Remote Sensing Applications: Society and Environment 41 (2026) 101912

Contents lists available at ScienceDirect

Remote Sensing Applications: Society and Environment

journal homepage: www.elsevier.com/locate/rsase

Informing snow measurement site selection with remote sensing and local ecological knowledge: A case study in Oregon

Hannah Steele *, Kelsey Emard, Mark S. Raleigh

College of Earth, Ocean, and Atmospheric Sciences, Oregon State University, Corvallis, OR, 97331, USA

ARTICLE INFO

Keywords:
Snow hydrology
Remote sensing
Local ecological knowledge
Site suitability analysis
Participatory methods

ABSTRACT

Seasonal snow provides critical water resources for communities throughout the western United States where melting snowpack drives much of the summer water supply. Water resource planning in western basins depends on reliable snowpack data; however, many basins lack a local snow measurement system, instead relying on data from measurements sites in neighboring basins with different landscape dynamics. Ensuring best site locations before installing snow measurement stations promotes optimal use of resources, improves data quality, and supports local water planning. Using the Chewaucan Basin in Oregon as a case study, this research examines how two novel and previously underutilized information sources - satellite remote sensing data and local knowledge - can help inform site selection for a snow measurement station. Using a 23-year record of daily snow cover mapping from the Moderate Resolution Imaging Spectroradiometer (MODIS), a 500m resolution spatial map of correlations between annual snow disappearance date and summer streamflow volume was derived. This correlation map served as an input to a GIS model alongside key landscape and infrastructure variables to determine potential site locations for an automated snow measurement system. The potential sites were shared with local water users to gather feedback on local conditions that may not be well represented in available geospatial data. The final site recommendation reflected both the modeled suitability analysis and the water users' ecological knowledge. This study demonstrates a method for integrating remote sensing data and local ecological knowledge to inform the selection of snow measurement locations.

1. Introduction

Winter snowpack and springtime streamflow from snowmelt are critical components of water availability, impacting water management decision-making for local, state, and federal stakeholders in mountain regions across the globe. This is the case in many basins throughout the U.S. Pacific Northwest where increasing temperatures and climatic factors are resulting in lower snow water equivalent (SWE, i.e., the amount of water in snow) and changing both spring and summer streamflow timings (Dalton and Fleishman, 2021; Mote et al., 2018). Current methods for tracking and measuring snowpack amounts in the western United States primarily rely on the USDA Natural Resources Conservation Service (NRCS) SNOwpack TELemetry network (SNOTEL; Fleming et al., 2023). SNOTEL sites are equipped with automated sensor arrays that collect data on precipitation, snow depth, snow water equivalent, and temperature. These snow measurements are crucial for informing water management decisions and streamflow forecasting, but they are

* Corresponding author.
E-mail address: steeleha@oregonstate.edu (H. Steele).

https://doi.org/10.1016/j.rsase.2026.101912
Received 11 August 2025; Received in revised form 12 December 2025; Accepted 3 February 2026
Available online 3 February 2026

not available in many rural basins due to various factors (e.g., costs and time to install and maintain). This can hinder water assessment capabilities for local communities. As a result, snowpack data for unmeasured basins are often extrapolated from the nearest measurement station(s), which can be several basins away. This can increase uncertainty in forecasts and leaves stakeholders lacking key information about local conditions when making water management decisions. In areas where streamflow volume and timing are tied to key agricultural activities such as growing cycles and animal movements, this absence of information on snowpack conditions can be particularly challenging.

When resources are available to install a new snow measurement station in a basin, the challenge for agencies like the NRCS is to identify a location where snow is hydrologically predictive and where site installation is possible. Typically, location selection for SNOTEL stations involves examining data related to a variety of factors such as accessibility, landscape features, and representativeness of land cover conditions in the majority of the basin (United StatesNatural Resources Conservation Service, 2011). However, site selection has the capacity to be more fully informed by leveraging two sources of data that have not been widely applied to snow measurement site selection: remote sensing and local ecological knowledge (LEK). LEK constitutes information held by individuals and communities regarding landscape dynamics, environmental relationships, and change over time at multiple scales relevant to resource management (Charnley et al., 2007; Knapp and Fernandez-Gimenez, 2009). Research has shown that LEK can provide valuable information for water management and policy decisions (Sobczak et al., 2013; Iniesta-Arandia et al., 2015.) However, to our knowledge LEK has not been commonly utilized within the field of snow hydrology. Meanwhile, satellite remote sensing data are widely available and can provide medium to coarse resolution data on snowpack (e.g., snow presence) and water resources. By integrating these two novel data sources into a site selection methodology, there is an opportunity to identify locations where snow is most predictive of summer streamflow within a given basin, in turn informing site selection for more effective forecasting.

Remotely sensed snow data offers a unique opportunity to help identify spatial locations in which snowpack and streamflow are highly correlated, and thus more effective locations to measure snowpack (e.g., Raleigh et al., 2025). Snow remote sensing has advanced in recent decades, with a variety of available methods being developed for satellite imagery (for a review see Nolin, 2010) as well as the commercial operationalization of aerial lidar for snowpack measurement (e.g., Painter et al., 2016). Multiple studies have shown how near real-time satellite snow cover mapping can improve forecasts of streamflow and water supply (e.g., Sproles et al., 2018; Bennett et al., 2019; Fleming et al., 2024). However, there has been less attention to how satellite remote sensing can inform selection for new ground-based measurements. Satellite remote sensing can yield maps of annual metrics like snow disappearance date (SDD) and snow cover frequency, which have been identified as indicators of changes in mountain snowpack (Nolin et al., 2021). Recent work by Bishay et al. (2023) showed that satellite derived SDD was strongly correlated to summer water supply across 15 test basins in the United States. This result is explainable because SDD is often strongly correlated with maximum SWE (e.g., Trujillo and Molotch, 2014), and SWE often has a strong correlation with summer water supply (e.g., Fleming et al., 2023). SDD can be readily mapped from satellite data as demonstrated by SnowCloudMetrics, developed by Crumley et al. (2020), providing a data source for analyzing potential snow measurement locations.

In addition to remote sensing, local ecological knowledge also offers valuable information about local snowpack dynamics. Participatory modeling approaches, in which LEK holders are engaged in the development and testing of scientific models, can deepen our understanding of the phenomena being studied by providing long-time observations at finer scales than we have in measurements and perspectives about local dynamics and human use that scientists may not be aware of (Belisle et al., 2018; Bartlett et al., 2012). As an example, in Kyrgyzstan, researchers found that local knowledge was able to identify similar trends to those calculated from satellite derived Normalized Difference Vegetation Index (NDVI) at finer scales (Eddy et al., 2017). Recent research on participatory modeling with GIS showed this kind of knowledge production can be used to verify and augment authoritative datasets by collecting community input on local conditions (Fagerholm et al., 2021; Alessa et al., 2016). Beyond improvements in research results, participatory modeling approaches can also benefit communities by channeling resources and improved environmental data to them (Voinov and Gaddis, 2008). Finally, participatory processes have been shown to engage and empower communities to take primary ownership of scientific data collection and interpretation (Eitzel et al., 2021). These examples illustrate the opportunities and benefits provided by participatory modeling approaches.

This research introduces and applies a methodology for incorporating both remote sensing data and local ecological knowledge as novel inputs into the site selection process for expanding a snow measurement network. This is accomplished through a case study in the Chewaucan River Basin (Oregon, USA), which lacks any local snowpack measurement stations, but where the local community has expressed interest in obtaining such a station. First, we utilize a widely available remote sensing product (MODIS-based SDD) to determine localized areas with strong historic relationships between snowpack and summer streamflow as measured by a USGS stream gauge. Second, we utilize the results of the site selection model to facilitate a participatory exercise with community members and demonstrate how LEK can provide detailed information regarding local landscape characteristics. Leveraging the LEK of long-term residents and resource managers in previously unmeasured basins provides a unique opportunity to integrate lived experiences of previous snowpack with scientific models to create more accurate basin level data and improve community adaptive capacity and investment in scientific data. To demonstrate the proposed method for site suitability analysis, this paper examines two research questions: 1) How can spatial maps of remotely sensed SDD be used alongside more commonly used geospatial data to inform site selection for a snow measurement station? And 2) What kinds of information provided by LEK can be leveraged in site selection for scientific instrumentation? Together, these research questions help provide novel insights for snow measurement network design and expansion.

