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Technical report: The design and evaluation of a basin-scale wireless sensor network for mountain hydrology

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Abstract

A network of sensors for spatially representative water-balance measurements was developed and deployed across the 2000 km^2 snow-dominated portion of the upper American River basin, primarily to measure changes in snowpack and soil-water storage, air temperature, and humidity. This wireless sensor network (WSN) consists of 14 sensor clusters, each with 10 measurement nodes that were strategically placed within a 1 km^2 area, across different elevations, aspects, slopes, and canopy covers. Compared to existing operational sensor installations, the WSN reduces hydrologic uncertainty in at least three ways. First, redundant measurements improved estimation of lapse rates for air and dew-point temperature. Second, distributed measurements captured local variability and constrained uncertainty in air and dew-point temperature, snow accumulation, and derived hydrologic attributes important for modeling and prediction. Third, the distributed relative-humidity measurements offer a unique capability to monitor upper-basin patterns in dew-point temperature and characterize elevation gradient of water vapor-pressure deficit across steep, variable topography. Network statistics during the first year of operation demonstrated that the WSN was robust for cold, wet, and windy conditions in the basin. The electronic technology used in the WSN-reduced adverse effects, such as high current consumption, multipath signal fading, and clock drift, seen in previous remote WSNs.

Keywords: wireless-sensor network, water-information system, snow observation, mountain hydrology, Sierra Nevada

1 Introduction

Currently, in situ measurements of mountain water cycles at the basin scale are limited in both spatial coverage and temporal resolution, with data largely provided by a relatively small number of operational precipitation, snowpack, climate, and stream-gauging stations [*Bales et al.*, 2006; *Dozier*, 2011]. In the Sierra Nevada, measurement sites supporting operational water-resources decision making are also biased to middle and lower elevations and flat terrain in forest clearings [*Molotch and Bales*, 2005].

Hydrologic prediction, particularly when constrained by the practical demands of water-resources management, relies heavily on calibrated models to mitigate both limitations in model formulation and inadequate data for rigorous model testing [*Kuczera et al*., 2010; *Semenova and Beven*, 2015]. There are increasing demands on distributed models as predictive tools for situations in which lumped models may fall short, such as nonstationarity in catchment conditions or climate; however, their use in water-resources management is limited by the level of field data available [*Refsgaard*, 1997]. The need for improved coverage by in situ measurements is both local and global, and new network designs should complement satellite data [*Wood et al*., 2011]. Ground-based sensors provide critical ground truth for remotely sensed satellite and aircraft data, and offer a wide suite of independent data that can help provide much-needed gains in predictive modeling. Realizing gains in accuracy from the next generation of spatially explicit models at the scale of water-resources decision making will require both the broad spatial coverage of remotely sensed data and the accuracy of in situ measurements [*Lehning et al*., 2009]. An adaptive rather than one-size-fits-all approach is needed to realize these gains [*Fenicia et al*., 2008].

Wireless Sensor Networks (WSNs) are an efficient and economical solution for distributed sensing. It is often costly and disruptive to create networks of spatially representative wired sensors at the scale desired since it might require kilometers of cables placed either above ground or buried. Similarly, access to data for distributed sensors with only local logging is limited by the need to visit sites to download data. Reliable wireless solutions are now enabled by reduced production costs of wireless equipment and by advances in networking protocols, effectively combining traditionally wired sensors with a wireless platform [*Akyildiz et al*., 2002; *Yick et al*., 2008; *Gilbert*, 2012].

A few WSN solutions, using different network technologies, were developed specifically for applications in hydrology. These studies have not provided quantifiable assessments of network design, operation, and hydrologic results at the river-basin scale. A review of these prior deployments, and a comparison of three existing WSN solutions that have been used, is provided in supporting information Text S1 [*Digi*, n.d.; *Bogena et al*., 2010; *Pister and Doherty*, 2008; *Gungor and Hancke*, 2009; *International*, 2009; *Ritsema et al*., 2010; *Simoni et al*., 2011; *Trubilowicz et al*., 2010; *Horvat*, 2012; *Huang et al*., 2012; *Kerkez et al*., 2012; *Accettura and Piro*, 2014; *Pohl et al*., 2014; *Document*, 2009].

While sensor networks deployed in headwater catchments for short durations offer lessons for local-scale WSNs, they provide limited guidance for WSN design, performance, and hydrologic benefits for systems in larger mountain river basins, characterized by steep gradients in temperature, precipitation, rain-versus-snow fraction, growing season, vegetation density, and evapotranspiration. The proposed approach to scaling WSN measurements to larger basins involves strategically placing local clusters to capture the variability in hydrologically important basin attributes [*Welch et al*., 2013].

The aim of the research described in this technical report is to develop a flexible, robust method for measurement of the spatial water balance across a seasonally snow-covered mountain basin. In doing this, we address three questions. First, to what extent can a basin-scale distributed wireless-sensor network with a limited number of sensors arrayed in local clusters sample hydrologic variables across a representative range of landscape attributes in a seasonally snow-covered mountain basin? Second, to what extent can this low-power, distributed wireless-sensor network reliably provide hydrologic data during harsh winter conditions? Third, what types of gains in hydrologic information may result from this network? Further development and more-detailed analysis of the third question is also the subject of subsequent analysis.

2 Methods

The network was deployed in the American River Hydrologic Observatory (ARHO), in the upper, snow-dominated portion of the American River basin on the western slope of the Sierra Nevada in California (36.069 N, 120.583 W). The basin is incised with steep river canyons and is comprised of three subbasins: the North, Middle, and South forks, which combine to form a drainage basin of 5311 km^2 above the Folsom Reservoir, the main impoundment on the river (Figure 1a). Basin elevations range from 15 m at Folsom to 3147 m at the Sierra crest, with precipitation transitioning from rain to snow at about 1400–1600 m elevation [*Raleigh and Lundquist*, 2012; *Klos et al*., 2014]. Forty percent or about 2000 km^2, of the basin is above 1500 m, the lowest elevation for siting our WSNs. About 0.5% of the basin is above the highest node that was sited (2678 m).

