Design and Performance of a Wireless Sensor Network for Catchment-scale Snow and Soil Moisture Measurements

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Abstract

A 57-node wireless sensor network (WSN) was deployed as part of a water-balance instrument cluster across a forested, 1-km² headwater catchment in the southern Sierra Nevada of California. The network integrates readings from over 300 sensors, measuring snow depth, solar radiation, relative humidity, soil moisture, and matric potential. Measurement locations were selected to reflect the distribution of site-specific physiographic parameters. The ability of this densely instrumented watershed to capture catchment-scale snow depth, and soil moisture distributions was investigated through comparison with three comprehensive gridded surveys, as well as snow-on, and snow-off LIDAR data. Statistical analysis showed that the network effectively characterized catchment-wide distributions of snow depth and soil moisture, while offering a cost-effective, reliable, and energy-efficient means for collecting distributed data in real-time. A three-phase design procedure was used to optimize the WSN deployment. First, as off-the-shelf performance of current WSN platforms for large-scale, long-term deployments cannot be guaranteed, statistics from a prototype deployment were analyzed. Two indicators of network performance, the packet delivery ratio and received signal strength indicator, showed that for our site conditions, a conservative 50-m node-to-node spacing would ensure low-power, reliable, and robust network communications. Second, results from the prototype were used to refine hardware specifications, and to guide the layout of the full 57-node network. Further analysis of network statistics was conducted during the third, operational, phase to validate system performance.

Index terms: [4894] Instruments, sensors, and techniques; [1972] Sensor web; [1804]

Catchment
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1. Introduction

A comprehensive understanding of the Critical Zone demands a deeper insight into the spatiotemporal coupling between various hydrologic processes at the headwater-catchment, and larger-basin scales. This is particularly true in the mixed-conifer zone of California’s Sierra Nevada, a productive ecosystem situated in the mid-elevation rain-snow transition zone, where rain falls at elevations below 1500 m, and snow accumulates above 2200m [Bales et al., 2006]. It has been noted that this transition zone is sensitive to annual temperature fluctuations, both in terms of the quantities of accumulated snow, as well as melt timing [Christensen et al., 2008]. A complete understanding of the links between snow cover and soil moisture on the forest water cycle is still lacking [Bales et al., 2011], but the spatial variability of these processes across the rain-snow transition permits a sampling strategy to substitute space for time, thus facilitating an accelerated analysis of catchment-, and basin-scale hydrologic processes.

Spatial measurement of hydrologic processes at the catchment-, and basin-scales is subject to significant constraints in energy, accessibility, sensor coverage area, and cost. Many off-the-shelf data-logging components do not lend themselves to real-time data acquisition when sensors are spatially distributed at the km scale, as wiring runs are limited by signal noise and the need to maintain acceptable levels of current. Distributed real-time data are often essential, especially when considering their use for operational hydrology. Transmission along wires is further complicated by heavy snow loads, and the proclivity of rodents to chew on cables. Recent advances in sensing technology, particularly in the area of Wireless Sensor Networks (WSNs),
enable for the monitoring of environmental phenomena in real-time, and at unprecedented spatial
and temporal scales. Rice and Bales [2010] analyzed the performance of a prototype WSN and
concluded that the technology can be effectively used to capture spatially representative
measurement of snow depth with relatively few sensors.

For most spatially distributed sensor deployments it is often challenging, and inconvenient,
to physically collect cached data, readily detect faulty hardware, and alter equipment parameters.
While there are many commercial wireless systems that can transmit data between two points,
such hardware generally utilizes relatively high-powered radios and requires substantial energy
for transmission. Such point-to-point transmission systems operate independently, and can
interfere with each other if multiple links are deployed within a region. WSN technology offers
an alternative for cost-effective instrumentation of extended regions with limited accessibility,
while permitting real-time data access to distributed sensors through a centralized
communication architecture. Given the nascent nature of low-power wireless, in particular for
remote field applications, off-the-shelf performance cannot be guaranteed, and much work
remains to be conducted to quantify the real-world performance of WSNs for hydrologic
monitoring.

The research reported in this paper aims to develop techniques for efficient, scalable, and
robust WSN deployments for monitoring hydrologic phenomena, although the methods can
readily be extended for purposes of most environmental monitoring applications. We address
four specific questions: First, how well do strategically distributed sensors in a densely
instrumented watershed capture the spatial distribution of snow and soil moisture when
compared to gridded surveys and LIDAR data? Second, what is the performance of a large-
scale, low-cost WSN built from off-the-shelf hardware, when exposed to the harsh conditions in
the snow-covered Sierra Nevada? Third, which metrics can be used to quantify WSN performance and to evaluate the design of the wireless monitoring system? Fourth, what is an efficient approach to designing and deploying WSNs for long-term environmental monitoring campaigns, while maintaining robust and reliable network performance?

2. **WSN design principles**

The core component of a WSN is known as a *mote* - a tiny, ultra-low power radio operated by a micro-controller, and featuring analog, and digital, interfaces to which sensors can be connected (Figure 1). A mote exchanges information wirelessly with neighboring motes in a distributed network, which can relay this information to their neighbors, until it reaches a central hub. Software optimization of power control (also known as duty cycling) allows some devices to operate for several years on a pair of AA batteries [Karl and Willig, 2005; Dust, 2006]; embedded software can be optimized to permit motes to remain in an extremely low-power state the majority of the time (powering the most necessary components, such as the clock and basic micro-controller features), waking up only periodically to transmit or receive data [Dust, 2011; IEEE, 2009]. The recent mass adoption of these devices, particularly for industrial applications, has made them an extremely cost-effective alternative to placing wires [Emerson, 2010; Honeywell, 2010; ISA, 2009; Song et al., 2008].

Depending on the implementation and protocols of the *network stack* (the general hardware and software architecture), motes can aggregate into a number of network topologies. The two most common are the *star*- and the *mesh*-topology (Figure 2). In a *star* configuration, each mote exchanges information only with a central base station. In the majority of such implementations, the base station is programmed to keep its radio on continuously to listen for incoming
transmissions, which results in high energy usage. The span of a star-network is limited by the
distance of a single link between a mote and its network manager. The network manager is thus
often placed in a central location; multiple managers are required if the region being
instrumented cannot be covered by a single star-network.

In a mesh-based topology, motes communicate with multiple neighbors to create an
internally redundant multi-hop network. Multiple paths between network nodes allow data to be
transmitted even if certain network links fail [Karl and Willig, 2005]. Although requiring a
relatively larger software overhead, mesh networks can adapt their topology to reflect varying
attenuation of radio signals caused by changes in the environment, or changing needs of the
operator. The mesh-topology thus allows the network to span much larger areas, compared to a
star layout, as out-of-range motes can exchange data by transmitting, or hopping, it via other
motes in the mesh.