2. Study area

The Chewaucan Basin is an endorheic basin located in Lake County, Oregon that encompasses approximately 2200 km^2 (Fig. 1). There are several unique hydrologic features including the 85.2 km long Chewaucan River and over 121 km^2 of flood irrigated marshes that serve as critical ecosystems for migratory bird species. The Chewaucan Basin encompasses the town of Paisley (population 255), the unincorporated community of Valley Falls, and a number of private residences scattered throughout the uplands of the basin. Ranching and hay production are major economic drivers in Lake County and together make up 97% of agricultural revenues for the county (USDA, 2022). The Chewaucan River terminates in Lake Abert, which is Oregon's only hypersaline lake and is identified as an Area of Critical Environmental Concern by the Bureau of Land Management (Bureau of Land Management, 1995). In recent years, several desiccation events have occurred at Lake Abert, and research has shown that decreasing snowpack and increasing aridification are contributing to more frequent drying events (Hall et al., 2023). The diverse hydrological, ecological, and economic landscape of the Chewaucan Basin is supported primarily by snowpack and springtime streamflow. This includes agricultural activities such as ranching and hay production which are highly dependent on water availability throughout the spring and early summer months to irrigate native grasses in the Chewaucan marshes, which are later harvested to serve as feed for cattle. As such, information about snowpack is highly relevant to producers in the region, whose economic livelihoods are sustained by snowmelt.

3. Data and methods

The study methodology consists of a multi-step process, illustrated by the conceptual workflow in Fig. 2. The first step involves collecting and standardizing relevant geospatial and snow remote sensing data (section 3.1). This includes clipping layers to the study basin, ensuring that all data layers have the same projection and coordinate system, and calculating the correlation between remotely sensed snowpack data and streamflow volume using Python (see section 3.2). Next, the geospatial and remote sensing data are used as inputs to a site selection model built in ArcGIS Pro (section 3.3). The output of this site selection model is then shared with community members and stakeholders who are involved in water management and usage in the study basin through a focus group (sections 3.4-3.5). The results of the focus group (both via a questionnaire and from general group discussion) are then incorporated into the last step which is the identification of a final site recommendation.

3.1. Geospatial data

To construct the GIS model, geospatial data layers were compiled and standardized across projection and coordinate systems using ArcGIS Pro software (ESRI, Release 3.2.1, 2023). The data layers included land cover/land use, land ownership, and roads. The official Oregon Digital Elevation Model (DEM) was used to generate slope and aspect data layers. Land cover was derived from the 2023 National Land Cover Database, and land ownership was obtained from the Oregon Land Management dataset published by the State of

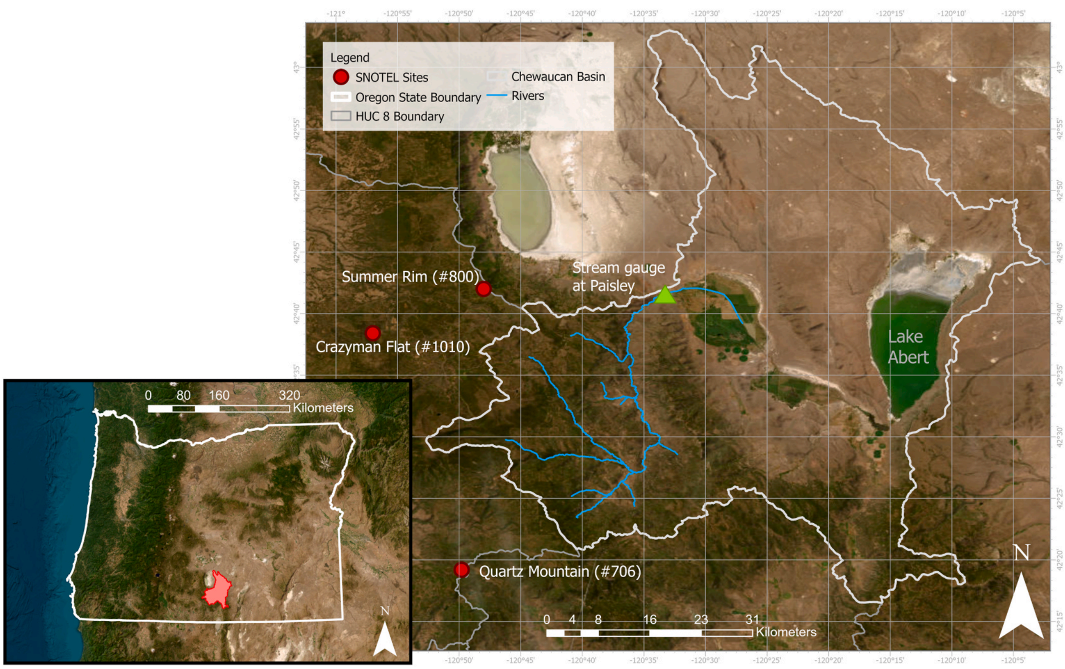

Fig. 1. A map showing the Chewaucan Basin and its location in Oregon, as well as nearby SNOTEL sites (with NRCS site numbers included) and the streamflow gauge (described in section 3.2).

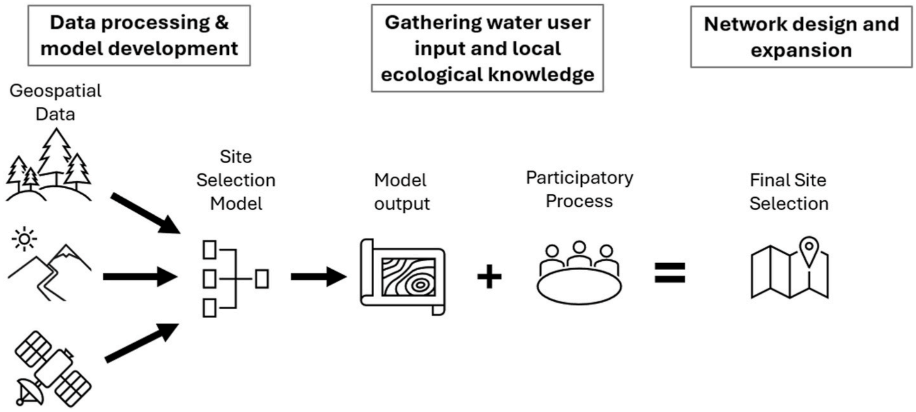

Fig. 2. A conceptual figure showing the methodological workflow of incorporating GIS, remote sensing, and LEK into a site selection process.

Table 1
Lists each input to the model, the original data attribute names, and their reclassified suitability (where 1 = most suitable and 5 = least suitable). Aspect numbers refer to cardinal and intercardinal directions followed by corresponding degrees (0° – 360°).

Input data	Original data layers	Classification for model
Land ownership	US Forest Service	1
	Bureau of Land Management	2
	Private	3
	Oregon Dept. of Transportation	4
	Oregon State Land Board	5
Aspect	Flat (−1)	4
	North (0-22.5, 337.5-360)	1
	Northeast (22.5-67.5)	2
	East (67.5-112.5)	3
	Southerly (112.5-247.5)	5
	West (247.5-292.5)	3
	Northwest (292.5-337.5)	2
Slope	≤1.72 to ≤ 11.3	1
	≤14.04	2
	≤16.7	3
	≤21.8	4
	≤30.96 to ≤ 90	5
Land cover	Open water (11)	5
	Perennial Ice/snow (12)	4
	Developed open Space (21)	4
	Developed, low intensity (22)	4
	Developed, medium intensity (23)	5
	Developed, high intensity (24)	5
	Barren land (31)	4
	Deciduous forest (42)	2
	Evergreen forest (42)	1
	Mixed forest (43)	2
	Shrub/scrub (52)	2
	Grassland/herbaceous (71)	3
	Pasture/Hay (81)	4
	Cultivated Crops (82)	5
	Woody Wetlands (90)	5
	Emergent Wetlands (95)	5
Roads	≤0.5 mi	1
	≤1 mi	2
	≤1.5 mi	3
	≤2 mi	4
	>2	5
Snow-to-Flow R^2	≤0.40	5
	≤0.50	4
	≤0.60	3
	≤0.70	2
	>0.70	1

Oregon (Oregon GEOHub, 2024). Roads were obtained from the National Transportation Dataset created by the United States Geological Survey (USGS, 2024). All data layers were clipped to the extent of the Chewaucan Basin from the National Hydrography Dataset, Hydrologic Unit Code 8 boundaries (USGS, 2023). Data sources were selected for this project based on public availability, dataset age, and frequency of maintenance.

