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Quantification of Hydrologic Response to Forest Disturbance in Western U.S. Watersheds

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QUANTIFICATION OF HYDROLOGIC RESPONSE TO FOREST DISTURBANCE

IN WESTERN U.S. WATERSHEDS

by

Sara A. Goeking

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This work is dedicated to my parents, Carla Jean and Harold Goeking.

ABSTRACT

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by

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Forests influence the partitioning of precipitation into evapotranspiration and streamflow water balance components. Forest cover and streamflow are generally expected to be related because forest cover impacts evapotranspiration. In coniferous western forests, recent widespread tree mortality has provided opportunities to improve understanding of the relationship between forest cover change and water yield and inform management of forested watersheds in the context of climate change, increased demands on water, and drought.

This work investigated hydrologic response to forest disturbance in the western United States. First, I synthesized findings from 78 published studies of streamflow or snowpack response to forest disturbances. Results indicated that streamflow and snowpack may increase, not change, or even decrease with reduced forest cover due to disturbance. Decreased streamflow occurred due to net increases in evapotranspiration, particularly following non-stand replacing disturbance. Higher post-disturbance subcanopy radiation caused increased evaporation from soil or snowpack, and rapid post-disturbance vegetative recovery resulted in increased transpiration.

Next, I investigated streamflow response to forest disturbance in 159 watersheds using hydrologic, climatic, and forest data from an existing curated hydro-climatological watershed dataset and the US Forest Service's Forest Inventory and Analysis (FIA) dataset. Streamflow change due to tree mortality was found to depend on aridity. In wetter watersheds, disturbances tended to increase streamflow, while post-disturbance streamflow more often decreased in arid watersheds with high potential evapotranspiration to precipitation ratio.

Several physically based hydrologic models recognize the different influences that overstory versus understory canopies exert on hydrologic processes, yet most inputs to such models consist only of total leaf area index (LAI) rather than LAI differentiated by strata. I developed LAI datasets for separate overstory and understory canopy strata with the intent of providing improved canopy inputs for ecohydrologic modeling. These datasets were created using a novel method for estimating LAI from FIA plot data. Time series of overstory and understory LAI demonstrated that interannual variability of understory LAI exceeds that for overstory LAI. The separation of LAI into overstory and understory components is anticipated to improve the ability of LAI-based analyses and models to simulate the influence of forest canopies on hydrologic processes.

(210 pages)

PUBLIC ABSTRACT

Quantification of Hydrologic Responses to Forest Disturbance

in Western U.S. Watersheds

Sara A. Goeking

Forested watersheds produce more than half of the water supply in the United States. Forests affect how precipitation is partitioned into available water versus evapotranspiration. This dissertation investigated how water yield and snowpack responded to forest disturbance following recent disturbances in western U.S. forests during the period 2000-2019.

Chapter 2 systematically reviewed 78 recent studies that examined how water yield or snowpack changed after forest disturbances. Water yield and snowpack often increased after disturbance, but decreased in some circumstances. Decreased water yield was most likely to occur following disturbances that did not remove the entire forest canopy. It was also more likely to occur in more arid watersheds at lower latitudes, such as in the southwestern U.S., and on south-facing aspects.

Chapter 3 examined 159 watersheds across the western U.S. to determine how often and where water yield increased or decreased following forest disturbance. Overall, more severe forest disturbances, particularly in relatively wet watersheds such as in the Northern Rocky Mountains or Pacific Northwest, were more likely to produce larger water yield. However, forest disturbances in very arid watersheds, such as those in the southwestern U.S., were more likely to result in less water yield.

Chapter 4 developed a new method for more precisely mapping forest canopies and understory forest vegetation. This method used data collected by the U.S. Forest Service's Forest Inventory and Analysis Program. The maps of separate forest canopy and understory vegetation layers are expected to allow hydrologists to make more accurate predictions regarding the effects of future vegetation changes on water supply.

Previous studies that monitored water yield before and after clearcut timber harvests concluded that forest disturbances would lead to increased water yield. In contrast, the work presented here found that disturbances that do not remove the entire canopy (e.g., due to insects, drought, disease, thinning, low-severity wildfire) may lead to different water yield and snowpack responses than disturbances that remove the entire canopy (e.g., clearcut harvesting, severe wildfire). This work has therefore helped us better understand how future water supply, for people and for ecosystems, will be affected by future forest changes.

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CHAPTER 1

INTRODUCTION

Forest ecosystems provide most of our water supply in the western U.S. This dissertation describes research that enhances our understanding of how forest cover, disturbance, and climate interact to affect streamflow. Forests influence the partitioning of precipitation into runoff and evapotranspiration through several hydrologic processes. Our understanding of the interacting effects of climate and forest dynamics on streamflow requires observational examination of how streamflow has responded to recent forest disturbances. Our ability to predict the effects of future forest changes on water supply depends on this understanding and also on our ability to better represent forest cover and forest cover change in hydrologic models.

This study has advanced our understanding of the effects of changes in forest cover on streamflow through investigations of the effects of forest disturbance on streamflow. First, I conducted a systematic review of literature on this topic. From this synthesis, I drew conclusions about how forest disturbance affects snowpack and streamflow, identified factors that may influence post-disturbance streamflow, and formulated testable hypotheses. Second, I tested my hypotheses from the earlier work using a sample of many watersheds across the western US. This analysis combined watershed-scale data from the CAMELS hydroclimatic dataset (Addor et al. 2017), which is a curated dataset representing carefully selected watersheds within the U.S., with forest cover and disturbance data from the U.S. Forest Service's Forest Inventory and Analysis (FIA) dataset (Burrill et al. 2018). Third, I developed a spatially and temporally enhanced representation of forest cover that may improve future performance of distributed hydrologic models.

Objectives and hypotheses

This dissertation addressed three specific research objectives. Each objective is described below, followed by a brief statement of our expectation or hypothesis related to that objective.

Objective 1: Determine how recent forest disturbances have influenced streamflow and snowpack via canopy ecohydrologic processes.

Expectation/hypothesis: I hypothesized that recent forest disturbance has led to variable streamflow responses, including no effect, increases, and decreases. I expected that disturbance has led to increased throughfall of precipitation and decreased interception and transpiration, leading to increases in streamflow, but has also resulted in increased solar energy fluxes that may lead to increased evaporation from soil and faster melting and sublimation of snowpack, thereby decreasing streamflow. The balance of these process-level responses was hypothesized to dictate whether streamflow increased or decreased.

Objective 2: Determine how recent forest disturbances have influenced streamflow, using a novel combination of systematic forest inventory data and a curated large-sample hydrologic dataset.

Expectation/hypothesis: I expected that (a) annual streamflow is generally inversely and nonlinearly related to forest cover, (b) annual streamflow following disturbance may be more likely to decrease in watersheds where aridity and incoming solar radiation are relatively high, e.g., in the Southwestern U.S., and (c) the interaction of disturbance severity and aridity affect not only the magnitude but also the direction of post-disturbance change in streamflow.

Objective 3: Develop a method for producing separate overstory and understory leaf area index (LAI) datasets for input to hydrologic models, produced using a combination of data from an existing forest monitoring network, remote sensing data, and spatially explicit biophysical data. This objective was intended to bridge the gap between how foresters typically characterize forests, using metrics such as tree diameter, height, basal area, and canopy cover, versus how hydrologists characterize vegetation using LAI in hydrologic models.

Expectation/hypothesis: I expected the result from combining these data to provide more detailed forest cover information than is currently available from nationwide remote sensing LAI products.

Addressing these three objectives led to two major accomplishments: 1) new insights regarding how forest cover and climate interact to influence streamflow, and 2) a new method for combining forest monitoring data with biophysical and remote sensing information to improve the quantitative characterization of forest structure, with separate layers representing overstory versus understory density, for input to hydrologic modeling. These outcomes will improve the ability of researchers and resource managers to evaluate the effects of future changes in forest cover on streamflow, both through modeling and through improving what we know about how the relationship between forest cover and streamflow varies across different environments. Addressing these objectives and their respective hypotheses has provided information that can be used for forest and water management and planning.

Forest hydrology overview: Linkages between forest cover and streamflow

All three objectives drew upon knowledge of forest hydrology derived from the disciplines of forestry and hydrology. Principles of forest hydrology include the effects of tree canopies on the main water balance components of the hydrologic cycle. Forests influence the partitioning of precipitation into runoff versus evapotranspiration through several hydrologic processes. Tree cover intercepts precipitation, affects wind patterns and thus snow redistribution (Broxton et al. 2015), produces litter and roots that affect infiltration rates (Dingman 1993), transpires water from the soil into the atmosphere (Biederman et al. 2015), and influences local energy balance and snow water equivalent (Broxton et al. 2015; Mahat and Tarboton 2014; Veatch et al. 2009). Thus, changes in forest cover may affect the relationship between precipitation and runoff.

The influence of forest cover on hydrologic processes implies that changes in forest cover may alter the timing and magnitude of runoff. A classic long-term study of paired watersheds at the Fool Creek drainage in Colorado found that clearcutting a coniferous forest resulted in earlier and higher peak flows, as well as higher annual streamflow, relative to an uncut watershed (Troendle and King 1985). However, changes in forest cover range from complete removal of the canopy (e.g., due to clearcutting, stand-replacing fire, or conversion to another land use or cover type) to proportional reduction in forest cover due to minor disturbances such as low-severity fire, drought, or insect epidemics. Such proportional reductions were observed after a mountain pine beetle outbreak in the 1970s in Jack Creek, Montana (Potts 1984), which increased total runoff and caused earlier peak flows. In the case of both clearcutting and insect epidemics, the primary explanation for increased streamflow is that reductions in forest cover resulted in decreased evapotranspiration and canopy interception (Potts 1984; Troendle and King 1985).

These previous observations led to the expectation that reductions in forest cover would result in increased streamflow. This expectation has been tempered in snow dominated regions by findings that forests of intermediate cover (25-50%) can retain the greatest snow water equivalent due to tradeoffs between interception and shading (Veatch et al. 2009). Furthermore, dense forests may actually exhibit lower snowpack retention times if they have lower albedo or emit more downward longwave radiation than sparser stands (Lundquist et al. 2013).

Recent tree mortality in the western U.S. has provided an opportunity to study the linkage between forest disturbance and streamflow. Tree mortality has been extraordinarily high over the past two decades due to a combination of drought, insects, and non-stand replacing wildfire, all of which reduce tree cover rather than remove the entire canopy, as well as severe wildfire that does remove the canopy (van Mantgem et al. 2009). Some studies have confirmed the general expectation that minor forest disturbance increases streamflow due to increased throughfall and decreased canopy sublimation and evapotranspiration (e.g., Livneh et al. 2015; Wei and Zhang 2010). However, these effects are not universally observed because increased sublimation and increased transpiration in surviving, understory vegetation may offset the decreased evapotranspiration caused by overstory mortality, either immediately post-disturbance

(Biederman et al. 2015) or over time if regrowth of understory vegetation occurs rapidly and evapotranspiration increases to pre-disturbance levels (Wei and Zhang 2010). Indeed, reductions in forest cover may either increase or decrease streamflow. Decreased streamflow is hypothesized to occur after forest disturbance in catchments with low precipitation or abundant understory vegetation (Adams et al. 2011). Thus, the existing evidence does not unambiguously support the expectation that reductions in forest cover will increase streamflow. Rather, it verifies the importance of considering individual hydrologic processes, energy budget components, and their respective contributions to streamflow. The variable results summarized above underscore the complexity of forest-streamflow interactions and the need for future investigation of the link between forest disturbance and streamflow (Vose et al. 2016).

Several reviews of research on forests and streamflow (Brown et al. 2005; Andréassian 2004; Bosch and Hewlett 1982) identified similarities among previous studies and then outlined gaps to be filled by future research. First, there is a dearth of research on watersheds larger than those considered in paired-catchments studies (Brown et al. 2005; Bosch and Hewlett 1982), most of which are less than 2 km^2 (Andréassian 2004). Observations of many watersheds across a broad area, or simulation models of larger watersheds, may be required in lieu of paired-catchment observation in larger watersheds due to the difficulty of finding similar-sized control catchments (Andréassian 2004). Second, forest cover is characterized as percent forested area in both observational and simulation studies (Andréassian 2004), where a 20% reduction in forest area across a catchment is thought to produce a measurable hydrologic response (Brown et al. 2005; Bosch and Hewlett 1982). Thus, most studies answer questions about reductions in forest area rather than reduction in tree cover, e.g., a 20% loss of forest canopy across the forested portion of a watershed. Given high recent tree mortality across the western U.S. (van Mantgem 2009), a more realistic representation of forest cover will include intrinsic attributes of patches within watersheds, such as basal area or leaf area per patch or per pixel, which may be acquired from existing forest monitoring institutions (Andréassian 2004).

The value of improved vegetation inputs for hydrologic modeling

Water planners and managers are interested in hydrologic response at the scale of individual watersheds and river basins (Andréassian 2004). Water researchers are also interested in questions about how well site-specific processes scale up to entire watersheds. Spatially distributed models allow estimation of interception, sublimation, and evaporation within coniferous forest canopies, often at flexible spatial scales ranging from individual trees to forest patches to entire catchments.

Existing hydrologic models vary with respect to their representations of vegetation and its effects on ecohydrologic processes in simulations of streamflow. Many hydrologic models do not incorporate a lot of vegetation detail, and some represent vegetation only in terms of land cover or land use classes. Two models that are capable of representing spatial distributions of forest canopies within a watershed are the Distributed Hydrology Soil Vegetation Model (DHSVM; Wigmosta et al. 1994) and the Regional Hydro-Ecologic Simulation System (RHESSys; Tague and Band 2004). DHSVM allows vertical representation of two canopy layers (Wigmosta et al. 1994), and RHESSys can simulate ecohydrologic fluxes within multiple canopy layers, an understory vegetation layer, and a litter layer at multiple spatial scales within a watershed (Tague and Band 2004). Both RHESSys and DHSVM are distributed, physically based models, wherein inputs and outputs are spatially explicit and temporally dynamic, and algorithms represent physical processes rather than statistical or empirical relationships (Tague and Band 2004; Wigmosta et al. 1994). For example, RHESSys uses a mass-balance approach to simulate streamflow as well as ecosystem processes such as evapotranspiration and net photosynthesis (Tague and Band 2004; Band et al. 1996). Among existing models that can simulate the effects of forest cover changes on hydrology, these models stand out due to their physically based representation of hydrologic processes within multiple vegetation strata in a spatially distributed framework. Thus, they represent a methodology for expanding ecohydrologic research beyond the spatial scale considered in most observational studies (Andréassian 2004) and for considering the possibility of increases vs. decreases in total evapotranspiration following disturbances that differentially affect canopy strata (Adams et al. 2011).

Most applications of RHESSys and DHSVM do not fully exploit their capabilities to represent the effects of multiple vegetation layers on hydrologic processes because of input data limitations. RHESSys and DHSVM, as well as some other physically based hydrologic models, characterize canopy strata in terms of leaf area index (LAI, i.e., m^2 foliage per m^2 ground area). In the absence of leaf area index data, estimates of LAI are generated from internal lookup tables based on land cover classes from the National Land Cover Dataset (Tague and Band 2004). Therefore, the accuracy and precision of vegetation inputs to RHESSys and other models could be improved by developing a method for converting detailed forest data into leaf area index. Although Landsat-based

LAI recently became available for a wide range of years (Kang et al. 2021), such LAI datasets based on remote sensing alone represent total LAI and do not distinguish between LAI of the forest canopy layers (i.e., the overstory) and LAI of shorter herbaceous or shrub vegetation (i.e., the understory). Therefore, development of separate overstory and understory LAI datasets represents a potential improvement to the inputs to such hydrologic models. If vegetation inputs are more detailed and precise, then model-based predictions of how forest changes affect hydrologic processes and streamflow may be more accurate.

Strategic forest monitoring programs such as national-scale forest inventories are expected to provide the most detailed ground-based observations of forest vegetation for hydrologic modeling purposes (Andréassian 2004). Although hydrologic models typically characterize vegetation in terms of LAI, most forest monitoring protocols do not include observations or measurements of LAI (Härkönen et al. 2015) but do include measurements such as canopy cover by vegetation type as well as detailed measurement on individual trees (Korhonen et al. 2006; Jennings et al. 1999). Therefore, a need exists to translate forest inventory data into LAI estimates by canopy stratum. In previous studies, LAI was estimated from allometric equations based on other field measurements such as tree basal area or sapwood area (Bréda 2003). However, only a handful of forestry studies have developed allometric equations for estimating LAI for tree species in the western U.S. (Coops et al. 2007; McDowell et al. 2007; Smith et al. 1991). Such studies are sparse because they typically involve destructive sampling of entire trees, which is expensive and time-consuming. Therefore, one objective of this work was to develop methods for translating forest inventory data into separate overstory and understory LAI components, and then producing spatially explicit overstory and understory LAI datasets.

Significance

This dissertation enhances our understanding of the relationship between forest change and streamflow. This understanding, in turn, improves the ability of managers to anticipate the effects of future forest disturbance and recovery on water supply from forested watersheds. Managers of forested watersheds can use the results of this work to identify the likely hydrologic impacts of an observed forest disturbance, or they may decide that the risk of adverse water supply impacts from future forest disturbances may warrant vegetation management actions. For example, a watershed with a severe insect epidemic may be more or less likely to produce increased water yield, depending on factors such as watershed aridity and post-epidemic vegetation regrowth, or the risk of future severe wildfire may warrant preventative actions given its anticipated impacts to snowpack, streamflow magnitude, water quality, and peak flow timing.

This dissertation is presented as three papers, each submitted for publication separately to peer reviewed journals. The first paper, published as Goeking and Tarboton (2020), synthesized recent literature to identify the nuanced response of streamflow and snowpack to forest disturbance, including identification of process-level hydrologic responses that determine net streamflow and snowpack response. The next paper, published as a preprint in Goeking and Tarboton (2021), then tested hypotheses that were developed in the literature synthesis across a large-scale watershed dataset spanning the western U.S. This paper’s findings confirmed that streamflow response to forest disturbance is variable in both magnitude and direction, and also that the direction of streamflow response to forest disturbance is dependent on a combination of disturbance severity and aridity. The final paper produced an enhanced LAI dataset for hydrologic modeling. Two aspects of this last paper were novel: First, the use of detailed forest inventory measurements to estimate overstory and understory LAI for individual sample plots, and then the combination of plot-scale estimates of overstory and understory LAI with remote sensing and biophysical variables in a machine learning model to produce spatially explicit LAI layers for separate overstory and understory strata. The general methods developed in the last chapter could be applied to any part of the world where spatially representative forest cover data exist and are similar to the FIA data we used, which are available across the conterminous U.S.

The factors that affect streamflow and snowpack response to forest disturbance are not restricted to the study area of this dissertation. Therefore, our findings may be indicative of processes and streamflow changes occurring in other regions of the world that are subject to episodic reductions in forest cover.

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CHAPTER 2

FORESTS AND WATER YIELD: A SYNTHESIS OF DISTURBANCE EFFECTS ON STREAMFLOW AND SNOWPACK IN WESTERN CONIFEROUS FORESTS[1]

Abstract

In coniferous western forests, recent widespread tree mortality provided opportunities to test the long-held theory that forest cover loss increases water yield. We reviewed 78 studies of hydrologic response to standing-replacing (severe wildfire, harvest) or nonstand-replacing (drought, insects, low-severity wildfire) disturbances, and reassessed the question: Does water yield or snowpack increase after forest disturbance? Collective results indicate that postdisturbance streamflow and snowpack may increase, not change, or even decrease, and illuminate factors that may help improve predictability of hydrologic response to disturbance. Contrary to the expectation that tree mortality reduces evapotranspiration, making more water available as runoff, postdisturbance evapotranspiration sometimes increased—particularly following nonstand-replacing disturbance—because of (a) increased evaporation resulting from higher subcanopy radiation, and (b) increased transpiration resulting from rapid postdisturbance growth. Postdisturbance hydrologic response depends on vegetation structure, climate, and topography, and new hypotheses continue to be formulated and tested in this rapidly evolving discipline.

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[1] Goeking, S.A. and Tarboton, D.G. 2020. Forests and water yield: A synthesis of disturbance effects on streamflow and snowpack in western coniferous forests. *Journal of Forestry* 118: 172-192. DOI: https://doi.org/10.1093/jofore/fvz069.

Management Implications (Plain Language Summary)

Previous research on the link between forest management and water yield led to the expectation that water yield would increase following recent tree mortality in the Western US. This paper presents a review of papers published during 2000-2018 on the effects of forest disturbance on streamflow in western coniferous forests. While some studies observed post-disturbance increases in water yield, as expected, in many cases water yield did not change or even decreased. Decreases were generally observed in areas with the following characteristics: high total radiation and high solar radiation (i.e., at low latitudes and south-facing aspects); rapid growth of post-disturbance vegetation; and non-stand replacing disturbances, such as drought and insect-caused mortality. Although one objective of forest management may be to increase water yield, another might be to encourage post-disturbance forest recovery and resilience by optimizing growing-season soil moisture, which depends on snow accumulation and retention. The ability to meet such goals, and the treatments to accomplish them, depend on residual vegetation, latitude, and aspect. Our review suggests that recommendations for meeting specific management objectives in forested watersheds of the semi-arid West – and the best available scientific information about the link between forest cover and water yield – are changing rapidly.

Introduction

In 1967, Alden Hibbert concisely formulated three long-lived hypotheses about the relationship between forest cover and water yield: “1. Reduction of forest cover increases water yield. 2. Establishment of forest cover on sparsely vegetated land decreases water yield. 3. Response to treatment is highly variable, and, for the most part, unpredictable" (Hibbert 1967, p. 535). Decades of subsequent research have supported these hypotheses (Andréassian 2004; Bosch & Hewlett 1982; Hibbert 1967; Troendle 1983; Troendle & King 1985). However, recent studies suggest that the variability of water yield response is a fundamental characteristic of semi-arid western watersheds and raise questions about the universality of the first hypothesis regarding the relationship between forest cover and water yield (Biederman et al. 2015; Pugh & Gordon 2013).

Recent reviews have highlighted differences in the magnitude of water yield increases following disturbance, as well as variability in individual hydrologic processes that drive water yield response (Adams et al. 2012; Buttle et al. 2005; Mikkelson et al. 2013; Moore & Wondzell 2005; Pugh & Gordon 2013). The magnitude of post-disturbance water yield change varied widely in these reviews, from -50% to more than +200% although such large increases are questionable (Adams et al. 2012), and Pugh and Gordon (2013) predict either no change or increases up to +25%. However, even more recently, studies have concluded that water yield decreases following forest disturbance in semi-arid western watersheds (Bart et al. 2016; Bennett et al. 2018; Biederman et al. 2014; Biederman et al. 2015; Slinski et al. 2016). Because these recent studies contradict Hibbert's (1967) first hypothesis, additional review is needed to identify where and why decreases in water yield may occur and thus improve the predictability of post-disturbance hydrologic response.

Previous studies that observed increases in post-disturbance water yield, as expected, illuminated the mechanisms responsible (Bosch & Hewlett 1982; Hibbert 1967; Troendle 1983). Water yield is constrained by the amount of precipitation minus evapotranspiration, where vegetation affects the partitioning of precipitation into runoff versus evapotranspiration. When forest cover is decreased, two components of evapotranspiration decline (Figure 1). First, less precipitation is intercepted and subsequently sublimated (snow) or evaporated (rain) by tree canopies. Sublimation losses of canopy-intercepted snow can be as high as 20-30% of snowfall in western watersheds where a substantial fraction of precipitation falls as snow (Montesi et al. 2004; Schmidt et al. 1998), thus substantially reducing the amount of water available for streamflow. Second, transpiration decreases following death or removal of trees (Adams et al. 2012; Hibbert 1967; Troendle 1983; Troendle & King 1985; Wilm 1948).

As expected from these mechanisms, standing-replacing disturbances such as clearcut harvests often lead to increased streamflow (Hubbart et al. 2007; Stednick 1996; Troendle 1983; Troendle & King 1985; Troendle & King 1987). However, non-stand replacing disturbances may differ with respect to individual hydrologic processes such as interception of precipitation, radiation transmission, accumulation and retention of snowpack, and evapotranspiration from the overstory and understory. Partial-cut harvesting has both increased water yield (Hubbart et al. 2007) and failed to produce significant increases (Troendle & King 1987). Opportunistic studies of previous insect outbreaks concluded that streamflow increased following mortality (Figure 1a) (Bethlahmy 1974; Potts 1984), particularly after salvage clearcuts (Cheng 1989), although the increase was hypothesized to be modulated by radiation exposure (Bethlahmy 1975). Higher radiation exposure – which is related to a combination of slope, latitude, aspect, and temperature – translates to higher evaporative demand and thus higher potential evapotranspiration. In contrast to earlier studies, recent research has observed unchanged or even decreased streamflow following insect outbreaks, likely because increased evapotranspiration from understory vegetation overcompensated for decreased evapotranspiration from the overstory (Figure 1b) (Biederman et al. 2015).

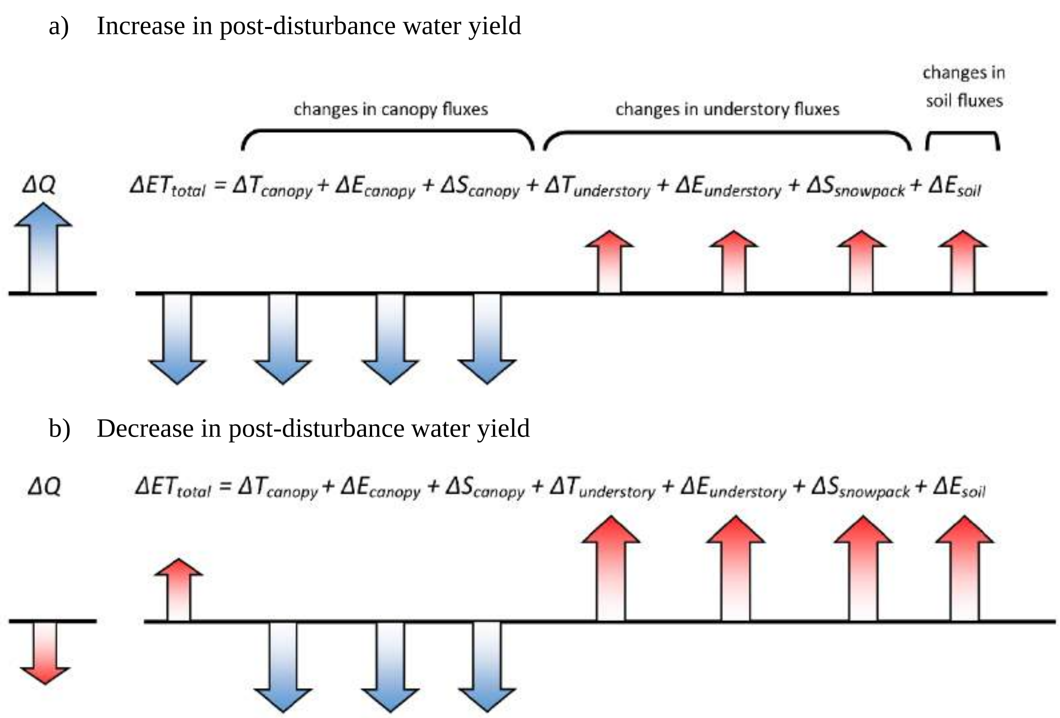

Figure 1. Post-disturbance increase (a) versus decrease (b) in net ET that determine water yield response, as determined by changes in individual components of evapotranspiration (ET) relative to pre-disturbance fluxes. Red arrows contribute to higher total ET and lower water yield; blue arrows contribute to lower total ET and higher water yield. Arrow sizes correspond to relative sizes of change in flux; in (a), blue arrows are larger than red arrows and drive a net decrease in ET, whereas in (b), red arrows are larger than blue arrows and drive a net increase in ET. ΔQ = change in water yield; ΔET_{total} = net change in evapotranspiration; ΔT_{canopy} = canopy transpiration; $\Delta \mathrm{E}_{canopy}$ = canopy (overstory) evaporation of liquid water; ΔS_{canopy} = sublimation of canopy-intercepted snow; $\Delta T_{understory}$ = understory transpiration; $\Delta E_{understory}$ = understory evaporation; $\Delta S_{snowpack}$ = sublimation of ground snowpack; and ΔE_{soil} = soil evaporation.

Recent widespread tree mortality across the western US (Anderegg et al. 2013; Breshears et al. 2005; Huang et al. 2015; van Mantgem et al. 2009) has provided opportunities to test hypotheses about the linkage between forest cover, disturbance, and water yield. Contemporary studies differ from historical watershed experiments in several important ways. First, recent mortality was caused by multiple factors that did not typically kill or remove 100% of trees in affected stands (Hicke et al. 2015), whereas most previous studies and reviews (Hubbart et al. 2007; Stednick 1996; Troendle 1983; Troendle & King 1985) focused on stand-replacing disturbances, mainly clearcut harvesting and severe wildfire. Second, the spatial scale of analysis can be much broader, given the widespread mortality and rapidly evolving spatial analysis tools, compared to most historical studies of watersheds smaller than 25 km^2 (Andréassian 2004; Bosch & Hewlett 1982). Third, the current state of physically-based, spatially distributed models – as well as spatially explicit input data on elevation, soil, and climate – enables disentangling climate versus vegetation effects (Biederman et al. 2015; Hallema et al. 2017; Perry & Jones 2017), assessment of multiple alternative climate and land cover scenarios (Du et al. 2016), and examination of large watersheds using a water budget approach (Andréassian 2004). This capability contrasts with paired-watershed studies that typically focus on small watersheds using before/after-control/impact experimental designs, and use streamflow data as the primary and often sole catchment-scale response variable (Bethlahmy 1974; Bethlahmy 1975; Biederman et al. 2015; Bosch & Hewlett 1982; Cheng 1989; Hewlett 1971; Hibbert 1967; Potts 1984; Troendle 1983; Troendle & King 1985). Fourth, quantifying evaporation is notoriously difficult, and eddy-covariance methods enable assessment of seasonal evapotranspiration (Biederman et al. 2014; Biederman et al. 2014).

Our objective was to synthesize recent findings and reassess the question: Does water yield increase following forest disturbance in western coniferous forests? We expected that water yield response may differ for stand-replacing versus non-stand replacing disturbances due to different process-level responses (Adams et al. 2012; Mikkelson et al. 2013; Pugh & Gordon 2013). A second objective was to assess whether the predictability of hydrologic response – particularly decreases in streamflow or snowpack – following forest cover loss has improved since Hibbert's (1967) review. Our review included both stand-replacing disturbances, such as severe wildfire and clearcutting, and non-stand-replacing disturbances such as drought, insects, and low- to moderate-severity fire. We included literature that identified the physical processes and components of the hydrologic cycle that drove overall hydrologic response, as well as studies that explicitly assessed annual streamflow (i.e., water yield). Although we did not seek to specifically focus on studies in catchments that receive most precipitation as snow, we found that the recent widespread tree mortality in western coniferous forests occurred primarily in regions with seasonal snowpack. Given the relatively recent, post-2000 timeframe of widespread natural forest disturbance in the West (Breshears et al. 2005; Huang et al. 2015; Williams et al. 2013), we focused on papers published after 2000.

Scope and Approach

To address our objectives, we first cast a wide net to include as many recent papers as possible, and then eliminated papers that did not focus on recent disturbances in western coniferous forests and also added papers that were not returned in our initial search that were recommended by colleagues and reviewers. The first step consisted of a Scopus search (scopus.com) resulting in 182 papers. Criteria for this search included titles, abstracts, or keywords that included "forest"; at least one term describing forest cover (forest cover, tree cover, or canopy cover); at least one term describing forest disturbance (tree mortality, forest disturbance, drought, water stress, fire, insects, beetle, drought, harvest, or thinning); at least one term describing hydrologic or ecohydrologic response (transpiration, evapotranspiration, snowpack, snow accumulation, snow retention, streamflow, water yield, or runoff); and publication in peer-reviewed journals in year 2000 or later, given the relatively recent increase in widespread tree mortality in the western US (Breshears et al. 2005; Huang et al. 2015; Williams et al. 2013). In the second step, we eliminated papers that did not focus on disturbance in coniferous forests or did not include an explicit evaluation of the effects of forest disturbance on hydrologic processes, and also added several papers that were cited in studies within our search or suggested by reviewers.

Our search resulted in a set of 78 papers (Table 1) published in 30 journals, plus older seminal papers and reviews on the relationship between forest cover, disturbance, and streamflow or snowpack in western forests. The number of papers published per year was higher in 2012-2017 than in 2000-2011, and was higher than expected given the rate of increase of all published papers during this period (Fig. 2). This trend possibly corresponds to increased tree mortality in the western US (van Mantgem et al. 2009), much of which was due to drought and insects (Meddens et al. 2012), and may reflect increased societal concern and scientific interest in water issues related to forest management. For each paper, we assessed several questions about how “forest” and “disturbance” were characterized, how hydrologic impacts were characterized, and whether confounding factors such as climate variability and post-disturbance recovery were considered. We also determined whether the disturbance under consideration was stand-replacing or non-stand replacing, what specific disturbance agents were considered (e.g., insects, drought, wildfire), and whether conclusions were based on observations, simulations, or both.

Table 1. Summary characteristics of 78 papers that met our search criteria.