Most data transmitted within WSNs is too large to be reliably transferred via a single
transmission, and has to be quantized into formatted data blocks called packets [Tanenbaum,
2003]. Transmission failures within the network only require the retransmission of specific
packets, mitigating the need to retransmit the entire data stream. A successful transmission is
achieved if the transmitting mote receives an acknowledgment from the receiving mote,
notifying it that the transmitted data packet has been received correctly. This acknowledgment
redundancy, while not built into all available WSN platforms, ensures that packets reach their
intended destination, even if retransmission is required.

Since remote wireless networks operate on battery power, overall power consumption
becomes a critical constraint. As radio transmission consumes up to 95% or more of power use
[Dust, 2006] (not including sensors), it is important to design WSNs that will minimize
retransmissions. Successful design and operation of such a field-deployed WSN hinges upon a rational set of metrics that can be used to quantify performance.

Extreme weather conditions, especially cold weather, can take significant tolls on hardware and batteries [Hasler et al., 2008; Mainwaring et al., 2002]. Furthermore, communication in WSNs is challenged by multipath radio propagation and narrow-band interference [Karl and Willig, 2005; Watteyne et al., 2010] where topography can result in radio signals bouncing off ambient surfaces, causing phase-shifted copies of the same signal to arrive at the receiver antenna. This can lead to destructive interference, which cancels out the original signal, effectively eliminating the ability of certain mote pairs to communicate. The adverse effects of multipath propagation on radio communications are a function of the deployment environment, and it has been shown that even slight changes in node-to-node distance (on the order of centimeters) can have significant impact on this behavior [Watteyne et al., 2009].

Advanced WSNs are equipped with the ability to operate on a number of transmission channels (or, narrow-band sub-frequencies) in an attempt to mitigate communication challenges posed by external interference and multipath propagation. In the 2.4GHz band there are 16 different frequency channels on which data can be transmitted [IEEE, 2009]. Improper channel selection can cause data to be lost during transmission, leading to the need to retransmit data, and manifesting itself in much higher energy requirements on the network [Watteyne et al., 2009]. A common approach to address this issue is to conduct an expert survey, which entails a physical visit to the field to select the frequency channel on which the loss of transmitted packets will be minimized. This approach has major drawbacks, as research has shown that the optimal channel may vary over time [Kerkez et al., 2009; Watteyne et al., 2010]. It has been shown that in arboreal environments propagation of radio waves is adversely affected [Oestges et al., 2009],
and fluctuations in the surrounding environment can cause poor performance on channels that
originally performed well. An option to address this time-varying behavior involves equipping
WSNs with the ability to *channel hop*. In such deployments, motes within the network randomly
select one of the available channels every time a transmission occurs, rather than persistently
transmitting information on a single channel. While still an area of ongoing research [Kerkez et
al., 2009; Watteyne et al., 2010], and requiring slightly larger implementation overhead, channel
hopping has been shown to reduce the effects of multipath propagation and external interference,
thus improving network reliability and battery lifetime.

A number of commercial WSN solutions are available [Crossbow, 2011; Dust, 2011; Ember,
2011; Jennic, 2011; Libelium, 2011; Nevis, 2011; Sentilla, 2011], each offering distinct platforms
with unique functionality, network stacks, and standards. The implementation of algorithms for
network topology, routing, and channel hopping is a nontrivial task, but advances in WSN
technology have alleviated, although not completely removed, many of these challenges. No
simple off-the-shelf solution exists for environmental monitoring applications, and hardware
performance can vary significantly depending on site conditions.

Deployments of WSNs have ranged from data center HVAC control [Bell and Federspiel,
2009] structural health monitoring [Kim et al., 2007; Rice and Spencer, 2008], and military
applications [Culler et al., 2001]. Notable deployments for environmental monitoring purposes
include habitat monitoring [Hart and Martinez, 2006; Mainwaring et al., 2002; Ramanathan et
al., 2006], permafrost detection [Hasler et al., 2008], the study of mountain ranges [Ingelrest et
al., 2010], and for purposes of snow depth monitoring [Rice and Bales, 2010]. A successful
short-term deployment of a WSN for the monitoring of hydrologic phenomena was conducted by
Trubilowicz et al. [2009], who noted that the technology they tested lacked ease of use and
reliability. Further examples of wireless deployments for ecological and environmental monitoring were conducted by Etzel and Braun [2005], Porter et al. [2005], and Szewczyk et al. [2004]. The hardware and software implementations in these studies varied significantly, making it difficult to gauge which hardware, software, and network protocol implementation will perform the best for a given deployment. The current lack of the out-of-the-box usability, coupled with the vast choice of available hardware and network protocols, has the potential to become a severe time drain for scientists designing an environmental monitoring system.

3. Methods

3.1 Network design

A 57-node WSN was designed and deployed to monitor water-balance variables in a remote, forested, headwater catchment along a 1.5-km transect in the Southern Sierra Critical Zone Observatory (CZO) (37°04’ N, 119°11’ W), which is co-located with the Kings River Experimental Watershed (KREW) [Bales et al., 2011; Hunsaker et al., submitted; Levia et al., 2011]. KREW spans the rain-snow transition zone, with lower elevations receiving more precipitation as rain. The WSN is located in a northern, relatively higher elevation catchment of KREW, where the majority of annual precipitation falls as snow. Site elevations in the WSN-instrumented catchment range from 1950 to 2010 m, with landscape varying over dense mixed-conifer forest (76-99%), open meadows, and across mixed chaparral, and barren land cover.

In the summer of 2009, sensors were placed at 23 locations prior to WSN design (Figure 3). The locations were selected in the field to reflect variability in catchment-wide physiographic parameters, such as aspect, elevation, and canopy cover. Particular focus was given to previous studies [Faria et al., 2000; Molotch and Bales, 2005; Musselman et al., 2008; Rice and Bales,
which identified these major physiographic parameters as driving explanatory variables for snow depth. Each location was instrumented with snow depth, solar radiation, and relative-humidity sensors (Table 1). One-meter-deep soil pits were excavated at each location and instrumented with soil moisture and matric potential sensors at 10, 30, 60, and 90 cm depths, unless physically prohibited by bedrock. The pits were then filled with soil, and the soil surface was compacted to reflect near-original soil conditions. A Judd snow depth sensor was also mounted 3 m above ground surface on a 75-cm cantilever beam.

Along with two additional temperature measurements, this provided over 15 sensors readings at each measurement node (Figure 4), giving a total of over 300 sensors for the entire network. Our deployment makes a distinction between sensor nodes, which are motes interfaced with the sensors and data-logging infrastructure (Figure 4), and repeater nodes, which only contain motes and a power source, placed to ensure mesh redundancy, to transfer data between locations which would otherwise be out of range.

