# Novel remote sensing approaches for monitoring seasonal and ephemeral water resources

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Micah Russell

Major Professor: Jan Eitel, Ph.D.
Committee Members: Lee Vierling, Ph.D.; Timothy Link, Ph.D.; Tracey Johnson, Ph.D.
Department Administrator: Timothy Link, Ph.D.

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## Authorization to Submit Dissertation

This dissertation of Micah Russell, submitted for the degree of Doctor of Philosophy with a Major in Water Resources and titled "Novel remote sensing approaches for monitoring seasonal and ephemeral water resources" has been reviewed in final form. Permission, as indicated by the signatures and dates below, is now granted to submit final copies to the College of Graduate Studies for approval.

Major Professor: ________________________________ Date: ____________
Jan Eitel, Ph.D.

Committee Members: ________________________________ Date: ____________
Lee Vierling, Ph.D.

________________________________ Date: ____________
Timothy Link, Ph.D.

________________________________ Date: ____________
Tracey Johnson, Ph.D.

Department
Administrator: ________________________________ Date: ____________
Timothy Link, Ph.D.

# Abstract

Seasonal and ephemeral surface water resources are essential to human consumptive uses and the nourishment of aquatic habitats, but they are increasingly threatened by climate-change related impacts. Western North America, for example, has already experienced significant declines in seasonal snow cover, which will have a range of effects on both human communities and aquatic ecosystems like wetlands. The swift rate of change requires consistent monitoring at scales that support adaptive management, but seasonal-ephemeral water resources are often distributed across vast areas that are poorly instrumented. As such, remote sensing is increasingly employed to monitor freshwater resources and understand hydrological processes. This dissertation investigates the application of novel remote sensing approaches to important questions involving the monitoring of seasonal snow supplies and snow-dependent, ephemeral wetlands. Also included is a study examining the socio-ecological context for climate change research and adaptation in the headwaters regions of a large watershed. The first research chapter explores the potential of using terrestrial laser scanning (TLS) for the estimation of intercepted snow masses on trees. The findings indicate good agreement ($R^2$ = 0.69, RMSE = 0.91 kg) between TLS estimates of snow mass and measurements made on trees suspended from load cells. With further refinement, this approach may prove to be a useful tool in calibrating snow interception models to different forest types. The second research chapter utilizes this new technique to fit a Random Forest model that predicts snow interception volume from a suite of canopy metrics derived from aerial laser scanning (ALS). The findings demonstrate good agreement ($R^2$ = 0.65, RMSE = 0.52 $m^3$) between observations and model predictions and identified the best suite of predictors. This suggests that metrics capturing the intrinsic, three-dimensional variability of tree canopies may be useful as new parameters in hydrological or snow interception models. The third research chapter analyzes a thirty-year time series of satellite imagery to identify trends in ephemeral wetland (playa) inundation, with the goal of informing land management practices and wetland restoration planning. The findings indicate that localized weather conditions and hydrologic modification history are important drivers of playa inundation, that reductions in habitat availability and inundation duration should be expected with intensifying droughts, and that a small number of playa have the potential to function as hydrologic refugia during drought years. The fourth research chapter analyzed the spatial and topical distribution of climate change research in the headwaters of the Columbia River Basin. The findings identify broad patterns in a large body of research, such as gaps in interdisciplinary and geographic collaboration, and suggest future directions for understanding climate change across the region. All told, this set of studies adds to the body of knowledge on remote sensing for seasonal-ephemeral water resources, as well as applications for water resources research and management.

## Acknowledgements

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This dissertation is indebted in part to the preparers of publicly available data, including the SNOTEL network, the Global Surface Water Explorer, and the WestWide Drought Tracker. I am grateful to have received funding from the National Science Foundation's Integrative Graduate Education and Research Traineeship (IGERT) program, the National Aeronautics and Space Administration Earth and Space Science Fellowship (NESSF) program, and the Curt Berklund Graduate Research Scholar Award. These sources of financial support have provided me with the freedom to determine my own research agenda and pushed me to develop quality multidisciplinary research with real-world applications.

## Dedication

This achievement is dedicated to my wife, Danielle Deschler. I would not have reached this milestone without her unwavering encouragement and support.

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## Statement of Contribution

The Introduction (Chapter 1) and Conclusion (Chapter 6) are sole-authored. In Chapters 2-3, the coauthors listed primarily acted in advisory roles. In Chapter 4, Dr. Jennifer Cartwright and myself contributed equally to the work, with the additional coauthors serving advisory roles. Chapter 5 is a collaborative project led by Dr. Adrienne Marshall. I participated as a coauthor in development of the conceptual framework for Chapter 5, as well as research activities and manuscript writing.

# Chapter 1: Introduction

Seasonal and ephemeral surface water resources are essential to human consumption and the nourishment of aquatic habitats. Roughly 1/6 of the world's population relies on water supplies derived from seasonal snow cover for agricultural, industrial and municipal use (Barnett et al., 2005). These uses are frequently in competition with water needed to sustain aquatic habitats like wetlands, which themselves supply a host of ecosystem services – everything from flood control to groundwater replenishment to conservation of biodiversity (Turner et al., 2008). Ephemeral and/or geographically isolated wetlands (GIWs) are particularly threatened, as they sometimes receive less protections and study (Golden et al., 2017). In addition, both the water supply (snow) and the snow-dependent systems (many GIWs) may be threatened by climate-change related impacts (Golden et al., 2017; Viviroli et al., 2011). Western North America, for example, has already experienced a 15-30% decline in snowpack since the middle of the 20th century, which will have a range of effects on both human uses and aquatic ecosystems (Mote et al., 2018).

These concerns, and the swift rate of change, necessitate vigilant monitoring of water resources and aquatic ecosystems at appropriate scales so as to inform adaptive management (Georgakakos et al., 2012). Seasonal-ephemeral water resources are often distributed across vast areas that are poorly instrumented with ground-based sensors. In response to this challenge, remote sensing approaches that employ aerial or space-based sensors are increasingly utilized to monitor freshwater resources and understand hydrological processes (e.g., Casenave et al., 2016; Pekel et al., 2017). Chapters 2-4 of this dissertation explore the application of remote sensing techniques to important questions surrounding seasonal-ephemeral water resources.

More specifically, Chapters 2 and 3 address novel methods for estimating canopy-intercepted snow, an ephemeral phenomenon that influences a seasonal resource. The structural characteristics and spatial arrangement of forests exert a significant control on the variability of accumulated snow (Varhola et al., 2009). Intercepted snow, for example, can account for up to 60% of total annual snowfall (Montesi et al., 2003; Storck et al, 2002), with subsequent wind-driven sublimation rates as high as 50% (Essery and Pomeroy, 2001; Hedstrom and Pomeroy, 1998). Partitioning snow interception from snow fall in hydrological models is therefore important, but most models rely on two, indirect metrics of forest character called Leaf Area Index (LAI) and Canopy Closure (CC) (Essery et al., 2009; Rutter et al., 2009). This is due, in part, to the fact that actual measurements of snow interception have only been produced by intensive, plot-scale experiments (e.g., Hedstrom and Pomeroy, 1998; Martin et al., 2013; Storck et al., 2002). Metrics like LAI and CC, however, do not capture the three-dimensional complexity of forests that influences snow interception potential and efficiency (Kobayashi 1987; Pfister and Schneebeli 1999). Chapter 2 details an alternative approach to plot-scale experiments in which I experimentally assess the potential of using terrestrial laser scanning (TLS) for the direct, visual estimation of intercepted snow masses on trees. In Chapter 3, we utilize this new technique to fit a Random Forest model that predicts snow interception from a suite of canopy metrics derived from aerial laser scanning (ALS). The results from this work provide novel avenues for improving snow interception estimates across larger areas.

Chapter 4 shifts from seasonal water supplies to a seasonal-ephemeral wetland ecosystem. Playas of the northern Great Basin, USA, fill with snowmelt in the spring, providing critical habitat to local and migrating wildlife, before drying out in summer and fall (Rosen, 1994). The hydro-ecological integrity of playas, however, may be degraded by drought intensification brought on by regional climate change (Ahmadalipour et al. 2017), as well as previous land use practices that prioritized livestock watering (Moffitt et al. 2019). To inform playa restoration planning, I used a thirty-year time series of satellite imagery to do the following: identify the drivers of playa inundation, project how intensifying droughts will affect habitat availability, identify any playas that act as hydrologic refugia during droughts, and determine the role of historical alterations to playa in the distribution of potential refugia. The results from this work can help to inform efforts to restore wetland functions and conserve habitats as climate conditions change.

Finally, monitoring and managing water resources requires collaboration across disciplines, institutions, and geopolitical boundaries. Such collaborations benefit from interdisciplinary science that synthesizes knowledge of the hydrological and socioecological impacts of climate change (Hulme 2010; Petticrew and McCartney, 2011). In the interdisciplinary Chapter 5, I was a coauthor on a project to characterize the spatial and topical distributions of climate change research in the headwaters of the Columbia River Basin (CRB). The CRB is an example of a large, transboundary river basin with complex human histories, and a dependency on seasonal snowmelt to maintain water supplies and ecosystem function (Mankin et al., 2015). We sought to map what science has been done, and where, in the CRB headwaters, and to what degree this science examines climate change impacts versus adaptation/mitigation. Our ultimate goal was to identify potential research gaps and suggest future directions for understanding climate change across the region.

Chapters 2-4 address utilizing new remote sensing approaches to meet the challenges of monitoring specific seasonal and ephemeral water resources, resources that are expected to be affected by climate change, while Chapter 5 examines the broader academic and socioecological context of climate change-related research across the region. All told, these studies will contribute knowledge and approaches to better manage and conserve seasonal and ephemeral surface water resources.

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# Chapter 2:
# Toward a novel laser-based approach for estimating snow interception

**Authors:** Micah Russell, Jan U.H. Eitel, Andrew J. Maguire, and Timothy E. Link

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## Abstract

Forests reduce snow accumulation on the ground through canopy interception and subsequent evaporative losses. To understand snow interception and associated hydrological processes, studies have typically relied on resource-intensive point scale measurements derived from weighed trees or indirect measurements that compared snow accumulation between forested sites and nearby clearings. Weighed trees are limited to small or medium sized trees and indirect comparisons can be confounded by wind redistribution of snow, branch unloading, and clearing size. A potential alternative method could use terrestrial lidar (light detection and ranging) because three-dimensional lidar point clouds can be generated for any size tree and can be utilized to calculate volume of the intercepted snow. The primary objective of this study was to provide a feasibility assessment for estimating snow interception volume with terrestrial laser scanning (TLS), providing information on challenges and opportunities for future research. During the winters of 2017 and 2018, intercepted snow masses were continuously measured for two model trees suspended from load-cells. Simultaneously, autonomous terrestrial lidar scanning (ATLS) was used to develop volumetric estimates of intercepted snow. Multiplying ATLS volume estimates by snow density estimates (derived from empirical models based on air temperature) enabled comparison of predicted vs. measured snow mass. Results indicate agreement between predicted and measured values ($R^2 \geq 0.69$, RMSE $\geq$ 0.91 kg, slope $\geq$ 0.97, intercept $\geq$ -1.39) when multiplying TLS snow interception volume with a constant snow density estimate. These results suggest that TLS might be a viable alternative to traditional approaches for mapping snow interception, potentially useful for estimating snow loads on large trees, collecting data in difficult to access terrain, and calibrating snow interception models to new forest types around the globe.

## Introduction

The hydrology of snow dominated forests is controlled by interactions of mass and energy fluxes between snow and forest structural elements. As forest cover increases, snow accumulation on the ground is typically reduced because of canopy snowfall interception and subsequent sublimation, which can account for as much as 60% of the cumulative snowfall depending on forest type, duration of snow storage in the canopy, and seasonal hydrometeorological conditions (Hedstrom and Pomeroy, 1998; Molotch et al., 2007). The sensitive connection between forest structure and snow interception therefore has important implications for the hydrology in any region around the globe where the major proportion of total water input comes from snow. Understanding this relationship is increasingly important with widespread observed and projected shifts from snow to rain (Klos et al., 2014), changes in the frequency of winter rain-on-snow events (Floyd and Weiler, 2008; Musselman et al., 2018), and changes in forest vegetation due to fire (Westerling, 2016), drought (Allen et al., 2010), insects (Bent et al., 2010; Frank et al., 2019) and other disturbance processes that might be altered by a changing climate and/or forest management.

While the importance of snow interception has long been acknowledged, it is also difficult to measure, map, and model. Direct measurement has typically been limited to resource-intensive point measurements derived from weighed trees, which are generally limited to small or medium trees (Hedstrom and Pomeroy, 1998; Knowles et al., 2006; Storck et al., 2002; Suzuki and Nakai, 2008) or tree branches (Brundl et al., 1999; Schmidt and Gluns, 1991). Indirect measurements have compared snow accumulation between forested sites and nearby clearings. Although indirect measurements have advantages (e.g. estimating spatial variance), the accuracy has long been questioned (e.g., Miller, 1964) and the measurements can be confounded by wind redistribution of snow, branch unloading, and reference site size (Moeser et al., 2015).

A potential novel method could use terrestrial lidar (TLS) because three-dimensional lidar point clouds, based on the laser return-time/distance relationship, can be generated for any size tree. The point clouds can be transformed into a convex hull with a polyhedral surface approximating the shape of the tree, from which volumes can be calculated (Edelsbrunner and Mucke, 1994; Lafarge et al., 2014; Pateiro-Lopez and Rodriguez-Casal, 2010). Intercepted snow volume can be estimated by subtracting snow-free tree volume from snow-on tree volume. This volume can be converted to snow mass by multiplying by fresh snow density, an important variable in snow interception processes [Hedstrom and Pomeroy, 1998; Judson and Doesken, 2000; Ryan et al., 2008a, 2008b]. Furthermore, novel autonomous terrestrial laser scanning (ATLS) systems (Eitel et al., 2013) could enable time-series characterization of seasonal dynamics associated with snow interception with minimal fieldwork and maintenance, as well as the flexibility to relocate the experiment to different forest types -- thereby overcoming some of the limitations of previous studies. Ultimately, TLS based snow interception may have a number of advantages over traditional methods, including: spatially explicit estimation of snow interception for different aspects or portions of tree canopies, data collection in difficult to access terrain (Adams et al., 2014) known to be important contributors to water budgets (Buhler et al., 2016; Hood and Hayashi, 2010) and providing time-efficient data for calibration of emerging aerial lidar (ALS)-based snow interception models to specific forest types (Deems et al., 2013; Moeser et al., 2016; Painter et al., 2016).

The objective of this study was to test the feasibility of using ATLS to estimate intercepted snow volume. In doing so, this study provides a preliminary feasibility assessment for estimating snow interception volume solely using terrestrial laser scanning, providing information on challenges and opportunities for future research.

## Methods and Materials

### *Study site*

Two artificial model hanging trees measuring 1.83 meters (m) in height and weighing 1.65 kg each (hereafter referred to “left tree” and “right tree” - see Figure 2.1) were installed prior to winter 2017 following established approaches outlined in Hedstrom and Pomeroy, 1998. The trees were off-the-shelf, bilaterally-symmetrical Christmas trees. The trees had 25 flexible limbs, multiple needle-types, and did not represent a specific species. The trees had an approximate leaf area index (LAI) of 5.15. LAI was estimated from ATLS point clouds using the LeafR R package (Almeida et al., 2019). Artificial trees were utilized to avoid desiccation and interception estimates that may be affected by progressive needle drop, in addition to minimizing field work and maintenance. The limbs (metal and plastic) were not analyzed for comparability to live wood elasticity. The trees were installed at the University of Idaho McCall Field Campus (44.9353472°, -116.0820167°) in the mountains of west-central Idaho, which receives an average of 3.4 m total snow fall (maximum 1.9 m snowpack depth) and 0.7 m total precipitation per year at 1528 m elevation (Western Regional Climate Center, 2016).

### *Field measurements*

Load cells measured strain gauge output (mV/V), an electrical signal which is proportional to the applied excitation voltage, from the hanging trees in one-minute intervals. The load cells were designed to maintain accuracy (within 0.03 mV/V) with temperatures as cold as -18°C and were shielded to prevent accumulation of snow and ice. Mean temperature during an ATLS scan was only below -18°C on one occasion (-20.6°C), which would have affected the maximum deviation of the calibration curve (a straight line drawn between minimum and maximum output) by no more than 0.0054% according to product specifications. Known masses were hung from the load cells to verify measurement accuracy and to develop a calibration equation (mass = 30.18 * mV/V – 4.6917) which converted strain gauge output to kg. The originating mass of a snow-free tree at the beginning of each winter was subtracted from subsequent measurements to calculate snow masses for each scan.

An ATLS scanned one side of the trees at a distance of 6.2 m and produced two high resolution point clouds per day (1.12 cm spot size and 0.20 cm point spacing at 10 m) (Figure 2.1b). The ATLS employs a rugged time-of-flight laser rangefinder (optoNCDT ILR 1191 with 905 nm near infrared laser and 1.7 mrad beam divergence; Micro-Epsilon Messtechnik GmbH & Co. KG, Ortenburg, Germany) designed for harsh environments (see Eitel et al., 2013 for more detail). The ATLS completed one scan in 13 hours.

Assuming each tree canopy to be bilaterally symmetrical and circular in shape, and given a known canopy diameter, distance from scanner to canopy perimeter, and location of the ATLS, trigonometric calculations yielded 47.7% of the tree canopy perimeter viewable by the ATLS. Rounded to 50% for the analyses, snow masses obtained from the load cells were therefore divided by two and averaged across each ATLS scan duration to allow for comparison with ATLS data.

*Lidar volume estimates*

The ATLS point clouds were transformed into convex hull structures approximating the shape and volume of the scanned trees using the “ashape3d” function in the alphashape3d R package (Lafarge et al., 2014). The convex hull is fitted with Delauney Triangulation (drawing triangles between points so that there is no overlap between triangles). The convexity parameter ($\alpha$) is selected by the user, corresponding to data resolution and units of the input data (Edelsbrunner and Mucke, 1994; Lafarge et al., 2014). A convexity parameter of 1 corresponds to the convex hull; as $\alpha$ approaches zero, triangle borders are deleted to yield a better fitting, flexible, and concave hull that captures more structural detail. In this case, the TLS data resolution (2.44 cm) is the sum of the spot size (1.12 cm x 2 points) and the point spacing (0.2 cm). This value was rounded to 2.5 cm (i.e., $\alpha$ = 0.025 m) for construction of all “snow-on” convex hulls. The “volume_ashape3d” function was then used to calculate volumes ($m^3$) of the convex hulls. The originating volume of a snow-free tree at the beginning of each winter ($\alpha$ = 0.010 m to capture fine-scale detail of branch structures) was subtracted from subsequent snow-on measurements to calculate snow volumes for each scan in the time series.

*Snow density estimates*

Hourly fresh snow density (kg/m$^3$) was estimated using hourly air temperatures ($Ta$; 0.1° C resolution) from a meteorological monitoring sensor equipped with a radiation shield (VP-4, METER, Pullman, WA) positioned on a pole directly above the ATLS. $Ta$ ranged from -20.6 to 6.9°C during the entire study period, with a mean of -2.3°C and standard deviation of 4.9°C. Several methods of estimating fresh snow density from air temperature were tested, including:

1. ρ (constant) = constant density of 100 kg/m$^3$

2. ρ (Diamond-Lowry) = 119 + (6.48*$Ta$) (Diamond and Lowry, 1953)

3. ρ (LaChapelle) =) 50 +1.7(Ta+15)$^{1.5}$ (Lachapelle, 1962)

4. ρ (Hedstrom-Pomeroy) = 67.92+51.25$e^{(Ta/2.59)}$ (Hedstrom and Pomeroy, 1998)

Mean fresh snow density was calculated for each ATLS scan time interval (13 hours). Estimates of intercepted snow mass were calculated by multiplying the ATLS derived snow volumes (m$^3$) by fresh snow densities derived from equations 1-4 (kg/m$^3$).

*Statistical analysis*

The precision and accuracy of ATLS derived estimates of intercepted snow mass was determined by fitting a simple linear regression model in R (R Core Development Team, 2013) between ATLS derived intercepted snow mass in kg (independent variable) and load cell derived intercepted snow mass in kg (dependent variable) (Pineiro et al., 2008). Estimates of $R^2$ (goodness-of-fit), root mean square error (RMSE) in kg, and regression intercept and slope (indicative of model bias) were determined for models utilizing each density estimation method (see section 2.4). The optimal model was determined by selecting the best performing snow density estimation method that yielded the least under/over estimation in ATLS derived mass predictions (i.e. closest to 1:1 line) and lowest RMSE.

## Results

Discounting days without snow, a total of 115 complete ATLS scans were recorded for the left tree in the first winter between January and April; a total of 69 complete ATLS scans were recorded for the left tree in the second winter between November and March. A total of 83 and 69 scans, respectively, were recorded for the right tree over the same time periods. Discrepancies in sample size between the left and right tree were related to incomplete ATLS scans in which scanner malfunction truncated a portion of the scene (e.g., see Figure 2.1b).

Data exploration using results from the left tree revealed that measured snow interception (averaged across multiple complete scans) in the first winter averaged 3.19 kg (1.0% of season total), with a standard deviation of 4.59 kg and a maximum of 16.95 kg (4.8% of season total). During the second winter, measured snow interception for the left tree averaged 3.31 kg (2.3% of season total), with a standard deviation of 2.76 kg and a maximum of 10.19 kg (4.5% of season total). Estimated mean fresh snow densities using equations 1-4 for the left tree in both winters are summarized in Table 2.1. Density values are similar to Mair et al. (2016) in which estimates produced by equation 2 approximated the constant of 100 kg/m$^3$, estimates produced by equation 3 were higher than the constant, and estimates produced by equation 4 displayed a wider range.

Analyses (Table 2.2) using data spanning both winters for both trees demonstrated that the fresh snow density constant consistently produced higher $R^2$ (model fit) and lower RMSE (unexplained variance) than empirical variable-density equations 2 (Diamond and Lowry, 1953), 3 (Lachapelle, 1962), and 4 (Hedstrom and Pomeroy, 1998), in that order. Simple linear regression utilizing the density constant yielded $R^2 = 0.71$ / RMSE = 1.06 kg for the left tree and $R^2 = 0.69$ / RMSE = 0.91 kg for the right tree. Simple linear regression using the density constant also produced slopes closest to a 1:1 calibration between ATLS and load cell masses (slope = 0.97 for the left tree and slope = 1.07 for the right tree) (see Table 2.2 and Figure 2.2). Intercepts of -1.39 for the left tree and -1.34 for the right tree further illustrate model bias and overestimation in TLS based mass estimates.

## Discussion

*The effect of snow density and scan duration on model performance*

To our knowledge, this is the first study that explores the suitability of high resolution, automated terrestrial lidar to estimate canopy snow interception, with direct comparison to the established hanging tree method (Hedstrom and Pomeroy, 1998). The most precise proxies for measured snow interception mass ($R^2 \geq 0.69$), with the least variation in unexplained variance (RMSE $\geq$ 0.91 kg), were obtained by multiplying the ATLS derived snow interception volume estimates by a fresh snow density constant of 100 kg/m$^3$.

In contrast, ATLS derived snow interception volume estimates in conjunction with dynamic fresh snow density estimation equations based on air temperature reduced $R^2$ and increased RMSE model estimates. It may be that because equations 2-4 are empirical, they represent relationships between fresh snow density and air temperature specific to their respective experimental locales: Sierra Nevada Mountains in California (Diamond and Lowry, 1953); mid-continental Canadian boreal forest (Hedstrom and Pomeroy, 1998); and, a variety of avalanche monitoring sites across the western

United States (Lachapelle, 1962). In addition, each snow density estimation method (1-4) was derived from ground-based samples and may not represent micro-climate conditions unique to tree canopies. Finally, it should be noted that equation 4 was derived from two sources of data (Diamond and Lowry, 1953; Schmidt and Gluns, 1991) with different collection methods and air temperature values mainly limited to –10°C and warmer (Fassnacht and Soulis, 2002). This may have contributed to poor model performance when incorporating equation 4 (Table 2.2). Experimental development of adjustment factors for these equations was not in the scope of this study.

Unexplained model variance in ATLS derived mass predictions may also be partially explained by the long ATLS scan duration (13 hours). Increases in air temperature and subsequent changes to the density of freshly intercepted snow (i.e. metamorphism) during the course of one scan, or retention of metamorphosed snow between snow events, may have resulted in unexplained model variance. Furthermore, this study was not designed to account for losses of intercepted snow due to wind-driven sublimation and/or unloading, or asymmetrical accumulation of snow on trees during periods of high wind and wet snow (Miller, 1964), processes that also may have resulted in unexplained model variance. Recent advances in lidar technology might help to address the slow scan duration time with the relatively new availability of rugged, relatively low-cost (< $10,000), fast scanning lidar instruments (Condliffe, 2018). Future experiments with faster scanning terrestrial lidar that more closely matches single load cell readings might allow estimating snow density (kg/m$^3$) from the division of load cell-derived masses (kg) by ATLS-derived volumes (m$^3$). This approach may offer a path to developing a new empirical snow density equation. Further, laser return intensity data obtainable from TLS might provide valuable insights on snow properties that affect density, such as changes in grain size/shape and overall wetness (Eitel et al., 2016; Kaasalainen et al., 2008). Although this study emphasized automated data collection, model performance could also have been improved with *in situ* density measurements of canopy intercepted snow; fresh snow density estimate equations 2-4 were derived from ground-based samples (Diamond and Lowry, 1953; Hedstrom and Pomeroy, 1998; Lachapelle, 1962). Further research is needed to devise a practical means of sampling snow density on trees.

*The effect of weather and snow properties on model performance*

TLS has been used to monitor changes in snowpack depth, but several factors were shown to decrease the number and intensity of received signals (Deems et al., 2013; Prokop, 2008). Atmospheric occlusion from heavy snow or fog can interfere with lidar returns, and wet snow surfaces can lead to adsorption of lidar pulses on the target itself (Deems et al., 2014; Kaasalainen et al., 2008; Prokop, 2008). Snow is also strongly forward-scattering; the proportion of forward scattering of lidar pulses increases with scan angle (Deems et al., 2013), potentially leading to missed returns on the edges of targets. Despite these issues, the short distance to target (6.2 m) and low scan angle (4.22°) should have minimized the variance between measured and ATLS derived snow mass due to atmospheric occlusion or forward scattering. Likewise, sampling during the coldest months should have minimized unexplained model variance due to lidar pulse adsorption by snow with high water content.

