period return on investments are estimated as presented in the boxplot in Fig. 3.12 as well as in Table 3.2. Even after constraining the valuation variables to the most commonly used values and holding the carbon sequestration variables constant even though they could have considerable uncertainty, estimates of the ROI from each conservation practice still range over three to four orders of magnitude.

Table 3.2. Estimates of ROI [million $] using the Pre-Post-COMET application with the COMET-Planner tool

Conservation Practice	Min	Q25	Median	Q75	Max
1. *Conversion of Annual Cropland to Non-Irrigated Grass/Legume Forage/Biomass Crops*	0.01	3.8	5.49	7.35	16.4
2. *Convert Irrigated Cropland to Permanent Unfertilized Grass/Legume Cover*:	0.01	3.48	5.02	6.72	15.04
3. *Conservation Cover* practice of *Convert Irrigated Cropland to Permanent Unfertilized Grass Cover*:	0	2.47	3.57	4.77	10.67

Footnote: In the Pre-Post-COMET application values presented in this table are displayed as pop-ups when the mouse cursor hovers above or around the violin plots.

The Pre-Post-COMET application explicitly accounts for uncertainty in valuation variables, but only indirectly accounts for uncertainty in climate futures, which is also significant. It indirectly accounts for uncertainty in climate futures by embedding that uncertainty into the valuation variables. One of the reasons there is high uncertainty in estimates of the social cost of carbon and other valuation variables is because of the uncertainty in climate futures. For example, if the climate future we end up realizing is on the severe side of estimates, then the social cost of carbon is much greater than if the future we realize is on the less-severe side of estimates.

Conclusions

The overall objective of this work was to enable easier assessment of the tradeoffs of potential uses of dried agricultural land to assist stakeholders and policymakers in the SPRB with making informed land development decisions. This overall objective was met by accomplishing two subobjectives.

1. Identify needs, traits, and options with respect to policy relevant valuation of ecosystem services:

Policy relevant valuation of ecosystem services requires methodologies that are timely, accurate enough, actionable, enable comparisons of scenarios, and not requiring an expert. They must be timely in that multi-year studies occur on a slower timescale than policy decisions are made so while important, are not adequate. 'Accurate enough' refers to the need for results that entail enough confidence to be trusted. Uncertainty should also be communicated as part of the decision of whether the method and/or results are accurate enough. Furthermore, communicating results without communicating the uncertainty associated with those results can cause more harm than good over the long term (Plummer 2009; Richardson et al. 2015). With respect to policy, the best way to ensure results are actionable is to provide estimates of the return on investment in terms of monetary value. To stay cost effective, the method should also enable comparisons of scenarios. If a new original study needs to be conducted each time a new scenario is considered, then cost may become prohibitive. Similarly, if an expert is required for each study or each analysis, then cost will likely become prohibitive.

2. Perform valuation of carbon related ecosystem services in the case of irrigated agriculture drying to more natural land cover in the SPRB:

The COMET-Planner tool was identified as the most appropriate tool for estimating the change in carbon sequestration in the scenario of irrigated agricultural land being dried to more natural grass cover. It does not require an expert, estimates relative change in carbon sequestration opposed to assigning absolute estimates of carbon storage to different land uses, and it makes place-based estimates of carbon sequestration impacts. To enable easier use of the COMET-Planner tool by non-experts, an application was developed for pre-processing inputs for the COMET-Planner tool using a shape file representing the area of interest. The application also enables post-processing using a stochastic valuation module to get from estimates of carbon sequestration to stochastic estimates of the return on investment from carbon sequestration. Both tools were used together and applied to an area of interest where estimates of the return on investment were shown to range from $0 to more than $10 million.

Future work should investigate the use of benefit-transfer using custom land use-land cover classifications. By working to identify land use-land cover types that are of interest in policy decisions and that also allow for differentiation of the value provided by carbon sequestration, estimates of return on investment can be calculated and priority data needs can be identified. There are many other important considerations regarding valuation of ecosystem services and policies that pay for ecosystem services. For example, it is important to be clear about who pays for the ecosystem services, who gets paid, who provides the services, and who benefits from the service. Ensuring that such programs do not exacerbate economic inequality should be prioritized (Van Hecken and Bastiaensen 2010). For a more in-depth report of the literature review performed in this chapter please see the Appendix where the Chapter 3-Full Report is available.

CHAPTER 4: PREDICTING MONTHLY, ANNUAL, AND MEAN ANNUAL WATER YIELD IN RESPONSE TO MIXED LAND USE-LAND COVER SCENARIOS AND UNDERSTANDING DRIVERS OF WATER YIELD

Introduction

Growing population and economic forces are driving rapid land conversion (e.g., urbanization) across the planet (Angel et al. 2005, 2010, 2011; United Nations and Social Affairs 2018). Land conversion can drastically alter catchment water yield (WY; defined here as the total volume of water flowing past a point of measurement in a stream over a given time) with significant implications for water resources, risk management, water rights, geomorphology, environmental and ecosystem health, and more (Haase and Nuissl 2007; Leopold 1968; Poff et al. 1997; Rogger et al. 2017; Sharafatmandrad and Khosravi Mashizi 2021; Walsh et al. 2005; Yu et al. 2015). Hydrologic impacts of land conversion and urbanization are likely to be exacerbated by climate change (DeWalle et al. 2000; Dow and DeWalle 2000; Jacobson 2011; Oudin et al. 2018; Tu 2009). In this time of rapid land-conversion and climate change, understanding and being able to predict WY under different land use-land cover (LULC) scenarios across physiographic and climatic settings is critical for informed decision-making by water managers, policy makers, and other relevant stakeholders (Liu et al. 2008; Sharafatmandrad and Khosravi Mashizi 2021; Yu et al. 2015).

The change in WY from different LULC complicates the already challenging practice of modeling and predicting WY. Catchments with mixed land uses (i.e., agricultural, urban, peri-urban, industrial, etc.) are characterized by extreme spatial heterogeneity (Cadenasso et al. 2007; Liu et al. 2008; Verburg et al. 2009), diverse hydrologic flow paths (Aliyari et al. 2019; Bhaskar et al. 2015, 2016a; Meyer 2005; Price 2011), and desired explanatory data are often sparce, inconsistent in quality, and held by disparate sources (Hrachowitz et al. 2013; Visessri and McIntyre 2016). Decades of efforts (Leopold 1968) to understand the impacts of land conversion on catchment hydrology have progressed our knowledge and ability to, with ample effort, predict streamflow response in a given catchment, but many challenges remain. One significant challenge is the need for a more generalized approach that applies across physiographic, climatic, and LULC scenarios (Beven 1987; Blöschl et al. 2019; Nearing et al. 2021; Rogger et al. 2017).

There are many methods used to understand and model mixed-land use catchment hydrology and to predict WY response to catchment properties such as LULC. Popular approaches include empirical and statistical methods (Bell et al. 2016; DeWalle et al. 2000; Oudin et al. 2018), lumped conceptual models (Liu et al. 2008; Reed et al. 2004), fully-distributed physically-based numerical models (Aliyari et al. 2019; Choat and Bhaskar 2020; Endreny and Collins 2009; Zoppou 2001), simpler methods like the semi-empirical Natural Resources Conservation Service Curve Number method (CN; previously known as the SCS CN), and more (Zhou et al. 2015). When simpler methods like the Curve Number are used to estimate impacts of LULC change, the uncertainty surrounding the parameters chosen for the new scenario impedes confidence in predictions (ASCE/EWRI Curve Number Hydrology Task Committee et al. 2009; Hawkins et al. 2019; Ogden et al. 2017; Puno et al. 2019). Approaches that consider more spatial heterogeneity and explicit flow paths require greater parameterization and data, impeding their ability to be easily applied to a wide range of scenarios. Despite the method used, however, hydrologic models of mixed land use catchments must be trained or calibrated to a given catchment, limiting the applicability to other catchments and scenarios. An approach that captures the physical heterogeneity of a catchment while maintaining ease of use is needed.

Predicting WY response to different LULC is akin to the regionalization problem of predicting WY responses in ungauged catchments. In both cases the objective is essentially to predict an unknown WY response as a function of relatively static watershed characteristics and dynamic meteorological forcings. Regional regression equations that relate climatic and physiographic catchment characteristics with WY or other flow statistics have been developed for unregulated and minimally disturbed catchments (Eurich et al. 2021; Ries III et al. 2017). Such approaches are limited in application however, due to their exclusion of catchments with anthropogenic alterations, such as mixed land use catchments (Ries III et al. 2017).

Factors driving WY are complex and interactive, but some patterns and trends have been identified. WY tends to increase with increasing precipitation and decreasing evapotranspiration (i.e., decreasing tree and vegetation coverage and air temperature; Bell et al. 2016; Bhaskar et al. 2016b; DeWalle et al. 2000; Hamel et al. 2020; Hopkins et al. 2014; Jacobson 2011; Sun et al. 2019; Tu 2009). WY is sensitive to catchment slope, soils (Hopkins et al. 2015), and geologic substrate (Eurich et al. 2021). Many anthropogenic impacts and activities interact with each other and natural characteristics to shape WY. Some anthropogenic impacts and activities include altered LULC and historical LULC patterns (Hopkins et al. 2014, 2015; Shi et al. 2015; Sun et al. 2019; Tu 2009), impervious cover (Bell et al. 2016; Chang 2007; Jacobson 2011; Oudin et al. 2018), inter-catchment transfers (Bhaskar et al. 2016a; Grimmond and Oke 1986; Hopkins et al. 2014), agricultural and landscape irrigation (Aliyari et al. 2019; Bhaskar et al. 2016a; Bhaskar and Welty 2015; Grimmond and Oke 1986), aging and leaking water infrastructure (Bhaskar and Welty 2012, 2015; Hopkins et al. 2014; Pangle et al. 2022), dams and reservoirs (Shi et al. 2015), stormwater infrastructure (Bell et al. 2016; Bhaskar et al. 2016a; b; Bhaskar and Welty 2015), and water treatment plant effluent (Meyer 2005; Oudin et al. 2018). Developing any model that is applicable across LULC, physiographic, and climatic conditions will require data that directly or indirectly (i.e., via indicators) reflects these factors.

The overall objective of this work was to gain fundamental insight into the important drivers of water yield and how they vary with spatial and temporal scale. By meeting this objective, useful models for predicting WY were developed, guidance was provided about what important parameters and processes need to be captured by a model to predict WY in a wide range of scenarios, and guidance was provided as to which factors managers considering WY should give special attention. We hypothesized that statistical and machine learning methods that apply across a broad range of catchment conditions would require a larger number of variables than typically considered in regional regression models (e.g., under 10).

To achieve our main objective and to test our hypotheses we asked the following questions:

1. What are the important drivers of water yield?
2. How do those drivers vary between monthly, annual, and mean-annual timescales?
3. How do the important anthropogenic drivers of water yield vary over regions of the U.S. and over monthly, annual, and mean-annual timescales?
4. Which modeling approach is most effective at predicting water yield at different timescales?

Methods

To identify important drivers of WY across climatic, physiographic, and LULC scenarios, this work utilized a variety of statistical and machine learning approaches to model WY in 2,913 catchments across the contiguous United States to produce skilled and explainable models. Multiple linear regression, least absolute shrinkage and selection operator (LASSO) regression (Tibshirani 1996), and the extreme gradient boosting supervised machine learning (XGBoost) algorithm were used in modeling. The most skilled models were investigated to understand the importance of the various explanatory variables included in them. These simpler methods were chosen over neural networks (e.g., Long Short-Term Memory) because interpretability was a priority in this study. To reduce the upfront assumptions about appropriate variables to be included or the number of variables to include, over 80 explanatory variables were considered, and different variable selection methods were used.

Data Collection

Similar to any statistical or physically-based hydrologic model, the required inputs for the models used in this study included catchment characteristics and weather forcings. Streamflow, being the target variable in this study, was needed for training, validating, and testing the models. The availability of daily USGS streamflow data was used to identify the most appropriate time-period to be used in the study. After quantifying how many catchments had continuous daily streamflow records for any given 10-, 15-, 20-, and 30-year period, a 15-year period was selected because 4,501 catchments had continuous streamflow records for at least one 15-year period and 15 years allowed for 10 years of training data and 5 years of testing data. Next, we investigated which 15-year period between 1976 and 2013 had the greatest number of catchments with complete records and aligned well with the variables present in the Geospatial Attributes of Gages for Evaluating Streamflow (GAGES-II; Falcone 2017, 2011) dataset. We used USGS mean daily streamflow (cfs). The total volume of water flowing past a gauge in a day (i.e., daily WY, ft^3) was calculated from mean daily streamflow and monthly and annual WY were calculated from daily WY. Area-normalized water yield (ft) was used in the modeling process to control for larger catchments having the potential to produce greater volumes of water yield.

The period from 1998 through 2012 was chosen because it had the second greatest number of catchments out of all 15-year periods considered and was best aligned with the GAGES-II variables, including the National Land Cover Data (NLCD) which was available for years 2001, 2006, and 2011. Catchments that were given a boundary confidence of 6 (Falcone 2011) or less were removed from the GAGES-II dataset resulting in 3,214 catchments. Of those 3,214 catchments only two had a dominant geology type of anorthositic and only one had a dominant geology type of intermediate, so those three catchments were removed. Weather data failed to download for another 298 catchments resulting in 2,913 catchments being used in the study. We eliminated catchments that experienced the top 5% of land cover change based on NLCD during the study period, to not investigate catchments with WY that was in transition during the study period and instead focus on more static LULC during the study period. Previous work specifically has investigated streamflow in GAGES-II watersheds with high urbanization change and found discharge can be different during rapid urbanization change compared to before or after rapid change (Bhaskar et al., 2020).

The GAGES-II dataset was used for catchment characteristics because it included both reference and non-reference catchments (i.e., catchments that have minimal human impacts and catchments that have been impacted by human activities), data for 9,322 total catchments (2,047 reference and 7,265 non-reference), and a wide range of catchment characteristics believed to be suitable to describe the hydrology of the included catchments. Fifty-seven variables from the GAGES-II dataset and 24 from the GAGES-II time series dataset, were identified for use (Table S4.1) and included climatic, physiographic, and anthropogenic variables. GAGES-II time series data were at either five- or ten-year resolution so values in between years with observations were interpolated. All variables considered in this study were continuous except for the dominant geology variable which was categorical and included six categories after removing two of them. To transform the dominant geology variable to a continuous variable it was one-hot encoded. One-hot encoding defines each category as a new variable and a 0 or 1 is assigned to each new variable. A 0 indicated a catchment's dominant geology was not represented by that variable and a 1 indicated a catchment's dominant geology was represented by that variable.

The daily surface weather and climatological summaries (DAYMET) dataset was used for weather forcings. Individual datasets of annual (Thornton et al. 2020a) and monthly (Thornton et al. 2020b) climate summaries and daily weather (Thornton et al. 2020c) were each downloaded directly for each catchment using catchment shape files included in the GAGES-II dataset. Annual and monthly climate summaries included summaries of five DAYMET variables: minimum and maximum temperature, precipitation, vapor pressure, and snow water equivalent. Daily weather data also included shortwave radiation and day length. DAYMET data came as 1km^2 gridded data. Mean values of the gridded data within each catchment for each variable were used as model inputs. DAYMET data was collected using the PyDaymet API from the HyRiver software stack (Chegini et al. 2021) in Python. Variables capturing antecedent precipitation and minimum and maximum temperature were also included as explanatory variables in annual and monthly models. For annual models, the previous year's total precipitation, average minimum daily temperature, and average daily maximum temperature were included. For monthly models, total precipitation, mean daily minimum temperature, and mean daily maximum temperature were included from the previous month and previous 12 months. Five variables from the DAYMET dataset were used (i.e., precipitation, snow water equivalent, maximum air temperature, minimum air temperature and water vapor pressure.

Data Partitioning

If the models developed in this study were truly capturing the important variables representing the most important drivers of water yield, then they should be able to predict water yield in catchments in which they were not trained (i.e., prediction in ungauged catchments (PUC)) as well as in catchments in which they were trained (non-PUC). Data was partitioned to allow for testing of models in PUC and non-PUC scenarios. To ensure that catchments partitioned to training and testing catchments to be used in the PUC analysis (training and testing-PUC) were from similar distributions, they were first partitioned such that each of the nine aggregated level II ecoregions defined in the GAGES-II dataset had proportional representation in each of the partitions. This was done using 10 different random seeds to produce 10 different partitions where 70% of the 2,913 catchments (2,039) were partitioned to training data, leaving 874 catchments to be used in testing of PUC performance (Fig. 4.4.1).

Next, for each of the 10 partitions resulting from the 10 random seeds, adversarial validation ("Adversarial validation, part one - FastML" 2016; Pan et al. 2020; Qian et al. 2021; Schifferer et al. 2020) was used to test whether the variables within each partition were from similar distributions. Adversarial validation assigns a binary variable (i.e., 0 or 1) to two datasets. In this case, for each random seed a 0 was first assigned to the training partition and a 1 to the rest of the data. The XGBoost algorithm for classification (Chen and Guestrin 2016) was then applied using 10-fold cross-validation to the time-averaged variables for each catchment. The objective was to predict if each catchment was from the training partition or from the other 30% of the data to be used for testing-PUC. The resulting metric from this analysis is the area under the receiver operating characteristic curve (AUC-ROC) which plots the true positive rate against the false positive rate. If the two data partitions being compared were from the same distribution, as desired, then the AUC-ROC value would be 0.5, indicating the classification algorithm is unable to predict which catchment is from which partition using the variables. The partition resulting in mean AUC-ROC values from cross-validation closest to 0.5 was chosen for use in the remainder of the study. For the non-PUC analysis, the catchments included in the training partition from the PUC-partitioning described above were used. The first 10 years (1998-2007) of the continuous 15 years were used for training and the following five years (2008-2012) were used for testing. Since we used one year of antecedent precipitation and temperature data the first year of the training period could not be used in training, so the models were trained on nine years of data (1999-2007). Cross-validation (k=10) was applied to identify the best model parameters allowing the full ten years of training data and all training catchments to be used for training and validation. Throughout the study, k-fold cross-validation with k=10 was chosen because a k=10 has been shown to provide a balanced tradeoff between bias and variance across a wide range of practical datasets (Kohavi 1995). Mean-absolute error was used to identify the best parameter sets for each predictive model when applying cross-validation.

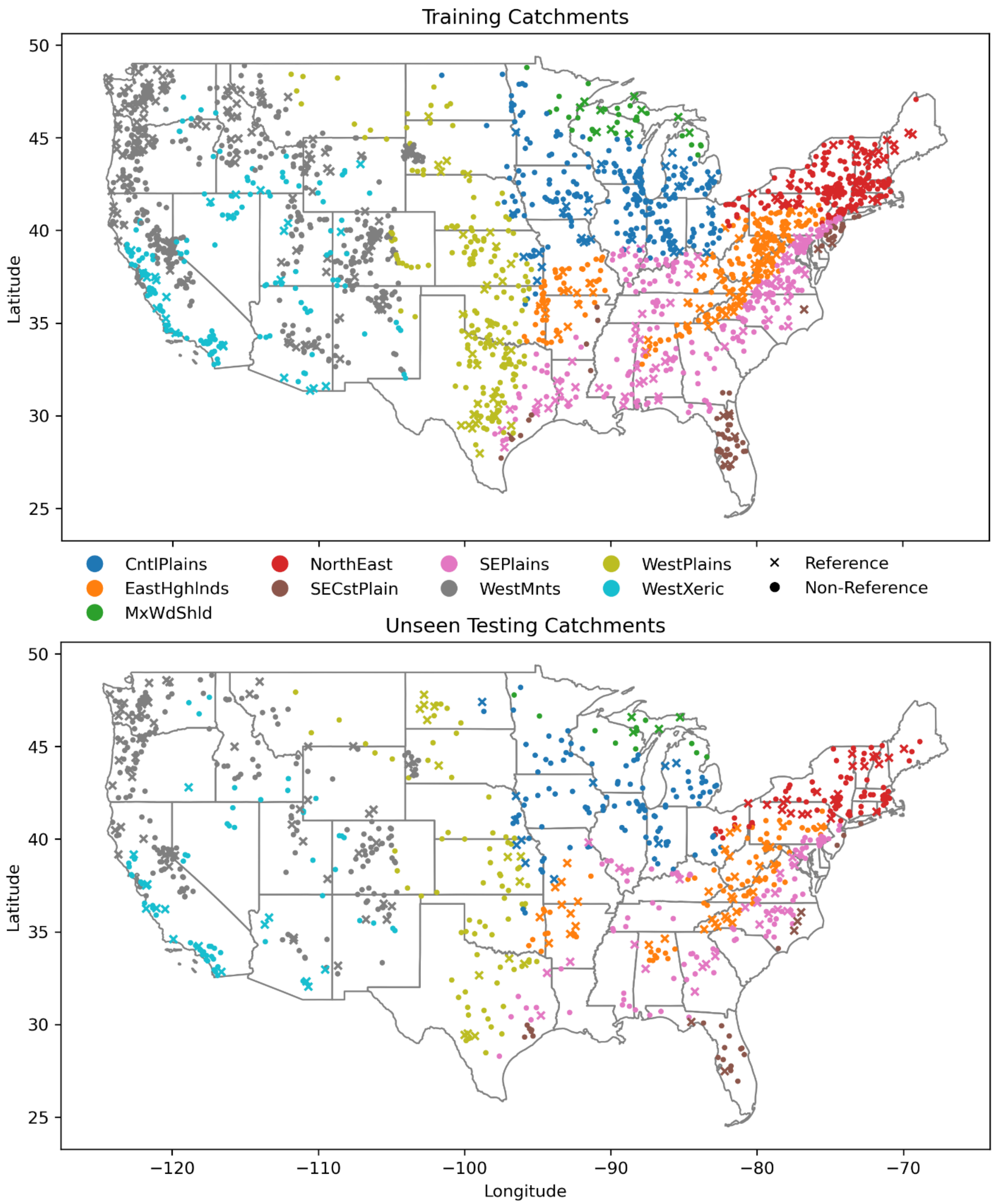

Fig. 4.4.1: Location of catchments used in this study including catchments used for training models (top) and catchments used for testing model predictions in unseen (ungauged) catchments (bottom).

Model Development

To identify models that offered sufficient predictive skill while maintaining interpretability, both of which were important for our research questions, three predictive models were considered: 1. Multiple linear regression, 2. LASSO regression and 3. XGBoost regression (Chen and Guestrin 2016). The following methods were explored: 1. None (raw data), 2. Data standardization (i.e., subtracting the mean from each value and dividing by the standard deviation), 3. Data standardization followed by principal component analysis (PCA; Pearson 1901) for dimension reduction, 4. Regionalization using the nine aggregated ecoregion-II regions included in the GAGES-II dataset, and 5. Using non-reference catchments and reference catchments as 'regions' or groups of catchments. Each of these preprocessing steps were attempted before multiple linear regression, raw data was excluded for LASSO application because standardized data is required, and standardization and PCA were excluded before XGBoost because it is capable of internally selecting variables and is not sensitive to non-normal data. Linear regression, LASSO regression, and XGBoost were applied using packages in Python (Linear regression and LASSO regression from Scikit-Learn, Pedregosa et al. 2011; XGBoost, Chen and Guestrin 2016). We used the variance inflation factor (VIF) to identify and eliminate multi-collinearity from the variables. A VIF threshold of 10 (Helsel et al. 2020) was used to eliminate multi-collinearity where variables with a VIF greater than 10 were eliminated one at a time until VIF for all variables was below 10. An exception to this was made to keep precipitation from being eliminated.

Linear Regression

For variable selection in multiple linear regression, a forward- stepwise algorithm was implemented that allows for variables to be removed during subsequent steps if their removal improves the model after the addition of another variable (Ferri et al. 1994; Pudil et al. 1994; Raschka 2018). At each step in stepwise regression (i.e., each time a variable was added or removed) 10-fold cross-validation was applied and the average R^2 value was used to identify the best combination of variables for each given number of variables considered. The number of variables considered in stepwise regression ranged from one to the smaller of either two less than the total number of variables or two less than the total number of samples. To avoid choosing models that suffered from overfitting, three criteria were considered: Akaike Information Criterion, Bayesian Information Criterion (BIC), and Mallows' Cp. BIC was shown to be the most conservative, meaning it selected the fewest number of variables in each instance, so it was ultimately used for selecting the number of variables to use in each regression model. BIC was calculated as,

(1) $BIC = n + n * \ln(2 * \pi) + n * \ln\left(\frac{SSE}{n}\right) + \ln(n)\,(p + 1),$

where n is the sample, SSE is the sum of squared residuals, and p is the number of variables in the model (Helsel et al. 2020).

Least Absolute Shrinkage and Selection Operator

LASSO regression applies L1 regularization which shrinks small variable coefficients towards zero resulting in sparse models, meaning that variable selection is part of the algorithm. The LASSO algorithm minimizes:

(2) $\sum_{i=1}^{N}\left(y_i - \sum_j x_{ij}\beta_j\right)^2 + \lambda \sum_{j=1}^{p}\left|\beta_j\right|$

where y_i is the ith observed value, x_{ij} are the j variables for the ith observation, B_j are the j regression coefficients for the ith observation, and λ is a tuning parameter that controls the strength of shrinkage applied to the regression coefficients. The case where $\lambda = 0$ is equivalent to ordinary least squares. This formulation of LASSO regression assumes variables have been standardized so does not include an intercept term. To select the best λ, 10-fold cross-validation was used and the λ resulting in the best validation scores was used in the final model.

Extreme Gradient Boosting for Regression (XGBoost)

XGBoost is a tree boosting algorithm that leverages weak learners (i.e., poorly predicted target variables) to efficiently improve predictive skill (Chen and Guestrin 2016). It uses additive functions (i.e., trees) to predict an output and stops once a user defined stopping criteria is reached. An output, $\hat{y}_i$, is predicted using K additive functions:

(3) $\hat{y}_i = \sum_{k=1}^{K} f_k(x_i)\,,\ f_k \in F,$

where f_k is an individual regression tree built with variables x_i. F represents the space of all possible individual regression trees. The following objective function is minimized to learn the set of functions used in the model:

(4) $L(\phi) = \sum_i l(\hat{y}_i,\, y_i) + \sum_k \Omega(f_k)$

where $\Omega(f) = \gamma T + \frac{1}{2}\lambda\left|\left|w\right|\right|^2$,

Here l is a differentiable loss function between the predicted value, $\hat{y}_i$ and the observed value, y_i. Ω is a regularization term that helps avoid overfitting by penalizing the model for complexity. The complexity of each leaf is represented by γ. T is the number of leaves in each tree, λ is a trade-off parameter that scales the penalty, and w is the vector of scores for each leaf. To overcome computational challenges the model is trained in an additive manner and uses the first and second order gradient statistics (i.e., gradient and Hessian) to optimize the objective function. For an in-depth look at the XGBoost algorithm please see Chen and Guestrin (2016) and Ni et al. (2020).

Other important regularization methods used in XGBoost include shrinkage, where newly added weights are scaled by a factor often called the learning rate, η, after each step and column sampling, where a specified ratio of all variables is sampled. These regularization methods were utilized in this work to help mitigate overfitting by the XGBoost algorithm. Other parameters considered in this study included the number of trees, the maximum tree depth, the γ complexity parameter, the λ trade-off parameter, and the learning rate, η.

Principal Component Analysis (PCA)

To understand if there was redundancy in the large number of variables present in the GAGES-II dataset, and to see if they could be well represented by their principal components, PCA was applied to training data. PCA uses singular value decomposition to identify eigenvalues and eigenvectors. Due to its linear nature, the variation in the data described by each component can be quantified. Multiple linear regression and LASSO regression were applied to the principal components describing 95% of the variation in the variables.

Parameter Importance and Model Assessment

Shapley additive explanations (SHAP; Lundberg et al. 2020; Lundberg and Lee 2017) were utilized to enable consistent comparison of variables between models. Shapley values were developed for application in game-theory to understand the contribution from each player to the game results (Shapley 1953). SHAP values quantify partial dependence of each variable by sampling the distribution of observations of that variable while assuming no dependence, or explicitly accounting for the dependence, from all other variables. The output explains how the prediction was driven from the expected prediction when no variables are present or known, to the prediction observed when variables are present. Applied to linear regression, SHAP values are roughly equivalent to regression coefficients if multicollinearity is not present. SHAP values were calculated for the best performing model in each region or cluster of catchments considered using the SHAP package (Lundberg and Lee 2017) in Python. The best performing model was taken to be the model with the largest median Nash-Sutcliffe efficiency (NSE) for monthly and annual timeseries results or the largest median coefficient of determination (R^2) for mean annual results. Nash-Sutcliffe Efficiency (NSE; Nash and Sutcliffe 1970)) was used to assess how well models performed. NSE is calculated as,

(5) $NSE = 1 - \frac{\sum_{t=1}^{T}(Q_o^t - Q_m^t)^2}{\sum_{t=1}^{T}(Q_o^t - \bar{Q}_o)^2}$,

where Q_o^t is the observed water yield at time t, Q_m^t is the modeled water yield at time t, and $\bar{Q}_o$ is the mean of observed water yields. Possible values of NSE range from $-\infty$ to 1, where 1 represents perfect prediction, 0 represents a model where using the mean would perform better.

Results

Model Performance

Model performance varied from poor to excellent between different regions (Fig. 4.4.2). In general, the eastern U.S. (e.g., North East and SE Plains) saw better performance than the western U.S. (e.g., West Xeric and West Plains). Adapting ratings of model performance based on NSE developed by Moriasi et al. (2007) to this work, models with a median NSE when applied to unseen catchments (NSE_m) > 0.5 were taken to be satisfactory, $NSE_m > 0.65$ were taken to be good, and $NSE_m > 0.75$ were taken to be very good. NSE was not able to be calculated for mean annual water yield, so R^2 values were used for assessing goodness-of-fit. For mean annual water yield, R^2 values ranged between 0.66 (WestPlains) and 0.94 (reference basins), except for the Mixed Wood Shield (MxWdShld) ecoregion which had a smaller sample size and performed poorly for all models. There, the R^2 value was 0.08. Best performing mean annual models included six XGBoost models, 2 LASSO models, 2 stepwise-multiple linear regression models, and 2 simple linear regression models with average precipitation as the only predictor.

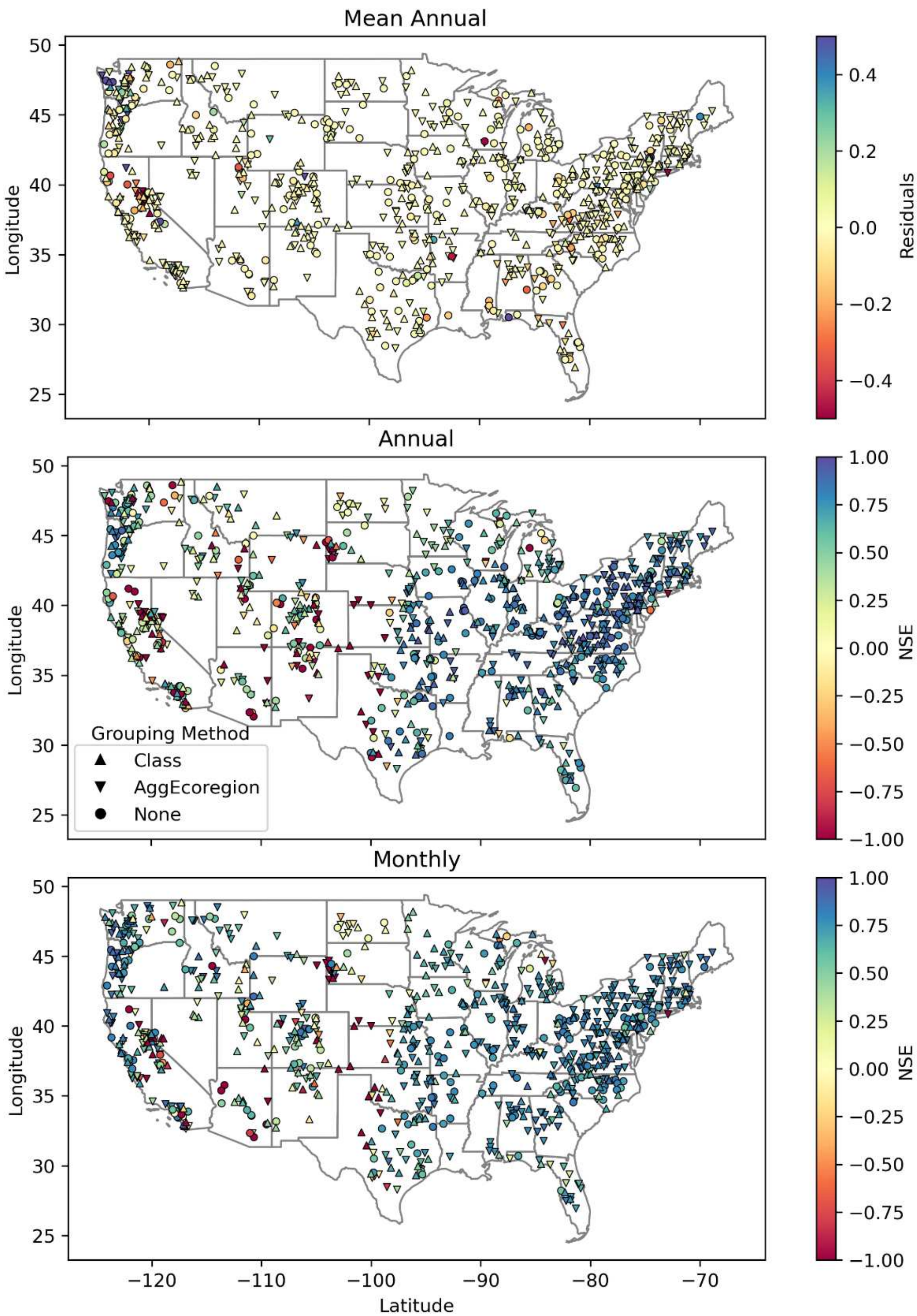

Fig. 4.4.2: Map of residuals from the model that performed best in each individual catchment at the mean annual scale (top) and NSE at the annual (middle) and monthly (bottom) timescales. Shape indicates which grouping method produced the best result in each individual catchment. At the mean annual time scale, yellow indicates the best performance. At annual and monthly timescales dark blue indicates best performance and dark red indicates worst performance.

For annual models, of the 12 regions considered (9 ecoregions, reference and non-reference catchments, and all catchments together) five had median NSE_m below 0.5. NSE_m for non-reference catchments was 0.49 however, so it was accepted as satisfactory, leaving four catchments with unsatisfactory performance (i.e., Mixed Wood Shield, West Mountains, West Plains, and West Xeric; Fig. 4.4.3). Including the non-reference catchments, five regions had satisfactory performance ($0.49 < NSE_m \leq 0.65$), one had good performance ($0.65 < NSE_m \leq 0.75$), and two had very good performance ($0.65 < NSE_m \leq 1$). Three of the poorly performing regions had a NSE_m less than 0, indicating that they performed worse than simply using mean water yield. XGBoost was the best performing annual model across all regions.

Based on NSE_m, monthly models outperformed annual models in all regions except for in the East Highlands ecoregion, where models of the two timescales performed similarly. West Xeric and West Mountains were the two regions experiencing the largest improvements between annual and monthly models. West Xeric's NSE_m improved by 0.41 (-0.23 to 0.18) and in the West Mountains, NSE_m improved by 0.50 (0.09 to 0.59). The performance of three monthly models was unsatisfactory, two models had satisfactory performance, four had good performance, and three had very good performance. No models had a NSE_m below 0, although NSE_m was near zero in the Mixed Wood Shield ecoregion. XGBoost was the best performing model for all regions except Mixed Wood Shield, where LASSO regression performed best.

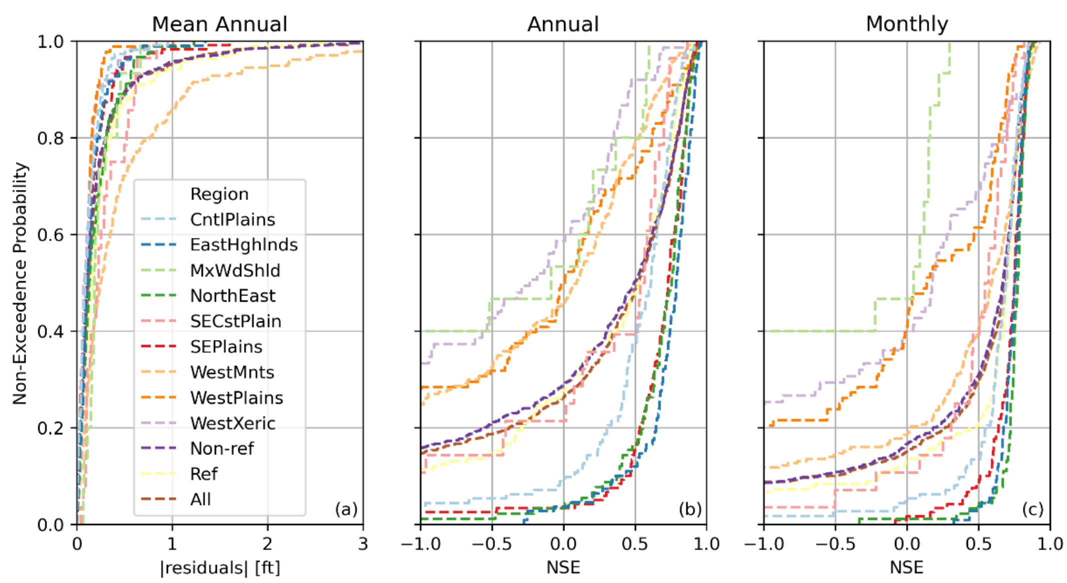

Fig. 4.4.3: Empirical cumulative distribution functions of (a) absolute value of residuals from mean annual predictions, (b) NSE from annual predictions, and (c) NSE from monthly predictions. Metrics are presented from each cluster/region modeled and are metrics from the best performing model in each region when applied to the unseen catchments. The x-axis is clipped at –1 for easier viewing.

Identifying Drivers of Water Yield

Variable reduction by removal of multicollinearity and PCA (principal component analysis)

Many variables played impactful roles in predicting WY. After removing collinearity from all explanatory variables for each model, between 17 and 60 variables remained for predicting mean annual data, between 29 and 64 variables remained for annual data, and between 31 and 69 for monthly data. Furthermore, PCA was not able to capture large portions of the variation in explanatory variables. To explain 95% of the variation in mean annual variables used in each model, it took between 10 and 39 components, for annual data it took between 17 and 40 components, and for monthly data, between 18 and 43. PCA was not further considered due to its inability to significantly reduce the number of variables.

Impacts of classes of variables

Explanatory variables used in this study were categorized into four classes of variables: climate, physiographic, anthropogenic impacts on water resources (AnthroHydro), and anthropogenic impacts on land (AnthroLand) (Table S4.1). As expected, climate variables were the most important predictor of WY in nearly every scenario (Fig. 4.4). The only exception was that the mean annual model applied in the SE Coastal Plains (SECstPlain) region where precipitation, the most impactful climate variable, did not remain in the stepwise regression model (Fig. 4.6 (a)). Despite precipitation not being included, that scenario had an R^2 of 0.70. Physiographic variables were the next most impactful variable type across all regions. In the Central Plains region, anthropogenic variables (AnthroHydro + AnthroLand) were as impactful as physiographic variables at the mean annual timescale, but not at the other two timescales. Generally, the impact from climate variables increased from mean annual to monthly timescales. This is likely due to more climate variables being included in annual and monthly models that captured antecedent precipitation and temperature.

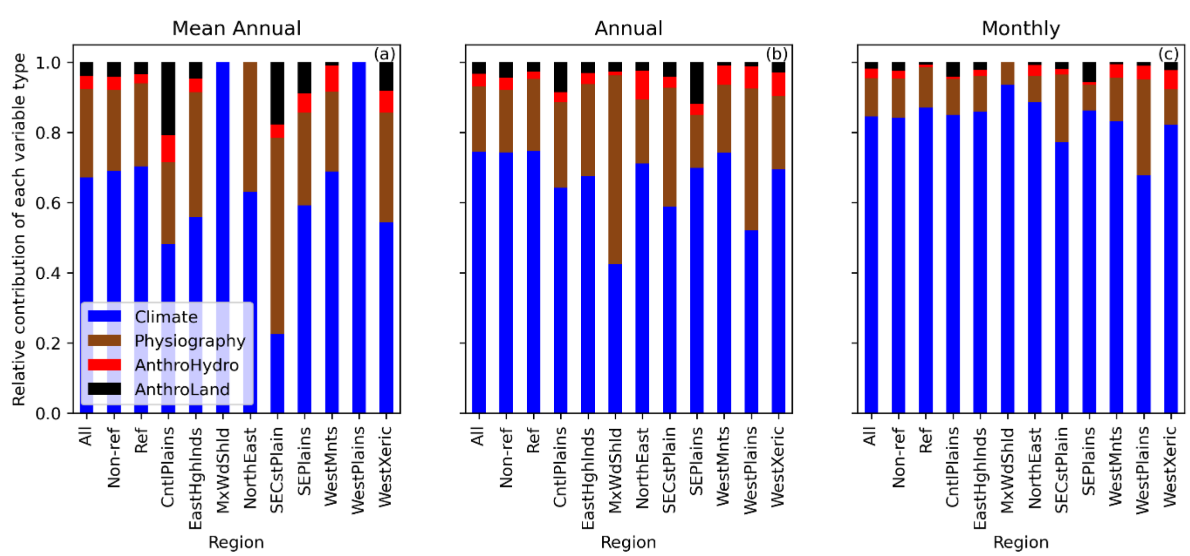

Fig. 4.4: Relative contributions from each variable type to the overall impact of all variables on predictions.

The relative sensitivity of WY to physiographic, AnthroHydro, and AnthroLand variables (Fig. 4.5), varied between regions. In particular, the Central Plains (CntlPlains) and Southeast Plains (SEPlains) were more sensitive to anthropogenic variables at all timescales. Central Plains were most sensitive to anthropogenic variables at the mean annual timescale whereas Southeast Plains were most sensitive to anthropogenic variables at the annual and monthly timescales. WY in the North East region showed no sensitivity to anthropogenic variables at the mean annual timescale, but was the second most sensitive at the annual timescale and third most sensitive at the monthly timescale. All catchments considered together (All) and non-reference catchments (Non-ref) showed substantial sensitivity to anthropogenic variables at all scales and that sensitivity did not vary considerably across timescales. On the other hand, reference catchments became less sensitive to anthropogenic variables as the timescale became finer (mean annual -> annual -> monthly). The relative contribution from AnthroHydro and AnthroLand variables varied extensively between regions and to a lesser extent between timescales. For example, AnthroLand variables were much more impactful in the SEPlains regions, especially at the monthly timescale, whereas AnthroHydro variables were much more impactful in the NorthEast region.

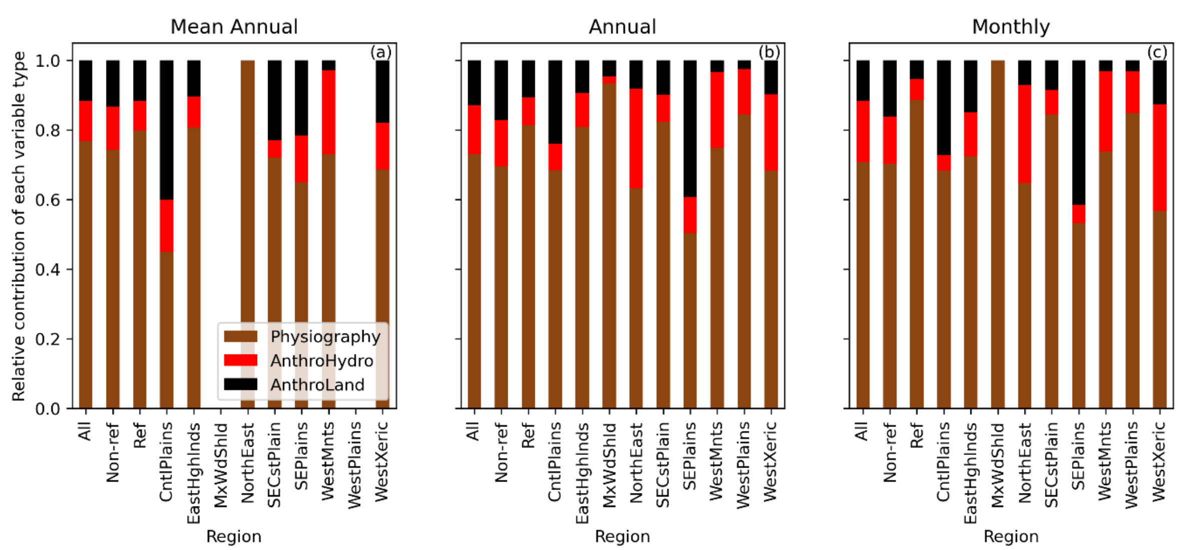

Fig. 4.5: Relative contributions from each variable type except climatic variables to the overall impact of all variables on predictions. Note that Mixed Wood Shield and West Mountain ecoregions are not shown for mean annual as there were only climate variables in these models.