Author	**Year**	**Journal**[1]	**Location**[2]	**Type of study**[3]
Adams et al.	2012	Ecohydrology[O]	NA (conceptual)	both
Bart et al.	2016	PLoS ONE[O]	CA	simulations
Bearup et al.	2014	Nature Climate Change[O]	CO	observations
Bennett et al.	2018	Hydrology & Earth System Sciences[H]	AZ, CO, NM, UT	simulations
Bewley et al.	2010	Journal of Hydrology[H]	BC	simulations
Biederman et al.	2014	Ecohydrology[O]	CO, WY	observations
Biederman et al.	2014	Water Resources Research[H]	CO, WY	observations
Biederman et al.	2015	Water Resources Research[H]	CO	observations
Boisrame et al.	2017	Ecosystems[O]	CA	both
Boon	2009	Hydrological Processes[H]	BC	both
Boon	2012	Ecohydrology[O]	BC	observations
Bright et al.	2013	J. Geophysical Res.: Biogeosciences[O]	CO	observations
Broxton et al.	2015	Ecohydrology[O]	CO, NM	both
Buma and Livneh	2015	Forest Science[F]	CO	simulations
Buma and Livneh	2017	Environmental Research Letters[O]	entire US	observations
Burles and Boon	2011	Hydrological Processes[H]	AB	both
Buttle et al.	2005	Hydrological Processes[H]	Canada (review)	both
Chen et al.	2015	Journal of Hydrometeorology[H]	WY	both
Concilio et al.	2009	Climatic Change[O]	CA	observations
Cristea et al.	2014	Hydrological Processes[H]	CA	simulations
Du et al.	2016	Hydrological Processes[H]	ID	simulations
Eaton et al.	2010	Earth Surf. Processes & Landforms[O]	BC	observations
Ellis et al.	2011	Canadian J. of Forest Research[F]	AB	observations
Ellis et al.	2013	Water Resources Research[H]	AB	observations
Gleason et al.	2013	Geophysical Research Letters[H]	OR	observations
Grant et al.	2013	Frontiers in Ecology & Environment[O]	NM	both
Green and Alila	2012	Water Resources Research[H]	BC, CO, ID, UT, WY	both
Guardiola-Claramonte et al.	2011	Journal of Hydrology[H]	AZ, CO, NM, UT	observations
Hallema et al.	2017	Ecohydrology[O]	AZ, CA	observations
Hallema et al.	2017	Hydrological Processes[H]	western US	observations
Harpold et al.	2014	Ecohydrology[O]	NM	observations
Harpold et al.	2015	Hydrological Processes[H]	CA, CO, NM	observations
Hernandez et al.	2018	Forests[F]	ID, MT	simulations
Hubbart et al.	2015	Forest Science[F]	ID	observations
Huff et al.	2000	Journal of Forestry[F]	CA	both
Jackson and Prowse	2009	Hydrological Processes[H]	BC	observations
Jacobs	2015	Ecohydrology[O]	NM	observations
Li et al.	2018	Journal of Hydrology[H]	BC, WA	observations
Livneh et al.	2015	Journal of Hydrology[H]	CO	both
Lundquist et al.	2013	Water Resources Research[H]	CA	observations
Mahat and Anderson	2013	Hydrology & Earth System Sciences[H]	AB	simulations
Maxwell et al.	2019	Forest Ecology & Management[F]	UT	observations
Meyer et al.	2017	Forest Ecology & Management[F]	BC	simulations
Mikkelson et al.	2013	Biogeochemistry[O]	NA (review)	both
Moore and Scott	2005	Can. Water Resources Journal[H]	BC	observations

Moore and Wondzell	2005	J. Am. Water Resources Assocn.[H]	AK, BC, ID, OR, WA	observations
Morillas et al.	2017	J. Geophysical Res.: Biogeosciences[O]	NM	observations
Penn et al.	2016	Water Resources Research[H]	CO	simulations
Perrot et al.	2014	Ecohydrology[O]	CO	observations
Perry and Jones	2017	Ecohydrology[O]	OR	observations
Pomeroy et al.	2012	Hydrological Processes[H]	AB	simulations
Poon and Kinoshita	2018	Journal of Hydrology[H]	NM	simulations
Pugh and Gordon	2013	Hydrological Processes[H]	western North America	simulations
Pugh and Small	2012	Ecohydrology[O]	CO	observations
Pugh and Small	2013	Hydrology Research[H]	CO	observations
Reed et al.	2014	Environmental Research Letters[O]	WY	observations
Reed et al.	2016	Theoretical & Applied Climatology[O]	WY	observations
Robles et al.	2014	PLoS ONE[O]	AZ	simulations
Saksa et al.	2017	Water Resources Research[H]	CA	simulations
Sankey et al.	2015	Remote Sensing of Environment[O]	AZ	observations
Sexstone et al.	2018	Water Resources Research[H]	CO	both
Slinski et al.	2016	Environmental Research Letters[O]	ID, MT, OR, UT, WA, WY	observations
Stevens	2017	Ecological Applications[O]	CA	observations
Sun et al.	2018	Hydrological Processes[H]	ID, WA	simulations
Svoma	2017	J. Geophysical Res.: Atmospheres[O]	AZ	simulations
Tennant et al.	2017	Water Resources Research[H]	CA, CO, NM, ID	observations
Tonina et al.	2008	Hydrological Processes[H]	ID	simulations
Vanderhoof & Williams	2015	Agricultural & Forest Meteorology[O]	CO, WY	both
Varhola et al.	2010	Canadian J. of Forest Research[F]	BC	both
Wei and Zhang	2010	Water Resources Research[H]	BC	observations
Wine and Cadol	2016	Environmental Research Letters[O]	NM	both
Wine et al.	2018	Environmental Research Letters[O]	western US	both
Winkler et al.	2005	Hydrological Processes[H]	BC	observations
Winkler et al.	2014	Hydrological Processes[H]	BC	observations
Winkler et al.	2015	Hydrology Research[H]	BC	observations
Winkler et al.	2017	Ecohydrology[O]	BC	observations
Yazzie and Chang	2017	Climate[O]	OR	simulations
Zhang and Wei	2012	Hydrology & Earth System Sciences[H]	BC	observations

[1]Primary discipline of journal (F=forestry, H=hydrology, and O=other/cross-disciplinary). [2]Locations are abbreviated using standard US state and Canadian province abbreviations. [3]Indicates whether results were based on observations, simulations, or both observations and simulations.

In the next section, we highlight unexpected hydrologic responses and the process-level mechanisms (e.g., post-disturbance transpiration and sublimation) that explain such responses. Subsequent sections provide a broader interpretation of the results that incorporates earlier (pre-2000) papers to highlight where recent studies reframe or underscore previous work. The section “Linkage between Forest Disturbance and Water Yield” section summarizes our conclusions and addresses our objectives of assessing Hibbert’s (1967) first and third hypotheses in the context of recent, post-2000 tree mortality in the West. In the "Improving Predictability" section, we highlight the strengths of selected papers and summarize needs for research that will improve predictive capabilities and facilitate future meta-analyses on the linkage between forest dynamics and water resources. The "Implications for Forest Management" section recognizes that managing for water yield and forest resilience may be distinct and not always compatible goals.

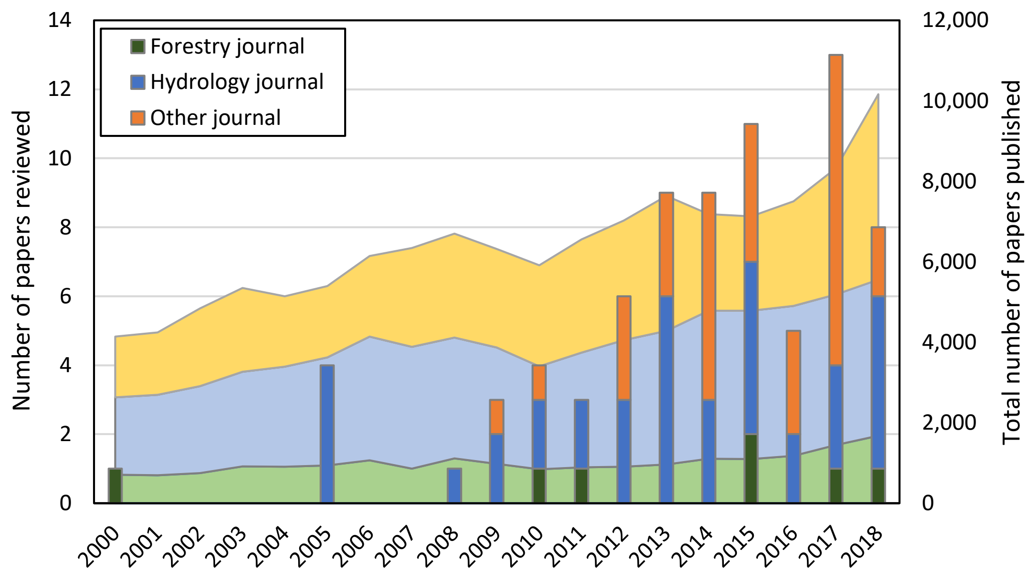

Figure 2. Publication year and journal discipline (forestry, hydrology, or "other" cross-disciplinary journal) of the 78 papers included in our review (vertical bars; left axis) and the total number of papers in each discipline (horizontal shaded areas; right axis). (Note that the journal PLoS ONE, which began publishing in 2006, is categorized as "other" yet omitted in the total number of papers (lines) because within five years of its founding, it published several times as many papers as all other journals in aggregate. Two papers in this review were published in PLoS ONE: one in 2014 and one in 2016.)

Post-disturbance Hydrologic Response

The 78 papers included in this review were based on observations (42 papers), simulations (18), a combination of observations and simulations (14), and conceptual models (4) of hydrologic fluxes. Here we summarize the findings with respect to post-disturbance water yield (i.e. annual streamflow), peak flows (magnitude and timing), low flow magnitude, and snow water equivalent (SWE).

Water Yield

Contrary to Hibbert's (1967) review, water yield decreased in nine of 31 studies that directly assessed streamflow response to disturbance (Table 2). Many studies found variable responses, such as both increases and decreases in different catchments. Collectively, recent research indicates that water yield is more likely to decrease following non-stand replacing disturbance (8 of 19 studies) compared to stand-replacing disturbance (3 of 17 studies; Table 3). Note that some studies found variable responses (e.g., increases, no change, or decreases in streamflow) given different disturbance scenarios, and some studies assessed both stand-replacing and non-stand replacing disturbance. Among the 31 studies that assessed annual streamflow response, 14 used direct flow measurements, nine used simulation models, five used a combination of observations and simulations, and three presented conceptual models based on previous literature.

When non-stand replacing disturbances result in decreased streamflow, is it because total post-disturbance evapotranspiration increases (Figure 1b), either as a result of increased transpiration in the understory, increased sublimation from snowpack, or increased soil evaporation due to more radiation reaching the surface (Bennett et al. 2018; Biederman et al. 2014) – all of which decrease the proportion of precipitation available for streamflow. Previous reviews concluded that streamflow response to non-stand replacing disturbance may be highly variable, relative to stand-replacing disturbances, and cite the competing responses of decreased overstory transpiration and decreased canopy interception losses, versus increased evapotranspiration from the understory and ground (Figure 1) (Adams et al. 2012; Mikkelson et al. 2013; Moore & Wondzell 2005; Pugh & Gordon 2013). The variable responses found by other studies, many of which were published after these reviews, found a combination of increases and no change (Boisramé et al. 2017; Huff et al. 2000; Penn et al. 2016; Winkler et al. 2015), a combination of all possible responses (Boisramé et al. 2017; Slinski et al. 2016), and either decreases or no change (Biederman et al. 2015). Eight studies found consistent water yield responses, including both consistent increases (Buma & Livneh 2017; Li et al. 2018; Livneh et al. 2015; Robles et al. 2014; Wine et al. 2018) and consistent decreases (Bennett et al. 2018; Biederman et al. 2014; Guardiola-Claramonte et al. 2011).

Table 2. Metrics of hydrologic response used in the 78 papers in this review. Numbers represent the number of papers that found increases, no change, or decreases in each metric. Totals do not always equal the sum of the papers across each row because many studies found variable responses (e.g., increases, no change, or decreases in streamflow given different disturbance scenarios). Similarly, the sum of the total number of papers does not equal 78 because many studies assessed multiple response metrics (e.g., both streamflow and evapotranspiration).

Response	**Total number of studies**	**Increase**	**No change**	**Decrease**
Streamflow (annual water yield)	31	26	16	9
Peak flow magnitude	22	19	10	7
Peak flow timing[1]	18	14	7	4
Low flow magnitude	25	14	9	9
Maximum SWE	42	34	10	10

[1]Peak flow timing "increase" represents earlier peak flows; "decrease" represents later peak flows.

Table 3. Response of annual streamflow (i.e., water yield) to disturbance. Totals do not equal the sum of the papers across each row and column because many studies found variable responses (e.g., increases, no change, or decreases in streamflow given different disturbance scenarios, and some studies assessed both stand-replacing and non-stand replacing disturbance.

Type of disturbance	**Total number of studies**	**Increase**	**No change**	**Decrease**
Stand-replacing	17	15	7	3
Non-stand replacing[1]	19	15	10	9

[1]Papers focused on non-stand replacing disturbances included three papers based on conceptual models, which predicted either an increase (3 papers), no change (3 papers), or decreases (1 paper) in streamflow.

Studies of stand-replacing disturbances, such as clearcutting or severe wildfire, confirm that water yield typically increases following stand-replacing disturbances, as expected from the previous reviews (Andréassian 2004; Bosch & Hewlett 1982; Hibbert 1967; Troendle 1983; Troendle & King 1985). However, they also suggest that post-disturbance vegetation characteristics determine the direction of response. Two of the three studies with decreases in annual streamflow following stand-replacing disturbances provide similar explanations for their results: water yield decreases when trees are replaced with shrubs with high leaf area and high transpiration rates (Figure 1b) (Bart et al. 2016; Bennett et al. 2018). The third study found decreases in streamflow within a geographically constrained region of rain-dominated catchments of the coastal Pacific Northwest, where decreases in water yield occur due to a decline in fog interception (Moore & Wondzell 2005). In contrast to these three studies, most studies concluded that water yield consistently increases following stand-replacing disturbance (Figure 1a) (Buma & Livneh 2015; Du et al. 2016; Hallema et al. 2017; Hernandez et al. 2018; Li et al. 2018; Sun et al. 2018; Wei & Zhang 2010; Winkler et al. 2015; Winkler et al. 2017; Zhang & Wei 2012), although several studies found variable streamflow response, depending on the disturbance scenario (Bart et al. 2016; Hallema et al. 2017; Moore & Wondzell 2005; Wine & Cadol 2016; Wine et al. 2018).

Among the simulation models used to assess post-disturbance water yield, only physically-based models predicted any decreases in water yield following disturbance, while simpler models predicted either no change or increases. Simulation-based studies that found decreases in post-disturbance streamflow are in similar types of catchments (i.e., those with high total radiation at low latitudes, and with dense post-disturbance vegetation) as observational studies that found decreases in streamflow due to net increases in evapotranspiration. Given that some observational studies also concluded that streamflow may decrease following disturbance, particularly following non-stand replacing disturbance, the ability to simulate post-disturbance decreases is a strength of physically-based models. Thus, physically-based models can complement paired-catchment studies to robustly assess the impacts of forest disturbance on streamflow (Moore and Scott 2005), whereas more empirically-based models may be incapable of simulating the conditions that lead to post-disturbance decreases in water yield. The degree of spatial distribution and the number of physical processes in the model varied, from the point-based WRENSS model applied to grid cells (Huff et al. 2000), to catchment-scale empirical or statistical models (Boisramé et al. 2017; Robles et al. 2017; Wine & Cadol 2016; Wine et al. 2018), semi-distributed models such as the Soil and Water Assessment Tool (SWAT) (Hernandez et al. 2018), and several fully distributed, physically-based models such as the Distributed Hydrology Soil Vegetation Model (DHSVM) (Buma & Livneh 2015; Du et al. 2016; Green & Alila 2012; Livneh et al. 2015; Sun et al. 2018); Regional Hydro-Ecological Simulation System (RHESSys) (Bart et al. 2016; Saksa et al. 2017); ParFlow (Penn et al. 2016); and Variable Infiltration Capacity (VIC) (Bennett et al. 2018).

Peak Flows

Twenty-two studies evaluated peak flow magnitudes, and most found that post-disturbance peak flows exceed pre-disturbance peaks (Table 2), regardless of whether disturbance is stand-replacing. However, three studies found that peak flows sometimes increase, do not change, or decrease (Bennett et al. 2018; Buma & Livneh 2017; Slinski et al. 2016), depending on disturbance severity and extent, post-disturbance vegetation recovery, and radiation budgets – all of which affect snowmelt rates (Mikkelson et al. 2013; Moore & Wondzell 2005; Pugh & Gordon 2013). For example, snowmelt occurs more rapidly – and thus produces higher peak flows – at sites with higher total radiation, which tend to occur on sites at lower latitudes, lower elevations, and south-facing slopes. Snowmelt in undisturbed forested watersheds is typically asynchronous by elevation (i.e., lower elevations melt earlier and higher elevations melt later), whereas post-disturbance synchronization of snowmelt leads to higher peak flows (Bewley et al. 2010; Pomeroy et al. 2012). Thus, variable responses in peak flows may be explained by the degree of synchronicity of snowmelt rates throughout a watershed (Pomeroy et al. 2012), and disturbance that reduces synchronicity of snowmelt can lead to smaller peak flows. Another factor that may reduce post-disturbance peak flows is a simultaneous shift in climate that results in more precipitation falling as rain versus snow (Jacobs 2015).

Post-disturbance peak flows typically occur earlier than pre-disturbance peaks (Table 2), as expected from previous reviews (Andréassian 2004). However, seven studies found variable responses with respect to peak flow timing, including later peaks in some cases (Bart et al. 2016; Buma & Livneh 2017; Cristea et al. 2014; Du et al. 2016; Livneh et al. 2015; Moore & Wondzell 2005; Pomeroy et al. 2012; Pugh & Gordon 2013; Slinski et al. 2016). Later peak flows are more likely to occur when snow accumulation increases following forest cover loss (Cristea et al. 2014); note that snow accumulation does not always increase following disturbance (Table 2). As with peak flow magnitude, peak flow timing may be affected by the degree of synchronization of snowmelt across elevation zones (Bewley et al. 2010; Pomeroy et al. 2012).

Low Flows

The response of low flows to forest disturbance is related to snow accumulation, snowmelt rates, and summer evapotranspiration rates. Low flows typically increase when more snow accumulates, snow melts more slowly, and/or summer evapotranspiration declines. Low flows can also be sensitive to time since disturbance. In the Pacific Northwest, conversion of mature forests to timber plantations may initially result in higher summer flows but then switch to lower low flows by 15 years post-harvest, and this decrease may persist for several decades (Perry and Jones 2017). Most of the studies considered here did not cover this length of time, and it is noteworthy that Perry and Jones (2017) concluded that initially inflated seasonal low flows may switch to deficits several years after disturbance. Moore and Wondzell’s (2005) review concluded that water yield may initially increase but then decrease in the longer term. In both papers, long-term streamflow declines were attributed to rapid post-disturbance vegetation growth.

Among the remaining studies, post-disturbance seasonal low flows increased in 14 of the 19 studies that evaluated low flows, nine studies found no change, and 8 studies found decreases (Table 2). However, given the rigor of Perry and Jones's (2017) long-term study, which ruled out climate variability as a cause of observed decreases in low flows, future research into the effects of disturbance on seasonal low flows must consider that the response may vary over decadal timescales.

Snow Water Equivalent (SWE)

While 34 of 42 studies that assessed SWE concluded that annual maximum SWE increases following forest disturbance, 10 studies concluded that it decreases (Table 2). Contributors to the variable response of SWE include the timing and magnitude of precipitation, as well as disturbance type (stand-replacing vs. non-stand replacing) and forest structure – which both affect radiation and thus sublimation (described in the next section) and SWE. In some studies, SWE in disturbed versus undisturbed stands differs in low-snow years but not in high-snow years, when the amount of snowfall presumably overwhelms trees' interception capacity (Boon 2012; Winkler et al. 2014). Several studies concluded that SWE in stands affected by non-stand replacing, insect-caused disturbances is more similar to undisturbed forests than to sites with recent stand-replacing disturbances (Boon 2009; Boon 2012; Burles & Boon 2011; Pomeroy et al. 2012; Winkler et al. 2014). This suggests that SWE responds to a continuum of disturbance levels, and that quantitative characterization of forest density – such as regressions between LAI or canopy cover and SWE (Varhola et al. 2010) – could lead to improved quantitative predictions of disturbance effects on SWE.

Patterns of SWE response vary geographically, with more consistent post-disturbance increases at higher latitudes and more variable responses at lower latitudes. Of 13 studies of SWE conducted in Canada and the northern US, nine consistently found higher SWE following disturbance (Boon 2009; Burles & Boon 2011; Chen et al. 2015; Du et al. 2016; Ellis et al. 2013; Gleason et al. 2013; Hubbart et al. 2015; Jackson & Prowse 2009; Varhola et al. 2010; Winkler et al. 2005), while four found variable response – i.e., a combination of increases, no change, and decreases (Boon 2012; Ellis et al. 2011; Winkler et al. 2014; Winkler et al. 2015). Among the 13 studies conducted farther south in the US, only five consistently found that SWE increases in disturbed stands (Biederman et al. 2014; Broxton et al. 2015; Harpold et al. 2015; Livneh et al. 2015; Pugh & Small 2013). Four studies found that SWE responds variably to reduced canopy density (Lundquist et al. 2013; Perrot et al. 2014; Pugh & Small 2012; Tennant et al. 2017). The remaining studies concluded that SWE does not change (Biederman et al. 2014; Maxwell et al. 2019; Sexstone et al. 2018) or decreases following disturbances (Harpold et al. 2014; Stevens 2017). Thus, post-disturbance SWE is more often observed to decrease or respond variably at low latitudes than at high latitudes, where it typically increases. Unexpected decreases in post-disturbance SWE are attributed to increased shortwave radiation, which results in increased ablation of the snowpack (Harpold et al. 2014; Stevens 2017), as well as decreased albedo following accumulation of needles, bark, and other organic matter on the snow surface, which also leads to snowpack ablation (Gleason et al. 2013; Pugh & Gordon 2013; Winkler et al. 2014). It is important to note that dividing ablation into sublimation versus melt is a difficult yet important task for estimating water budgets, because while melt clearly contributes to streamflow, sublimation represents evapotranspiration losses that can contribute to reduced streamflow.

Twenty-six studies quantified at least one component of radiation budgets that influences snowpack. Disturbance affects both shortwave (i.e., solar) and longwave radiation, which increase and decrease, respectively, as a result of reduced tree cover (Adams et al. 2012; Mikkelson et al. 2013; Pugh & Gordon 2013; Sun et al. 2018). Post-disturbance changes in the relative contributions of shortwave and longwave radiation are not linear, and their relative contributions vary throughout the seasonal snowpack season as sun angle changes (Boon 2009; Burles & Boon 2011; Ellis et al. 2011; Ellis et al. 2013; Harpold et al. 2014; Sun et al. 2018). Total radiation available for snowmelt sometimes increases by more than the increase in insolation alone, particularly when organic debris (i.e., needles, bark, branches) fall on the snowpack following tree mortality due to insects or wildfire (Gleason et al. 2013; Pugh & Gordon 2013). Debris-covered snowpack has a lower albedo than debris-free snowpack, and thus absorbs more radiation and melts or sublimates faster (Gleason et al. 2013; Pugh & Gordon 2013; Winkler et al. 2014). In the Sierra Nevada, disturbance severity is negatively related to SWE (Stevens 2017), presumably because denser, less disturbed stands shade the snowpack and slow snowmelt. While trees shade the snowpack from shortwave radiation, they also emit longwave radiation – which presents a tradeoff between shortwave and longwave radiation, as snowmelt is affected by total radiation (Lundquist et al. 2013; Sun et al. 2018). At temperatures near freezing, medium-density forests are likely to retain more snow than higher-density forests (with higher longwave radiation) or lower-density forests (with higher shortwave radiation) (Hubbart et al. 2015; Lundquist et al. 2013). For example, forest thinning in Arizona may decrease longwave radiation while having little effect on shortwave radiation reaching snowpack, resulting in decreased net radiation and thus increased SWE (Svoma 2017). In contrast, in areas with average winter temperatures below freezing, longwave radiation may be insufficient to melt midwinter snowpack, and shading becomes more important for snow retention in later winter (Ellis et al. 2011; Lundquist et al. 2013; Stevens 2017). The impact of radiation budgets on SWE suggests that physically-based models that include components of radiation could improve the predictability of hydrologic response to disturbance.

Several studies concluded that topographic aspect controls the effects of trees on snowmelt via its effects on shortwave radiation. In the Canadian Rockies, snow disappearance date either increases or decreases in clearings, relative to intact forest stands, depending on aspect (Ellis et al. 2011). Snowpack under undisturbed forests on south-facing slopes is shaded and thus receives less shortwave radiation – and retains snow longer due to slower snowmelt – than adjacent clearings, even though clearings may initially have higher total snowpack. In contrast, trees on north-facing slopes have higher late-winter snowmelt rates than clearings due to higher longwave radiation within forested stands (Ellis et al. 2011). In central Utah, which is at a lower latitude and thus has higher solar angle, stand-replacing wildfire results in earlier snow disappearance on both north- and south-facing slopes, relative to unburned stands (Maxwell et al. 2019). Two studies – one west-wide (Tennant et al. 2017) and one in New Mexico (Harpold et al. 2014) – concurred that in areas with relatively high solar radiation, e.g., at low latitudes, aspect exerts a greater control on SWE than vegetation characteristics.

Evapotranspiration

The long-held expectation that post-disturbance water yield will increase is based on the assumption that evapotranspiration will decrease (Figure 1a), thus making more water available for streamflow (Adams et al. 2012; Pugh & Gordon 2013). Here we examine three components of evapotranspiration that have been cited as driving gains in streamflow following disturbance: transpiration; sublimation of snow, both from canopies and from snowpack; and evaporation from soil (Figure 1). All were found to respond variably to disturbance, as described below.

Few studies have asked whether the expectation of reduced post-disturbance transpiration holds true for non-stand replacing disturbances such as the widespread recent die-off (Hicke et al. 2015). Two case studies highlight mechanisms that may result in unexpected increases in evaporation. First, although mountain pine beetle epidemics kill overstory trees and thus lead to declines in overstory transpiration, increased transpiration of surviving vegetation, including advance regeneration (i.e., seedlings and saplings that were present in the understory prior to the epidemic), can lead to increased total evapotranspiration and decreased streamflow (Biederman et al. 2014). Another study concluded that decreases in post-disturbance transpiration may be offset by increased soil evaporation, resulting in a net increase in evapotranspiration (Reed et al. 2016).

The assumption that reduced canopy interception will lead to a net decrease in post-disturbance sublimation, and thus an increase in SWE, is supported by stand-replacing disturbances such as clearcutting (Stednick 1996). However, two observational studies – one in Colorado (Biederman et al. 2014) and one in New Mexico (Harpold et al. 2014) – and one simulation study (Sexstone et al. 2018) found that increased sublimation from the snowpack can offset decreases in canopy sublimation. High radiation reaching the snowpack surface, as well as increased turbulence beneath the reduced post-disturbance canopy, can cause unexpectedly high sublimation from snowpack (Biederman et al. 2014; Sexstone et al. 2018).

Finally, evaporation from soil represents not only a component of evapotranspiration but also a constraint on forest regeneration and growth. Most of the 18 studies that assessed post-disturbance soil moisture evaluated non-stand replacing disturbances. Approximately equal numbers of studies concluded that soil evaporation increases, decreases, or does not change following disturbance, and several studies found variable responses (Adams et al. 2012; Bart et al. 2016; Boisramé et al. 2017; Grant et al. 2013; Harpold et al. 2015; Pugh & Gordon 2013; Reed et al. 2014). Post-disturbance soil moisture may increase due to decreased transpiration (Concilio et al. 2009; Mikkelson et al. 2013; Penn et al. 2016; Reed et al. 2018; Saksa et al. 2017), but it may also decrease, particularly during the growing season, due to increased evaporative demand driven by higher solar radiation following overstory canopy loss (Bennett et al. 2018; Biederman et al. 2014; Chen et al. 2015). Soil moisture response may vary due to differences in snow retention – the date of complete snow disappearance (Grant et al. 2013; Harpold et al. 2015) – and depletion of soil moisture by growing-season evapotranspiration (Bart et al. 2016; Bennett et al. 2018). As with seasonal low flows, soil moisture response to disturbance may vary over long timescales (Perry & Jones 2017).

Linkage Between Forest Disturbance and Water Yield

This synthesis of recent literature indicates that forest disturbance may increase or decrease water yield, leading to two important conclusions about the linkage between forest disturbance and water yield in semi-arid western watersheds: 1) the hypothesis that forest cover reduction leads to increased water yield is not universally true, and in some cases post-disturbance water yield may actually decrease, and 2) although the "response to treatment [or disturbance] is highly variable" (Hibbert 1967, p. 535), the ability to predict where water yield may increase vs. decrease following disturbance is improving. Thus, this review contributes insights beyond those of other recent reviews by identifying circumstances that may exhibit decreased post-disturbance water yield. Silvicultural prescriptions such as fuels treatments and forest thinning often mimic non-stand replacing disturbances such as those summarized here, and therefore they may fail to increase water yield in semi-arid western watersheds.

Studies that found decreases in water yield highlight important exceptions to Hibbert's (1967) first hypothesis that forest cover loss leads to increased water yield. Two previous reviews (Adams et al. 2012; Pugh & Gordon 2013) hypothesized that water yield could actually decrease following non-stand replacing tree die-off, and several studies have now confirmed this response. These unexpected results facilitate formulation of new hypotheses about when water yield – and potentially snowpack – might actually decrease following forest disturbance. First, all of these studies occurred in a semi-arid region. Second, two factors that lead to decreased post-disturbance water yield and snowpack are: 1) high density and growth rates, and thus transpiration, of post-disturbance vegetation (Bart et al. 2016; Bennett et al. 2018; Biederman et al. 2014; Guardiola-Claramonte et al. 2011), and 2) high total radiation (Biederman et al. 2015; Harpold et al. 2014; Stevens 2017), which leads to increased sublimation from the snowpack (Biederman et al. 2014; Harpold et al. 2014), and increased evaporation of soil moisture (Bennett et al. 2018; Biederman et al. 2014; Chen et al. 2015). In short, increases in evapotranspiration (Figure 1b, red arrows) more than compensate for the decreases (Figure 1b, blue arrows). The relative magnitudes of the responses exhibited by individual components of evapotranspiration (Figure 1) are related both to the type and density of post-disturbance vegetation, and also to net radiation, which drives evaporative demand. Net radiation is partly a function of latitude and aspect, which have long been identified as a control on the magnitude of water yield increases following harvest in wetter areas such as Coweeta, NC, and Fernow, WV (Hibbert 1967).

Previous reviews provided rule-of-thumb thresholds for when and where forest disturbance is likely to increase water yield: in watersheds where at least 20% of tree cover is removed (Adams et al. 2012; Brown et al. 2005; Stednick 1996) and precipitation is at least 500 mm/year (Adams et al. 2012). Given that most studies reviewed here characterized pre-disturbance conditions categorically rather than quantitatively (Table 4), the interpretation of the 20% rule-of-thumb is likely to be applied to entire stands (e.g., 20% of area within a catchment, based on delineation of polygons) rather than to the density within individual stands (e.g., 20% density reduction in stands of known density). However, the relationship between forest cover and streamflow response is complex and nonlinear (Moore & Wondzell 2005). An "area affected" characterization can mask the variability of stand densities within a catchment, where density is known to affect snow accumulation and retention (Lundquist et al. 2013), and perpetuates the categorical characterization of forests and disturbance (e.g., "disturbed" vs. "undisturbed"), as described below. In regards to precipitation thresholds, decreases in post-disturbance water yield occurred in watersheds with precipitation greater than the rule-of-thumb of 500 mm/year (Table 5).

Two recent high-profile papers underscore the ongoing interest and uncertainty regarding the factors that determine water yield response to forest disturbance and recovery. In an analysis of 251 catchments worldwide, Evaristo and McDonnell (2019) report that among catchments where streamflow increased following removal of forest cover, the best predictor of the magnitude of streamflow increase was subsurface storage potential (i.e., depth to bedrock). However, a subsequent critique (Kirchner et al. 2019) of Evaristo and McDonnell (2019) illuminates the obstacles inherent in amassing reliable broad-scale datasets, building robust models, and extending findings to new watersheds. As suggested by Kirchner et al. (2019), shortcomings in the ability to predict streamflow response to forest cover change could result in forest policy and management that may have unquantified effects over both short- and long-term timescales, and also at spatial scales ranging from watersheds to continental-scale linkages between cover type and downwind precipitation. Thus, the disciplines of forestry and hydrology have much work to do, both individually and collectively, to improve the predictability of the effects of forest dynamics on water resources, as discussed below.

Table 4. Metrics used to describe forest disturbance and conditions. More than half of papers described forests and disturbances in categorical terms rather than quantitative ones; the most common quantitative metric was leaf or plant area index (LAI/PAI).

Metric	Forest condition	Disturbance
% of area forested/disturbed	3	14
% canopy cover at catchment scale	5	1
categorical	41	44
LAI/PAI	15	8
standard forestry measurements	11	5
tree growth and/or mortality rates	1	4
NA (review papers)	2	2
Total	78	78

Table 5. Summary of studies that detected decreased water yield following disturbance. Where rain vs. snow domination of precipitation regime was found to be important, it is noted under "Factors leading to decreased Q" (Q=water yield). Note that most studies also detected increases or no change in some circumstances; only conditions leading to decreased Q are indicated.

Paper	Type of study	Location	Annual precipitation	Magnitude of water yield change	Extent of disturbance	Type of disturbance	Factors leading to decreased Q
Adams et al. 2012	Review paper	NA (review)	NA (review)	-50% to +250% (highest values not realistic: Adams et al. 2012)	20% forest loss	Non-stand replacing mortality due to drought and insects (<100% mortality)	Precipitation <~500 mm/yr, not snowmelt-dominated, rapid understory growth that results in increased evapo-transpiration
Bart et al. 2016	Simulation (RHESSys)	Sierra Nevada (CA)	1297 mm/yr	-30% to +155%	50%-100% forest loss	Stand-replacing wildfire	High transpiration by dense post-disturbance shrubs
Bennett et al. 2018	Simulation (VIC)	San Juan Basin, (AZ, CO, NM, UT)	666 mm/yr	-21% to -15%	>50% forest loss	Multiple agents (disturbance projections based on climate), including stand-replacing and non-stand replacing mortality	High transpiration by dense post-disturbance shrubs
Biederman et al. 2014	Observation	Rocky Mountains (CO, WY)	600-800 mm/yr	-74% to -62%	Up to 80% or area affected	Non-stand replacing mortality due to insects (<100% mortality)	Increased post-disturbance evapo-transpiration, including sublimation from snowpack
Biederman et al. 2015	Observation	Rocky Mountains (CO)	730-830 mm/yr	-29% to -11%	35% to 50% of area affected	Non-stand replacing mortality due to insects (<100% mortality)	Increased post-disturbance evapo-transpiration, mainly due to transpiration of understory vegetation
Guardiola-Claramonte et al. 2011	Observation	Colorado Plateau (AZ, CO, NM, UT)	208-480 mm/yr	Up to -50%	3%-21% mortality of trees	Non-stand replacing mortality due to drought (<100% mortality)	Increased transpiration by herbaceous understory vegetation and increased soil evaporation due to increased insolation of the soil surface

Pugh and Gordon 2013	Review paper	NA	NA (review)	Decreases recognized in conceptual model	Not specified	Non-stand replacing mortality due to insects (<100% mortality)	Increased post-disturbance evapo-transpiration
Slinski et al. 2016	Observation	CO, ID, MT, OR, SD, UT, WY	NA (not reported across 33 catchments)	Not reported	21% to 72%	Non-stand replacing mortality due to insects (<100% mortality)	Increased post-disturbance evapo-transpiration

Improving Predictability of Hydrologic Response to Disturbance

Extending recent findings to forest and watershed management, and predicting the response of any given watershed to disturbance, requires an improved quantitative framework linking forest conditions, disturbance severity, and hydrologic response. Despite the recent increase in the number of papers focused on this linkage, less than half of studies characterized forest cover and forest disturbance quantitatively rather than categorically (Table 4). Given that individual components of the hydrologic cycle are affected by vegetation composition (Bart et al. 2016; Bennett et al. 2018), structure (Broxton et al. 2015), density (Hubbart et al. 2015; Lundquist et al. 2013), and radiation exposure (i.e., aspect) (Ellis et al. 2011; Harpold et al. 2014; Tennant et al. 2017), a more precise understanding of the linkage between disturbance and hydrologic response requires analysis of quantitative (e.g., LAI, basal area, canopy cover) rather than categorical or qualitative (e.g., forest vs. nonforest, disturbed vs. undisturbed) attributes.