### *The effect of changing tree geometry on model performance*

It may be that occlusions due to heavy snow loading, or reductions in occupied space resulting from branch deflection, affected ATLS derived volume estimates and led to unexplained model variance. On the other hand, the process of snow bridging may fill interstitial spaces between branches and accumulate in new space beyond the original canopy profile, thereby counteracting underestimation due to canopy occlusion or branch deflection. This study was not designed to specifically examine the relationship between branch deflection and changes to tree geometry, or to examine how plastic limb strength might compare with natural wood in its interaction with air temperature. A faster scanning ATLS could, in the future, be utilized in a similar experiment to assess variability in branch deflection, and physical laboratory testing could evaluate material elasticity. In addition, future research could explore the sensitivity of TLS to variable snow volumes within live trees of variable height, canopy density, and needle structure, as well as different air temperature conditions that affect tree geometry through branch deflection.  Alternative approaches that minimize occlusion could include reducing beam divergence with more accurate TLS equipment, scanning from different scan positions (Zande et al., 2008), using full-waveform lidar (Deems et al., 2013), or exploring emerging ray tracing approaches (Xie et al., 2018) to reconstruct occluded canopy components.

### *Conclusions*

This study provides valuable insights into the use of TLS for estimating intercepted snow volume. Initial results indicate agreement between predicted and measured values of intercepted snow mass ($R^2 \geq 0.69$ and RMSE $\geq 0.91$ kg) when utilizing a constant snow density estimate (100 kg/m$^3$). To further improve TLS derived snow interception estimates, future research is needed to develop improved approaches to estimate density of canopy intercepted snow *in situ*, explore the sensitivity of TLS snow volume estimates to changing snow conditions and quantities within the canopies of a variety of live trees of different sizes and for a range of temperatures that affect branch flexibility, and/or reduce beam divergence and reconstruct occluded structural elements. Snow interception is challenging to measure and model, but our findings highlight the potential of lidar technology to efficiently and accurately estimate intercepted snow mass. This is a potentially useful development for the collection of interception data in remote terrain, as well as the calibration of aerial lidar-based snow interception models to distinct forest types around the globe.

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## Tables

Table 2.1. Mean snow density estimates for the left tree in both winter sampling periods utilizing each of the density estimation equations 1-4 (Diamond and Lowry, 1953; Lachapelle, 1962; Hedstrom and Pomeroy, 1998).

| **Density Estimation Method** | **mean fresh snow density ($kg/m^3$): winter 2017** | **mean fresh snow density ($kg/m^3$): winter 2018** |
|---|---|---|
| 1. Constant | 100 | 100 |
| 2. Diamond-Lowry | 111.59 ± 29.46 | 99.58 ± 23.77 |
| 3. LaChapelle | 141.49 ± 39.52 | 123.20 ± 31.81 |
| 4. Hedstrom-Pomeroy | 142.58 ± 150.61 | 105.19 ± 53.30 |

Table 2.2. Simple linear regression results comparing predicted and measured snow interception mass for each of the density estimation equations 1-4 (Diamond and Lowry, 1953; Lachapelle, 1962; Hedstrom and Pomeroy, 1998). Data spans winters 2017-2018. Equation 1, the snow density constant, produced the best model fit and lowest error for both trees.

Left Tree

| Density Method | $R^2$ | RMSE (kg) | slope |
|---|---|---|---|
| 1. Constant | 0.71 | 1.06 | 0.97 |
| 2. Diamond-Lowry | 0.53 | 1.35 | 0.98 |
| 3. LaChapelle | 0.53 | 1.36 | 0.80 |
| 4. Hedstrom-Pomeroy | 0.05 | 1.93 | 0.17 |

Right Tree

| Density Method | $R^2$ | RMSE (kg) | slope |
|---|---|---|---|
| 1. Constant | 0.69 | 0.91 | 1.07 |
| 2. Diamond-Lowry | 0.51 | 1.14 | 1.13 |
| 3. LaChapelle | 0.47 | 1.19 | 0.89 |
| 4. Hedstrom-Pomeroy | 0.01 | 1.63 | 0.03 |

**Figures**

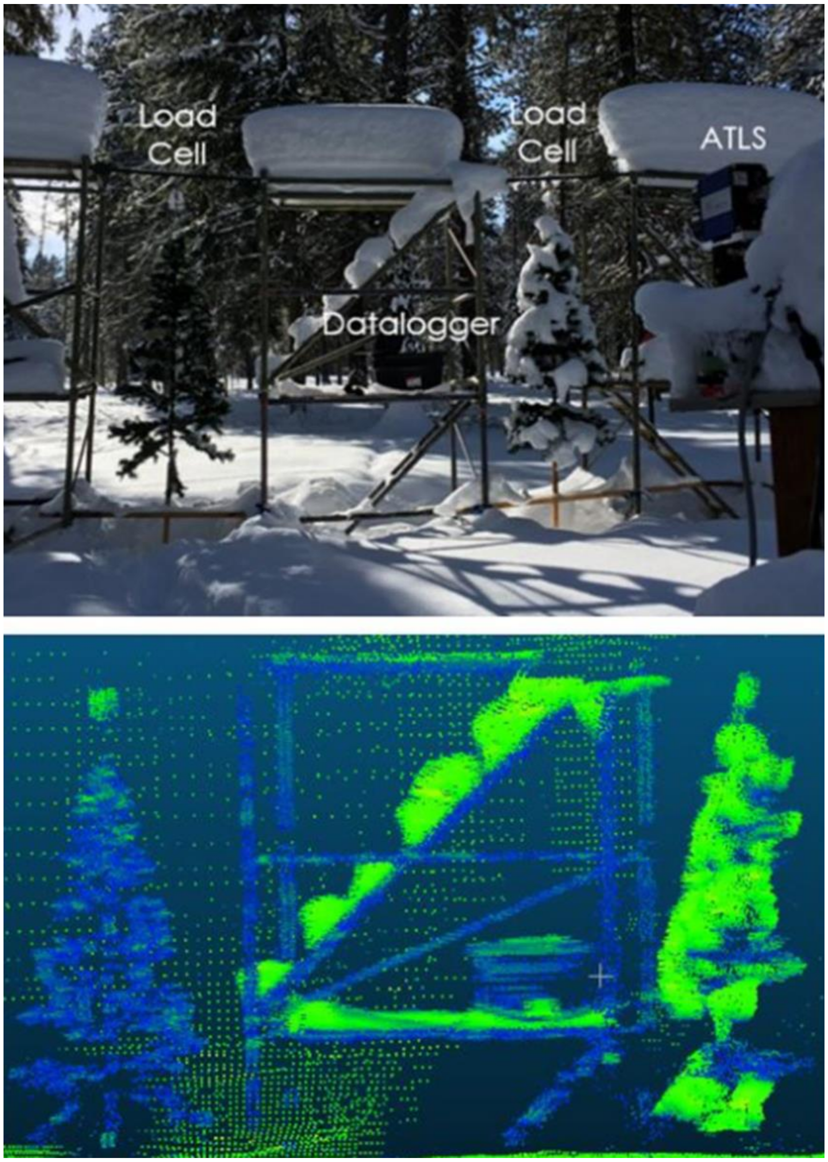


Figure 2.1a (top). Study site showing duplicate model trees hanging from load cells, datalogger, and automated terrestrial laser scanner (ATLS; see Eitel et al., 2013). “Left tree” to left of image with snow removed for illustration; “right tree” to right of image. Figure 2.1b (bottom). Scan of the trees on the same day.

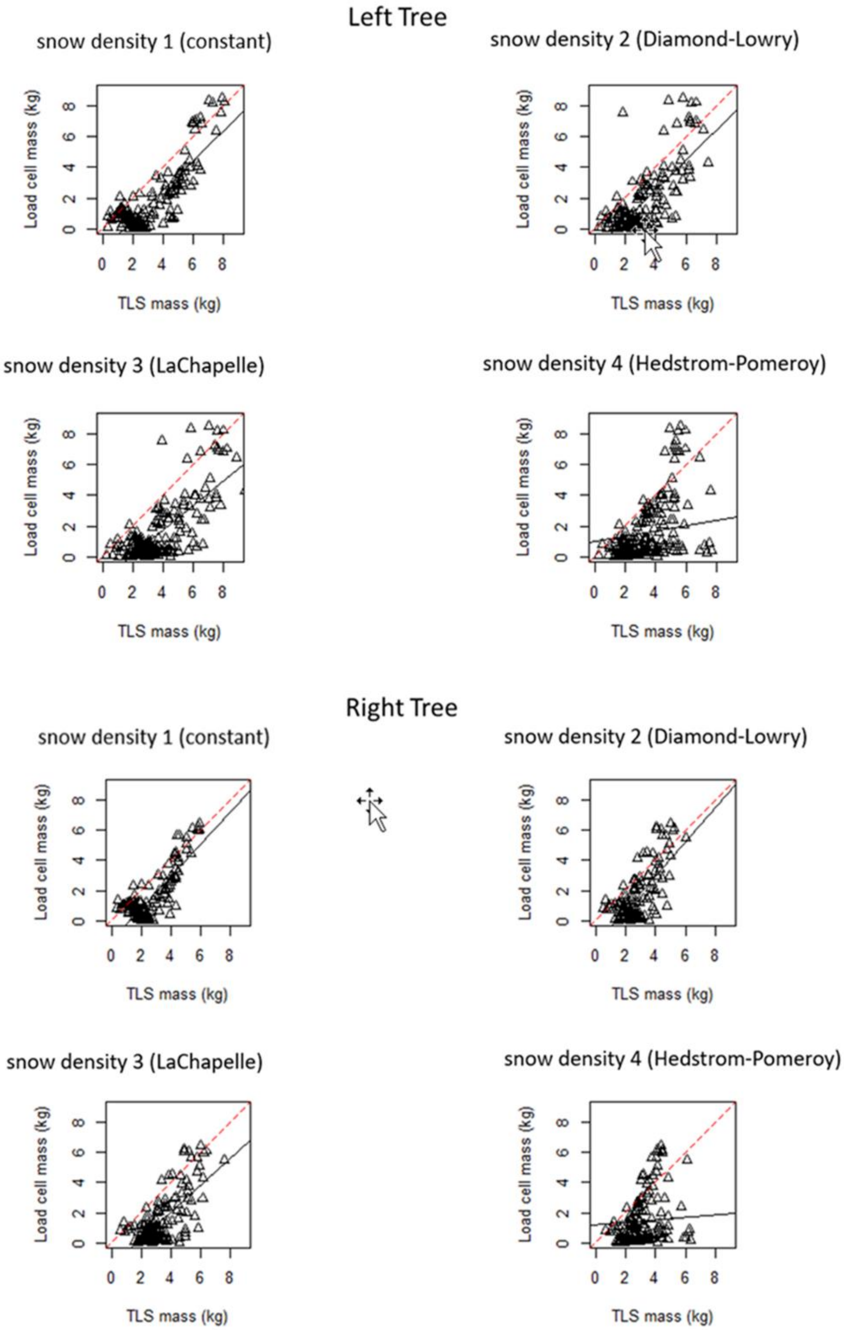


Figure 2.2. Simple linear regression results comparing predicted (TLS) and measured (load cell) snow interception mass for density estimation equations 1-4 (Diamond and Lowry, 1953; Lachapelle, 1962; Hedstrom and Pomeroy, 1998). Data spans winters 2017-2018. Black lines = regression lines; red lines = 1:1 lines.

# Chapter 3:
# Important aerial lidar metrics of canopy structure for estimating snow interception

**Authors:** Micah Russell, Jan U.H. Eitel, Carlos A. Silva, Timothy E. Link

In preparation


## Abstract

Forest canopies exert significant controls over the spatial distribution of snow cover. Canopy snow interception efficiency is controlled by intrinsic processes (e.g., canopy structure), extrinsic processes (e.g. meteorological conditions), and the interaction of intrinsic-extrinsic factors (i.e., air temperature and branch stiffness). In hydrological models, intrinsic processes governing snow interception are typically represented by two-dimensional metrics like Leaf Area Index (LAI). To improve snow interception estimates and their scalability, new approaches are needed for better characterizing the three-dimensional distribution of canopy elements. Aerial laser scanning (ALS) provides a potential means of achieving this, with recent research focused on using ALS-derived metrics that describe forest spacing to predict interception storage. A wide range of canopy structural metrics that describe individual trees can also be extracted from ALS, although relatively little is known about which of them, and in what combination, best describes intrinsic canopy properties known to affect snow interception. The overarching goal of this study was to identify important ALS-derived canopy structural metrics that could help to further improve our ability to characterize intrinsic factors affecting snow interception. Specifically, we sought to determine how much variance in canopy intercepted snow volume can be explained by ALS-derived crown metrics, and what suite of existing and novel crown metrics most strongly affects canopy intercepted snow volume. To achieve this, we first used terrestrial laser scanning (TLS) to estimate snow interception on fourteen trees. We used these data to fit a Random Forest model with ALS-derived crown metrics as predictors. Next, we bootstrapped 1000 calculations of variable importance (percent increase in mean squared error when a given explanatory variable is removed), keeping nine canopy metrics for the final model that exceeded a variable importance threshold. ALS-derived canopy metrics describing intrinsic, tree structure explained approximately two-thirds of snow interception variability ($R^2 \geq 0.65$, RMSE $\leq$ 0.52 $m^3$) in our study when extrinsic factors were kept as constant as possible. The three most important predictor variables were canopy length, whole-tree volume, and unobstructed returns (a novel metric). These results suggest that a suite of intrinsic variables may be used to map

interception potential across larger areas and provide an alternative to interception estimates based on LAI.

## Introduction

Forests within the northern hemisphere are estimated to contain 20% of global winter snow cover and 17% of global winter freshwater storage (Guntner et al., 2007; Rutter et al., 2009). The structure and arrangement of the forest canopy is a significant control on the distribution of snow, as well as runoff rates and volumes (Varhola et al., 2009). Canopy intercepted snow can account for up to 60% of the total annual snowfall, depending on forest type, forest structural properties, and meteorological conditions (Montesi et al., 2003; Storck et al, 2002) with subsequent sublimation as high as 25-50% in cold, dry environments (Essery and Pomeroy, 2001; Hedstrom and Pomeroy, 1998). Canopy-interception processes are thus important to consider when modeling the hydrology of snow-dependent regions and their water supplies (Mussellmen et al., 2008).

Despite its importance as a variable in hydrological models (Essery et al., 2009; Pomeroy et al., 2007; Rutter et al., 2009), accurately estimating snow interception remains challenging due to complex interactions between intrinsic and extrinsic factors (Fig. 3.1). Intrinsic, structural factors like branch/canopy arrangement and vegetation stiffness and their effect on snow storage dynamics have been studied at the branch-level with physical models (Kobayashi, 1987; Pfister and Schneebeli, 1999), excised branches (Schmidt and Gluns, 1991), and time-lapse video (Brundl et al., 1999). These studies described how branch architecture influences micro-scale (sub-centimeter) mechanisms that control how and where snow accumulates, as well as the rate of accumulation. For example, Pfister and Schneebeli (1999) found that snow interception efficiency increased with the width of the branch due to reduced snow crystal rebound near the edges, and irregularly shaped branch models with low inclination angles had significantly higher accumulations. Schmidt and Gluns (1991) observed how differences in branch structure between conifer species affect mechanisms of snow interception efficiency (e.g., crystal rebound, snow bridging), although meteorological conditions produced greater differences in snow interception. Indeed, snow interception is also partially controlled by extrinsic hydrometeorological factors (e.g. air temperature, snow water content, wind speed, etc.) that affect crystal type, snow adhesion to vegetation, and bridging of snow due to cohesion (Satterlund and Haupt, 1970). Furthermore, the interaction between extrinsic air temperature and intrinsic branch flexibility affects snow interception efficiency through the process of mass unloading (Schmidt and Pomeroy, 1990).

To estimate snow interception, point-scale measurements (e.g. data from load cells, lysimeters, and pressure sensors) have been made (e.g., Hedstrom and Pomeroy, 1998; Martin et al., 2013; Storck et al., 2002). Scaling up measurements of whole-tree interception is problematic, however, because the methods are resource-intensive and not representative across complex terrain. Alternatively, snow interception estimates obtained indirectly by comparing forested and non-forested sites are prone to error due to confounding processes (e.g. wind redistribution of snow and branch unloading) (Varhola et al., 2009). Due to these challenges, most hydrological models infer snow interception from two-dimensional metrics of canopy architecture like Leaf Area Index (LAI) or Canopy Closure (CC) (Essery et al., 2009; Rutter et al., 2009), data that are relatively easy to obtain from *in situ* field observations or remote sensing (Breda, 2003; Song, 2013). Interception is partitioned from total snowfall by estimating the maximum snow load that can be captured by a canopy as an empirical function of LAI (e.g., Hedstrom and Pomeroy, 1998). Authors of the Snow Model Intercomparison Project 2 (SNOWMIP2) (Essery et al., 2009; Rutter et al., 2009) reported that most of the thirty-three models of forest-snow processes they examined rely on LAI to predict maximum interception. They cautioned that they found inconsistency in the methods used to calculate LAI. In addition, although many of the models employ the empirical equation used in Hedstrom and Pomeroy (1998) that defines the LAI-interception relationship, there is inconsistency in how this scheme is implemented (Bartlett et al., 2006) and concern that it may underpredict snow interception in environments outside the boreal forest zone where it was developed (Martin et al., 2013). Beyond the aforementioned issues, both LAI and CC also do not capture the fundamental, three-dimensional (3-D) spatial arrangement of canopy features that accounts for the intrinsic, baseline snow interception efficiency (Kobayashi, 1987; Pfister and Schneebeli, 1999). Hence, to improve snow interception estimates and their scalability, approaches are needed that characterize the 3-D arrangement of canopy elements – a key intrinsic factor known to affect canopy interception (Friesen et al., 2015).

Aerial laser scanning (ALS), commonly known as lidar (light detection and ranging) presents a potential means of meeting this need. For each survey point that reflects an emitted laser beam back to the ALS sensor, a datalogger records spherical coordinates (distance from scanner, azimuth angle, polar angle) that are later converted to Cartesian x,y,z coordinates, as well as return intensity of the laser beam (Eitel et al., 2013). A point cloud contains all of these spatial coordinates and is subsequently utilized for classifying and mapping the 3-D structural properties of earth surface features such as terrain, forests, and snow cover (Deems et al., 2016; Eitel et al., 2016; Timothy et al., 2016; Wulder et al., 2012). Moeser and colleagues (2015a) combined an underlying snow interception efficiency distribution with ALS-derived estimates of LAI, CC, tree size, and novel intrinsic metrics of canopy spacing (i.e., forest gap size and horizontal position) to model snow interception. They found a 27% increase in model fit ($R^2 = 0.66$) when compared to previous models at the point scale (e.g., Hedstrom and Pomeroy, 1988). Furthermore, Moeser and colleagues (2015b) found that ‘total gap area’ (average r = 0.78) was more highly correlated with interception than LAI (average r = 0.57), and that intrinsic, overhead canopy elements are more important than extrinsic, snowfall intensity in predicting maximum interception. Roth and Nolin (2019) furthered this modeling approach by modifying the ALS-derived intrinsic variables (e.g., gap length) to integrate information on vertical position in space and focusing on two extrinsic variables (i.e., snowfall, air temperature). They found that forest structure sets the baseline potential or likelihood of a given forest to intercept, with air temperature influencing the rate of interception. Finally, Mazzotti and colleagues (2019) utilized ALS to extract a spatially continuous canopy metric (distance to canopy edge), finding that it performed better than CC and could be aggregated to the watershed scale.

These studies demonstrate the potential for modeling snow interception based on ALS-derived information on intrinsic forest spacing (e.g., gaps), extrinsic meteorological data, and indirect validation data. In addition, intrinsic factors affecting snow interception could be characterized with canopy structural metrics of *individual* trees derived from ALS. ALS-derived canopy structural metrics are widely employed for the efficient estimation of forest biomass across large areas (Lefsky et al., 2002; Means et al., 2000). For example, Means and colleagues (2000) used ALS to estimate forest structural parameters (e.g., tree height percentiles, basal area, tree volume) over a Douglas-fir-dominated temperate forest in western Oregon, finding good correspondence to field validation data ($R^2$ = 0.93-0.98). Other studies extracted metrics from canopy vertical profiles, including height and volume distributions (e.g., Coops et al., 2007; Hilker et al., 2010; Klauberg et al., 2019). All these studies demonstrate the wide range of different canopy structural metrics that can be derived from ALS but relatively little is known about which of them, and in what combination, best describes intrinsic canopy properties known to affect snow interception. This is due, in part, to the difficulty of efficiently obtaining validation data of interception variability across a range of trees. Yet recent research advances suggest that terrestrial laser scanning (TLS) could be a valuable validation tool for directly mapping and quantifying snow interception in field plots (Russell et al., *in review*).

The overarching goal of this study was to identify important ALS-derived canopy structural metrics that could help to further improve our ability to characterize intrinsic factors affecting snow interception. Specifically, our objectives were as follows: 1) determine how much variance in canopy intercepted snow volume can be explained by ALS-derived crown metrics; and 2) identify a suite of existing and novel crown metrics that most strongly correlates with canopy intercepted snow volume. Outcomes of this study will provide insights on what canopy structural information from lidar remote sensing could best contribute to the effort to further improve the modeling and monitoring of snow interception processes across larger spatial scales.

## Methods and Materials

*Field data*

Field data were collected at Bear Basin Meadows in the Payette National Forest (McCall Ranger District) near McCall, Idaho at 1640 m elevation (Fig. 3.2). Bear Basin Meadows is a large meadow complex surrounded by montane forest in the mountains of west-central Idaho.

Fourteen snow-free trees of varying size classes (maximum height = 31.7 m; minimum height = 1.4 m; mean height = 11.7 m; standard deviation = 9.6 m) and structural forms (e.g., maximum width = 13.9 m; minimum width = 2.6 m; mean width = 8.1 m; standard deviation = 3.3 m) were scanned with a Leica Scan Station 2 (Leica Geosystems AG Heerbrugg, Switzerland) TLS (distance accuracy ± 4 mm with 0.15 mrad beam divergence) on October 25, 2018. Trees (*Pseudotsuga menziesii* (n = 2), *Pinus contorta* (n = 10), *Pinus ponderosa* (n = 2)) were visually selected to represent variance in structure (e.g., canopy height, width, distribution of vegetation on stem, etc.) rather than species. The trees are all in open forest (i.e., minimal subcanopy) along the margins of a meadow. To fully capture the structural complexity of each tree, two scans were made from opposing sides of each tree (0.005 m horizontal/vertical scan resolution at 5 m) and included three TLS targets for co-registration of the scenes. To maximize variance in structure, scans included individual trees or small clumps of trees that were processed as one tree. Two subsequent snow-on data collections were performed on December 5, 2018 and January 1, 2019, during which the same methods were repeated (Fig. 3.3). The Bear Basin snow telemetry station (National Resource and Conservation Service SNOTEL Site #319) approximately 600 m from the study site reported mean air temperature during daylight hours was -11.2°C on December 5$^{th}$, with maximum air temperature of -6.4°C and snow depth on the ground surface measuring 13 cm. Mean air temperature during daylight hours was -9.0°C on January 1, with maximum air temperature of -6.2°C and snow depth on the ground surface measuring 71 cm. Snowfall prior to each snow-on data collection consisted of approximately 20 cm on December 2$^{nd}$ and 5 cm on December 31$^{st}$. We attempted to control for extrinsic factors affecting our results by scanning all trees during the same day under similar weather conditions (i.e., subfreezing, low wind) and in the same general area, thereby assuming that variability in interception between trees would primarily be caused by intrinsic factors. After field data collection, we followed the general workflow outlined in Figure 3.4 and described in detail in the following sections.

*TLS data preprocessing and canopy intercepted snow volume estimation*

Using the three TLS targets, point clouds acquired from two sides of a tree were registered with the ‘three point picking’ tool in the open source software package CloudCompare (version 2.10.2)

(2017). After registration, each point cloud was subsampled to a 0.05 m minimal point spacing to allow for uniform comparability throughout the individual tree canopies and between different trees. The subsampling distance was selected to reflect point spacing in the crown of the tallest tree sampled (i.e., furthest distance from scanner to target). To approximate a relative increase in volume with snow loading independent of confounding factors like occlusions due to laser absorption/scattering (Deems et al., 2013; Kaasalainen, Kaartinen, & Kukko, 2008; Prokop, 2008) and branch deflection (Schmidt and Pomeroy, 1990), "snow off" point clouds were added to their corresponding "snow on" point clouds using the automated registration within CloudCompare (2019). The point clouds were then transformed into convex hulls in R (R Development Core Team, 2013) using the 'alphashape3d' R package (Lafarge et al., 2014), which approximates the shape and volume of the scanned structure. The convexity parameter (α) was set to 0.05 m to match the point spacing of the underlying data. Only the upper 75% of each point cloud was utilized to construct convex hulls, excluding canopy components that were occluded by the snowpack and ice attached to the lowest portion of the tree canopies. Next, snow-free tree volumes were subtracted from snow-on tree volumes to calculate volumes of intercepted snow. This approach for approximating snow volume from TLS data was validated by integrating the methodology into data from Russell et al. (*in press*). The resulting model regression demonstrated good agreement between estimated TLS-derived snow interception and snow interception quantified by a load cell ($R^2 = 0.68$, RMSE = 1.66, slope = 1.55, intercept = -3.71). Finally, a Welch two sample t-test was utilized to test whether or not the means of the December and January samples were significantly different.

*Calculation of standard crown metrics from aerial laser scanning*

Aerial lidar data for the Bear Basin study site were downloaded from the "The National Map" (USGS, 2019). Data were acquired on March 15, 2018 for the United States Geological Survey (USGS) 3DEP LiDAR Project using a Leica ALS80 system (Leica Geosystems AG Heerbrugg, Switzerland) at an altitude of 1800 m (22 mrad beam divergence, 30º field of view, 39.6 cm laser pulse footprint diameter). The average first-return point density was 18.00 points/m$^2$, the average ground-return point density was 2.93 points/m$^2$, and RMSE was 0.37 m when compared to a bare earth digital elevation model. The aerial lidar tile encompassing the Bear Basin study site has a minimum elevation of 1587 m and a maximum elevation of 1952 m. CloudCompare was used to clip ALS-derived shapefiles corresponding to the 14 sampled trees.