Impacts of specific variables

SHAP values were used to understand the impact of individual explanatory variables on predictions of water yield. While climate and physiographic variables clearly had large impacts on predictions, many anthropogenic variables also impacted predictions of WY. After precipitation, other climate variables were the most impactful predictors of WY across timescales. The average of monthly maximum number of days receiving measurable precipitation (Mo Max Wet Days), catchment average relative humidity (Avg RH), and snow water equivalent (Snow Water Eq) averaged over each respective timescale appeared among the most important predictors of water yield across all timescales (Fig 6).

With few exceptions, the directional relationship between climate variables and water yield was consistent across regions (Fig. 4.6). One notable exception was the negative relationship between Avg RH and water yield in the SE Coastal Plains (SECstlPlain). This negative relationship was present across timescales but was most pronounced for the annual model (Fig. 4.6 (b)) and least pronounced for the monthly model (Fig. 4.6 (c)). The maximum temperature (Max Temp) for each time step being predicted also had varying importance as a predictor. It did not appear in the 30 most impactful predictors for mean annual water yield, only remained in two regions for annual models (Mixed Wood Shield and North East), but it was the fifth most impactful variable at the monthly timescale where it had varying impacts between catchments. In the West Mountains (WestMnts) region, reference catchments (Ref), and all catchments (All) models, Max Temp had a relatively strong and positive relationship with monthly WY, while it had a negative to neutral relationship with WY in the other regions. It has an especially strong and negative relationship with WY in the North East region at the monthly timescale. Similarly, the average percent of precipitation as snow (Snow %) was only impactful in the West

Mountains region and there, it was impactful across timescales. It was only impactful in other regions at the monthly timescale where it appeared as an important variable for all catchments (All) and non-Reference catchments (Non-ref). Antecedent weather forcings for annual and monthly WY were also impactful predictors. For annual WY, the previous year's precipitation (Precip-LB1) was the second most impactful variable behind the current year's precipitation (Precip). At the monthly timescale the average minimum temperature of the previous month (Min Temp-LB1) was the second most impactful predictor behind Precip, and it was immediately followed by the sum of the previous 12 months of precipitation (Precip-LB12) and the previous month's precipitation (Precip-LB1).

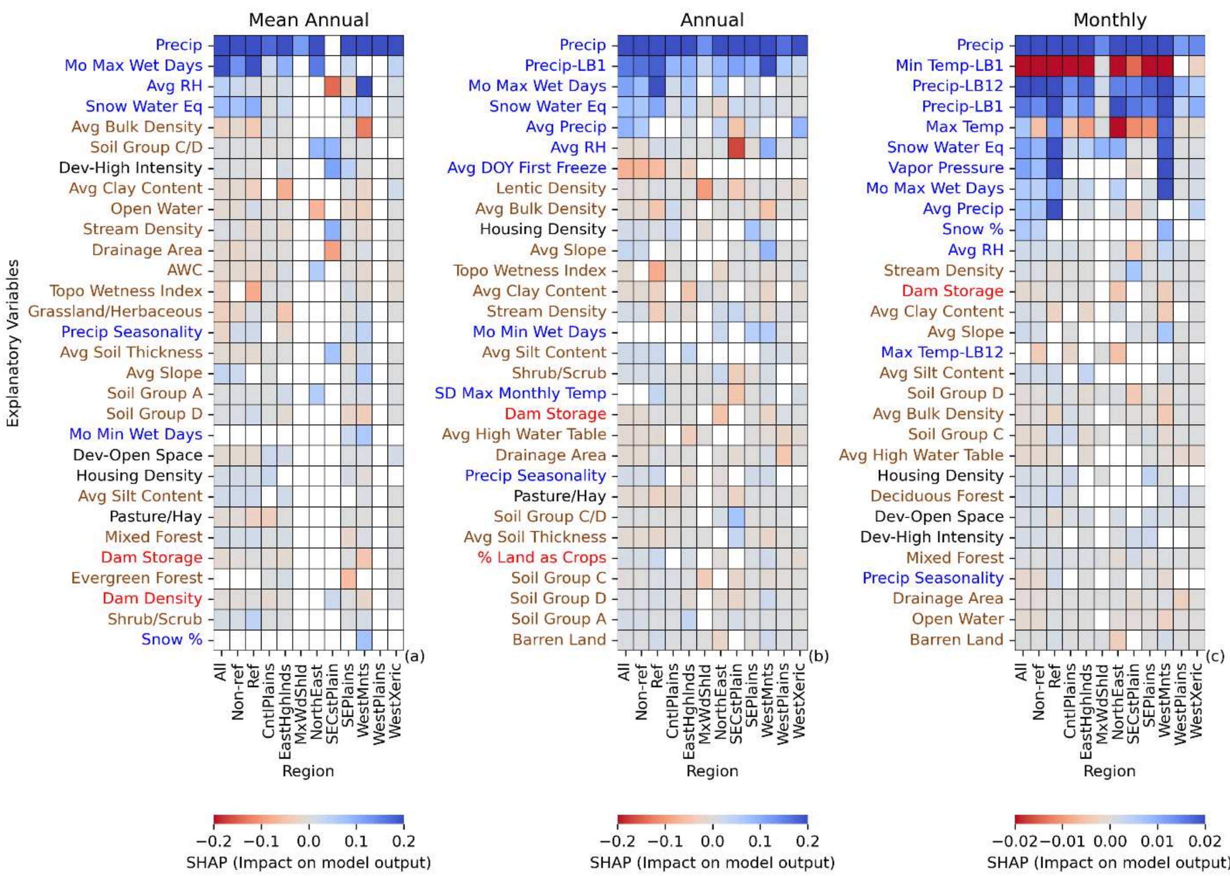

Fig. 4.6: Heatmaps presenting the direction and magnitude of SHAP values (impact of that variable on the model output) for each region/cluster considered, each timescale (a: mean annual, b: annual, c: monthly), and the 30 variables with the largest mean absolute value impact. Within the heatmap, blue indicates a positive relationship between the variable and water yield and red represents a negative relationship. The variable labels are colored by category: Blue represents climate variables, brown

represents physiographic variables, black represents land use variables, and red represents anthropogenic alterations of hydrology. For clearer interpretation, the limits of the color bar are –0.2 and 0.2 for mean annual and annual plots, and –0.02 and 0.02 for the monthly plot. White indicates that variable was not included in the model. Definitions of variables can be found in Table S4.1.

Anthropogenic variables varied in their relative impact on WY predictions across timescales and especially across regions. Three anthropogenic variables appeared among the five most impactful across timescales: Housing Density, area normalized dam storage in 2009 (Dam Storage), and developed-high intensity land cover (Dev-High Intensity) (Fig. 4.7). Increased Housing Density resulted in larger predictions of WY across regions. The only exceptions were observed in poorly performing models (i.e., West Mountains mean annual model and Mixed Wood Shield Annual model). Dam Storage had mixed impacts on WY predictions across regions, but the most significant impacts it had were to decrease predictions of WY. It was especially impactful in the North East region for annual and monthly timescales and in the West Mountains across timescales. Notably, Dam Storage had opposite impacts in reference and non-reference catchments. In reference catchments, increased Dam Storage produced greater predictions of WY and in non-reference catchments it produced smaller predictions. Greater Dev-High Intensity consistently led to greater predictions of WY. Contrasting with Dev-High Intensity, developed-open space land cover (Dev-Open Space) which was the second, sixth, and third most impactful anthropogenic variable at mean annual, annual, and monthly timescales, respectively, had mixed relationships between timescales and regions.

At the mean annual timescale, Dev-Open Space had negative relationships with WY predictions for all (All), reference (Ref), and non-reference (Non-ref) catchments but positive relationships for four other regions (Fig. 4.7 (a)). At the annual timescale Dev-Open Space had positive relationships with all regions when it was included in the best model, except for the North East and Reference regions. At the monthly timescale Dev-Open Space had a positive relationship for all regions in which it was included in the best model, including the North East region, but not for reference catchments. The percent of stream length coded as “Canal”, “Ditch”, or “Pipeline” in NHDPlus data (% Length as Canal) had strong negative relationships with WY across timescales in the West Mountains region. The relationship between pasture and hay land cover (Pasture/Hay) and WY was also notable. It was the fourth and third most impactful anthropogenic variable at mean annual and annual timescales, but only the ninth most impactful at the monthly timescale. It had mixed directional relationships across regions but had a consistent negative relationship with WY across timescales.

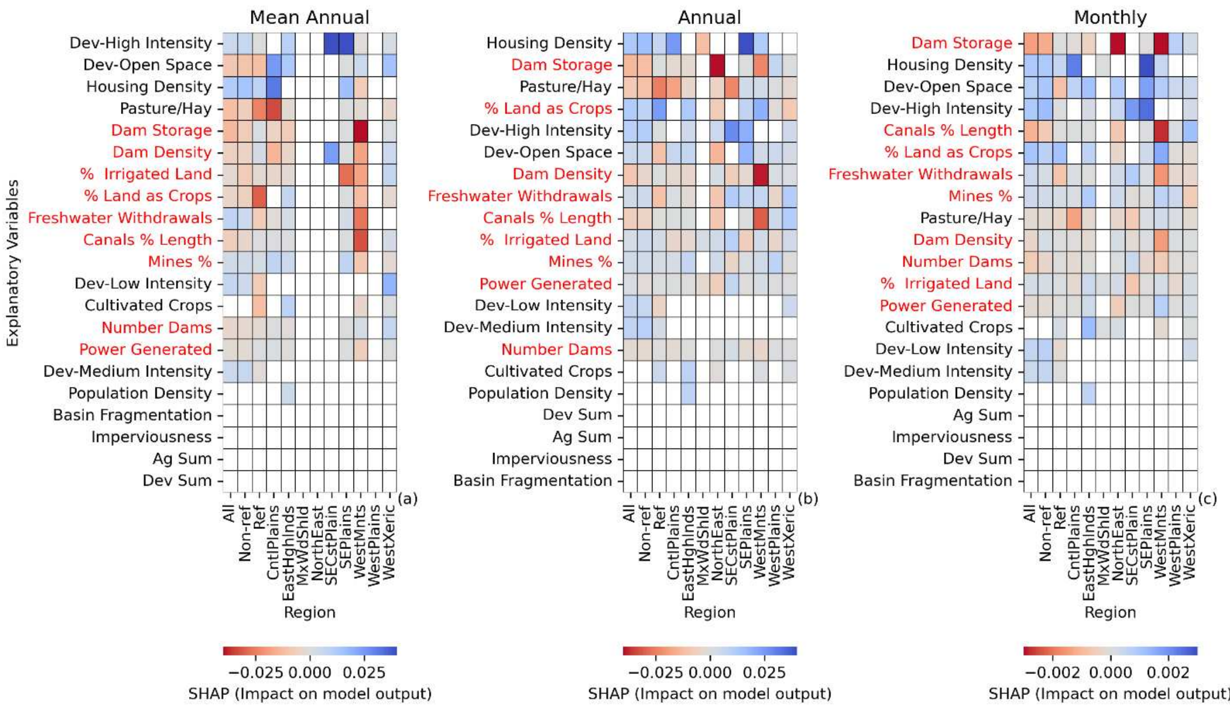

Fig. 4.7: Heatmaps presenting the direction and magnitude of SHAP values (impact of that variable on the model output) for each region/cluster considered at each timescale (a: mean annual, b: annual, c: monthly) and only including anthropogenic variables. Within the heatmap, blue indicates a positive relationship between the variable and water yield and red represents a negative relationship. The variable labels are colored by category: Black represents land use variables and red represents anthropogenic alterations of hydrology. For clearer interpretation, the limits of the color bar are –0.04 and 0.04 for mean annual and annual plots, and –0.003 and 0.003 for the monthly plot. White indicates that variable was not included in the model. Definitions of variables can be found in Table S4.1.

Discussion

There were clear spatial trends regarding performance of the models. Water yield in the eastern United States was much better predicted than the western United States. This could be due to several reasons. There was a greater density of catchments in the eastern part of the county which could have improved predictions. The areas which performed most poorly also tend to be in drier areas where water yield may experience greater impact from anthropogenic activities not well captured by the variables used in this study. Specifically, time series variables such as dam and reservoir management and water transfers were not well represented but would likely be important. The summary variables we have which are related, such as volume of dam storage, and five-year resolution water use still showed up as impactful predictors despite not having higher resolution time series data.

Climate, physiography, and many anthropogenic variables impacted predictions of water yield

After removal of collinearity, as well as consideration of PCA, several variables (or components) remained. Had there been significant redundancy in the explanatory variables each of these methods should have greatly reduced the number of variables considered in the models. That there can be so many hydrologically relevant variables that lack multicollinearity demonstrates the dynamic and complex nature of hydrology. As such, many variables had impacts on predictions of WY. It is important to note that average SHAP values were presented here. It could be that even if a variable showed relatively low impact on water yield on average, there could still be time periods in which that variable had larger impacts on predictions.

Climate, and in particular precipitation, were clearly the most impactful variables considered. In some cases, antecedent precipitation and temperature variables were nearly as important as climate variables for the timestep being predicted. Of the four classes of variables considered, physiographic variables were the most impactful other than climate variables. Variables such as Stream Density, soil variables (e.g., Avg Clay Content, Avg Bulk Density), and Avg Slope appeared as impactful variables at each timescale.

Anthropogenic variables were not consistently related to WY across regions, suggesting the effects of anthropogenic alterations of land or water resources have varying impacts on WY depending on the climatic and physiographic back drop. Neither variables representing anthropogenic alteration of land (AnthroLand) nor representing anthropogenic alterations to water resources (AnthroHydro) appeared to be consistently more impactful than the other. For example, Dev-High Intensity, Dam Storage, Housing Density, and Dev-Open Space appeared in the six variables with the greatest average impact on WY predictions among anthropogenic variables across timescales. This points towards the difficulty in modeling non-reference catchments where many factors have relatively equal impacts on water yield. Some regions did show one or two anthropogenic variables that were clearly more impactful than others, again suggesting impacts of anthropogenic activities are variable based on climate and physiography. It is possible this was due to inconsistent representation of anthropogenic activities in various regions.

Climate has consistent impacts on water yield across regions and timescales

Agreeing with hydrologic reason and as observed in other studies (e.g., Kratzert et al. 2019b; Sun et al. 2019), climate, especially precipitation, was consistently the most impactful class of variable. Its impact grew as the timescale became finer as Sun et al. (Sun et al. 2019) observed. This was largely due to the strong impact of antecedent precipitation and temperature variables which increased in number as the timescale became finer. There was no discernable pattern or trend among the other variable classes across timescales.

Other variables have inconsistent impacts on water yield across regions and timescales

Anthropogenic variables had varying levels of impact on WY predictions across regions and timescales. Generally, their impact on WY predictions across regions was much less consistent than with climate and physiographic variables. For example, in some regions increased dam storage had a strong tendency to decrease WY predictions while in other regions it increased them. This could be attributed to inter-basin transfers either into or out of the catchment of interest, which we did not have data for. It could also be due to higher evaporation from open bodies of water in some regions. Indicators of urbanization (e.g., Housing Density, Dev-Open Space, Dev-High Intensity) tended to have positive relationships with WY predictions, but there were a few exceptions. One consistent exception was that increased development-open space land cover tended to decrease WY predictions in reference catchments. The classification of reference versus non-reference catchments by the developers of the GAGES-II dataset (Falcone 2017, 2011) were somewhat subjective and did not consist of specific quantitative criteria. So, while there was much less anthropogenic activity in reference catchments, it was not completely negligible. Results suggest that there may be low thresholds of anthropogenic alterations of land and water resources that begin to have an impact on water yield. It is likely that Dev-High Intensity land cover tends to increase WY because water must be imported to those areas to meet water demand. It represents areas with 80-100% impervious cover where people reside or work in high numbers (Dewitz 2019a). Like dam storage, other anthropogenic variables representing activities such as agriculture, power production, and mining had mixed effects across regions. This also supports the idea that the impact of anthropogenic activities on WY varies depending on the climatic and physiographic settings in which they occur which has been suggested by others in slightly different context (Hopkins et al. 2015; McPhillips et al. 2019).

Model performance – understanding predictions of water yield in unseen catchments

XGBoost proved to be the most effective model at predicting WY. It best predicted WY in unseen catchments in half of the mean annual scenarios, all the annual scenarios, and all but one monthly scenario. While the use of many variables in predictive modelling is often discouraged due to fear of overfitting, especially with modelling approaches more advanced than linear regression, this study showed that there are numerous uncorrelated variables that help with predictions and allow for generalization to unseen or ungauged catchments. Despite the inclusion of non-reference catchments which is often avoided in studies such as this one, predictive skill was at least satisfactory in the majority of regions and scenarios considered, with several scenarios exhibiting good or very good predictions. WY in some regions was poorly predicted (e.g., West Plains, West Xeric, and Mixed Wood Shield). Similar spatial trends in performance have been observed in similar studies (e.g., Mai et al. 2022). Climate variables did not predict water yield as well in the poorly performing regions as in other regions. Those regions also had a larger coefficient of variation (i.e., mean/standard deviation) in water yield from year to year (Dettinger et al. 2011). Furthermore, there were a fewer number of catchments located in those regions compared to the regions that performed well.

One notable drawback of using XGBoost instead of linear regression is a slight loss in interpretability. Where linear regression models have consistent coefficients representing the sensitivity of water yield to individual explanatory variables, XGBoost captures non-linearity and interdependencies that may exist between variables which linear regression does not capture. Use of SHAP values enabled calculation of the average magnitude and directional impact of each explanatory variable and water yield, but when applied to boosted decision trees such as XGBoost some detail is lost compared to application to linear regression. For example, it could be that a variable sometimes increases water yield and sometimes decreases it, depending on the state of other variables.

Understanding results within the context of existing literature

Many of the drivers identified as important in other studies were identified in this study as well. Precipitation and variables related to evapotranspiration (e.g., temperature; Bell et al. 2016; Bhaskar et al. 2016a; Dow and DeWalle 2000; Hamel et al. 2020; Hopkins et al. 2014; Jacobson 2011; Sun et al. 2019; Tu 2009) had consistent directional relationships with water yield across temporal scales and regions. Slope and soil variables (Hopkins et al. 2015; Kratzert et al. 2019b) were found to be impactful across scenarios as well. Catchments with steeper slopes tended to produce greater water yield while soil variables had varying directional relationships with water yield between regions. Geologic substrate was not identified as an impactful predictor in any region or timescale contrasting with findings from Eurich et al. (2021). The proportion of land as irrigated agriculture (Aliyari et al. 2019) showed mixed directional relationships with water yield across regions, and became less impactful relative to other variables as timescale became finer. At annual and monthly timescales, the proportion of land as harvested crops was more impactful than the proportion of land as irrigated crops, perhaps better representing the effects of evapotranspiration in the region. While landscape irrigation (Bhaskar et al. 2016a; Bhaskar and Welty 2012; Grimmond and Oke 1986) in developed regions was not directly captured, developed open space land cover was identified as an impactful variable across timescales. Its directional relationship with water yield varied across regions, however. Impervious cover (Bell et al. 2016; Chang 2007; Oudin et al. 2018) did not make it into any of the final models due to multi-collinearity with other land cover variables such as Dev-High Intensity. Land cover variables were found to be impactful (Hopkins et al. 2014, 2015; Shi et al. 2015; Sun et al. 2019). Like Dev-Open Space, Dev-High Intensity land cover was impactful across timescales. On the other hand, it contrasted with Dev-Open Space in that it had a consistent positive relationship with water yield.

This study included some variables which were indicative of the variable at a point in time (e.g., Dam Storage was only from 2009) and others that were collected only once every five years (e.g., water use and land cover). Even so, these variables were shown to be impactful on predictions of water yield. Although we interpolated between the five-year resolution timeseries variables to produce one-year resolution timeseries representation of those variables, these results suggest that finer resolution timeseries representations of these dynamic anthropogenic variables could improve predictions of WY in poorly performing catchments. For example, Ouyang et al. (2021) found that information about dams improved predictions of daily streamflow in catchments with dams and that model performance depended not only on presence of dams, but for what purpose the dam was used (e.g., flood control and stormwater management, hydroelectric, irrigation). The importance of having finer-scale representations of these variables is likely to depend on the temporal scale at which the variables change. Land cover changes relatively slowly compared to water use for example, so including fine-scale representations of water use is likely to be more important than land cover. It may also be beneficial to model performance to provide information not only about water withdrawals, but about the specific use for which water withdrawals are occurring (Marston et al. 2022). For example, some uses such as power generation, can have low consumptive uses while others such as agriculture have high consumptive use. In theory, variables provided along with water withdrawals such as the proportion of land as irrigated crops, could allow the model to pick up on patterns such as consumptive use (e.g., Kratzert et al. 2018). Even then, providing explanatory variables at the same time scale at which water yield is being predicted, or finer, would likely lead to significant improvements in water yield predictions. Such datasets are currently lacking at scale, however.

There are yet other variables that were not well represented in any form in this study but are likely to have notable impacts on water yield. Four variables in particular may be important but were not captured by explanatory variables used in this study. 1. Information about aging and potentially leaking water infrastructure was not provided, but can have variable impacts on water yield depending on other factors such as depth to water table (Bhaskar and Welty 2012, 2015; Hopkins et al. 2014; Pangle et al.

2022), 2. Information about inter-catchment transfers was not provided, but has been shown to significantly improve predictions of water yield in ungauged catchments in Colorado (Eurich et al. 2021), 3. Stormwater infrastructure was not represented but is highly variable between cities (e.g., Chapter 2) and has been shown to have variable impacts on streamflow (Jefferson et al. 2017), and 4. Water treatment plant effluent was not represented and has been shown to increase low to moderate streamflow (Bhaskar et al. 2016a; Wang and Cai 2010; White and Greer 2006).

While these additional variables would likely improve predictions of water yield in anthropogenically altered catchments, this study provides value to similar studies in three important ways: 1. It is the first study to our knowledge that has explicitly investigated the relative magnitude and direction of the impact that many individual variables have on water yield across the contiguous United States and within regions of the United States, 2. It is one of few studies to consider anthropogenically altered catchments at all, and 3. Iit is the only study we are aware of that explicitly investigates how important predictors of water yield change with temporal scale. Each of these novel contributions is of importance to watershed planning and management.

Conclusions

This study utilized 2,039 catchments from across the contiguous United States to train multiple linear regression models with two variable selection methods and XGBoost models to predict mean annual, annual, and monthly water yield (WY). Those models were then assessed based on their ability to predict water yield in 887 unseen catchments, representing the prediction in ungauged catchments challenge. Models were applied to 12 regions or scenarios including nine aggregated ecoregion level-II regions, only non-reference catchments, only reference catchments, and all catchments together. After exhibiting satisfactory predictive performance, Shapley additive explanations (SHAP values) were used to understand which variables were important in predicting WY and how those variables varied in different regions and at different timescales.

The XGBoost regression algorithm proved to be superior to linear regression in nearly every scenario and in all timeseries models but one. Climate variables were the most impactful in predictions of WY, followed by physiographic variables, and lastly, anthropogenic variables. Whether water resources related anthropogenic variables such as dam storage or water use or land use related anthropogenic variables were more important varied significantly between regions and to a lesser extent, between timescales. The directional relationship between climate variables and WY tended to be consistent across regions whereas other variables showed more variability between regions. While climate and physiographic variables explained the greatest portion of WY predictions including anthropogenic variables improved predictive performance. No individual anthropogenic variable was consistently the most impactful across timescales nor regions.

Results highlight the complexity that anthropogenic activities introduce to hydrology and suggest that when modeling non-reference catchments high-dimensional models that capture many aspects of those activities are needed. Results also suggest that in non-reference regions or catchments that are less climate driven (e.g., precipitation) timeseries data about anthropogenic activities is needed. For example, timeseries data about dam and reservoir releases and water use should improve predictions in anthropogenically impacted catchments.

Future work should explore daily time series to further elucidate how the important drivers of WY vary across temporal scales. Such work would likely require more advanced models such as artificial neural networks. Inclusion of high-resolution anthropogenic time series variables would also be critical at the daily time scale and would greatly improve the operational capacity of the annual and monthly time series models developed in this work.

OVERALL CONCLUSIONS

The overall objective of this dissertation was to enable better decisions regarding urban stormwater management, land use of dried agricultural land, and water management of land use-land cover development. To meet that objective four primary questions corresponding to the four chapters were addressed:

Question 1: How can we advance the practice of stormwater management via information sharing and cross-jurisdiction communication?

City SCM inventories showed that record keeping and asset management of stormwater control measures (SCMs) varies between cities. Several previous calls have been made to construct a more uniform classification that effectively and efficiently communicates SCM form and function, but the work presented in this dissertation suggests such efforts are not possible. To effectively communicate the various functions and forms of SCMs, classification systems quickly becomes complicated, reducing the likelihood that they will be adopted. Instead, this work suggests cities report the specific functions being targeted by each SCM they implement. This would allow for clearer record keeping, for analyzing whether implemented SCMs are providing the intended functions while enabling hydrologic and water quality studies that move towards understanding the effects of networks of SCMs instead of individual SCMs.

Question 2: What variables explain the variation in selection of stormwater management approaches in various physiographic, climatic, socioeconomic, and regulatory settings?

Physical characteristics (e.g., depth to water table, variation in slope), federal regulation (e.g., MS4-phase, presence of combined sewers), and socioeconomic variables (e.g., median household income) best explained variation in SCM assemblages of 23 United States cities. Surprisingly, climate variables explained little of the variation in relative abundance of different SCM types between cities. Results suggest all cities are facing challenges of stormwater and water resources management across climates and the physical constraints and socioeconomic and regulatory drivers govern the rate at which different SCM types are selected. Cities looking to learn from other cities should consider each of the factors, including climate, when identifying leader cities to learn from.

Question 3: How can more informed decisions, regarding land use and ecosystem services, be made in the face of drying agricultural land as water is transferred to urban and industrial uses?

Within the context of policy and management decisions regarding land-use, there is a divergence in the literature, where policy needs include timely, affordable, and good-enough scenario analysis that does not require an expert, and academic efforts focus on long-term, expensive, and expert-driven studies. While this approach by academia is needed and may, in the long-term, result in applications fit for use in policy and management decisions, a short-term approach is needed that addresses the policy needs. Spatially-explicit benefit transfer offers an excellent path forward for valuation of ecosystem services, and also for identifying priority data needs. An application was developed for pre- and post-processing of data for use with the COMET-Planner tool which was found to be the most relevant tool regarding estimating effects of irrigated agricultural land drying to more natural grass cover on carbon sequestration.

Question 4: How do various land use-land cover scenarios impact water yield in diverse physiographic and climatic settings?

Climatic and physiographic variables were the most impactful in predicting water yield. However, many anthropogenic variables, including land-use variables, and variables representing more direct impacts to the hydrologic cycle (e.g., dam storage), had significant impacts as well. Those impacts were spread across several variables though. The relationships between water yield and anthropogenic variables are not as generalizable as climatic variables and results suggest that their impact depends on the climatic and physiographic settings in which the anthropogenic alterations occur. In some settings anthropogenic alteration of land use (e.g., Dev-Open Space, Housing Density) was more important than water resources alterations (e.g., Freshwater Withdrawals, % Irrigated Land) at the annual scale, and in some settings the opposite was true. Identifying the important predictors in a given region of study is critical for modeling water yield in non-reference catchments.

Despite the tremendous amount of data that has been and is being collected around the world, there is still insufficient data for policy and management decisions regarding many pressing issues such as land use-land cover change, stormwater management, and ecosystem services. As data becomes more integrated across sectors, scales, and available to decision makers, having cohesive and standardized application-agnostic plans for generating, reporting, and storing data would be of great benefit. Less profit-driven applications (e.g., stormwater management and ecosystem services) can learn from the profit-driven data industry which has exploded, to better engage with data.

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APPENDIX – Chapter 1

CHAPTER 1 – SUPPLEMENTARY MATERIAL

Table S1.1. Terms appearing in cities' SCM inventories by our coarse and fine classification systems based on WEF and ASCE's manual of practice (2012). *Coarse SCMs*: SCMs from the coarse classification. *Fine* SCMs: SCMs from the fine classification. *Reported Terms*: Terms appearing in Cities' SCM inventories.

Coarse SCMs	Fine SCMs	Reported Terms
Basins	Wet Basin	"Detention Pond-Wet", "Water Quality Pond", "Pocket Pond", "Extended Detention Structure-Wet", "Wet Detention Basin", "Wet Pond", "Ponds", "Extended Detention Wet Pond", "Retention Pond (Wet Pond)"
	Wetland	"Constructed Wetland", "Constructed Wetland Pond", "Wetland", "Stormwater Wetland", "Constructed Wetland Basin", "Wetland Pond"
	Dry Basin	"Detention", "Detention Basin", "Underground", "Detention Pond", "Detention Pond-Dry", "Underground Detention", "Detention Structure (Dry Pond)", "Extended Detention Structure-Dry", "Micropool Extended Detention Pond", "Extended Dry Detention Basin", "Flood Control Basin", "Blue Roof", "Detention System", "Dry Pond", "Subsurface Detention Basin", "Surface Detention Basin", "Flood Detention", "Parking Lot Detention", "Extended Detention Basin", "Detention Cells", "Detention Structure", "Extended Detention Dry Pond", "Landscape Detention Structure", "Regional Extended Detention Basin", "ED", "Underground Storm Detention", "Underground Detention Structure", "Underground Deten Pipes-HDPE", "swsDetention Pond", "Detention Tank"
	Vaults Swirl Concentrator	"Storm Vault", "Underground Chambers", "Detention Vault", "Aqua-Swirl", "Aqua-Shield-Swirl", "Swirl Separator", "Sedimentation Box", "Sedimentation Manhole", "Hydrodynamic Separation Systems", "HYDSEP", "BMP Vault", "Separator Unit", "Separator-Bay Saver", "CDS", "Hydrodynamic-CDS Structure", "CDS Units", "Downstream Defender", "Silt Basin", "Sedimentation Chamber", "Water Quality Dynamic Separator", "Hydrodynamic Separator", "Vortsentry HS", "W Quality Dynamic Separator-Vortex", "Interceptor", "Baffle Box", "Water Quality Vault", "Underground Vault", "Water Quality Manhole", "AquaShield_hydrodynamic"
	Oil Water Separator	"O-W Separator", "Oil Separating Incerts", "Oil-Grit Separator", "Stormceptor Multiple", "Vortechs", "Stormceptor", "AquaShield_OWSeparation"
	Forebay	"Plunge Pool", "Sedimentation Only", "Forebay", "Sediment", "Sedimentation"
	Cistern	"Rainwater Harvesting", "Rain Harvesting", "Rain Barrel", "Cistern", "Cisterns for Recycling", "Roof Top Detention", "SW-Reuse", "Cistern-Rain Barrel", "Rain Tank", "Rainstore", "Rainstore Water Harvest", "RainStore System", "RainTank System", "Rainwater Harvesting-Cistern", "Rooftop Storage"
	Basin Unknown	"Basin", "Storage", "Subsurface Storage System"

Swales & Strips	Swale	"Curbcut Bioswale", "Swale", "Grass Swale", "Bio-Swale", "Bioswale", "Dry Swale", "Grass Channel", "Vegetated Ditch", "Biofiltration Swale", "Conveyance Swale", "Dry Grass Swale", "Open Channel BMPs", "Vegetated Swale", "Water Quality Swale", "Wet Swale", "ROW-Bioswale"
	Strip	"Vegetated Filter Strip", "Swales-Vegetated Filter Strips", "Vegetative Grass-Turf Cover", "Vegetated Biofilter-Swale-Strip", "Vegetative Filter Strip", "Filter Strip", "Buffer Strips", "ROW-Greenstrips", "Vegetative Buffer Strip"
Filters	Sand Filter	"Sand Filter Extended Detention Basin", "Perimeter (Sand) Filter", "Sand Filter", "Aboveground Sandfilter", "Delover Sandfilter", "Surface Sandfilter", "Open Sand Filter", "Sandfilter", "Manhole Sandfilter", "Single Chamber Sandfilter", "Sand Box", "Surface Sand Filter", "Sand Filtration", "SandSeparator", "Bisected CMP Sandfilter", "Underground Sandfilter"
	Bioretention	"Non-infiltrating Bioretention", "Bioretention Basin", "Bio-Retention", "Bioretention", "Micro-Bioretention", "Biofiltration", "Biofiltration-Bioretention", "Bioretention-Lined", "Bioretention-Unlined", "Vegetated Filter", "Porous Landscape Detention", "Bio-Infiltration Trench", "Planter", "Downspout Planter", "Contained Planter Box", "Flow Through Planter Box", "Stormwater Planter", "Engineered Soil Tree Pit", "Filtera-Tree Box", "Tree Trench", "Tree Pit", "Stormwater Tree Pit", "Tree Filter", "Engineered Treepits", "Rain Garden", "Rain Gardens", "ROW Rain Garden", "Bayscaping", "Rain Garden-Bioretention", "Residential Rain Gardens"
	Landscaped Roof	"Green Roof", "Combined Blue-Green Roof", "Rooftop Farm", "Green Roof & tree Box", "Vegetated Roof", "Ecoroof", "Intensive Green Roof", "Extensive Green Roof"
	Drain Inlet Insert	"Hydro-Kleen Filter System", "Water Quality Inlet Insert", "Drainage Insert", "Fossil Filter", "Catch Basin-StormFilter", "Inlet with Insert", "Storm-Pure Filtration System"
	Manufactured Filter	"StormFilter System", "StormFilter", "BayFilter", "JellyFish", "Downspout Filter", "Downspout Filtration", "Storm Filter-Canister", "AquaShield_Filter"
	Filter Unknown	"Filtration Only", "Filtering System", "Filtration", "Media Filter", "Underground Filter"
	Gravel Wetland	Submerged Gravel Wetlands
Infiltrators	Infiltration Basin	"Bumpout", "Retention Basin", "Infiltration Basin", "Retention Pond", "Infiltration Berms", "Subsurface Detention System", "ROW Subsurface Pipe-Broken Stone", "Synthetic Turf Field Storage Layer", "Sythetic Field", "Surface Infiltration Basin", "Gravel Storage", "Subsurface Infiltration Basin", "Infiltration-Basin", "Infiltration Planter Box", "ROW Infiltration Basin", "ROW Stormwater Seepage Basin", "Stormtech Infiltration Basin", "Infiltrating Bioretention", "Storm Bio Infiltration", "Bioinfiltration", "U-G Detention", "U-G Retention"
	Infiltration Vault	"Leaching Tank", "Storm Chamber System"
	Trench	"French Drain", "Infiltration Trench", "Infiltration Storage Trench", "Ex-Filtration Trench", "Infiltration-Storage Trench", "Trickle", "Soakage Trench", "Storm Infiltration Trench", "Trench"
	Dry Well	"Dry Well", "Infiltration-Dry Well", "Drywell", "Perforated Pipe Infiltration", "Underground Infiltration", "Underground Injection Cell", "Drywell-Aggregate Filled"

	Permeable Pavement	"Permeable Pavement", "Porous Pavement Detention", "Pervious Pavement", "Permeable Pavers", "Porous Asphalt", "Porous Concrete", "Pavers", "ROW Porous Concrete", "Porous Pavement", "Permeable Pavement System", "Permeable Pavements", "Grass Pavers", "Permeable Friction Course", "Permeable Paver Friction Course", "Permeable Pavement-Standard", "Permeable Paver", "Permeable Surface", "Pervious Asphalt", "Pervious Concrete", "Porous Pavers", "ROW Permeable Pavers", "Brickpavers"
	Infiltration Unknown	"Infiltration", "Infiltration BMPs", "Infiltration Basin or Trench"
Gross Pollutant Traps	Screens Nets Baskets Racks	"Trench Drain", "Catch Basin Drain", "Curb Inlet w-Grate", "Grated Inlet", "Bar Screen-Outlet Screen", "MH Inlet: Grated Cover", "Netting", "Trash Rack", "Drain Box"
	Hood	"Mechanical Separation", "Snout", "Modified Manhole with Snout"
	Gross Pollutant Trap Other	“Debris Basin”
	Gross Pollutant Trap Unknown	"Water Quality Inlet", "Single Water Quality Inlet", "Double Water Quality Inlet", "Triple Water Quality Inlet", "Curb Inlet", "Drop Inlet", "Catch Basin", "Inlet"
Disconnection	Disconnection	"Impervious Surface Removal", "Disconnection of Non-Rooftop Runoff", "Disconnection of Rooftop Runoff", "Impervious Surface Elimination", "Depaving", "Grass", "Simple Disconnection to a Conservation Area", "Simple Disconnection to a Pervious Area", "Simple Disconnection to Amended Soils"
Other	Other	"Other", "Sheetflow to Conservation Areas", "Misc Structures", "Envirochamber", "Modified Catchment Manhole", "Green Wall", "Naturalized Meadow", "Riparian Buffer-Stream Restoration", “Lakes and Ponds", "Lawn Reseeding", "Soil Quality", "Storage Practices", "Naturalized Landscape", "Daylight Ditch", "LID-Other Surface Flow Inlet Point", "Water Quality Pretreament Facility", "Tree Planning And Preservation", "Green Alley", "Greenstreets", "Planting Area", "Pond", "Regenerative Stormwater Conveyance Technique", "Regenerative Stormwater Conveyance", "Rip Rap", "Shade Tree", , "Storm Energy Dissipator", "Stormwater Regenerative Conveyance", "Stream Restoration", "Tree Planting", "Tree Preservation", "Irrigation", "Irrigation System", "Riparian Buffer", "ROW Structural Soil", "Vegetated Landscape"
Stormwater Conveyance	Stormwater Conveyance	"Culvert", "Level Spreader", "Scour Hole", "Cleanout", "Culvert Inflow", "Culvert Outflow", "Junction Box", "Maintenance Hole", "Area Drain", "Flow Control MH", "Riser", "Riserpipe", "Separator-Low Flow Diversion", "Storm Water Inlet Drain", "LID-Other Surface Flow Outlet Point", "Step Pool", "Junction Box with Sump", "Caltrans Drain", "Track Drain"
Unknown	Unknown	"Unknown", "Unregulated", "WQ Treatment Device", "Proprietary Practice", "Proprietary", "Proprietary Devices", "Storm Structures", "ROWEB-Unknown", "BaySaver", "BaySaver WQ Structure", "Stormwater Treatment System", "Vortechnics", "Filtration System", "Retention-HDPE", "Water Quality Structure", "Retention", "Retention Structure"
Not an SCM	None	"None", "Proposed", "CDA to a Shared BMP", "Rexus D-400 Square, Hinged CB Cover", "Wave House", "Hunters Point Shipyard Artists Parcel; Commercial Kitchen", "Potrero Ave Condos", "Psuedo Drain for Model ONLY"

Multiple	Multiple	"Multiple GI Components", "Filtration-Detention", "Infiltration-Detention", "Retention-Infiltration", "Retention-Irrigation", "Sediment-Detention", "Sediment-Filtration-Infiltration", "Sediment-Filtration-Irrigation", "Wet Pond-Irrigation", "Detention Tank-Irrigation System", "Sediment-Biofiltration-Infiltration", "Sedimentation-Sand Filtration", "Bioretention-Bioswale", "Bioretention-Infiltration", "Dual System", "Sand Filter-Infiltration", "Sediment-Infiltration", "Permeable Paver-Infiltration", "Aqua-Shield-Filter", "Aqua-Filter"

Table S1.2: k-means clusters based on unit processes provided. SCMs are ordered by groupings based on all listed unit processes and colors show SCMs that grouped together regardless of which unit processes were used for clustering. Groups for each unit process column are labeled according to that unit process (e.g., group 1A indicates the first group in A or 'all' unit processes). SCMs in cells with light gray lines oriented diagonally were not consistently grouped with each other or other SCMs. Original MOP-coarse groups are presented as: (I) = Infiltrators, (S) = Swales and Strips, (B) = Basins, and (F) = Filters.