Among the majority of studies that characterized forests and disturbance categorically rather than quantitatively (Table 4), descriptors of "forest" (i.e., pre-disturbance conditions) included three types of categories: forest vs. nonforest; forest type or cover type; or forest density classes. The most common categorical characterizations of forest disturbance (Table 4) consisted of simply "disturbed" vs. "not disturbed" (17 papers), where disturbance thresholds were defined either within the study or by an external dataset (e.g., Aerial Detection Surveys). For mountain pine beetle disturbance, some studies further distinguished between green, red, and gray phases of infestation (see Pugh and Gordon 2013, for phase definitions), which were expected to differentially affect snow water equivalent via their effects on snowpack albedo, shading, and interception (Biederman et al. 2014; Biederman et al. 2014; Penn et al. 2016; Perrot et al. 2014; Pugh & Small 2013; Pugh & Small 2012; Pugh & Gordon 2013; Winkler et al. 2005). Other papers included scenarios of either multiple disturbance agents or multiple severities of a single agent, as well as one study that characterized cover type conversion from forest to multiple nonforest scenarios with varying vegetation densities (Bart et al. 2016).

Several studies concluded that forests affected by non-stand replacing disturbance should be considered a distinct cover type, based on observations that non-stand replacing disturbances exhibit a range of hydrologic responses between those observed in undisturbed forests versus those subject to stand-replacing disturbances such as clearcut harvests or severe wildfire (Boon 2009; Boon 2012; Pomeroy et al. 2012; Winkler et al. 2014). One of these studies (Boon 2012) proposed the concept of a "forest structure continuum" (p. 284), which represents a step toward quantifying forests and forest disturbance numerically rather than applying categories of disturbance or cover. This recommendation underscores the importance of characterization forests and disturbance quantitatively rather than categorically.

Quantitative Characterization of Forests and Disturbance

Among the minority of studies that quantitatively related forest conditions to hydrologic fluxes (Table 4), the most common metric for characterizing forest conditions was leaf area index (LAI). Process-based simulation models, such as the RHESSys (Tague & Band 2004) and DHSVM (Wigmosta et al. 1994) ecohydrologic models and one snowpack model (Broxton et al. 2015), include the capability to represent forest canopy densities in terms of LAI. Because standard forestry assessments do not include

LAI, (Härkönen et al. 2015; USDA 2017; plus the majority of studies in this review), a disconnect exists between standard forestry measurements and quantitative forest metrics used in hydrology. Future efforts to improve quantitative predictions of disturbance effects on water resources should thus include spatially explicit estimation of LAI. Abundant research has improved the ability to estimate LAI on the ground using light sensors or hemispherical photography (Jonckheere et al. 2004), or remotely via airborne or space-based light detection and ranging (Tang et al. 2014), as efficient alternatives to destructive sampling that may have the added benefit of separating understory from overstory LAI. In recent studies, both the scale and grain (e.g., ability to distinguish overstory from understory LAI) of LAI assessments has varied widely, depending mainly on data availability. At the broadest scale of assessment, a single LAI value represented each cover or disturbance class (Broxton et al. 2015; Penn et al. 2016; Perrot et al. 2014; Sexstone et al. 2018; Svoma 2017). Other studies spatially averaged LAI within disturbance severity classes (Pomeroy et al. 2012; Reed et al. 2016). The most data-intensive studies represented spatially and temporally explicit LAI in empirical analysis (Bewley et al. 2010), process-based numerical models (Chen et al. 2015; Reed et al. 2014), or ecohydrologic simulation models (Bennett et al. 2018; Huff et al. 2000; Livneh et al. 2015; Saksa et al. 2017).

Of the studies that collected detailed forestry measurements, exclusive of LAI, the majority did not quantitatively analyze those data relative to hydrologic effects and presented quantitative data only in a site-descriptive context. Only a single study related quantitative forestry measurements to hydrologic response, using correlations of forest cover against maximum SWE and snowpack ablation rate (Varhola et al. 2010). Standard forestry measurements included stand-level quantitative metrics such as basal area, tree density, and tree volume, as well as tree-level attributes such as diameter, height, and species. Although allometric equations allow estimation of LAI based on standard forestry measurements, they are typically applicable only in the localized regions and for the species for which they were developed (Jonckheere et al. 2004). The scale of forest characterization also ranged from site-specific evaluation to watershed-scale assessment based on maps or remote sensing. Two studies in Table 1 (Li et al. 2018; Zhang & Wei 2012) quantified disturbance effects in terms of Equivalent Clearcut Area (ECA) (King 1989) – which accounts for the density and extent of disturbed areas for the purpose of predicting peak flow changes – and one paper presented a brief critical review of the concept (Varhola et al. 2010). As discussed above, hydrologic response to disturbance is influenced by stand structure, density, and radiation exposure, which all affect snow accumulation, snowmelt rates, and evapotranspiration. Because these influences are almost certainly nonlinear (Moore & Wondzell 2005), it is unlikely that ECA can accurately represent the hydrologic impacts of spatially heterogeneous, non-stand replacing forest disturbances.

Direct and Indirect Hydrologic Effects of Forest Disturbance and Climate

Aside from the most data-intensive LAI assessments, nearly all other studies in our review assumed post-disturbance LAI to be time-invariant, therefore not accounting for growth of post-disturbance vegetation. Applying new findings to management requires not only improving our quantitative representation of vegetation in hydrologic analyses, but also accounting for post-disturbance vegetation dynamics and response to future climate (Andréassian 2004; Bennett et al. 2018; Buma & Livneh 2015). Future disturbance and climate will have both direct effects on streamflow (e.g., warmer temperatures will result in more precipitation falling as rain rather than snow) and indirect effects as mediated through vegetation changes (e.g., warmer temperatures lead to tree die-off, which in turn affects evapotranspiration). Accounting for post-disturbance vegetation dynamics and climate scenarios is possible given the current state of physically-based eco-hydrologic modeling (Tague & Band 2004; Wigmosta et al. 1994), which again requires better quantitative characterization of forest conditions.

Post-disturbance recovery and regrowth can cause streamflow to either increase or decrease, depending on seasonality, time since disturbance, and density and rate of regrowth (Perry & Jones 2017). Twenty-six of the 78 studies considered in this review incorporated either past or future climate forcing data, while only 21 included multi-annual forest dynamics, i.e., regeneration or regrowth, in their assessments of hydrologic response to disturbance. Beyond timescales of about a decade, initial hydrologic responses, such as seasonal low flows or water yield, may return to baseline conditions or even differ in sign (increase vs. decrease) from the immediate post-disturbance response (Perry & Jones 2017). However, in studies focused on sufficiently short timelines (<10 years), the assumption of static vegetation may be acceptable in the slow-growing coniferous forests of the western US. Studies that accounted for vegetation dynamics used a variety of methods, ranging from time-based thresholds for reversion from "disturbed" to "undisturbed" (Hernandez et al. 2018) to classification of stands or catchments in various stages of recovery, as observed either through ground observations or remote sensing (Boisramé et al. 2017; Li et al. 2018; Meyer et al. 2017; Robles et al. 2014; Vanderhoof & Williams 2015; Wei & Zhang 2010; Winkler et al. 2014; Zhang &

Wei 2012) or simulation of future vegetation growth (Bart et al. 2016; Buma & Livneh 2015; Grant et al. 2013; Penn et al. 2016; Saksa et al. 2017). Simulations of vegetation recovery vary from species-specific bioclimatic envelopes (Buma & Livneh 2015) to species-invariant simulated canopy growth (Bart et al. 2016; Grant et al. 2013; Saksa et al. 2017).

Inter-annual climate variability can also mask streamflow and snowpack responses to disturbance. The largest differences in snowpack between disturbed vs. undisturbed stands occur in low-snowfall years (Boon 2012; Winkler et al. 2014), which are expected to become more common in western North America (Fyfe et al. 2017), as larger snowfall overwhelms the interception capacity of the overstory. Additionally, tree mortality is likely to increase due to drought- and heat-related factors (Adams et al. 2009; Allen et al. 2010; Anderegg et al. 2013; McDowell et al. 2016; Williams et al. 2013). Simulations that include both vegetation dynamics and climate projections suggest that vegetation may have a stronger influence on the future water yield than climate alone in dry regions (Bart et al. 2016; Bennett et al. 2018). In contrast, inter-annual precipitation variability in wetter areas exerts a stronger control than forest conditions on streamflow (Burt et al. 2015).

Finally, future studies can help improve the predictability of hydrologic response to disturbance by quantifying and reporting the magnitude of changes in both forest conditions and hydrologic fluxes. Such quantification will allow differentiation of initial forest densities or structures, disturbance severities, and subsequent hydrologic response. In Bosch and Hewlett’s (1982) review, their Figure 1 presented a quantitative relationship between the percent reduction in forest cover and the annual streamflow increase. Their review differed from this paper in that it focused on stand-replacing disturbances – primarily harvesting – while our review included numerous cases of both stand-replacing and non-stand replacing disturbances, which we conclude may exhibit different hydrologic responses. Although we initially sought to quantify the magnitude of increases or decreases in snowpack and water yield that were observed in different studies, too few of the papers reviewed here reported magnitudes of change in a way that enabled meta-analysis. Therefore we recommend that future papers explicitly report the following metrics: quantitative forest density (e.g., in terms of LAI, basal area per acre, or canopy cover percentage), quantitative disturbance effects (e.g., reduction in LAI, area affected), scale of assessment (e.g., stand, hillslope, or catchment), annual precipitation, annual maximum SWE, and magnitude of hydrologic change as well as results of any statistical significance tests.

Implications for Forest Management: Balancing Water Yield and Forest Resilience

Given that tree mortality in the West is likely to continue at a historically high rate in the future (Allen et al. 2010; Anderegg et al. 2013; Williams et al. 2013), management objectives may seek to maximize the adaptive capacity of forested watersheds by optimizing growing-season soil moisture (Grant et al. 2013), e.g., by maximizing snow retention. The same factors that affect post-disturbance water yield also may affect snow retention and soil moisture. Although soil moisture sometimes increases in the years following harvest in relatively wet areas (Perry & Jones 2017; Ziemer 1964), it may decline if snowpack decreases or melts earlier. Decreases in snow accumulation, snow retention, or soil moisture most often occur at lower latitudes and south-facing aspects where solar radiation dominates the radiation budget (Bennett et al. 2018; Biederman et al. 2014; Chen et al. 2015; Ellis et al. 2011; Harpold et al. 2014; Lundquist et al. 2013). At such sites, stand structure and density can have important effects on snow accumulation and retention (Broxton et al. 2015; Lundquist et al. 2013), which in turn affect growing-season soil moisture (Grant et al. 2013; Harpold et al. 2015; Tague et al. 2009).

The studies that found decreases in post-disturbance water yield (Table 5) or snowpack mainly occurred in catchments that coincide with regions that are expected to receive less precipitation as snow in the future (Fyfe et al. 2017). Even in catchments receiving more rain than snow, die-off may increase the vulnerability of surviving trees to future mortality if understory transpiration and soil evaporation overcompensate for the decrease in canopy evapotranspiration (Morillas et al. 2017). In stands already affected by natural, non-stand replacing disturbance such as drought- or insect-related die-off, post-disturbance salvage logging in high-radiation environments may allow increased solar radiation to drive earlier snowmelt and subsequent depletion of soil moisture, either through soil evaporation or transpiration by understory vegetation (Boon 2009; Gleason et al. 2013; Morillas et al. 2017; Perrot et al. 2014; Winkler et al. 2015). Such treatments in high-radiation environments may not only lead to reduced summer flows and possibly reduced water yield, but also hinder future forest recovery and resilience if soil moisture decreases as a result of increased solar radiation reaching the soil surface. Additionally, harvest treatments have additional effects if they include road-building, which can affect infiltration and both surface and subsurface runoff pathways and rates (Moore & Wondzell 2005).

Toward the goal of optimizing soil moisture, studies summarized here provide some guidelines for maximizing snow retention. In areas where average winter temperature is less than -1° C, longwave radiation in dense forests is typically insufficient to melt midwinter snowpack, and dense canopies provide shade that slows spring snowmelt (Lundquist et al. 2013). Thus, retaining moderately dense forest cover should be a goal in colder areas if forest resilience is a management objective, particularly on south-facing slopes where they provide solar shading (Ellis et al. 2011). However, snow retention at relatively windy sites in cold regions may be controlled more by winds (i.e., with longer retention in forests than in clearings where wind scours the snowpack) (Dickerson-Lange et al. 2017). In warmer areas, i.e., those where mean winter temperature is warmer than -1° C, sparser tree cover may optimize snow retention by providing solar shading with minimal longwave radiation emittance (Lundquist et al. 2013). For example, maximum snow retention was observed in Arizona at sites that were thinned and burned to about 24-30% of initial density (Sankey et al. 2015; Svoma 2017), where treatments provided the added benefit of lower fire risk. In such warm areas, or in colder areas on north-facing slopes (Ellis et al. 2011), managing for less dense forests may minimize total melt energy – i.e., by blocking shortwave radiation while emitting less longwave radiation than denser stands – and thus maximize snow retention.

Future management-driven research should attempt to improve predictions of when snow retention will respond positively or negatively to silvicultural treatments such as thinning or salvage harvests. Physically-based models already include the capability for simulating the effects of canopy density (typically in terms of LAI) on radiation, snowpack, and evaporation (Tague & Band 2004; Wigmosta et al. 1994), and may thus serve as tools for comparing management alternatives. At finer scales that are relevant to individual forest management projects, physically-based models can be used to comparatively assess alternative silvicultural prescriptions – including site aspect, elevation, and the number and size of harvest gaps – for maximizing hydrologic objectives such as snow retention, water yield, or seasonal low flow targets (Ellis et al. 2013; Sun et al. 2018).

Conclusions

A review of 78 studies on hydrologic response to forest disturbance indicates that this topic has received increased attention in the literature, and that new hypotheses continue to be formulated as understanding increases in this rapidly evolving discipline. While one long-held hypothesis – that forest cover loss results in increased water yield due to decreased evapotranspiration – still applies in many cases, it was found to be incorrect under some conditions, and identifying these conditions will improve predictability of streamflow response to forest disturbance. Water yield and snowpack are more likely to decrease or not change in areas with rapid post-disturbance growth and in watersheds where net radiation is greater, such as at lower latitudes and south-facing aspects. Both observational and simulation studies concluded that post-disturbance streamflow and snowpack may decrease under these conditions, yet only physically-based models were able to simulate any reductions in yield, underscoring the importance of continued investment in physically-based modeling to support forest management. The use of such models to evaluate management alternatives will require improved quantitative characterization of forest density and disturbance effects, particularly in terms of leaf area index, which is the metric currently used for most quantitative linkages between forests and hydrologic response.

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CHAPTER 3

VARIABLE STREAMFLOW RESPONSE TO FOREST DISTURBANCE IN THE WESTERN US: A LARGE-SAMPLE HYDROLOGY APPROACH[2]

Abstract

Forest cover and streamflow are generally expected to vary inversely because reduced forest cover typically leads to less transpiration and interception. However, recent studies in the western US have found no change or even decreased streamflow following forest disturbance due to drought and insect epidemics. We investigated streamflow response to forest cover change using hydrologic, climatic, and forest data for 159 watersheds in the western US from the CAMELS dataset for the period 2000-2019. Forest change and disturbance were quantified in terms of net tree growth (total growth volume minus mortality volume) and mean annual mortality rates, respectively, from the US Forest Service's Forest Inventory and Analysis database. Annual streamflow was analyzed using multiple methods: Mann-Kendall trend analysis, time trend analysis to quantify change not attributable to annual precipitation and temperature, and multiple regression to quantify contributions of climate, mortality, and aridity. Many watersheds exhibited decreased annual streamflow even as forest cover decreased. Time trend analysis identified decreased streamflow not attributable to precipitation and temperature changes in many disturbed watersheds, yet streamflow change was not consistently related to disturbance, suggesting drivers other than disturbance, precipitation, and

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temperature. Multiple regression analysis indicated that although change in streamflow is significantly related to tree mortality, the direction of this effect depends on aridity. Specifically, forest disturbances in wet, energy-limited watersheds (i.e., where annual potential evapotranspiration is less than annual precipitation) tended to increase streamflow, while post-disturbance streamflow more frequently decreased in dry water-limited watersheds (where the potential evapotranspiration to precipitation ratio exceeds 2.35).

Key Points

- Large-sample analyses found that while streamflow often increased following forest disturbance, it decreased in some watersheds.
- The direction of streamflow response to forest disturbance (increase vs. decrease) is dependent on aridity.
- Forest disturbance is more likely to occur in arid locations, which is also where disturbance tends to result in decreased streamflow.

Plain Language Summary

Forest disturbance is typically expected to lead to increased runoff, and therefore more water available for aquatic ecosystems and people, because loss of forest vegetation results in less water being taken up and transpired by plants. We examined streamflow and forest change in 159 watersheds in the western U.S. to test this expectation. We found that not all disturbed watersheds experienced increased streamflow. Very dry watersheds were more likely to produce less runoff following forest disturbance and were also more likely to experience forest disturbance.

1. Introduction

Based on decades of research, forest cover and streamflow are generally expected to vary inversely (Andréassian, 2004; Bosch & Hewlett, 1982; Hibbert, 1967; Troendle, 1983). Such research is based on a combination of paired watershed experiments (e.g., Brown et al., 2005; Moore et al., 2020), post-hoc analysis of streamflow data in unpaired watersheds where streamflow can be modeled as a function of climatic observations (e.g., Biederman et al., 2015; Zhao et al., 2010), and simulation modeling that encompasses various levels of complexity (e.g., Bennett et al., 2018; Buma and Livneh, 2015; Sun et al., 2018). The mechanism behind the inverse relationship between forest cover and streamflow includes a combination of reduced evaporation of canopy-intercepted precipitation, and reduced canopy transpiration following forest cover loss (Adams et al., 2012; Hibbert, 1967; Pugh & Gordon, 2012). Conversely, forest recovery or afforestation are assumed to increase total transpiration and evaporative losses of canopy-intercepted precipitation, thus leading to decreased runoff (Andréassian, 2004; Hibbert, 1967).

Contrary to the hypothesis of an inverse relationship between forest cover and streamflow, observed streamflow changes following recent forest disturbances have been variable in magnitude and direction (Boisramé et al., 2017; Goeking & Tarboton, 2020; Ren et al., 2021; Slinski et al., 2016). Over the past two decades, widespread but low- to moderate-severity forest disturbance has occurred as a result of drought stress, insect epidemics, and disease epidemics, as well as altered wildfire regimes (Adams et al., 2012; Williams et al., 2013), thus providing opportunities to identify circumstances leading to decreased post-disturbance streamflow. Most exceptions to the inverse relationship between forest cover and streamflow occurred as post-disturbance decreases in streamflow, typically at low latitudes and south-facing aspects with high aridity, high incoming solar radiation, and/or where tree canopies were replaced by rapid growth of dense herbaceous vegetation or shrubs (Bennett et al., 2018; Goeking & Tarboton, 2020; Guardiola-Claramonte et al., 2011; Morillas et al., 2017; Ren et al., 2021). Even in studies that found conforming streamflow increases following disturbance, the magnitude of streamflow increases was modulated by aridity (Saksa et al., 2019). Although such findings are anomalous in the larger context of decades of forest hydrology research, they highlight alternative hypotheses to the inverse relationship between forest cover and streamflow. One such alternative hypothesis is that although streamflow typically increases following forest disturbance, post-disturbance conditions that lead to increased evaporation (i.e., increased energy at snowpack or soil surface) or increased transpiration (i.e., replacement of sparse trees with dense shrubs) lead to a reduced streamflow response.

While numerous studies of runoff response to forest change have focused on site-specific treatments (e.g., harvest, planting) or severe disturbance (e.g., stand-replacing wildfire, clearcuts) in one or two small watersheds, fewer studies have examined lower severity disturbances across broader geographic areas or across more gradual timescales than episodic timber harvesting or wildfire (Andréassian, 2004; Hallema et al., 2017; Wine et al., 2018). Response to low to moderate severity forest disturbances may fundamentally differ from severe, stand-replacing disturbances (generally defined as <70% tree mortality) due to their different effects on energy balances affecting snowpack and soil moisture as well as different transpiration rates for pre-disturbance versus post-disturbance vegetation (Adams et al., 2012; Pugh & Gordon, 2012; Reed et al., 2018). Recent tree die-off events spanning western North America have provided the opportunity to examine streamflow responses to disturbance that is less severe but more widespread than the forest changes considered in most previous forest hydrology studies (Adams et al., 2012; Hallema et al., 2017). Studies based on both observations (Biederman et al., 2014, 2015; Guardiola-Claramonte et al., 2011) and simulations (Bennett et al., 2018; Ren et al., 2021) have revealed unexpected post-disturbance decreases in streamflow. Streamflow response to disturbance at broader scales may not reflect hypotheses developed from study of small watersheds that are commonly the focus of paired watershed experiments (Andréassian, 2004), which underscores the value of broad-scale evaluation of hypotheses that were developed at fine scales.

A challenge in testing such hypotheses is the need to balance breadth with depth, i.e., gathering fine-scale observations from individual watersheds versus coarser observations from many watersheds (Gupta et al., 2014). Large-sample hydrology can complement fine-scale studies of individual small watersheds by identifying broad-scale patterns in streamflow response to forest disturbance. Fine-scale studies have produced useful information about the response of streamflow (e.g., Biederman et al., 2015; Guardiola-Claramonte et al., 2011), snowpack (e.g., Broxton et al., 2016; Moeser et al., 2020), and individual ecohydrological processes to forest change (e.g., Biederman et al., 2014; Reed et al., 2018). In contrast, large-sample hydrology can evaluate hypotheses across many watersheds to identify circumstances that conform to or deviate from hypothesized relationships (Addor et al., 2019; Gupta et al., 2014; Newman et al., 2015). Another challenge is accounting for the effects of climate variability in streamflow assessments, such that the effects of vegetation change on streamflow are not confounded with climate effects. To address this challenge, quantitative models of streamflow response to vegetation change often include precipitation and temperature as explanatory variables (Zhao et al., 2010).

In this study, we used a large sample of catchments to test hypotheses about the direction of runoff response following forest disturbance in semi-arid catchments. Observations consisted of streamflow, vegetation, and climate data, which allowed us to account for streamflow changes related to variability in precipitation and temperature and thus disentangle climate from vegetation effects. Based on previous studies finding exceptions to the inverse relationship between forest cover and streamflow, we developed two alternative hypotheses. First, post-disturbance runoff in catchments conforms with the commonly held paradigm that runoff increases with tree mortality or reductions in net growth. Second, an alternative hypothesis is that in watersheds with higher aridity and incoming solar radiation, runoff is more likely to decrease or not change than in watersheds with lower aridity and solar radiation. A corollary of this hypothesis is that a threshold of aridity index exists above which disturbance results in a decrease in runoff. Our results find this threshold to be an aridity index of 2.35.

2. Data and Methods

We combined data from the CAMELS large-sample hydrology dataset (CAMELS; Addor et al., 2017) and the US Forest Service's Forest Inventory and Analysis (FIA) forest monitoring dataset (Bechtold & Patterson, 2005) to answer four questions (Table 1). The ability of each question's analytical framework to disentangle climatic from forest disturbance effects on streamflow successively increases from the first to the fourth question. For analyses that do not explicitly permit such disentangling, we interpret the results in the context of factors that were not included in the analysis.

Table 6. The four questions addressed in this study, the analytical framework used to address each question, and the variables included in the analysis. Q=streamflow; P=precipitation; PET=potential evapotranspiration; T=temperature.

Question	Analytical	Variables analyzed
1) To what extent and where do watersheds exhibit a consistent trend in annual Q, Q/P, P, PET, and T, regardless of forest change effects?	Mann-Kendall trend tests (univariate)	Annual Q, Q/P, P, PET, and T
2) To what extent and where do trends in runoff ratio and changes in forest density demonstrate an inverse relationship?	Trend in Q/P vs. net tree growth	Trend (Kendall's Tau) in annual Q/P; net tree growth
3) To what extent has streamflow changed in watersheds with substantial forest disturbance?	Time trend analysis (comparison of observed vs. predicted Q)	Annual Q, P, and T; disturbance (disturbed/not disturbed)
4) How well does the severity of forest disturbance, and the interaction of disturbance severity with aridity, predict change in streamflow?	Multiple regression	Annual Q, P, T; tree mortality; aridity (PET/P)

2.1. Data sources

2.1.1. Streamflow and climate data

Watersheds were selected from the CAMELS dataset, which was compiled for watersheds that have little or no known land-use change and whose streamflow is relatively unimpacted by storage or diversions (Addor et al., 2017). However, watersheds in the CAMELS dataset have been subject to disturbance from wildfire and other causes of tree mortality that have been quantified by FIA. From the entire CAMELS dataset, we first constrained our analysis to watersheds in the western US for which we could obtain estimates of forest characteristics from the FIA dataset. Then we removed watersheds where runoff ratio was calculated as larger than 1.0 (runoff greater than precipitation) in any one year, which indicates an impossible water budget and where data is presumed to be in error. Precipitation and streamflow data within the CAMELS dataset were derived from Daymet climate data and USGS streamflow gages, respectively (Addor et al., 2017), and these separate data sources do not impose constraints of water budget closure. While we recognize that some catchments may have runoff ratios greater than 1.0, e.g., in volcanic or karst landscapes, and that runoff ratios near but less than 1.0 may be similarly implausible, we had no means of quantifying realistically vs. unrealistically high runoff ratios. These constraints yielded 159 watersheds, out of 211 candidate watersheds as 52 (25%) had runoff ratio greater than 1.0. The fact that 25% of watersheds had runoff ratios greater than 1.0 is indicative of the uncertainty and difficulty in compiling quality controlled data over large samples, even for curated datasets such as CAMELS. The watersheds selected had a wide range of physical and land cover characteristics (Table 7), runoff ratios, and humidity indices (Fig. 3), giving the study a broad degree of generality. Given the criteria for inclusion in the CAMELS dataset (Addor et al., 2017), we assumed that stream gauges for each watershed quantify actual runoff, and that withdrawals, transfers, and changes in storage are negligible.

Table 7. Characteristics of 159 watersheds used in this study. Values are summarized from CAMELS attributes (Addor et al., 2017).

	Area (km^2)	Mean slope	Mean elevation (m)	Runoff ratio	P (mm/yr)	PET (mm/yr)	Fraction forested
Median	238	92.8	1,613	0.419	822	1,084	0.76
Mean	649	92.0	1,650	0.409	1,062	1,088	0.64
Standard deviation	1,454	35.3	882	0.241	674	206	0.34

The CAMELS dataset includes daily time series of climatic variables and streamflow as well as time-averaged catchment characteristics. We used temporally averaged variables representing basin characteristics such as mean incoming solar radiation (SRAD), and aridity, defined as the ratio of mean annual potential evapotranspiration (PET) to mean annual precipitation, all from the CAMELS dataset (Addor et al., 2017). We summed CAMELS daily streamflow and precipitation values to get total annual water year streamflow and precipitation. Annual mean temperature was calculated by first averaging CAMELS minimum and maximum daily temperature to get daily mean temperature and then averaging the daily mean temperature. Additionally, we estimated annual PET by first using the Hamon method (Hamon, 1963; Lu et al., 2005) to estimate daily PET based on precipitation, temperature, and day length from the CAMELS dataset, and then aggregating daily values to annual PET.

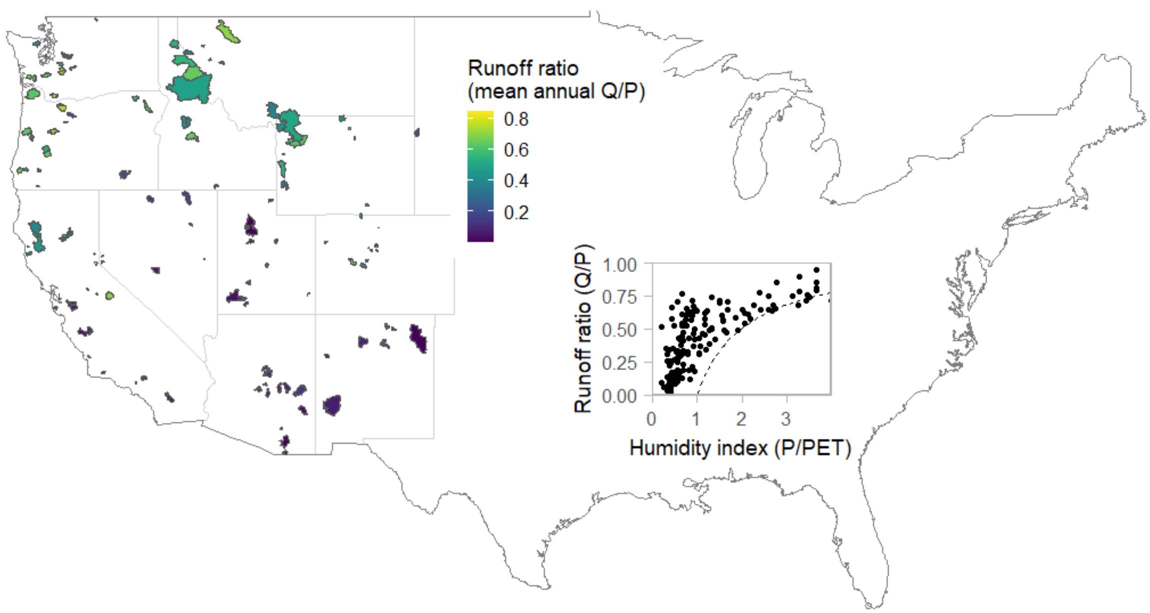

Fig. 3. Watersheds from the CAMELS database used in our analyses (n=159). Inset plot shows watersheds in nondimensional space based on long-term CAMELS attributes; the dashed curve represents energy limitation. the dashed curve represents energy limitation on streamflow, expressed as Q=P-PET framed in terms of the dimensionless axes as Q/P=1-1/(P/PET), where Q=annual streamflow, P=annual precipitation, and PET=annual potential evapotranspiration.

Because the CAMELS dataset extends only through water year 2014, while available forest data extend through 2019, we used USGS streamflow data and Daymet gridded climate data for water years 2015-2019 to extend the record of our analysis through water year 2019. USGS streamflow data were obtained through the R package *DataRetrieval* (Hirsch & De Cicco, 2015). Daymet gridded precipitation, minimum temperature, and maximum temperature values were downloaded using the R package *daymetr* (Hufkens et al., 2018) and extracted as area-weighted averages within each CAMELS catchment boundary, following the methods used to construct the CAMELS time series (Newman et al., 2015). That extraction process yielded time series analogous to the time series within the CAMELS dataset. We then aggregated daily values to annual values in the same manner as described above for the CAMELS time series. We cross checked our extended dataset by ensuring that we could replicate water year 2014 in the CAMELS data, finding that the only differences were due to numerical rounding.

2.1.2. Forest and disturbance data

Data on forest conditions and disturbances were obtained from the US Forest Service's Forest Inventory and Analysis (FIA) program. The FIA program established plot locations using probabilistic sampling to obtain a representative sample with mean spacing of 5 km across all forest types and owner groups (Bechtold & Patterson, 2005). In the western US, 10% of plots are measured each year and each plot is therefore measured once every ten years. Each year's subsample of plots is spatially distributed such that the sample of forest conditions is both spatially and temporally balanced. This sampling design was developed to produce unbiased estimates of forest attributes that represent discrete areas such as watersheds (Bechtold & Patterson, 2005).

Data collected from FIA plots include detailed tree measurements that permit calculation of plot-level volume of both live and dead trees, volume of net tree growth, volume of trees that recently died (i.e., "mortality trees"), and many other variables (USDA, 2010). Each plot is associated with an expansion factor that facilitates estimation of forest characteristics and their associated sampling errors for discrete areas, based on data from multiple plots over the same sampling period (Bechtold & Patterson, 2005; Burrill et al., 2018). FIA estimates are updated annually based on a 10-year moving window such that the estimate in any one year is based on data collected during the previous 10 years (e.g., an estimate with a nominal date of 2019 is based on data collected during 2010-2019). FIA implemented this nationally consistent, probabilistic sample in 2000, although the onset of data collection varied among states, with Wyoming being the last state to fully implement this design in 2011.

We characterized forest disturbance using FIA's estimates of net tree growth and tree mortality and their associated standard errors, for the period 2010-2019, from the publicly accessible EVALIDator tool (USDA, 2020). Each estimate was constrained to a watershed represented by an 8-digit Hydrologic Unit Code (HUC8) that contains a CAMELS catchment. Although ideally we would have produced FIA estimates at the scale of CAMELS watersheds, these smaller watersheds contained small sample sizes of FIA plots and thus were associated with high uncertainty at the CAMELS scale. The forested portions of most HUC8 catchments exist at relatively high elevations that tend to be less impacted by water transfers and human activities (i.e., nonforest land uses), which is also where CAMELS watersheds occur (Addor et al., 2017). To test whether forest conditions in CAMELS versus HUC8 watersheds were similar, we computed the percentage of area at each scale that experienced forest change between 2001 and 2019 as determined from the National Land Cover Database change product (Homer et al., 2020).

