Revolutionizing observations and predictability of Arctic system dynamics through next-generation dense, heterogeneous and intelligent wireless sensor networks with embedded AI

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Focal Areas

- Data acquisition and assimilation revolutionized by next-generation dense, heterogeneous, and intelligent wireless sensor networks (WSN) with embedded AI
- Insight gleaned from complex data using AI

Science Challenge

The Arctic region is a complex and dynamic system, where changes in temperature and partitioning between water in solid, liquid and vapor phase are fundamentally reshaping hydro-biogeochemical fluxes from the bedrock to the atmosphere. The increasing temperature and frequency of extreme heat, precipitation and fire events (Wang et al., 2017; Meredith et al., 2019) have critical consequences for the Arctic ecosystems and people, as well as for the global climate system. Although many observational and remote sensing activities have been on-going, detailed ecosystem processes – particularly related to controls on and impacts of permafrost thaw – are difficult to detect or measure. To improve the understanding and prediction of these extreme events and their consequences, we need a revolution in the way we collect ground-based observations from hillslope to pan-Arctic scales and couple them with satellite imagery and models to deliver rich, actionable, and scale-appropriate data.

Rationale

Next-generation intelligent wireless sensor networks (WSN) (Serpen et al., 2013; Beckman et al., 2016; Wielandt et al., 2021) – providing an unprecedented amount of heterogeneous, dense and valuable measurements at low cost – have the potential to revolutionize the observation and predictability of Earth systems once adequately integrated with advanced data analytics (incl., AI/ML), existing observational networks, remote sensing (RS) data, and multi-physics models. This revolution is critical because the current sparsity in observations limits the multi-scale sampling of hydrological, thermal, and biogeochemical gradients needed to generate highly-resolved data products, capture extreme events, improve model process representation and parameterization, and deliver rich, actionable, and scale-appropriate information.

AI will be critical in deploying, operating and managing the next-generation WSNs. The deployment, which will involve thousands to tens of thousands of devices, will need to be designed intelligently, guided by the potential value of measurements and locations for complementing RS data and improving

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multi-physics models. In addition, the devices in the WSNs will require AI/ML capabilities on edge for acquiring, selecting, compressing and transmitting measurements to reduce maintenance, power-requirement and footprint to the strict minimum. The management of an ultra-large number of measurements will need automated procedures for data assessment, processing, and management to produce high value and FAIR (Findable, Accessible, Interoperable, and Reusable) products (Wilkinson et al., 2016; Fagnan et al., 2019).

A major barrier in understanding and predicting complex processes, beyond the acquisition of observations at a resolution, dimensionality and relevance much higher than is currently possible, is to perform analysis and fusion of time-series from various data sources, estimate system characteristics indirectly (Tran et al., 2017), detect changes in trajectories, quantify inter-dependencies (Dafflon et al., 2017), and improve model parameterization, prediction and validation. AI will be critical to advance current analytical methods that lack automation, wide applicability, learning capacity, and flexibility to merge various data sources and extract actionable information.

In the Arctic environment, the next-generation AI-guided WSNs coupled with RS data will revolutionize the multi-scale observations of changes in thermal-hydrology (Bennett and Walsh, 2015; Bennett et al., 2015), biogeochemical fluxes, slope stability and susceptibility of infrastructure (Instanes et al., 2016), with sufficient spatiotemporal resolution to capture their response to the warming Arctic and extreme events (e.g., wildfire, atmospheric rivers, heat waves, thick snowpack, and pest infestations). In particular, the spatiotemporally resolved products will provide actionable information in near real-time for detection and assessment of extreme events. These developments will improve the system predictability, resource management, natural hazard risk mitigation, and bring new light in poorly understood processes such as for example the controls on and implication of changing landscape morphology, the impact of extreme concurrent events on hydro-biogeochemical fluxes, and the controls on and impact of changes in subsurface hydraulic parameters on the water and carbon cycle.

Narrative

The next-generation dense, heterogeneous, and intelligent WSNs will have AI embedded in the edge and fog layer and in the connected High-Performance Computing (HPC) resources. The boundless distributed computational resources in the network will unleash an ability to acquire and manage observations at thousands to tens of thousands of locations, while minimizing the total cost and maximizing the value of the collected information based on several factors including model and data knowledge and need. Advances in 5G/6G and satellite communication networks will ease data transmission, while novel techniques will be needed to minimize further the WSN nodes’ energy consumption and footprint. The implementation of intelligence in the network edge and fog layer will enable event and model driven data acquisition frequency, extraction of relevant information, advanced data compression, and thus the reduction of power consumption for data acquisition and transfer.

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The density and heterogeneity of next-generation WSNs will be strongly influenced by the data value and the total cost of the network (incl., sensor, deployment, maintenance, management, and data curation). To this end, AI will be critical to optimize the WSN's "Vs" (velocity, volume, variety, value, and veracity) and balance them with regard to the total data cost. The optimization of data value will be enabled by AI enhanced measurements, increasing sensing capabilities and improving information processing under variable conditions. In the reduction of data cost, the role of AI will be in assessing the information contained in available data (incl., WSN, RS) and model interactions to enable adaptive node deployment, adaptive sensing based on a sensor's "Vs", and compression based on data characteristics.

The ultra large number of heterogenous sensor nodes in dense WSNs and their coupling to RS data will allow novel applications of ML/AI techniques in a "Big Data" context for scientific discovery, detection of changes in trajectories or response to disturbance, model parameter estimation, and quantification of processes and their interdependences. The hybridization of AI, models, and statistical formulation (e.g., Balasis et al., 2013; Jiang and Kumar, 2019) will be critical to perform fusion of time-series data from heterogeneous sources, and mine and quantify complex spatial and temporal interdependencies in unprecedented multi-dimensional datasets. Quantifying processes and their controls at hillslope to possibly pan-Arctic scale, will serve to infer new highly resolved data products that will improve model parameterization and validation, as well as provide actionable information in a near real-time manner. Highly resolved products obtained through coupling WSN, RS and model data in the Arctic could include probabilistic maps of surface deformation and related ice-content, snow water equivalent, and changes in soil water/carbon/nitrogen content.

An additional opportunity will be to connect the WSN's AI-enabled infrastructure to multi-scale and multi-physics model simulations in order to revolutionize how WSN and RS data and models interact in the MODEX framework. For example, ML/AI techniques will enable the identification of high-dimensional relationships in the data and in the models, which can identify key knowledge, accuracy or resolution gaps. The identified gaps will guide improvements in the process-based model representation or parameterization. The AI-based analysis of models, real-time WSN data and near-real time satellite data will accelerate the data collection to science discovery loop.

The 10-year vision is a multi-scale AI-guided WSN infrastructure that will measure and process high-quality observational data and integrate them with RS, intensive site and model data to infer products with unprecedented resolution and value. The spatiotemporally resolved products will provide actionable information in near real-time. The future development of AI-guided WSNs and integration with RS and model data is aimed at being applicable to a wide range of environments besides the Arctic system. Open-source hardware and software, tight connections to data repository platforms and standards, as well as the development of a next-generation WSN community, will ensure that the produced datasets follow the FAIR principles.

Suggested Partners

This vision can be achieved by building a next-generation WSN community to accelerate developments initiated by various groups and projects. Partners could include team members of projects that could benefit from next-generation WSNs (e.g., NGEEs, SFA projects, Ameriflux, E3SM), as well as of DOE relevant facilities (e.g., ESnet, ARM).

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