

Snowcloud: A Complete Data Gathering System for Snow Hydrology Research

Christian Skalka and Jeffrey Frolik

University of Vermont, {ceskalka, jfrolik}@cems.uvm.edu

Abstract. Snowcloud is a data gathering system for snow hydrology field research campaigns conducted in harsh climates and remote areas. The system combines distributed wireless sensor network technology and computational techniques to provide data to researchers at lower cost and higher spatial resolution than ground-based systems using traditional “monolithic” technologies. Supporting the work of a variety of collaborators, Snowcloud has seen multiple Winter deployments in settings ranging from high desert to arctic, resulting in over a dozen node-years of practical experience. In this paper, we discuss both the system design and deployment experiences.

1 Introduction

The ability to characterize snowpack state, as well as snowmelt, is broadly important for understanding hydrological and ecological processes and incorporating those processes in agricultural, ecological, etc. models [11]. Snowmelt is the primary source of water in many mountainous regions of the world and as a result is a critical necessity for about 16% of the world’s population [16]. Current climate model simulations show that snow processes are not stationary [3] and observations show snowpack has declined across much of the US in recent decades [2]. Despite the importance of data gathering in this realm, there exist major gaps in observing snowmelt and runoff [20, 14], even in relatively well-instrumented regions of the US. Current observations are relatively sparse and correlations among point measurements and model estimates can vary significantly [15]. Improved snow observations are thus desperately needed to provide objective measures for verification of hydrologic model forecasts [18] and to better streamflow predictions through updating the modeled snow water equivalence (SWE) [5].

Wireless sensor networks can address this need, especially for ground-truth data gathering. WSNs have significant advantages over existing methods in terms of combined temporal and spatial resolution, deployment flexibility and low environmental impact, and low cost. Snow courses are accurate, but invasive, human-resource intensive, and usually have poor temporal resolution. Traditional ground-based automated sensors such as SNOTEL sites have good temporal resolution, but are limited in terms of spatial resolution due to the high cost of deployment and maintenance. Finally, both manual surveying and SNOTEL sites are ill-suited to forested areas and highly variable topologies, settings in which spatial and temporal variability of snowpacks need to be better understood.

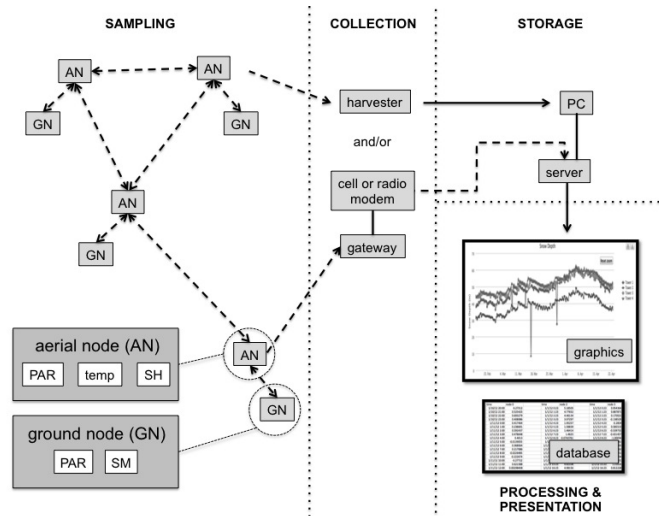


Fig. 1. Snowcloud System Components and Data Life Cycle

Our system, Snowcloud, leverages the advantages of WSNs for snow hydrology research. It was specifically developed as an instrument for short- and medium-term field research campaigns in remote locations, that could be used by a variety of researchers, and easily re-tasked to a diverse range of studies. Snowcloud was thus designed to be low-cost and within the budget constraints of academic researchers, to be modular for ease of shipping/transport to and assembly at remote locations, and to not be dependent on any existing infrastructure for data collecting. Furthermore, Snowcloud is a *complete* system, comprising data production, collection, and presentation. Our online presentation of data also anticipates public use.