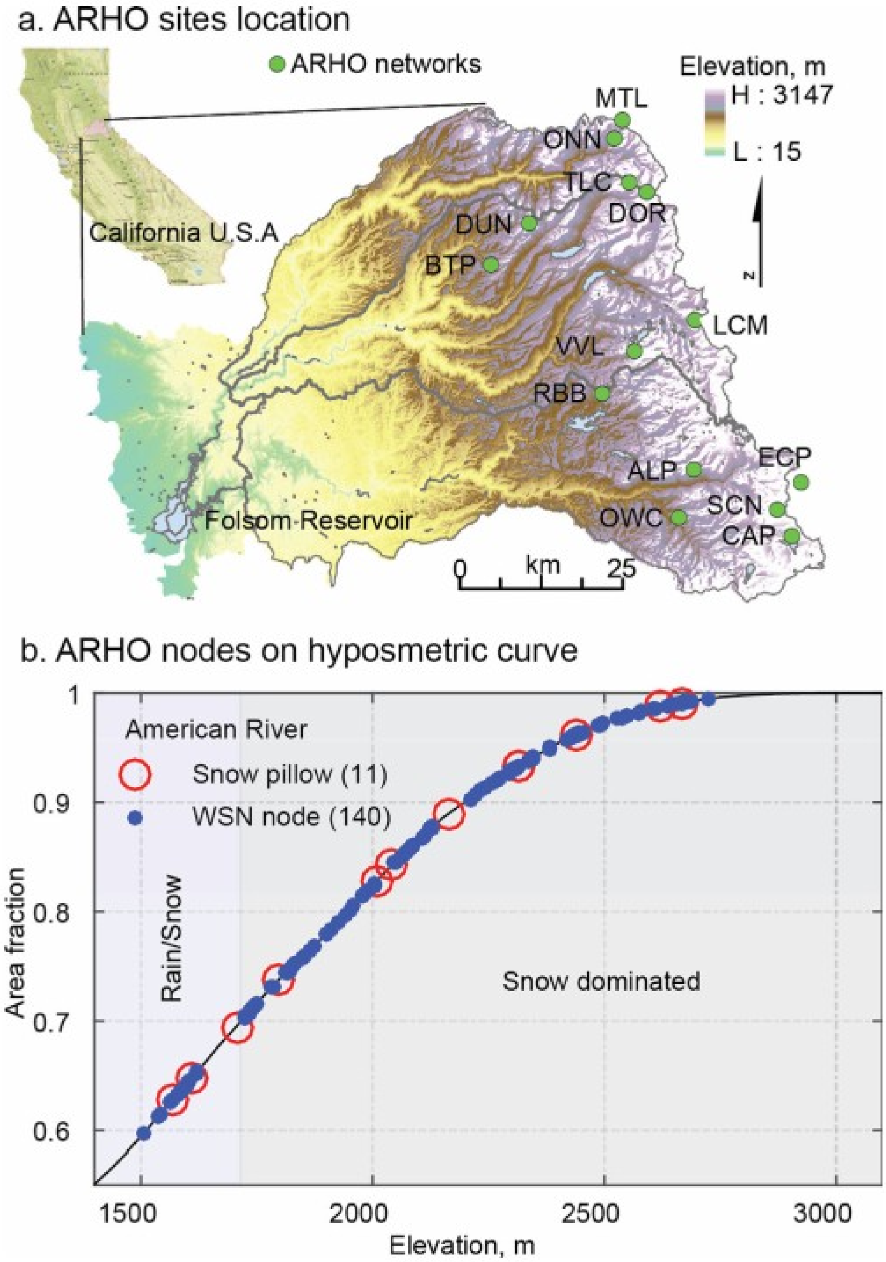

Figure 1. (a) Location of American River basin and 14 sensor clusters deployed in the upper part of the basin. (b) WSN nodes on hypsometric curve with existing snow pillows.

In 2013–2015, 14 clusters of wireless nodes were deployed (Figure 1a), with locations selected to represent the range of elevation, aspect, canopy coverage, and solar loading in the basin (Figure 1b and supporting information Figure S1). Each node had a number of sensors, as described in supporting information; with air temperature, relative humidity, and snow depth the subject of this report. The number of local clusters was based on results of *Welch et al*. [2013], and constrained by project budget. The Welch et al. analysis used spatial time-series data over 11 years and a rank-based clustering approach to identify measurement locations that will be most informative for real-time estimation of snow depth, and derived a set of regions that remained relatively stable over time. They found a point of marginal return at about 15 measurement locations, after which placing more local sensor networks did not significantly improve estimation performance. The Welch et al. study also showed that there is some flexibility in placing the local clusters to capture representative parts of the basin, and thus all sites, except MTL and DOR, were colocated with existing snow pillows and met stations. Each cluster consists of ten measurement nodes, limited due to budget, seven to 35 signal-repeater nodes, and a network manager (see supporting information Table S1 for details and Figure S2 for system hierarchy).