The CrownMetrics function in the ‘rLiDAR’ package (Silva et al., 2015) was used to produce eleven structural canopy metrics (e.g. maximum height, mean height, etc.) for each sample tree. The normalmixEM function from the ‘mixtools’ R package (Benaglia et al., 2009) was employed to calculate crown base height from the vertical profiles of heights within the crown polygon. The chullLiDAR3D function in ‘rLiDAR’ (Silva et al., 2015) was used to produce convex hulls derived from ALS returns within the crown segments and calculate crown surface area/volume. The ‘alphashape3D’ package (Lafarge et al., 2014) was utilized to calculate whole-tree volumes for three arbitrary α values (α = 0.25, 0.50, 0.75) spanning the α range (0 – 1). Twenty-three total standard canopy metrics were included in subsequent modeling (see Table 3.1 for definitions). Metrics based on laser return intensities were excluded as candidate variables because they have been thought to be mainly sensitive to intrinsic factors (e.g., Deems et al., 2013; Kaasalainen, Kaartinen, & Kukko, 2008) of snow interception which is not the focus of this study.

*Calculation of novel canopy metrics from aerial laser scanning*

Original metrics that quantify the number of unobstructed (i.e., first return) and obstructed returns (height values less than the first return) (Table 3.1) were produced as a proxy for the amount of vegetative structure on the exterior surfaces of trees. These metrics follow the principle that the first surfaces snow crystals encounter are most likely to intercept and accumulate snow; snow accumulation in the interior of the canopy is limited to snow crystals that slide down steeply angled branches to accumulate at branch attachments to the trunk (Pfister and Schneebeli, 1999) or deposit in high wind / wet snow conditions (Miller, 1964). The unobstructed returns (UNOB) metric is a count of first returns only. The UNOBDK metric weights overlapping returns with an exponential decay function in which:

*subtract* = 0.0498*exp(0.5 * n), where *n* is the number of overlapping returns within the laser footprint (39.6 cm in this study, see section 2.3).

*Subtract* is the value to be subtracted from the total number of returns in the point cloud. If the number of overlapping returns exceeds six then a value of one is subtracted. The exponential decay function accounts for the assumption that the likelihood of intercepting snow decreases exponentially with the number of canopy layers. Percent unobstructed returns (UNOB%) and percent unobstructed returns with decay function (UNOBDK%) present UNOB and UNOBDK values as a ratio of the total returns.

*Modeling*

To address our first objective of determining how much variance in canopy intercepted snow volume is explained by ALS-derived canopy metrics, we fit a Random Forest (RF) model between observed, TLS-derived snow volumes estimates and ALS-derived structural metrics. This modeling approach was informed by Maguire et al. (2019). RF is a non-parametric machine learning approach that makes no assumptions about the distribution/independence of variables (Cutler et al., 2007) and can accommodate many predictor variables relative to the number of observations, with each individual predictor providing limited information (Breiman, 2001). RF uses a random subset of predictors and observations to construct many regression trees. This approach is therefore robust against overfitting and multicollinearity by distributing variable importance across all correlated predictors (Belgiu and Drăgu, 2016; Cutler et al., 2007; Dormann et al., 2013). Predictions from all the trees were combined for an estimate of model variance and error. All RF models were fit with the 'randomForest' R package (Liaw and Wiener, 2002) with the default settings for mtry (i.e., the number of predictors sampled at each node: 1/3 of total predictors) and ntree (i.e., the number of regression trees grown for each RF run) set to 1000.

Because our second objective was identifying lidar structural metrics best suited to help predict intercepted snow volume, we did not reduce our model to include only predictor variables below a certain correlation threshold (e.g., R = 0.9 in Genuer et al., 2010). Instead, we relied on RF estimates of variable importance to determine the most parsimonious model. Variable importance is a measure of the increase in mean squared error (MSE) when a given explanatory variable is removed (Stroble et al., 2007). To account for stochasticity in variable importance estimates (Liaw and Wiener, 2002; Millard and Richardson, 2015) we iterated the calculation 1000 times (bootstrapped without replacement). Variables that exceeded a 0.2 variable importance threshold, a default value in many RF modeling applications (e.g. Probst and Janitza, 2019), across all runs were retained for fitting the final RF model.

Predicted values of snow interception volume were produced by the final RF model in predict mode. To determine how much variance in canopy intercepted snow volume can be explained by ALS derived crown metrics (objective 1), we regressed observed (i.e., TLS-derived) against predicted snow interception volume and evaluated the precision and accuracy of the model based on the coefficient of determination ($R^2$) and root mean squared error (RMSE), respectively. Having identified the suite of existing and novel crown metrics that most strongly affects canopy intercepted snow volume (objective 2), we then ranked the final suite of variables by importance (i.e., % increase MSE if removed from the model).

## Results

Estimates of snow interception from December 5th ranged between 0.15 – 4.48 $m^3$ per tree (mean 1.20 $m^3$; standard deviation 2.26 $m^3$). Estimates of snow interception from January 1st ranged between 0.08 – 2.64 $m^3$ (mean 0.98 $m^3$; standard deviation 1.30 $m^3$). Higher snow volume estimates were recorded for 12 of 14 trees on December 5th compared to January 1st. A Welch two sample t-test showed that the means of each sample were not significantly different ($t = 0.967$, $df = 27.634$, p-value = 0.171 with a 95% confidence interval).

The RF model with all variables included produced the following estimates of model fit and error: $R^2 = 0.65$ and RMSE = 0.52 $m^3$. After iteratively calculating variable importance 1000 times (bootstrapped without replacement), 11 out of 28 variables were removed from the model for not exceeding the 0.2 variable importance threshold across all runs. The reduced model produced estimates of $R^2 = 0.66$ and RMSE = 0.52 $m^3$. Next, HMIN and the remaining height percentile metrics (e.g. HQR, H25TH, etc.) were removed because they did not add meaningfully to interpretation of modeling results in the context of snow interception processes and the TLS-derived snow volumes were limited to the upper 75% of the tree crowns. HMAX was removed from the final model due to redundancy with a metric that produced a higher variable importance score, HRANGE; ASV0.75 was removed from the final model due to redundancy with a metric that produced a higher variable importance score, ASV0.5. The final RF model consisted of nine predictor metrics in the following expression:

Snow Volume ~ CL + ASV0.5 + UNOBDK + CBH + HSD + HRANGE + CSA + HMEAN + CV

The final model yielded $R^2 = 0.65$ and RMSE = 0.52 $m^3$. A plot of predicted versus measured snow volumes (Fig. 3.5) demonstrated the final model approached a 1:1 relationship (slope = 1.05; intercept = -0.06) and revealed a possible outlier (tree #10 in December), the highest measured snow volume in the sample.

Plots of variable importance with and without the inclusion of height percentile metrics (Fig. 3.6) indicate that crown length (CL) is consistently the most important variable. The five most important variables for the final model (Fig. 3.7, right) are ranked (from most to least important) as follows: CL, ASV0.5, UNOBDK, CBH, and HSD.

## Discussion

We determined the amount of variance in canopy intercepted snow volume explained by ALS-derived canopy metrics in our study ($R^2 = 0.65$, RMSE = 0.52 $m^3$) that describe intrinsic, tree structure. We developed an effective model to predict intercepted snow volume (Fig. 3.5) and identified the suite of

ALS canopy metrics that explained most of the variance in snow interception volumes (Fig. 3.6). These results suggest that while extrinsic variables may be necessary to model exponential interception efficiency (Satterlund and Haupt, 1970; Schmidt and Pomeroy, 1990), intrinsic variables alone may be used to map interception likelihood, or maximum interception potential, across larger areas. Our findings are consistent with branch-level experimental studies (Pfister and Schneebeli, 1999; Schmidt and Gluns, 1991) that found snow interception efficiency was due, at least in part, to branch width and other structural characteristics. Furthermore, Roth and Nolin (2019) demonstrated in a larger-scale interception study that forest structure determines the baseline potential of a given forest to intercept. Although we focused exclusively on canopy metrics for individual trees, our suite of predictors explained an equivalent amount of snow interception variability when compared to Moeser and colleagues' full model (2015a) containing both intrinsic and extrinsic variables ($R^2$ = 0.66). Researchers may want to consider future studies that integrate our ALS-derived canopy structure metrics model with extrinsic variables (e.g., air temperature, snowfall magnitude) to estimate how much intercepted snow exists in a forest at the stand-level.

Given the effectiveness of our model, our approach may offer a viable alternative to utilizing maximum snow interception estimates based on LAI and CC. These metrics have been shown to be both inconsistently obtained and applied in hydrological models (Essery et al., 2009; Rutter et al., 2009), and do not represent the three-dimensional spatial arrangement of canopy features associated with intrinsic, baseline snow interception efficiency (Kobayashi 1987; Pfister and Schneebeli 1999). Our suggestion that predicting snow interception with canopy structural metrics may offer an alternative to LAI-based estimates of snow interception employed in many hydrological models is consistent with the findings of Moeser and colleagues (2015b). They found that novel ALS-derived metrics of canopy spacing (e.g., total gap area) were more highly correlated with snow interception than LAI. In future studies that utilize ALS data for estimating snow interception, we also suggest researchers should consider combining canopy structural metrics, highlighted here as important predictors of snow interception volume, with canopy spacing metrics.

*Variable selection*

Random Forest modeling revealed that the nine most important canopy metrics for predicting intercepted snow volume (Fig. 3.6) were measures of crown length and distribution on the stem (CL, CBH), tree and crown volume (ASV0.5, CV), unobstructed laser returns (UNOBDK), tree height (HRANGE, HSD, HMEAN), and crown surface area (CSA).

Crown length (CL) was ranked the most important variable, with greater than 13% percent increase in mean squared error when removed from the model (Fig. 3.6). CL characterizes the portion of vegetative structure located above the crown base height. CBH was the fourth most important variable in our model, and is also an important biophysical parameter for many other applications in forest management, fuels treatment, wildfire modeling, etc. (Luo et al., 2018). Our results suggest that variability in CBH, coupled with its correlation with other metrics (i.e., CL, CSA, CV), is an important factor in predicting variability of canopy intercepted snow. Visual examination of our study trees reveals the relationship between CL, CBH, and the location of intercepted snow within each tree (Fig. 3.7). For example, the tallest tree in our sample (tree #3; 31.7 m) intercepted 1.25 $m^3$ of snow (averaged across December and January samples) with CBH = 18.7 m and CL = 13.0 m. Much of the canopy structure is in the upper 1/3 of the tree (Fig. 3.7 histogram of height returns) and visual inspection of the intercepted snow with unmanned aerial systems imagery (Fig. 3.7, top right) shows most of the snow was captured by the uppermost crown. A shorter tree in our sample (tree #4; 17.3 m) averaged slightly higher intercepted snow (1.89 $m^3$) with CBH = 3.3 m, CL = 14.0 m, and the canopy structure was more evenly distributed in the upper half of the tree.

Whole-tree volume (ASV0.5) was ranked the second most important variable (Fig. 3.6). This metric is an indicator of the overall structural potential for a tree to intercept snow anywhere along its stem. Examining the model performance in the context of individual trees, whereas whole tree volume of tree #3 (ASVO.5 = 42.90 $m^3$) was significantly higher than that of tree #4 (ASVO.5 = 13.03 $m^3$), it intercepted 0.64 $m^3$ less snow (Fig. 3.8). This suggests that different canopy structural metrics interact to affect snow interception, and that snow interception cannot be predicted by a simple linear regression model with an individual metric. Indeed, such models do not perform as well as our Random Forest approach. For example, simple linear regressions fit with the two most important variables, CL and ASV0.5, generated lower estimates of model fit ($R^2 \leq 0.24$) and higher estimates of model error (RMSE >= 0.60 $m^3$) (Fig. 3.8). It should be noted that these simple linear regression models were fit separately for each sampling date to avoid temporal autocorrelation.

Finally, except under conditions of high wind and wet snow, snow crystals deposit from a more or less vertical direction (Miller, 1964). Hence, our novel metrics of unobstructed aerial lidar returns were especially well suited to characterize vegetation structure that snow crystals first encounter when falling on to a tree. These metrics follow the principle that the first surfaces snow crystals encounter are the surfaces most likely to intercept and accumulate snow. While only one of our four novel metrics exceeded the 0.2 variable importance threshold, UNOBDK is the third most important metric (Fig. 3.6). The importance of UNOBDK (versus UNOB) indicates that including an exponential decay function to account for some passage of snow below the first of overlapping returns is appropriate. This provides mechanistic evidence, given that some snow crystals may rebound and accumulate lower on the tree, or are later redistributed by wind and branch unloading (Schmidt and Pomeroy, 1990).

*Study assumptions and potential sources of error*

We used TLS for model fitting. This remote sensing approach has been proposed as a viable, direct sampling alternative (Russell et al., *in press*) to traditional indirect sampling (e.g. forest/clearing comparisons in Moeser et al., 2015) or intensive controlled experimentation (e.g. weighing lysimeters in Storck et al., 2002). TLS-derived snow interception estimates have shown good agreement with snow interception estimates when compared against load cell measurements (Russell et al., *in press*). TLS-derived snow volumes, however, should be viewed as relative, rather than exact, measurements. In designing this study, we assumed that the processes of snow cohesion and bridging would fill interstitial spaces between branches and accumulate in new space beyond the original canopy profile, thereby counteracting potential TLS-based underestimation of snow volume due to branch deflection (Schmidt and Pomeroy, 1990), gap creation through snow bridging (Satterlund and Haupt 1970), or occlusions in point clouds due to laser adsorption by snow (Deems et al., 2013; Kaasalainen, Kaartinen, & Kukko, 2008; Prokop, 2008) or laser scattering along the edges of the target (Deems et al., 2013; Painter and Dozier, 2004). Periodic reductions in tree volume with snow loading were observed, though, suggesting that (although out of scope for this study) further study is needed on: 1. how snow loading affects whole-tree geometry of different species, and 2. if, and to what magnitude, occlusions result from the interactions of laser energy and snow.

Model performance may have also been affected by the inclusion of outlier values associated with tree #10. Tree #10 is distinct from other individual-tree samples because it is a large, dense clump of multiple trees. This tree recorded the highest measured snow volume in both the December and January samples. Removal of these values from the final model increased model fit ($R^2$ = 0.88; +0.22 compared to final model) and reduced model error (RMSE = 0.19 $m^3$; -0.33 $m^3$ compared to final model) (Fig. 3.9). These results imply that future research that applies our modeling approach to a larger area, particularly one with dense forest, may necessitate: 1. calibration of individual tree detection algorithms that allow detecting individual trees from ATLS data (e.g., FindTreesCHM function in ‘rLiDAR’ package; Silva et al., 2015), and 2. validation of how accurately these algorithms partition individual trees from clumps of trees (e.g., randomized visual inspection of ALS data or randomized field sampling). If there are limitations applying our modeling approach in dense forests due to challenges related to individual tree classification, or reduced canopy penetration by the laser beam (e.g., Broxton et al., 2015; Zheng et al., 2015), this may lend further credence to our suggestion that snow interception models include both canopy structural metrics and forest spacing metrics. Combining the two suites of intrinsic predictors – one suite providing data on individual trees and one suite providing data on canopy spacing – may reduce unexplained model variance by virtue of not relying on a single data type and its respective limitations.

*Conclusions*

The findings from this work suggests that ALS-derived canopy metrics can explain at least two-thirds of the variance in snow interception volume when extrinsic factors are kept constant. We also determined the specific suite of variables that generated the best fitting model, which included whole-tree volume, crown length, and weighted unobstructed returns. This study provides a potential alternative to parameterizing interception hydrological models based on metrics like Leaf Area Index or Canopy Closure. Researchers interested in extending this work may look to understand how well this approach performs across broader spatial extents encompassing a wider range of forest densities and may consider including both canopy metrics and forest spacing metrics in the intrinsic portion of snow interception models.

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# Tables

Table 3.1. ALS-derived tree crown metrics evaluated in this study. Metrics original to this study indicated with a '*'.

| Abbreviation | Definition |
|---|---|
| HMIN (m) | minimum crown height |
| HMAX (m) | maximum crown height |
| HMEAN (m) | mean crown height |
| HSD (m) | crown height standard deviation |
| HSKE | skewness of heights |
| HKUR | kurtosis of heights |
| HRANGE | HMAX - HMIN |
| HQR | interquartile range (H75TH - H25TH) |
| H25TH (m) | crown height 25th percentile |
| H50TH (m) | crown height 50th percentile |
| H75TH (m) | crown height 75th percentile |
| H90TH (m) | crown height 90th percentile |
| H95TH (m) | crown height 95th percentile |
| H99TH (m) | crown height 99th percentile |
| CL (m) | crown length (HMAX – CBH) |
| CBH (m) | crown base height (1.5 standard deviations below the height returns mean) |
| CRATIO | crown ratio (CL / HMAX) |
| CPA (m2) | crown area (π*CRAD2) |
| CV (m3) | crown volume as the convex hull 3D |
| CSA (m2) | crown surface area as the convex hull 3D |
| CDENS | percent crown density (returns ≥ CBH / total returns) |
| ASV0.25 | whole tree volume (α=0.25) |
| ASV0.5 | whole tree volume (α=0.50) |
| ASV0.75 | whole tree volume (α=0.75) |
| UNOB | number of unobstructed returns* |
| UNOB% | percent unobstructed returns* |
| UNOBDK | number of unobstructed returns with decay function for weighted returns* |
| UNOBDK% | percent unobstructed returns with decay function for weighted returns* |

**Figures**

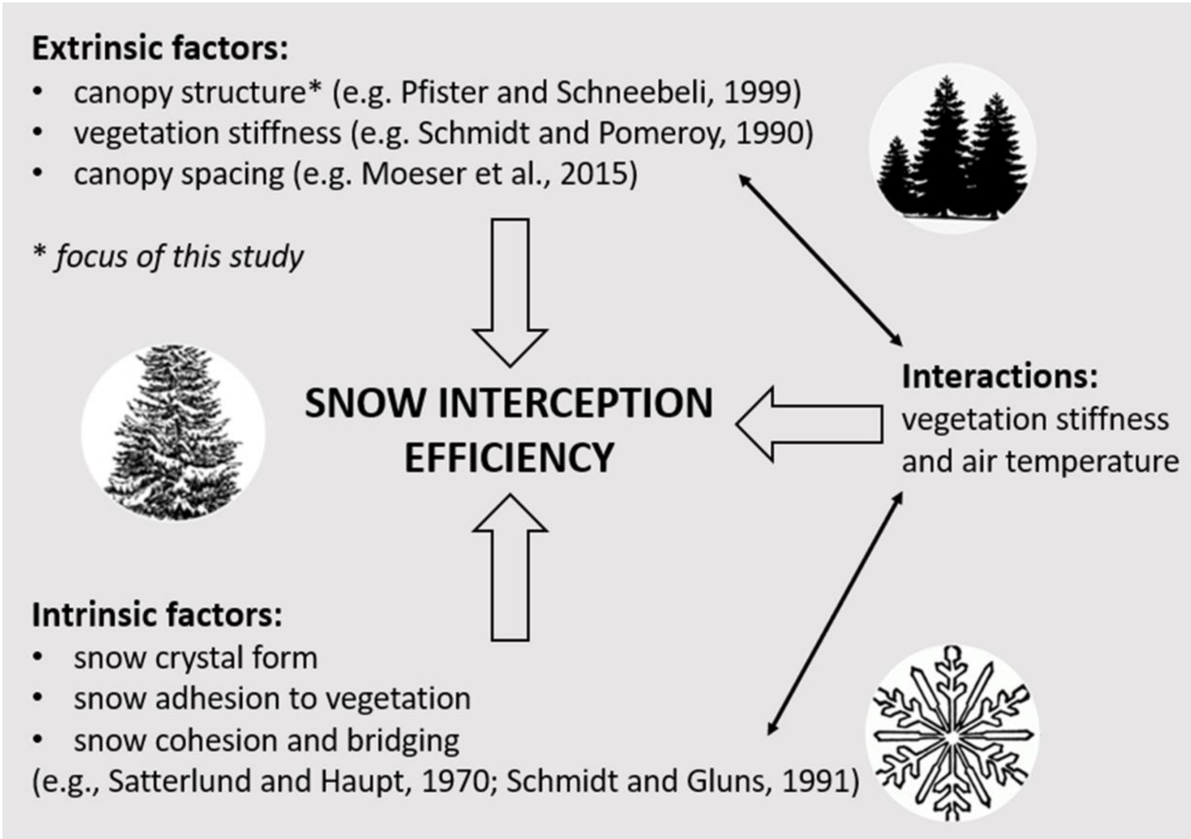


Figure 3.1**.** Factors controlling snow interception efficiency (figure adapted from Klamerus-Iwan et al., 2020).


Figure 3.2. Study site location: Bear Basin Meadows, Payette National Forest, McCall Ranger District, Idaho.

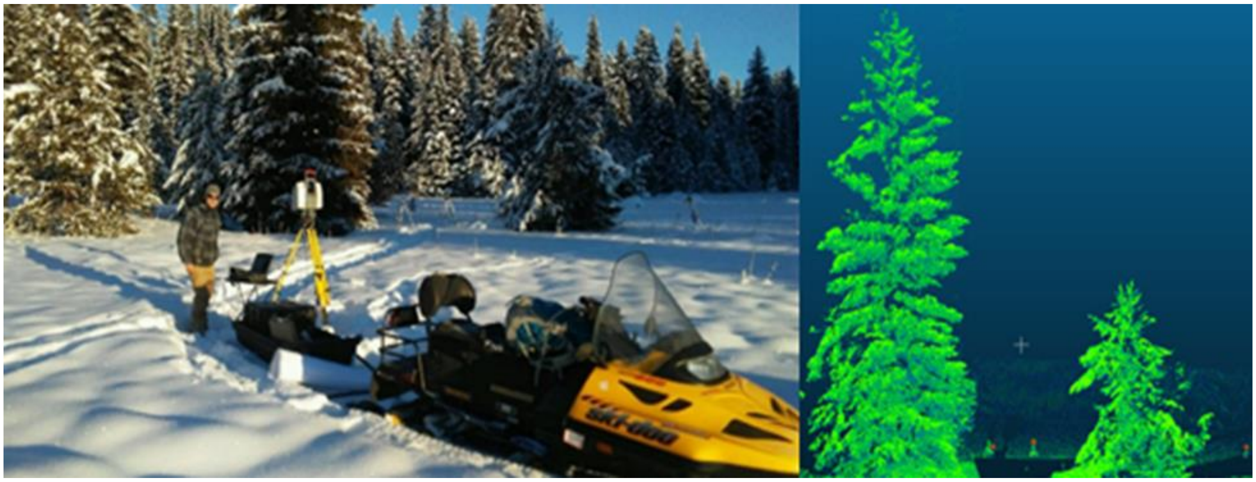


Figure 3.3. Photo of lead-author conducting terrestrial laser scanning (TLS) at Bear Basin on December 5, 2018 (left). Raw TLS point cloud data of two trees (right).

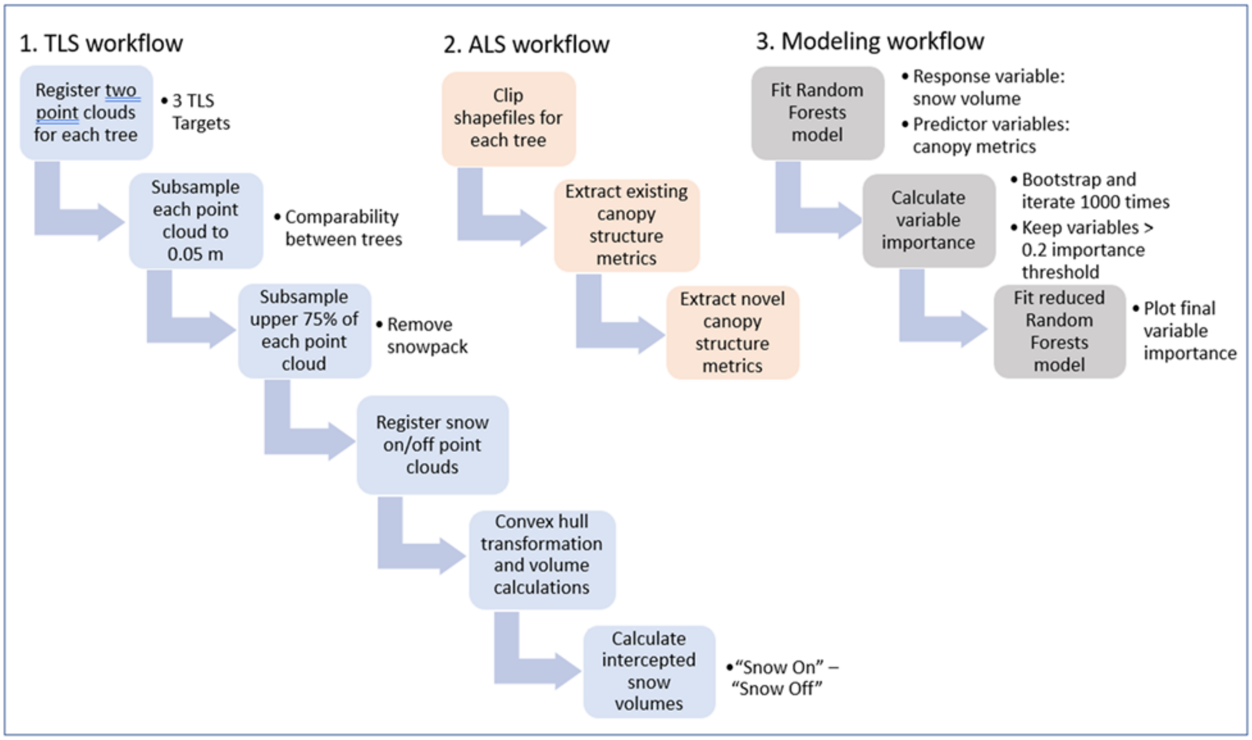


Figure 3.4. Workflow for all analyses.