The WSN deployment was carried out in two steps. A smaller-scale prototype deployment was conducted in September 2009, relying on manufacturer-specified transmission distances as guide to mote placement (Figure 5). Site-specific network statistics were collected to evaluate the performance of the WSN prototype. An analysis of these statistics, utilizing a set of WSN metrics, was then used to inform a network-wide redesign. Further repeater nodes were then added to the network, and exiting repeater nodes were re-located to ensure desirable network performance.

### 3.2 Synoptic surveys

To evaluate the ability of the WSN to capture catchment-scale hydrologic variability, data from gridded synoptic surveys were used to provide ground truth for the distribution of soil
moisture and snow depth. The surveys were carried out in the larger CZO, but this analysis will only focus on the measurements specific to the sub-catchment instrumented by the WSN. The survey grid points were selected to evenly cover 125-m intervals (Figure 3). The points were located in the field using a Magellan handheld GPS unit with 3-5m accuracy. A snow depth survey was carried out on April 7-9, 2010. At each point, three depth measurements were taken 5m apart in a N-S transect using a snow depth probe. When possible, each of the three measurements was taken under varying canopy cover (under canopy, canopy drip edge, and open terrain). Two soil moisture surveys were also conducted on June 14-17, and September 6-10 using a hand-held Hydrosense soil moisture system. In few cases, field conditions and accessibility did not permit some survey points to be sampled.

One m² resolution LIDAR data sets were also collected both for snow-on and snow-off conditions [Guo et al., 2010]. The snow-on LIDAR data set was collected on March 22-23, 2010, and the total snow cover was calculated by subtracting the snow-off raster from the snow-on raster in the ArcGIS software package. Furthermore, the snow-off LIDAR raster was used to delineate the catchment instrumented by the WSN using the Spatial Analyst toolbox in ArcGIS. The resulting delineation is shown in Figure 3 as a shaded relief map.

3.3 Hardware

The fluctuating humidity, heavy storms, and extreme temperatures at the site called for special considerations during the design of the monitoring hardware. Reliability requirements demanded specific attention to the underlying network-control algorithms, as well as the selection of the appropriate transmission frequencies. The system uses wireless devices developed by Dust Networks [Dust, 2011], a company that primarily develops wireless data transfer technologies
for industrial automation applications. The core software backbone of the Dust WSN relies on the time synchronized mesh protocol architecture [Dust, 2006]. Each mote is powered by a 3V battery and has a manufacturer-specified battery life of over two years. This low power consumption is made possible by extremely tight time synchronization (on the order of milliseconds), and an extremely efficient duty cycle (less than 1%), which ensures that the mote remains in a low-power state for the majority of its operation, consuming little current (<20μA) compared to the much larger amount required for data transmission (20 mA).

Dust Networks’ hardware accounts for real-time fluctuations within the radio space by dividing the 2.4GHz band into 16 channels, and features a randomized channel hoping protocol, providing real-time selection of transmission frequencies [Dust, 2006]. The technology also features dynamic smart-meshing algorithms, which allow each mote to automatically join the network, and adaptively communicate with multiple neighbors. The adaptive nature of this WSN also changes network paths (links, or node-to-node routes) dynamically to reflect possible network interference from outside sources, or changing field conditions.

The availability of the above features, which are not standard on most other WSN platforms, removes the need for low-level programming by the user, significantly curtailing development time. Our WSN featured one base station, or network manager, that acted as a central network controller. The network manager communicated with a low-power, embedded Linux computer via Ethernet and the two devices exchanged commands over an extended mark-up language (XML) interface to actuate motes within the network, log sensor readings, and gather network statistics. The embedded computer was located at the base of a 50-m tower used for eddy correlation. A cellular modem positioned 25m up the tower provided Internet connection for the transfer of real-time data to an off-site location.
Anomaly detection within the network was conducted by custom software that was written to interact continuously with the network manager to monitor network statistics and sensor readings, informing network operators of impending battery outages, sensor failures, or other events of interest. To further improve transmission distance, physically hardened, high-gain 8dBi antennas were mounted 3m above ground surface at each network node.

A custom data-logging board was designed to control and power the sensor array, as well as to form the data into serial packets required for transmission by the Dust Networks mote. The board is the EME Systems OWL2pe data logger [EME, 2011], and interfaces nine analog and twenty digital inputs, allowing for further sensors to be attached in the future. The board requires about 100 mW of power while actuating sensors, but spends 99% of its time in an extremely efficient low-power mode. The OWL2pe can be self contained, or controlled remotely via the WSN, and built in flash memory allows the assembly to log data locally in case the WSN becomes unresponsive. Lack of accessibility to the physical network, especially during heavy snow periods, as well as the possibility of long-lasting diminution of solar radiation, played a significant role in the design of the power-management infrastructure. Monitoring requirements called for data to be collected on ten to fifteen minute intervals, and calculations (proven correct in the field) indicated that a 12 Volt, 7 Amp-hour lead-acid battery, and a 10 W solar panel, could reliably power the data logger and sensor assembly. To mitigate the effects of extremely cold temperatures, the repeater nodes were equipped with 3.6V lithium thionyl chloride batteries. The power consumption of the components that comprise each sensing-node is shown in Table 2.
3.4 WSN Metrics

The packet delivery ratio (PDR), and received signal strength indicator (RSSI) are two metrics that provide particular insight when evaluating WSN performance [Al Basset Almamou et al., 2009; Karl and Willig, 2005]. PDR is a metric that captures the overall communication efficiency of a link between two WSN nodes, and is defined as the number of successfully transmitted packets divided by the total number of transmitted packets. It can be thought of as the probability that a transmission between two nodes will succeed. Needless retransmission of a packet can take a significant toll on battery resources. Conservation of network resources ideally demands a PDR of 100% on all links used by the network. An understanding of the interplay between spatial network coverage and deployment-specific PDR characteristics is thus required.

Since a primary motivation of using WSN hardware for environmental monitoring purposes is the ability to span large areas, optimization of a field deployment demands a balance between the need to maximize battery life (power cost) while minimizing the number of required motes (capital and operational costs).

