A multiscale perspective of water resources and ecosystem services

by

Kelsey Rose McDonough

B.S., North Carolina State University, 2014
M.S., Kansas State University, 2015

AN ABSTRACT OF A DISSERTATION

submitted in partial fulfillment of the requirements for the degree

DOCTOR OF PHILOSOPHY

Department of Biological and Agricultural Engineering
College of Engineering

KANSAS STATE UNIVERSITY
Manhattan, Kansas

2018

Abstract

Water security is one of the greatest challenges of this century. The anthropogenic and environmental demand for water could likely outpace the freshwater availability in the future due to challenges caused by the growing world population, technological and economic advancements, and climate change. The ability to ensure adequate quantities of safe, affordable, and accessible water in the future requires innovative and interdisciplinary approaches to water management using a systems perspective across multiple spatial and temporal scales. This dissertation provides a multi-scale perspective of water resources and associated ecosystem services to understand drivers of change in surface water availability across spatiotemporal scales. The ultimate goal of this work is to advance the development of water security solutions by contributing to the current water resources and ecosystem services knowledge base.

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Dedication

I dedicate this dissertation to my parents.

To my father, for his unwavering support, encouragement, and friendship.

To my mother, whose love will always be my guiding light.

Chapter 1 - Introduction

An estimated two billion people in the world today are considered water insecure (Gleick, 2016). The ability to provide adequate quantities of safe, affordable, and accessible water to the growing world population while meeting the environmental freshwater demand is one of the greatest challenges of this century (Kumar, 2015; Reddy et al., 2015; Mekonnen and Hoekstra, 2016). This challenge was formally recognized in Target 7 of the United Nations Millennium Development Goals (UN, 2000; UN, 2015a; Reddy et al., 2015) and in SDG 6 of the United Nations Sustainable Development Goals (UN, 2015b; UN, 2018). The World Economic Forum recognized water crises, and their potential world impact, as the largest global risk today (WEF, 2015; Kumar, 2015; Mekonnen and Hoekstra, 2016).

Water insecurity has far-reaching consequences that significantly influence many other world challenges, including food security, poverty, ecosystem degradation, and world peace (Hanjra and Qureshi, 2010; Gleick, 2016). The United Nations identified water insecurity as the largest determinant of food insecurity in the future, outweighing land scarcity (UNDP, 2006; Hanjra and Qureshi, 2010). According to the International Food Policy Research Institute, the failure to address water security challenges through policy reform would result in a global grain production decline by 10% (Rosegrant et al., 2006), thus increasing health risks and leading to adverse environmental consequences (Hanjra and Qureshi, 2010). Furthermore, water security has long been cited as a driver of political instability in regions of the world where water has historically been scarce (Gleick, 2016). Water-related conflicts have increased by 85% since 1935 (Gleick, 2016; Pacific Institute, 2018) and thus the National Intelligence Council highlighted water security as a significant threat to the national security of the United States (Defense Intelligence Agency, 2012; Gleick, 2016).

The increase in global water scarcity is driven primarily by the escalation in anthropogenic water demand due to the growing world population and coupled economic and technological advancements (Oki and Kanae, 2006; Veldkamp et al., 2015; Mekonnen and Hoekstra, 2016). The IPAT equation (Equation 1-1), developed by Ehrlich and Holdren (1971), mathematically describes this phenomenon under the assumption that population growth negatively affects the environment.

$$I = P * F(P) = P * A * T \qquad \text{(Equation 1-1)}$$

The IPAT equation models environmental impact (I) as the product of population (P), affluence (A), and technology (T), and is widely used to assess the driving forces of environmental change (Ehrlich and Holdren, 1971; York et al., 2003). Following this ideology, Mekonnen and Hoekstra (2016) attributed the increase in global water demand to "the increasing world population, improving living standards, changing consumption patterns, and expansion of irrigated agriculture." Furthermore, the relative contribution of socioeconomic change (e.g., rising socioeconomic status) to shortages in water from 1960 to 2000 has increased globally from zero to 76.2% (Veldkamp et al., 2015). It was estimated that the volume of water needed to adequately provide for the 2050 global population must increase to 12,400 km^3 yr^{-1} from the 6800 km^3 yr^{-1} of water currently used today due to the simultaneous increase in population, affluence, and calorie consumption (Hanjra and Qureshi, 2010). The global demand for water has tripled since the 1950s (Hanjra and Qureshi, 2010) and is expected to increase in the future (Cook et al., 2015), thus leading to negative environmental impacts and intensifying water security challenges.

Benjamin Franklin once stated, "When the well is dry, we know the worth of water" (Hanjra and Qureshi, 2010). The severe undervaluation of water as a resource (Reddy et al., 2015) has exacerbated water scarcity issues by driving consumption rates that significantly exceed resource renewal rates in many areas of the world. For example, groundwater stores, which supply approximately one-third of the world population (Hanjra and Qureshi, 2010), have historically enabled people to mitigate the impacts of drought (Cook et al., 2015). However, global declines in groundwater availability (Hanjra and Qureshi, 2010; Famiglietti and Rodell, 2013) due to overconsumption and the failure to monitor both withdrawal and recharge rates (Gleick, 2016) has begun to threaten water security in many areas of the world. The cultivated area overlying the Ogallala Aquifer, for example, is now the largest contiguous area of local water stress in the United States (Moore et al., 2015).

Climate change will exacerbate the aforementioned water security challenges by placing additional pressure on global water resources through changes to the hydrologic cycle (Sheffield and Wood, 2007; Hanjra and Qureshi, 2010). Anthropogenic climate change is characterized by increased concentrations of greenhouse gases in the atmosphere, which inhibit longwave cooling and increase the vapor pressure deficit (Cook et al., 2014). As a result, temperature rises and the atmospheric demand for moisture increases as governed by the Clausius-Clapeyron equation (Sheffield and Wood, 2007; Kundzewicz et al., 2010; Cook et al., 2014). An increase in atmospheric moisture demand increases both evapotranspiration and precipitation, thus intensifying the hydrologic cycle from its current state (Sheffield and Wood, 2007; Kundzewicz et al., 2010; Cook et al., 2014).

Current estimates of the impact of climate change on the global hydrologic cycle paint a grim picture. The majority of global climate models predict that current dry regions of the world will become drier by the end of the century, and wet regions will become wetter (Famiglietti and Rodell, 2013). Global aridity is expected to rise, leading to an increase in the frequency and intensity of future droughts (Sheffield and Wood, 2007; Cook et al., 2014; Cook et al., 2015). In the United States, average annual temperatures are expected to rise by 1.4ºC (2.5ºF) and rainfall is predicted to increase in both intensity and frequency (USGCRP, 2017). Climate change will exacerbate declining streamflow trends (Brikowski, 2008) and severely alter streamflow regimes (Chatterjee et al., 2018). The number of regions around the world that experience severe water scarcity issues will increase as hydroclimatic variability accelerates with climate change.

1.1 – Spatiotemporal Assessment

Addressing global water security issues and adapting to the effects of climate change will require strategic research that aims to understand all facets of the hydrologic cycle across varying spatiotemporal scales. "Our ability to overcome complex system challenges will rely on expanding our understanding of elementary processes while at the same time identifying couplings that allow us to explore more deeply the feedback across their complex, often hierarchical assemblage," (Kumar, 2015). There is a need to continue to investigate fundamental hydrologic science (Gleick, 2016) so that we might understand the spatiotemporal drivers of water insecurity (Hein et al., 2006; Kumar, 2015).

The spatiotemporal mechanisms underpinning the hydrologic cycle have long been topics of interest to hydrologists (Hoque et al., 2014). Hydrologic variability and the non-stationarity of climate processes drive inter- and intra-annual variations in precipitation patterns (Kumar, 2015; Moore et al., 2015; Veldkamp et al., 2015) resulting in water resources that are highly variable across spatiotemporal scales (Oki and Kanae, 2006; Hein et al., 2006; Laterra et al., 2012). Physical environmental processes and human activities interact across scales to influence the provision of water resources (Hein et al., 2006; Van Wijnen et al., 2012; Laterra et al., 2012; Kumar, 2015).

“Scales refer to the physical dimension, in space or time, of phenomena and observations,” (Hein et al., 2006).

Research that aims to understand hydrologic mechanisms across varying spatiotemporal scales can be an integral step towards resolving global water security challenges. However, it is important to use spatially explicit information that is appropriate for the scale of analysis when conducting water resources research. Key variables and fundamental relationships that govern the hydrologic cycle at the global scale can change when considering continental, regional, or local scales (Sheffield and Wood, 2007). Assessments that use coarse resolution data will fail to capture the spatiotemporal dynamics of the hydrologic cycle at finer scales (Mekonnen and Hoekstra, 2016). For example, the recent examination of precipitation derived from Global Climate Models (~200 km spatial resolution) in the Great Lakes region of North America revealed that the models failed to capture the regional phenomenon of lake effect snow (Gula and Peltier, 2012; Hall, 2014). Moore et al. (2015) reported that the severity of water scarcity intensified as the spatial and temporal scale of assessment increased in resolution, and Hoque et al. (2014) found that the spatial scale of analysis altered outcomes from a risk-based watershed health assessment. Furthermore, assessments that are conducted on an annual temporal scale can be useful towards understanding broad trends, but they mask inter-annual variability and can underestimate water scarcity throughout the year (Mekonnen and Hoekstra, 2016). It is clear that spatially and temporally disaggregated data are critical to investigate the unsustainable use of water resources and to determine regions of water scarcity (Moore et al., 2015).

There is a significant need for research that aims to understand the complex, non-linear, and dynamic relationships (Costanza et al., 2017) between humans and hydrologic ecosystems across varying spatial and temporal scales. Understanding the current state and trends of water resources is critical for shaping future water policy (Maes et al., 2012; Moore et al., 2015), thus spatially and temporally explicit research outcomes can inform management and policy decisions in an effort to address global water security challenges. Research still remains limited, however, due to lack of continuous, high-resolution monitoring networks that yield data sufficient for comprehensive spatiotemporal assessment (Famiglietti and Rodell, 2013). The advancement of remote sensing technology and Earth-observation frameworks offer a promising avenue for the examination of hydrologic mechanisms across spatial and temporal scales (Cord et al., 2015). Integrated, dynamic, and spatially explicit computer models also provide the ability to explore complex environmental interactions (Costanza et al., 2017), and new theoretical frameworks, such as the ecosystem services concept, enable the examination of coupled natural-human systems across scales.

1.2 – The Ecosystem Services Concept

The impact of humans on the world today has become so significant and widespread that the current geological era was popularly renamed the "Anthropocene" to reflect the dominant influence of humans on both climate and environment (Oki and Kanae, 2006). Climate change is undoubtedly caused by human activities on the environment. Thus, it no longer makes sense to contemplate the environment as an individual and distinct system, closed off and removed from the effects of anthropogenic activities (Oki and Kanae, 2006). "Increasing human pressure on water resources, changing societal needs and water-related risks, and increasing demands for energy and food, are triggering a global water emergency," (Montanari, 2015). Human activities have altered basic environmental metabolic processes, creating trade-offs and synergies across spatial and temporal scales. The assumption that humans are considered to be a "boundary condition or external forcing" (Di Baldassarre et al., 2013) to hydrological systems is the fundamental flaw of traditional hydrology, as it has become increasingly evident that the activities of humans inherently influence the internal dynamics and feedbacks that characterize hydrological systems.

The ecosystem services concept provides the opportunity to consider humans as an intrinsic member of the environmental system (Kumar, 2015). Ecosystem services are the "benefits that humans obtain from ecosystems" (Braat and de Groot, 2012; Maes et al., 2012) or "the ecological characteristics, functions, or processes that directly or indirectly contribute to human well-being" (Costanza et al., 2017). The initial focus of the ecosystem services concept was to provide a "utilitarian framing of those ecosystem functions … deemed beneficial to society, as economic services," (Braat and de Groot, 2012). The foundation of ecosystem services research was in economic analysis, with significant research fixated on the economic valuation of services within the global GDP (e.g., Costanza et al., 1997; Fisher et al., 2009; Bagstad et al., 2012). Since its inception, however, the ecosystem services concept has evolved and is now regarded as a valuable tool for the integrated assessment of coupled natural and human systems. The Convention on Biological Diversity defined this approach as "a strategy for the integrated management of land, water and living resources that promotes conservation and sustainable use in an equitable way," (Naumann et al., 2011). The utilization of cross-disciplinary metrics within the ecosystem service concept enables people to speak the same "language" that results in desirable management outcomes (Arkema et al., 2015). The concept has been hailed as a "whole system aware view of humans embedded in society and embedded in the rest of nature," (Costanza et al., 2017).

"Human well-being is widely regarded as a central component of the ecosystem service paradigm," (Potschin-Young et al., 2018) and "biodiversity, ecosystems, and the services they provide underpin all dimensions of human, societal, cultural, and economic well-being," (Wood et al., 2018). Following this ideology, the ecosystem services concept has the potential to resolve global water security challenges by providing for human well-being through the sustainable management of ecosystems. Policy initiatives around the world have already adopted the concept as a means to obtain desirable outcomes for both ecosystem and human well-being. The European Commission's 2012 blueprint to safeguard the future of European waters by 2015 highlighted the ecosystem services concept as an effective impact assessment tool (Maes et al., 2012). The European Water Framework Directive utilized ecosystem service terminology to outline future water policy with a focus on maintaining the quality and quantity of freshwater and preserving water heritage (Bouwma et al., 2018). Even the White House Council on Environmental Quality in 2013 requested consideration of ecosystem services in regard to federal water resources investments (Olander et al., 2018).

1.3 – Dissertation Objectives

The overarching objective of this research is to examine water resources and ecosystem services across spatiotemporal scales in order to understand drivers of change in water availability and to inform management and policy decisions. The chapters of this dissertation are organized in ascending order according to the spatial extent of each individual project. The intent of this organizational scheme is to demonstrate the evolution of research projects as the spatial scale of assessment changes. Each chapter provides individual, unique insight towards understanding the physical environmental and anthropogenic mechanisms that influence the hydrologic cycle, which can ultimately inform water security management and policy initiatives.

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Chapter 2 - Analysis of publication trends in ecosystem services research

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2.1 – Introduction

Ecosystem services (ES) have been the focus of intense debate and analysis in scientific literature throughout the last several decades. The concept has gained significant traction as a valuable tool for assessing and managing relationships between ecosystems and human activities (Busch et al., 2012). There have been numerous calls to action to improve understanding of all facets of ES with publications such as the Millennium Ecosystem Assessment (MEA, 2005) and The Economics of Ecosystems and Biodiversity (TEEB, 2008), along with the development of classification systems such as the Common International Classification for Ecosystem Services (CICES; Haines-Young and Potschin, 2010). Over 118 countries were signatories in the formation of the Intergovernmental Platform on Biodiversity and Ecosystem Services (IPBES, 2012), whose mission under the United Nations is to assess the state of the planet's ecosystems, biodiversity, and associated services (Polasky et al., 2015). ES have been addressed at the national level in the United States with the establishment of the United States Department of Agriculture (USDA) Office of Environmental Markets (2008), programs such as the President's Council of Advisors on Science and Technology (PCAST, 2011) requesting assessment of ES trends to improve decision-making processes (Schaefer et al., 2015), and with the development of the Final Ecosystem Goods and Services Classification System (FEGS-CS, 2013) at the Environmental Protection Agency (Landers and Nahlik, 2013).

Scholarly journal publications on the topic of ecosystem services have substantially grown throughout the past decade, which is illustrated by an expanding world-wide research base. While considering the number, trends, and disciplinary scope of ES publications, it is also important to recognize that several challenges in the field of ES remain, specifically the need to reconcile terminology, classification systems, research methods, and reporting requirements adopted by different disciplines engaged in ES research (Busch et al., 2012; Maes et al., 2012; Polasky et al., 2015; Wong et al., 2015). These challenges represent knowledge gaps that, once overcome, would simplify direct comparison of different ES research efforts and facilitate integration of ES concepts into the management and policy realms.

Here, the temporal development and disciplinary focus of global ES research over the last decade is assessed using a meta-analysis of peer-reviewed journal publications. This analysis evaluates patterns of ES publications by subject area, scholarly journal, citation count, and country of origin to gain insight into current ES research across a range of disciplines and governmental structures. Analysis is supplemented by discussion of factors pertaining to ES research and how experimental findings, in turn, influence policy. The effectiveness of ES research, or its influence on policy and management decisions, may not be adequately reflected by the meta-analysis but can instead be estimated by the development of federal programs and governmental reports.

2.2 - Methods

To understand the nature and volume of ES research in academic publications, a non-statistical meta-analysis was conducted using journal articles published from 2005-2016 that contained the term “ecosystem services” in the title, abstract, or keywords. Articles were sourced from four major science databases managed by different publishing companies: SCOPUS (published by Elsevier), Web of Science Core Collection (published by Thomson Reuters), CABI: CAB Abstracts (published by CABI Publishing), and Environmental Sciences and Pollution Management (published by ProQuest). The SCOPUS database was selected due to its diverse range of journal articles covering physical sciences, life sciences, health sciences, social sciences, and humanities subject areas. The Web of Science Core Collection database also covers the physical sciences, social sciences, and humanities, but focuses its collection on publications considered to be more impactful. The CABI database contains publications in subject areas including agriculture, environmental science, health and nutrition, public health, and recreation/leisure/tourism. The Environmental Science and Pollution Management is a smaller database due to its limited subject area, but retrieves publications within the environmental science discipline that may be overlooked in larger databases.

2.3 - Results and Discussion

The following section presents results of the meta-analysis with accompanying discussion, and is summarized by (1) number of publications, (2) disciplinary contributions to the ES literature, (3) the country of origin of ES publications, and (4) journal relevance and influence.

2.3.1 – Number of Publications on Ecosystem Services

The number of journal articles focusing on ES has increased substantially over the last decade in all four databases (Figure 2-1). The number of scholarly articles published in the year 2016 was approximately 3000 articles in both SCOPUS and Web of Science (Figure 2-1), though there is likely overlap in articles between the two databases. This can be compared to an analysis of ES publications by Costanza and Kubizewski (2012), who reported that since 1983, a total of 2386 papers on this topic appeared in journals included in the ISI Web of Science database. This work by Costanza and Kubizewski (2012) was published in the inaugural issue of *Ecosystem Services*, a scholarly journal whose creation alone is an indication of the growing interest in, and relevance of, ES research.

Each database produced a similar distribution of journal articles citing the term "ecosystem services" in the title, keywords, or abstract. Therefore, for the purpose of length and to prevent overestimating articles due to listings in multiple databases, the remaining discussion will represent data obtained from the SCOPUS database, as this database is generally representative of the remaining three databases in its results.

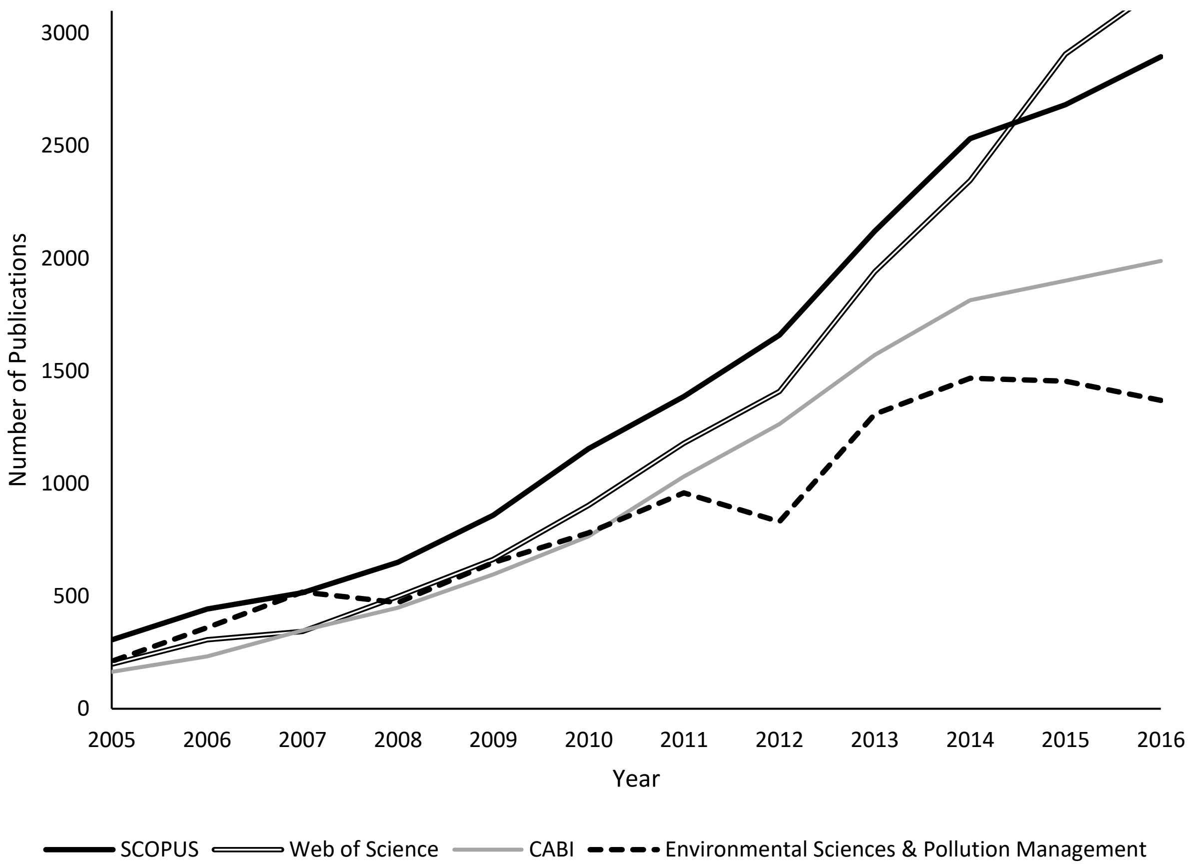

Figure 2-1. Number of articles published each year by database, citing the term "ecosystem services" in the title, keywords or abstract.

It is possible that this proliferation of published works is related to the release of major reports such as the MEA, TEEB, and CICES that have helped draw attention to the topic of ES. The MEA (2005) is a governmental report, commissioned by the United Nations, whose objective was to evaluate the consequences of global ecosystem change and identify actions needed to protect these ecosystems through conservation and sustainable use. The TEEB study, which is a series of reports from 2008 up to now (see teebweb.org), was originally financed by the European Commission and several EU Member States and sought to highlight the economics of biodiversity loss and decline in global ecosystem services. Following the TEEB study, the European Commission (2011) released the *EU Biodiversity Strategy to 2020,* which established a series of goals (targets) and associated actions to limit biodiversity losses and manage ecosystem services. Simultaneously with the publication of these governmental reports were the release of two ES classification systems; the CICES (Haines-Young and Potschin, 2010) and FEGS-CS (Landers and Nahlik, 2013). CICES was released by the European Environment Agency, while FEGS was developed by the United States Environmental Protection Agency (US-EPA). In 2015, the US-EPA also released the National Ecosystem Services Classification System (NESCS) which classifies the flows of final ES (US-EPA, 2015). These documents and classification systems, including published amendments, have supplemented individual research on ES during the past decade by providing updates on the field of ES to the academic community and beyond.

2.3.2 - Disciplinary Contributions to Ecosystem Services

An analysis of ES publications by subject area as distinguished by SCOPUS revealed that environmental sciences (34%) and agricultural and biological sciences (27%) accounted for a majority of the journal articles published between 2005-2016, with social sciences (10%) and economics (3%) comprising a smaller proportion of scholarship (Figure 2-2). Multidisciplinary publications and decision sciences are represented at a mere 1% of publications. These database categorizations may not be truly representative of the actual interdisciplinary publications on ES, however, because the fundamental thought behind ES is that the topic inherently combines the natural and social sciences, which is a phenomena not easily represented by subject area categorizations.

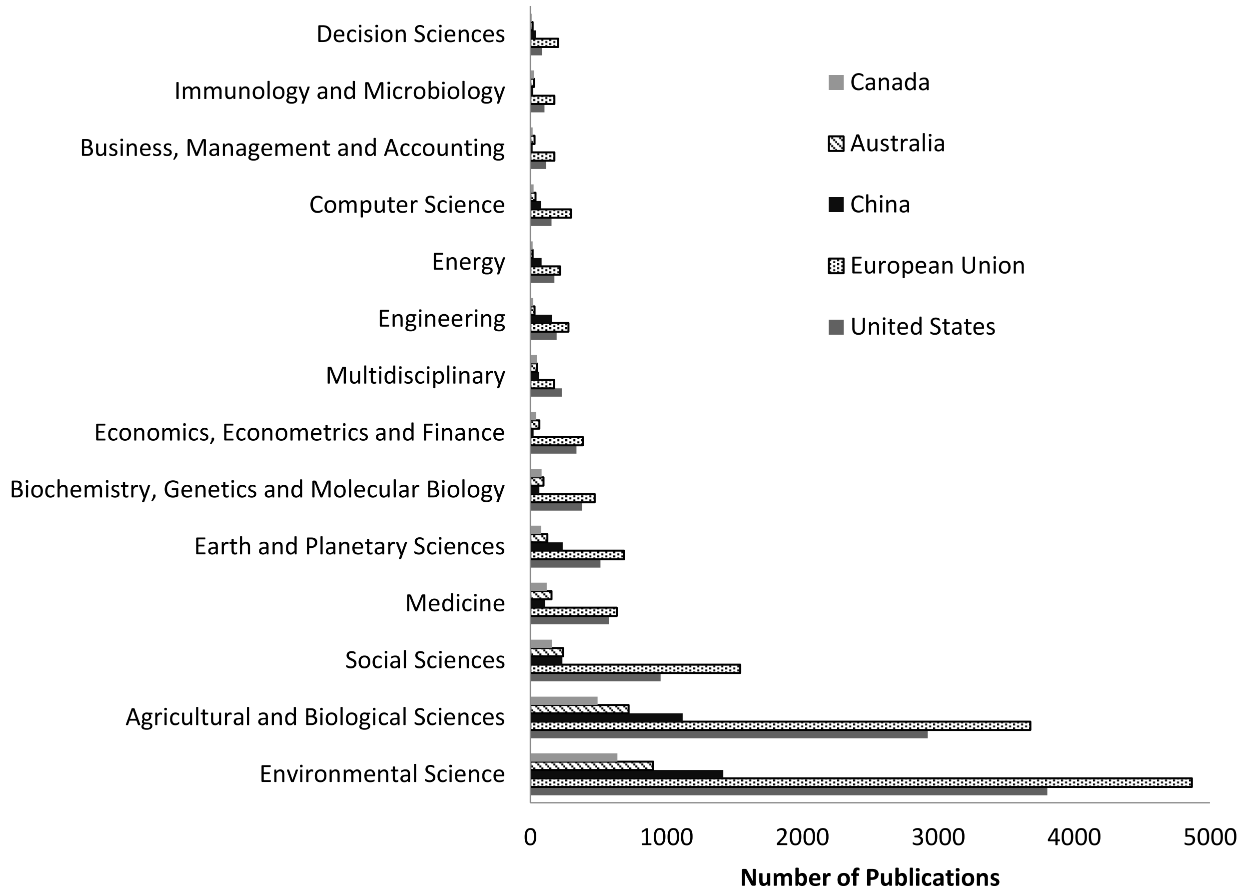

Figure 2-2. Total number of publications (2005-2016) per subject area citing the term "ecosystem services" in the title, keywords, or abstract from the database SCOPUS. The subject area categories are set by the database and reflect a “classical” structure of science.

Ecosystem services are, by nature, a multidisciplinary concept and thorough analyses require collaboration between numerous disciplines. There are a number of challenges associated with interdisciplinary research including fundamental differences in epistemologies and methods, different ways of formulating research questions, and differences in communication (Bracken and Oughton, 2006). Often when setting the stage for interdisciplinarity, disciplines unknowingly “create artificial barriers to asking appropriately scaled questions and create perspectives, worldviews, and modes of thought unique to individual disciplines,” (Costanza and Kubiszewski, 2012). It is not unheard of for individual research disciplines to approach ES research with the intent to adapt the concept by way of reframing definitions and/or terminology to fit within a respective discipline (e.g. Boyd and Banzhaf, 2007; Boykin et al., 2013; Burkhard et al., 2014; Fisher et al., 2009; Serna-Chavez et al., 2014; Wallace, 2007). This approach to research complicates the advancement and transfer of knowledge between disciplines and may be prone to errors.

The still limited availability of standards among ES terminology, classification schemes, acceptable data and methods, and reporting requirements impedes translation of concepts into management and policy decisions (Busch et al., 2012; Maes et al., 2012; Polasky et al., 2015; Wong et al., 2015). For example, the debate over ES definitions and classification schemes is well-documented among governmental publications of the MEA, TEEB, CICES, and FEGS, where each present a new definition or method of ES classification. These definitions and classification systems are further amended and revised in academic journal publications (e.g. Andersson et al., 2015; Boyd and Banzhaf, 2007; Burkhard et al., 2014; Costanza, 2008; Fisher et al., 2009; Gomez-Baggethum and Barton, 2013; Syrbe and Walz, 2012; Wallace, 2007). This repeated re-evaluation of fundamental terms and concepts creates a confusing research environment where it is not clear which terminology or research approach is the most accepted. Though discussion over terminology and methodology is expected in the establishment of a new field, the prolonged inability to achieve consensus may pose a challenge for policy- and decision-makers who aim to incorporate ES into their respective organizations (Polasky et al., 2015).

As ES research progresses, there will be continued and increasing demand for interdisciplinary research approaches to overcome specialization and answer complex questions that are beyond the expertise of individual disciplines (Bracken and Oughton, 2006). Bracken and Oughton (2006) stated that “the key to effective research is the development of awareness of language differences and of the time needed to ensure that experts from different disciplines develop a common understanding.” A consensus in definitions, terminology, research methods, and classification schemes must be achieved to promote effective interdisciplinary research communication and comprehensive ecosystem service analyses that incorporate the environmental science, policy, and socioeconomic domains appropriately and simultaneously.

2.3.3 – Origin of Ecosystem Services Publications

The European Union (EU) leads the number of scholarly publications across all subject areas (Figure 2-3). Much of the research behind the EU publications is funded by the European Commission, which has focused on policy-oriented ES research over the past several years and often receives co-funding by member states. However, an analysis of ES publications by singular country of origin shows the United States accounts for 30% of publications, with countries such as the United Kingdom, China, Germany, and Australia close behind (Figure 2-3). Costanza and Kubiszewski (2012) found that publications on ES originated from 24 countries; however, current data reveals this number has expanded to 139 individual countries.

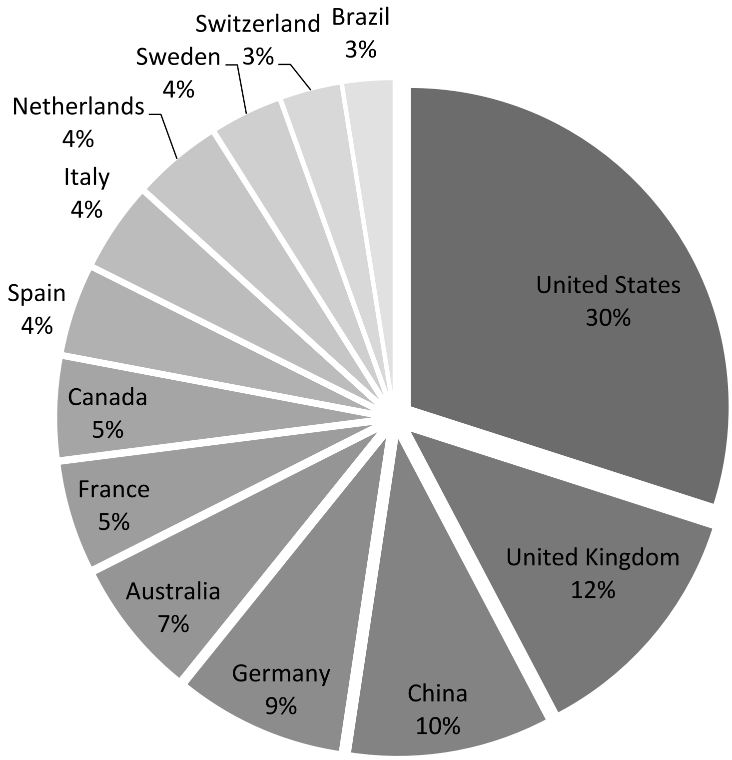

Figure 2-3. Total percentage of articles published (2005-2016) by country of origin containing the term "ecosystem services" in the title, keywords, or abstract from the database SCOPUS.

ES research initiatives in the United States are numerous and diverse, ranging from federal governmental programs to non-governmental organization and university-based activities. Examples of United States ecosystem services research programs include the National Ecosystem Services Partnership (a subset of the global Ecosystem Services Partnership) and the Natural Capital Project, as well as the development of USEPA's EnviroAtlas tool. An exhaustive list of ES programs and research initiatives operating under federal governmental agencies can be found in Cox et al. (2013) and Schaefer et al. (2015).