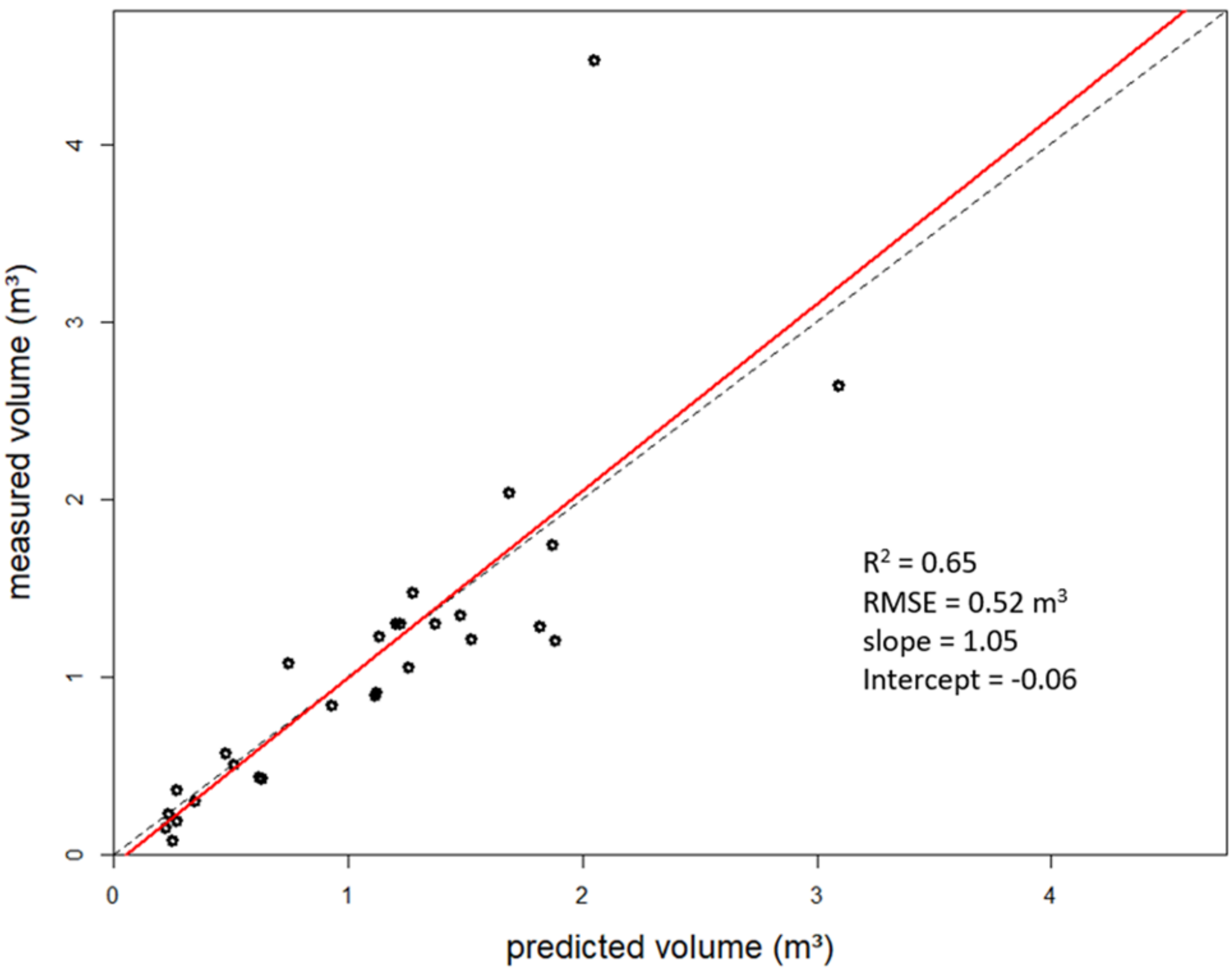


Figure 3.5. Predicted versus measured volume ($m^3$) for the final Random Forest model. Dashed black line is 1:1 line; solid red line is regression.

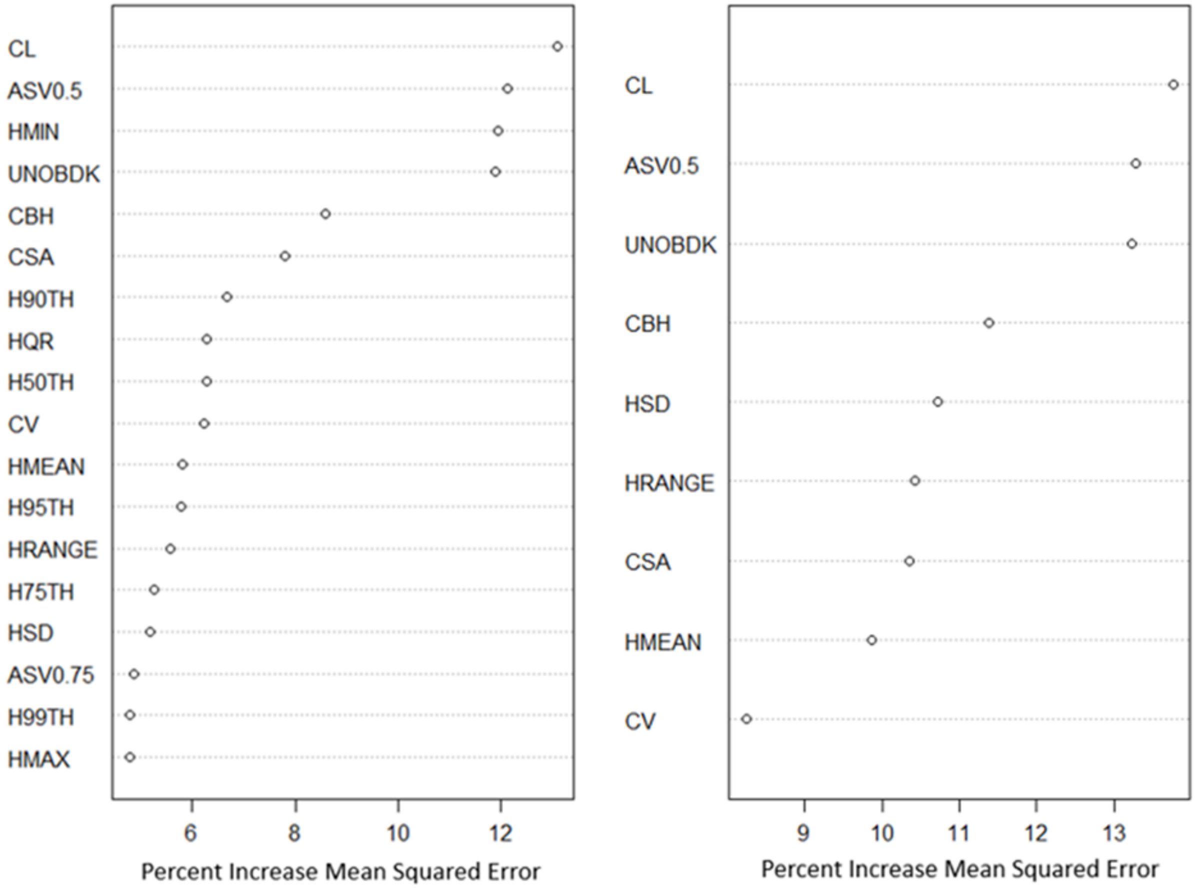


Figure 3.6. Variable importance plots (with percentiles on the left; without percentiles on the right) indicating percent increase in mean squared error when each variable is removed from the model.

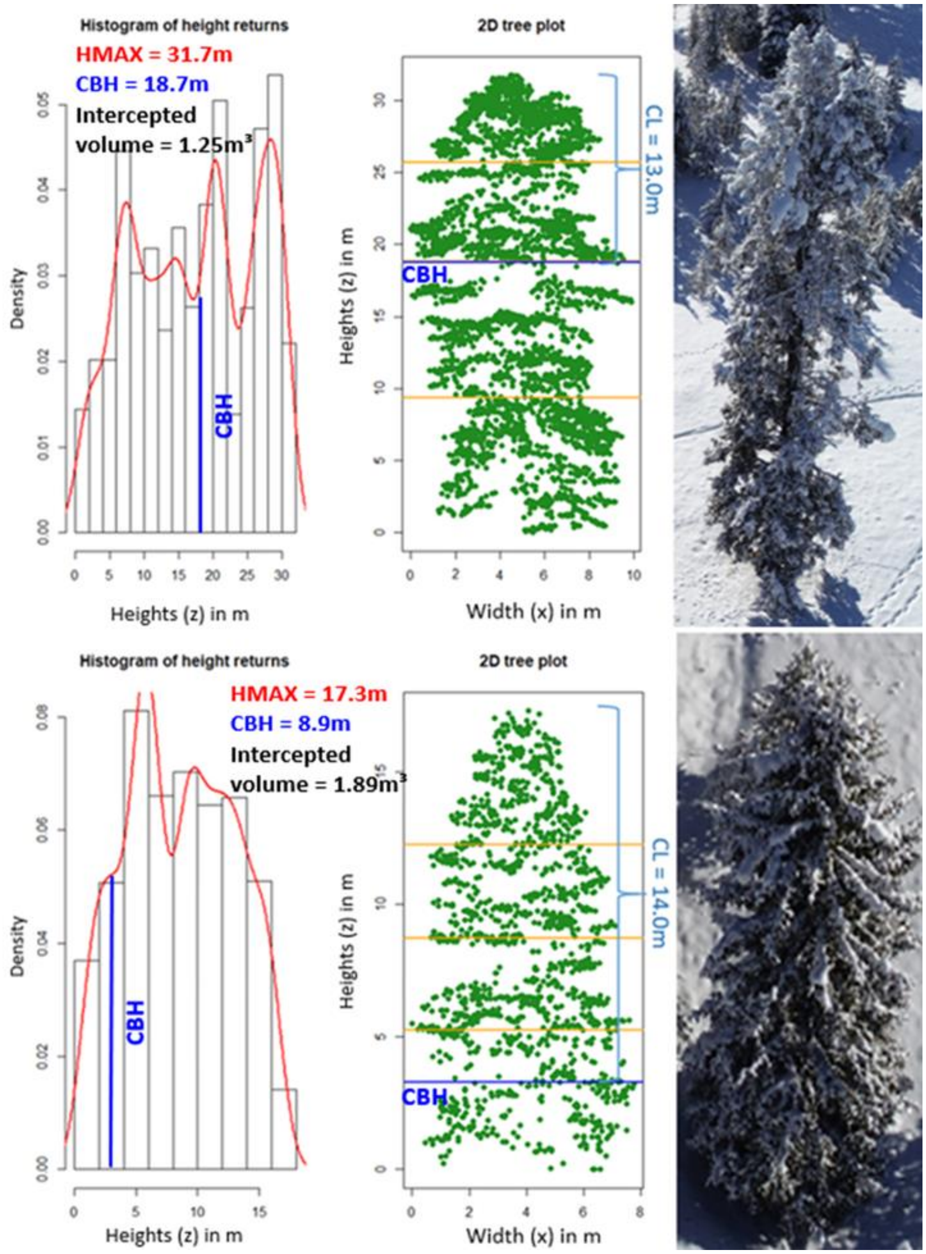


Figure 3.7. From left to right (31.7 m Tree #3 above and 17.3 m Tree #4 below): histogram of ALS height returns (z) with canopy base height (CBH) in dark blue; 2-dimensional tree plot of x and z coordinates with 25%, 50%, and 75% quartiles in orange and canopy length in light blue; unmanned aerial system image of tree from Dec. 5, 2018. Tree #3 averaged 1.25 $m^3$ intercepted snow volume and Tree #4 averaged 1.89 $m^3$ intercepted snow volume.

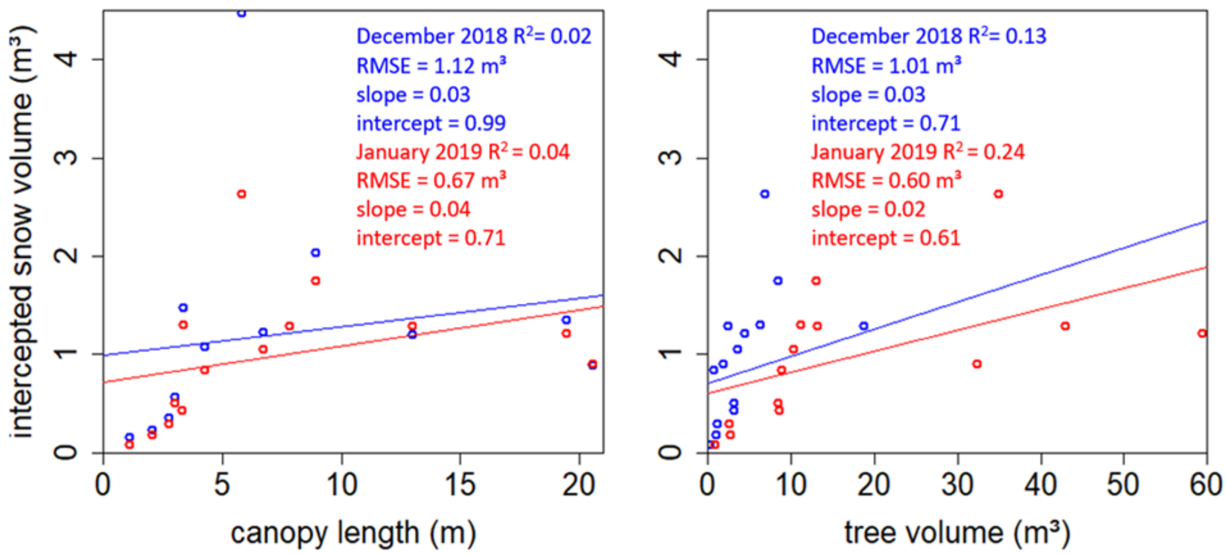


Figure 3.8. Scatterplot and simple regression models of canopy length (CL) in m and volume intercepted snow in $m^3$ (left); scatterplot and simple regression models of whole-tree volume (ASV0.5) in $m^3$ and volume intercepted snow in $m^3$ (right);. December samples are indicated by blue points and blue fitted linear regression; January samples are indicated by red points and red fitted linear regression.

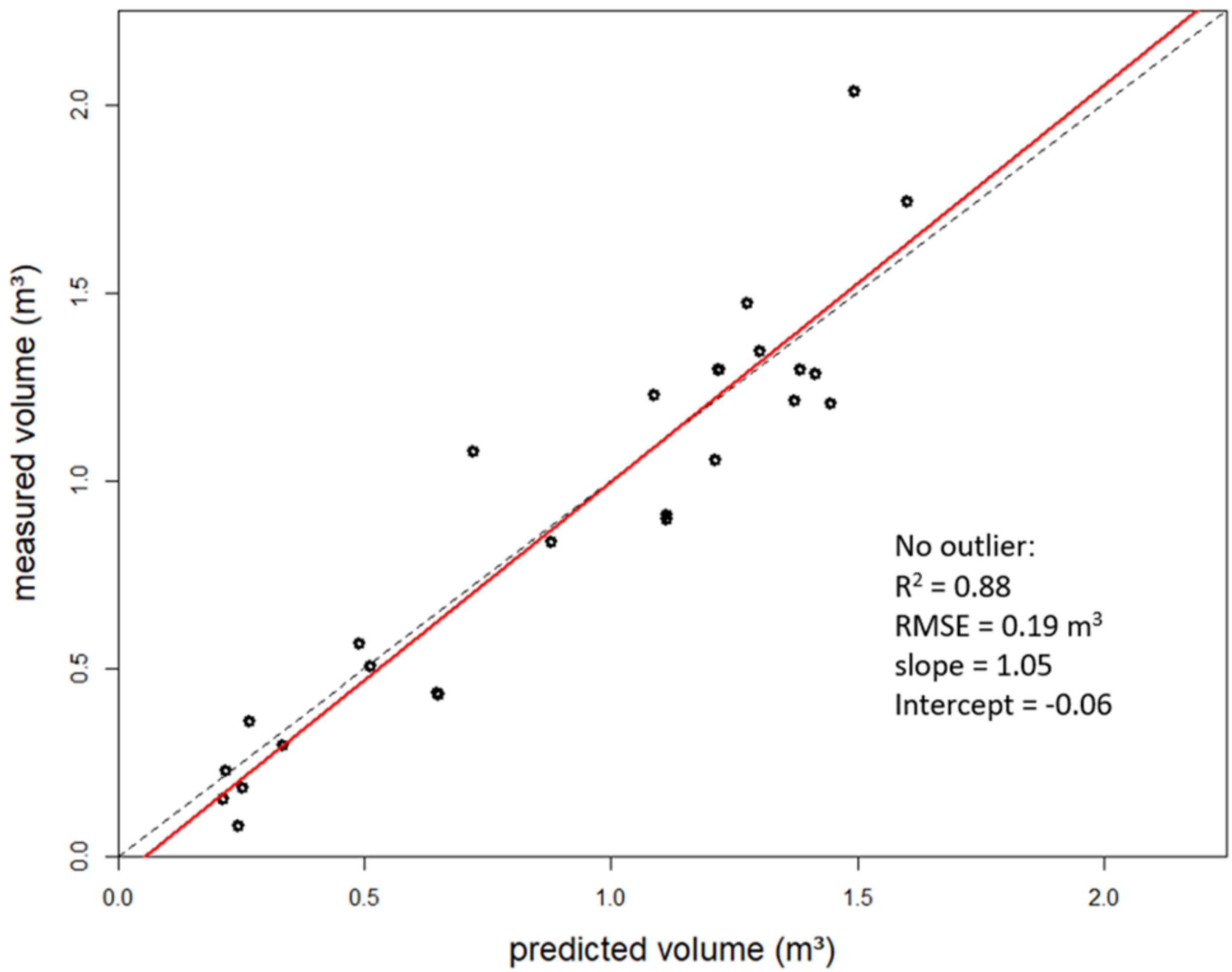


Figure 3.9. Predicted versus measured volume (m$^3$) for the final Random Forest model without potential outlier values obtained from tree #10. This tree recorded the highest measured snow volumes in each sample and is distinct from other individual-tree samples because it is a large, dense clump of trees with several stems. Dashed black line is 1:1 line; solid red line is regression line.

# Chapter 4:

# Legacy effects of hydrologic alteration in playa wetland responses to droughts

**Authors:** Micah Russell, Jennifer M. Cartwright, Gail H. Collins, Ryan A. Long, Jan H. Eitel

In revision: *Wetlands*

**Abstract**

Wetland conservation increasingly must account for climate change and legacies of previous land-use practices. Playa wetlands provide critical wildlife habitat, but may be impacted by intensifying droughts and previous hydrologic alterations. To inform playa restoration planning, we asked: (1) what are the drivers of playa inundation and how might intensifying droughts affect habitat availability? (2) do certain playas provide hydrologic refugia during droughts, and if so, how are refugia patterns related to historical alterations? Using remotely sensed surface-water data, we evaluated a 30-year time series (1985-2015) of inundation for 153 playas of the Great Basin, USA. Inundation likelihood and duration increased with wetter weather conditions and were greater in developed (altered) playas. Inundation probability was projected to decrease from 22% under average conditions to 11% under extreme drought, with annual inundation decreasing from 1.7 to 0.9 months. Only 4% of playas were inundated for at least two months in each of the five driest years, suggesting their potential as drought refugia. Refugial playas were larger and more likely to be developed, possibly because previous land managers selected refugial playas for development. These inundation patterns can inform efforts to restore wetland functions and to conserve playa habitats as climate conditions change.

## Introduction

Geographically isolated wetlands provide important ecosystems services—including wildlife habitat, water-quality maintenance, and biogeochemical cycling—but commonly lack legal protections and may be inadequately understood in terms of key drivers of wetland hydrology (Bolpagni et al., 2019; Leibowitz, 2003; Tiner, 2003). These issues may be especially acute for seasonal wetlands (i.e., temporary or ephemeral wetlands) which are typically inundated for only part of each year, with hydroperiods (i.e., durations of inundation) that can vary substantially from one wetland to another across small geographic scales (Calhoun et al., 2017; Davis et al., 2019). Climate-change impacts on biodiversity in geographically isolated, seasonal wetlands will likely be driven largely by changes in wetland hydroperiod and may be most readily discernible during periods of climatic extremes, such as droughts (Davis et al., 2019; Walls et al., 2013). In some cases, climate-change effects on wetland inundation may interact with legacy effects from past land-management practices, ranging from unintentional effects (e.g., wetland soil compaction from livestock trampling) to direct, intentional hydrologic and geomorphic alteration (e.g., ditching, dredging, or filling). As climate conditions change, some localized areas may change more gradually and thus serve as climatic refugia (Morelli et al., 2016), while sites of persistent wetness despite climatic drying may provide hydrologic refugia (McLaughlin et al., 2017). However, few studies have sought to identify potential hydrologic refugia for geographically isolated, seasonal wetlands. Identification of such refugia could improve wetland management and climate adaptation, and potentially inform wetland restoration efforts.

In the semi-arid sagebrush-steppe ecosystems of the northern Great Basin, USA, snowmelt and surface runoff from summer thunderstorms collect in terminal wetlands, salt lakes, and playas. Playas are seasonal (ephemeral) wetlands that form in closed basins with a negative annual water balance and remain dry throughout much of the year (Rosen ,1994). Playas are often associated with surface evaporites and concentrations of clay minerals that impede infiltration; thus, they may become flooded after small amounts of precipitation (Rosen, 1994). Playas in the northern Great Basin typically retain shallow water (from a thin film of water to tens of centimeters) from late winter through early summer, after which evaporation dries them out (Fig. 4.1). The degree of groundwater connectivity, if any, for most playas in the region is unknown, but a three-year study in which a playa was equipped with piezometers did not detect any subsurface soil saturation (Clausnitzer et al., 2003). Playas in the northern Great Basin exhibit considerable seasonal and inter-annual variability in inundation quantity and timing, and unlike more southern playas, they often support diverse vegetation and are not saline (Moffitt et al., 2019).

When inundated, some of these seasonal wetlands teem with aquatic invertebrates that provide a rich food source for migrating birds (O'Neill, 2014). Cumulatively, hundreds of small playas throughout the northern Great Basin may be important spring migration habitats for shorebirds, providing resting and foraging opportunities as stepping-stones between large marsh complexes (Oring et al., 2000). Migratory spotted sandpiper (*Actitis macularius*) and killdeer (*Charadrius vociferus*) have been observed on central Oregon playas (Moffitt et al., 2019). Later in the season, some moist playa soils support grasses, sedges, and forbs that provide forage for wildlife including pronghorn (*Antilocapra Americana*), mule deer (*Odocoileus hemionus*), and Greater sage grouse (Centrocercus urophasianus). Greater sage grouse, a federally-listed species of concern, sometimes use playas as leks (strutting grounds) and depend on the diverse forage and associated insects that grow in some playas for brood-rearing when upland communities have already desiccated (Hagen, 2011). In a survey of 70 central Oregon playas, Bureau of Land Management (BLM) technicians identified 159 vascular plants, 51 bird species, 13 non-bat mammal species, 12 bat species, and 62 species of aquatic macro-invertebrates (Moffitt et al., 2019). Although little research has been conducted on playas in the northern Great Basin, studies from other regions suggest that playa wetlands are important to biodiversity across much larger areas than the playas themselves (Haukos and Smith, 2003).

Because playa inundation is likely driven largely by precipitation, snowmelt, and evaporation, the water and food resources playas provide to wildlife may be vulnerable to droughts. Summer drought conditions in the northern Great Basin are projected to intensify under climate change (Ahmadalipour et al., 2017), which may exacerbate the ecological consequences of drought (Crausbay et al., 2017), including degradation of ecosystem services provisioned to wildlife from playas. In this context, variable inundation patterns among playas could imply that a small subset of playas might provide important localized refugia from droughts, i.e. isolated patches of viable habitat and resources during droughts that might help sustain wildlife populations under increasingly dry conditions (Dickman et al., 2011; Hermoso et al., 2013; McLaughlin et al., 2017; Selwood et al., 2015). If so, identifying which playas potentially function as drought refugia could help managers anticipate and potentially mitigate drought impacts on playa ecosystem services.

Strategies for mitigating drought impacts on playa habitats may include addressing the ecological impacts of previous land-use practices. In the northern Great Basin, many playas have been developed (hydrologically modified) by constructing berms and digging pits (referred to as “dugouts”) to retain water for livestock later into the summer and fall (Fig. 4.1b). Many playas on public and private lands with the potential for holding water were developed between 1950 and 1970, some with multiple dugouts, concentrating livestock impacts in sensitive playa habitats. This form of hydrologic alteration may concentrate water in a small area in and around the dugout, preventing the playa basin from filling to capacity and altering the playa hydroperiod, with possible consequences for wetland productivity (Moffitt et al., 2019). Subsequent desiccation of portions of the playa may lead to encroachment of invasive exotic grasses and silver sage (Artemisia cana) (Bureau of Land Management, 2013), as well as a general reduction in water quality (Wyland, 2013). Though dugouts allow for enhanced summertime water retention, their steep bathymetry and reduction of playa inundated area may limit their functionality as habitat for all but a small number, and few species, of shorebirds (Moffitt et al., 2019).

The BLM Prineville District in central Oregon has implemented an experimental playa restoration program that involves filling dugouts, fencing playas from livestock, mowing silver sage to create opportunities for native grass recolonization, and removing encroaching juniper (Bureau of Land Management, 2013). BLM hydrological models suggest the resulting increases in wetted playa surface area will depend on the relationship between playa volumetric capacity and dugout volumetric capacity. For example, restoring a 5.99-hectare (ha) playa with a 15.45% ratio of dugout-to-playa capacity was predicted to increase playa areal inundation by 20.98%, whereas restoring a 88.27 ha playa with a 0.45% ratio of dugout-to-playa capacity was predicted to increase playa area inundation by only 0.50% (Bureau of Land Management, 2013). Restoration may also decrease water availability late in the season, potentially representing a trade-off between improved sage-grouse forage and overall playa conditions versus negative impacts to other species that may have extended their ranges with artificial late-season water sources (Moffitt et al., 2019). Researchers using remotely sensed soil conductivity found preliminary evidence of successful rewetting of playa basins following restoration (Reuter et al., 2013), but long-term effectiveness monitoring data are not yet available.

U.S. Fish and Wildlife Service (USFWS) land managers at the Sheldon-Hart Mountain National Wildlife Refuge Complex in southern Oregon and northern Nevada (hereafter ‘the Refuge’), which no longer supports livestock operations and manages the landscape for conservation of a variety of wildlife and habitats (U.S. Fish and Wildlife Service, 1994 and 2013), are similarly interested in restoring some playas to more natural hydrologic conditions. Information is currently limited to help land managers understand where and why this highly intermittent water resource is available from year to year, such as drivers of playa inundation or spatial-temporal trends in playa inundation. Furthermore, land managers are tasked with conserving the key wildlife habitat features of playas despite projections of increasing summer drought severity across the northern Great Basin due to climate change (Ahmadalipour et al., 2017). Future projections of climate variables for the Refuge for the years 2055 and 2085 generally suggest drier summer climate conditions for the Great Basin, primarily due to increased evapotranspiration (Fig. 4.2).

To better understand playa hydrology and inform Refuge restoration planning efforts, we addressed the following questions: (1) What are the drivers of playa inundation? (2) How is playa inundation affected by increasingly severe drought? (3) Are there particular playas that remain wet under meteorologically dry conditions and thus could provide hydrologic refugia during droughts? and (4) How are these refugial patterns related to playa development? In addition to contributing to the body of knowledge on geographically isolated wetlands in the region (Comer, 2005), addressing these questions may assist land managers in considering potential restoration options and in managing playas so they continue to provide critical habitat for animal and plant species in a drier climate.

