



1 A low-cost, autonomous system for distributed snow depth 2 measurements on sea ice

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8 **Abstract.** Snow is a critical component of the Arctic sea ice system. With its low thermal conductivity and high
 9 albedo, snow moderates energy transfer between the atmosphere and ocean during both winter and summer, thereby
 10 playing a significant role in determining the magnitude, timing, and variability of sea ice growth and melt. The depth
 11 of snow on Arctic sea ice is highly variable in space and time, and accurate measurements of snow depth and
 12 variability are central to improving our basic understanding, model representation, and remote sensing observations
 13 of the Arctic system. Our ability to collect those measurements has hitherto been limited by the high cost and large
 14 size of existing autonomous snow measurement systems. We designed a new system called SnoTATOS (the Snow
 15 Thickness and Temperature Observation System) to address this gap. SnoTATOS is a radio-networked, distributed
 16 snow depth observation system that is 95% less expensive and 93% lighter than existing systems. In this manuscript,
 17 we describe the technical specifications of the system and present results from a case study deployment of four
 18 SnoTATOS networks (each with ten observing nodes) in the Lincoln Sea between April 2024 and January 2025.
 19 The study demonstrates SnoTATOS' utility in collecting distributed, in situ snow depth, accumulation, and surface
 20 melt data. While surface melt varied within each network by up to 38%, mean surface melt between networks varied
 21 by only up to 9%. Similarly, whereas initial snow depth varied by up to 42% within each network, a comparison of
 22 mean initial snow depth between networks showed a maximum difference of only 26%. This indicates that floe-
 23 scale measurements made using SnoTATOS provide more representative data for regional intercomparisons than
 24 existing single station systems. We conclude by recommending further research to determine the optimal number
 25 and arrangement of autonomous stations needed to capture the variability of snow depth on Arctic sea ice.

26 1 Introduction

27 September Arctic sea ice area has diminished by ~50% since satellite observations began in 1979 (Meier et al.,
 28 2023; Onarheim et al., 2018; Peng and Meier, 2018). The remainder is predominantly thin first- and second-year ice
 29 (FYI, SYI) (Kwok, 2018). The Arctic Ocean may experience ice-free summers within the next decade (Jahn et al.,
 30 2024). The thinning and loss of Arctic sea ice has increased Arctic coastal erosion (Barnhart et al., 2014; Eicken and
 31 Mahoney, 2015), diminished habitat (Laidre et al., 2015; Post et al., 2013), impeded hunting, fishing, and
 32 transportation over sea ice, and created new opportunities and uncertainties for shipping, tourism, military activity,
 33 and geopolitical conflict in the Arctic (Backus, 2012; Bystrowska, 2019; Carman, 2002). Understanding the Arctic
 34 ice pack is more important than ever. At the same time, rapidly changing conditions, in addition to baseline spatial



35 and temporal variability, present considerable challenges for our efforts to observe, understand, and predict changes
 36 in this environment.

37 Our fundamental understanding and model representations of the Arctic sea ice system are limited by the
 38 spatial and temporal resolution, consistency, coverage, representativeness, and scalability of available snow
 39 observations. Zampieri et al. (2024) and Clemens-Sewall et al. (2024b) both found that neglecting sub-meter to
 40 meter-scale snow depth variability results in a 10% underestimation of modeled conductive heat flux through the
 41 Arctic sea ice cover during winter, yielding a directly proportional underestimation of ice growth. Snow also
 42 influences the timing of melt onset (Holland et al., 2021), and the formation and distribution of melt ponds
 43 (Polashenski et al., 2012), both of which impact the magnitude and spatial variability of sea ice melt. Clemens-
 44 Sewall et al. (2024b) and Holland et al. (2021) conclude that more observations of the spatial heterogeneity of snow
 45 depth are needed to improve model representations of sea ice conditions. Further, Gerland et al. (2019) identified the
 46 sparsity of in situ measurements of snow depth as an essential gap in our understanding of Arctic sea ice, and in a
 47 review of snow in the contemporary sea ice system, Webster et al. (2018) stated that “Major questions remain ... as
 48 to the exact role of snow, how it varies regionally and seasonally, how snow conditions on sea ice are changing and
 49 what effects these changes have on the atmosphere–sea ice–ocean interactions,” and that, “first and foremost, our
 50 limited understanding stems from the complexity of the snow–sea ice systems and the scarcity of observations.” In
 51 short, we need high-spatial-resolution observations of snow depth to constrain spatial variability, validate remote
 52 sensing observations, advance model physics, and maintain an observational record of snow depth in the Arctic.

53 Remote sensing observations give broad and consistent geographical coverage, but do not afford the
 54 necessary spatial resolution or measurement precision (Meier and Markus, 2015; Webster et al., 2018). Crewed, in
 55 situ drift and station experiments – e.g., the 1997–1998 SHEBA expedition (Perovich et al., 1999, 2003; Sturm et
 56 al., 2002), the 2015–2016 N-ICE experiment (Granskog et al., 2018; Merkouriadi et al., 2017; Rösel et al., 2018),
 57 the 2018–2019 MOSAiC expedition (Itkin et al., 2023; Nicolaus et al., 2022; Raphael et al., 2022), and the long-
 58 running Russian drifting ice station program (Colony et al., 1998) – are important, but only partial, solutions. They
 59 provide opportunities to densely sample sea ice and snow conditions, usually alongside a rich suite of atmosphere,
 60 ocean, and contextual information. However, each expedition offers only a snapshot in space and time.

61 Autonomous in situ instruments can provide wide spatial coverage and high temporal resolution, and
 62 several autonomous systems exist that offer precise, in situ measurements with selectable sampling frequency and
 63 up to 1–2 year endurance (Liao et al., 2019; Nicolaus et al., 2021; Planck et al., 2019). These systems are regularly
 64 deployed in the Arctic, but are expensive, heavy, and difficult to transport to and in the field (Table 1). This has
 65 historically limited their use to one to two instruments installed per floe, and few (<10) per region, the rare
 66 exceptions being major expeditions like N-ICE (Itkin et al., 2017; Nicolaus et al., 2021) and MOSAiC (Nicolaus et
 67 al., 2022; Rabe et al., 2024). Even on such major campaigns, relatively few units have been deployed on a single
 68 floe. These limited point measurements are usually taken as representative local snow depths. However, snow depth
 69 on Arctic sea ice can vary by 2 orders of magnitude over decimeter to kilometer length-scales due to topographical
 70 features, surface conditions of the underlying ice and snow, and ice age (and resultant accumulation time), among



other factors (Clemens-Sewall et al., 2024a; Iacozza and Barber, 1999). A point measurement is unlikely to capture the mean (and, by definition, cannot capture the variance) of snow depth in complex local snow fields.

We need a new snow sensing technology that will improve the spatial density of Arctic snow depth measurements. The system must be inexpensive, easy to transport, use, and install, and have similar measurement precision and endurance to existing systems. We have designed, built, tested, and deployed the Snow Thickness and Temperature Observation System (SnoTATOS) to meet this need (Table 1). SnoTATOS is an autonomous, radio-networked, distributed snow depth measurement system that will accurately observe the mean and variance of snow depth on Arctic sea ice at meter to regional spatial scales. Throughout the design process, we focused on affordability; ease of manufacturing, transport, use, and deployment; and matching or exceeding existing measurement standards. Our ultimate goal is to reduce or eliminate barriers to deploying the system in large numbers across the Arctic.

In this manuscript, we describe the characteristics of the SnoTATOS system, share bench-testing performance evaluations, and present results from SnoTATOS prototype networks deployed in the Lincoln Sea in May 2024.

Table 1: Specifications of several polar snow depth measurement systems (all specifications are per unit/station)

System	Approximate cost	Weight	Size	Time to deploy	Endurance	Measurement precision ^a
MetOcean Snow Buoy	\$9,400 USD	40 kg	2.55 m x 1 m x 1 m	30–40 min	12–18 months	± 1 mm
SAMS SIMBA buoy	\$10,000 USD	25 kg	~0.55 m x 0.30 m x 0.20 m	20–30 min	> 12 months	± 2 cm
SIMB3	\$18,000 USD	36 kg	4.87 m x 0.25 m x 0.11 m	20–30 min	24 months	± 1 mm
SnoTATOS	\$500 USD ^b	1.8 kg	2.44 m x 0.15 m x 0.1 m	<10 min	4.5 years ^c	± 1 mm

^aThis value specifies the instrument's stated measurement precision, not the accuracy of the snow depth retrieval. The precision of the ultrasonic rangefinders is ± 1 mm, while accuracy depends on temperature compensation, ice/snow surface conditions, sensor icing, etc. The precision of digital temperature chain instruments (e.g., the SIMBA) is ± 2 cm (the separation between any two temperature sensors in the chain), while the accuracy depends on the thermal characteristics of the snow, ice, and atmosphere, which affect the feasibility of determining the interfaces between the three media.