Several pre-analysis steps were taken to prepare the data for the site suitability model. This involved using analysis tools within ArcGIS Pro including: *create buffer*, *pairwise intersect*, and *merge* to join data, *polygon to raster*, *raster math*, and the *reclassify* tool. To process the road data, *pairwise intersect* was used to show only roads that intersect with the Chewaucan Basin boundaries, *merge* combined multiple line features within that dataset to one layer, and finally *create buffers* was used to calculate various distances from a roadway at 0.5 mile intervals. The land ownership data were originally a set of polygon features, but given that all input layers for the model were required to be rasters, the *polygon to raster* tool was used to convert the data to the necessary data type. *Raster math* calculated the "snow-to-flow" R^2 correlations map described below (section 3.2). Reclassification was performed on each input layer into a classification scheme of 1 through 5, where 1 is 'most preferable' for a potential site, and 5 is 'least preferable'. These classifications were based on existing NRCS guidelines for snow measurement site selection, such as a northerly aspect, low slope (<10%), public land, accessibility to roads (<1.5 mi.), and representative land cover (U.S. NRCS National Engineering Handbook, 2011). Table 1 shows reclassified values for the suitability analysis.

3.2. Remotely sensed SDD and correlations with streamflow

To provide information on snow dynamics within the basin, annual SDD maps for the years of 2001-2023 were derived from the MODIS sensor aboard the Terra satellite at a 500m spatial resolution, using the SnowCloudMetrics (Crumley et al., 2020) tool in Google Earth Engine (Gorelick et al., 2016). The source data used to derive SDD comes from daily measurements of Normalized Difference Snow Index (NDSI) from the MOD10A1 product (Hall and Rigs, 2016). NDSI leverages the unique electromagnetic reflectance characteristics of snow, which is high reflectance of visible wavelengths and low reflectance of shortwave infrared wavelengths. By calculating the difference between band 4 (visible green) and band 6 (shortwave infrared), NDSI can be used to detect the presence of snow. SnowCloudMetrics extracts SDD by masking out images with clouds and areas with water bodies, then determines snow presence for each day of the specified water year. Users set the NDSI threshold, as well as the number of days snow must be absent to determine the snow disappearance date at each pixel. In this study, 0.15 was used for the NDSI threshold value, and the number of days without snow to determine SDD at each pixel was set at 5 days. SDD can be highly correlated with snow accumulation and SWE (e.g., Wayand et al., 2018) and has been shown to be predictive of water supply (Bishay et al., 2023). We use it as a proxy for SWE, such that locations with later (earlier) SDD tend to have higher (lower) peak SWE (Trujillo and Molotch, 2014). In the supplemental information document, we compare SDD and peak SWE at nine nearby SNOTEL sites (Fig. S1), which shows that SDD is a reasonable proxy for SWE in our study region. We note that other studies have used gridded SWE to detect locations in a basin where snow data have potential predictive value for streamflow (Raleigh et al., 2025), but we focus on SDD instead of SWE here because it is more straightforward to derive from remote sensing and because it is globally available.

At each 500m pixel location in the basin, the annual SDD values (n = 23) were extracted and a correlation was computed with annual values of summer streamflow volume (1 April - August 31st) of the Chewaucan River, measured by the Oregon Department of Water Resources (OWRD) streamflow gauge near Paisley, OR (USGS gauge ID: 10384000, OWRD). The Pearsons correlation coefficient (r value) was calculated and provided a numerical, linear representation of the correlation between SDD at a given 500m pixel location and summer streamflow volume. This process was repeated for every pixel in the basin, until correlation values were calculated at all

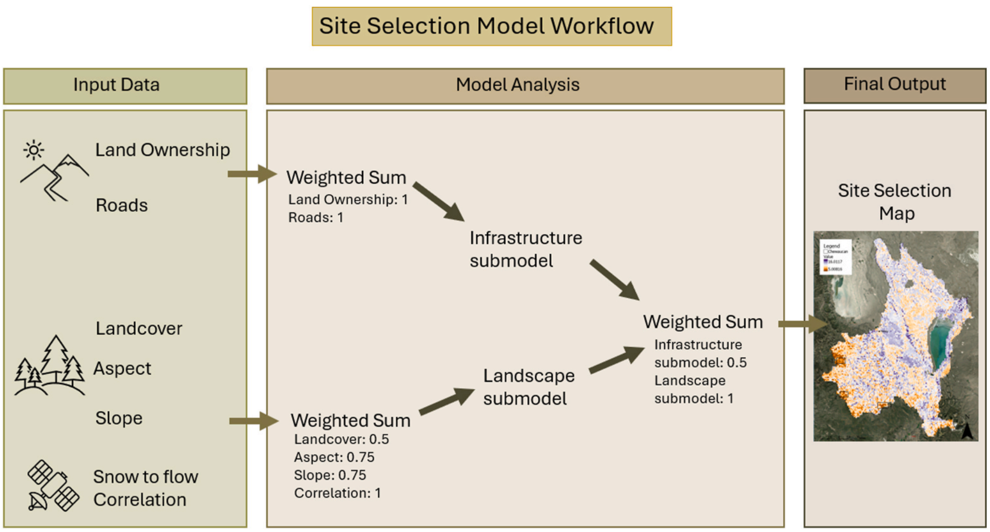

Fig. 3. A diagram showing the general workflow and operations utilized in the site selection model.

locations. Then, the square of each correlation value was taken to get the snow-to-flow R^2 value for every pixel. This quantifies the proportion of variance in summer streamflow explained by SDD at each pixel. The resulting R^2 correlation map was used as the final input into the site selection in the ArcGIS model.

A further analysis was done to compare how the remotely sensed correlation data compared to the same correlation of SDD and Chewaucan River streamflow from the nine nearest SNOTEL Sites. This helped to demonstrate the potential value of adding a new local site in the Chewaucan Basin versus using an existing station in a nearby basin (as is currently done by operational forecasters). The SNOTEL sites included Summer Rim (#800), Gerber Reservoir (#945), Silver Creek (#756), Silvies (#759), Dismal Swamp (#446), Taylor Butte (#810), Quartz Mountain (#706), Strawberry (#794), and Crazyman Flat (#1010), with data for each site extracted using MATLAB. Daily time series were obtained at each site from water years 2001 to 2023. Annual SDD values were then derived at each site by finding the last day with snow (i.e., SWE>0 mm) for the main snow season. The correlation between SDD and streamflow was then calculated, and snow-to-flow R^2 values were recorded for each site. Then, a cumulative distribution function was created for the MODIS-based snow-to-flow R^2 map using python, which was compared to the snow-to-flow R^2 values from the nine nearby SNOTEL sites.

3.3. Geospatial processing and modeling

The modelBuilder function in ArcGIS Pro was used to create a site suitability model. Two submodels (infrastructure and landscape) were created to aggregate the influence of various input data to the model as a whole. These two submodels were differentiated by the input data they received. The infrastructure submodel controlled data relating to human created systems (i.e., road network and land ownership). The landscape submodel focused on input data relating to physiographic features of the basin (e.g., slope, aspect, land cover) and the correlation between snowpack and streamflow (i.e., snow-to-flow R^2). Weighted sum operations were used to allow greater significance to be assigned to certain inputs within the model as a whole. The weights used within the model are listed in Fig. 3 under each associated weighted sum tool. The infrastructure submodel (inf) was calculated as:

$$Submodel_{inf} = W_{Own}Own + W_{road}Road \tag{1}$$

where W_{own} is the weight for land ownership, Own is the ownership classification, W_{road} is the weight for roads and Road is the road classification (see Table 1).

The landscape submodel (land) was calculated as:

$$Submodel_{land} = W_{corr}R^2 + W_{lc}LC + W_{asp}Asp + W_{slp}Slp \tag{2}$$

where W_{corr} is the weight for snow-to-flow correlation, R^2 is the snow-to-flow correlation class, W_{lc} is the weight for land cover, LC is the land cover class, W_{asp} is the weight for aspect, Asp is the aspect class, W_{slp} is the weight for slope, and Slp is terrain slope class (see Table 1).

The final model was computed as:

$$Site\ selection = W_{inf}Submodel_{inf} + W_{land}Submodel_{land} \tag{3}$$

We note that both the weights in the modelBuilder (Fig. 3) and the suitability classifications (Table 1) were manually specified, introducing an element of subjectivity into the model. In Section 5, we discuss this choice further as well as resulting uncertainty levels and include a simple sensitivity analysis (Fig. S2). Using the model set-up and eight weights outlined above, an output score of 4 is the lowest (best) value possible, while 20 is the highest (worst) value. However, in reality, there is no location in the basin that meets all criteria perfectly, nor is there a location in which every possible unfavored characteristic exists, meaning that the actual model output ranges somewhere between these two extreme values.

3.4. Localized maps

In preparation for engaging local community members in assessing site suitability, three high resolution local maps were created. U.S.D.A. National Agriculture Imagery Program (NAIP) imagery over the state of Oregon from 2022 at 30 cm spatial resolution was used as the basemap to show land cover. Roads and landmarks, such as viewpoints, mountain peaks, and lakes, were labeled in order to establish clear locational reference points that could be identified while discussing the maps with participants. The maps were labeled 1-3 and corresponded with the three areas with the best (i.e., most suitable) potential for snow measurement locations, as identified on the final site selection model output map (see previous section).