Other projects have previously leveraged WSN technology to study cold-lands processes. Embedded wireless sensing has been used to study glacial movement [6] and permafrost [7]. In addition, WSNs have been proposed to better understand snow in terms of structure [10] and conditions leading to avalanches [8, 17, 1]. Most closely related to our work is an extensive, long-term network deployed at the Southern Sierra Critical Zone Observatory (CZO) [9]. As a complement to the extensive CZO site instrumentation, this wireless sensor network consists of 23 nodes each with an extensive suite of science-grade instrumentation along with additional 34 nodes to ensure network connectivity. In comparison to alternative methods (e.g., wired data loggers), the CZO deployment provides the ability to collect data nearly continuously and present it in near real-time from across the 1 km² study site. But in contrast to our work, this is a longer-term, larger-scale, higher cost project, designed for a very specific purpose. Snowcloud is intended to be a smaller, more affordable tool for use in a broad range of studies.

Herein, we present the Snowcloud system in the context of the life cycle of data from sampling to storage and presentation (Figure 1). We highlight the technical details that

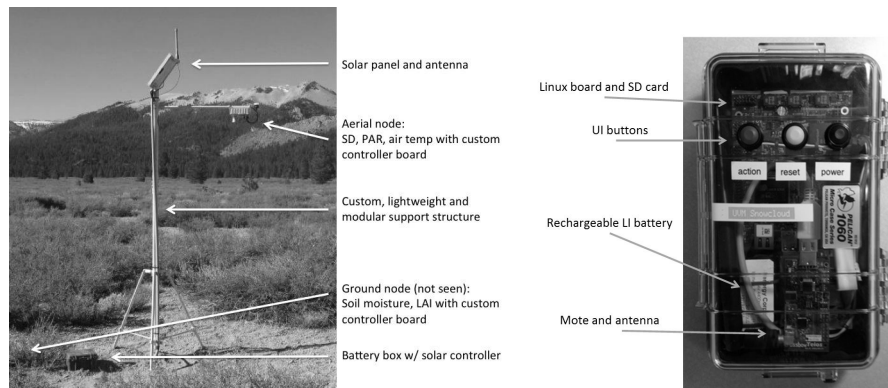


Fig. 2. Snowcloud Tower (L) and Harvester Device (R)

support our stated aims. In Section 2, we describe the network hardware and software platforms, and how data is sampled and formatted. In Section 3, we discuss solutions employed to collect and report data. In Section 4, we present an oft overlooked aspect of WSN, specifically the processing of data and its presentation to end users via a publicly available database. We discuss several Snowcloud deployments to date in Section 5 along with some key technical and practical experiences. We conclude by discussing future work related to algorithms and sensors.

2 Sampling Data

The Snowcloud network consists of multiple towers (Figure 2), each hosting one or two wireless sensor devices (i.e., nodes) that collect the pertinent data. Nodes are deployed above the snowpack (i.e., aerial nodes) and sometimes below the snowpack (i.e., ground nodes) depending on the science objectives. Nodes communicate via a TinyOS mesh network. Depending on the sensor suite and battery requirements, a completed single tower ranges in cost from \$500 to \$1000. We detail these various aspects of the platform in the following paragraphs.

Computation, Timing, and Communications. The nerve center of each tower is a MEMSIC TelosB mote [12], pictured in Figure 3, running the TinyOS2 operating system. We have developed a suite of programs for sensor control, including power cycling and sample rates, and on-mote datalogging and reporting. Regardless of the remote data collection method used, each tower logs sampled data in non-volatile flash memory on the mote for backup. The on-board clock is used to time sampling epochs, and each sample is timestamped with node-local time.