^bCost of components only (not including manufacturing and assembly) is approximately \$200.

^cThis is a nominal endurance based on power consumption measurements in a laboratory setting. We expect the effective endurance to be reduced by low temperatures and any radio communication reattempts.



2 System description

2.1 Overview of SnoTATOS

A standard SnoTATOS network consists of several autonomous snow measurement stations (hereafter called “nodes”) linked to a central server by a LoRa radio network (Augustin et al., 2016) (Fig. 1). The number of nodes in a network is theoretically unlimited. Each node is equipped with an ultrasonic rangefinder (HRXL-MaxSonar-WR Datasheet, 2024) for monitoring the snow or ice surface position; additional sensors (e.g. temperature sensors) can be added with minimal engineering effort. The network is synchronized such that all nodes simultaneously collect samples and transmit their data back to the server at regular intervals, with random transmission jitter introduced to reduce packet collisions. The sampling frequency is programmable with a typical interval set at four hours. We designed the server to integrate into a SIMB3 ice mass balance buoy (Planck et al., 2019, p.201), thereby taking advantage of the SIMB3’s existing Iridium telemetry. The server can also operate in a freestanding mode, either transmitting data to a landside server using satellite telemetry or storing data locally on an SD card. In the following sections, we will describe the node and server electronics, physical characteristics, radio network, and operating software.

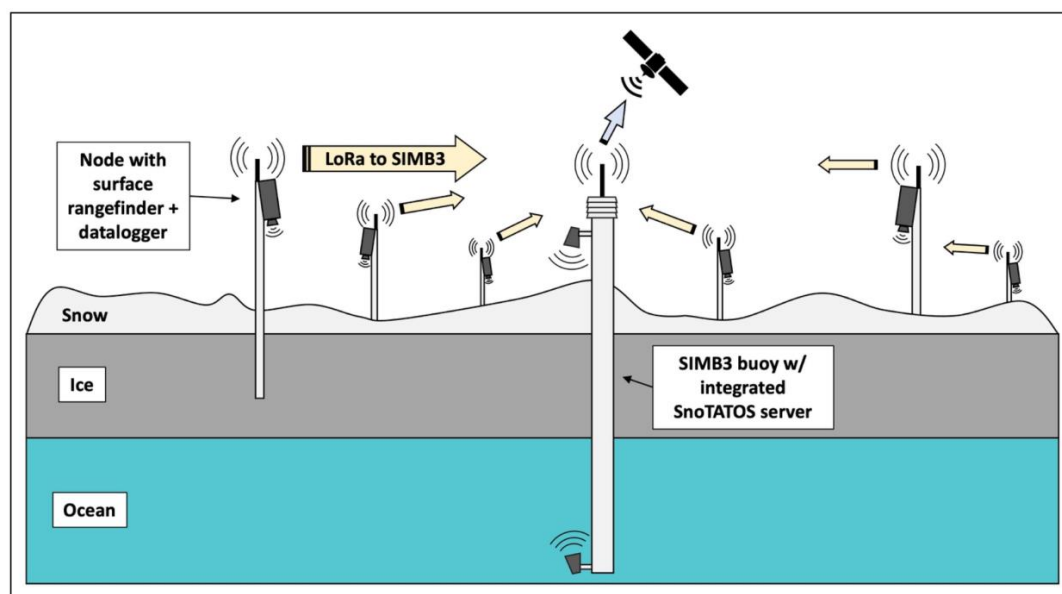


Figure 1: Diagram of a SnoTATOS network. SnoTATOS data is collected at each node in a distributed network, and transferred to the server via radio, either directly (in the hub-and-spoke network model) or via relay through peers (in the mesh network model). The server collects all SnoTATOS data and relays it to the SIMB3, which handles satellite telemetry to a land-side server.

2.2 Node overview and physical characteristics

A SnoTATOS node consists of a MaxBotix 7389-200 ultrasonic surface rangefinder; a microcontroller that manages sampling, datalogging, and radio communications with the server; a nickel-metal hydride (NiMH) battery power-



119 bank; and ancillary electronics. Figure A1 shows a system block diagram. The electronics are housed in a watertight
 120 plastic enclosure (Fig. 2). The rangefinder is mounted directly to a sidewall of the enclosure (Fig. 2). The resulting
 121 sensing unit is 0.08 m x 0.19 m x 0.09 cm and weighs approximately 0.62 kg. The sensing unit is mounted on a 2.44
 122 m x 0.038 m x 0.038 m (8 feet x 1.5 inches x 1.5 inches) wooden stake (Fig. 3). The long edges of the stake are
 123 filleted so that the stake fits snugly in a standard 5 cm (2 inch) diameter ice auger hole. The total weight of an
 124 individual node is approximately 1.80 kg, representing a 96% mass reduction compared to the MetOcean Snow
 125 Buoy. The stake length maximizes the range of observable snow depths while conforming to less-than-truckload
 126 (LTL) and passenger aircraft lower deck freight limitations.
 127

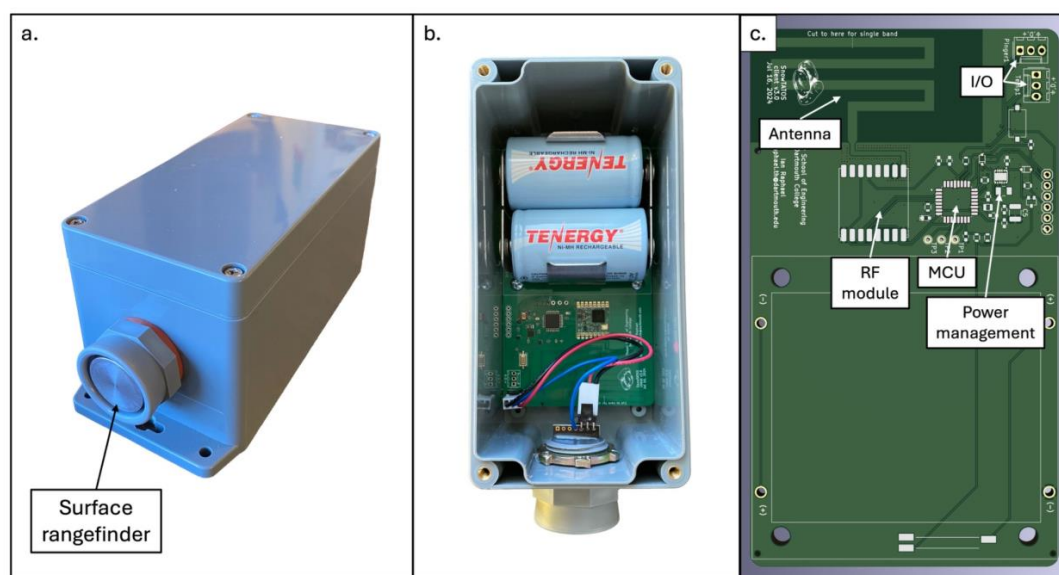


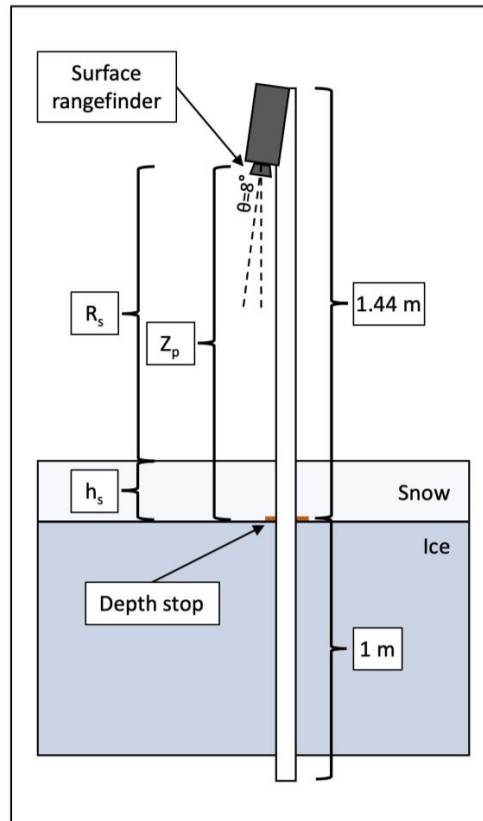
Figure 2: SnoTATOS node sensing unit. Panel (a) is a photograph of a SnoTATOS sensing unit, showing the ABS plastic enclosure and ultrasonic surface rangefinder mounted in the sidewall of the enclosure. Panel (b) is a top down photograph of the sensing unit with lid removed, showing the PCB, rangefinder wiring harness, and battery bank. Panel (c) shows an annotated digital model of a node PCB with key features identified.