## Methods and Materials

### *Study area*

The Sheldon-Hart Mountain National Wildlife Refuge Complex (Fig. 4.3) consists of two co-managed National Wildlife Refuges (NWR): Hart Mountain NWR (1093 km2) in southeastern Oregon and Sheldon NWR in northern Nevada (2321 km2). Hart Mountain NWR ranges in elevation from 1097 – 2458 m, consisting of a fault block ridge rising steeply from the Warner Basin to the west, with low hills and ridges descending gradually to the east. Sheldon NWR consists of rimrock tablelands, rolling hills, and gorges ranging in elevation from 1250 – 2195 m. Annual precipitation in the form of winter snow and spring rain averages 305 mm for Hart Mountain NWR, and is slightly less for Sheldon NWR, with surface water in both refuges limited to springs, intermittent streams, and shallow playas. Soils and plants are typical of a high desert sagebrush-steppe ecosystem, and the land is managed for conservation of over 340 species of wildlife (U.S. Fish and Wildlife Service, 1994 and 2013).

### *Modeling drivers of playa inundation and the effects of drought*

We evaluated time series of inundation patterns for 153 playas on the Refuge, roughly half of which were developed (contained dugouts), using remotely sensed presence or absence of surface water. Monthly surface water data (30-m resolution) covering all areas within the refuge boundaries were obtained from the Global Surface Water Explorer (GSWE) API (Pekel et al., 2016), a tool for visualizing water occurrence, seasonality, and persistence based on calibrated Landsat 5, 7, and 8 images acquired between March 1984 and October 2015. GSWE relies on an expert systems procedural decision tree to classify pixels as water, land, or non-valid observations using Landsat-derived multispectral and multitemporal attributes. Equations in the decision tree were determined by visual analytics derived from a spectral library of the three classes across a wide variety of conditions, as well as images enriched by Normalized Difference Vegetation Index and Hue-Saturation-Value transformations. For pixels that could not be assigned to a class because of spectral overlap, evidential reasoning was used, taking into consideration geographic location and temporal trajectory in establishing likelihood of water presence. Validation by Pekel et al. (2016) integrated visual confirmation of over 40,000 randomly selected points distributed geographically, temporally, and across sensors. Overall errors of omission were reported as less than 5%, with overall errors of commission less than 1% (Pekel et al., 2016).

We hypothesized that playas would be responsive to local climatic conditions, and that inundation of an individual playa may also be related to its size and development history. We thus modeled playa inundation with the following covariates: playa size ($m^2$), development status (dugout presence/absence), and Standardized Evapotranspiration Precipitation Index (SPEI). We obtained monthly SPEI data (4-km resolution) from the West Wide Drought Tracker (Abatzoglou et al., 2017). SPEI subtracts monthly evapotranspiration (based on average monthly air temperature) from monthly precipitation to create a simple water balance. SPEI ranges from -5 to 5 and is standardized such that a value of 0 represents the long-term average conditions for a site, negative values indicate conditions drier than the long-term average, and positive values indicate wetter-than-average conditions. We represented climatic moisture conditions for each year using October 12-month SPEI (SPEI-12), which integrates climate conditions from November of the previous year through October of the year in question. Shapefiles representing playa borders, area, and development status were provided by USFWS.

After re-projecting and stacking the data in R (R Core Team, 2018), we calculated the areal percentage of each playa that was wet at each monthly time step (February through October, 1985 through 2015; an example is shown in Appendix A). Data from November through January were commonly not available due to cloud cover and were not used. To examine annual wetted duration, we calculated the number of months (zero to nine) in each year that each playa held any amount of water. Data exploration revealed high frequencies of zero values for both monthly percent wet and annual wetted duration. We therefore fit Generalized Linear Mixed-Effects Models (GLMMs) to both datasets using the lme4 package (Bates et al., 2015) in R, with SPEI-12, playa area, and playa development status as covariates. GLMM modeling was performed in the following sequence: 1. Determination of optimal random and fixed-effects structure based on computed Akaike Information Criterion (AIC) values, 2. model averaging to produce parameter estimates (necessary when no combination of fixed effects results in a model with substantially lower AIC), and 3. estimation of marginal and conditional $R^2$ to quantify predictive power of the best model (lowest AIC) in each of the two model sets.

Overdispersion, or variance larger than the mean, in the monthly percent wet data due to high frequencies of zero values was addressed by converting percentages to a binomial distribution (i.e., water presence/absence) (Zuur et al., 2009). We reasoned that this binomial representation of water availability was ecologically justified because even a small amount of observed inundation could potentially represent valuable habitat given the minimum surface-water detection size of 900 m2 (i.e., a single 30-m x 30-m Landsat pixel) and the general aridity of the landscape. We used a Poisson distribution to model annual wetted duration (measured as a count of total months wet); no modification was necessary to address overdispersion. We rescaled continuous predictor variables (SPEI-12 and playa area) by subtracting the mean and dividing by the standard deviation to facilitate direct comparison of model coefficients and to aid in model convergence.

GLMMs account for autocorrelation in time-series data by explicitly modeling correlation of subsamples within sampling units (i.e., groups) in the context of a user-specified random-effects structure. We used a unique identifier for each playa nested within Refuge units (i.e., Hart Mountain NWR or Sheldon NWR) as the grouping variable in our analyses. Iterative inclusion of random slopes for each predictor variable to allow for heterogeneity among groups in the influence of fixed effects did not improve model fit based on AIC values, indicating that the “random intercept-only” model represented the optimal random-effects structure. Accordingly, we fit random intercept-only models with all combinations of fixed effects to determine the optimal fixed-effects structure (Zuur et al., 2009). Because no combination of fixed effects resulted in substantially lower AIC for either model set, we then used model-averaged parameter estimates and associated 95% confidence intervals (estimated from weighted unconditional standard errors) as our basis for inference; if the 95% confidence interval for a fixed effect overlapped zero, we concluded a non-significant effect. Next, we estimated values of marginal and conditional $R^2$ to quantify predictive power of the best model (lowest AIC) in each of the two model sets (Nakagawa and Schielzeth, 2013).

To examine how playa inundation is affected by increasingly severe drought, the GLMM models for water presence (binomial) and water duration (Poisson) were fitted with the 12-month SPEI values representing historical average conditions (SPEI = 0), moderate drought (SPEI = -1.0), severe drought (12-month SPEI = -1.5), and extreme drought (12-month SPEI = -2.0), following thresholds on drought severity used by Yu et al. (2014) and Ahmadaliour et al. (2017). The binomial model was used to determine the mean probability of predicted wetness in each scenario, and the Poisson model was used to determine the mean predicted months wet per year in each scenario.

*Identification of hydrologic refugia during droughts*

To identify playas that might serve as hydrologic refugia during droughts (i.e., a small subset of playas that might hold water even under the driest conditions in our dataset), we began by identifying the five years (from 1985 through 2015) that had the lowest observed playa inundation (fewest numbers of wet playas) in the study area. Although we selected these years based solely on observed playa inundation patterns, we also used October SPEI-12 to confirm that these years adequately represented meteorological drought conditions for the study area.

We reasoned that in the five years of scarcest playa inundation, the few playas that did retain water might serve as potential refugia (water and/or food sources) for wildlife during droughts. In particular, we sought to identify refugia that demonstrated temporal stability across multiple drought years. For each playa, we calculated the number of years wet (from zero to five) and the average number of months wet during each of the five driest years. We classified playas as potential drought refugia if they remained wet in all five of the driest years and held water for at least two months on average during the five driest years. After identifying playas that served as possible drought refugia, we asked whether these playas were generally represented by playas that consistently held water each year across a range of climate conditions, i.e. whether playas that were generally wet under average weather conditions could be used to identify refugial playas during droughts. To that end, we calculated the total number of years each playa was wet (defined as any amount of wetness for any length of time) from 1985 through 2015, excluding the five dry years. We then compared these patterns ("all other years") to the playa inundation patterns for the 5 driest years. Finally, we examined relationships between drought-refugia metrics (number of years wet and average number of months wet during the five dry years) and playa size using Spearman correlations, and relationships of these metrics with development status using a one-way analysis of variance (ANOVA).

## Results

Playas on the refuge varied greatly in size, from approximately 0.5 ha to >1,000 ha, although the majority (roughly two-thirds) of playas were <20 ha. The number of wet playas across the Refuge varied by month and year (Fig. 4.4), ranging from zero to 95 out of a total of 153. Notably, even under the wettest conditions, more than a third of all playas (58 out of 153) were dry. Playa wetness across the Refuge generally peaked in spring (March through May) as a result of rainfall and snowmelt and declined over the course of the summer (Fig. 4.4).

*Drivers of playa inundation*

AIC values and associated AIC weights (*wi*) used for model averaging of both the water presence (binomial) and water duration (Poisson) model sets are presented in Table 4.1. Model convergence was achieved for 79% of models. In both models sets, model-averaged parameter estimates were statistically significant (i.e., confidence intervals did not overlap zero) for SPEI and development status, but not playa area (Fig. 4.5a). SPEI was positively related to water presence (Fig. 4.5a) and water duration (Fig. 4.5b), indicating that wetter climate conditions increased the probability and seasonal length of playa inundation. Negative parameter estimates for development status indicated that the probability of a playa holding water and its duration of inundation were significantly lower if it was undeveloped.

The best models (lowest AIC values) for water presence and duration produced low marginal $R^2$ (0.11 and 0.10, respectively) but higher conditional $R^2$ (0.78 and 0.82, respectively), indicating that there was considerable variation among playas in the presence and duration of water, and that accounting for that variation through the inclusion of a random effect substantially improved model fit.

Using the water presence (binomial) model with drought scenarios (i.e., SPEI-12 values indicating various levels of drought severity), the mean probability of a playa being wet across the full range of all other predictor variables declined from 22% (historical average), to 15% (moderate drought), to 13% (severe drought), to 11% (extreme drought) (Fig. 4.6a). Similarly, using the water duration (Poisson) model with drought scenarios, the predicted mean number of months wet per year for a playa across the full range of all other predictor variables declined from 1.69 (historical average), to 1.20 (moderate drought), to 1.01 (severe drought), to 0.85 (extreme drought) (Fig. 4.6b).

*Refugial playas during droughts*

We selected the years 1987, 1992, 2012, 2014, and 2015 to represent drought conditions based on playa inundation patterns (Fig. 4.7, see dashed vertical lines in (a) and solid circles in (b)). Specifically, these were the years with the lowest average numbers of wet playas across the study area: from 9.1 to 13.1 playas were wet (averaged from February through October), compared to a mean value of 29.1 wet playas across all years, 1985-2015. These five years also had the lowest annual maximum number of wet playas (maximum in each year from February through October), ranging from 22 to 28, compared to a mean of 57.9 from 1985-2015. In general, playa inundation (represented both as mean annual and annual maximum number of wet playas) was positively associated with October SPEI-12 (Fig. 4.7b). The five years that exhibited minimum playa wetness in the study area were characterized by moderate to severe drought conditions (all had October SPEI-12 < -0.8). Indeed, one of the selected years (1992) had the lowest October SPEI-12 value between 1985 and 2015 (-1.66, indicating severe drought), and three of the selected years (1992, 2012, and 2014) were among the four driest years in the study (all had October SPEI-12 < -1.4).

Nearly half of all playas (71 out of 153 playas; 46%) had no water in any of the five dry years selected for drought-refugia analysis. Of the remaining 54% that contained water in at least one dry year, 27% held water in at least three years, 15% held water in at least four years, and only 6% (nine playas total) held water in all five of the dry years. Notably, the nine playas that were wet in all five years were (by definition) wet in 1992, a year of severe drought in which the vast majority of playas on the refuge became dry (Fig. 4.7).

The average number of months wet during the five dry years varied among playas, ranging from 0 to 6.8 months (Fig. 4.8a). The majority of playas (105 out of 153; 69%) were wet in fewer than 3 of the 5 dry years and for less than one month per year on average during those years. Of the nine playas that held water during all five of the dry years, six of them (4% of all playas) also held water for at least two months on average during those years, meeting our criteria for drought refugia. These six playas appear exceptional in their history of providing water during drought conditions, and specifically during times when playa inundation is exceedingly scarce across the landscape.

Playas that were wet during most or all of the five driest years (i.e., with higher values on the horizontal axes of Fig. 4.8) also tended to be wet during most other years (note absence of points in the lower right quadrant of Fig. 4.8b). Thus, any playas identified as drought refugia based on dry-year analysis were also likely to be wet in other (non-drought) years. However, the reverse was not necessarily true: consistent wetness in all other years (i.e., higher values on the vertical axis of Fig. 4.8b) did not always imply consistent wetness during dry years (note presence of points in the upper left portion of Fig. 4.8b, representing playas that were generally wet in most years but often dried out during the 5 driest years). These results indicate that playas that were consistently inundated during non-drought years did not necessarily serve as drought refugia.

Based on Spearman correlation, larger playas were more likely to hold water during droughts: $\rho(151) = 0.35$, $P<0.001$ for the relationship between playa size and number of years wet during the five driest years and $\rho(151) = 0.36$, $P<0.001$ for the relationship between playa size and average months wet during those five years. In addition, developed playas held water for a greater number of years during the 5 driest years (F=14.96, P<0.001) and for more months on average during those driest years (F=9.58, P<0.01) compared to undeveloped playas. Developed playas also were more likely to hold water during all years (1985 through 2015) across a range of climate conditions (F=10.4, P<0.01). Of the nine playas that held water in all five dry years, seven (78%) were developed. Of the 6 refugial playas (wet in all five dry years for at least two months on average), 5 (83%) were developed. Notably, developed playas also tended to be larger in size than undeveloped playas (F=9.83, P<0.01). Collectively, these results suggest strong positive associations between playa size, development status, and functional status as drought refugia.

## Discussion

Interannual variation in weather conditions is a clear driver of playa inundation in this study area. Although groundwater connectivity of playas has not been rigorously studied in this region, we found that playa inundation is closely tied to local precipitation and evapotranspiration patterns, suggesting that most playas are likely not receiving large groundwater subsidies. Analysis of piezometer data from a playa roughly 100 km north of the study area similarly indicated lack of groundwater connectivity (Clausnitzer et al., 2003).

Our results confirm expectations that under drought conditions, managers can anticipate fewer playas to hold water and for those playas to be inundated for shorter seasonal periods. For example, during the dry years 2012 through 2015, in which October SPEI-12 ranged from -0.33 to -1.45, the number of inundated playas in our study area in July ranged from 1 to 9, compared to a July average from 1985-2011 of 26 inundated playas. Playa responses to droughts may have important implications in the context of regional concerns about drought intensification under climate change, i.e. droughts that may become longer, more frequent, and/or more severe. For example, Ahmadalipour et al. (2017) projected long-term changes in summer 3-month SPEI in the northern Great Basin under an RCP8.5 emissions scenario averaging -0.02 units per year, equivalent to a decrease of 0.5 SPEI units over 25 years. In a future climate with drier summers and greater evaporative demand (see Fig. 4.2), periodic droughts will likely exacerbate loss of ecosystem services and aquatic habitat provided by playas and may highlight the importance of the few playas that can provide drought refugia to wildlife. The ability of playa wetlands that have historically functioned as drought refugia to continue doing so in a drier future climate is unknown. Thus, conservation of playa-dependent plant and animal species may necessitate further study of the hydrogeologic and hydrogeomorphic properties of playas identified as potential drought refugia, including improved understanding of the roles of basin bathymetry and possible shallow groundwater interactions.

As managers plan for climate-change impacts to playa wetlands, they may simultaneously be considering hydrologic and ecological restoration efforts. Although we found that playas with dugouts were more likely to hold water, to retain water for longer periods, and to serve as drought refugia, we stress that correlation between development status and observed playa hydrology does not reveal the nature or direction of causation. Indeed, far from being a randomly assigned treatment, playa development may have been guided by natural variability in playa hydrology that was observed by previous generations of land managers. Although documentation of historical playa development decisions by land management agencies and individual ranchers is scarce, we speculate that in many cases land managers may have chosen to develop those playas that they noticed were consistently holding water from one year to another, and perhaps also playas that were observed to hold water in dry years. Such targeted development could have benefited livestock operations by optimizing water retention on the landscape for a given amount of investment. If so, the positive association we observed between development status and playa inundation may be due at least in part to the historical selection of drought refugia as sites for development.

Because water developments for livestock are no longer needed to support grazing operations, Refuge managers are considering hydrologic restoration of some playas, which could include leveling berms and filling dugouts to create a smoother playa surface that more closely approximates the geomorphology of undeveloped playas. Such restoration efforts would be aimed, in part, at increasing the geographic extent of playa surface inundation and lengthening playa hydroperiods by preventing water from draining into dugouts. Although we did not perform a comprehensive assessment of dugout locations relative to playa wetness patterns, we noticed that not all dugouts are located within the most-inundated zones of their respective playas. Examination of two playas that held water in all of the five driest years (Fig. 4.9) helps to illustrate several management considerations that are relevant to restoration planning. One playa (Fig. 9a and 9b) has a dugout located within the zone of greatest wetness in the lowest-elevation area of the playa. In such a case, filling the dugout might reduce drainage of water from the playa surface and enlarge the inundated extent within the playa. However, in another example (Fig. 9c and 9d), the dugout is located almost 3 m above the lowest area of the playa and is not within the most frequently inundated zone. In this case, it is unclear how dugout filling might affect playa hydroperiod and areal extent of inundation. This comparison underscores the importance of site-specific restoration planning and suggests how remote-sensing inundation analysis could help inform such planning efforts. Furthermore, restoration planners may need to consider playa area and the ratio of dugout-to-basin volumes. Large “lakebed playas” may provide more consistent water, emergent vegetation, and aquatic invertebrates than small “ponded clay playas,” which often have encroaching sagebrush (Moffitt et al., 2019). However, relative gains in inundated area resulting from filling dugouts may be limited in large playas due to a low ratio of dugout volumetric capacity to playa volumetric capacity.

Because playa development was not a randomly assigned experimental treatment, our study was by nature observational, and hence it does not resolve the mechanisms by which development may increase or decrease the ecosystem services provided by playas as water and food sources within the landscape, or as potential drought refugia. One future approach to addressing this question could involve incorporating a randomized experimental design into future playa restoration efforts. For example, if a randomly chosen subset of developed playas was assigned to undergo restoration as an experimental treatment (withholding all other developed playas as a control), then the effects of restoration on playa hydrology and ecosystem services could be rigorously assessed. Such considerations in the design of ecological restoration programs can increase the knowledge and insights gained from subsequent monitoring programs (Block et al., 2001). In addition, pre- and post-restoration field monitoring of ecosystem services provided by playas (e.g., migratory bird use, aquatic habitat and invertebrate food resources provided, late-season forage for terrestrial wildlife) could help ascertain the ecological consequences of attempts to restore playas to more natural hydrologic conditions.

*Refugial playas during droughts*

Playa wetlands are an understudied but important seasonal water and food resource for migrating birds and other wildlife that may be negatively impacted by climate drying and drought intensification. This study identified drivers of playa inundation in the northern Great Basin, simulated the effects of intensifying droughts on playas, and identified a subset of playas that appear to function as hydrologic refugia during droughts. Historically, larger playas and playas with dugouts were more likely to provide drought refugia; however, the ability of these playas to function as refugia under climate change and in the context of hydrologic restoration efforts is unknown. To adequately prepare for climate-change impacts and assess possible implications of restoration, more research is needed on playa geomorphology and hydrogeology, potentially coupled with rigorously controlled experimental restoration studies and long-term monitoring of restoration effectiveness.

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**Tables**

Table 4.1. Akaike Information Criterion (AIC) values, Delta AIC (ΔAIC), and AIC weights ($w_i$) used in Generalized Linear Mixed-Effects Model (GLMM) averaging.

| Water Presence Model | AIC | ΔAIC | $w_i$ |
|---|---|---|---|
| SPEI + status | 26365.3 | 0 | 0.69833 |
| SPEI + status + area | 26363.3 | 3 | 0.15582 |
| SPEI + area | 26368.8 | 3.5 | 0.12135 |
| SPEI | 26374.2 | 6.7 | 0.02450 |
| status + area | 26463.4 | 2098.1 | 0 |
| status | 28466.2 | 2098.7 | 0 |
| area | 28466.7 | 2099.2 | 0 |

| Water Duration Model | AIC | ΔAIC | $w_i$ |
|---|---|---|---|
| SPEI + status | 11276.2 | 0 | 0.74316 |
| SPEI + status + area | 11274.8 | 3.6 | 0.12284 |
| SPEI + area | 11280.4 | 4.2 | 0.09101 |
| SPEI | 28463.4 | 5.7 | 0.04299 |

**Figures**

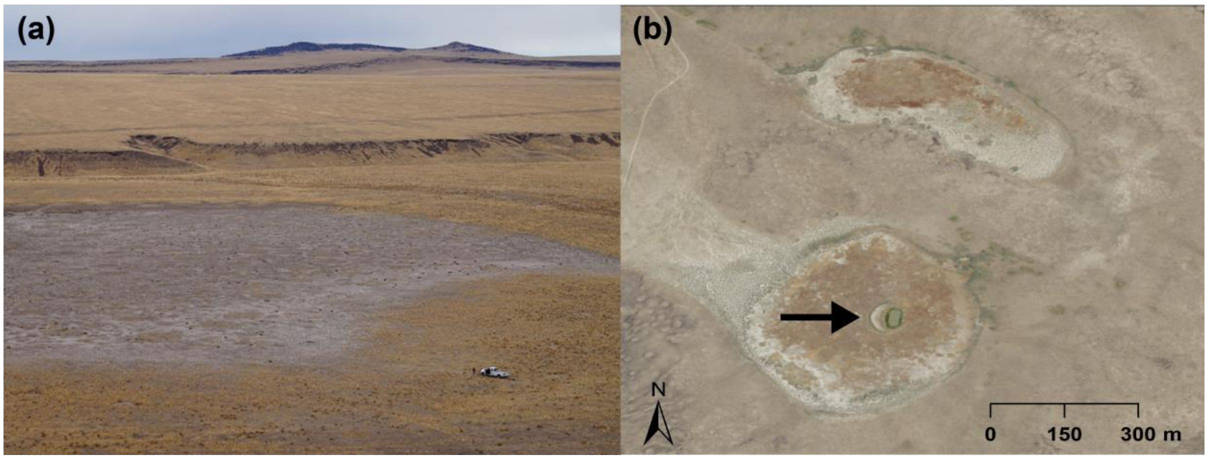


Figure 4.1. Dry playa viewed (a) from the ground and (b) in aerial imagery. In (b), the playa to the north has not been developed, whereas the playa to the south has a berm and pit ("dugout"), indicated by the black arrow, that were constructed to provide water to livestock.

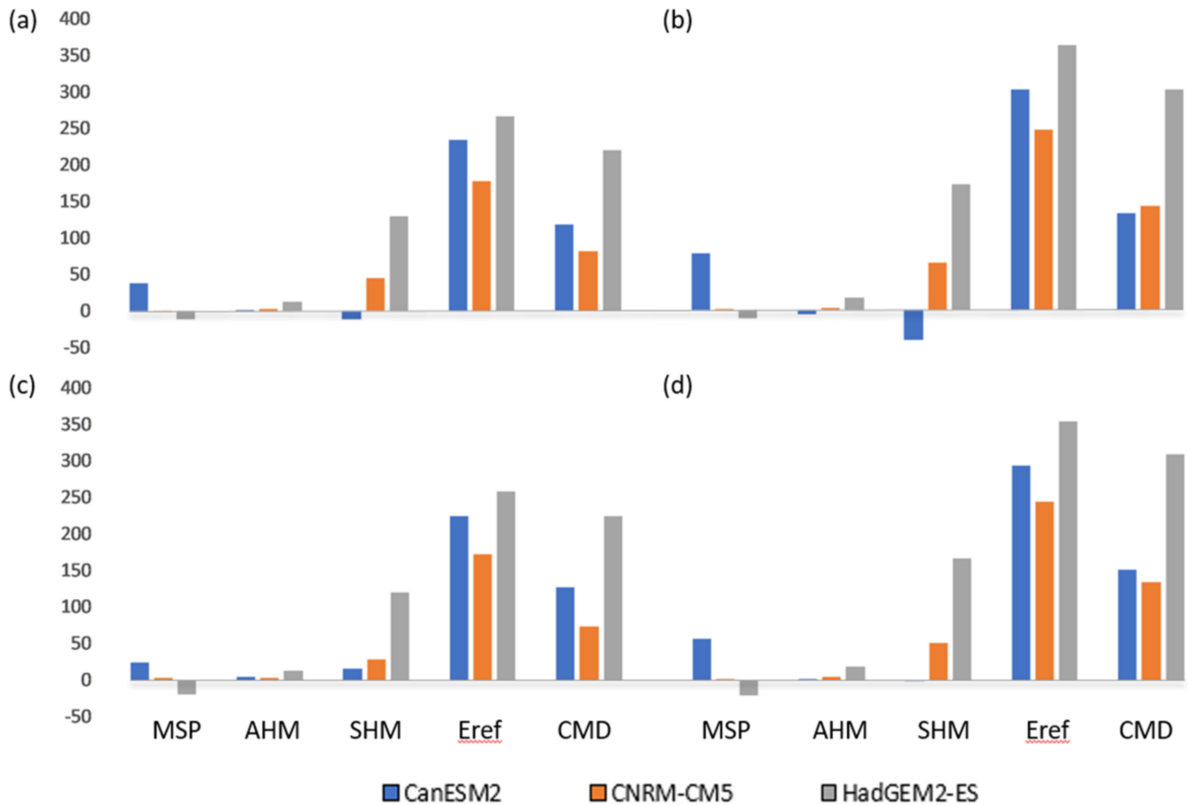


Figure 4.2. CanESM2, CNRM-CM5, and HadGEM2-ES climate model predictions for (a and b) Sheldon National Wildlife Refuge in 2055 and 2085, and (c and d) Hart Mountain National Wildlife Refuge in 2055 and 2085, represented as changes from 1971-2000 historical means. Climate variables represented are: mean summer precipitation (MSP), annual heat-moisture index (AHM), summer heat-moisture index (SHM), reference evaporation (Eref), and climatic moisture deficit (CMD) All climate variables were obtained from ClimateWNA (2019).