		Cluster Groups					Quantity.control						Pollutant.control								Biological				Other			
MOP23-Fine (Original MOP23-coarse class)	# Processes Provided	All, k = 6	Quantity, k = 4	Pollutant, k = 4	Biological, k = 4	Other, k = 3	Peak flow attenuation	Runoff volume reduction	Infiltration	Dispersion	ET	Runoff collection usage	Sedimentation	Flotation	Laminar separation	Swirl concentration	Sorption	Precipitation	Coagulation	Filtration	Plant metabolism	Nitrification denitrification	Sulfate reduction	Organic compound degradation	Pathogen dieoff	Temperature reduction	Disinfection	Screening
Infiltration Basins (I)	13	1A	1Q	1P	1B	1O	x	x	x				x	x			x	x	x			x		x	x	x	x	
Infiltration Vaults (I)	13	1A	1Q	1P	1B	1O	x	x	x				x				x	x	x			x		x	x	x	x	x
Trenches (I)	12	1A	1Q	1P	1B	1O	x	x	x				x				x	x	x			x		x	x	x	x	
Dry Wells (I)	12	1A	1Q	1P	1B	1O	x	x	x				x				x	x	x			x		x	x	x	x	
Permeable pavement (I)	10	1A	1Q	1P	1B	1O	x	x	x								x	x	x					x	x	x	x	
Swales (S)	4	2A	2Q	2P	2B	2O			x	x											x					x		
Strips (S)	5	2A	2Q	2P	2B	2O			x	x			x								x					x		
Landscaped roofs (F)	6	2A	2Q	2P	2B	2O	x			x	x						x				x					x		
Wet basins (B)	14	3A	3Q	3P	3B	1O	x	x			x	x	x	x			x				x	x	x	x	x		x	x
Wetlands (B)	13	3A	3Q	3P	3B	1O	x	x			x	x	x	x			x				x	x	x	x	x		x	
Sand filters (F)	6	4A	4Q	4P	1B	3O	x						x	x						x		x					x	
Vaults and swirl concentrators (B)	4	4A	4Q	3P	4B	3O	x						x	x		x												
Oil Water Separators (B)	3	4A	4Q	3P	4B	3O							x	x	x													
Forebays (B)	2	4A	4Q	3P	4B	3O							x	x														
Dry basins (B)	4	5A	1Q	2P	4B	3O	x	x	x				x															
Cisterns (B)	2	5A	4Q	2P	4B	3O		x					x															
Drain inlet inserts (F)	2	5A	4Q	4P	4B	3O							x							x								
Manufactured filters (F)	2	5A	4Q	4P	4B	3O							x							x								
Bioretention (F)	16	6A	3Q	1P	3B	2O	x	x	x		x	x	x	x			x	x	x	x	x	x		x		x	x	

APPENDIX – Chapter 2

CHAPTER 2 – SUPPLEMENTARY MATERIAL

Table S2.1 Explanatory variables, data source, methods, and hypotheses examples

Type of Variable	Description (Label used in figures)	Data Source	Methods	Hypotheses	Is Hypothesis Supported? (Y or N
Phys.-Cont.	Impervious Percentage (IP)	(Homer et al. 2012)	1. Download NLCD data 2. Project to appropriate coordinate system 3.Run "zonal statistic as table" tool using city boundaries layer as zones. Get mean and st. deviation.	With greater IP a greater abundance of SCMs with smaller footprints or that can more easily be placed in a heavily lined catchment are implemented. Less basins and infiltrators and more filters and strips	Y, Fig. 5, Table 2
Phys.-Cont.	Mean slope in the city based on 3dep (Mean.Slope)	(U.S. Geological Survey 2019)	1. Define geographic coordinate system and project to appropriate projected coordinate system 2. Use "slope (spatial analyst)" to produce a slopes raster for 3DEP elevation data 3. Use "zonal statistics as table" with city boundaries layer as zones. 4.Get mean and st. deviation of slope	With greater or more variable slope there are more smaller footprint SCMs implemented (filters and swales & strips).	N, less Basins, Fig. 5,
Phys.-Cont.	Standard dev. of slope in the city based on 3dep (StDev.Slope)	(U.S. Geological Survey 2019)	1. Define geographic coordinate system and project to appropriate projected coordinate system 2. Use "slope (spatial analyst)" to produce a slopes raster 3. Use "zonal statistics as table" with city boundaries layer as zones. 4.Get mean and st. deviation of slope	With greater or more variable slope there are more smaller footprint SCMs implemented (filters and swales & strip).	N, less Basins More infiltrators, Fig. 5, Table 2
Phys.-Cont.	Ratio of total withdrawals as groundwater (GrnWtr_ratio)	(Dieter et al. 2018)	1. Identify what counties are in or encapsulate the cities of interest 2.Record total surface water and groundwater withdrawal volumes for those counties 3.Take the ratio of total withdrawals that are made of surface water and groundwater withdrawals, independently	With greater use of groundwater for water supply more infiltrators are implemented.	N
Phys.-Cont.	Annual minimum (spatially) depth to water table (min.DTWT) (m)	(Fan et al. 2013)	1. Define geographic coordinate system and project to appropriate projected coordinate system 2. Use "Zonal Statistics as Table" tool with city boundaries as zones	More infiltrators are implemented with greater min.DTWT. Of those, there are less subsurface infiltration (dry wells) with shallower min.DTWT	Y, Fig. 5, Table 2, Fig. S2.3
Phys.-Cont.	Annual maximum (spatially) depth to water table	(Fan et al. 2013)	1. Define geographic coordinate system and project to appropriate projected coordinate system 2. Use "Zonal Statistics as Table" tool with city boundaries as zones	More infiltrators are implemented with greater max.DTWT. Of those, there are more subsurface infiltration (dry wells) with deeper max.DTWT	Y, Fig. 5, Table 2, Fig. S2.3
Phys.-Cont.	Annual mean (spatially) depth to water table (mean.DTWT)(m)	(Fan et al. 2013)	1. Define geographic coordinate system and project to appropriate projected coordinate system 2. Use "Zonal Statistics as Table" tool with city boundaries as zones	More infiltrators are implemented with greater mean.DTWT.	Y, Fig. 5, Table 2, Fig. S2.3

Clim.-Cont.	30 Year Average Precipitation (AP)(in.)	(PRISM Climate Group n.d.)	1. Download 4 km resolution PRISM data for precipitation, min, max, and mean temperature, and min and max vapor pressure deficit 2.Use annual data to get representative values for each parameter using "Zonal Statistics as Table" tool with city boundaries as zones	There are a greater abundance of basins with greater AP.	N, More swales & strips and filters w/less infiltrators, Fig. S2.3
Clim.-Cont.	Magnitude of the 2-year, 24-hour precipitation event (IDF.2yr.24hr.in)(in.)	(NOAA n.d.)	NOAA14: Go to https://hdsc.nws.noaa.gov/hdsc/pfds/pfds_map_cont.html. Enter City, St into the "By Address" space and press enter. If the IDF table is available it will show up. NOAA2: go to https://www.nws.noaa.gov/ohd/hdsc/noaaatlas2.html, Enter the latitude and longitude of the city of interest and click submit.	With greater 2yr-24hr return storm intensity there are more basins implemented	Y, when design storm depth > 1.97 in., Fig. S2.2
Clim.-Cont.	30 Year Average Max Temperatures (AMAT_F)(Deg. F)	(PRISM Climate Group n.d.)	1. Download 4 km resolution PRISM data for precipitation, min, max, and mean temperature, and min and max vapor pressure deficit 2.Use annual data to get representative values for each parameter using "Zonal Statistics as Table" tool with city boundaries as zones	Cities with greater AMAT_F will use more stormwater infiltration	N, Less filters at higher AMAT_F, Fig. S2.3
Clim.-Cont.	30 Year Average Mean Temperatures (AMET_F)(Deg. F)	(PRISM Climate Group n.d.)	1. Download 4 km resolution PRISM data for precipitation, min, max, and mean temperature, and min and max vapor pressure deficit 2.Use annual data to get representative values for each parameter using "Zonal Statistics as Table" tool with city boundaries as zones	Cities with greater AMET_F will use more stormwater infiltration	N, More swales & strips with with higher AMET_F, Fig. S2.3
Clim.-Cont.	30 Year Average Min Temperatures (AMIT_F)(Deg. F)	(PRISM Climate Group n.d.)	1. Download 4 km resolution PRISM data for precipitation, min, max, and mean temperature, and min and max vapor pressure deficit 2.Use annual data to get representative values for each parameter using "Zonal Statistics as Table" tool with city boundaries as zones	Cities with greater AMIT_F will use more stormwater infiltration	N, More swales & strips with higher AMIT_F, Fig. S2.3
Clim.-Cont.	30 Year Average Max Vapor Pressure Deficit (AMAVPD_hpa) (hPa)	(PRISM Climate Group n.d.)	1. Download 4 km resolution PRISM data for precipitation, min, max, and mean temperature, and min and max vapor pressure deficit 2.Use annual data to get representative values for each parameter using "Zonal Statistics as Table" tool with city boundaries as zones	Cities with greater AMAVPD_hpa will use more stormwater infiltration	N, More Basins and less swales & strips and filters at higher AMAVPD_hpa , Fig. S2.3
Clim.-Cont.	30 Year Average Min Vapor Pressure Deficit (AMIVPD_hpa) (hPa)	(PRISM Climate Group n.d.)	1. Download 4 km resolution PRISM data for precipitation, min, max, and mean temperature, and min and max vapor pressure deficit 2.Use annual data to get representative values for each parameter using "Zonal Statistics as Table" tool with city boundaries as zones	Cities with greater AMIVPD_hpa will use more stormwater infiltration	N, Less filters with increasing AMIVPD_hpa
Clim.-Cont.	Aridity Index based on Köppen approach (AI)(mm/C)	(Köppen 1923; Quan et al. 2013; PRISM Climate Group n.d.)	Köppen approach (MAP/(MAT + 33)) [mm/C] (Note: lower AI → more arid)	More arid cities (smaller AI) will use more stormwater infiltration	Y, more infiltrators and less swales & strips and

					filters, Fig. S2.3
Soc.-Cont.	Population Density (DPS_personmi2) (person/mi²)	(U.S. Census Bureau 2012)		With greater population density there are less basins and more small footprint SCMs like swales & strips, and filters	Y, Fig. 5, Table 2
Soc.-Cont.	Median Household Income (MHI_Dollar) (2013-2017)	(U.S. Census Bureau 2012)		Areas with greater MHI there are more SCMs implemented and a more diverse composition of SCMs implemented.	Y, Fig. 5., Table 2
Soc.-Cont.	Median Housing Age (MHA_yrs)(Years)	(U.S. Census Bureau 2012)		With greater MHA there are a less diverse composition of SCMs	N, Less basins, More swales & strips and filters, and increased diversity, Fig. 5
Reg.-Cont.	Percent of lentic waterbody area considered impaired (303d) (ImpairedArea.perc)	(U.S. Geological Survey n.d.; US EPA n.d.)	1. Download 303d impaired water data and NHD high resolution dataset 2.Merge NHD files and project to appropriate coordinate system 3.Clip to city boundaries layer 4. Join NHD and 303d data using "Reach Code" field using "Join Field" tool 5.Join "attgeo_303dcaussrce" tables data with joined NHD-303d layers 6.Use "Tabulate Intersection" tool to get cumulative lengths and areas by city and contaminant parent description 7. Finish processing in R; get percent impaired and predominant contaminant.	With greater impaired area there are more filters and less basins implemented	N
Reg.-Cont.	Percent of lotic waterbody length considered impaired (303d) (ImpairedLength.perc)	(U.S. Geological Survey n.d.; US EPA n.d.)	1. Download 303d impaired water data and NHD high resolution dataset 2.Merge NHD files and project to appropriate coordinate system 3.Clip to city boundaries layer 4. Join NHD and 303d data using "Reach Code" field using "Join Field" tool 5.Join "attgeo_303dcaussrce" tables data with joined NHD-303d layers 6.Use "Tabulate Intersection" tool to get cumulative lengths and areas by city and contaminant parent discription 7. Finish processing in R; get percent impaired and predominant contaminant.	With greater impaired length there are more filters and less basins implemented	Y, Fig. 5, Table 2
Reg.-Cat.	MS4 Phase (I or II) (MS4P)	(“Enforcement and Compliance History Online” n.d.)		MS4 phase 1 cities will have greater diversity SCMs	N, More swales and strips in MS4 Phase I cities, Fig. 6
Reg.-Cat.	Are combined sewers present in the city (Y or N) (CSO)	t and Compliance History Online” n.d.)		Cities with CSOs will have greater SCM diversity with more filters and infiltrators	Y, except no evidence for swales & strips instead of infiltrators, Fig. 6

Reg.-Cat.	Is the city under a consent decree with the US EPA (Y or N) (CD)	(US EPA and OECA n.d.)		Cities under a consent decree will select for water quality SCMs such as filters over other SCM types	Y, Also more SCM diversity, Fig. 6

Note: Variable type is denoted in the first column and by the color of the rows. A brief description of the variable is presented in the second column along with the acronym used for the variable (Description). The citation of the data source is presented in the third column (Data Source). Basic processing steps applied to each explanatory variable is presented in the fourth column (Methods). Example hypotheses are presented for each explanatory variable in the fifth column (Hypotheses). If the hypothesis was supported by the analysis or not (Y or N) is presented along with figures that support the conclusion.

Table S2.2: Values of explanatory variables used in this analysis.

City	State	Imperv %	Mean Slope	St.Dev. Slope	Grnd Wtr Ratio	Min. DTWT	Max. DTWT	Mean DTWT	Avg. Precip.	IDF 2yr-24hr	Avg. Max. Temp	Avg. Mean Temp.	Avg. Min. Temp.	Avg. Max. VPD	Avg. Min. VPD	Aridity Ind.	Pop. Density	Med. Household Income	Median Housing Age	Impaired Area %	Impaired Length %	MS4P	CSO	CD
Austin	TX	25.79	3.91	5.18	0.1	0.03	75.4	14.65	33.59	4.14	79.33	67.9	56.47	21.11	1.63	14.39	2653.2	63717	33	0	6.36	Phase I	N	N
Baltimore	MD	46.16	3.87	4.04	0.04	0.02	51.9	13.87	44.84	3.24	65.68	56.07	46.46	13.4	1.79	22.02	7671.5	46641	77	0.95	6.77	Phase I	N	Y
Bozeman	MT	27.85	1.65	3.01	0.03	0.85	94.6	20.36	17.46	1.17	57.08	43.92	30.75	13.06	1.27	9.45	1950	49217	33	0	6.68	Phase II	N	N
Cary	NC	16.61	4.25	3.24	0.18	1.39	52.2	16.11	45.92	3.44	70.77	59.61	48.46	15.36	1.06	21.39	2488.4	97755	23	4.64	15.43	Phase II	N	N
Denver	CO	35.96	2.03	2.43	0.01	0.37	52.7	16.86	16.13	1.83	64.73	50.64	36.54	17.37	2.16	8	3922.6	60098	57	26.97	16.52	Phase I	N	N
Fayetteville	AR	15.64	3.99	4.34	0.36	1.55	71.5	24.01	47.45	3.94	68.69	57.82	46.95	13.86	1.06	22.58	1336.4	41158	25	67.8	2.13	Phase II	N	N
Fort Collins	CO	27.32	2.13	3.03	0.01	0.88	33.5	10.12	16.19	1.97	63.48	49.02	34.56	16.09	1.4	8.14	1114.7	60110	32.5	47.53	12.57	Phase II	N	N
Grand Rapids	MI	43.51	2.87	3.47	0.89	0.04	19.6	6.63	36.41	2.58	57.11	47.53	37.95	9.55	0.71	19.7	4235.6	44369	64	0	55.3	Phase II	Y	N
Lincoln	NE	36.71	2.71	2.77	0.91	0.38	24.3	8.67	30.32	3.02	62.6	51.35	40.11	13.22	1.17	15.4	1240.5	53089	49	1.78	26.45	Phase I	N	N
Los Angeles	CA	42.95	7.42	10.47	0.38	0.12	223	16.59	17.86	2.77	75.6	64.6	53.6	20.35	2.94	7.93	8092.3	54501	59	33.57	2.8	Phase I	N	N
NYC	NY	62.04	1.96	2.96	0	0.02	44	6.27	47.33	3.51	62.41	54.64	46.86	11.07	2.1	24.09	27012	57782	71	2.66	7.86	Phase I	Y	N
Philadelphia	PA	50.9	2.93	3.8	0	0.14	40.2	5.2	46.7	3.26	64.34	55.48	46.62	12.29	1.6	23.27	11380	40649	73	2.64	36.08	Phase I	Y	N
Phoenix	AZ	31.48	2.92	6.59	0.58	3.72	165	42.56	9.4	1.44	85.47	72.06	58.64	35.71	10.27	3.81	2797.8	52080	38	1.43	0	Phase II	N	N
Pittsburgh	PA	42.8	9.64	8.49	0.04	1.2	82.2	30.11	37.61	2.35	61.78	51.88	41.99	11.47	1.17	19.28	5521.4	44092	77	0	35.47	Phase II	Y	N
Pocatello	ID	29.21	4.58	5.77	0.51	4.03	85	36.18	14.05	1.12	59.51	46.68	33.84	15.33	1.84	7.39	1683.8	42979	48	0	16.02	Phase II	N	N
Portland	OR	43.29	5.08	7.28	0.5	0.16	86.3	18.37	42.81	2.52	62.7	53.13	43.55	10.97	0.81	21.72	4375.3	61532	61	1.37	3.06	Phase I	Y	N
Sacramento	CA	42.87	1.47	2.29	0.64	0.41	10.8	3.18	19.41	2.16	74.36	61.6	48.84	21.19	1.86	8.72	4764.2	54615	47	5.68	18.04	Phase I	Y	N
San Diego	CA	33.57	7.47	8.4	0.18	0.2	124	38.76	11.76	1.78	72.74	63.17	53.59	15.03	2.02	5.37	4020.4	71535	43	51.35	12.38	Phase I	N	Y

San Francisco	CA	58.76	5.66	6.21	0.04	0.35	52.4	21.08	24.08	2.29	63.31	56.91	50.51	8.6	1.41	12.14	17179	96265	77	72.22	64.78	Phase I	Y	Y
Seattle	WA	30.61	2.99	4.83	0.41	0.34	81.2	27.47	36.71	1.96	59.48	52.52	45.56	8.11	1.01	19.32	7250.9	79565	58	0.68	4.19	Phase I	Y	Y
Springfield	MO	30.69	1.93	2.39	0.14	0.93	34.9	15.51	40.96	3.6	61.81	51.97	42.14	11.01	0.87	20.99	1951.8	34775	42	2.57	4.26	Phase I	N	N
Tucson	AZ	26.68	1.97	2.96	0.89	1.22	105	38.38	12.18	1.73	83.55	69.15	54.75	34.3	7.31	5.02	2294.2	39617	41	0	0	Phase I	N	N
Washington	DC	37.94	4.09	4.49	0	0.03	53.9	16.91	42.93	3.13	66.46	56.72	46.98	13.5	1.54	20.91	9856.5	77649	68	23.06	58.35	Phase I	Y	Y

Note: Sources and methods used to arrive at these values are presented in Table S2.1.Imperv = impervious, St. Dev. = standard deviation, Grnd Wtr = Groundwater, DTWT = depth to water table, Precip. = precipitation, IDF = Intensity Duration Frequency, Temp. = temperature, VPD = vapor pressure deficit, Ind. = index, Pop. = population, MS4P = municipal separate storm and sewer system phase, CSO = combined sewers, CD = consent decree

Table S2.3. Classification systems and associated unit processes. Modified from Table 4.2 (WEF and ASCE-EWRI 2012).

			Quantity control						Pollutant control								Biological				Other			
MOP-Coarse	MOP-Fine	# Processes Provided	Peak flow attenuation	Runoff volume reduction	Infiltration	Dispersion	ET	Runoff collection usage	Sedimentation	Flotation	Laminar separation	Swirl concentration	Sorption	Precipitation	Coagulation	Filtration	Plant metabolism	Nitrification denitrification	Sulfate reduction	Organic compound degradation	Pathogen dieoff	Temperature reduction	Disinfection	Screening
	Wet basins	14	x	x			x	x	x	x			x				x	x	x	x	x		x	x
	Wetlands	13	x	x			x	x	x	x			x				x	x	x	x	x		x	
	Dry basins	4	x	x	x				x															
	Vaults and swirl concentrators	4	x						x	x		x												
	Oil Water Separators	3							x	x	x													
	Forebays	2							x	x														
	Cisterns	2		x					x															
Basins	Basin Unknown*	?																						
Swales and Strips	Swales	4			x	x											x					x		
	Strips	5			x	x			x								x					x		
	Sand filters	6	x						x	x						x		x					x	
	Bioretention	16	x	x	x		x	x	x	x			x	x	x	x	x	x		x		x	x	
	Landscaped roofs	6	x			x	x						x				x					x		
	Drain inlet inserts	2							x							x								
	Manufactured filters	2							x							x								
	Filter Unknown*	?																						
Filters	Gravel Wetland*	?																						
	Infiltration Basins	13	x	x	x				x	x			x	x	x			x		x	x	x	x	
	Infiltration Vaults	13	x	x	x				x				x	x	x			x		x	x	x	x	x
	Trenches	12	x	x	x				x				x	x	x			x		x	x	x	x	
	Dry Wells	12	x	x	x				x				x	x	x			x		x	x	x	x	
	Permeable pavement	10	x	x	x								x	x	x					x	x	x	x	
Infiltrators	Infiltration Unknown*	?																						
	Screens nets baskets racks	1																						x
	Hoods	1								x														
	Gross Pollutant Trap Other*	?																						
Gross Pollutant Traps	Gross Pollutant Trap Unknown*	?																						
	Other*	?																						
Other*	Stormwater Conveyance*	?																						
Unknown*	Unknown*	?																						

Note: *****'s in row headings under MOP-coarse and MOP-fine notate SCM classes we added to the original table to allow all listed SCMs to be placed in a category. Reported unit processes (x) are from the original table (WEF and ASCE-EWRI, 2012).

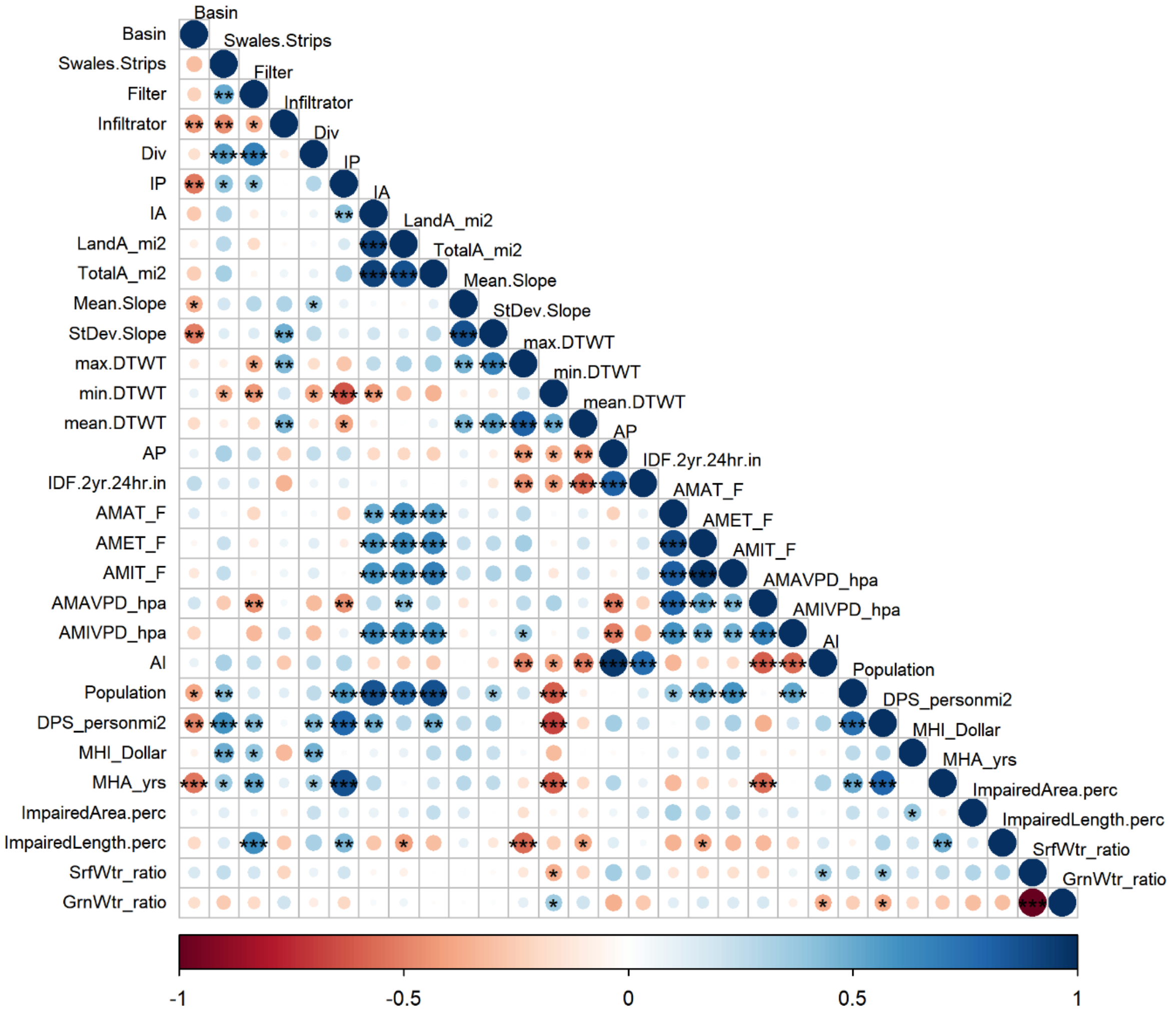

Fig. S2.1: Correlogram of Spearman's correlation coefficients between Hellinger-transformed MOP-coarse SCMs, Shannon diversity index (Div) of those SCMs, and explanatory variables. All explanatory variables are presented. Red represents negative correlations and blue represents positive correlations. The size of the circle represents the magnitude of the correlation coefficients (e.g., large dark red circles represent strong negative correlations and large dark blue circles represent strong positive correlations). *'s specify p-values: *p≤0.1, **p≤0.05, ***p≤0.01

Figures S2.2 and S2.3, along with Table S2.3, present breakpoints and thresholds that may be considered when investigating the effects of climatic variables and depth to water table. It is important to note though, that the threshold values identified should not be interpreted within the context of implementing a single SCM at a site, but rather, as being indicative of overall conditions within a city.

Breakpoints in Fig. S2.2 were identified using strucchange package (Zeileis et al. 2002, 2003) in R. It identifies breakpoints by minimizing the overall ordinary least squares.

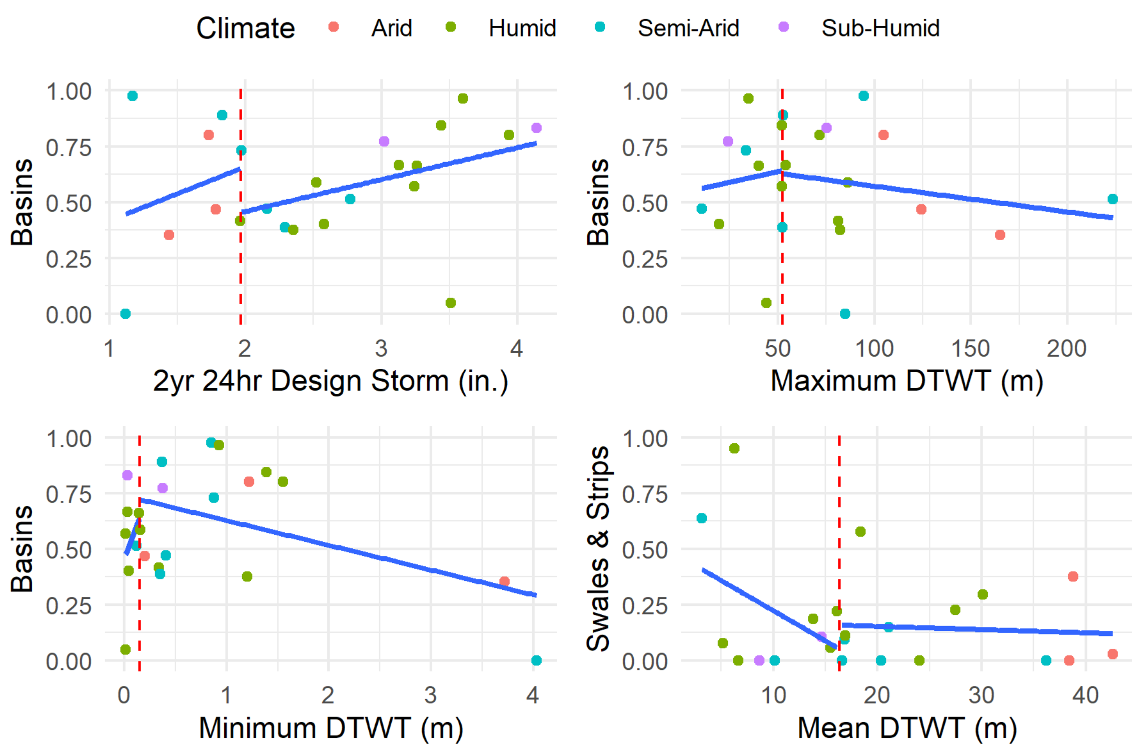

Fig. S2.2: The four single variate regression relationships between explanatory variables and Hellinger that had small overall residuals with the introduction of a breakpoint. The blue lines are the lines of best fit. The vertical dashed redline represents the breakpoint. The breakpoints are: top-left = 1.97 in., top-right = 52.28 m, bottom-left = 0.15 m, bottom-right = 16.35 m.

Table S2.3: Spearman correlation results from Fig. S2.2

SCM (Hellinger transformed)	**Explanatory Var**	**Data Included in Regression**	**Spearman ρ**	**p-value**
Basins	Design Storm	All	0.26	0.226
		$\leq 1.97\ in,$	0.21	0.645
		$> 1.97\ in.$	0.53	0.036
		$> 1.97\ in. with\ outlier\ removed$	0.71	0.003
Basins	Max DTWT	All	-0.11	0.609
		$\leq 52.28\ m$	0.22	0.576
		$> 52.28\ m$	-0.19	0.523
Basins	Min DTWT	All	0.10	0.654
		$\leq 0.15\ m$	0.11	0.819
		$> 0.15\ m$	-0.06	0.820
Swales & Strips	Mean DTWT	All	-0.09	0.695
		$\leq 16.35\ m$	-0.13	0.723
		$> 16.35\ m$	0.06	0.854

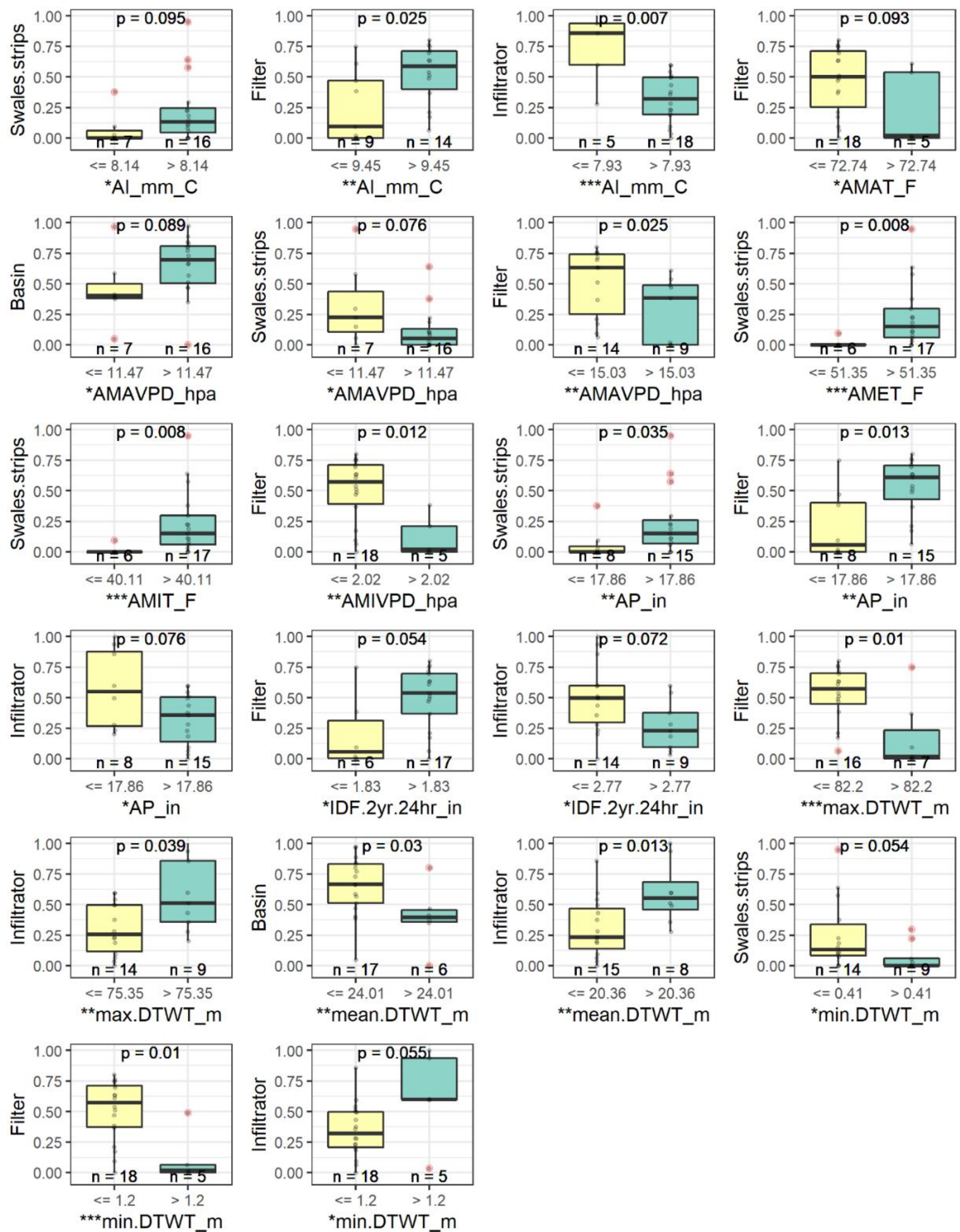

Fig. S2.3: Boxplots presenting Hellinger-transformed SCMs implemented in cities where the explanatory variable is less than or equal to some threshold (<=TH) and greater than that threshold (≤ TH). Only results with a p-value ≤ 0.1 are presented. Asterisks next to the x-axis labels note whether the results are *p≤0.1, **p≤0.05, or ***p≤0.01 and the p-value is presented at the top of each boxplot. Units of explanatory variables are presented in the x-axis titles (e.g.,units of mm/C in AI_mm_C). See Table S2.1 for the meaning of acronyms. Red dots represent outliers. The middle line of each box represents the median value, the top and bottom lines of the boxes represent the 25% and 75% quantile, and the whiskers extend to the smallest and largest values or no longer than the 25% and 75% quantiles plus 1.5 * the inter-quartile range. Note that aridity increases with decreases AI.

APPENDIX – Chapter 3

CHAPTER 3 – Supplementary Material: FULL REPORT: ESTIMATING CARBON SEQUESTRATION UNDER VARIOUS LAND-USE SCENARIOS OF DRIED AGRICULTURAL LAND IN THE SOUTH PLATTE RIVER BASIN

Executive Summary

Growing urban populations are accelerating land-use change (LUC) around the globe, as witnessed in the Front Range of Colorado (Angel et al. 2011; Colorado Water Conservation Board 2015; United Nations and Social Affairs 2018). In recent history, we have witnessed LUC exacerbating climate change due to disturbed soils, development of greenhouse gas (GHG) producing land uses, and more (Houghton et al. 2012). This trend is a product of our approach to land management however and is not a required feature of human progress. Local decisions determine how LUC manifests with significant implications for local livability and the global challenge of climate change.

An increasingly common trend in water-scarce regions is the permanent transfer of water from irrigated agriculture to municipal uses (i.e., urban and industrial uses), commonly known as buy-and-dry. Irrigated agriculture is a key economic driver of many of the more rural communities of the South Platte River Basin (SPRB). So, as those irrigated acres are dried, there will be significant economic and societal impacts such as the loss or alteration of employment opportunities, the local tax base, and general experience of agrarian culture. Of growing importance is the question of how to help maintain rural economies that will see significant declines in irrigated agriculture.

An ideal option would address both the desire to incentivize local land-use decisions that produce positive outcomes locally and globally and the need to maintain rural economies in the face of diminishing irrigated agriculture and a changing climate. One such option is for the public to pay private landowners for public goods or benefits that have not been historically recognized by the market. For example, if the land is used to provide some ecosystem service which benefits the public, such as water purification or carbon sequestration, then the landowner may be paid for that service. There can be direct payments for ecosystem services or payments via other programs, such as conservation easements, which have been used extensively in Colorado. As policymakers in the SPRB make decisions that will directly impact which land remains as irrigated agriculture, which land is dried, and which land is developed, it is important for them to have good information about the potential implications of those decisions. This report was motivated by the demand for easily performed scenario analysis to analyze such tradeoffs.

Overview

Growing urban populations are accelerating land-use change (LUC) around the globe, as witnessed in the Front Range of Colorado (Angel et al. 2011; Colorado Water Conservation Board 2015; United Nations and Social Affairs 2018). In recent history, we have witnessed LUC exacerbating climate change due to disturbed soils, development of greenhouse gas (GHG) producing land uses, and more (Houghton et al. 2012). This trend is a product of our approach to land management however and is not a required feature of human progress. Local decisions determine how LUC manifests with significant implications for local livability and the global challenge of climate change.

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For an overview of this report, I suggest visiting Section 5 (Conclusions) and reviewing the summary information provided as well as the information provided in the tables and figures throughout the report.

Section 1 (Introduction and Background), discusses the South Platte River Basin, relevant changes it is undergoing, the concept of paying private landowners for public goods not traditionally recognized by the market, and establishes the need for scenario analysis.

Section 2 (Climate and Land Use-Land Cover Review) discusses literature related to carbon, natural and working lands, soil, and developed lands.

Section 3 (Carbon Sequestration Valuation) discusses the valuation of carbon sequestration and related challenges.

Section 4 (Scenario Analysis) discusses methodologies related to spatially explicit scenario analysis related to ecosystem services generally and climate-related ecosystem services specifically.

Section 5 (Conclusions) provides an overarching summary of the report and several bullet points of open questions, suggestions, and other take home messages.

Section 6 (Existing Tools to Assist in Prioritizing LULC) explores eight online tools that may be useful for policy making decisions related to LULC and ecosystem services. Of particular interest may be the discussion of the COMET-Planner. After extensively reviewing the literature and available tools, I conclude that the COMET-Planner tool is perhaps the most relevant tool to understanding the climate-related ecosystem services related to natural and working lands. In Section 6.1.2, I apply the COMET-Planner tool to three areas of interest in the SPRB. I then utilize information gathered via literature review to expand that analysis so that estimates of ROI are presented.

Interdisciplinary Considerations

This report was motivated by an interdisciplinary challenge and utilized an interdisciplinary approach to address that challenge. Broadly, the disciplines important to the review and analysis presented in this report include economics, policy, natural resources and land management, and ecosystem services.

Economic Considerations

Sustaining rural economies in the face of drying irrigated agriculture was a primary motivation for this work. A methodological review and application of benefits transfer and valuation of carbon sequestration was performed. Specific methods for spatially explicit scenario analysis and return on investment from ecosystem services are suggested based on literature review. For example, I suggest caution when applying benefit transfer when needed data is sparce, recommend inclusion of uncertainty when developing or using tools for return on investment from ecosystem services, and estimate return on investment for three scenarios of conversion of irrigated agriculture to more natural land covers in three areas of interest in the South Platte River Basin (SPRB). Those three areas were Greeley's long range expected growth area, Brighton's South Platte River Heritage Corridor, and properties in Weld and Larimer counties that have been purchased by the City of Thornton with the intention of transferring the water from irrigated agricultural to municipal uses.

Policy Considerations

As the SPRB experiences rapid land conversion due to the drying of irrigated agricultural land, policy will help shape the outcomes and experiences for agrarian communities. Therefore, this work included multiple policy considerations. A review of payment for ecosystem services schemes with a focus on payments for conservation and payments for carbon sequestration is provided. Valuation of ecosystem services can help prioritize which irrigated land to keep in production and which to target with conservation programs and/or payment for ecosystem services programs, having implications for natural resources and land management related policy.

Systems-Thinking Considerations

The overall motivation for this report originates from a systems-thinking perspective. Specifically, growing urban populations are placing pressure on urban water resources, so municipalities are responding by purchasing agricultural water rights, drying what was irrigated cropland, and transferring the water to urban uses. In response, agrarian economies are likely to be strained due to the loss of substantial acreage of irrigated agriculture. This report addresses one potential response to the economic damage caused by buy-and-dry water transfers – paying landowners for ecosystem services.

Stakeholder Engagement

While this work did not specifically include stakeholder engagement as a method, it was motivated by work with the Colorado Water Conservation Board (who may be considered a stakeholder). The report also poses the question of whether the landowners in the communities in which payment for ecosystem services programs may be implemented have any interest in such programs.

DPSIR

Growing urban populations and reduced commodity prices are *driving* the transfer of water from irrigated agriculture to urban and municipal uses. Cities in the SPRB of Colorado are actively securing water supply to meet the demands of growing urban populations and industry and to ensure those demands can be met well into the future. With limited opportunities to develop new water sources, cities are resorting to the purchase of agricultural water rights with older water rights being in greater demand due to the enhanced security they provide.

Irrigated agriculture has become the cornerstone of many of the rural landscapes and economies of the SPRB. As water is transferred away from irrigated agriculture significant *pressures* are being placed on both the landscapes and economies in the agrarian communities. Land that was once irrigated is being converted to other land uses such as urban development, non-irrigated agriculture, or more natural land cover such as native grasslands. Communities that have come to rely on irrigated agriculture will experience loss or alteration of employment opportunities and the local tax base.

To characterize the situation within the SPRB important *states* to consider include: 1. The SPRB is home to 70% of the Colorado's population, 2. It demands over 2.5 million acre-ft of water for irrigated agriculture annually, 3. There are over 4 million acre-ft of water diverted from surface water sources, for all uses, annually, 4. There are another 500,000 acre-ft of groundwater withdrawn annually, 5. There are only about 1.4 million acre-ft of native water available annually, 6. Due primarily to the purchase of water rights by municipalities from irrigators (i.e., buy-and-dry), a decline of between 131,900 and 174,000 acres of irrigated agriculture is excepted to be dried by 2050 (~15-20%).

While there will be many *impacts* from the buy-and-dry trend in the SPRB, this document focuses on the *impacts* that local communities and economies which have been built around irrigated agriculture will experience as the vital economic driver and core aspect of local culture (i.e., irrigated agriculture) is significantly reduced.

The primary objectives of this document are related to a potential *response* to ease the impacts of buy-and-dry on local economies and communities while also mitigating any negative land use changes that may occur as what has been irrigated agriculture is altered to other land uses.

Intellectual Merit and Broader Impacts

This document is intended to be of practical interest to policy-oriented professionals working in the SPRB, that are also interested in climate, buy-and-dry, and ensuring the agrarian communities in the SPRB do not experience undue harm as water is transferred away from irrigated agriculture. A thorough literature review related to payment for ecosystem services with a focus on climate related ecosystem services is presented. Key points, considerations, and open questions are identified and a framework for policy-relevant and spatially explicit valuation of ecosystem services is discussed. Furthermore, a review of potentially relevant existing web tools is presented as a reference for those seeking easy access to relevant analyses. Finally, a web-tool which extends the COMET-Planner tool is presented with three example areas of interest within the SPRB. The web-tool enables easy estimates of the return on investment from conservation measures present in the COMET-Planner tool, at a property scale resolution. The work presented herein is not extremely novel, but rather, synthesizes and extends existing knowledge for policy-relevant professionals.

Chapter 3 – Full Report - Table of Contents

Table of Figures and Tables

1. Introduction and Background

1.1 The South Platte River Basin

The South Platte River Basin (SPRB; Fig. S3.1) is Colorado's most populous, economically diverse, and agriculturally productive basin. It is home to 70% of the state's residents and demands over 2.5 million acre-feet of water for irrigated agriculture annually (Colorado Water Conservation Board 2015). Other than agriculture and livestock, its important economic sectors include tourism, recreation, manufacturing, service and trade industries, and government services ("NAWQA South Platte River Basin Study" n.d.). Municipal and rural stakeholders are in competition for water resources in the basin as there are only about 1.4 million acre-ft of native water (i.e., sourced from within the basin) available annually while annual water diversions of surface water are around 4 million acre-ft, with groundwater withdrawals accounting for another 500,000 acre-ft of supply.

Like many semi-arid and arid regions of the world, the substantial gap between the supply and demand of water in the SPRB is driving competition for water supply between economic sectors. Of heightened interest is the competition between municipal (e.g., industrial and residential) and rural (e.g., irrigated agriculture) water users which has driven the phenomenon known as buy-and-dry. Within the doctrine of prior appropriation, which governs water rights in Colorado, a water user owns the rights to use water for some beneficial use, such as growing crops or an industrial use, but that water user may not use or lease the water for a different use. As the SPRB has witnessed rapid urban and industrial growth it has become more common for municipalities to purchase water rights from irrigated agriculture to secure water supply for the near and long-term future of the municipality. While there are ongoing efforts to figure out ways to allow for the transfer of water without permanently drying irrigated agricultural land, the buy-and-dry trend is expected to continue through at least 2050 leading to a decline of between 131,900 and 174,000 acres of irrigated agriculture (Colorado Water Conservation Board 2019).

While direct development of land will account for a significant portion (~6-7%) of the expected land-use change coming to the SPRB over the coming decades, the primary driver will be buy-and-dry. Although urbanization is relatively compartmentalized spatially, its indirect effects will be experienced throughout the basin. Many rural areas of the basin rely on irrigated agriculture to support their economies. The loss of that economic driver is likely to have significant social, cultural, and economic implications for those agrarian communities as the local tax base, employment opportunities, and general experience of living in an agricultural area are lost or altered. Of growing importance is the question of how to help maintain rural economies in the SPRB that will experience significant declines in irrigated agriculture.

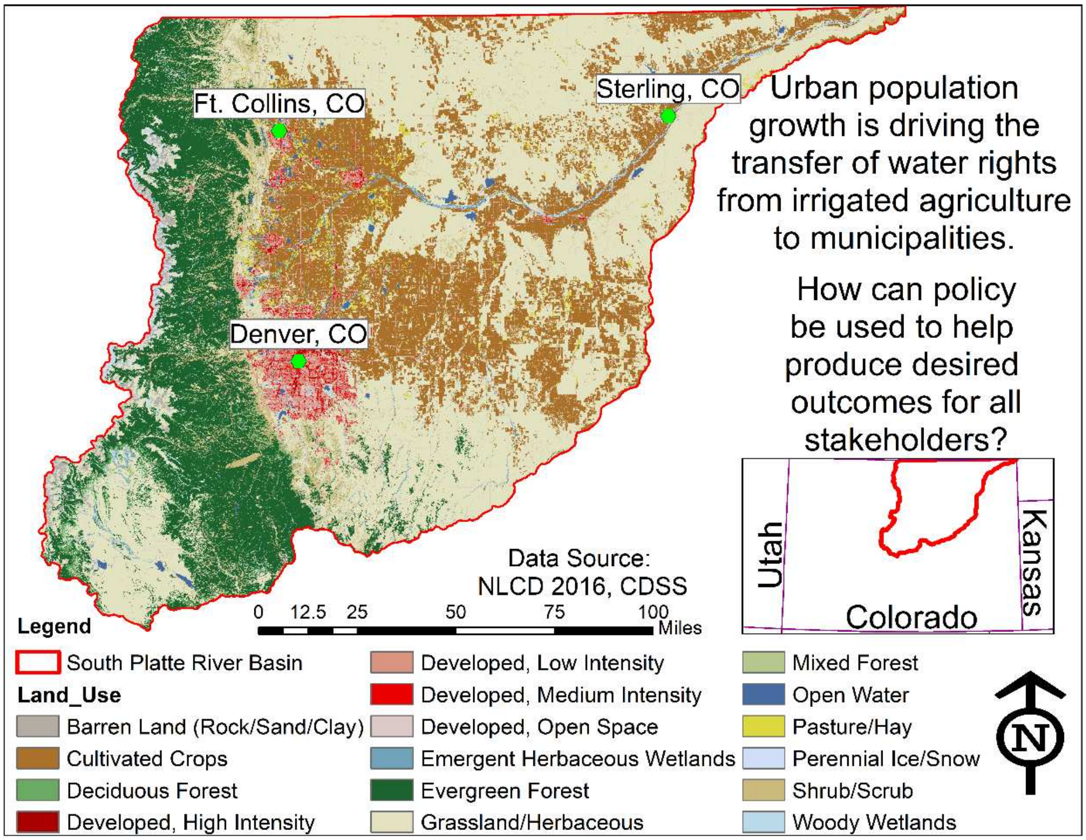


***Fig. S3.1**: The South Platte River Basin of Colorado.* Land Cover is from the 2016 National Land Cover Database (Dewitz 2019b). Assigning different values of carbon sequestration and/or return on investment to different land cover types is one approach to comparing carbon sequestration and ROI of different land-use scenarios.

1.2 Change in the SPRB and Opportunities it Presents

Not only is the SPRB experiencing growing urban populations and land-use change, but it is also dealing with the local effects of global climate change. In the SPRB temperatures are expected to increase driving greater atmospheric demand for water, altering the timing of snow-melt which drives the hydrology of the basin, and decreasing the volume of water from transmountain sources (e.g., Colorado Big Thompson Project) likely exacerbating the supply-demand gap (Colorado Water Conservation Board 2019). Each of these changes is expected to amplify the competition for water resources and points toward a challenging and complex future with regards to water management in the basin. The SPRB will not be alone in facing the challenges that climate change presents. Just as the challenges presented by climate change are shared across the globe, so must be the responsibility of taking action to mitigate and reverse climate change and its effects.

Times of change provide opportunities for innovation, reorientation of goals, and for new approaches to be used to reach those goals. In early 2021 Governor Jared Polis' office in Colorado released a roadmap for the state's goals of reducing greenhouse gas (GHG) production. Within that document several steps and important considerations are highlighted that will enable Colorado to meet its ambitious climate-change goals. Of particular relevance to this work is the key finding that, "protecting, restoring, and enhancing the resilience of Colorado's natural and working lands is critical for sequestering carbon (Governor Jared Polis' Office 2021)." The Colorado Water Plan (Colorado Water Conservation Board 2015) also identified the need for additional incentives to assist basins in implementing agricultural efficiency and conservation practices to support the ecosystem services that agriculture can provide. By paying private landowners or other relevant stakeholders for providing the public good of carbon sequestration by implementing climate-smart strategies on their land, rural economies can gain an additional source of revenue. Owners of land that transition from irrigated agriculture to another land use can maintain some income while those that are fortunate enough to keep their land in production can add the additional income to their portfolio.