RSSI, conventionally measured in decibels and referenced to 1 milliwatt (dBm), represents the power in a signal when it arrives at the receiving antenna. As a rule of thumb, the RSSI decreases as the distance between two nodes increases. The true behavior of RSSI over node-to-node distance depends upon a number of factors, such as multipath radio propagation and environmental obstructions but can be roughly captured by an idealized Friis antenna propagation model [Friis, 1946; Friis, 1971; Kraus, 1988]. Since this theoretical propagation model is valid only in free space, and does not take into account the effect of multipath radio propagation, the model cannot, in most cases, be used to accurately predict the behavior of most real world phenomena. Generally, WSN hardware has a manufacturer-predefined RSSI
threshold (sometimes also referred to as *receiver sensitivity*) below which signals cannot be reliably decoded by the hardware. Changes in the physical environment affect the received signal strength, thus causing RSSI to fluctuate over time. The operational RSSI threshold (one that gives reliable performance in the field) can often exceed, or under-perform, manufacturer specifications, thus placing the onus of classifying link reliability onto the WSN operator. Since RSSI threshold is often used to specify reliable transmission distances, optimizing network performance depends on understanding the link-specific RSSI behavior for any given deployment. Improper determination of these thresholds can lead to network collapse and the need for reconfiguration during the actual deployment.

Motes have the ability to enter any number of possible sleep states [Karl and Willig, 2005; IEEE, 2009], where significant portions of the mote are shut off to conserve energy. A particular problem resulting from an extended lack of communication occurs when motes enter a deep-sleep, or hibernation, state. In such cases, motes that have not been able to establish communications with the network manager through their neighboring motes for a period of time, power off the majority of resources, and wake up only sporadically to rejoin the network by listening to advertising beacons from neighbors. This feature, although not standard on all platforms, was designed to conserve power in industrial mesh networks. When implemented, field experience has shown that it can take significant portions of time (hours to days) for motes to rejoin the network upon entering the deep sleep state. In relatively low node-density networks, such as those used for environmental monitoring applications, a mote in a deep sleep state is effectively removed from the network, which has the potential to severely compromise the mesh topology, and can lead to outages of entire subsets of the network. This behavior
further underscores the need to understand path specific PDR and RSSI characteristics for ensuring network robustness, and avoiding network outages due to drops in connectivity.

4. Results

4.1 Prototype deployment.

During on-site evaluation of the motes it became apparent that the initial prototype network layout (Figure 5) did not perform up to manufacturer-provided specifications. The specifications indicated an RSSI threshold of -89dBm, with a prescribed mote-to-mote spacing of up to 200-300 meters. In practice, few reliable paths at such distances could be observed, and RSSI values between -80 and -90 dBm were experienced for significantly shorter network links. Network statistics were collected over a 25-day period, beginning with 10 motes on September 15, 2009 and expanding to 19 motes by September 18 (Figure 5). RSSI and PDR value were averaged over 15-minute intervals for each path in the network, providing a range of values over which to determine proper hardware thresholds and evaluate network performance. Over this 25-day period, the number of paths (or links between nodes) varied as the WSN automatically adjusted the network topology to account for fluctuations in communication reliability (Figure 6). Generally, a larger number of paths are desirable since it permits for greater diversity of routes on which data packets can be transmitted. The spike around September 18 corresponds to the time at which the full 19-node prototype network was deployed. As more motes joined the network, the number of paths increased correspondingly. The average network RSSI dropped as a result, implying that the newly formed network paths possessed low connectivity. This correlation was observed for the remainder of the 25-day evaluation of the network prototype, and indicates that not all network paths were equally reliable. Ideal performance would have
kept average RSSI steady, regardless of the number of newly created network paths, indicating that all paths reflect similar communication reliability. Further investigation into possible causes of network behavior showed that both the average network-wide RSSI and the average relative humidity experienced fluctuations over time, but did not appear to be positively correlated (Figure 6).

The western portion of the prototype network experienced a complete outage on September 19, leaving only a few network paths operational (Figures 5-6); no prior indication of an impending network outage was evident. During the outage, the total number of paths in the network dropped significantly and abruptly. This can be attributed to a bottleneck effect within the network. In a meshed topology, child nodes far from the network manager need to transmit data through neighboring parent nodes (nodes closer to the network manager), which in turn pass the data further along the mesh until it reaches the network manager. On September 19 critical parent nodes in the mesh drifted into a hibernation state due to a drop in connectivity (most likely due to low RSSI values exhibited by network paths in the center of Figure 5), and child nodes that depended on these connections lost connectivity to the network manager. Child nodes in the western portion of the network were thus forced to enter a hibernation state as well. To avoid this bottleneck phenomenon, redundancy and robustness needed to be built into the network to ensure that no single outages can cause the remainder of the network to fail. This bottle-necking behavior further explains why average network RSSI was inversely proportional to the number of paths. Following this outage, only stable links with high RSSI values remained in the network.

The mote hibernation state was designed to conserve power during network communication outages, since transmission during such instances of low connectivity can significantly shorten
battery life. Once in the hibernation state, it could take days for the mote to rejoin the network depending on field conditions. A physical reset was required to bring motes out of hibernation, and to re-establish the entire WSN mesh. Once the network hardware was reset a week into the prototype deployment, the number of network paths increased and stayed constant for the following two-week period.

Relative humidity did not seem to affect the overall behavior of the network (Figure 6), but a rainstorm around October 3, 2009 coincided with another network collapse and a significant drop of nodes from the network. To mitigate future network collapse, mote software could either be modified to lower the threshold for entering the hibernation state, or additional repeater motes could be added to ensure that required RSSI thresholds would be met. It was deemed that the low-power sleep mode was necessary for efficient network operations, and that a redesigned network layout would offer a better alternative. This was again confirmed when noticing a significant drain on mote battery life after forced resets.

Part of the pre-deployment site analysis involved determining the field RSSI as a function of node-to-node distance. Figure 7 presents a logarithmic plot of RSSI vs. path distance for the prototype deployment, and for comparison, the idealized Friis propagation model [Friis, 1946], which governs how the hardware-specific RSSI between two nodes should change assuming perfectly isotropic antenna and free space conditions. The measured relationship was not monotonic, nor sharply delineated, and showed considerable uncertainty, which was most likely a function of multipath effects on radio propagation. The in situ network statistics showed a significant reduction in transmission distance compared to the manufacturer-specified 200-300 m outdoor range. As expected, the observed average RSSI decreased as the distance between nodes increased, but a significant spread existed around the mean (shown by an estimate of the 95%
The mean RSSI reached the manufacturer specified threshold of -89 dBm at a transmission distance of 130-150 m, while a large portion of paths performed below this threshold. At 100-120 m separation, a significant portion of network paths had the tendency to drop below this threshold, under-performing manufacturer specifications of a 200 m range. For distances below 25 m, the network links outperformed the predictions made by the Friis propagation model but mean RSSI significantly deviated from the idealized Friis model after the 25-m mark.