We found that the distributions of forest change at the two scales were not significantly different based on p=0.51 from the Kolmogorov-Smirnov test for equal distributions. This result supports the use of FIA data at the HUC8 scale as representative of CAMELS watersheds.

Mean annual net growth and mortality rates are expressed as volume per year (Burrill et al., 2018) rather than numbers of trees because under normal conditions with no disturbance, small trees typically die at higher rates than larger or older trees due to self-thinning that occurs naturally as forest stands develop over time (Reineke, 1933; Yoda et al., 1963). Net growth is defined as volumetric growth of all live trees minus the total volume of trees that died in the previous ten years (i.e., mortality volume). Values of net growth greater than zero indicate that tree growth has outpaced mortality, while negative net growth is indicative of mortality that occurred faster than growth of live trees. To assess the severity of forest disturbance, we estimated each watershed's mean annual mortality rate and standardized that rate by the total of live volume plus mortality volume. Note that watersheds with high mean annual mortality can also have positive net growth if post-disturbance recovery and live tree growth occurs more rapidly than mortality. A strength of using net growth and mortality estimates is that it permits assessment of quantitative relationships between forest conditions and hydrologic variables, as opposed to being limited by categorical mapping of disturbance or rules-of-thumb such as having >20% of area affected (Goeking & Tarboton, 2020).

2.2. Methods

We used multiple analytical methods to address our objectives. First, we used trend analysis to identify monotonic trends in individual water budget components and drivers. Second, we qualitatively related trends in runoff ratio to forest change across gradients of latitude and aridity. Third, we used time trend analysis (Zhao et al., 2010) to quantify the magnitude of streamflow change that cannot be attributed to precipitation and temperature drivers, and then correlated the magnitude of unattributed streamflow change with forest disturbance, latitude, solar radiation, and aridity. Fourth, we evaluated the relative importance of several factors – including temperature, precipitation, and the interaction of forest disturbance and aridity – for predicting change in streamflow across decades using a multiple regression model.

2.2.1. Trends in water budget components and drivers

Our first question was whether runoff ratio has changed over time, i.e., whether there is any monotonic trend, regardless of climate or forest disturbance effects. We answered this question using the nonparametric Mann-Kendall trend test, which determines whether the central tendency of a variable changes solely as a function of time (Helsel et al., 2020). We tested for trends in annual runoff ratio (Q/P) as well as water budget components and drivers, including annual streamflow (Q), annual total precipitation (P), annual mean temperature (T), and annual potential evapotranspiration (PET). Each variable was tested independently of vegetation effects. Each test evaluated two time periods: first, the period 2000-2019, which was the basis for our subsequent analyses of streamflow response to forest disturbance, and second, 1980-2019, for the purpose of determining whether any other long-term trends exist that extend prior to the period covered in our analysis.

Watersheds with significant trends in Q, P, Q/P, T, and PET were identified based on two-sided p-values associated with Kendall’s tau (Helsel et al., 2020) evaluated with the *MannKendall* function in the *Kendall* package (McLeod, 2011) for R statistical analysis software (R Core Team, 2020). Two-sided p-values <0.1, which correspond to one-side p-values <0.05, were considered statistically significant.

2.2.2. Runoff ratio and forest density change

Our second question was whether there is general support for the hypothesis that forest cover is inversely related to annual runoff, across a large sample of watersheds spanning a range of aridity, incoming solar radiation, and latitude. Under this hypothesis, we expected that most watersheds that experienced forest cover loss (i.e., disturbance) exhibited increases in runoff ratio, and that watersheds that experienced forest cover gain (i.e., increased tree density in the absence of disturbance) exhibited decreases in runoff ratio. An alternative hypothesis, based on recent observations of decreased streamflow following forest disturbance as summarized by Goeking and Tarboton (2020), is that post-disturbance runoff sometimes decreases in more arid, low-latitude watersheds with higher incoming solar radiation.

To characterize watersheds as disturbed versus undisturbed and as having increased versus decreased runoff ratio, we determined whether net growth and trend in runoff ratio (Q/P) were each positive or negative for each watershed. Watersheds were characterized as having increased versus decreased runoff ratio on the basis of Kendall's tau, which allows dimensionless comparison of trends in runoff ratio across watersheds whose runoff ratios may vary widely (Helsel et al., 2020), again using R package Kendall (McLeod, 2011).

Net tree growth estimates for 2010-2019 encompass a temporal averaging period beginning in 2000 for plots measured in 2010, and in 2009 for plots measured in 2019, because growth is calculated from individual tree growth representing the 10 years prior to plot measurement (USDA, 2010). Therefore, we conducted trend analysis for the period 2000-2019, which encompasses the averaging period for FIA plot measurements.

We categorized watersheds into two groups: those that met the expectation that the change in runoff ratio is inversely related to forest cover change (conforming watersheds), and those that did not meet this expectation (nonconforming watersheds). Conforming watersheds included watersheds where tree volume increased (i.e., positive tree growth) and Q/P decreased, as well as those where tree volume decreased (i.e., negative tree growth) and Q/P increased. Similarly, nonconforming watersheds consisted of those where both tree volume and Q/P increased and where both tree volume and Q/P decreased. This categorization resulted in four combinations of change in tree volume and trend in Q/P.

We assessed differences in aridity, solar radiation, and latitude among the four categories of conforming and nonconforming watersheds. Aridity was compared among watersheds in the context of evaporative index and aridity index, as defined by Budyko (Budyko and Miller, 1974), to assess whether nonconforming watersheds (i.e., those with forest disturbance and decreased streamflow) were more likely to occur in water-limited watersheds than in energy-limited ones. Evaporative index represents the proportion of precipitation that evaporates, on a mean annual basis, and is equal to the quantity 1–Q/P. Aridity index is the ratio of mean annual PET to mean annual P. Long-term values of mean annual Q, mean annual P, aridity, and incoming solar radiation for each watershed were obtained from the CAMELS dataset (Addor et al., 2017). We also tested for significant differences in latitude, aridity, and solar radiation among conforming versus nonconforming watersheds using the nonparametric Kruskal-Wallis test for multiple comparisons, which was conducted using the function kruskal in R package agricolae (de Mendiburu, 2020).

2.2.3. Expected streamflow change in watersheds with and without forest disturbance

To address the question of whether streamflow has changed as a result of forest disturbance over discrete time periods, we used time trend analysis, which is an analytical framework used to quantify streamflow change resulting from vegetation change (Zhao et al., 2010). The premise of time trend analysis is that expected streamflow can be predicted from a small number of predictor variables for a calibration period, and then applied to a later time period to compare predicted to observed runoff for that time period. Computationally, a linear regression model is calibrated on an initial time period, applied to a second time period, and the residuals (i.e., the difference between the observed and predicted values in the second time period) are assumed to be due to factors not included in the model. Although previous applications of time trend analysis have used a linear regression model, we initially attempted to conduct this analysis using a machine learning model structure, specifically random forests (Breiman, 2001), but found that random forests performed similarly to linear regression but presented the disadvantage of not producing easily interpretable coefficients.

For the purposes of time trend analysis, we split our period of record into two time periods: 2000-2009 and 2010-2019. We calibrated and validated the linear regression model for time trend analysis using data from water years 2000-2009. Odd-numbered years were used for calibration, and even-numbered years for validation.

Preliminary analysis indicated that our dataset met the assumptions required for linear regression (Helsel et al., 2020). Given that temperature exhibited a significant positive trend at many watersheds (Fig. 2) and was a significant predictor, we included it in our model. Thus, the regression model took the form:

$$Q_1 = a_1 * P_1 + b_1 * T_1 + c_1 + e \qquad (1)$$

In Eq. (1), Q=annual streamflow; P=annual precipitation; T=annual mean temperature; subscripts represent values from the calibration/validation period (time 1, or 2000-2009); a, b, and c are coefficients; and e represents model residuals. We also tested whether the model improved when we included the interaction of T and P as a product term, and seasonal rather than annual T and P; neither of these options improved model fit, so we proceeded with the simpler Eq. (1). The regression held a and b the same across all watersheds, for two reasons. First, the processes that relate P and T to streamflow should be consistent across all watersheds, and second, allowing these coefficients to vary would effectively create a separate model for each watershed, which would result in many watersheds being omitted due to years with missing data during the calibration period. The intercept, c, was allowed to vary among watersheds to capture watershed specific differences with respect to factors that were not included in this linear model. The application of this model to the evaluation period (time 2) uses time 1 coefficients and time 2 observations of annual precipitation and temperature to predict annual streamflow over time period 2 (2010-2019):

$$Q'_2 = a_1 * P_2 + b_1 * T_2 + c_1 \qquad (2)$$

The difference between observed ($\overline{Q_2}$) and predicted ($\overline{Q_2'}$) mean annual streamflow during the evaluation period is represented as the quantity:

$$\overline{Q_{obs-exp}} = \overline{Q_2} - \overline{Q_2'} \tag{3}$$

where $\overline{Q_{obs-exp}}$ represents the magnitude of streamflow change that cannot be attributed to precipitation and temperature and thus is typically interpreted to be due to vegetation change (Zhao et al. 2010).

One objective of time trend analysis was to determine how runoff responds to disturbance. As in our other analyses, we hypothesized that runoff is likely to increase in disturbed watersheds, although a secondary hypothesis was that runoff response depends not only on magnitude of disturbance but also on aridity and/or incoming solar radiation. To answer the question of whether streamflow has increased or decreased in disturbed watersheds, we interpreted significant change in streamflow, from our time trend analysis results (i.e., deviation in observed Q from predicted Q) in the context of disturbance. Significant change in annual streamflow was identified using a one-sample t-test (Biederman et al., 2015), wherein the null hypothesis was that there has been no change in streamflow due to factors other than precipitation and temperature ($Q_{obs-exp} = 0$). P-values less than 0.05 were identified as significant deviations in streamflow. Disturbed watersheds were defined as those where tree mortality exceeded 10% of initial live tree volume.

2.2.4. Streamflow change as a function of disturbance severity and climate

We used multiple regression to address two objectives: 1) to evaluate the relative importance of several factors for predicting change in streamflow (ΔQ), which allowed isolation of the relative contributions of climate versus disturbance to ΔQ, and 2) to determine whether the interaction of forest disturbance severity with aridity or solar radiation affects runoff response to forest disturbance. A regression model was developed to predict ΔQ across two discrete time periods, 2000-2009 versus 2010-2019.

To enable disentangling the confounding effects of climate versus vegetation changes, we initially considered a large set of predictor variables encompassing time varying climatic variables (e.g., change in mean annual precipitation) as well as time-invariant climate descriptors (e.g., long-term mean incoming solar radiation) that are specific to each watershed. The initial set of potential predictors included baseline Q and baseline P for 2000-2009 ($\overline{Q}_1$and $\overline{P}_1$, respectively), mean watershed aridity and solar radiation, tree mortality during 2010-2019, and change in temperature, precipitation, and potential evapotranspiration (PET) between the two time periods. To meet the assumption of noncollinearity among predictors, we then reduced the number of predictors by evaluating pairwise correlations among all predictors and removing predictors with correlation coefficients with absolute values of 0.6 or greater, where the predictor with the lower correlation with ΔQ was removed. In this manner, PET, solar radiation, and aridity were removed due to their respective correlations with temperature and $\overline{P}_1$; solar radiation and aridity were represented in the model in interaction terms with tree mortality. Due to multicollinearity between the interactions of mortality with solar radiation and aridity, we removed the interaction of mortality with solar radiation as it was a less useful predictor than the interaction of mortality with aridity. Thus, the final regression model took the form:

$$\Delta Q = b_0 + b_1 \overline{P_1} + b_2 \Delta P + b_3 \Delta T + b_4 \text{mortality} + b_5 \text{mortality} * \text{aridity} \tag{4}$$

where $\overline{P}_1$ represents mean annual precipitation for 2000-2009; ΔP and ΔT were differences in mean annual precipitation (mm) and mean annual temperature (°C) between 2000-2009 and 2010-2019; and bx refer to coefficients. As before, we tested whether model fit improved with the inclusion of a product term representing interactions between ΔP and ΔT, and also using differences in seasonal rather than annual P and T to consider the effects of precipitation phase and snowpack, and the model did not improve so we implemented Eq. (4) using annual observations of P and T. For this analysis, mortality was standardized by total volume of trees in the watershed, i.e., as the volume of trees that died during the study period relative to initial live tree volume, thus having possible values of 0 to 1 (USDA, 2020). The last term, mortality*aridity, represents the interaction of tree mortality with aridity, which was included to test the hypothesis that streamflow response to forest change is influenced by aridity. We used the p-value associated with the coefficient of each predictor variable in Eq. (4) to assess its significance as a predictor of ΔQ. We then compared standardized regression coefficients for each variable to determine the relative importance of climatic factors, forest disturbance, and interaction of forest disturbance with aridity for predicting ΔQ.

Based on the predominant hypothesis that runoff increases following forest disturbance, we expected that tree mortality would have a positive coefficient in the regression model, i.e., that larger levels of tree mortality would lead to positive ΔQ. Our alternative hypothesis – that disturbance may decrease runoff at high aridity or solar radiation – led to the expectation that the coefficient for the interaction of tree mortality with aridity or solar radiation would be negative, even as the coefficient for tree mortality alone was positive. To interpret the ability of each predictor variable to explain additional variability in ΔQ, we examined partial regression plots for each predictor (Moya-Laraño and Corcobado, 2008). Partial regression plots, also known as added variable plots, isolate the explanatory capability of a single variable relative to that of all other variables (Moya-Laraño and Corcobado, 2008). Although pairwise scatterplots between a predictor and ΔQ would be appropriate for simple (single-variable) regression, in the context of multiple regression, such plots ignore the effects of other variables in the model and can thus be misleading representations of the contribution of each variable to explaining variability in the response variable (Moya-Laraño and Corcobado, 2008). Partial regression plots were developed to address this concern using the R package car (Fox and Weisberg, 2019). To visualize the interactive effect of disturbance severity and aridity on streamflow change, we also examined marginal effects of the interaction between mortality and aridity using R package sjPlot (Lüdecke, 2021).

To interpret our regression model in the context of climatic warming, we used the regression model (Eq. 4) to evaluate the sensitivity of streamflow changes to tree mortality and aridity, both with and without 1° C of warming. We compared our results to those of previous studies that projected decreases in streamflow with climate warming across the western US (McCabe et al., 2017; Udall and Overpeck, 2017).

3. Results

3.1. Trends in water budget components and drivers

Most watersheds (>60%) did not experience significant monotonic trends in any water budget components or drivers during 2000-2019 (Fig. 2). P increased significantly between 2000 and 2019 in 26% of watersheds, driving some increasing trends in Q (13%) and Q/P (10%). P and Q decreased in <1% of watersheds, and Q/P decreased significantly 6% of watersheds. T and PET increased significantly in 40% and 23% watersheds, respectively, and both decreased in ≤1% of watersheds (Fig. 2), which is consistent with general climate warming. Significant changes in Q/P, P, Q, T, and PET were widespread with no clear geographic patterns (Fig. 2a-f).

When we repeated the Mann-Kendall trend test for the entire period of record (1980-2019), results were very different than for 2000-2019. More watersheds experienced significant decreases in P, Q/P, and Q (7%, 24%, and 17%, respectively), and only 8% of watersheds exhibited significant increases in Q and Q/P. This pattern coincides with significant increases in T (84%) and PET (81%), both of which decreased in <1% of watersheds. Thus, while an appreciable percentage of watersheds show evidence for long-term (1980-2019) increases in T and PET, only a small percentage show evidence for changes in Q and Q/P.

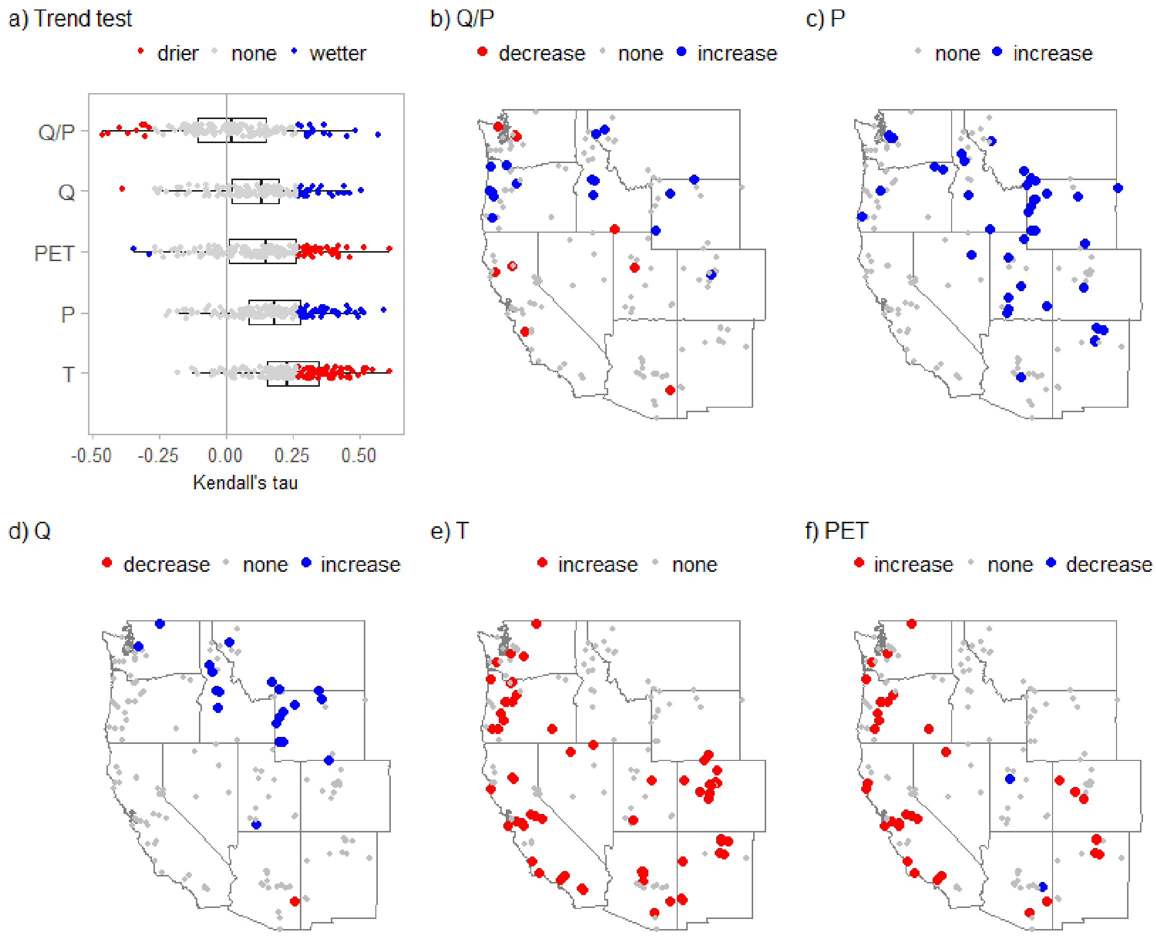

Fig. 4. Significant trends in annual water budget components and drivers over the period 2000-2019, based on the Mann-Kendall trend test (p<0.1). Q= streamflow; P=precipitation; T=temperature; and PET=potential evapotranspiration.

3.2. Runoff ratio and forest change

This analysis sought to test the hypothesis that forest cover is inversely related to runoff, and comparison of trends in runoff ratio (Q/P) to net tree growth demonstrated only moderate support for this hypothesis. Slightly less than half of all watersheds (43%) met the expectation that Q/P is inversely related to change in forest density (Fig. 5, upper left and lower right quadrants, with 24 and 44 watersheds, respectively), and the remaining watersheds (57%) did not conform to this expectation (Fig. 5, lower left and upper right quadrants). However, a small proportion of watersheds exhibited statistically significant trends in Q/P, as we found in the previous section. Note that in Fig. 5a, watersheds in both left quadrants experienced negative net tree growth, i.e., mortality exceed growth by surviving or newly established trees, which indicates disturbance and decrease in volumetric forest density. To quantify the degree to which estimated net growth might reflect random sample variability or noise, which is higher in smaller watersheds due to smaller sample sizes, we examined the standard errors associated with the estimated net growth in each watershed as produced by the EVALIDator tool. For >75% of watersheds, net growth differed from 0 by more than one standard error. Thus, we inferred that most watersheds have sufficient sample size to reliably indicate positive vs. negative net growth.

Trends in Q/P that contradict the expectation that Q/P is inversely related to change in forest density occurred in two situations. First, Q/P decreased in watersheds with negative net tree growth, i.e., greater mortality than live tree growth (Fig. 5a, lower left quadrant). This response was observed mainly in water-limited catchments where PET/P>1 and at lower latitudes in the southwestern US (Fig. 5b-e, magenta symbols). Second, Q/P increased while net tree growth was positive (Fig. 5a, upper right quadrant). This response was generally observed in energy-limited or moderately water-limited (PET/P<2) watersheds at higher latitudes of the Pacific Northwest and northern Rocky Mountains (Fig. 5b-e).

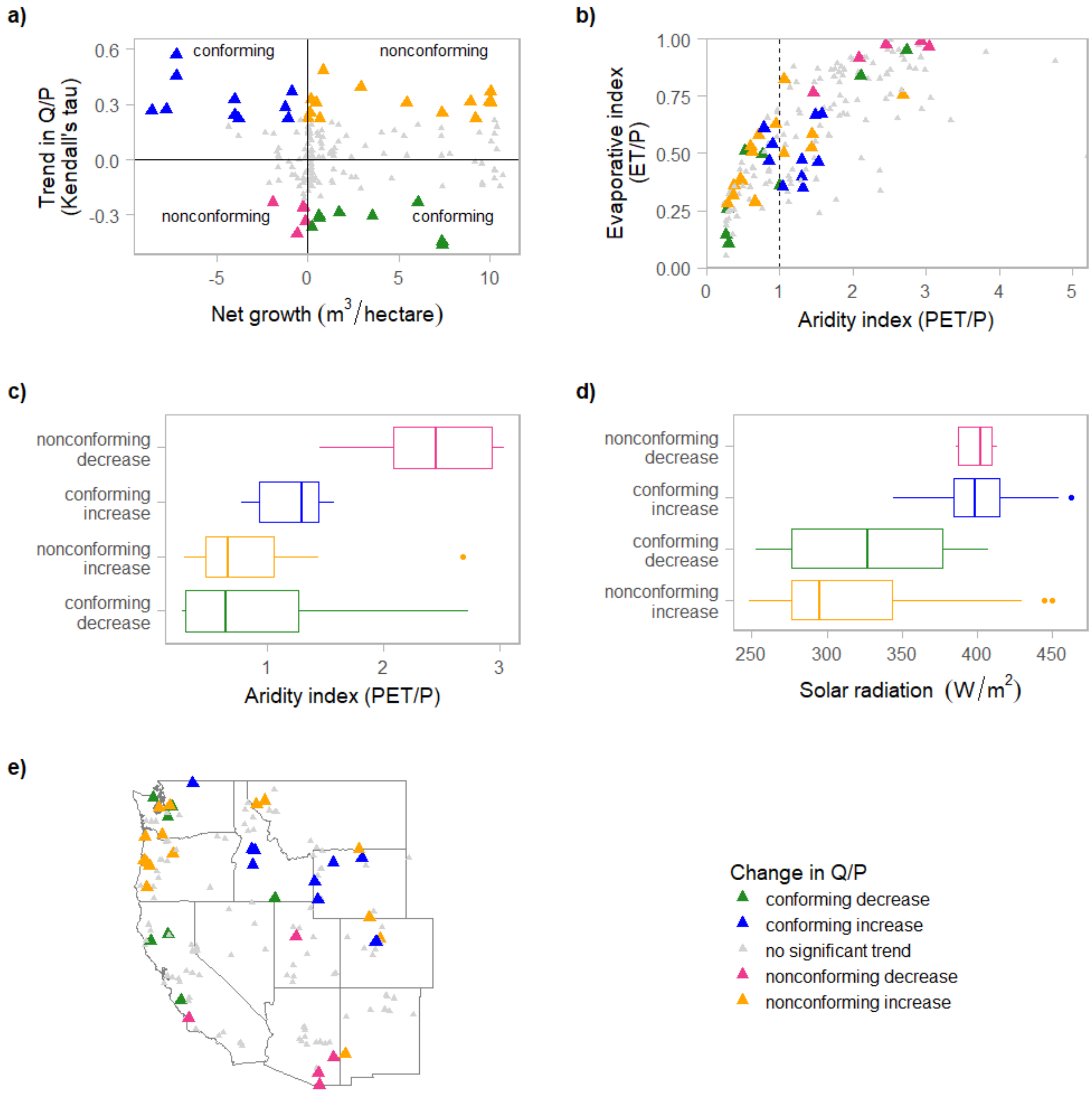

Fig. 5. Relationship between trend in Q/P (measured as Kendall's tau) and net growth of trees for 2000-2019. (a) Positive values of Kendall's tau indicate a monotonic increase in Q/P. Colors for watersheds with significant trend over time are assigned based on quadrants, where upper left and lower right quadrants conform to expected Q/P response to forest changes, and lower left and upper right exhibit runoff ratio trends do not conform to expectations. (b) Position of watersheds in the Budyko framework of evaporative index (1-Q/P) versus aridity index (PET/P). (c & d) Aridity and incoming solar radiation, with watersheds grouped into the quadrants in (a). Boxes represent interquartile ranges; horizontal bars within boxes represent medians. Boxes were not statistically significantly different, based on Kruskal-Wallis test (α=0.1). (d) Geographic distribution of watersheds, with colors as assigned in (a). Q= streamflow; P=precipitation; ET=evapotranspiration; PET=potential evapotranspiration.

Given recent research questioning the inverse relationship between forest cover and runoff (Goeking and Tarboton, 2020), an alternative hypothesis is that runoff ratio is more likely to decrease following forest disturbance in watersheds with high aridity and at lower latitude. However, we found that forest disturbance itself was more widespread and severe within water-limited watersheds, as evidenced by the preponderance of magenta and blue symbols where $PET/P>1$ (Fig. 3b-c) and where incoming solar radiation is relatively high (Fig. 5d). Results of the Kruskal-Wallis test showed no significant differences in aridity or solar radiation among disturbed watersheds with increased versus decreased runoff ratio, nor were there significant differences among relatively undisturbed watersheds with increased versus decreased runoff ratio (Fig. 5c-d). However, these results do not account for an increasing trend in P over 2000-2019 (see previous section). The following two analyses do account for this effect and thus allow better separation of forest disturbance versus climate effects on streamflow.

3.3. Streamflow change as a function of precipitation and temperature vs. other drivers

Time trend analysis and subsequent t-tests for significant deviations in streamflow indicated that observed streamflow changed significantly in 44 (28% of) watersheds in 2010-2019 relative to 2000-2009 (Fig. 6) due to factors other than precipitation and temperature. Of these watersheds, streamflow decreased and increased by statistically significant magnitudes in 30 and 14 watersheds, respectively (Table 3). Validation of the linear model (Eq. 1) had adjusted $r2=0.98$. As expected, both precipitation and temperature were significant predictors ($p<0.01$ for both variables).

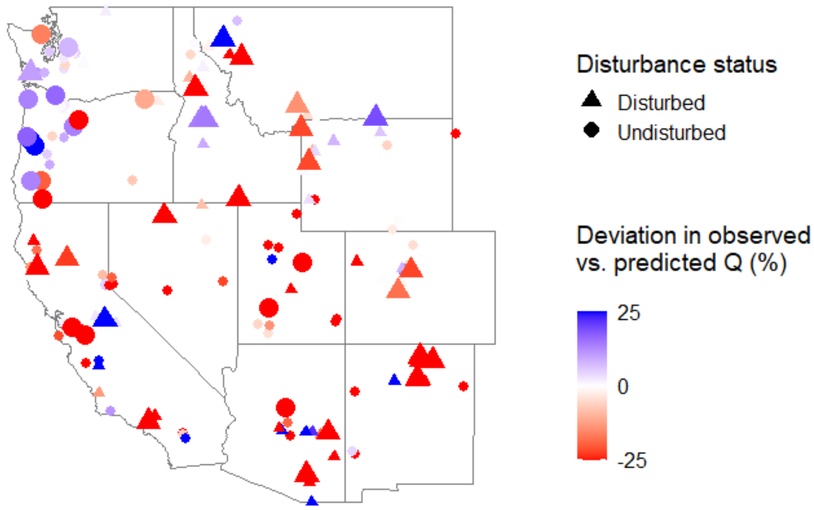

Fig. 6. Percent deviation in observed mean annual streamflow (Q) for 2010-2019, relative to Q predicted by time trend analysis (calibrated for 2000-2009). Watersheds with statistically significant deviation in Q (large symbols) were identified using on a one-sample t-test (p<0.05); small symbols represent watersheds with no significant deviation in Q (p≥0.05). Disturbed watersheds (triangles) are those where tree mortality exceeded 10% of initial live tree volume.

Table 8. Results of time trend analysis, which predicts mean annual streamflow from observed precipitation and temperature and then compares observed to predicted streamflow for a future time period. Disturbed watersheds are defined as those where tree mortality exceeded 10% of initial live tree volume. Significant change in annual streamflow was identified as p<0.05 from a one-sample t-test.

	Runoff lower than expected (decreased Q)		Runoff higher than expected (increased Q)	
	Any change	Significant change	Any change	Significant change
Disturbed (n=67)	42	20	25	6
Not disturbed (n=92)	56	10	36	8
Total	98	30	61	14

Only 26 watersheds experienced both disturbance and significant change in streamflow, as determined by time trend analysis, and streamflow decreased in 20 of these watersheds (Table 3). This finding contradicts the hypothesis that streamflow increases following disturbance. The geographic distribution of significant decreases in streamflow in disturbed watersheds (Fig. 6) partially supports our secondary hypothesis that streamflow response to disturbance is influence by factors such as incoming solar radiation, aridity, or latitude. Additionally, 18 undisturbed watersheds had significant changes in streamflow (10 decreases and 8 increases; Fig. 6). These results imply that deviations in observed vs. expected streamflow, as predicted from a linear model based on precipitation and temperature, cannot be attributed to vegetation change alone, which has commonly been an interpretation of time trend analysis (Biederman et al., 2015; Zhao et al., 2010). However, unlike the univariate trends shown in Fig. 4 and Fig. 5, time trend analysis accounts for changes in P and T over time and evaluates Q relative to those changes.

We considered the possibility that our choice of disturbance threshold could affect our results and therefore evaluated the direction of streamflow response given different disturbance thresholds. Among all watersheds, 67 met our initial disturbance criterion of >10% tree mortality during 2010-2019. Different thresholds (5%, 15%, and 20%) did not lead to different conclusions about the proportion of disturbed watersheds that experience decreased versus increased streamflow. For all thresholds of disturbance, a slight majority (>54%) of disturbed watersheds exhibited decreased streamflow, based on observed streamflow compared to that predicted by the time trend analysis model.

3.4. Streamflow change as a function of climate and disturbance

All coefficients in the multiple regression model for ΔQ (Eq. 4) were statistically significant ($p<0.05$; Table 4) with adjusted model r2=0.70 ($p<0.01$). The average change in runoff (ΔQ) across all 159 watersheds during the time period considered in this analysis was positive (63 mm/yr), consistent with an increase in P (mean ΔP was 91 mm/yr). Standardized regression coefficients indicate the direction and relative impact of each predictor on ΔQ (Fig. 7a) and indicate that $\overline{P_1}$ had the largest impact on ΔQ, which may be due to a positive association of $\overline{P_1}$ and ΔP between 2000-2009 and 2010-2019 in watersheds that were already relatively wet. $\overline{P_1}$, ΔP, and mortality all had positive coefficients and thus positive effects on ΔQ, while ΔT and the interaction of mortality with aridity had negative coefficients (Table 4; Fig. 7a). Partial regression plots (Fig. 7b-f) illustrate the ability of each predictor variable to explain variability in ΔQ that is not specifically accounted for by other predictors. Note that partial regression plots are not scatterplots of pairwise variables but instead represent the effect on model residuals of adding an additional model term to an existing model. The slopes of the lines in the partial regression plots (Fig. 7b-f) are equal to the regression coefficients and are all significantly different than zero (Table 4), which indicates that each predictor provides useful information in predicting ΔQ. Examination of model diagnostics verified that residuals were normally distributed and independent of predictor values. Fig. 7 shows that some observations exert high leverage for some predictors.

Table 9. Regression coefficients, standard errors, t-statistics, and associated p-values for multiple linear regression of ΔQ between 2000-2009 and 2010-2019.