Early implementation of ES into United States policy began with the 2008 Farm Bill, which called for the investigation of ES and their application to environmental markets (Schaefer et al., 2015). This bill sparked establishment of ES-focused research programs, such as the Office of

Environmental Markets at the USDA, but failed to promote any significant policy initiatives. While not explicitly mentioning the term "ecosystem services", Executive Order 13514 issued by President Obama in 2009 called for governmental agencies to "safeguard the health of our environment" and "prioritize actions based on full accounting of both economic and social benefits and costs" (Schaefer et al., 2015). More recently, the 2015 White House Memorandum (M-16-01) called for the incorporation of ES into federal decision-making and policies (Donovan et al., 2015).

In contrast to the United States, the European Union (EU) has been extremely proactive in implementing the ES concept into policy over the past decade. For example, the *EU Biodiversity Strategy to 2020* set several ES-based targets designed for member states to meet biodiversity goals by 2020 (European Commission, 2011). *Target 2* in the Biodiversity Strategy openly addresses ES, stating that "by 2020, ecosystems and their services are maintained and enhanced by establishing green infrastructure and restoring at least 15% of degraded ecosystems" (European Commission, 2011). *Target 2* (*Actions 5-7*) explicitly directs member states to conduct ES-based research, integrate ecosystem services into national frameworks and policies, and ensure that there is no net loss of ES (European Commission, 2011).

The ES strategy implemented by the EU has been effective. The Mapping and Assessment of Ecosystems and their Services (MAES) technical report, published in 2016, highlighted several case studies of ES initiatives by EU member states (European Commission, 2016). These case studies showcased ES policy and actions taken in major EU cities, including Barcelona, Lisbon, Rome, Oslo, and Utrecht. Beyond the strategic implementation of urban green space, these cities have also developed a number of ecosystem service tools including sustainable development indicators, biodiversity indices, tree databases, and education plans intended to promote and sustainably manage ES across each individual municipality (European Commission, 2016). Each member state has also completed, or is in the process of finishing, maps of ES provision within their respective regions. The proliferation of ecosystem service programs is evidenced beyond the *EU Biodiversity Strategy to 2020* and the MAES technical report by the number of published scholarly articles (Figure 2-1).

The total percentage of ES articles published by EU member states sums to 42% (Figure 2-3), which outpaces the United States' singular research activities (30%). It is difficult to conclude from the data analyzed here whether actions by EU member states led to the development of the *EU Biodiversity Strategy to 2020* or if the *Strategy* required implementation of country-based ES initiatives. Regardless, there is a clear and collective effort in the EU to understand and preserve ecosystem services evidenced in the publication record. As noted by Schaefer et al. (2015) "widespread adoption of ecosystem services approaches in planning and regulatory contexts could drive a fundamental shift in environmental governance." Such a shift is ongoing within the EU.

2.3.4 – Journals Publishing Ecosystem Services Research

The journals of *Shengtai Xuebao Acta Ecologica Sinica, Ecosystem Services, PLoS One*, and *Ecological Economics* lead scholarly journals publishing ES-focused articles (Figure 2-4). *Ecological Economics*, a peer-reviewed journal established in 1989, is focused on publishing transdisciplinary research that connects ecology and economics (Elsevier B.V., 2017b). With an impact factor of 3.227 in 2015 (Elsevier B.V., 2017b), *Ecological Economics* leads this group of journals in citation count, second only to *Science* in total citations (Figure 2-5) from 2005-2016. *PLoS One*, a scholarly research journal that publishes a variety of research from all disciplines (PLOS, 2017), has fewer total citations, though the 2015 impact factor of 3.057 (Thomson Reuters, 2015) suggests that the influence of the journal is comparable to *Ecological Economics.* The journal of *Ecosystem Services* publishes economic, social, and policy research incorporating the natural science basis of ecosystem services (Elsevier B.V., 2017c). An impact factor of 4.307 in 2015 (Thomson Reuters, 2015) for *Ecosystem Services* conveys the considerable influence on research by this journal, which started in 2012, despite a citation count lower than that of *Ecological Economics* and *PLoS One*. *Shengtai Acta Ecologica Sinica* is an international journal focused in the area of ecology and aims to foster ecological studies in China (Elsevier B.V., 2017a). Both the impact factor of 0.27 in 2015 (ResearchGate, 2017) of *Shengtai Xuebao Acta Ecologica Sinica*, and the low citation count (less than 1000) indicates that this journal is fairly low impact even with the large volume of published articles.

Though journals such as *Science* and the *Proceedings of the National Academy of Science*s are just as highly cited as *Ecological Economics* (Figure 2-5) they are not publishing the same number of articles on ES (Figure 2-4), and therefore are not contributing the same volume of information to the subject. It is important to note that while there are known limitations related to using citation analysis to assess influence (see Costanza et al., 2016), it is a powerful quantitative guide to evaluate the relative influence of a publication on the academic community (Costanza et al., 2016).

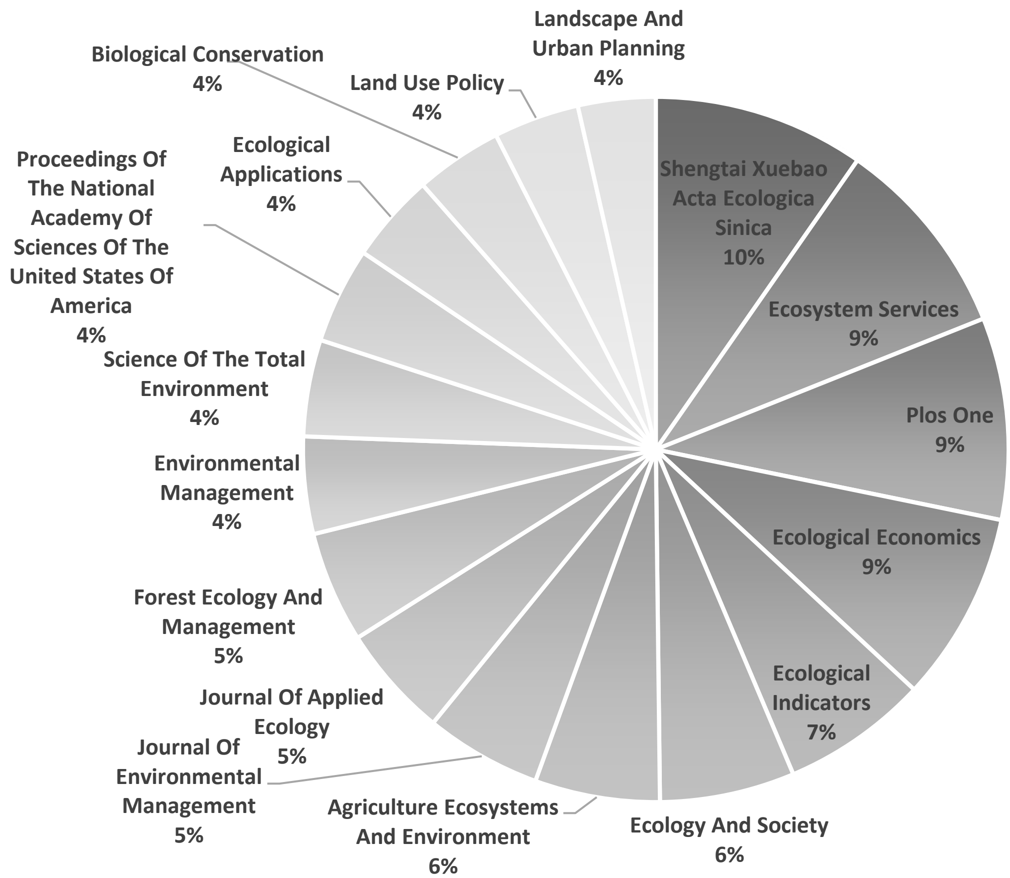

Figure 2-4. Total percentage of articles published (2005-2016) by scholarly journals citing the term "ecosystem services" in the title, keywords, or abstract from the database SCOPUS. Journals representing less than 4% of publications on the topic of ecosystem services are not included.

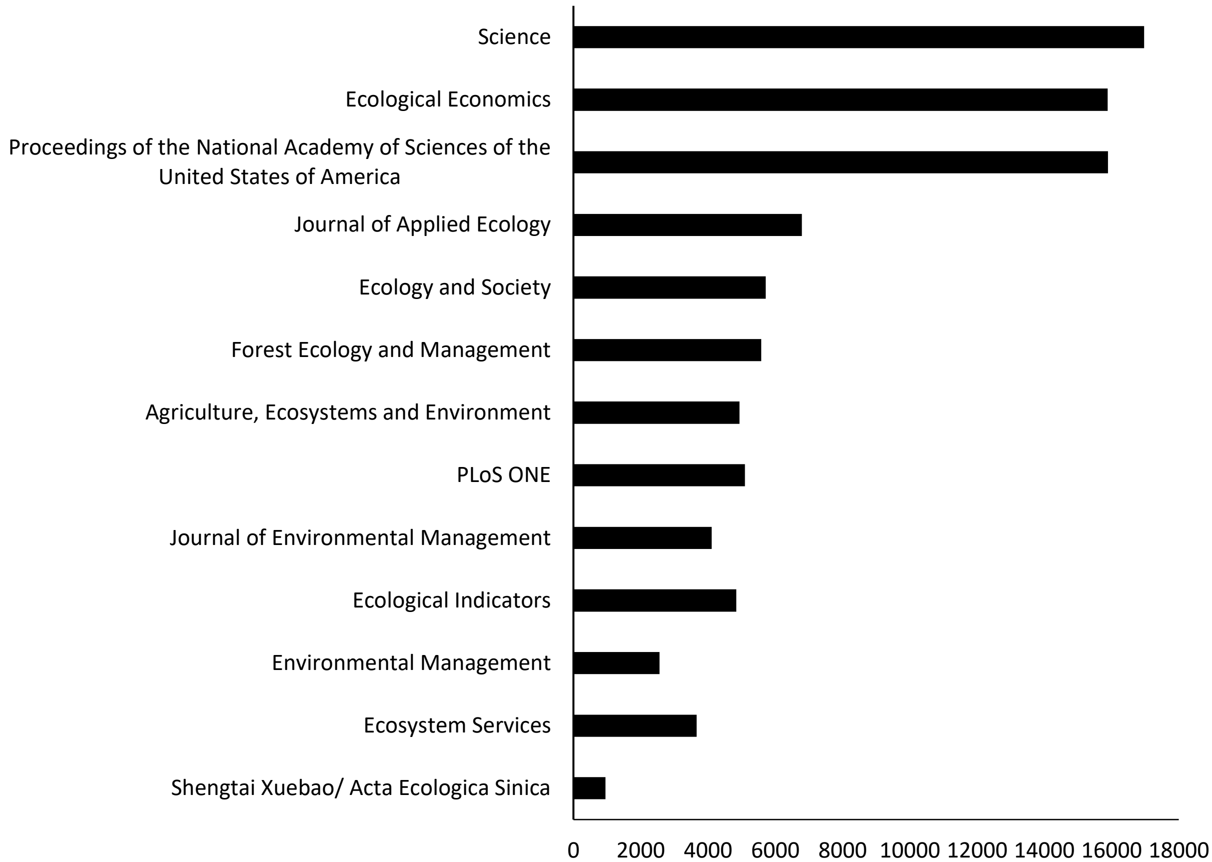

Figure 2-5. Total number of citations per scholarly journal (2005-2016) from articles that cite the term "ecosystem services" in the title, keyword, or abstract from the database SCOPUS.

The journals *Ecological Economics* and *PLoS One* publish research that is both related and unrelated to ES, though the number of publications on ES in *Ecological Economics* has increased over the past decade. Costanza et al. (2016) found that, from the period 2004-2014, approximately half of the most highly cited *Ecological Economics* articles contain the terms "ecosystem" and "service" or "environmental" and "service" in the title, while the remainder of articles appear to discuss the topic, which indicates the growing importance of ES in this journal.

The journal of *Ecosystem Services* is dedicated to publication of ES-based research alone and is supported by the Ecosystem Services Partnership, a global organization that supports the science and application of ES (Ecosystem Services Partnership, 2016). The growing influence of

Ecosystem Services is impressive, especially since the journal has only been in existence for five years and has the potential to become a strong leader for ES research. The expansion of scholarly aims to include physical science-based research in addition to economic, social, and policy research would enable *Ecosystem Services* publications to better encompass the wide breadth of ES research. This group of scholarly journals, specifically *PLoS One*, *Ecological Economics*, and *Ecosystem Services*, could be leaders in any effort to clarify terminology, improve classification, and strengthen valuation.

Ecosystems are dynamic and adaptive systems characterized by complex feedback loops, which require serious effort to understand and quantify the mechanisms that drive ecosystem service provision (Costanza, 2008). As a result, many questions remain regarding underlying ecosystem components and processes (Cook and Spray, 2012; Fremier et al., 2013; Naumann et al., 2011; Polasky et al., 2015). This issue is compounded by the fact that identifying and quantifying a complete suite of ecosystem benefits is a significant undertaking due to the lack of an evidence base and the non-linear, complex relationships among these benefits (Busch et al., 2012; Carpenter et al., 2009; Cook and Spray, 2012; Howe et al., 2014; Mace et al., 2012; Naumann et al., 2011; Qiu and Turner, 2013). This complexity leads to "cherry-picking" from a small subset of ecosystem services for research based on data availability and ease of quantification. As of 2011, fifty percent of studies on ES examined a single service, failing to consider other services or interactions between them (Kull et al., 2015). As a result, many ES are ignored and/or undervalued, essentially pushing policy and management decisions towards maximizing a select few services with possible negative consequences for those other services that were not considered (Kull et al., 2015). Both effective policymaking and innovation of nature-based solutions require a sound knowledge base that understands fundamental baseline ecosystem relationships, socioeconomic valuation of ES, and how anthropogenic changes ultimately impact environmental condition and provision of said services. Implementation of publication policies by journals, such as *Ecosystem Services*, that serve to limit the number of publications ignoring multiple ecological interactions associated with ES provision encourages a more holistic research approach. Transdisciplinary journals such as *Ecosystem Services*, *Ecological Economics*, and *PLoS One* can foster interdisciplinary ES research while discouraging the use of discipline-specific terminology and methods.

2.4 – Conclusion

A meta-analysis of ecosystem services was performed to assess the focus of ecosystem service publications over the last decade. It is evident that the publication of peer-reviewed articles within the realm of ecosystem services will continue to grow, and thus it is essential to establish a standardized knowledge base from which research may diverge. Future publications on the subject should consider impacts on all disciplines, cultures, and political structures in the development of terminology, classification schemes, or methods, noting that it may be impossible to develop a "one-size-fits-all" solution. Proposed management strategies should recognize their limitations of applicability (e.g. to a singular field of research) to prevent bias in quantification or valuation as knowledge is shared. Though it may be impossible to develop a universal solution, a concerted effort should be made to advance interdisciplinary research and cross-communication that will expand and enhance our understanding of ecosystem services. Scholarly journals may lead this endeavor, by implementing policies that discourage the application of discipline-specific terminology and methods while promoting interdisciplinary research. The standardization of terminology and methodology across the environmental, economic, and social sciences will allow for meaningful comparisons to be made and improve the integration of ecosystem services into policy and natural resources management.

A next step for the ecosystem service research community would be to address some of the research gaps outlined here and to move beyond the debate on ecosystem services lexicon to develop real, applied, and integrated socio-ecological solutions using novel, interdisciplinary approaches. Governmental structures around the world could expand upon some of the ES actions taken by the EU to develop or improve policy initiatives and management programs that increase both basic and applied ecosystem services research. While the concept of ecosystem services can be complex and encompass a broad range of disciplines, cultures, and applications, its inclusion into future policy initiatives will stimulate progress by improving the understanding of ecosystem services and expanding our basic and applied research toolkits.

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Chapter 3 - Spatial configurations of land cover influence ecosystem service provision

This chapter is a manuscript in preparation to be submitted for publication. The co-authors on this manuscript include Stacy Hutchinson, Jia Liang, Shawn Hutchinson, and Trevor Hefley.

3.1 – Introduction

Floods are responsible for more human fatalities than any other natural disaster (Watson et al., 2016). In the last decade of the 20th century, approximately 100,000 people were killed by floods worldwide (Jonkman, 2005). Furthermore, flooding causes severe damage to both infrastructure and ecosystems, leading to both significant socioeconomic and environmental losses. The annual damages from flooding in the United States are estimated to be as high as $2.9 billion (Javaheri and Babbar-Sebens, 2014).

The European Water Framework Directive recognized the ability to mitigate flooding effects through the adoption of land use adaptation measures (Article 4.7 of the Water Framework Directive; Barbedo et al., 2014). “There are a variety of land and water management practices available that could shift flow regimes back toward more natural conditions,” (Baker et al., 2004). Land use change influences ecosystem services by altering the human demand for services, by shifting the pathways via which humans access and use services, and through the modification of ecological structure and functions that underpin the supply of services (Sonter et al., 2017). Management approaches that focus on enhancing flood mitigation services to offset the negative effects of urbanization and human activities offer a promising solution to mitigate flood events through the strategic utilization of the natural environment.

Urbanization is one of “the most dramatic forms of irreversible land transformation” (Aguilera et al., 2011) that leads to declines in the provision of flood mitigation ecosystem services through the conversion of natural ecosystems to impervious surfaces. More impervious surface area reduces the rate of infiltration and minimizes available soil water storage capacity (Wheater and Evans, 2009; Yao et al., 2016; Miller et al., 2018), thereby converting a greater volume of precipitation into runoff (Wheater and Evans, 2009; Coles et al., 2012; Miller et al., 2018) which drives flood events. Impervious surfaces also increase the value of the runoff coefficient (Kundzewicz et al., 2010), which, when combined with the implementation of artificial drainage networks, speeds runoff conveyance and reduces the time to concentration (Kundzewicz et al., 2010; Miller et al., 2018). Furthermore, urbanization is often associated with the channelization of rivers and construction of levees that disconnect rivers from their associated floodplains (Watson et al., 2016). Traditional engineered infrastructure is often implemented to control local flooding, which often only serves to exacerbate flooding issues elsewhere (Watson et al., 2016).

Natural ecosystems, in contrast, have the potential to offset the negative impacts of urbanization through attenuation of flooding. These natural ecosystems, such as floodplains and wetlands, provide the necessary hydrologic mechanisms to capture and infiltrate precipitation at the source, thus minimizing the flooding event both locally and downstream (Watson et al., 2016; Brody et al., 2017). The protection of floodplains along riparian corridors has been shown to minimize inundation by maintaining the natural storage capacity of the landscape (Brody and Highfield, 2013; Watson et al., 2016; Brody et al., 2017). Forest land cover has demonstrated the ability to slow and capture runoff, thus reducing the magnitude of the flood peak (Brody et al., 2017). Wetlands have also proven effective at mitigating flooding by reducing the flood peak and increasing the flood return period (Brody and Highfield, 2013; Kadykalo and Findlay, 2016; Watson et al., 2016).

Quantifying the spatial dynamics of flood mitigation services is multifaceted and challenging. To begin with, the distribution of ecosystem services throughout the landscape is spatially heterogeneous due to variations in both the locations of ecological supply and the locations of the beneficiaries who use them (Sonter et al., 2017). The pathways of flood mitigation service delivery are well established, as they are defined by the hydrologic flow of rivers (Sonter et al., 2017) which move in a unidirectional manner downstream from the service supply area to the location of the beneficiaries (Syrbe and Walz, 2012; Sonter et al., 2017). However, the biophysical drivers that control the supply of upstream flood mitigation services are significantly more complex. These drivers, which include patterns of land use and land cover (LULC), interact across spatial and temporal scales to influence the actual provision of services throughout the landscape.

Configurations of land use can initiate trade-offs or synergies in ecosystem service provision across the landscape over both space and time (Brody et al., 2011; Frank et al., 2012; Deasy et al., 2014; Tolessa et al., 2017; Sonter et al., 2017; Wood et al., 2018). The flooding response to urbanization and anthropogenic activities is spatially heterogeneous (Mogollón et al., 2016) and dependent on the location and character of precipitation and LULC throughout the area in question (Jacobson, 2011). The majority of studies that have focused on flood mitigation ecosystem services, however, have failed to capture the spatial relationship between biophysical drivers of flood mitigation and the provision of the service itself. The spatial configuration of LULC, for example, have rarely been considered when evaluating drivers of flooding across the landscape (Jacobson, 2011; Deasy et al., 2014; Brody et al., 2017). There is a substantial need for research that investigates the dynamics and drivers of flood mitigation ecosystem services across spatial and temporal scales (Brody et al., 2013; Koellner et al., 2018).

Our study examines the relationship between spatial patterns of land cover and flooding to understand how land cover configuration can interact to influence the provision of ecosystem services across spatial scales. We seek to understand the mechanisms that influence the biophysical supply of flood mitigation services, rather than on the delivery, use, and valuation of the service itself. The main objective of our study is to (1) identify spatial configurations of land cover that significantly increase or mitigate stream flashiness and (2) understand the areal extent of this influence throughout the watershed. Spatial patterns of land cover will be characterized using landscape metrics, which are mathematical indices that enable the quantification of landscape composition (Frank et al., 2012; Brody et al., 2013; Inkoom et al., 2018; Miller et al., 2018).

"Landscape metrics provide a useful tool because they quantify specific spatial characteristics of individual land patches and the spatial relationship among multiple patches," (Brody et al., 2017). The application of landscape metrics to hydrology has been limited (Uuemaa et al., 2013; Miller et al., 2018), but they have been previously used to characterize the spatial heterogeneity of landscapes with applications to landscape ecology (Uuemaa et al., 2013; Plexida et al., 2014), urban planning (Aguilera et al., 2011), and ecosystem services (Syrbe and Walz, 2012; Almeida et al., 2016). The combination of landscape metrics and ecosystem services to understand flood mitigation services can help identify those areas, at the landscape level, that are vulnerable to change and pinpoint opportunities for future land management opportunities (Tolessa et al., 2017).

3.2 - Methods

3.2.1 Study Area

The Blue River Watershed (HUC #1030010101) spans the state border between Kansas and Missouri within the Central Great Plains region of the United States (Figure 3-1). The 1127 km^2 watershed encompasses portions of Johnson County in Kansas, as well as Jackson County and Cass County in Missouri. Approximately 60% of the watershed is located in Kansas, with the remaining 40% in Missouri (Patti Banks Associates, 2007). The Blue River Watershed is part of the Lower Missouri-Crooked Watershed (HUC #10300101) in the greater Missouri River Basin.

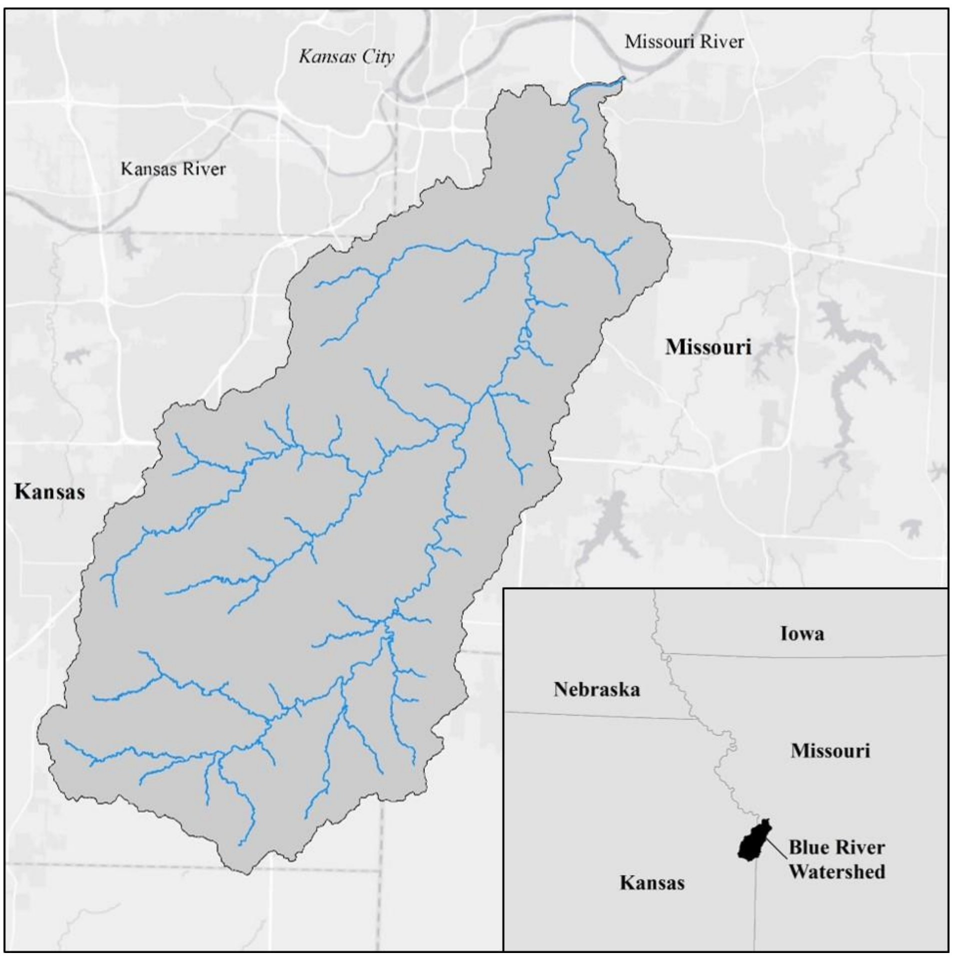

Figure 3-1. The Blue River Watershed (gray) is a tributary to the Missouri River. The watershed crosses the Kansas-Missouri state border (insert) and is located south of the Kansas City metropolitan area.

The Blue River Watershed is classified as a "developing urban watershed" due to the gradient of land use/land cover that spans from rural cropland and grassland in the headwaters to intensive urban development near the outlet. A study conducted by the U.S. Geological Survey in 2005 examined land uses across the watershed and reported rapid urbanization in the northern (downstream) portion of the watershed, while the headwaters of the Blue River Watershed remained primarily undeveloped. However, Ji et al. (2006) reported that urbanization in the greater Kansas City area was increasing at an average rate of 4.25% per year, with rapid urbanization (8.89%/year) in Johnson County (Kansas), which comprises much of the headwaters of the Blue River Watershed. Portions of the lower Blue River have been extensively modified by the U.S. Army Corps of Engineers and the City of Kansas City, Missouri for flood control, with an estimated $250 million spent as of 2003 (Patti Banks Associates, 2007).

Population and urbanization within the Blue River Watershed are projected to increase exponentially in coming decades, which will magnify environmental pressures on the central riparian Blue River corridor. The Mid-America Regional Council predicted a 40% population growth in Johnson County alone by 2020 (Patti Banks Associates, 2007). Land use projections estimate that the upper portion of the Blue River Watershed will exceed 25% imperviousness in 20 years (Patti Banks Associates, 2007).

3.2.2 Climatic and Hydrologic Data

Daily precipitation data from 2001-2006 were obtained from PRISM Climate Group (2004) for ten locations throughout the Blue River Watershed. PRISM provides modeled precipitation data, which is developed using climatologically-aided interpolation and the 30-year normal, at a 4-km spatial resolution (PRISM Climate Group, 2004). The precipitation data was obtained at locations that corresponded with the locations of the USGS streamflow gauge stations within the Blue River Watershed (Figure 3-2).

Streamflow data was obtained from ten USGS gauge stations located throughout the Blue River Watershed (Figure 3-2). Daily data were obtained for the years 2001 through 2016, though the temporal availability of data between stations varied during this period (Table 3-1). These data were used to compute the Richards-Baker Flashiness Index, or R-B Index (Equation 3-1), a dimensionless index that measures change in flow relative to total flow (Baker et al., 2004), on a daily, monthly, and annual time scale for all USGS gauge stations between 2001 and 2016.

$$R - B\ Index = \frac{\sum_{i=1}^{n} |q_i - q_{i-1}|}{\sum_{i=1}^{n} q_i} \qquad (3\text{-}1)$$

The R-B Index provides a measure of stream flashiness and has been useful metric to assess anthropogenic disturbance over time (Baker et al., 2004; Mogollón et al., 2016). The index is positively correlated with increasing frequency and magnitude of precipitation events, and is negatively correlated with base flow and watershed area (Baker et al., 2004; Mogollón et al., 2016). Streams characterized as “flashy” typically have high rates of change in streamflow, while more stable streams have slower rates of change (Poff et al., 1997; Baker et al., 2004; Jayakaran et al., 2016). Stream flashiness typically increases with urbanization and increases in impervious cover (Roodsari et al., 2017).

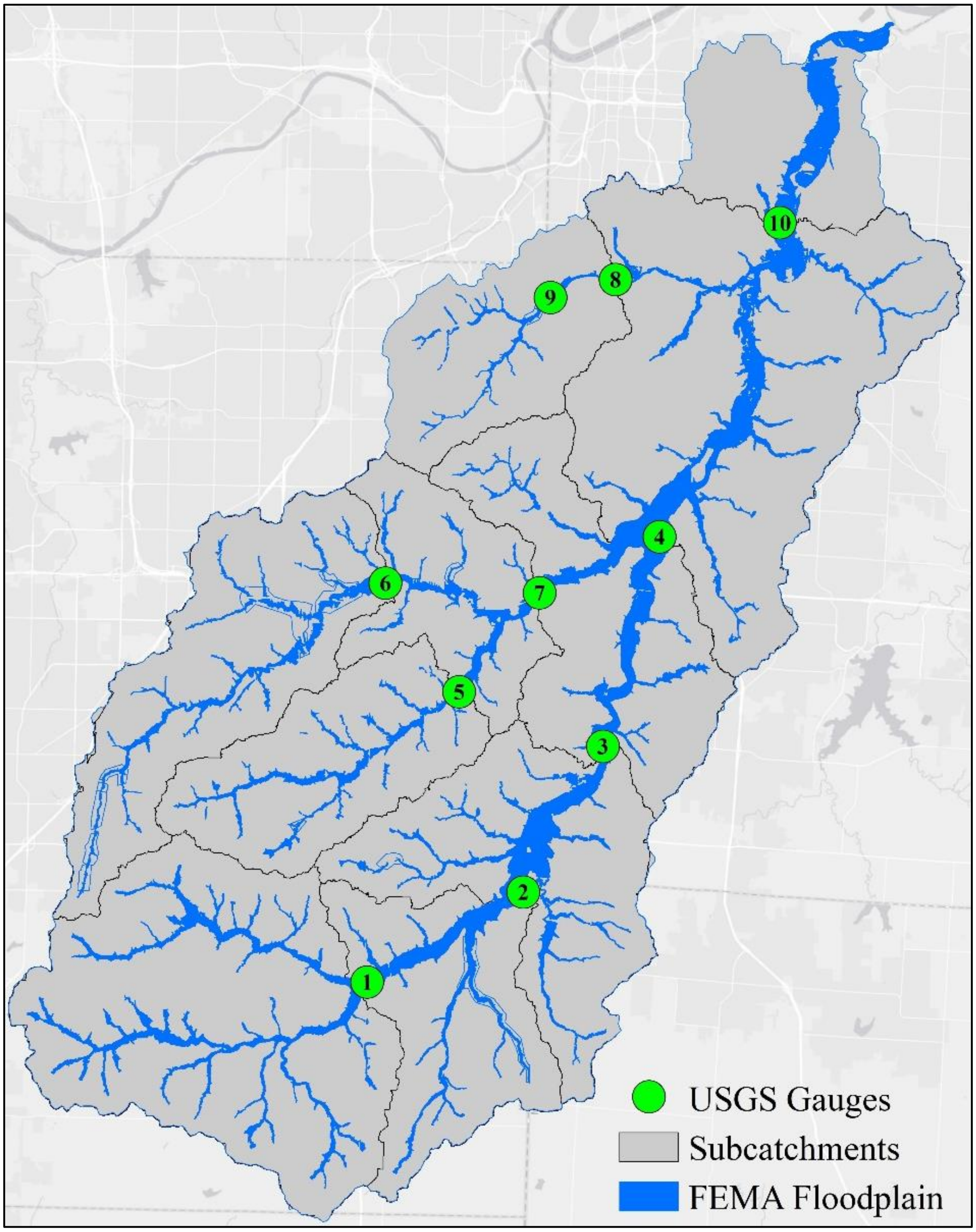

Figure 3-2. Locations of the USGS streamflow stations throughout the Blue River Watershed. Gauge numbers increase in value towards the watershed outlet and, generally speaking, also increase in areal coverage of developed LULC.

Table 3-1. USGS gauge stations within the Blue River Watershed from which streamflow data was obtained for this study.