Although network time synchronization protocols such as FTSP are available in TinyOS, using node-local time without network synchronization has generally been

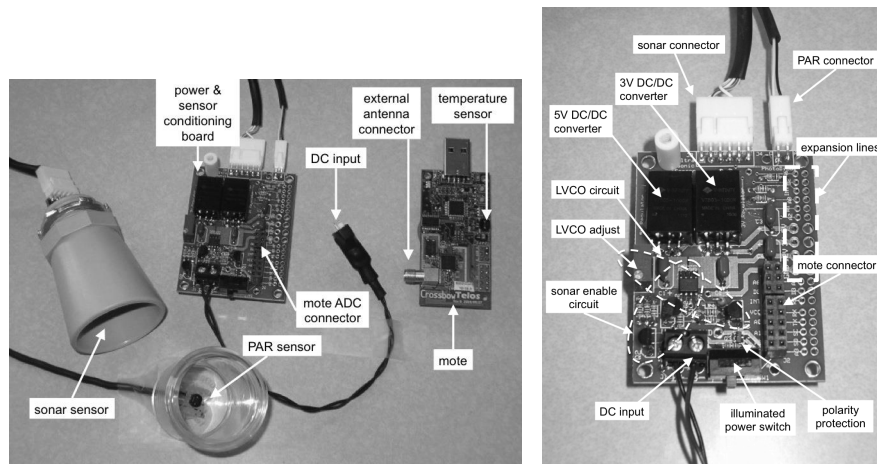


Fig. 3. Snowcloud Sensors and Electronics (L) and Control Board Features (R)

adequate for existing deployments. There has been very little node power cycling, and deployments are typically serviced and restarted within 8 months—TelosB clock drift during such a period is tolerable in this application. Also, protocols such as FTSP are intended for much more precise time synchronization than we need. The benefit of ignoring time synchronization is simplification of code development, which is non-trivial since node programs are already quite complex and difficult to debug. Also, new gateway technology as discussed in Section 3 will provide the network with a battery backed real-time clock. However, network time synchronization would certainly provide a more robust system and allow nodes to periodically operate in low-power mode, so we intend to include time synchronization in future iterations of the system.

Custom Control Board. We have developed a custom control board (Figure 3) with a number of hardware features useful in this application space. The control board includes basic features such as voltage regulators for the mote and sensors and breakouts for the mote ADC pin array. It also contains a switch allowing the mote to power cycle sensors, supporting an energy-efficient power regime defined at the software level—in short, active sensors are powered off when they are not sampling. The board includes a low voltage cutoff (LVCO) circuit to protect draw-down of batteries in case solar recharging is interrupted for extended periods, for example during Winter storm cycles, or due to solar panel snow loading. A voltage sensor is also incorporated to monitor solar panel/battery voltage.

Sensor Systems and Sampling Regime. The Snowcloud system can be configured to support a variety of sensors. The current “standard” configuration for the aerial node includes an ultrasound sensor, and air temperature sensor, a photosynthetically active

radiation (PAR) sensor, and a system voltage sensor. The low-cost ultrasound sensor is a ruggedized Maxbotix sensor with a 15 cm to 4 m range, which produces a voltage proportional to the round-trip time of flight. These sensors are pictured in situ in Figure 2, and in detail in Figure 3. We have also implemented ground nodes for measuring soil moisture and ground level PAR, the latter being useful for ascertaining bush leaf-area-index (LAI). Due to the short link lengths, ground nodes have no difficulty, using just a patch antenna, communicating through the snowpack with aerial nodes to disseminate collected data.

Sampling intervals are determined by user requirements and expected solar exposure and power availability. As snowpack evolution is a slow process, typical sampling intervals utilized for Snowcloud deployments are either 1 or 3 hours. The ultrasound sensor is powered off by software when not sampling. Multiple samples are taken in each sampling cycle, aka *epoch*, typically 12 ultrasound readings, 5 PAR readings, and 3 temperature readings. Only median values for each sensor type are stored in mote flash memory to conserve log space.

Power System. Snowcloud towers are powered by a combination of 12 V lead acid batteries and a 12 W photovoltaic panel. This is a popular solution and many related products are available, including solar controllers. Although lead acid batteries are heavy, robustness to cold temperatures and a wide recharge range make them our preferred choice. The TelosB platform has a 20-30 milliamp draw on average, which is easily powered by the solar panel in full solar exposure. However, adequate battery power is required at night, during extended storm cycles, and at the depths of Winter in arctic deployments. Deployed battery capacity has varied from 12 to 55 amp hours depending on deployment conditions. In all cases, the control board's LVCO prevents battery draw down below a 10 V to 11 V adjustable threshold. The LVCO circuit is to prevent deep battery discharge as most solar controllers will not recharge batteries drawn down below 9 V. If a node is shut off by the LVCO, it will automatically restart when battery charge comes back above the threshold.