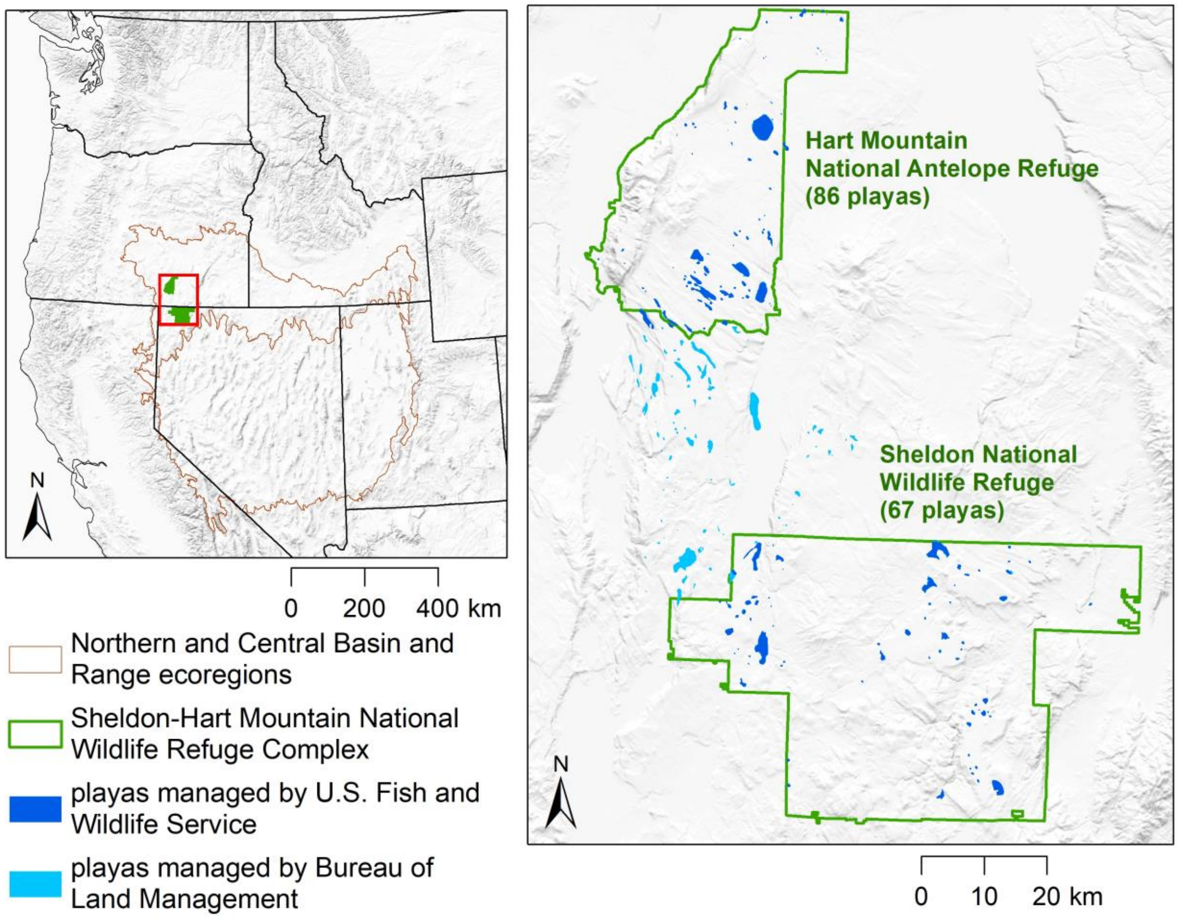


Figure 4.3. The study area contains 153 playas managed by the U.S. Fish and Wildlife Service on the two wildlife refuges that comprise Sheldon-Hart Mountain National Wildlife Refuge Complex, in southern Oregon and Northern Nevada, USA.

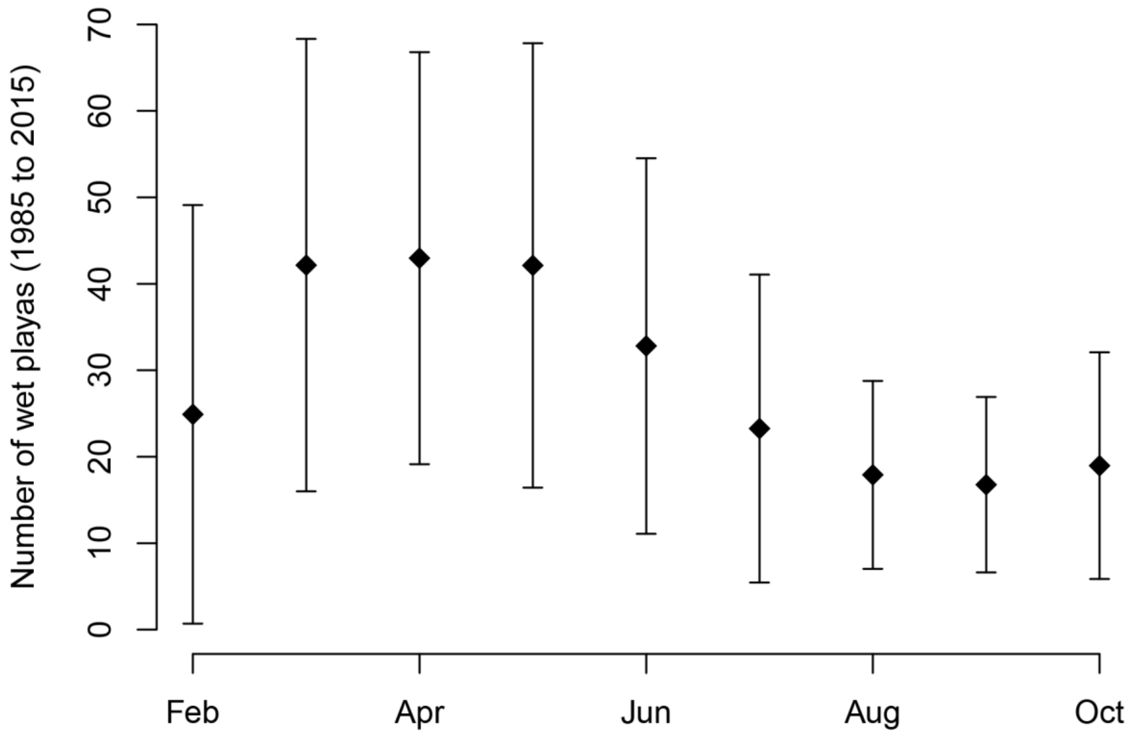


Figure 4.4. Mean (±SD) number of wet playas (out of a total of 153) between February and October, 1985-2015.

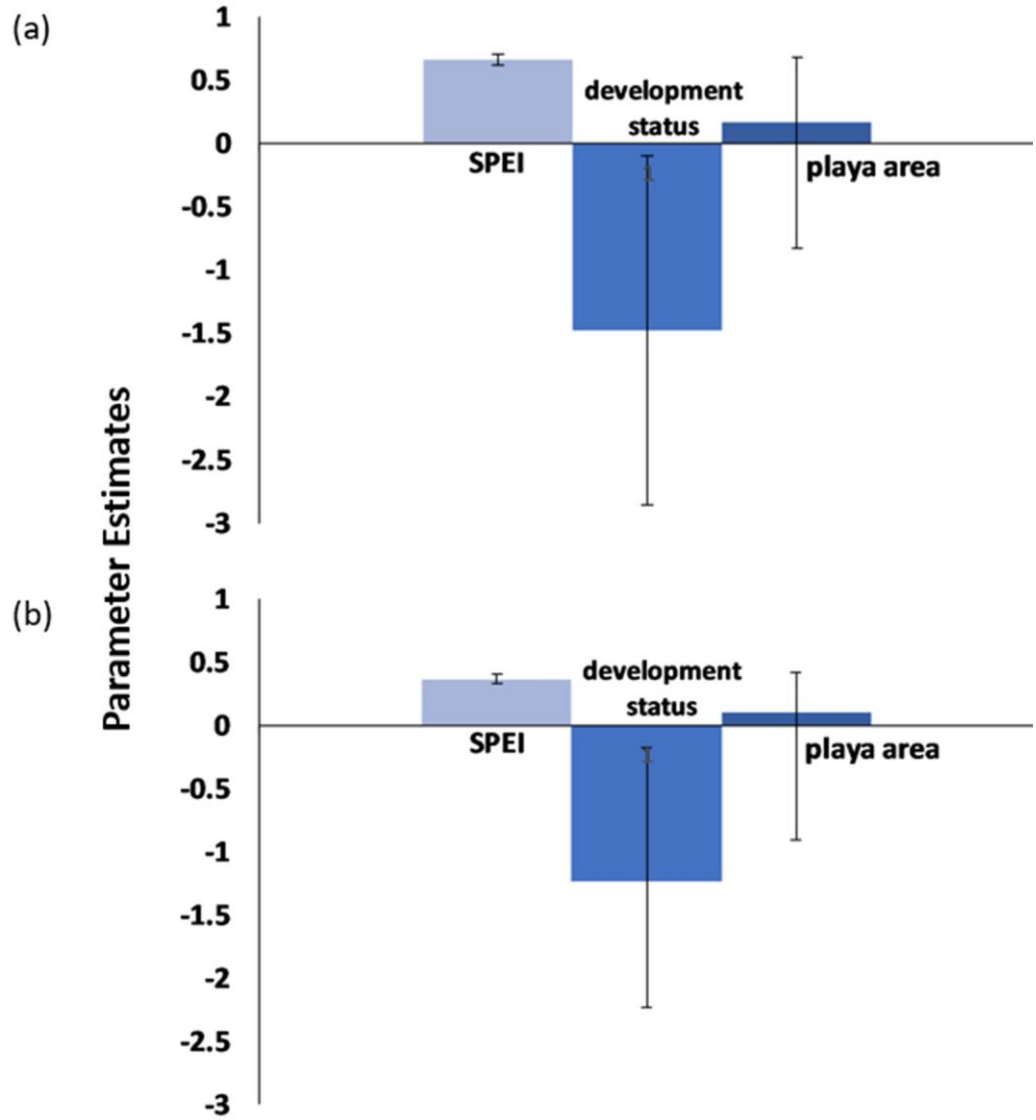


Figure 4.5. GLMM model-averaged parameter estimates and 95% confidence intervals for water presence (a) and water duration (b).

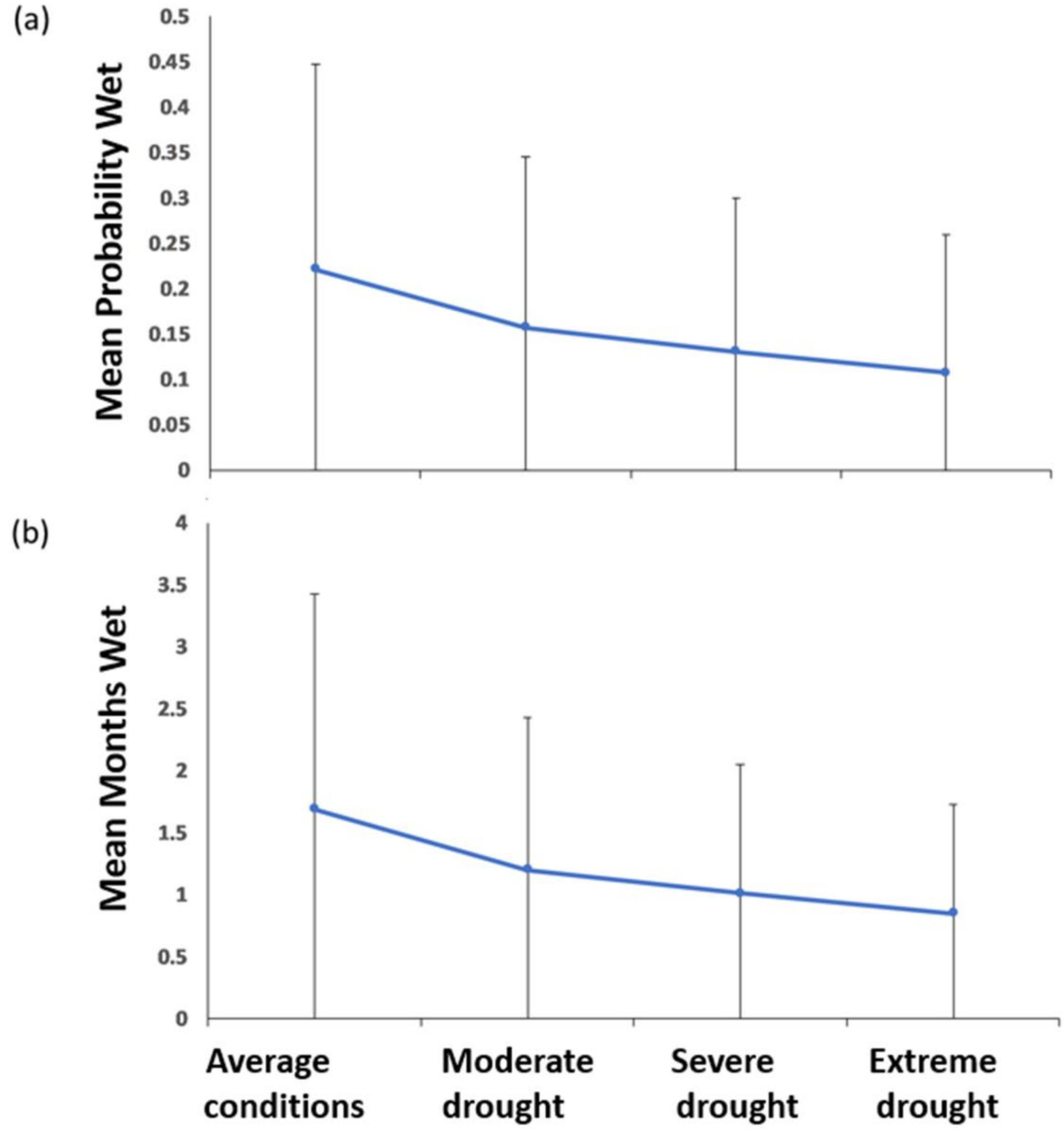


Figure 4.6. Using drought scenarios (i.e., SPEI-12 values indicating various levels of drought severity), GLMM-derived mean and standard deviation for (a) percent probability of predicted wetness for a playa, and (b) predicted months wet per year for a playa (out of 9), across the full range of all other predictor variables. Drought scenarios include: long-term, historical average conditions (SPEI=0), moderate drought (SPEI=-1), severe drought (SPEI=-1.5), and extreme drought (SPEI=-2).

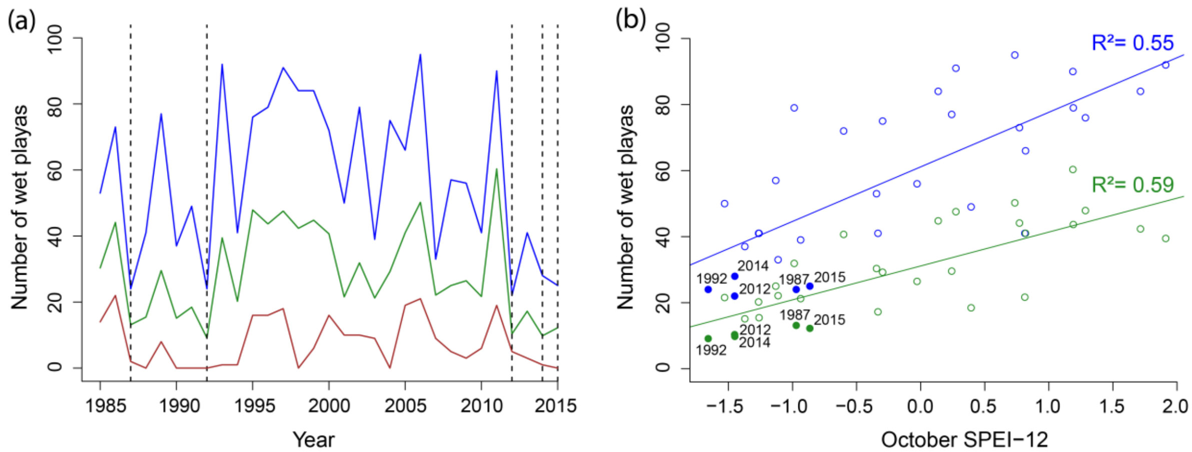


Figure 4.7. Selection of the five driest years of the study based on observed playa inundation. Time series plots in (a) depict the annual maximum (blue), annual mean (green), and annual minimum (brown) number of wet playas in the study area between February and October of each year. The five years with the lowest annual mean and lowest annual maximum number of wet playas are indicated by vertical dashed lines. These five years are depicted in (b) as closed, labelled circles; all other years are open circles. Relationships between numbers of wet playas and October SPEI-12 (Standardized Precipitation Evapotranspiration Index in October of each year using 12 months of antecedent climate conditions) are represented in (b), with annual maximum and annual mean numbers of wet playas in blue and green, respectively. Simple linear regression lines with $R^2$ values quantify relationships between October SPEI-12 and playa wetness from 1985-2015.

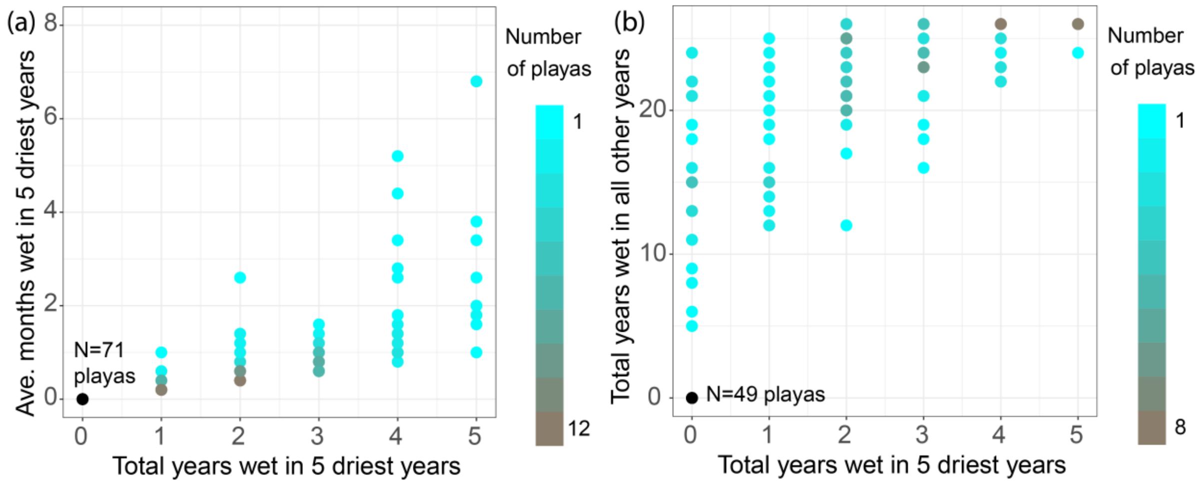


Figure 4.8. Distribution of playas in the Sheldon-Hart Mountain National Wildlife Refuge Complex based on (a) the number of years wet and average months wet during the five driest years, and (b) number of years wet in the five driest years and number of years wet in all other years from 1985-2015. In (a), 71 playas (46%) had no observed inundation in any month during the five dry years. In (b), 49 playas (32%) had no observed inundation in any year from 1985-2015, including during the five driest years.

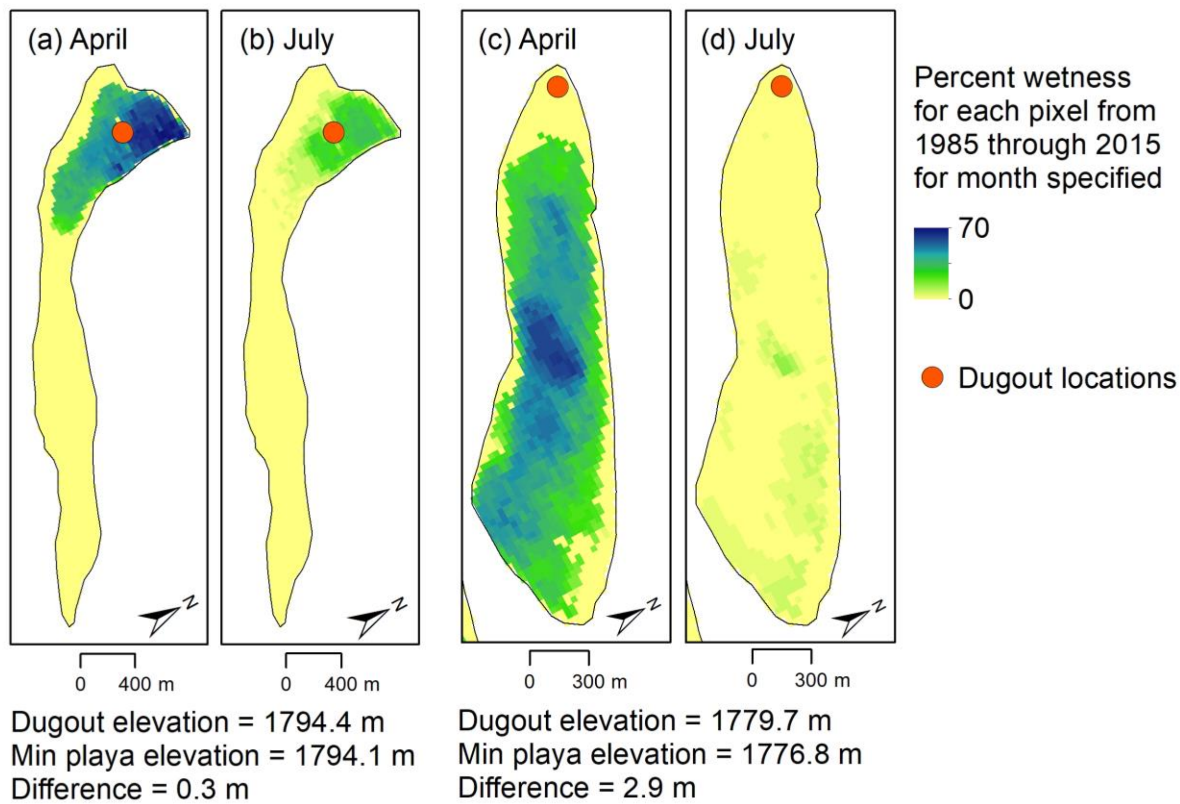


Figure 4.9. One example playa (a and b) showed inundation concentrated near the dugout location in (a) April and (b) July, averaged over 1985 through 2015. In this playa, the dugout is located near the lowest-elevation zone of the playa. By contrast, in another example (c and d), the dugout is not located in the areas of greatest wetness in (c) April or (d) July and is instead located almost 3 m higher than the lowest-elevation zone of the playa.

# Chapter 5:
# Climate change knowledge and gaps in mountainous headwaters: spatial and topical distribution of research in the Columbia River Basin

**Authors:** Adrienne M. Marshall, Meghan Foard, Courtney M. Cooper, Paris Edwards, Shana L. Hirsch, Micah Russell, and Timothy E. Link

In review: *Regional Climate Change*


## Abstract

Climate change is altering mountainous headwaters and the biophysical and social systems that depend on them. While scientific knowledge on climate change abounds, literature syntheses are needed to understand the multidisciplinary impacts, identify critical knowledge gaps, and assess potential management and policy responses. In this study, we systematically map and analyze the topical and spatial distribution of climate change research in the mountainous headwaters of a major transboundary watershed, the Columbia River Basin (CRB). We find that climate change research in the CRB focuses on impacts much more frequently than adaptation, while mitigation is rarely a focus. Most studies assess trends at large spatial extents, use secondary data, and make projections of climate change impacts rather than observations. The spatial distribution and thematic content of research varies across an international border, with greater concentrations of research in the United States than Canada. A general scarcity of social science research and limited interaction between social and biophysical content reinforce the need for increased collaboration between disparate disciplines. Future research focus areas should include research related to climate change adaptation and mitigation, increased integration between social and biophysical sciences, and collaborations that bridge the international border for a more unified basin-wide focus. Focusing on these new directions for research will increase the potential for science and management communities to co-produce actionable science and effective responses to climate change.


## Introduction

*Study context*

Climate change in mountainous regions is projected to have serious consequences for social and ecological systems due to impacts on snowpack and hydrological dynamics, fire regimes, biodiversity, and ecosystem function, many of which are already occurring (La Sorte and Jetz, 2010; Nogués-Bravo et al., 2007; Viviroli et al., 2011). These remote environments are critically important for many societies; for example, one-sixth of the global population resides in areas that depend on mountain meltwaters (Parry, 2007). Due to their importance and complexity, research on climate change in mountainous landscapes spans many disciplines, scales, and methodologies. The research that is conducted ultimately shapes the breadth and depth of the body of knowledge influencing governance and natural resource management (Jasanoff, 2004). Moreover, the spatial distribution of research activity is surprisingly difficult to elucidate, yet has important consequences for our understanding of natural systems (Karl et al., 2013; Wallis et al., 2011). It is therefore imperative to understand what research themes are (and are not) well studied, as well as the geographic distribution and disparities of these themes in order to gain a holistic understanding of these systems and develop effective strategies to adapt to change.

The headwaters of the Columbia River Basin (CRB) are an important test case for understanding the state of knowledge about climate change in a mountainous region that is profoundly affected by non-stationary climatology. It serves as an example of a large, transboundary river basin with diverse ecosystems, complex socio-political histories, and a dependency on seasonal snowmelt to maintain water supplies and ecosystem function (Mankin et al., 2015). The region's water resources generate over half of the United States' hydroelectric power production, position the CRB as the leading producer of 22 key agricultural commodities, and sustain a population growing at more than twice the rate of the national average (EIA, 2018; USDA, 2018; US Census Bureau, 2017). The region has the scientific and policy-making infrastructure to support a large volume of research and engages in relatively extensive climate change adaptation efforts through, for example, government-led vulnerability assessments (Muccione et al., 2016; Olson, 2017). Because of the broad scope of climate change-related science in the CRB, and the outsized impact of its mountainous natural resources on society at large, rigorous assessment of topical and spatial trends in research is needed to identify critical knowledge gaps.

*Motivation for knowledge synthesis*

Calls for approaches to systematically assess climate change research are ubiquitous (Hulme 2010; Petticrew and McCartney, 2011), yet conducting comprehensive reviews is challenging because the scope of climate change involves synthesis across multiple disciplines and large bodies of literature (Lenhard et al., 2006). Berrang-Ford et al. (2013) describe the diverse set of approaches used in modern research syntheses, ranging from narrative reviews to scientometrics. While traditional narrative reviews typically provided detailed assessments of the findings of a particular field, science mapping (scientometrics) and systematic review approaches have gained popularity in recent years due to their utility in characterizing interdisciplinary fields and making sense of large, disparate bodies of literature. Specifically, scientometric approaches use data from citation indices to measure scientific activity on specific themes. Systematic reviews vary widely in their implementation but typically apply rule-based methods for document inclusion and emphasize quantitative analyses of a body of research (Berrang-Ford et al., 2013; Gough and Oliver, 2012). Several systematic reviews in recent years have assessed trends and gaps in climate change research, often with focuses on adaptation and impacts (e.g., Ford and Pearce, 2010; Ford et al., 2012; Sud et al., 2015; Tuihedur Rahman et al., 2018).