As the basin takes on the challenges of minimizing the water supply-demand gap and addressing climate change, there are ample opportunities to synergize those efforts. **One of the most obvious synergies is the improvement of soil health associated with carbon sequestering practices on crop and rangelands.** One study found counties in the United States with higher soil organic matter (i.e., stored carbon) had greater yields, lower yield losses, and lower rates of crop insurance payouts under drought (Kane et al. 2021). Not only should this motivate crop farmers to improve their soil health, but it also points towards the possibility of insurance companies offering incentives for farmers to improve their soil health. Many such practices are also associated with greater carbon sequestration and/or storage (Denef et al. 2011).

1.3 Paying Private Landowners for Public Goods

Economic activities such as industrial manufacturing, oil and gas extraction and production, or agricultural production often have unintended consequences which can have positive or negative impacts on society (i.e., externalities). The concept of paying landowners or other relevant entities for goods or benefits not historically acknowledged by the market, such as the positive externalities of certain land uses or land management approaches, or for mitigating some negative externality, is not a novel idea (Adhikari and Boag 2013; Farley and Costanza 2010; Van Hecken and Bastiaensen 2010). Many efforts have worked to encourage different conservation practices, motivated by the understanding that healthy land provides many services from which the public benefits.

During the 2013 fiscal year the United States government spent more than $6 billion to encourage voluntary adoption of conservation practices (Claassen et al. 2014). In Colorado, the Great Outdoors Colorado (GOCO) and Conservation Easement Tax Credit programs have been utilized extensively to incentivize the acquisition of conservation easements which in return, are thought to provide significant returns on investment (ROI) to the public via ecosystem services such as water purification, air quality improvements, and more (Seidl et al. 2017). These programs offer financial and tax incentives for restricting development on private lands. Seidl et al. (2017) found that Colorado's two primary conservation easement programs had conserved nearly 1.5 million acres of crucial habitat, 300,000 acres of prime farmland, 270,000 acres of elk severe winter range, 4,100 miles of stream, creek, or river frontage, and 19% of the Gunnison Sage-Grouse production areas occurring on private land. While acknowledging significant uncertainty in the analysis of ROI from ecosystem services, they found that Colorado's investment of about $1.1 billion (in US$2017) had produced a ROI to the public of between $5.5 - $13.7 billion (US$2017), a $4-$12 return for each $1 invested. There is clearly substantial uncertainty in these estimates. Nonetheless, these results suggest a clear benefit returned from the investments resulting from Colorado's conservation programs.

Economic difficulties arise when it comes to paying private landowners for public goods such as carbon sequestration and storage causing some to argue against the commodification of ecosystem services. For example, for a market to set a price there must be an interplay between supply and demand generated by economic providers and consumers. Without this flow of information generated by the interaction of supply and demand it can be very difficult, if not impossible, to identify an economically efficient price (Farley and Costanza 2010). Other considerations that complicates such programs is the concept of additionality – only paying landowners for services that are in addition to what they would have been doing without the payment (Claassen et al. 2014), and misalignment between the scale at which a service is produced and at which its benefits are realized (Richardson et al. 2015). There are many other difficulties such as the facts that markets cannot be evaluated without existing in an array of informal and formal institutional arrangements which may not currently be established, that markets evolve over time, and asking whether the carbon market will act as a force in favor of, or against, poverty alleviation. Despite these challenges, such programs have become common around the globe (Adhikari and Boag 2013; Farley and Costanza 2010; Michaelowa et al. 2019; Van Hecken and Bastiaensen 2010), largely driven by the lack of a clearly-better option.

1.4 A Need for Scenario Analysis – Land Use-Land Cover, Ecosystem Services, and ROI

As the South Platter River Basin evolves as a socio-hydrological system, policy decisions are being made that will help determine the future economic, environmental, and societal health of the basin. For good decisions to be made good information must be available. If policy makers and entities that help inform them (e.g., the Colorado Department of Natural Resources or the CWCB) require an expert each time they need to explore the climate change implications of various LULC scenarios then cost in and of itself may become prohibitive to desired programs (Paustian et al. 2016; Van Hecken and Bastiaensen 2010). What is needed is a robust, yet easy to use tool that does not require expertise. Of particular interest is the ability to explore various LULC scenarios (e.g., Fig. S3.2) to allow for the prioritization of various policies and decisions.

Since the price paid in *payment for ecosystem services* programs, such as those that pay landowners for carbon sequestration, is largely driven by policy it is essential to have good estimates of the return on investment (ROI) from such payouts. In this way, appropriate decisions can be made that will both optimize the public's ROI while allowing for appropriate prices to be set. One example of the benefits of such a tool would be to prioritize what land has the greatest potential to sequester carbon in the absence of agriculture and which land has the greatest potential to produce valuable crops. Being able to understand which land should be prioritized for what use is essential to help direct limited state funds to the most impactful conservation projects and would also help direct federal spending.

Fig. S3.2: Four different land-use types in the South Platte River Basin. Images captured with Google Earth. (A) Pivot irrigation agriculture, (B) Medium-intensity residential development, (C) Peri-urban low intensity development, (D) High-intensity development. Growing populations in urban areas (D) are drying irrigated land (A). What are the implications of different land-use decisions with regard to water management and climate change?

2. Climate and Land Use-Land Cover Review

Many of the early actions surrounding GHGs and climate change were motivated by country, multiple country, or global scale efforts. As a result, many of the more relevant methodologies that are well-established were developed at the same scale. For international agreements and other actions taken at the national or global scales it is important to consider GHG emissions and sequestration at those same scales, however it provides little actionable insight to local policy and decision makers that would like to incorporate relevant considerations into policy and decisions (Gurney et al. 2015). Considering an appropriate spatial scale (e.g., a river basin versus national) is also important to understand the relative tradeoffs of various scenarios. If decision makers in the SPRB for example, want to understand the tradeoffs between two LULC scenarios they may find the difference to be negligible when compared to the most impactful land uses and GHG sources globally. Understanding how carbon storage in an alternative LULC scenario compares to global observations is of little interest, while understanding how the alternative LULC scenario performs compared to the current LULC scenario is critical to making informed local decision. Locally based GHG inventories have also been shown to be more accurate than global inventories with differences between global and regional inventories of anthropogenic carbon emissions differing by about 20% while global and locally-derived inventories were between 50% to 250% different (Gately and Hutyra, 2017), highlighting the need for bottom-up versus top-down estimates of GHG emissions for local decisions.

2.1 Carbon, Natural and Working Lands, and Soil

There is a vast amount of literature related to GHG production, sequestration, and storage. A quick search using the keywords "greenhouse gases" in the Web of Science results in 87,762 results, 31,707 open access articles, 6,352 review articles, and 1,385 highly cited papers (https://www.webofscience.com/wos/woscc/summary/04d67fc8-021b-4fad-8a07-149346d558bb-0df31403/relevance/1). With respect to carbon sequestration and storage, there is a significant focus on soils (e.g., Alexander et al. 2015; Conant et al. 2017; Entry et al. 2007; Kane et al. 2021; Paustian et al. 2016, 2019; Smith et al. 2020) due to a few primary reasons. First, within the top meter of soils globally, there is an estimated stock of around 5,500 – 8,800 Gt CO_2 with the lower range representing about three times the total stock of CO_2 found in vegetation and twice that found in the atmosphere. Second, as a result of cultivation and agricultural management practices it is estimated soils have lost around 510 – 550 Gt CO_2 since agriculture became popular around 8,000 years ago (Smith et al. 2020). A 2018 systematic literature review concluded that soil carbon sequestration has the potential to sequester about 2 to 5 Gt CO_2 annually (Fuss et al. 2018). Lastly, using soil to sequester carbon can improve soils, make them more resilient to drought and climate change, and improve overall agricultural productivity (Fuss et al. 2018; Kane et al. 2021). Essentially, the literature shows that carbon sequestering agricultural practices are likely good for agricultural production and the fact that they sequester carbon is a bonus.

While we have a decent understanding of large-scale carbon storage in soils, extreme spatial heterogeneity makes it very difficult to generalize carbon storage based on management practice from place to place. Soil carbon storage is location specific, depending on climate, previous and current land-use/management, soils, and other factors (Fig. S3.3; Ramesh et al. 2019).

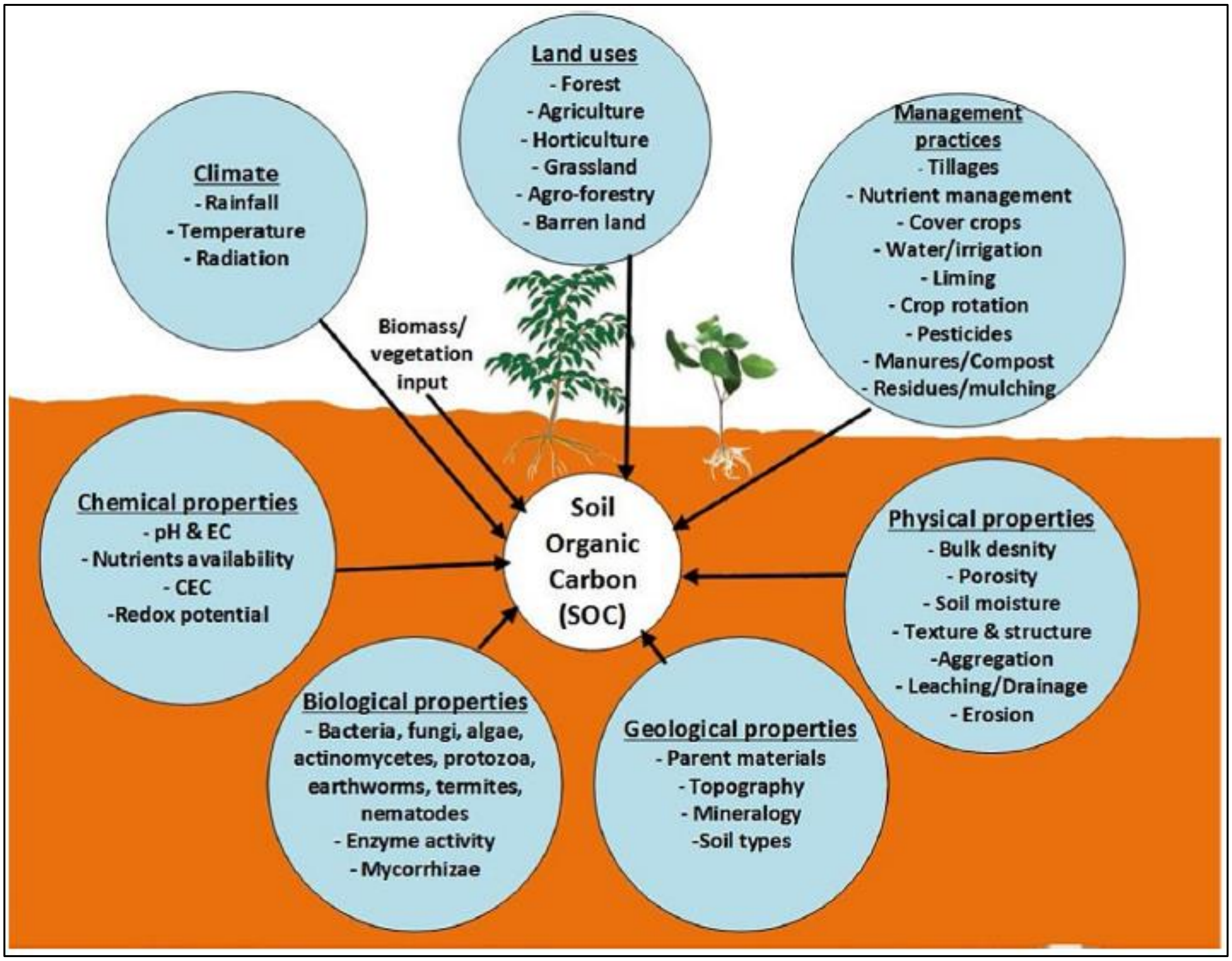


Fig. S3.3. *Schematic diagram of the factors influencing carbon dynamics in soil.* (From Ramesh et al. 2019)

Conant et al. (2017) performed an extensive literature review to synthesize experiments that have compared soil carbon storage between a control treatment (e.g., traditional irrigated agriculture or an ungrazed grassland) with an 'improved' or experimental treatment (e.g., cropland transitioned to pasture or a grazed grassland). The studies took place over 37 countries representing a wide variety of conditions. They found, "improved grazing management, fertilization, sowing legumes and improved grass species, irrigation, and conversion from cultivation all tend to lead to increased soil C, at rates ranging from 0.105 to more than 1 MgC/ha-yr." To see if we could learn more from the data used in that study, which the authors made publicly available, I performed a brief data analysis. The data included observations from 241 papers, with each study comparing two or more treatments. For example, one study may have compared soil carbon in an irrigated crop plot to the soil carbon in a native grassland. Values related to soil carbon were reported in terms of storage per acre [tC/ha]. Although, in the related paper the authors present results in terms of carbon sequestration [MgC/ha-yr]. First, I plotted the full range of all observed stored carbon as boxplots (Fig. S3.4 – left) and then plotted the same data except limited to relatively non-humid areas of the USA (Fig. S3.4 – right) which resulted in data from 10 states. Then I plotted the data from the USA with the control treatments and "improved" (i.e., test) treatments split (Fig. S3.5 – left). Last, I plotted boxplots of study-wise differences between the control and "improved" treatments, with positive values representing better performance by the "improved" treatment and negative values representing better performance by the control treatment (Fig. S3.5 – right). Boxplots were used because they allow for an easy comparison between treatments.

The range of values of observed carbon storage per area is larger when studies from around the globe are included (Fig. S3.4 – left) compared to studies from more similar climatic and geographic areas (Fig. S3.4 – right). This is potentially simply due to fewer datapoints being included in the plot presenting observations from non-humid areas of the USA, but the idea that more similar climatic and geographic areas store more similar magnitudes of carbon follows reason (Paustian et al. 2016; Ramesh et al. 2019). In Fig. S3.4 we also observe that for four treatments (e.g., shift from ag. to pasture or modified grazing intensity) the observed carbon storage per area ranged over three orders of magnitude, highlighting the uncertainty in such measurements.

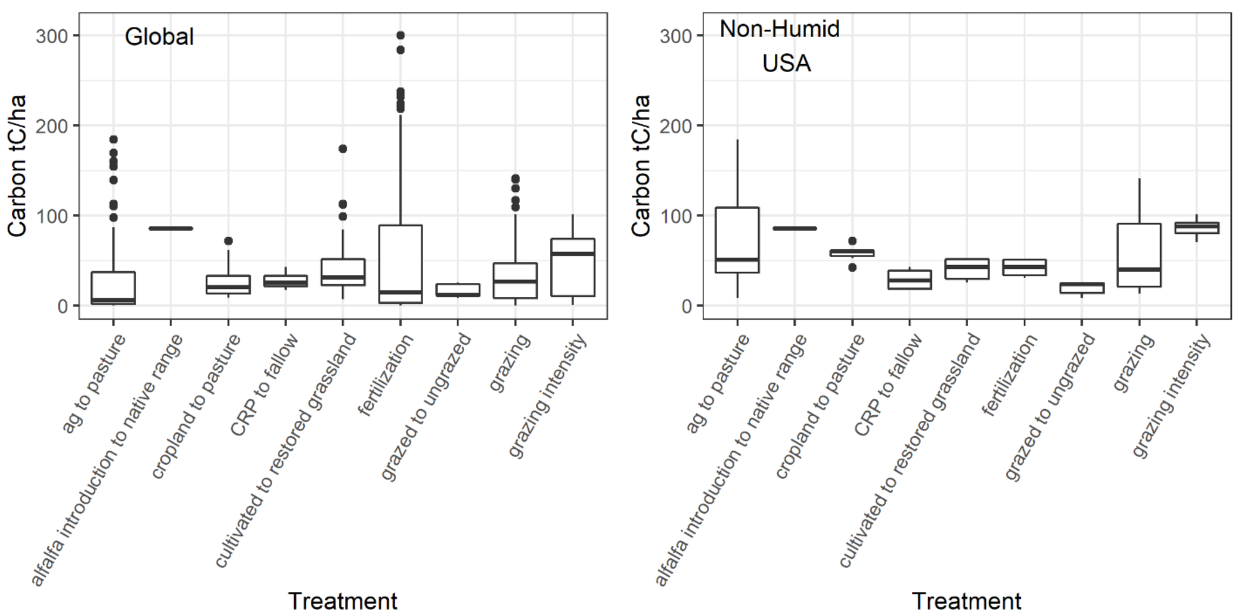


Fig. S3.4. Boxplots presenting carbon storage per area [tC/ha] based on studies around the globe (left) and on studies from the USA with humid regions removed (right). Boxplots represent the 25th and 75th percentiles as the edges of the box, the 50th percentile (median) as the line lying within the box, and the largest and smallest values falling within 1.5 times the interquartile range above the 75th percentile or below the 25th percentile, respectively. (Data from Conant et al. 2017)

Further highlighting the site-specific nature of soil carbon storage, we see that when comparing all control treatments with all "improved" treatments (Fig. S3.5 – left) it is very difficult, if not impossible, to generalize across locations. On the other hand, if we look at the study-wise differences between control and "improved" treatments (Fig. S3.5 – right) the range of observations narrows. For example, values of carbon storage per area (Fig. S3.5 – left) for conversion from *ag to pasture* range from near 0 to about 175 tC/ha. In contrast, looking at the study-wise differences of the same treatment (i.e., *ag to pasture* in Fig. S3.4 - right) reveals that lands converted from agriculture to pasture almost always increase in soil carbon storage. Those differences ranged from about 0 to just over 20 tC/ha, which is nearly an order of magnitude smaller than the range observed when looking at carbon stored per area (i.e., 20 tC/ha vs 175 tC/ha). Looking at the study-wise differences between control and “improved” treatments (Fig. S3.5 – right) also shows that many treatments thought to improve (or increase) soil carbon do not always perform as expected. Taking the shift from *cropland to pasture* as an example, we see that sometimes soil carbon is increased and other times it is decreased. This inconsistent behavior is likely due to differences in soils, climates, and/or previous management or land uses (Conant et al. 2017; Olsson et al. 2014; Pouyat et al. 2006; Ramesh et al. 2019). Overall, the data from Conant et al. (2017) show us that the differences in observed soil carbon between locations is greater than the difference between management approaches. **This highlights the difficulty in generalizing observations in soil carbon between locations. To minimize uncertainty in scenario analysis it may be better to use relative performance of sequestration instead of an absolute measure, similar to the [COMET planner tool](#).**

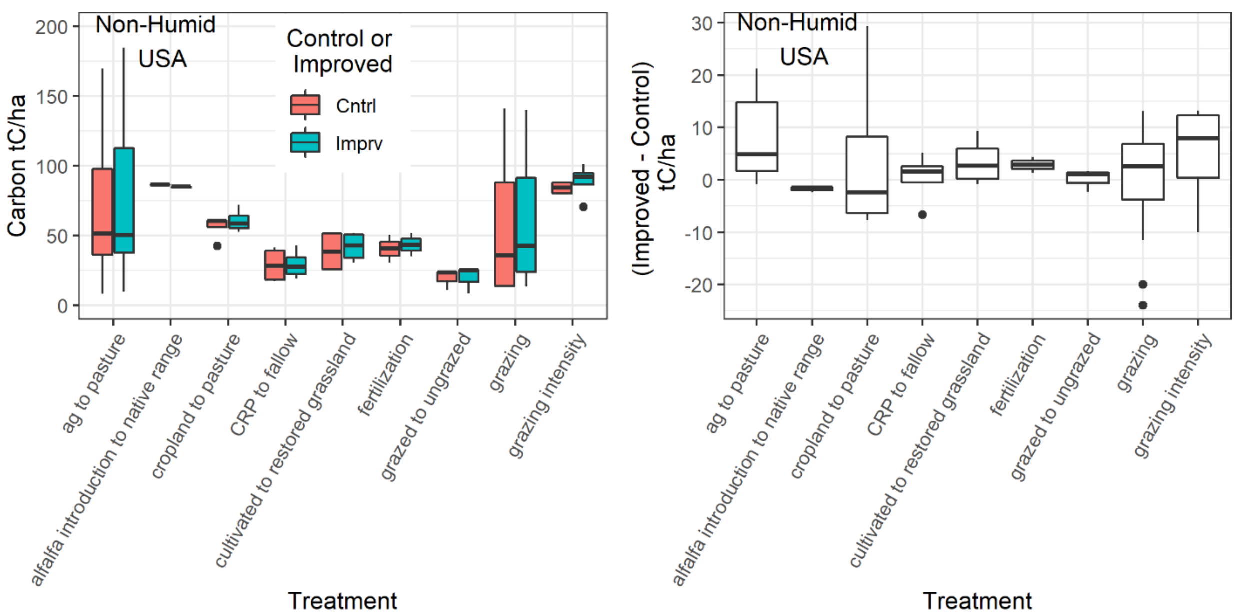


Fig. S3.5. Boxplots comparing the overall observations of carbon per area [tC/ha] between the control and “improved” treatments in all of the reviewed studies (left) and showing the study-wise differences between the control and “improved” treatments (right). Note that CRP = conservation reserve program. (Data from Conant et al. 2017)

2.2 Carbon and Developed Lands

Due to the vast land area that agriculture occupies compared to urban areas, urban areas have received relatively little attention despite their substantial contribution to global GHG production. One study in the northeast U.S.A. found that urban emissions accounted for 25 to 85% of all carbon emissions in the 13 study states in the northeast U.S., with on-road transportation being the largest emitters at state and city levels (Gately Hutyra). The relative contribution of different sectors (i.e., electricity production, on-road vehicle emissions, commercial/industrial, non-road vehicle emissions, and residential) varied significantly between cities however, pointing to the need for policy specific to each individual urban area. There is a strong push for compact urban form as a more sustainable development option (Artmann et al. 2019), but understanding the climate change implications of urban areas requires inclusion of considerations that reach far beyond a city's boundaries. One study found that greater than 70% of CO_2 emissions related to goods consumed within the cities of Beijing, Shanghai, and Tianjin, China were produced outside of city limits (Feng et al. 2014).

Other than more technological solutions that can improve efficiency of energy intensive processes or directly filter/capture GHG emissions, whether a city is a net source or sink of biogenic GHG (e.g., GHG produced to land-use change or sequestered by vegetation) depends on how a city is developed and managed. For example, with proper management of greenspaces the emissions produced by land-use change can be offset by vegetation and greenery (Milnar and Ramaswami 2020). Urban trees can play an important role in managing GHGs in urban areas. A study in 10 U.S. cities found carbon storage in urban trees ranged from 46.9 tC/ha in Sacramento to 5 tC/ha in Jersey City and that annual carbon sequestration varied from 150 +/- 30 kg/ha to 940 kg/ha (Nowak and Crane 2002). Another study across 28 U.S. cities estimated the total tree carbon storage in U.S. urban areas to roughly 643 million tonnes with an annual sequestration rate of roughly 25.6 million tC (about 0.28 kgC/m^2 of tree cover) with the most influential factors being tree diameter distribution, tree density, and to a lesser extent, species composition (Nowak et al. 2013). Even if the carbon sequestration and storage provided by urban areas is relatively small compared to the vast areas occupied by natural and working lands, climate change is a problem that will require an "all of the above" approach, so urban areas must be considered (Pacala and Socolow 2004; Paustian et al. 2016).

3. Carbon Sequestration Valuation

To assist with policy decisions, quantifying the ROI from carbon sequestration/GHG mitigation is highly desirable. The vast majority of efforts attempting to so consider the ROI to be the social cost of carbon (SCC) avoided. That is to say, if sequestering a ton of carbon today avoids $200 of social damage (e.g., property destruction or loss of national or global GDP) then the ROI of sequestering one ton of carbon is taken to be $200. Quantifying a value for the SCC includes extensive uncertainty and is a highly debated topic (Drupp et al. 2015; Interagency Working Group 2013; Pindyck 2019; Plummer 2009; Ricke et al. 2018). There are many ways to approach to this challenge. The Natural Capital Project's InVEST carbon model takes a simple but well-accepted approach (Sharp et al. 2020) so I use it as an example here.

3.1 A Valuation Formulation

Data requirements for valuating carbon storage and sequestration in the InVEST carbon model and many other approaches include price per metric ton of carbon, the market discount in price of carbon, and the annual rate of change in the price of carbon (Sharp et al. 2020). Price per metric ton of carbon is based on the social damage avoided as discussed above. The market discount in price of carbon refers to society's preference for present benefits over future benefits. The annual rate of change in the price of carbon is an input used to capture how the value of carbon sequestration may change over time based on the damages caused by climate change. Setting the annual rate of change to a value greater than 0% means you assume the societal value of carbon sequestered today is greater than the value of carbon sequestered in the future (Sharp et al. 2020). For example, it could be argued that sequestration has greater value now because sequestration of the same amount of carbon now compared to later may have a greater impact on climate change. Discount rates can be considered in different ways with some combining the market discount and annual rate of change for example (Pindyck 2019; Ricke et al. 2018) with others suggesting a dynamic discount rate that changes with time (Ricke et al. 2018). Discounting is consistently shown to be one of the largest sources of the differences in estimates of SCC (Ricke et al. 2018). Both market discount in the price of carbon and the annual rate of change in the price of carbon can be set to 0 in the InVEST model. Ultimately, the value of sequestered carbon over time for a given parcel, $value_{seq_x}$ (i.e., LULC pixel) is calculated as,

$$Eq. 1. \quad value_{seq_x} = V \frac{sequest_x}{yr_{future} - yr_{current}} \sum_{t=0}^{yr_{future} - yr_{current} - 1} \frac{1}{\left(1+\frac{r}{100}\right)^t \left(1+\frac{c}{100}\right)^t},$$

where V is the price per metric ton of elemental carbon (not CO_2), $sequest_x$ is the amount of carbon sequestered, yr_{future} and $yr_{current}$ are the future and current years being simulated, respectively, r is the market discount in price of carbon [%], t is the time elapsed since the current year being simulated, and c is the annual rate of change in the price of carbon [%]. It is important to note that this approach assumes a constant carbon sequestration rate over time but a constant rate is unlikely to be observed in reality (Sharp et al. 2020). Due to this assumption though, this formulation of the value of sequestered carbon lends itself to accepting outputs such as those provided by COMET-Planner (*seqrate;* e.g., amount of carbon sequestered per year). By simply replacing, $\frac{sequest_x}{yr_{future} - yr_{current}}$, with the carbon sequestration rate provided by COMET-Planner, $seqrate$, we arrive at the following formulation of the value provided by scenario being considered ($value_{seq}$; e.g., conversion of irrigated agriculture to native grassland).

$$Eq. 2. \quad value_{seq} = (V * seqrate) \sum_{t=0}^{yr_{future} - yr_{current} - 1} \frac{1}{\left(1+\frac{r}{100}\right)^t \left(1+\frac{c}{100}\right)^t},$$

with t now being the total number of years to be included in the valuation. For example, if we wanted to estimate the value of carbon sequestration provided if 640 acres of land were converted from irrigated agriculture to a native grassland today, we must decide how far into the future we want to assume the constant sequestration reasonably applies? **Lands will eventually reach an equilibrium with regard to carbon storage, where the net amount of carbon being sequestered is essentially zero** (i.e., the amount being sequestered is equal to the amount being released; Entry et al. 2007).

3.2 Review of Valuation Input Variables

Deciding how far into the future to consider when estimating the value from carbon sequestration or GHG mitigation provided by a LULC scenario is not the only complicating factor. Due to sources of uncertainty related to nearly every variable used to quantify the SCC the resulting uncertainty is extreme. Ricke et al. (2018) estimated the global social cost of carbon (GSCC) by considering possible socioeconomic pathways (SSP), possible climate futures (i.e., representative concentration pathways-RCP), the potential negative impacts of climate change on the economy (i.e., using damage functions), and various discounting approaches. The resulting estimates of the GSCC are presented in Fig. S3.6 where the extensive uncertainty in the estimates can be clearly seen to range over three orders of magnitude (color bars represent the 66% confident intervals).

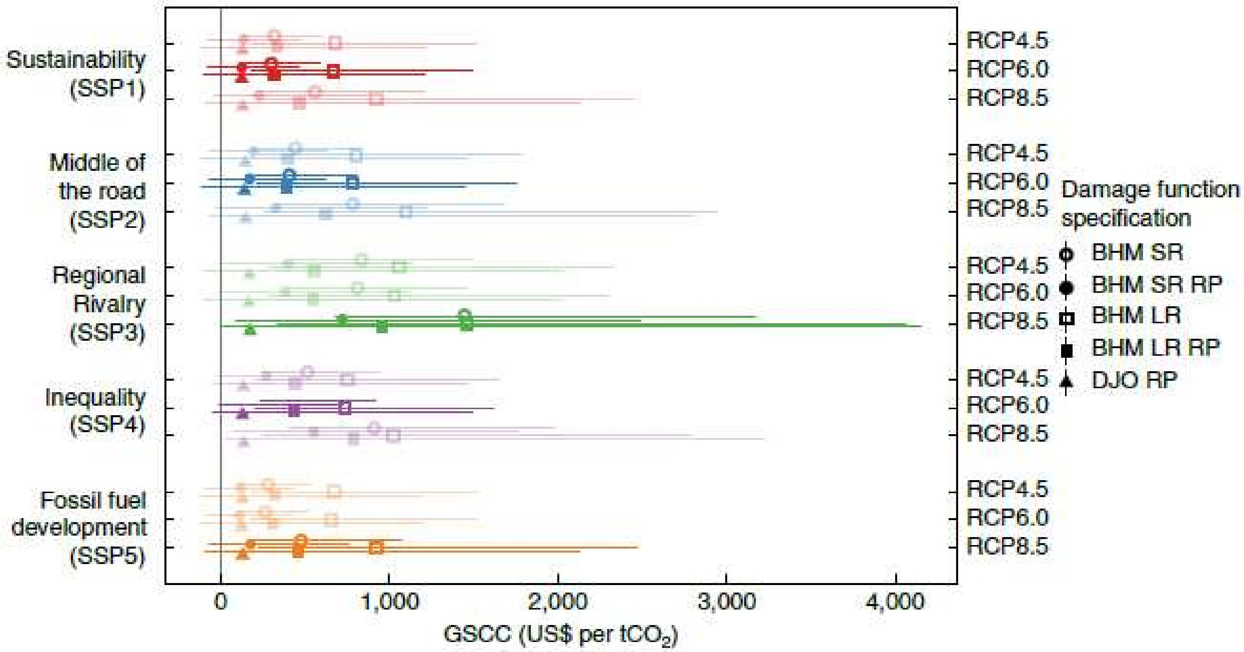


Fig. S3.6. *Global SCC in 2020 under various assumptions and scenarios.* Median estimates and 16.7% to 83.3% quantile bounds for GSCC under SSPs 1–5, and RCPs 4.5, 6.0 and 8.5. For each SSP, the darker colors indicate the SSP–RCP pairing with a superior consistency. The values displayed assume growth-adjusted discounting with a pure rate of time preference of 2% per year and elasticity of marginal utility substitution (μ) of 1.5. Supplementary Fig. S3.3 in the original document compares these results with fixed discounting (rate of 3%). Colored bars represent the 66% CIs. SSP = socioeconomic pathway scenarios as based on: O'Neill, B. C. et al. A new scenario framework for climate change research: the concept of shared socioeconomic pathways. *Climatic Change* **122**, 387–400 (2013). RCP = Representative Concentration Pathway as accepted by the IPCC. BHM = Burke-Hsiang-Miguel damage function (a model used to estimate social cost of carbon). DJO = Dell-Jones-Olken (another model used to estimate social cost of carbon). This graph and footnote are taken directly from Ricke et al. (2018).

The Interagency Working Group on Social Cost of Greenhouse Gases (IAWG; Interagency Working Group 2013) considered 150,000 estimates from 10,000 simulations for discount rates of 2.5, 3, and 5 percent. Those estimates were based on average SCC values produced by three integrated assessment models and the 95th percentile estimate which assumes an unlikely but highly costly scenario (i.e., close to worst-case scenario). The full distribution of the results for the three discount rates are shown in Fig. S3.7 and. Average values of the SCC were $12, $42, $62, and $123 for the 5%, 3%, 2.5%, and the close to worst-case scenario, respectively. Like results of Ricke et al. (2018) discussed above, these results also show high uncertainty in estimates of the SCC. The range of values estimated by the IAWG is much narrower than those arrived at by Ricke et al. likely reflecting their lack of consideration of uncertainty related to factors other than discounting.

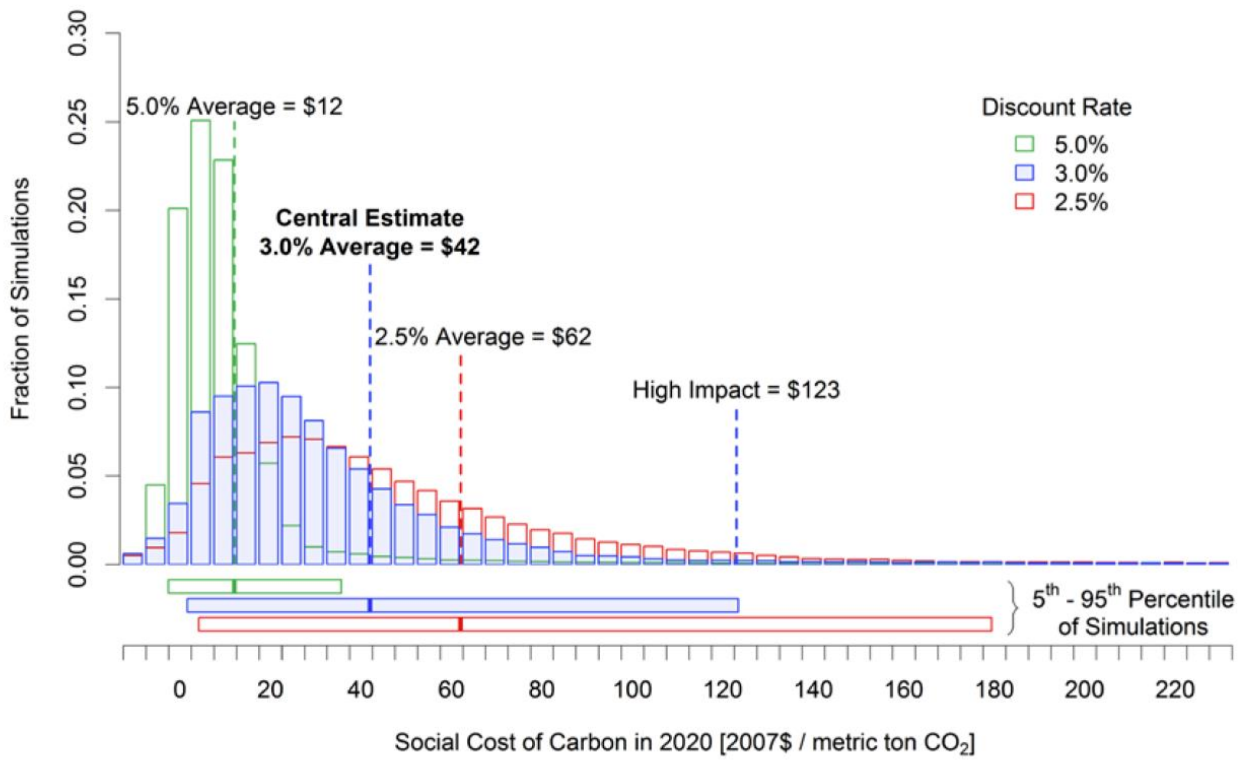


Fig. S3.7*. Frequency distribution of SCC estimates for 2020.* "Presents the frequency distribution of the SC-CO2 estimates for emissions in 2020 for each of the three discount rates. Each of these distributions represents 150,000 estimates based on 10,000 simulations for each combination of the three models and five socioeconomic and emissions scenarios.16 In general, the distributions are skewed to the right and have long right tails, which tend to be even longer for lower discount rates. To highlight the difference between the impact of the discount rate on the SC-CO2 and other quantified sources of uncertainty, the bars below the frequency distributions provide a symmetric representation of quantified variability in the SC-CO2 estimates conditioned on each discount rate. The full set of SC-CO2 results through 2050 is available on OMB's website. This may be useful to analysts in situations that warrant additional quantitative uncertainty analysis (e.g., as recommended by OMB for rules that exceed $1 billion in annual benefits or costs). See OMB Circular A-4 for guidance and discussion of best practices in conducting uncertainty analysis in RIAs." Based on integrated assessment models (IAMs; DICE, FUND, and PAGE) which are used by the U.S. gov't to estimate the social cost of carbon (CO2). (Interagency Working Group 2013)

Pindyck (2019) took a different approach and surveyed 386 experts including 113 economists and 220 climate scientists with 170 of those experts being from North America, 158 from Europe and 30 from developing countries. The range of SCC values resulting from the expert surveys exhibited large uncertainty and was between that of Ricke et al. (2018) and the IAWG (2013) (about one third of responses were between $0 and $100, several were spread across $100 and $700, and the mean was

$291; Fig. S3.8). The primary source of uncertainty though, was related to the potential impacts of climate change and not the discount rate which was help constant at 3% for the survey questions. Also seen if Fig. S3.8 is a gamma function fit to the data as a probability distribution function (pdf; red line) that best fit the responses of all surveyed experts. Using a pdf is one way in which uncertainty may be included in estimates of the SCC and ROI from various LULC decisions. There was a marked difference in the values provided by economists and climate scientists (Fig. S3.9). Climate scientists tended to suggest much higher SCC (average of $316.3) than economists (average of $173.7), but both the averages and distributions of estimates from North America and Europe were very similar with averages of $284.5 and $284.2, respectively.

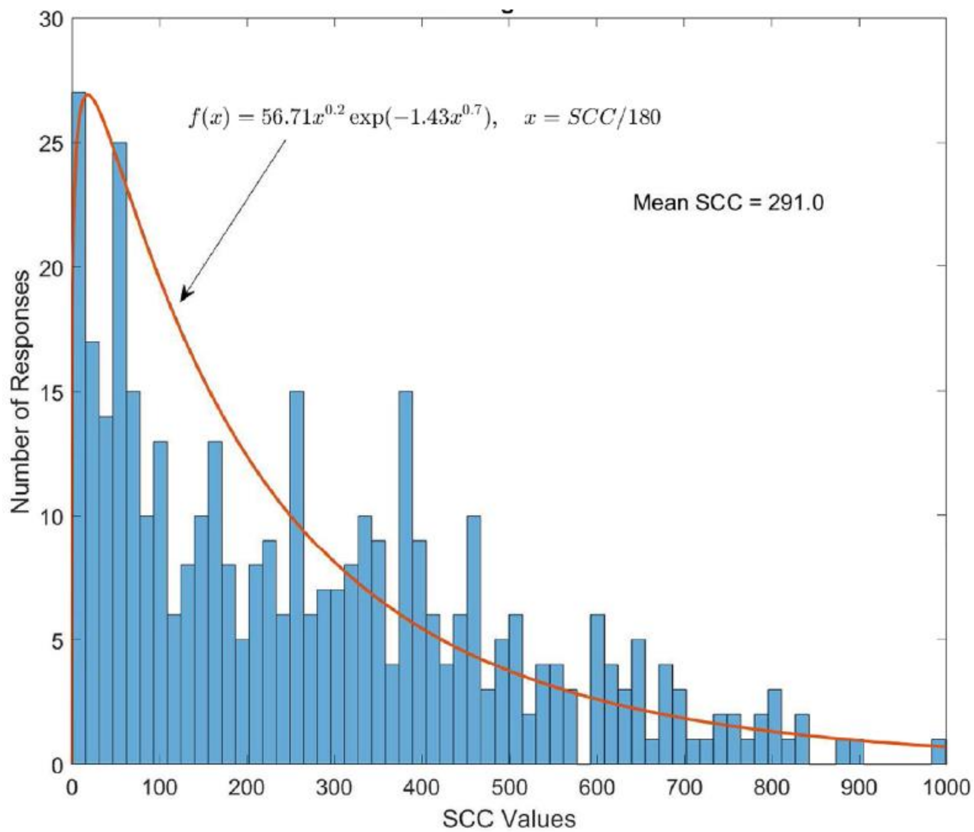


***Fig. S3.8**. The social cost of carbon based on an expert survey of 386 experts.* (Pindyck 2019)

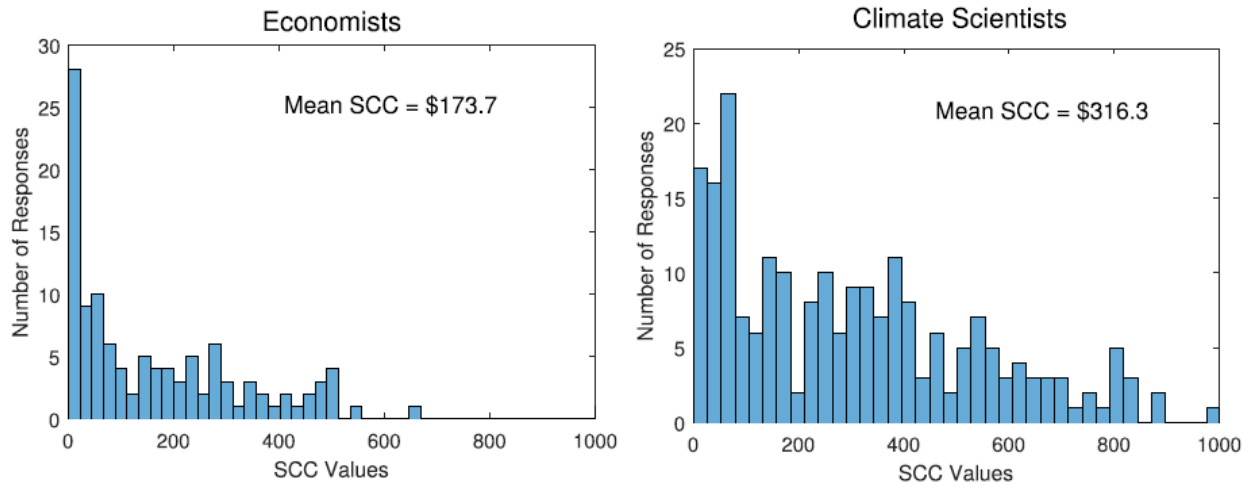


Fig. S3.9. The social cost of carbon based on surveys of economists (left) and climate scientist (right). (Pindyck 2019)

Estimates of the SCC, discount rates, and time preference rates from various scholarly literature are presented in Table S3.1. Estimates of the SCC in the table reflect averages or likely ranges opposed to the full range of estimates found in each study. The range of the SCC was from $12 to $300. The range of discount rates was 1% to 7% with 2.5, 3, and 5 being the most common. Time preference ranged from 0% to 6% with values between 1% and 2% being the most common. Inclusion of the full range of values presented in Table S3.1 when estimating the ROI from climate-related ecosystem services will produce more robust estimates, but the range of estimates values will be larger.

***Table S3.1**. Estimates of the social cost of carbon (SCC), discount rate, and time preference for estimates of ROI*

Notes	Social cost of carbon	Units	Discount Rate [%]	Time Preference [%]	Citation (See articles for their references)
"Conservative estimate"	21	US$/ton CO_2	7	0	Bagstad et al. 2012
"Non-conservative estimate"	85	US$/ton CO_2	1	6	Bagstad et al. 2012
India (66% C.I.)	86 ($49-$157)	US$/ton CO_2	3, 5, and growth adjusted	1, 2	Ricke et al. 2018
U.S.A. (66% C.I.)	48 ($1-$118)	US$/ton CO_2	3, 5, and growth adjusted	1, 2	Ricke et al. 2018
Saudi Arabia (66% C.I.)	47 ($27-$86)	US$/ton CO_2	3, 5, and growth adjusted	1, 2	Ricke et al. 2018
Brazil (66% C.I.)	24 (14–41)	US$/ton CO_2	3, 5, and growth adjusted	1, 2	Ricke et al. 2018
China (66% C.I.)	24 (4–50)	US$/ton CO_2	3, 5, and growth adjusted	1, 2	Ricke et al. 2018
United Arab Emirates (66% C.I.)	24 (14–48)	US$/ton CO_2	3, 5, and growth adjusted	1, 2	Ricke et al. 2018

USEPA estimate	12	US$/ton CO_2	5	1	IAWG 2013
USEPA estimate	42	US$/ton CO_2	3	1	IAWG 2013
USEPA estimate	62	US$/ton CO_2	2.5	1	IAWG 2013
SCC Survey of 386 experts	80 - 300	US$/ton CO_2	NA	NA	Pindyck 2019
SCC Survey w/outliers trimmed	80 - 100	US$/ton CO_2	NA	NA	Pindyck 2019
SCC	121	US$/ton CO_2	2.5	0	Pindyck 2019
SCC	101	US$/ton CO_2	3	0	Pindyck 2019
SCC	81	US$/ton CO_2	4	0	Pindyck 2019
SCC	65	US$/ton CO_2	6	0	Pindyck 2019
Discount rate only	NA	NA	1 - 3 (mean = 2.25, median = 2)	mode = 0, mean = 1.1%, median = 0.5%	Drupp et al. 2015

4. Scenario Analysis

4.1 Important considerations in scenario analysis

Scenario analysis is a critical tool for making policy decisions. It can provide an estimate of the relative performance of one scenario over another. However, for that comparison to be possible, data must be available for all scenarios of interest. Having an estimate for only one of the scenarios does not provide actionable insight unless it can be compared to the alternative scenarios. Let's take two scenarios for example. In scenario 1 there are 640 acres of irrigated corn being grown and in scenario 2 those 640 acres are converted to unirrigated grassland. If we know that scenario 2 will provide roughly 1 Mg C/ha-yr of carbon sequestration, we still have no idea which scenario provides greater sequestration and storage unless we can quantify the carbon sequestration and storage provided by the irrigated corn as well. This greatly complicates scenario analysis because in almost all cases, carbon storage can only be empirically quantified for the existing scenario while one or more scenarios will always be estimates based on various methods, such as process-based modeling. However, even empirical approaches, which are typically thought of as the gold standard in environmental sciences, can be as or more uncertain than process-based models due to limited spatial and temporal resolution of measurements (Paustian et al. 2016). Since both approaches are site-specific though, they are likely to produce more certain results than benefit transfer methods which are widely applied (Plummer 2009; Richardson et al. 2015).

