



Hypersurface Observation Network (Hyperon) — What it is and why we need it

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Surface-atmosphere interface observation

The surface-atmosphere interface (SAI) remains a primary source of uncertainty in Earth system models due to planetary feedbacks between living and climate systems hypothesized by Lovelock, who upscaled the thermodynamical view of life of Lotka and Schrödinger. Existing observations of the SAI, proximal and remote, fail to capture these and other dynamics critical to understanding and simulating the Earth system. Relevant dynamics extend from the biogeochemical and energetic exchanges long the focus of land modeling to the physiological, ecological, and evolutionary processes of life that give rise to these dynamics through a combination of information, graph, game, automata, and optimization theory.

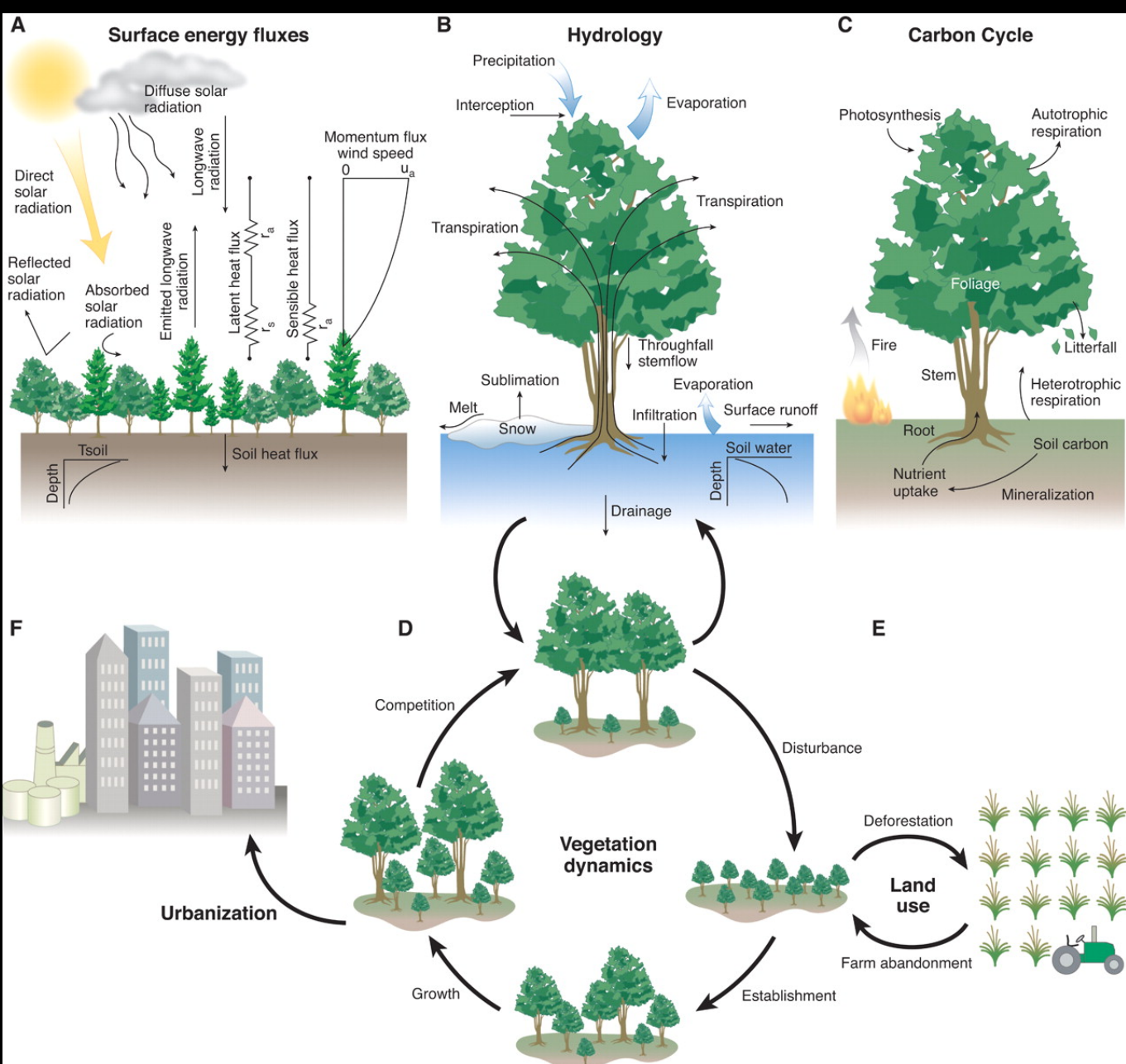


Figure 1. Forest ecosystem SAI dynamics from Bonan (2008).