Support Structure and Enclosures. As seen in Figure 2, the Snowcloud support structure consists of a vertical mast from which the aerial node is cantilevered. At the top of the mast is the solar panel and communication antenna. The standard tower for deployment in areas with high annual snowfall provides approximately 2.5 m of clearance between the ultrasound sensor and the ground. The mast is readily assembled from 1 m segments of aluminum thereby allowing tower height to be readily increased or decreased, and easily packed. The structure has been tested in Solidworks[®] and is designed to withstand winds up to 100 mph. The most challenging aspect of the structure design is the anchoring mechanism as the ground at our deployment sites has ranged from granite to sand to bog. We have used both a plate anchor that is affixed to the ground, and a tripod base combined with a buried ballast (e.g., a plastic bucket filled with rock). The latter approach is easily installed and results in more stable structure.

For electronics enclosures, we have used Pelican[®] cases of various sizes. Especially for batteries, these are relatively cheap, adaptable solutions, and can be easily drilled to accommodate wiring pass-throughs.

3 Collecting and Storing Data

We now consider how we collect and report data. By “collect” we mean how we manage voltage samples as data once they are registered on mote ADC ports. By “report” we mean how we communicate that data to a permanent storage device, i.e., a database on a lab-accessible file server. The interpretation and visualization of pure voltage data is treated as a separate matter in Section 4.

Data Storage Layers and Redundancy. In the Snowcloud system, data is potentially stored at three layers: permanent storage, a data collection device, and non-volatile flash memory on the nodes themselves. Each node’s flash memory space is adequate to store a year of data for sensors with hourly sampling rates. In our experience, this storage mechanism is highly robust and can always be relied upon when all else fails. The use of data collection devices, described in detail below, provides more reliability, convenience, and near-real-time data reporting, and also interesting automated systems control opportunities that we envision as future work.

Data Harvester and Pull Protocol. We have developed and implemented a hand-held *Harvester* device to serve as the primary data collection device for areas without cellular coverage. Users transport the device to and from the site, and collect data while in network proximity by issuing a command from a simple push-button interface. The device is waterproof for use in snow, and has a rechargeable lithium-ion battery. The Harvester leverages TinyOS ad-hoc mesh networking, so that a communication link only needs to be established between it and one arbitrary tower in a connected network.

Device status during use is provided by built-in LEDs on processor boards, while input is provided by external buttons wired to the user and reset buttons on a TelosB mote inside the Harvester. This mote establishes a network connection with the Snowcloud deployment and issues requests for data. Reported data is relayed via USB to a Technologic Systems TS7260 board with 12GB of flash memory, where it is available for subsequent download in the lab e.g. via ethernet. Harvester operation is based on a custom-designed pull protocol layered over the TinyOS *Dissemination* protocol and *Collection Tree Protocol* (CTP). The protocol provides a “push button” user experience, where a single button push initiates collection of all data within the network. The protocol will not interfere with normal network operation, i.e., sampling. It is scalable to arbitrary network size, and is robust to node failure during reporting. Otherwise, the protocol does not provide integrity or reliability guarantees beyond those provided by CTP. We impose a data reporting flow control for the connection between the mote and the TS7260, since in testing we encountered data loss without it. Total collection times vary depending on number of nodes, length of deployment, and sampling rates, but after a few months of deployment pulling data tends to take between 10 and 60 minutes.