3.5. Participatory methods

A focus group with 10 participants was conducted in January 2025 at the Paisley Community Center, with participants who are long-term residents of the Chewaucan Basin. For this project, a long-term resident is defined as someone who has lived or worked within the basin for over two decades. Participants were identified by key informants with whom the author was already working in a separate collaborative water management initiative via the Partnership for Lake Abert and the Chewaucan (PLACe). The focus group took place at an already-scheduled, multi-day PLACe meeting, though participants of this study were not all members or active participants in PLACe. Participants included multi-generational residents and ranchers as well as long-time natural resource managers from county and state water management agencies. Given the low population of the Chewaucan Basin (the largest town in the area has a population of 255), our sample size of ten participants comprises approximately three percent of the local population, and their many years observing snow and water patterns in the basin provided extensive LEK to the project. Nevertheless, there were some limitations to our sample. For example, our sample did not include members of the Northern Paiute (Numu) people, for whom the Chewaucan Basin and Lake Abert are traditional homelands. Living descendants of the Northern Paiute people are now part of four federally recognized tribes including the Burns Paiute, Confederated Tribes of Warm Springs, the Klamath Tribes, the Fort Bidwell Indian Community, the Fort McDermitt Paiute, and the Shoshone Tribes, all of whom reside primarily outside of the Chewaucan Basin today (Partnership for Lake Abert and The Chewaucan, 2024). Participant recruitment focused solely on those currently living and working in the Basin. Due to histories of forced removal and the contemporary residence of the Northern Paiute descendants outside of the basin, no Tribal members participated in this study. In future work, expanding the participant pool to include Native peoples who live outside the basin but hold generational LEK and sacred connections to the basin would add an important perspective to this research.

The focus group took one hour. All participants were provided with information about the project, and each gave verbal informed consent to participate. The focus group opened with participants completing a set of 10 questions on a worksheet individually. The questions were designed to understand the types of scientific information (if any) being utilized by participants to inform their water management decisions. Specific themes of trust in the accuracy of currently available snowpack and streamflow data were targeted to help measure the importance of installing a local snow measurement station. Questions aimed at assessing whether participants considered localized data more trustworthy than data from a neighboring basin were used to measure the potential utility of a new station for decision making.

The second phase of the focus group began with an explanation of the site selection model (see section 3.3) to participants,

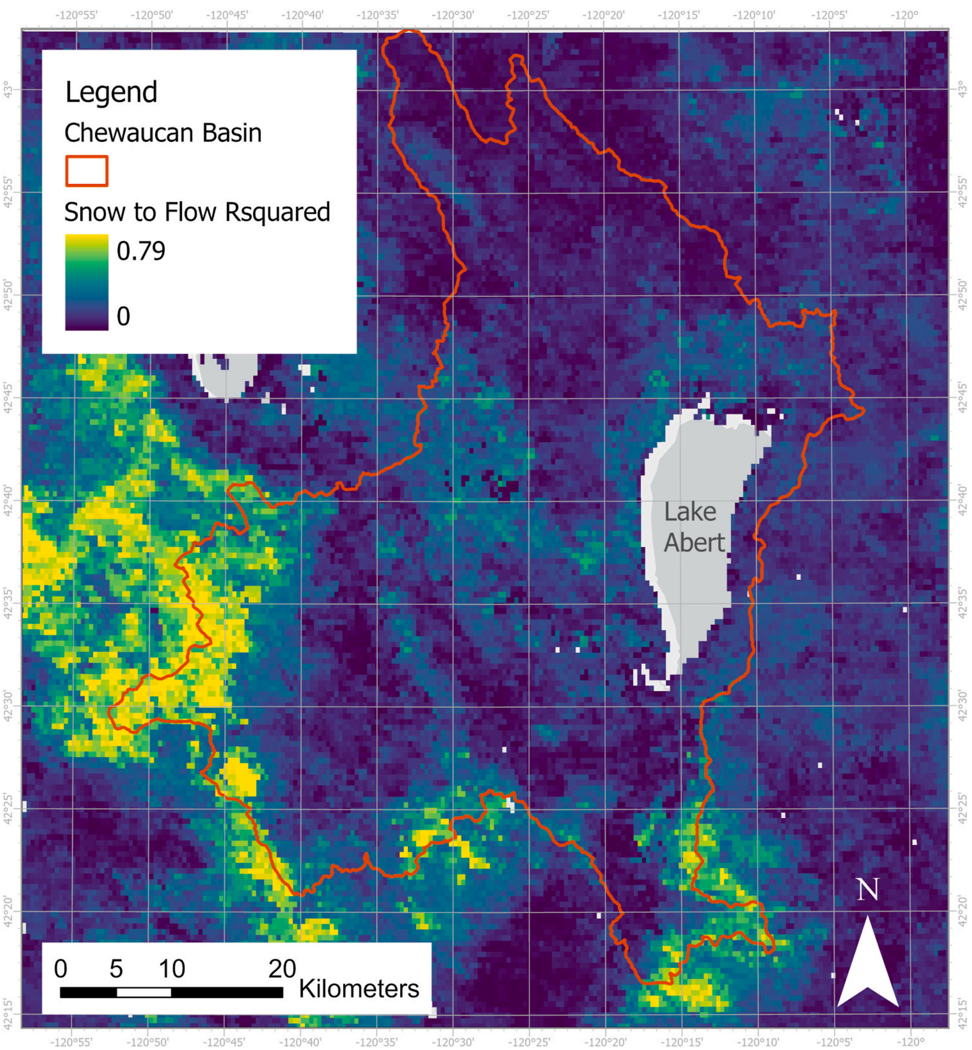

Fig. 4. The spatial distribution of snow-to-flow R^2 values resulting from the Pearson correlation coefficient of annual SDD and summer streamflow volume across 23 years.

including what input data were used and how the model was built, and asking participants for questions or concerns. Then, participants reviewed each of the three potential sites and discussed them as a group. After discussing all three locations, participants were asked to return to their worksheets and rank the three sites from 'best' to 'worst'. Finally, participants were given time to ask any additional questions relating to snow hydrology, snow measurement systems, operational snow measurement, or other areas of interest. In addition to the ten individually completed worksheets, the research team took extensive notes during the focus group discussions. Both the worksheets and notes were thematically coded using inductive codes to identify LEK that would inform the assessment of potential snow measurement sites' suitability.

4. Results

4.1. Remote sensing and geospatial analysis

The spatial analysis of snowpack and streamflow shows that snow-to-flow R^2 values ranged from 0 to 0.79 across the study basin (Fig. 4). Higher correlation areas are concentrated along the western and southern ridgelines of the basin, while low and zero correlation values are found in the lower elevations where snow is infrequent. When examining the elevation patterns, many of the highest correlation areas occur between 2000 m and 2560 m. Many of these areas have primarily south, west, and north facing aspects. Additionally, high correlations are in areas of the landscape that exhibit slopes ranging from 11% to 30% slope but also includes some areas with more gentle slopes. These high correlation areas are typically consistent with regions of the basin where SDD occurs later in the year.

Remote sensing data provides the opportunity to assess the potential utility of new local measurements compared to existing sites in nearby basins. A cumulative distribution function (CDF) of snow-to-flow pixel values within the borders of the Chewaucan Basin alongside the same SDD and streamflow correlations of the nine nearest SNOTEL sites are shown in Fig. 5. The SNOTEL site with the highest correlation value (0.67 at Dismal Swamp #446), was below the highest values of our remote sensing based correlation (between 0.70 and 0.79, corresponding to classes 1 and 2 in Table 1). While on the graph there appear to be relatively few pixels in this upper range, the land area represented by the highest correlation values is still significant given the 500m resolution of a single MODIS pixel. Just over 1% of the Chewaucan Basin had snow-to-flow R^2 values greater than 0.70, corresponding to a land area of about 20 km^2, a large area with many potential locations with predictive value for a new snow measurement station. We discuss issues related to spatial scale (i.e., 500m versus snow station) in Section 5.

The final output of the site selection model is shown in Fig. 6. The model output ranged from lower values (~5) for more suitable locations to higher values (>14) for unsuitable locations. This was visualized spatially and allowed the assessment of spatial patterns of potential site suitability. Three areas in the model output had high concentrations of pixels that indicated potentially suitable site locations (orange zones in Fig. 6). These areas were identified by visual and individual pixel inspection and were indicated with a number identifier box (annotated by the numbers '1', '2', and '3'). This map was shared at the focus group to elicit discussion and responses (see section 4.2).