Ecological and evolutionary processes include tropism, competition, cooperation, reproduction, migration, adaption, and selection. These have led to the development of language and intelligence that underlie a 100 ky human transformation of the Earth system. These observation and knowledge gaps carry implications for our ability to understand and predict planetary systems here and elsewhere.

Surface-atmosphere interface simulation

Challenges in simulating the SAI extend beyond coupling fine-scale atmosphere models to land-surface and ocean models. Existing models are capable only of coarse-scale dynamics with few spatial interactions, altogether lacking representation of the processes of life. As theorized by Lovelock, these processes have been shown to be critical to the reliable simulation of the climate system, explaining primary uncertainties. Furthermore, the growing imperative of biological conservation necessitates an expanded role of ecology and evolution in models.

Hyperon: a robotic network for inferential hypersensing

Hyperon is a common set of specifications for SAI observation platforms suited to different surface domains and budgetary constraints. Each is based on two fundamental components: (1) a robotic motion system; (2) a Modular Robotic Instrument Pod or MRIP. Hyperon is intended to provide detailed 4-D observations with spectral and angular information across a variety of domains, using little more than commodity image sensors in the most constrained case.

While precision sensing systems are needed for model training and/or validation in new domains, Hyperon minimizes cost, volume, weight, and energy by relying on low-cost sensors and edge inference for inferential sensing. Preference is given to commodity image and LiDAR sensors designed for autonomous systems (e.g., drones, self-driving cars) for their ideal properties in this regard.

Robotic motion system

These can range from rotating booms to tower- or crane-based trolleys on cables or rails to tethered drones. For trolley systems, a quad-pole configuration allows for XY axis motion similar to a 3-D printer for high-repeat scanning.

Modular Robotic Instrument Pod (MRIP)

The MRIP concept includes an embedded system for edge acceleration and 5G communication, as well as commodity image and IMU-GPS sensors parallel to optional hyperspectral VIS-NIR, microwave, LiDAR, and RaDAR instrument modules. Optional subsystems include (1) a commodity gimbal system to correct for wind disturbances or to enable angular measurements and (2) a winch system for lowering the pod for maintenance when using tension structures.

Neural, symbolic, and neurosymbolic models

Hyperon is intended to facilitate human-like object-based scene understanding with intuitive physics as well as superhuman perception leveraging the spatial, angular, spectral, and temporal correlation structure of observations.

1. **Object detection, panoptic segmentation, and tracking** for image and point-cloud data to monitor ecological processes such as 4-D vegetation dynamics. These allow for learning object-based ecological interactions.
2. **Hyperspectral reconstruction** to resolve latent biogeochemical dynamics.
3. **Geometric, angular, and radiative reconstruction** per NeRF to monitor radiative transfer for energetic processes and remote sensing fidelity.
4. **Neurosymbolic model discovery** to learn biogeochemical, energetic, physiological, and ecological processes models from data.
5. **Instrument models** to learn models of and between sensor modalities.

Existing global observation networks

Currently, there are no general SAI observation systems or global networks. Existing proximal networks, including FluxNet, SpecNet, and PhenoCam in the terrestrial domain, remain focused on narrow sensing modalities. A unifying vision, cost, and complexity are three key limiting factors contributing to this situation.

Ubiquitous mobile sensing and inference

Meanwhile, autonomous systems have attracted accelerated investment following the deep learning breakthrough. Related advances in edge accelerators and small low-cost sensors, originally intended for smartphones, are enabling these and other breakthroughs in mobile robotics. Leading the realization of intelligent real-world robotics are makers of self-driving cars and small UAS systems. Common among these systems is a reliance on deep learning, a recent branch of artificial intelligence (AI) focusing on deep neural networks, and related edge accelerators for processing parallel data streams from commodity sensors.

Intelligent robotic systems for hypersensing

While seemingly unrelated, we argue that these technologies are critical to realizing so-called *flux towers in the sky*. This is because the same approach can allow us to improve the fidelity of surface observations with air- and space-borne measurements, overcoming the shortcomings of existing proximal observations related to joint spatial, angular, temporal, and radiometric surface (hypersurface) information. By combining robotic motion with inferential sensing, we argue for a global network of intelligent observation systems to recover system information at minimal cost and packaging constraints. This system would rely on cloud-based data storage, autolabeling, and model training per a standard MLOps workflow, using 5G networks to pull observations and push model updates to edge devices.

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