Figure 8 presents another, and perhaps better, indicator of network performance - an analysis of PDR (%) as a function of RSSI (dBm). Although fluctuations of PDR around specific RSSI values existed, it is evident that for values of RSSI over -80 dBm, the PDR remained around 100%, implying high reliability and that few, or no retransmissions were required to successfully deliver network packets to their destination. For values below this RSSI threshold, paths experienced sudden drops of PDR, falling entirely to 0% for RSSI values of -90dBm and lower. This sudden drop is often referred to as waterfall behavior when describing the effect of RSSI on PDR.

4.2 Post-deployment analysis.

Following the prototype deployment, an analysis of network metrics was used to inform a re-design. More repeater nodes were added to the network, and existing repeater nodes were re-located to improve performance and prevent network outages, leading to the final network configuration shown in Figure 9. After re-design, the network did not experience any more spontaneous outages. A histogram of PDR values for all paths in the network (Figure 10) over a two-day period, a month after network reconfiguration, shows that about 80% of total PDR
values were within a desirable 85-90% performance range, with more than half of all paths experiencing 100% PDR (particularly nodes spaced less than 50 m apart). Nodes communicated not only with their closest neighbors, but also with more distant nodes to maintain the mesh network topology. In the final deployment, network nodes had, at all times, a stable connection to at least two neighbors located 50 m or closer.

A 24-hour sample for all paths in the final network shows the average network-wide PDR to be within an 85-95% window, revealing only slight, and gradual fluctuations (Figure 11). The low-frequency excursion from the design threshold did not exhibit any clear correlation with collected environmental variables (such as temperature, or humidity). Average network-wide PDR characteristics reflected those shown in Figure 11 for the remainder of the deployment lifetime.

Figure 12 shows a sample of PDR evolution for three randomly selected paths in the final network configuration. Though average network PDR remained high, path A exhibited a sudden drop at the four-hour mark, only to recover within one hour. Path B exhibited fluctuations of PDR for the entire sample period. While requiring multiple retransmissions of the packets, this path did not drop from the network and its PDR never dropped below 80%. The figure also shows a new network path C being established during this 24-hour window, which is a positive indication that the self-healing network algorithms dynamically allocated paths to take advantage of more stable connections, thus alleviating otherwise relatively less stable connections and creating further redundancy. The formation of new paths between nodes was caused by fluctuation in the radio space, and is further motivation for using an adaptive, self-healing network.
During network operation, there were some instances of paths longer than 200 m experiencing RSSI values greater than -60dBm, while some paths less than 50 m operated with RSSI values of -80dBm. This behavior was not consistent across the network, and could not be directly attributed to physiographic features of terrain (such as elevation differences, or line of sight), thus further underscoring the unpredictability of the wireless environment.

4.3 Network measurement validation

The distribution of aspect and slope captured by the network and synoptic surveys reflected those of the more comprehensive LIDAR survey (Figure 13ab), but the network did not capture some of the higher elevations (1990-2040m) located in the northern portion of the catchment (Figure 13c). These locations were excluded from the original sensor placement in favor of sampling nearer the stream.

The mean snow depth measured by the network on March 22-23, 2010, was 139 cm, versus a 145-cm mean from the LIDAR data (Figure 14a). On April 7, 2010, the network measured a mean snow depth of 142 cm, versus 140 cm for the synoptic survey. Although the network and LIDAR data showed similar variance for March 22, the network measurements of snow depths varied between 70-242 cm, while the LIDAR snow depths varied between 0-300 cm. The April 7 synoptic survey showed very similar observations compared to the network, both in terms of variance, and the minimum and maximum observed values (Figure 14a).

For the June soil moisture study, the network and synoptic survey measured a mean of 0.23 (Stdev. 0.14) and 0.25 (Stdev. 0.09) Volumetric Water Content (VWC), respectively. In September, the network reported a mean of 0.15 VWC (Stdev. 0.12), compared to the 0.09 VWC (Stdev. 0.03) in the synoptic survey (Figure 14b). Three network readings, in particular, showed
relatively high VWC during the September survey. Each of these corresponding sensor nodes was located in flat-aspect terrain, in open meadows.

A histogram of snow depth distribution, based on the March 22 LIDAR point-cloud, shows that snow depth was near-normally distributed (Figure 14c). This distribution was obtained after removing a small set of outliers (< 0.1%); i.e. negative values, and extremely large positive values (depths > 3.5m). Given this near-normal distribution of snow depth, as well previously observed tendencies of spatial VWC to follow a normal distribution [Grant et al., 2004; Famiglietti et al., 1998; Western et al., 2002], a two-sample t-test, and two-sample f-test [Wackerly et al., 2008], were carried out at a 5% significance level ($\alpha=0.05$) to assess the equality of the means and standard deviations between the surveys and network readings. With the exception of the September soil moisture study, these test confirmed null hypothesis $H_0$ (namely, the equality of the mean and standard deviation between survey and network data). The difference between the September soil moisture survey and network data was deemed statistically significant, with attained significance values ($p$-values) of $p=0.046$ and $p<0.0001$ for the mean, and standard deviations tests, respectively.

Figure 14c also draws a distinction between those portions of the LIDAR data that fell below and above the respective minimum and maximum measurements captured by the network. These extreme readings, although not captured fully by the sensors nodes, did not have a significant impact on the overall mean. The majority of locations with snow depth values below those captured by the network were located in the northwestern portion of the network (Figure 15). Larger patches with snow depth values above those captured by the network were located in the centrally situated, open meadow (Figure 15). The distribution of physiographic attributes of un-instrumented locations, for which the set of depth values fell below those captured by the
network, did not show significant deviations from those observed on the overall site. In the case of both the LIDAR and synoptic surveys, three particular sensor-node locations (Figure 15, yellow stars), situated in a north-facing aspect, and across varying canopy cover, reflected measurements very close to the catchment mean (± 9 cm).

4.4 Variability of snow depth and soil moisture

The majority of snow depth readings for water year 2010 (WY2010, starting in October 2009) reached an average peak accumulation of 160 cm in April of 2010, although a subset of nodes experienced this same average peak in the middle of January (Figure 16a). Snowmelt timing showed notable variability, with a three-week span between first and final melt-out dates at sensor-node locations. Nodes located on flat facing aspects generally saw faster melt rates than those on north- and south-facing aspects, while average accumulation showed little variability across different aspects. Sensor nodes located under canopy, measured, on average, 40 cm and 80 cm less, than those located under drip-edge, and open-cover, respectively. In general, sensor nodes located in the open meadow regions experienced relatively higher snow depths.