Measurement-node placement consisted of three steps. First, major physiographic variables that affect snow distribution, and by extension other components of the water balance, were characterized in a 1 km^2 area around each site [*Balk and Elder*, 2000; *Erxleben et al*., 2002; *Anderton et al*., 2004; *Essery and Pomeroy*, 2004; *Sturm and Benson*, 2004; *Erickson et al*., 2005; *Marchand and Killingtveit*, 2005; *Bales et al*., 2006]. Second, at each site, 10 points representing different physiographic attributes were selected by a random-stratified technique, and the attributes aggregated to assess their representativeness in the larger basin (see supporting information Text S2) [*Jin et al*., 2013]. *Rice and Bales* [2010] showed that a 10 sensor network could capture the mean and distribution of snow depths at this scale. Third, final location adjustments were made in the field to a small subset of sensor nodes, ensuring a complete sampling of the physiographic features together with a strong WSN connection mesh. See supporting information Text S3 for node details.

The network statistics presented were evaluated over a period of 7 months. Each node provided 15 min data for snow depth, air temperature, and relative humidity. Hourly and daily products were developed for periods where no less than 75% of data were present and valid within the averaging window. Extreme values in the data were removed following *Daly et al*. [2008]. Operational data were downloaded from the California Department of Water Resources (http://cdec.water.ca.gov/). Data from SNODAS, a gridded national operational product that is developed from weather-forecast and snowmelt models, plus ground-based and remotely sensed data, were used as an additional point of comparison with our snow measurements (http://nsidc.org/data/). Hourly dew-point temperature for each node was computed based on an empirical equation [*Lawrence*, 2005].

3 Results

3.1 WSN Performance

The wireless-network links formed a redundant multihopped mesh network of sensors and repeaters for data transport. Figure 2 shows the stable layout of sensor nodes for the Alpha cluster (ALP), and illustrates how repeaters were nonuniformly distributed to connect the sensor nodes via at least two independent paths to the base station (see supporting information Figure S5 for photographs of base station, nodes and repeater). During 213 days of consecutive recording only 662 out of over 56 million packets were lost in transmission. The average number of hops for packets to transmit from a node to the base station was 3.6 and the maximum seven. The average latency of the network, the time it takes from the packet being sent until it arrived at the base station, was 1.01 s. On average, each node received 181,000 packets over the period when network statistics were gathered.

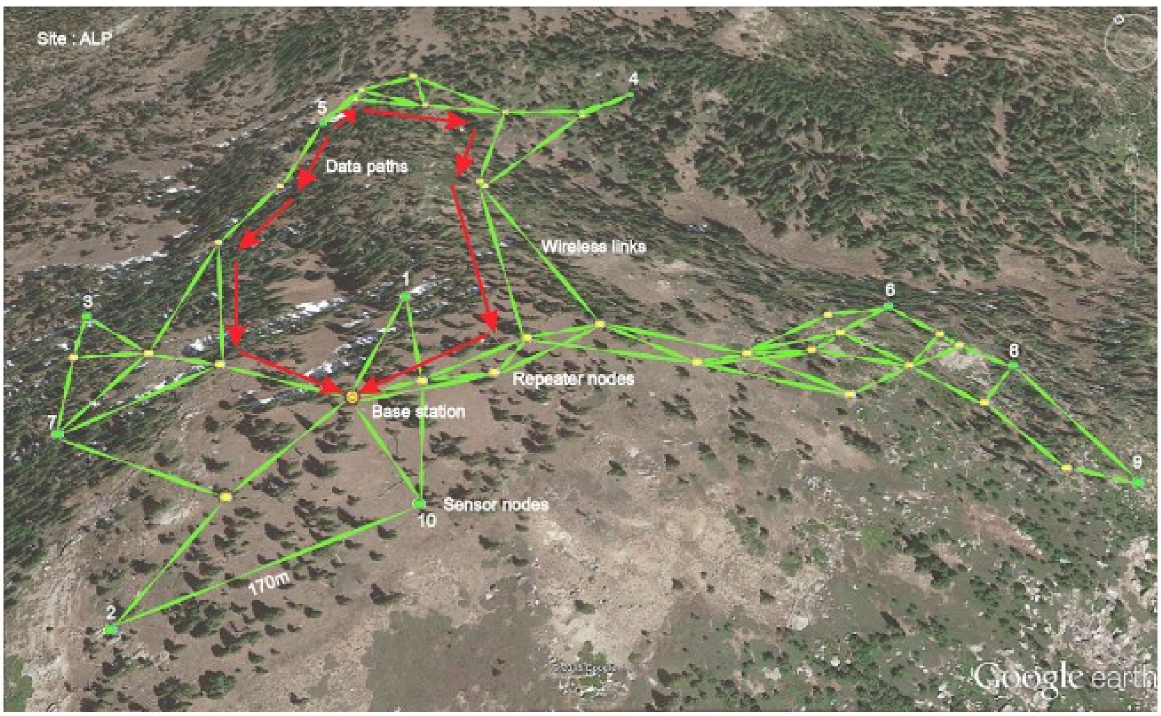

Figure 2. Node layout and steady state network connections (green lines) at ALP, overlain on Google Map. Sensor nodes are numbered. Two possible paths of data out from sensor node 5 to the base station are marked with red arrows.

Two measures indicate the reliability and performance of the network: (i) the number of other sensor or repeater nodes connected to each node and (ii) the average received signal strength indicator (RSSI). RSSI is closely associated with an important network-performance indicator called packet delivery ratio (PDR). In aggregate, each node was connected to at least two other nodes over 95% of the time, and to three or more nodes 68% of the time (see supporting information Figure S6). Taking all nodes together, RSSI values were above −85 dBm, the manufacturer-specified threshold for efficient transmission over 54% of the time, with values above −80 dBm 33% of the time.