135 The Maxbotix ultrasonic rangefinder detection cone has an approximately 40° aperture angle, so spurious
 136 detection of the mounting stake was a significant design concern. We conducted a series of experiments to
 137 determine the optimal sensor look-angle (θ) and standoff of the sensor from the mounting stake. We determined that
 138 a sensor standoff between 5–40 cm and $5^\circ < \theta \leq 35^\circ$ yielded the lowest error rate (between 4–6%). Taking this into
 139 account, we mounted the enclosure on an inclined face of the stake, with $\theta = 8^\circ$ off-nadir and a standoff of 0.05 m.
 140 The rangefinder's projected beam has a roughly circular footprint with a diameter of approximately 0.60 m at typical
 141 ranging distances.

142 During installation, a 5 cm (2 inch) diameter hole is drilled into the ice and the stake is inserted until a
 143 depth stop is at the ice surface, then allowed to freeze in. The initial snow depth and distance between the snow



144 surface and rangefinder are then measured. The rangefinder is thus situated at a known height (Z_p) above the ice
 145 surface, and subsequent snow depth (h_s) can be determined from the range value (R_s) as $h_s = Z_p - R_s$. The
 146 installation process requires ~2 to 10 minutes per node depending on conditions, reducing deployment time by at
 147 least 50% compared to other systems.
 148



149
 150 **Figure 3: Schematic diagram of a SnoTATOS node.** Snow depth (h_s) can be calculated by subtracting the
 151 range reading (R_s) from the rangefinder offset (Z_p). Through experimental measurements we have
 152 determined that the range reading does not vary appreciably for $5^\circ < \theta \leq 35^\circ$, so we do not perform a
 153 trigonometric correction for R_s .

154 2.3 Sensing unit electronics

155 Here, we summarize the selection of key components in the sensing unit and their notable features. The sensing unit
 156 is built around an ATmega4808 AVR microcontroller unit (MCU). The ATmega4808 is an 8-bit reduced instruction
 157 set computer (RISC) (Patterson, 1985) with 48 KB of program memory and 6 KB of RAM. The chip is equipped
 158 with an onboard 10-bit analog-to-digital converter (ADC). We added an external crystal oscillator which drives a
 159 one-second precision system clock, enabling an ultra-low-power standby mode with programmable, alarmed
 160 wakeups. In standby mode, unused peripheral devices are depowered and the MCU sleeps until woken, either by a



161 programmed alarm or by an external interrupt on a general-purpose input/output (GPIO) pin. We selected the
 162 ATmega4808 for its low power consumption, affordability, and programming simplicity. The MCU has an operating
 163 input voltage range of 1.8–5.5 V, however, logic levels and GPIO output voltage are dependent on MCU input
 164 voltage. We added a low-quiescent-current (0.3 μ A) buck-boost converter with a 1.8–5.5 V input voltage range and
 165 a fixed 3.3 V output. This achieves 3.3 V board logic and GPIO output voltage while maintaining flexibility in
 166 power supply voltage.

167 We selected the HopeRF RFM95-915 LoRa module for radio communications. The module operates at 915
 168 MHz with a maximum output power of 20 dBm. The 902–928 MHz frequency range is a license-free Industrial,
 169 Scientific, and Medical (ISM) radio band in the Americas (including the United States, Greenland, Canada, and
 170 South and Central America). The unit is directly exchangeable for the RFM95-868, which operates at 868 MHz,
 171 within the European ISM band (including Russia). These two options ensure system compliance for any Arctic
 172 deployment. Either option is suitable for deployments in international waters. The authors are not aware of any
 173 regulations restricting radio frequency use in Antarctica.

174 Most snow accumulation observation systems use one of several models of the Maxbotix ultrasonic
 175 rangefinder. Maxbotix offers many variations of their basic rangefinder, including snow-specific models. We chose
 176 to use their general-purpose model with the compact horn option (MB7389-200).

177 We use NiMH batteries for the power bank due to their improved cold-weather performance vs. alkaline
 178 batteries (Fetcenko et al., 2007) and less stringent shipping regulations compared to lithium-ion batteries. We used
 179 Tenenergy Power D-cells, rated to 10,000 mAh per cell. Each node has a power bank of 4-cells, arranged in two
 180 parallel pairs of two cells in series. A NiMH battery has a functional voltage of ~ 1.2 V for most of its discharge life
 181 in normal conditions, yielding a nominal supply voltage $V_n = 2.4$ V and a nominal energy capacity of 24 Wh.

182 We designed a custom printed circuit board (PCB) to integrate all components (Fig. 2). The PCB is a two-
 183 layer board designed on a 1.6 mm FR-4 substrate. We designed a monopole PCB trace radio antenna adapted from a
 184 Texas Instruments design (Wallace, 2013).

185 **2.4 Server electronics**

186 The SnoTATOS server uses the same MCU, radio module, and antenna design as the node sensing units. However,
 187 the server is not equipped with sensors. Further, the server is designed to use the SIMB3's 18 V power supply. We
 188 used a Pololu D24V5F5 buck converter to step the 18 V SIMB3 supply down to 5V. We integrated all components
 189 using a custom PCB similar to the node PCB.

190 **2.5 Software**

191 **2.5.1 Node operations**

192 The system software is written in C and C++, using the Arduino hardware abstraction layer (HAL) to interface with
 193 the MCU. The nodes follow the high-level logical flow shown in Fig. 4. When powered on, the node enters the
 194 `Setup` function, where it initializes the memory state, system clock, radio module, and rangefinder, and sets
 195 input/output pin states. The node then moves into the `Loop` function, where it will remain for its lifetime unless it is



196 power-cycled. In `Loop`, the node first samples the rangefinder to obtain a snow depth reading at “wake-up” time.
 197 The node then checks its synchronization state. If it is not synced with the server (as is the case upon initial power-
 198 up), it will wait at this stage until it receives a synchronization broadcast message from the server. After
 199 synchronizing with the server, the node immediately sets an RTC alarm to wake after the appropriate elapsed time
 200 (the sampling interval). The node then reads its battery voltage, packs this and the rangefinder data into a buffer, and
 201 attempts to transmit the buffer to the server. If the transmission is successful and acknowledged by the server, the
 202 node depowers all unnecessary peripherals and enters a deep sleep state until triggered by the RTC alarm. However,
 203 if more than three *unsuccessful/unacknowledged* transmissions occur, the node returns to an unsynced state and
 204 remains awake until resyncing with the server. We implemented this failsafe to prevent network failure in case of
 205 clock drift or other errors resulting in network desynchronization over the course of the deployment.
 206

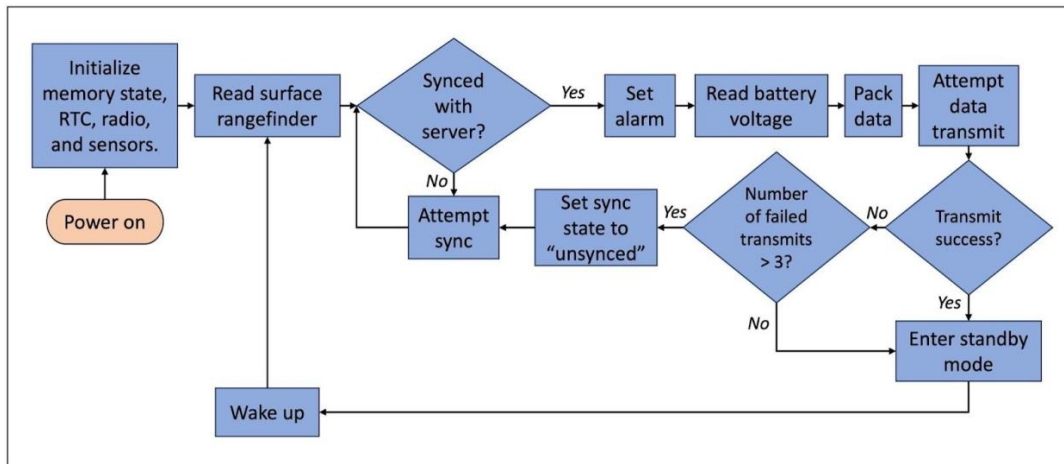


Figure 4: Node flow diagram. The high-level logic of a SnoTATOS node equipped with only a snow surface rangefinder is shown. Additional sensors may be added, which would be read at the same stage as the surface rangefinder.