Site ID	Station Name	Station Number	Latitude	Longitude	Availability
1	Blue R NR Stanley, KS	06893080	38°48'45"	94°40'32"	9/20/1974-Present
2	Kenneth Rd., Overland Park, KS	06893100	38°50'32"	94°36'44"	4/16/2003-Present
3	Blue River at Blue Ridge Blvd Ext in KC, MO	06893150	38°53'21.9"	94°34'50.4"	6/1/2002-Present
4	Blue River at Kansas City, MO	06893500	38°57'25.2"	94°33'32.0"	5/1/1939-Present
5	Tomahawk C NR Overland Park, KS	06893350	38°54'22"	94°38'24"	9/20/1974-Present
6	Indian C at Overland Park, KS	06893300	38°56'26"	94°40'16"	3/7/1963-Present
7	Indian C at State Line Rd., Leawood, KS	06893390	38°56'18"	94°36'28"	4/22/2003-Present
8	Brush Creek at Rockhill Road in Kansas City, MO	06893562	39°02'21.3"	94°34'43.4"	7/30/1998-Present
9	Brush Creek at Ward Parkway in Kansas City, MO	06893557	39°01'59.1"	94°36'19.4"	7/15/1998-Present
10	Blue River at Stadium Drive in Kansas City, MO	06893578	39°03'30"	94°30'42"	7/1/2002-Present

3.2.3 Land Cover and Landscape Metrics

Land use/land cover (LULC) data for the Blue River Watershed was obtained from the National Land Cover Database at a 30-m resolution for 2001 (Homer et al., 2007), 2006 (Fry et al., 2011), and 2011 (Homer et al., 2015). LULC in the watershed varies from rural cropland and grassland in the headwaters to intensive urban development downstream (Figure 3-3). The software program FRAGSTATS (McGarigal et al., 2012) was used to compute landscape metrics from each land cover dataset (Figure 3-3) to characterize the spatial configurations of land cover across the watershed.

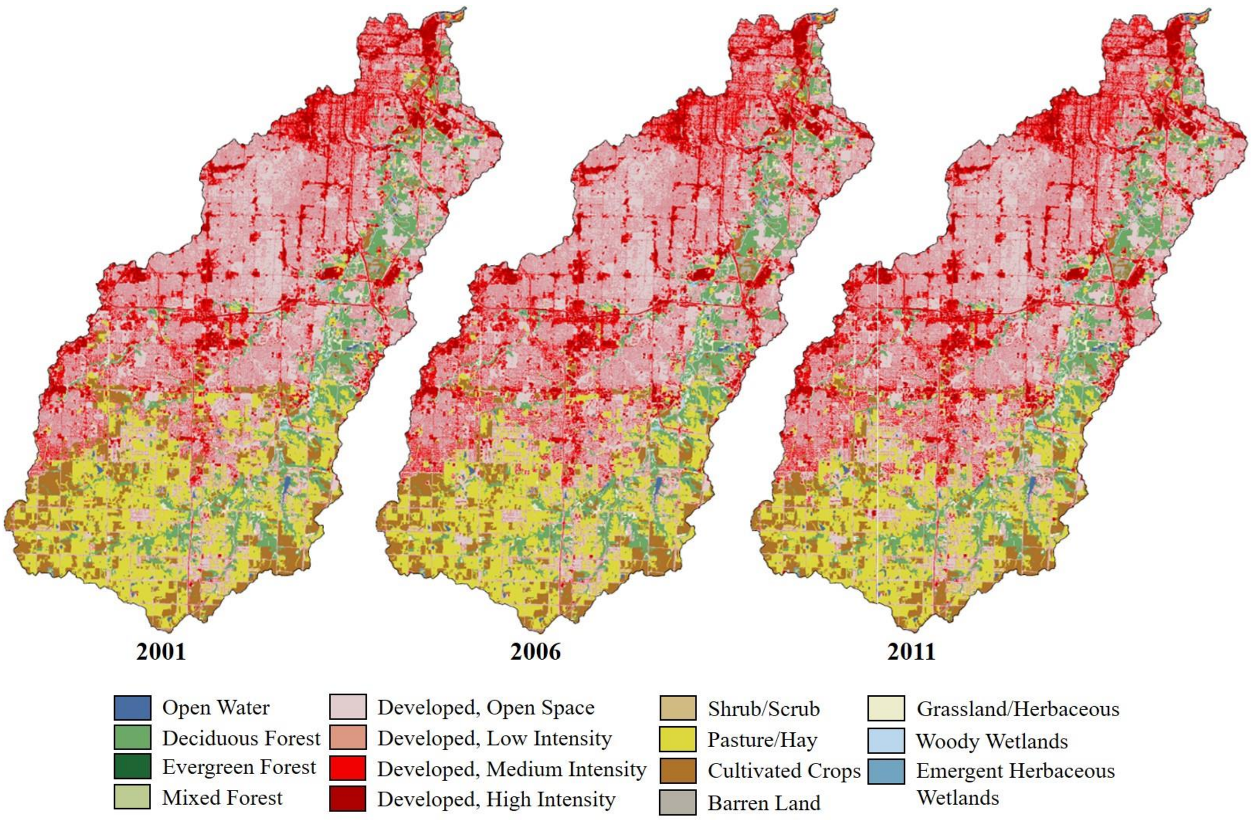

Figure 3-3. Land use/cover across the Blue River Watershed from 2001 to 2011.

Four landscape metrics (Table 3-3) were computed using the FRAGSTATS program to characterize the spatial pattern of land cover across the Blue River Watershed. The usefulness and suitability of individual landscape metrics have been thoroughly examined in the literature (e.g., Plexida et al., 2014; Inkoom et al., 2018). Thus, each metric was chosen based on recommendations from prior research to represent a specific component of landscape composition, such as connectivity or fragmentation.

Table 3-3. Description of spatial landscape metrics utilized to characterize the landscape in this study (McGarigal, 2015).

Metric	Level	Description	Function

Percentage of landscape (PLAND)	Class	The percentage of the landscape comprised of a particular patch type	0 < PLAND ≤ 100
Patch density (PD)	Class	Density (#/ha) of patches	PD > 0, constrained by cell size.
Area-weighted mean patch radius of gyration (GYRATE)	Class	Provides a measure of landscape continuity	GYRATE ≥ 0, without limit. Will increase in value as the patch increases in extent.
Clumpiness index (CLUMPY)	Class	A normalized index depicting the deviation from a random distribution; provides an effective index of fragmentation of the focal class.	-1 ≤ CLUMPY ≤ 1 ; Equals -1 when the focal patch is maximally disaggregated, equals 0 when distributed randomly, and equals 1 when maximally aggregated.

The percentage of the landscape (PLAND) is a metric that provides a "fundamental measure of landscape composition" and describes the proportion of the landscape that is comprised of a particular patch (i.e. land cover) type (McGarigal, 2015). PLAND has been utilized in a number of previous studies (e.g., Aguilera et al., 2011; Fan et al., 2014; Kim & Park, 2016; Brody et al., 2017) and provides important information about the richness of individual patch types across the landscape (Kim & Park, 2016). A higher value indicates the presence of larger shapes and increased dominance by a single land use/cover type in the watershed.

Patch density (PD) provides a simple measure of subdivision across a landscape (McGarigal, 2015). "Subdivision deals explicitly with the degree to which patch types are broken up (i.e., subdivided) into separate patches (i.e., fragments)," (McGarigal, 2015). PD has been used, for example, to estimate the degree of urban sprawl across a landscape (Brody et al., 2013; Brody et al., 2017) and has been informative for spatial differentiation (e.g., Botequilha Leitão; Syrbe & Walz, 2012). PD also facilitates comparisons among landscapes of varying sizes as a fundamental measure of land cover pattern (Ji et al., 2006; Brody et al., 2013).

The area-weighted mean patch radius of gyration (GYRATE) is an indicator of landscape continuity of a specific patch (McGarigal, 2015) by representing the compaction or elongation of a single patch across the landscape (Aguilera et al., 2011). GYRATE "gives the average distance one can move from a random starting point and travel in a random direction without leaving the patch" (McGarigal, 2015). Higher values of GYRATE indicate elongation or connectivity of patches, while lower values indicate compaction (Aguilera et al., 2011; Brody et al., 2017).

The clumpiness index (CLUMPY) is utilized to provide a measure of dispersion (or disaggregation) vs. aggregation of a patch type (McGarigal, 2015). Literature has associated habitat loss and fragmentation with disaggregated patch types (McGarigal, 2015), and thus CLUMPY can be useful as an indicator to represent patterns of fragmentation across the watershed. The clumpiness index has been used previously in a number of studies, including Miller et al. (2018).

3.2.4 Hypotheses and Statistical Analysis

The main objective of this research was to (1) identify spatial configurations of land cover that significantly increase or mitigate stream flashiness and (2) understand the areal extent of this influence throughout the watershed. As part of the first objective, five hypotheses were developed to examine the spatial configurations of land cover and their relationship with stream flashiness (

Table 3-2). Each hypothesis addressed a group of land cover classes, which were organized accordingly:

- Developed: Developed Open Space, Developed Low Intensity, Developed Medium Intensity, Developed High Intensity
- Natural, Forested: Deciduous Forest

- Natural, Non-Forested: Shrub/Scrub, Grassland/Herbaceous
- Wetlands: Woody Wetlands
- Agricultural: Pasture/Hay, Cropland

The notation to describe the variables included in each hypothesis was indicated by the abbreviation of the landscape metric and land cover class (
Table 3-2). For example, to indicate that the landscape metric, "patch density", was utilized to examine the "grassland/herbaceous" land cover class, the notation "PD.GH" was used.

Ordinary least squares regression was used to evaluate each hypothesis for all locations throughout the Blue River Watershed. One of the major challenges in utilizing landscape metrics to examine the influence of spatial configurations of land cover on environmental parameters is that many landscape metrics are highly correlated with one another (Brody et al., 2013; Jayakaran et al., 2016). High collinearity exists because landscape metrics "measure the same (or similar) construct being quantified" (Brody et al., 2013). A variety of statistical methods, including ordinary least squares regression (Brody et al., 2011; Kim and Park, 2016; Brody et al., 2013), partial least squares regression (Jayakaran et al., 2016) and principal component analysis (Almeida et al., 2016; Inkoom et al., 2018), have been used in innovative ways to avoid the collinearity issue. This research used ordinary least squares regression, following Brody et al. (2013), because the objective of this study was to isolate the effects of individual landscape patterns, such as aggregation or connectivity, on stream flashiness. However, following regression, each hypothesis was ranked using the Akaike Information Criterion (AIC) to provide an estimate of relative quality for each statistical model.

To address the second objective, the relationship between stream flashiness and each landscape metric/land cover class variable was individually evaluated using ordinary least squares regression at every USGS stream gauge. The intent of this approach was to understand the spatial extent at which flood mitigation services are influenced by configurations of land use/land cover. This approach also facilitated conclusions on the location of "usage areas" where beneficiaries have the opportunity to utilize flood mitigation services provided by the different configurations of LULC.

For this study, the Blue River Watershed was subdivided into ten sub-watersheds, where the outlet of each sub-watershed corresponded with a USGS stream gauge (Figure 3-2; Table 3-1). Only those land cover classes that were present in every sub-watershed throughout the entire Blue River Watershed were included in this study to simplify the comparison and analysis of results. Following this approach, the sub-watersheds upstream of USGS gauges 06893562 (Site ID 8) and 06893557 (Site ID 9) were excluded from landscape metric analysis since only four classes of land cover were present in these areas. The land use/land cover classes that were not incorporated in this research include barren land, evergreen forest, mixed forest, and emergent herbaceous wetlands.

Table 3-2. The hypotheses, and corresponding variables, to be tested in this research.

	Hypothesis	Variables Included
1	A percent increase in the percentage, density, connectivity, and fragmentation of developed land cover classes will increase stream flashiness	PLAND.DHI, PLAND.DMI, PLAND.DLI, PLAND.DOS, PD.DHI, PD.DMI, PD.DLI, PD.DOS, GYRATE.DHI, GYRATE.DMI, GYRATE.DLI, GYRATE.DOS, CLUMPY.DHI, CLUMPY.DMI, CLUMPY.DLI, CLUMPY.DOS
2	A percent decrease in the percentage, density, and connectivity and a percent increase in the fragmentation of natural (forested) land cover classes will increase stream flashiness	PLAND.DF, PD.DF, GYRATE.DF, CLUMPY.DF

3	A percent decrease in the percentage, density, and connectivity and a percent increase in the fragmentation of natural (non-forested) land cover classes will increase stream flashiness	PLAND.GH, PLAND.SS, PD.GH, PD.SS, GYRATE.GH, GYRATE.SS, CLUMPY.GH, CLUMPY.SS
4	A percent decrease in the percentage, density, and connectivity and a percent increase in the fragmentation of wetlands will increase stream flashiness	PLAND.WW, PD.WW, GYRATE.WW, CLUMPY.WW
5	A percent increase in percentage, density, connectivity, and fragmentation of agricultural land will increase stream flashiness	PLAND.CC, PLAND.PH, PD.CC, PD.PH, GYRATE.CC, GYRATE.PH, CLUMPY.CC, CLUMPY.PH

3.3 – Results and Discussion

3.3.1 General flashiness patterns

General patterns in stream flashiness were first examined to understand overall flashiness, and thus flash flooding behavior, throughout the study area. A significant, negative relationship ($p \leq 0.05$) was found between stream flashiness and the size of the contributing watershed (Figure 3-4; Table 3-3), which is consistent with previous results (e.g., Baker et al., 2004; Mogollón et al., 2016). Small watersheds tend to be flashier than larger watersheds (Baker et al., 2004; Mogollón et al., 2016), and therefore it is expected that stream flashiness would be greater in the headwaters of the Blue River Watershed than downstream towards its outlet.

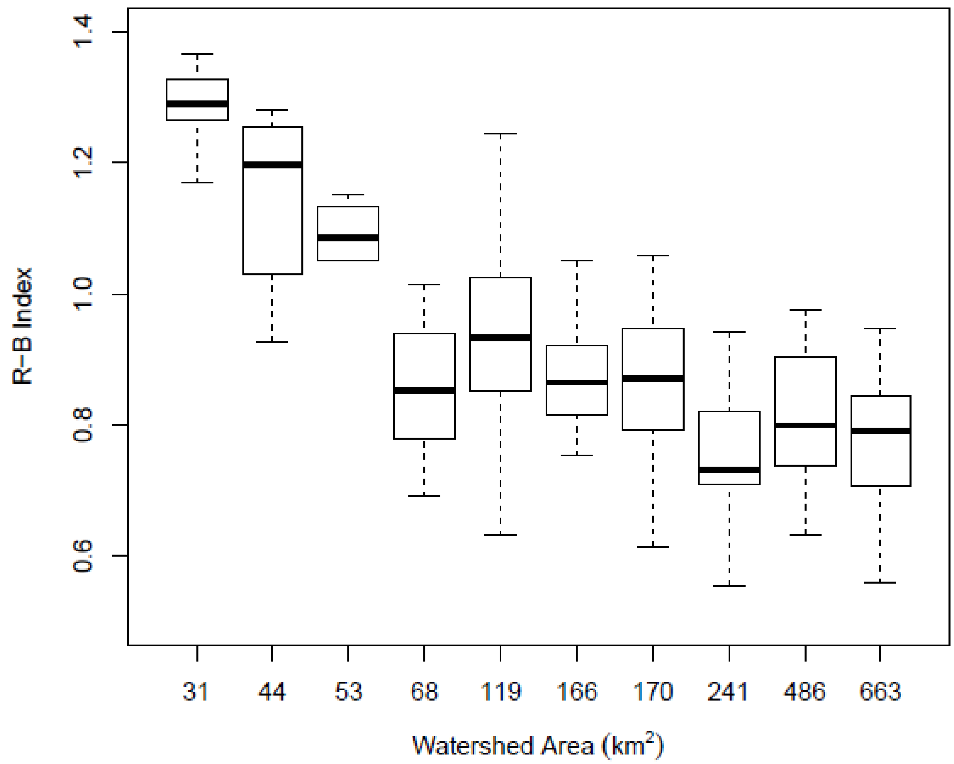

Figure 3-4. Relationship between contributing watershed area and annual stream flashiness. A significant, negative relationship is evident between the R-B Index and watershed area ($p \leq 0.05$).

Table 3-3. Variation in annual stream flashiness at each USGS gauge location throughout the study area. Stream flashiness decreases in magnitude as the size of the contributing watershed increases.

USGS Gauge	Watershed Area (km^2)	Number of observations	*Quantile* 0%	25%	50%	75%	100%
06893557	31	16	0.921	1.269	1.291	1.327	1.563
06893562	44	10	0.177	1.063	1.197	1.251	1.280
06893350	53	6	0.845	1.058	1.085	1.123	1.152
06893300	68	16	0.690	0.779	0.852	0.936	1.015
06893080	119	16	0.631	0.857	0.932	1.025	1.244
06893390	166	14	0.752	0.816	0.865	0.921	1.050
06893100	170	14	0.614	0.793	0.871	0.935	1.059
06893150	241	15	0.555	0.709	0.732	0.822	0.941
06893500	486	16	0.632	0.739	0.800	0.886	0.976
06893578	663	15	0.559	0.707	0.791	0.844	0.948

It is important to note, however, that the Blue River Watershed becomes increasingly impervious as one moves downstream through the watershed and the size of the contributing watershed increases. The majority of previous research has shown that urban streams are flashier than those in less developed areas (Baker et al., 2004; Coles et al., 2012; Jayakaran et al., 2016). However, recent research by Roodsari et al. (2017) reported that larger catchments with impervious coverage between 15-26% were hydrologically stable, while small catchments with impervious coverage that exceeded 12% demonstrated higher magnitude flows and greater flashiness. While the comparison between watersheds in this study is difficult due to the nested nature of the subwatersheds, it appears that the results follow those of Roodsari et al. (2017), where stream flashiness is higher in smaller watersheds though the percentage of impervious cover is less. This effect is further confounded by the considerable flood mitigation efforts that have been undertaken by the U.S. Army Corps of Engineers near the watershed outlet, which is the most heavily urbanized portion of the study area (Patti Banks Associates, 2007).

The R-B Index was calculated on a monthly time scale to assess typical flashiness patterns in months throughout the year. Examination of all USGS gauges as a group demonstrates a seasonal flashiness pattern, with low R-B Index values in the winter months and high R-B Index values in the summer (Figure 3-5), which likely indicates that stream flashiness is driven by precipitation patterns in this region. Analysis of monthly pattern behavior at individual USGS gauge locations reveals that the majority of locations adheres to this general seasonal pattern (e.g., Figure 3-6). However, one location (USGS Gauge 06893562) does not follow the general seasonal flashiness pattern (Figure 3-7), which suggests that other factors, such as urbanization, wield a stronger influence on stream flashiness than precipitation at this location.

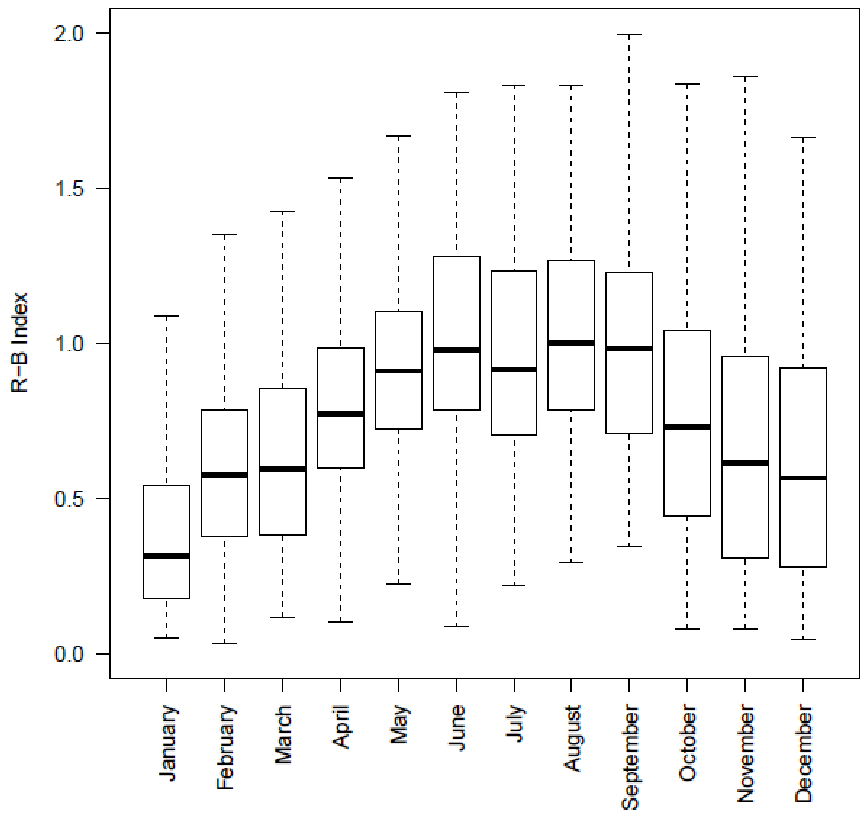

Figure 3-5. Monthly R-B Index values for all USGS gauges throughout the time period of the study.

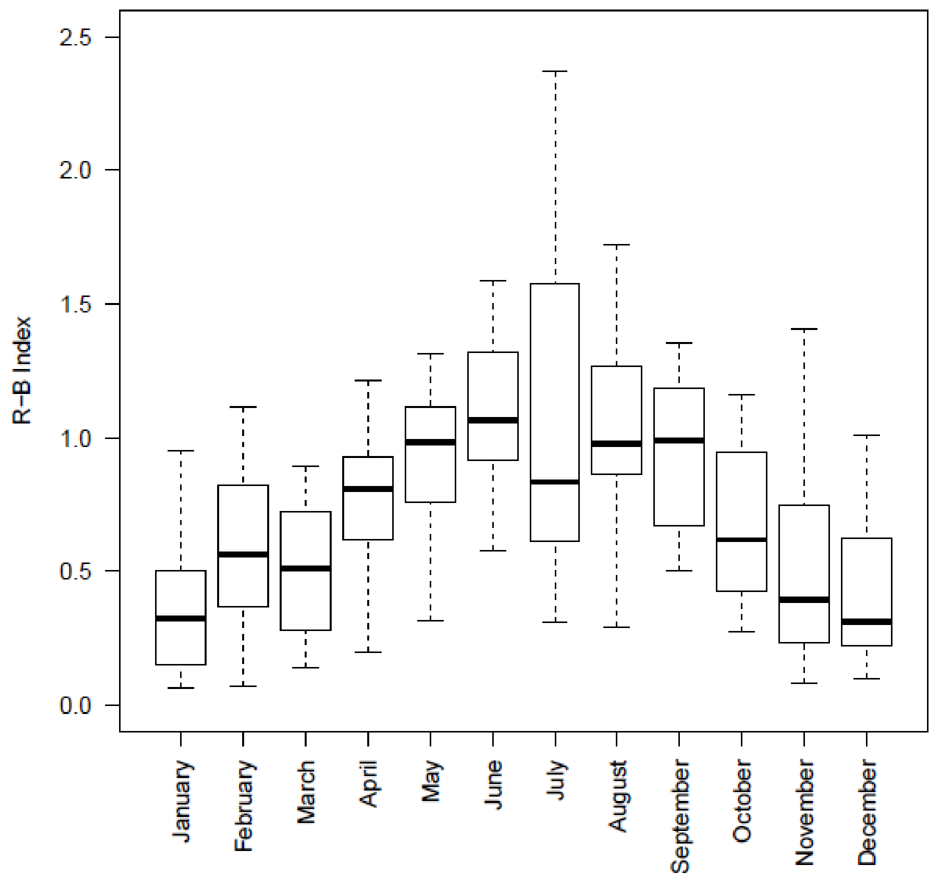

Figure 3-6. The monthly R-B Index values for USGS gauge 06893080, which exemplifies the typical seasonal pattern in stream flashiness across the study area.

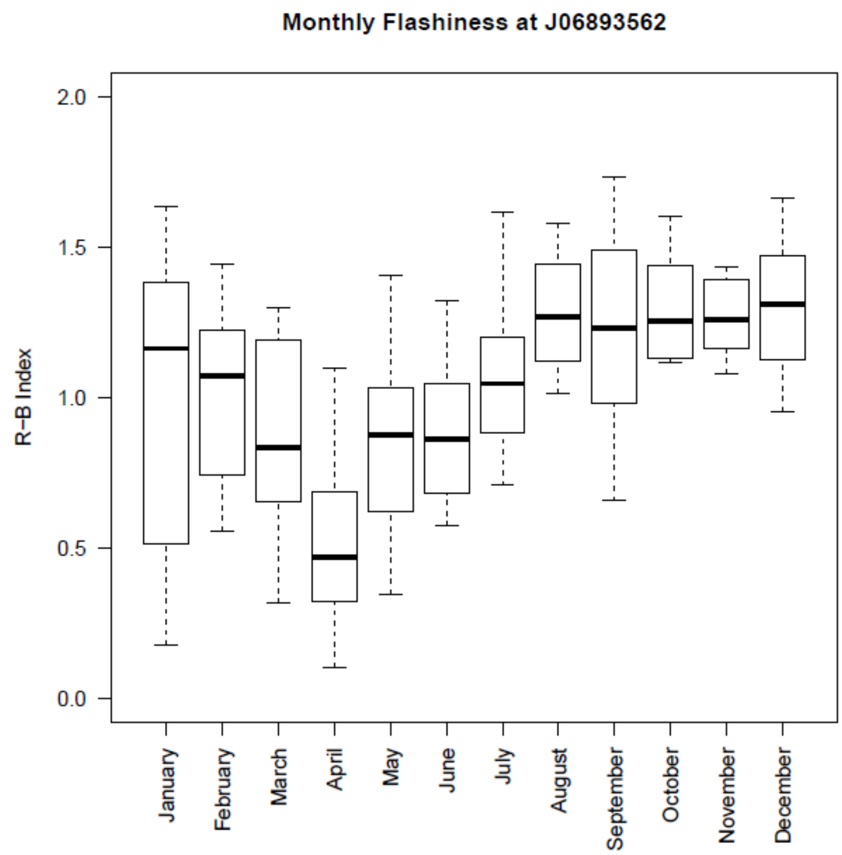

Figure 3-7. The monthly R-B Index values for USGS gauge 06893562. The deviation from the general seasonal flashiness pattern suggests that a factor other than precipitation is driving stream flashiness at this location.

3.3.2 Changes in landscape configuration

The spatial configuration of land cover in the Blue River Watershed was analyzed using a set of landscape metrics in 2001, 2006, and 2011. Results demonstrate an increase in the percentage and patch density for all of the developed land cover classes from 2001 to 2011 for the largest (and furthest downstream) sub-watershed in the Blue River Watershed (Table 3-4). This result indicates a steady increase in urbanization in the watershed during this time. The connectivity of developed patches increases for developed medium intensity and developed open space, but decreases for high intensity and low intensity patches. There are no notable changes in the aggregation of patches, demonstrated by the CLUMPY metric, for the developed group.

The most substantial declines in percentage of land cover from 2001 to 2011 are evident in the deciduous forest (-0.6%), cultivated crops (-2.1%), and pasture/hay (-2.5%) land cover classes (Table 3-4). Interestingly, neither the patch density nor the aggregation (CLUMPY) of these land cover classes demonstrate any notable change during this time. However, the elongation or connectivity of patches as demonstrated by the GYRATE metric does decline over this period for both the cultivated crops and pasture/hay classes.

Table 3-4. Landscape configuration for the sub-watershed upstream of 06893578.

Land	PLAND			PD			GYRATE			CLUMPY		
Cover	2001	2006	2011	2001	2006	2011	2001	2006	2011	2001	2006	2011
DHI	3.6	4.2	4.4	3.4	4.2	4.6	224	209	204	0.65	0.64	0.63
DMI	9.8	11.2	11.7	10.0	11.2	11.7	447	481	498	0.50	0.49	0.48
DLI	28.9	29.8	30.0	8.7	9.4	9.9	2683	2676	2391	0.55	0.53	0.53
DOS	19.4	20.1	20.8	15.7	16.5	16.4	305	304	316	0.56	0.55	0.55
DF	9.4	9.0	8.8	1.2	1.2	1.2	428	435	430	0.80	0.80	0.80
GH	1.2	1.1	1.2	0.5	0.5	0.5	115	115	117	0.68	0.68	0.68
SS	0.3	0.3	0.2	0.4	0.3	0.3	48	47	47	0.45	0.45	0.45
WW	0.4	0.4	0.4	0.3	0.3	0.3	135	136	138	0.58	0.58	0.58
CC	9.1	7.5	7.0	0.7	0.6	0.5	336	338	321	0.85	0.85	0.85
PH	17.0	15.4	14.5	0.9	0.9	0.9	480	441	433	0.84	0.85	0.84

Examination of one of the smaller sub-catchments, located in the headwaters of the Blue River Watershed, reveals similar changes in land use configuration when compared to the overall watershed (e.g., at gauge 06893578). Though the relative initial configuration of land use is different than that of the overall watershed (e.g., agricultural land cover classes are the largest percentage of land use in this area of the watershed), the land use trade-offs that occur from 2001 to 2011 were relatively similar (Table 3-5). The percentage of deciduous forest, cultivated crop, and pasture/hay land cover decreased while the percentage of developed land cover classes increased. However, the patch density and connectivity increases for all developed land cover classes in the headwaters, which is in contrast to the overall watershed where declines were evident in in the connectivity (GYRATE) metric of the high intensity and low intensity land cover classes. The connectivity of deciduous forest land cover increases, while it decreases for cultivated crops and pasture hay classes, which is consistent with the behavior of the overall watershed. However, there is relatively little change in the patch density or aggregation of the deciduous forest, cultivated crops, or pasture/hay land cover classes.

Table 3-5. Landscape configuration for the sub-watershed upstream of 06893080.

Land	PLAND			PD			GYRATE			CLUMPY		
Cover	2001	2006	2011	2001	2006	2011	2001	2006	2011	2001	2006	2011
DHI	0.1	0.3	0.4	0.4	0.6	0.9	44	47	54	0.58	0.58	0.58
DMI	1.1	2.1	2.6	2.1	3.0	3.9	116	132	119	0.45	0.48	0.47
DLI	6.9	8.2	9.2	7.7	8.3	9.4	187	236	236	0.48	0.48	0.46
DOS	8.4	10.7	12.7	8.4	9.4	9.3	244	279	296	0.51	0.54	0.55
DF	7.4	7.3	7.0	1.6	1.5	1.5	409	415	425	0.77	0.77	0.77
GH	0.8	0.8	0.8	0.3	0.3	0.3	103	103	106	0.72	0.72	0.72
SS	0.3	0.3	0.3	0.5	0.5	0.4	45	44	45	0.44	0.44	0.44
WW	0.2	0.2	0.1	0.3	0.2	0.2	42	41	39	0.50	0.48	0.49
CC	23.7	21.4	20.1	1.5	1.5	1.4	357	350	313	0.84	0.84	0.84
PH	49.3	47.0	44.9	1.3	1.4	1.5	610	538	533	0.80	0.80	0.80

3.3.3 Linking landscape patterns to stream flashiness

A set of five hypotheses were developed to examine spatial configurations of land cover throughout the Blue River Watershed and evaluate the influence on stream flashiness. Each hypothesis was ranked using the Akaike Information Criterion (AIC) to provide an estimate of the relative quality for each statistical model (Table 3-1). To account for the negative relationship between stream flashiness and the size of the contributing watershed, the RB Index was normalized by the size of the contributing watershed area at each USGS streamflow gauge.

Hypothesis 4, which examined correlations between spatial patterns of wetlands and stream flashiness, had the lowest AIC value (Table 3-6). This reveals that changes in the configuration of wetland cover, though a relatively small percentage of the overall land cover, is the best predictor to understand changes in stream flashiness, and thus the provision of flood mitigation services from the landscape, of the five hypotheses tested. Hypothesis 3, which examined the influence between spatial patterns of natural, non-forested land cover and stream flashiness, had the second lowest AIC value. This suggests that the spatial configuration of grassland/herbaceous and shrub/scrub land cover also predicts changes in stream flashiness fairly well, compared to the other five hypotheses that were tested.

Interestingly, the hypothesis that examined the relationship between developed land cover classes and stream flashiness (hypothesis 1) had the highest AIC value (Table 3-6). This indicates that the spatial configuration of developed land cover classes are a relatively poor predictor of changes in stream flashiness, and thus the provision of flood mitigation services, compared to the other hypotheses tested. Hydrology literature often directly attributes changes in the streamflow regime to changes in the configuration of impervious cover, which is a characteristic feature of developed land cover classes. However, this result suggests that this conclusion fails to understand the complex biophysical interactions of the entire system. Our result suggests that it is the loss of the ecosystem function (and thus, the loss of ecosystem service) that is provided by natural land cover classes (e.g., infiltration, detention, and storage), not the introduction of impervious land cover, that caused the observed changes to the streamflow regime.

Table 3-6. The Akaike Information Criterion (AIC) for each hypothesis.