VWC showed variations in magnitude across the catchment, but generally exhibited similar behavior across most sensors in the network (Figure 16b). At most sensor nodes, peak VWC levels of 0.31-0.32 were reached at the beginning of June 2010, coinciding with the melt-out of the snowpack. A subset of nodes experienced peak VWC in the middle of an October 2009 rainfall event. The remainder of VWC fluctuations corresponded with the snowmelt cycle. Soil moisture sensors near the surface generally measured lower VWC values compared to those placed at greater depths (Figure 16b). On average, sensor nodes located on flat aspects experienced VWC 5%-10% greater than those situated on north and south facing aspects. The
major contribution to this relatively higher average VWC was by sensor nodes placed in the flat meadow regions, where catchment melt water accumulated and some locations experienced VWC of up to 0.60. On average, nodes placed under canopy, and in open areas, reflected similar VWC behavior, while nodes placed along the drip-edge exhibited relative larger VWC (by 0.05). Further findings regarding variability of snowmelt and soil moisture agreed with those obtained by Bales et al. [2011], who conducted a detailed analysis of a comparable dataset in a different segment of the larger basin.

4. Discussion

4.1 Wireless sensor network

We define an optimal network deployment as the one that maximizes PDR, while minimizing RSSI (implying greater transmission distances). On average, the need to retransmit data will then be reduced, while spatial coverage of the network will be maximized. Based on this design criterion, Figure 8 shows that this value corresponds approximately to -80dBm (although there begins to be a significant spread of PDR for values below -70dBm). This waterfall behavior is a further indicator that a manufacturer-specified RSSI *receiver sensitivity* threshold of -89 dBm should not be employed as a proxy for reliability. In the case of this study, it is apparent than no packets can be received beyond the manufacturers specified -89 dBm, but PDR begins to exhibit non-desirable qualities well before this threshold. As such, the manufacturer specified RSSI threshold thus presents a worst-case performance indicator, rather than serving as a guide for reliable communications. A deployment-specific waterfall plot will however go a long way towards helping to design a reliable WSN.
For our deployment, -70 dBm was chosen as a conservative, but reliable, RSSI threshold to account for adverse effects due to unexpected wintertime fluctuations. Given the measured -70 dBm needed for acceptable communications reliability, a design path distance was then extracted from Figure 7. For further reliability, the lower 95% confidence bound, rather than the mean RSSI, was used as the design criteria. For the installation, this resulted in the derivation of a 50-m mote-to-mote spacing. Similarly, reliable mote-to-mote spacing would approximately correspond to 100 m for the manufacturer-specified sensitivity of -89dBm.

We propose a three-step design procedure to optimize a WSN deployment (Figure 17). A WSN deployment can be separated into *pre-deployment, deployment*, and *post-deployment* phases, which, when carried out properly, will ensure robust and reliable network communications while maximizing battery lifetime and transmission distances (and thus reducing the number of required motes).

First, in the *pre-deployment* phase, a prototype network (or a subset of the actual network) should be deployed a priori to gauge the actual performance of the wireless hardware under operating conditions. The pre-deployment analysis should be carried out in environments similar to those of, or preferably at, the actual deployment site, with an attempt to cover a range of terrain parameters. Networks statistics, specifically RSSI and PDR, should be collected for several days, or longer, to capture possible fluctuations in performance. This will place manufacturer specified performance thresholds into context and will permit site-specific network behavior to be evaluated prior to a full-scale deployment. A *waterfall* plot of the effects of RSSI on PDR (such as the one in Figure 8) should be constructed to extract the site-specific RSSI threshold. The primary design objective entails maintaining stable network links (high PDR values) and ensuring robust network performance. This will prevent network outages and
collapse due to the inability of motes to communicate. While maximizing network-wide PDR will reduce re-transmissions, and thus also prolong battery life, there is a trade-off associated with placing many repeater nodes. A PDR of 100% is thus not desirable, and may, in fact, be physically unattainable. Calculations should be conducted to evaluate the effect of average PDR on site-specific battery resources, but in most cases a PDR value of 85-90% provides a realistic performance goal. Such an analysis will maximize node-to-node spacing, while reducing drain on battery resources, and will facilitate robust and reliable network links. It is critical to develop a statistically meaningful RSSI threshold from the PDR behavior to account for possible fluctuations in performance. This threshold can then be used to determine transmission distances (in this case from Figure 7), and will provide a reliable estimate of the number of nodes that will be required to cover the sensing region.

Second, the deployment phase of the final network (placement of sensing nodes, repeater nodes, or star-layout) should be carried out based on the previous analysis of network statistics, keeping in mind that these statistics provide only a bound on performance behavior. Signal attenuation and multipath propagation characteristics adversely affect specific network links. Brief field checks during the actual placement of nodes should be made to ensure that each network path meets the desired RSSI threshold. Often, simply moving nodes by a few meters will establish a more robust link.

Third, in the post-deployment phase, collection of network statistics should be continued in order to evaluate the in situ performance of the network and to capture possible long-term fluctuations in connectivity. Depending on the observed behavior, these statistics should be further analyzed, and adjustments to the network can be made to achieve a desired performance, by adding, removing, or re-locating WSN nodes.
In our case, the data obtained through the analysis of the network prototype was used to
gauge the future behavior and provided a set of valuable thresholds upon which to re-design the
network. Analysis of such results would have saved a significant amount of time if conducted
prior to the deployment of the network. A network design procedure using the above steps will,
in most cases, ensure that WSN performance will meet the demands of an environmental
monitoring application, by maximizing path reliability, battery life, and spatial coverage.

While the outlined methods apply to a broad range of available WSN platforms, initial
hardware selection should still be strongly guided by built-in network features. The choice of
WSN hardware for this deployment was based on battery life, as well as its ability to set up and
maintain an adaptive self-healing, multi-hop, mesh network. There is a significant cost if the
direct user is required to design and implement low-level control of the WSN hardware, as well
as the complex algorithms necessary for efficient channel hopping and mesh topologies.
Transmission distances can be further improved by using high-gain antennas to replace the more
traditional mote whip antennas. Close attention to details, such as maintaining sufficient battery
voltage at each mote, will additionally help to avoid network blackouts in winter. As most
battery chemistries are adversely affected by colder weather, battery specifications should be
checked to ensure the minimum amount of current required by the mote can at all times be drawn
from the battery, regardless of external temperature.

4.2 Network measurement validation and variability analysis

The ability of the WSN to capture catchment-wide snow depth mean and variability has
been confirmed through statistical and qualitative comparison with the data obtained by the
LIDAR and synoptic surveys. Given this agreement, it is reasonable to suggest that a placement
strategy based on evenly instrumenting major physiographic parameters performs well with
regard to characterizing the distribution of catchment-wide snow depth at the km² scale. Our
analysis limits its scope mainly to characterizing these distributions since further data collection
is necessary to shed insight into the main spatio-temporal factors that guide detailed snow depth
variability across this catchment. Application of non-linear classification techniques [Balk and
Elder, 2000; Molotch et al., 2005] could reveal if the un-instrumented regions can be more
accurately predicted from the instrumented subset of the catchment.