2.5.2 Radio communications

The radio network is implemented using LoRa, a long-range, low-power radio technology (Augustin et al., 2016). Nominal LoRa radio ranges are up to 10–20 km with clear line of sight. The RFM95 LoRa transceiver manages the physical layer of the Open Systems Interconnection (OSI) network model (Zimmermann, 1980), handling bitwise data encoding, chirp spread spectrum (CSS) modulation, and physical transmission of the data. We used the open source `RadioLib` library (RadioLib - Arduino Reference, 2024) to implement the data link layer atop the physical layer; this handles data-packet to dataframe formatting and the digital interface between the MCU and the RFM95 module.

We developed software to implement the Network, Transport, Session, and Presentation layers of the OSI model. These handle data packet assembly, addressed packet transmission, packet receipt acknowledgment, failed transmission reattempts, packet transmission timeouts, and network collision handling. These are well established



222 general concepts in computer networking, which we implemented in a lightweight C++ library for handling small-
 223 packet data transmission in an addressed, reliable network, with options for either hub-and-spoke or mesh network
 224 topologies. We gave particular attention to robust packet acknowledgement and secure server–node transactions,
 225 since this reduces network airtime for each node (by preventing unnecessary reattempts), in turn reducing potential
 226 node–node collisions. This results in a more reliable network, with less power expended on multiple transmission
 227 reattempts and unnecessary node waketime.

228 The system’s standard network topology is the hub-and-spoke model, where individual nodes (the
 229 “spokes”) communicate directly with the server (the “hub”). This network topology is simple to implement and is
 230 also typically the least power-intensive network model. In this topology, network sizes are limited by the 10–20 km
 231 nominal LoRa range given line-of-sight between node and server. Range and reliability may be impeded in complex
 232 terrain, such as in highly deformed sea ice where direct line-of-sight between the server and each node may not be
 233 possible. We implemented an alternative mesh network topology to address this limitation. We use a naive flooding
 234 protocol (Zahn et al., 2009) with acknowledged packet receipt. A detailed description of the node-side mesh network
 235 implementation is included in Appendix B.

236 2.5.3 Server operations

237 The server follows the high-level logical flow shown in Fig. 5. When powered on, the server enters the `Setup`
 238 function, where it initializes its memory state, system clock, radio module, SIMB3 communications (if integrated
 239 into SIMB3), and sets input/output pin states. The server then moves into the `Loop` function, where it will remain
 240 for its lifetime unless it is power-cycled. In `Loop`, the server first sets a “bedtime” alarm, which will trigger when
 241 the server wake-period ends and it is time for the server to enter standby mode. It then broadcasts a sync message to
 242 the network, and proceeds to loop through two stages until the bedtime alarm triggers.

243 In the first stage, the server checks to see if it has received a message from a node. If it has, it writes the
 244 node’s data to the appropriate location in its memory buffer for later transfer to SIMB3, then returns an ACK
 245 message to the originating node. In the standard hub-and-spoke topology, this is a unicast message directly to the
 246 originating node. A description of the server-side mesh network operations is included in the Appendix B.

247 In the second stage, the server checks to see if the SIMB3 has requested the data from the server. If the
 248 SIMB3 has requested data, the server passes the buffer to the SIMB3, then resets the buffer to default values. Under
 249 normal conditions, all nodes are expected to have transmitted their data to the server before the SIMB3 requests
 250 data. The server will not wait for all nodes to transmit before passing data to the SIMB3; this prevents the server
 251 from hanging if a node fails to transmit or is otherwise inoperable. The server continues checking these two
 252 conditions (“Received data from a node?” and “SIMB3 requested data?”) until it is time to sleep, at which point it
 253 will set an alarm corresponding to the sampling interval and enter standby mode. Despite the server checking the
 254 “SIMB3 requested data?” condition multiple times, the SIMB3 is expected to request data only once during a given
 255 sampling interval. However, due to communications protocols between the SIMB3 and the server, it is beneficial to
 256 respond to any hypothetical SIMB3 request as legitimate, even if the server responds with default buffer values.

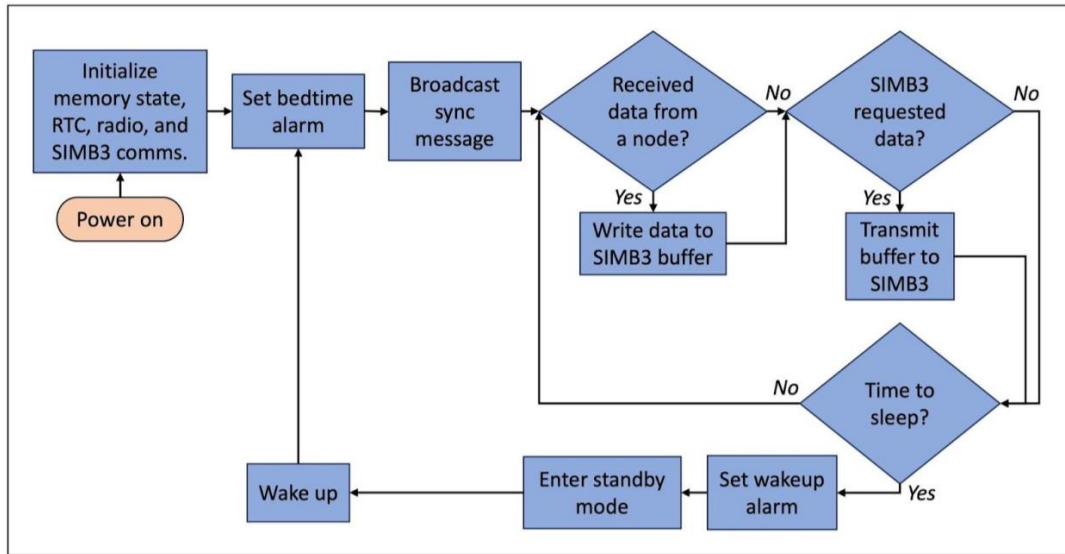


Figure 5: Server flow diagram. The high-level logic of a SnoTATOS server that is integrated into a SIMB3 buoy is shown. The server may also operate in standalone mode. In this case, the SIMB3 communications stages would be eliminated, and an Iridium telemetry stage would be added.

2.6 SIMB3 integration

We used the I2C (Inter-Integrated Circuit) protocol to establish communications and data transfer between the server and the SIMB3. I2C is a serial communication protocol that allows a controller device (in this case, the SIMB3) to query packetized data from an addressed target device (the server). In addition to the standard I2C SDA (serial data) and SCL (serial clock) lines, we added a low-active chip select line (CS). The server and SIMB3 share a common ground line. When the SIMB3 is preparing to retrieve data from the server, it pulls the CS line to ground. The server then prepares the data buffer for the SIMB3 and stands by until the SIMB3 retrieves the data through an I2C request or the transaction has timed out. The SIMB3 adds the retrieved data to its existing Iridium message and transmits it to a land-side server.