Most interestingly, when a Harvester device is introduced to the network by the user, it becomes a CTP “root node” to receive data— but although it is not well-documented, our field experience has revealed that CTP does not support a network with *zero* root nodes, which is the case when the Harvester is removed. Rather, CTP that has been running for about a day or more will no longer accept roots and report data. Thus, the

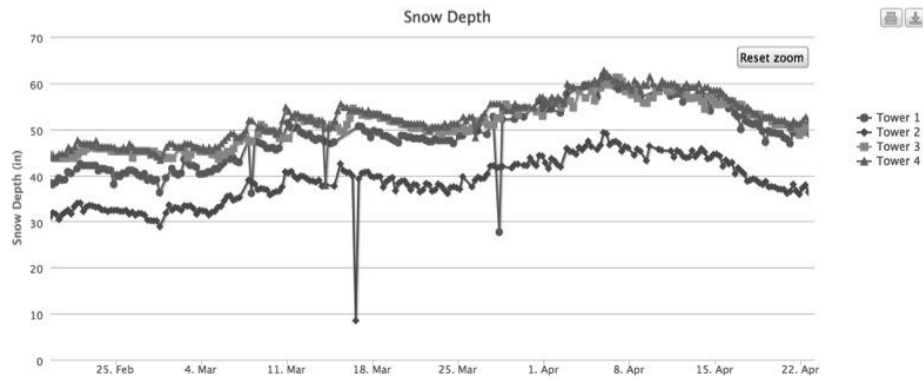


Fig. 4. Screenshot of Snow Depth Data from Sulitjelma, Norway, 2013

Harvester pull protocol uses Dissemination to stop and restart CTP at the removal and reintroduction of the device by the user.

Data Gateway and Push Protocol. We are currently developing and testing a *Gateway* device, that will receive data from the sensor network and report it in near-real-time over the Internet. This device is essentially the same hardware platform as the Harvester, coupled with a cellular modem, a battery backed real time clock, and an external power supply. The Gateway receives and stores sensor network data in a local MySQL database. This provides a second layer of data redundancy in the system— in the absence of cellular connectivity, data can be manually retrieved from the gateway device, e.g., by pulling the SD card. In the presence of cellular connectivity, a program periodically runs on the gateway and reports new data over the GSM cellular modem to the Internet via FTP. Periods are application dependent.

The Gateway currently uses CTP and a push protocol in the network. Nodes report samples to it as they are taken. The Gateway timestamps samples as they are received. Note that this protocol is more robust to node failure: in particular, if the network pull protocol is used and a node stops and restarts due to battery charge and LVCO operation, the “restart time” of the node cannot be known and subsequent node local timestamps cannot be correlated with real time. In contrast, the Gateway can always assign real timestamps when samples are immediately pushed by sensor nodes. And in the event of Gateway stop and restart, a Harvester-type pull protocol can be automatically run on restart to retrieve missed data.

4 Processing and Presenting Data

Data Pipeline Whether a Harvester or Gateway is used to collect data from the network, it is initially available in permanent storage in flatfiles. Each entry records the mote ID, the sensor type, data represented in ADC counts, and a sample timestamp.

Snowcloud Mammoth

Processed Data | Raw Data

Tower #	Longitude	Latitude	Sensors
<input type="checkbox"/> Tower 1	50	100	Snow Depth: <input type="checkbox"/> Sky PAR: <input type="checkbox"/> Air Temp: <input type="checkbox"/> Voltage: <input type="checkbox"/>
<input type="checkbox"/> Tower 2	100	100	
<input type="checkbox"/> Tower 3	150	100	Ground PAR: <input type="checkbox"/> Soil Moisture 1: <input type="checkbox"/> Soil Moisture 2: <input type="checkbox"/>

Start time:

End time:

Plot: Table:

[Reset Fields](#)

Fig. 5. Web-Based User and Administrative Interfaces

Node local timestamps are automatically converted to real timestamps given the known node start time. This data is easily parsed and entered into a relational database. Once in the database, data processing scripts are applied to obtain physical interpretations of sensor voltages as described below, e.g., ultrasound and temperature sensor samples are combined to obtain snow depth readings. It is then available to users via online web interfaces.