Variable	**Units**	**Coefficient**	**Standard error**	**t-statistic**	**P-value**
Intercept	mm/yr	-29.20	10.20	-2.860	0.005
$\overline{P_1}$	mm/yr	0.087	0.008	11.473	<0.001
ΔP	mm/yr	0.107	0.047	2.279	0.024
ΔT	°C	-27.85	6.895	-4.038	<0.001
Mortality	proportion	250.3	67.91	3.685	<0.001
Mortality*Aridity	proportion	-108.4	43.59	-2.488	0.014

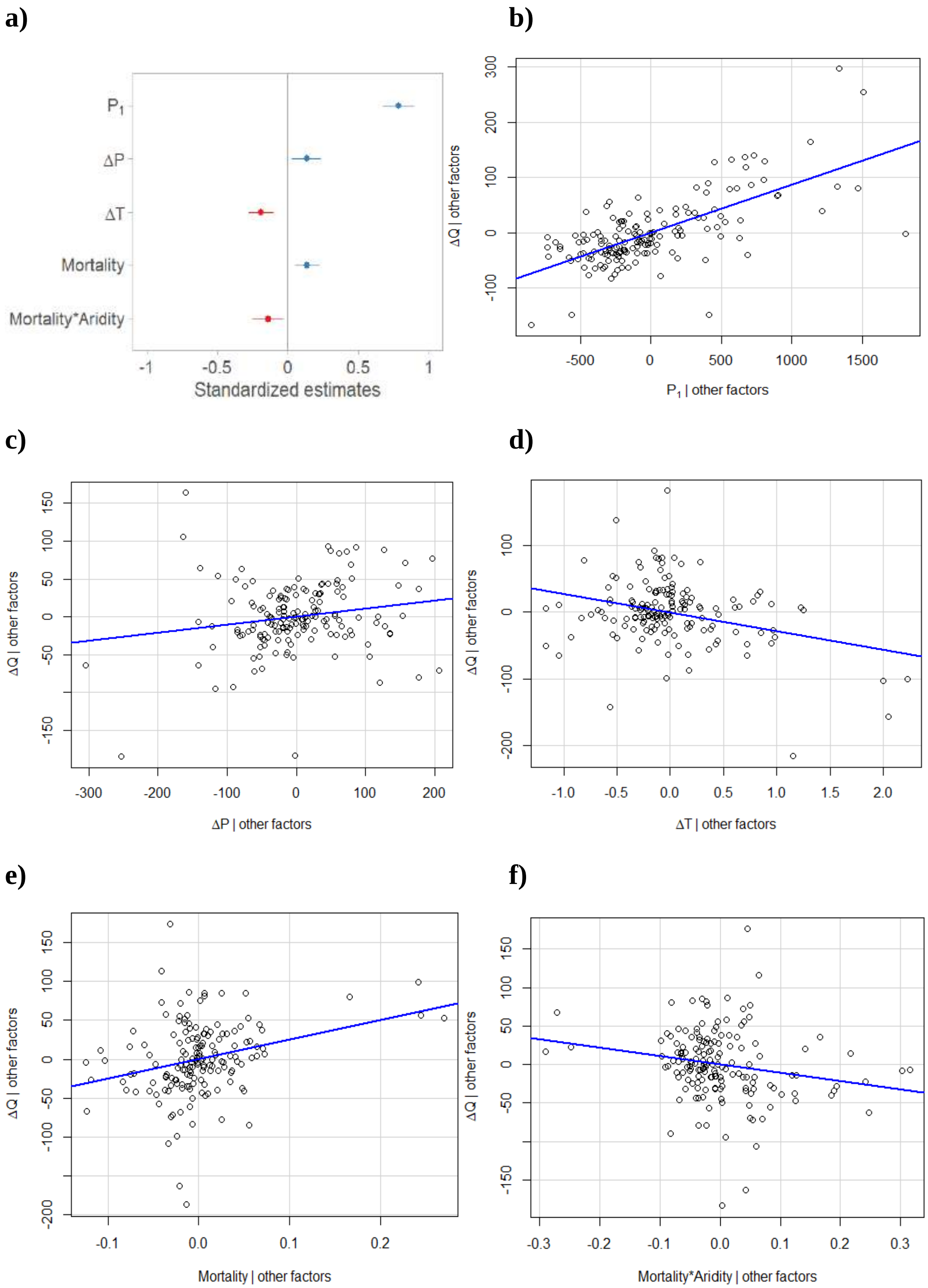

Fig. 7. Effect of each variable on change in annual streamflow (ΔQ), in mm/yr, from 2000-2009 to 2010-2019: a) Unitless standardized coefficient estimates, which indicate the magnitude of change in ΔQ, in standard deviations, for a change equal to one standard deviation of each predictor variable. $\overline{P_1}$=mean annual P for 2000-2009, ΔP=change in precipitation, and ΔT=change in temperature. b-f) Partial regression plots for each

predictor variable. Each plot depicts the relationship between the named predictor and ΔQ while accounting for the explanatory capability of all other predictors. Values along the x axis of each plot represent the residuals of a model omitting the named variable, values along the y axis represent the residuals of a model of the named predictor as a function of all other predictors, and the slope of the line is equal to the multiple regression coefficient for the named variable.

One purpose of this regression analysis was to test the hypothesis that runoff increases following tree mortality, and as an alternative hypothesis, that the sign (positive or negative) of runoff response to disturbance is affected by aridity. Our results provide partial support for both hypotheses. As expected, the coefficient for tree mortality was positive (Table 4; Fig. 7a); the statistical significance of this positive coefficient supports the first hypothesis that runoff increases with decreased forest cover. However, the significant and negative coefficient for the interaction of mortality and aridity also supports our alternative hypothesis that mortality does not result in increased runoff in all cases. In particular, runoff response to disturbance may be negative in very arid watersheds. Fig. 8a illustrates ΔQ as a function of mortality and aridity based on observations (i.e., not modeled values), demonstrating two important results. First, relatively wet watersheds (aridity<1.5) generally had positive ΔQ, and ΔQ was larger for watersheds with more tree mortality. Second, very dry watersheds (aridity>2.5) generally experienced negative ΔQ, and higher mortality was associated with larger decreases in Q. In interpreting these results, it is important to note that overall ΔP was positive, which is expected to contribute to positive ΔQ; thus, the dashed line representing ΔP in Fig. 8a provides a more neutral axis of reference than ΔQ=0.

Fig. 8b illustrates predictions and 90% prediction intervals for ΔQ as a function of tree mortality for aridity at its observed 5th percentile, median, and 95th percentile, assuming that all other variables are held constant at their mean observed values. The value of aridity at which tree mortality was predicted to have a negative effect on Q was 2.35. Thus, for watersheds with PET/P≥2.35, ΔQ decreased with tree mortality. Thus, in these very water-limited watersheds there is an inverse relationship between ΔQ and tree mortality. Note that 95% of watersheds experienced levels of tree mortality less than 33%, so predictions above this level of mortality are beyond the range of most data and therefore uncertain.

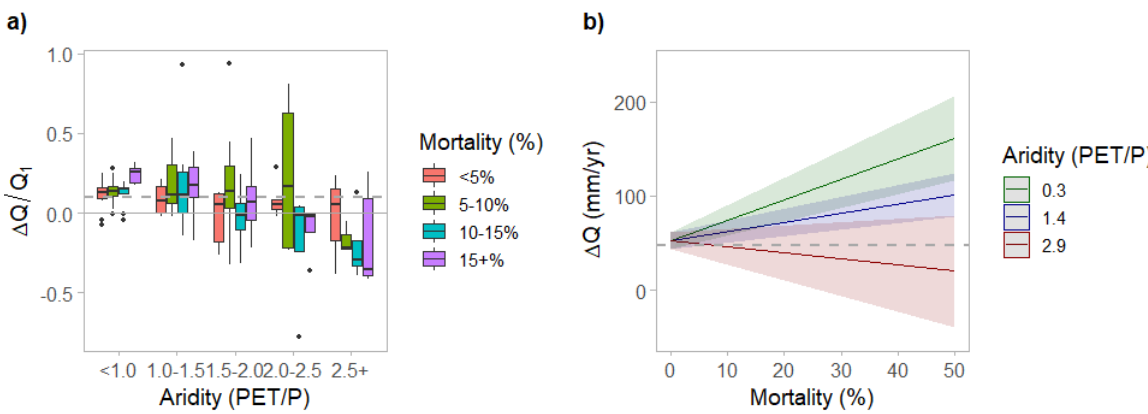

Fig. 8. Interacting effect of tree mortality and aridity on ΔQ (2000-2009 vs. 2010-2019). a) Boxplots of ΔQ (as a proportion of Q1) based on observed values from 159 watersheds. b) Marginal effects of mortality and aridity, based on the multiple regression model (i.e., values of ΔQ for different values of mortality and aridity when values of other predictors are held constant); values of aridity represent the 5th percentile (0.3), median (1.4), and 95% percentile (2.9) of watersheds examined in this study. In both plots, horizontal dashed lines represent ΔP times P1/Q1, (relative to Q1 for 6a), which illustrates the expected ΔQ based solely on ΔP.

As shown in Eq. (4), the regression model accounted for changes in precipitation and temperature. The modeled relationship between mortality, aridity, and ΔQ (Fig. 8b) demonstrates the same variable response to disturbance as that shown by observations (Fig. 8a), illustrating that the response of ΔQ to disturbance and the interaction of disturbance with aridity is not explained by precipitation and temperature changes alone.

Thus, decreased streamflow in response to increased temperature or decreased precipitation may be modulated (in wet watersheds) or exacerbated (in dry watersheds) by disturbance.

To assess the overall sensitivity of our modeled ΔQ to potential warming, we summarized ΔQ for several values of mortality and aridity, with and without 1° C of warming (Table 5) and with no change in precipitation. Specifically, equation 4 was applied with ΔP=0 and ΔT=0 or 1. The model predicted a mean decrease in streamflow of 5.6% for 1° C of warming. Regression-based estimates for ΔQ at various levels of tree mortality and aridity generally suggest that streamflow is expected to increase at increasing levels of disturbance for watersheds at low to moderate values of aridity, while the opposite is true in very arid watersheds, specifically with PET/P>2.35, as manifested in the rightmost column of Table 5. Left to right in Table 5, the model indicates greater percentage increases in streamflow following disturbance in more humid watersheds, trending down to a decrease in streamflow for the most arid watersheds. For 1° C of warming, the 5.6% decrease in streamflow is superimposed on these trends.

Table 10. Predicted change in mean annual streamflow (expressed as a percentage of Q_1, or initial mean Q) for different levels of tree mortality and aridity, with and without a 1° C temperature increase and assuming no change in precipitation.

		Aridity (PET/P)				
	Tree mortality	0.30 (5th percentile)	0.77 (25th percentile)	1.44 (Median)	2.08 (75% quantile)	2.93 (95th percentile)
No warming	0%	0.0%	0.0%	0.0%	0.0%	0.0%
	10%	4.4%	3.4%	1.9%	0.5%	-1.3%
	25%	11.0%	8.5%	4.8%	1.3%	-3.4%
1° C warming	0%	-5.6%	-5.6%	-5.6%	-5.6%	-5.6%
	10%	-1.2%	-2.3%	-3.7%	-5.1%	-7.0%
	25%	5.4%	2.8%	-0.9%	-4.4%	-9.1%

4. Discussion

We found variable runoff response to forest disturbance using multiple analysis methods: Mann-Kendall trend analysis, time trend analysis of predicted vs. observed streamflow based on observed precipitation and temperature, and multiple regression using both climatic and disturbance variables. Collectively, our results confirm, via systematic broad-scale analysis, that the generally held hypothesis that forest cover and streamflow are inversely related is not universal in semi-arid western watersheds. Examination of the relationship between Mann-Kendall trend in Q/P versus net tree growth allowed us to identify two scenarios that do not conform to this relationship (Fig. 3). First, statistically significant decreases in Q/P occurred during a period of forest cover loss in a small number of watersheds (four) that occur in areas of high aridity (PET/P) and high incoming solar radiation. Second, 10 watersheds exhibited statistically significant increases in Q/P during a period of forest cover growth. Time trend analysis indicated that among watersheds with significant changes in streamflow, 77% (20 of 26) of disturbed watersheds, and only 56% (10 of 18) undisturbed watersheds, experienced decreased streamflow. Thus, significantly decreased streamflow was more prevalent in disturbed than undisturbed watersheds, counter to commonly held expectations. Increased streamflow in 44% (8 of 18) of undisturbed watersheds coincided with higher precipitation overall in 2010-2019 compared to 2000-2009. Multiple regression analysis showed that mortality explains some variability in ΔQ that is not explained by climatic drivers, and that the direction of streamflow response to mortality (i.e., increase vs. decrease) is affected by aridity.

Among our analysis methods, only the multiple regression quantitatively assessed change in streamflow as a function of both climatic and disturbance variables in a way that allowed isolating and quantifying climate and disturbance effects. Therefore, the finding that disturbance severity (i.e., magnitude of tree mortality) is a significant predictor with a positive coefficient supports the overarching hypothesis that streamflow increases as a result of disturbance, and that disturbance effects on streamflow are separable from climate effects. However, the interaction of mortality and aridity had a negative coefficient, which signifies a decrease in streamflow as a result of disturbance in very arid watersheds. Observational data (Fig. 8a) as well as our multiple regression results (Fig. 8b) provide quantitative evidence that disturbances at high aridity are more likely to result in decreased streamflow than those at lower aridity. These findings are consistent with a recent modeling study (Ren et al., 2021), which concluded that of runoff responds variably to forest disturbance caused by mountain pine beetle, that the response depends on both mortality level and aridity, and that drier years tend toward decreased post-disturbance streamflow. In that study, the inflection from increased to decreased runoff occurred between aridity values of 2.0 and 3.0, or in wetter areas with mortality levels less than 40%, and decreased runoff was explained by either increased canopy evapotranspiration or increased ground transpiration following disturbance (Ren et al., 2021).

Independent of forest cover changes, we observed decreased streamflow associated with increased T and PET. Our multiple regression model predicted a mean decrease in streamflow of 5.6% for 1° C of warming, which is consistent with the 6% reduction per degree C that is predicted for the entire Colorado River Basin (Udall and

Overpeck, 2017) and 6-7% reductions per degree that are predicted for the Upper Colorado River Basin (McCabe et al., 2017; Udall and Overpeck, 2017). Our study period, 2000-2019, coincides with the onset of above-average temperatures in the Colorado River Basin that began in 2000 and contributed to below-average streamflow (Udall and Overpeck, 2017). Although this trend has been previously documented in western US watersheds (Brunner et al., 2020; Udall and Overpeck, 2017), the time trend and multiple regression analyses presented here disentangle climate from vegetation effects and offer a refined understanding of the role of forest change effects on streamflow in these trends.

Increasing T and PET are driving not only decreases in streamflow in many western watersheds (Brunner et al., 2020; Udall and Overpeck, 2017) but also increases in tree mortality (Williams et al., 2013). Our analysis of trend in Q/P relative to net tree growth, and our regression model of ΔQ as a function of tree mortality, show relatively high forest disturbance in watersheds with high aridity and solar radiation (Fig. 3c-d). Higher T and PET may affect streamflow both directly, via increased evaporative demand, and indirectly via vegetation-mediated effects such as replacement of trees with vegetation that may actually have higher total evapotranspiration (Bennett et al., 2018; Guardiola-Claramonte et al., 2011; Morillas et al., 2017). Additionally, increases in T and PET that result in increased soil evaporation can increase vegetation moisture stress and susceptibility to disturbance such as wildfire (Groisman et al., 2004).

Possible mechanisms for nonconforming decreases in runoff in watersheds with decreased forest cover (i.e., lower left quadrant in Fig. 3a) may be a combination of increased transpiration by surviving or newly established vegetation, as well as increased solar radiation reaching snowpack and soil surfaces, either of which may increase total evapotranspiration. The first mechanism, net increase in evapotranspiration due to increased total transpiration, has been observed following insect outbreaks with rapid growth of surviving trees (Biederman et al., 2014), simulated tree die-off that resulted in increased herbaceous transpiration (Guardiola-Claramonte et al., 2011), and replacement of trees with dense shrubs (Bennett et al., 2018); all three of these studies were conducted in semiarid to arid watersheds. Further, short-term streamflow response may contradict longer-term response as young trees grow rapidly during forest recovery (Perry and Jones, 2017) in a phenomenon known as the Kuczera effect (Kuczera, 1987), and the use of net growth as a disturbance metric can quantify the extent to which post-disturbance regrowth may produce this effect. The second mechanism, increased solar radiation as a result of canopy loss, could result in earlier snowpack ablation (Lundquist et al., 2013) driven by increased sublimation (Biederman et al., 2014) and increased evapotranspiration from soil and non-canopy vegetation (Morillas et al., 2017; Reed et al., 2018). Changes to post-disturbance energy budgets have been observed following multiple disturbance types and severities (Cooper et al., 2017; Maness et al., 2013). Just as net increases in evapotranspiration can occur following forest disturbance and lead to decreased streamflow, the converse is that net decreases in evapotranspiration can occur during periods of forest cover growth and thus lead to increased streamflow (i.e., upper right quadrant in Fig. 3a). Independently of forest disturbance or growth, an additional contributing factor to decreased runoff may be a long-term decline in deep soil moisture due to recent droughts (Iroumé et al., 2021; Peterson et al., 2021; Williams et al., 2020).

Another potential confounding effect is the type of winter precipitation (rain vs snow). In this study, we accounted for precipitation and temperature at annual and not seasonal time scales; neither the regression model used for time trend analysis nor the multiple regression model for ΔQ improved appreciably when seasonal rather than annual timescales were tested. Previous work has observed both streamflow increases (Hammond and Kampf, 2020) and decreases (Berghuijs et al., 2014) in response to winter precipitation phase (snow to rain) shifts. Warmer temperatures have been observed to result in decreased streamflow in watersheds with high snow fraction, i.e., >0.15, although the causal mechanism for this observation is unknown (Berghuijs et al., 2014). In contrast, Hammond and Kampf (2020) observed both increased and decreased streamflow following shifts from snow to mixed rain and snow. Streamflow response to snow-to-rain transitions appear to be more strongly associated with the seasonal timing, particularly relative to the seasonal timing of maximum annual evapotranspiration, than the type of precipitation (de Lavenne and Andréassian, 2018; Knighton et al., 2020; Robles et al., 2021). In our study, increasing trends in Q/P and simultaneous increases in tree growth occurred in a wide variety of environments (Fig. 3e), including the temperate Pacific Northwest, where snow fraction may be less than 0.15, as well as high-elevation forested watersheds across the western US where winter precipitation phase change may translate to more rain-on-snow events that produce rapid winter runoff. Because seasonal snowpack represents storage of water that becomes available for transpiration by plants during the growing season, seasonal asynchrony between water availability and the growing season may dampen any relationship between forest cover changes and streamflow response (Knighton et al., 2020).

Results of our time trend analysis demonstrate that streamflow has deviated from predictions based on precipitation and temperature at many watersheds across the western US, regardless of forest disturbance (Table 3). An assumption of time trend analysis is that any change not predicted by factors included in the model, typically precipitation and temperature, is due to factors not included in the model, typically vegetation (i.e., land cover) change or land use change (Zhao et al., 2010). However, time trend analysis provides observational but not causal links of change in streamflow to factors such as vegetation change. Incongruities between the subset of watersheds that were disturbed and those with significant streamflow change (Table 3) call into question the underlying premise of time trend analysis that deviations of observed from predicted streamflow are due to vegetation change alone (Zhao et al., 2010). In our exploration of whether changes in streamflow were correlated with changes in T and PET over longer time periods, we found that although T and PET increased in most watersheds, increases in T and PET were not strongly correlated with changes in streamflow or runoff ratio. Given that Mann-Kendall trend tests detected significant increases in T and PET for 1980-2019 that were not detectible during the period covered by our time trend analysis (2000-2019), it is possible that model coefficients for T over multiple decades may not remain constant as temperature increases beyond the range of observed T during 2000-2009. In other words, the assumptions inherent in time trend analysis may not hold in a nonstationary climate as changes may go beyond ranges for which the model was calibrated. Other possible explanations for significant changes in streamflow include shifts in winter precipitation phase (from snow to rain), the timing of seasonal precipitation, longer term increases in T and PET that are occurring beyond the timeframe considered in this analysis, seasonal T and precipitation extremes that are not reflected in annual mean values, and/or forest disturbance below the threshold considered in our analysis.

A caveat of this study is that we characterized disturbance across entire watersheds, when in reality, disturbance is typically patchy and may include a combination of stand-replacing and nonstand-replacing disturbances. For example, less severe disturbance may be uniformly distributed throughout a watershed whereas more intense disturbances that may affect only small portions of a watershed, where both scenarios would lead to comparable watershed-scale metrics of forest cover loss or tree mortality. Previous studies illustrated that forest structure affects snowpack (Broxton et al., 2016; Moeser et al., 2020), so this distinction may be important for determining disturbance effects on runoff. The ability to project future changes in streamflow due to both changing climate and forest disturbance will likely improve with enhanced spatial representation of forest characteristics.

Several challenges exist in combining observational datasets from different disciplines and using different temporal and spatial sampling frames, and here we describe some of those challenges and potential future solutions. First, the analyses conducted in this study required using forest inventory data collected across multiple years rather than an annual time step. It is not currently possible to produce estimates of the FIA attributes used in this analysis at an annual time step at the scale of individual watersheds, and this constraint undoubtedly dampens observed hydrologic response to acute, episodic disturbances such as severe wildfire. Ongoing work in the area of statistical small area estimation (Coulston et al., 2021; Hou et al., 2021) demonstrates promising capabilities for characterizing forest attributes at finer spatial and temporal scales. Combining FIA-based estimates with other datasets, e.g., the Monitoring Trends in Burn Severity (MTBS) dataset that delineates large wildfires by severity class (Eidenshink et al., 2007), could illuminate how specific disturbances may have unique or compounding effects on streamflow and snowpack. Application of such techniques to future investigations will require identification of appropriate lag effects and legacy effects (e.g., response to recovery from severe disturbance versus persistent response to the initial severe disturbance).

Second, most CAMELS watersheds are smaller than the encompassing HUC8 watersheds that we used to summarize forest data, although we found that forest change metrics from the National Land Cover Database (Homer et al., 2020) were statistically similar at the two scales. Compatibility of these datasets could be improved by combining ground observations from forest monitoring plots with remote sensing and other ancillary data, e.g., via the small area estimation techniques described above. Ongoing extension of the period of record and improved precision in estimates for individual watersheds will enhance our ability to relate forest characteristics and dynamics to changes in hydrologic processes and flux magnitudes. In particular, improved precision of future monitoring may help quantify important relationships among modulating factors such as aridity and incoming solar radiation.

Correlation is not causation, and therefore we cannot be sure that any observed changes in streamflow are due to forest disturbance or the lack thereof. Our results, which are based on observations across many watersheds, underscore the need for process-based modeling to understand where, why, and to what degree unexpected streamflow responses may occur as a result of the combined effects of forest change and climate change. Although there may indeed be forest disturbance effects on streamflow, hydrologic responses may be modulated, offset, or intensified by factors such as aridity and incoming solar radiation and by changes in forcing such as increasing temperature.

4. Conclusions

We used a large-sample hydrology approach to combine hydrologic, climatic, and forest data within 159 watersheds in the western US to assess evidence for the hypothesis that forest cover loss leads to increased streamflow. This study expanded on previous studies that have linked streamflow to climatic drivers by also considering quantitative forest disturbance information, which allowed us to disentangle climate effects from forest disturbance effects on streamflow. Multiple analysis methods – including simple trend analysis, time trend analysis accounting for climate variables, and multiple regression – demonstrated that streamflow in some disturbed watersheds was lower than expected based on climatic drivers (i.e., P and T) alone. Results of both observations and multiple regression modeling showed that streamflow response to disturbance was modulated by aridity. Although disturbed watersheds exhibited increased streamflow at low to intermediate aridity, which is consistent with the hypothesis that reduced forest cover produces increased water yield, we found that disturbance in very arid watersheds (aridity>2.35) was associated with streamflow. Disturbance was also more prevalent in watersheds with high solar radiation and high aridity, the very watersheds that are more likely to be vulnerable to decreased streamflow following disturbance. These results suggest that very arid watersheds may be more susceptible to both increased forest disturbance and decreased streamflow in the future.

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Data and code availability statement

In an effort to make this study reproducible, the data and computational scripts used to produce the study results have been made publicly available in HydroShare (Goeking & Tarboton, 2021).

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CHAPTER 4

SPATIALLY DISTRIBUTED OVERSTORY AND UNDERSTORY LEAF AREA INDEX ESTIMATED FROM FOREST INVENTORY DATA[3]

Abstract

Forest cover type, density, and change over time affect the relative magnitudes of ecohydrologic fluxes such as evapotranspiration (ET) and streamflow. However, much is unknown about the sensitivity of streamflow response to vegetation disturbance, recovery, or conversion from forest to nonforest. Several physically based models recognize the different influences that overstory versus understory canopies exert on these processes, yet most input datasets to such models consist only of total leaf area index (LAI) rather than LAI differentiated by strata. Here we developed LAI datasets for overstory and understory canopy strata with the intent of providing improved representation of canopy strata for ecohydrologic modeling. We applied three preexisting methods for estimating overstory LAI, and one new method for estimating both overstory and understory LAI, to measurements collected from a permanent, probability-based plot network established by the US Forest Service's Forest Inventory and Analysis (FIA) program. We then combined plot-level LAI estimates with gridded spatial datasets (i.e., topographic, climatic, and spectral remote sensing predictor variables) in a machine learning algorithm (random forests) to produce annual gridded LAI datasets across a modeling domain in northwestern Montana, USA. Each method of estimating plot-level LAI was thus used to produce a gridded LAI dataset, which we then compared with

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[3] Coauthored by Sara A. Goeking and David G. Tarboton.

Landsat-based LAI estimates. The method that estimates total LAI (i.e., both overstory and understory layers) is most strongly correlated with Landsat-based LAI, while among methods that only estimate overstory LAI, the simplest method is most strongly correlated with Landsat-based LAI. Time series of overstory and understory LAI from 1984-2019 demonstrated that interannual variability of understory LAI exceeds that for overstory LAI, and this variability may affect partitioning of precipitation to ET vs. runoff at annual timescales. The separation of LAI into overstory and understory components is anticipated to improve the ability of LAI-based analyses and models to simulate the influence of forest canopies on hydrologic processes.

Introduction

Forest cover type, density, and dynamics (i.e., change over time) affect the relative magnitudes of ecohydrologic fluxes such as evapotranspiration (ET) and streamflow (Adams et al., 2012; Bosch & Hewlett, 1982; Hibbert, 1967). Thus, water supply is influenced, at least in part, by how vegetation partitions precipitation into ET vs. streamflow. Forest canopies exert particularly strong effects on this partitioning because they intercept precipitation, which is often then lost to evaporation rather than accumulating as seasonal snowpack or reaching the ground surface to contribute to either runoff or recharge (Adams et al., 2012; Hibbert, 1967; Molotch et al., 2007; Stottlemyer & Troendle, 2001). After more than a century of research into vegetation-streamflow linkages (Andréassian, 2004), questions remain about how future forest disturbance, recovery, or conversion to nonforest vegetation, as well as differences between overstory and understory influences on hydrologic processes, may affect future water supply (Adams et al., 2012; Molotch et al., 2007; Tague et al., 2019).

While observational studies of individual or paired catchments provide insights to the mechanisms of hydrologic response to vegetation change (Brown et al., 2005), for logistical and practical reasons, the ability to study individual or paired catchments in detail is largely confined to small watersheds (Andréassian, 2004). Broad-scale questions about hydrologic response to forest change can be answered by using process-based models that are capable of representing vegetation in multiple canopy strata, such as the Regional Hydro-Ecologic Simulation System (RHESSys; Tague & Band, 2004) and Distributed Hydrology-Soil-Vegetation Model (DHSVM; Wigmosta et al., 1994). Such models, and indeed most quantitative relationships of hydrologic processes to vegetation states, express vegetation density in terms of leaf area index (LAI) (Goeking & Tarboton, 2020). Often these models are applied using coarse-resolution total LAI derived from remote sensing platforms such as MODIS (e.g., Rouhani et al., 2021) if higher-resolution observations are not available. An advantage of LAI datasets based on spectral remote sensing is their wall-to-wall spatial coverage and fine temporal resolution, i.e., interannual or seasonal variability, but a disadvantage is that they represent total LAI and do not distinguish overstory from understory LAI. To capitalize on the ability of hydrologic models to provide insights into the linkage between water resources and forest disturbance or vegetation type changes, better representations of actual forest vegetation strata (i.e., overstory vs. understory) are required.

In contrast to remote sensing-based LAI, ground-based observations have the potential to distinguish overstory from understory LAI and also attribute causes of change such as type and severity of disturbance. It is possible that interpolation models, e.g., random forests or other machine learning algorithms, that are developed from sparse plot-based LAI and spatially continuous predictors (e.g., reflectance, elevation, aspect) may produce improvements in gridded LAI estimates representing overstory and understory strata, compared to estimates of total LAI produced using remote sensing data alone. Ground-based observations ideally would be unbiased and representative of the full range of variability of forest characteristics that occurs within a domain of interest, but sites are often selected for a specific purpose that may lead to biased inference when taken as generally representative (Klesse et al., 2018). Several countries, including the USA, are monitored continuously by strategic national forest inventories that conduct probabilistic and repeated sampling of permanent plots that could provide inputs for plot-level LAI estimates. In the USA, the US Forest Service's Forest Inventory and Analysis (FIA) program monitors a plot network of over 300,000 plots nationwide, across all forest types and ownership categories with a mean plot spacing of about 5 km (McRoberts et al., 2005). FIA collects detailed information on trees and the overstory canopy, understory vegetation, and causes and timing of disturbances (Burrill et al., 2018). However, FIA and other national-scale forest inventories do not measure LAI (Härkönen et al., 2015; USDA, 2019). Thus, a method of using existing inventory data to estimate plot-scale LAI is needed.

In the absence of ground-based LAI measurements such as those obtained via techniques such as light-sensing instruments or hemispherical photography, previous research has derived LAI estimates based on other available measurements such as tree canopy cover or canopy closure (e.g., Broxton et al., 2015; Varhola et al., 2010). Methods and mathematical forms typically fall into the following categories, where the choice depends on the intended purpose: 1) a linear scaling factor relating canopy cover to LAI, where a local maximum LAI is imposed on the scaling factor (e.g., Broxton et al., 2015); 2) an exponential function relating tree canopy cover to LAI for the purposes of modeling snow cover (eq. 4 in Varhola et al., 2010, derived from Pomeroy et al., 2002); or 3) allometric equations based on destructive measurements and detailed dissections of a small sample of trees (e.g., Kaufmann et al., 1982). The main limitation of these ground-based methods for measuring or estimating LAI is that they are spatially discontinuous and thus require interpolation to produce gridded LAI datasets for use in spatially distributed hydrologic models.

This study bridges the gap between remote sensing and ground-based estimates of LAI using data from the USA national forest inventory. The objectives of this study were, first, to use multiple LAI estimation methods to estimate plot-scale LAI for overstory and understory canopy strata from standard forestry measurements at FIA plots; and second, to combine plot-scale LAI data with spectral reflectance and other gridded variables in a machine-learning algorithm to produce spatially and temporally explicit maps of overstory and understory LAI on an annual basis. We compared alternative methods for estimating plot-level LAI, developed a machine learning method for interpolating yearly gridded overstory and understory LAI across large watersheds, and compared gridded estimates of annual LAI to Landsat-based LAI. Finally, we examined annual time series of overstory and understory LAI for two test watersheds that have experienced natural disturbances but no land use change.

Methods

Study area

The study area encompassed the South Fork Flathead River and Middle Fork Flathead River watersheds of northwestern Montana, USA (Fig. 9). Most of the South Fork watershed and part of the Middle Fork watershed are within the Bob Marshall Wilderness Area, which was designated in 1964 and precluded any substantial vegetation management since that time. The South Fork and Middle Fork are 83% and 75% forested, respectively, with mean elevations of 1,870 and 1,722 m; areas of 3,002 and 2,914 km^2; mean annual temperatures of 2.63 and 2.46 ºC; and annual precipitation of 1,248 and 1,268 mm (U.S. Geological Survey, 2016).

Our first objective was to use multiple methods to estimate plot-scale LAI for overstory and understory canopy strata at Forest Inventory and Analysis (FIA) plots. This section first describes field sampling protocols and the FIA dataset. Then we summarize the four alternative methods that we used to estimate plot-level LAI based on FIA data, followed by a description of model development and validation. Fig. 10 illustrates how this study’s workflows involve plot data vs. gridded data as well as validation of plot-scale vs. gridded LAI estimates.

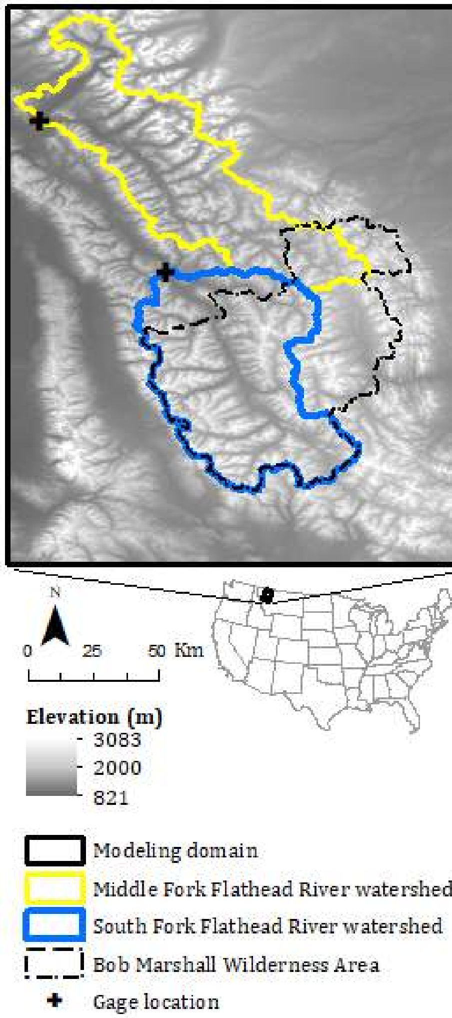


Fig. 9. Digital elevation map of the study area. Domain for modeling leaf area index (LAI) is shown by the outer rectangle; domains for time series analysis of LAI and evapotranspiration are the South Fork Flathead River and Middle Fork Flathead River watersheds (outlined in blue and yellow, respectively).