4.2 Benefit Transfer

Benefit transfer is a widely applied methodology for assessing how policy decisions may impact the value provided by ecosystem services (Johnston and Rosenberger 2009; Plummer 2009; Richardson et al. 2015; Troy and Wilson 2006). It refers to the application of existing information for a purpose and/or at a location which is different than the purpose or location for which the information was originally collected. Here I provide a relatively extensive discussion of benefit transfer methodology because it is widely applied in the context of policy, ecosystem services, and valuation due to the relative ease and speed with which it can be applied, and there are highly relevant examples from Colorado.

Example applications of benefit transfer studies applied to LULC and ecosystem services include the works of Sargent-Michaud (2009) and Seidl et al. (2017) who estimated the ROI from conservation easement programs in Colorado and of The Trust for Public Land (TPL; 2016), who estimated the ROI from conservation programs in Virginia. Each of these studies used National Land Cover Dataset (e.g., Dewitz 2019) landcover types to delineate ecosystems. Then they performed literature review and assigned a value per acre [$/acre] for ecosystem services provided by each ecosystem (i.e., landcover type). Once a value per acre was identified, it was multiplied by the acreage of each ecosystem type to arrive at an overall estimate of ROI. Benefit transfer methodology has the huge advantage of convenience, but also has many potential limitations with respect to accuracy (Plummer 2009; Richardson et al. 2015).

Such studies that do not consider uncertainty in ROI estimates should be interpreted with great care. For example, TPL found that for each $1 invested there would be a $4 ROI through 2024. This is an overly specific value, and it is not possible that such an uncertain analysis can generate such a specific value. The authors (TPL 2016) acknowledge that there can be significant uncertainty in benefit transfer studies but conclude that the lack of better options justify the application of the methodology. This gets at the core of the state of ecosystem service ROI methodologies – there do not seem to be any great options for quantifying ROI with accuracy so those performing such studies are choosing what they perceive to be the least-bad option (Johnston and Rosenberger 2009; Plummer 2009; Richardson et al. 2015).

Similarly, Sargent-Michaud (2009) arrived at an estimated ROI of $6 for every $1 invested – an overly specific estimate. In their work they used work by Ingraham & Foster (2008) for estimates of ROI from deciduous forests, evergreen forests, mixed forests, scrub/shrubs, and open water. All but the *open water* ecosystem type were stated as providing carbon sequestration, among other services. Ingraham and Foster's work however, used few studies to arrive at their estimates of carbon sequestration and ROI. They state, "We recognize that the number of studies used is small and may therefore lead to large errors in our resulting value estimates … The intent of the study was not to derive an inarguably accurate or precise value of the ecosystem services provided … rather to offer a first approximation to be used as a reference point for policy and management decisions [at the national scale], and to demonstrate that the total value is likely much higher than values based solely on recreational use." After extensive literature review, I am not convinced we have moved beyond this "first approximation".

Where Sargent-Michaud propagated the uncertainties included in the work Ingraham and Foster, Seidl et al. included uncertainty in their estimates of ROI from conservation easements, by including estimates from both TPL (2016) and Sargent-Michaud (2009) which is undoubtedly better than performing an analysis that arrives at an overly specific value of ROI. While uncertainty was included in the analysis the use of values from the two previous studies mentioned highlights how uncertainty can easily be propagated through subsequent studies that use previously derived values. The values from

TPL (2016) were derived specifically for Virginia, most of which is considered to be a humid subtropical climate (https://learn.weatherstem.com/modules/learn/lessons/148/07.html) meaning that transferring those values to Colorado, which is not a humid subtropical climate (much of the state is considered cold semi-arid) is likely to produce poor estimates of ecosystem services. On the other hand, using estimates from Sargent-Michaud relies on a source that didn't include uncertainty, and is based on yet another study that also did not consider uncertainty in their estimates. As noted by Sargent-Michaud, "It is important to note that benefit transfers can only be as accurate as the initial study."

Essentially, each of these three efforts represents what should be thought of as rough first estimates of ROI from ecosystem services. Such estimates are necessary as the science progresses and are not entirely inappropriate for the applications for which they were performed. Specifically, using the average of observed/simulated values to estimate the ROI from larger scale areas (e.g., all of conserved land in Colorado) is likely to produce more reasonable results than applying the same values to plots of agricultural land, assuming the average value was derived from observations across the same or similar spatial scale at which the analysis is performed (Richardson et al. 2015). For an individual plot, the actual carbon sequestration, for example, may range anywhere from the maximum observed to the minimum observed (or beyond). Therefore, when looking to perform scenario analysis at smaller scales (e.g., 100's of acres) to help prioritize what land to conserve or keep in production, finer resolution information is needed.

Furthermore, it is generally important to know who will pay, who will produce the benefit, and who will benefit when paying for ecosystem services or performing a benefit transfer in order to better understand the socioeconomic implications and appropriateness of the payment or transfer (Johnston and Rosenberger 2009; Plummer 2009; Van Hecken and Bastiaensen 2010). With respect to paying for carbon sequestration (e.g., via a conservation easements) the taxpayers of the relevant government body (e.g., state or federal) are the ones who pay, in the case of working lands the farmers or landowners can be thought of as producing the benefit, and the global population is the party that benefits. However, if the landowner is using the land to farm, then they too may directly benefit from improved production.

Despite its limitations, the benefits of convenience, speed, and low costs make a benefit transfer approach the most appropriate methodology for low-cost and timely estimates of ROI from ecosystem services such as carbon sequestration. What is currently missing though, is adequate quantification of the services provided by various LULC types (Johnston and Rosenberger 2009; Paustian et al. 2016; Plummer 2009; Richardson et al. 2015). Without such values it is not reasonable to expect accurate estimates of ROI from climate-related ecosystem services provided by various LULC scenarios. Caution should be taken to avoid use of poorly performed benefit transfers. As Richardson et al. (2015) state, "Frequent use of highly flawed welfare estimates in the policy process may affect the policy relevance of the whole field, which would have adverse consequences for society's wellbeing by undermining improved natural resource policy making." This risk can be avoided if guidelines and recommendations for benefit transfer for ecosystem service valuation are followed, allowing benefit transfer to continue to make an increasingly important contribution to natural resource management." I have summarized important considerations and basic guidelines for benefit transfer in Table S3.2 below.

Table S3.2. *Considerations in benefit transfers.* Table is primarily based on three review papers.

Important Consideration	**Citation(s)** (These are review papers. Please see the papers themselves for more specific references)
From an economic perspective, value is not intrinsic to a particular site or ecological system. It must be evaluated in the context of specific biophysical and human characteristics.	Plummer 2009
There is a divergence between benefit transfer practices recommended in scholarly literature and those applied in policy	Richardson et al. 2015; Johnston and Rosenberger 2010; Plummer 2009
This divergence may be largely attributed to the scattered nature of relevant literature and to the need for decision makers to have quick and cheap methods, while scholarly work is tending towards more costly and time-consuming methods in the name of accuracy	Richardson et al. 2015; Johnston and Rosenberger 2010; Plummer 2009
Poor application of benefit transfer methodologies could undermine the inclusion of ecosystem services in policy considerations. Biased estimates can lead to badly misguided policy.	Richardson et al. 2015; Plummer 2009
Benefit transfer is never the best choice, but if original valuation of the site(s) of interest is not possible, then benefit transfer is a better option than qualitative judgement.	Richardson et al. 2015
Collection of original data/performance of original valuation is time consuming and expensive inhibiting application in policy decision making that requires timely and affordable information	Richardson et al. 2015; Johnston and Rosenberger 2010; Plummer 2009
Benefit transfer is appropriate in cases where greater precision of estimates would not greatly alter the results. Benefit transfer will never be able to replace primary study/data collection.	Richardson et al. 2015; Johnston and Rosenberger 2010; Plummer 2009
There are three approaches to unit value transfers (e.g., $/ha): 1. Use an estimate from a single source that is very similar to the one of interest in all ways 2. Apply an average value from several studies 3. Use administratively approved values An alternative approach is to use a willingness to pay function or a benefit transfer function (but these can be much more time and resource intensive)	Richardson et al. 2015

The more closely the benefit transfer meets the following criteria, the more valid it will be: - Based on adequate data - Sound economic method - Correct empirical technique - The nonmarket commodity valued at the study and policy sites (AOI) are identical - The populations affected by the nonmarket commodity at the study and policy sites have identical characteristics - Similarity between sights is of the utmost importance (e.g., populations, resources, markets, and other site attributes - Assignment of property rights at both sites must lead to the same theoretically appropriate welfare measures. - Full and consistent reporting of information on the current environmental quality of the sites - Use objective, quantitative measures of quality - Use consistent definitions and measurements of demographic data - When necessary, use average values of study-specific variables - Distinguish between intermediate ecosystem services and final ecosystem services for valuation (e.g., farmers benefit from increased soil quality and global population benefits from mitigated climate change) - Define ecosystem services in benefit specific terms - Care should be taken to not double count benefits - Particular attention should be given to: · scope (i.e., non-constant marginal value of ecosystem services) · geographic scale (i.e., values estimated at one scale cannot be expanded to another scale via a convenient index of area such as hectares or acres) · substitutability (i.e., that the value in the policy location can be substituted with value from the study location) - Transfers of measures of economic value should be based on consideration of the entire original valuation study context - Temporal components of transfers are important to consider (i.e., comparing studies from very different times may be difficult to advances in methodologies and older studies may no longer be appropriate)	Richardson et al. 2015; Johnston and Rosenberger 2010; Plummer 2009
Use of measures of central tendency (e.g., average) may be preferable to point estimates in two cases: 1. There are multiple sites meeting the criteria for a valid transfer 2. No studies meet all criteria for an ideal transfer. Using average values may cancel out some biases of individual studies	Richardson et al. 2015
Greater similarity (i.e., correspondence) between the original study site and the policy site of interest typically leads to smaller transfer errors. Site characteristics are only one of many considerations though, so site similarity in and of itself is not enough to guarantee a valid benefit transfer.	Richardson et al. 2015; Johnston and Rosenberger 2010; Plummer 2009

It is the role of both practitioners and policymakers to understand the role and limitations of benefit transfer and to communicate what they are. Both should be aware that careless benefit transfers can result in highly biased estimates and may hinder the continued integration of natural resources values into decision making.	Richardson et al. 2015
Programs such as InVEST and ARIES should be used only as a first-cut, order-of-magnitude value estimate.	InVEST: https://naturalcapitalproject.stanford.edu/software/invest-models/carbon ARIES: https://aries.integratedmodelling.org/carbon-sequestration-storage/ Richardson et al. 2015
The most effective way to reduce transfer errors is to build a better collection of primary ecosystem service valuation studies that lend themselves to benefit transfer. **Agencies should strategically fund original studies whose purpose is to fill priority gaps in the literature for use in benefit transfer.**	Richardson et al. 2015; Plummer 2009
Greater interaction between researchers and policy makers could reduce some limitations in benefit transfer	Richardson et al. 2015
Appropriate transfers require an understanding of the underlying quantities and qualities (i.e., definitions of non-market goods) at both study and policy sites.	Richardson et al. 2015; Johnston and Rosenberger 2010; Plummer 2009
Some bias is inevitable in benefit transfers as implicit assumptions are rarely satisfied. Two primary implicit assumptions are: 1. The underlying body of valuation literature is a random, unbiased sample of the population of empirical estimates and 2. Empirical estimates provide an unbiased representation of true, underlying resource values	Johnston and Rosenberger 2010
If biases can be identified, then practitioners should attempt to minimize them or explicitly account for them	Johnston and Rosenberger 2010
In identifying the extent of the market for any given benefit transfer, the practitioner must consider two related questions: 1. What population is assumed to have a value for the environmental change in question? 2. What are the expected patterns of preference or value over the spatial extent of the market (i.e., does the willingness to pay change systematically over space?)	Johnston and Rosenberger 2010; Plummer 2009
Benefit transfers over long time horizons are less certain despite inclusion of methods that attempt to address them such as discount rates.	Johnston and Rosenberger 2010
There is a recognition that improved reporting, documentation and dissemination of study methods and data would provide a means to conduct more valid transfers, but academic incentives are misaligned with this need	Johnston and Rosenberger 2010

4.3 Spatially Explicit Mapping of Ecosystem Services

Although availability of data is limiting, methodology to allow for spatially explicit scenario analysis related to LULC and carbon sequestration and storage (or other ecosystem services) mapping is available. For such analysis I recommend referencing Troy and Wilson's (2006) suggested methodology for mapping ecosystem services (Fig. S3.10). Using existing software such as the Natural Capital Project's Integrated Valuation of Ecosystem Services tool (Sharp et al. 2020) along with Troy and Wilson's suggested methodology for mapping carbon sequestration and storage and the value it provides could provide a relatively quick and affordable means of performing policy relevant scenario analysis.

I do highlight again however, that the lack of standardized and reliable data at appropriate spatial and temporal scales is a significant barrier. Using the methodologies suggested here without appropriate estimates of carbon storage and/or sequestration related to the LULC types of interest in the analysis should be avoided. Richardson et al. (2015) wrote, "… In other words, the flip side of 'some number is better than no number' is that "bad numbers may drive out all numbers.'" I echo their cautions – if we abuse the methods presented here, providing flawed estimates of the ROI from climate-related ecosystem services may permanently damage the confidence that the public and policy makers have in our ability to meaningfully include natural resources and ecosystem services in policy decision. Such a loss in confidence could undermine the inclusion of such considerations and science-based decisions in policy making. The proposed methodology here should further motivate the notion that **funding agencies should be directing funds to original studies aiming to fill priority knowledge gaps related to benefit transfer**, which is the largest bottleneck to quickly, easily, and confidently estimating the ROI from various LULC scenarios.

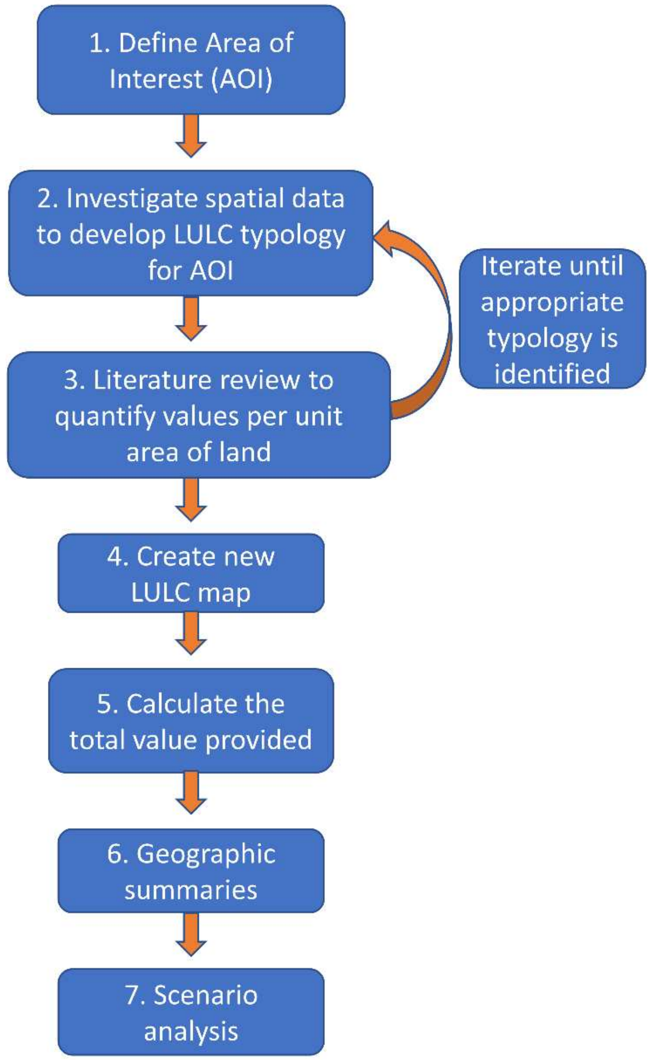


Fig. S3.10. *Suggested methodology for mapping of ecosystem services.* Adapted from Troy and Wilson's (2006) Mapping Ecosystem Services Methodology

1. Define the area of interest.
    a. The area of interest must be carefully defined because sometimes small adjustments to the boundaries of the area can have large impacts on the estimated value provided by the ecosystem service of interest.
2. Investigate GIS data of the area of interest to begin developing a LULC typology that is of relevance to the analysis.
    a. That is to say, identify LULC types that provide enough detail to perform meaningful analysis.
    b. As part of this stage, some preliminary literature review may be conducted to identify if needed information is available. Needed information, for example, may include the potential carbon storage of a given LULC.
3. In-depth literature search and analysis.

a. Empirical studies from similar contexts are collected and analyzed to extract valuation coefficients (e.g., value of the potential carbon storage per area [$/ha]) or other relevant coefficients (e.g., potential carbon storage per area [tC/ha]) of the different LULC classes.
b. Suggested data to be collected includes the ecosystem services of interest (e.g., carbon sequestration and storage), the LULC type to be valued, the valuation method used, the year of the study, and the per area value estimates, among other attributes.

4. New LULC map creation.
    a. Combine relevant data layers to create a final LULC map.
5. Total value calculation
    a. Assuming the data was located in step 3, after assigning each mapping unit (e.g., raster cell) a LULC type, then the value per area can be multiplied by the area of each mapping unit generating an estimated value for each mapping unit.
    b. Similarly, the total value provided by a given landcover type can be calculated by summing the values provided by each mapping unit classified as that landcover type.
    c. If the value being transferred is not a monetary value, then following the previous two steps (5a and 5b) there will be a need to multiply the transferred value by a unit monetary value (e.g., $/tC).
6. Geographic summaries
    a. Summaries of the results can be aggregated to geographic extents of interest, such as towns, counties, watersheds, or other areas of interest.
7. Scenario analysis
    a. Different LULC scenarios can then be investigated by changing the LULC types associated with the mapping units. For example, if an agricultural area is under consideration for development, then those mapping units representing the area can be changed to high-intensity development.

There may be a need to iterate between steps 2 and 3 in order to arrive at a LULC typology that is specific enough to allow for differentiation between carbon sequestration/storage related to the different LULC types, while not being too specific such that relevant data is not available. This step also provides an opportunity for semi-automating the process by using clustering methodologies (e.g., k-means clustering) to automatically generate unique LULC types. There would still need to be input from the user to ensure the suggested groups are appropriate for the policy analysis.

Of these seven suggested steps there are two that I found to be limiting for the easy implementation of such analysis. The first and most significant limitation was my inability to locate estimates of the carbon storage potential of different LULC types that were appropriate for benefit transfer. This is discussed in more depth in the previous section. The second notable limitation was finding good literature about how to value the social benefits of the sequestered and stored carbon. In fact, as I performed the literature review, I found these limitations to be a common occurrence for other researchers as well (Bagstad et al. 2012; Paustian et al. 2016; Plummer 2009; Troy and Wilson 2006).

It is worth noting that the InVEST carbon model, which lends itself to the methodology suggested here, accepts inputs of four carbon pools for each LULC type at the starting and end times of the simulation. In the face of such extensive uncertainty this seems like an overparameterization of the carbon model, and other than bookkeeping, the four carbon pools do not play an important role in the overall carbon sequestration values. **As demonstrated by the Conant et al. (2017) data, the uncertainty associated with overall carbon storage for a given LULC type is more uncertain than the relative improvement in net carbon sequestration as one land use is converted to another.** This suggests better options may be approaches such as the one taken in the COMET-Planner tool that assumes a constant sequestration rate over time as one land use is converted to another (e.g., irrigated agriculture converted to grazing grasslands).

5. Conclusions

Growing populations in the SPRB are driving growing demands for land and water. With some land being developed and other land converting uses due to the transfer of water from irrigated agriculture to municipal uses, important policy decisions are being made that will help shape what land is conserved, dried, developed, or managed in other ways. For good policy decisions to be made there is a need for quick, easy, and reliable assessment of various LULC scenarios and the resulting ecosystem services (or disservices) that may occur. This report focused on the ecosystem service of carbon sequestration and storage with an emphasis on natural and working lands.

There is methodology available that allows for reasonably quick, easy, and reliable LULC scenario analysis (e.g., InVEST) but there are significant limitations to said methodology being implemented. This methodology depends heavily on benefit transfer - the ability to identify existing data that allows certain carbon storages or sequestration rates and their related value to be transferred from one scenario (e.g., climate, ecoregion, and LULC type) to another scenario that is of interest to policy (e.g., conversion of irrigated agriculture to a native grassland). Benefit transfer is widely applied, but still controversial. The methodology is very easy to implement which has led to its applications in inappropriate situations. This widespread application to inappropriate conditions has led to calls to use extreme caution as to not abuse the methodology and undermine the inclusion of ecosystem services in policy making (Plummer 2009; Richardson et al. 2015; Troy and Wilson 2006).

Nearly all aspects of quantifying the ROI from climate-related ecosystem services include significant uncertainty. The amount of biogenic carbon stored by various land uses is highly variable with many factors driving the potential of carbon to be stored. GHG emissions are perhaps even more difficult to generalize as they depend heavily on development form, industrial processes, and other attributes that are difficult, if not impossible, to generalize. Even if estimates of carbon sequestration, storage, and/or emissions are made there is still large uncertainty in estimating the value of a sequestered ton of carbon, for example. The ROI or value of sequestered and stored carbon or mitigated GHG is typically taken to be the social cost of carbon avoided. While appropriate, this definition leads to uncertainty related to the potential effects of climate change and the monetary value associated with it as well as uncertainty related to economic discounting and the overall formulation of value (i.e., what variables are included, and which equations are used).

Many efforts focusing on climate-related ecosystem services have focused at large scales (e.g., state or national). When considering policy decisions at the scale of the SPRB or even smaller areas within the basin however, many of the approaches and the data used in analyses at larger scales are likely not appropriate. When considering spatially explicit scenario analysis at the plot scale (e.g., 100's of acres or smaller), a higher resolution of temporal and spatial data is needed. Until that data has been collected, applying benefit transfer must be advised against. More appropriate methods include those used in the COMET-Planner tool. The COMET-Planner tool is based on extensive literature review by experts and provides county specific estimates of the relative improvement in carbon sequestration (or reduction in GHG production) between two scenarios. By considering the change of one land use type (e.g., irrigated agriculture) to another (e.g., natural grassland), variables such as climate, which have significant implications for total soil carbon storage, are removed. Furthermore, the COMET-Planner tool only considers well documented scenarios related to natural and working lands and does not attempt to consider the tradeoffs of converting natural or working lands to developed lands. Comparing the overall carbon budgets of natural and working lands with the budgets of developed lands is desirable and necessary for robust tradeoff analysis of LULC scenarios, however, the limited data availability and inability to generalize the carbon budgets related to developed lands make this inappropriate at this time. **As more data becomes available then tradeoff analysis will become increasingly easy, accurate, and appropriate.**

5.1 Challenges and Cautions

There are many challenges and cautions related to understanding the tradeoffs between LULC scenarios and the associated climate-related ecosystem services. Here I provide bullet points highlighting some of those challenges and cautions.

- Although technologies to quantify carbon concentrations in soils exist and have been used for decades, there is a problematic lack of standardization across measurement efforts, applied methods can be expensive and time consuming while results often suffer from inhibiting noise, and there is extreme heterogeneity in soil carbon stocks so it is difficult to generalize point measurements to landscapes (Paustian et al. 2019).

- There is a critical need to standardize urban carbon monitoring and reporting with perhaps the most essential need being operational measurement and monitoring (Gurney et al. 2015).

- Many studies and/or tools looking to perform or enable carbon sequestration scenario analysis related to LULC, rely on benefits transfer which can be easily misapplied resulting in invalid and erroneous estimates. Abusing benefit transfer by applying it in scenarios where adequate data is not available (in quality and/or quantity) may undermine the inclusion of ecosystem services in policy decisions (Plummer 2009; Richardson et al. 2015).

- The condition of additionality seems to run the risk of paying landowners and/or managers that have historically implemented practices that are unhealthy for the land while not paying those have implemented practices that are healthy for the land.

- Socioeconomic considerations should be included in scenario analysis related to payments for ecosystem services and/or conservation. There is a risk of exacerbating socioeconomic inequalities so it should always be asked, "who pays and who benefits" (Van Hecken and Bastiaensen 2010).

- Landowners must be included in policy decisions and scenario analysis related to payment for ecosystem services or conservation. It is not clear that the agrarian communities of Colorado which may stand to benefit the most from such programs, are interested in participating in them.

5.2 Relevant Questions, Suggestions, and Take-Home Messages

During literature review and exploration of tools related to LULC, ecosystem services, and scenario analysis several questions and suggestions were identified. Here I provide bullet points with some of those questions and suggestions. This list is by no means meant to be exhaustive.

5.2.1 Questions

- If additional trees are planted in urban and peri-urban areas, what are the potential synergies and tradeoffs between enhanced GHG sequestration and storage and water resources related implications (i.e., water demand and potential changes in recharge)?

- Should water used by trees that were planted for carbon offsets or other ecosystem services be considered a consumptive use?

- If a landowner receives revenue for services provided by their land, but less revenue than when the land was under agricultural production, how is the local economy affected? For example, when the land was under production then it likely created jobs and had other benefits to the local economy, whereas payments for ecosystem services provided by land do not necessarily create jobs.

- Are the landowners living in the SPRB interested in policy that may pay them for conservation and/or directly for ecosystem services?

- What is the overall impression of such policies and programs in the agrarian communities where they may be implemented?

- With respect to payments for carbon sequestration/storage/mitigation, who pays and who benefits? There is a misalignment between those who provide the service (i.e., landowners), those who pay for the service (i.e., taxpayers within the relevant area), and those who receive the benefits of the service (i.e., global population). This misalignment may lead to increased challenges for such programs being accepted by the local population. One notable caveat is that farmers who adopt carbon sequestering practices may find improved soil health which can also lead to more consistent and resilient production in the face of drought and changing climates.

- If it can be more conclusively shown that the practices that may lead to carbon sequestration and storage in working lands also lead to better soil health which in turn, leads to better agricultural production and lower risk, is there any opportunity for agriculture and farming insurance companies to offer incentives for those practices?

5.2.2 Suggestions and Important Take-Home Messages

- **When looking to direct funds to promote climate-related ecosystem services, funding agencies should place an emphasis on original research aiming to close priority knowledge gaps**. More specifically, the largest bottleneck in the methodology proposed in this report is the lack of adequate data for applying benefit transfer. Extensive efforts need to be (and are being) undertaken to produce more and better estimates of carbon sequestration and storage and GHG production related to various LULC types. **As more data becomes available then tradeoff analysis will become increasingly easy, accurate, and appropriate.**

- **Uncertainty associated with overall carbon storage for a given LULC type is more uncertain than the relative improvement in net carbon sequestration as one land use is converted to another.** For example, assuming the carbon storage in an irrigated corn field in a humid climate with clayey soils is similar to that in an irrigated corn field in an arid climate with sandy soils entails much more uncertainty than assuming either of those fields is converted to a natural grassland (i.e., climate, soils, and other factors can have more influence on soil carbon than management practice).

- **Uncertainty in the ROI of climate-related (or other) ecosystem services increases as we project farther into the future.** Related policy should avoid making any assumptions far into the future and should focus on relative improvements in the near-term (i.e., coming decades).

- **Despite its limitations, the benefits of convenience, speed, and low costs make a benefit transfer approach the most appropriate methodology for low-cost and timely estimates of ROI from ecosystem services such as carbon sequestration.** But extreme caution should be taken as to not abuse the ease with which such methodologies can be applied. Good data is required but hard to come by!

- **Lands will eventually reach an equilibrium with regard to carbon storage, where the net amount of carbon being sequestered is essentially zero.** When applying methodologies that assume constant sequestration rates over time, caution should be taken to avoid projecting those sequestration rates too far into the future.

- **One of the most obvious possible synergies between the goals of the Colorado Water Plan and Colorado's climate ambitions is the improvement of soil health associated with carbon sequestering practices on crop and rangelands.**

6. Existing Tools to Assist in Prioritizing LULC

This report focused on the ecosystem services of carbon sequestration and/or other actions to help mitigate climate change. While an important ecosystem service, it is far from the only one. Colorado's Water Plan also identifies flow regulation, flood attenuation, water purification, erosion control, dilution and flushing of contaminants, and habitat protection as ecosystem services. While these services were not the focus of this work, here I present seven online tools that may assist evaluation and prioritization of land conservation programs based on various ecosystem services. To illustrate the outputs and utility of each tool, when possible, I applied them to three areas of interest in the SPRB: Brighton's South Platte River Heritage Program, Greeley's Long-Range Expected Growth Area, and Thornton's Northern Properties in Weld and Larimer Counties (Fig. S3.11).

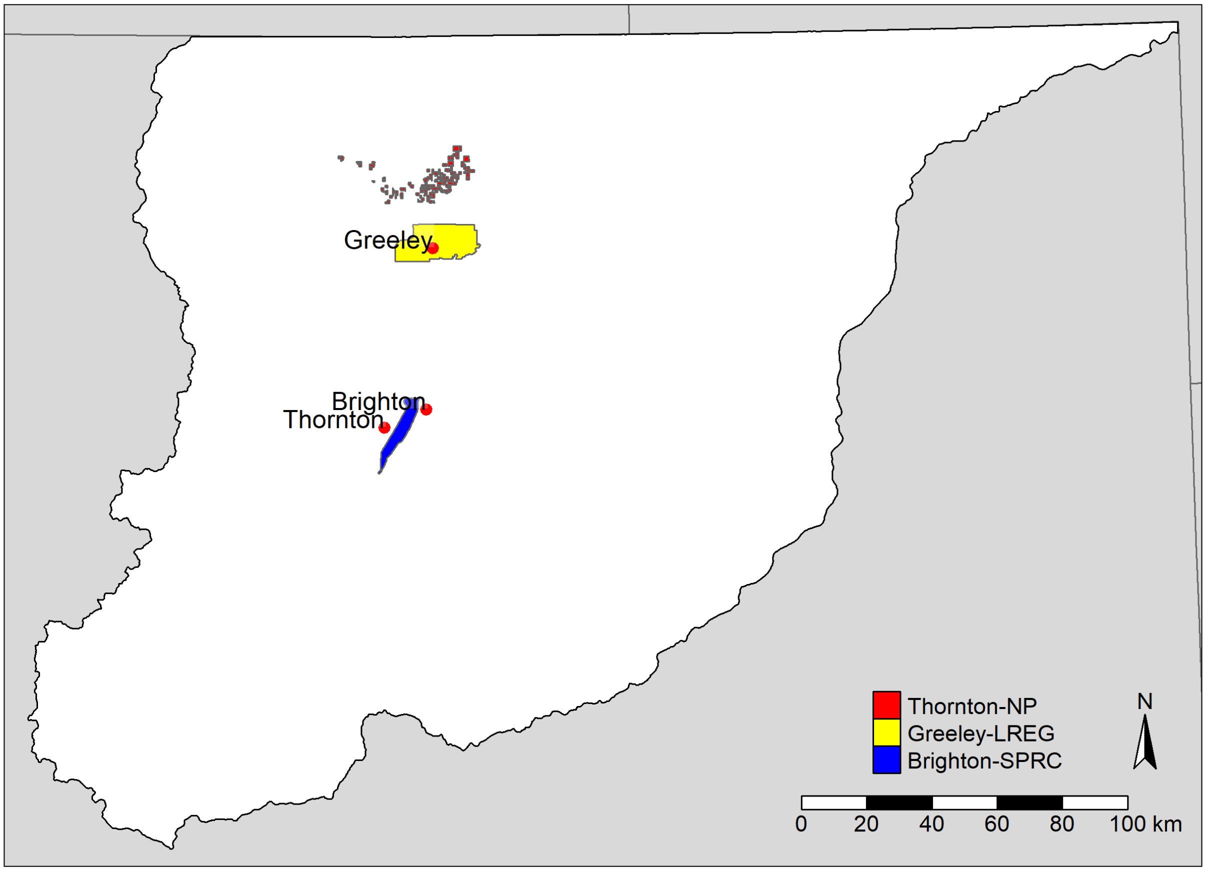


Fig. S3.11. Three AOIs in the South Platte River Basin. Brighton, Greeley, and Thornton are marked by red points. Polygons represent three areas of interest to which the tools of interest were applied.

A general summary of the tools is presented below in Table S3.3.

Table S3.3. *Overview of 8 tools that provide different data and analysis that are relevant to land use planning with respect to ecosystem services*

Tool (Hosting Org)	Website	Suggested Use(s)	Data/Analysis Available	Scale of Data/Analysis	Notes
Resilient Land Mapping tool (The Nature Conservancy)	http://maps.tnc.org/resilientland/ https://www.conservationgateway.org/ConservationPractices/Climate Change/Pages/Climate-Resilience.aspx	• A starting point for conversations with local communities, indigenous tribes, land trusts, agencies, corporations, and funders on how to coordinate conservation efforts to increase our collective impact and sustain nature. • Helps identify sites (ecosystems) that are more likely to be resilient against climate change, meaning as the climate changes more resilient sites are likely to sustain themselves better than less resilient sites.	• Resilient sites (i.e., landscape diversity, local connectedness, geology and soils, elevation, landforms, migration space for tidal habitat) • Resilient and connected network (resilient to biodiversity loss due to climate change, flow of species along connected corridors, biodiversity) • Carbon data available as Forest Ecosystem Carbon (2010 or 2015), potential forest ecosystem carbon sequestration (2010-2050), and soil organic carbon, but this data does not seem to be available for download	• Depends on data. Allows project shape files to be drawn or uploaded as a zipped .shp file. Analysis is performed on data falling within the polygon drawn or uploaded. • Forest carbon applies to forested 30 m pixels of NLCD data. • Soil organic carbon is at 250 m resolution resampled to align with 30 m resolution NLCD data and includes estimates for the top 30 cm of soil. • Carbon data is not available for download.	• Resilient land mapping tool provides a nice output of summary statistics including the number of acres in each category (e.g., # acres in 'Resilient, Diffuse Flow, Recognized Biodiversity'). • Data available for download for USA, by state, or by region at: http://www.conservationgateway.org/ConservationPractices/ClimateChange/Pages/RCN-Downloads.aspx • Some carbon data is available as 'forest ecosystem carbon' and soil organic carbon, but this data does not seem to be available for download.
Farms Under Threat: The State of the States (American Farmland Trust)	https://csp-fut.appspot.com/	• Farms Under Threat provides actionable information on the location and quality of agricultural land, the threats posed by development, and state-level policies that can help protect farmland and ranchland.	• Map of productivity, versatility, and resiliency (PVR) values for 2016 (higher values indicate higher suitability for long-term, intensive crop production, especially for food crops) • Map of non-federal farmland and rangelands	• Data appears to be based on 30 m resolution data, but analysis is only available at the state scale. • Data may be requested however	• Downloadable spatial data is only available by request, and it may take 30 days or more to get a reply. Data may be requested here: https://survey123.arcgis.com/share/3f8d2e46cec64288b53d235fa7cf7d40 • It does not seem to be possible to get a summary of a user-defined area. Summaries are only provided at a state level.

		• No ability to produce report of specified areas other than states and the entire U.S.A.	that were converted to other land uses between 2001 and 2016 • Nationally Significant agricultural land (2016)		• Original data sources are listed here: https://csp-fut.appspot.com/downloads/AFT_FUT_SoS_Appendix%20II.pdf • Soil organic carbon for 0-30 cm depths is available at: https://daac.ornl.gov/cgi-bin/dsviewer.pl?ds_id=1737
Carbon Reduction Potential Evaluation (CaRPE) Tool™ (USDA-ARS and American Farmland Trust)	https://carpe.shinyapps.io/CarpeTool/	• In order to evaluate the current and projected GHG mitigation potential we developed the interactive Carbon Reduction Potential Evaluation (CaRPE) ToolTM to quantify and visualize county-level GHG emission reductions resulting from the implementation of a suite of cropland and grazing land management practices. • The CaRPE Tool™ is designed to provide high level estimates (i.e., county/state) that can be used to generate maps and data to inform and prioritize conservation planning and practice implementation.	• Includes AgCensus data every five years between 1997 and 2017 including: • Cropland acres of total cropland, commodity-specific, and fallow/idle acres and • Grazing land acres • There are many conservation practices available to evaluate the impact of those services at different levels of adoption • Many other data from the AgCensus	County, state, region, or national level	The CaRPE Tool™ scales the emission reduction coefficients (ERC) extracted from the COMET-Planner tool to the county level by coupling the coefficients with acreages from the USDA Census of Agriculture (AgCensus). See page 44 (appendix I) in the COMET report for details on emission reduction coefficients (https://planner-prod-dot-comet-201514.appspot.com/static/media/COMET-Planner_Report_V1Legacy.d4f77ec6.pdf)
Colorado Wetland Inventory (Colorado Natural Heritage Program)	https://csurams.maps.arcgis.com/apps/webappviewer/index.html?id=a8e43760cb934a50	• Intended to assist in identifying wetland and riparian areas and provides only potential and approximate locations of the features mapped. The data shown are not intended for regulatory purposes and	• Information on the location, extent and type of wetlands in Colorado allows land managers and state agencies to make informed decisions about wetland resources.	• Seems there is no built-in analysis. Rather, the data is just presented within the state of Colorado. • Tool is good for exploring data within the state as along as a	

	84e89e469 22580cc	do not serve as a jurisdictional delineation for any local, state or federal purposes. • The Colorado Wetlands Inventory Mapping Tool displays several datasets depicting the location and classification of wetlands and riparian areas in Colorado.	• CNHP's Colorado Wetland Inventory mapping tool shows detailed wetland mapping created by the CNHP, U.S. Fish and Wildlife Service's National Wetland Inventory (NWI) program, and several other partners.	summary report is not desired.	
Colorado Watershed Planning Toolbox (Colorado Natural Heritage Program)	https://csurams.maps.arcgis.com/apps/webappviewer/index.html?id=0e2d5ffb9f1745fbbe4f92806a7048eb	• Intended to assist wetland managers, landowners, and enthusiasts with incorporating wetlands into watershed planning, restoring wetlands, to improve watershed health, and identifying opportunities for wetland conservation. The data displayed in the Toolbox are not intended for regulatory purposes and do not serve as jurisdictional delineation for any local, state, or Federal agency. • A comprehensive resource for incorporating wetlands and streams into watershed planning, restoring wetlands to improve watershed health, and identifying opportunities for wetland conservation. • The Toolbox includes an interactive mapping platform that allows users	• Emphasis on upper South Platte River Basin and upper Arkansas River Basin • Landscape disturbance index 2016, Land Management (from COMaP v 10), EPA Level IV EcoRegions, River basin boundaries, County Boundaries • Other data available, but only for limited area outside of the South Platte River Basin	• Many Toolbox data layers have statewide coverage, while some more detailed layers for wetland functions and priority conservation and restoration are building out from the Arkansas and South Platte Headwaters Project Area. • Reports are only produced for the narrow area southwest of Denver and east of Fort Carson and Colorado Springs. • Can enter location name, draw a polygon, or upload a zipped shape file to get summary	• Data from available layers is not downloadable, and the tool does not produce a summary report except for a narrow area. • Loading a shape file does not extract any information from the layers as expected. • Generally, I did not find this tool easy to use, and it rarely produced results as anticipated. • CoDEX should replace this tool.

		to view wetlands, streams, likely aquatic ecosystem functions, ecological stressors, and high-priority sites for conservation and restoration at the landscape scale. • Along with geospatial data, the Toolbox includes a gateway to a variety of other restoration and conservation resources via the Working in Wetlands web pages.			
Colorado Ownership, Management, and Protection database (COMaP) (Colorado Natural Heritage Program)	https://cnhp.colostate.edu/projects/comap/ https://comap.cnhp.colostate.edu/comap/	• Primarily provides maps of protected lands, including both public and private lands • Conservation planning/analyses • tourism and promotion • land acquisition/land exchanges • appraisals and land values • Threatened and Endangered species surveys • return on investments • site assessments • priority habitat identification • conservation easement baseline reports • optimization tool support • emergency services • cultural and historic preservation planning • long-range strategic planning • developing management goals	• State's premier map of protected lands • Find local open spaces, natural areas, parks, and conservation easements • Identify which ecosystems or species lack adequate protection • Analyze patterns, identify wildlife corridors, or find stakeholders and partners • Calculate the benefits of open space • Wetland mapping tool • Promote your recreation areas or scope out new areas to protect • If you need information to support these tasks and more, COMaP is the dataset for you • Terrestrial Ecological System Patches (2011) • Species or natural communities that are currently, potentially, or	• Depends on data. • Advertises that it allows project shape files to be uploaded with subscription, but I was not able to utilize that function.	• Service is advertised as allowing for notes and your own shape files to be added to the map, but on testing this, I found they are only allowing for notes and shape files to be uploaded to COMaP, and they do not show on the active map. • COMaP is offered as a service and requires a free annual subscription. Check out our website at https://comap.cnhp.colostate.edu/ Subscription benefits include: Access to the online interactive map where you can load in your Google map layers or zipped shapefiles, download spreadsheets, and add notes to the map A download page to access the latest GIS files, with options to host your own map service for outward-facing websites Biannual data update • CODEX should replace

		• identifying partnerships • identifying linkages and corridors • permitting •risk management • decision support • wildland fire mitigations • future water supply options • planning for trails • outdoor recreational planning • utility work • grant writing • stakeholder identification • conflict avoidance • and more ...	historically located on 7.5-minute quadrangles • Statewide potential conservation areas Statewide networks of conservation areas • Terrestrial Ecological System Patches		
Colorado Conservation Data Explorer (CODEX) (Colorado Natural Heritage Program, Colorado Parks and Wildlife, and NatureServe)	https://cnhp.colostate.edu/maps/codex/	• Includes a set of tools to support conservation planning, environmental review, evaluation of conservation portfolios, education, and more. • It allows users to develop project maps and run queries, save them securely in a personal portfolio, and submit them for review to multiple stakeholders. • CODEX users will be able to access an extraordinary range of pertinent data in context with project boundaries.	• All of COMAP functionality • During the time of my apprenticeship I never gained access to this tool, so was unable to fully explore the data and analyses available • Based on the example provided by the kind people at CNHP, this will be the most useful tool in terms of land-use planning and estimating return on investment from various ecosystem services which are tied to a given land use or land cover, although I recommend proceeding with extreme caution if using their values until	• Analysis should be available at any scale • Once the tool is operational the intention is to allow for a polygon to be drawn or a shape file loaded, to define a project area and then the tool will produce estimates of different land use/land cover types in the project area and the associated return on investment with respect to ecosystem services	This tool is not yet available (10/4/2021)

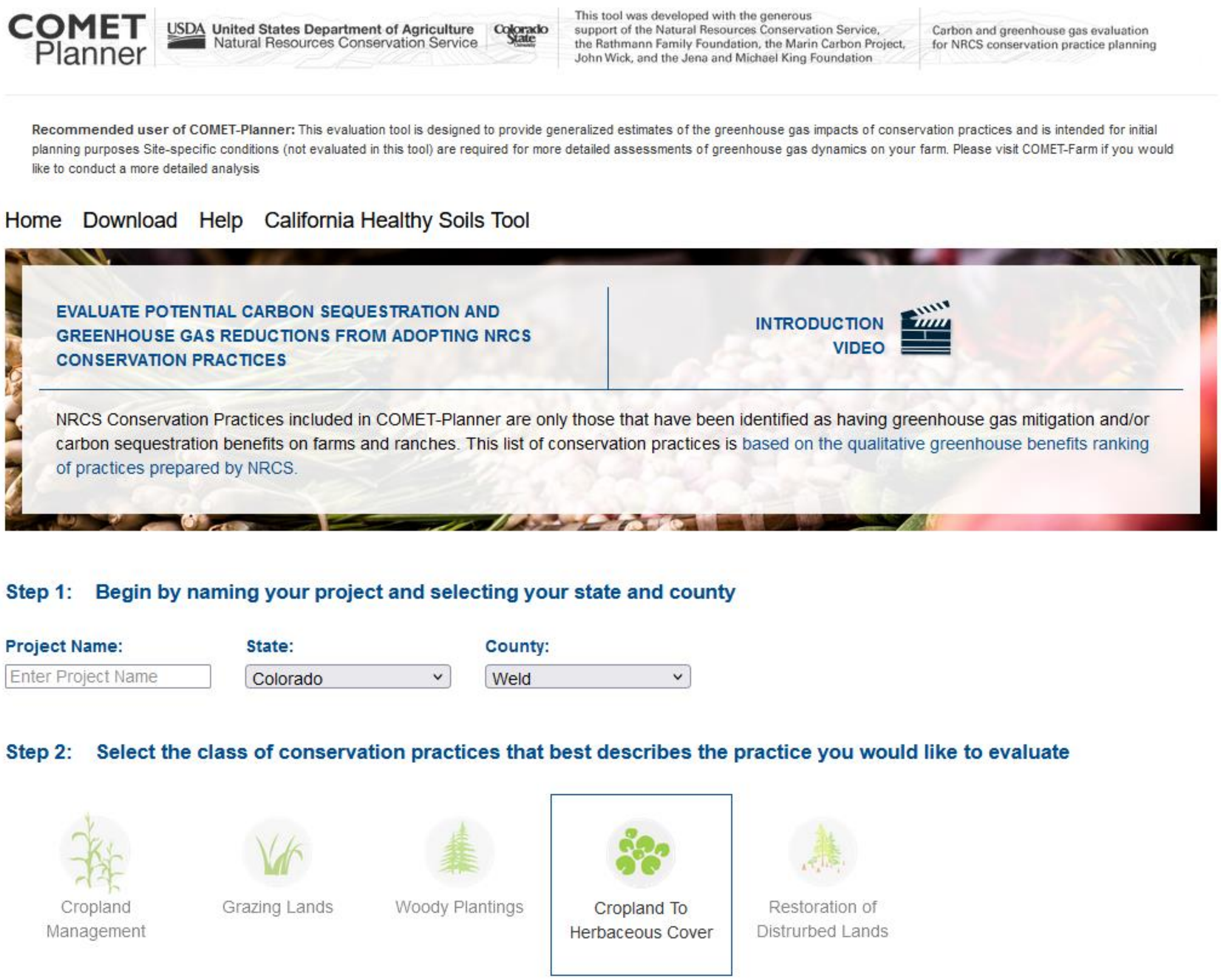
			they become further refined. • The methodology being used to estimate the ecosystem services and return on investment do not seem adequate to provide such specific values and little consideration of uncertainty was included, at least in the early stages of the tool (as of 10/4/2021) • The tool is expected to develop over time with added functionality and improved estimates.		
COMET Planner (USDA-NRCS and Colorado State University)	http://comet-planner.com/	This evaluation tool is... • designed to provide generalized estimates of the greenhouse gas impacts of conservation practices • intended for initial planning purposes • Site-specific conditions (not evaluated in this tool) are required for more detailed assessments of greenhouse gas dynamics on your farm. • Please visit COMET-Farm if you would like to conduct a more detailed analysis	• Evaluate potential carbon sequestration and greenhouse gas reductions from adopting NRCS conservation practices • Provides regionally specific estimates based on state and county • Conservation practices generally include 'Cropland Management', 'Grazing Lands', 'Wood Plantings', 'Cropland to Herbaceous Cover', and 'Restoration of Disturbed Lands' •Within each general category of conservation practices there are several more specific options	• Emission reduction coefficients were largely derived using a sample-based approach and model runs in COMET-Farm, which utilizes USDA entity-scale greenhouse gas inventory methods. • Coefficients were generalized by multi-county regions defined by USDA Major Land Resource Areas. • Emissions estimates represent field emissions only, including those associated with soils and woody biomass as appropriate, and do not include off-site emissions, such as those from transportation,	The input is simply acreage of the conservation practices of interest, so this tool may require some preprocessing to get those values.

