



Artificial Intelligence for Exploring Climate Change Mitigation Strategies and Advancing Earth System Prediction

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Fragile Earth 2022

AI for climate mitigation,
adaptation, and
environmental justice

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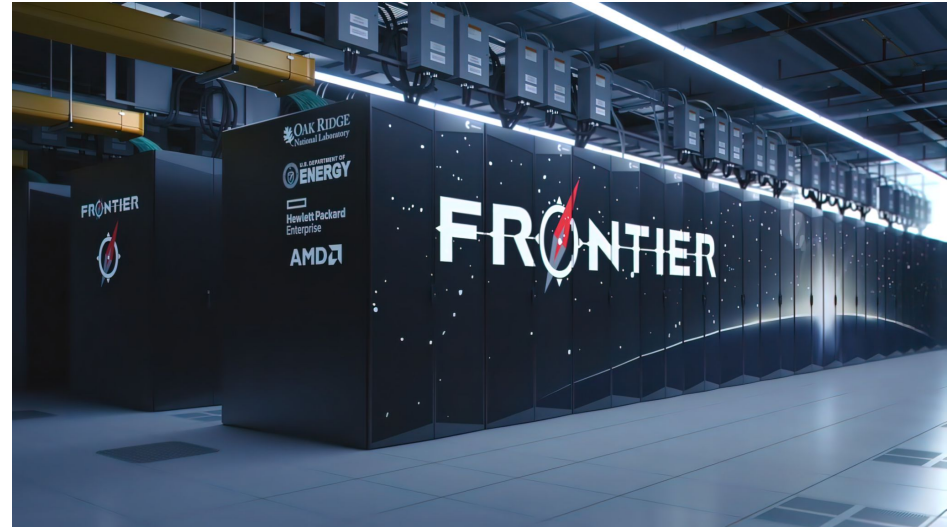
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Introduction

- Observations of the Earth system are increasing in spatial resolution and temporal frequency, and will grow exponentially over the next 5–10 years
- With Exascale computing, simulation output is growing even faster, outpacing our ability to analyze, interpret and evaluate model results
- Explosive data growth and the promise of discovery through data-driven modeling necessitate new methods for feature extraction, change/anomaly detection, data assimilation, simulation, and analysis



Frontier at Oak Ridge National Laboratory is the #1 fastest supercomputer on the [TOP500](#) List and the first supercomputer to break the exaflop barrier (May 30, 2022).

*This article is the second in a two-part series.
The first part, "How to Build a Hypercomputer," by
Thomas Sterling, appeared in the July 2001 issue.*

The Do-It-Yourself Supercomputer

By William W. Hargrove,
Forrest M. Hoffman and
Thomas Sterling

Photographs by Kay Chernush

Scientists have
found a cheaper way
to solve
tremendously
difficult
computational
problems:
connect ordinary
PCs so that they
can work together

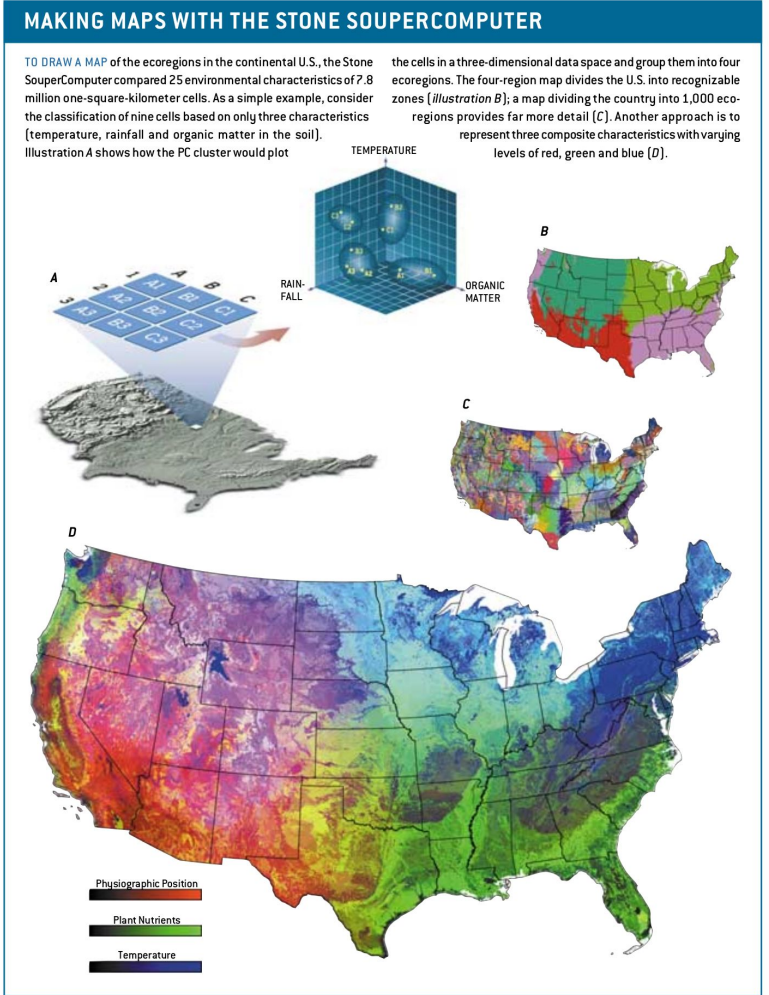
CLUSTER OF PCs at the
Oak Ridge National
Laboratory in Tennessee
has been dubbed the
Stone SouperComputer.

Hargrove, W. W., F. M. Hoffman, and T. Sterling (2001), The
Do-It-Yourself Supercomputer, *Sci. Am.*, 265(2):72-79,
<https://www.scientificamerican.com/article/the-do-it-yourself-superpc/>

Multivariate Geographic Clustering

- Ecoregions have traditionally been created by experts
- Our approach has been to objectively create ecoregions using continuous continental-scale data and clustering
- We developed a highly scalable *k*-means cluster analysis code that uses distributed memory parallelism
- Originally developed on a 486/Pentium cluster, the code now runs on the largest hybrid CPU/GPU architectures on Earth

Hargrove, W. W., F. M. Hoffman, and T. Sterling (2001), The Do-It-Yourself Supercomputer, *Sci. Am.*, 265(2):72-79, <https://www.scientificamerican.com/article/the-do-it-yourself-superc/>



New Analysis Reveals Representativeness of the AmeriFlux Network

PAGES 529, 535

The AmeriFlux network of eddy flux covariance towers was established to quantify variation in carbon dioxide and water vapor exchange between terrestrial ecosystems and the atmosphere, and to understand the underlying mechanisms responsible for observed fluxes and carbon pools. The network is primarily funded by the U.S. Department of Energy, NASA, the National Oceanic and Atmospheric Administration, and the National Science Foundation. Similar regional networks elsewhere in the world—for example, CarboEurope, AsiaFlux, OzFlux, and Fluxnet Canada—participate in

synthesis activities across larger geographic areas [Baldocchi et al., 2001; Law et al., 2002]. The existing AmeriFlux network will also form a backbone of “Tier 4” intensive measurement sites as one component of a four-tiered carbon observation network within the North American Carbon Program (NACP). The NACP seeks to provide long-term, mechanistically detailed, spatially resolved carbon fluxes across North America [Wolry and Harris, 2002]. For both of these roles, the AmeriFlux network should be ecologically representative of the environments contained within the geographic boundaries of the program. A new ecoregion-scale analysis of the existing AmeriFlux network reveals that, while central continental environments are well-represented, additional flux towers are needed to represent environmental

BY WILLIAM W. HARGROVE, FORREST M. HOFFMAN, AND BEVERLY E. LAW

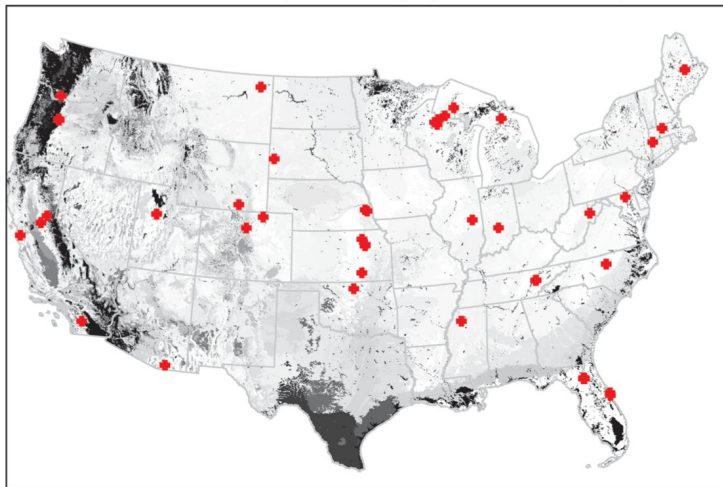


Fig. 1 The representativeness of an existing spatial array of sample locations or study sites—for example, the AmeriFlux network of carbon dioxide eddy flux covariance towers—can be mapped relative to a set of quantitative ecoregions, suggesting locations for additional samples or sites. Distance in data space to the closest ecoregion containing a site quantifies how well an existing network represents each ecoregion in the map. Environments in darker ecoregions are poorly represented by this network.

Network Representativeness

- The n -dimensional space formed by the data layers offers a natural framework for estimating representativeness of individual sampling sites
- The Euclidean distance between individual sites in data space is a metric of similarity or dissimilarity
- Representativeness across multiple sampling sites can be combined to produce a map of network representativeness

Hargrove, W. W., and F. M. Hoffman (2003), New Analysis Reveals Representativeness of the AmeriFlux Network, *Eos Trans. AGU*, 84(48):529, 535, doi:[10.1029/2003EO480001](https://doi.org/10.1029/2003EO480001).

Environmental Monitoring Network for India

An integrated monitoring system is proposed for India that will monitor terrestrial, coastal, and oceanic environments.

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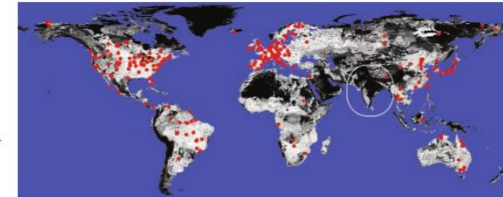
Understanding the consequences of global environmental change and its mitigation will require an integrated global effort of comprehensive long-term data collection, synthesis, and action (1). The last decade has seen a dramatic global increase in the number of networked monitoring sites. For example, FLUXNET is a global collection of >300 micrometeorological terrestrial-flux research sites (see figure, right) that monitor fluxes of CO₂, water vapor, and energy (2–4). A similar, albeit sparser, network of ocean observation sites is quantifying the fluxes of greenhouse gases (GHGs) from oceans and their role in the global carbon cycle (5, 6). These networks are operated on an ad hoc basis by the scientific community. Although FLUXNET and other observation networks cover diverse vegetation types within a 70°S to 30°N latitude band (3) and different oceans (5, 6), there are not comprehensive and reliable data from African and Asian regions. Lack of robust scientific data from these regions of the world is a serious impediment to efforts to understand and mitigate impacts of climate and environmental change (5, 7).

The Indian subcontinent and the surrounding seas, with more than 1.3 billion people and unique natural resources, have a significant impact on the regional and global environment but lack a comprehensive environmental observation network. Within the government of India, the Department of Science and Technology (DST) has proposed filling this gap by establishing INDOFLUX, a coordinated multidisciplinary environmental monitoring network that integrates terrestrial, coastal, and oceanic environments (see figure, right).

In a workshop held in July 2006 (8), a team of scientists from India and the United States developed the overarching objectives for the proposed INDOFLUX. These are to

The authors were members of an indo-U.S. bilateral workshop on INDOFLUX. Affiliations are provided in the supporting online material.