	Hypothesis	AIC
1	A percent increase in the percentage, density, connectivity, and fragmentation of developed land cover classes will increase stream flashiness	8214.9

2	A percent decrease in the percentage, density, and connectivity and a percent increase in the fragmentation of natural (forested) land cover classes will increase stream flashiness	-160253.8
3	A percent decrease in the percentage, density, and connectivity and a percent increase in the fragmentation of natural (non-forested) land cover classes will increase stream flashiness	-161270.6
4	A percent decrease in the percentage, density, and connectivity and a percent increase in the fragmentation of wetlands will increase stream flashiness	-161446.9
5	A percent increase in percentage, density, connectivity, and fragmentation of agricultural land will increase stream flashiness	-160844.3

Examination of the results from the ordinary least squares regression provide further support that declines in natural land cover, as opposed to just increases in impervious area in and of itself, drive streamflow flashiness (Table 3-7). None of the factors tested in hypothesis one are significant, with the exception of the PRISM rainfall, which supports the theory that changes in the spatial configuration of developed land cover classes are not directly causing changes to the streamflow regime in terms of stream flashiness. However, it is important to note here that the authors are not arguing that increases in impervious cover are essentially negligible on the riparian ecosystem. There are other ways that increases in impervious cover may cause detrimental effects on the riparian ecosystem, including changes in temperature, water quality, etc. We merely present the argument that it is the tradeoff that occurs between natural land cover classes and impervious cover, rather than the existence of impervious cover alone, that manifests in changes to the streamflow regime in terms of stream flashiness.

Analysis of hypotheses two through five, which examine the relationship between the configuration of groups of natural land cover and stream flashiness, shed more light on how changes in spatial patterns of land cover influence the provision of flood mitigation ecosystem services. Results from the second hypothesis, which postulated that decreases in the percentage, density, connectivity, and aggregation of natural, forested land cover increased stream flashiness, revealed that declines in the percentage of forested cover, coupled with increases in the patch density, leads to increases in flashiness (Table 3-7). This suggests that a large percentage of forest cover distributed across the landscape in low-density patches may be more effective in minimizing flash flooding effects in the riparian corridor.

The third hypothesis theorized that declines in the percentage, density, connectivity, and aggregation of natural, non-forested land cover would result in increases in stream flashiness. Examination of the results, however, reveal a somewhat different picture (Table 3-7). Declines in the percentage and connectivity of grassland/herbaceous land cover, coupled with increases in the patch density, predict significant increases in stream flashiness. This suggests that, in order to minimize stream flashiness, patches of this land cover should be distributed in a highly connected, low-density arrangement covering as much of the landscape as possible. The percentage of shrub/scrub classes, however, should be minimized to decrease stream flashiness, though those patches that do exist should be arranged in a high density, high connectivity, and aggregated configuration.

Hypothesis 4, which evaluated the relationship between the spatial configuration of wetlands and stream flashiness, also reveals different behavior than was theorized (Table 3-7). The percentage of wetland cover does not appear to significantly influence stream flashiness, which is likely because the overall percentage of wetland cover in the study watershed did not change substantially throughout the study period. However, results reveal that dense and connected wetland patches that are distributed in a disaggregated manner across the landscape will significantly influence (and minimize) stream flashiness in the riparian corridor. The magnitude of these results (Table **3-7**) suggests that even slight changes in the spatial configuration of wetlands, even though they are a small percentage of the overall watershed land cover (Table 3-4; Table 3-5), can significantly influence the behavior of the streamflow regime.

Finally, hypothesis 5 examined the relationship between agricultural land cover classes and stream flashiness throughout the watershed. Results reveal that both decreases in cultivated crops and pasture/hay classes lead to increases in stream flashiness (Table 3-7). Furthermore, as the density and aggregation of patches of cropland increases, and as the aggregation of pasture/hay increases, stream flashiness will increase. This suggests that cropland should be distributed in a low-density, disaggregated manner across the landscape to minimize detrimental effects on the streamflow regime. While the GYRATE (connectivity) metric was also significant, its magnitude was low, suggesting a low overall impact on the influence of stream flashiness behavior.

Table 3-7. Results from ordinary least squares regression on each hypothesis.

Metric	Hypothesis 1	Hypothesis 2	Hypothesis 3	Hypothesis 4	Hypothesis 5
PRISM	0.0015***	0.0004***	0.0004***	0.0004***	0.0004***
PLAND.DHI	0.0206	-	-	-	-
PLAND.DMI	-0.0148	-	-	-	-
PLAND.DLI	0.0000	-	-	-	-
PLAND.DOS	0.0002	-	-	-	-
PD.DHI	0.0043	-	-	-	-
PD.DMI	0.0095	-	-	-	-
PD.DLI	-0.0054	-	-	-	-
PD.DOS	-0.0026	-	-	-	-
GYRATE.DHI	0.0002	-	-	-	-
GYRATE.DMI	-0.0001	-	-	-	-
GYRATE.DLI	-0.0000	-	-	-	-
GYRATE.DOS	0.0001	-	-	-	-
CLUMPY.DHI	-0.0818	-	-	-	-
CLUMPY.DMI	0.2659	-	-	-	-
CLUMPY.DLI	-0.2013	-	-	-	-
CLUMPY.DOS	-0.1228	-	-	-	-
PLAND.DF	-	-0.0032***	-	-	-
PD.DF	-	0.0101***	-	-	-
GYRATE.DF	-	0.0000*	-	-	-
CLUMPY.DF	-	-0.0403	-	-	-
PLAND.GH	-	-	-0.0445***	-	-

PLAND.SS	-	-	0.1241**	-	-
PD.GH	-	-	0.1027***	-	-
PD.SS	-	-	-0.1178***	-	-
GYRATE.GH	-	-	-0.0006***	-	-
GYRATE.SS	-	-	-0.0042***	-	-
CLUMPY.GH	-	-	-0.0309	-	-
CLUMPY.SS	-	-	-0.0378***	-	-
PLAND.WW	-	-	-	-0.0120	-
PD.WW	-	-	-	-0.0285***	-
GYRATE.WW	-	-	-	-0.0001***	-
CLUMPY.WW	-	-	-	0.0583***	-
PLAND.CC	-	-	-	-	-0.0047***
PLAND.PH	-	-	-	-	-0.0011***
PD.CC	-	-	-	-	0.0975***
PD.PH	-	-	-	-	0.0016
GYRATE.CC	-	-	-	-	-0.0001***
GYRATE.PH	-	-	-	-	0.0001***
CLUMPY.CC	-	-	-	-	0.5928***
CLUMPY.PH	-	-	-	-	-0.4258***

Ordinary least squares regression was used to individually examine the relationship between stream flashiness and each landscape metric/land cover class variable at every sub-watershed within the Blue River Watershed to understand the areal extent of the influence of changes in land cover configuration. Overall, the location in the watershed where beneficiaries have the potential to significantly benefit from (or be impacted by) upstream configurations in land cover include the area immediately upstream of gauge 06893150 (Figure 3-8a), though the area immediately upstream of gauge 06893578 is trending towards significance. This suggests that changes in the configuration of land cover in the watershed headwaters significantly influence downstream stream flashiness through the provision of flood mitigation services at a minimum sub-watershed area of 241 km^2. Interestingly, sub-watershed 06803500, located between 06893150 and 06893578, is not significant, which we theorize is due to biophysical effects that are not captured by this study at the confluence of the Indian and Blue Rivers, where the Blue River switches from a fourth order stream to a fifth order (Missouri Department of Conservation, 2018). It is likely that this effect, combined with implementation of flood control infrastructure by the Army Corps of Engineers (Patti Banks Associates, 2007), influences the spatial influence of upstream land cover patterns.

Interestingly, the areal spatial extent of influence of both the GYRATE (Figure 3-8d) and CLUMPY (Figure 3-8e) metrics extends further than the PLAND (Figure 3-8b) and PD (Figure 3-8c) metrics, which perform similarly to the overall watershed. Sub-watersheds 06893150 and 06893578 are significant for both metrics, indicating that upstream configurations of patch connectivity and aggregation can enable the delivery of flood mitigation services over a larger spatial extent.

Along this line of thinking, the areal spatial extent of natural, non-forested land cover and wetland land cover demonstrate comparable behavior. The spatial extent of influence of natural, non-forested land cover extends from sub-watershed 06893150 through 06893578 (Figure 3-8h), which reveals the potential for configurations of natural, non-forested land cover to enhance natural ecosystem function and enable the provision of flood mitigation services across the watershed area. Wetland land cover performs similarly, influencing stream flashiness in sub-watershed 06893150 and 06893578.

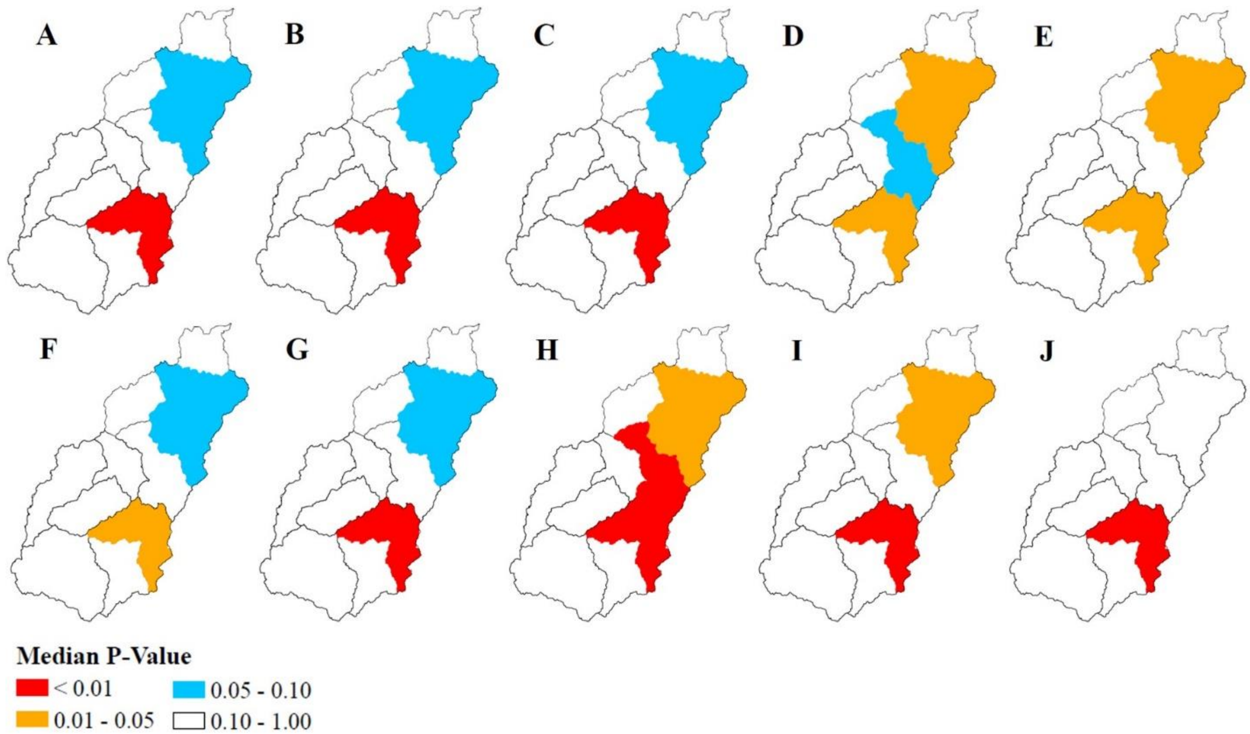

Figure 3-8. Service usage areas in the watershed where beneficiaries can use the flood mitigation services provided by upstream configurations of land cover. Colored sub-watersheds represent the level of significance as represented by the median p-value of all landscape metrics and/or land cover groups that were examined. Each map shows the (A) overall influence of all metrics and land cover classes together, (B) influence of the PLAND metric, (C) influence of the PD metric, (D) influence of the GYRATE metric, (E) influence of the CLUMPY metric, (F) influence of developed land cover classes, (G) influence of forested land cover classes, (H) influence of natural, non-forested land cover classes, (I) influence of wetland land cover classes, and (J) influence of agricultural land cover classes.

3.4 – Conclusion

The intent of this research was to examine the relationship between spatial patterns of land cover and flooding to understand how configurations of land cover influence the provision of ecosystem services across spatial scales. The two main objectives of this study were to (1) identify the spatial configurations of land cover that significantly influence stream flashiness and (2) understand the areal extent of this influence throughout the watershed.

Results revealed that spatial configurations of wetland and natural, non-forested land cover were the best predictors of stream flashiness of the five hypotheses that were tested. Management strategies that utilize (1) a large percentage of forest cover distributed across the landscape in low-density patches and (2) dense and connected wetland patches distributed in a disaggregated manner across the landscape may be best at minimizing flash flooding effects in the riparian corridor. Interestingly, the spatial configuration of developed land cover classes were a relatively poor predictor of changes in stream flashiness compared to the other hypotheses tested, which suggests that it is the loss of the ecosystem function (and thus, the loss of ecosystem service) that causes the observed changes to the streamflow regime.

On average, the location in the watershed where beneficiaries have the potential to significantly benefit from (or be impacted by) upstream configurations in land cover included the area immediately upstream of gauge 06893150 (Figure 3-8a). It is evident that changes in the configuration of land cover in the watershed headwaters significantly influence downstream stream flashiness through the provision of flood mitigation services at a minimum sub-watershed area of 241 km^2. At larger sub-watershed areas, however, the magnitude of this influence may be muted by the change in stream order and the implementation of flood control infrastructure. Further examination of spatial effects revealed that upstream configurations of patch connectivity and aggregation can enable the delivery of flood mitigation services over a larger spatial extent, while configurations of natural, non-forested land cover and wetlands also enhance natural ecosystem function and enable the provision of flood mitigation services throughout the watershed extent.

The findings of this research have the potential to be highly beneficial for watershed managers and regional planners who aim to create urban development strategies that utilize strategic configurations of land cover to minimize flooding impacts. This research demonstrates that spatial configurations of land cover significantly influence the streamflow regime through measurement of stream flashiness and demonstrate the potential of land use patterns to provide flood mitigation ecosystem services throughout the watershed extent. Furthermore, outcomes from this research advances the current understand of how spatial configurations of land cover interact and influence the provision of flood mitigation services over the landscape extent.

Of course, there were several limitations to this study. A measure of stream flashiness (as provided by the RB Index) was the only metric used to examine changes in the streamflow regime. Future examination of this topic would benefit from work that expands upon the research presented here to evaluate other parts of the streamflow regime that relate to flood events, such as the peak flow and flood volume. Furthermore, future research would benefit from understanding how the spatial configuration of physical environmental characteristics, such as slope or soil texture, influence the streamflow regime and flood events.

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Chapter 4 - Hydrologic model development for watershed-scale research applications

This chapter provides an overview of the development of a watershed-scale hydrologic model using PCSWMM software. This model will be utilized in future research activities, beyond this dissertation, to examine the vulnerability of urban infrastructure to flooding and to evaluate the influence of land management practices on the streamflow regime.

4.1 - Introduction

A model is a series of equations that, together, represent some aspect of the physical world (Zeckoski et al., 2015). The field of hydrology utilizes models to represent the "complex physical, chemical, and biological processes governing the hydrology" (Moriasi et al., 2015) of an area. These models have the ability to simulate the movement of water and pollutants across a landscape (James et al., 2010) and can be useful to evaluate the impacts of changes in land use, watershed management, and climate on water resources (Moriasi et al., 2015).

Hydrologic models have been widely used to evaluate watershed condition (e.g., Ahiablame and Shakya, 2016; McDonough et al., 2017). These models can be useful tools to inform all aspects of water resources management, from the planning and design of infrastructure to policy and regulatory decisions (James et al., 2010; Moriasi et al., 2015). It is important to note, however, that regardless of the level of detail in a model, a model is "a simplification of the natural system in which some processes are characterized by rates and thresholds whose values are unknown," (Moriasi et al., 2015). There is always some level of error and uncertainty associated with a model that aims to represent some aspect of the physical world (Farmer and Vogel, 2016).

We developed a watershed-scale, hydrologic model using PCSWMM software. PCSWMM is a process-based hydrologic modeling software (McDonough et al., 2017) that was developed by Computational Hydraulics International, Inc. This watershed-scale model was developed to simulate water quantity impacts of land use/land cover change in the Blue River Watershed. The following chapter provides an overview of the model development, including calibration and validation results.

4.2 - Methods

4.2.1 Study Area

The Blue River Watershed (HUC #1030010101) is the largest watershed within the Kansas City metropolitan area. The 1127-km^2 watershed crosses the state border between Kansas and Missouri, and encompasses portions of Johnson County in Kansas, as well as Jackson County and Cass County in Missouri (Figure 4-1). The Blue River, which is the river for which the watershed was named, flows northeast from the headwaters in Johnson County where it joins the Missouri River on the east side of Kansas City. The main tributaries to the Blue River are Wolf Creek, Coffee Creek, Brush Creek, Indian Creek, and Tomahawk Creek. The Blue River Watershed is part of the Missouri River Basin in the central Great Plains region of the United States.

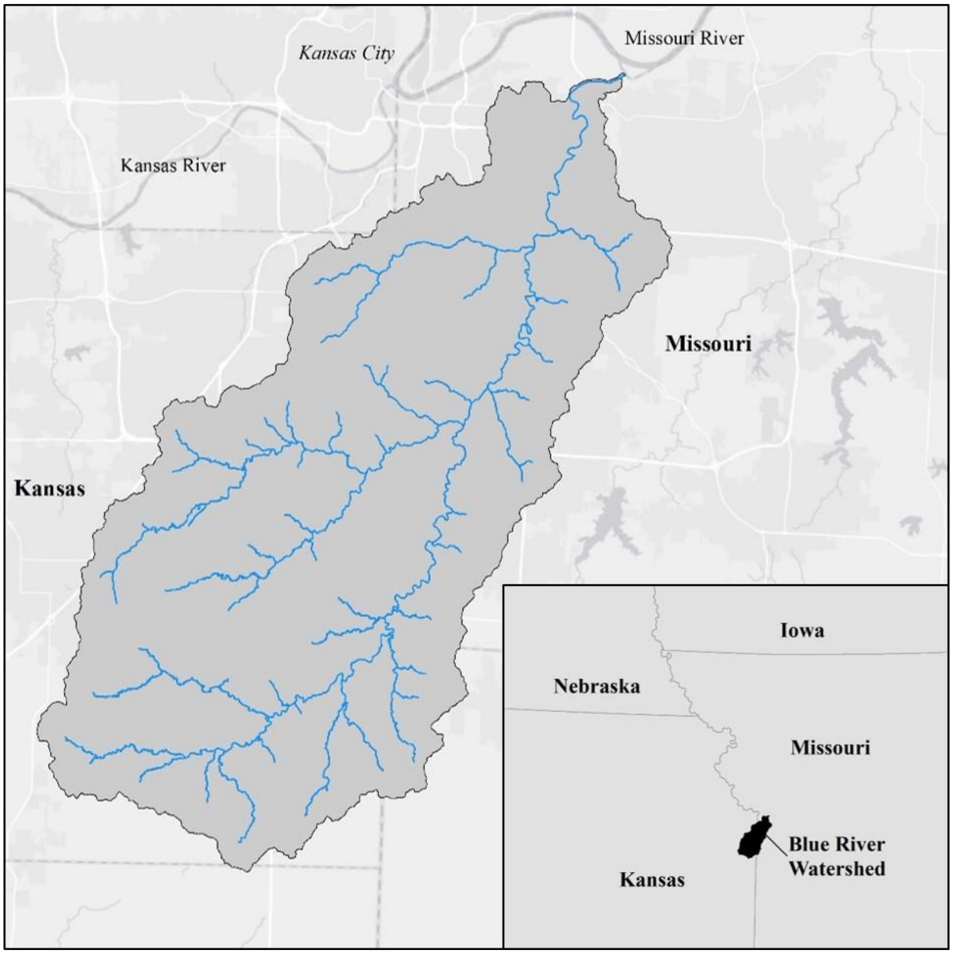

Figure 4-1. Location of the Blue River Watershed.

The Blue River Watershed is located in the Central Irregular Plains ecoregion, which includes the Wooded Osage Plains, Osage Cuestas, Rolling Loess Prairies, and Missouri Alluvial Plains (USGS, 2015). The topography is characterized as gently rolling to moderately hilly (USGS, 2015). The majority of the watershed has been developed, although a large rural-urban gradient remains (Figure 4-2). The headwaters of the watershed, in Johnson County, consists primarily of agricultural land (e.g., pasture/hay and cultivated crops) compared to the downstream watershed, which has been highly developed.

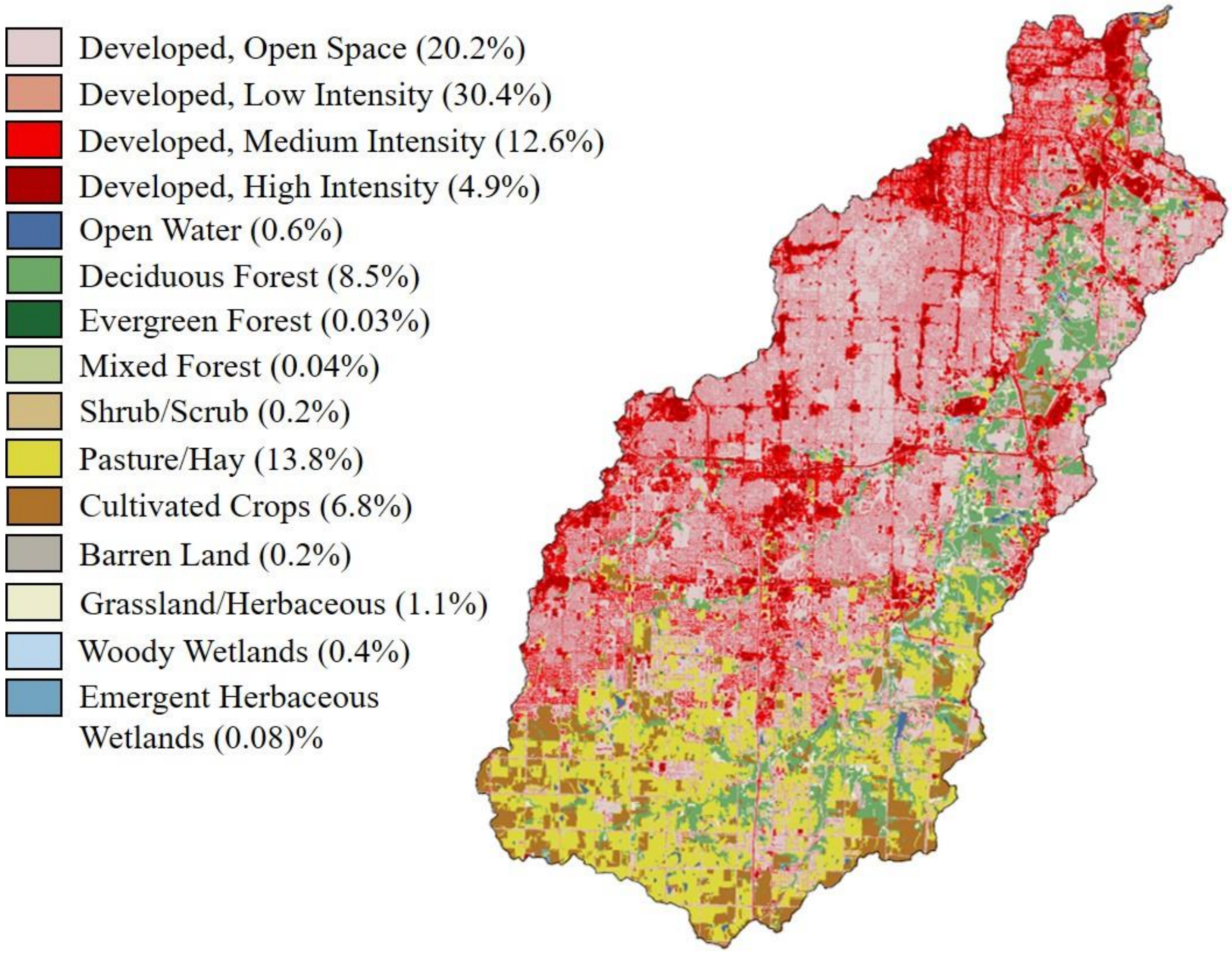

Figure 4-2. Land use/land cover in the Blue River Watershed from the 2011 National Land Cover Dataset (Homer et al., 2015).

The Kansas City metropolitan area has experienced severe flood events many times throughout the past, including, most notably, in 1951, 1961, 1977, 1984, 1990, 1998, and 2010 (USGS, 2015). These flood events have resulted in the loss of life and significant damages to infrastructure (USGS, 2015; Mid-America Regional Council, 2015). “Since 1993, the [Kansas City] region has suffered a cumulative total of one injury, 14 deaths, $49 million in crop damages, and $111.6 million in property damage as a result of floods,” (Mid-America Regional Council, 2015).

The most severe damages from each of these Kansas City flood events have been within the Blue River Watershed (USGS, 2015). Locations along the Blue River, as well as the Indian Creek and Brush Creek tributaries, have been pinpointed as the most affected (USGS, 2015; Mid-America Regional Council, 2015). To address many of the flooding issues in the lower part of the watershed, an estimated $250 million was spent (as of 2003) to extensively modify portions of the lower Blue River for flood control purposes by the U.S. Army Corps of Engineers and the City of Kansas City, Missouri (Patti Banks Associates, 2007). However, flood control still remains a challenge for many areas of the watershed.

Population and urbanization within the Blue River Watershed are projected to exponentially increase in coming decades, which will increase environmental pressure on the Blue River corridor and its tributaries. The Mid-America Regional Council predicted a 40% population growth in Johnson County alone by 2020 (Patti Banks Associates, 2007). Furthermore, ;and-use projections estimate that the headwaters of the Blue River Watershed will exceed 25% imperviousness in twenty years (Patti Banks Associates, 2007).

4.2.2 Model Development

PCSWMM, a process-based hydrologic modeling software (McDonough et al., 2017), was utilized to develop a model of Blue River Watershed (version 7.1.2480). PCSWMM is a physically based, semi-lumped, deterministic model (Zeckoski et al., 2015) that has the ability to simulate environmental conditions across a range of spatial scales. The PCSWMM software enables watershed modeling in both urban and rural areas through the full integration of the Storm Water Management Model (SWMM, version 5.0.013-5.1.012) from the United States Environmental Protection Agency coupled with Geographic Information Systems (GIS; Rossman, 2008; James et al., 2010; Ahiablame and Shakya, 2016). PCSWMM "contains a wide variety of hydrologic and hydraulic capabilities such as flow routing, snow accumulation and melting, evaporation of standing surface water, rainfall interception in depression storage, flow routing through closed and open conduit networks of unlimited size, two dimensional flood routing, and modeling of backwater, surcharging, reverse flow, and surface ponding," (Ahiablame and Shakya, 2016). The PCSWMM software also has the capability to estimate pollutant loading for water quality applications, simulate low-impact development/green infrastructure, and conduct sensitivity, calibration, and error analyses (Rossman, 2008; James et al., 2010). Furthermore, PCSWMM has been widely used for a variety of modeling applications in urban areas (e.g., Ahiablame and Shakya, 2016; McDonough et al., 2017).

Several geospatial datasets are necessary to build a complete hydrologic model in PCSWMM. A digital elevation model (DEM) with 3-meter spatial resolution was obtained to describe the watershed topography (USGS, 2009); where "no data" pixels within the DEM raster were filled using the Raster Calculator tool within ArcGIS (ESRI, 2011). The National Hydrography Dataset (USGS, 2001) stream network was utilized alongside the DEM within PCSWMM's Watershed Delineation Tool (CHI, 2017) to automatically delineate the watershed area and create subcatchments according to a target discretization level of 500 acres. A total of 375 subcatchments were created in this process, along with the innumerable conduits and junctions, to represent the natural hydrology of the watershed.

The 2011 National Land Cover Dataset (NLCD) was used to describe land cover throughout the watershed at a 30-km resolution (Homer et al., 2015). PCSWMM's Area Weighting Tool (CHI, 2017) was employed to determine the following model attributes for each subcatchment from the 2011 NLCD layer (Table 4-1): percent impervious (%IMPERV), Manning's roughness impervious (NIMPERV), Manning's roughness pervious (NPERV), depression storage impervious (DSIMPERV), and depression storage pervious (DSPERV). Soil survey spatial and tabular data (SSURGO 2.2) was acquired to describe soil hydraulic properties throughout the watershed (USDA-NRCS, 2016). The Area Weighting Tool was again applied using SSURGO 2.2 data to determine values of conductivity, suction head, and initial deficit (Table 4-2) for each subcatchment (James et al., 2010; USDA-NRCS, 2016).

Table 4-1. Land use-derived model properties (James et al., 2010).

Land Use/ Land Cover	Gridcode	%IMPERV	DSPERV (in)	DSIMPERV (in)	NPERV	NIMPERV
Open Water	11	0	0	0	0	0
Perennial Ice/Snow	12	0	0	0	0	0
Developed, Open Space	21	10	0.1	0.05	0.034	0.012
Developed, Low Intensity	22	30	0.1	0.05	0.034	0.012
Developed, Medium Intensity	23	60	0.1	0.05	0.034	0.012
Developed, High Intensity	24	90	0.1	0.05	0.034	0.012
Barren Land	31	0	0.1	0	0.05	0
Deciduous Forest	41	0	0.3	0	0.40	0
Evergreen Forest	42	0	0.3	0	0.40	0
Mixed Forest	43	0	0.3	0	0.40	0
Dwarf Scrub	51	0	0.2	0	0.24	0
Shrub/Scrub	52	0	0.2	0	0.24	0
Grassland/ Herbaceous	71	0	0.2	0	0.24	0
Sedge/ Herbaceous	72	0	0.2	0	0.24	0
Lichens	73	0	0.2	0	0.15	0
Moss	74	0	0.2	0	0.15	0

Pasture/Hay	81	0	0.2	0	0.13	0
Cultivated Crops	82	0	0.2	0	0.17	0
Woody Wetlands	90	0	0.3	0	0.40	0
Emergent Herbaceous Wetlands	95	0	0.3	0	0.15	0

Table 4-2. Soil hydraulic properties by soil type used in the development of the model (James et al., 2010).

Soil Type	Suction Head (in)	Conductivity (in/hr)	Initial Deficit (frac.)
Sand	1.95	4.74	0.417
Loamy Sand	2.41	1.18	0.401
Sandy Loam	4.33	0.43	0.412
Loam	3.5	0.13	0.434
Silt Loam	6.57	0.26	0.486
Sandy Clay Loam	8.6	0.06	0.33
Clay Loam	8.22	0.04	0.309
Silty Clay Loam	10.75	0.04	0.432
Sandy Clay	9.41	0.02	0.321
Silty Clay	11.5	0.02	0.423
Clay	12.45	0.01	0.385

The slope (%), area (acres), and width (ft) of each individual subcatchment were derived from the DEM layer in the delineation process. Subarea routing for all subcatchments was "PERVIOUS", with the Zero Imperv (%) and Percent Routed (%) characteristics initially set at 50 and 25, respectively. The geographical cross-section of each conduit, or stream segment, within the model was determined by utilizing the DEM layer with the Transect Creator tool in PCSWMM (CHI, 2017). The Manning's Roughness coefficient (Manning's N) for each stream segment and adjacent stream bank was assigned using visual imagery of each stream section and land use/land cover data (Table 4-3).

Table 4-3. Manning's N values for each stream segment (James et al., 2010; Huffman et al., 2011).

Land Cover	Manning's N
Streambank	
Bermuda Grass, short	0.034
Impervious (Concrete, Asphalt)	0.015
Wooded	0.40
Stream Channel	
Natural channel, fairly regular	0.032
Natural channel, irregular with pools	0.05
Lined Channel	0.012

The Green-Ampt equation (Equation 4-1), which is an empirical equation used to estimate infiltration, was used as the infiltration model. The Green-Ampt equation assumes "vertical flow, uniform initial water content, and uniform soil hydraulic conductivity" (Huffman et al., 2011).

$$F = K_e t + S_{avg} M \ln[1 + \frac{F}{S_{avg} M}] \qquad \text{(Equation 4-1)}$$

The effective hydraulic conductivity (K_e), time (t), average matric suction at the wetting front (S_{avg}), and fillable porosity (M) are used as inputs to calculate the cumulative infiltration depth at time t (F; Huffman et al., 2011).

The Hazen-Williams equation (Equation 4-2), which estimates friction or head loss through a pipe, was assigned as the force main equation in the model. The Hazen-Williams equation is defined as;

$$H_f = \frac{1.21X10^{10} L(\frac{q}{C})^{1.852}}{D^{4.87}} \qquad \text{(Equation 4-2)}$$

where pipe length (m), discharge (q), pipe roughness coefficient (C), and inside pipe diameter (D) are used to calculate the friction loss in the pipe (H_f; Huffman et al., 2011).

Dynamic wave routing, which solves the complete one-dimensional Saint-Venant flow equations, was chosen as the routing method for the model. The Saint-Venant flow equations calculate the flow within an individual conduit according to the continuity (Equation 4-3) and momentum (Equation 4-4) equations;

$$\frac{\partial A}{\partial t} + \frac{\partial Q}{\partial x} = 0 \qquad \text{(Equation 4-3)}$$

$$\frac{\partial Q}{\partial t} + \frac{\partial (\frac{Q^2}{A})}{\partial x} + gA\frac{\partial H}{\partial x} + gAS_f + gAh_L = 0 \qquad \text{(Equation 4-4)}$$

where distance (x), time (t), cross-sectional area (A), flow rate (Q), hydraulic head (H), friction slope (S_f), local energy loss per unit length of the conduit (h_L), and acceleration due to gravity (g) are the input parameters (James et al., 2010). Dynamic wave routing is considered the most "theoretically accurate" (James et al., 2010) routing method as it can account for channel storage, backwater flow, entrance/exit losses, flow reversal, and pressurized flow.