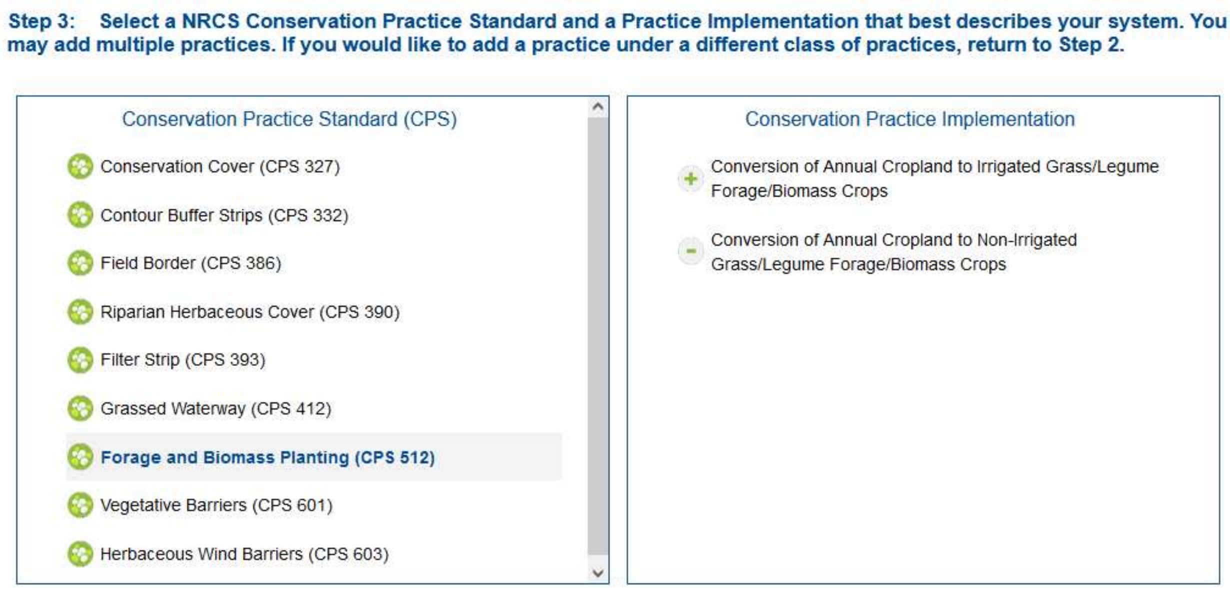
			• After entering an estimated acreage for each conservation practice of interest estimates of carbon sequestration and greenhouse gas emissions reductions are provided. These include CO2, N2O, CH4, and the results of all three in terms of CO2 equivalents (tonnes CO2 equivalent per year) • Also provided are emission reduction coefficients (tonnes CO2 per acre per year)	manufacturing, processing, etc. More information on quantification methods can be found in the COMET-Planner Report	

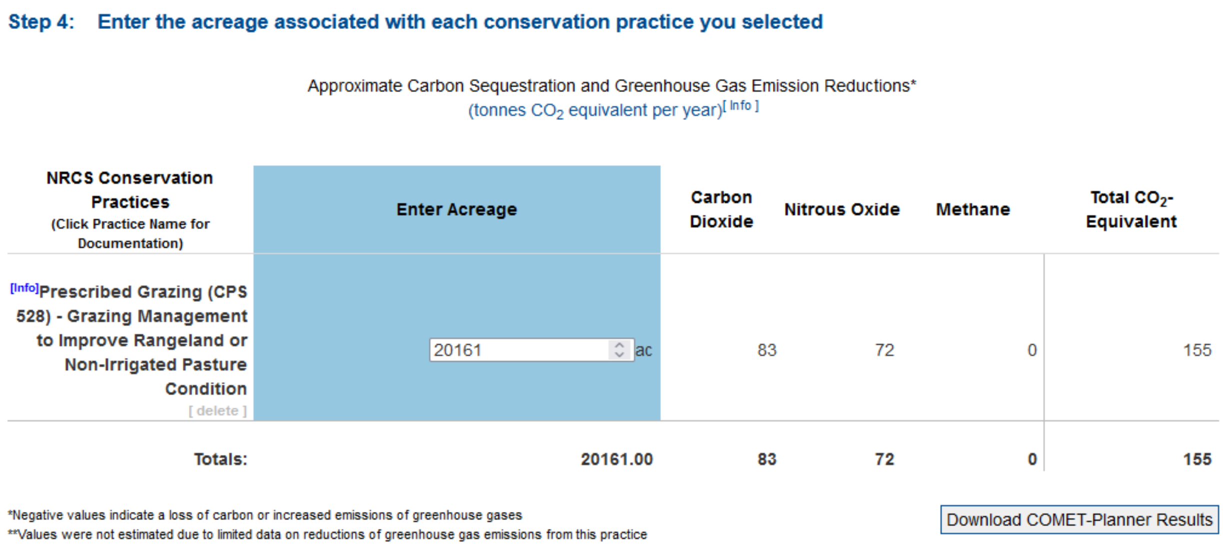
6.1 COMET-Planner

The COMET-Planner tool was, “designed to provide generalized estimates of the greenhouse gas impacts of conservation practices,” and, “is intended for initial planning purposes.” As far as performing carbon sequestration and GHG related scenario analysis in working land settings, this is the best tool out of those listed here.

6.1.1 About the Tool







6.1.2 Application to Three Areas of Interest

Out of the tools investigated, COMET-Planner is the most relevant with respect to comparing the carbon sequestration between two scenarios of natural and working lands. Here I present results from the COMET-Planner tool applied to three areas of interest. Spatial analysis was performed to identify privately owned irrigated land in the areas of interest (Fig. S3.12) because it is likely the land of interest when conservation or payment for ecosystem programs are considered. After identifying the total acreage of privately owned irrigated land in each area of interest, the acreage totals were used as inputs into the COMET-Planner tool which takes county, area, and alternative land management approach as inputs. The output from COMET-Planner is a total annual sequestration rate [tCO_{2eq}/year]. Using the values in Table S3.1 and equation 1 (Eq. 1.) I then used the COMET-Planner outputs as inputs to derive a range of realistic values for the ROI from the sequestered carbon considering a time of 50 years into the future (Table S3.4). It is important to note that COMET-Planner tool does NOT include any considerations of uncertainty, so the methodology applied here only considers uncertainty related to the ROI (i.e., social cost of carbon; SCC).

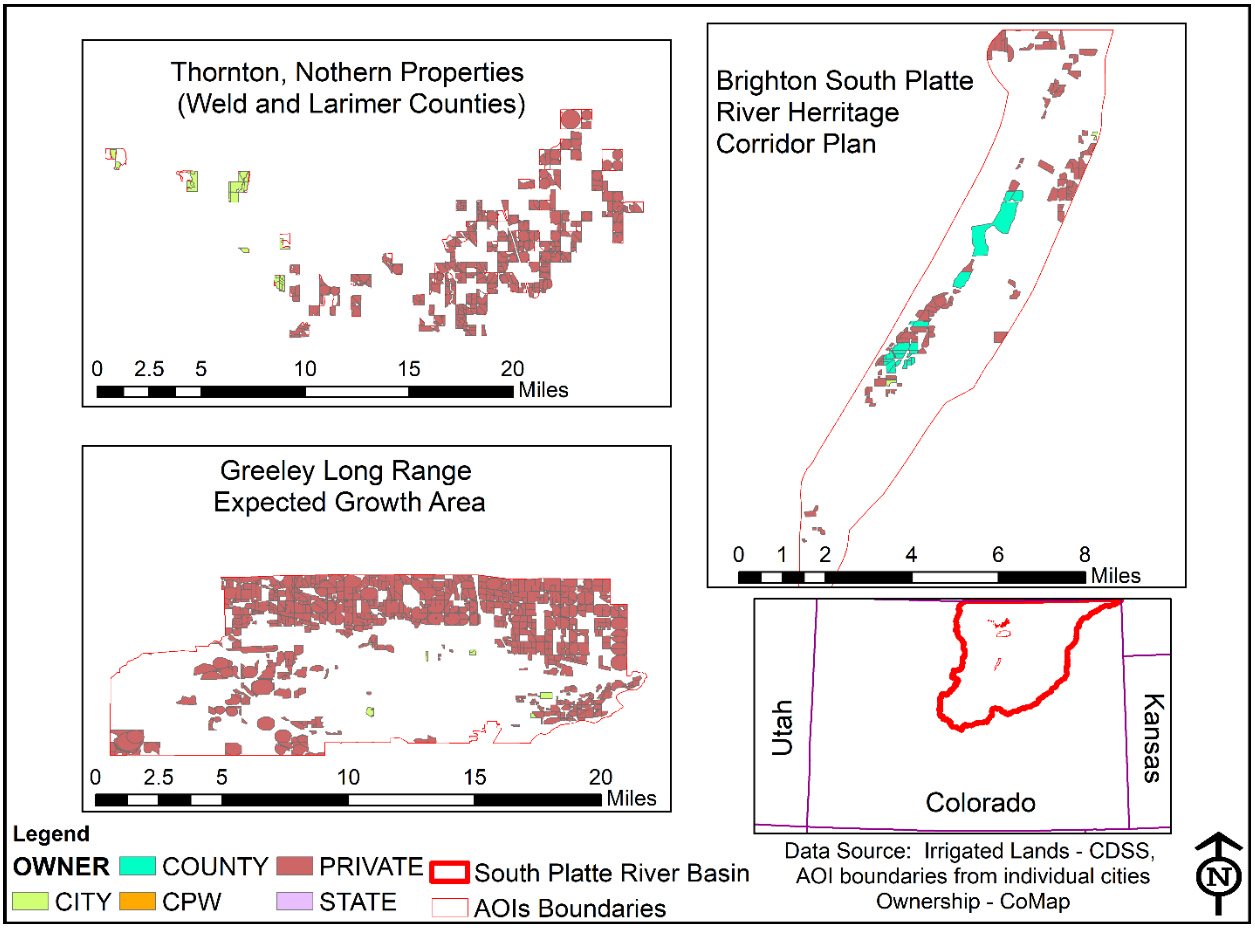


Fig. S3.12. Ownership of irrigated lands within each of the three areas of interest.

To investigate the ROI from the conservation practices listed in Table S3.4, I drew 500 random samples from a uniform distribution of SCC ranging from \$12 to \$300 as representing estimates from around the globe as based on the values presented in Table S3.1. Then, using values of 1, 2.5, 3, 5, and 7 for discount rates and 1, 2, and 4.4 for time preference, I calculated the ROI after 50 years for all combinations of those variables along with the three sequestration rates returned by COMET-Planner from the three conservation practices being investigated (Fig. S3.13). That resulted in 22,500 total estimates or 7,500 for each conservation practice.

Table S3.4. *Annual GHG (CO_2, N_2O, CH_4) sequestration and/or reduction in emissions in AOI's* if all of the privately owned irrigated cropland in the three AOI's were converted to the three represented conservation practices. All GHG reduction/sequestration values are in tonnes of CO_2 equivalents per year. ROI values assume 50 years of sequestration.

	Greeley-LREGA (Weld County)		**Thornton-NP (Weld County)**		**Brighton-SPRHCP (Adams County)**	
Acres of privately owned irrigated land	20,161		16,152*		1,440	
Output [units]	Seq. Rate [tCO_{2eq}/year]	ROI [millions$] Mean, SD	Seq. Rate [tCO_{2eq}/year]	ROI [millions$] Mean, SD	Seq. Rate [tCO_{2eq}/year]	ROI [millions$] Mean, SD
Conservation Cover (CPS 327) – Convert Irrigated Cropland to Permanent Unfertilized Grass/Legume Cover	11,522	32.37, 21.57	9,231	26.18, 16.69	823	2.26, 1.52
Conservation Cover (CPS 327) – Convert Irrigated Cropland to Permanent Unfertilized Grass Cover	7,833	22.01, 14.66	6,275	17.79, 11.35	560	1.54, 1.03
Forage and Biomass Planting (CPS 512) – Conversion of Annual Cropland to Non-Irrigated Grass/Legume Forage/Biomass crops	5,377	15.11, 10.07	4,308	12.22, 7.79	385	1.06, 0.71

Footnote: *About 22 of the 16,152 acres of Thornton's northern properties are located in Larimer County. The proportion of property in Larimer County was so small however, that the analysis was performed assuming all property was in Weld County.

Fig. S3.13 presents the distributions of results for each of the three conservation practices and each of the three areas of interest. On the y-axes is the sequestration rate for each of the three conservation practices as noted in the second column of Table S3.4. The x-axis of Fig. S3.13 presents the return on investment (ROI) in millions of dollars assuming the sequestration rates from COMET-Planner are appropriate to apply 50 years into the future. The area of privately owned irrigated land is the most apparent driver of total ROI with Greeley producing the greatest ROI and Brighton producing the smallest. The conservation practices themselves do make some difference with CPS 327 – Conversion of irrigated cropland to permanent unfertilized grass/legume cover producing the greatest ROI, followed by conversion with only grass (legumes excluded) and then by the conversion of annual cropland to non-irrigated grass/legume forage/biomass crops. The value of the SCC in each simulation was the major driver of the resulting ROI. It is important to note the extreme uncertainty, and how it grows with the area which is being considered (e.g., Greeley included the largest area, and thus sequestration). Average values of ROI (Table S3.4) ranged from about $1 million to over $30 million.

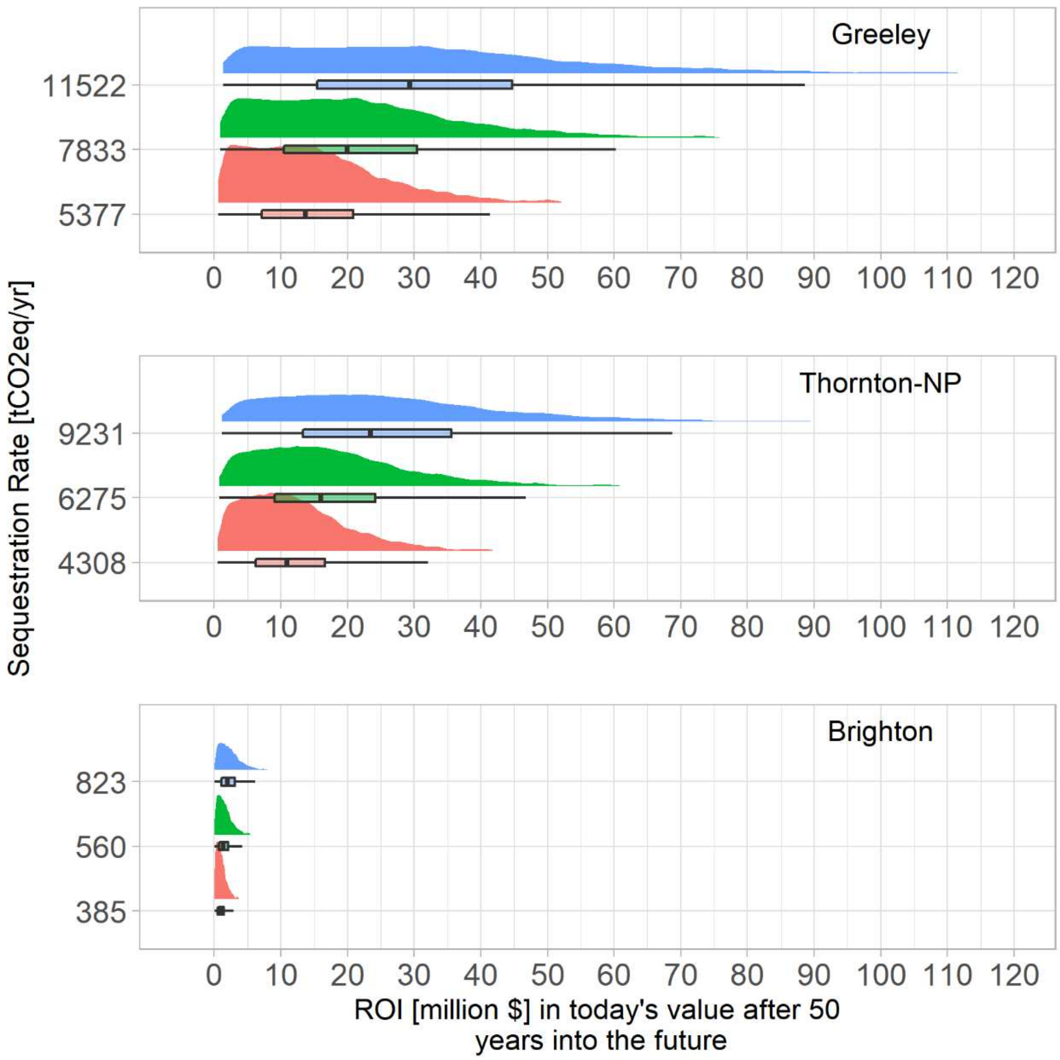


Fig. S3.13. *Probabilities of the ROI based on outputs from COMET-Planner and valuation parameters from literature review.* The y-axis presents the sequestration rates from COMET-Planner. See Table S3.4 for the related conservation practices. The x-axis presents the ROI in millions $.

6.1.3 Development of Pre- and Post-Processor App for Easily Repeating Analysis

While the analysis presented in section 6.1.2 represents uncertainty as presented by estimates of the social cost of carbon (SCC) from around the globe, other estimates may be desired, as estimated for local areas. To enable easy re-creation of the earlier analysis using different distributions (i.e., normal, lognormal, and uniform) I created an R-Shiny application which can be attained via emailing me directly (ben.choat@colostate.edu) as well as online. The online version cannot handle large areas however, such as the Greeley Long Range Expected Growth Area.

The application consists of four pages (Figs. 14 – 17). The first page (Fig. S3.14) is an introduction page with some instruction about use. The second page (Fig. S3.15), “1. Area of Interest”, allows you to upload spatial files of your area of interest in the South Platte River Basin, or use the three areas of interest presented in the previous analysis. The third page (Fig. S3.16), “2. COMET-Planner”, provides a link to the COMET-Planner website and summarized the acreage within the area of interest by landowner type. The fourth page (Fig. S3.17), “3. Valuation”, allows the user to choose between normal, lognormal, and uniform distributions to represent the uncertainty of the SCC and allows the user to specific the parameters for the chosen probability distribution. After simulating the SCC based on the specified distribution and parameters, the user can provide the sequestration rates which are outputs from the COMET-Planner tool, how many years into the future the user would like to estimate the ROI, as well as maximum and minimum values for the discount and time preference rates. Six values of the discount and time preference rates ranging from the minimum to maximum values specified are included in simulations.

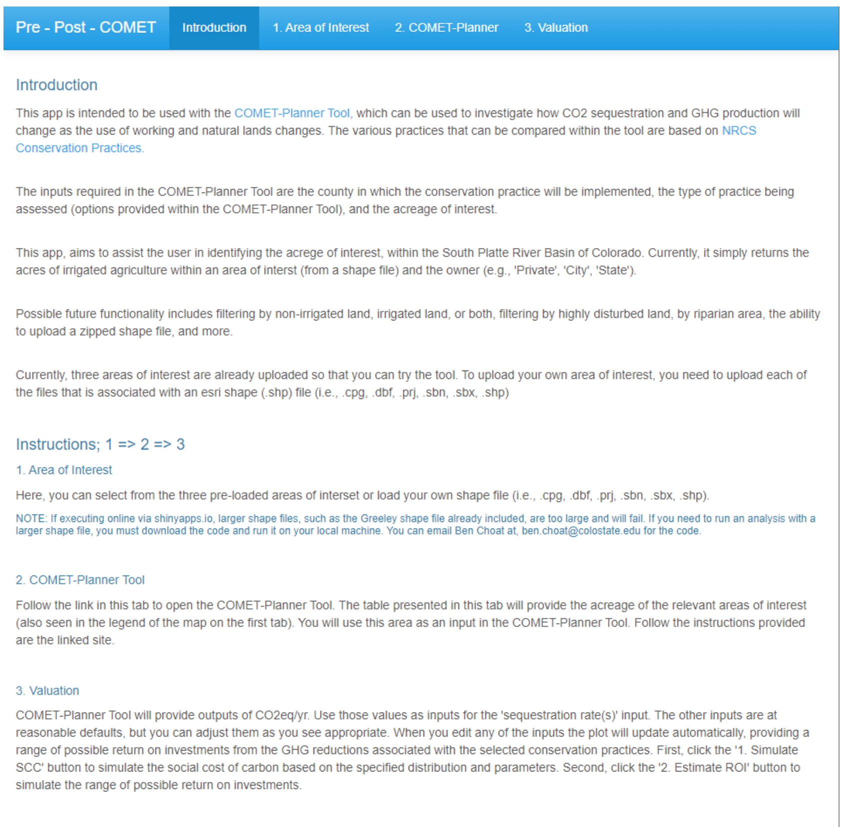


Fig. S3.14. *Introduction page of the Pre – Post – COMET application*

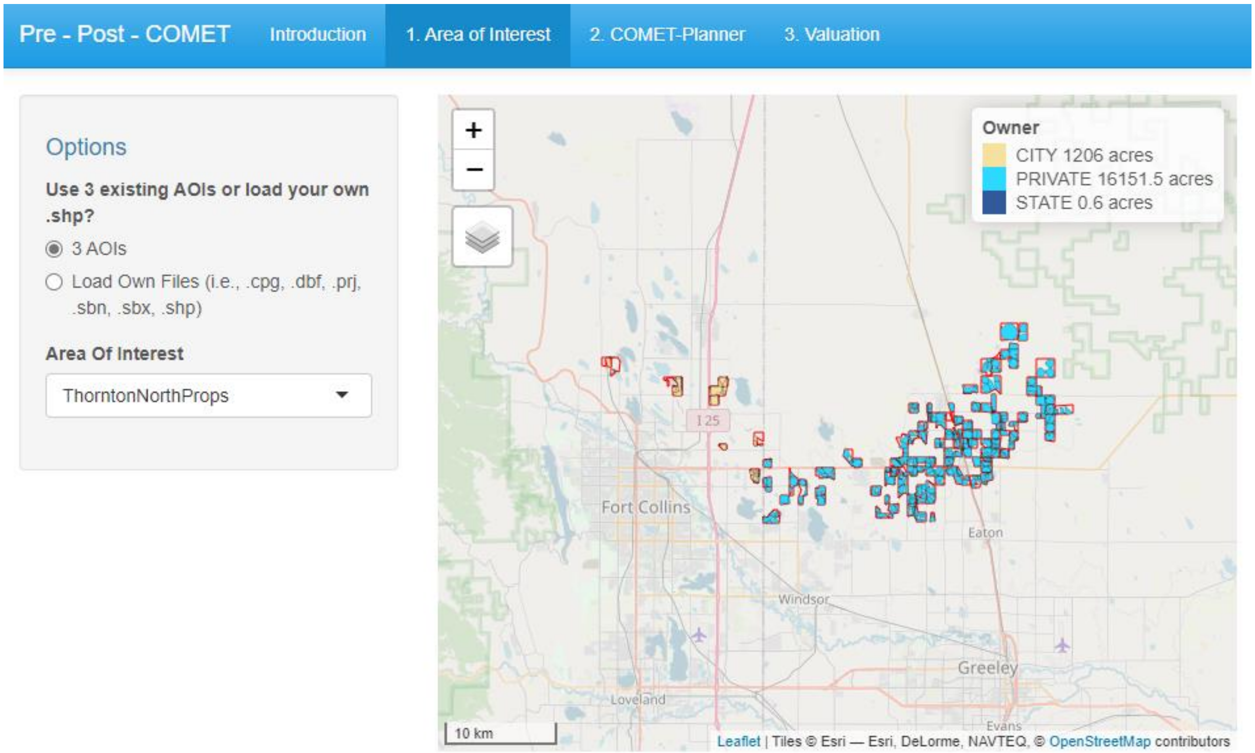


Fig. S3.15. *Selection area of interest in the Pre – Post – COMET application*

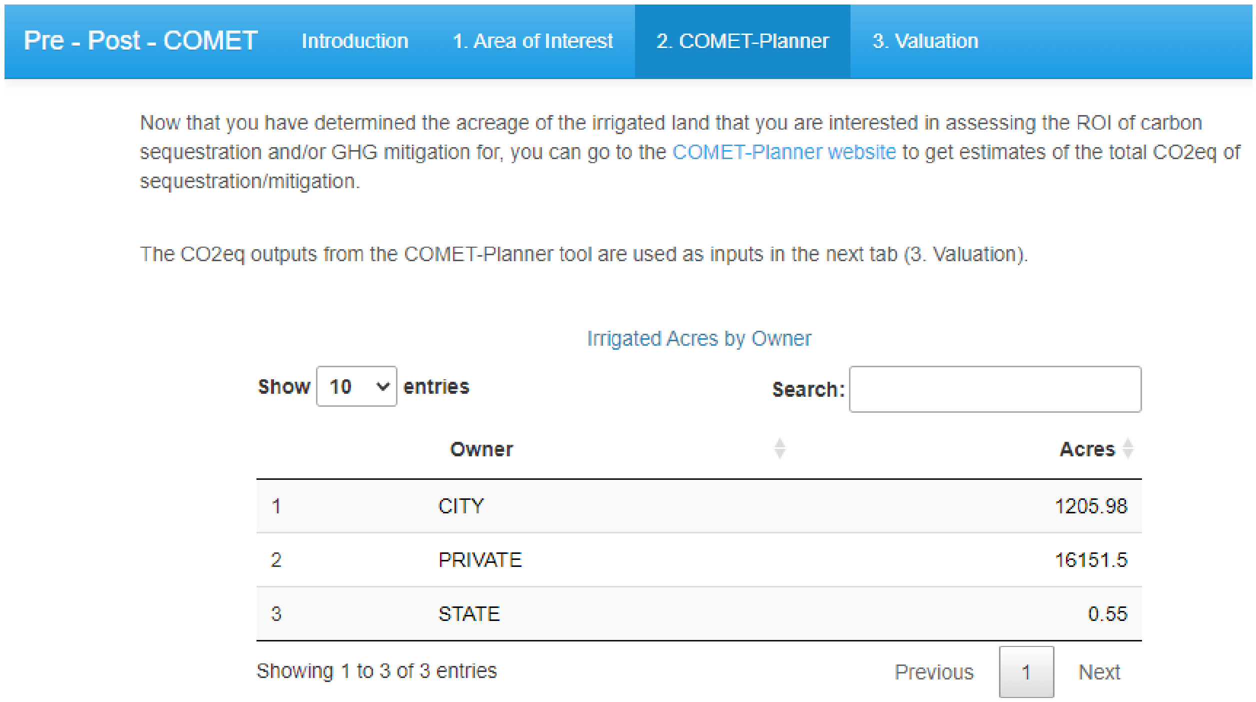


Fig. S3.16. *Values from the Pre – Post – COMET application to be used in the COMET-Planner tool*

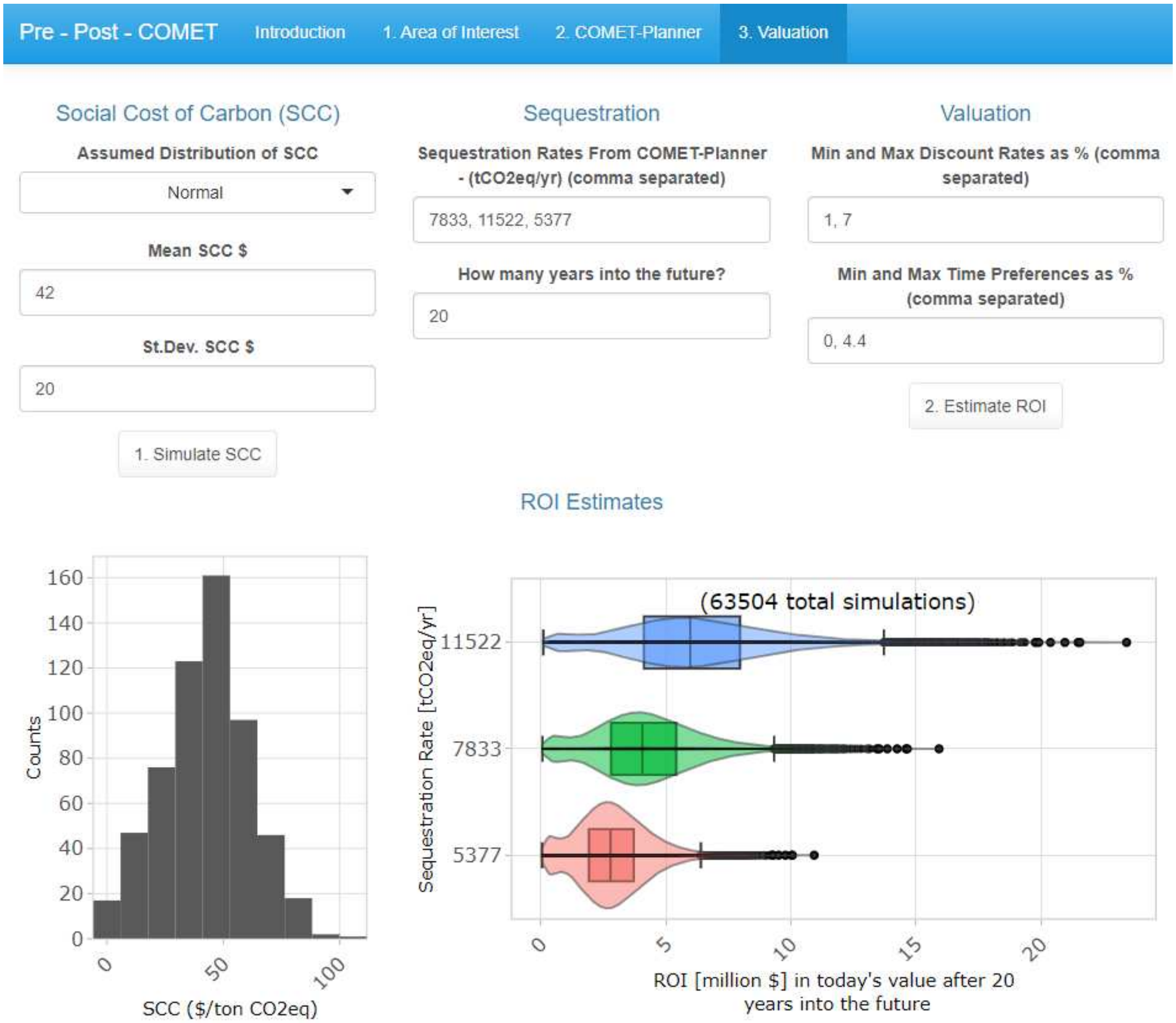


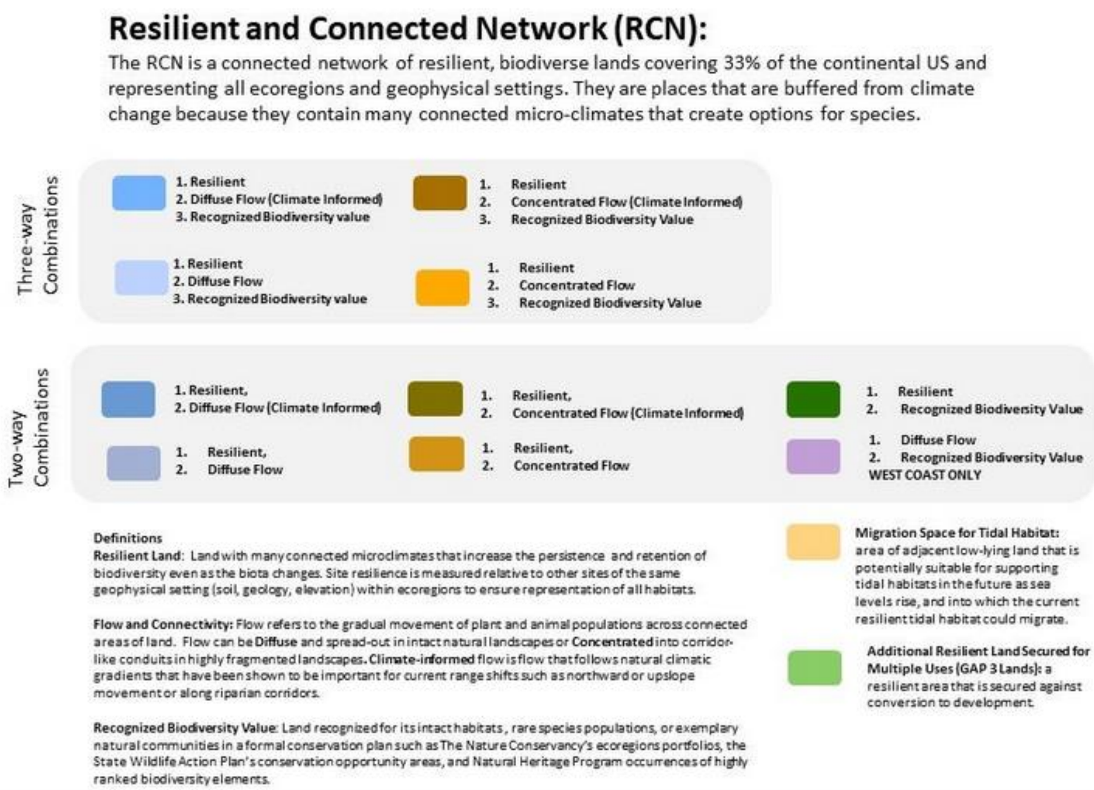
Fig. S3.17. *Estimates of the Social Cost of Carbon and Return on Investment from the Pre – Post – COMET application*

6.2 Resilient Land Mapping Tool

The Resilient Land Mapping Tool's primary functions are to provide data about *resilient sites*, *local connectedness*, and *recognized biodiversity*. A *resilient site* is, "an area of land where high microclimatic diversity and low levels of human modification provide species with connected, diverse, climatic conditions they will need to persist and adapt to changing regional climates." *Local connectedness*, "refers to the degree of fragmentation and strength of barriers that create resistance to movement within a landscape. A highly connected landscape promotes resilience by allowing species to move through the landscape and find suitable microclimates where they can persist. In this study, we calculate local connectedness by measuring the amount and configuration of human-created barriers like major roads, development, energy infrastructure, and industrial farming and forestry land." To quantify *recognized biodiversity* the nature conservancy, "assembled information on places recognized for their biodiversity value (rare species, intact habitat, or exemplary natural communities) in separate studies. These include the results of 67 ecoregional assessments completed by The Nature Conservancy between 1999 and 2009, which identified sites representing multiple-viable examples of rare species and natural communities (Groves 2003). Additionally, we reviewed the results of 48 state wildlife action plans, and integrated information from 35 of them, to create maps of conservation opportunity areas for species of greatest conservation need. We also include recent information from the Natural Heritage Network (and other sources) on high quality species and community occurrences, and protected land managed for biodiversity and natural processes (GAP 1). This assessment ensures that the network encompasses the footprint of current biodiversity areas while integrating them with representative abiotic features which underpin that biodiversity, ensuring that networks of resilient sites are distributed across all abiotic 'stages' needed to conserve future biodiversity." See more details below.

Opposed to recreating the valuable information presented on the Resilient Land Mapping Tool website, below are screenshots from the website which provide insight as to how the tool presents results and what factors are considered by the tool and shown in the results.

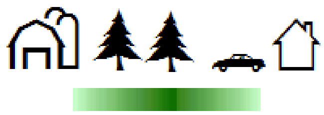
Resilient and Connected Networks (Detailed):

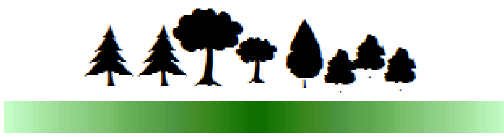


Resilience Score: A site's Resilience Score estimates its capacity to maintain species diversity and ecological function as the climate changes. It was determined by evaluating and quantifying physical characteristics that foster resilience, particularly the site's landscape diversity and local connectedness. The score is calculated within ecoregions based on all cells of the same geophysical setting and is described on a relative basis as above or below the average. For example, cells of granite bedrock were compared with all other cells of granite bedrock, and coastal plain sands were compared with other coastal plain sands. Our goal was to identify the places most resilient to climate change for each geophysical setting within each ecoregion.

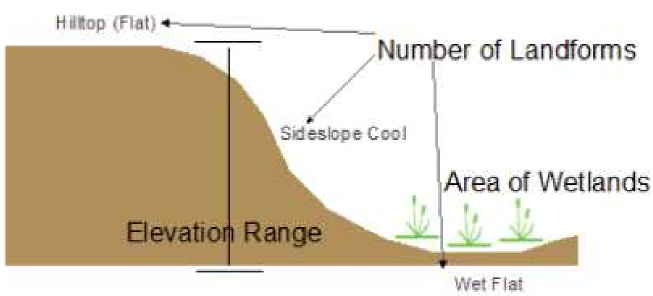
Coastal areas were evaluated separately from terrestrial areas. To learn more about the methods and results, visit the Resilient Coastal Sites web site

Local Connectedness: Refers to the degree of fragmentation and strength of barriers that create resistance to movement within a landscape. A highly connected landscape promotes resilience by allowing species to move through the landscape and find suitable microclimates where they can persist. In this study, we calculate local connectedness by measuring the amount and configuration of human-created barriers like major roads, development, energy infrastructure, and industrial farming and forestry land. Read the methods for your region: Eastern US, Great Lakes and Tallgrass Prairie, Great Plains, Lower Mississippi and Ozarks, Rocky Mountains and Desert Southwest, Pacific Northwest, Calmeasureifornia





Landscape Diversity: Refers to the microhabitats and climatic gradients available in the immediate neighborhood surrounding any 30-m cell of land. The persistence of species in an area increases in landscapes with a wide variety of microclimates created by the topography (topo-climates), elevation and hydrology. In this study, we measure microclimates by counting the variety of small-scale landforms, measuring elevation range, and evaluating the density and configuration of wetlands in a 100-acre neighborhood around every point on the landscape. Read the methods for your region: Eastern US, Great Lakes and Tallgrass Prairie, Great Plains, Lower Mississippi and Ozarks, Rocky Mountains and Desert Southwest, Pacific Northwest, California



Carbon

Forest Carbon: Estimates of 2010 forest carbon stock and components (aboveground, coarse woody debris, and soil/other) are from Williams et al. (in press) following methods described for the Southeast US in Gu et al. (2019). To estimate carbon stock, attributes were determined for all forested 30-m pixels in the continental United States. A forest carbon cycle model trained to match Forest Inventory and Analysis (FIA) data was used to predict carbon stocks for 2010 based on site-level attributes of forest type group, years since disturbance, and site productivity class. Results were iterated backward in time to provide continuous, annual reporting of forest carbon dynamics for each pixel. Most prior studies lacked spatial detail on the age of forest stands that persisted in a forested condition during the satellite data era, but this study used remotely sensed biomass to estimate the stand age condition of these persisting, intact forests, distinguishing relatively young stands (e.g., 30 to 50 years old) from older stands.

Future Forest Carbon Stock & Potential Sequestration: The method used to calculate the 2050 carbon stocks was the same as described above, except that the model assumed no disturbances to the forests after year 2010. Because the modeled forests grow undisturbed from 2010 onward, the results can be used to estimate the potential carbon sequestration if the forest were free of harvest, fire, or conversion. While conservation efforts can limit harvest and conversion, it is difficult to predict future disturbances and users should be aware that the actual sequestration may be less than predicted. The *Total Annual Sequestration* is estimated as: *(2050 stock - 2010 stock)/40 years*. The analysis tool also calculates the **Average Annual Sequestration Rate** per selected **site** *(2050 stock - 2010 stock/40 years)* and per **acre** *(2050 stock-2010 stock/40 years/acres)*.

Gu, H., Williams, C. A., Hasler, N., & Zhou, Y. (2019). The carbon balance of the southeastern U.S. forest sector as driven by recent disturbance trends. Journal of Geophysical Research: Biogeosciences, 124, 2786– 2803. https://doi.org/10.1029/2018JG004841

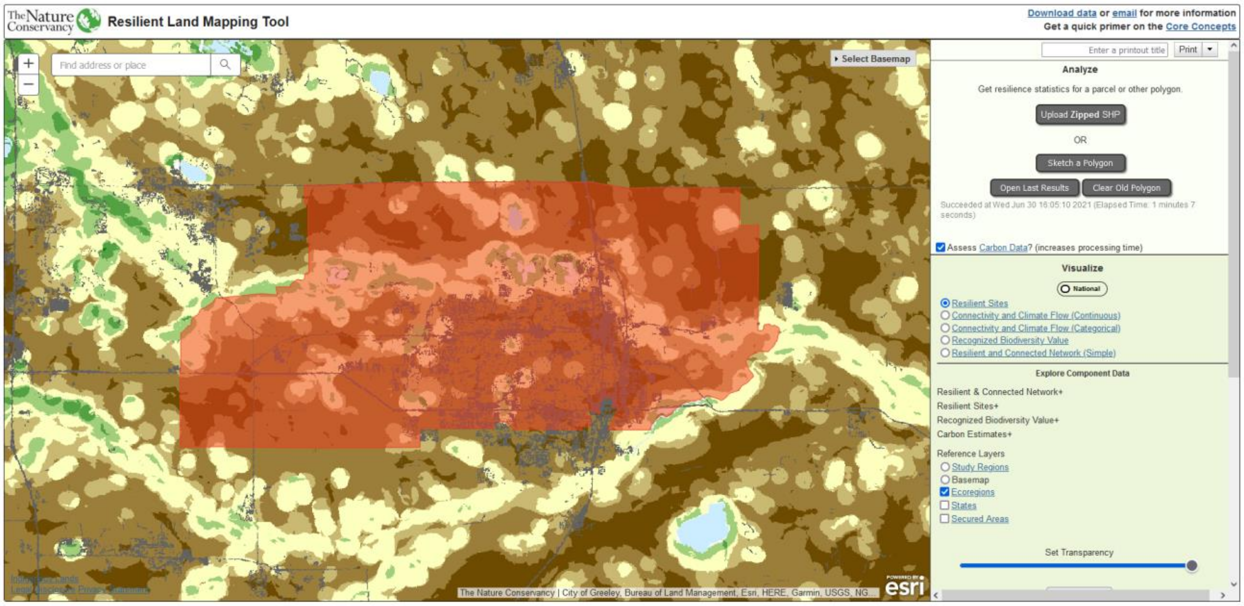
Reforestation: This tool is not designed to identify places with the highest potential for reforestation to increase carbon sequestration. To address that question, check out www.ReforestationHub.org

Soil Carbon: Estimates of soil organic carbon (SOC) for 0-30 cm topsoil layer at 250-m resolution for the conterminous USA (CONUS) are from Oak Ridge Lab (Guevara et al. 2020). The estimates are for the period 1991-2010 and were derived using the USDA Rapid Carbon Assessment (RaCA), which used over 6000 field soil samples and multiple environmental variables representative of the soil-forming environment coupled with a machine learning approach (i.e., simulated annealing) and regression tree ensemble modeling for optimized SOC prediction. Across the continental US, nearly 31% of SOC was found in forests, 28% in croplands, and 35% in grasslands and shrublands respectively.