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Current monitoring sites in FLUXNET. Sites are shown in red, and global representativeness is estimated by Global Multivariate Clustering Analysis (24–26). Darker areas are poorly represented by the existing FLUXNET towers. Environmental similarity was calculated from a set of variables (precipitation, temperature, solar flux, total soil carbon and nitrogen, bulk density, elevation, and compound topographic index) at a resolution of 4 km.

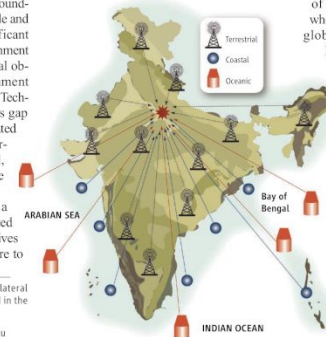
provide a scientific understanding (i) of the coupling of atmospheric, oceanic, and terrestrial environments in India; (ii) of the nature and pace of environmental change in India; and (iii) of subsequent impacts on provision of ecosystem services. Also, in order to evaluate what will enable India to sustain its natural

resources, these goals include an assessment of the vulnerability and consequent risks to its social and natural systems.

Climate change will alter the regional biosphere-climate feedbacks and land-ocean coupling. Although global models reliably predict the trend in the impact of climate change on India's forest resources, the magnitude of such change is uncertain (9). Similarly, whereas all oceans show the influence of global warming (10), the Indian Ocean has shown higher-than-average surface warming, especially during the last five decades (11, 12). This warming may have global impacts (13, 14), even though the impact on the Indian summer monsoons is not well understood (15, 16). These uncertainties highlight the need for regional models driven by regional data.

As the hypoxia observed in the Gulf of Mexico is related to agricultural practices in the watershed (17), Indian Ocean studies also indicate couplings between mainland activities and offshore and

A schematic of the INDOFLUX proposal. Placement of stations reflects different climate, vegetation, and land-use areas. Final locations will be determined as part of the formal science plan.



Optimizing Sampling Networks

- Our group produced this network representativeness map for the authors from global climate, edaphic, and elevation and topography data
- Dark areas, including most of the Indian subcontinent, were poorly represented by the constellation of eddy covariance flux towers participating in FLUXNET in the year 2007

Sundareshwar, P. V., et al. (2007), Environmental Monitoring Network for India, *Science*, 316(5822):204–205, doi:[10.1126/science.1137417](https://doi.org/10.1126/science.1137417).

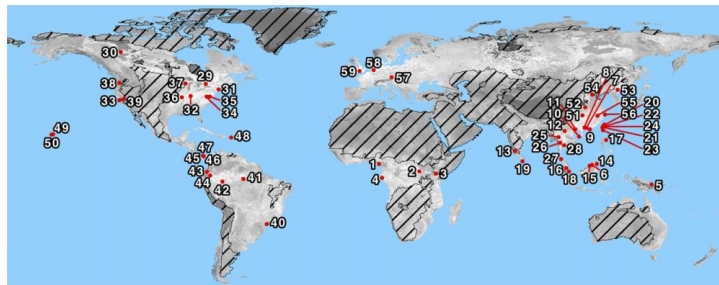


Fig. 1 Map of the CTFS-ForestGEO network illustrating its representation of bioclimatic, edaphic, and topographic conditions globally. Site numbers correspond to ID# in Table 2. Shading indicates how well the network of sites represents the suite of environmental factors included in the analysis; light-colored areas are well-represented by the network, while dark colored areas are poorly represented. Stippling covers nonforested areas. The analysis is described in Appendix S1.

Table 1 Attributes of a CTFS-ForestGEO census

Attribute	Utility
Very large plot size	Resolve community and population dynamics of highly diverse forests with many rare species with sufficient sample sizes (Losos & Leigh, 2004; Condit <i>et al.</i> , 2006); quantify spatial patterns at multiple scales (Condit <i>et al.</i> , 2000; Wiegand <i>et al.</i> , 2007a,b; Detto & Muller-Landau, 2013; Lutz <i>et al.</i> , 2013); characterize gap dynamics (Feeley <i>et al.</i> , 2007b); calibrate and validate remote sensing and models, particularly those with large spatial grain (Mascaro <i>et al.</i> , 2011; Réjou-Méchain <i>et al.</i> , 2014)
Includes every freestanding woody stem ≥ 1 cm DBH	Characterize the abundance and diversity of understory as well as canopy trees; quantify the demography of juveniles (Condit, 2000; Muller-Landau <i>et al.</i> , 2006a,b).
All individuals identified to species	Characterize patterns of diversity, species-area, and abundance distributions (Hubbell, 1979, 2001; He & Legendre, 2002; Condit <i>et al.</i> , 2005; John <i>et al.</i> , 2007; Shen <i>et al.</i> , 2009; He & Hubbell, 2011; Wang <i>et al.</i> , 2011; Cheng <i>et al.</i> , 2012); test theories of competition and coexistence (Brown <i>et al.</i> , 2013); describe poorly known plant species (Gereau & Kenfack, 2000; Davies, 2001; Davies <i>et al.</i> , 2001; Sonké <i>et al.</i> , 2002; Kenfack <i>et al.</i> , 2004, 2006)
Diameter measured on all stems	Characterize size-abundance distributions (Muller-Landau <i>et al.</i> , 2006b; Lai <i>et al.</i> , 2013; Lutz <i>et al.</i> , 2013); combine with allometries to estimate whole-ecosystem properties such as biomass (Chave <i>et al.</i> , 2008; Valencia <i>et al.</i> , 2009; Lin <i>et al.</i> , 2012; Ngo <i>et al.</i> , 2013; Muller-Landau <i>et al.</i> , 2014)
Mapping of all stems and fine-scale topography	Characterize the spatial pattern of populations (Condit, 2000); conduct spatially explicit analyses of neighborhood influences (Condit <i>et al.</i> , 1992; Hubbell <i>et al.</i> , 2001; Uriarte <i>et al.</i> , 2004, 2005; Rüger <i>et al.</i> , 2011, 2012; Lutz <i>et al.</i> , 2014); characterize microhabitat specificity and controls on demography, biomass, etc. (Harms <i>et al.</i> , 2001; Valencia <i>et al.</i> , 2004; Chuyong <i>et al.</i> , 2011); align on the ground and remote sensing measurements (Asner <i>et al.</i> , 2011; Mascaro <i>et al.</i> , 2011).
Census typically repeated every 5 years	Characterize demographic rates and changes therein (Russo <i>et al.</i> , 2005; Muller-Landau <i>et al.</i> , 2006a,b; Feeley <i>et al.</i> , 2007a; Lai <i>et al.</i> , 2013; Stephenson <i>et al.</i> , 2014); characterize changes in community composition (Losos & Leigh, 2004; Chave <i>et al.</i> , 2008; Feeley <i>et al.</i> , 2011; Swenson <i>et al.</i> , 2012; Chisholm <i>et al.</i> , 2014); characterize changes in biomass or productivity (Chave <i>et al.</i> , 2008; Banin <i>et al.</i> , 2014; Muller-Landau <i>et al.</i> , 2014)

Optimizing Sampling Networks

- The CTFS-ForestGEO global forest monitoring network is aimed at characterizing forest responses to global change
- The figure at left shows the global representativeness of the CTFS-ForestGEO sites in 2014
- Non-forested areas are masked with hatching, and as expected, they are consistently darker than the forested regions, which are represented to varying degrees by the monitoring sites

Anderson-Teixeira, K. J., *et al.* (2015), CTFS-ForestGEO: A Worldwide Network Monitoring Forests in an Era of Global Change, *Glob. Change Biol.*, 21(2):528–549, doi:[10.1111/gcb.12712](https://doi.org/10.1111/gcb.12712).

Representativeness for Alaska

Data Layers

Table: 37 characteristics averaged for the present (2000–2009) and the future (2090–2099).

Description	Number/Name	Units	Source
Monthly mean air temperature	12	°C	GCM
Monthly mean precipitation	12	mm	GCM
Day of freeze	mean	day of year	GCM
	standard deviation	days	
Day of thaw	mean	day of year	GCM
	standard deviation	days	
Length of growing season	mean	days	GCM
	standard deviation	days	
Maximum active layer thickness	1	m	GIPL
Warming effect of snow	1	°C	GIPL
Mean annual ground temperature at bottom of active layer	1	°C	GIPL
Mean annual ground surface temperature	1	°C	GIPL
Thermal offset	1	°C	GIPL
Limnicity	1	%	NHD
Elevation	1	m	SRTM

Hoffman, F. M., J. Kumar, R. T. Mills, and W. W. Hargrove (2013), Representativeness-Based Sampling Network Design for the State of Alaska, *Landscape Ecol.*, 28(8):1567–1586, doi:[10.1007/s10980-013-9902-0](https://doi.org/10.1007/s10980-013-9902-0).

Representativeness-based sampling network design for the State of Alaska

Forrest M. Hoffman · Jitendra Kumar · Richard T. Mills · William W. Hargrove

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Abstract Resource and logistical constraints limit the frequency and extent of environmental observations, particularly in the Arctic, necessitating the development of a systematic sampling strategy to maximize coverage and objectively represent environmental variability at desired scales. A quantitative methodology for stratifying sampling domains, informing site selection, and determining the representativeness of measurement sites and networks is described here. Multivariate spatiotemporal clustering was applied to down-scaled general circulation model results and data for the State of Alaska at 4 km² resolution to define multiple sets of ecoregions across two decadal time periods. Maps of ecoregions for the

present (2000–2009) and future (2090–2099) were produced, showing how combinations of 37 characteristics are distributed and how they may shift in the future. Representative sampling locations are identified on present and future ecoregion maps. A representativeness metric was developed, and representativeness maps for eight candidate sampling locations were produced. This metric was used to characterize the environmental similarity of each site. This analysis provides model-inspired insights into optimal sampling strategies, offers a framework for up-scaling measurements, and provides a down-scaling approach for integration of models and measurements. These techniques can be applied at different spatial and temporal scales to meet the needs of individual measurement campaigns.