Environmental factors have been thought to impact the performance of WSNs [*Boano et al*., 2010; *Marfievici et al*., 2013]. For our local clusters, there was no clear influence of environmental factors, e.g., temperature, humidity, and snow-induced topographic changes, on network performance (Figure 3). Each node was connected to one to five other nodes at each time step (Figure 3a). RSSI values at each node typically fluctuated ±5 dBm, and the average RSSI (Figure 3b) depended on node location as opposed to temperature (Figure 3c), humidity (Figure 3d), or topographic changes due to snow accumulation (see water-year days 72 and 80, Figure 3e). What was found was that antenna-choice-had the largest influence on connectivity. Surprisingly it turns out that 4 dB antennas, with a “fatter” radiation pattern, performed better than 12 dB antennas.

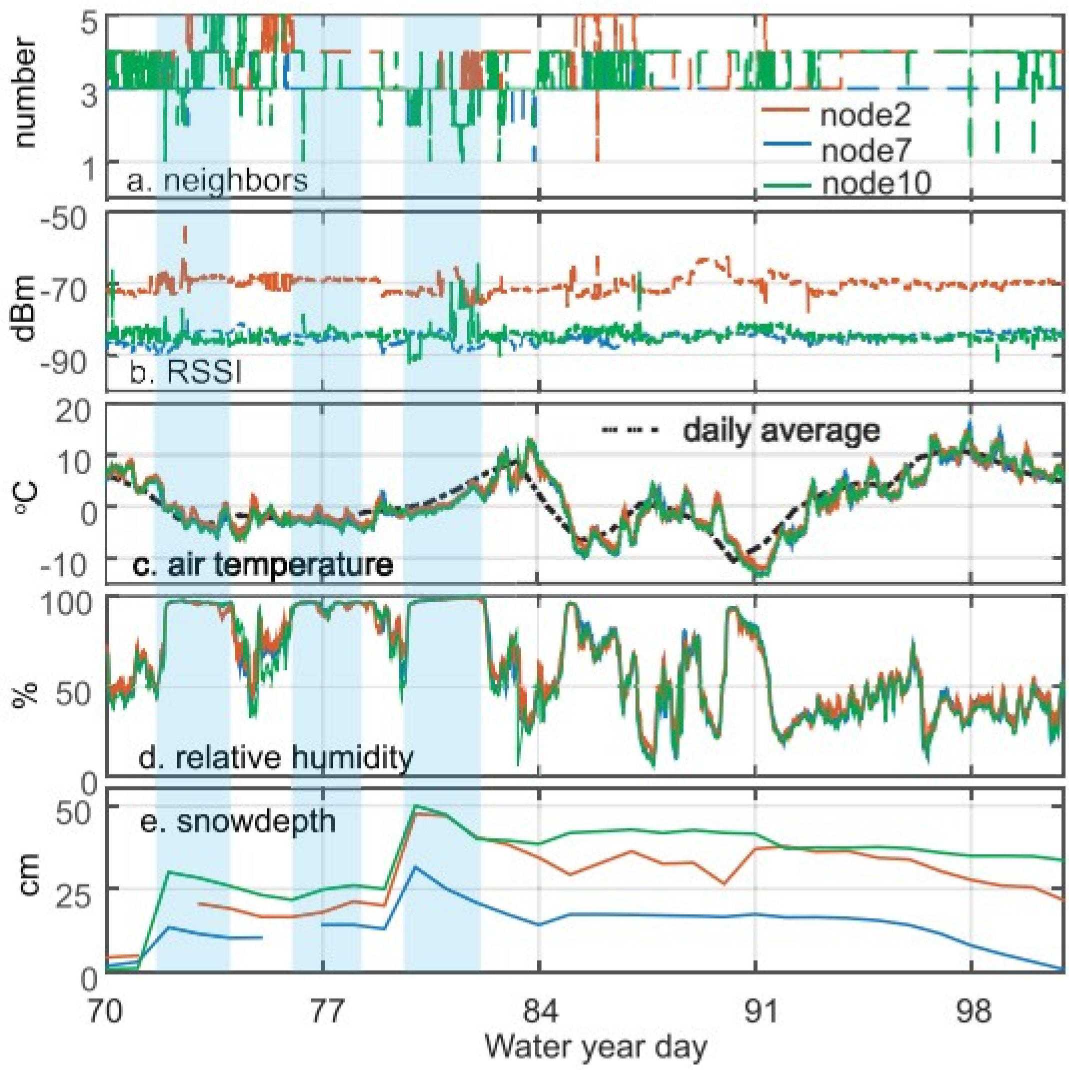

Figure 3. Network performance of sensor nodes 2, 7, and 10 at ALP: (a) hourly data of network neighbors number, (b) the corresponding average RSSI, (c) average air temperature, (d) hourly average humidity, and (e) daily average snow depth. Shaded periods represent precipitation events. For clarity, data from three sensor nodes are presented.

3.2 Temperature, Humidity, and Snow Patterns

Daily air and dew-point temperatures from the 10 wireless-sensor clusters that were installed prior to the 2014 water year showed very similar temporal patterns (Figure 4a), with average temperature differences reflecting elevation differences between clusters. Temperatures for all pairs of clusters were highly correlated, $r > 0.91$ for air temperature and $r > 0.86$ for dew-point temperature, $p < 0.05$.