*Research questions and objectives*

In this study, we blend elements of scientometric approaches with a systematic review in order to identify the thematic content and spatial attributes of peer-reviewed research related to climate change in the mountainous regions of the CRB. The specific questions that we address are: (1) What are the common thematic foci and relative deficiencies in this body of research? (2) What are the spatial scales and distribution of climate change research in the headwater regions of the CRB? (3) Is the thematic content of research clustered spatially or conducted at specific scales in a way that suggests a need for further study of particular topics, specific places, or both?

The primary outcome of this work is the elucidation of knowledge gaps in areas of scientific inquiry that are strategically beneficial to improving our understanding of changing mountain landscapes. These outcomes are accomplished with a systematic review of peer-refereed literature to improve the potential for identifying research needs and untapped opportunities of greatest potential benefit. By extension, this improves the potential for the co-production of actionable science and management-relevant science, and facilitates a more tailored “call and response” relationship among science producers and science consumers or decision makers (DeCrappeo et al., 2018). We expect the results of this review methodology to be useful to scientists seeking opportunities to advance needed interdisciplinary research, and resource managers crafting management responses to climate change.

## Methods and Materials

*Literature acquisition*

We identified studies that (1) are in the CRB, (2) specifically address climate change impacts, adaptation, or mitigation, and (3) address mountainous environments (Figure 5.1). We used a multi-database search, incorporating literature from the Web of Science, Cabdirect, Proquest, and Crossref databases. We assessed each of the articles for inclusion in the corpus of literature based on their titles and abstracts, referring to full texts when necessary. Articles were included if they were peer-reviewed and included a substantial focus on climate change impacts, mitigation, or adaptation in mountain regions of the CRB. Articles were excluded if they did not address climate change, studied paleoclimate, or were conducted at a spatial extent greater than the western United States (Figure 5.1).

*Literature content analysis*

Each article was analyzed to determine its spatial extent, location, and thematic content. We used a Google-form electronic questionnaire and a detailed codebook to ensure consistency among reviewers. To record location, we selected the US Geological Survey six-digit hydrologic unit codes (HUC-6) to identify the watershed(s) where each study took place. If a study included data from fewer than six individual locations, the latitude(s) and longitude(s) were recorded. Spatial extent, which we defined as the largest area to which findings were extrapolated within the western United States and British Columbia, was selected from seven classifications. We also selected the biome(s) where each study took place from a list of global biomes from Woodward et al. (2004). Freshwater biomes were added to distinguish studies between aquatic and terrestrial biomes.

We developed several categories to analyze the topical and disciplinary content of the research. Using definitions from the Intergovernmental Panel on Climate Change, studies were categorized based on whether the primary knowledge contribution of each article was related to climate change impacts, adaptations, or mitigation (Parry, 2007). If the article addressed impacts, we determined whether evidence was presented regarding observed historic impacts and/or modeled projected future impacts. Finally, we specified the primary discipline(s) and topics addressed in each article. Discipline was determined based on the article and journal titles, primary author’s discipline, and the primary knowledge contribution of the article, while topics were selected more inclusively and included any important knowledge contribution. Topics that occurred extremely infrequently were binned into more inclusive categories when possible.

*Data analysis*

Summary statistics were calculated to summarize frequencies for each of the content categories. To assess potential interdisciplinarity, we calculated the frequency of disciplinary co-occurrence to derive a network map. To explore the relationships among topics we conducted a hierarchical cluster analysis (HCA), using topics that occurred in at least five articles. We used Ward's least square error method of clustering because it is less susceptible to noise and outliers, and it yielded the highest agglomerative coefficient (Tan, 2007). This method groups topics into similar nested clusters and minimizes the similarity between clusters. Topics that co-occur more frequently are joined early in the clustering process. Inclusive clusters are joined together by branches in a dendrogram.

The relationships between different coding categories were also assessed using correspondence analysis. This method calculates factor scores for two categorical variables and converts them to Euclidean distances, which can be mapped together to visualize relationships in two-dimensional space. The proximity in this space between variables indicates the frequency with which they are researched together (Abdi and Williams 2010).

To compare studies that occurred only in Canada, the U.S., or spanning the international boundary, we used a Fisher's exact test. This method identifies whether there are significant differences in the topical distributions of national and transboundary studies. The Fisher's exact test was selected because we had small sample sizes. Results from a Chi-squared test were then used to determine which topics contributed to the differences.

*Article abstract analysis*

In order to test the strength of our findings regarding the frequency of disciplinary co-occurrence, we conducted a text mining analysis on the article abstracts. Direct analysis of abstract texts provides a data source that is independent from our coded analysis of the papers, and therefore serves as a check on the data collection process. Abstracts were available for 515 out of our total corpus of 558 studies. Common stop words (commonly used words, such as "and", "also", etc.) and words that occurred less than 20 times were removed, and Pearson correlation coefficients for each remaining pair of words were calculated based on the frequency of co-occurrence in each abstract. Correlations are only reported for cases where Pearson's $p < 0.05$. For cases where other analyses suggested that topics were particularly likely or not to co-occur, we used these correlation coefficients as an additional line of evidence to test our results.

**Results**

*Research in the CRB includes an abundance of studies on physical and ecological disciplines and topics.*

Articles in the corpus generally focus on physical and ecological disciplines. The most commonly identified disciplines are ecology (204 articles), hydrology (160), climatology (120), and forestry (108), as shown in Figure 5.2. There are 156 (28%) articles with two or more disciplines and 402 single-discipline articles (72%). The most common combinations of disciplines are hydrology and climatology (39), and ecology and forestry (24) (Figure 5.2a).

There are an average of 6.12 (±2.5 s.d.) topics per article. The six most common topics are temperature (86% of articles), precipitation (76%), forest ecology (47%), snow (40%), management (40%), and streamflow (37%). The frequency of these topics suggests a dominance of forest ecology and water issues, with fairly frequent discussion of management. The prevalence of management as a topic is important to note, given the paucity of policy or management as a discipline (8%). This discrepancy arises because our methods were relatively exclusive when coding for discipline and inclusive when coding for topic, and suggests that few studies have management or policy as a primary focus, but many still address management to some extent. The paucity of climate change studies on social science aligns with the global distribution of competitive research funding for climate change, which tends not to support social science studies (Overland and Sovacool, 2020).

The HCA illustrates the tendency for groups of topics to be researched together. Physical science topics related to physical hydrology, precipitation, water quantity, streamflow, and snow cluster together (cluster 1, Figure 5.3). The appearance of these topics in the first cluster demonstrates that hydrological topics are common in the corpus and confirms that they are consequential in relation to climate change in the mountainous regions of the CRB. The word correlation analysis of article abstract text provides supporting evidence for the HCA findings. Indeed, words associated with topics within cluster 1 (precipitation, streamflow, and snow) correlate positively.

*Some disciplines and topics are infrequently researched together, suggesting an opportunity for further disciplinary integration.*

Several lines of evidence indicate that some disciplines and topics are relatively infrequently researched in conjunction with each other. These include the frequency of disciplinary co-occurrence (Figure 5.2), the HCA (Figure 5.3), and correlational analysis of abstract texts.

One area of research where deeper disciplinary integration may be needed is the associations between terrestrial and aquatic processes. For example, the disciplines of hydrology and forestry show a fairly strong negative correlation. In the HCA, topics related to forest ecology and water resources form two distinct clusters in branches two and three, also suggesting separation between these topics. The text analysis of abstracts also supports the idea that forest and aquatic issues are not well integrated; for example, word pairs with negative correlations include forest/fish and fire/fish. Of the minority of articles that do integrate topics related to forests, fires, and fish, five out of seven model the additive effects of climate change, altered forest vegetation, wildfire, and/or other disturbances on aquatic habitat (Davis et al., 2013), stream temperatures (Holsinger et al., 2014; Isaak et al., 2010) or sediment delivery (Neupane and Yager, 2013; Rugenski et al., 2014). All five articles conclude that that combined effects of climate change and forest disturbances are detrimental to aquatic habitat. The other two articles focusing on fish, fire, and forests do not directly investigate these topics, but instead consider their confounding influence on stream diversions (Walters et al., 2013) or as determining indicators of climate change (Klos et al., 2015). These studies reinforce the interconnection of forests, fires, and stream habitat and highlight both the necessity and further opportunities to integrate forest disturbances into climate change research on aquatic habitat.

Similarly, studies of fire and snow do not tend to be well integrated, as demonstrated by their distinct clusters in the HCA; these terms are also negatively correlated in the abstract text analysis. The topic of snow appears in 42% (236) of the corpus studies, while the topic of fire appears in 20% (113) of articles. However, articles including both snow and fire make up only 5% (27) of the total. Given that snowpack and summer moisture deficit have been described as leading causes of increases in large wildfire occurrence (Westerling, 2006; 2016), this may indicate an area where further thematic integration is needed to address potential fire-snow feedbacks.

Our findings also suggest that biophysical disciplines are generally not studied in conjunction with social science disciplines, with a few exceptions. Community resilience and attitudes and beliefs are separated from all other clusters in the HCA, indicating that they are more frequently discussed within the same publications than they are with other topics (Figure 5.3). This also appears to be true in the analysis of disciplinary co-occurrence. Of the five most commonly studied disciplines, none show positive correlations with social science disciplines, such as sociology, policy, or economics.

The studies that do demonstrate deep integration of biophysical and social disciplines may provide models for future interdisciplinary research. Several studies link hydrology with policy; these include studies of water resources engineering and supply management issues (e.g., Lee et al., 2009; Hatcher and Jones, 2013). Only five studies address sociology or policy in conjunction with biophysical disciplines. These include agent-based modeling for planning around future watershed conditions (Nolin, 2012), a synthesis of biophysical climate change indicators and feedback from resource managers (Klos et al., 2015), and an analysis of forest managers' responses to climate change (Blades et al., 2016). These findings are generally in agreement with Bjurström and Polk (2011), who analyzed interdisciplinarity within climate change research through a co-citation analysis of the IPCC Third Assessment report and found that closely related disciplines commonly co-occur, while more disparate disciplines are clearly separated.

*Studies on climate change impacts are much more common than those on adaptation or mitigation.*

Articles analyzing climate change impacts are much more common than those addressing adaptation or mitigation: 88% (489) primarily focus on climate impacts, while 10% (56) focus on adaptation and 2% (13) are on climate change mitigation. Ford and Pearce (2010) observe an increasing "adaptation gap," where the number of studies addressing climate change impacts is much larger than those addressing mitigation, and the gap between the two has grown over time, particularly as the number of studies on impacts has increased. The studies in our corpus similarly reflect an adaptation gap; comparing the 10-year periods from 1996-2005 and 2005-2015 shows that the gap between the number of adaptation and impacts papers has increased from 63 to 302, though adaptation papers represent a larger portion of the corpus in the later period than earlier, increasing from 3% to 11% of papers. A similar gap exists for mitigation studies; the gap increased from 64 to 334 papers, though the fraction of papers coded as mitigation increased from 1% to 3%. However, while these changes represent fairly small increases in the total number of papers, the three-to-fourfold increase in frequency indicates considerable growth in adaptation and mitigation research.

Studies primarily assessing climate change impacts, adaptation, and mitigation have distinctly different patterns of disciplinary and topical distributions (Figure 5.4). Articles on climate change impacts tend to be associated with the disciplines of hydrology, climatology, and ecology. In contrast, studies of climate change adaptation are most commonly associated with the disciplinary categories of policy, sociology, forestry, biology, ecology. The topics represented by adaptation articles are heavily skewed towards water quantity, silviculture, species range shifts, attitudes and beliefs, and pests and disease. A relatively small percentage of adaptation articles address groundwater (9%), climate oscillations (2%), or carbon cycling (4%); no adaptation articles studied glaciers. The relative lack of adaptation studies on these topics may suggest important knowledge gaps and therefore opportunities for adaptation research.

Mitigation studies are disciplinarily concentrated in biology, ecology and forestry, and topically focused on carbon cycling, forest ecology, wildfire, silviculture, and management. These findings reflect established understanding that forest management and wildfire are large components of carbon budgets in mountainous regions (Schimel et al., 2002). However, this also suggests potential research needs related to, for example, freshwater carbon budgets, the carbon budget of recreational activities, and climate change mitigation policy in mountainous regions (though a few studies address policy related to mitigation; see Wiedinmeyer and Hurteau, 2010; Stockmann et al., 2012; Law et al., 2018).

*Research is predominantly focused at relatively large scales, makes projections of future rather than observed conditions, and uses existing rather than new data.*

Articles in the corpus range in spatial extent from point or plot scale to the western U.S. The Pacific Northwest (660,000 $km^2$) and the Western U.S. extents are the most common and include 37% of articles (205). Another 22% of articles (121) span between 40,000 $km^2$ and the Pacific Northwest (660,000 $km^2$). The remaining 42% of articles (232) report on studies at spatial extents less than 40,000 $km^2$. Different disciplines generally associate with different spatial extents (Figure 5.5). For example, articles with climatology as a discipline tend to occur more frequently at larger extents. This is to be expected, given the nature of the discipline, though it may raise questions about whether microclimates and refugia are adequately studied from a climatological perspective (e.g. Curtis et al., 2014; Daly et al., 2010).

Projections of climate change impacts are more common than observations. Of the 507 articles that study climate change impacts, 35% (171) make formal projections of climate change impacts; 28% (139) focus on observed environmental trends and discuss their attribution to climate change, while 42% (205) assess a climate change impact but do not explicitly discuss observed or projected trends. Reporting on new field data is also relatively uncommon; only 34% (188) of studies include new data. The frequency with which studies include observed or projected impacts vary by discipline (Figure

5.6). Articles with disciplines categorized as ecology, forestry, biology, policy, or geology tend to reference climate change implications, rather than explicitly making observations or projections of climate change. In contrast, hydrology and climatology have more studies of projected and observed climate change impacts. While trends vary by discipline, the relative preponderance of research based on simulated and/or remotely-sensed data at fairly coarse resolutions and large scales raises questions about whether these large-scale findings are adequately supported by observed data, which is usually collected at much smaller scales and may have important variations within simulation grid cells (e.g. McKelvey et al., 2011).

*The quantity of research conducted varies spatially, and is concentrated at long-term research sites.*

Research is unevenly spatially distributed across the CRB (Figure 5.7). The quantity of research we identified is much less in Canada (84) than in the U.S. (405). For studies conducted at smaller extents, research activities are concentrated at several locations that appear to be fairly well explained by geographical features, such as the location of long-term research sites. For example, notable concentrations of research appear to occur at the H.J. Andrews Experimental Forest in Oregon, Mount Rainier National Park in Washington, and in the Reynolds Creek Experimental Watershed in Idaho. Another relatively high concentration of studies occurs in the Okanagan Basin, Canada, though these are not clustered at a particular research site.

*Biophysical context influences the spatial distribution of research themes.*

The thematic content of research is unevenly distributed across HUC-6 watersheds (Figure 5.8). Correspondence analysis reveals groupings of watersheds and disciplines. Research in the Upper Snake and Snake Headwaters tends to encompass the same disciplines and is closely associated with policy and ecology. Sociology is frequently coupled with the Okanagan (Canada), Columbia (Canada), and Spokane watersheds, with sociology studies in Canada commonly focused on social issues shaping forest management (Goemans and Ballamingie, 2013; Furness and Nelson, 2015; Carolan and Stuart, 2016). Hydrology is also associated with Okanagan (Canada), Columbia (Canada), Spokane, Yakima, and John Day watersheds. Forestry is closely coupled with the Willamette, Kootenai, and Upper Columbia River watersheds, though the topic's central location within the correspondence analysis graph indicates that it is researched frequently within most watersheds. Maps of the spatial distribution of selected topics support the correspondence analysis and demonstrate that the topical distribution of research varies in space (Figure 5.8). For many topics, the variability between the U.S. and Canada is much larger than within-country differences; however, we focus our discussion here on within-country differences followed by discussion of transboundary differences in section 3.7.

Disturbance history influences the topical distribution of research. For example, the preponderance of forest ecology and wildfire studies in the Greater Yellowstone Ecosystem may be due to the 1988 Yellowstone Fires, as evident in the many studies that reference these fires (e.g., Romme et al., 2011; Donato et al., 2016; Seidl et al., 2016; Zhao et al., 2016). Studies of pests and disease are also relatively common in the Greater Yellowstone Ecosystem, as well as the Salmon River watershed (Figure 5.9). Many of these studies are focused on bark beetle outbreaks (e.g. Buotte et al., 2016; Logan et al., 2010; Seidl et al., 2016; Simard et al., 2012).

A relatively large portion of the research conducted in the Upper Snake and Snake River Headwaters addresses management implications. Articles addressing management in this area predominantly focus on interactions between water resources management and biophysical conditions under climate change (Loinaz et al., 2014; Qualls et al., 2013; Ryu et al., 2012; Sridhar and Anderson, 2017); forest and terrestrial ecosystem management, often specific to unique species such as whitebark pine (Logan et al., 2010; Macfarlane et al., 2013); or sagebrush steppe communities (West and Yorks, 2006). Interestingly, despite the relative prevalence of management topics in these two watersheds, adaptation studies are about as common (10% of studies) as in the entire corpus. This finding suggests that a high proportion of impacts-focused studies in this region also address management implications, which may be a result of the long history of conservation planning efforts in the Greater Yellowstone Ecosystem (Clark et al., 1991).

Within Canada, management is frequently researched in the Upper Columbia watershed (85% of Canadian policy articles, n=18). Of these management articles, 67% (12) focused on forests (e.g., Nitschke and Innes, 2008; Goemans and Ballamingie, 2013; Seely et al 2015), 17% (3) on wildlife (Bunnell et al., 2011; Festa-Bianchet et al., 2011; McNay et al., 2011), 11% (2) on human dimensions (Turner and Clifton, 2009; Furness and Nelson, 2016), and less than 1% (1) on avalanches (Sinickas and Jamieson, 2016). Water management topics are not addressed in management-related articles in Canada, despite the fact that some research suggests that demand for irrigation water may frequently exceed supply in future climates in the Okanagan basin (Neilsen et al., 2006).

*Research themes vary among studies in Canada, the United States, and transboundary studies.*

We compared thematic content of articles exclusively in the U.S., in Canada, and those that are transboundary. The comparison suggests that the topical distributions of articles in these three categories are significantly different from each other (Fisher's exact test $p < 0.001$). The prevalence of articles addressing insects and disease and glaciers in Canada are the largest contributors to this difference, though topics related to human dimensions (policy, management, attitudes and beliefs, community resilience) are also more common in Canada than in the U.S. The extensive forested areas and recent pest outbreaks in the Canadian headwaters of the CRB may explain the greater research focus on forest insect and disease impacts. Climate change contributes to the rapid expansion of new bark beetle species at these latitudes, raising concerns for forest health in Canada (Anderegg et al., 2015; Bentz et al., 2010). Concerns about forest health issues due to the close proximity of communities and forests in Canada may influence the more frequent occurrence of topics related to the human dimensions of climate change (e.g., Furness and Nelson, 2016; Parkins, 2008; Parkins and MacKendrick, 2007). The topical focus on glaciers in Canada within the corpus is likely due to the relatively high prevalence and hydrologic importance of glaciers in this area (Moore et al., 2009).

Transboundary studies ($n = 69$) are distinguished by a relatively high frequency of studies addressing climate oscillations, streamflow, anadromous fish and restoration, and a relatively low frequency of studies on policy, forest disturbances, silviculture and carbon cycling. These include studies describing results of climate models across the entire CRB (e.g., Rupp et al., 2016); hydro-climatological models representing downscaled impacts of climate change on hydrology (e.g., Hamlet et al., 2013); comparative streamflow and water temperature modeling (e.g., Ficklin et al., 2014); and models of declining snowpack (e.g., Abatzoglou, 2011). Reconstruction of historical flows or trends are also common across transboundary studies (e.g., Waples et al., 2008). Only five transboundary studies explicitly address policy and management issues (Sopinka and Pitt, 2014; Beechie et al., 2013; Schwandt et al., 2010; Lee et al., 2009; Bisson et al., 2009), and only one of these represents a collaboration between U.S. and Canadian authors (Schwandt et al, 2010). These studies focus on flood control, streamflow, and anadromous fish. A potential issue in interpreting the thematic content of these transboundary studies is that many transboundary studies tend to occur at relatively large scales (70% were larger than the Pacific Northwest, in contrast to only 37% in the full corpus). Therefore, there may be a confounding effect between topics that tend to be researched at large scales and those that are of particular interest across international borders.

*Assumptions and limitations*

Several assumptions and limitations should be considered when interpreting our findings. We used multiple rounds of coding and lines of evidence, but as in any such investigation, errors may occur. Our methods required that each article was categorized as either adaptation, mitigation, or impacts.

Therefore, while studies that address both mitigation and adaptation may exist, they would have been coded in only one category. Further, we identified several areas of thematic content, which we argue have two important, yet poorly integrated, topics or disciplines. To support these conclusions, we used multiple lines of evidence where possible, but these analytical methods can only identify research integration that is *relatively* infrequent. Importantly, the identification of geographic disparities or relatively under-studied research themes does not necessarily imply a need for more research. The findings presented here provide a basis to aid experts in the subjective evaluation of areas that may need more research.

Moreover, while we used multiple databases to identify research, there are likely some relevant articles that were omitted. In particular, because our study was limited to peer-reviewed literature, grey literature such as legal reviews (e.g., Cosens and Fremier, 2014) is not represented. This may, in part, explain why we identified so few policy-related studies. It is also important to note that our literature search was conducted in December 2016; while there are undoubtedly many new studies available, we expect that the general patterns and trends characterizing the science conducted in this region have remained relatively constant.

**Discussion**

Science produced in mountainous headwaters of the CRB affects our understanding of climate change impacts on social and ecological systems, as well as our understanding of potential adaptation and mitigation strategies. While a number of trends in the thematic and spatial distribution of climate related research in the CRB can be discerned, the relative gaps in knowledge and effort are of the most concern. The following conclusions represent our evaluation of the most important gaps that present significant opportunities for further research:

(1) Only 10% (56) of the articles in our corpus focus on the adaptation of human systems to actual or expected climate change. This may be emblematic of a disconnect between the practice and applications of science - especially applications that build adaptive capacity in social-ecological systems.

(2) Only 2% (13) of the studies included in this review focused on improving knowledge of, or intervening in, carbon cycles to potentially reduce the effects of anthropogenic forcing on the climate system, despite large tracts of forested lands, a significant biomaterials industry, and increasing concerns about climate change feedbacks due to forest disturbance. More research may therefore be

needed on climate change mitigation in this region, and potentially in other mountainous regions around the globe.

(3) There is also an opportunity for more climate-related social science research, and more integration of social science with biophysical disciplines. Only five of 558 studies included in this review represented sociology or policy in conjunction with biophysical disciplines, a glaring disparity given the feedbacks between a growing population, climate change, ecosystem services, and land management.

(4) Finally, there is an important opportunity for further transboundary climate change research with an integrated, basin-wide focus. For example, only five of 558 studies explicitly addressed policy and management issues on both sides of the US-Canada border, and only one of these five represents a collaboration between U.S. and Canadian authors. This is surprising, given the interconnectedness of ecological and social systems throughout the watershed and the pervasiveness of observed and predicted climate stressors. In addition to a need for more transboundary research, this suggests a role for further research on the role of international collaborations for understanding climate change impacts, adaptation, and mitigation in this region.

This study quantified thematic and spatial knowledge and gaps in climate change related research for the mountainous headwaters of a large and complex watershed, allowing science and management communities to leverage resources more effectively and, in turn, increasing the potential for the co-production of actionable science and effective responses to climate change. Implementing similar analyses elsewhere could expand understanding of gaps and knowledge structures in the larger body of climate change research for mountainous regions. Moreover, further work could provide important comparisons for models of how to conduct interdisciplinary reviews to advance the management of complex river basins in a changing climate.

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## Tables

Table 5.1. Definitions used to assess area of primary knowledge contribution.

* based on the 2007 Intergovernmental Panel on Climate Change definitions.

| Term | Definition used in study |
| --- | --- |
| *Adaptation* | Adjustment in human systems in response to actual or expected climatic stimuli or their effects, which moderates harm or exploits beneficial opportunities.* |
| *Mitigation* | An anthropogenic intervention aimed at reducing the anthropogenic forcing of the climate system.* |
| *Impacts* | The effects of climate change on natural and human systems.* We categorized impacts as *observed*, in which trends were noted in empirical data and attribution to climate change was discussed, *projected,* in which the impacts of climate change were quantitatively modeled for future scenarios, and *implications*, in which the climate sensitivity of a system was assessed. |

**Figures**

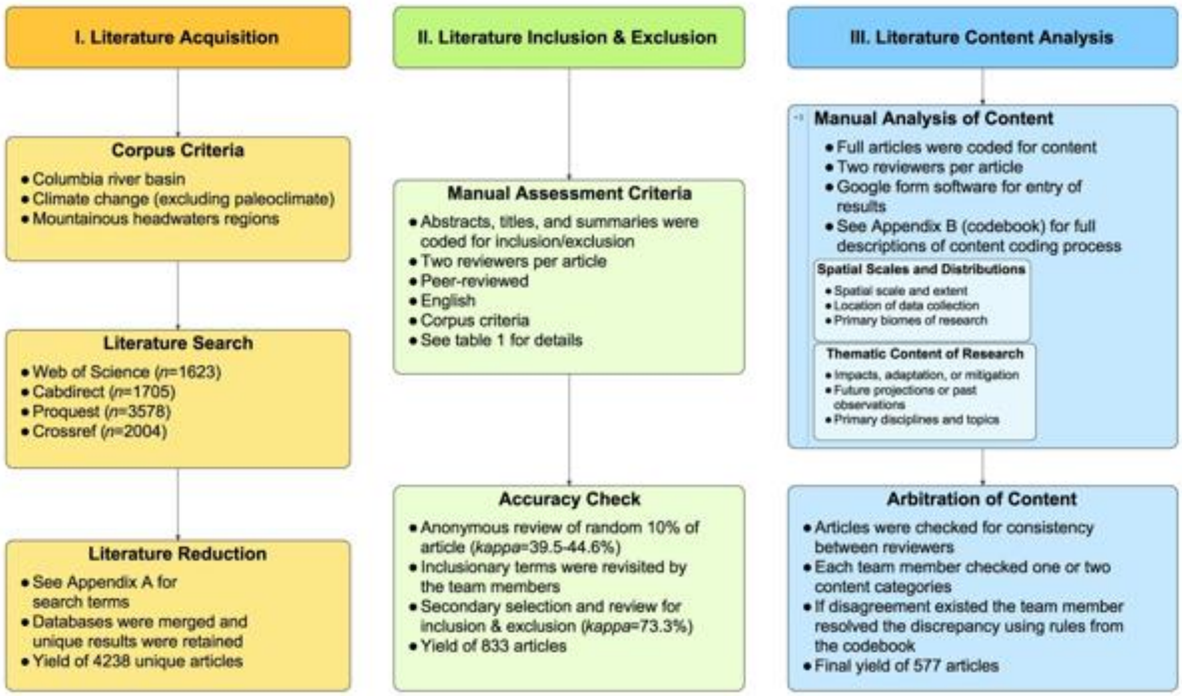


Figure 5.1. Flowchart for methods of literature acquisition, inclusion, exclusion, and content analysis.