Data Processing and Interpretation The final product of the Snowcloud system is processed sensor data. An example of Snowcloud snow depth data inferred from four deployed nodes is in Figure 4. Processing includes some conservative noise removal, where sensor readings that are definitely spurious given known possible value ranges are filtered out, otherwise smoothing is left to the end user. Processing also includes transformation of raw ADC voltage datapoints into physical units. These transformations depend on the sensors used and desired physical units. The air temperature and soil moisture sensors we’ve used come with factory-specified calibration curves for converting sensor voltages into physical units. Interpreting snow depth, PAR, and system voltages requires customized techniques since the relevant sensors are not “out of the box” for these applications. But for all sensors that we use, calibration curves are linear.

Snow depth. Ultrasound sensors directly measure the time for a sonic pulse to travel from the sensor to a solid surface and back. Distance to the surface is easily inferred from this, though air temperature must also be known since the speed of sound varies with it. As the distance to ground surface G from any fixed sensor can be measured prior to snowfall, snow depth D is interpreted from an input temperature reading t in physical units and an ultrasound reading s in raw voltage as follows, where SOS is the speed of sound as a function of temperature, and C is the ultrasound calibration curve that converts raw voltage to time of flight: $D = G - ((C(s)/2) * SOS(t))$. The calibration curve C is not factory supplied, and ultrasound performance tends to vary, so each Snowcloud SD sensor array is calibrated individually to obtain a tower-specific C . This is done in lab conditions by recording sensor readings at defined distances and known temperatures, and performing a simple linear regression on the results.

PAR, V sensors. Both PAR and system voltage readings are directly interpreted from sensor data. Although calibration curves must be obtained, we have found these curves to be quite consistent across sensor instances. For PAR sensors, we obtained a calibration curve for converting raw ADC counts to readings in micromoles/sec², by plotting a set of ADC readings against PAR levels measured with a Decagon AccuPAR LP-80 ceptometer and performing simple linear regression. For system voltage calibration, we plotted voltage sensor ADC counts against input voltage levels, accurately set with a power supply, and performed a simple linear regression on the graph.

Web Interfaces Both raw voltage and interpreted data is made available to users via online interfaces. A screenshot of the user interface for our Mammoth Lakes, CA deployment is shown in Figure 5. The intent of the interface is to allow basic visualizations, and provide raw material for input into other tools, e.g., GIS. Thus, data can be presented in either graphical or tabular format. The graph in Figure 4 is a screenshot of the web interface for a current deployment, and has interactive features online.

We have also developed web interfaces to improve administrative efficiency when setting up new sites, and maintaining existing ones. All software used in our system is largely consistent over various deployments, except processing scripts in particular are parameterized by the calibration curves used for deployed sensors. An administrative web interface allows calibration curves to be entered into the database and associated with specific sensor arrays for data processing.

5 Deployments and Field Experience

To date, we have deployed several Snowcloud systems to support scientists from several institutions. Deployment environments have included the Sierra Crest, the Eastern Sierra high desert, a New England forest, and arctic Norway. Thus deployment latitudes, altitudes, and climates have varied widely, as have research applications. This requires a highly adaptable, flexible, and robust data gathering system. Furthermore, these field experiences have motivated a number of refinements to our system hardware and software as discussed in the preceding text.

The deployments described here have succeeded insofar as usable datasets have been generated by each, and all but the Sagehen Creek dataset are available online at www.cs.uvm.edu/snowcloud. (Valid date ranges fall within deployment periods stated below.) Furthermore, analysis of this data reinforces the benefits of an automated, distributed system to capture highly variable snowpack properties [13]. As exemplified in Figure 4, snowpack evolution typically exhibits clear spatiotemporal variability at different locations in deployments, so a distributed sensor system is well-suited for data gathering in this context. This evolution cannot be captured with the same temporal resolution using manual snow courses, or with the same spatial resolution using single-point measurement of a SNOTEL site.