Guevara, M., C.E. Arroyo-cruz, N. Brunsell, C.O. Cruz-gaistardo, G.M. Domke, J. Equihua, J. Etchevers, D.J. Hayes, T. Hengl, A. Ibelles, K. Johnson, B. de Jong, Z. Libohova, R. Llamas, L. Nave, J.L. Ornelas, F. Paz, R. Ressl, A. Schwartz, S. Wills, and R. Vargas. 2020. Soil Organic Carbon Estimates for 30-cm Depth, Mexico and Conterminous USA, 1991-2011. ORNL DAAC, Oak Ridge, Tennessee, USA. https://doi.org/10.3334/ORNLDAAC/1737

Total Carbon: Estimates for total carbon in the carbon calculator use Forest Carbon 2010 for all cells with forest cover and Soil Carbon 2010 for all cells with non-forest cover. To combine the two datasets, we resampled the SOC data to a 30-m resolution to align with our other data products, and then removed developed lands using the 2016 National Land Cover Dataset (NLCD). Please note that resampling to a higher 30-m resolution introduces false accuracy as the original SOC data was at a lower 250-m resolution.

6.2.1 Greeley's long range growth area as an example



Resilient Land Summary

Resilience Results | Carbon Results

Total land area: 58,461.2 acres in the Great Plains study area(s) in the Central Shortgrass Prairie ecoregion(s).

The area of interest includes 288 acres of exisiting conservation land.
(GAP 1=0 ac, GAP 2=169.9 ac, GAP 3=118.8 ac)

Resilient and Connected Network Results

Note: These results are based on the **nationally-consistent** ecoregional data. They are derived from the detailed representations of the Resilient and Connected Networks which can be visualized under the Resilient & Connected Network Components section at right.

Resilience, Flow and Recognized Biodiversity: 0

Resilience and Flow: 0 ac.

Resilience and Recognized Biodiversity: 41.1 ac.

Resilient, Recognized Biodiversity: 41.1 ac.

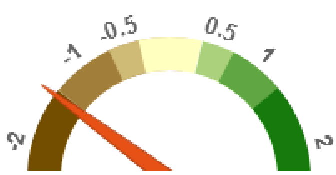
Outside Prioritized Network: 58,898.7 ac.

Additional Resilient Secured (GAP 3): 3.3 ac.

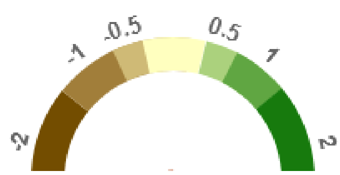
Average Terrestrial Resilience with Polygon

(all scores relative to ecoregion)

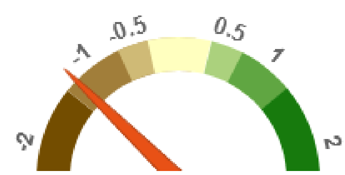
Resilience
Below Average (-1.4 SD)



Local Connectedness
Far Below Average (-2.5 SD)

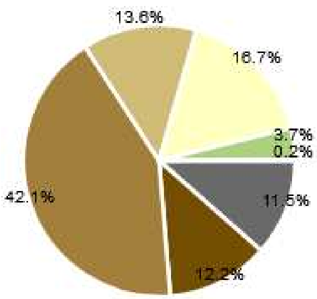


Landscape Diversity
Below Average (-1.2 SD)

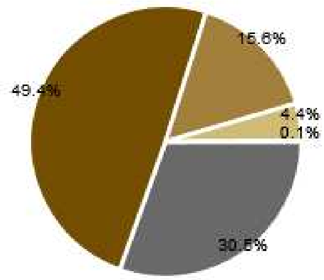


Terrestrial Resilience Categories

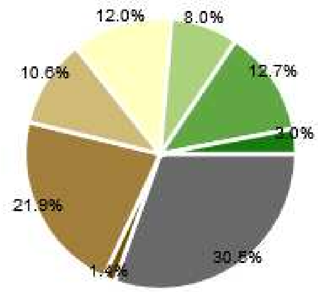
Resilience



Local Connectedness



Landscape Diversity



Geophysical Setting Results

The mean elevation in the polygon is 1455.32 m (4774.67 ft) and the three most common geophysical settings are:

Sand : 31,214 acres

Calcareous Loam : 19,690 acres

Circumneutral Sedimentary : 7,558 acres

OK Print

(Formatting may be altered when printed)

Resilient Land Summary

Resilience Results | **Carbon Results**

These national datasets can be used to get a **estimate** of a site's carbon stock. The datasets are at different scales, are derived from different methods, and overlap so the results cannot be simply added together. Taken separately, each dataset reveals information about potential carbon at the site.

Forest Carbon 2010 dataset (Williams et al. in press) applies only to forested pixels only and uses a sophisticated model to estimate Total Forest Carbon for 2010, which includes above-ground biomass, coarse woody debris, soil carbon and other pools. More detail

The **Forest Carbon 2050** (Williams et al. in press) applies only to forested pixels only and uses the same model as the Total Forest Carbon 2010 but runs the model to 2050, assuming no disturbance (conversion, harvest, fire). Actual sequestration may be lower if the forest is disturbed. **Annual sequestration rate** is estimated as: *(Carbon 2050 – Carbon 2010)/40 years.*

Soil Carbon 2010 (Guevara et al 2020) is at a coarser scale and only calculated for the upper 30 cm of soil. Soil carbon values were predicted using soil samples and multiple environmental variables coupled with a machine learning approach and regression tree ensemble modeling. In forested areas, this carbon overlaps with carbon in the forest belowground/other category of Forest Carbon 2010.

The **Land Cover 2016** uses the National Land Cover Dataset (NLCD) to show land cover and human use at 30-m resolution. It can be used to determine if, or where, the land cover has changed since 2010.

Total Carbon 2010 for a site is estimated as metric tons of **forest carbon in forested areas** plus metric tons of **soil carbon in non-forested areas**.

Forest Carbon

mt = metric tonnes

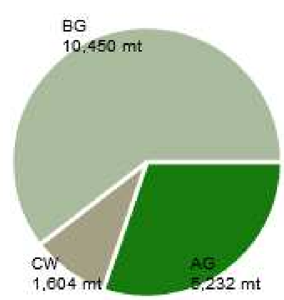
Forest Carbon 2010

Total Forest Ecosystem Carbon: **17,286** mt

Avg. Forest Ecosystem Carbon: **20.6** mt/ac

Forest Carbon 2010

Forest Carbon Components



AG: Aboveground Wood, CW: Coarse Woody Debris, BG: Belowground/Other

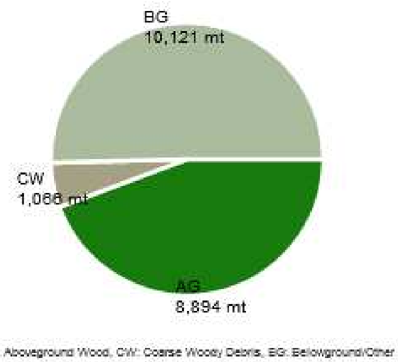
Forest Carbon 2050

Total Forest Ecosystem Carbon: **20,081** mt

Avg. Forest Ecosystem Carbon: **23.9** mt/ac

Forest Carbon 2050

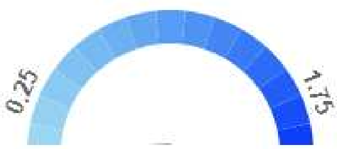
Forest Carbon Components



Potential Forest Carbon Sequestration 2010-2050

40-yr Total for Site: **2,795** mt

Annual Rate per Acre: **0** mt/ac/yr



Annual Rate for Site: 69.9 mt/yr

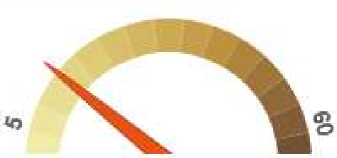
Soil Carbon & Land Cover

mt = metric tonnes

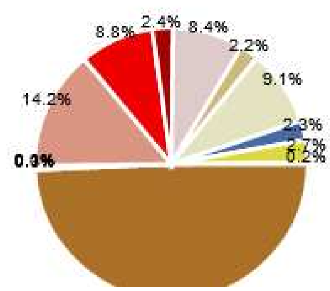
Soil Carbon 2010 (upper 30 cm)

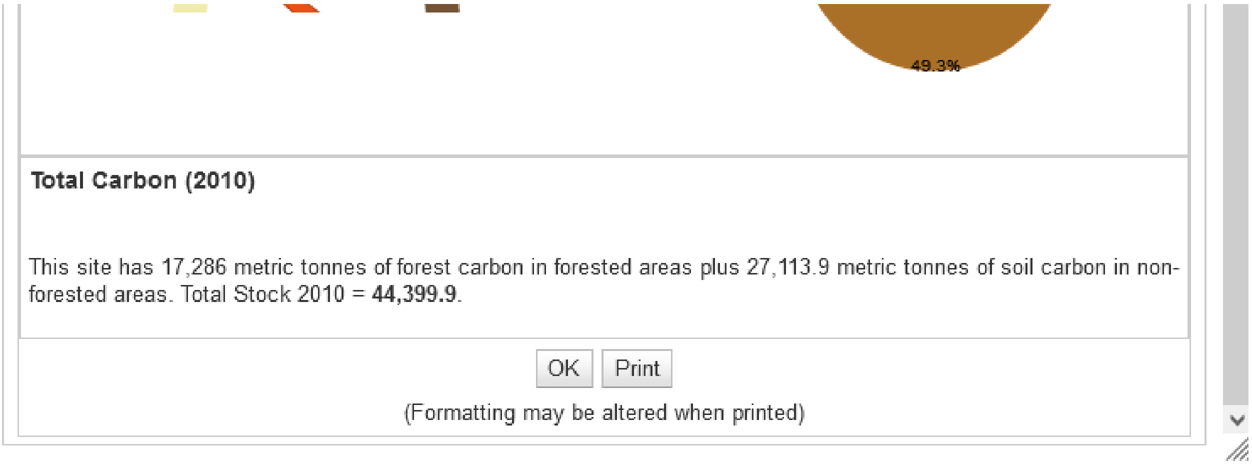
Total Soil Organic Carbon: **27,324** mt

Avg. Soil Organic Carbon: **14** mt/ac

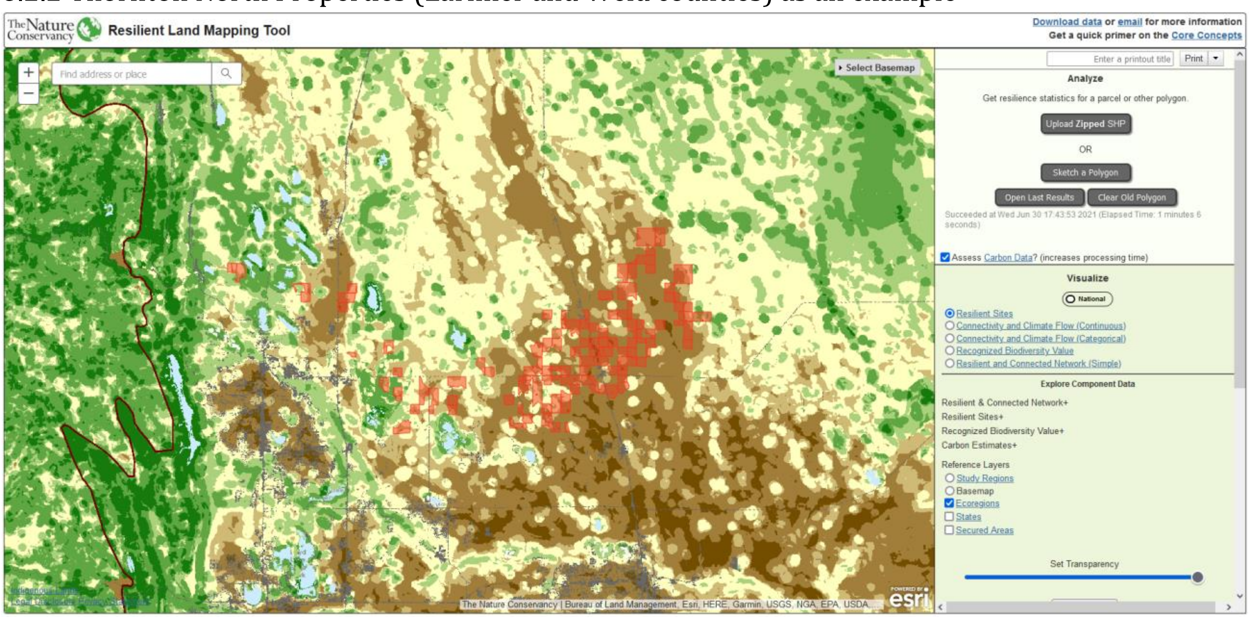


Landcover 2016





6.2.2 Thornton North Properties (Larimer and Weld counties) as an example



Resilient Land Summary

Resilience Results | Carbon Results

Total land area: 20,621.4 acres in the Great Plains study area(s) in the Central Shortgrass Prairie ecoregion(s).

The area of interest includes **0** acres of exisiting conservation land.
(GAP 1=0 ac, GAP 2=0 ac, GAP 3=0.7 ac)

Resilient and Connected Network Results

Note: These results are based on the **nationally-consistent** ecoregional data. They are derived from the detailed representations of the Resilient and Connected Networks which can be visualized under the Resilient & Connected Network Components section at right.

Resilience, Flow and Recognized Biodiversity: 0

Resilience and Flow: 1.6 ac.

Resilient, Diffuse Flow: 1.6 ac.

Resilience and Recognized Biodiversity: 0.2 ac.

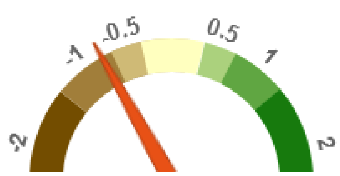
Resilient, Recognized Biodiversity: 0.2 ac.

Outside Prioritized Network: 20,619.6 ac.

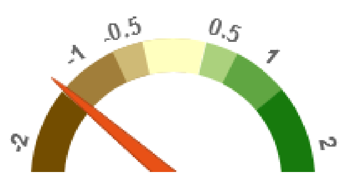
Average Terrestrial Resilience with Polygon

(all scores relative to ecoregion)

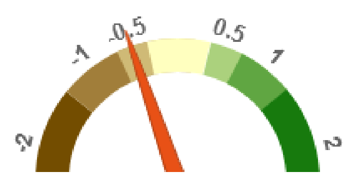
Resilience
Slightly Below Average (-0.9 SD)



Local Connectedness
Below Average (-1.3 SD)

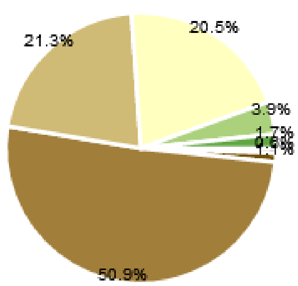


Landscape Diversity
Average (-0.5 SD)

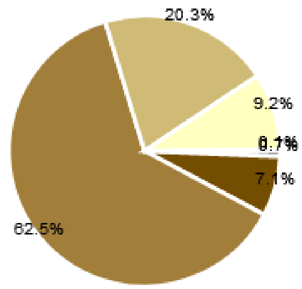


Terrestrial Resilience Categories

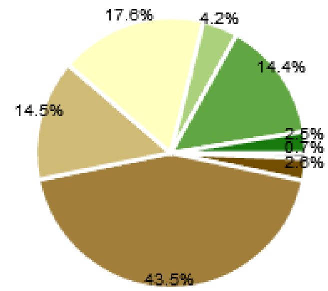
Resilience



Local Connectedness



Landscape Diversity



Geophysical Setting Results

The mean elevation in the polygon is 1521.74 m (4992.6 ft) and the three most common geophysical settings are:

Circumneutral Sedimentary : 11,796 acres

Sand : 8,250 acres

Calcareous Loam : 575 acres

OK Print

(Formatting may be altered when printed)

Resilient Land Summary

Resilience Results | **Carbon Results**

These national datasets can be used to get a **estimate** of a site's carbon stock. The datasets are at different scales, are derived from different methods, and overlap so the results cannot be simply added together. Taken separately, each dataset reveals information about potential carbon at the site.

Forest Carbon 2010 dataset (Williams et al. in press) applies only to forested pixels only and uses a sophisticated model to estimate Total Forest Carbon for 2010, which includes above-ground biomass, coarse woody debris, soil carbon and other pools. More detail

The **Forest Carbon 2050** (Williams et al. in press) applies only to forested pixels only and uses the same model as the Total Forest Carbon 2010 but runs the model to 2050, assuming no disturbance (conversion, harvest, fire). Actual sequestration may be lower if the forest is disturbed. **Annual sequestration rate** is estimated as: *(Carbon 2050 – Carbon 2010)/40 years.*

Soil Carbon 2010 (Guevara et al 2020) is at a coarser scale and only calculated for the upper 30 cm of soil. Soil carbon values were predicted using soil samples and multiple environmental variables coupled with a machine learning approach and regression tree ensemble modeling. In forested areas, this carbon overlaps with carbon in the forest belowground/other category of Forest Carbon 2010.

The **Land Cover 2016** uses the National Land Cover Dataset (NLCD) to show land cover and human use at 30-m resolution. It can be used to determine if, or where, the land cover has changed since 2010.

Total Carbon 2010 for a site is estimated as metric tons of **forest carbon in forested areas** plus metric tons of **soil carbon in non-forested areas**.

Forest Carbon

mt = metric tonnes

Forest Carbon 2010

Total Forest Ecosystem Carbon: **531** mt

Avg. Forest Ecosystem Carbon: **13** mt/ac

Forest Carbon 2010

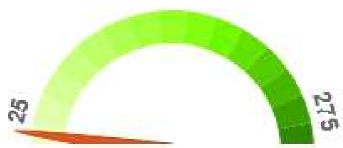
Forest Carbon Components

AG: Aboveground Wood, CW: Coarse Woody Debris, BG: Belowground/Other

Forest Carbon 2050

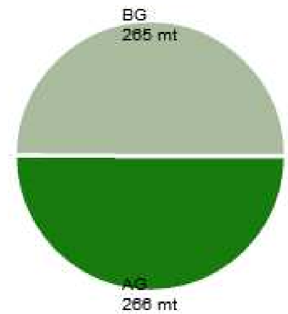
Total Forest Ecosystem Carbon: **531** mt

Avg. Forest Ecosystem Carbon: **13** mt/ac



Forest Carbon 2050

Forest Carbon Components

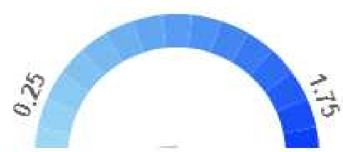


AG: Aboveground Wood, CW: Coarse Woody Debris, BG: Belowground/Other

Potential Forest Carbon Sequestration 2010-2050

40-yr Total for Site: **0** mt

Annual Rate per Acre: **0** mt/ac/yr



Annual Rate for Site: 0 mt/yr

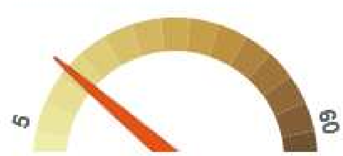
Soil Carbon & Land Cover

mt = metric tonnes

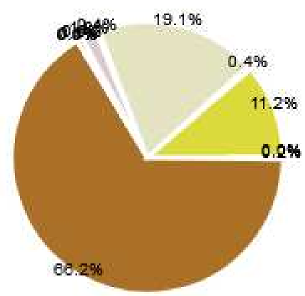
Soil Carbon 2010 (upper 30 cm)

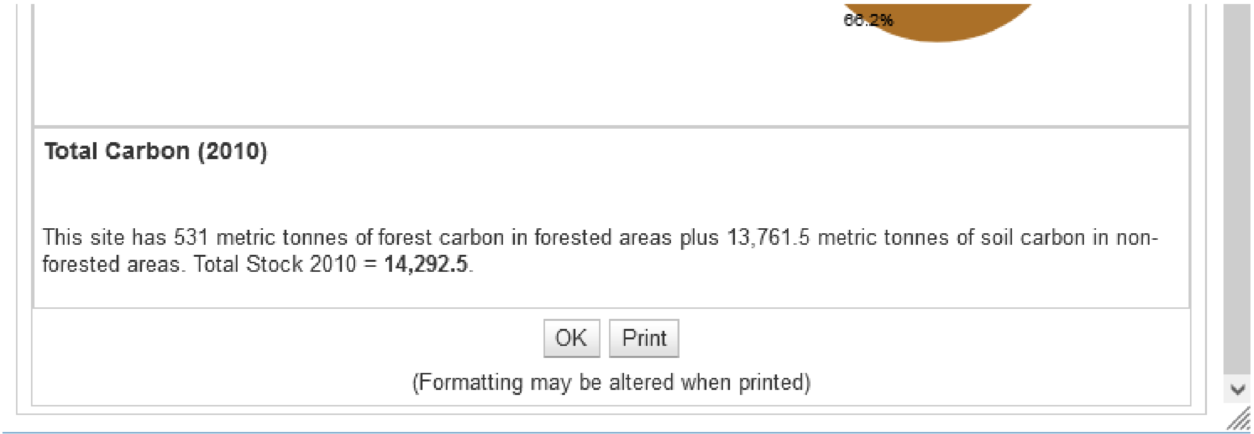
Total Soil Organic Carbon: **13,786.9** mt

Avg. Soil Organic Carbon: **15** mt/ac

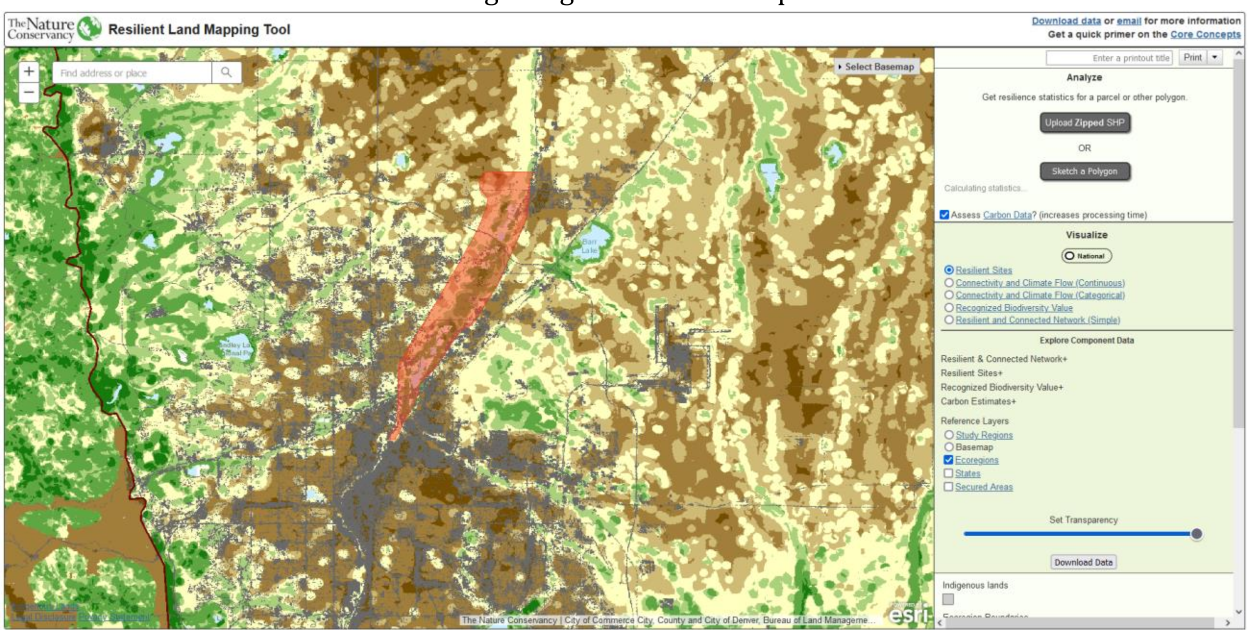


Landcover 2016





6.2.3 South Platte River Corridor through Brighton as an example



Resilient Land Summary

Resilience Results | Carbon Results

Total land area: 17,251.7 acres in the Great Plains study area(s) in the Central Shortgrass Prairie ecoregion(s).

The area of interest includes **1,605** acres of exisiting conservation land.
(GAP 1=0 ac, GAP 2=1,341.9 ac, GAP 3=263.1 ac)

Resilient and Connected Network Results

Note: These results are based on the **nationally-consistent** ecoregional data. They are derived from the detailed representations of the Resilient and Connected Networks which can be visualized under the Resilient & Connected Network Components section at right.

Resilience, Flow and Recognized Biodiversity: 0

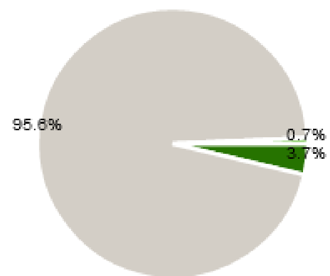
Resilience and Flow: 0 ac.

Resilience and Recognized Biodiversity: 697.7 ac.

Resilient, Recognized Biodiversity: 697.7 ac.

Outside Prioritized Network: 18,072.2 ac.

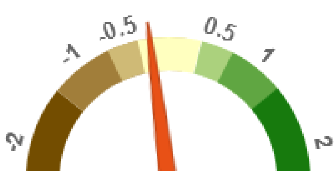
Additional Resilient Secured (GAP 3): 131.9 ac.



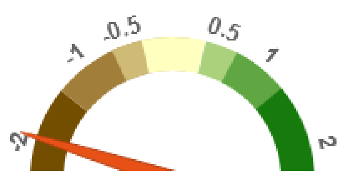
Average Terrestrial Resilience with Polygon

(all scores relative to ecoregion)

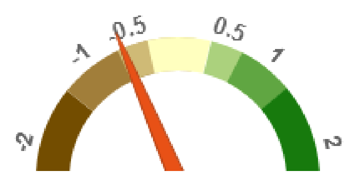
Resilience
Average (-0.2 SD)



Local Connectedness
Below Average (-1.9 SD)

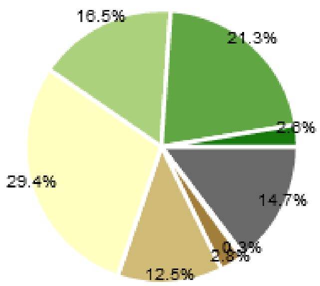


Landscape Diversity
Slightly Below Average (-0.6 SD)

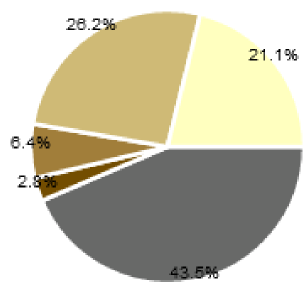


Terrestrial Resilience Categories

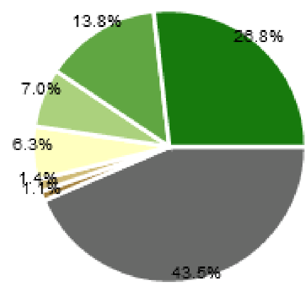
Resilience



Local Connectedness



Landscape Diversity



Geophysical Setting Results

The mean elevation in the polygon is 1540.79 m (5055.1 ft) and the three most common geophysical settings are:

Sand : 12,880 acres

Circumneutral Sedimentary : 4,362 acres

OK Print

(Formatting may be altered when printed)

Resilient Land Summary

Resilience Results | **Carbon Results**

These national datasets can be used to get a **estimate** of a site's carbon stock. The datasets are at different scales, are derived from different methods, and overlap so the results cannot be simply added together. Taken separately, each dataset reveals information about potential carbon at the site.

Forest Carbon 2010 dataset (Williams et al. in press) applies only to forested pixels only and uses a sophisticated model to estimate Total Forest Carbon for 2010, which includes above-ground biomass, coarse woody debris, soil carbon and other pools. More detail

The **Forest Carbon 2050** (Williams et al. in press) applies only to forested pixels only and uses the same model as the Total Forest Carbon 2010 but runs the model to 2050, assuming no disturbance (conversion, harvest, fire). Actual sequestration may be lower if the forest is disturbed. **Annual sequestration rate** is estimated as: *(Carbon 2050 – Carbon 2010)/40 years*.

Soil Carbon 2010 (Guevara et al 2020) is at a coarser scale and only calculated for the upper 30 cm of soil. Soil carbon values were predicted using soil samples and multiple environmental variables coupled with a machine learning approach and regression tree ensemble modeling. In forested areas, this carbon overlaps with carbon in the forest belowground/other category of Forest Carbon 2010.

The **Land Cover 2016** uses the National Land Cover Dataset (NLCD) to show land cover and human use at 30-m resolution. It can be used to determine if, or where, the land cover has changed since 2010.

Total Carbon 2010 for a site is estimated as metric tons of **forest carbon in forested areas** plus metric tons of **soil carbon in non-forested areas**.

Forest Carbon

mt = metric tonnes

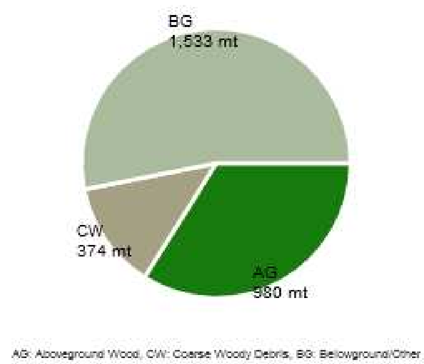
Forest Carbon 2010

Total Forest Ecosystem Carbon: **2,887** mt

Avg. Forest Ecosystem Carbon: **26** mt/ac

Forest Carbon 2010

Forest Carbon Components



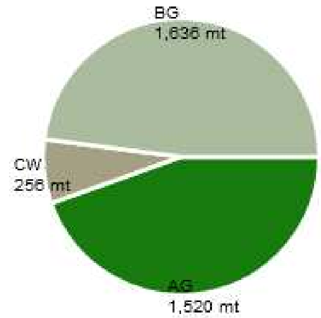
Forest Carbon 2050

Total Forest Ecosystem Carbon: **3,412** mt

Avg. Forest Ecosystem Carbon: **30.7** mt/ac

Forest Carbon 2050

Forest Carbon Components



AG: Aboveground Wood, CW: Coarse Woody Debris, BG: Belowground/Other

Potential Forest Carbon Sequestration 2010-2050

40-yr Total for Site: **525** mt

Annual Rate per Acre: **0** mt/ac/yr

Annual Rate for Site: 13.1 mt/yr

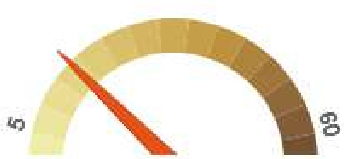
Soil Carbon & Land Cover

mt = metric tonnes

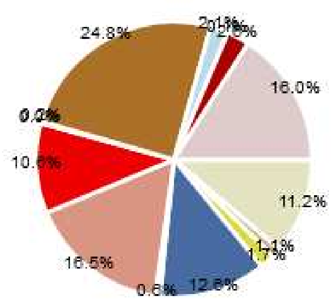
Soil Carbon 2010 (upper 30 cm)

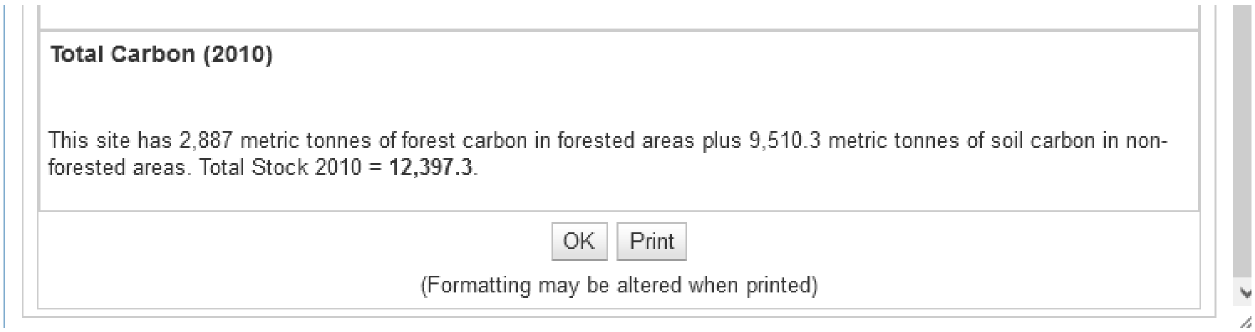
Total Soil Organic Carbon: **9,568.2** mt

Avg. Soil Organic Carbon: **16** mt/ac



Landcover 2016



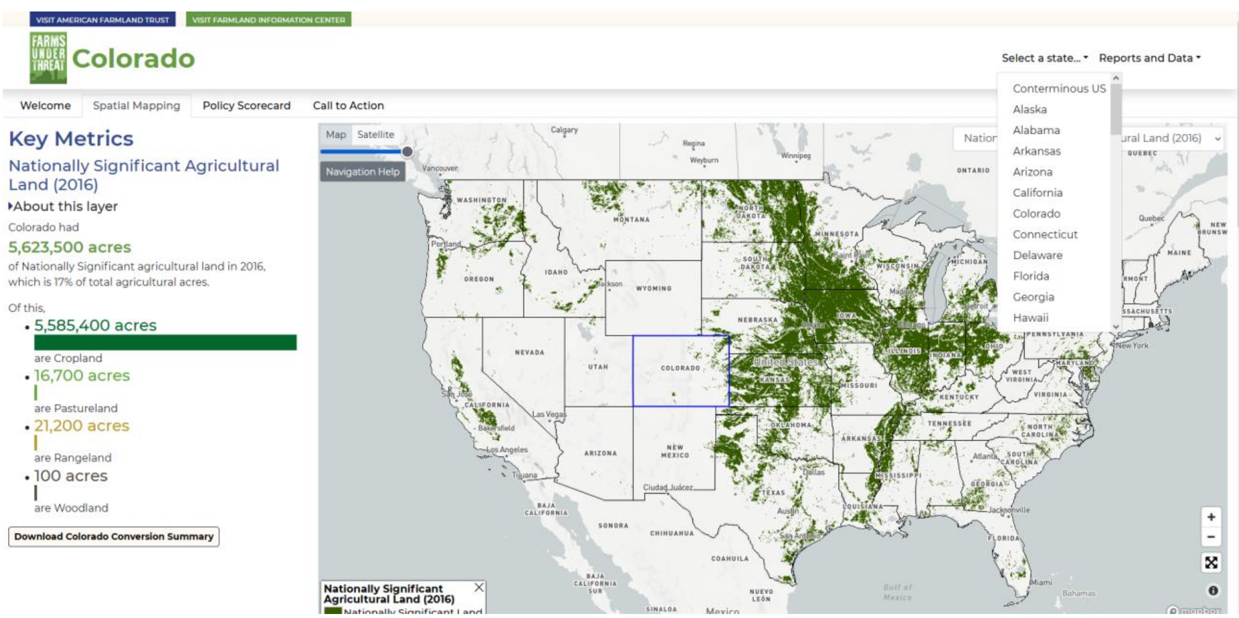


6.3 Farms Under Threat: The State of the States

"Farms Under Threat provides actionable information on the location and quality of agricultural land, the threats posed by development, and state-level policies that can help protect farmland and ranchland." For a state of interest, a general overview of nationally significant agricultural lands, relevant policies, and the alignment between the two are reported.

AFT's State of States tool only produces summary reports at the state level inhibiting its application to our areas of interest (i.e., SPR corridor through Brighton, Greeley, and Thornton's northern properties). Reports on land conversion and policy summary can be generated for a selected state. Data can be requested from the AFT if finer resolution analysis is desired.

A state can be selected via a dropdown list or by clicking on the state in the map.



Once a state is chosen the dashboard automatically updates all the statistics to reflect the statistics for that state. See the left side of the above image or the image below.

Development Threatens Colorado's Agricultural Land

From 2001-2016, 234,900 acres acres of Colorado's agricultural land was developed or compromised.

Colorado's farmland and ranchland was converted to:

- **Urban and highly developed (UHD)** land use, including commercial, industrial, and moderate-to-high-density residential areas.
- **Low-density residential (LDR)** land use, where scattered large lot development fragments the agricultural land base and limits production, marketing, and management options for the working farms and ranches that remain.

124,300 acres	110,600 acres
53%	**47%**
of conversion was to UHD	of conversion was to LDR

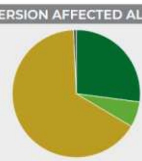
LDR PAVES THE WAY FOR FURTHER DEVELOPMENT

Agricultural land in LDR areas in 2001 was

60 TIMES MORE LIKELY

to be converted to UHD by 2016, compared to other agricultural land.

CONVERSION AFFECTED ALL TYPES OF AGRICULTURAL LAND



CROPLAND:	**63,600 acres**
PASTURELAND:	**15,200 acres**
RANGELAND:	**154,300 acres**
WOODLAND:	**1,700 acres**

Colorado's Best Agricultural Land is Under Threat

We used our unique **PVR index**, which quantifies the productivity, versatility, and resiliency of agricultural land, to identify:

1. **Colorado's best land**, which has PVR values above the state median, and
2. **Nationally Significant land**, which is the country's best land for long-term production of food and other crops. **17%** of Colorado's agricultural land, or **5,623,500 acres acres**, falls in this category.*

Protecting high-PVR land is critical for the long-term sustainability of agriculture, yet from 2001-2016:

- **112,400 acres**
  of Colorado's best land were converted to UHD and LDR uses.
- **16,300 acres**
  of Colorado's Nationally Significant land were converted.

*These two categories overlap and the same land may be included in both.

Disclaimer

American Farmland Trust makes no warranties as to the suitability of the data and information found here for any particular purpose or user. Data and information may not be used for any commercial purpose. The spatial data may be used as an informative inventory of agricultural land use, land quality, and specific types of conversion. The policy data may be used as an informative inventory of state policies and programs in their roles in retaining agricultural land, regardless of whether this is their stated purpose, and recognizing the difficulty of evaluating policies across 50 states. Please refer to the report and technical documentation for an explanation of the methods used to develop the data and the limitations of the data. For more information or suggestions regarding the data on this site, please contact AFT's Farmland Information Center: **www.farmlandinfo.org** or (800) 370-4879.

A policy scorecard for the state is also available:

Welcome | Spatial Mapping | Policy Scorecard | Call to Action

Agricultural Land Protection Scorecard

Navigation Help

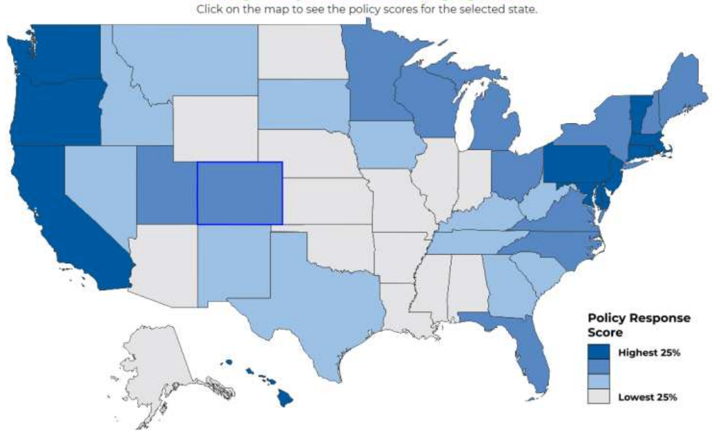
The Agricultural Land Protection (ALP) Scorecard is a state-by-state analysis of policies and programs that address the loss of farmland to development. Intended to inform decision-making and legislative action, it assesses state actions, measures their performance, and highlights effective aspects of the following programs and policies:

1. Purchase of agricultural conservation easement programs (PACE)
2. Land-use planning and growth management
3. Property tax relief for agricultural land
4. Agricultural district programs
5. Farm Link programs
6. State leasing programs

We used quantitative and qualitative factors to compare approaches across 50 states. The results for each policy are summarized in the *policy scoresheets*. We rolled up the totals from each scoresheet to generate Policy Response Scores, which are presented in the *ALP Scorecard* and serve as an indicator of each state's overall policy response. The map shows state Policy Response Scores by quartile.

Policy Response Scores by Quartile

Click on the map to see the policy scores for the selected state.



Welcome | Spatial Mapping | Policy Scorecard | Call to Action

Colorado Policy Scores

Download Colorado Policy Summary

This bar chart shows the policy scores for Colorado compared to the the median and the highest scores achieved by all states that have implemented each policy. Even among high-response states, no state received a perfect score for any individual policy; every state has the potential to do more. Click on the name of a policy to learn more about it and see the detailed scoresheet.

About the Policies and Programs

Select a policy from the drop down menu to learn more about the approach and the factors we used to evaluate it. Select policy or program ▾

The Agricultural Land Protection Scorecard reports the scores earned by states for six policies and programs intended to protect and retain agricultural land. It also indicates the relative importance of each approach and combines the values into a single Policy Response Score, which demonstrates states' relative efforts to address the threat of development.

A scoresheet is produced for a selected policy or program type where the states performance can be compared to other states.

Select a policy from the drop down menu to learn more about the approach and the factors we used to evaluate it. Select policy or program ▾

Purchase of agricultural conservation easement (PACE) programs permanently protect farmland and ranchland from non-farm development. They compensate landowners who voluntarily place an agricultural conservation easement on their property.

Scoresheet for Purchase of Agricultural Conservation Easement (PACE) Programs

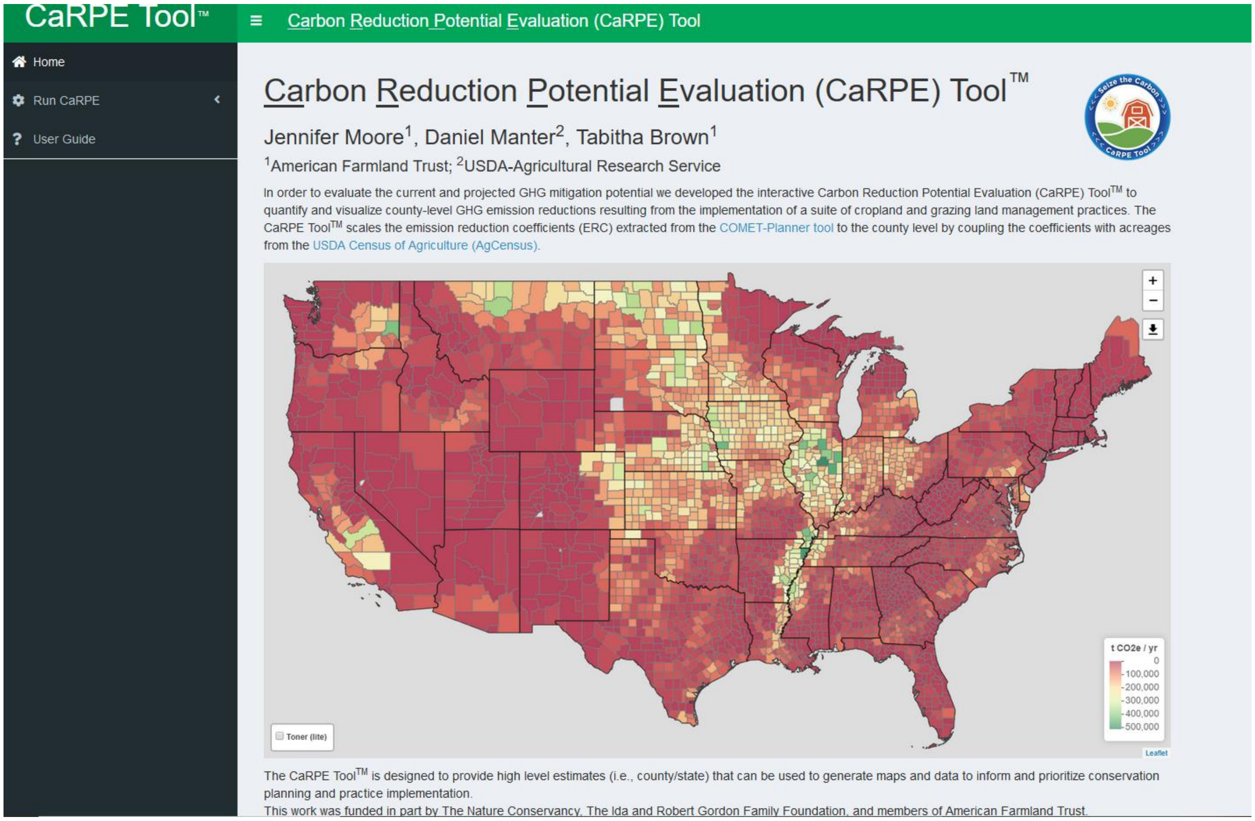
This table can be sorted by clicking on the column heading. The weights used to combine the scores are shown in the column headings.