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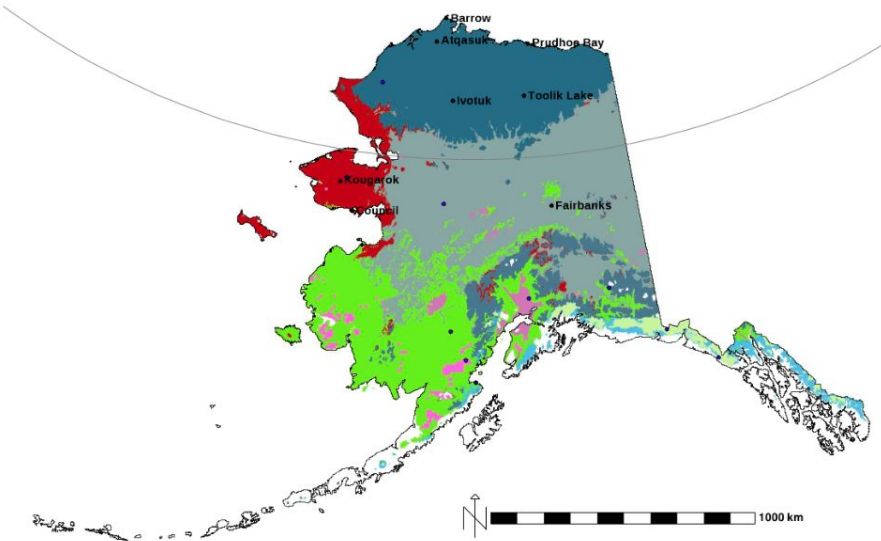
Keywords Ecoregions · Representativeness · Network design · Cluster analysis · Alaska · Permafrost

Introduction

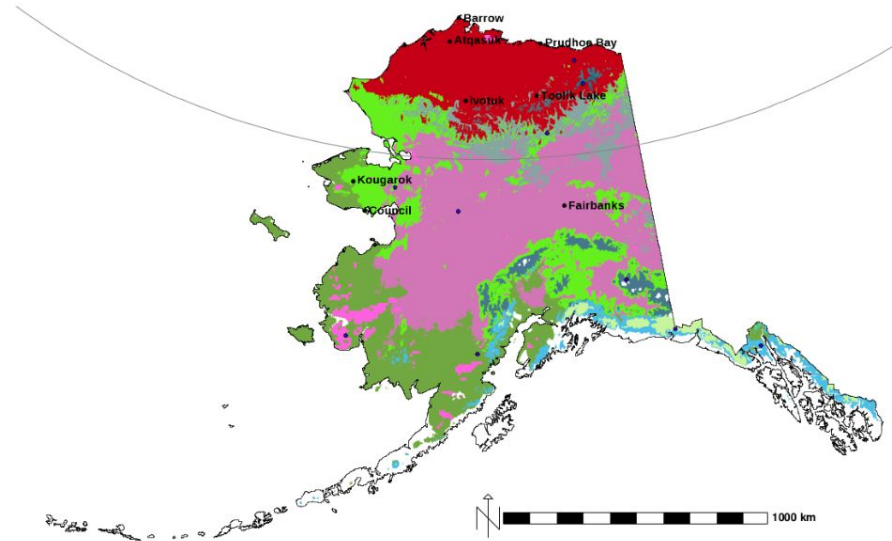
The Arctic contains vast amounts of frozen water in the form of sea ice, snow, glaciers, and permafrost. Extended areas of permafrost in the Arctic contain soil organic carbon that is equivalent to twice the size of the atmospheric carbon pool, and this large stabilized

10 Alaska Ecoregions, Present and Future

(Hoffman et al., 2013)



2000–2009

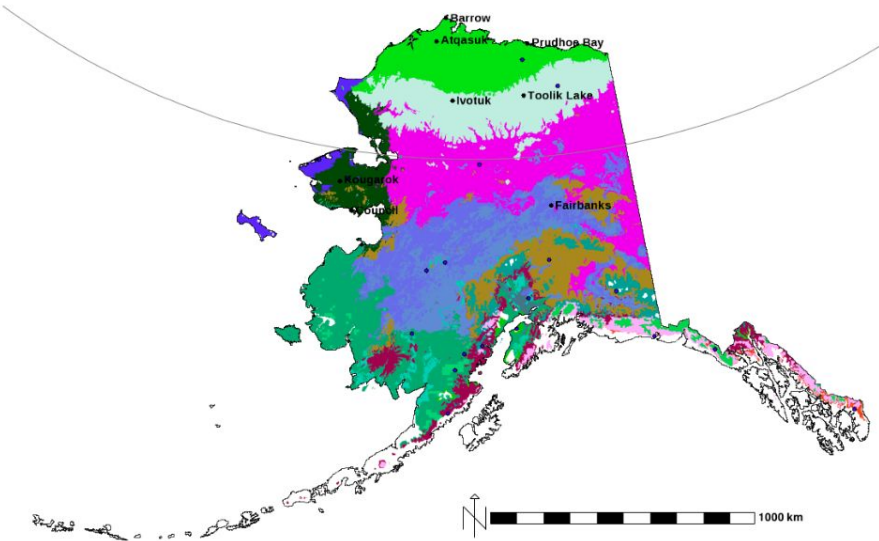


2090–2099

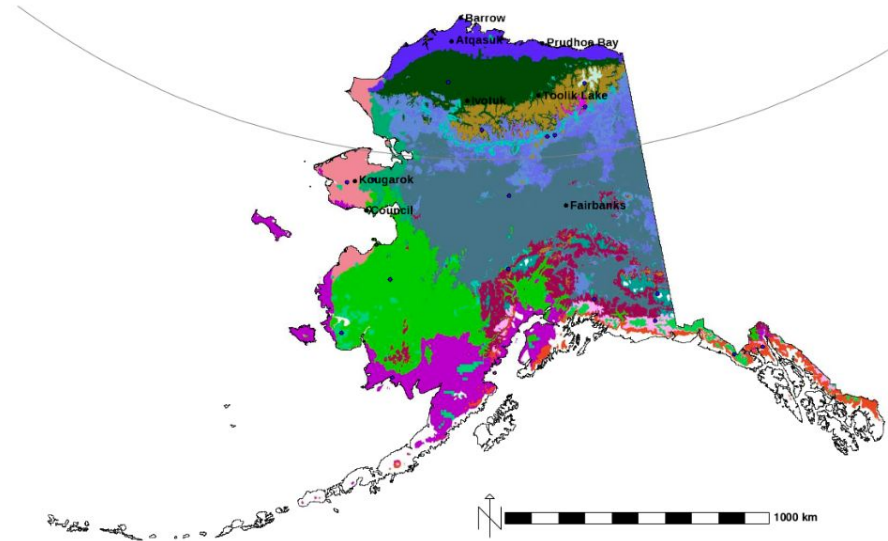
- Since the random colors are the same in both maps, a change in color represents an environmental change between the present and the future.
- At this level of division, the conditions in the large boreal forest become compressed onto the Brooks Range and the conditions on the Seward Peninsula “migrate” to the North Slope.

20 Alaska Ecoregions, Present and Future

(Hoffman et al., 2013)



2000–2009



2090–2099

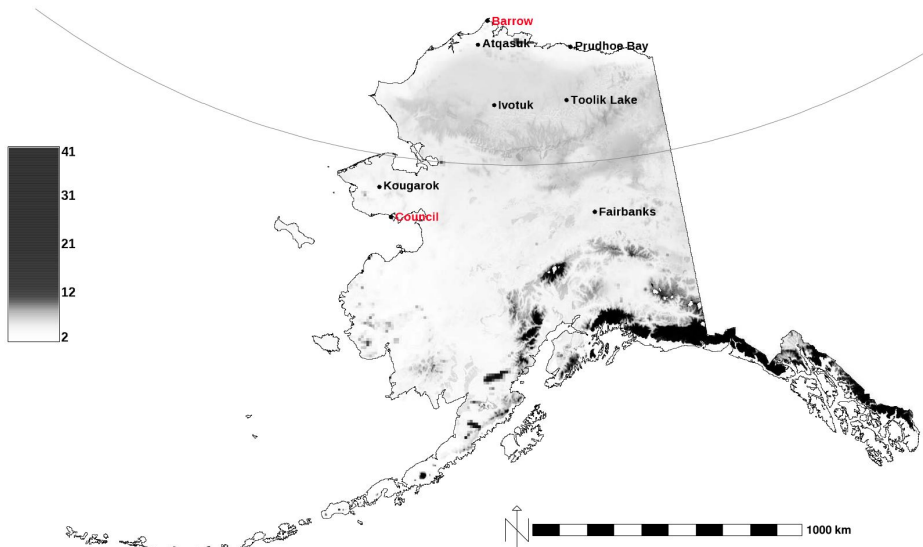
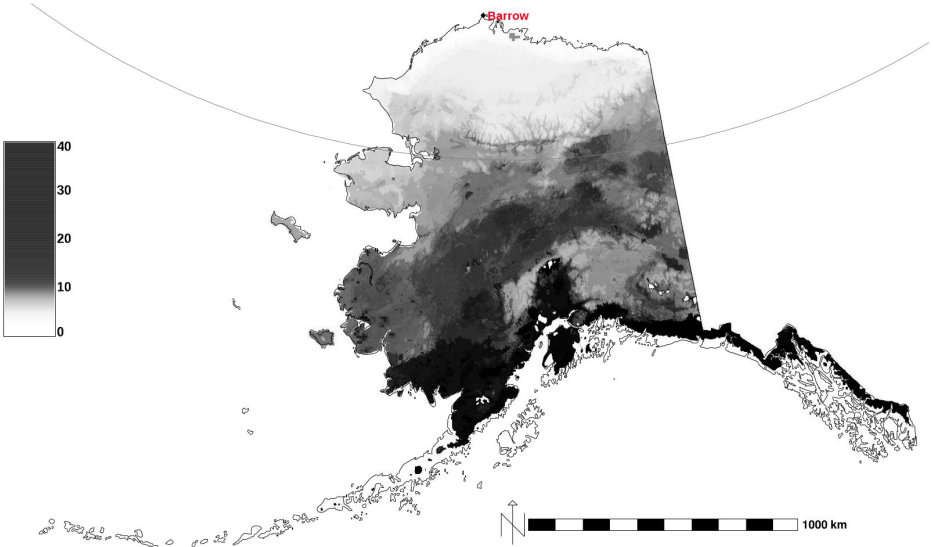
- Since the random colors are the same in both maps, a change in color represents an environmental change between the present and the future.
- At this level of division, the two primary regions of the Seward Peninsula and that of the northern boreal forest replace the two regions on the North Slope almost entirely.

Sampling Site Representativeness

- This representativeness analysis uses the standardized n -dimensional data space formed from all input data layers
- In this data space, the Euclidean distance between a sampling location (like Barrow) and every other point is calculated
- These data space distances are then used to generate grayscale maps showing the similarity, or lack thereof, of every location to the sampling location
- In the subsequent maps, white areas are well represented by the sampling location or network, while dark and black areas are poorly represented by the sampling location or network
- This analysis assumes that the climate surrogates maintain their predictive power and that no significant biological adaptation occurs in the future

Network Representativeness: Barrow vs. Barrow + Council

(Hoffman et al., 2013)



Light-colored regions are well represented and dark-colored regions are poorly represented by the sampling location listed in **red**.

State Space Dissimilarities: 8 Sites, Present and Future

Table: Site state space dissimilarities between the present (2000–2009) and the future (2090–2099).

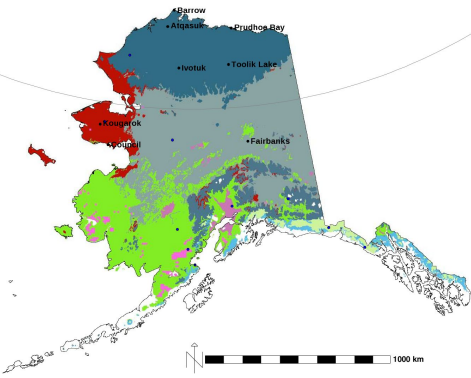
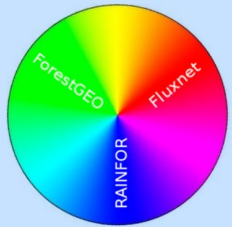
		<i>Future (2090–2099)</i>							
		Barrow	Council	Atqasuk	Ivotuk	Toolik Lake	Kougarok	Prudhoe Bay	Fairbanks
<i>Present (2000–2009)</i>	Sites								
	Barrow	3.31	9.67	4.63	6.05	5.75	9.02	3.69	11.67
	Council	8.38	1.65	8.10	5.91	6.87	3.10	7.45	5.38
	Atqasuk	6.01	9.33	2.42	5.46	5.26	8.97	2.63	10.13
	Ivotuk	7.06	7.17	5.83	1.53	2.05	7.25	4.87	7.40
	Toolik Lake	7.19	7.67	6.07	2.48	1.25	7.70	5.23	8.16
	Kougarok	7.29	3.05	6.92	5.57	6.31	2.51	6.54	5.75
	Prudhoe Bay	5.29	8.80	3.07	4.75	4.69	8.48	1.94	9.81
Fairbanks	12.02	5.49	10.36	7.83	8.74	6.24	10.10	1.96	