4.2.3 Climatology

Observed, hourly precipitation from three locations (Table 4-4) throughout the Blue River Watershed were obtained from the National Oceanic and Atmospheric Administration (NOAA) Local Climatological Dataset (LCD). Each observed dataset was screened for errors and flags. Any trace amount of precipitation denoted with a "T", which indicates a rainfall amount too small to measure (typically <0.005 inches), during the period of record were assumed to be zero. Time periods that were blank (e.g., unreported data) or tagged as missing were also assumed to be zero. Any data denoted with an "s" to designate a "suspect value" was assumed to be the amount written.

Table 4-4. Precipitation stations from NOAA LCD in the Blue River Watershed.

Name	Network ID	Latitude	Longitude	Period of Record
Olathe Johnson County Executive Airport, KS US	WBAN: 03967	38.85º	-94.73917º	1/1/2006 – Present

Kansas City Downtown Airport, MO US	WBAN: 13988	39.1208º	-94.5969º	1/1/1957 – Present
Lee's Summit Municipal Airport, MO US	WBAN: 53879	38.95972º	-94.37139º	1/1/2006 - Present

Evaporation data from the Kansas City area were used to calculate average, monthly evaporation in the PCSWMM model (Table 4-5). The average, monthly pan evaporation for the Kansas City area (Table II; NOAA, 1982a) was multiplied by a coefficient of 74% (Map 4; NOAA, 1984b) to convert Class A pan evaporation to free water surface evaporation. Evaporation from the free water surface was used as the average, monthly evaporation rate in the model.

Table 4-5. Average monthly evaporation for Kansas City, Missouri.

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Average pan evaporation (in/day)	1.37	1.83	3.47	5.45	7.34	7.94	8.84	8.09	5.69	4.47	2.39	1.56
Average free water surface evaporation (in/day)	1.01	1.35	2.57	4.03	5.43	5.88	6.54	5.99	4.21	3.31	1.77	1.15

4.2.4 Streamflow

Streamflow data was obtained from ten USGS gauge stations located throughout the Blue River Watershed (Table 4-6; Figure 4-3). Average daily streamflow data were obtained for the years 2001 through 2016, though the temporal availability of data between stations varied in this time period.

Table 4-6. USGS stream gauge stations in the Blue River Watershed.

Site ID	Station Name	Station Number	Latitude	Longitude	Availability
1	Blue R NR Stanley, KS	06893080	38°48'45"	94°40'32"	9/20/1974-Present
2	Kenneth Rd., Overland Park, KS	06893100	38°50'32"	94°36'44"	4/16/2003-Present
3	Blue River at Blue Ridge Blvd Ext in KC, MO	06893150	38°53'21.9"	94°34'50.4"	6/1/2002-Present
4	Blue River at Kansas City, MO	06893500	38°57'25.2"	94°33'32.0"	5/1/1939-Present
5	Tomahawk C NR Overland Park, KS	06893350	38°54'22"	94°38'24"	9/20/1974-Present
6	Indian C at Overland Park, KS	06893300	38°56'26"	94°40'16"	3/7/1963-Present
7	Indian C at State Line Rd., Leawood, KS	06893390	38°56'18"	94°36'28"	4/22/2003-Present
8	Brush Creek at Rockhill Road in Kansas City, MO	06893562	39°02'21.3"	94°34'43.4"	7/30/1998-Present
9	Brush Creek at Ward Parkway in Kansas City, MO	06893557	39°01'59.1"	94°36'19.4"	7/15/1998-Present
10	Blue River at Stadium Drive in Kansas City, MO	06893578	39°03'30"	94°30'42"	7/1/2002-Present

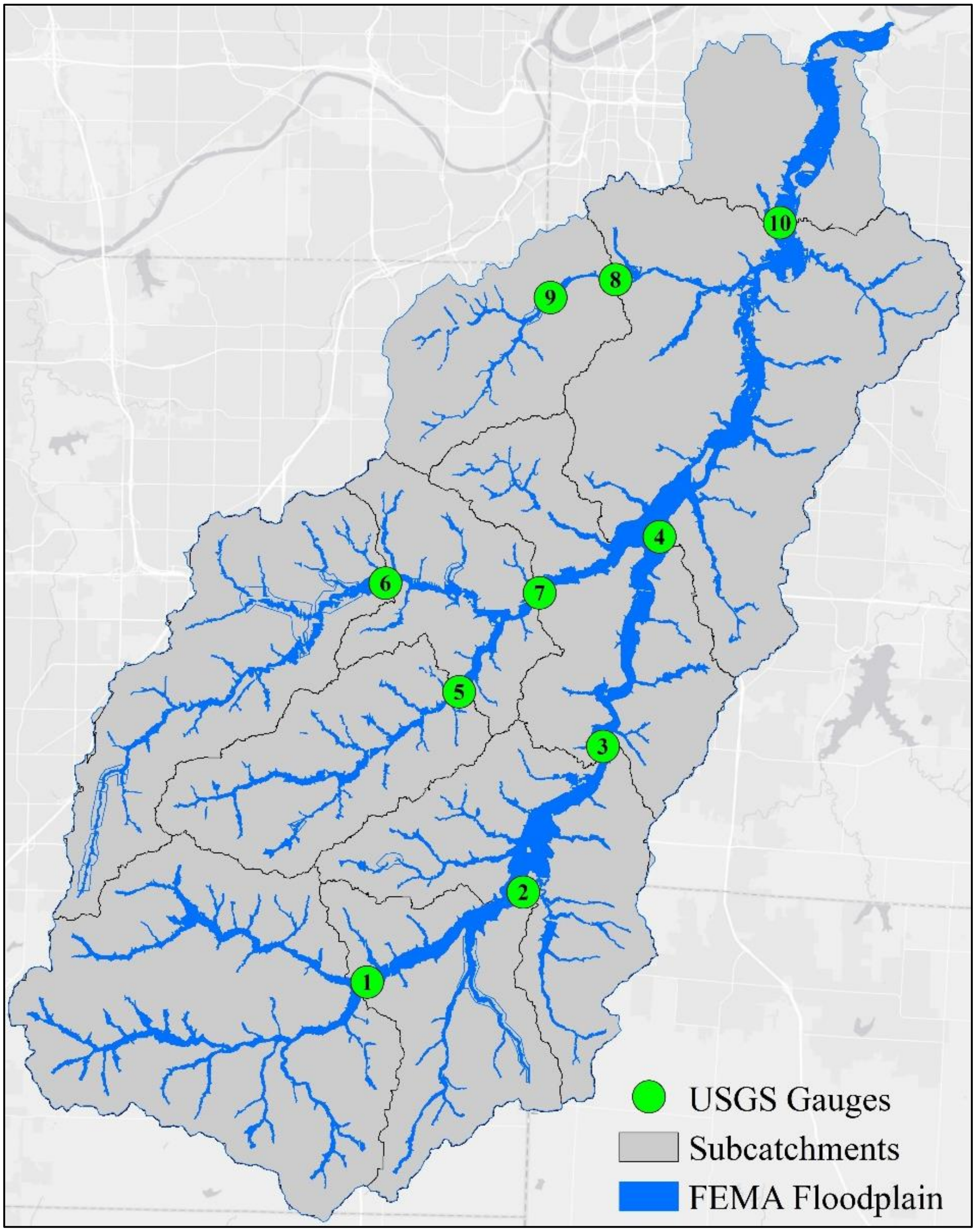

Figure 4-3. Location of the USGS stream gauges in the Blue River Watershed.

4.2.5 Calibration/Validation Methodology

Streamflow was calibrated/validated on a daily timescale at six USGS stream gauge stations within the study area. The following stations were used for calibration/validation using the Sensitivity/Based Radio Tuning Calibration (SRTC) tool: 06893080, 06893100, 06893300, 06893350, 06893557, and 06893578. The SRTC tool is an automatic calibration method that allows the user to calibrate each individual model parameter to a specified level of uncertainty by optimizing the Nash-Sutcliffe Efficiency (NSE) between the model simulated and observed streamflow hydrographs (James et al., 2010; McDonough et al., 2017). A select group of model parameters were calibrated within an acceptable recommended level of uncertainty (Table 4-7), as recommended by James (2003).

Table 4-7. Model parameter calibration uncertainty as recommended by James (2003).

Model Parameter	Layer	Uncertainty (%)
Invert Elevation	Junctions	10
Baseline	Junctions	25
Length	Conduits	10
Roughness	Conduits	10
Area	Subcatchments	10
Width	Subcatchments	100
Slope	Subcatchments	100
% Impervious	Subcatchments	50
N Imperv	Subcatchments	25
N Perv	Subcatchments	100
Dstore Imperv	Subcatchments	50
Dstore Perv	Subcatchments	100
Zero Impervious	Subcatchments	100
Percent Routed	Subcatchments	100
Suction Head	Subcatchments	50
Conductivity	Subcatchments	50
Initial Deficit	Subcatchments	100
Left Bank Roughness	Transects	10
Right Bank Roughness	Transects	10
Channel Roughness	Transects	10

The Nash-Sutcliffe Efficiency (NSE) is a statistical measure that compares the simulated hydrograph to the observed (Engel et al., 2007; Zeckoski et al., 2015; McDonough et al., 2017). The NSE is commonly used to assess the performance of a model through calibration and validation. “An NSE of 1 indicates perfect correlation; NSE < 0 indicates that an average of the observed data would be a better predictor than the simulated data,” (Zeckoski et al., 2015). A literature review of acceptable hydrologic modeling calibration statistics by Engel et al. (2007) found that model performance was deemed satisfactory with a NSE coefficient greater than 0.4. A range of NSE ratings proposed by Shamsi and Konan (2017) are similar, who stated that an NSE value within the range of 0.4-1.0 is acceptable for all model applications (Table 4-8).

Table 4-8. Recommended statistical ratings for model calibration/validation. Adapted from Shamsi and Konan (2017).

NSE Range	Rating	Model Application
0.5-1.0	Excellent	Planning, preliminary design, final design
0.4-0.49	Very good	Planning, preliminary design, final design
0.3-0.39	Good	Planning, preliminary design
0.2-0.29	Fair	Planning
<0.2	Poor	Screening

Both continuous and event-based calibration methods were used to assess the overall performance of the model. Traditionally, event-based methods have been used for calibration and validation due to the limited availability of continuous observed streamflow datasets. The event-based method compares the simulated hydrograph to the observed hydrograph for a minimum of five to ten storm events (Shamsi and Konan, 2017). As continuous streamflow datasets have become more available, continuous calibration and validation methodology has become more popular. Continuous calibration compares the simulated hydrograph against the observed hydrograph over a continuous period of time. For a complete description of the two calibration and validation methodologies, refer to Shamsi and Konan (2017).

4.3 – Calibration and Validation

Continuous and event-based calibration was conducted at six locations throughout the Blue River Watershed. The model was calibrated from June 1, 2014 - September 30, 2014 and validated from April 1, 2014 - May 31, 2014. The model was calibrated to optimize the NSE for total streamflow on both an event- and continuous-basis.

Results show, on a continuous basis, that the model-simulated streamflow was comparable to observed streamflow with a rating of "very good" or "excellent" at all locations (Table 4-9; Figure 4-4). The average NSE value for the calibration period, validation period, and overall were 0.60, 0.65, and 0.60, respectively. These results demonstrate that the model, in its current state, accurately simulates the surface hydrology mechanisms of the Blue River Watershed is suitable for associated planning, preliminary design, and final design purposes (Table 4-8).

Table 4-9. Continuous streamflow (cfs) calibration and validation results for the Blue River Watershed model.

Location	Calibration (6/1/2014-9/30/2014)	Validation (4/1/2014-5/31/2014)	Overall (4/1/2014-9/30/2014)
06893080	0.563	0.65	0.569
06893100	0.486	0.622	0.47
06893300	0.665	0.552	0.621
06893350	0.562	0.589	0.567
06893500	0.647	0.787	0.677
06893578	0.672	0.701	0.678

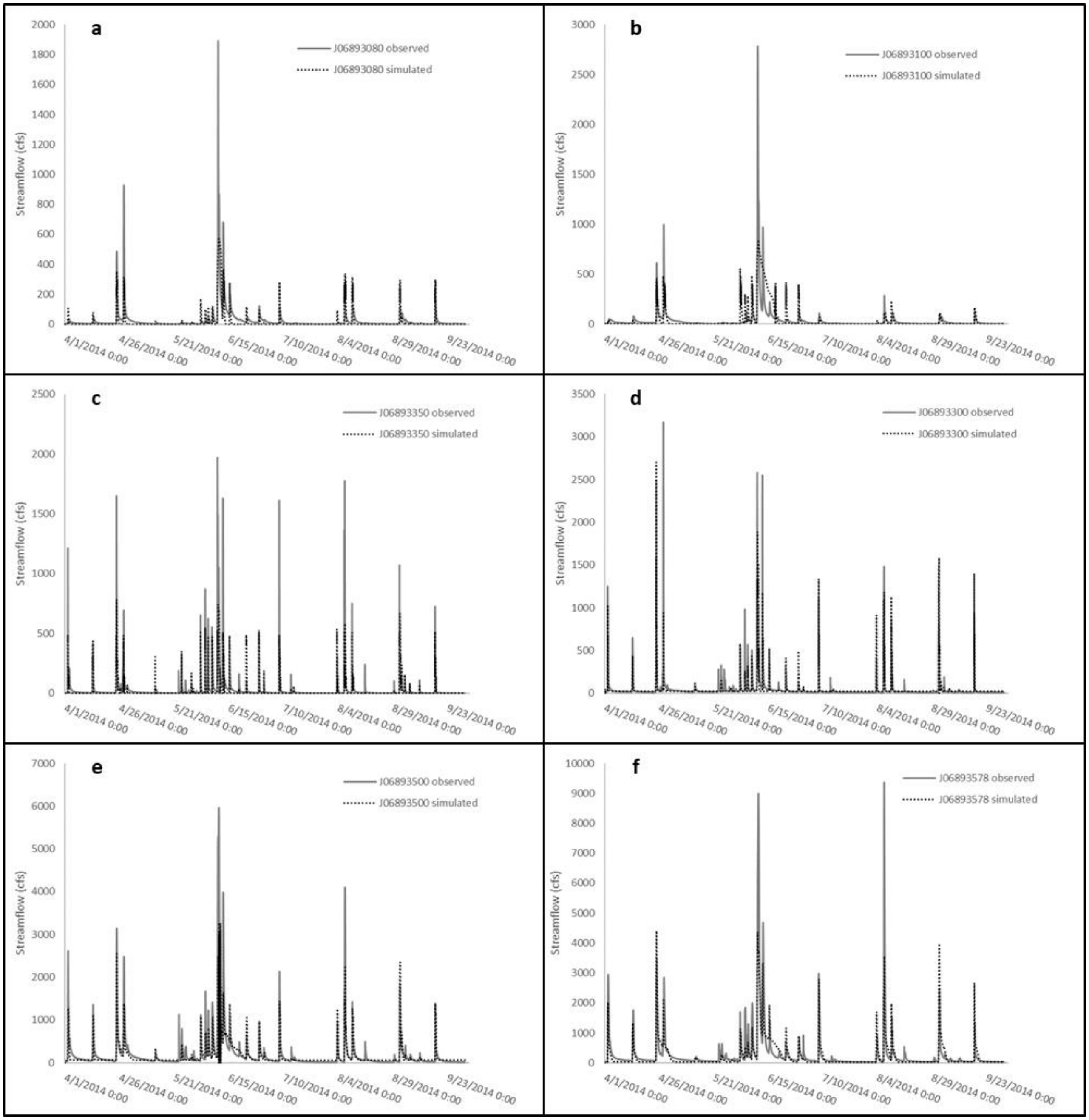

Figure 4-4. Continuous calibration/validation results throughout the Blue River Watershed at a) J06893080, b) J06893100, c) J06893350, d) J06893300, e) J06893500, f) J06893500.

In addition to continuous calibration, the model was calibrated to optimize the total streamflow of the model at each location on an event-basis. The simulated total streamflow was comparable to observed streamflow with all reported NSE values above 0.4 (Table 4-10). The average NSE values for the calibration period, validation period, and overall were 0.75, 0.70, and 0.69, respectively. Again, and similarly to the results of the continuous calibration, these results demonstrate that the model in its current state accurately simulates the surface hydrology mechanisms of the Blue River Watershed and is suitable for associated planning, preliminary design, and final design purposes (Table 4-8).

Table 4-10. Event-based total streamflow calibration and validation results for the Blue River Watershed model.

Location	Calibration (6/1/2014-9/30/2014)	Validation (4/1/2014-5/31/2014)	Overall (4/1/2014-9/30/2014)
06893080	0.913	0.76	0.896
06893100	0.576	0.923	0.6
06893300	0.874	0.46	0.44
06893350	0.802	0.658	0.827
06893500	0.587	0.712	0.627
06893578	0.746	0.707	0.738

The model behavior for event-based mean streamflow and event-based maximum streamflow is also reported (Table 4-11; Table 4-12). While the model was not calibrated to specifically optimize these parameters, knowledge of how the model is performing for all aspects of the hydrograph will be important in the assessment of future results. The reported NSE was above 0.4 for the majority of locations for both mean and maximum streamflow. The average NSE for mean streamflow was 0.67, 0.70, and 0.73 for the calibration period, validation period, and overall, respectively, and the average NSE for maximum streamflow was 0.41, 0.49, and 0.43 for the same periods.

Those locations that reported lower NSE values (e.g., 06893300, 06893100, 06893350) are located in the headwaters of the watershed. These lower NSE values indicate that the model does not capture the hydrograph extremes well, particularly the peaks. However, the lower NSE values in the headwaters may be attributed to the generally "flashy" behavior of watersheds in these areas, which was extremely difficult for the model to capture. To maintain computational efficiency, the model does not include the extensive artificial stormwater network that is maintained throughout the Blue River Watershed. The lack of inclusion of features characteristic to the stormwater network, such as box culverts and levees, may be one reason that the model does not simulate flashy behavior as well as it could. Unfortunately, a dataset that describes the artificial stormwater network in this area was not available at the time of model development but future iterations of this model may consider including this information to improve simulation accuracy. Future applications of this model in its current state should proceed with caution when reporting streamflow extremes, particularly in reference to maximum streamflow values.

Table 4-11. Event-based mean streamflow calibration and validation results for the Blue River Watershed model.

Location	Calibration (6/1/2014-9/30/2014)	Validation (4/1/2014-5/31/2014)	Overall (4/1/2014-9/30/2014)
06893080	0.887	0.739	0.86
06893100	0.641	0.945	0.653
06893300	0.623	0.371	0.87
06893350	0.686	0.693	0.709
06893500	0.497	0.701	0.559
06893578	0.701	0.768	0.711

Table 4-12. Event-based maximum streamflow calibration and validation results for the Blue River Watershed model.

Location	Calibration (6/1/2014-9/30/2014)	Validation (4/1/2014-5/31/2014)	Overall (4/1/2014-9/30/2014)
06893080	0.454	0.521	0.468
06893100	0.36	0.519	0.373
06893300	0.544	0.533	0.558
06893350	0.204	0.417	0.221
06893500	0.491	0.42	0.503
06893578	0.418	0.502	0.43

4.4 – Conclusion

A watershed-scale, hydrologic model of the surface hydrology throughout the Blue River Watershed was developed using PCSWMM software. The intent of this watershed-scale model is to examine the vulnerability of urban infrastructure to flooding and to evaluate the influence of land management practices on the streamflow regime within the Blue River Watershed.

Results of the calibration and validation process reveal that the model-simulated hydrograph is comparable to the observed hydrograph, on a continuous basis, for all calibration locations throughout the watershed. Each location reported a Nash-Sutcliffe Efficiency of greater than 0.4, or a rating of “very good” or “excellent”, which demonstrates that the model is suitable for planning, preliminary design, and final design purposes. Similar results are reported following the calibration and validation of total streamflow on an event-basis.

This Blue River Watershed model is suitable for planning, preliminary design, and final design purposes that relate to the simulation of water quantity mechanisms of surface hydrology throughout the Blue River Watershed.

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Chapter 5 - Validation and assessment of SPoRT-LIS surface soil moisture estimates for water resources management applications

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5.1 – Introduction

A thorough understanding of soil moisture across multiple spatiotemporal scales is essential for many applications, including drought and flood prediction, weather forecasting, climatology, agricultural production, and water resources management (An et al., 2016; Blankenship et al., 2016; Dobriyal et al., 2012; Fascetti et al., 2016; Griesfeller et al., 2016). Soil moisture has a significant impact on the partitioning of moisture for evapotranspiration and surface-sensible and latent heat fluxes (Blankenship et al., 2016; Griesfeller et al., 2016) and thus plays a major role in understanding land-atmosphere interactions and climate change projections (An et al., 2016; Griesfeller et al., 2016). The European Space Agency identified soil moisture as one of the fifty essential climate variables in 2010 (An et al., 2016; Griesfeller et al., 2016) due to its role as a key variable in the characterization of the global climate (Fascetti et al., 2016).

With respect to water resources applications, soil moisture plays an influential role within the hydrologic cycle due to its ability to control the rainfall-runoff response in catchments (Dobriyal et al., 2012; Al-Shrafany et al., 2014; Alvarez-Garreton et al., 2014; Grillakis et al., 2016; Li et al., 2018; Meng et al., 2017), which then influences the streamflow regime and evapotranspiration (Dobriyal et al., 2012; Xia et al., 2015b; Grillakis et al., 2016; Meng et al., 2018). Soil moisture is an important determinant of available water and can dictate productivity of natural and agricultural ecosystems (Dobriyal et al., 2012). Monitoring of soil moisture has proven useful for the allocation of limited water resources during drought, coordinating relief efforts during floods, and for preventing desertification (Moran et al., 2004; Dobriyal et al., 2012). Furthermore, surface soil moisture is an important initial condition for hydrologic modeling (Meng et al., 2017; Li et al., 2018) and flood forecasting (Alvarez-Garreton et al., 2014; Meng et al., 2017). The assimilation of remotely sensed soil moisture has shown to improve streamflow prediction (Alvarez-Garreton et al., 2014; Brocca et al., 2012; Li et al., 2018) and has demonstrated potential to advance short-term flood forecasting (Meng et al., 2017).

Soil moisture data across a range of scales is primarily obtained from in situ observations, remotely-sensed satellite observations, and climate and land surface models (Xia et al., 2015a). In situ data provides a valuable point-scale estimate of soil moisture that is useful for the evaluation of remotely-sensed and modeled soil moisture (Albergel et al., 2012). However, dense ground-based networks would be necessary to truly capture the spatial and temporal heterogeneity of soil moisture over large scales due to the high variability of soil properties, precipitation, and other physical and climatological factors that influence patterns of soil moisture (Dobriyal et al., 2012; Al-Shrafany et al., 2014). In reality, the availability of in situ soil moisture over large areas and long temporal periods is extremely limited, which makes it makes it challenging to infer spatiotemporal patterns of soil moisture from in situ observations alone.

Soil moisture derived from remote-sensing platforms provides a promising avenue to examine the spatiotemporal variability of soil moisture at larger scales. Satellite-derived soil moisture observations have become a powerful tool that have enhanced our ability to understand land-atmosphere processes (Griesfeller et al., 2016) by providing global coverage at regular time intervals (Alvarez-Garreton et al., 2014). A number of satellite missions have been launched for the purpose of global soil moisture observation, including the Advanced Microwave Sounding Radiometer (AMSR-E; Reichle et al., 2007), the Advanced SCATterometer (ASCAT; Wagner et al., 1999), Soil Moisture Ocean Salinity (SMOS; Kerr et al., 2001), and Soil Moisture Active Passive (SMAP; Entekhabi et al., 2010). While these satellites enable the global observation of soil moisture in a way that was not previously possible with in situ measurements, the ability of each satellite to accurately estimate soil moisture has proven to be variable over time and space (Brocca et al., 2012; de Jeu & Dorigo, 2016). "The continuous increase of sensors and retrieval methods makes it difficult for the user community to understand what the exact quality of a soil moisture product is for a specific sensor and how it can be used in applications," (de Jeu & Dorigo, 2016). Furthermore, there are serious limitations to many satellite-derived soil moisture products, which include the coarse spatial and temporal resolution of data and the capability to only measure the first few centimeters of soil from microwave sensors (Al-Shrafany et al., 2014; Alvarez-Garreton et al., 2014; Brocca et al., 2012; Cammalleri et al., 2015).

Land surface models (LSMs) provide a viable alternative to satellite-derived soil moisture observations. LSMs enable simulation of soil moisture based upon forcing variables, such as precipitation, wind speed, and physical properties such as soil texture and land cover (Koster et al., 2009; Blankenship et al., 2016). A major advantage of model-based soil moisture estimates is their ability to use real-time or retrospective weather and climate information (Xia et al., 2015a) and provide estimates of soil moisture to several meters of depth at hourly, daily, and monthly time steps (Moran et al., 2004; Cammalleri et al., 2015). The ability of different LSMs to estimate soil moisture has been found comparable to in situ and remotely-sensed soil moisture (e.g. Al-Shrafany et al., 2014; Srivastava et al., 2015; Fang et al., 2016). However, the reliability of model-based soil moisture is heavily dependent on accurate surface forcing data and parameterization (Camalleri et al., 2015; Yang et al., 2016; Koster et al., 2009; Xia et al., 2015a). Regardless, LSM-derived soil moisture has tremendous potential to be useful in a variety of applications due to its capability to estimate soil moisture across the entire contiguous United States (CONUS) domain at high spatiotemporal resolutions.

This research examines the validity of LSM-derived surface soil moisture for the purpose of surface water resources applications within the central United States. Surface soil moisture was obtained from SPoRT-LIS, which is an observation-driven, real-time simulation of the unified Noah LSM (Chen & Dudhia, 2001; Ek et al., 2003). The main objective of this research was to assess the ability of SPoRT-LIS to provide reliable estimates of surface soil moisture for surface water resources operational and research applications through validation against in situ soil moisture in the Missouri and Arkansas-Red-White River Basins in the U.S. Great Plains region. The SPoRT-LIS software was selected for analysis due to its potential to provide accurate volumetric surface soil moisture estimates in real-time at a higher spatial and temporal resolution than is currently provided by satellite observations or in situ measurements of the same product.

5.2 – Methods

5.2.1 Study Area

The Missouri and Arkansas-Red-White River Basins are located in the central United States and cover the majority of the U.S. Great Plains region (Figure 5-1). The area of the two basins, combined, equates to approximately 2 million square kilometers. The study area encompasses ten climate regions as defined by the Köppen-Geiger climate classification, ranging from fully humid and temperate areas in the northeast to arid and dry zones in the southwest (Rubel & Kottek, 2010). There is a diverse gradient of rainfall across the study area, with annual precipitation ranging from 200 mm in the west to 1000 mm in the east (PRISM Climate Group, 2015).

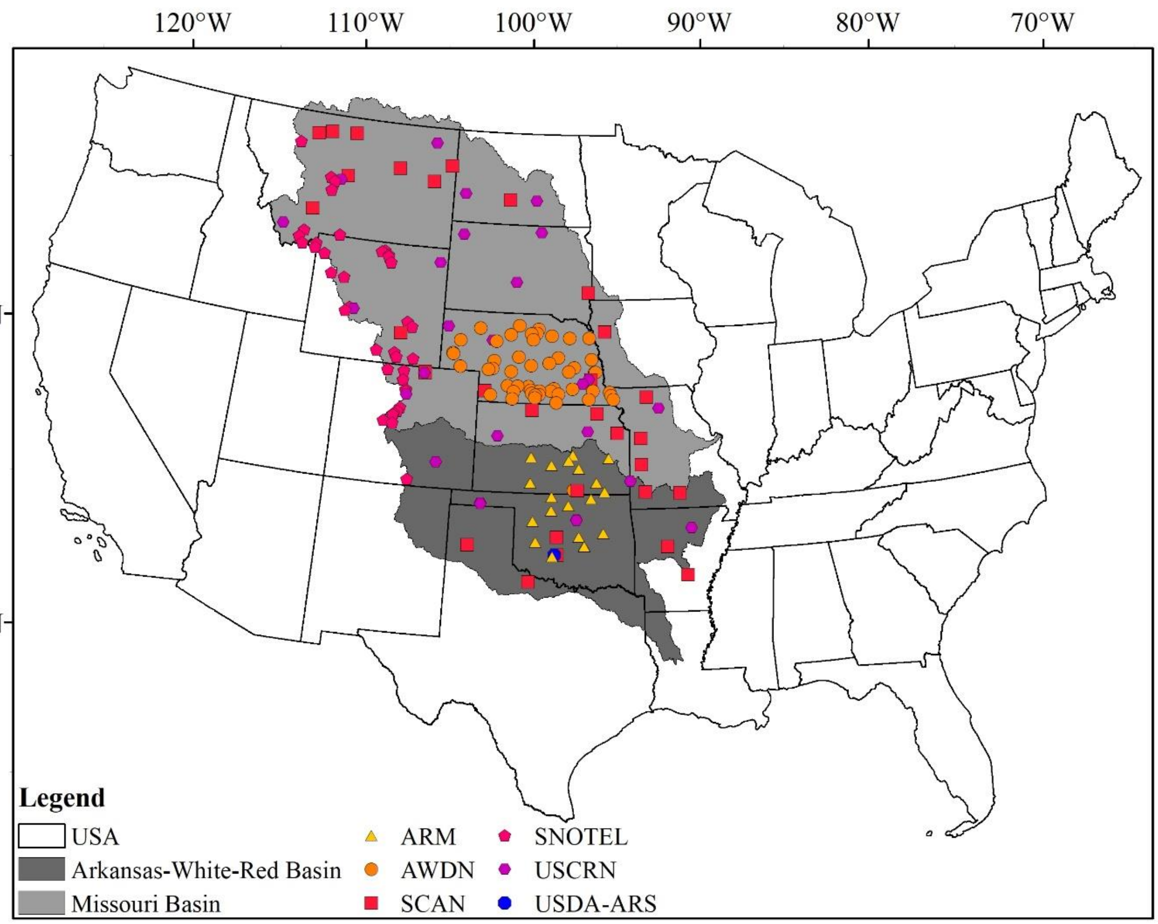

Figure 5-1. The location of in situ monitoring points from the International Soil Moisture Network located within the Missouri and Arkansas-Red-White Basins. The network that maintains each in situ station is designated on the map.

5.2.2 In situ soil moisture data

In situ soil moisture data was provided by the International Soil Moisture Network (ISMN; Dorigo et al., 2011; Dorigo et al., 2013) on a daily time scale from 2000-2016. The ISMN is a global soil moisture database that compiles in situ data from operational partners around the world for validation of satellite observations and land surface models (Dorigo et al., 2011; Dorigo et al., 2013). In situ soil moisture data is an invaluable source of information for calibration and validation of remotely-sensed and model-based soil moisture (Xia et al., 2015a). Soil moisture data from ISMN is widely utilized in research applications throughout the world (e.g. Albergel et al., 2012; An et al., 2016), and its data quality and measurement errors have been thoroughly investigated (e.g. Dorigo et al., 2013; Gruber et al., 2013). The measurement error of networks within the ISMN ranges from 0.02 to 0.06 (Gruber et al., 2013), with the average error for most networks estimated at 0.03 (Xia et al., 2015a). In situ soil moisture data was obtained for 165 stations within the Missouri and Arkansas-Red-White River basins at depths of 5-cm and 10-cm (Figure 5-1). This data was maintained in ISMN by five operational soil moisture networks (Table 5-1). Any data that was flagged by the ISMN as "questionable/ dubious" and did not receive a designation of "G" for "good data" was removed from the dataset and omitted from analysis.

Table 5-1. In situ soil moisture data obtained from the International Soil Moisture Network.