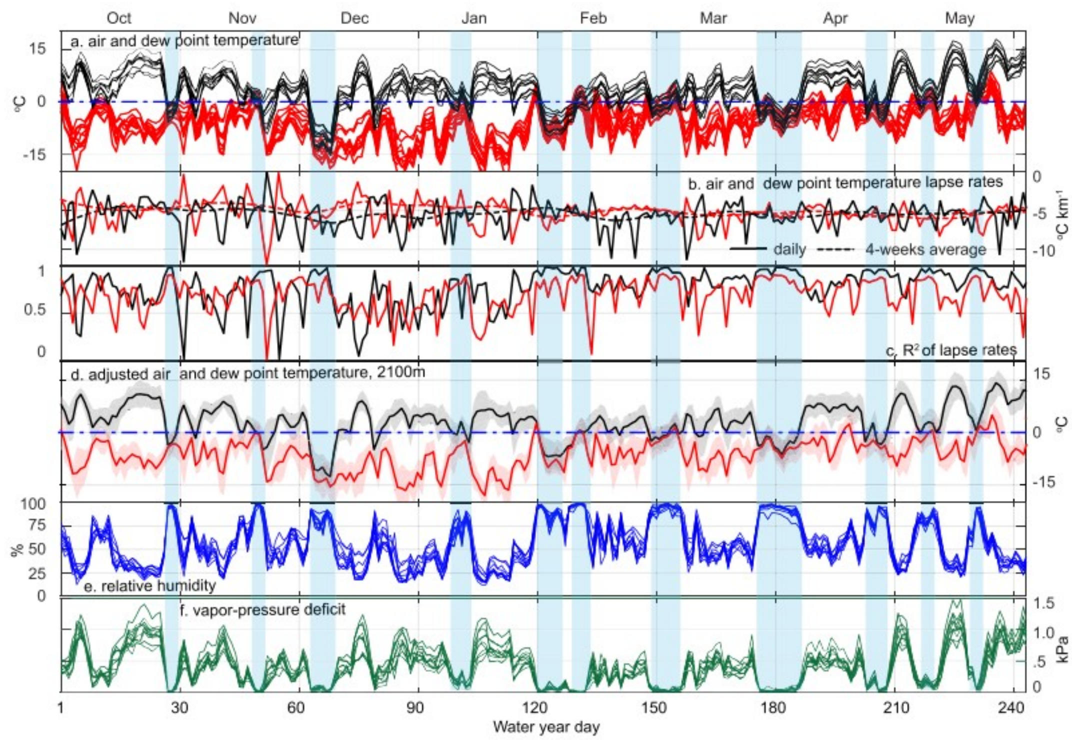

Figure 4. Data from 10 clusters for 8 month period: (a) cluster-mean daily averaged air (black traces) and dew-point (red traces) temperature, (b) air and dew-point temperature lapse rates, (c) R^2 value of daily lapse rates, (d) mean (dashed lines) and standard deviation (shading) of site air and dew-point temperatures adjusted to 2100 m elevation using the daily lapse rate, (e) mean daily average relative humidity, and (f) mean daily vapor-pressure deficit calculated from mean daily temperature and relative humidity of each cluster. Shaded periods represent precipitation events. Data for only 10 of the 14 local clusters are shown, as 4 were brought online after the period reported here.

Daily temperatures were used to derive surface-level lapse rates, which over the 8 month period varied from close to zero to −12°C/km for both air and dew-point temperatures (Figure 4b). The respective average lapse rates for the months before snow accumulation (October–December) were −4.6 and −5.7°C/km, increasing to −5.5°C/km for air temperature and decreasing to −4.7°C/km for dew-point temperature during the snow season. The day-to-day variability in lapse rates during the snow-covered period was also lower than earlier in the water year. The transition to a period with less variability in lapse rate is also illustrated by the higher R^2 values starting on water-year day 121, when snow started accumulating in the basin (Figure 4c). Note that less-negative air-temperature lapse rates, associated with lower R^2 values, were associated with temperature inversions.

Daily mean air and dew-point temperatures taken across the 10 clusters were adjusted to 2100 m using the mean daily lapse rates (Figure 4d). The average standard deviation is 3.3°C for air temperature and 3.5°C for dew-point temperature, a variability equivalent to the average difference over about 600 m and 545 m elevation based on the 8 month average lapse rate of −5.5 and −5.0°C/km, respectively. While any index elevation could be used for this comparison, 2100 m is generally representative of the upper part of the rain-snow-transition elevation zone.

Mean relative humidity across WSN clusters varied from 15 to 100%, with similar patterns across all 10 clusters (Figure 4e). The correlations were strong; $r = 0.91$, $p < 0.05$, for all pairs of clusters. Differences in absolute humidity and vapor-pressure deficit between clusters were in some cases relatively large. The mean water vapor-pressure deficit for each cluster ranged from zero to 1.5 kPa (Figure 4f), with daily intercluster differences between the lowest and highest values as much as 55%. The highest variability in vapor-pressure deficit was associated with periods of higher temperature and lower relative humidity, indicating a warmer and drier condition. Periods with lower variability of intersite vapor-pressure deficit were closely associated with subzero temperatures in the basin, typically triggered by precipitation events.

Snow-depth data (Figure 5) show a clear elevation trend, with variability also increasing with elevation. One exception was SCN, which has a tighter grouping of measured snow depths as compared to lower-elevation sites. During the very warm and dry WY-2014 snow season, sustained snow cover accumulated mainly at elevations above 2100 m.