Sampling Network Design

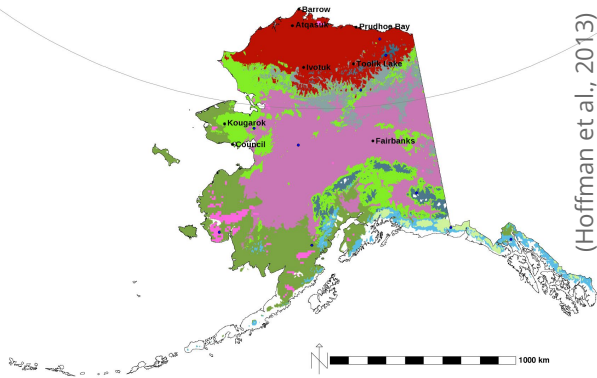


NSF's NEON Sampling Domains

Gridded data from satellite and airborne remote sensing, models, and synthesis products can be combined to design optimal sampling networks and understand representativeness as it evolves through time

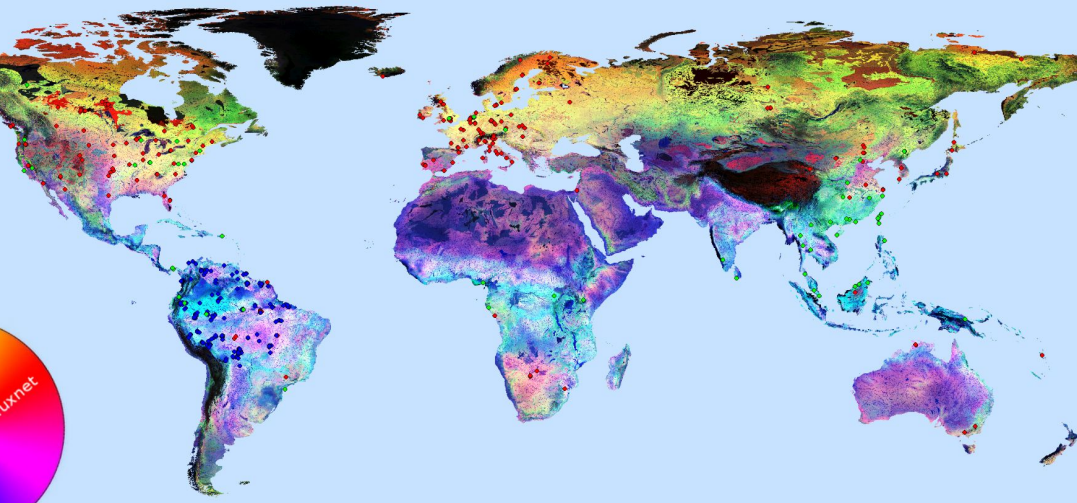


2000-2009



2090-2000

Triple-Net Global Representativeness



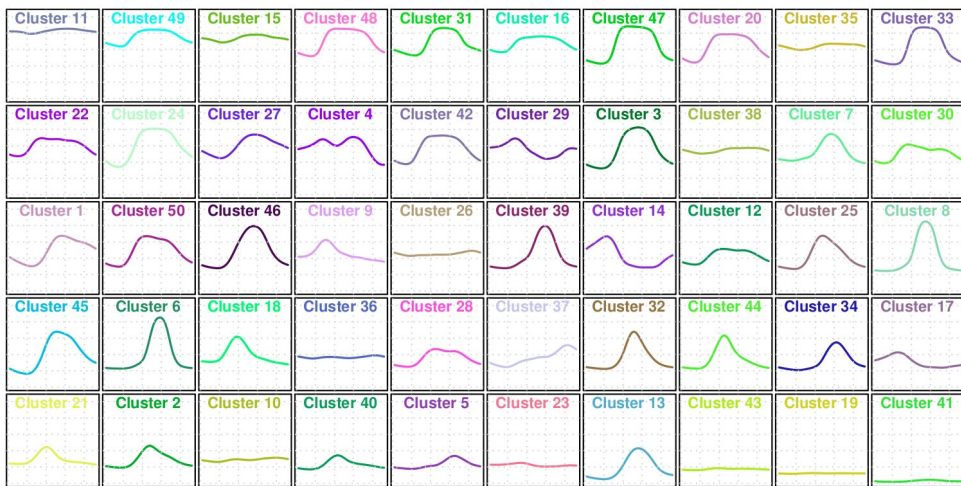
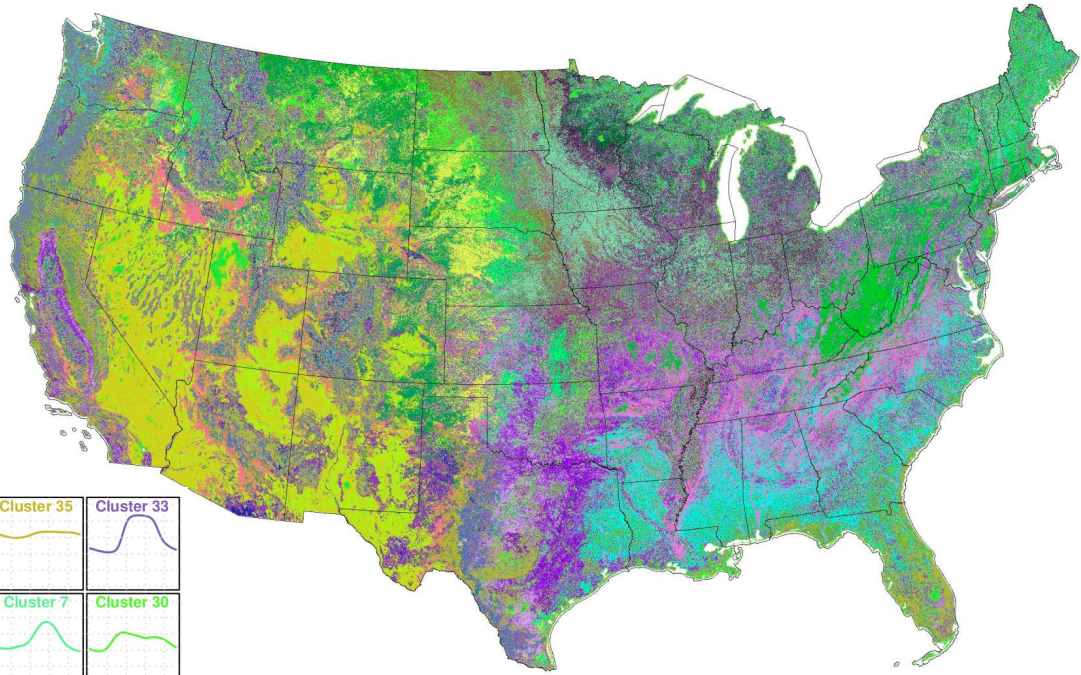
(Maddalena et al., in prep.)

50 Phenoregions for year 2012 (Random Colors)

250m MODIS NDVI

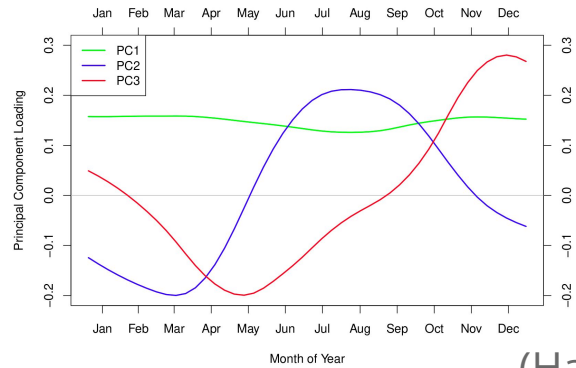
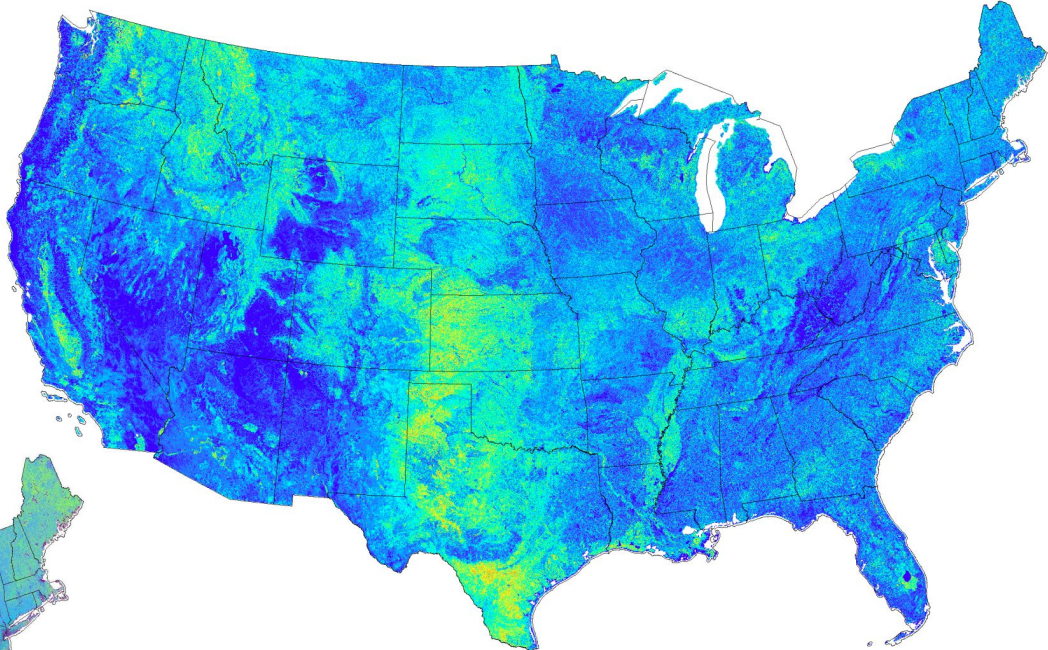
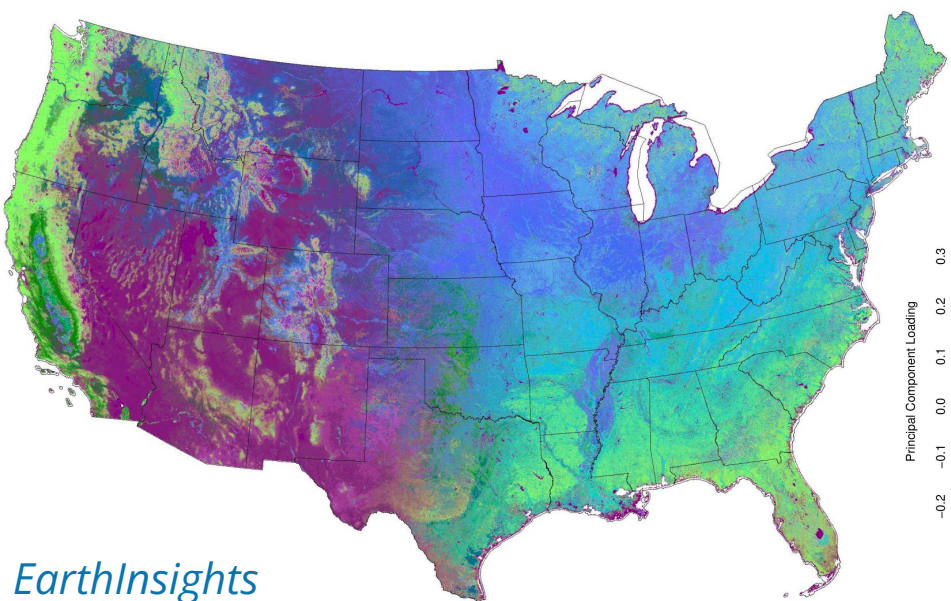
Every 8 days (46 images/year)