2.7 Bench tested power characteristics

We performed laboratory tests to estimate the power characteristics of the sensing unit using the shunt-resistor method and linear circuit analysis. By measuring the voltage drop, V_r , across a resistor with a known and low value, R , one can use Ohm's law ($V_r = IR$) to determine the corresponding circuit current, I . With a known supply voltage, V_s , one can then use the power law ($P = IV$) to determine the circuit power demand, P . We used an oscilloscope to make time-resolved voltage measurements through all phases of the node's operating cycle, then converted these measurements to time-resolved power (Fig. A2).

We tested over a range of supply voltages that the node might typically experience, from $V_s = 1.6$ V (below the buck/boost converter threshold voltage of 1.8 V) to $V_s = 3.3$ V (above the nominal battery bank supply voltage, $V_n = 2.4$ V). We determined that at $V_s = V_n = 2.4$ V, the average circuit current across all phases of the typical 4-



hour duty cycle is 254 μ A, and the average power demand is 610 μ W. With a 24 Wh power bank (two 10,000 mAh D-cell batteries), each node has an estimated endurance of $\sim$ 1,639 days, or $\sim$ 4.5 years (far longer than the lifetime of any sea ice on which it is likely to be installed). However, this does not account for battery efficiency losses due to cold temperatures, nor atypical conditions such as radio transmission retries.

We conducted similar power tests for the server, finding an average current draw of 1.03 mA at $V_s = 18$ V, yielding an average power demand of 18.54 mW. This is approximately 30% of the SIMB3's power budget (Planck, 2021), yielding an estimated endurance of approximately 560 days, or slightly more than 1.5 years. Operating in standalone mode, the power supply can be reduced to $V_s = 3.4$ V, increasing efficiency and reducing average power demand to approximately 2,500 μ W. This produces a nominal endurance of 4.4 years with a 96 Wh battery bank (eight 10,000 mAh D-cell batteries).

3 Case study, Lincoln Sea, April 2024–January 2025

We deployed four SnoTATOS networks in the Lincoln Sea in late April and early May, 2024, during the NASA ARCSIX project (McNamee, 2024) (Fig. 6). Each network consisted of ten nodes and a server integrated into a SIMB3 buoy. We deployed the networks in multiyear ice just before the onset of surface melt. We placed the nodes randomly between 25 and 200 m from each buoy, with clear line-of-sight to the buoy. We measured initial snow depth at each node, and ice thickness and snow depth at each SIMB3. As of 3 January, 2025, three networks (2024L, 2024O, and 2024R) were no longer reporting. The failure of 2024O is consistent with an I2C communications failure between the server and SIMB3 MCU. The steady attrition of nodes and their location in a shear band suggest that networks 2024L and 2024R were destroyed by ice dynamics. 2024P continues to report, with four nodes surviving; the rest were likely destroyed by ice dynamics. We will now describe the general results from these installations. We include data from network 2024O in summary visualizations for completeness, however, we do not consider these data in our analysis.

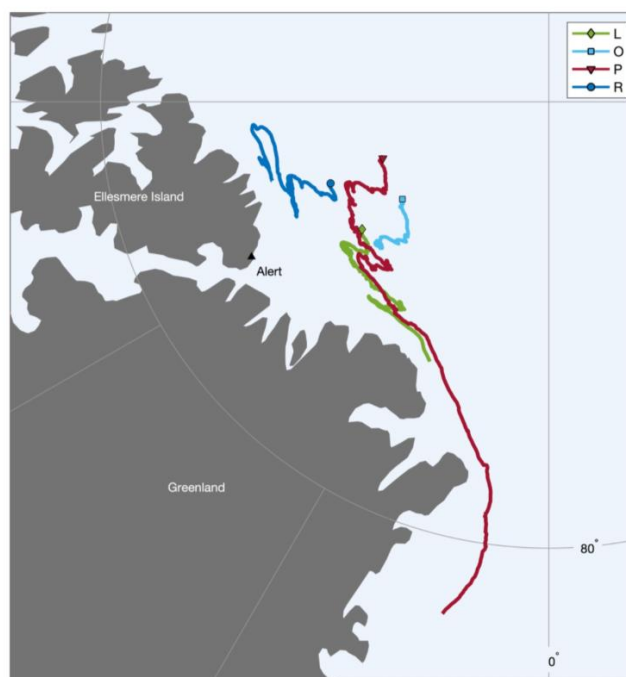


Figure 6: Drift tracks of four SnoTATOS networks deployed in the Lincoln Sea in April and May, 2024.

The mean installation conditions for the four networks are given in Table 2. The time series of snow depth and surface melt for all nodes at each network is shown in Fig. 7. We observed between 0.05 and 0.10 m of snow accumulation at each network between installation in late April and late May. Surface melt in the region began in late May, after which snow depth decreased steadily at all nodes, reaching 0 m between 12 June and 8 July. On average, snow persisted longest at network P, which also had the deepest initial snow cover (Fig. 8). Ice surface melt then commenced, continuing until early August (Fig. 9).

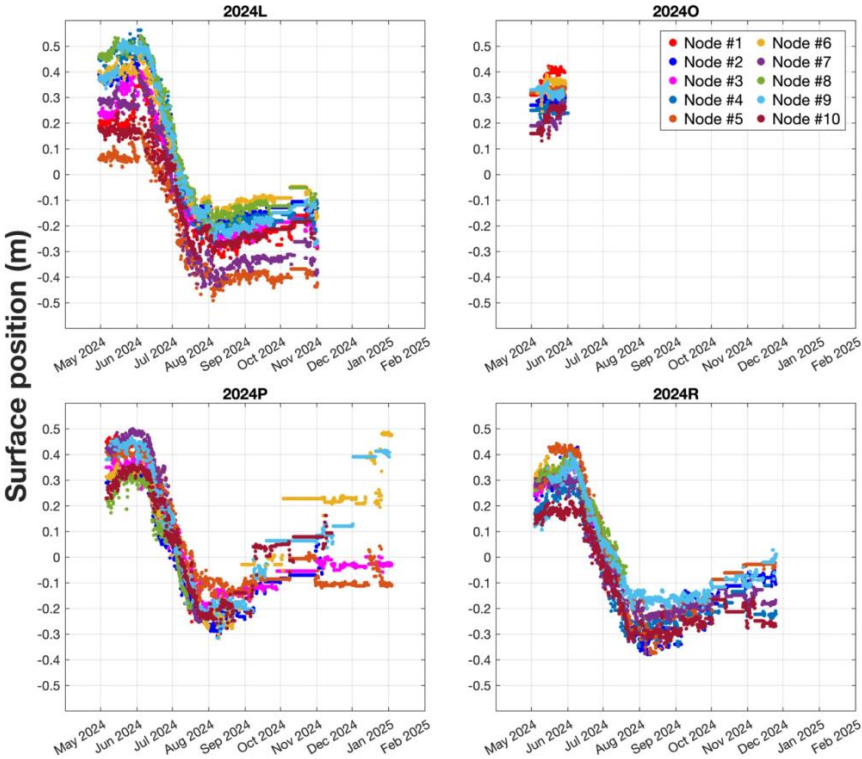


Figure 7: Time series scatterplots of surface position at four SnoTATOS networks. Time series data of surface position is shown for each node at the four ARCSIX SnoTATOS networks. “Surface position” is the position of the surface sensed by the ultrasonic rangefinder (air–snow or air–ice interface) relative to the initial snow–ice interface (surface position 0). Each node initially demonstrates a positive surface position value, indicating a positive snow depth. Snow depth increases until around early June at all nodes. Snow melt then begins around mid-June, continuing at each node until the surface position reaches 0, indicating complete snow melt and the onset of ice surface melt. Ice surface melt continues until early August. From that point on, any positive change in surface position indicates new snow accumulation.

The results show substantial variability in initial snow depth, magnitude and timing of surface melt, and snow accumulation. Mean initial snow depths varied between networks by up to 26% (0.23 m at R vs. 0.31 m at L and P). Within the networks, initial snow depth variability ranged from 26% at network R to 42% at network L.