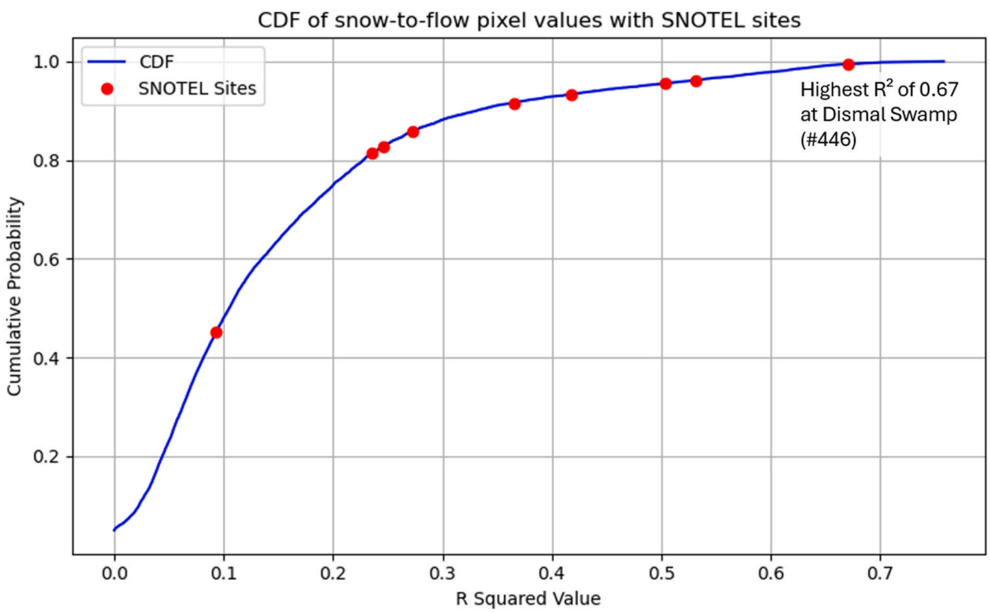

Fig. 5. The cumulative distribution function (CDF) of remotely sensed snow-to-flow R^2 values within the Chewaucan Basin, compared to the snow-to-flow R^2 values computed from data at the nine nearest SNOTEL sites outside of the Chewaucan Basin. The SNOTEL site with the highest correlation is labeled (#446 Dismal Swamp).

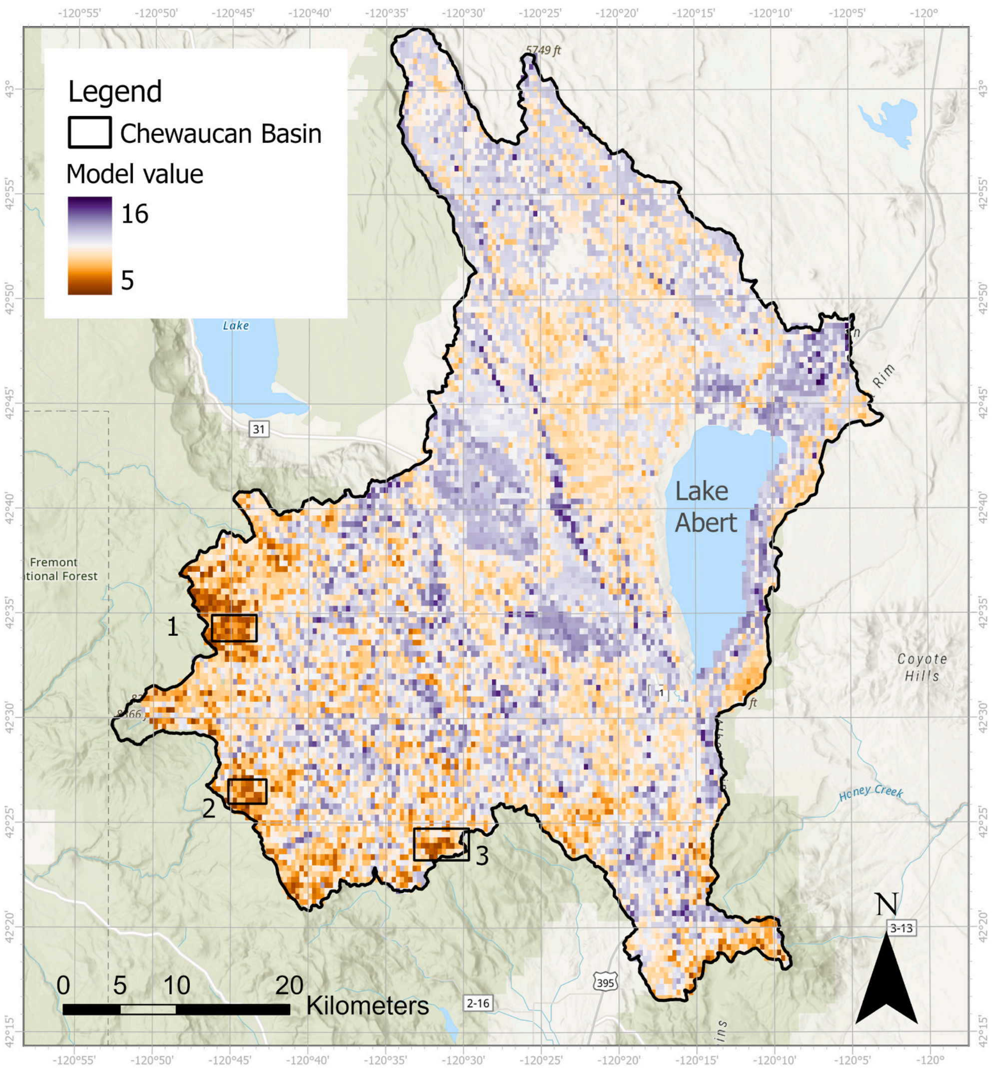

Fig. 6. The final site selection model output. Higher values (purple) indicate unsuitable areas, while lower values (orange) indicate more suitable areas in which many or all site selection preferences were present. Three proposed sites were identified (numbered black boxes) for discussion with the focus group.

4.2. Community LEK and focus group

During the focus group, participants first individually completed a questionnaire (see summarized results of the questionnaire in Table 2). These responses elicited information about data availability and needs, as well as trust in currently available scientific data. Responses indicate that NRCS and Oregon Water Resources Department (OWRD) are the most used and trusted sources of information on snowpack and streamflow for water users in the Chewaucan Basin. However, trust in the accuracy of that data was moderate: when asked on a Likert scale from 1 to 5 with 5 indicating the highest level of trust in the data, the average response was 3.25.

While 6 out of 10 respondents stated that current data met their needs at least at a minimum level, all of them indicated problems with current data, including concerns about the locations of measurements. For example, one respondent wrote, “No, [it is not meeting my needs], it would be nice to see data from inside the Chewaucan Basin.” When asked on a Likert scale question from 1 to 5 how important having a snow measurement station within the Chewaucan Basin was to them, with 5 being highly important, the average ranking was 4.8, indicating a very high preference among water users for measurements within the basin. A participant explained, “[a snow measurement site within the basin would provide] a more accurate representation of water that is captured and available in our watershed”.

Following completion of the questionnaire, the group engaged in rich discussion about the maps produced using the suitability model for each recommended site LEK that emerged from the discussion included knowledge about drainage patterns in the basin, the importance of various tributaries to the main stem of the Chewaucan River, how those tributaries responded to snowmelt, vegetation patterns, land cover changes resulting from recent wildfires that may impact snowpack characteristics, and activities taking place at

Table 2
Shows the questions that appeared on the questionnaire given to participants, with responses generalized or averaged for each question.