Network	Operating Agency	# of Stations	Depths (m)	Soil Moisture Sensor
ARM	U.S. Department of Energy (Atmospheric Radiation Measurement Climate Research Facility)	22	0.05	Water Matric Potential Sensor 229L
AWDN	High Plains Regional Climate Center	50	0.10	Vitel, ThetaProbe ML2X

SCAN	U.S. Department of Agriculture Natural Resources Conservation Service (NRCS)	31	0.05, 0.10	Hydraprobe Analog (2.5 Volt, 5.0 Volt), Hydraprobe Digital Sdi-12 (2.5 Volt, Thermistor)
SNOTEL	U.S. Department of Agriculture Natural Resources Conservation Service (NRCS)	36	0.05, 0.10	Hydraprobe Analog (2.5 Volt, 5.0 Volt), Hydraprobe Digital Sdi-12 (2.5 Volt)
USCRN	National Oceanic and Atmospheric Administration's National Climatic Data Center (NCDC)	26	0.05, 0.10	Stevens Hydraprobe II Sdi-12

5.2.3 SPoRT-LIS

The NASA Land Information System (LIS) is a high-performance land surface modeling and data assimilation system that can be used to run a variety of LSMs through the integration of satellite-derived datasets, ground-based observations and model re-analyses to characterize land surface states and fluxes (Kumar et al., 2006; Peters-Lidard et al., 2007). LIS can run LSMs regionally or globally with a grid spacing as fine as one kilometer by using scalable, high-performance computing and data management technologies. LIS features an Ensemble Kalman Filter algorithm (Evensen, 2003) to conduct land surface data assimilation (Kumar et al., 2008; Kumar et al., 2009) for a variety of datasets and variables such as soil moisture, land surface temperature and snow (e.g. Liu et al., 2013). The system also supports an optimization and uncertainty analysis for calibrating LSM parameters to observations (Santanello et al., 2013). In addition to operating in an offline (standalone) mode, LIS has been coupled to the Weather Research and Forecasting (WRF) model (Kumar et al., 2007) for Numerical Weather Prediction (NWP) research applications as part of the NASA Unified-WRF modeling framework (Peters-Lidard et al., 2015) to enhance the land-atmosphere interactions within WRF.

NASA's Marshall Space Flight Center's Short-term Prediction Research and Transition (SPoRT) Center (Jedlovec, 2013) has developed a real-time application of the NASA LIS for use in experimental operations by both domestic and international operational weather forecasters (Case, 2016; Case et al., 2016; Case and Zavodsky, 2018; Zavodsky et al,. 2013). This software, SPoRT-LIS, is an observation-driven, real-time simulation of the unified Noah LSM (Chen and Dudhia, 2001; Ek et al., 2003) over a full contiguous U.S. domain. The SPoRT-LIS provides soil moisture estimates at an approximately 3-km grid resolution over a 2-meter deep soil column. Detailed information regarding the input parameters and methodology that constitutes SPoRT-LIS can be obtained from Zavodsky et al. (2016) and Case and Zavodsky (2018).

The SPoRT-LIS top-layer volumetric soil moisture (0-10 cm) estimate was selected for validation against in situ soil moisture data from ISMN at depths of 5- and 10-cm. SPoRT-LIS soil moisture was obtained on a daily temporal scale from 2000 to 2016 for the continental United States and masked to the study area extent (Figure 5-1).

5.2.4 Validation

The accuracy of soil moisture estimates from satellite platforms or LSMs can vary by region and climate zone, and thus it is important to conduct validation to determine an individual product's reliability within different areas of study (Wang et al., 2016). There is currently no standard method of validation that dictates how remotely-sensed products should be evaluated (de Jeu and Dorigo, 2016). However, metrics commonly used to evaluate soil moisture derived from satellites and LSMs include bias, root mean square difference (RMSD), root mean square error (RMSE), Spearman's ranked correlation coefficient (Spearman's ρ), and Pearson's correlation coefficient (Albergel et al., 2012; An et al., 2016; Fascetti et al., 2016).

The validation of remotely-sensed data with in situ observations is not straightforward due to differences in spatial resolution, observation depth, and measurement uncertainty (An et al., 2016; Xia et al., 2015a). The spatial and temporal heterogeneity of the soil limits verification of remotely-sensed soil moisture (An et al., 2016; Blankenship et al., 2016). Furthermore, this issue is confounded by differences in spatial resolution between measurement techniques. The horizontal and vertical resolutions of in situ data and remotely-sensed data are different (Draper et al., 2009; Xia et al., 2015a; Xia et al., 2015b). For example, in this research, the SPoRT-LIS soil moisture estimate has a 3-km horizontal spatial resolution at a vertical depth of 0-10 cm, while the in situ soil moisture is a point scale measurement at independent depths of 5-cm and 10-cm. These discrepancies in resolution between measurement techniques make the validation process complex. Furthermore, in situ measurements may contain errors and therefore cannot be considered a "true" value of soil moisture (Albergel et al., 2012; Draper et al., 2009).

This study employed several different validation metrics and methods of assessment to assess the reliability of the SPoRT-LIS volumetric surface soil moisture estimate compared to situ soil moisture data. Spearman's ρ, RMSE, and bias (%) were used to compare the SPoRT-LIS surface soil moisture estimate (0-10 cm) and in situ soil moisture data (5- and 10-cm depths) from 2000-2016. Spearman's ρ was used to assess the degree of similarity between SPoRT-LIS soil moisture and in situ soil moisture, while RMSE was used to assess overall model error (Xia et al., 2015a). A measure of bias was used to assess model systematic error, and evaluate possible over- or under-estimation of soil moisture (Xia et al., 2015a). As there is currently no standard method for evaluation of soil moisture estimates (de Jeu and Dorigo, 2016), past research was used as a guide to assign performance labels for assessing validation results. Previous work has established the comparison between remotely-sensed or modeled soil moisture estimates against in situ data to be "satisfactory" when reporting correlation values of 0.42 (Wang et al., 2016), 0.53-0.70 (Albergel et al., 2012), and 0.52-0.72 (Griesfeller et al., 2016). In this study, correlation values above 0.50 are considered to be "satisfactory" for research applications, though values exceeding 0.75 are preferable for decision-making practices (Moran et al., 2004).

Validation performance was assessed on a daily basis to understand the ability of the SPoRT-LIS soil moisture estimate to capture the daily variations in surface soil moisture. Analysis of daily soil moisture on a seasonal basis was conducted to evaluate short-term variability (Albergel et al., 2012). Following Albergel et al. (2012), the seasons were defined as summer (June, July, August), fall (September, October, November), winter (December, January, February), and spring (March, April, May). The potential for frozen soils during the winter months will affect in situ soil moisture data (Xia et al., 2015a), especially in higher latitudes of the study area. However, the analysis of soil moisture over a yearlong period can provide invaluable information about annual and seasonal soil moisture trends for water resources management applications. In addition, there are numerous examples in the literature of annual and seasonal validation of soil moisture estimates (e.g. Albergel et al., 2012; Fascetti et al., 2016).

Physical environmental characteristics, such as soil texture and land cover, strongly affect soil moisture (Xia et al., 2015b). Thus the influence of physical environmental factors on the comparison between the SPoRT-LIS soil moisture estimate and in situ data was analyzed using the Kruskal-Wallis rank sum test. Only those values of Spearman's ρ that were statistically significant (i.e., $p\text{-value}<0.05$) were utilized for this part of the analysis. The physical environmental factors that were examined included land cover, soil texture, dominant hydrologic soil group, slope, and aspect. Land cover data was obtained from the 2011 National Land Cover Dataset at 30-m resolution (Homer et al., 2015) and soil data was acquired from the Digital General

Soil Map of the U.S. (STATSGO2) at a 1:250,000 resolution (NRCS, 2006). Topographic data was obtained from the U.S. 3D Elevation Program (3DEP) at a 30-m resolution (USGS, 2016). This approach facilitated comparisons between the mean correlation value in regions of cropland, for example, and the mean correlation value in areas of forest cover to determine whether the validation performance varied between land cover types. This statistical approach enabled identification of physical areas where the reliability of the SPoRT-LIS soil moisture estimate might differ. Finally, the Tukey Honest Significant Difference test was used to compare the validation performance between ground-based measurement stations at depths of 5-cm and 10-cm to determine if the vertical resolution of measurement affected overall validation performance.

Finally, to account for discrepancies in spatial resolution between measurement techniques, the Shannon Diversity Index (SHDI) was calculated and used to assess the influence of pixel heterogeneity across the 3-km grid on validation performance. The SHDI was determined using the FRAGSTATS software program, which is a spatial pattern analysis program for categorical maps (McGarigal et al., 2012). SHDI was calculated to provide a value of heterogeneity across the 3-km grid for land cover, soil texture, and dominant hydrologic soil group using the 2011 National Land Cover Dataset (Homer et al., 2015) and STATSGO2 (NRCS, 2006). This approach enabled evaluation of whether a high degree of heterogeneity in soil texture across a 3-km grid, for example, might affect the ability of SPoRT-LIS to accurately estimate soil moisture when compared to ground-based measurements. Thus, this analysis enabled conclusions about the influence of discrepancies in measurement scale between remotely-sensed and ground-based soil moisture.

5.3 – Results and Discussion

5.3.1 Validation Results

The SPoRT-LIS volumetric surface soil moisture estimate (0-10 cm) was validated against in situ surface soil moisture on a daily basis at depths of 5- and 10-cm using Spearman's ρ. Approximately 52% of points analyzed yielded a correlation value of greater than 0.5 (Figure 5-2; Figure 5-3). At depths of 5-cm and 10-cm, 53% and 51% of the data returned a correlation value greater than 0.5, respectively. In total, and for both measurement depths, the average and median correlation values were just below and above 0.5 (Table 5-2).

Validation metrics of bias and RMSE were also calculated to assess reliability of the SPoRT-LIS soil moisture estimate. Typical RMSE values were at or below 0.1 (Table 5-2), which exceeds the typical measurement error (0.02-0.06 $m^3 m^{-3}$) of in situ data. RMSE values that surpass the corresponding (in situ) instrument measurement errors indicate that simulation errors are derived from model limitations, such as inaccurate forcing data (Xia et al., 2015a). The average bias for both measurement depths was high, though the median bias was much closer to zero with both values below ten (Table 5-2). These values of bias indicate that there may be overestimation of soil moisture by SPoRT-LIS when compared to in situ data. This result is consistent with previous analysis of the Noah land surface model conducted by (Xia et al., 2015a), who reported that the high values of bias indicated "that models and model forcings still have room to improve." The combination of high bias and RMSE values that exceed instrument measurement errors suggest that further refinement of the SPoRT-LIS software may be necessary. Interestingly, RMSE and bias values for the 10-cm measurement depth were slightly lower than the 5-cm measurement depth, which is likely due to less variability in soil moisture at the deeper 10-cm depth.

Table 5-2. Results of the annual correlation analysis between the SPoRT-LIS surface soil moisture estimate and in situ measurements.

	Average		Median	
	5-cm	10-cm	5-cm	10-cm
Spearman's ρ	0.4824	0.4722	0.5059	0.5034
RMSE	0.1064	0.0960	0.0982	0.0834
Bias (%)	27.8089	23.1894	8.2000	2.5500

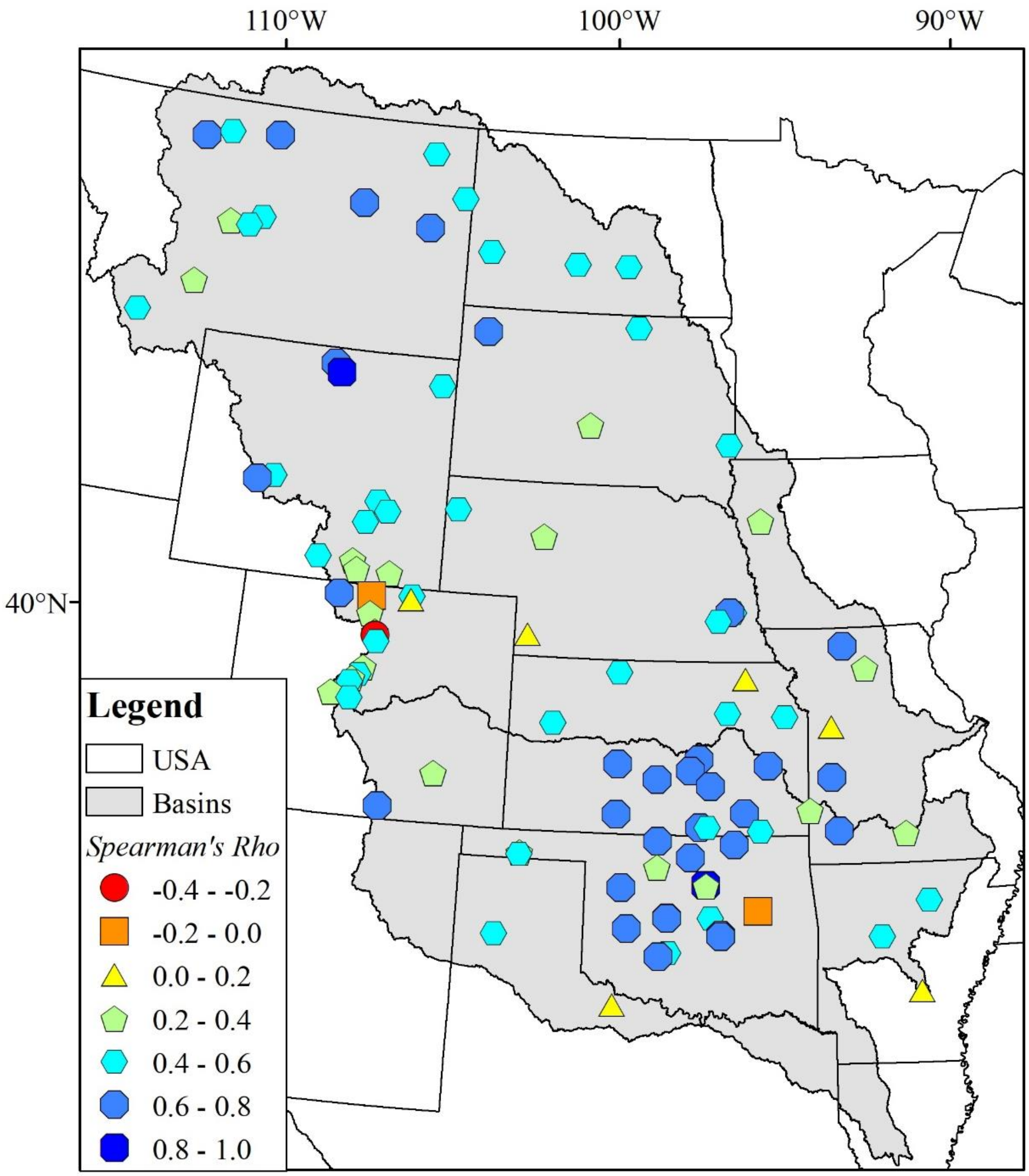

Figure 5-2. Validation of the SPoRT-LIS soil moisture estimate throughout the Missouri and Arkansas-Red-White River Basins at 5-cm depth.

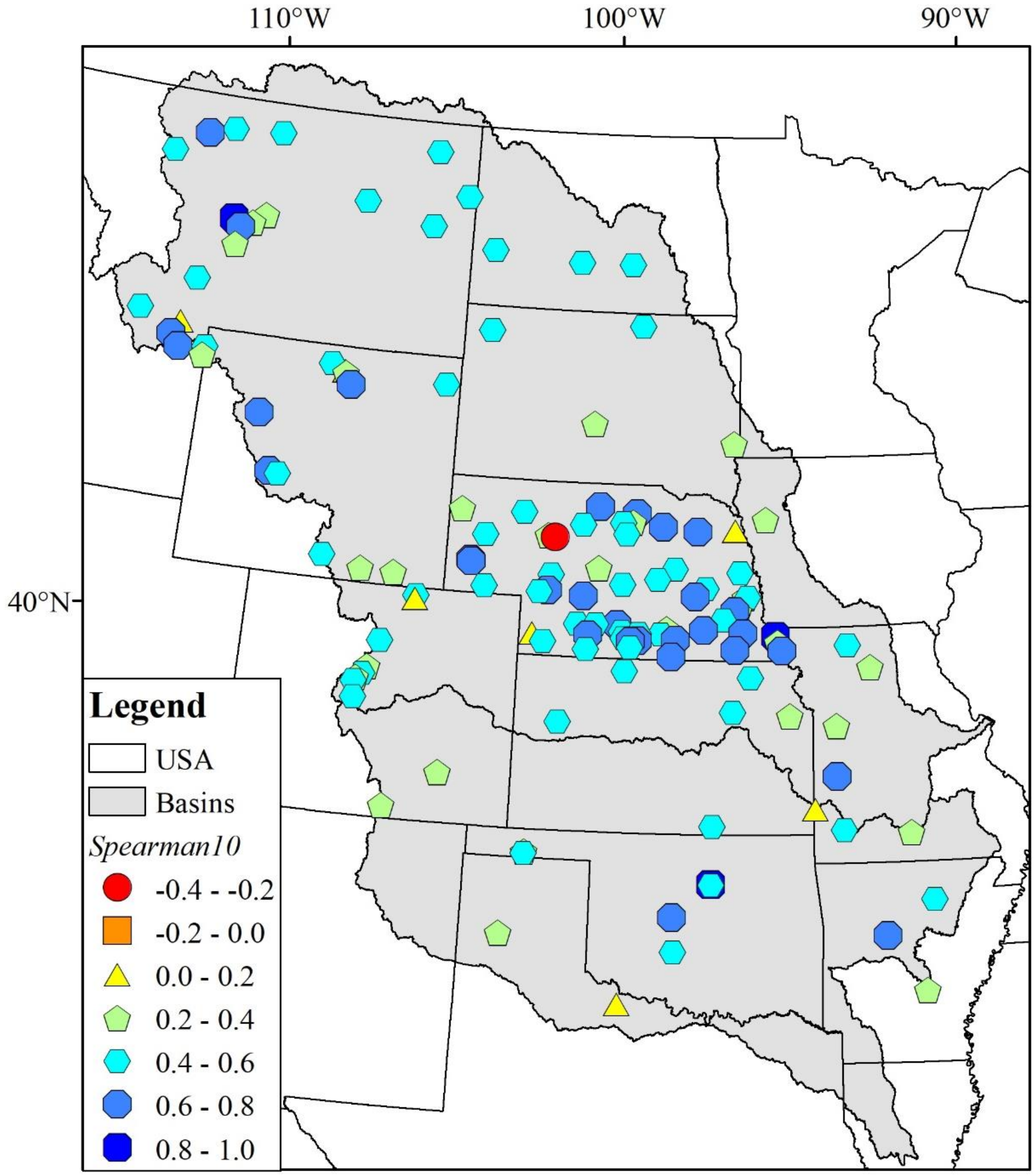

Figure 5-3. Validation of the SPoRT-LIS soil moisture estimate throughout the Missouri and Arkansas-Red-White River Basins at 10-cm depth.

The SPoRT-LIS soil moisture estimate was comparable, on a daily basis, to many of the ground-based stations from 2000-2016. For example, at the Stillwater 5WNW ground measurement station (Figure 5-4), the pattern of the SPoRT-LIS surface soil moisture estimates closely mirrored in situ soil moisture, with a correlation value of 0.8544. However, at this same location, SPoRT-LIS seemed to overestimate soil moisture during dry periods (0-0.3 $m^3\ m^{-3}$) and slightly underestimate soil moisture during saturated soil conditions (>0.3 $m^3\ m^{-3}$). After examining validation data at several stations, this same overestimation during dry conditions and underestimation during saturated soil conditions seemed common. This could be attributed to multiple factors, including misrepresentation of soil properties and/or land cover characteristics at the in situ measurement station, challenges associated with validating a 3-km grid cell against a point-scale observation, or model limitations on behalf of the SPoRT-LIS software as discussed above.

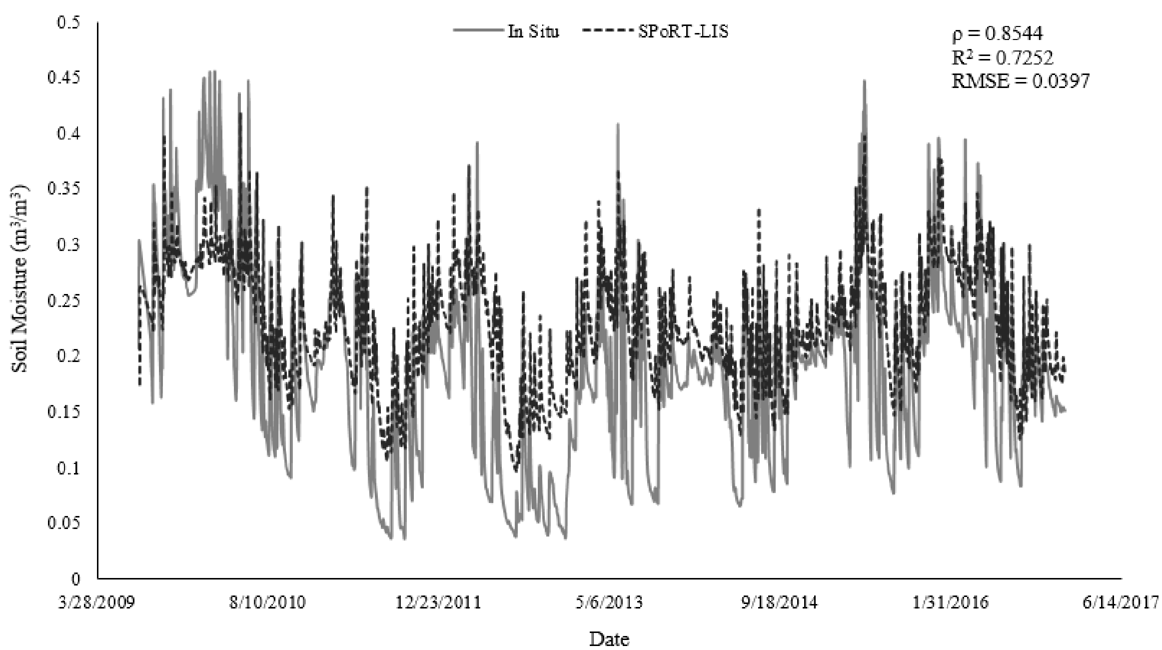

Figure 5-4. Time series validation of the SPoRT-LIS soil moisture estimate against the 5-cm Stillwater 5WNW in situ station.

To determine whether the SPoRT-LIS soil moisture estimate demonstrated significant variability over the vertical soil profile, the validation performance was further assessed by depth of the in situ measurement. Of the ground-based measurements, 101 stations had a soil moisture measurement depth of 5-cm while 132 stations reported soil moisture a depth of 10-cm. In comparison, the SPoRT-LIS surface soil moisture estimate reflects a volumetric column depth from 0-10 cm.

The Kruskal-Wallis test was used to statistically compare the mean Spearman's ρ, bias, and RMSE values at both depths of measurement. While the results suggested that there was not a significant difference in the Spearman's ρ (p-value=0.643) and bias (p-value=0.497) values, a significant difference was found in the mean RMSE values (p-value=0.009) between the two depths of measurement (Figure 5-5). This suggests that the SPoRT-LIS surface soil moisture product had a slightly better fit with the in situ measurement at the 10-cm depth. However, from a practical perspective, there is no substantial difference in the validation performance between the two depths of measurement, as the magnitude of difference between the RMSE values is small (~0.012). Therefore, it is evident that the depth of the in situ measurement does not wield a substantial influence on the daily validation performance of SPoRT-LIS.

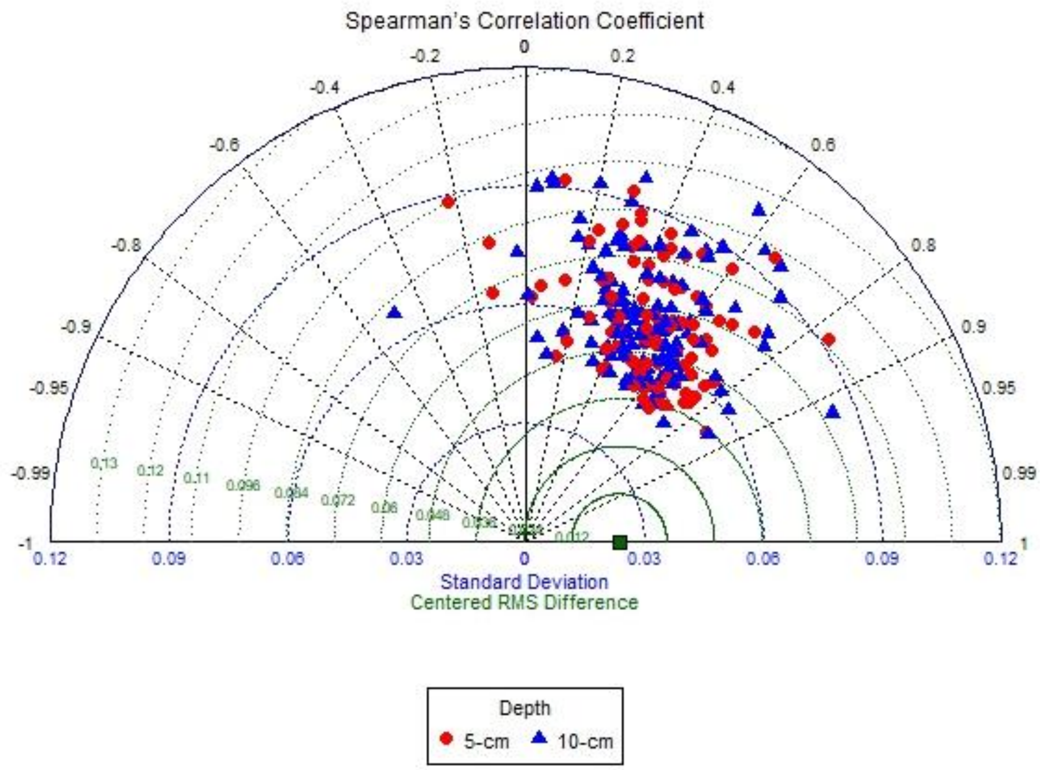

Figure 5-5. Taylor diagram illustrating the comparison between the SPoRT-LIS soil moisture estimate and in situ soil moisture observations.

5.3.2 Seasonal analysis

The daily validation performance of the SPoRT-LIS volumetric surface soil moisture estimate (0-10 cm) against in situ surface soil moisture was assessed on a seasonal basis at depths of 5- and 10-cm using Spearman's ρ. Seasonal analysis was conducted to assess how validation performance varied between the seasons throughout the year. In general, the seasonal validation performance at a depth of 5-cm was comparable to the overall validation performance, with average Spearman's ρ values above 0.4 for summer, fall, and winter (Table 5-3). However, at the 10-cm depth, only the summer and fall seasons exhibited an average Spearman's ρ value above 0.4. At both depths, the validation performance was highest and exhibited the least variability during the summer months, which is consistent with (Xia et al., 2015a), who validated the Noah

LSM and demonstrated correlations that were larger in the summer months than in the winter season.

Typical values of RMSE throughout all four seasons were just above or below 0.1, which was consistent with the overall validation performance. Validation at depths of 10-cm consistently demonstrated lower RMSE values than validation at the 5-cm depth (Table 5-3). The average bias was high for all four seasons, which was also comparable to the overall validation performance, though winter exhibited the highest values of average bias. However, values for median bias were at or below 10 for almost all of the seasons with the exception of summer (5-cm depth) and winter (10-cm depth). Upon further examination, validation performance in the winter season differed significantly between the 5-cm and 10-cm depth, which is likely due to the occurrence of frozen soils at deeper depths during that period.

Table 5-3. Results of the seasonal correlation analysis between the SPoRT-LIS surface soil moisture estimate and in situ measurements.

		Average		Median	
		5-cm	10-cm	5-cm	10-cm
Summer	Spearman's ρ	0.4913[a]	0.5027[a,b]	0.5032	0.5448
	RMSE	0.1009	0.0879	0.0969	0.0777
	Bias (%)	32.8000	25.8328	15.2500	3.5000
Fall	Spearman's ρ	0.4241	0.4196[a,b]	0.4813	0.4617
	RMSE	0.1043	0.0917	0.0944	0.0849
	Bias (%)	35.3386	28.6394	10.2000	4.2500
Winter	Spearman's ρ	0.4210	0.2986	0.5028	0.3499
	RMSE	0.1136	0.1071	0.1061	0.0956
	Bias (%)	56.8400	49.6581	7.9000	17.4000
Spring	Spearman's ρ	0.3265	0.3128	0.3817	0.3435
	RMSE	0.1102	0.1024	0.0936	0.0892
	Bias (%)	19.8190	19.1815	1.1000	-3.0500

[a]Indicates a significant difference when compared to spring
[b]Indicates a significant difference when compared to winter

Tukey's Honest Significant Difference was used to statistically compare the validation performance between seasons. At the 5-cm depth, only a significant difference (p-value=0.0006) was found upon comparison of the mean Spearman's ρ for spring against the same value for summer (Figure 5-6), though, from a practical perspective, the difference between the means in spring and summer is relatively small. At a depth of 10-cm (Figure 5-7), however, a significant difference was found between spring and fall (p-value=0.009), winter and fall (p-value=0.002), summer and spring (p-value=0.000), and winter and summer (p-value=0.000). The slightly lower validation performance in the spring and winter seasons, particularly at the 10-cm depth, could be attributed to the challenge of estimating soil moisture during periods of saturation in spring or frozen soils in winter. This result reveals that, on a seasonal basis, the validation performance of SPoRT-LIS soil moisture at the 10-cm depth is poor in comparison to the 5-cm depth due to the low Spearman's ρ in the winter season. Therefore, based upon both the daily and seasonal validation results, the authors conclude that the SPoRT-LIS soil moisture estimate is comparable with the in situ soil moisture measurements at the 5-cm depth throughout the year. SPoRT-LIS surface soil moisture is satisfactory for water resources applications, though some caution should be applied when utilizing the soil moisture estimates within the spring months.

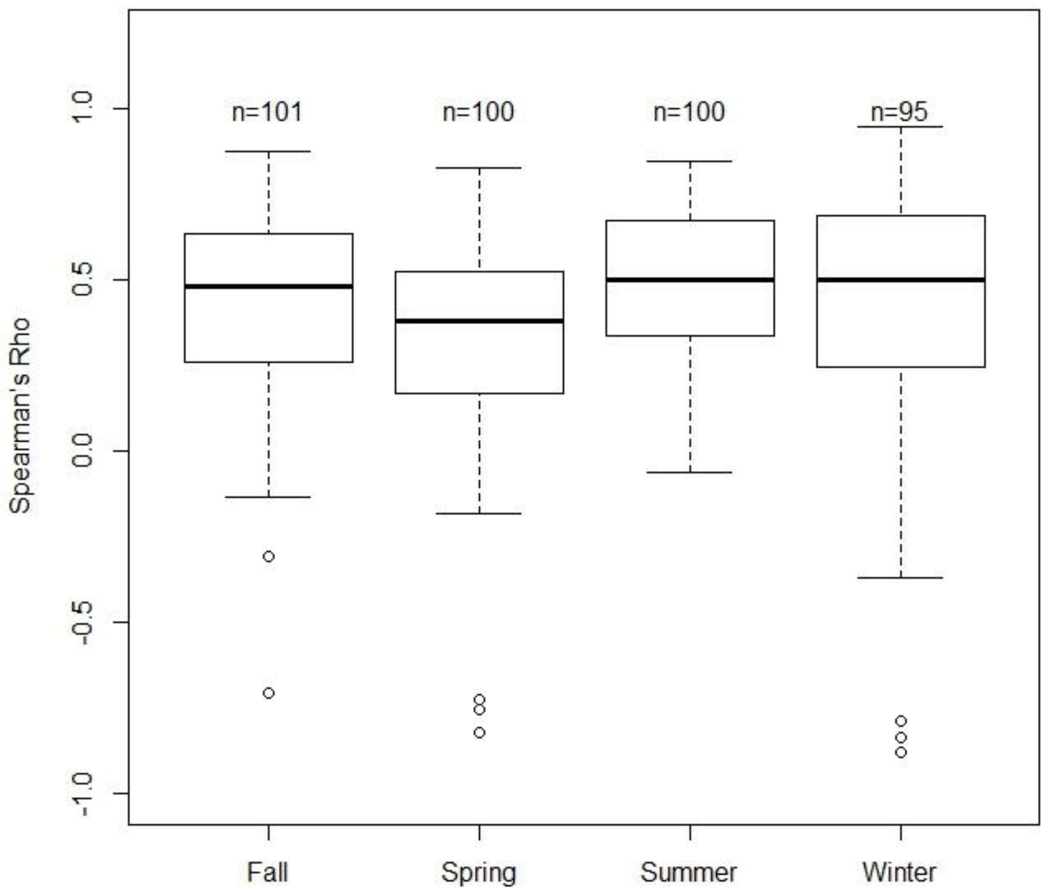

Figure 5-6. Seasonal validation of the SPoRT-LIS surface soil moisture estimate at a 5-cm depth.