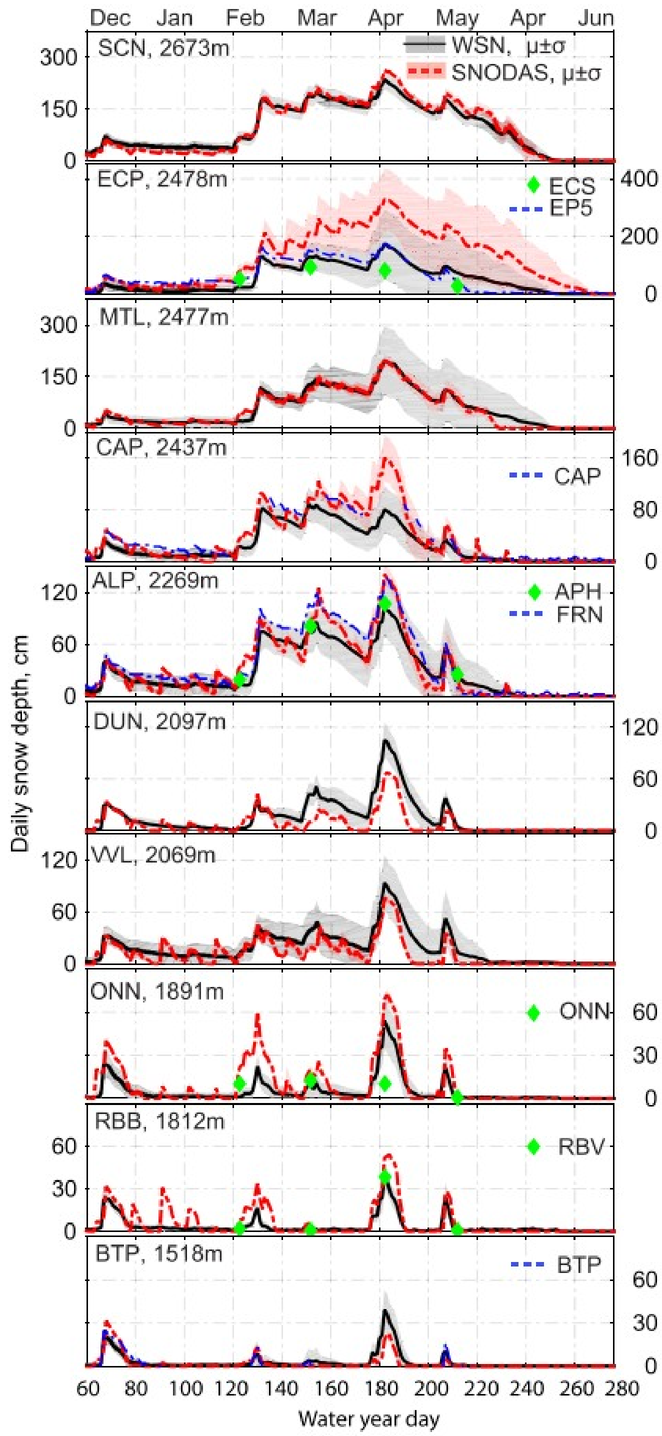

Figure 5. Daily mean (μ) and standard deviation (σ) of snow depth from the WSN clusters and SNODAS, including available operational snow-depth-sensor data (blue dashed), and snow courses (green diamond). See supporting information Figure S4 for calculation of SNODAS mean and standard deviation.

Snow depths were also compared with colocated or nearby snow-course measurements (Figure 5). At lower-elevation clusters, due to the timing of the snow-course measurements, most surveys missed the snow-cover peak accumulation. At ONN, snow-course data showed a small amount of snow throughout the season, missing the few individual peaks. Snow-course values at ECP were generally lower than the mean cluster value across the season.

There were substantial differences between the WSN, nearby operational snow-depth sensors, and SNODAS snow depth at most clusters. Compared to WSN means, nearby operational sensors tended to overestimate snow depth during early season (e.g., at ECP, CAP, and ALP), and better matched the WSN mean at peak accumulation. Nearby operational sensors also showed faster melt than indicated by cluster means for the same sites. The time series of SNODAS values is comparable to the WSN data at MTL and SCN for much of the season, with similar magnitude and high correlation. SNODAS data generally fall within one standard deviation of WSN nodes at these sites. At lower-elevation sites, such as BTP, VAN, and DUN, SNODAS underestimated snow depth at peak accumulation by as much as 50% compared to the WSN. At all other sites, SNODAS overestimated peak-accumulation snow depth by as much as 80% compared to the WSN mean.

A one-way analysis of variance analysis (ANOVA) was done for a 20 day period around the time of peak snow accumulation to assess within-cluster versus between-cluster variability. On average, over 85% of the variability in daily air temperature is between clusters, with a peak within-cluster variability of 24% (Figure 6a). The within-cluster variation can be more significant at night, as seen by the pattern in the hourly data, when up to 40% of the variability was within cluster. We also considered the difference between daily temperatures for operational sites versus cluster values. Comparing sensor-node values for sensor stations having the same landscape features as operational measurements (flat, open) to other nodes shows a 0.8°C difference for one site, and 0–0.3°C for five other sites; however the values are not different at the 95% confidence level (supporting information Figure S8a).