Question	Summarized finding
1. When you want to know about current snowpack conditions in the Chewaucan Basin, what source(s) of information do you rely on?	7 out of the 10 respondents reported relying primarily on NRCS data for current information on snowpack and streamflow. Other reported data sources included personal observations/visual assessments and information provided by Eric Snodgrass via the AgWest website.
2. What about current information on streamflow?	A variety of sources were reported including the Oregon Water Resources Department (OWRD) website (5 out of 10 responses), the NRCS website (1), and visual observation (1).
3. Do you ever access or try to find historical data on snowpack and/or streamflow? Where do you look?	8 out of 10 participants use either the NRCS or OWRD website. One participant said they did not look up historical data, and one participant said they used web searches.
4. How would you rank your level of trust in the accuracy of currently available snowpack information?	In a ranking from 1 to 5, where 5 was the highest level of trust, the average response was 3.25, indicating a moderate level of trust in the currently available data
5. Can you explain why you chose that number?	4 participants stated that their trust was impacted by the negative effects of wildfire on the closest current SNOTEL site. Another participant shared that their moderate level of trust resulted from not knowing how sites are selected to begin with.
6. Does the currently available data meet your needs when it comes to water management or decision making about water?	4 participants answered 'no' or 'not really' while others identified nuances such as wanting more data specific to the Chewaucan, or the impacts of interannual variability on how useful data is for management
7. How would you rank the importance of having a snow measurement station within the Chewaucan Basin?	In a ranking from 1 to 5, where 5 was highly important, the average participant ranking was 4.8. This indicated a high level of interest in localized snow information by participants.
8. Can you explain why you chose that number?	All 10 participants noted that their rating was based on the fact that there is no SNOTEL site in the basin or because data from a SNOTEL would be informative for water management decisions.
9. Would having a new snow measurement station within the basin be useful to you and/or your community? If so, how?	All participants answered 'yes'. Responses included how a station could help establish a baseline for conditions in the upper basin, how it would provide more accurate information of both snowpack and water resources, and that it would help management and planning efforts.
10. Of the three potential sites you've seen, can you rank the sites from 'best' to 'worst'?	9 out of 10 participants identified site 1 as the 'best' location. Site 2 was most often ranked as 'moderate' and site 3 was most often ranked as the 'worst' site.

each location (such as ranching, camping, hunting, etc.). Participants also discussed their observations of snowpack in the basin, particularly related to how one nearby SNOTEL site (Summer Rim #800) in an adjacent basin was impacted by a wildfire in 2022. They discussed how the fire had caused measurements at the site to become significantly less accurate as the area is now highly susceptible to wind transport due to changes in tree cover. The increased influence of wind transport at the nearby SNOTEL site has made measurements from that site less representative of basin characteristics in the Chewaucan. The decrease in measurement accuracy at Summer Rim #800 that participants identified was confirmed by NRCS personnel (personal communication) and from visual observations of fire damage to the landscape made by the author during a visit to the SNOTEL site.

Participants provided perspectives to the site selection process that were not considered in the original model suitability analysis. For example, participants discussed potential implications of having a snow measurement station visible from a road and whether that may lead to station tampering. When asked to rank the three possible locations from most to least preferred for a snow measurement station, participants overwhelmingly (9/10 participants) identified site 1 as their ideal location (Fig. 6). Participants were asked to make their rankings individually on their worksheet, rather than verbally within the group to document individual perspective and disagreement. However, participants' rankings for preferred site locations were very similar. Reasons given by participants for their selection of site 1 included: the site's relative proximity to the Summer Rim SNOTEL station, its familiarity to them personally, and their belief that the snowpack in that area exhibit accumulation and melt patterns that are typical of the upper elevations of the Chewaucan where most snowpack occurs.

5. Discussion

There has been relatively minimal work on how spatial snow data from remote sensing or local ecological knowledge can inform site selection and expansion of snow monitoring networks, with few exceptions (e.g., Gleason et al., 2017; Raleigh et al., 2013). Thus, this case study demonstrates a new workflow that leverages two novel data sources (quantitative remote sensing and qualitative LEK) to inform the site selection process. Locations with water supply predictability can be spatially mapped with satellite remote sensing (Fig. 4), and the relative value of these new measurement locations can be compared to existing stations in neighboring basins (Fig. 5). The proposed method has the potential to inform local monitoring needs and where NRCS and other organizations place snow, water, and weather measurement stations, potentially resulting in more predictive and relevant data for community water users and managers (e.g., summer water supply in this case study). This research provides an avenue to formalize the process of site selection, moving from an informed but largely unstructured and intuitive approach currently utilized by managers, to a systematic methodology that could be applied elsewhere. While this model contains subjectivity in the form of user chosen weights (section 3.3), it nevertheless offers a consistent and systematic method for integrating diverse data and perspectives to support the decision-making process. Additionally, this methodology could be useful to a wide range of scientific measurement questions, including informing other kinds of site selection processes like the placement of scientific field campaigns where in situ and specialized measurements are made.

Site selection for both new and existing networks such as SNOTEL comes with other considerations like snow spatial variability and climate change, neither of which is addressed here. First, it has been noted that current site selection requirements used by NRCS often result in a network that is physiographically homogenous (Welch et al., 2013), with stations typically in relatively flat clearings (Farnes, 1967) and often at mid-elevations (e.g., Gleason et al., 2017). This can result in snowpack measurements that are not spatially representative of snow across the basin or the area around a station (Herbert et al., 2024). Snowpack variability across a basin is controlled by a range of factors, including the significant effect of orographic precipitation, elevation-dependent freezing levels, wind redistribution, and forest processes (Clark et al., 2011; Dickerson-Lange et al., 2017). Nevertheless, the NRCS chooses new site locations based on where it is most likely to serve as an index of water available for runoff generation in a given basin, and these sites have been useful for water supply forecasting for almost a century (Fleming et al., 2023) despite not being spatially representative. Second, SNOTEL stations are not placed with consideration of future climate scenarios (e.g., Gleason et al., 2017), meaning that in the future some stations may see less consistent snowpack during winter months. Recent research suggests that existing stations will become less representative of basin snowpack in the future, but resilient snowpack estimation is still possible with data-driven analysis (Cowherd et al., 2024). Additionally, adding a new measurement station to a basin cannot address the missing record of snowpack conditions in past years which are necessary for developing statistical water supply forecast models (Fleming et al., 2023) or for modeling future scenarios. Though our proposed model does not account for potential future climate conditions when locating new station locations, this could be included in future work. While climate change and snow patterns are important considerations, these challenges are not unique to our study and do not preclude the use of snow monitoring stations to help address the information needs of current or future water users.

This work demonstrates that local community members hold detailed and valuable knowledge of landscape dynamics that can inform scientific measurement site selection and network design. Participants in this study had extensive experience with water resources in their basin. Despite having limited to no formal hydrology training, they identified important hydrological features and processes and shared detailed information about snowpack variables and behaviors in the study basin during the group discussion. Our study highlights the value of engaging LEK when selecting measurement sites in the future. Our experience also revealed some participatory dynamics that future researchers engaging in participatory modeling approaches should be mindful of. For example, the researcher conducting the focus group noticed that many participants knew one another, and that relational dynamics such as deference to older community members was prominent among participants. Younger participants indicated they valued the opinions of older participants above their own. This particular community dynamic may have impacted how some participants responded within the focus group setting. Asking participants to respond to an individual questionnaire prior to the group discussion was a useful tool for minimizing the impacts of this dynamic.

There are multiple limitations related to the use of snow remote sensing data in this study. First, there is greater uncertainty of snow detection in forests when using satellite remote sensing products (Raleigh et al., 2025; Stillinger et al., 2022). This is notable given that much of the upper Chewaucan Basin is coniferous forest, and there are likely some areas in which the moderate 500m resolution of MODIS may have higher uncertainty in capturing snow disappearance. Higher resolution remote sensing products such as data from Landsat (30m) and Sentinel-2 (20m) may improve snow cover mapping in discontinuous forests and forest gaps, however with a trade-off in temporal resolution. Work by Stillinger et al. (2022) provides a comprehensive analysis of errors over forested areas from a number of remote sensing sources including MODIS, Landsat, and VIIRS. Second, the 500m spatial resolution of MODIS is different from the scale at which snow measurement stations capture data (typically with a ~9 m^2 snow pillow), and this complicates direct comparisons (e.g., Fig. 5) and site identification. Herbert et al. (2024) found that SNOTEL sites overestimate snow depth (and thus likely, SWE) compared to larger areal means of 50m and 500m by 10 cm at half of locations tested. Additional work is needed to refine how to identify specific locations within a 500m pixel where snow has relatively higher correlations with streamflow over time. Third, we used SDD as a proxy for SWE, but they are different metrics and SDD may only explain ~60% of spatial variance in peak SWE (e.g., Wayand et al., 2018). However, work by Bishay et al. (2023) has shown that SDD can still be predictive of water supply. An additional analysis comparing peak SWE and SDD at each of the 9 nearest SNOTEL sites to the Chewaucan Basin supports our use of SDD as a SWE proxy (see Fig. S1 in the supplement).

Another important caveat is that subjective decisions were made in the geospatial site selection model and focus group. Notably, specific weights were assigned to input layers (Table 1), and within the weighted sum operations of the model (Fig. 3). These decisions were at the discretion of the researcher, following relevant guidance (U.S. NRCS National Engineering Handbook, 2011) where possible. However, we emphasize that our weights are a first-order approximation for the purpose of our case study and are not the result of a comprehensive optimization of parameters. Others interested in reproducing this method may prefer to assign other weights. The final site selection output map can be dependent on these weights. A simple sensitivity analysis was performed in which different combinations of weights were applied to the model to examine changes in input (see Fig. S2 in the supplemental information document), and showed broadly consistent maps when infrastructure and landscape weights were made equal; however, this should not be considered an exhaustive analysis. Future work focused on further investigating model sensitivity and structure may be useful in informing future decision making and potential integration of this method into existing protocols. Additionally, the researcher referenced the different potential measurement sites using the numbers '1', '2', and '3' in materials presented to focus group participants. It is possible that this numbering choice influenced participants site rankings, as 9 out of 10 participants chose site "1" as their first choice. In future work, potential sites could be labeled using custom names reflecting location characteristics or geographic location to avoid the risk of influencing participant opinion.