Clustered from year 2000 to present



50 Phenoregion Prototypes (Random Colors)

50 Phenoregions Persistence and 50 Phenoregions Max Mode (Similarity Colors)

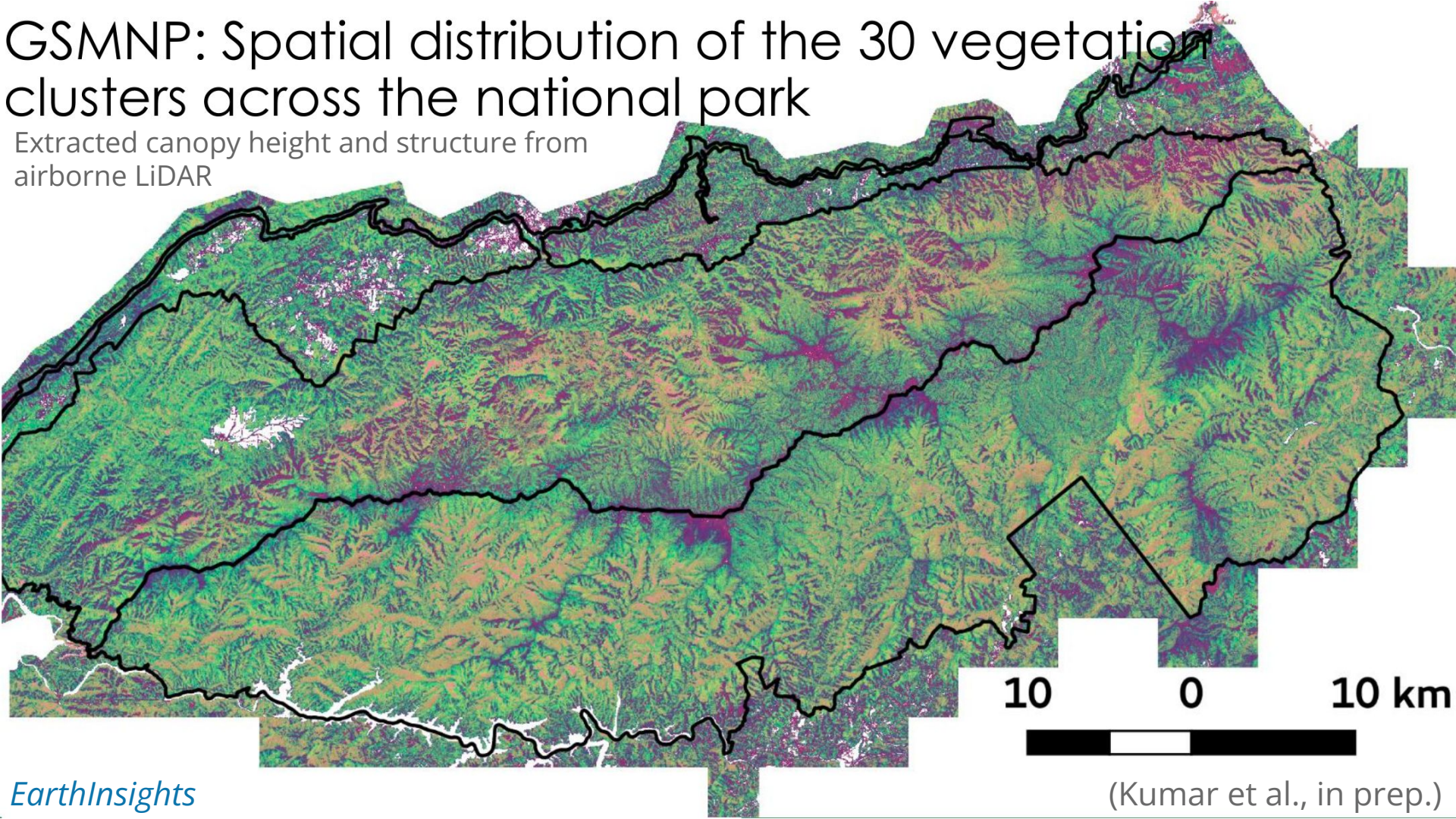


Principal Components Analysis

- PC1 ~ Evergreen
- PC2 ~ Deciduous
- PC3 ~ Dry Deciduous

GSMNP: Spatial distribution of the 30 vegetation clusters across the national park

Extracted canopy height and structure from
airborne LiDAR

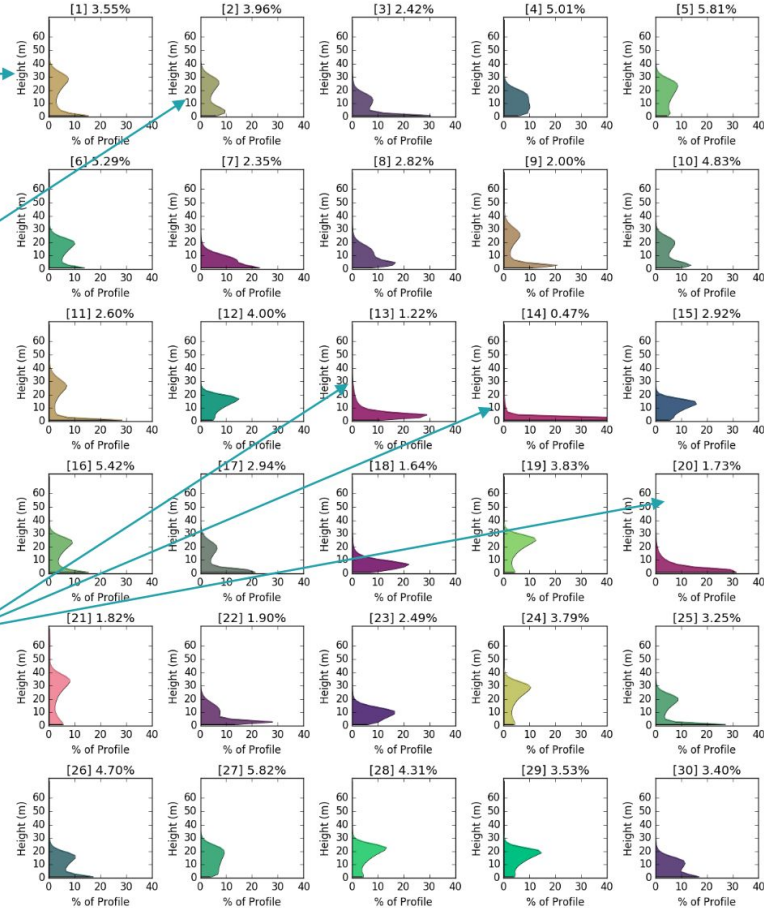


GSMNP: 30 representative vertical structures (cluster centroids) identified

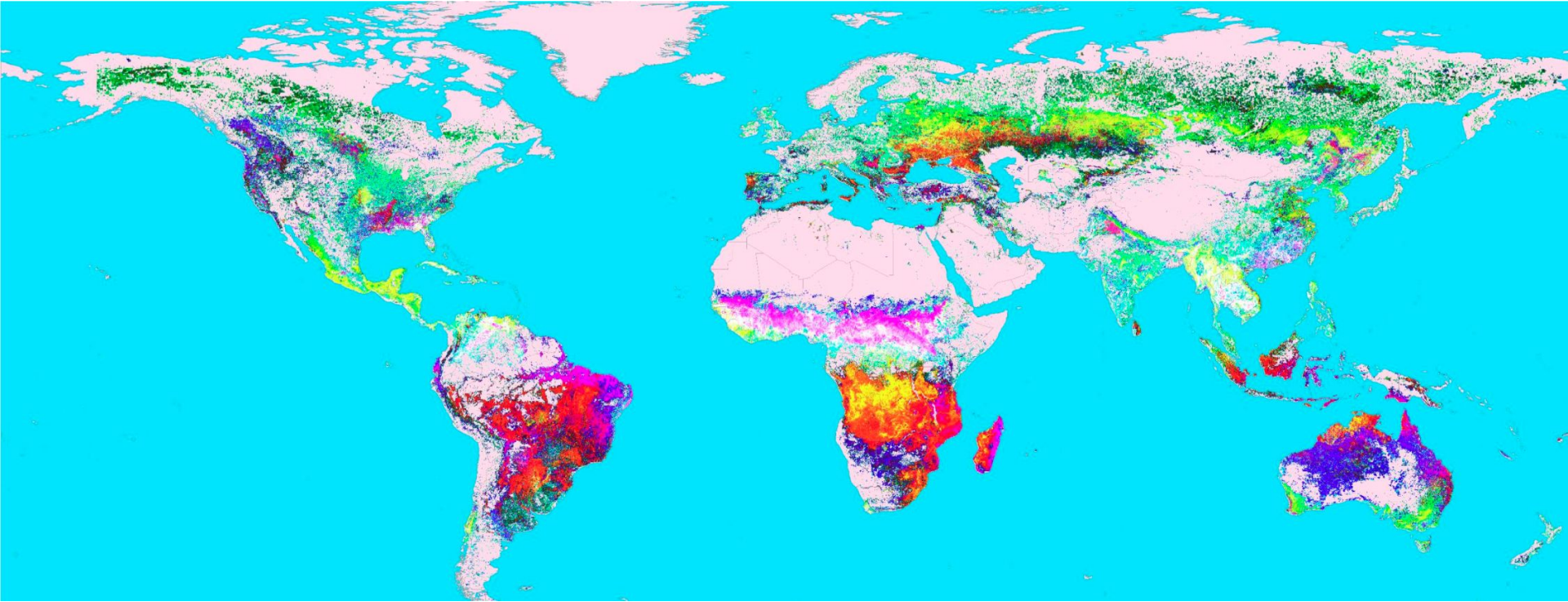
tall forests with low understory vegetation

forests with slightly lower mean height with dense understory vegetation

low height grasslands and heath balds that are small in area but distinct landscape type



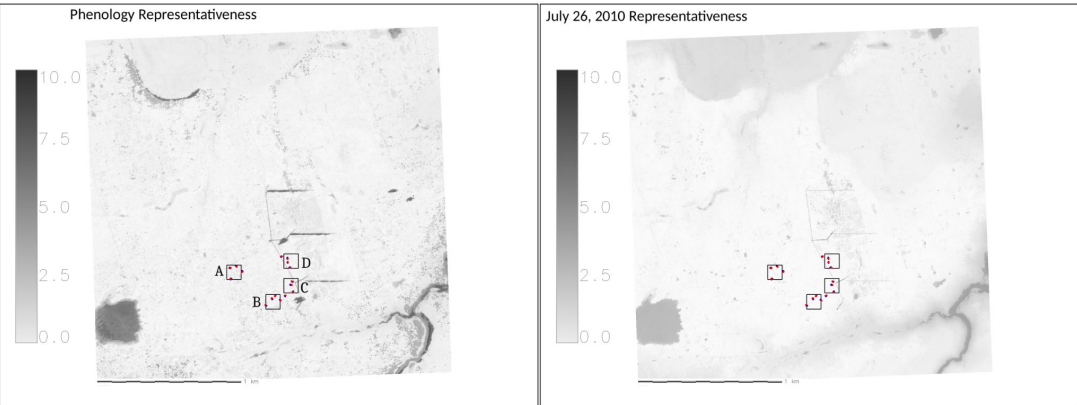
Global Fire Regimes



Regions that exhibit similar fire seasonality globally

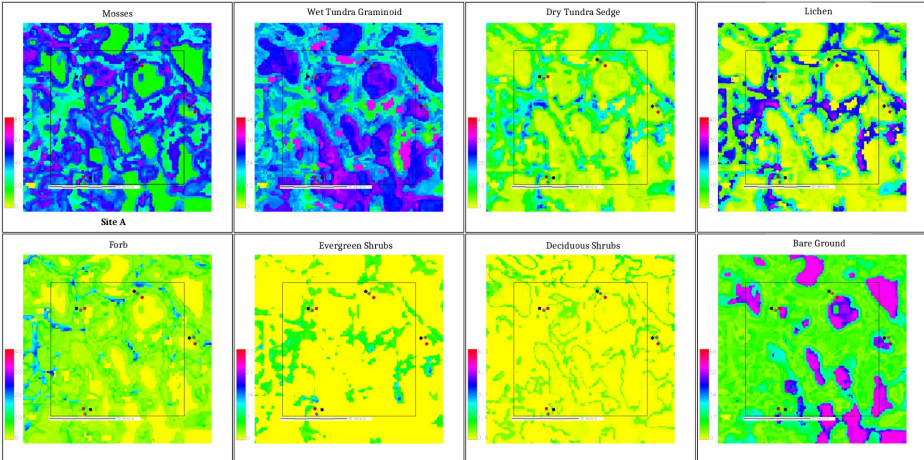
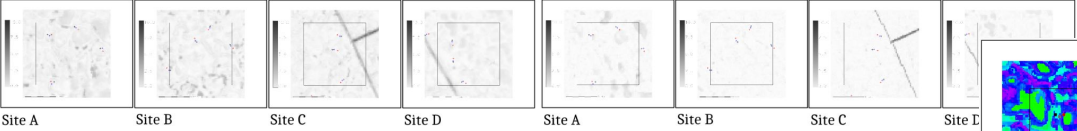
From MODIS "Hotspots" at 1 km resolution from 2002–2018