Table 2: ARCSIX summary conditions

Network name	Duration	Initial ice thickness (m)	Mean initial snow depth ± standard deviation (m)	Mean ice surface melt (m)	Mean combined ice equivalent surface melt (m)	Site description



2024L	29 April–1 November, 2024	1.96	0.31 ± 0.13	0.23 ± 0.11	0.33 ± 0.08	Level multiyear ice (MYI) floe. Potential hummocks which snow has filled, rendering a smooth surface.
2024O	5 May–1 June, 2024	1.72	0.29 ± 0.09	~	~	Large MYI or SYI pan with relatively level surface. May have experienced little surface melt.
2024P	6 May, 2024–3 January, 2025 ^a	2.16	0.31 ± 0.10	0.20 ± 0.06	0.31 ± 0.05	Hummocky MYI floe in ridged area. Floe too thick to drill in some places (> 4 m).
2024R	4 May–25 November, 2024	2.40	0.23 ± 0.06	0.23 ± 0.11	0.30 ± 0.11	Hummocky MYI floe.

327 ^aFour nodes from network P were still reporting as of 3 January, 2025.

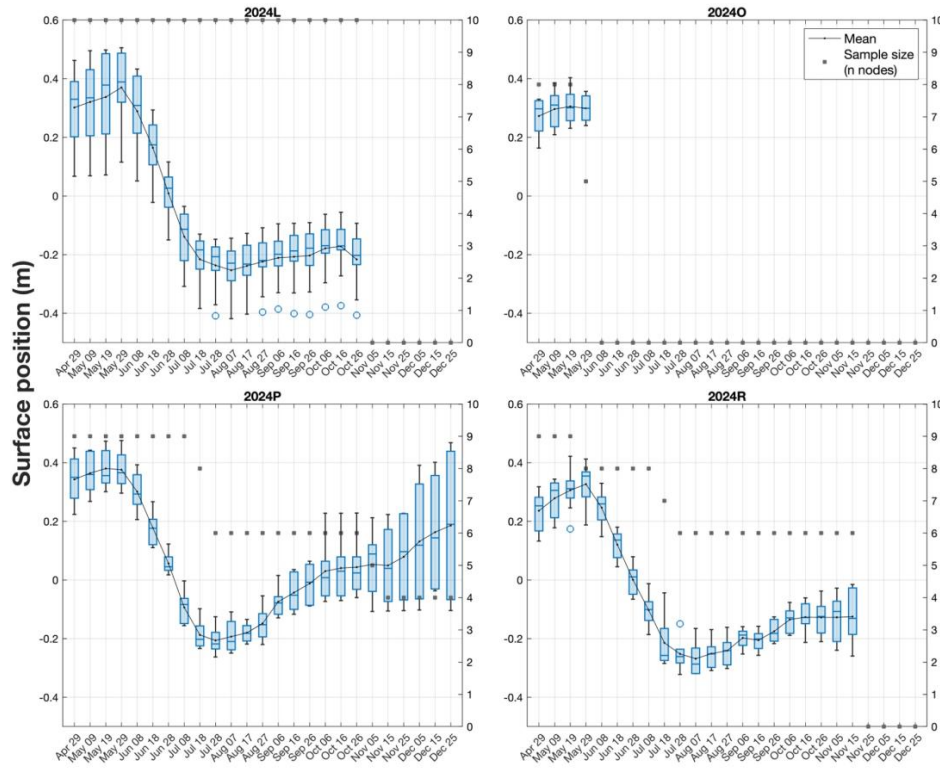


Figure 8: Box-and-whisker time series of surface position at four SnoTATOS networks. Each box-and-whisker shows the spatial distribution of the ten-day-average surface position for a given network. The lower and upper edge of each box show the first and third quartiles, the bar in the box shows the median, and the whiskers indicate the minimum and maximum non-outlier values. Outliers are shown as open blue circles, and are defined as more than 1.5 times the interquartile range lesser or greater than the first and third quartiles, respectively. The small, dotted markers and interpolated line show the spatial mean for each ten-day bin. The square, grey markers indicate the sample size (number of nodes) included in the distribution at each time step, with a separate Y-axis shown on the right of each pane.

We computed the ice equivalent snow melt (snow–ice equivalent; SIE) using Eq. 1:

$$H_{\text{sie}} = \rho_s / \rho_i * H_{\text{snow}}, \quad (1)$$

where ρ_i is the density of sea ice (0.9 g cm^{-3} , Perovich et al., 2003), ρ_s is the density of snow (0.3 g cm^{-3} , Sturm et al., 2002), H_{snow} is the observed snow melt, and H_{sie} is the SIE melt. We combined H_{sie} with the observed ice surface melt to determine the total ice equivalent surface melt for each station. Average ice-equivalent melt was 0.33 m at L, 0.31 m at P and 0.30 m at R, indicating very similar net surface melt across the region. Net ice-only surface melts were also quite similar with 0.23 m at L, 0.20 m at P and 0.23 m at R. The network with the deepest initial snow depth (P) also had the smallest ice melt, presumably because deeper snow increased albedo and physically



protected the ice, delaying surface melt onset (Fig. 9). Compared to variability between regions or years within the Arctic (e.g., Perovich (2014) or Planck (2022)), however, these variations in mean behavior are quite small.

A key note here is that variability in surface melt (both ice surface melt and combined equivalent melt) was relatively low *between* networks, the largest variability being a 13% difference in ice surface melt between R and P (R higher), and a 9% difference in combined equivalent melt between L and R (L higher). However, melt variability *within* networks was higher, at 31–46% for ice surface melt, and 15–38% for combined equivalent melt. This suggests that networks of this size (on the order of ten nodes) may be adequate for accurately capturing the local variability of surface melt.

Snow accumulation began soon after the conclusion of surface melt, in early to mid August. Network L saw 0.08 m snow accumulation by 16 October, then a decrease to 0.04 m snow depth by 26 October, when the network ceased reporting. The air temperature record suggests that the decrease was caused by wind removal rather than surface melt. Network R saw 0.14 m of new snow by 15 November, when it also ceased returning data. As of 3 January, 2025, network P has seen a mean snow accumulation of 0.39 m and a range of 0.12–0.80 m.

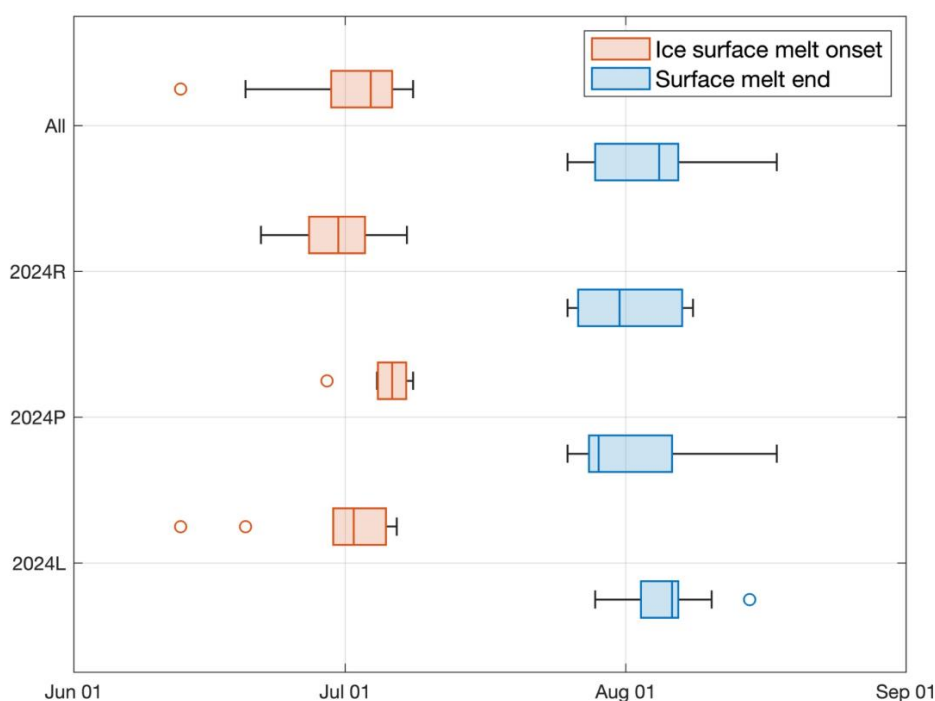


Figure 9: Box-and-whisker plot showing the distribution of ice surface melt onset and surface melt end dates. Ice surface melt onset is shown in orange, and surface melt end is shown in blue for the nodes within each network. Network 2024O is excluded since the network stopped reporting before surface melt onset. “All” shows the combined distribution of all active nodes in 2024R, 2024P, and 2024L.