Although not deemed statistically significant, the slightly higher mean of the April 7
survey, when compared to data captured by the network (Figure 14a), could be explained by
noting that the survey did not cover the northern portion of the catchment (Figure 3). Based on
inferences from the LIDAR data (Figure 15), this region of the catchment would have been
expected to experience lower depth values. Future synoptic surveys will be expanded to include
these northern locations of the catchment. Other measurement discrepancies between the data
sets can be attributed to general sensor calibration error. Reflection due to canopy cover may
also have introduced noise into the LIDAR data set. Additionally, four of the Judd snow depth
sensors malfunctioned during the study, eliminating those readings from the analysis.

Given the near-normal distribution of snow depth exhibited in the LIDAR data set
(Figure 14c), an under-sampling of the catchment would not likely capture the extreme values of
snow depth. Although the mean and variance estimates were not significantly affected, an
example of such under-sampling is given by WSN measurements on March 22, which did not
capture the relatively low-values in the northwestern region of the catchment, and relatively high
values in some of the open meadow regions (dark and light locations in Figure 15). Future
placement of a set of sensor nodes in these areas is expected to minimize this bias in coming
studies. The nature of WSN technology will permit for the seamless integration of these sensing locations into the existing network.

The existence of three sensor-node locations (Figure 15, yellow stars), which consistently reflected snow depth mean, suggests that it may be possible to identify key measurement locations which capture mean snow depth across the catchment. This notion has been addressed in previous studies [Molotch and Bales, 2005], but analysis of multi-year data is required to validate this claim. These points are not associated with any particular physiographic features that could explain this behavior, suggesting that specific spatial coordinates, rather than physiographic attributes, could also serve as indicators of the overall catchment mean.

A qualitative analysis of snow depth variability suggests that canopy cover was one of the major factors guiding variability during the WY2010 accumulation period. In general, deeper snow depths are expected to correspond with areas where tree-cover does not impede snow accumulation. Although a similar analysis in regard to aspect did not reveal trends in snow accumulation, sensor-nodes in flat-facing aspects experienced melt earlier in the season, most likely because the majority of flat-facing sensor nodes was located in open meadow regions, which received larger amounts of solar radiation.

Although standard deviation values of VWC in this study correspond with those of previous research [Grant et al., 2004; Famiglietti et al., 1998; Western et al., 2002], our study comprised a notably larger area, and thus may have been prone to the effects of spatial scaling. This could partly explain the discrepancies exhibited when comparing the synoptic survey with the network data, especially when considering the extreme values captured through each method. This is particularly true in the case of the September VWC study, in which the network captured
high VWC values in meadow regions, thus shifting the estimate of the mean, and increasing overall variability. The layout of the synoptic survey may have under-sampled the wet meadow regions, while the spacing between survey locations may have missed the short-scale variations in VWC. Sampling error could also have been introduced by the hand-held GPS units used in the study.

Initial analysis confirms the importance of spatial snow distribution as a guiding factor of VWC variability [Grant et al., 2004; Williams et al., 2009]. Note that the June survey and network readings (which were more directly affected by snowmelt) showed greater agreement, while the September studies exhibited statistically significant discrepancies. Although discrepancies exist between the VWC values captured by the network and synoptic surveys, results suggest that a strategically placed sensor network can effectively characterize the distribution of catchment-wide soil moisture at the km$^2$ scale, especially during and shortly after snowmelt. This follows in agreement with Grant et al. [2004], who noted that catchment-wide soil moisture could effectively be characterized by few samples. As Western et al. [2002], noted however, capturing the statistical distribution of VWC is important for number of applications, but it may often be of interest to understand the detailed spatial arrangement, and effects of physiographic parameters on soil moisture. Such a detailed spatio-temporal analysis [Famiglietti et al., 1998; Williams et al., 2009] requires denser synoptic data collection in our study area. Future studies will need to be expanded to capture sub-grid variability, while statistical methods will be coupled with a more comprehensive conceptual understanding of soil moisture dynamics to investigate the detailed controls of physiographic parameters on VWC.
6. Conclusions

When compared to synoptic surveys and dense LIDAR data, a sensor-placement strategy based on coverage of physiographic attributes can effectively capture the mean and variability of snow depth across a catchment. Such a strategy also performs well in the case of soil moisture, especially during periods of snowmelt, but it was shown that VWC variability was less likely to be captured by evenly sampling physiographic features of the terrain. A weighted sampling approach, based on the relevance of physiographic parameters and known soil moisture-, and snowmelt-dynamics, may be more suitable for characterizing the VWC behavior at the km² scale.

Although WSN technology is continuously improving, no off-the-shelf solution exists for the harsh conditions experienced during most environmental monitoring campaigns. Results gathered from the 57-node WSN mesh described in this paper partially fill that gap, by demonstrating a cost-effective means by which to instrument a large, and remote area in complex terrain. Low-power and reliable performance can be achieved by proper evaluation of hardware behavior in the specific field conditions. This deployment successfully covered a 1.5-km transect with 50 m node-to-node distances, and continues to reliably transmit data from more than 300 sensors every 15 minutes.

The sheer scale of future monitoring campaigns will demand many network nodes, making it impractical to optimize every single link. In situ network behavior must be quantified to derive average indicators of performance. Gathered over a span of several days, PDR and RSSI should be sufficient to estimate operational path behavior. It is expected that these network characteristics will vary based on site-specific terrain. Unless obvious physical obstacles exist (e.g. large rock outcroppings or metal surfaces blocking a path), the average maximum
transmission distance extracted from such an analysis should be sufficient to inform network

design.

An open mindset to current limitations of the hardware, and continuous monitoring of
network statistics (for at least a year throughout the initial deployment), lead to an iterative
deployment approach, which can be split into three distinct phases. Following the design
procedure outlined in Figure 17 will result in near-optimal and reliable node-to node spacing.

Since maintaining reliable network performance is the most important design imperative, trading
transmission distance for a robust, hardened network is the proper decision. More repeater nodes
can be added to improve connectivity and increase connection redundancy, but only collection
and analysis of network statistics can shed light on actual causes of network failure, and lead to
rational strategies for improving performance. Using this approach, the network presented in
this study experienced significant boosts in performance, and no further collapses.

The implementation of the above deployment strategies should lead to successful WSN
deployments of up to 100 nodes, and spanning 1-2 km². Environmental monitoring deployments
of networks beyond this size should use multiple network managers, each responsible for
networks of up to 100 motes. This will reduce the likelihood of large-scale network outages
caused by bottleneck effects, while simplifying the identification and management of network
behavior. Such architecture permits for a manageable approach to scaling, when considering the
instrumentation of large areas such as entire basins, or mountain ranges. The network described
in this paper is a prototype for monitoring such large areas, and future work will investigate the
feasibility and methods of scaling this deployment strategy to cover significantly larger areas.