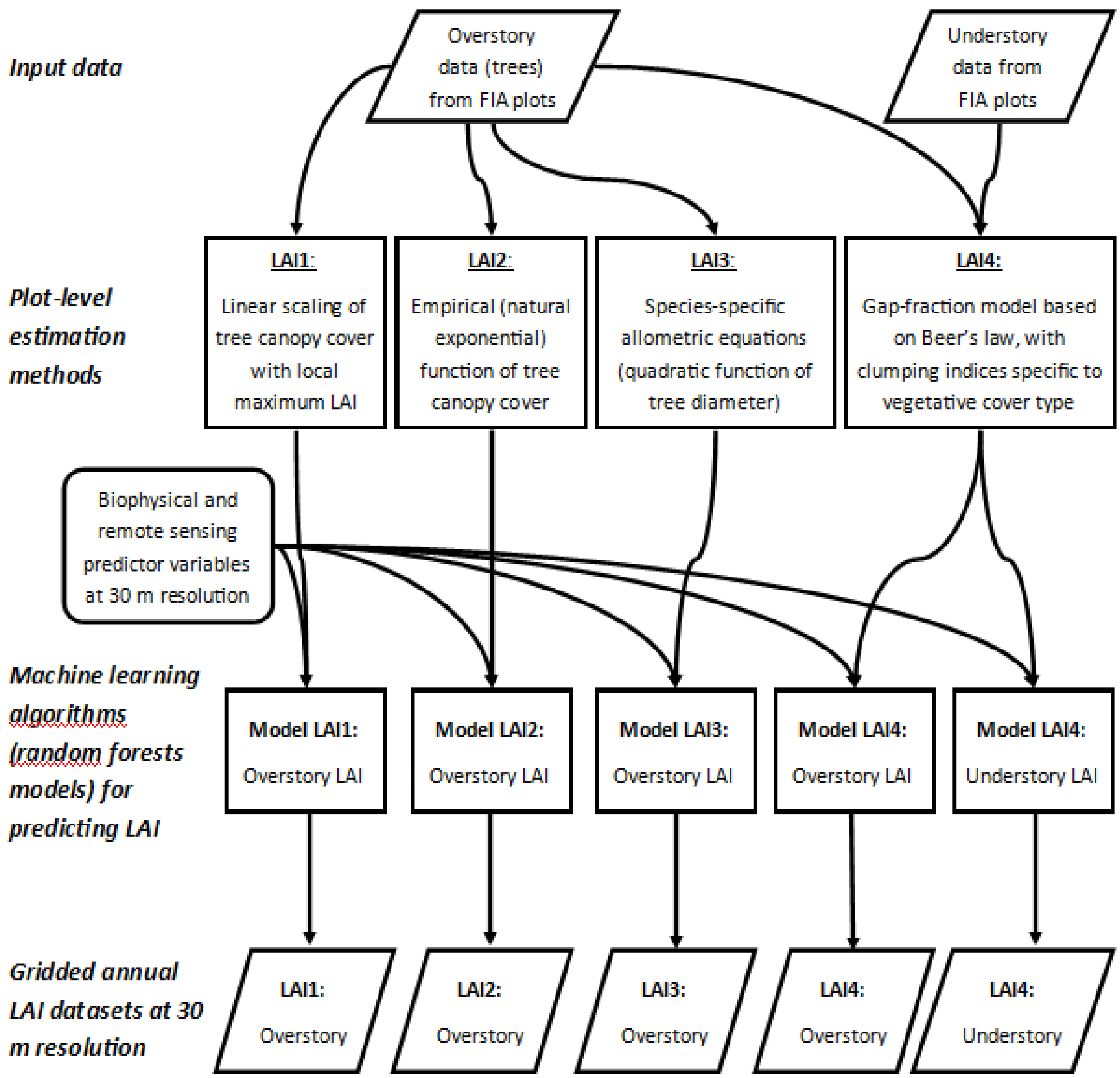


Fig. 10. Data sources and methods used to produce plot-level LAI and gridded LAI datasets. Biophysical and remote sensing predictor variables are described in Table 11.

Field Sampling Protocols

In Montana, FIA began measuring permanent plots in 2003. Plots were established in a semi-systematic grid where each plot represents approximately 2,400 hectares, with a remeasurement period of 10 years, and a representative sample of 10% of all permanent plots measured each year (Burrill et al., 2018). Each plot consists of four subplots, each with radius 7.3 m, where one subplot is centrally located and the other three subplots are established 36.6 m from the first subplot's center at azimuths of 0, 120, and 240 degrees (Fig. 11). On each subplot, field crews measure and record information about the site (e.g., slope and aspect), understory vegetation by growth habit (tree, shrub, graminoid, or non-graminoid herbaceous vegetation), and individual live and dead trees that are at least 12.7 cm at a height of 1.35 m (USDA, 2019), which is commonly known as breast height and the measurement is thus known as diameter at breast height (DBH). Characteristics of trees with DBH<12.7 cm are measured on a 2.1-m radius subsample of each subplot (USDA, 2019).

A total of 976 plots were measured within the study area between 2003 and 2012, during the first 10-year measurement cycle, and 644 plots were measured between 2013 and 2019 during the second measurement cycle. From the measurements collected by FIA, the variables used in this study were tree canopy cover, defined as the vertical projection of live tree crowns (USDA, 2019) and identified as the variable "LIVE_CANOPY_CVR_PCT" in the FIA database, FIADB (Burrill et al., 2018); DBH and species identity of live trees (DIA and SPCD in FIADB); and total aerial cover (LAYER=5 in FIADB) of understory vegetation (COVER_PCT) by growth habit (GROWTH_HABIT_CD). These variables are described in detail within the FIA database documentation (Burrill et al., 2018). FIA does not specifically distinguish between overstory and understory canopies, and for this study we defined overstory cover as percent tree canopy cover and understory cover as the aerial cover of non-tree life forms, averaged across the four subplots.

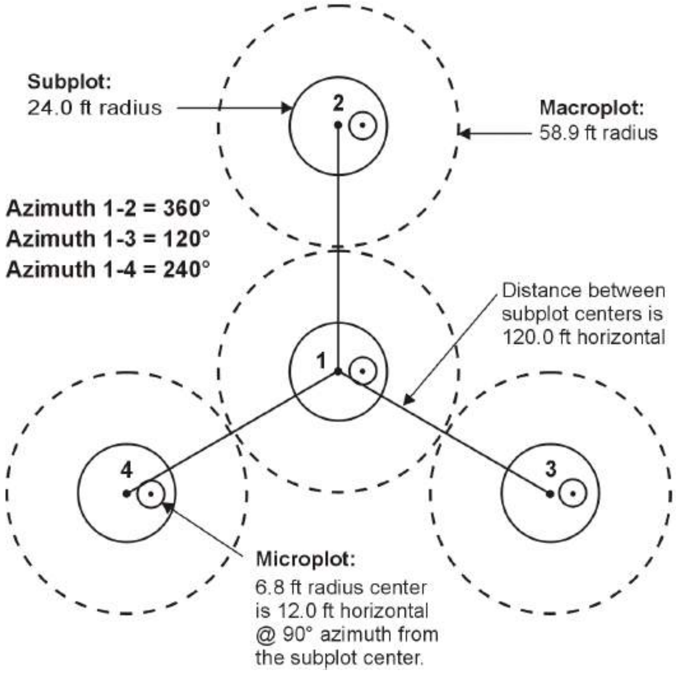


Fig. 11. FIA plot configuration (Burrill et al., 2018). Metric units: Subplots have radius of 7.3 m with subplot centers 36.6 m apart; microplots have radius of 2.1 m and are located 3.6 m from subplot centers; and macroplots were not used in this study.

FIA defines forest as land that either currently contains, or previously supported, at least 10% tree cover, with a minimum forest patch size of 0.4 ha. Thus, plots that burned, or otherwise lost all tree cover due to natural disturbance, are still defined as "forest" but may have zero percent tree canopy cover until trees regenerate. For plots that did not meet FIA's definition of "forest" (i.e., there is no evidence that the site previously supported at least 10% tree cover), we assumed overstory LAI to be zero. If understory vegetation data were collected on a nonforest plot, we used the field-collected vegetation measurements to estimate understory vegetation cover for that plot. If understory vegetation data were not collected (i.e., for efficiency reasons of focusing on forest plots), we treated the plot's understory vegetation data as nonresponse (i.e., no data rather than zero).

Estimation of plot-level LAI

We estimated LAI at each FIA plot using four plot-level estimation methods (Table 11). Among these four methods, the first method is most commonly used in previous literature and consists of linear scaling of tree canopy cover fraction, C, which ranges from 0 to 1, relative to LAI ranging from 0 to a local maximum that must be obtained from either ground observations or previous studies (Broxton et al., 2015). We used a local maximum LAI of 5.3 (Pierce & Running, 1988). The second method was developed to relate tree canopy cover to snow cover (Pomeroy et al., 2002), using the following equation, which is the inverted form of Eq. 4 in Varhola et al. (2010):

$$LAI = e^{(C\,-\,0.55)\,/\,0.29} \tag{1}$$

Table 11. Empirical methods used for estimating plot-level LAI at Forest Inventory & Analysis (FIA) plots.

Label	Method	FIA Inputs	Outputs	Source
LAI1	Linear scaling of tree canopy cover with local max LAI	Tree canopy cover	Overstory LAI	Broxton et al. (2015) for method; Pierce & Running (1988) for max LAI
LAI2	Empirical (natural exponential) function of tree canopy cover	Tree canopy cover	Overstory LAI	Varhola et al. (2010)
LAI3	Species-specific allometric equations (quadratic function of tree diameter)	Tree species & diameter	Overstory LAI	Kaufmann et al. (1982)
LAI4	Gap-fraction model based on Beer's law, with clumping indices specific to vegetative cover type	Tree & understory vegetation cover; forest type; understory vegetation type	Overstory & understory LAI	Chen et al. (2005) for equation and clumping indices

For the third method, we estimated LAI as a function of tree diameter and species-specific coefficients, based on destructive sampling of a small number of trees of four tree species (Kaufmann et al., 1982): Engelmann spruce (*Picea engelmannii* Parry), subalpine fir (*Abies lasiocarpa* (Hook.) Nutt.), lodgepole pine (*Pinus contorta* var. *latifolia* Engelm.), and quaking aspen (*Populus tremuloides* Michx.).

The fourth method for estimating LAI is has not, to our knowledge, been previously used to estimate LAI directly. This method (LAI4) used percent cover of understory and overstory (tree) vegetation as inputs to an inverted gap-fraction model based on Beer's law (Chen et al., 2005, eq. 1):

$$P(\theta) = e^{-G(\theta) * LAI * \Omega \,/\, \cos(\theta)} \tag{2}$$

In Eq. 2, $P(\theta)$ is the gap fraction at zenith angle of view θ representing the fraction of canopy gaps through which light would penetrate to the ground if illuminated from that angle of view; $G(\theta)$ is the extinction coefficient of light, which has a value of 0.5 for random leaf and branch arrangements; LAI is leaf area index; and Ω is a dispersion parameter, or clumping index, that is specific to vegetation type and was conceptually developed by Nilson (1971). When leaf arrangement is truly random, then Ω is equal to 1.0, but for most vegetation clumping of leaves and branches means that Ω is less than 1. Canopy fraction measured on FIA plots is the fraction of area that is canopy when viewed from above. Thus taking θ to be zero, canopy fraction becomes 1.0 minus gap fraction, cos(θ) becomes 1, and the equation above can be inverted to solve for LAI, resulting in:

$$LAI = \frac{\ln(1-C)}{-0.5*\Omega} \tag{3}$$

Values for the clumping index, Ω, were based on those developed by Chen et al. (2005; see table 3 in that paper). We associated each FIA vegetation type with a Chen et al. (2005) clumping index category to determine its clumping index value (Table 12). Understory vegetation was assigned the clumping index that Chen et al. (2005) assigned to barren areas (i.e., 0.75) because their clumping indices for non-tree vegetation were less than 0.75 and resulted in unrealistically high LAI values compared to known local values and Landsat-based values.

Table 12. Look-up table used to assign clumping index values to each vegetation type for method LAI4. Clumping index categories that do not occur in the study area are omitted.

FIA vegetation type[1]	**Clumping index category**[2]	**Clumping index**[2]
Hardwood deciduous forest types (codes 501-988, with canopy cover ≥65%)	2: Tree cover, broadleaf, deciduous, closed	0.69
Hardwood deciduous forest types (codes 501-988, with canopy cover <65%)	3: Tree cover, broadleaf, deciduous, open	0.70
Softwood evergreen forest types (codes 101-319 & 341-391)	4: Tree cover, needleleaf, evergreen	0.62
Softwood deciduous forest type (code 321)	5: Tree cover, needleleaf, deciduous	0.68
Oak/pine forest types (forest type codes 401-409)	6: Tree cover, mixed leaf type	0.69
Nonstocked forest type (code 999) and nonresponse (inaccessible) plots with possible tree cover	9: Mosaic: Tree cover/other natural vegetation	0.72
Understory vegetation and nonforest plots where vegetation data were collected	14: Sparse herbaceous or sparse shrub cover	0.75

[1]FIA forest types and nonforest/nonresponse status are described by the variables FORTYPCD and COND_STATUS_CD in Burrill et al. (2018). [2]Clumping index categories and values are from Table 3 of Chen et al. (2005).

Validation of the four plot-scale LAI estimation methods (Table 11) was accomplished by means of comparison with Landsat-based total LAI at 30-m resolution (Kang et al., 2021). For this comparison, we used plot-scale estimates for plots measured in 2019 (n=87) and Landsat-based LAI for the 2019 growing season at those same plot locations. We compared the frequency distributions of the four plot-scale estimation methods with the frequency distribution of Landsat total LAI, produced scatterplots of plot-based vs. Landsat-based LAI for each plot-scale estimation method, and compared the correlation coefficient of each method's plot-scale LAI with Landsat LAI.

For all of these comparisons, methods LAI1, LAI2, and LAI3 represent only overstory LAI, while method LAI4 represents overstory LAI, understory LAI, and total LAI as the sum of overstory and understory LAI estimates (Table 11). Landsat-based LAI represents total (i.e., overstory plus understory) LAI but is known to saturate at a value of about 4 (Kang et al., 2021). Thus, we expected that our overstory LAI estimates would not precisely equal Landsat-based LAI but that there should be some correlation given that most of the study area is forested with overstory contributing the majority of total LAI. Also, ground-based estimates that include both understory and overstory vegetation may exceed Landsat-based estimates because ground-based estimates are not subject to the same saturation constraints as reflectance-based LAI. Therefore, we expected that LAI4 might produce total LAI estimates that exceed Landsat-based total LAI.

Interpolation of gridded LAI datasets

Our second objective was to combine plot-scale LAI with spectral reflectance data and other spatially explicit variables in a machine learning algorithm to produce spatially and temporally explicit maps of overstory and understory LAI on an annual basis. We focused on annual maximum LAI because variations in forest LAI over time have been mainly attributed to interannual changes in tree cover due to management or disturbance, where such interannual dynamics are greater in magnitude than growing-season variability in LAI (Le Dantec et al., 2000). Plot-scale LAI estimates were derived using four different methods, described above. The machine learning algorithm we used was random forests, which is a nonparametric statistical technique that builds an ensemble model from many iterations of individual classification or regression trees and uses bootstrapping, or bagging, to train and improve model performance (Breiman, 2001). We developed five separate random forests regression models: one for each of four overstory estimation methods (LAI1, 2, 3, and 4) plus one understory estimation method (LAI4).

Like other supervised statistical models or machine learning algorithms, a random forests model requires specification of a response variable and a set of predictor variables. For each model, plot-scale LAI served as the response variable. All models included the same set of predictor variables (Table 13). Predictor variables included composite maximum annual greenness quantified using normalized difference vegetation index (NDVI) from Landsat 5 or Landsat 7 (Table 13), acquired from Google Earth Engine (Gorelick et al., 2017). The maximum annual greenness for each pixel was calculated as the highest recorded NDVI from the images available for that year. The training dataset included plots measured in any year, but for any particular plot only the composite maximum annual greenness for the year that plot was measured was included in the training dataset. Other predictors included elevation and other topographic variables derived from elevation, including slope and aspect (Hijmans, 2021), topographic wetness index (Beven & Kirkby, 1979) calculated using TauDEM (Tarboton, 2016), and a topographic exposure index (Mikita & Klimánek, 2010); tree canopy cover from the National Land Cover Dataset (Yang et al., 2018); precipitation and temperature (Daly et al., 1994); and soils hydrologic group code (USDA-NRCS, 2021) as a categorical input variable to random forests. The value of each predictor variable was extracted at the spatial location of each plot to create a plot-based training dataset.

Table 13. Predictor variables used in all random forests models for predicting LAI.

Description	**Source**	**Citation**
Composite maximum annual greenness	Google Earth Engine (GEE) image collections	GEE image collections: LANDSAT_LE07_C01_T1_ANNUAL_GREENEST_TOA (years 1999-2019) and LANDSAT_LT05_C01_T1_ANNUAL_GREENEST_TOA (years 1984-1998)
Elevation	Digital elevation model (DEM) from The National Map	https://apps.nationalmap.gov/services/
Slope	DEM processed in R package 'raster'	Hijmans (2021)
Aspect	DEM processed in R package 'raster'	Hijmans (2021)
Topographic wetness index	DEM processed in TauDEM	http://hydrology.usu.edu/taudem/
Exposure index	DEM processed in ArcGIS	Mikita and Klimánek (2012)
Tree canopy cover	National Land Cover Dataset	Yang et al. (2018)
Precipitation; min & max temperature	PRISM	Daly et al. (2020)
Soils unit	STATSGO (attribute 'hydgrpdcd')	USDA-NRCS (2021)

To assess the random forests models' performance, we compared R^2 and mean of the squared residuals from the out-of-bag observations, which for each model are calculated across the ensemble of all trees. Because each iteration of the regression tree calibrates the model on approximately 2/3 of training observations, the remaining 1/3 of observations constitute the out-of-bag sample and produce an unbiased estimate of model performance that approximates k-fold cross-validation, thus negating the need for a separate validation dataset (Breiman, 2001). Model calibration, performance evaluation based on out-of-bag observations, and application to gridded predictor variables to produce gridded LAI outputs were all performed in the package 'randomForests' (Liaw & Wiener, 2002) within the R statistical analysis software (R Core Team, 2020).

After the models were trained on plot-level observations, each model was then used with spatially gridded predictor variables as inputs (Table 13) to produce annual gridded LAI datasets. Note that the plot-level LAI estimates were used only for model calibration and were not needed for making predictions of LAI based on predictor variables. Thus, we were able to produce annual maximum LAI estimates for any year for which maximum annual greenness exists, including years in which no plots were measured (i.e., as early as 1984). Beyond the plot based out-of-bag random forest validation, we also assessed agreement between our gridded LAI outputs and Landsat-based LAI (Kang et al., 2021) for a single year. We selected the year 2003 for this assessment because the Landsat-based LAI had minimal missing pixel values for that year. Assessment metrics included correlation coefficient, mean absolute error, mean bias error, and root mean squared error, which is similar to mean absolute error in that it ignores the direction of error (i.e., bias) but penalizes for larger individual errors.

Time series of LAI for two large watersheds

After producing gridded LAI datasets for multiple years, we identified the two plot-level LAI estimation methods that showed the best agreement with Landsat-based LAI and used those methods to produce a time series of annual LAI gridded datasets from 1984 to 2019. We examined these time series within two large watersheds, the South Fork Flathead River and Middle Fork Flathead River, in our modeling domain (Fig. 9). We tested the time series of overstory LAI for monotonic temporal trend using the Mann-Kendall trend test (Helsel et al., 2020) via R package ‘Kendall’ (McLeod, 2011).

We also examined the time series of annual evaporative (ET) ratios, estimated as the proportion of precipitation that did not result in runoff and calculated as 1 minus the ratio of annual streamflow to annual precipitation for each year. ET ratio for the Middle Fork Flathead River watershed was obtained from the CAMELS dataset for US

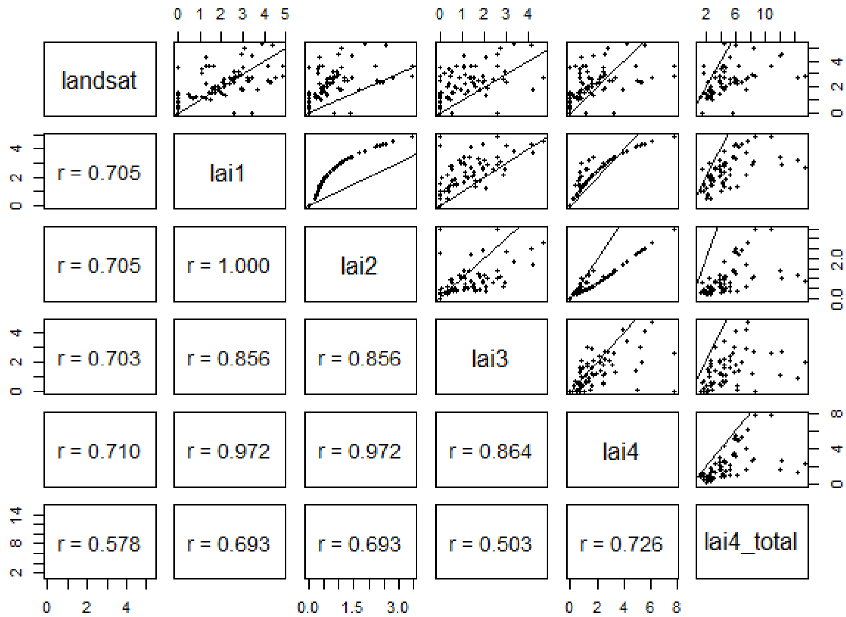
Geological Survey (USGS) gage 12358500 (Addor et al., 2017). For the South Fork Flathead River, daily streamflow data were obtained for USGS gage 12359800 from R package 'dataRetrieval' (De Cicco et al., 2021). Both gage locations are shown in Fig. 9. South Fork precipitation data were compiled from Daymet gridded data, which is the same source data used to compile the CAMELS dataset (Addor et al., 2017), using R package 'daymetr' (Hufkens et al., 2018). We assessed the strength of correlations between each LAI estimation method and ET ratio based on these time series. Although we tested for a lagged correlation between LAI and ET ratio, there was no significant lag detected and we therefore did not implement a lag in the correlation analysis.

Results

Estimation of plot-level LAI

Correlation coefficients for estimates of plot-scale overstory LAI relative to Landsat-based total LAI were between 0.703 and 0.710, while for the combination of overstory and understory based on method LAI4 the correlation was 0.578 (Fig. 12a). Plot-based methods for estimating overstory LAI were strongly correlated with each other (pairwise $r > 0.85$ for all pairs), which suggests that the choice of one method over another may not be tremendously impactful for estimating overstory LAI alone. Scatterplots between each plot-scale estimation method vs. Landsat reveal that methods LAI2, LAI3, and LAI4 (overstory) underestimate LAI (Fig. 12a) relative to Landsat. Violin plots also demonstrate this pattern (Fig. 12b), which is unsurprising given that Landsat-based LAI detects all vegetation without distinguishing between overstory and understory strata, while our ground-based overstory LAI methods did not include the understory vegetation component. This result is somewhat expected because most forests in the region are relatively open and do not have fully closed canopies. In contrast, the sum of overstory and understory LAI estimates produced by method LAI4 overestimate LAI relative to Landsat-based estimates (Fig. 12a and b), which may reflect the fact that ground-based estimates of multi-layered LAI are not subject to the saturation that occurs at a value of about 4 for Landsat-based LAI (Kang et al., 2021). Thus, the ability of method LAI4 to estimate total LAI represents a contribution in overcoming a known limitation of total LAI as estimated from spectral remote sensing. Among all methods, method LAI4 showed the widest dispersion of LAI values (Fig. 12b).

A)



B)

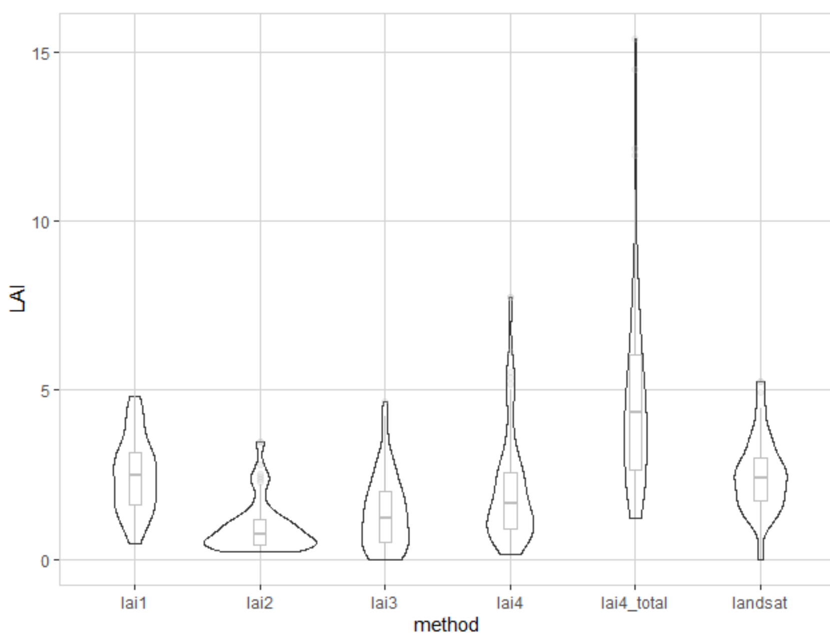


Fig. 12. Comparisons of plot-level leaf area index (LAI) at Forest Inventory & Analysis (FIA) plots based on four methods for estimating overstory LAI (LAI1, LAI2, LAI3 and LAI4), one method for estimating both overstory and understory LAI (lai4_total), and Landsat-based total LAI at plot locations (from Kang et al. 2021), all using data collected in 2019. Individual LAI estimation methods are described in Table 11. A) Scatterplots and correlations; R=Spearman's rank correlation coefficient. B) Violin shapes show frequency distribution, and boxplots show median (horizontal bar) and interquartile range (box).

Interpolation of gridded LAI datasets

The assessment above described how well plot-level LAI estimates correspond to Landsat-based LAI, and here we describe machine learning models that used those plot-level LAI estimates as calibration data for estimating LAI from gridded biophysical and remote sensing predictor variables that we extracted at FIA plot locations (Fig. 10). For all LAI estimation methods, the machine learning algorithms had value of model $r^2 > 0.6$ (Table 14). In contrast, understory LAI (method LAI4_under) had a very weak model ($r^2 = 0.03$), which might reflect that understory vegetation may be undetectable by remote sensing-based predictor variables (i.e., composite maximum annual greenness and the NLCD tree canopy cover layer) due to tree canopies obscuring this vegetation on forest plots. Among all plot-scale LAI estimation methods, the random forests model based on method LAI1 had the highest proportion of LAI variability explained by the model while method LAI2 had the lowest model error (mean squared residual, or MSR, in Table 14). Method LAI4's overstory model had the lowest model r^2 among overstory estimation methods, although differences among models were not large. Note that these metrics of model performance reflect the ability of the predictor variables to explain (via random forests regression) the plot-to-plot variability in each plot-level LAI estimation method, and thus they do not reflect the accuracy of any particular method.

All four LAI estimation methods produced gridded datasets that are strongly correlated with Landsat-based gridded LAI (Table 15). Although an ideal accuracy assessment would have used ground-based measurements of LAI that were collected using a light-sensing device or hemispherical photography, such an approach was not feasible at the spatial scale of this study. Absent such intensive data collection, Landsat-based total LAI provides evidence of whether our gridded LAI values are realistic. Method LAI4's total LAI (i.e., overstory plus understory) was most strongly correlated with Landsat (r=0.80). Mean absolute error, mean bias error, and root mean squared error were all lowest for method LAI1, followed closely by method LAI4, and were all highest for method LAI2. These pixel-based comparisons show a bias similar to that exhibited by plot-based comparisons: all overstory methods have a positive mean bias error, and are thus lower than Landsat-based total LAI, while total LAI produced by method LAI4 is higher than Landsat-based LAI and has a negative mean bias error (Table 15). As discussed above, it is realistic that overstory LAI alone would be lower than Landsat-based total LAI and that ground-based total LAI (method LAI4) would be higher than Landsat-based LAI.

Table 14. Performance metrics for random forests models of LAI based on four overstory estimation methods (LAI1, LAI2, LAI3, and LAI4) and one understory method (LAI4_under). Mean of squared residuals (MSR) and model R^2 are based on out-of-bag samples from 500 trees.

Method	MSR	Model R^2
LAI1	0.46	0.77
LAI2	0.17	0.66
LAI3	0.40	0.69
LAI4	0.92	0.64
LAI4_under	5.79	0.03

Table 15. Pixel-to-pixel comparisons of multiple gridded LAI datasets relative to Landsat-derived LAI (Kang et al. 2021) as estimated for 2003. MAE=mean absolute error; MBE=mean bias error; RMSE=root mean squared error. LAI1, LAI2, LAI3, and LAI4, represent overstory LAI; LAI4_total represents the sum of overstory and understory LAI.

2003	Pearson's r	MAE	MBE	RMSE
LAI1	0.75	0.97	0.83	1.28
LAI2	0.72	1.78	1.77	2.12
LAI3	0.71	1.48	1.44	1.80
LAI4	0.72	1.15	1.04	1.46
LAI4_total	0.80	1.11	-0.99	1.42

The wider dispersion of total LAI values produced by method LAI4, particularly when understory vegetation is included, more closely resemble the spatial variability and dispersion of values demonstrated by Landsat-based total LAI (Fig. 13). This pattern is evident for two different years, 2003 and 2019, which were used to assess not only single-year LAI estimates (above) but also change in LAI over time. Based on visual comparisons of change in Landsat-based estimates versus change in our gridded LAI datasets between 2003 and 2019, methods for estimating overstory LAI – particularly LAI2 and LAI3, and to a lesser extent LAI1 and LAI4 overstory – are missing a lot of change that is captured by Landsat-based LAI and total LAI as estimated by method LAI4. Notable differences still exist in the amount of change in LAI observed from Landsat compared to total LAI as estimated by method LAI4; these differences may be due to inaccuracies in either Landsat-based LAI or our plot-based method of estimating LAI, but resolving the ultimate cause of the discrepancy would require ground validation data and was beyond the scope of this study.

Time series of LAI for two large watersheds

Time series of LAI for 1984-2019 yielded a subtle but statistically significant ($p < 0.05$) decreasing trend in overstory, understory, and total LAI in the South Fork Flathead River watershed (Fig. 14). Methods LAI1 and LAI4 both detected a decrease in overstory LAI, although this decrease was small compared to the decrease in understory and total LAI detected by method LAI4. In contrast to the South Fork, the Middle Fork watershed did not exhibit any significant trend in overstory LAI, although method LAI4 did detect a significant decrease in total LAI from 1984 to 2019 (Fig. 14). There were no significant trends in ET ratio in either watershed.

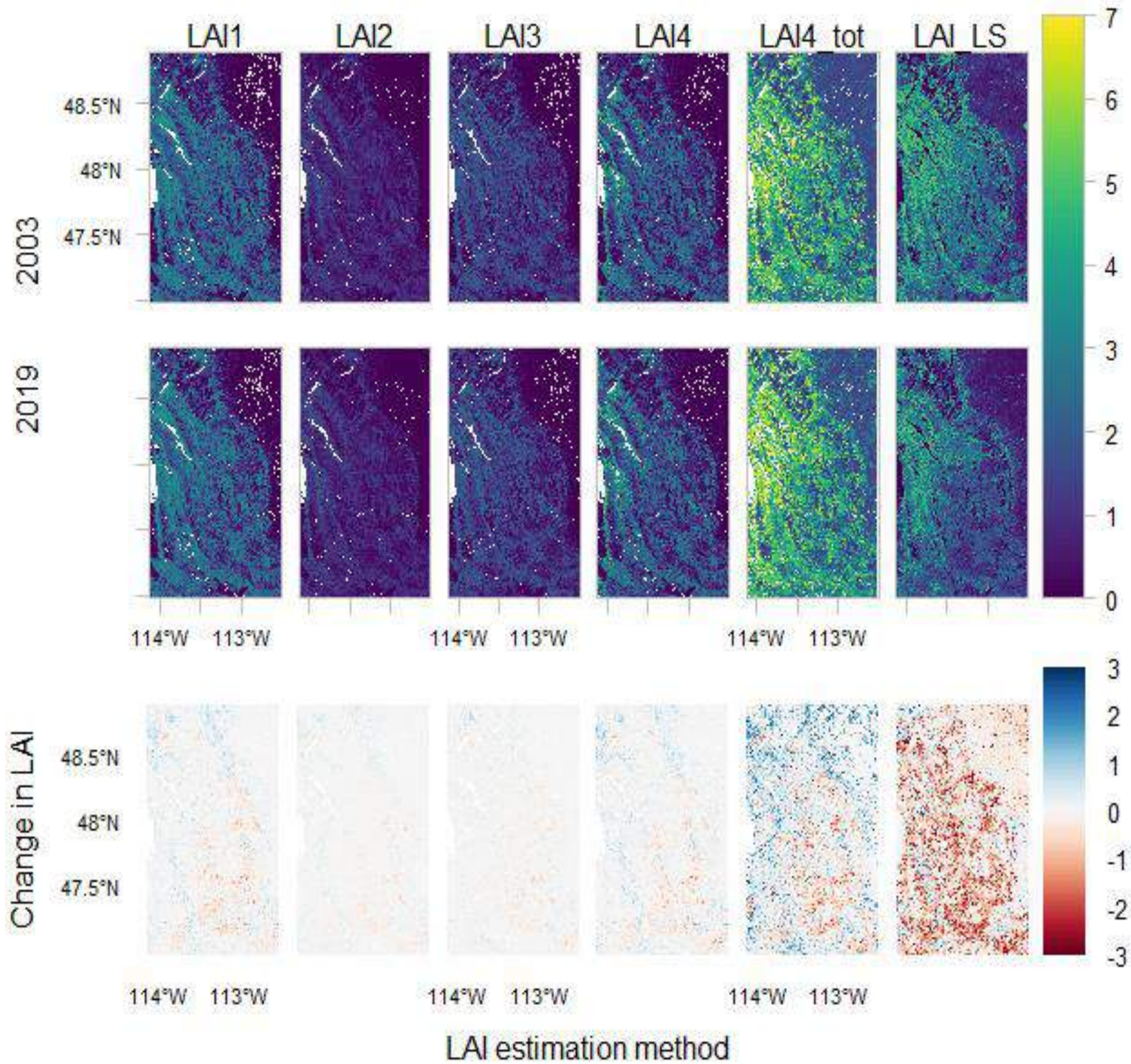
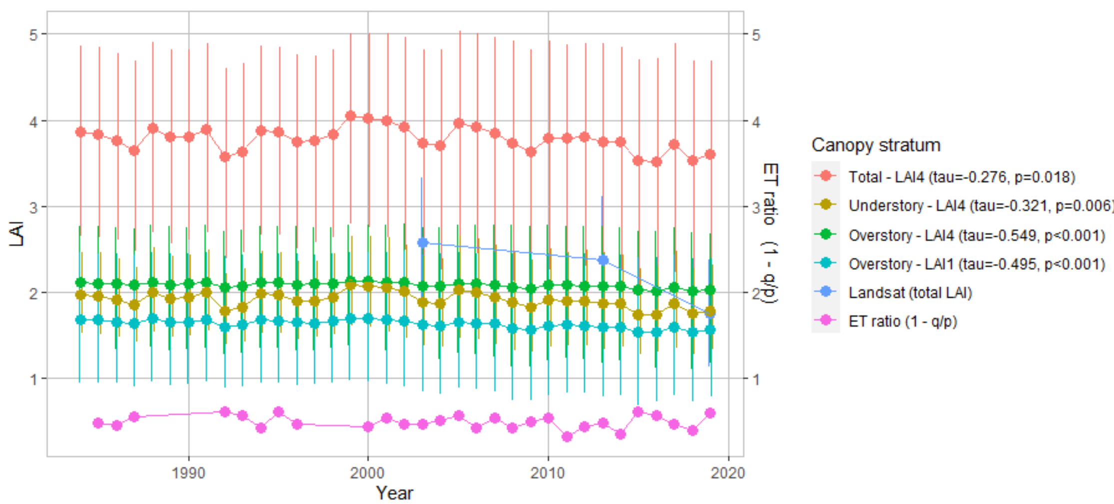


Fig. 13. Maps of LAI based on random forests interpolations of empirical plot-based methods (LAI1, LAI2, LAI3, and LAI4 for overstory LAI; LAI4_tot for overstory + understory LAI), and Landsat total LAI (LAI_LS) for 2003 and 2019 (top and middle rows, respectively) and for the difference between 2003 and 2019 (bottom row) for the entire modeling domain shown in Fig. 1. Negative change represents decreases in LAI.