365 Despite relatively small geographical separation, snow accumulation varied significantly between
 366 networks. We compare the snow accumulation at networks L, P, and R during the period from freezeup around early
 367 August, through 26 October, when network L failed. The networks were deployed within 113 km of each other, and
 368 by 26 October, networks L and P were still within 98 km of each other. Meanwhile, network R drifted to 306 km
 369 from network L, and 398 km from network P. During this period, 0.04 m of snow accumulated at network L, 0.25 m
 370 of snow accumulated at network P, and 0.14 m of snow accumulated at network R. This indicates a roughly 84%
 371 difference in snow accumulation between networks L and P in that period, despite their relative proximity.

372 Further, the variability of snow accumulation within each network is evident in the widening box-and-
 373 whisker distributions in Fig. 8. This variability increases as accumulation continues through the winter at network R
 374 and, in particular, at network P. The attrition of nodes at network P during this period prompted us to consider
 375 whether the increase in the interquartile range (IQR) is an artifact of the declining sampling size or a real signal.
 376 Because the increase in IQR occurs primarily during a period when the sample size is constant ($n = 4$), we suggest
 377 that the increase in the IQR is a real signal that is amplified by the small sample size.

378 Finally, the range of snow depth on 26 October was approximately equal to the range at time of installation
 379 for network L, slightly higher at network R, and substantially higher at network P. This is potentially the result of
 380 both interannual as well as spatial variability (due to ice advection). As many studies have confirmed, snow depth on
 381 sea ice is highly variable; this case study suggests that SnoTATOS can observe that variability, though the number
 382 of nodes needed to fully constrain it is unclear. In order to facilitate efficient use of resources and enable accurate,
 383 error-constrained data collection, we recommend further research into the number and arrangement of sampling
 384 points needed to measure the spatial and temporal variability of the snow cover on Arctic sea ice.

385 **4 Conclusions**

386 This work documents the development, testing, and a case study deployment of SnoTATOS, a new autonomous
 387 system for collecting distributed, in situ snow depth measurements on sea ice. Responding to community calls for
 388 the widespread snow depth measurements that are needed to understand the changing Arctic sea ice system, and
 389 recognizing the lack of suitable, affordable tools, we set out to create a low-cost, easy-to-use system to fill the gap.
 390 The resulting radio-networked snow depth measurement stations are only 5% of the cost and 7% of the weight of
 391 existing systems, with identical measurement functionality. A case study deployment of four SnoTATOS networks
 392 in the Lincoln Sea in April 2024 1) validates the functionality of SnoTATOS, including the system's ease of
 393 transport, rapid installation, and collection of high-quality, in situ snow depth and surface melt measurements, 2)
 394 demonstrates the substantial spatial and temporal variability in snow accumulation and ice surface melt at the floe
 395 scale, and 3) suggests that even relatively small SnoTATOS networks (on the order of 10 nodes) are capable of
 396 capturing that variability. Based on the last finding, we recommend focused studies to determine the number and
 397 placement of autonomous sampling stations needed to accurately capture snow accumulation, depth, and surface
 398 melt variability.

399 Of the forty nodes installed in April 2024, four were still reporting by the beginning of January 2025. The
 400 character of the failures suggests most (26) failed by physical damage. High attrition rates resulting from ice



dynamics and wildlife are a reality for autonomous instruments installed on Arctic sea ice. This, in addition to a need for more comprehensive observations of Arctic variability, is a strong motivation to transition towards the use of large, redundant networks of lightweight, inexpensive sensing stations, an approach also recommended by Lee et al. (2022) and Webster et al. (2022). In its current permutation, SnoTATOS can accommodate additional sensors such as barometric pressure or temperature sensors. We plan to build on this technology to create a modular “polar Internet of Things” sensing system capable of hosting plug-and-play sensors, making radio-networked distributed sensing more accessible for the polar regions. We anticipate that SnoTATOS will also prove useful for monitoring snow accumulation and ice surface melt in alpine, glacier, and tundra environments.

Appendix A: sensing unit components and power test

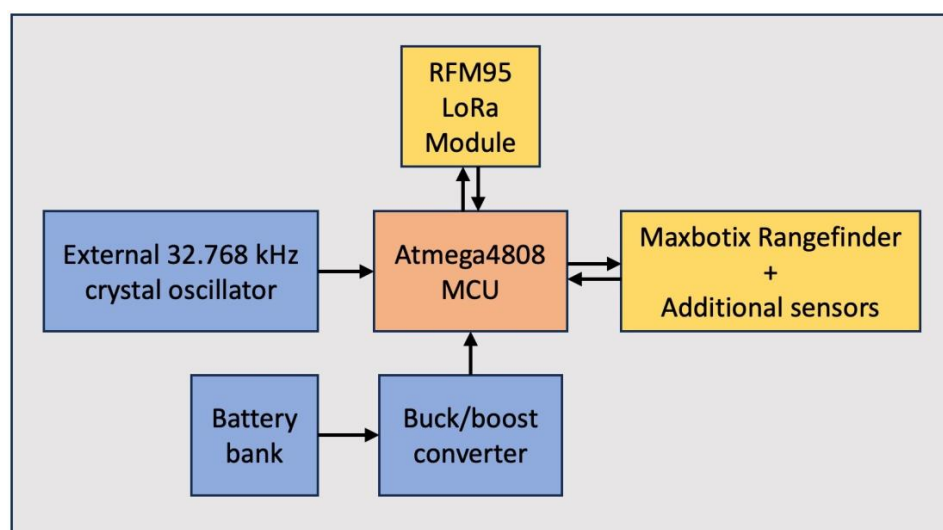


Figure A1: Schematic block diagram of SnoTATOS sensing unit electronics. The figure shows the major electronics components of the SnoTATOS sensing unit. Blue blocks indicate external power and clock components for the MCU, which is shown in orange. Yellow blocks indicate I/O modules that the MCU interacts with for collecting and transmitting data.

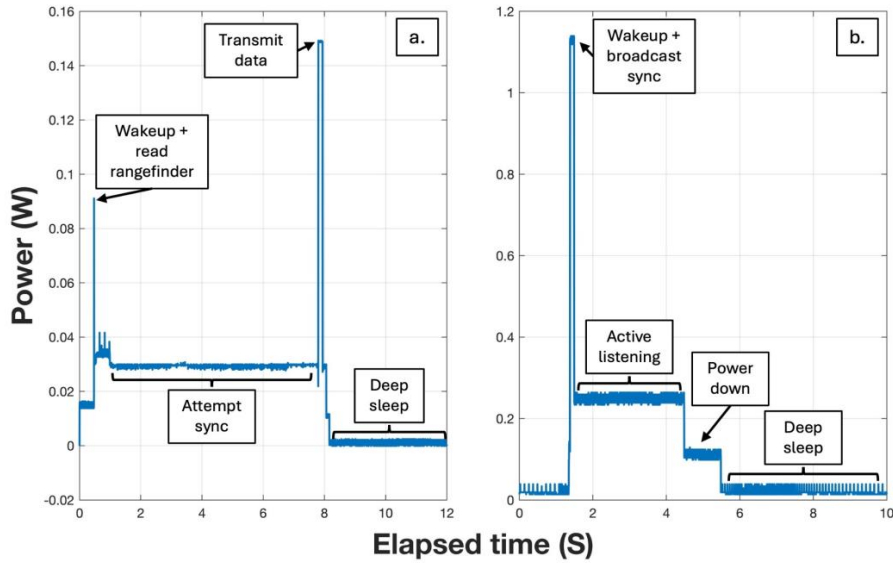


Figure A2: Time-resolved power demand for the node and server during pre-deployment bench testing. Panel (a.) shows the power demand during the various stages of the duty cycle for a node with $V_s = 2.4$ V. Panel (b.) shows the power demand during the various stages of the duty cycle for the server with $V_s = 18$ V.

Appendix B: mesh network implementation

The node-side logical flow for mesh network packet handling is shown in Fig. B1. During a data transmission attempt, a node will first attempt to unicast the message directly to the server. If an acknowledgment (ACK) is received, then the message has been transmitted successfully and the attempt ends. If an ACK is not received within a timeout period, the node then reattempts transmission, either repeating a unicast if the last ACK'd message was *not* a broadcast, or progressing directly to broadcast attempts if the node knows that the last message it successfully transmitted to the server was a broadcast message. If an ACK is not received within the allotted number of reattempts, or the timeout period expires, then the transmission attempt has failed. The attempt ends, and it is counted towards the number of allowable failed transmissions before the node is prompted to resync with the server.