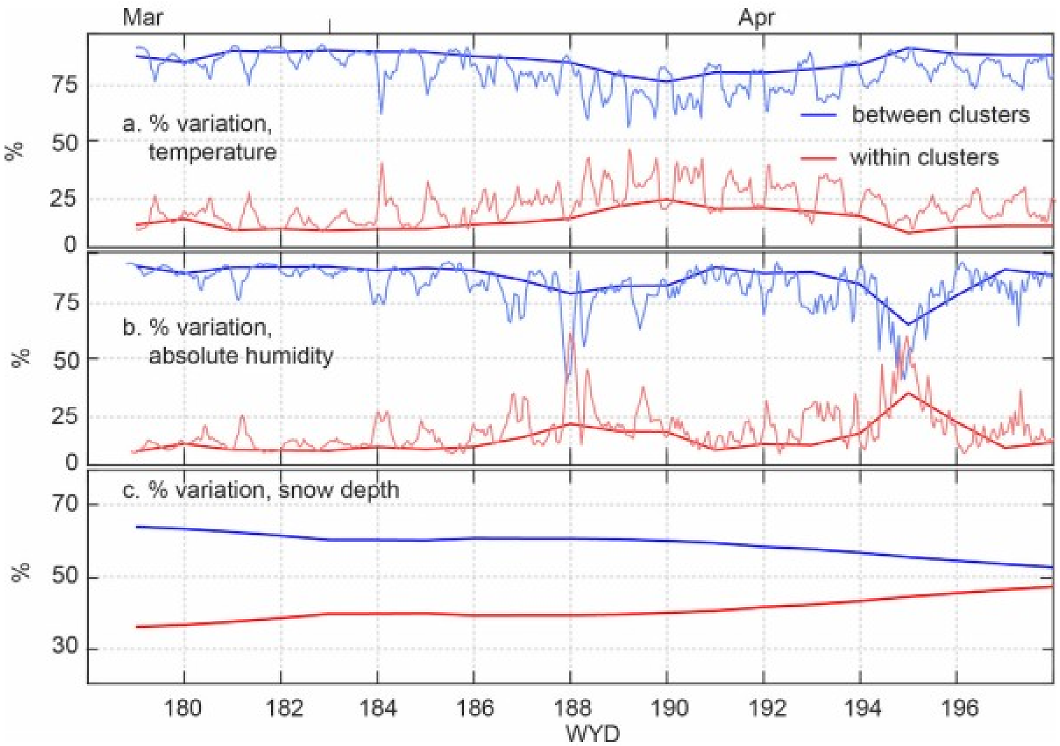

Figure 6. ANOVA results for 20 day period around peak snow accumulation, for between and within-cluster variations in measurements of: (a) hourly and daily temperature, (b) hourly and daily relative humidity, and (c) daily snow depth. See supporting information Figure S7 for data used in the analysis.

The ANOVA results for daily snow depth show the importance of within-cluster and between-cluster variability. About 60% of the variability was between clusters and 40% within clusters immediately after the accumulation event ending on water-year day 183, with both values converging toward 50% over the next 2 weeks. The compared nodes having landscape attributes like those of operational sites (flat, open). At most of the six sites evaluated (supporting information Figure S8c) there were relatively large within-cluster differences between the compared sets.

4 Discussion

4.1 WSN Design and Performance

With 555 sensors across 14 clusters, the WSN offers representative, real-time monitoring of the meteorological and hydrologic conditions of much of the upper reaches of the basin. The size of this network, arguably the largest long-term, remote wireless-sensor platform deployed for environmental monitoring, shows that WSNs are now capable of being used for major instrumentation projects. Even though some aspects of the networks in ARHO share similar properties with the prototype installation at the Southern California Critical Zone Observatory [*Kerkez et al.*, 2012], the more-recently recorded network statistics help to resolve several previously unanswered networking questions important to the broader wireless communications community as well as to field hydrologists. The longer-term performance of the networks, subjected to the test of a full snow season, showed that WSNs can be a viable solution for distributed sensing at this scale. ARHO networks showed resilience to factors such as humidity and snow-induced topographic changes across different part of the basin. The positive result is likely due to the combination of the Dust Network's radio technologies such as time-synchronized channel-hopping, time-slotted mesh protocol (see supporting information section S1.2.3 for details of the technology), effective network topology, and the use of lower-gain antennas.

A stringent criterion of design was low power consumption, allowing the sensor node to be powered with a 6 Ah battery recharged by a 10 W solar panel. The low-power requirement constrains radio-power output, so the range of the radio limits the size and performance of the network. Through iterative design and careful control over circuitry, we were able to attain our goal. The final design is basically two very low-power-consumption microchips—a Cypress PSoC5 and Dust Networks radio module. This design is useful to the community, which by and large uses systems based on technology that has 100 or more times the power consumption (see supporting information).

Topographic relief is one of the more-serious challenges to overcome for good system performance. Different from earlier installations, the networks in ARHO encountered more-challenging, steep-forested terrain. A lower-gain 4 dBm omnidirectional antenna provided improved network connectivity due to its “fatter” radiation pattern, especially in steep terrain, compared to the 12 dBm antennas used by *Kerkez et al* [2012] on more-even terrain. Even with the improvement, the capability of the network to communicate over steep slopes is limited by the antenna. The ALP site is a good example of where some radio links operated at the edge of the acceptable RSSI level due to steep topography. A relatively large number of repeaters were installed to provide redundant paths to sensor nodes 6, 8, and 9, where a steep change in slope produced a radio path “kink” and reliable network links were challenging to establish. The network performance was stable but less efficient, indicated by the lower PDR values, compared to *Kerkez et al*. [2012], who had shorter data hops.

4.2 Spatial Pattern and Variability of Hydrologic Attributes

The following three examples illustrate how our spatially distributed, daily data over complex terrain set provides improved estimates of important hydrologic attributes, compared to less-dense operational measurements. A more-detailed analysis will be the subject of a subsequent report.

4.2.1 Air and Dew-Point Temperature

A widely accepted model of near-surface air temperature in mountains is the ground-level lapse rate [*Dodson and Marks*, 1997; *Rolland*, 2003; *Huang et al*., 2008; *Kirchner et al*., 2013]. Scientists and modelers use lapse-rate-derived temperature to evaluate model responses due to temperature perturbations [*Gardner and Sharp*, 2009; *Bales et al*., 2015]. In those applications the lapse rate, often averaged over a monthly to annual period, is used to approximate input temperature for models with a much shorter (daily) time increment. This approach, however, does not account for short-term variability. WSN data show that the day-to-day lapse rate was highly variable, particularly before snow accumulation (Figure 4b). Not only does the array of sensors provide a more temporally resolved lapse-rate estimate, we also found that the redundancy of sensors provides a more-robust estimate of the amplitude. Linear models of daily air temperature were constructed with a training set and a cross-validation set of 60 randomly selected nodes. The results were compared with models computed using seven nearby met stations. On average, the cross-validation root-mean-square error was reduced from 1.4 to 1.2°C using random sets of 60 measurements versus data from seven nearby met stations. The uncertainty in air temperature was reduced by 16%.