Vegetation Distribution at Barrow Environmental Observatory



Representativeness map for vegetation sampling points in sites A, B, C, and D with phenology (left) and without (right) from WorldView2 multispectral imagery for the year 2010 and LiDAR data

Example plant functional type (PFT) distributions scaled up from vegetation sampling locations

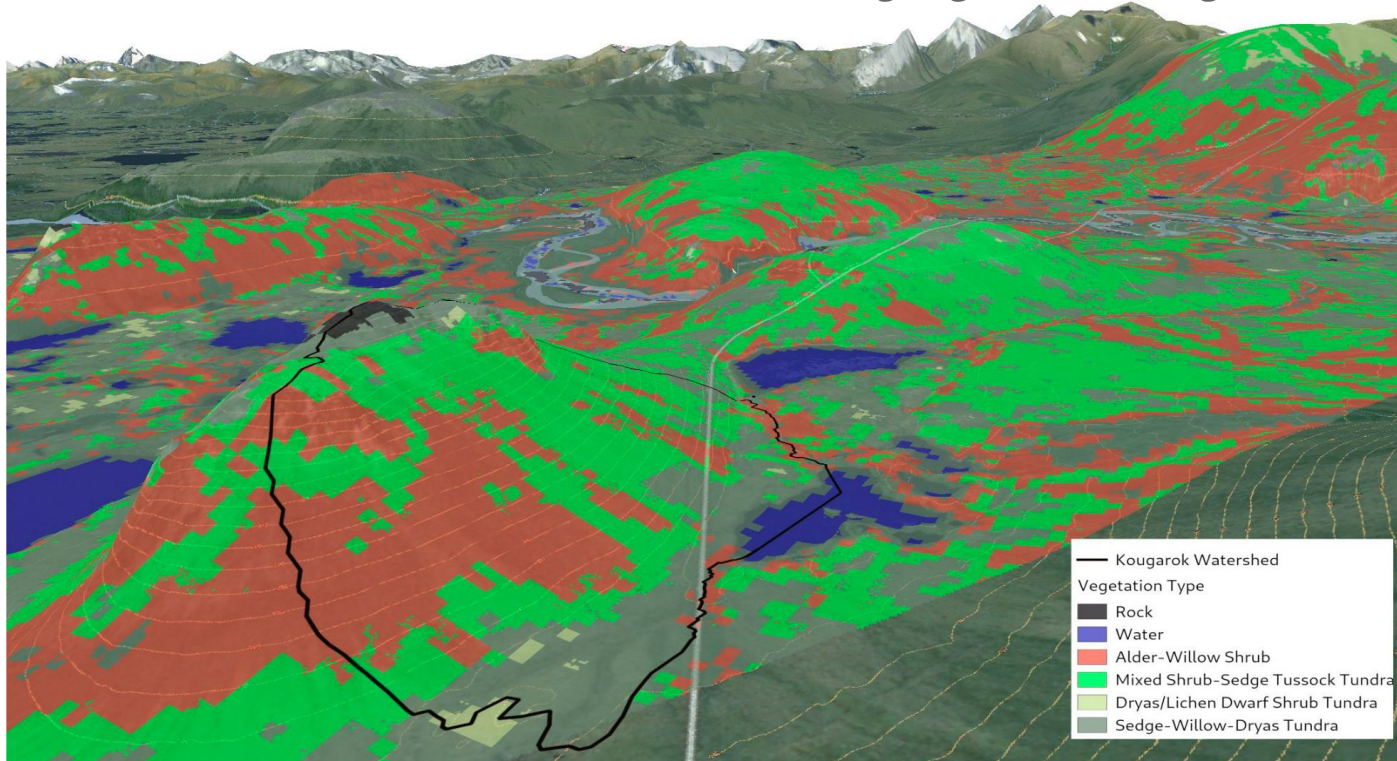


In situ data from field measurement activities inform the development of wide-scale maps of vegetation distribution through inference using remote sensing data as surrogate variables, and relationships with environmental controls can be extracted

Langford, Z. L., et al. (2016), Mapping Arctic Plant Functional Type Distributions in the Barrow Environmental Observatory Using WorldView-2 and LiDAR Datasets, *Remote Sens.*, 8(9):733, doi:[10.3390/rs8090733](https://doi.org/10.3390/rs8090733).

Arctic Vegetation Mapping from Multi-Sensor Fusion

Used Hyperion Multispectral and IfSAR-derived Digital Elevation Model, applied cluster analysis, and trained a convolutional neural network (CNN) with Alaska Existing Vegetation Ecoregions (AKEVT)



Langford, Z. L., et al. (2019), Arctic Vegetation Mapping Using Unsupervised Training Datasets and Convolutional Neural Networks, *Remote Sens.*, 11(1):69, doi:[10.3390/rs11010069](https://doi.org/10.3390/rs11010069).

Satellite Data Analytics Enables Within-Season Crop Identification

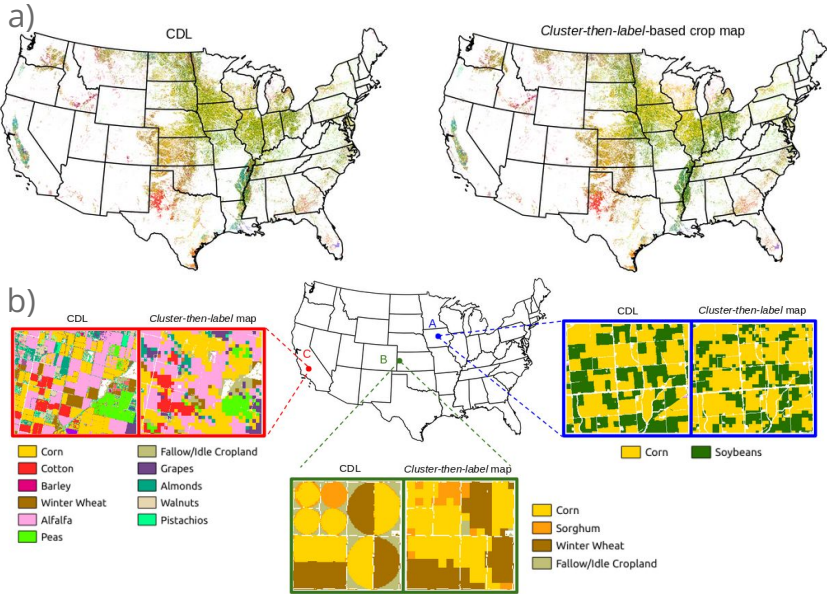
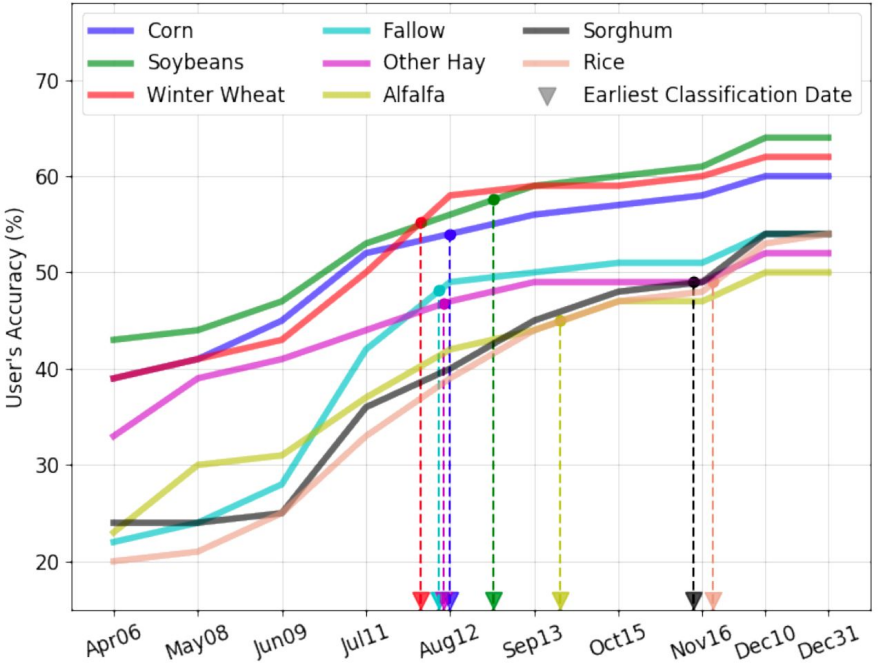