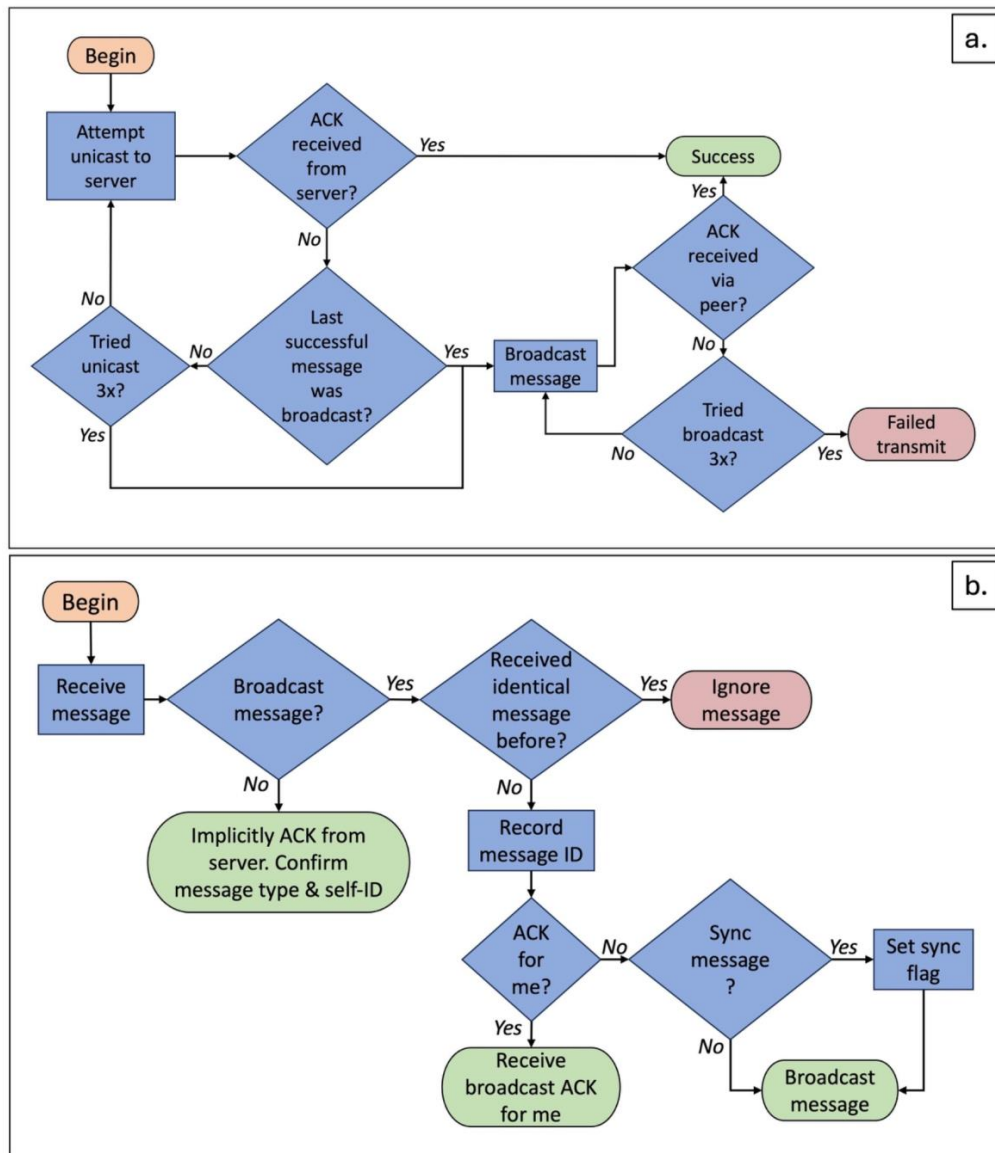


Figure B1: Logical flow diagram for node-side mesh network packet handling. Panel (a.) shows the logical flow for handling a mesh network message transmission attempt. Panel (b.) shows the logical flow for handling a received mesh network message.

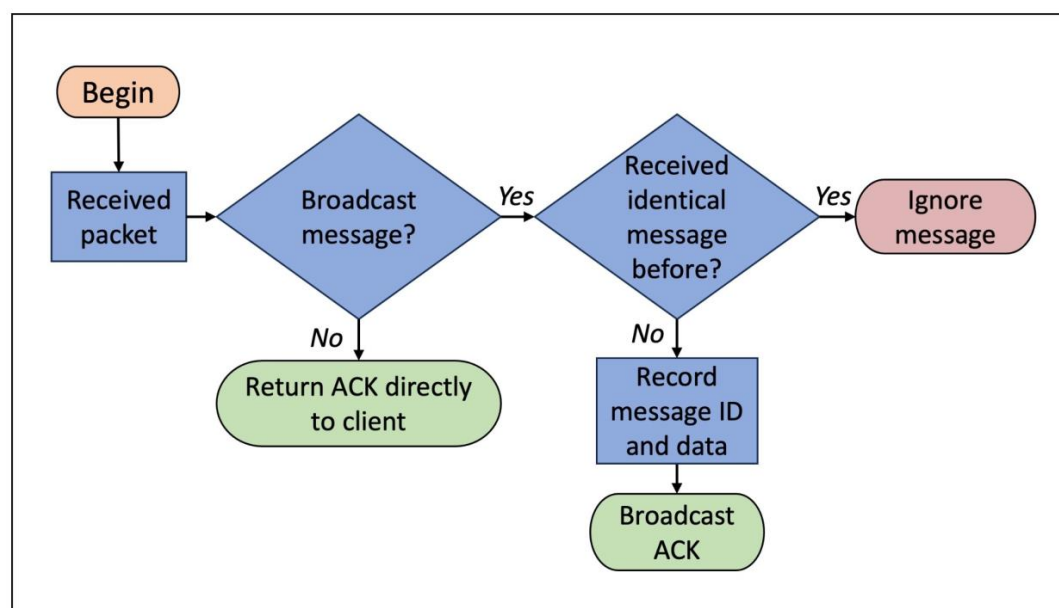
In the mesh network model, whenever a node receives a message, it first checks whether it is a broadcast message. If it is not a broadcast message, it is implicitly a unicast ACK message from the server. The node confirms that it is an ACK message and that it is addressed to itself, and if so, records the acknowledgement. If it is a broadcast message (either from the server or via a peer), and it is not a message that it has already received, the node will first note the message ID, then process the message contents. If it is addressed to itself, it is implicitly a



439 broadcast ACK message originating from the server (likely received via a peer). If the node confirms that it is an
 440 ACK message with its own address, it records the acknowledgement. If it is not addressed to itself, it could be a data
 441 message originating from a peer and addressed to the server; an ACK message originating from the server and
 442 addressed to a peer, or a sync message originating from the server and addressed to the entire network. In the first
 443 two cases, the node rebroadcasts the message without further processing. In the latter (sync) case, the node first sets
 444 its synchronization flag, then rebroadcasts the message to the network.

445 In a mesh topology network, the server follows the logical flow shown in Fig. B2. First, the server checks
 446 to see if the received message is a broadcast or unicast message. If it is unicast, the server returns a unicast ACK.
 447 If it is a broadcast message, and if it is not a repeat message, the server broadcasts an ACK message addressed to the
 448 originating node.

449



450

451 **Figure B2: Logical flow diagram for server-side mesh network packet handling.** The logical flow for
 452 receiving a mesh network message and returning an acknowledgement is shown.

453 Data accessibility

454 SnoTATOS data from the Lincoln Sea case study have been submitted for archive at the Arctic Data Center and will
 455 be available upon archive publication at: doi:10.18739/A2RX93G1Q

456 Author Contributions

457 IAR, DKP, and CMP conceived the study. IAR designed and built the system under study with supervision and
 458 feedback from DKP, CMP, and RLH. CMP deployed the sensors. IAR drafted the manuscript. All authors
 459 contributed to editing and review. All authors approved the manuscript for submission.



460 **Competing Interests**

461 The authors declare that they have no conflict of interest.

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