Dew-point temperature complements air temperature in providing a reliable estimate of the timing and phase of precipitation. The reduction of uncertainty in temperature and humidity patterns helps to better determine the elevation range of the rain/snow transition. Air temperature is approximately equal to dew-point temperature, indicating saturated air, when precipitation occurs (Figure 4). The phase change from rain to snow usually occurs around the 0°C dew-point [*Marks et al*., 2013]. Compared to air-temperature-based methods, dew-point temperature is a less geographically dependent variable to determine the solid or liquid precipitation [*Ye et al*., 2013]. Due to lack of relative-humidity measurements for most met stations, calculation of dew-point temperature cannot be performed from met-station data alone.

Feld et al. [2013] assessed various methods of estimating daily dew point, and found that a weather-forecast model that captured some aspects of local topography provided less-biased estimates than did simpler constant-lapse-rate or constant-humidity approaches. Their median dew-point lapse rate, based on 15 met stations and 35 hygrochons deployed in the North Fork American basin and averaged over 3 years, was −5.3°C/km, comparable to our mean of −5.0°C/km. However, our −5.5°C/km mean air-temperature lapse rate was smaller than their 3 year average of −6.3°C/km. More extensive analysis of our seasonal and spatial patterns will be the subject of a subsequent report.

4.2.2 Evaporative Potential

Direct measures of vapor-pressure-deficit patterns from a dense array of ground-based sensors can be important for scaling evapotranspiration and assessing forest health [*Oren et al*., 1999, 2001; *Bowling et al*., 2002]. Accurately estimating vapor-pressure deficit is crucial as the saturation-pressure deficit becomes relatively more important in the Penman-Monteith equation [*Ziemer*, 1979]. Despite the importance of the variable, reliable field-based estimates of vapor-pressure deficit in mountains are rare. The performance of satellite-based estimates varies, with RMSE values from upwards of 0.3–1.1 kPa, limiting their accuracy as estimates of vapor-pressure deficit across steep terrain [*Prince et al*., 1998; *Hashimoto et al*., 2008]. A WSN with relative-humidity measurement at every sensor node fills this gap.

The ANOVA results for daily relative humidity are similar to those for temperature, with most of the variance being between versus within clusters (Figure 6b). There was, however, no clear day-night pattern. In addition, there were only small differences in humidity between nodes that represent the landscape attributes of operational sensors, versus values for other nodes. One of the six sites evaluated had a significant difference, reflecting in large part the temperature differences (supporting information Figure S8b).

4.2.3 Snow Depth

The differences in snow depth between WSN and nearby operational sensors can be explained by the patterns of snow accumulation. Operational snow-depth sensors are typically placed near flat meadows or ridge tops free of overhead obstructions or hazards, which produce known biases [*Molotch and Bales*, 2006; *Ainslie and Jackson*, 2010; *Rice and Bales*, 2010]. We placed our nodes in both forested and nonforested area to produce a more spatially representative measurement. Figure 5 indicates that operational snow-depth sensors data had a systematic positive bias in snow depth in the early season. During the melting season, the canopy acts as a shield, limiting energy input to the snowpack [*Marks et al*., 1998; *Sicart et al*., 2004; *Pomeroy et al*., 2012]. The canopy also shelters the snow surface from wind, reducing turbulent heat transfer. The net result is an extended melt season recorded by sensor nodes in the forested area compared to the operational snow-depth sensors.

Due to local redundancy of the WSN, the data stream is more complete than operational snow-depth sensors at CAP and BTP. Large sections of data were missing from the operational-snow-depth sensors from those two sites during the storm around water-year day 180 (Figure 5). This reflects a reality of operational water-resources networks, namely the ability to respond in a timely manner to problems in remote sensors. The redundancy provided by our WSNs helps to address this constraint.

The differences in snow depth between SNODAS and the WSN were less systematic, as there is no apparent trend in the bias across different sites. One pronounced difference between WSN and SNODAS snow depth was at the steep ECP site, where the 1 km^2 SNODAS product overestimated snow depth compared to our measurements (Figure 5). This follows previous reports that without sufficient data, estimates of snow depth under these conditions can be difficult and error prone due to the underlying variance in elevation within grid boundaries [*Hedrick et al*., 2015]. *Clow et al*. [2012] showed that while over forested regions of the Colorado Rockies, SNODAS estimates of snow depth accounted for as much as 72% of the variance line (1 km resolution) in forested areas, SNODAS was able to account for only 16% of snow-depth variance in areas above the treeline.

5 Conclusions

A wireless-sensor network distributed over the 2000 km^2 snow-dominated portion of a mountain basin provided effective coverage of watershed attributes. With 10 measurement nodes per each of 14 clusters, the WSNs reliably provided spatially distributed measurements of temperature, relative humidity, and snow depth every 15 min over the basin. The WSN also provided measurements of the significant within-cluster spatial variability of these attributes, which were influenced by local topography, possibly through cold-air drainage effects on temperature.

Compared to existing operational sensors, the wireless-sensor network reduces uncertainty in water-balance measurements in at least three distinct ways. Redundant measurements in temperature improved the robustness of temperature lapse-rate estimation, reducing cross-validation error compared to that of using met-station data alone. Second, distributed measurements capture local variability and constrain uncertainty, compared to point measures, in attributes important for hydrologic modeling, such as air and dew-point temperature and snow precipitation. Third, the distributed relative-humidity measurements offer a unique capability to monitor upper-basin patterns in dew-point temperature and better characterize precipitation phase and the elevation of the rain/snow transition.

Acknowledgments

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