South Fork Flathead watershed



Middle Fork Flathead watershed

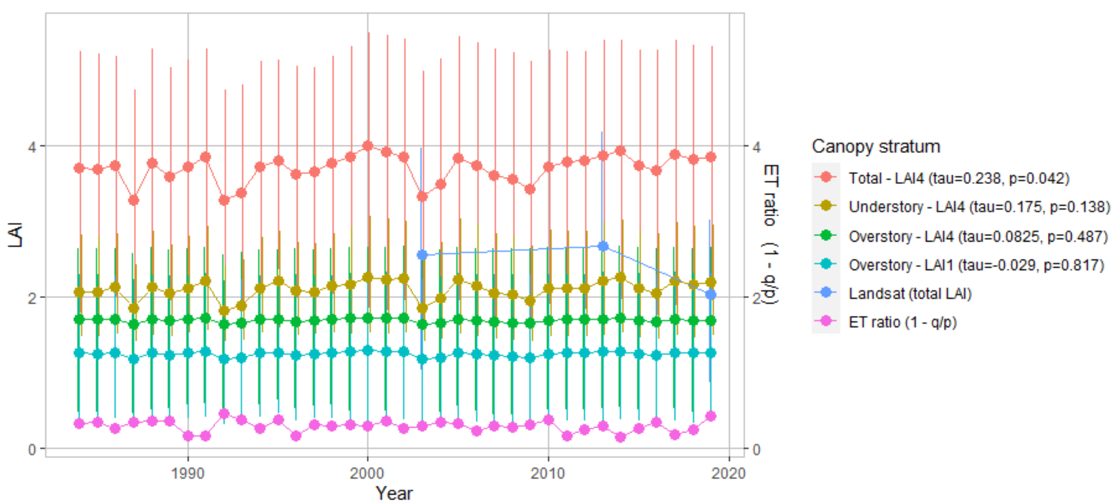


Fig. 14. Annual time series of overstory, understory, and total leaf area index (LAI) in the South Fork Flathead River and Middle Fork Flathead River watersheds for 1984-2019, as produced by random forests models based on methods LAI1 and LAI4; Landsat-based LAI (Kang et al. 2021) for 2003, 2013, and 2019; and ET ratio (1 – ratio of mean annual streamflow to mean annual precipitation). LAI points represent watershed-scale medians and bars represent the 1st (lower) and 3rd (upper) quartiles. Values of tau and associated p-values in the legend represent results of the Mann-Kendall trend test. Note missing observations for some years in the South Fork Flathead River due to lack of streamflow data.

Annual median LAI for overstory, understory, and total LAI based on methods LAI1 and LAI4 were strongly correlated with one another, with R>0.8 for all pairwise comparisons (Fig. 15). Thus, methods LAI1 and LAI4 produce highly correlated watershed-scale LAI estimates (r=0.977 for the South Fork, and r=0.962 for the Middle Fork, for LAI1 vs. LAI4 overstory LAI). Correlations with ET ratio show some minor differences among LAI estimation methods. In the South Fork watershed, ET ratio is very weakly correlated with overstory LAI as estimated by methods LAI1 and LAI4, and slightly more strongly correlated with understory and total LAI produced by method LAI4 (Fig. 15a). In the Middle Fork watershed, correlations between annual median LAI and ET ratio were stronger, and as in the South Fork, ET was more strongly correlated with total LAI as estimates by method LAI4 than with other estimates.

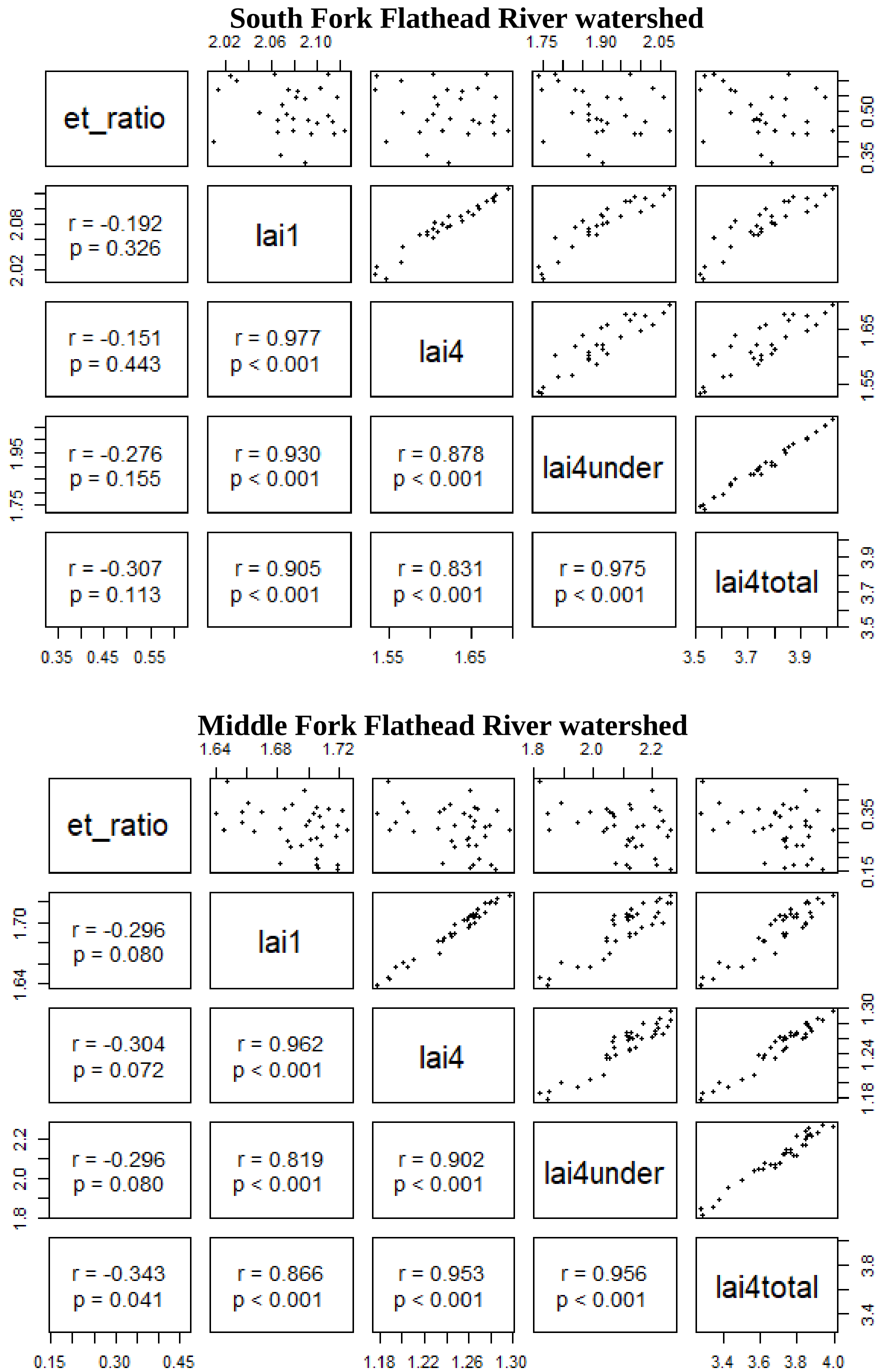


Fig. 15. Comparisons of annual ET ratio and watershed-scale median leaf area index as estimated using methods LAI1 and LAI4 (overstory), LAI4under (understory) and LAI4total (total LAI) for water years 1984-2019. ET ratio is defined as 1 minus the ratio of mean annual streamflow to mean annual precipitation. R represents the Spearman rank correlation coefficient.

Discussion

This study demonstrated development of gridded LAI datasets that are not subject to the same constraints as remote sensing-based datasets, namely the inability to separate LAI into overstory vs. understory strata, as well as the saturation that occurs at specific LAI values and above which remote sensing-based methods cannot distinguish variability in LAI densities. The methods demonstrated here illustrate a potential linkage between machine learning or artificial intelligence algorithms, such as random forests models, and physically based hydrologic models that may use the outputs of random forests models as inputs. In this study, machine learning models were used to interpolate forest vegetation from plot scales to spatially continuous LAI datasets. This is thus a specific case of machine learning algorithms informing and working in tandem with physically based models.

We compared four methods of estimating plot-scale LAI from forest inventory data and found that three of the four overstory LAI methods produced estimates lower than Landsat-based total LAI. The only method that produced estimates of total LAI, separated into overstory and understory strata, overestimated total LAI relative to Landsat-based estimates. This result suggests that method LAI4 does indeed overcome the limitation of saturation that is characteristic of remote sensing-based LAI. Although new methods for estimating Landsat-based LAI have become computationally efficient and publicly available on Google Earth Engine (Kang et al., 2021), this algorithm was developed for Landsat 5 and later versions of Landsat and is thus not applicable to the full Landsat record. In contrast, our machine learning models used only a single Landsat-based predictor variable that is available beginning in 1984, and it is thus possible to produce gridded datasets of maximum annual LAI for any year from 1984 to the most recent growing season.

Among the four alternative methods we tested for estimating plot-scale LAI and then interpolating gridded LAI datasets, methods LAI1 and LAI4 performed the best overall in comparison to Landsat-based LAI. Each of these methods has specific strengths and weaknesses. Method LAI1 has the advantage of requiring only a single ground measurement – plot-level tree canopy cover – and is thus more parsimonious. Although method LAI1 also requires estimating local maximum LAI, the value of 5.3 that we used for our study area (Pierce & Running, 1988) is likely close enough to the value at which Landsat-based LAI saturates that it may be a realistic maximum to use regardless of study location. Because method LAI4 uses a clumping index that is specific to forest type, it requires a more complex crosswalk of FIA's forest types to the cover types specified for clumping indices in Chen et al. (2005). However, scripting is provided to accomplish this task, and this method could more reliably be applied to FIA data anywhere in the USA, unlike method LAI1 which may require tuning of local maximum LAI based on direct field measurements of LAI. Method LAI4 has the advantage of producing not only overstory LAI but also understory and thus total LAI. Total and understory LAI, as produced by method LAI4, demonstrated the greatest sensitivity to change in LAI over time, as compared to Landsat-based LAI, and LAI4's total LAI was more strongly correlated than LAI1 to evaporative fraction.

The choice of the most appropriate plot-scale LAI estimation method depends largely on the intended application or question. For consideration of overstory LAI only, linear scaling of tree canopy cover with LAI, i.e., method LAI1, may be sufficient and parsimonious. For studies investigating processes within overstory vs. understory strata, e.g., carbon allocation or partitioning of precipitation into various hydrologic pathways, LAI4 would be most appropriate because it is capable of estimating not only overstory but also understory and thus total LAI, without the saturation constraint imposed by remote sensing-based total LAI datasets. Although we used composite maximum annual greenness as a predictor variable in our machine learning models, and greenness is subject to the same saturation effect as Landsat-based LAI, the fact that we used machine learning models with additional biophysical (non-spectral) predictor variables may help to overcome constraints imposed by spectral remote sensing.

The need to couple understory and overstory vegetation in models has been previously recognized due to the interactions between forest vegetation layers (Landuyt et al., 2018; Thrippleton et al., 2016). Overstory and understory vegetation have distinct but interacting responses to both disturbance and post-disturbance recovery (Carter et al., 2022; Laughlin & Fulé, 2008), which may have unknown ramifications for fluxes of water, energy, and carbon. The ability to estimate LAI for multiple canopy strata could be leveraged in models that have distinct representations of separate strata, and such applications could enhance our understanding of the process-level responses to disturbances that alter forest structure or result in type changes from forest to nonforest vegetation.

One outcome of this study is the comparative evaluation of several previously used and published methods for estimating LAI when direct measurements or remote sensing-based data are not available. Specifically, methods LAI1, LAI2, and LAI3 have been used by prior studies to estimate overstory on the basis of tree canopy cover or the combination of species identity and DBH. We found that the simplest of these methods, LAI1, produced the best agreement with Landsat-based LAI. However, although method LAI2 did not agree as well with Landsat data, it may be preferable for snow modeling applications, which was the original purpose of that LAI estimation method (Pomeroy et al., 2002; Varhola et al., 2010).

A unique benefit of using national forest inventory (NFI) data, such as that collected by FIA which we used to produce plot-based estimates of LAI, is that ground data are acquired from an ongoing data collection program with a probabilistic sample and methods that are consistent over time. Although lidar acquisitions such as ICESat-1, ICESat-2, and GEDI all present promising capabilities to estimate vertically integrated LAI (Tang et al., 2014), thus far such space-based missions are temporally constrained compared to ongoing ground data collection by NFIs. Thus, this approach to estimating annual LAI could be applied in other countries that have ongoing NFIs that include measurements of overstory and understory canopy cover. For any NFI that records causal agents of mortality and disturbance as well as disturbance severity and indicators of recovery time, another strength of this approach is that it allows differentiation of the drivers of changes in LAI over time. Future research may examine how specific disturbance types affect the distribution of carbon and hydrologic fluxes among overstory vs. understory canopies.

Although this study presents novel methods of estimating LAI both as plot-scale estimates and as gridded datasets, it does come with caveats. First, the methods tested here obviously require ground observations and do not provide LAI estimates within a year or season. In contrast, Landsat-based LAI from radiative transfer models can provide greater temporal resolution and thus seasonal (intra-annual) LAI, but again with the caveat that it estimates only total LAI. Second, validating any LAI dataset is challenging, and our study was limited by having only Landsat-based total LAI to use as a point of reference. However, the Landsat-based dataset we used was well calibrated and validated using widely distributed, intensively studied sites throughout the U.S. (Kang et al., 2021). Although we did not present the results within this paper, we did investigate the use of LAI datasets derived from MODIS and ICESat-1 as validation datasets. We found that pairwise correlations among these datasets were very weak ($r<0.2$), possibly due to spatial offsets and scale discrepancies that are difficult to resolve, and thus they are not included here.

We recommend that future studies conduct additional validation of both plot-based and gridded LAI produced using methods LAI1 and LAI4. Plot-based validation could be accomplished by measuring LAI using light-sensing devices (e.g., LI-COR sensors) on a subsample of FIA plots and then using those LAI values for calibrating and validating various methods that estimate LAI based on other FIA measurements. For example, calibration might include improved parameterization of clumping indices – possibly using light-sensing devices, drones, or lidar – for specific vegetation or forest types in support of method LAI4. Plot-based LAI measurements could also be used to test the assumption inherent in method LAI1, i.e., that a single maximum LAI value could be implemented across broad regions as the constraining upper limit for scaling canopy cover against overstory LAI. Gridded LAI datasets could be further evaluated by comparing the performance of a physically based hydrologic model using alternative LAI datasets as inputs. Specifically, parallel model simulations could assess the impact of using strictly remote sensing-based total LAI, compared to overstory and understory gridded LAI based on plot-scale methods as described here, on the ability to estimate hydrologic fluxes (e.g., canopy evapotranspiration, soil evaporation, maximum snow water equivalent, etc.).

Finally, we recommend that broad applicability of our findings will likely require development of tools that allow others to define an area of interest and produce multi-strata gridded LAI datasets. To facilitate widespread and innovative use of these methods, such applications would ideally occur within cloud-based computing platforms that consume FIA plot data as well as the predictor variables used in our random forests models. However, in the case of the USA, such development will require cooperative agreements between FIA and cloud-based computing platforms that protect the confidentiality of plot locations as required by federal law (Sabor et al., 2007). Such advances could allow scientists in forestry and hydrology to use overstory and understory LAI datasets, rather than simply total LAI, for multiple purposes. Incorporation of overstory and understory LAI into physically based ecological and hydrologic models could enhance future understanding of how forest disturbance, recovery, and land cover change affect both forest and water resources.

Conclusions

This study compared four methods for estimating plot-scale leaf area index, and then used those plot-scale estimates in a machine learning algorithm to produce gridded LAI datasets on an annual basis. We evaluated these four alternative methods by comparing both plot-based and gridded LAI estimates against Landsat-based total LAI.

We found that the simplest LAI estimation method performed well at estimating overstory LAI but did not address our objective of estimating both overstory and understory LAI. The method based on an inverted gap-fraction model, combined with previously published clumping indices that are specific to vegetation type, performed best at capturing trends over time and also produced separate estimates of understory, overstory, and total LAI. Future research could improve validation and parameterization of plot-based LAI estimates and test the assumption that gridded LAI datasets that partition LAI into multiple canopy strata will lead to enhanced performance in hydrologic models.

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CHAPTER 5

SUMMARY, CONCLUSIONS, AND RECOMMENDATIONS

Summary and conclusions

The research presented in this dissertation enhances our understanding of how forests and forest disturbances affect streamflow and thus water supply. Recent forest disturbances throughout the western United States have already affected both water quality and water quantity. These impacts are partly due to naturally occurring disturbances but are also related to changes in forest dynamics related to warmer temperatures and changing climate. Temperatures are projected to continue increasing in the future, which will almost certainly lead to increased moisture stress and thus continued drought-related forest disturbances such as wildfires, insect epidemics, disease, and drought-induced tree die-off. Ongoing forest disturbances, and even type changes from forest to nonforest land cover types, will continue influencing the water supply available both for ecosystems and for people.

The objective of the literature synthesis reported in Chapter 2 was to determine how forest disturbance influences streamflow and snowpack via canopy ecohydrologic processes. I hypothesized that forest disturbance not only increases the throughfall of precipitation and decreases interception and transpiration, but also alters energy fluxes that in some cases lead to faster melting and sublimation of snowpack. Both hypotheses were supported by evidence from a systematic review of 78 previous studies over the period 2000-2019. This review showed that post-disturbance streamflow and snowpack increased in some cases, did not change in some cases, and decreased in other cases.

The variable results that were found in the systematic review in Chapter 2 can be explained by either net increases or net decreases in total evapotranspiration following disturbance, which in turn determines the associated increase or decrease in annual streamflow. The cases of decreased post-disturbance streamflow do not conform to conventional wisdom and occur when post-disturbance evapotranspiration exceeds pre-disturbance evapotranspiration. This overcompensating effect was observed most frequently following non-stand replacing disturbances, such as those caused by insects, drought, disease, and low-severity wildfire. In such situations, increased evaporation (which sometimes included increased sublimation of snow) resulted from higher subcanopy radiation. The overcompensating effect (i.e., a net increase in evapotranspiration) was also observed or in watersheds with rapid post-disturbance vegetation growth, which resulted in a net increase in transpiration compared to pre-disturbance canopy transpiration. I concluded from this review that hydrologic response following forest disturbance depends on nuances of vegetation structure, climate, and topography that need to be quantified and understood to make predictions for any particular site or disturbance.

The literature synthesis in Chapter 2 also led to two conclusions about how foresters and hydrologists study forest disturbance effects on streamflow and snowpack. First, although both observational and model-based studies concluded that streamflow and snowpack may decrease following forest disturbance, physically based models were better than more empirically based models at simulating reductions in water yield. Second, most studies characterized forests and forest disturbances in categorical terms (e.g., forest vs. nonforest, or disturbed vs. undisturbed) rather than in quantitative metrics such as leaf area index, basal area, canopy coverage, or similar numerical quantities.

In Chapter 3, my objective was to determine how recent forest disturbances have influenced streamflow, using a novel combination of systematic forest inventory data and a curated large-sample hydrologic dataset. This analysis was catalyzed by merging the disciplines of forestry, including background experience with national forest inventory data, and hydrology. The analysis tested three hypotheses: 1) annual streamflow is generally inversely related to forest cover; 2) annual streamflow following disturbance may be more likely to decrease in watersheds where aridity and incoming solar radiation are relatively high, e.g., in the Southwestern U.S.; and 3) the interaction of disturbance severity and aridity affect not only the magnitude but also the direction of post-disturbance change in streamflow. This large sample hydrologic analysis was novel in its evaluation of quantitative and numerically continuous metrics representing forest cover and disturbance. The use of quantitative metrics in Chapter 3 directly addressed a finding from Chapter 2, which was that most previous studies of forest disturbance effects on streamflow only considered categorical land cover metrics such as forest vs. nonforest or disturbed vs. undisturbed.

The results of the large sample analysis in Chapter 3 confirmed that although post-disturbance streamflow increased in many watersheds, it decreased in some watersheds. The direction of streamflow response to forest disturbance was found to be dependent, in part, on aridity. Further, the interaction of aridity and the severity of disturbance, as measured by tree mortality, influence both the magnitude and direction of streamflow response to disturbance. Statistical modeling identified an aridity threshold value of 2.35 (Fig. 16), above which watersheds are likely to exhibit decreased streamflow following disturbances. This threshold might be helpful to identify a class of watersheds characterized as very arid and at risk for decreased streamflow. However, this threshold is subject to uncertainty and based on observations between 2000 and 2019 and therefore may not generalize to future conditions. Thus, any use of this threshold for prediction of potential streamflow response to climate or vegetation change should take an adaptive forecasting approach with iterative updating as conditions change.

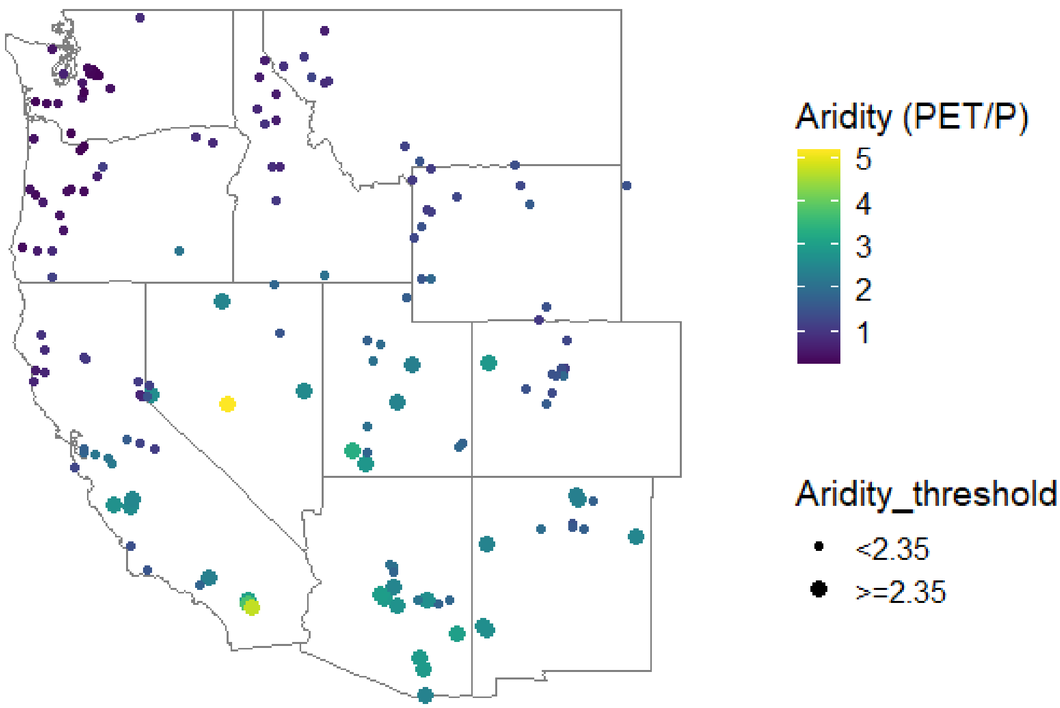

Fig. 16. Aridity (potential evapotranspiration / precipitation) at 159 watersheds evaluated in Chapter 3.

Finally, results of Chapter 3 showed that forest disturbances were observed more frequently and at greater severity in these very arid watersheds, which also experienced increased temperatures during the study period. This result, when considered in combination with projections of continuing increases in temperature, suggests that both disturbance and streamflow will continue to be influenced by future climate change. Chapter 3 includes projections of streamflow response, or sensitivity, to various disturbance severities for watersheds at different aridity, both assuming no climate change and assuming 1º C of warming.

The objective of Chapter 4 was to develop a method for producing detailed forest cover datasets, based on an existing forest monitoring network combined with remote sensing and biophysical variables in a machine learning model, for input to hydrologic models. I anticipated that detailed vegetation data collected from a network of permanent forest monitoring plots can provide better leaf area index (LAI) information than is currently available from remote sensing products. Among the four methods I compared for producing annual maximum LAI for overstory forest vegetation, existing methods did not perform as well as a newly developed method. The new method not only correlated more strongly with Landsat-based LAI compared to the three other methods, but it also allowed distinguishing understory and overstory LAI. Because existing LAI datasets do not separate overstory from understory LAI, the ability to produce LAI datasets by canopy stratum represents a potential improvement in the representation of forest vegetation in physically based ecohydrologic models. Time series of overstory and understory LAI for 1984-2019 demonstrated that interannual variability of understory LAI exceeds that for overstory LAI, and this variability may affect partitioning of precipitation to ET vs. runoff at annual timescales.

In summary, these three papers have provided new insights as to how forest cover, disturbance, and climate interact to influence streamflow. The conclusions about how streamflow and snowpack respond to disturbance, and how that response is influenced by aridity, were first developed in the systematic literature review of Chapter 2 and then confirmed by broad-scale analysis of multiple watersheds in Chapter 3. Chapter 3 also confirmed that streamflow response to disturbance is determined not only by disturbance severity but by the interaction of disturbance severity with aridity, such that streamflow is more likely to decrease following disturbance in very arid watersheds. Chapter 4 presented a new method for translating existing forest monitoring data at sample plots into overstory and understory LAI at plot scales, which can then be combined with remote sensing and biophysical variables to produce spatially explicit, gridded LAI datasets that can serve as inputs for hydrologic modeling. These outcomes will collectively improve the ability of researchers and resource managers to evaluate the effects of past and future changes in forest cover on water availability.

Recommendations

The research presented in this dissertation has led to recommendations for future research and management applications. These recommendations can help researchers and managers more efficiently apply new knowledge to resource problems in the face of increasing temperatures and increasing forest disturbance in the water-limited western U.S.

One recommendation pertains to how ecohydrologic modelers select the types of models used and the way vegetation is represented in such models. One result of the literature synthesis in Chapter 2 was that among simulation models, physically based models were capable of predicting decreased snowpack or streamflow following disturbance whereas more empirically based hydrologic models were not. This capability underscores the need to continue investing in and improving physically based models to support forest and watershed management. Another finding was that hydrologists use leaf area index to describe vegetation, while foresters collect a vast suite of measurements that often does not include leaf area index (Härkönen et al. 2015). Further, researchers from both disciplines tend to characterize forests and disturbances in categorical terms such as forest versus nonforest or disturbed versus undisturbed, rather than recognizing the continua of forest cover and disturbance. Strategic national-scale forest inventories have previously been recognized as a potential source of quantitative forest and disturbance data for hydrologic modeling and water resources assessments (Andréassian 2004), and Chapters 3 and 4 of this work present methods for capitalizing on forest inventory data for these purposes. Future research should seek to expand on the use of more informative vegetation metrics that enable the development of quantitative relationships between climate, vegetation, and hydrologic processes. Implementation of these recommendations to represent vegetation quantitatively, possibly based on national-scale forest inventory data and remote sensing data, within physically based models is likely to improve the accuracy of such models' predictions.

The separation of LAI into overstory and understory components is anticipated to improve the ability of LAI-based analyses and models to simulate the influence of forest canopies on hydrologic processes. Future research should investigate whether or by how much an enhanced representation of overstory and understory LAI improves the performance of physically based models. For example, if the goal of future research is to develop a model that accurately predicts streamflow or snowpack based on forest vegetation change over time, then simulations could compare the predictive capability of the model using separate overstory and understory LAI layers as inputs, relative to its predictive capability using total LAI based on remote sensing data as an input.

Another area for future research is to consider not only the direct effects of changing climate on streamflow and snowpack, but also the indirect effects of climate as mediated by vegetation. The recent increasing temperature trend has resulted in historically large extents of tree mortality across the western U.S. (Williams et al. 2013) as well as an increase in severe fire (van Mantgem et al. 2013). Thus, models that seek to make predictions about how future climate will affect water should incorporate vegetation-climate feedbacks rather than assuming static vegetation, particularly in forested watersheds.

The results of Chapters 2 and 3 present a cautionary tale to forest managers who seek to increase water yield by thinning forests. Based on historical studies of water yield response to clearcut harvesting, forest managers may assume that reduced forest cover due to natural disturbance (e.g., due to insects or drought-induced die-off) will produce more runoff. While reductions in forest cover do often result in increased water yield, they tended to have the opposite effect in very arid watersheds. Further, these arid watersheds also experienced more tree mortality than wetter watersheds, possibly due to increased temperatures. Thus, a more critical management objective may be managing for increased snow retention or soil moisture to mitigate against future forest disturbance, including severe wildfire. Future research could improve our knowledge of when and where streamflow or snowpack are likely to increase versus decrease, and by how much, using physically based models that account for forest structure, forest density, and vegetation-climate feedbacks. Climate-driven forest changes could be expected to impact hydrologic processes and water supplies just as management-driven forest change would. Thus, forest management projects such as fuels treatments or thinning could benefit from using physically based models to determine how the project will affect snowpack and streamflow.

The final recommendation of this work relies not on its findings alone, but on its findings in the context of other recently published research confirming that forest management actions can successfully address specific objectives in forested watersheds. For example, forest thinning has been shown to lead to increased soil moisture in the rooting zone and thus can improve forest resilience (Belmonte et al. 2022). Experimental fuels treatments, including mechanical thinning and prescribed fire, have been shown to either increase forest resilience (i.e., by decreasing tree mortality) or increase water yield, but not both, and aridity appeared to determine which outcome occurred as a result of treatments (Bart et al. 2020). Fuels treatments are of great interest because severe wildfire poses huge risks, including a greater risk to water supplies than other disturbance types (e.g., drought, insects, disease, or low severity fire) due to its complete removal of vegetation and likelihood of producing erosion and sedimentation (Sankey et al. 2017). By combining information from forestry, hydrology, and wildfire science, future applied research could lead to a decision support framework for practitioners who seek to meet specific forest and watershed management objectives.

Forest and watershed managers often seek to address multiple objectives such as reducing fuels to minimize the risk of future severe fire, thinning forests to increase snow retention and thus soil moisture, or thinning or harvesting forests to maximize snow retention in ways that lead to increased spring and summer streamflows. Knowledge on the pieces needed to answer these questions exists, but it has rarely been compiled and aggregated to address management questions for specific watersheds or project locations and may require refinement to achieve the specificity needed for such aggregation. While some research has investigated the tradeoffs between managing for water versus managing for resilient forests (e.g., Bart et al. 2020), the potential risk to water supplies posed by severe wildfire (Sankey et al. 2017) could be mitigated by careful planning with expertise from multiple disciplines. Meeting this need requires expertise from fire science regarding how to conduct fuels treatments that reduce the risk of future severe wildfire; from forestry regarding the types of silvicultural treatments that can meet fuels reduction objectives; and from hydrology regarding how the alternative silvicultural treatments are expected to affect snowpack, streamflow, or soil moisture.

Given the challenges inherent in each of these tasks, I recommend development of a decision-making framework for practitioners that combines vegetation management with hydrologic modeling and identifies the steps needed to simulate the impact of alternative silvicultural prescriptions on hydrologic processes and fluxes of interest. Specific steps might be to first delineate the project area. Second, identify the locations and vegetation targets for fuel reduction treatments. This step is recommended early in the process because strategically placed fuels treatments can mitigate the spread of future wildfires, e.g., by providing a fuel break that prevents an out-of-control wildfire from spreading to high-risk areas such as dense forest stands, developed areas, or critically important water supply catchments. Third, develop a handful of silvicultural prescriptions to meet the fuels treatment objectives. The feasibility of particular silvicultural treatment options may be determined in part by the strategic locations identified in the second step.

The number of options should be sufficiently small to allow efficient comparison in the next step. The last step is then hydrologic modeling to evaluate the effects of the alternative silvicultural practices on water resources objectives. For example, if the goal of watershed managers is to increase summer streamflow, this final step might evaluate summer streamflow explicitly as a result of snow accumulation and retention. Modeling results would then allow practitioners to select the best silvicultural prescription for meeting hydrologic objectives.

The decision support tool described here would include uncertainty and would obviously not guarantee project success. However, managers are already asking for such information. A structured decision support framework may help to address the ongoing problem of how to manage forests, mitigate wildfire risk, and protect water supplies in the future.

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Research Interests: Forest hydrology, forest dynamics, inventory and monitoring, surface hydrology, snow hydrology, geospatial information analysis and terrain analysis, ecological modeling, remote sensing applications to vegetation and hydrology, water resources planning and management, forest resources planning and management

EDUCATION

Doctor of Philosophy in Watershed Science/Hydrology, 2022; Utah State University, Logan

- Dissertation research focused on streamflow response to forest disturbance
- 18 semester credit hours in hydrology and statistics
- Extracurricular workshops included team science leadership and communication; CUAHSI master class in Snow Measurement Field School; CUAHSI master class in Advanced Techniques in Watershed Science

Master of Science in Forest Ecology –2003, Utah State University, Logan

- Thesis research focused on riparian vegetation, remote sensing-based vegetation classifications, and spatial modeling of vegetation dynamics
- 38 semester credit hours in Natural Resource disciplines

Bachelor of Science in Environmental Science – 1996, Utah State University, Logan

- Minor in Biology/Plant Science; Magna cum laude, Department & University Honors
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EMPLOYMENT HISTORY

Supervisory Biologist – USDA Forest Service, Rocky Mountain Research Station, Ogden, Utah, July 2020 – present

- Served as Deputy Program Manager for the Forest Inventory and Analysis Program
- Provided Program leadership, financial management, strategic scientific leadership, project management, and work environment leadership

Biological Scientist – USDA Forest Service, Rocky Mountain Research Station, Ogden, Utah, November 2010 – July 2020

- Conducted independent research using strategic forest inventory data
- Conducted tech transfer, capacity building, and outreach in multiple countries in support of the US Forest Service International Programs Office and multinational climate and carbon agreements

Ecologist – USDA Forest Service, Rocky Mountain Research Station, Ogden, Utah, March 2004 – November 2010

- Led small teams in remote field locations to survey forest vegetation

- Assessed and revised data collection and analysis protocols to meet resource needs

Research Associate – Fluvial Geomorphology Lab, Utah State University, Logan, Utah, December 2000 – March 2004

- Identified and conducted appropriate spatial and statistical analysis methods to study long-term trends in sediment deposits on the Green and Colorado Rivers
- Created and digitized maps of channel and floodplain topography from field data and air photos to quantify resource change over time

Biological Technician (Vegetation) – Denali National Park and Preserve, Denali Park, Alaska, May 2000 – November 2000

- Conducted a geospatial simulation to compare the efficacy of long-term vegetation monitoring regimes, and their ability to capture natural variation, at various spatial scales within Denali National Park and Preserve
- Used a variety of field techniques for sampling vegetation at remote field sites

Graduate Research Assistant and Teaching Assistant – Utah State University, Logan, September 1996-April 2000

- Classified historical air photos and Landsat imagery to produce vegetation maps and detect change over time
- Created spatially explicit models for predicting the distribution of the exotic species *Tamarix ramosissima* and the native species *Populus fremontii*
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US mentor, SilvaCarbon Women in Forest Carbon Initiative, September 2021-present. Served as US-based co-mentor, along with two co-mentors in the Democratic Republic of Congo (DRC), to two early-career mentees in DRC.