A final potential limitation of this study is that the participant pool was relatively small at only 10 participants. Most participants were farmers and ranchers, whose livelihood dependence on water shaped their perspectives. Participants from other backgrounds may have had different perspectives on the relevance of snowpack to issues beyond economics (such as recreation, ecological importance, or spiritual connections). In future work on this topic, engaging a greater number of participants from a variety of different backgrounds, particularly Tribal members, would likely yield additional important information for scientific measurement site selection processes. Despite the potential of participatory approaches that integrate LEK into site selection or other environmental monitoring, literature on these approaches has flagged important challenges. Namely, at times local ecological knowledge will not match with data produced through other scientific methods. When this occurs, it is critical that local ecological knowledge is not viewed as subordinate to western science. Researchers must be ready to hold two potentially contradictory sets of knowledge in relation to one another, without forcing one to assimilate into the other (Emard et al., 2024; Reid et al., 2021; Wheeler et al., 2020). This may limit the ability to make clear recommendations or the usability of data generated through participatory processes.

6. Conclusion

This case study demonstrates how two novel data sources, namely remotely sensed snow information and local ecological knowledge held by community members, can enrich the site selection process for scientific measurement systems. The analysis addresses two research questions: 'how can spatial maps of remotely sensed snow disappearance date be used alongside more commonly used geospatial data to inform site selection for a snow measurement station?' and 'what kinds of information provided by LEK can be leveraged in site selection for scientific instrumentation?' Our results illustrate that widely available snow remote sensing data can be combined with streamflow volume to identify where local measurements could be most effective for water resources. Additionally, this research provides a new dimension to snow hydrology research by incorporating participatory methods to incorporate LEK in scientific network expansion. Our findings illustrate that community members hold valuable LEK relating to snowpack, water, and landscape dynamics, as well as the importance of localized snow measurements in a rural, agricultural community. This work engages with novel data sources that have thus far not been utilized in site selection, meaning it provides valuable guidance for potential future work in monitoring network expansion. This approach utilize relatively simple statistical metrics and geospatial software making it flexible to apply in other regions.

CRediT authorship contribution statement

Hannah Steele: Writing – original draft, Visualization, Methodology, Formal analysis, Data curation, Conceptualization. **Kelsey Emard:** Writing – review & editing, Methodology, Formal analysis, Data curation, Conceptualization. **Mark S. Raleigh:** Writing – review & editing, Supervision, Project administration, Methodology, Formal analysis, Data curation, Conceptualization.

Data statement

All of the datasets utilized in this study are publicly available. The Oregon Land Management dataset and the Oregon 10m DEM can be found at https://geohub.oregon.gov/. The National Transportation Dataset and the National Hydrography dataset can be found using https://apps.nationalmap.gov/downloader/#/. The National Land Cover Dataset can be found using https://earthexplorer.usgs.gov/. Remotely sensed snow data such as SDD can be accessed on Google Earth Engine through the SnowCloudMetrics app and code at https://www.snowcloudmetrics.app/. SNOTEL data can be accessed via the USDA NRCS report generator (https://wcc.sc.egov.usda.gov/reportGenerator/). Streamflow data for the Chewaucan River can be found using the Oregon Water Resources Department Gage Data Request https://apps.wrd.state.or.us/apps/sw/hydro_report/gage_data_request.aspx?station_nbr=10384000.

Ethical statement

We, the authors, declare that this manuscript is our original work, and was created through transparent and ethical research practices. All authors have approved the manuscript and agreed to its submission to Remote Sensing Applications: Society and Environment (RSASE).

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Hannah Steele reports financial support was provided by Oregon State Legislature. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

The authors sincerely thank Colleen Withers and Tess Baker for providing feedback on this manuscript. We also thank all of the participants who generously contributed their time and insights during the focus group. Finally, funding that supported this work through a partial Graduate Research Assistantship came from the Oregon State Legislature as part of H.B. 2010.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.rsase.2026.101912.

Data availability

Data will be made available on request.

References

Alessa, Kliskey, L.A., Gamble, J., Fidel, M., Beaujean, G., Gosz, J., 2016. The role of Indigenous science and local knowledge in integrated observing systems: moving toward adaptive capacity indices and early warning systems. Sustain. Sci. 11, 91–102. https://doi.org/10.1007/s11625-015-0295-7.

Bartlett, C., Marshall, M., Marshall, A., 2012. Two-eyed seeing and other lessons learned within a co-learning journey of bringing together Indigenous and mainstream knowledges and ways of knowing. J. Environ. Stud. Sci. 2 (4), 331–340. https://doi.org/10.1007/s13412-012-0086-8.

Bélisle, A.C., Asselin, H., LeBlanc, P., Gauthier, S., 2018. Local knowledge in ecological modeling. Ecol. Soc. 23 (2), 14. https://www.jstor.org/stable/26799118.

Bennett, K.E., Cherry, J.E., Balk, B., Lindsey, S., 2019. Using MODIS estimates of fractional snow cover area to improve streamflow forecasts in interior Alaska. Hydrol. Earth Syst. Sci. 23 (5), 2439–2459. https://doi.org/10.5194/hess-23-2439-2019.

Bishay, K., Bjarke, N.R., Modi, P., Pflug, J.M., Livneh, B., 2023. Can remotely sensed snow disappearance explain seasonal water supply? Water 15 (6), 1147. https://doi.org/10.3390/w15061147.

Charnley, S., Fischer, A.P., Jones, E.T., 2007. Integrating traditional and local ecological knowledge into forest biodiversity conservation in the Pacific Northwest. For. Ecol. Manag. 246 (1), 14–28. https://doi.org/10.1016/j.foreco.2007.03.047.

Clark, M.P., Hendrikx, J., Slater, A.G., Kavetski, D., Anderson, B., Cullen, N.J., Kerr, T., Örn Hreinsson, E., Woods, R.A., 2011. Representing spatial variability of snow water equivalent in hydrologic and land-surface models: a review. Water Resour. Res. 47 (7), W07539. https://doi.org/10.1029/2011WR010745.

Cowherd, M., Mital, U., Rahimi, S., Girotto, M., Schwartz, A., Feldman, D., 2024. Climate change-resilient snowpack estimation in the Western United States. Commun. Earth Environ. 5 (1), 1–10. https://doi.org/10.1038/s43247-024-01496-3.

Crumley, R.L., Palomaki, R.T., Nolin, A.W., Sproles, E.A., Mar, E.J., 2020. SnowCloudMetrics: snow information for everyone. Remote Sens. 12 (20), 3341. https://doi.org/10.3390/rs12203341.

Dalton, M.M., Fleishman, E., 2021. Fifth Oregon climate assessment. https://doi.org/10.5399/osu/1160.

Dickerson-Lange, S.E., Gersonde, R.F., Hubbart, J.A., Link, T.E., Nolin, A.W., Perry, G.H., Lundquist, J.D., 2017. Snow disappearance timing is dominated by forest effects on snow accumulation in warm winter climates of the Pacific Northwest, United States. Hydrological Processes 31 (10), 1846–1862. https://doi.org/10.1002/hyp.11144.

Eddy, I.M., Gergel, S.E., Coops, N.C., Henebry, G.M., Levine, J., Zerriffi, H., Shibkov, E., 2017. Integrating remote sensing and local ecological knowledge to monitor rangeland dynamics. Ecol. Indic. 82, 106–116. https://doi.org/10.1016/j.ecolind.2017.06.033.

Eitzel, M.V., Solera, J., Hove, E.M., Wilson, K.B., Ndlovu, A.M., Ndlovu, D., Changarara, A., et al., 2021. Assessing the potential of participatory modeling for decolonial restoration of an agro-pastoral system in rural Zimbabwe. Citiz. Sci. Theory Pract. 6 (1). https://doi.org/10.5334/cstp.339.

Emard, K.A., Edgeley, C.M., Hazard, C.A.W., Sarna-Wojcicki, D., Cannon, W., Cameron, O.Z., et al., 2024. Connecting local ecological knowledge and Earth system models: comparing three participatory approaches. Ecol. Soc. 29 (4). https://doi.org/10.5751/ES-15570-290443.