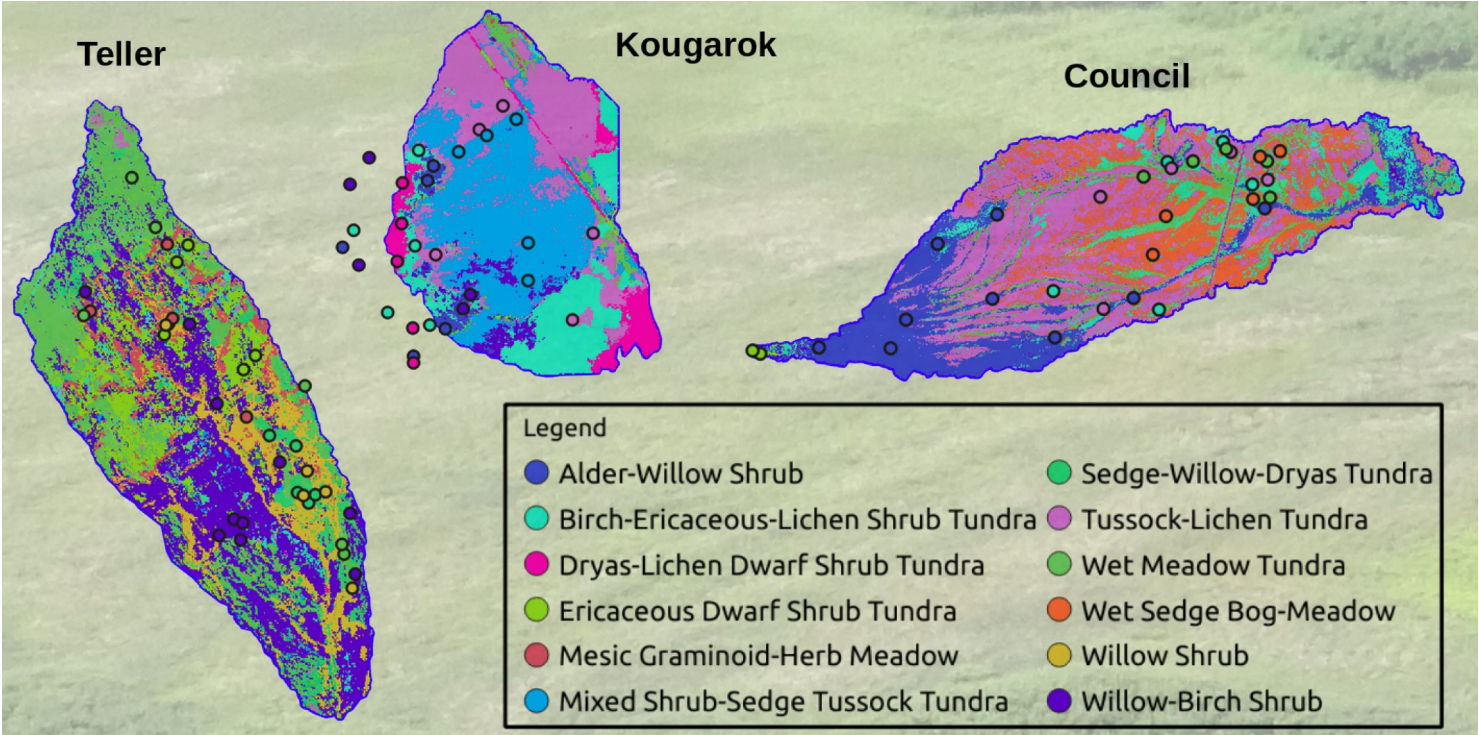
Figure: a) Comparison of cluster-then-label crop map with USDA Crop Data Layer (CDL) shows similar patterns at continental scale. b) Good spatial agreement is found at three selected regions, but cluster-then-label crop maps lack sharpness at field boundaries due to coarser resolution of MODIS data.

Earliest date for crop type classification



Konduri, V. S., J. Kumar, W. W. Hargrove, F. M. Hoffman, and A. R. Ganguly (2020), Mapping Crops Within the Growing Season Across the United States, *Remote Sens. Environ.*, 251, 112048, doi:[10.1016/j.rse.2020.112048](https://doi.org/10.1016/j.rse.2020.112048).

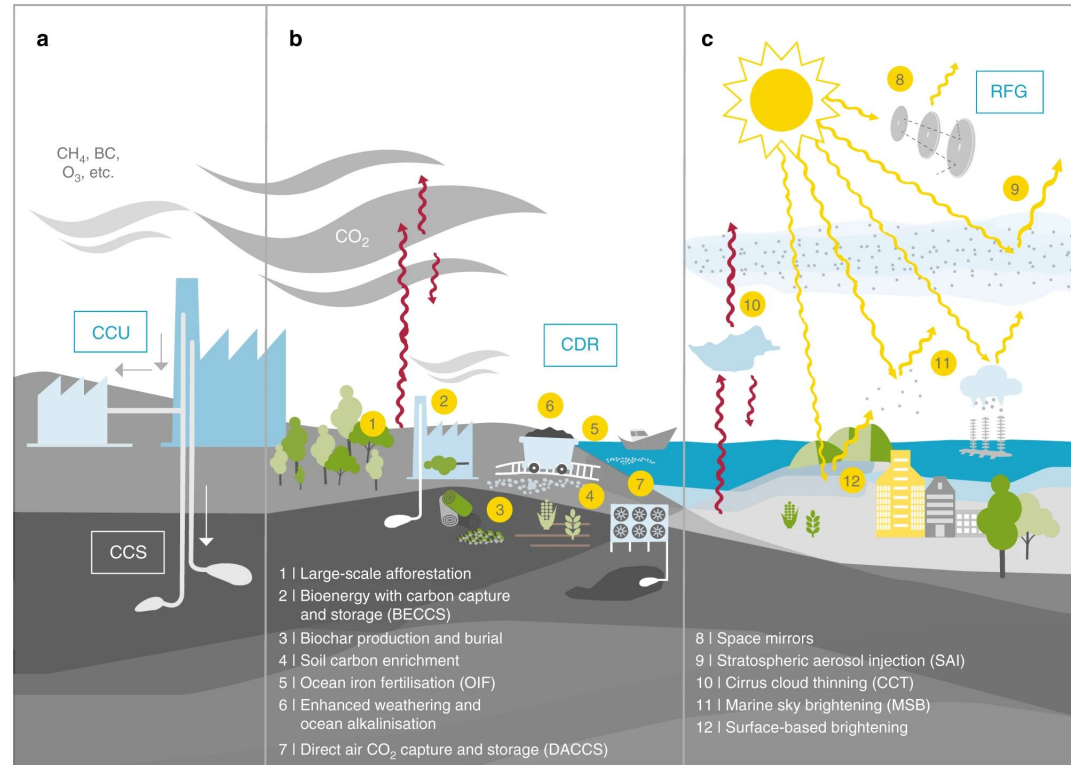
Watershed-Scale Plant Communities Determined from DNN and AVIRIS-NG



At the watershed scale, vegetation community distribution follows topographic and water controls. At a fine scale, nutrients limit the distribution of vegetation types.

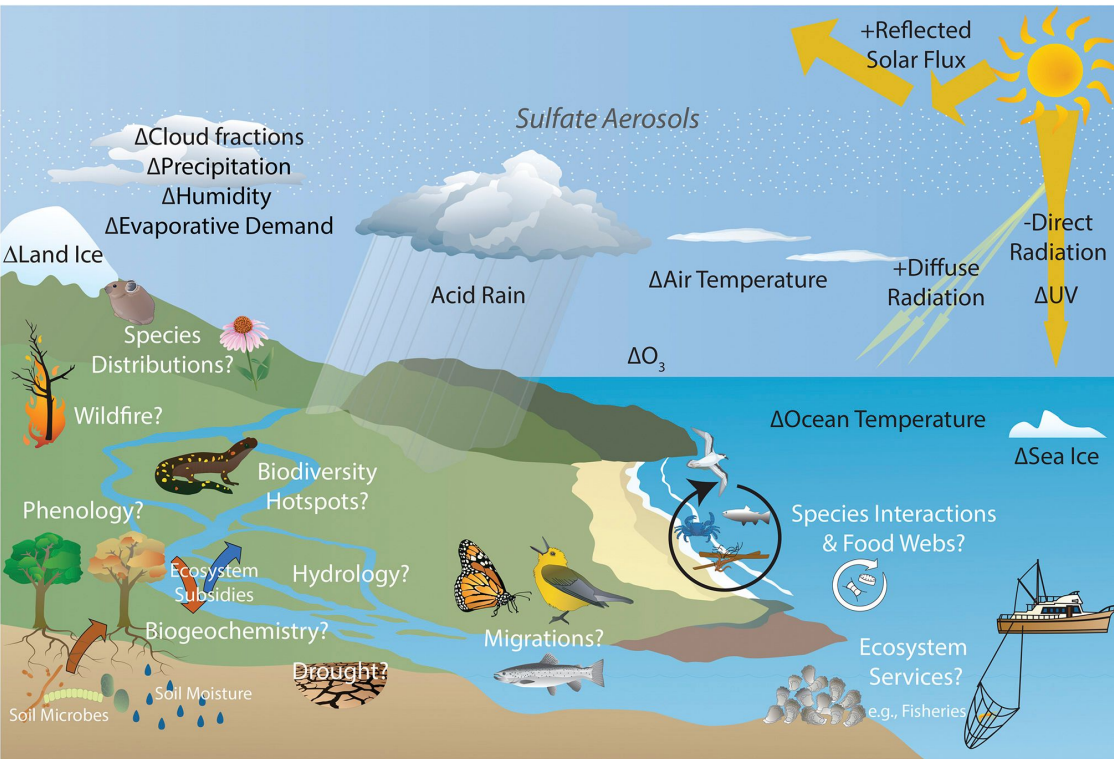
Climate Change Mitigation through Climate Intervention

- The increasing severity of extreme events and wildfire is threatening utilities, built infrastructure, and economic & national security
- Loss of life and property is motivating consideration of *climate intervention* or *geoengineering*
- In addition to *carbon dioxide removal (CDR)* through *direct air capture (DAC)* and other means, interest is growing in reducing or stabilizing Earth's surface temperature
- *Solar radiation management (SRM)* is an approach to partially reduce warming, and *stratospheric aerosol intervention (SAI)* by injecting sulfur into the lower stratosphere is considered the most feasible scheme



A wide variety of natural solutions and geoengineering techniques are proposed for mitigating the effects of climate change. Adopted from Lawrence et al. (2018).

Potential Ecological Impacts of Climate Intervention



Although some effects of SRM with SAI on climate are known from certain SAI scenarios, the effects of SAI on ecological systems are largely unknown. Adopted from Zarnetske et al. (2021).

- While climate research has focused on predicted **climate effects of SRM**, few studies have investigated **impacts that SRM would have on ecological systems**
- **Impacts and risks posed by SRM would vary** by implementation scenario, anthropogenic climate effects, geographic region, and by ecosystem, community, population, and organism
- A **transdisciplinary approach** is essential, and **new modeling paradigms are required**, to represent complex interactions across Earth system components, scales, and ecological systems

Climate Intervention Research

A 2021 report from the National Academies of Sciences, Engineering, and Medicine (NASEM) concludes **a strategic investment in research is needed** to advance policymakers' understanding of climate response options.

The US should develop a transdisciplinary research program, in collaboration with other nations, to advance understanding of solar geoengineering's technical feasibility and effectiveness, possible impacts on society and the environment, and social dimensions such as public perceptions, political and economic dynamics, and ethical and equity considerations.

The National Academies of
SCIENCES • ENGINEERING • MEDICINE

CONSENSUS STUDY REPORT



Reflecting Sunlight

Recommendations for Solar
Geoengineering Research
and Research Governance

Geoengineering Increases the Global Land Carbon Sink

Objective: To examine stratospheric aerosol intervention (SAI) impacts on plant productivity and terrestrial biogeochemistry.

Approach: Analyze and compare simulation results from the Stratospheric Aerosol Geoengineering Large Ensemble (GLENS) project from 2010 to 2097 under RCP8.5 with and without SAI.

Results/Impacts: In this scenario, SAI causes terrestrial ecosystems to store an additional 79 Pg C globally as a result of lower ecosystem respiration and diminished disturbance effects by the end of the 21st century, yielding as much as a 4% reduction in atmospheric CO₂ mole fraction that progressively reduces the SAI effort required to stabilize surface temperature.

Yang, C.-E., F. M. Hoffman, D. M. Ricciuto, S. Tilmes, L. Xia, D. G. MacMartin, B. Kravitz, J. H. Richter, M. Mills, and J. S. Fu (2020), Assessing Terrestrial Biogeochemical Feedbacks in a Strategically Geoengineered Climate, *Environ. Res. Lett.*, doi:[10.1088/1748-9326/abacf7](https://doi.org/10.1088/1748-9326/abacf7).