State	Authority	Average Percentage of Ag Land Protected	Average Number of Easements Acquired	Average Funds Spent Per Capita	Provisions Promoting Agricultural Use and Ownership	Frequency of On-site Monitoring	Acres Protected to Acres Converted	Total Raw Score (MAX 350)	Total Weighted Score (MAX 50)	Final Score (MAX 100)
	15%	20%	20%	20%	5%	10%	10%			
Delaware	40	49	22	50	25	50	31	267	40	79
New Jersey	50	50	33	39	0	50	24	246	39	79
Vermont	50	36	19	41	25	50	50	271	38	76
Maryland	50	38	32	37	0	9	32	198	33	66
Pennsylvania	40	27	50	33	0	25	22	197	33	65
Massachusetts	30	32	18	19	50	20	24	193	25	50
Colorado	30	17	17	28	0	50	28	170	25	49
Connecticut	40	29	12	19	0	25	25	150	23	46
Rhode Island	50	32	7	20	0	17	22	148	23	46
New Hampshire	40	18	7	13	0	50	16	144	20	40
Ohio	30	9	18	10	25	50	7	149	19	38
Maine	50	9	5	12	0	50	10	136	19	37
California	40	6	11	7	0	50	5	119	16	33
New York	40	11	14	13	25	0	9	112	16	32

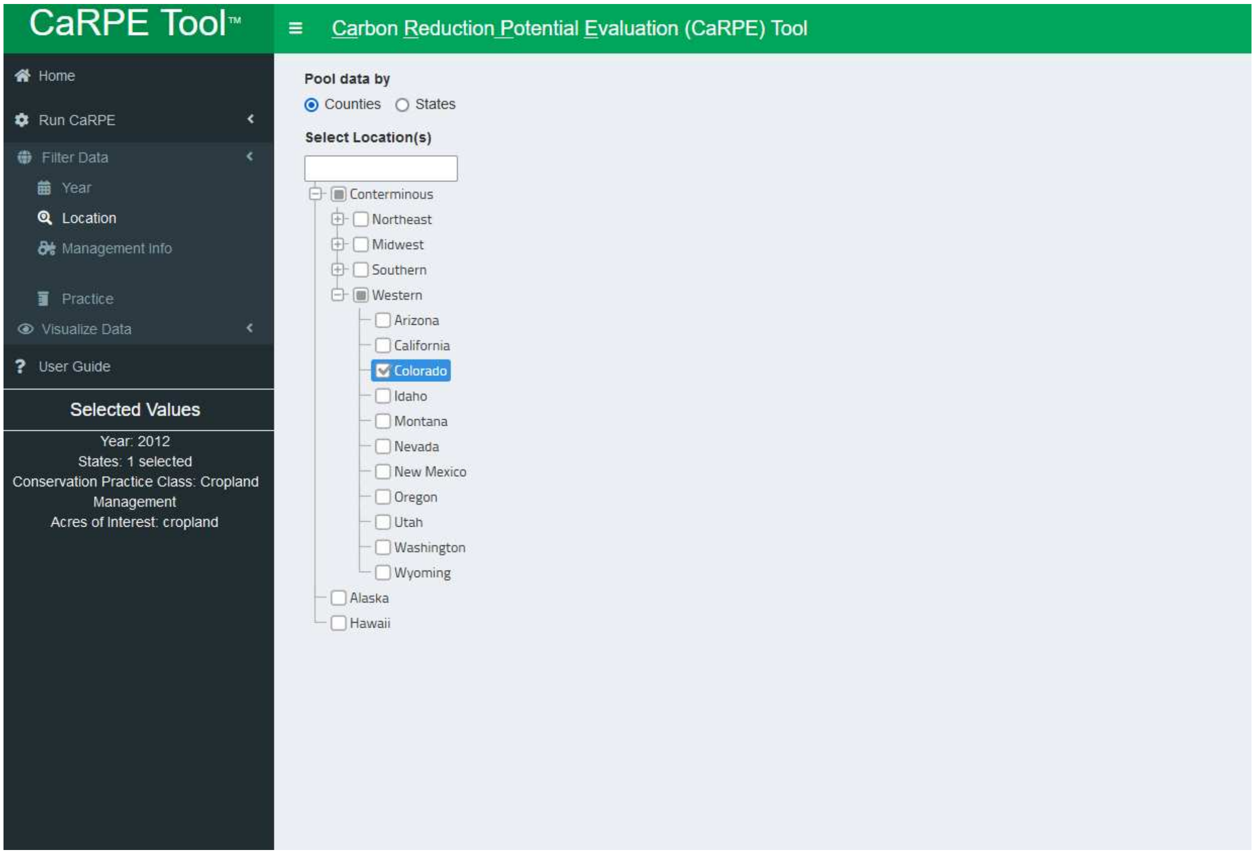
6.4 Carbon Reduction Potential Evaluation (CaRPE) Tool™

The CaRPE Tool was created to help quantify and visualize county-level GHG emissions reductions resulting from the implementation of a suite of cropland and grazing land management practices. Results produced by the CaRPE Tool are based on methodology used to develop the COMET-Planner tool, and the COMET-Planner tool seems to be more appropriate for scenario analysis.

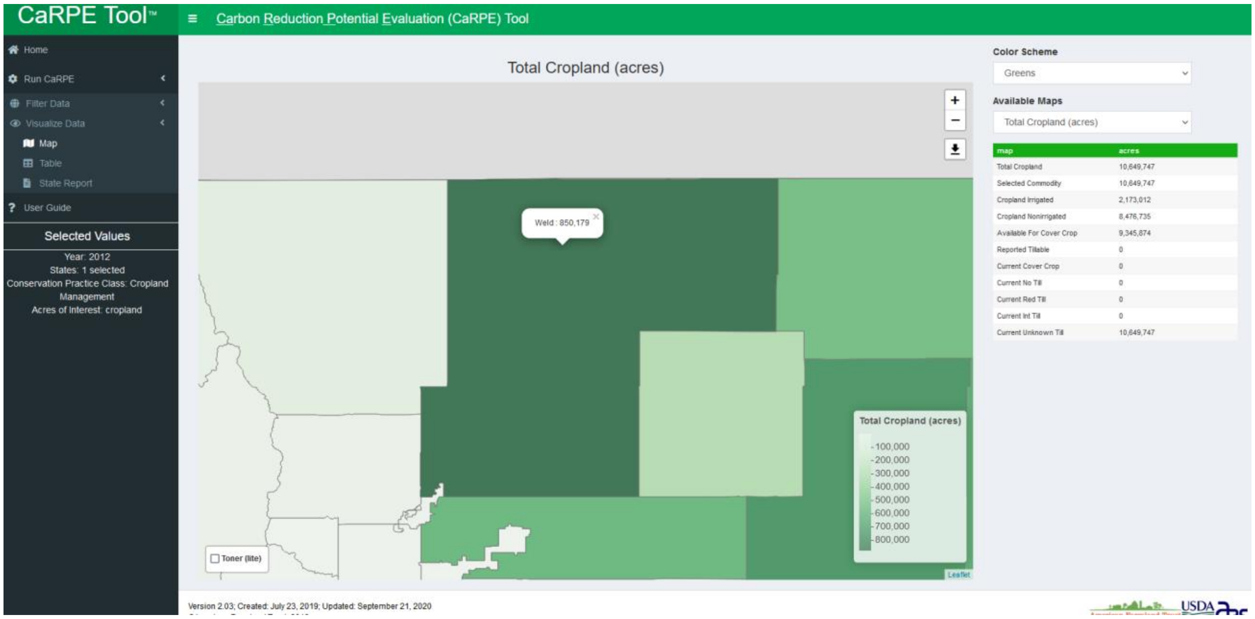
The CaRPE Tool executes at the county, state, or regional scale meaning that analysis of our selected areas of interest (i.e., South Platte River Corridor in Brighton, Greeley, and Thornton's north properties) is not possible.

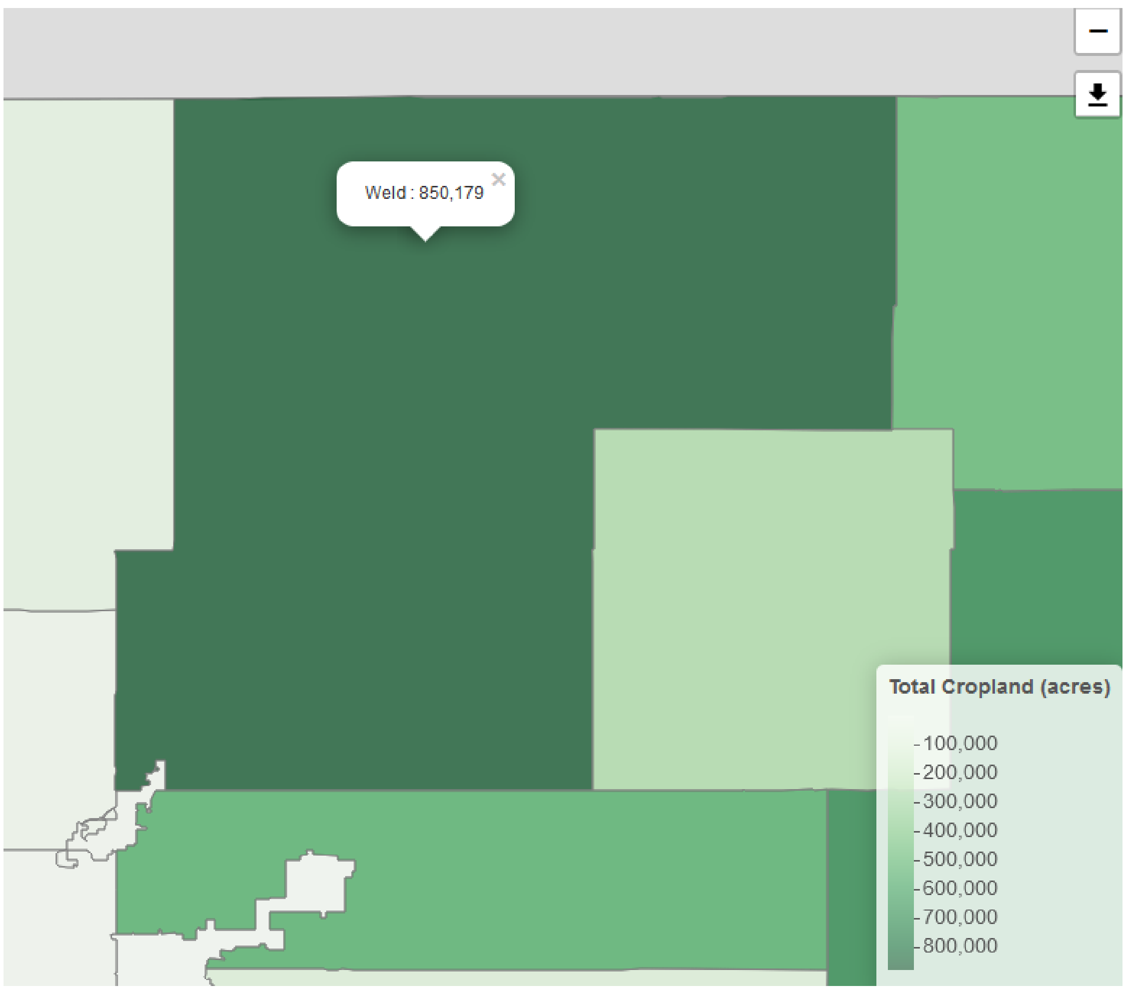

CaRPE Tool™
Carbon Reduction Potential Evaluation (CaRPE) Tool
Home
Run CaRPE
User Guide
Carbon Reduction Potential Evaluation (CaRPE) Tool™
Seize the Carbon CaRPE Tool
Jennifer Moore1, Daniel Manter2, Tabitha Brown1
1American Farmland Trust; 2USDA-Agricultural Research Service
In order to evaluate the current and projected GHG mitigation potential we developed the interactive Carbon Reduction Potential Evaluation (CaRPE) Tool™ to quantify and visualize county-level GHG emission reductions resulting from the implementation of a suite of cropland and grazing land management practices. The CaRPE Tool™ scales the emission reduction coefficients (ERC) extracted from the COMET-Planner tool to the county level by coupling the coefficients with acreages from the USDA Census of Agriculture (AgCensus).
t CO2e / yr
0
100,000
200,000
300,000
400,000
500,000
Toner (lite)
Leaflet
The CaRPE Tool™ is designed to provide high level estimates (i.e., county/state) that can be used to generate maps and data to inform and prioritize conservation planning and practice implementation.
This work was funded in part by The Nature Conservancy, The Ida and Robert Gordon Family Foundation, and members of American Farmland Trust.

Area of analysis may include county, state, region (i.e., multiple states), or national scales.

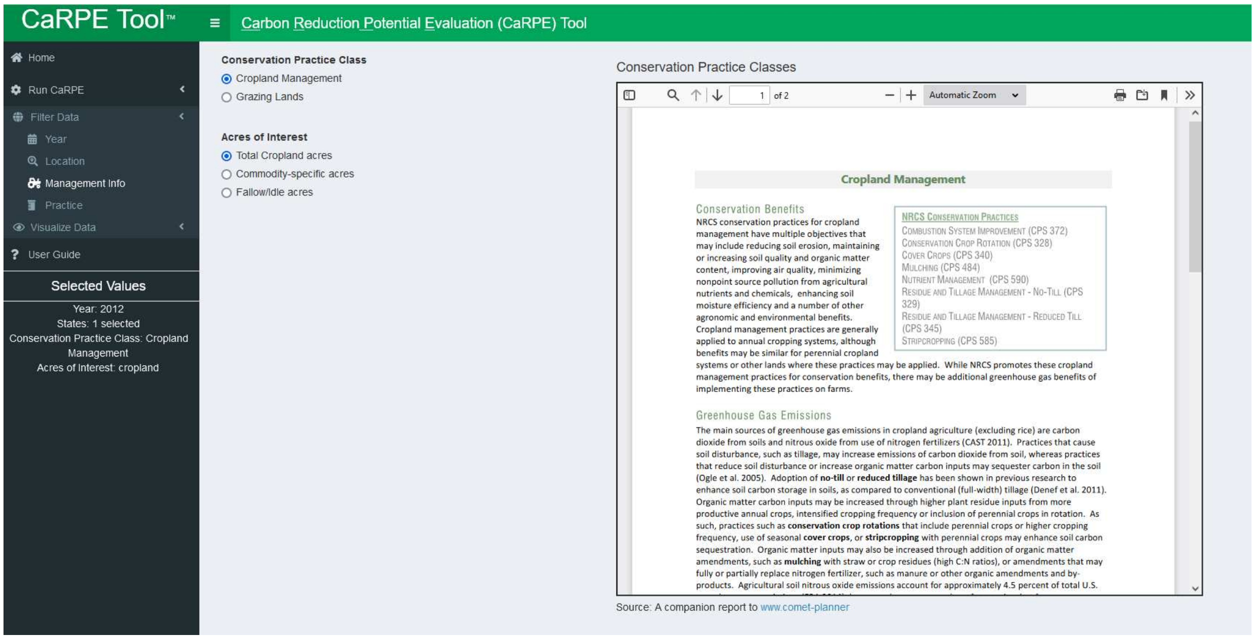


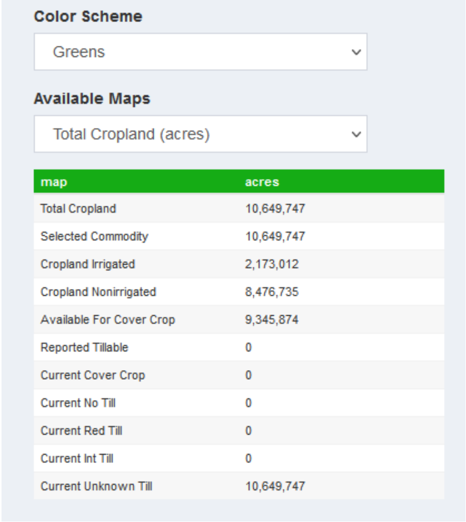
For the selected area, different metrics are presented. These include total cropland, irrigated cropland, non-irrigated cropland, and area in which the selected conservation practice of interest is being implemented.


CaRPE Tool™
Carbon Reduction Potential Evaluation (CaRPE) Tool
Home
Run CaRPE
Filter Data
Visualize Data
Map
Table
State Report
User Guide
Selected Values
Year: 2012
States: 1 selected
Conservation Practice Class: Cropland Management
Acres of Interest: cropland
Total Cropland (acres)
Weld : 850,179
Toner (lite)
Total Cropland (acres)
100,000
200,000
300,000
400,000
500,000
600,000
700,000
800,000
Leaflet
Color Scheme
Greens
Available Maps
Total Cropland (acres)
map
acres
Total Cropland
10,649,747
Selected Commodity
10,649,747
Cropland Irrigated
2,173,012
Cropland Nonirrigated
8,476,735
Available For Cover Crop
9,345,874
Reported Tillable
0
Current Cover Crop
0
Current No Till
0
Current Red Till
0
Current Int Till
0
Current Unknown Till
10,649,747
Version 2.03; Created: July 23, 2019; Updated: September 21, 2020
USDA


Weld : 850,179
Total Cropland (acres)
100,000
200,000
300,000
400,000
500,000
600,000
700,000
800,000

The GHG emissions/carbon sequestration effects of various conservation practices can be investigated.





Color Scheme

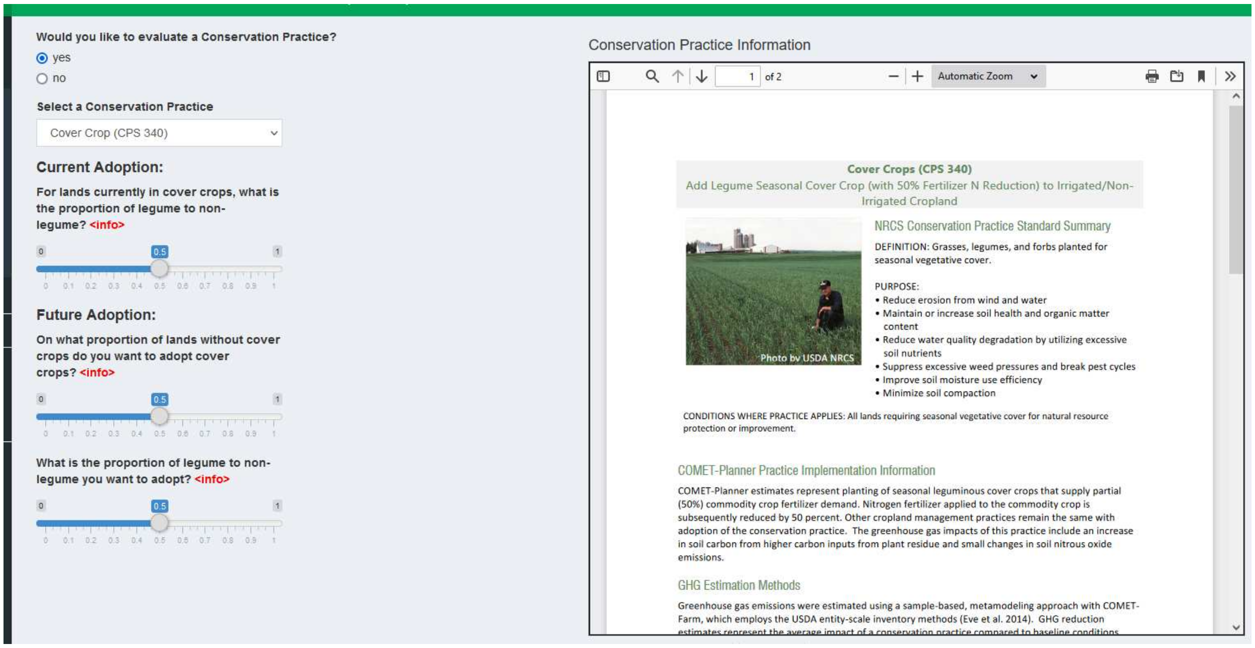
Greens

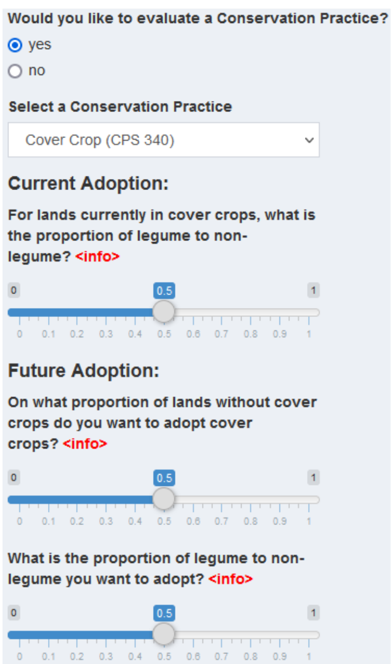
Available Maps

Total Cropland (acres)

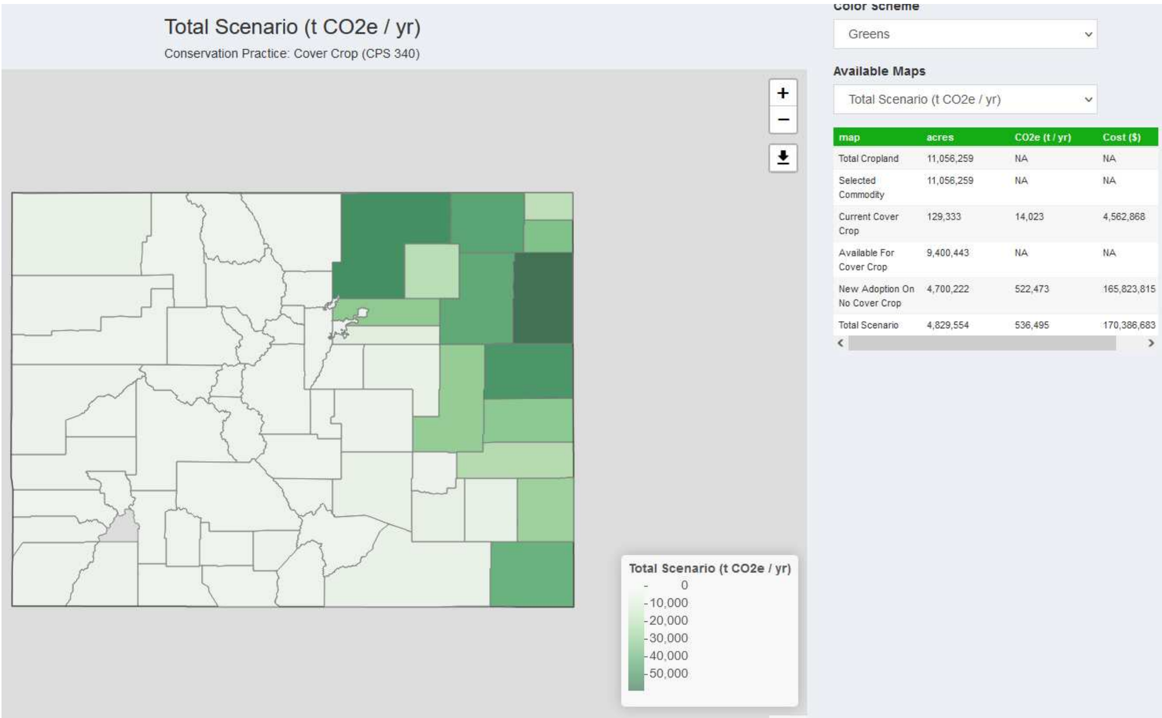
map	acres
Total Cropland	10,649,747
Selected Commodity	10,649,747
Cropland Irrigated	2,173,012
Cropland Nonirrigated	8,476,735
Available For Cover Crop	9,345,874
Reported Tillable	0
Current Cover Crop	0
Current No Till	0
Current Red Till	0
Current Int Till	0
Current Unknown Till	10,649,747

The percentage of the area of interest incorporating the selected conservation practices can be selected.

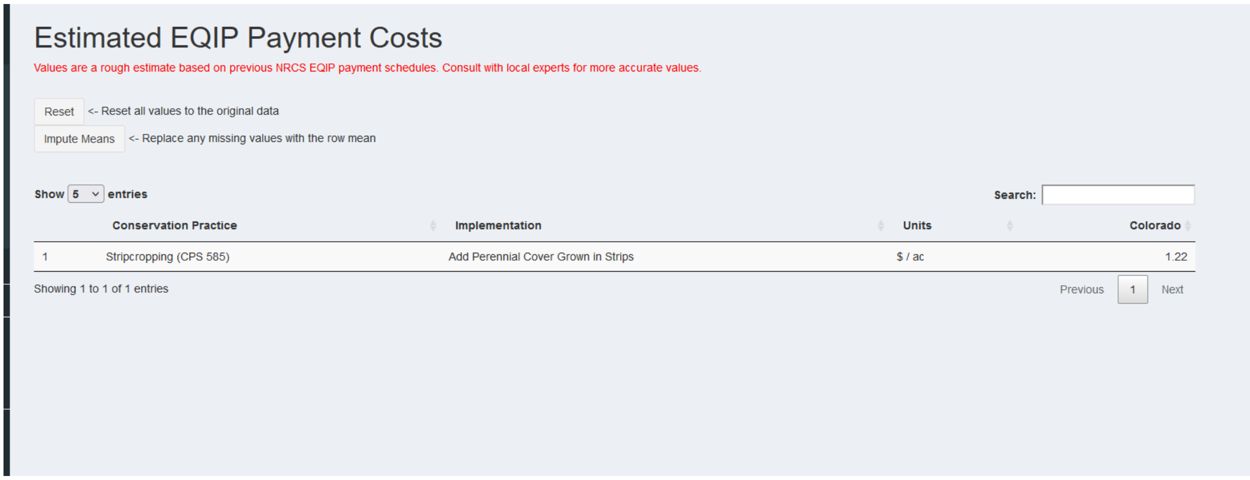

Would you like to evaluate a Conservation Practice?
yes
no
Select a Conservation Practice
Cover Crop (CPS 340)
Current Adoption:
For lands currently in cover crops, what is the proportion of legume to non-legume? <info>
Future Adoption:
On what proportion of lands without cover crops do you want to adopt cover crops? <info>
What is the proportion of legume to non-legume you want to adopt? <info>
Conservation Practice Information
1 of 2
Automatic Zoom
Cover Crops (CPS 340)
Add Legume Seasonal Cover Crop (with 50% Fertilizer N Reduction) to Irrigated/Non-Irrigated Cropland
NRCS Conservation Practice Standard Summary
DEFINITION: Grasses, legumes, and forbs planted for seasonal vegetative cover.
PURPOSE:
• Reduce erosion from wind and water
• Maintain or increase soil health and organic matter content
• Reduce water quality degradation by utilizing excessive soil nutrients
• Suppress excessive weed pressures and break pest cycles
• Improve soil moisture use efficiency
• Minimize soil compaction
Photo by USDA NRCS
CONDITIONS WHERE PRACTICE APPLIES: All lands requiring seasonal vegetative cover for natural resource protection or improvement.
COMET-Planner Practice Implementation Information
COMET-Planner estimates represent planting of seasonal leguminous cover crops that supply partial (50%) commodity crop fertilizer demand. Nitrogen fertilizer applied to the commodity crop is subsequently reduced by 50 percent. Other cropland management practices remain the same with adoption of the conservation practice. The greenhouse gas impacts of this practice include an increase in soil carbon from higher carbon inputs from plant residue and small changes in soil nitrous oxide emissions.
GHG Estimation Methods
Greenhouse gas emissions were estimated using a sample-based, metamodeling approach with COMET-Farm, which employs the USDA entity-scale inventory methods (Eve et al. 2014). GHG reduction


Would you like to evaluate a Conservation Practice?
yes
no
Select a Conservation Practice
Cover Crop (CPS 340)
Current Adoption:
For lands currently in cover crops, what is the proportion of legume to non-legume? <info>
0
0.5
1
Future Adoption:
On what proportion of lands without cover crops do you want to adopt cover crops? <info>
0
0.5
1
What is the proportion of legume to non-legume you want to adopt? <info>
0
0.5
1

For the specified scenario, output includes acres of the practice, total CO_2 equivalents sequestered or mitigated, and the estimated payout based on the EQIP payment schedule.



Estimates of payments per acre as provided by the Environmental Quality Incentives Program (EQIP) for different conservation practices are provided. The EQIP Conservation Incentives Contract (EQIP-CIC) is a new enrollment option created by section 2304 of the 2018 Farm Bill and will be implemented in fiscal year 2021. Payment schedules for EQIP are available here.



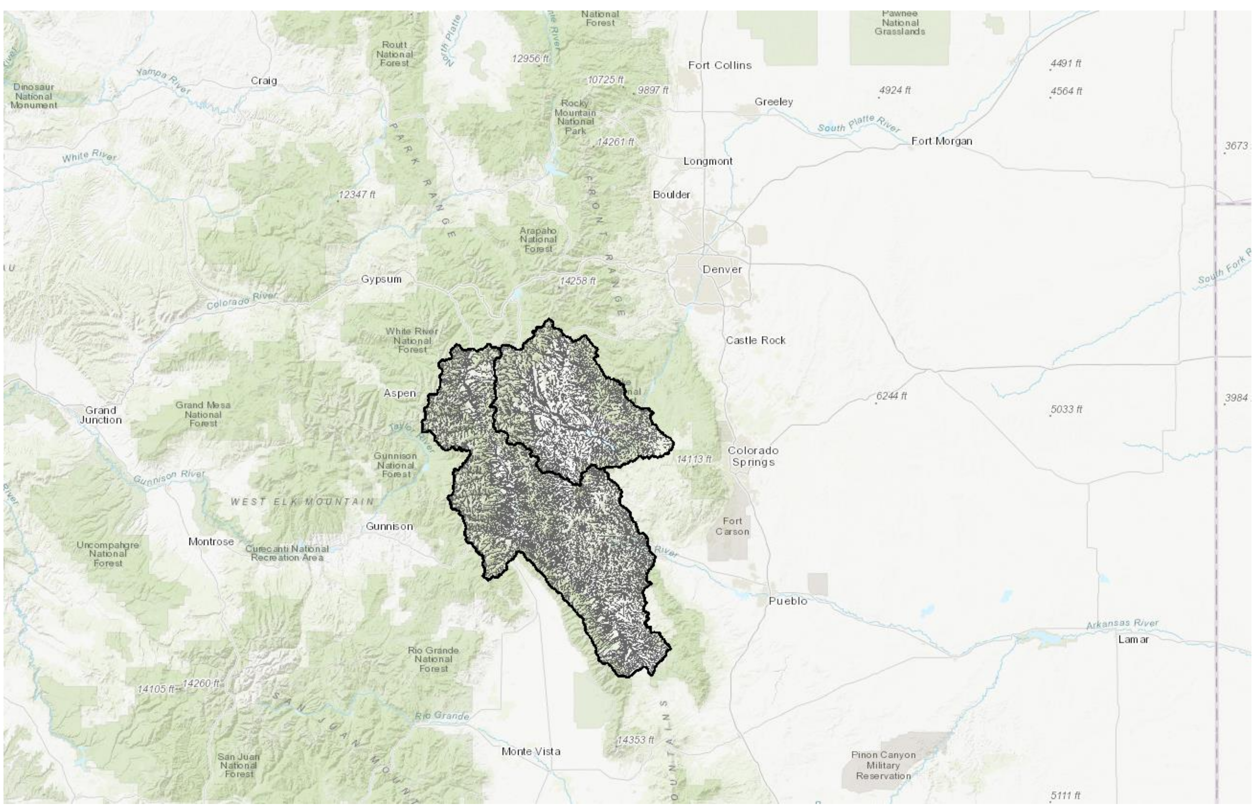
6.5 Colorado Wetland Inventory

The Colorado Wetland Inventory is, "intended to assist in identifying wetland and riparian areas and provides only potential and approximate locations of the features mapped… The Colorado Wetlands Inventory Mapping Tool displays several datasets depicting the location and classification of wetlands and riparian areas in Colorado."

This is less of an analysis tool, and more of a data visualization tool. It does not allow for any analysis to be executed within an area of interest, but rather shows wetland data for the state of Colorado. Therefore, this tool was not applied to the three areas of interest to this project.

6.6 Colorado Watershed Planning Toolbox

The Colorado Watershed Planning tool is, "a comprehensive resource for incorporating wetlands and streams into watershed planning, restoring wetlands to improve watershed health, and identifying opportunities for wetland conservation." Most of the core data included in this tool and the only data that is included in the analysis tool only covers a relatively small area southwest of Denver and West of Fort Carson and Colorado Springs (Figure below). There is other statewide data available via the tool's website, but the analysis tool does not utilize it.



6.7 Colorado Ownership, Management, and Protection Database (CoMaP)

The primary function of the CoMaP tool seems to provide maps of protected lands, including both public and private lands, as well as the entity that owns and/or manages that land. There is other data available for download by request via the CoMaP website, but the CoMaP tool does not use that data.

There does not seem to be a functioning ability to analyze an area of interest, but by downloading the available data, analyses can be performed independently. It seems that once CODEX is operational it will make CoMaP obsolete.

6.8 Colorado Conservation Data Explorer (CODEX)

The Colorado Conservation Data Explorer (CODEX) tool was not available for use during my apprenticeship. It seems as though it will be the best option, out of the tools listed here, with respect to performing analysis of various ecosystem services and land use related scenarios. It, “includes a set of tools to support conservation planning, environmental review, evaluation of conservation portfolios, education, and more.”

APPENDIX – Chapter 4

CHAPTER 4 – SUPPLEMENTARY MATERIAL

Table S4.1: All variables considered in the modeling process. Alias is what the variable is called in this text, features is what the variable is called in the data source and/or in the analysis code, variable classes were categorized in this analysis, and variable description, units, and source are also given.

Alias	Features	Variable Class	Variable Description	Units	Data Source
Day Length	dayl	Climate	Day length	s/day	DAYMET
Precip	prcp	Climate	Precipitation	mm/day	DAYMET
Solar Radiation	srad	Climate	Shortwave radiation	W/m2	DAYMET
Snow Water Eq	swe	Climate	Snow water equivalent	kg/m2	DAYMET
Max Temp	tmax	Climate	Maximum air temperature	degrees C	DAYMET
Min Temp	tmin	Climate	Minimum air temperature	degrees C	DAYMET
Vapor Pressure	vp	Climate	Water vapor pressure	Pa	DAYMET
Precip-LB12	d12_prcp	Climate	total precipitation over previous 12 months	mm	DAYMET
Precip-LB1	d1_prcp	Climate	total precipitation over previous month or year	mm	DAYMET
Max Temp-LB12	d12_tmax	Climate	mean daily maximum air temperature over past 12 months	degrees C	DAYMET

Max Temp-LB1	d1_tmax	Climate	mean daily maximum air temperature over past month or year	degrees C	DAYMET
Min Temp-LB12	d12_tmin	Climate	mean minimum daily air temperature over previous 12 months	degrees C	DAYMET
Min Temp-LB1	d1_tmin	Climate	mean minimum daily air temperature over previous month or year	degrees C	DAYMET
Drainage Area	DRAIN_SQKM	Physiography	drainage area	sqkm	GAGESII
Basin Compactness	BAS_COMPACTNESS	Physiography	basin compactness area/perimeter^2 * 100	-	GAGESII
Avg Precip	PPTAVG_BASIN	Climate	Average annual precipitation	cm	GAGESII
Avg Temp	T_AVG_BASIN	Climate	Average annual temperature	degrees C	GAGESII
Avg Max Monthly Temp	T_MAX_BASIN	Climate	Average maximum monthly air temperature	degrees C	GAGESII
SD Max Monthly Temp	T_MAXSTD_BASIN	Climate	Standard devaiation of maximum monthly air temperature	degrees C	GAGESII
Avg Min Monthly Temp	T_MIN_BASIN	Climate	Average minimum monthly air temperature	degrees C	GAGESII

SD Min Monthly Temp	T_MINSTD_BASIN	Climate	Standard deviation of minimum monthly air temperature	degrees C	GAGESII
Avg RH	RH_BASIN	Climate	Watershed average relative humidity	%	GAGESII
Avg DOY First Freeze	FST32F_BASIN	Climate	Average day of year of first freeze	day of year	GAGESII
Avg DOY Last Freeze	LST32F_BASIN	Climate	Average day of year of last freeze	day of year	GAGESII
Avg Annual Wet Days	WD_BASIN	Climate	Average annual number of days of measurable precipitation	days	GAGESII
Mo Max Wet Days	WDMAX_BASIN	Climate	Average of monthly maximum number of days with measurable precipitation	days	GAGESII
Mo Min Wet Days	WDMIN_BASIN	Climate	Average of monthly minimum number of days with measurable precipitation	days	GAGESII
Potential ET	PET	Climate	Mean annual potential evapotranspiration	mm/yr	GAGESII
Snow %	SNOW_PCT_PRECIP	Climate	snow percent of total annual precipitation	%	GAGESII
Precip Seasonality	PRECIP_SEAS_IND	Climate	precipitation seasonality index	-	GAGESII

Gneiss	GEOL_REEDBUSH_DOM_gneiss	Physiography	If relevant geology type was dominant (1 or 0)	-	GAGESII
Grantic	GEOL_REEDBUSH_DOM_granitic	Physiography	If relevant geology type was dominant (1 or 0)	-	GAGESII
Quarternary	GEOL_REEDBUSH_DOM_quarternary	Physiography	If relevant geology type was dominant (1 or 0)	-	GAGESII
Sedimentary	GEOL_REEDBUSH_DOM_sedimentary	Physiography	If relevant geology type was dominant (1 or 0)	-	GAGESII
Ultramafic	GEOL_REEDBUSH_DOM_ultramafic	Physiography	If relevant geology type was dominant (1 or 0)	-	GAGESII
Volcanic	GEOL_REEDBUSH_DOM_volcanic	Physiography	If relevant geology type was dominant (1 or 0)	-	GAGESII
Stream Density	STREAMS_KM_SQ_KM	Physiography	stream density	km of streams per watershed area	GAGESII
Max Strahler Order	STRAHLER_MAX	Physiography	maximum Strahler stream order in watershed	-	GAGESII
Topo Wetness Index	TOPWET	Physiography	topographic wetness index	ln(m)	GAGESII
% Lengths as Canal	PCT_NO_ORDER	Physiography	Percent of stream lengths without a streamorder in NHDPlus (typically canals, pipelines, ditches)	%	GAGESII
Number Dams	NDAMS_2009	Anthro_Hydro	number of dams in watershed	-	GAGESII

Dam Density	DDENS_2009	Anthro_Hydro	dam density	#/sqmi	GAGESII
Dam Storage	STOR_NID_2009	Anthro_Hydro	dam storage	mealiter/sqkm	GAGESII
Canals % Length	CANALS_PCT	Anthro_Hydro	Percent stream km as "Canal", "Ditch", or "Pipeline"	%	GAGESII
Mines %	MINING92_PCT	Anthro_Hydro	Percent 1992 quarries-strip mines-gravel pits land cover in watershed		GAGESII
Power Generated	POWER_SUM_MW	Anthro_Hydro	Sum of MW operating capability of electric generation power plants in watershed of type "coal", "gas", "nuclear", "petro", or "water"	MW	GAGESII
Basin Fragmentation	FRAGUN_BASIN	Anthro_Land	Fragmentation index of "undeveloped" land	-	GAGESII
Lentic Density	HIRES_LENTIC_DENS	Physiography	Density of lakes/onds + Reservoir water bodies	#/sqkm	GAGESII
Soil Group A	HGA	Physiography	Percentage of soils in hydrologic group A	%	GAGESII
Soil Group B	HGB	Physiography	Percentage of soils in hydrologic group B	%	GAGESII

Soil Group A/D	HGAD	Physiography	Percentage of soils in hydrologic group A/D	%	GAGESII
Soil Group C	HGC	Physiography	Percentage of soils in hydrologic group C	%	GAGESII
Soil Group D	HGD	Physiography	Percentage of soils in hydrologic group D	%	GAGESII
Soil Group A/C	HGAC	Physiography	Percentage of soils in hydrologic group A/C	%	GAGESII
Soil Group B/D	HGBD	Physiography	Percentage of soils in hydrologic group B/D	%	GAGESII
Soil Group C/D	HGCD	Physiography	Percentage of soils in hydrologic group C/D	%	GAGESII
Soil Group B/C	HGBC	Physiography	Percentage of soils in hydrologic group B/C	%	GAGESII
Soil Group VAR	HGVAR	Physiography	Percentage of soils in hydrologic group VAR	%	GAGESII
AWC	AWCAVE	Physiography	Average value for the range of available water capacity for the soil layer or horizon	in/in	GAGESII
Avg Permeability	PERMAVE	Physiography	Average permeability	in/hr	GAGESII
Avg Bulk Density	BDAVE	Physiography	Average bulk density	g/cm3	GAGESII

Avg High Water Table	WTDEPAVE	Physiography	Average depth to seasonally high water table	ft	GAGESII
Avg Soil Thickness	ROCKDEPAVE	Physiography	Average value of total soil thickness	in	GAGESII
Avg Clay Content	CLAYAVE	Physiography	Average value of clay content	%	GAGESII
Avg Silt Content	SILTAVE	Physiography	Average value of silt content	%	GAGESII
Avg Sand Content	SANDAVE	Physiography	Average value of sand content	%	GAGESII
Avg Elevation	ELEV_MEAN_M_BASIN	Physiography	Mean watershed elevation	m	GAGESII
Relief Ratio	RRMEDIAN	Physiography	Dimensionless relief ratio (median)	-	GAGESII
Avg Slope	SLOPE_PCT	Physiography	mean watershed slope	%	GAGESII
Avg Aspect	ASPECT_DEGREES	Physiography	Mean watershed aspect	degrees	GAGESII
Housing Density	TS_Housing_HDEN	Anthro_Land	Housing density	units/sqkm	GAGESII-TS
Open Water	TS_NLCD_11	Physiography	open water	%	GAGESII-TS
Perennial Ice/Snow	TS_NLCD_12	Physiography	Perennial Ice/Snow	%	GAGESII-TS
Dev-Open Space	TS_NLCD_21	Anthro_Land	Developed, Open Space	%	GAGESII-TS
Dev-Low Intensity	TS_NLCD_22	Anthro_Land	Developed, Low Intensity	%	GAGESII-TS
Dev-Medium Intensity	TS_NLCD_23	Anthro_Land	Developed, Medium Intensity	%	GAGESII-TS
Dev-High Intensity	TS_NLCD_24	Anthro_Land	Developed, High Intensity	%	GAGESII-TS
Barren Land	TS_NLCD_31	Physiography	Barren Land (Rock/Sand/Clay)	%	GAGESII-TS
Deciduous Forest	TS_NLCD_41	Physiography	Deciduous Forest	%	GAGESII-TS

Evergreen Forest	TS_NLCD_42	Physiography	Evergreen Forest	%	GAGESII-TS
Mixed Forest	TS_NLCD_43	Physiography	Mixed Forest	%	GAGESII-TS
Shrub/Scrub	TS_NLCD_52	Physiography	Shrub/Scrub	%	GAGESII-TS
Grassland/Herbaceous	TS_NLCD_71	Physiography	Grassland/Herbaceous	%	GAGESII-TS
Pasture/Hay	TS_NLCD_81	Anthro_Land	Pasture/Hay	%	GAGESII-TS
Cultivated Crops	TS_NLCD_82	Anthro_Land	Cultivated Crops	%	GAGESII-TS
Wood Wetlands	TS_NLCD_90	Physiography	Woody Wetlands	%	GAGESII-TS
Emergent Herbaceous Wetlands	TS_NLCD_95	Physiography	Emergent Herbaceous Wetlands	%	GAGESII-TS
Ag Sum	TS_NLCD_AG_SUM	Anthro_Land	Sum NLCD 81/82	%	GAGESII-TS
Dev Sum	TS_NLCD_DEV_SUM	Anthro_Land	Sum NLCD 21-24	%	GAGESII-TS
Imperviousness	TS_NLCD_imperv	Anthro_Land	Imperviousness	%	GAGESII-TS
Population Density	TS_Population_PDEN	Anthro_Land	population density	person/sqkm	GAGESII-TS
Freshwater Withdrawals	TS_WaterUse_wu	Anthro_Hydro	Freshwater withdrawals	1e6 gal/day-sqkm	GAGESII-TS
% Land as Crops	TS_ag_hcrop	Anthro_Hydro	proportion land as harvest crops	%	GAGESII-TS
% Irrigated Land	TS_ag_irrig	Anthro_Hydro	proportion land in irrigated land	%	GAGESII-TS