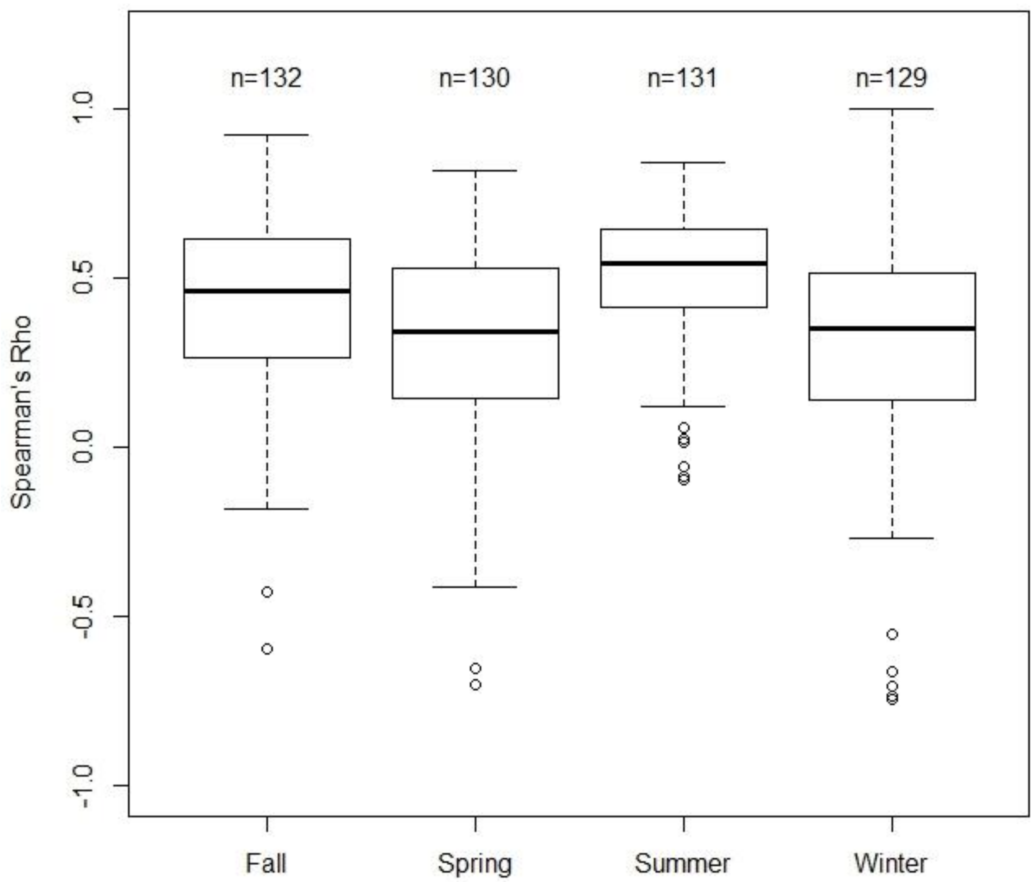

Figure 5-7. Seasonal validation of the SPoRT-LIS surface soil moisture estimate at a 10-cm depth.

5.3.3 Physical environmental characteristics

Soil properties and land cover can substantially influence soil moisture and are important factors in water resources management (Xia et al., 2015b). Thus, the physical environmental characteristics at the location of each in situ measurement were assessed to evaluate the influence of environmental conditions surrounding the in situ measurement on validation performance. Soil texture, dominant hydrologic soil group, land cover, aspect, and slope were considered.

Examination of the influence of soil texture on validation performance revealed no substantial influence of soil type at the in situ station on the validation performance of the SPoRT-LIS soil moisture product (Figure 5-8). No significant difference among soil texture classes was found after comparing values of Spearman's ρ (p-value=0.167). Examination of the RMSE values revealed a significant difference between the loam and sandy loam texture classes (p-value=0.029), which indicates that SPoRT-LIS soil moisture had a slightly better fit with in situ measurements in loam soils compared to sandy loam soils. Silt loam and silty clay loam were found to be somewhat less biased than sandy loam, though this comparison was not significant. Similar results were found at the 10-cm depth.

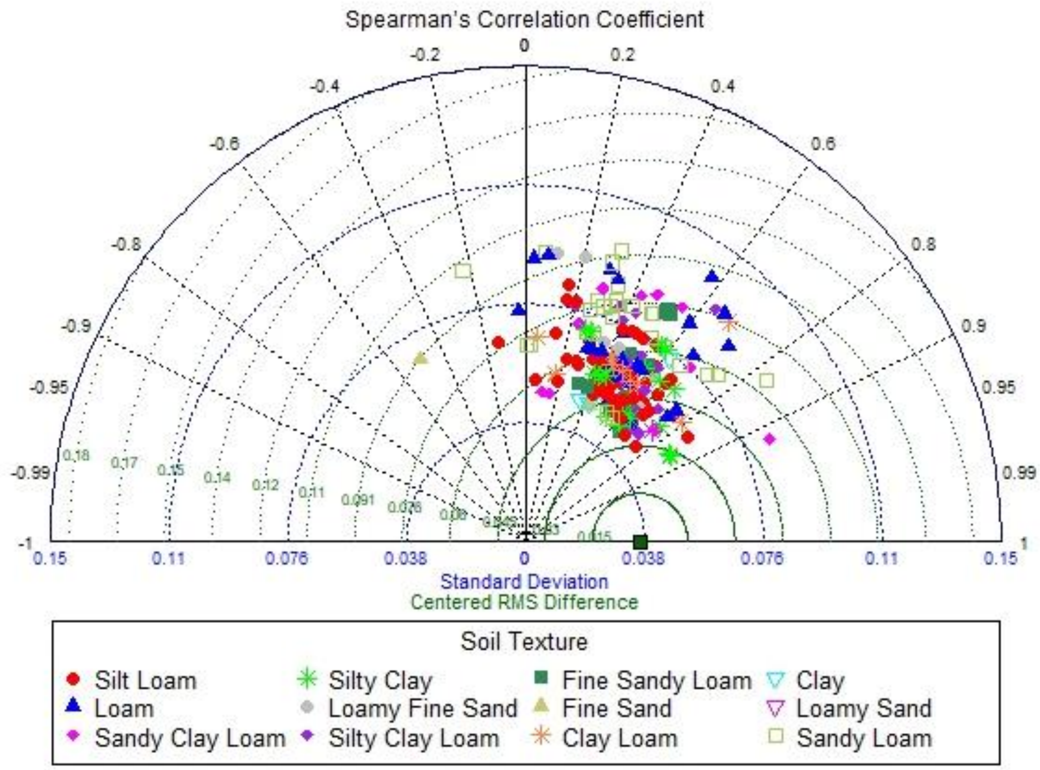

Figure 5-8. Taylor diagram illustrating the influence of soil texture on the comparison between the SPoRT-LIS soil moisture estimate and in situ soil moisture at a 5-cm depth of measurement.

The dominant hydrologic soil group at the in situ measurement site was analyzed to assess its influence on validation performance. Hydrologic soil groups provide an estimate of runoff potential from low runoff potential, Group A, to the highest runoff potential, Group D. Thus, the dominant hydrologic soil group is the prevailing soil group within a specific area. None of the comparisons between soil groups were found to be significantly different after comparing the Spearman's ρ (p-value=0.103), RMSE (p-value=0.421), or bias (p-value=0.0797) at either measurement depth (Figure 5-9). However, some interesting patterns emerge in the results. While not significant, hydrologic soil group C demonstrates higher mean correlation values, with lower RMSE and bias, when compared to group A, which exhibits opposite patterns (Figure 5-9; Figure 5-10). This may indicate that SPoRT-LIS is better suited, in its current configuration, for soil moisture estimation in poorly drained than in well-drained soils. However, this difference could be due to the time lag between the time of a rainfall event and the time that the soil moisture measurement/estimate was taken or mis-characterization of soil properties at the in situ measurement site. Similar results were found at the 10-cm depth.

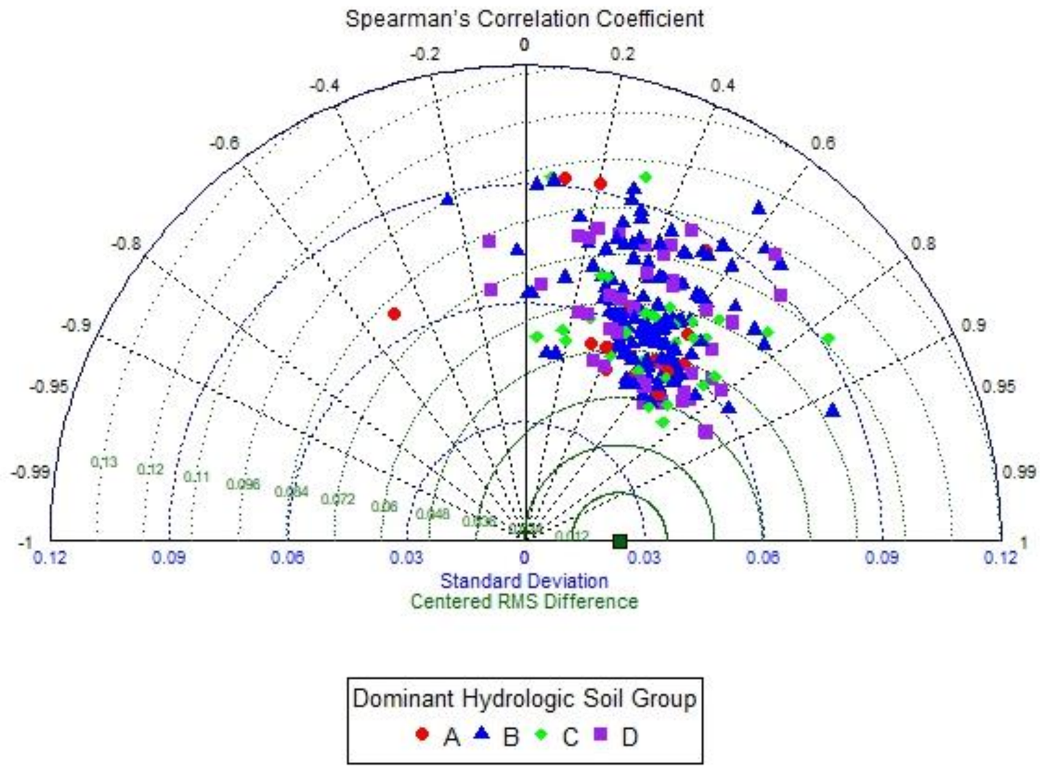

Figure 5-9. Taylor diagram illustrating the influence of donimant hydrologic soil group on the comparison between the SPoRT-LIS soil moisture estimate and in situ soil moisture at the 5-cm depth of measurement.

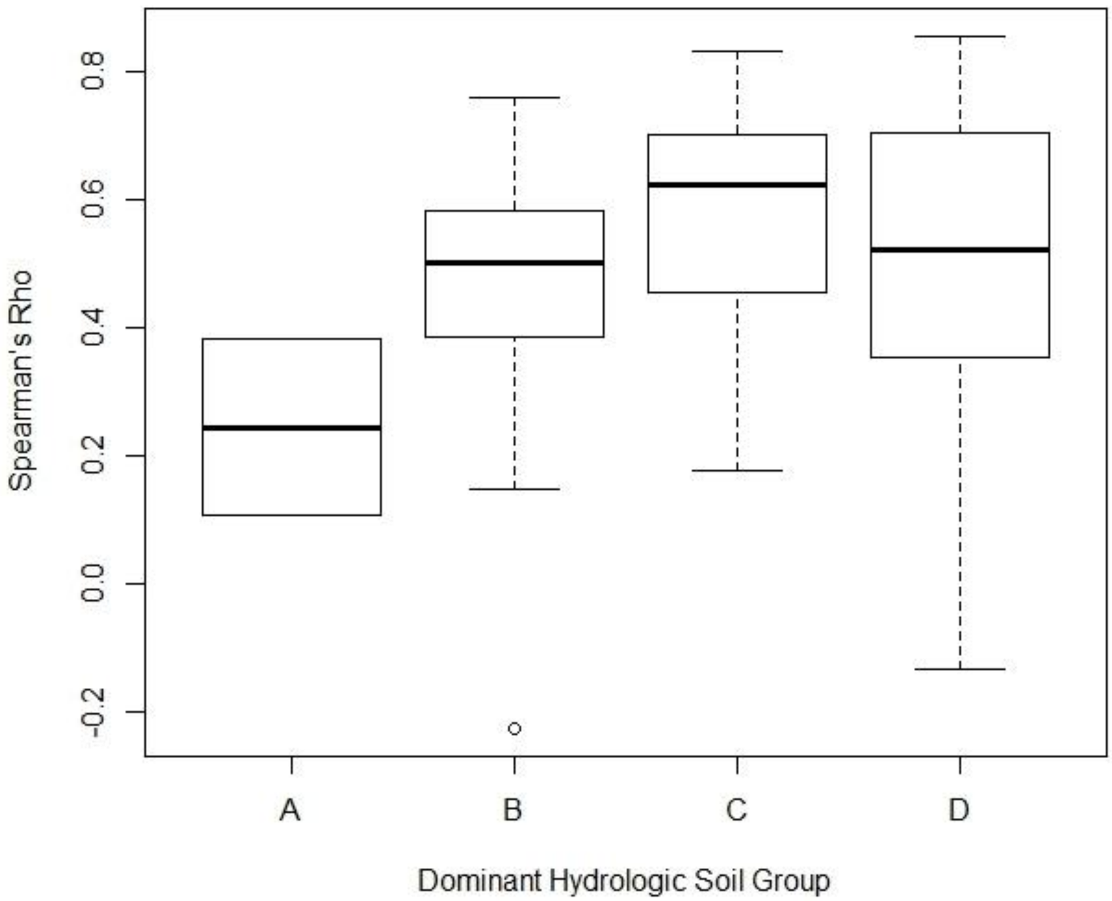

Figure 5-10. The influence of dominant hydrologic soil group on the correlation (Spearman's ρ) between the SPoRT-LIS soil moisture estimate and in situ soil moisture at the 5-cm depth of measurement.

The land cover classification at the ground-based monitoring stations was analyzed to assess its influence on validation performance of the SPoRT-LIS soil moisture estimate. The incorrect classification of land cover can potentially assign the wrong root zone depth or leaf area index within the model (Xia et al., 2015b), which will lead to inaccurate soil moisture estimates. No significant difference (p-value=0.199) was found upon comparison of mean Spearman's ρ values between land cover classes (Figure 5-11). However, the evergreen forest land cover class exhibited significantly higher values of RMSE (p-value=0.0112) when compared to cultivated crops and herbaceous land cover classes and displayed significant higher bias values (p-value=0.0115) when compared to hay/pasture. In general, the forested land cover classes (evergreen, deciduous, and mixed forest) demonstrated poorer correlation performance, higher RMSE values, and higher bias than other land cover classes, though this difference is not significant (other than the aforementioned performance of the evergreen forest class). These results may be attributed to the high vegetation density of forested land cover classes, which have been known to yield poor correlation results (Yang et al., 2016). Given their distribution on the Taylor diagram, the land cover classes of herbaceous, pasture/hay, and cultivated crops appear to demonstrate the best overall fit (Figure 5-11).

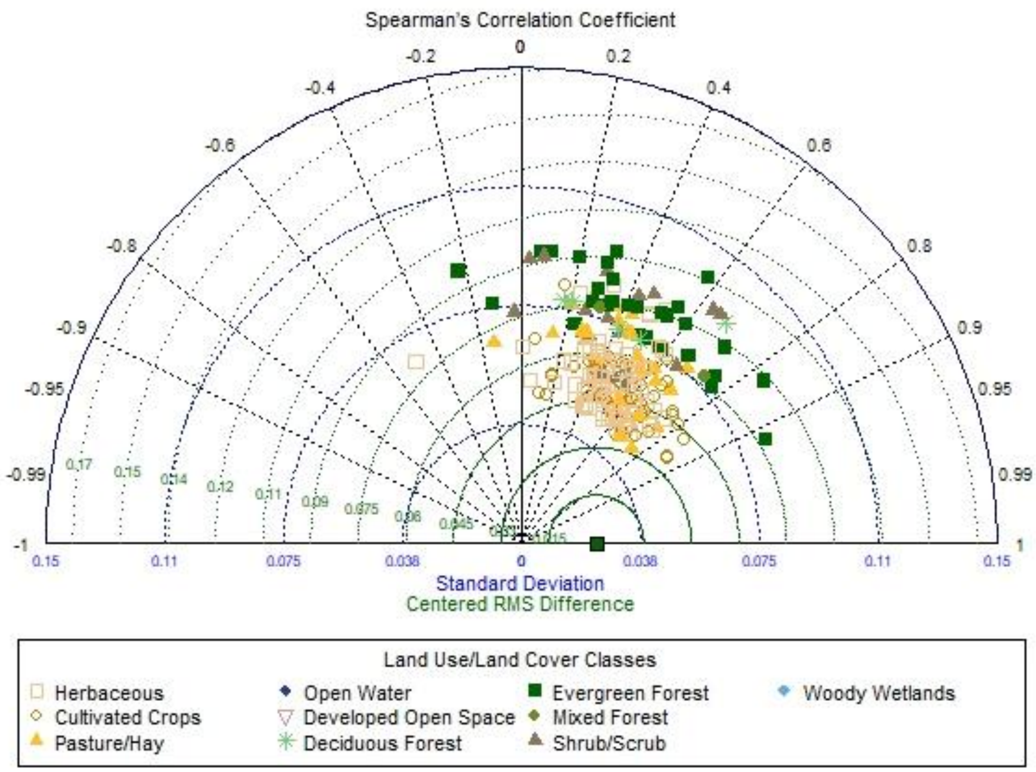

Figure 5-11. Taylor diagram illustrating the influence of land use/land cover classes on the validation between the SPoRT-LIS soil moisture estimate and in situ soil moisture at a 5-cm measurement depth.

Finally, the influence of aspect and slope on the validation performance was evaluated through examination of the Spearman's ρ, RMSE, and bias values at each depth of measurement. No significant trend was evident between either aspect nor slope and any of the validation metrics. This suggests that neither aspect nor slope (at this scale of resolution) has any influence on validation performance.

5.3.4 Grid heterogeneity

Differences in measurement resolution can lead to errors in analysis, especially with validation of remotely-sensed data. The SPoRT-LIS surface soil moisture estimate is measured at a spatial resolution of 3-km, while the in situ soil moisture data is a point-based measurement. Soils and land cover can vary significantly across a 3-km grid and thus can influence the estimate from SPoRT-LIS (Figure 5-12). To address whether this spatial scale mismatch wielded a substantial influence on validation performance, each 3-km grid containing an in situ measurement point was examined to analyze the influence of grid heterogeneity on validation performance. The program FRAGSTATS was used to calculate the Shannon Diversity Index (SHDI) for soil texture, dominant hydrologic soil group, and land cover classes. A SHDI value of zero represents completely homogeneous conditions, and increases in value as the grid cell conditions become more heterogeneous.

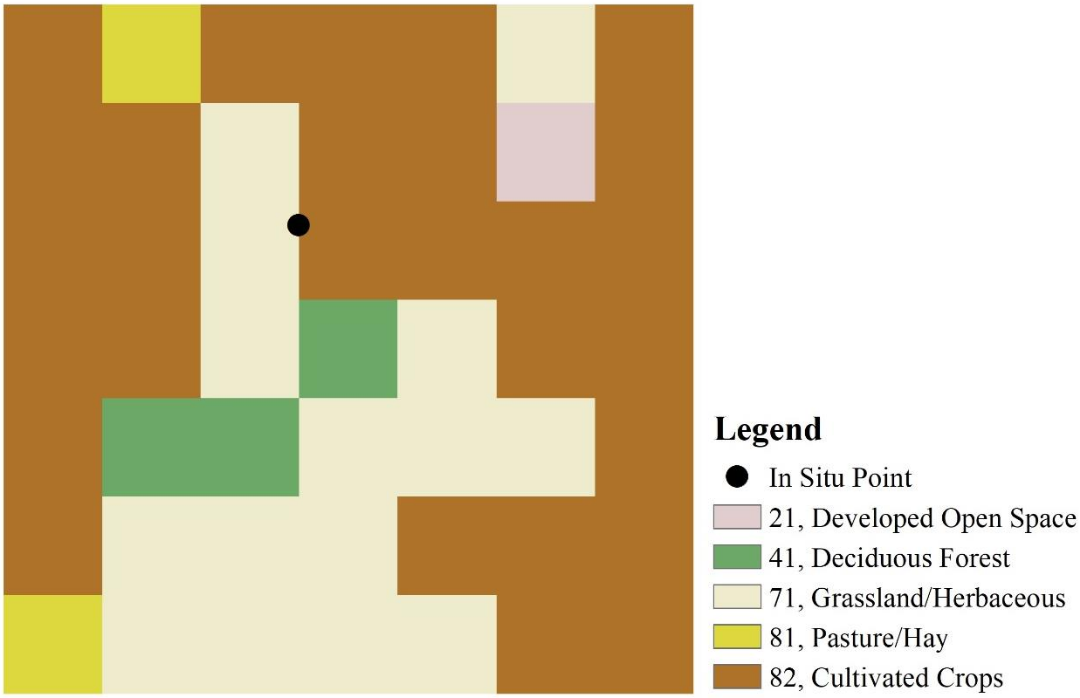

Figure 5-12. An example of the difference in spatial resolution between the 3-km SPoRT-LIS pixel and the in situ point measurement. The above pixel demonstrates a high degree of heterogeneity, with five different land cover classes encased in a single pixel.

The average and median SHDI values for both soil texture and the hydrologic soil group were close to zero, indicating mostly homogeneous soil conditions across the 3-km grid at all validation points (Table 5-4). Land cover was much more heterogeneous, with average and median SHDI values approaching one. Results demonstrate that neither the heterogeneity of the hydrologic soil group, soil texture, or land cover had any significant effect on validation performance, indicating that SPoRT-LIS yields reasonable soil moisture estimates across the landscape.

Table 5-4. Average and median SHDI values for all grids containing an in situ measurement point within the study area.

Factor	Average		Median	
	5-cm	10-cm	5-cm	10-cm
Soil Texture	0.1440	0.1609	0	0
Hydrologic Soil Group	0.1647	0.1113	0	0
Land Cover	0.8163	0.7310	0.8501	0.7594

5.4 – Conclusion

The objective of this study was to validate the SPoRT-LIS volumetric surface soil moisture estimate (0-10 cm) against in situ soil moisture observations across the Missouri and Arkansas-Red-White River Basins within the U.S. Great Plains and assess whether this estimate of soil moisture was suitable for water resources management applications. The SPoRT-LIS soil moisture estimate demonstrated satisfactory correlation with in situ data, with 52% of validation points yielding a significant positive correlation and a Spearman's ρ value greater than 0.5 on a daily basis. Analysis of validation performance on a seasonal basis revealed that soil moisture estimates in summer, fall, and winter were comparable to the overall validation at the 5-cm depth, with Spearman's ρ exceeding 0.4 for all seasons with the exception of spring. However, at the 10-cmdepth, Spearman's ρ values only exceeded 0.4 during summer and fall. Thus, it is evident that the SPoRT-LIS surface soil moisture estimate is comparable with in situ soil moisture at a depth of 5-cm, however caution should be applied when utilizing SPoRT-LIS soil moisture estimates during the spring season due to the low correlation values. The high values of bias and RMSE values exceeding those of the in situ measurement error indicate that further refinement of the SPoRT-LIS software may be necessary.

The influence of physical environmental characteristics, including soil texture, hydrologic soil group, land cover, aspect, and slope, were also analyzed to assess whether these factors exhibited any substantial effect on the validation. While not statistically significant, there was some indication that the SPoRT-LIS soil moisture estimate may be most reliable for areas characterized by poorly-drained soils (e.g., hydrologic soil group C). In addition, forested land cover classes (evergreen, deciduous, and mixed forest) demonstrated poorer correlation performance, higher RMSE values, and higher bias values than other land cover classes. These results suggest that the SPoRT-LIS soil moisture estimate might have a more difficult time capturing soil moisture fluxes in forested land, which may be attributed to dense vegetation, tree canopy and forest litter complicating the estimation of soil moisture in these areas. However, in general, the majority of the environmental parameters that were examined failed to have a significant effect on the validation performance. This is consistent with validation results of the Noah LSM found by (Xia et al., 2015b) who demonstrated that utilization of site-observed soil texture and vegetation type did not improve soil moisture simulations.

Finally, the heterogeneity of soil texture, dominant hydrologic soil group, and land cover across the 3-km grid at each validation point were analyzed to assess whether differences in spatial resolution of measurement points influenced validation performance in any way. Results show that heterogeneity of these three physical factors did not influence validation performance, though these results may be attributed to the generally low measures of heterogeneity calculated for the validation locations. Further analysis using higher resolution land cover and soils data might be able to yield a better understanding of the effect of surface heterogeneity on the validation of remotely-sensed soil moisture.

The results described here suggest that SPoRT-LIS surface soil moisture estimates are comparable to in situ soil moisture at a measurement depth of 5-cm, and that no physical environmental factors or discrepancy in measurement scale influenced the validation performance in any substantial way. Thus it is viable to conclude that the SPoRT-LIS surface soil moisture estimate is satisfactory for research and operational water resources management applications within the Missouri and Arkansas-Red-White river basins. The ability to utilize soil moisture estimates with a high spatial and temporal resolution will be invaluable for analysis of spatiotemporal soil moisture patterns that will aid in the allocation of resources in drought periods, prevent desertification, and manage flood situations. Soil moisture estimates from SPoRT-LIS may also be useful for assimilation in hydrologic modeling and flood forecasting applications.

Future considerations to improve SPoRT-LIS soil moisture may include the assimilation of satellite data, such as from SMAP or SMOS, as the assimilation of passive microwave data into LSMs is known to improve soil moisture estimation (Yang et al., 2016). Data assimilation can be used to update LSMs by combining model states with observations of state variables to provide an updated model analysis superior to either data source alone using satellite data (Blankenship et al., 2016). Future research may investigate the influence of anthropogenic inputs, such as irrigation, on in situ soil moisture as this type of phenomenon is not currently captured in the LSM simulation. The validation of root zone soil moisture estimates from SPoRT-LIS in future examinations of the software would also prove valuable for additional water resources applications.

5.5 – References

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Chapter 6 - Declining soil moisture threatens water availability in the U.S. Great Plains

This chapter is in preparation to be submitted for publication. Co-authors on this manuscript include Stacy Hutchinson and Shawn Hutchinson.

6.1 – Introduction

Soil moisture is an Essential Climate Variable due to its substantial role in the characterization of the global climate (Dorigo et al., 2012; McDonough et al., 2018). Global water and energy cycles are driven by the soil moisture-controlled latent and sensible heat fluxes between the land and atmosphere (Dorigo et al., 2012; Qiu et al., 2016; Lai et al., 2016). In transitional climate zones, such as the central United States, soil moisture influences regional precipitation patterns through "hotspots" of high land-atmosphere coupling (Koster et al., 2004). Furthermore, soil moisture affects the productivity of natural and agricultural ecosystems (McDonough et al., 2018; Dobriyal et al., 2012) and plays a key role in hydrologic processes (Albergel et al., 2013). The spatiotemporal dynamics of soil moisture drive the runoff response in catchments by regulating rainfall infiltration (Qiu et al., 2016), where extreme variations in soil water storage are manifested as regional flood and drought events (Famiglietti and Rodell, 2014).

Monitoring soil moisture in real- or near-real time has proven useful for managing water resource allocation and the development of solutions to global water security challenges (McDonough et al., 2018; Dobriyal et al., 2012). Similarly, the long-term study of regional soil moisture trends, as a measure of the change in soil water storage within a region, is necessary to help us fully appreciate the effects of climate change on water resources (Qiu et al., 2016; Albergel et al., 2013). The majority of previous research on long-term soil moisture trends have been conducted at the global and continental scales (e.g., Dorigo et al., 2012; Albergel et al., 2013; Feng and Zhang, 2015) using relatively coarse data insufficient to capture details of local and regional climate dynamics (Hall, 2014). Unfortunately, few in situ hydrologic observation networks operate at scales conducive for monitoring changes in total water stored throughout a region (Famiglietti and Rodell, 2014). Because of this, the influence of fine-grained variations in soil moisture on regional patterns of precipitation, temperature, and evapotranspiration are not well understood (Cook et al., 2014). Advances in satellite sensor technology and the development of a suite of land surface models, however, now permit novel assessments of soil moisture over large areas spanning long time periods at ever-finer spatiotemporal resolutions.

We examined spatially explicit regional trends in annual surface soil moisture (0-10 cm) across the Missouri and Arkansas-White-Red River Basins for the period 1987-2016. These large watersheds span the central United States (Figure 6-1), including a majority of the U.S. Great Plains region. Soil moisture was estimated by SPoRT-LIS, an observation-driven, real-time simulation of the unified Noah land surface model (McDonough et al., 2018; Chen and Dudhia, 2001; Ek et al., 2003) which measures soil water content at a 6-hour time step across a 3-km grid for the contiguous United States (McDonough et al., 2018). Temporal decomposition of this time series was performed using the Breaks for Additive Seasonal and Trend (BFAST) method (Hutchinson et al., 2015; Verbesselt et al., 2010). Long-term inter-annual trends in soil moisture were dictated by the sign and magnitude of the linear slope computed at the pixel level for the decomposed trend component across the study period (Verbesselt et al., 2010).

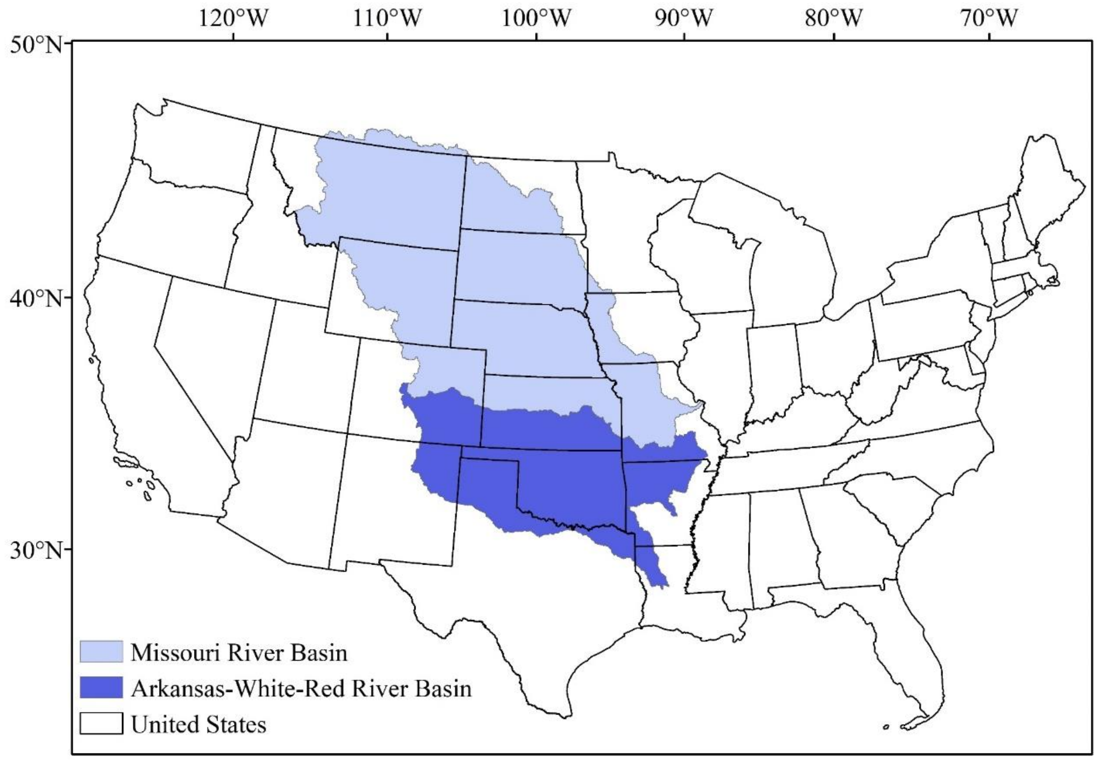

Figure 6-1. The location of the Missouri and Arkansas-White-Red River Basins in the central United States.

6.2 – Methods

Surface soil moisture estimates were obtained from SPoRT-LIS, which is an observation-driven, real-time simulation of the unified Noah land surface model (Chen and Dudhia, 2001; Ek et al., 2003) that provides soil moisture estimates on a 6-hour time step across a 3-km grid (McDonough et al., 2018). Daily soil moisture estimates for a depth of 0-10 cm were estimated across the Missouri and Arkansas-White-Red River Basins from 1987-2016. A daily average soil moisture was computed from the 6-hourly measurement, so that a total of 43,800 images were processed to describe variations in soil moisture from 1987 through 2016. The 0-10 cm SPoRT-LIS soil moisture estimate was previously validated within the Missouri and Arkansas-White-Red River Basins and deemed acceptable for water resources management applications (McDonough et al., 2018). SPoRT-LIS was originally developed by NASA's Marshall Space Flight Center's Short-term Prediction Research and Transition (SPoRT) Center for operational weather forecasting (McDonough et al., 2018).

The Breaks for Additive Seasonal and Trend (BFAST) method was utilized for temporal decomposition (Hutchinson et al., 2015; Verbesselt et al., 2010) and to determine the long-term regional trend in soil moisture throughout the study area. Temporal decomposition enables the division of an original time series dataset into seasonal, trend, and noise components (Hutchinson et al., 2015; Verbesselt et al., 2010). This methodology facilitates examination of the long-term change in soil moisture by removing the seasonal pattern characteristic to soil moisture and any noise from the trend component. Only the trend component was analyzed for this research to understand the surface soil moisture trend from 1987 to 2016. Long-term trends in soil moisture were identified by the linear slope of the decomposed trend component across the entire study period (Verbesselt et al., 2010). Simple linear regression was utilized to determine the statistical significance ($p=0.05$) of the long-term trend at each 3-km pixel within the study area.