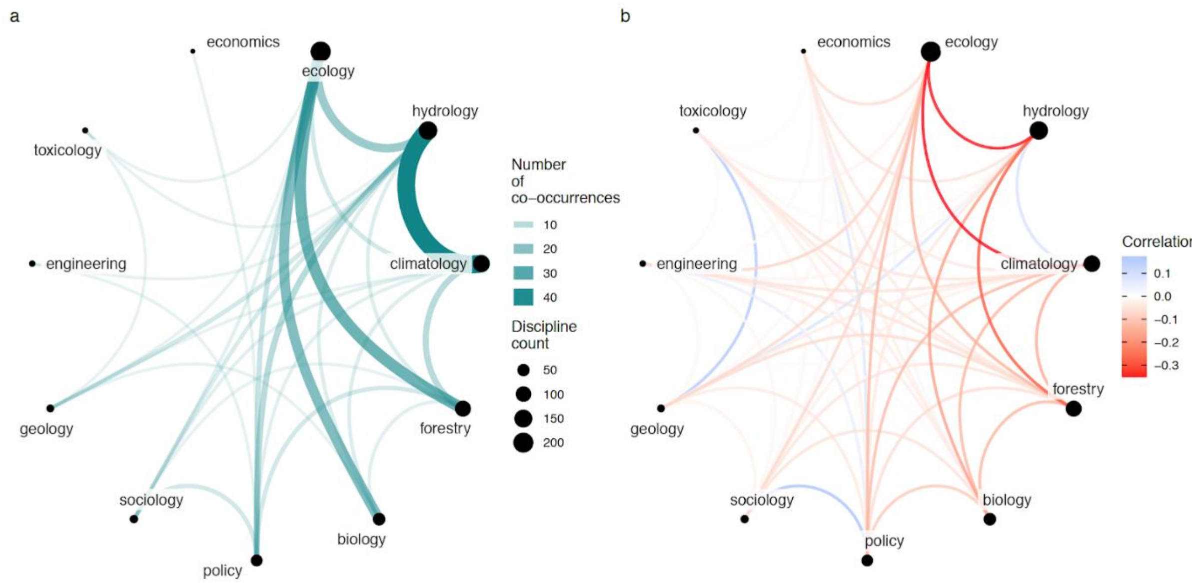


Figure 5.2. Network map of co-occurring disciplines, showing (a) number of co-occurrences, indicated by edge width and color, and (b) correlation coefficients between disciplines. Size of points indicates number of times each discipline occurred.

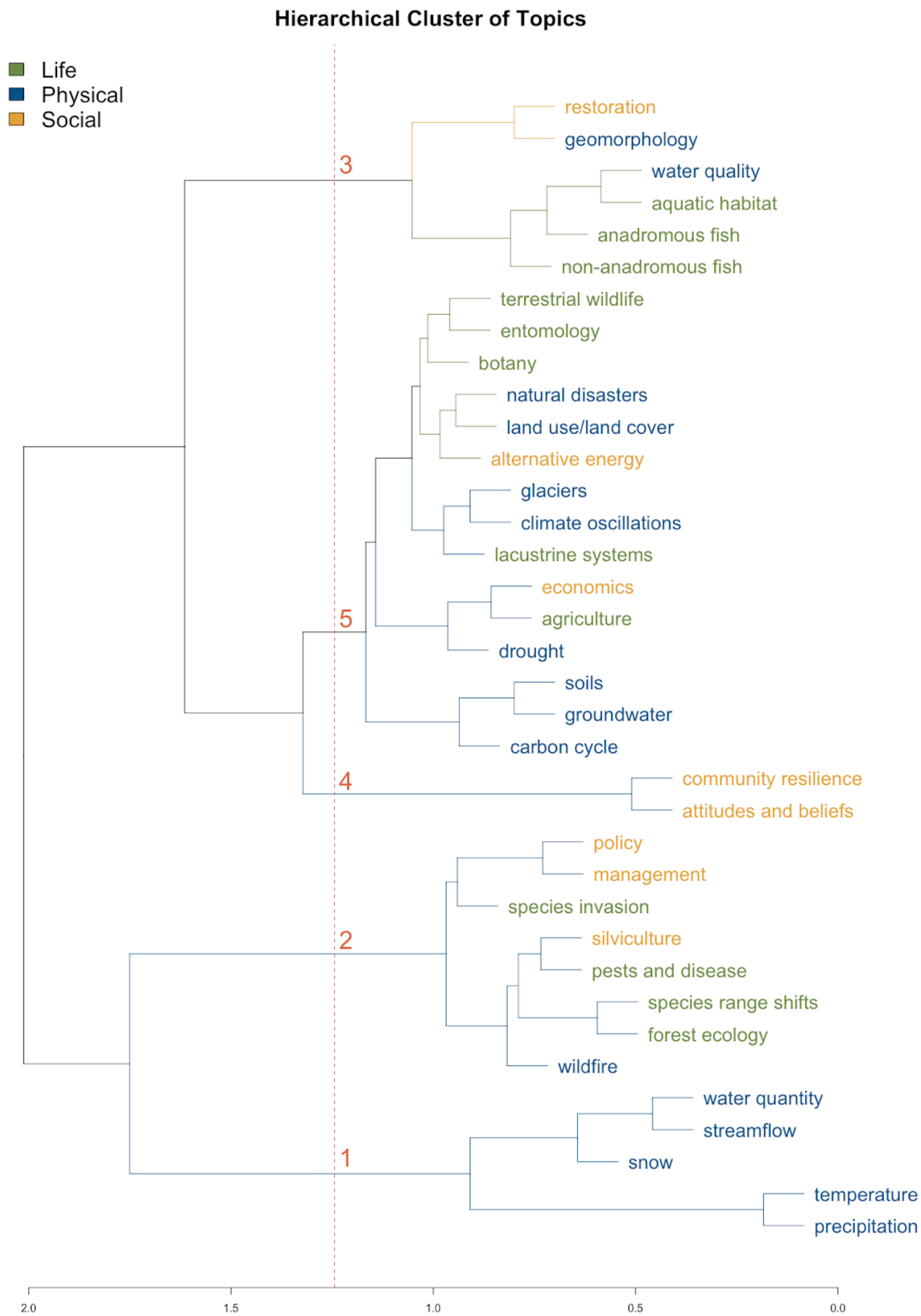


Figure 5.3. Dendrogram of hierarchical cluster analysis (HCA) of topical co-occurrences. The HCA measures the dissimilarity between variables and represents them in nested clusters. The x-axis shows the dissimilarity between topics. Topics that are grouped together near the right (distance = 0) are frequently coupled in the literature. Cluster numbers in red are referenced in the text. Colors of topics indicate whether each topic was classified as primarily related to the social (yellow), life (green), or physical (blue) sciences.

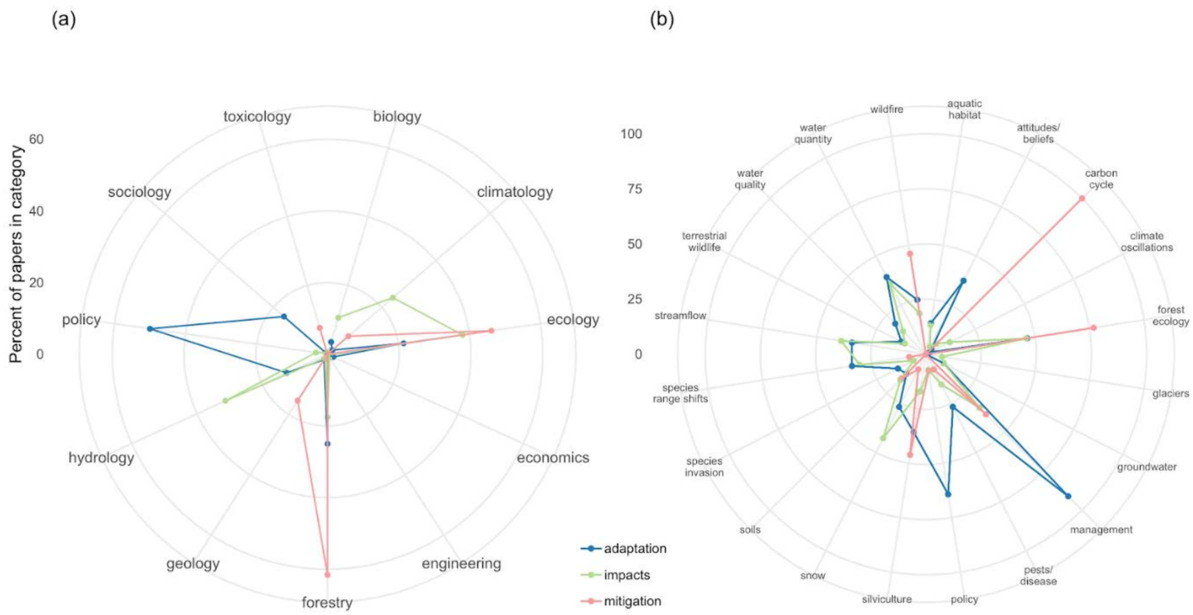


Figure 5.4. Radar plots showing the distribution of adaptation, impacts, and mitigation paper by (a) discipline and (b) topic. Axis displays the percent of papers in the adaptation, mitigation, and impacts categories that address a particular topic or discipline.

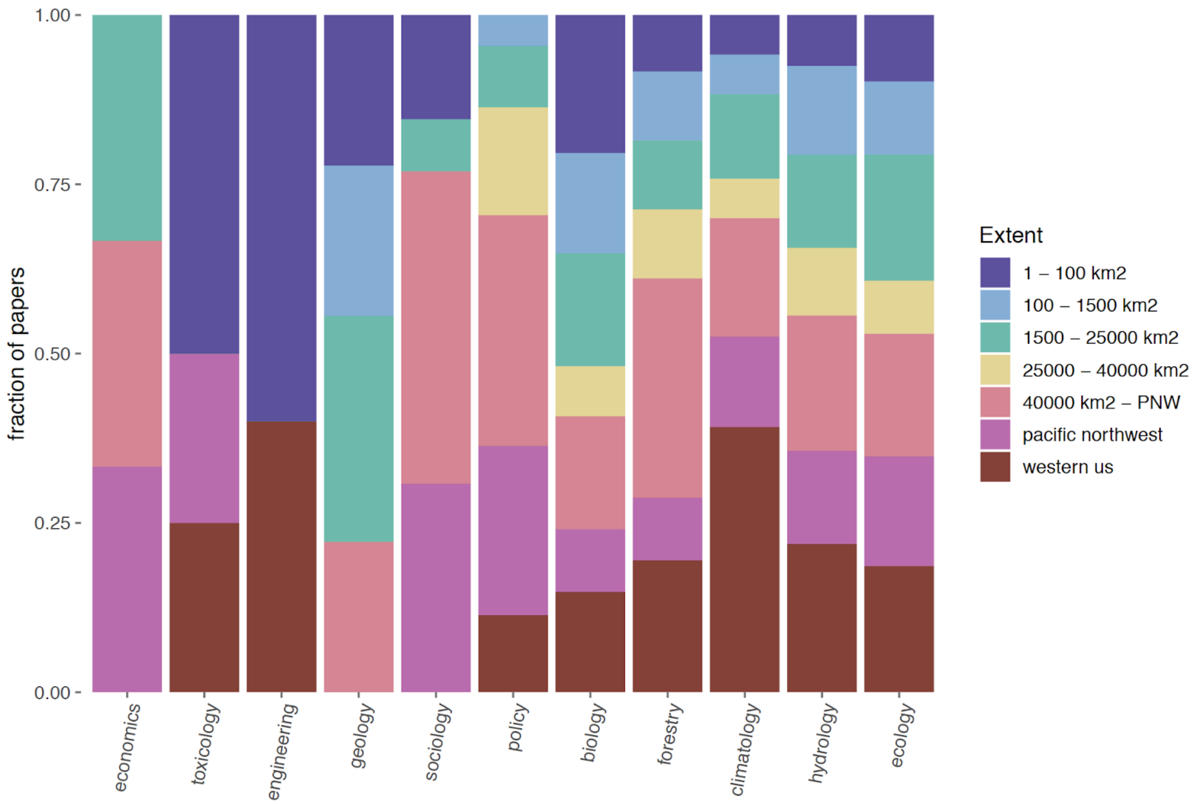


Figure 5.5. Spatial extent of disciplines. Disciplines are arranged in ascending order of frequency within the dataset.

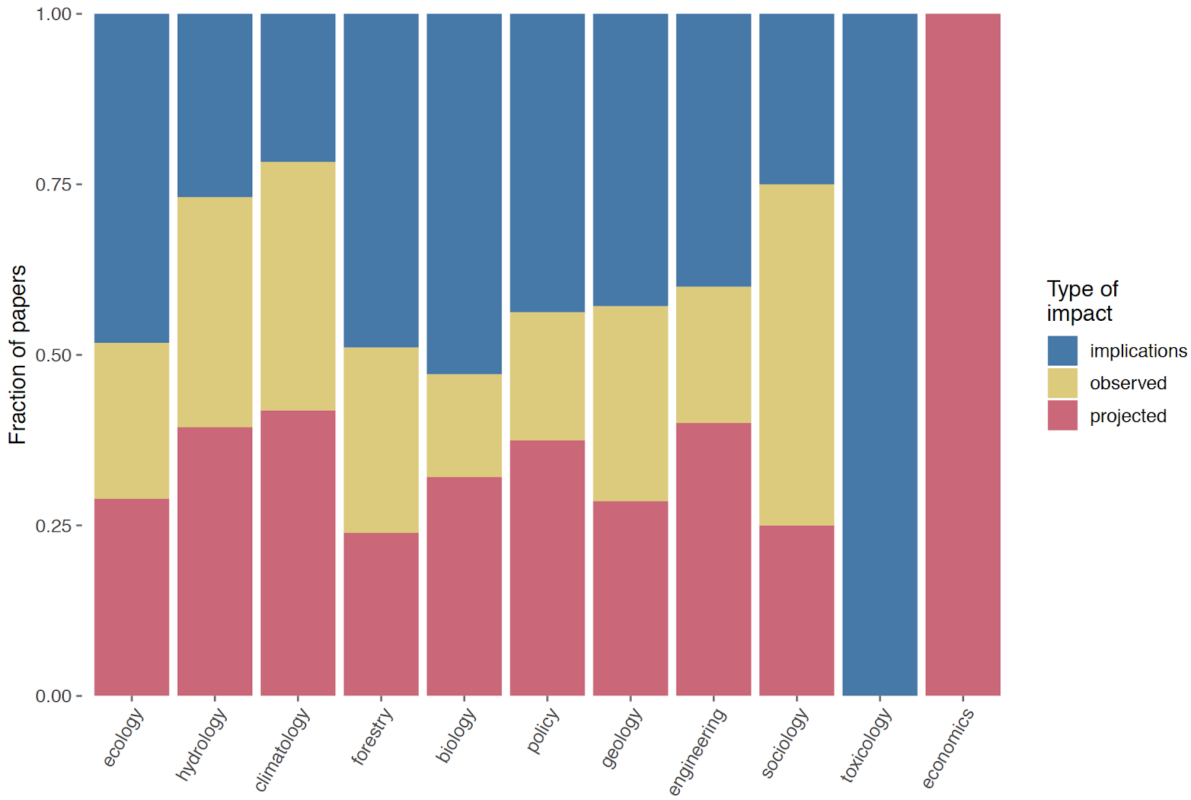


Figure 5.6. Studies of climate change impacts that identify climate change implications or observed or projected impacts, by discipline.

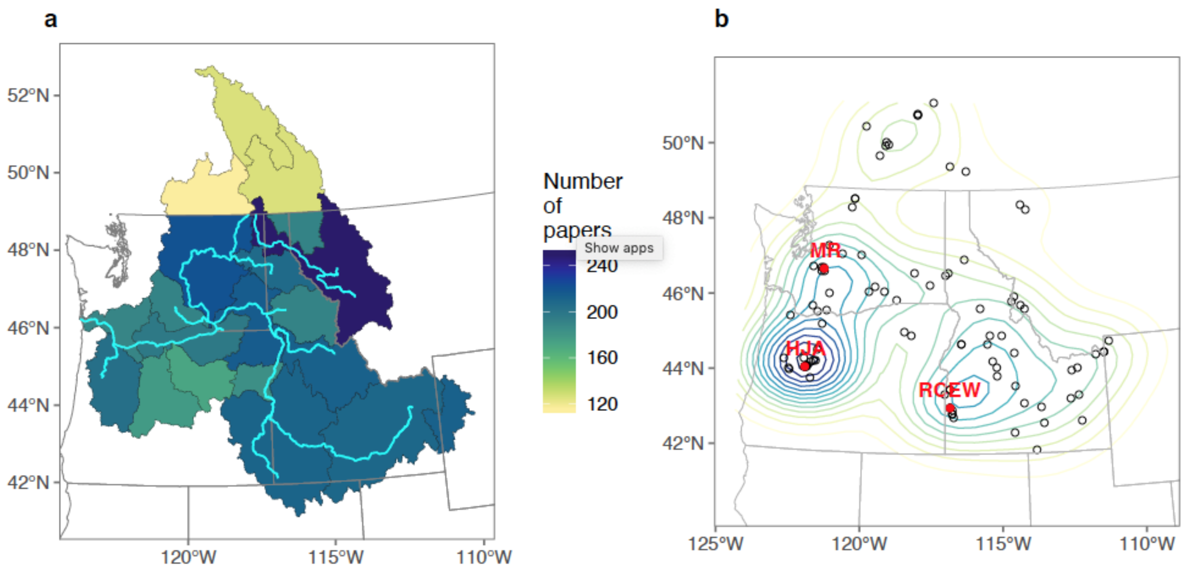


Figure 5.7. Spatial distribution of literature, displayed as (a) total number of papers per HUC-6 watershed and (b) point locations for studies with spatial extents less than 1500 km$^2$, with contours showing estimated density of studies. Rivers are displayed in cyan; points of interest with high concentrations of research are in red. MR = Mount Rainier; HJA = H.J. Andrews Experimental Forest; RCEW = Reynolds Creek Experimental Watershed.

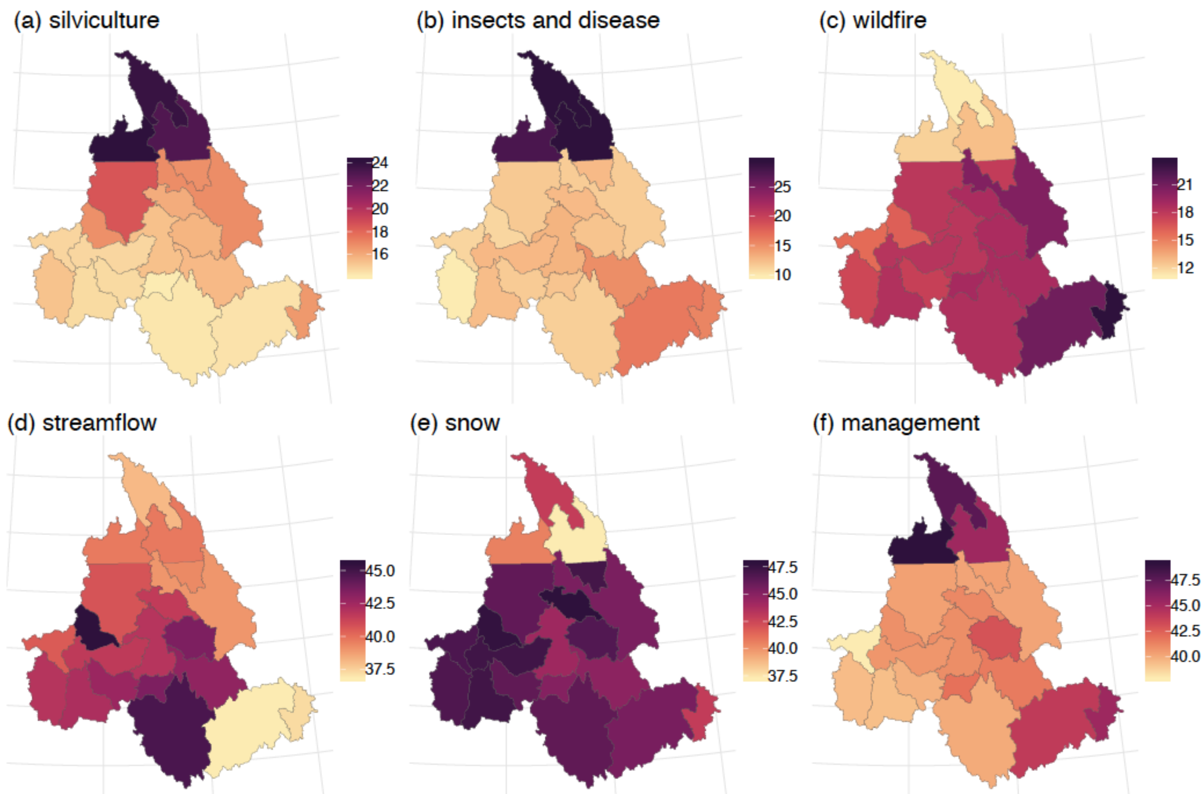


Figure 5.8. Spatial distribution of selected topics by HUC. Each legend shows the percent of papers in a given HUC that addresses the topic.

# Chapter 6: Conclusion

This dissertation includes three disciplinary chapters that applied remote sensing approaches to the analysis of seasonal-ephemeral water resources, specifically canopy intercepted snow and snow-fed playa wetlands. The fourth interdisciplinary chapter synthesized climate change research in the headwaters regions of the Columbia River Basin. To further contribute to understanding climate change impacts on seasonal-ephemeral water resources and ecosystems, as well as the socio-ecological context for climate change study and adaptation, suggestions to extend the analyses in each chapter are offered below.

Chapter 2 examined the promising use of terrestrial laser scanning (TLS) for estimating snow interception. With further investigation, this approach has the potential to offer increased scalability and portability compared to previous methods, and may prove to be a useful tool in calibrating snow interception models to different forest types. Experimental findings indicated good agreement between TLS estimates of snow mass and measurements made on trees suspended from load cells. To further refine this methodology and explore larger-scale applications, a number of research extensions are proposed. For instance, the experiment can be repeated with live trees of different species, with particular attention paid to the sensitivity of TLS-based estimates to changes in tree geometry with i) snow loading, and ii) the interaction between branch flexibility and air temperature (Schmidt and Pomeroy, 1990). The experiment could also be adapted to include laser return intensity data, which may provide information about snow properties (e.g., snow density) (Deems et al., 2013). Finally, research on an in situ means of measuring canopy-intercepted snow density is needed to reduce error in mass calculations that currently rely on empirical air temperature-snow density relationships (e.g., Lachapelle, 1962).

Chapter 3 applied the knowledge gained from the previous chapter by utilizing TLS-based snow interception estimates obtained from a variety of live trees of different species. I fit a model that predicted these estimates from aerial laser scanning (ALS)-derived metrics of canopy structure. The research findings demonstrated good agreement between observations and model predictions and identified the best suite of predictors. The results suggest that metrics capturing the intrinsic, three-dimensional variability of tree canopies may be an appropriate alternative to the two-dimensional metrics currently utilized in hydrological models for estimating snow interception (e.g., leaf area index, canopy closure) (Essery et al., 2009; Rutter et al., 2009). Researchers looking to extend this work may be interested in testing our approach across different forests with a range of canopy densities, as our findings are limited to a small sample of individual trees along the margins of a forest edge. It may also be beneficial to combine the canopy metrics we identified as important with forest spacing metrics used in a recent studies (e.g., Moeser et al., 2015; Roth and Nolin, 2019) to see if there is improvement in the performance of snow interception models that incorporate both structural (intrinsic) and hydrometeorological (extrinsic) variables. Finally, extending this study would benefit from addressing the uncertainties regarding TLS as a tool for estimating interception that are outlined in the previous paragraph discussing extensions to Chapter 1.

Chapter 4 identified drivers of hydrology for seasonal-ephemeral playa wetlands in the northern Great Basin. Employing a 30-year time series of satellite imagery, this study also demonstrated how playas may respond to intensifying droughts, identified a subset of playas that may function as hydrologic refugia during droughts, and explored the role of past land uses in determining which playas may be refugia. While the results from my work could assist land managers in planning restoration of playa hydrology, the effectiveness of Great Basin playa restoration in the context of climate change is unknown. Studies of playa restoration in other regions, however, do indicate the potential of extending the hydroperiod, regaining native species assemblages, and restoring ecosystem services like groundwater recharge (Smith et al., 2010). To prepare for climate change-related impacts and assess the implications of restoration, this research may be extended with ground-level studies of playa geomorphology and hydrogeology, as well as controlled experimental restoration studies coupled with long-term monitoring.

Chapter 5 analyzed the spatial and topical distribution of climate change research in the headwaters of the Columbia River Basin. While the findings identified broad patterns in a large body of research, additional investigation of specific findings would extend the impact and applicability of this work. For example, future researchers may be interested in focusing on the apparent differences in research topics between the portions of watershed contained in the United States versus Canada. In addition, implementation of social science methodologies – such as qualitative surveys – could illuminate the perceived relative importance of research gaps identified in this study (e.g. the small number of studies bridging aquatic and terrestrial disciplines).

Each of these chapters adds to the body of knowledge on remote sensing for seasonal-ephemeral water resources, as well as applications for water resources management. By examining the processes affecting snow supplies and snow-fed ecosystems, as well as the state of climate change science across headwaters in a large watershed, I have had the opportunity to think about hydrological systems holistically. I have also experienced tremendous growth, intellectually, from tackling a diverse and challenging set of research questions. In the manner of most scientific studies, however, each chapter offers but a small scientific contribution with the hope that future researchers will incorporate or extend this work, and this work will inform the sustainable management of our water resources.

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# Appendix A:

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