Reviewer for the following journals: Ecohydrology, Environmental Research Letters, Forest Ecology and Management, Forest Science, Forests, Hydrology and Earth System Sciences, Journal of Forestry, Proceedings of the National Academy of Sciences, Remote Sensing, Western North American Naturalist

Member of the following professional organizations: American Association for the Advancement of Science, American Geophysical Union, American Water Resources Association, International Association for Landscape Ecology, Society of American Foresters, Society for Conservation GIS

PUBLICATIONS

Peer-reviewed publications:

Goeking, S.A.; Windmuller-Campione, M.A. 2021. Comparative species assessments of five-needle pines throughout the western United States. Forest Ecology and Management 496: 119438.

Woodall, C.W.; Fraver, S.; Oswalt, S.N.; Goeking, S.A.; Domke, G.M.; Russell, M.B. 2021. Decadal dead wood biomass dynamics of coterminous US forests. Environmental Research Letters 16(10): 104034. 14 p. https://doi.org/10.1088/1748-9326/ac29e8.

Goeking, S.A.; Tarboton, D.G. 2020. Forests and water yield: A synthesis of disturbance effects on streamflow and snowpack in western coniferous forests. Journal of Forestry 118: 172-192.

Steed, J.E.; Goeking, S.A. 2020. Western larch regeneration responds more strongly to site and indirect climate factors than to direct climate factors. Forests. 11: 482.

Wurtzebach, Z.; DeRose, R.J.; Bush, R.R.; Goeking, S.A.; Healey, S.; Menlove, J.; Pelz, K.A.; Schultz, C.; Shaw, J.D.; Witt, C. 2019. Supporting National Forest System planning with Forest Inventory and Analysis data. Journal of Forestry. doi: 10.1093/jofore/fvz061.

Goeking, S.A.; Izlar, D.K. 2018. Pinus albicaulis Engelm. (whitebark pine) in mixed-species stands throughout its US range: Broad-scale indicators of extent and recent decline. Forests 9: 131.

Goeking, S.A.; Izlar, D.K.; Edwards, T.C. 2018. A landscape-level assessment of whitebark pine regeneration in the Rocky Mountains, USA. Forest Science 65: 87-99.

Zhao, F.; Healey, S.P.; Huang, C.; McCarter, J.B.; Garrard, C. Goeking, S.A.; Zhu, Z. 2018. Assessing the effects of fire disturbance and timber management on carbon storage in the

Greater Yellowstone Ecosystem. Environmental Management. doi: 10.1007/s00267-018-1073-y.

Shaw, J.D.; Goeking, S.A.; Menlove, J.; Werstak, C.E., Jr. 2017. Assessment of fire effects based on Forest Inventory and Analysis data and a long-term fire mapping data set. Journal of Forestry 115: 258-269.

Goeking, S.A. 2015. Disentangling forest change from forest inventory change: A case study from the U.S. Interior West. J. of Forestry 113: 475-483.

Technical reports and publications:

Wheeler, Kevin; Kuhn, Eric; Bruckerhoff, Lindsey; Udall, Brad; Wang, Jian; Gilbert, Lael; Goeking, Sara; Kasprak, Alan; Mihalevich, Bryce; Neilson, Bethany; Salehabadi, Homa; Schmidt, John C. 2021. Alternative management paradigms for the future of the Colorado and Green Rivers. The Future of the Colorado River Project, White Paper No. 6. Logan, UT: Utah State University, Quinney College of Natural Resources Center for Colorado River Studies. 132 p.

Salehabadi, H.; Tarboton, D.; Kuhn, E.; Udall, B.; Wheeler, K.; Rosenberg, D.; Goeking, S.; Schmidt, J.C. 2020. The future hydrology of the Colorado River Basin. The Future of the Colorado River Project, White Paper No. 4. Logan, UT: Utah State University, Quinney College of Natural Resources Center for Colorado River Studies. 71 p.

Espejo, A.; Federici, S.; Green, C.; Amuchastegui, N.; d'Annunzio, R.; Balzter, H.; Bholanath, P.; Brack, C.; Brewer, C.; Birigazzi, L.; Cabrera, E.; Carter, S.; Chand, N.; Donoghue, D.; Eggleston, S.; Fitzgerald, N.; Foody, G.; Galindo, G.; Goeking, S.; Grassi, G.; Held, A.; Herold, M.; Kleinn, C.; Kurz, W.; Lindquist, E.; McRoberts, R.; Mitchell, A.; Næsset, E.; Notman, E.; Quegan, S.; Rosenqvist, A.; Roxburgh, S.; Sannier, C.; Scott, C.; Stahl, G.; Stehman, S.; Tupua, V.; Watt, P.; Wilson, S.; Woodcock, C.; Wulder, M. 2020. Integration of remote-sensing and ground-based observations for estimation of emissions and removals of greenhouse gases in forests: Methods and guidance from the Global Forest Observations Initiative, Edition 3.0. Rome, Italy: U.N. Food and Agriculture Organization. 300 p.

Witt, C.; Shaw, J.D.; Menlove, J. ; Goeking, S.A.; DeRose, R.J.; Pelz, K.A.; Morgan, T.A.; Hayes, S.W. 2019. Montana s forest resources, 2006-2015. Resour. Bull. RMRS-RB-30. Fort Collins, CO: U.S. Department of Agriculture, Forest Service, Rocky Mountain Research Station. 102 p.

DeRose, R.J.; Shaw, J.D.; Goeking, S.A.; Marcille, K.; McIver, C.P.; Menlove, J.; Morgan, T.A.; Witt, C. 2018. Wyoming’s forest resources, 2011-2015. Resour. Bull. RMRS-RB-28. Fort Collins, CO: U.S. Department of Agriculture, Forest Service, Rocky Mountain Research Station. 132 p.

Shaw, J.D.; Menlove, J.; Witt, C. Morgan, T.A.; Amacher, M.C.; Goeking, S.A.; Werstak, C.E., Jr. 2018. Arizona’s forest resources, 2001-2014. Resour. Bull. RMRS-RB-25. Fort Collins, CO: U.S. Department of Agriculture, Forest Service, Rocky Mountain Research Station. 126 p.

Witt, C. DeRose, R.J.; Goeking, S.A.; Shaw, J.D. 2018. Idaho's forest resources, 2006-2015. Resour. Bull. RMRS-RB-29. Fort Collins, CO: U.S. Department of Agriculture, Forest Service, Rocky Mountain Research Station. 84 p.

Goeking, S.A.; Menlove, J. 2017. New Mexico's forest resources, 2008-2014. Resour. Bull. RMRS-RB-24. Fort Collins, CO: U.S. Department of Agriculture, Forest Service, Rocky Mountain Research Station. 68 p.

Thompson, M.T.; Shaw, J.D.; Witt, C. Werstak, C.E., Jr.; Amacher, M.C.; Goeking, S.A.; DeRose, R.J.; Morgan, T.A.; Sorenson, C.B.; Hayes, S.W.; Menlove, J.. 2017. Colorado's forest resources, 2004-2013. Resour. Bull. RMRS-RB-23. Fort Collins, CO: U.S. Department of Agriculture, Forest Service, Rocky Mountain Research Station. 136 p.

Toone, M.G.; Goeking, S. 2017. Application of rangeland health indicators on forested plots on the Fishlake National Forest, Utah. Res. Note RMRS-RN-76. Fort Collins, CO: U.S. Department of Agriculture, Forest Service, Rocky Mountain Research Station. 25 p.

Menlove, J.; Shaw, J.D.; Witt, C. Werstak, C.E., Jr.; DeRose, R.J.; Goeking, S.A.; Amacher, M.C.; Morgan, T.A.; Sorenson, C.B. 2016. Nevada's forest resources, 2004-2013. Resour. Bull. RMRS-RB-22. Fort Collins, CO: U.S. Department of Agriculture, Forest Service, Rocky Mountain Research Station. 167 p.

Werstak, C.E., Jr.; Shaw, J.D.; Goeking, S.A.; Witt, C. Menlove, J.; Thompson, M.T.; DeRose, R.J.; Amacher, M.C.; Jovan, S.; Morgan, T.A.; Sorenson, C.B.; Hayes, S.W.; McIver, C.P. 2016. Utah's forest resources, 2003-2012. Resour. Bull. RMRS-RB-20. Fort Collins, CO: U.S. Department of Agriculture, Forest Service, Rocky Mountain Research Station. 159 p.

Barbosa, P.; Herrera, F.; Goeking, S.; Nieto, V.; Pena, M.; Ortiz, S. 2014. Manual de control de calidad del Inventario Forestal Nacional (IFN) [Quality control manual of the National Forest Inventory (NFI)]. Bogota D.C., Colombia: IDEAM. 40 p.

Goeking, S.A.; Shaw, J.D.; Witt, C. Thompson, M.T.; Werstak, C.E., Jr.; Amacher, M.C.; Stuever, M.; Morgan, T.A.; Sorenson, C.B.; Hayes, S.W.; McIver, C.P. 2014. New Mexico's forest resources, 2008-2012. Resour. Bull. RMRS-RB-18. Fort Collins, CO: U.S. Department of Agriculture, Forest Service, Rocky Mountain Research Station, 144 p.

Goeking, S.A.; Patterson, P.L. 2013. Stratifying to reduce bias caused by high nonresponse rates: A case study from New Mexico's forest inventory. Res. Note RMRS-RN-59. Fort Collins, CO: U.S. Department of Agriculture, Forest Service, Rocky Mountain Research Station. 22 p.

Witt, C.; Shaw, J.D.; Thompson, M.T.; Goeking, S.A.; Menlove, J.; Amacher, M.C.; Morgan, T.A.; Werstak, Charles. 2012. Idaho's Forest Resources, 2004-2009. Resour. Bull. RMRS-RB-14. Fort Collins, CO: U.S. Department of Agriculture, Forest Service, Rocky Mountain Research Station. 134 p.

Schmidt, J.C.; Topping, D.J.; Rubin, D.M.; Hazel, J.E., Jr.; Kaplinski, M.; Wiele, S.M.; Goeking, S.A. 2007. Streamflow and sediment data collected to determine the effects of low summer steady flows and habitat maintenance flows in 2000 on the Colorado River between Lees Ferry and Bright Angel Creek, Arizona: U.S. Geological Survey Open-File Report 2007-1268, 79 p. [http://pubs.usgs.gov/of/2007/1268/].

Grams, P.E.; Schmidt, J.C.; Topping, D.J.; Goeking, S.A. 2004. The degraded reach: rate and pattern of bed and bank adjustment of the Colorado River in the 25 km immediately downstream from Glen Canyon Dam. Technical report to the USGS Grand Canyon Monitoring and Research Center, 111 p.

Goeking, S.A., 2003. Long-term dynamics of riparian vegetation, and their relation to hydrology and geomorphology, along the Green River in the Uintah Basin. Master's Thesis, Utah State University, Logan.

Goeking, S.A.; Schmidt, J.C.; Webb, M.K. 2003. Spatial and temporal trends in the size and number of backwaters between 1935 and 2000, Marble and Grand Canyons, Arizona. Technical report to USGS Grand Canyon Monitoring and Research Center, 15 p.

Schmidt, J. C.; Goeking, S.A.; Topping, D.J.; Rubin, D.; Lockwood, B.; Hazel, J.E.; Kaplinski, M.; Wiele, S.; Franseen, M. 2003. Stream flow and sediment data collected to determine the effects of low summer steady flows and habitat maintenance flows in 2000 on the Colorado River between Lees Ferry and Bright Angel Creek, Arizona. Technical report to the USGS Grand Canyon Monitoring and Research Center, 54 p.

Birchell, G.J.; Christopherson, K.; Crosby, C.; Crowl, T.A.; Gourley, J.; Townsend, M.; Goeking, S.; Modde, T.; Fuller, M.; Nelson, P. 2002. The levee removal project: assessment of floodplain habitat restoration in the middle Green River. Final report. Upper Colorado River Endangered Fish Recovery Program Project CAP-6-LR. Utah Division of Wildlife Resources, Salt Lake City. 257 pages + appendices.

Schmidt, J.C.; Topping, D.J.; Goeking, S.A.; Sondossi, H.; Hazel, J.E.; Grams, P.E. 2002. System-wide changes in the distribution of fine-grained alluvium in the Colorado River corridor between Lees Ferry and Bright Angel Creek, Arizona, 1980s to 2001. Technical report to the USGS Grand Canyon Monitoring and Research Center, 86 p.

Crowl, T.A.; Gourley, J.A.; Townsend, M.; Goeking, S.A. 2000. The Levee Removal Project, Technical Report to the USFWS Recovery Implementation Program for Endangered Fish Species in the Upper Colorado River Basin, Salt Lake City, Utah.

Conference proceedings papers:

Goeking, S.A.; Tarboton, D.G. 2020. An enhanced representation of forest cover for distributed hydrologic modeling based on forest inventory data. FIA Stakeholders Science Meeting, Knoxville, TN. November 2019.

Goeking, S.A.; Tarboton, D.G. 2019. A method for partitioning total leaf area index into overstory and understory strata for distributed hydrologic modeling based on forest inventory, remote sensing, and biophysical data. Joint 11th Federal Interagency

Sedimentation Conference and 6th Federal Interagency Hydrologic Modeling Conference, Reno, NV. June 2019.

Goeking, S.A.; Dooley, K.; Hayden, H.L.; Lambert, D.; Lister, A. 2017. Quality assurance in national forest inventories: Lessons learned from international partnerships. In: Healey, Sean P.; Berrett, Vicki M., comps. 2017. Doing more with the core: Proceedings of the 2017 Forest Inventory and Analysis (FIA) Science Stakeholder Meeting; 2017 October 24- 26; Park City, UT. Proc. RMRS-P-75. Fort Collins, CO: U.S. Department of Agriculture, Forest Service, Rocky Mountain Research Station. 56 p.

Goeking, S.A.; Izlar, D.K. 2015. Using landscape-level forest monitoring data to draw a representative picture of an iconic subalpine tree species. In: Stanton, S.M.; Christensen, G.A., comps. Pushing boundaries: new directions in inventory techniques and applications: Forest Inventory and Analysis (FIA) symposium 2015. 2015 December 8–10; Portland, Oregon. Gen. Tech. Rep. PNW-GTR-931. Portland, OR: U.S. Department of Agriculture, Forest Service, Pacific Northwest Research Station. Pp. 296-301.

Goeking, S.A.; Patterson, P.L. 2015. Redrawing the baseline: A method for adjusting biased historical forest estimates using a spatially and temporally representative plot network. In: Stanton, S.M.; Christensen, G.A., comps. Pushing boundaries: new directions in inventory techniques and applications: Forest Inventory and Analysis (FIA) symposium 2015. 2015 December 8–10; Portland, Oregon. Gen. Tech. Rep. PNW-GTR-931. Portland, OR: U.S. Department of Agriculture, Forest Service, Pacific Northwest Research Station. Pp. 228-232.

Goeking, S.; Izlar, D. 2014. Natural regeneration of whitebark pine: Factors affecting seedling density. The International Forestry Review. 16(5): 133. [Abstract]

Goeking, S.A. 2012. Trends in standing biomass in Interior West forests: Reassessing baseline data from periodic inventories. In: Morin, Randall S.; Liknes, Greg C., comps. Moving from status to trends: Forest Inventory and Analysis (FIA) symposium 2012; 2012 December 4-6; Baltimore, MD. Gen. Tech. Rep. NRS-P-105. Newtown Square, PA: U.S. Department of Agriculture, Forest Service, Northern Research Station. [CD-ROM]: 453-460.

Goeking, S.A.; Liknes, G.C. 2012. Is lodgepole pine mortality due to mountain pine beetle linked to the North American Monsoon? In: Morin, Randall S.; Liknes, Greg C., comps. Moving from status to trends: Forest Inventory and Analysis (FIA) symposium 2012; 2012 December 4-6; Baltimore, MD. Gen. Tech. Rep. NRS-P-105. Newtown Square, PA: U.S. Department of Agriculture, Forest Service, Northern Research Station. [CD-ROM]: 448-452.

Goeking, S.A.; Liknes, G.C.; Lindblom, E.; Chase, J.; Jacobs, D.M.; Benton, R. 2012. A GIS-based tool for estimating tree canopy cover on fixed-radius plots using high-resolution aerial imagery. In: Morin, Randall S.; Liknes, Greg C., comps. Moving from status to trends: Forest Inventory and Analysis (FIA) symposium 2012; 2012 December 4-6; Baltimore, MD. Gen. Tech. Rep. NRS-P-105. Newtown Square, PA: U.S. Department of Agriculture, Forest Service, Northern Research Station. [CD-ROM]: 237-241.

Liknes, G.C.; Woodall, C.W.; Walters, B.F.; Goeking, S.A. 2012. Unlocking the climate riddle in forested ecosystems. In: Morin, Randall S.; Liknes, Greg C., comps. Moving from status to trends: Forest Inventory and Analysis (FIA) symposium 2012; 2012 December 4-6; Baltimore, MD. Gen. Tech. Rep. NRS-P-105. Newtown Square, PA: U.S. Department of Agriculture, Forest Service, Northern Research Station. [CD-ROM]: 99-103.

Patterson, P.L.; Goeking, S.A. 2012. Estimators used in the New Mexico inventory: practical implications of "truly" random nonresponse within each stratum. In: Morin, Randall S.; Liknes, Greg C., comps. Moving from status to trends: Forest Inventory and Analysis (FIA) symposium 2012; 2012 December 4-6; Baltimore, MD. Gen. Tech. Rep. NRS-P-105. Newtown Square, PA: U.S. Department of Agriculture, Forest Service, Northern Research Station. [CD-ROM]: 330-333.

Goeking, S.A. 2012. Potential applications of prefield land use and canopy cover data: Examples from nonforest and nonsampled forest inventory plots. In: McWilliams, Will; Roesch, Francis A. (eds.), Monitoring Across Borders: 2010 Joint Meeting of the Forest Inventory and Analysis (FIA) Symposium and the Southern Mensurationists. e-Gen. Tech. Rep. SRS-157. Asheville, NC: U.S. Department of Agriculture Forest Service, Southern Research Station. 299 p.

Goeking, S.A.; Liknes, G.C. 2009. The role of pre-field operations at four forest inventory units: We can see the trees, not just the forest. In: McWilliams, Will; Moisen, Gretchen; Czaplewski, Ray, comps. Forest Inventory and Analysis (FIA) Symposium 2008; October 21-23, 2008; Park City, UT. Proc. RMRS-P-56CD. Fort Collins, CO: U.S. Department of Agriculture, Forest Service, Rocky Mountain Research Station. 12 p.

Kaplinski M.; Hazel, J.; Manone, M.; Parnell R.; Schmidt, J.C.; Goeking, S.; Topping, D.J.; Rubin, D.; Melis, T.S. 2003. A fistful of sand: Monitoring the fate of fine-grained sediment in the Colorado River, Grand Canyon, Arizona. Geological Society of America Abstracts with Programs, v. 35, n. 6, p. 314. [Abstract]

Goeking, S.A.; Sondossi, H.; Schmidt, J.C.; Grams, P.E. 2001. Quantification of long-term trends in sand storage at site-specific and reach scales in Grand Canyon National Park. Poster presentation to the Annual Meeting of the American Geophysical Union, San Francisco, CA. [Abstract]

MacDonald, T.; Roland, C.; Fried, J.; Goeking, S.; Oakley, K. 2001. Simulation of long-term monitoring sample designs in Denali National Park, in D. Harmon, ed., Crossing Boundaries in Park Management: Proceedings of the 11th Conference on Research and Resource Management in Park and on Public Lands. George Wright Society, Inc.

Sondossi, H.A., J.C. Schmidt, J.E. Hazel, and S.A. Goeking, 2001. Methods of using detailed, small-scale data to calibrate reach-scale GIS data in order to detect changes caused by individual floods in a debris fan-dominated river. Poster presentation to the Annual Meeting of the American Geophysical Union, San Francisco, CA. [Abstract]

PRESENTATIONS

Workshops (including planning, facilitation, and individual presentations):

Quality assurance for national forest inventories. March 2021. Four-hour workshop presented to the national forest inventory team of Mexico. Virtual.

Use of Global Navigation Satellite Systems (GNSS). April 2017. Two-day workshop on GNSS use for documentation of forest degradation and illegal logging. Danang Province, Viet Nam.

Quality assurance for Colombia's national forest inventory. July 2016. Two-week workshop combining classroom sessions, field data collection, analysis, and protocol revision. Bogotá, Colombia, and Chicaque Natural Park, Colombia.

Cameroon national forest monitoring system design workshop #2. June 2015. One-week workshop to validate definitions of land use classes and parameters to be used in Cameroon's national forest monitoring system. Yaoundé, Cameroon.

Cameroon national forest monitoring system design workshop #1. March 2015. One-week workshop to facilitate feedback from Cameroonian REDD+ Secretariat, Cameroonian technical experts, multinational partners (FAO, GIZ, JICA, and others), and civil society to identify the primary objective and sub-objectives of Cameroon's national forest monitoring system. Doula and Yaoundé, Cameroon.

Implementation of Colombia's national forest inventory. October-December 2014. Two-month workshop to develop national forest inventory documentation: Sample design, plot configuration, quality control, and socialization. Bogotá, Colombia.

Chaired conference sessions:

Linking forest disturbance and forest dynamics to water quantity and quality. November 2019. Forest Inventory & Analysis Science Stakeholders Meeting. Knoxville, TN.

National forest inventories: Globally unique challenges. October 2017. Forest Inventory & Analysis Science Stakeholders Meeting. Park City, UT.

Invited presentations:

Goeking, S.A.; Windmuller-Campion, M. 2021. Comparative species assessments of five-needle pines throughout the western United States. The H5II Conference: The Second Conference on the Research and Management of High Elevation Five Needle Pines (virtual). September 2021.

Goeking, S.A. 2021. Overview of the Data Component of the Global Forest Observations Initiative. GFOI Plenary (virtual). September 2021.

Goeking, S.A.; Tarboton, D.G. 2021. Streamflow response to forest disturbance in the western US over the past two decades. American Water Resources Association Summer Conference: Connecting Land & Water for Healthy Communities. July 2021.

Goeking, S.A.; Tarboton, D.G. 2020. Links between disturbance, snowpack, and streamflow in western coniferous forests. Presentation to Wildland Resources Departmental Seminar, Utah State University, Logan, UT. September 2020.

Goeking, S.A. 2019. Whitebark pine status in northwestern Montana and the Pacific Northwest. Whitebark Pine Ecosystem Foundation meeting, Pablo, MT. September 2019.

Goeking, S.A.; Tarboton, D.G. 2019. Forests and water yield: A synthesis of recent disturbance effects on snowpack and streamflow in western coniferous forests. Intermountain Society of American Foresters Spring Meeting, Logan, UT. March 2019.

Goeking, S.A.; Tarboton, D.G. 2018. Forests and water: A synthesis of recent effects of forest disturbance on water yield in the West. Restoring the West conference, Logan, UT. October 2018.

Goeking, S.A.; Izlar, D.K.; Edwards, T.C. 2018. Whitebark pine in mixed-species stands throughout the western US: Broad-scale indicators of extent, regeneration and recent decline. Whitebark Pine Ecosystem Foundation meeting, Stanley, ID. September 2018.

DeRose, R.J.; Goeking, S.A. 2016. Applications of the Forest Inventory and Analysis Program. Invited presentation to the Broader-Scale Monitoring Workshop, Laramie, Wyoming. May 2016.

Goeking, S.A. 2016. Applications of the Forest Inventory and Analysis Program. Invited presentation to National Forest Systems Region 4 Silviculturists' meeting, Ogden, Utah. March 2016.

Goeking, S.A.; Izlar, D.K. 2015. Using landscape-level forest monitoring data to draw a representative picture of an iconic subalpine tree species. Invited presentation to National Forest Systems Region 1 webinar series. February 2016.

Goeking, S.A.; Shaw, J.D. 2016. Interdisciplinary applications of the Forest Inventory and Analysis Program. Dept. of Wildland Resources weekly seminar, Utah State University, Logan, Utah. January 2016.

Goeking, S.A.; Shaw, J.D.; Menlove, J.; Werstak, C.E., Jr. 2015. Insights into fire severity and post-fire recovery from an integrated analysis of forest inventory data and long-term fire mapping datasets. Restoring the West conference, October 29, 2015, Utah State University, Logan, UT. [https://www.youtube.com/watch?v=Te96fG_PC7Y]

Goeking, S.A. 2011. Regional trends in standing forest biomass. Restoring The West conference, Logan, Utah. October 19, 2011.

Contributed presentations and posters (with no published proceedings):

Goeking, S.A.; Windmuller-Campione, M. 2021. Broad-scale assessments of five-needle white pines in the western US using forest inventory data. Society of American Foresters Convention (virtual). November 2021.

Goeking, S.A.; Bakken, J.L.; Dodson, E.K.; Downey, C.; Blackard, J.A.; Menlove, J. 2021. Delineating within-plot cover types on fixed-area forest monitoring plots: Does it affect estimates and precision of land area by cover type? International Association for Landscape Ecology Annual Meeting. April 2021.

Goeking, S.A.; Tarboton, D.G. 2021. Assessing annual streamflow response to forest disturbance in the western US: A large-sample hydrology approach. European Geophysical Union General Assembly. April 2021.

Goeking, S.A.; Tarboton, D.G. 2020. Large-sample forest hydrology: Forest Inventory & Analysis data adds value to broad-scale hydrology datasets. Society of American Foresters Convention (virtual). October 2020.

Goeking, S.A. (moderator). 2019 Partnerships in national forest inventories: Benefits, challenges, and characteristics. A Panel of International Invited Speakers. FIA Stakeholders Science Meeting, Knoxville, TN. November 2019.

Goeking, S.A.; Tarboton, D.G. 2019. Forests and water yield: A review of recent disturbance effects on streamflow and snowpack in western forests. FIA Stakeholders Science Meeting, Knoxville, TN. November 2019.

Goeking, S.A.; Tarboton, D.G. 2019. Forests and water yield: A review of recent disturbance effects on streamflow and snowpack in western forests. Society of American Foresters Convention, Louisville, KY. November 2019.

Goeking, S.A.; Burgess, W.; Morrone, J.; Narduzzi, J.; Simons, R.; Frescino, T.; Menlove, J.; Snyder, M. 2019. Development of FIA 101: A training module for FIA staff and aspiring FIA data users. FIA Stakeholders Science Meeting, Knoxville, TN. November 2019.

Goeking, S.A. 2019. Moderated panel discussion of partnerships as part of session "Global view of national forest inventories (NFIs): how they have progressed, ways they have utilized partnerships, and possibilities for the future." FIA Stakeholders Science Meeting, Knoxville, TN. November 2019.

Goeking, S.A.; Tarboton, D.G. 2019. Forests and water yield: A synthesis of recent disturbance effects on snowpack and streamflow in western coniferous forests. Society of American Foresters Convention, Louisville, KY. October 2019.

Goeking, S.A.; Tarboton, D.G. 2019. Hydrologic impacts of forest disturbance: New and improved data inputs. Society for Conservation GIS conference, Pacific Grove, CA. July 2019.

Goeking, S.A.; Tarboton, D.G. 2018. An enhanced representation of forest cover for distributed hydrologic modeling. American Geophysical Union, Washington, DC. December 2018.

Goeking, S.A.; Tarboton, D.G. 2018. An enhanced representation of forest cover for distributed hydrologic modeling. CUAHSI Biennial Colloquium, Shepherdstown, WV. August 2018.

Goeking, S.A. 2017. Revisiting classic watershed experiments after recent tree mortality: Does disturbance increase streamflow? Society of American Foresters Convention, Albuquerque, NM. November 2017.

Goeking, S.A. 2017. Forests and watershed values: Expanding FIA data to quantitative water resources planning. FIA Science Stakeholder Meeting, Park City, Utah. October 2017.

Goeking, S.A.; Izlar, D.K. 2016. A landscape-level assessment of whitebark pine regeneration, growth, and mortality in mixed-species stands. Society of American Foresters Convention, Madison, WI. November 2016.

Goeking, S.A.; Stam, C.; Goetz, W.; Liknes, G.C.; Meneguzzo, D.; Finco, M. 2016. A hydrology-dependent method for delineating riparian areas. Society for Conservation GIS conference, Pacific Grove, CA. July 2016.

Pelz, K.A.; Goeking, S.; DeRose, R.J. 2016. Variability in piñon-juniper woodlands across the interior West: What can we learn from broad-scale datasets to improve restoration outcomes? Poster presentation at Sagebrush Ecosystem Conservation: All lands, all hands Conference, February 23-25, 2016, Salt Lake City, UT.

Goeking, S.A. 2015. A regression-modeling approach for aligning temporally inconsistent forest inventory estimates. Society of American Foresters Convention, Baton Rouge, LA. November 2015.

Goeking, S.A.; Izlar, D.K. 2015. Biophysical characterization of an iconic pine from landscape-level forest monitoring data. Society of Conservation GIS, Pacific Grove, CA. July 2015.

Goeking, S.A. 2014. Disentangling real change from changing methods: Trends from the Interior West's forest inventories. Society of American Foresters Convention and International Union of Forest Research Organizations, Salt Lake City, Utah. October 2014.

Goeking, S.A.; Izlar, K.D. 2013. Natural regeneration of whitebark pine: Factors affecting seedling density across Idaho, Montana, and Wyoming. Restoring the West conference, Logan, Utah. October 2013.

Goeking, S.A.; Liknes, G.C. 2013. Linking precipitation and temperature with forest inventory data. ESRI Southwest Users Group meeting, Salt Lake City, Utah. November 2013.

Patterson, P.; Goeking, S. 2013. Estimators used in the New Mexico inventory: practical implications of "truly" random nonresponse within each stratum. Joint Statistical Meetings, Montreal.

Goeking, S.A.; Liknes, G.C. 2012. Is lodgepole pine mortality due to mountain pine beetle linked to the North American Monsoon? In: Morin, Randall S.; Liknes, Greg C., comps. Moving from status to trends: Forest Inventory and Analysis (FIA) symposium 2012; 2012 December 4-6; Baltimore, MD. Gen. Tech. Rep. NRS-P-105. Newtown Square, PA: U.S. Department of Agriculture, Forest Service, Northern Research Station. [CD-ROM]: 448-452.

Goeking, S.A. 2012. Trends in standing biomass in Interior West forests: Reassessing baseline data from periodic inventories. In: Morin, Randall S.; Liknes, Greg C., comps. Moving from status to trends: Forest Inventory and Analysis (FIA) symposium 2012; 2012 December 4-6; Baltimore, MD. Gen. Tech. Rep. NRS-P-105. Newtown Square, PA: U.S. Department of Agriculture, Forest Service, Northern Research Station. [CD-ROM]:

Goeking, S.A.; Deblander, L.; Bakken, J.L.; Toombs, J. 2008. Expanding forest inventories: A comparison of traditional methods of remotely estimating woody crown cover. Presentation to the Twelfth Annual USDA Forest Service Remote Sensing Applications Conference, Salt Lake City, Utah.

Sondossi, H.A.; Schmidt, J.C.; Hazel J.E.; Goeking, S.A. 2001. Methods of Using Detailed, Small-Scale Data to Calibrate Reach-Scale GIS Data in Order to Detect Changes Caused by Individual Floods in a Debris Fan-Dominated River. Poster presentation to the Annual Meeting of the American Geophysical Union, San Francisco, CA.

Goeking, S.A.; Roland, C.; Paynter, J. 2000. Comparison of Six Spatial Scales of Long-term Vegetation Monitoring Among Biophysically Diverse Environments: A Modeling Approach. Poster presentation to the Denali Long-Term Ecological Monitoring conference, Fairbanks, AK.

Goeking, S.; Crowl, T.A.; Stone, K.; Roberts, D.R. 1996. Remote classification methods for riparian vegetation in Ouray National Wildlife Refuge. Oral presentation to the Annual Meeting of the Desert Fishes Council, La Paz, Mexico.

SKILLS

Software: Spatial data analysis software, including ArcGIS/ArcPro/ESRI, QGIS, Google Earth Engine, and ERDAS; relational databases in MS Access and PL/SQL Developer

Programming: R statistical analysis software; OpenGRADS software for analyzing gridded climate datasets; SAS Institute software for statistical analysis and dataset management; SQL queries for Oracle databases

Field techniques:

- Vegetation sampling methods, including quadrats, transects, ocular cover estimates, voucher collections, and standard forestry measurements
- Snowpack measurements, including density, depth, snow water equivalent, and components of radiation that affect snowpack

- Physical stream surveys, including measurement of stream discharge, cross-sectional surveys, longitudinal profiles, and sediment transport using drift nets and Helley-Smith samplers
- Sampling of stream biota using snorkel counts, Surber samplers, drift nets, and minnow traps

Backcountry field skills:

- Ability to locate research plots using map, compass, air photo, and/or GPS
- Experience rowing 12’-16’ inflatable rafts in class 3-4 whitewater in remote areas
- Wilderness First Aid certification and specialized (Level 2) avalanche training
- Experience with potentially hazardous wildlife encounters and hazard mitigation
- Experience planning and executing logistics for large expeditions on foot, boat, horse, and skis