Sagehen Creek Field Station, California, USA (Fall 2009-Spring 2010) Sagehen is situated just east of the Sierra Crest at an elevation of 2000 m. The deployment period

was December 2009 through June 2010. In addition to prototype testing, this deployment was used for collaborative research with University of Nevada, Reno (UNR). The results of this research demonstrated that the combination of telemetry obtained from a Snowcloud deployment, with models obtained using statistical techniques including linear regression and kriging, allows more accurate prediction of areal SWE averages than standard techniques [13]. This full-season field campaign served to validate basic functionality and robustness of the Snowcloud platform in its intended environment, and to demonstrate that our low-cost ultrasound-based approach to SD measurement specifically is effective.

The deployed network consisted of six sensor nodes, each supporting an aerial node with temperature and ultrasound sensors. The deployment covered a 1 hectare location with variety of terrain and canopy features. As a field research station, we were able to report data as it was collected, via the aforementioned collection tree protocol (CTP), to a base station mote connected to a laptop in a laboratory building proximal to the deployment site. As this laptop was connected to AC power and the Internet, data was available in near-real-time and data collection and reporting never failed. As we discuss in the subsequent deployments, such convenience in reporting is not the norm in practice.

Mammoth Lakes, California, USA (Winter 2012-date) An active Snowcloud network is currently deployed at an Easter Sierra Mountain site (elevation 2300 m) near Mammoth Lakes. The data gathered by this network supports research directed by researchers from University of California, Santa Cruz (UCSC). The purpose of this research is to study the effects of climate change on alpine snow hydrology and high-desert flora, specifically the effect of increased rain-on-snow events on shrub communities. This deployment consists of three towers deployed over a 300 m transect, each with a fully-instrumented aerial node (SD, PAR and temperature) and a ground node (PAR, soil moisture at 10 cm and 1m). Leaf area index is derived from the difference between the PAR sensors in the aerial and ground arrays. Furthermore, the voltage sensor (discussed in technical detail in Section 2) provides useful *system* telemetry, i.e., an indication of battery levels over time. Both Harvester and Gateway device prototypes have been utilized for data collection in this deployment.

Hubbard Brook Experimental Forest, New Hampshire, USA (Fall 2012-date) and Sulitjelma, Norway (Winter 2013-date). During the past year we have deployed the Snowcloud system in two disparate but low altitude settings. The first site is on the forested slopes of the Hubbard Brook Experiment Forest in New Hampshire, USA (elevation 300 m). This area has been a site of a long term study to better understand snow and its impact on streams and watersheds. This particular deployment supports researchers from the University of New Hampshire (UNH) who are studying the effects of forest canopies on snow accumulation and melt. For this purpose we have installed three towers with aerial nodes to provide continual sampling at sites where manual snow courses are conducted nominally on a biweekly basis. Our second recent deployment is outside the town of Sulitjelma, Norway in collaboration with researchers at Stockholm University (SU). This site (elevation 150 m) is above the arctic circle which impacted

greatly our ability to rely on solar for months during the winter, and gave our system its most extreme test to date. We have four towers with aerial nodes at this site and a two-month sample of the collected snow depth data can be seen in Figure 4. The variability seen between towers deployed in near proximity (approximately 50 m apart) will help researchers develop more informative models for areal SWE for the purposes of validating airborne data. The Harvester device has been successfully used by our collaborators to retrieve data from both of these deployments.

6 Conclusion

In this paper, we have described the Snowcloud system for snow hydrology research applications, that implements a complete data collection pipeline from *in situ* sampling to online presentation. The main novelty of the system is its application space, and its design support for strategic short- and medium-term studies and adaptability to a variety of missions. The system has been successfully deployed in harsh Winter conditions in a number of settings, demonstrating the robustness of its design and the effectiveness of distributed WSN technology for monitoring snowpack evolution.

As future work, we intend to expand applications of our system, and refine and deploy our Gateway technology during the upcoming 2014 snow season. We also intend to investigate network control algorithms to reduce system power consumption. These algorithms will leverage global knowledge and higher computing power on the Gateway, and will build on so-called backcasting techniques [19] for network control and new programming languages technology for control orchestration in WSNs [4]. Finally, we are working to augment Snowcloud with additional sensing capabilities including *in situ* temperature profiling and microwave attenuation to better characterize snowpack dynamics during melt onset.

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