Using these heuristics, deployment time can be significantly reduced, thus allowing more
resources to be devoted to the actual scientific program.
6. Acknowledgements

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Table 1. Sensor characteristics.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Sensor</th>
<th>Manufacturer</th>
<th>Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>Snow depth</td>
<td>Ultrasonic</td>
<td>Judd Communications</td>
<td>±1 cm</td>
</tr>
<tr>
<td>Volumetric water content</td>
<td>EC-TM</td>
<td>Decagon</td>
<td>±3% VWC</td>
</tr>
<tr>
<td>Matric potential</td>
<td>MPS-1</td>
<td>Decagon</td>
<td>Calibration dependent (max ±40%)</td>
</tr>
<tr>
<td>Solar radiation</td>
<td>LI-200</td>
<td>LI-COR</td>
<td>±5%</td>
</tr>
<tr>
<td>Humidity and Temperature</td>
<td>SHT15</td>
<td>Sensirion</td>
<td>±2%, ±0.5°C</td>
</tr>
</tbody>
</table>
Table 2. Power consumption of various components in the network.

<table>
<thead>
<tr>
<th>Component</th>
<th>Voltage - V</th>
<th>Current – A (idle mode)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mote</td>
<td>3</td>
<td>0.02 (&lt;2x10^-5)</td>
</tr>
<tr>
<td>Data logger</td>
<td>12</td>
<td>0.01 (2x10^-4)</td>
</tr>
<tr>
<td>WSN network manager</td>
<td>12</td>
<td>0.06</td>
</tr>
<tr>
<td>Sensors</td>
<td>5-12</td>
<td>0.15-0.2 (0)</td>
</tr>
<tr>
<td>Cellular modem</td>
<td>12</td>
<td>0.2 (&lt;0.1)</td>
</tr>
<tr>
<td>Embedded computer</td>
<td>5</td>
<td>0.4</td>
</tr>
</tbody>
</table>
List of Figures

Figure 1. Mote architecture.

Figure 2. WSN Topologies.

Figure 3. Site layout showing location of sensor nodes, and synoptic survey sampling points.

Figure 4. Sensor node architecture.

Figure 5. Snapshot of the prototype network.

Figure 6. Network behavior over a 25-day period, starting on September 15, 2009.

Figure 7. Plot of RSSI vs. path distance.

Figure 8. A plot of PDR as a function of RSSI.

Figure 9. Final wireless sensor network layout at the Kings River Experiment Watershed.

Figure 10. A histogram of PDR values for all paths in the network.

Figure 11. Average network-wide PDR over a 24-hour period.

Figure 12. The fluctuations of PDR over time for three specific paths in the network.

Figure 13. Comparison of physiographic parameters captured by LIDAR, against those covered by the sensor-nodes, and synoptic survey.

Figure 14. Mean and variability of snow depth, and VWC on four survey dates, and histogram of snow depth values calculated from LIDAR data.

Figure 15. Total snow-cover calculated from LIDAR data sets at 1m² resolution (March 22-23, 2010).

Figure 16. Time series of mean snow depth, and soil moisture for water year 2010.

Figure 17. The three phases of a WSN deployment.
Figure 1. Mote Architecture.
Figure 2. WSN network topologies. (a) WSN *star-topology*: all motes have a direct link to the network manager; the span of this network is limited by the distance between a mote and the manager. (b) WSN *mesh-topology*: motes exchange information with neighbors to create a redundant *multi-hop* network.
Figure 3. Site layout showing location of sensor nodes, and synoptic survey sampling points.
Figure 4. Sensor node architecture. (1) Mote, (2) custom data-logger to interface the sensor array, (3) on-site memory storage, (4) 12V battery, (5) snow depth sensor, (6) humidity and temperature sensor, (7) solar radiation sensor, (8) 10W solar panel, (9) external 8dBi antenna, (10) four soil moisture, temperature, and matric potential sensors at varying depths.
Figure 5. Snapshot of the prototype network. Circles indicate locations of motes. The figure lists path-specific RSSI values in dBm (decibels referenced to 1 mW).
Figure 6. Network behavior over a 25-day period, starting on September 15, 2009. Network resets are evident as the sudden spikes in number of network paths. The average RSSI of nodes in the network dropped as more paths were created (more nodes joined the network). A rainstorm, evident around October 3, coincided with a significant drop of paths from the network.
Figure 7. Plot of RSSI vs. path distance. The RSSI decreased with an increase in path distance, and significantly fluctuated around the mean. A number of *in situ* radio links experienced RSSI values below the manufacturer-specified -89 dBm threshold at approximately 100-120 m.
Figure 8. A plot of PDR as a function of RSSI. Gray points reflect observed behavior, while the solid black line represents an idealized waterfall fit. Most packets are transmitted successfully for an RSSI above -80 dBm, after which there is a sudden drop in PDR. The dashed line provides a conservative, and lower bound design curve.
Figure 9. Final wireless sensor network layout. The base station, located at an eddy flux tower, houses a network manager and acts as a central data aggregation point.
Figure 10. A histogram of PDR values for all paths in the network following a reconfiguration of the network. About 80% of all network paths are performing within the desired 85-90% design value, and over 50% of all paths are at 100% PDR.
Figure 11. Average network-wide PDR over a 24-hour period; no clear correlation exists between deviations in PDR and either temperature or humidity.
Figure 12. The fluctuations of PDR over time for three specific paths in the network over a 24-hour period.
Figure 13. Comparison of physiographic parameters captured by LIDAR, against those covered by the sensor-nodes, and synoptic survey.
Figure 14. Mean and variability of snow depth (a), and VWC (b) on four survey dates. Measurements are shown as grey circles (except for the large number of points in the LIDAR data set). The line denotes the mean; the dark region denotes one standard deviation, and the light region denotes the standard error of the mean. c) Histogram of snow depth values calculated from LIDAR data. Partitioned regions indicate low, and high values not captured within the range the WSN measurements. The same regions are highlighted in figure 15.
Figure 15. Total snow cover calculated from a snow-off and snow-on LIDAR data sets at 1m² resolution (March 22-23, 2010). White squares indicate location of sensor nodes. The yellow stars indicate locations of the three sensor-nodes that persistently recorded snow depth values closest to the mean of both the LIDAR-, and synoptic-survey. The color scheme reflects that of figure 14c.
Figure 16. Time series of snow depth and VWC values for water year 2010. a) Average snow depth (one standard deviation shown in gray), b) Average VWC at varying soil depths.
Figure 17. The three phases of a WSN deployment.