Fagerholm, N., Raymond, C.M., Olafsson, A.S., Brown, G., Rinne, T., Hasanzadeh, K., et al., 2021. A methodological framework for analysis of participatory mapping data in research, planning, and management. Int. J. Geogr. Inf. Sci. 35 (9), 1848–1875. https://doi.org/10.1080/13658816.2020.1869747.

Farnes, P., 1967. Criteria for determining mountain snow pillow sites. In: Proc. 35th Western Snow Conf, pp. 59–62.

Fleming, S.W., Zukiewicz, L., Strobel, M.L., Hofman, H., Goodbody, A.G., 2023. SNOTEL, the soil climate analysis network, and water supply forecasting at the natural resources conservation service: past, present, and future. JAWRA J. Am. Water Res. Assoc. 59 (4), 585–599. https://doi.org/10.1111/1752-1688.13104.

Fleming, S.W., Rittger, K., Oaida Taglialatela, C.M., Graczyk, I., 2024. Leveraging next-generation satellite remote sensing-based snow data to improve seasonal water supply predictions in a practical machine learning-driven river forecast system. Water Resour. Res. 60 (4). https://doi.org/10.1029/2023WR035785 e2023WR035785.

Gleason, K.E., Nolin, A.W., Roth, T.R., 2017. Developing a representative snow-monitoring network in a forested mountain watershed. Hydrol. Earth Syst. Sci. 21 (2), 1137–1147. https://doi.org/10.5194/hess-21-1137-2017.

Gorelick, N., Hancher, M., Dixon, M., Ilyushchenko, S., Thau, D., Moore, R., 2016. Google Earth engine: planetary-scale geospatial analysis for everyone. Rem. Sens. Environ. 202, 18–27. https://doi.org/10.1016/j.rse.2017.06.031.

Hall, D.K., Kimball, J.S., Larson, R., DiGirolamo, N.E., Casey, K.A., Hulley, G., 2023. Intensified warming and aridity accelerate terminal Lake desiccation in the great basin of the Western United States. Earth Space Sci. 10 (1). https://doi.org/10.1029/2022EA002630 e2022EA002630.

Hall, D.K., Riggs, G.A., 2016. *MODIS/Terra Snow Cover Daily L3 Global 500m SIN Grid*. (MOD10A1, Version 6), NASA National Snow and Ice Data Center Distributed Active Archive Center, Boulder, Colorado USA. https://doi.org/10.5067/MODIS/MOD10A1.006.

Herbert, J.N., Raleigh, M.S., Small, E.E., 2024. Reanalyzing the spatial representativeness of snow depth at automated monitoring stations using airborne lidar data. Cryosphere 18 (8), 3495–3512. https://doi.org/10.5194/tc-18-3495-2024.

Iniesta-Arandia, I., Del Amo, D.G., García-Nieto, A.P., Piñeiro, C., Montes, C., Martín-López, B., 2015. Factors influencing local ecological knowledge maintenance in Mediterranean watersheds: insights for environmental policies. Ambio 44, 285–296. https://doi.org/10.1007/s13280-014-0556-1.

Knapp, C.N., Fernandez-Gimenez, M.E., 2009. Knowledge in practice: documenting rancher local knowledge in northwest Colorado. Rangel. Ecol. Manag. 62 (6), 500–509. https://doi.org/10.2111/08-175.1.

Mote, P.W., Li, S., Lettenmaier, D.P., Xiao, M., Engel, R., 2018. Dramatic declines in snowpack in the western US. npj Clim. Atmos. Sci. 1 (1), 2. https://doi.org/10.1038/s41612-018-0012-1.

Nolin, A.W., 2010. Recent advances in remote sensing of seasonal snow. J. Glaciol. 56 (200), 1141–1150. https://doi.org/10.3189/002214311796406077.

Nolin, A.W., Sproles, E.A., Rupp, D.E., Crumley, R.L., Webb, M.J., Palomaki, R.T., Mar, E., 2021. New snow metrics for a warming world. Hydrol. Process. 35 (6), e14262. https://doi.org/10.1002/hyp.14262.

Painter, T.H., Berisford, D.F., Boardman, J.W., Bormann, K.J., Deems, J.S., Gehrke, F., et al., 2016. The airborne snow observatory: fusion of scanning lidar, imaging spectrometer, and physically-based modeling for mapping snow water equivalent and snow albedo. Rem. Sens. Environ. 184, 139–152. https://doi.org/10.1016/j.rse.2016.06.018.

Partnership for Lake Abert and the Chewaucan Joint Fact-Finding Subcommittee, 2024. Shared narratives. Available at: https://oregonconsensus.org/projects/partnership-for-lake-abert-and-the-chewaucan-place/.

Raleigh, M.S., Rittger, K., Moore, C.E., Henn, B., Lutz, J.A., Lundquist, J.D., 2013. Ground-based testing of MODIS fractional snow cover in subalpine meadows and forests of the Sierra Nevada. Remote Sensing of Environment 128, 44–57.

Raleigh, M.S., Small, E.E., Bair, E.H., Wobus, C., Rittger, K., 2025. Snow monitoring at strategic locations improves water supply forecasting more than basin-wide mapping. Commun. Earth Environ. 6 (1), 665. https://doi.org/10.1038/s43247-025-02660-z.

Reid, A.J., Eckert, L.E., Lane, J., Young, N., Hinch, S.G., Darimont, C.T., Cooke, S.J., Ban, N.C., Marshall, A., 2021. "Two-Eyed seeing": an Indigenous framework to transform fisheries research and management. Fish Fish. 22 (2), 243–261. https://doi.org/10.1111/faf.12516.

Sobczak, J., Valduga, A., Restello, R., Cardoso, R., Hepp, L.U., Siqueira, A., 2013. Local ecological knowledge as a complementary basis for the management of water resources. Ethnobiol. Conserv. 2.

Sproles, E.A., Crumley, R.L., Nolin, A.W., Mar, E., Moreno, J.I.L., 2018. SnowCloudHydro—A new framework for forecasting streamflow in Snowy, data-scarce regions. Remote Sens. 10 (8), 1–15. https://doi.org/10.3390/rs10081276.

Stillinger, T., Rittger, K., Raleigh, M.S., Michell, A., Davis, R.E., Bair, E.H., 2022. Landsat, MODIS, and VIIRS snow cover mapping algorithm performance as validated by airborne lidar datasets. Cryosphere Discuss. 2022, 1–37. https://doi.org/10.5194/tc-17-567-2023.

Trujillo, E., Molotch, N.P., 2014. Snowpack regimes of the Western United States. Water Resour. Res. 50 (7), 5611–5623. https://doi.org/10.1002/2013WR014753.

United States Bureau of Land Management, 1995. High desert management framework draft plan amendment and environmental impact statement for the proposed Lake Abert area of special environmental concern (ACEC). In: Lake County, Oregon, p. 106 and appendices.

U.S. Department of Agriculture, National Agricultural Statistics Service, 2022. Census of agriculture – county profile: lake county (CP-41037). https://data.nass.usda.gov/Publications/AgCensus/2022/Online_Resources/County_Profiles/Oregon/cp41037.pdf.

United States, Natural Resources Conservation Service, 2011. *National Engineering Handbook*. Part 622, Snow Survey and Water Supply Forecast. United States Department of Agriculture.

Voinov, A., Gaddis, E.J.B., 2008. Lessons for successful participatory watershed modeling: a perspective from modeling practitioners. Ecol. Model. 216 (2), 197–207. https://doi.org/10.1016/j.ecolmodel.2008.03.010.

Wayand, N.E., Marsh, C.B., Shea, J.M., Pomeroy, J.W., 2018. Globally scalable alpine snow metrics. Rem. Sens. Environ. 213, 61–72. https://doi.org/10.1016/j.rse.2018.05.012.

Welch, S.C., Kerkez, B., Bales, R.C., Glaser, S.D., Rittger, K., Rice, R.R., 2013. Sensor placement strategies for snow water equivalent (SWE) estimation in the American river basin. Water Resour. Res. 49 (2), 891–903. https://doi.org/10.1002/wrcr.20100.

Wheeler, H.C., Danielson, F., Fidel, M., Hausner, V., Horstkotte, T., Johnson, N., Lee, O., Mukherjee, N., Amos, A., Ashthorn, H., Ballari, O., Behe, C., Breton-Honeyman, K., Retter, G.-B., Buschman, V., Jakobsen, P., Johnson, F., Lyberth, B., Parrott, J.A., Pogodaev, M., Sulyandziga, R., Vronski, N., 2020. The need for transformative changes in the use of Indigenous knowledge along with science for environmental decision making in the Arctic. People Nat. 2 (3), 544–556. https://doi.org/10.1002/pan3.10131.