The 30-year normal (1981-2010) precipitation and temperature data, as well as the elevation data, were obtained from PRISM Climate Group at a 4-km spatial resolution (PRISM Climate Group, 2015). Soil texture data was acquired from the Digital General Soil Map of the United States (STATSGO2) at a 1:250,000 spatial resolution (NRCS, 2006).

6.3 – Results and Discussion

Average annual soil moisture within the Missouri and Arkansas-White-Red River Basins during the study period ranged from 0.08 m^3 m^{-3} to 0.38 m^3 m^{-3} (Figure 6-2), with the spatial distribution of values generally following the normal precipitation gradient (Figure 6-3). Soil moisture and rainfall were highest in the southeast and declining to the west and northwest, except at the boundary of the Rocky Mountain range. The spatial distribution of temperature (Figure 6-4), elevation (Figure 6-5), and soil texture (Figure 6-6) also influence patterns of soil moisture. Approximately 70% of the study area had an average annual soil moisture below 0.25 m^3 m^{-3}.

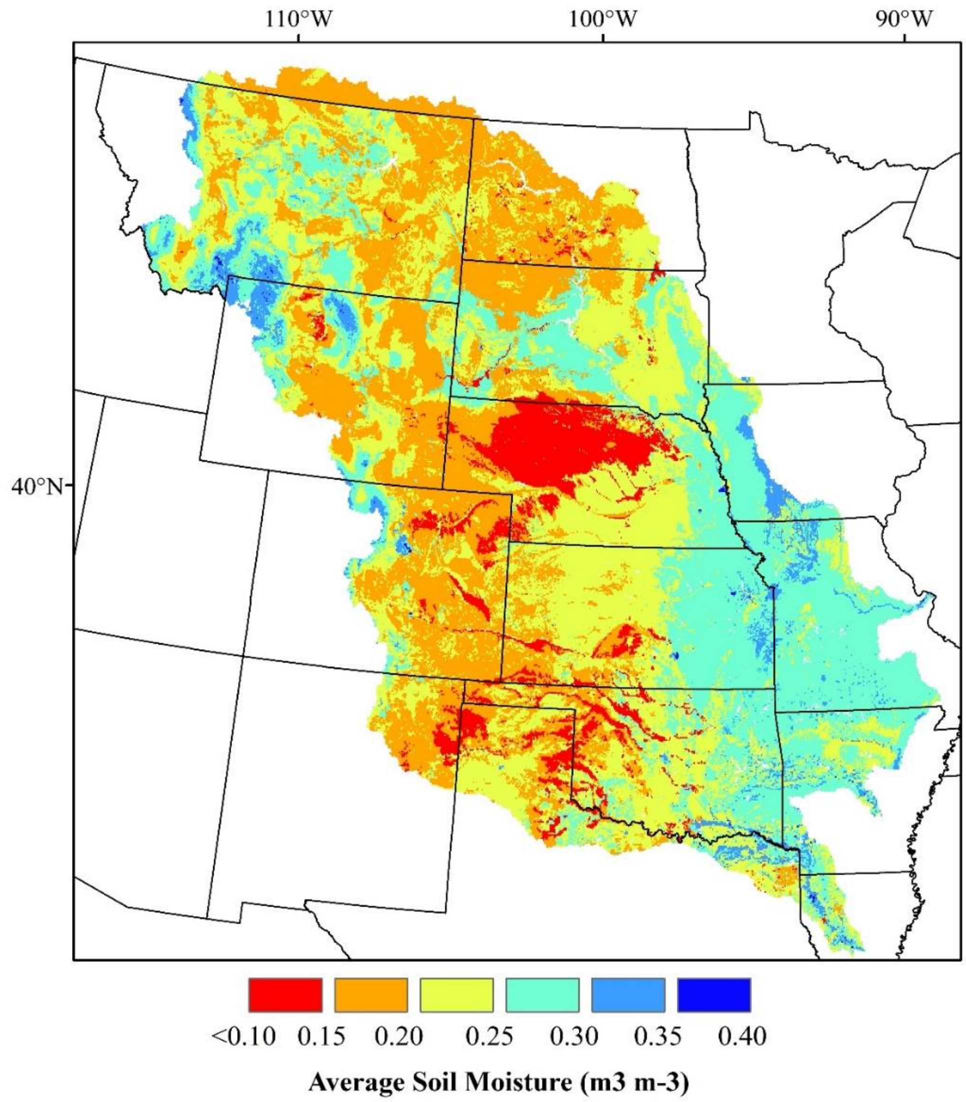

Figure 6-2. Average surface soil moisture (0-10 cm) over the period 1987-2016 within the Missouri and Arkansas-Red-White River Basins.

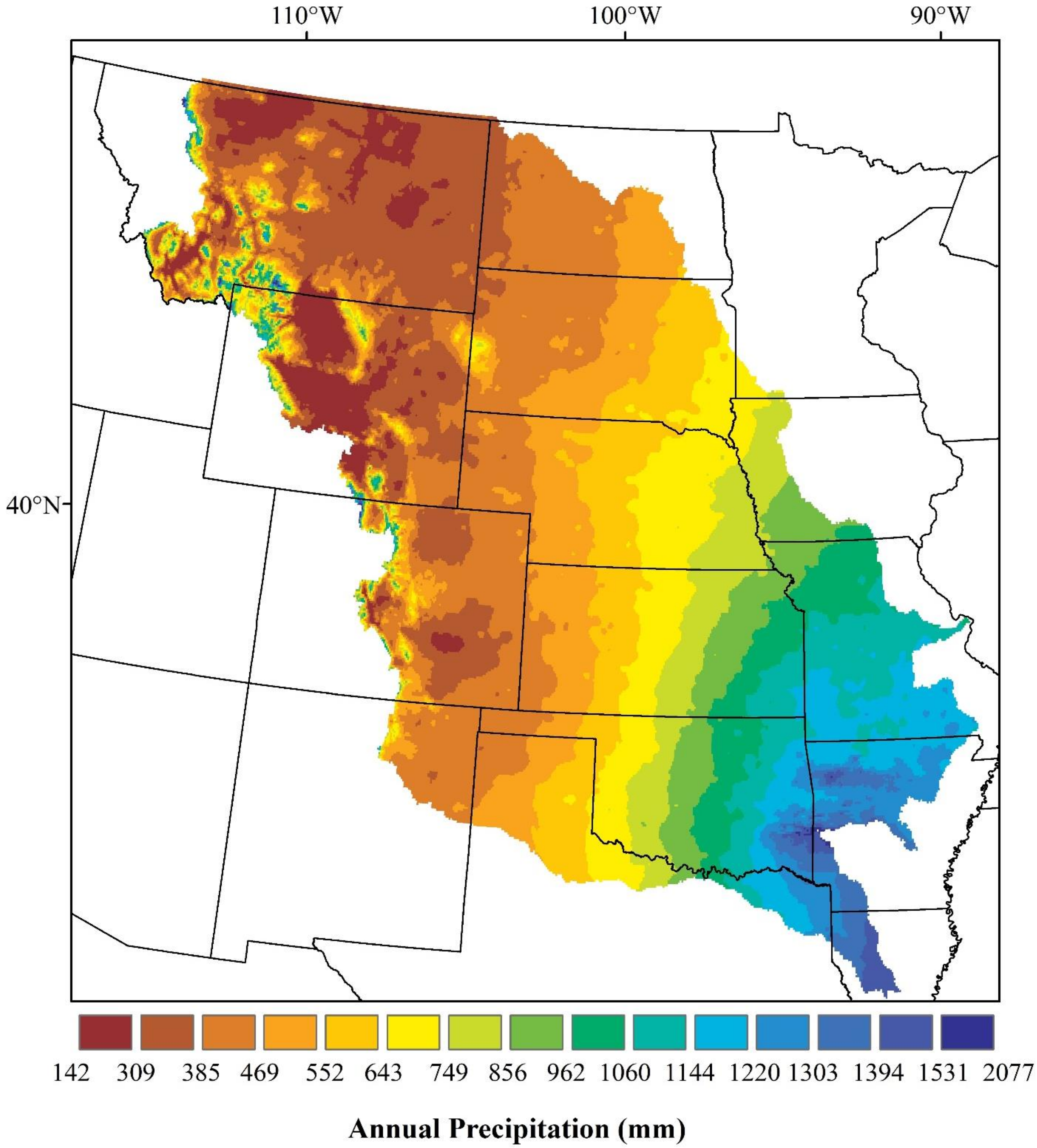

Figure 6-3. Annual precipitation (mm) from the PRISM 30-year normal (1981-2010) dataset (PRISM Climate Group, 2015).

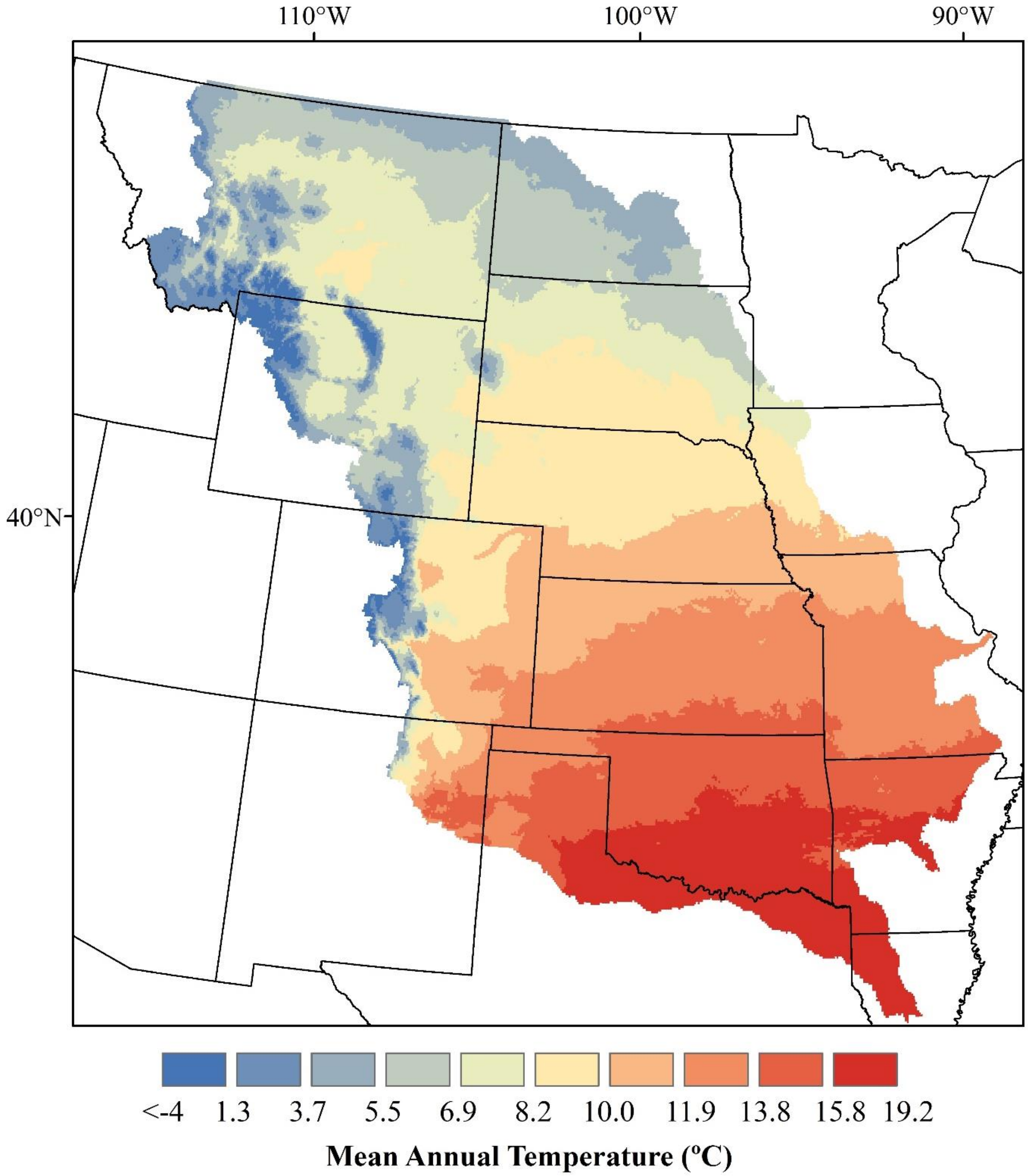

Figure 6-4. Mean annual temperature (ºC) from the PRISM 30-year normal (1981-2010) dataset (PRISM Climate Group, 2015).

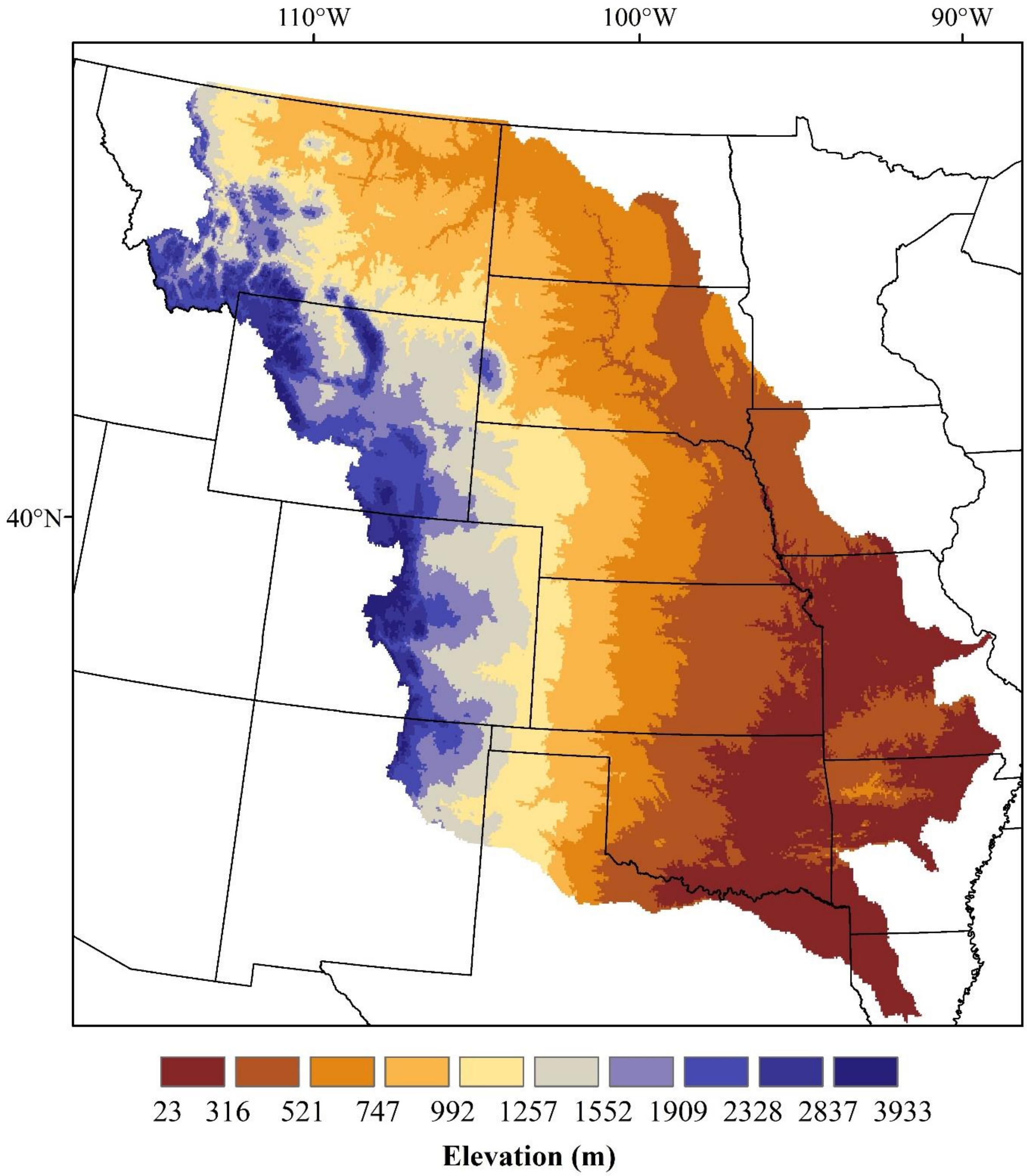

Figure 6-5. Elevation throughout the study area (PRISM Climate Group, 2015).

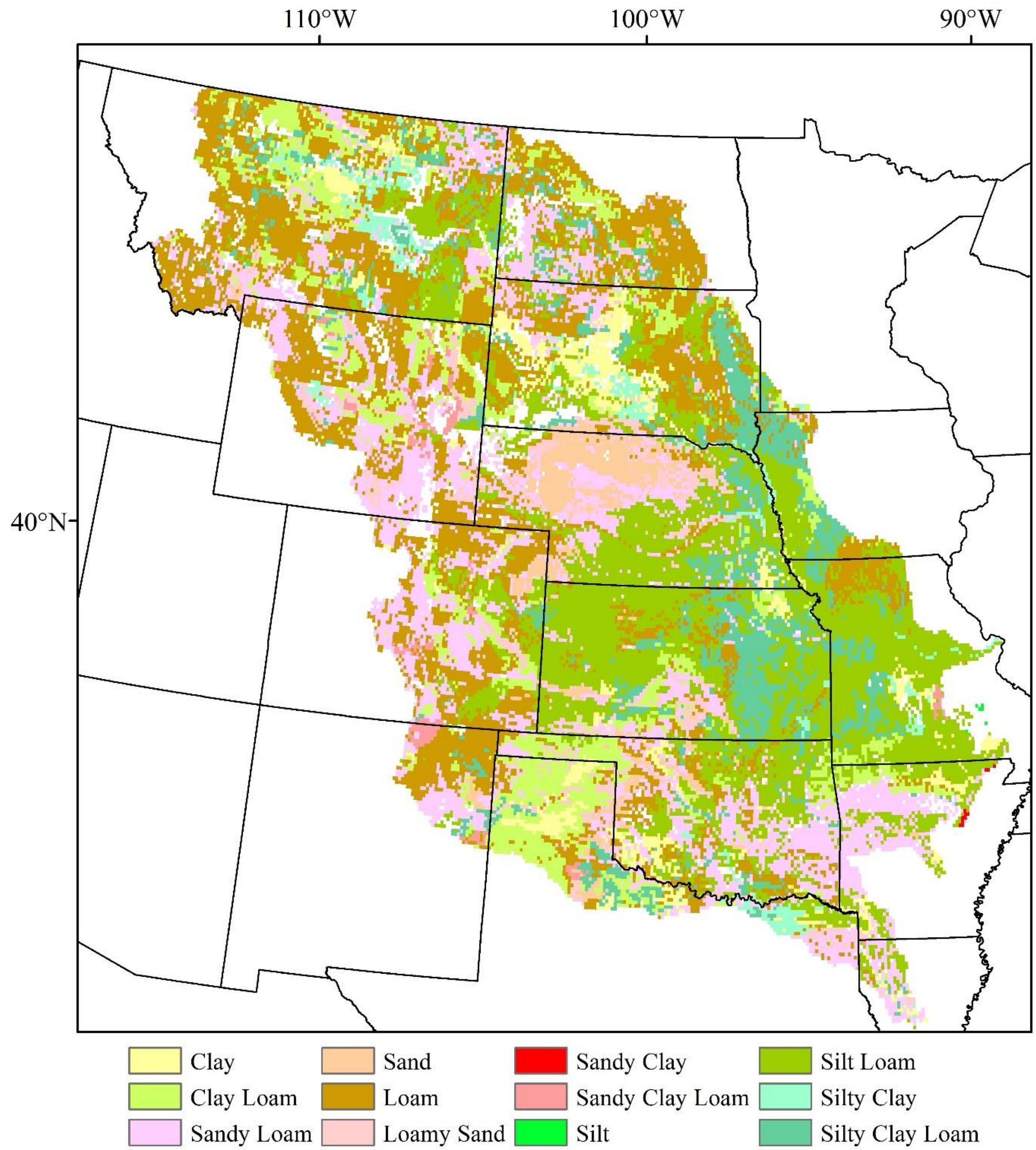

Figure 6-6. Soil texture across the Missouri and Arkansas-White-Red River Basins (NRCS, 2006).

The geography of soil moisture trends from 1987 to 2016 reveals that nearly 64% of the land area within the Missouri and Arkansas-White-Red River Basins, including a majority of the southern and central portions of the watershed, experienced a significant negative, or drying, trend

(Figure 6-7). Significantly positive, or wetting, trends were evident in the northwest at the base of the Rocky Mountain corridor and in small isolated pockets to the south. These results agree with previous global-scale soil moisture analyses which have reported drying in the southern United States, including the southern Great Plains, and increasingly moist conditions across the higher latitudes of North America (Dorigo et al., 2012; Albergel et al., 2013).

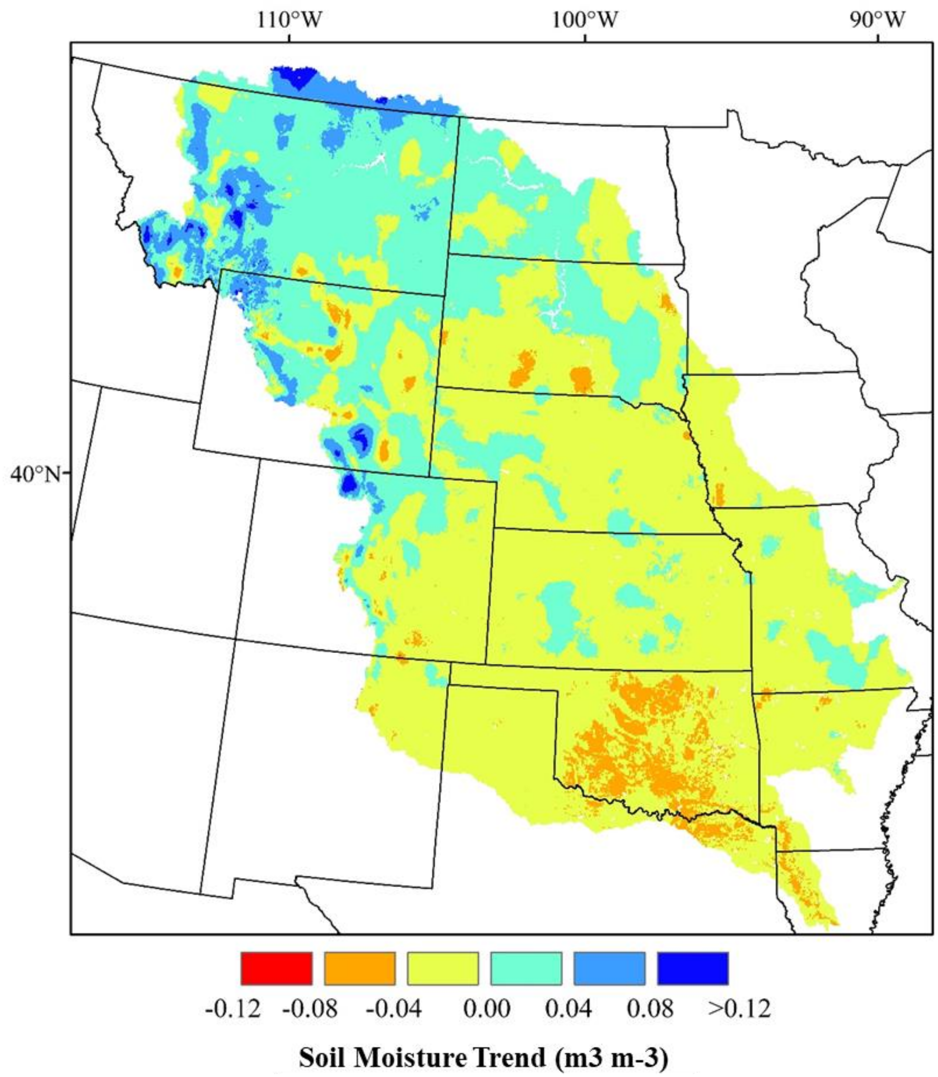

Figure 6-7. Trends in soil moisture ($m^3\ m^{-3}$) from 1987-2016 determined using BFAST statistical software. All trends were significant at $p = 0.05$.

However, comparing patterns of long-term soil moisture trends (Figure 6-7) with the normal average annual precipitation total (Figure 6-3) demonstrates that rainfall alone is an insufficient basis upon which to infer typical soil moisture levels. Across much of the area, the pattern of soil moisture trends deviates significantly from normal precipitation with drying trends dominating the southeast and wetting trends more common across precipitation-limited areas to the north and northwest. In the southeast, average annual soil moisture decreased by up to -0.04 m^3 m^{-3}, though annual precipitation normally exceeds 1000 mm/year. In contrast, soil moisture increased by up to 0.12 m^3 m^{-3} in the northwest, where average annual precipitation averages less than 400 mm/year. These findings tend to contradict estimates of future global surface water availability, which suggest that many of the world's regions will adhere to the "dry gets drier, wet gets wetter" paradigm by the end of the century (Dorigo et al., 2012; Famiglietti and Rodell, 2014; Feng and Zhang, 2015). In the Missouri and Arkansas-White-Red River Basins, positive soil moisture trends were evident in only 16% of "humid" climate zones while declines were present in only 17.6% of "dry" areas (Figure 6-7).

This research corroborates future projections of water availability in the U.S. Great Plains, which forecast continued drying trends in soil moisture (Ault et al., 2016; Cook et al., 2015) despite an expected increase in precipitation (Cook et al., 2014; Ault et al., 2016; Cook et al., 2015; Hoerling et al., 2012). The predicted increase in atmospheric water vapor, due to higher temperatures, will increase the number of high-intensity precipitation events in the U.S. Great Plains (USGCRP, 2017), which limits the opportunity for water to infiltrate into the soil profile and increases surface water runoff. The expected increase in evaporation will likely be sufficient to overcome increases in precipitation (Cook et al., 2014; Cook et al., 2015) and, when coupled with decreased infiltration resulting from high-intensity precipitation events, will move baseline soil moisture to drier conditions and enhance the megadrought risk in the second half of the 21st century (Ault et al., 2016).

6.4 – Conclusion

The availability of surface water stored within the soil profile across the U.S. Great Plains is a critical resource that impacts global agricultural production and the industrial and domestic needs of the region. Given its critical role in land-atmosphere exchanges and its influence on the hydrologic cycle, future studies have an opportunity to build upon these findings to examine inter- and intra-annual variations in soil moisture and identify scale-dependent drivers of soil moisture change. The evaluation of high-resolution soil moisture patterns will help to clarify current conflicting projections of streamflow timing and volume (IPCC, 2014) and associated impacts on reservoir storage (Mateus and Tullos, 2017; Soundharajan et al., 2016; Jaramillo and Destouni, 2015). The inclusion of fine-scale soil moisture estimates within a range of climate and hydrologic models may yield enhancements in accuracy similar to those noted in the performance of weather models used in experimental operations by both domestic and international forecasters (McDonough et al., 2018). Furthermore, routinely incorporating spatiotemporal soil moisture patterns generated from long-term, fine-scale data in regional hydrologic and climate assessments will enhance the development of mitigation and adaptation strategies that address global water security challenges (IPCC, 2014).

These results portray soil moisture in a unique space-time context that can inform and improve robust climate change mitigation and adaptation strategies to maintain adequate volumes of freshwater to meet human and environmental water demand (IPCC, 2014). If ignored, the gradual decline in soil moisture presented here, coupled with expected increases in anthropogenic and atmospheric water demand, will only compound an already uncertain water future for the U.S. Great Plains.

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Chapter 7 - Conclusion

Water security is one of the greatest challenges of this century (Kumar, 2015; Reddy et al., 2015; Mekonnen and Hoekstra, 2016). The anthropogenic water demand could likely outpace freshwater availability in the future as the growing world population, coupled with continuous economic and technological advancements, places significant stress on global water resources. Climate change, which will alter global hydrologic patterns and increase the atmospheric moisture demand, exacerbates this problem even further. However, we have never been better equipped to tackle this challenge than we are now. Substantial advancements in remote sensing technology and Earth-observation frameworks provide the ability to monitor global water resources at spatial and temporal scales that was not previously possible (Cord et al., 2015). Integrated, dynamic, and spatially explicit computer models offer the ability to explore complex environmental interactions (Costanza et al., 2017). Theoretical frameworks, such as the ecosystem services concept, facilitate interdisciplinary research and enable the examination of coupled natural-human systems across scales.

This dissertation provides a multiscale perspective of water resources and associated ecosystem services to understand drivers of change in water availability at the watershed-scale, within the Blue River Watershed, and at the larger basin-scale, throughout the Missouri and Arkansas-White-Red River Basins. Ensuring adequate quantities of safe, affordable, and accessible water in the future requires innovative, interdisciplinary research approaches to water management using a systems perspective across varying spatial and temporal scales. The ultimate goal of this work is to advance the development of water security solutions by contributing to the current water resources and associated ecosystem services knowledge base by 1) reframing the way that traditional hydrology approaches complex socio-environmental problems and 2) emphasizing the need to conduct research that spans multiple spatial and temporal scales.

7.1 – Reframing traditional hydrology

The activities of humans inherently influence the internal dynamics and feedbacks that characterize hydrologic systems, and thus the assumption that humans are a “boundary condition or external forcing” (Di Baldassarre et al., 2013) to hydrologic systems is the fundamental flaw of traditional hydrology. There is a substantial need to reframe this traditional method of thinking and incorporate humans and their associated activities as an intrinsic and influential member of the environmental system. The research within the Blue River Watershed addresses this need by connecting the hydrologic system to anthropogenic activities through the application of the ecosystem services concept.

Land use and land cover throughout Blue River Watershed was altered to accommodate the growing human population through housing development, the construction of industrial facilities, agricultural expansion, and more, which has resulted in dramatic, and possibly irreversible, changes to the pre-development streamflow regime that include an increase in flooding. Flooding is traditionally mitigated through the construction of artificial infrastructure that solves the problem at one location but often translates the problem elsewhere. Alternatively, the ecosystem services concept reframes the traditional approach to flood control by synergistically considering humans and the environment within a single ecosystem to enable flood mitigation. Using this approach, this research assessed the potential for patterns of land use/land cover as “service providing areas” of ecosystem services to provide flood mitigation benefits that ensure human well-being while simultaneously safeguarding the sustainable management of ecosystems.

7.2 – Emphasizing research across scales

The examination of fundamental, hydrologic science across spatial and temporal scales can be extremely useful to identify environmental problems, evaluate their driving mechanisms, and develop appropriate solutions. Spatially and temporally disaggregated data are critical to investigate the unsustainable use of water resources and to determine regions of water scarcity (Moore et al., 2015). Research that is conducted at the global scale, for example, can mask the spatiotemporal dynamics of the hydrologic cycle that are present at finer scales (Mekonnen and Hoekstra, 2016), as was evidenced by research conducted in the Great Lakes region of North America (e.g., Gula and Peltier, 2012; Hall, 2014).

The soil moisture research conducted in the Missouri and Arkansas-White-Red River Basins provides valuable information about long-term, spatially explicit trends in soil moisture from 1987 to 2016. Previous analyses of soil moisture at the global scale predict that current dry regions of the world will become drier by the end of the century, and wet regions will become wetter (Famiglietti and Rodell, 2013). The exact opposite of this phenomenon was found to exist in the Missouri and Arkansas-White-Red Basins, thereby emphasizing that the scale of analysis and associated resolution of data is important to truly understand the availability of water resources. It is important to conduct research at the global, continental, regional, and local scales to understand drivers of water availability and identify areas of water insecurity. Research that continues to investigate this type of fundamental, hydrologic science across spatial and temporal scales will be invaluable and informative to ensuring a water secure future.

7.3 – Future work

Future research will build upon the work presented here to continue to address gaps in the current knowledge base and contribute to future water security solutions. The pursuit of interdisciplinary approaches to socio-ecological systems using the ecosystem services concept will facilitate the uptake of scientific knowledge into management and policy initiatives. Work that examines the linkages between human activities and the environmental system – such as evaluating the influence of land use change on stream flashiness – will be useful as the world population continues to grow. Research that expands upon these results should continue to work within the coupled natural-human system to identify thresholds and feedbacks that exist between humans and the environment. We intend to continue this research path through the utilization of the PCSWMM model to investigate the impact of land management decisions and climate change on the urban streamflow regime.

Furthermore, real-time and continuous monitoring of physical environmental variables across spatial scales will be extremely important to understanding how the climate is changing and its associated impacts at global, continental, regional, and local scales. The development of satellite and remotely sensed technology enables us to ask research questions that were not previously possible and investigate, over large spatial scales, the inter- and intra-annual variations of environmental state variables. Future research should build upon the soil moisture trends presented here to identify the driving mechanisms of fluctuations in soil moisture to understand patterns of surface water availability and inform water resource managers around the world.

Water security is a global challenge that will become increasingly complex in the future due to climate change, the growing world population, and technological and economic advances.

Innovative and interdisciplinary research that utilizes technology and methodology from multiple disciplines will be the most effective at providing water security for the world.

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