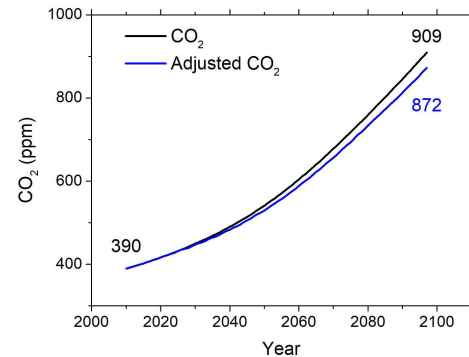
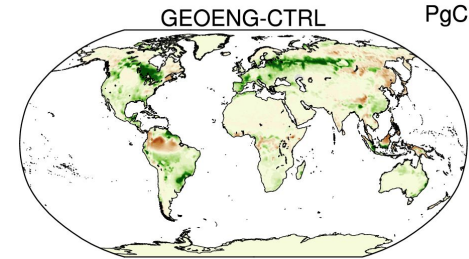
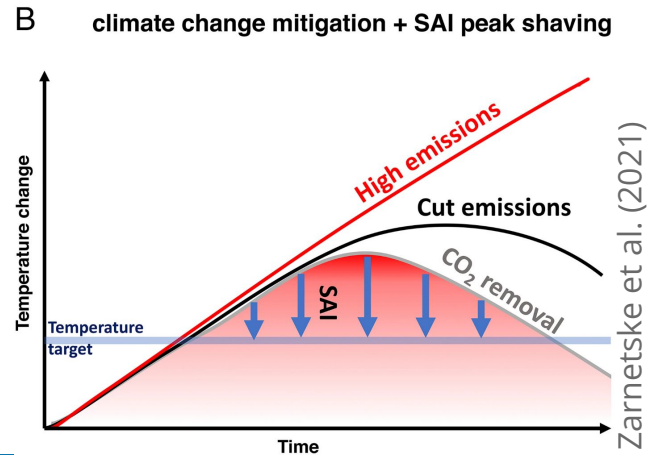
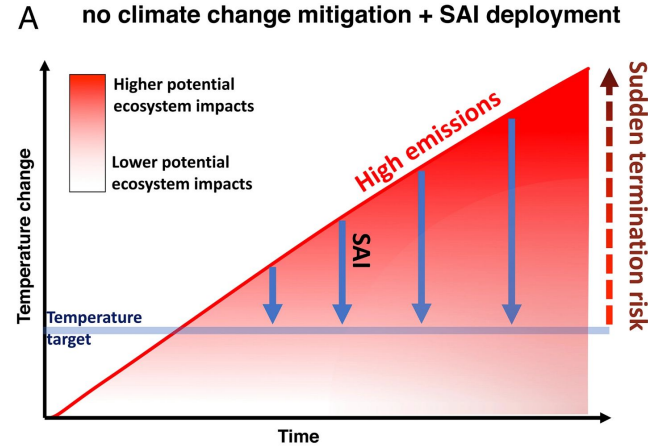


Figure: The larger sink under SAI increased land C storage by 79 Pg C by 2097, which would reduce the projected atmospheric CO₂ level.

Exploring Feedbacks of SAI

- To fill research gaps in understanding Earth system feedbacks of SAI on ecosystems, we are conducting a series of increasingly complex geoengineering simulations with **DOE's Energy Exascale Earth System Model (E3SM)**
- **Simulations will mimic effects of CDR, SAI, and CDR plus SAI**
- Start with SSP5-3.4-OS mid-range overshoot CO₂ trajectory from CMIP6, which prescribes a drawdown of CO₂
- Global surface temperatures will rise by >2.5°C around 2040, **above the 2°C threshold that may induce irreversible impacts**
- Next, introduce SAI to simultaneously cool the surface until drawdown is sufficient to assure < 2°C warming, called **temperature "peak shaving"**
- To quantify feedbacks from reducing, not increasing, atmospheric CO₂, **but may not capture all the as yet unobserved processes**



Leveraging Advances in Machine Learning for Earth Sciences

Existing machine learning techniques can improve understanding of biospheric processes and representation in Earth system models

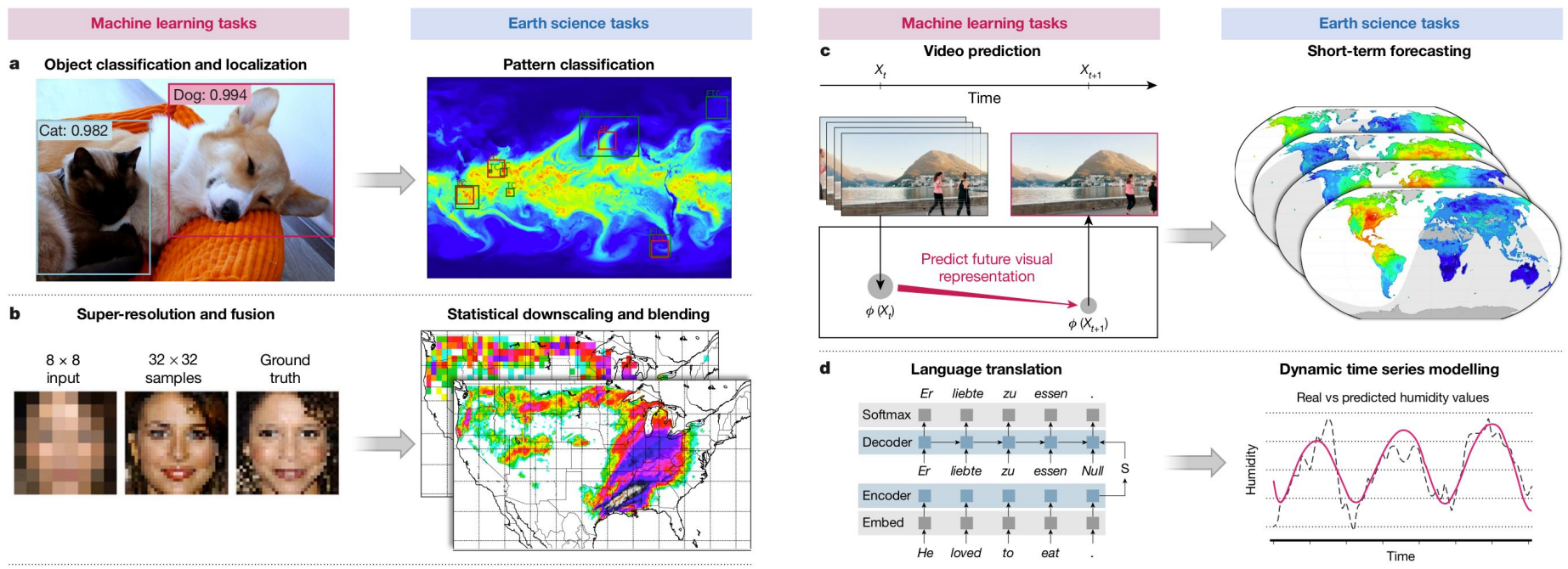
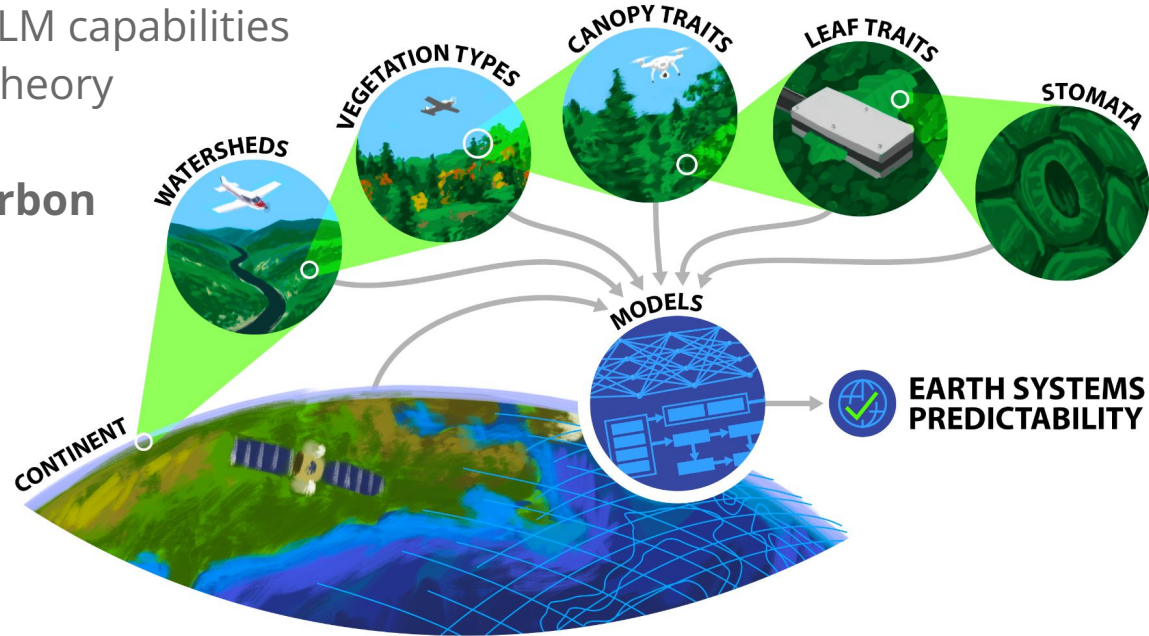


Figure 2 in Reichstein et al. (2019)

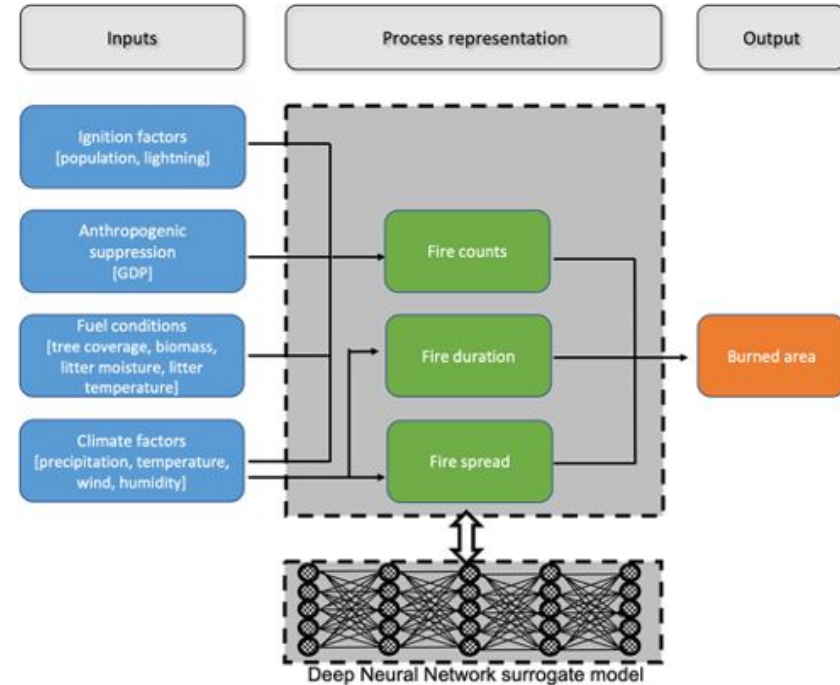
Machine Learning for Understanding Biospheric Processes

- Widening adoption of deep neural networks and growth of climate data are fueling interest in AI/ML for use in weather and climate and Earth system models
- ML potential is high for improving predictability when (1) *sufficient data are available for process representations* and (2) *process representations are computationally expensive*
- Example methods for improving ELM capabilities by exploring ML and information theory approaches:
 - **Soil organic carbon & radiocarbon**
 - **Wildfire**
 - **Methane emissions**
 - **Ecohydrology**
- All of these applications involve unresolved, subgrid-scale processes that strongly influence results at the largest scales



Hybrid Modeling of Wildfire Activities

- Improve model simulations of **wildfire processes**, including ignition, fire duration, and spread rate with Deep Neural Network models
- Improve simulated **wildfire emissions** and their impacts on atmospheric properties, including aerosols, greenhouse gases, phosphorus transport, and pollutants
- Improve the projection of near-future and long-term dynamics of wildfire activities
- Accelerate E3SM coupled land-atmosphere modeling activities for wildfire research
- Explore online ML training/validation strategy for E3SM coupled model simulations

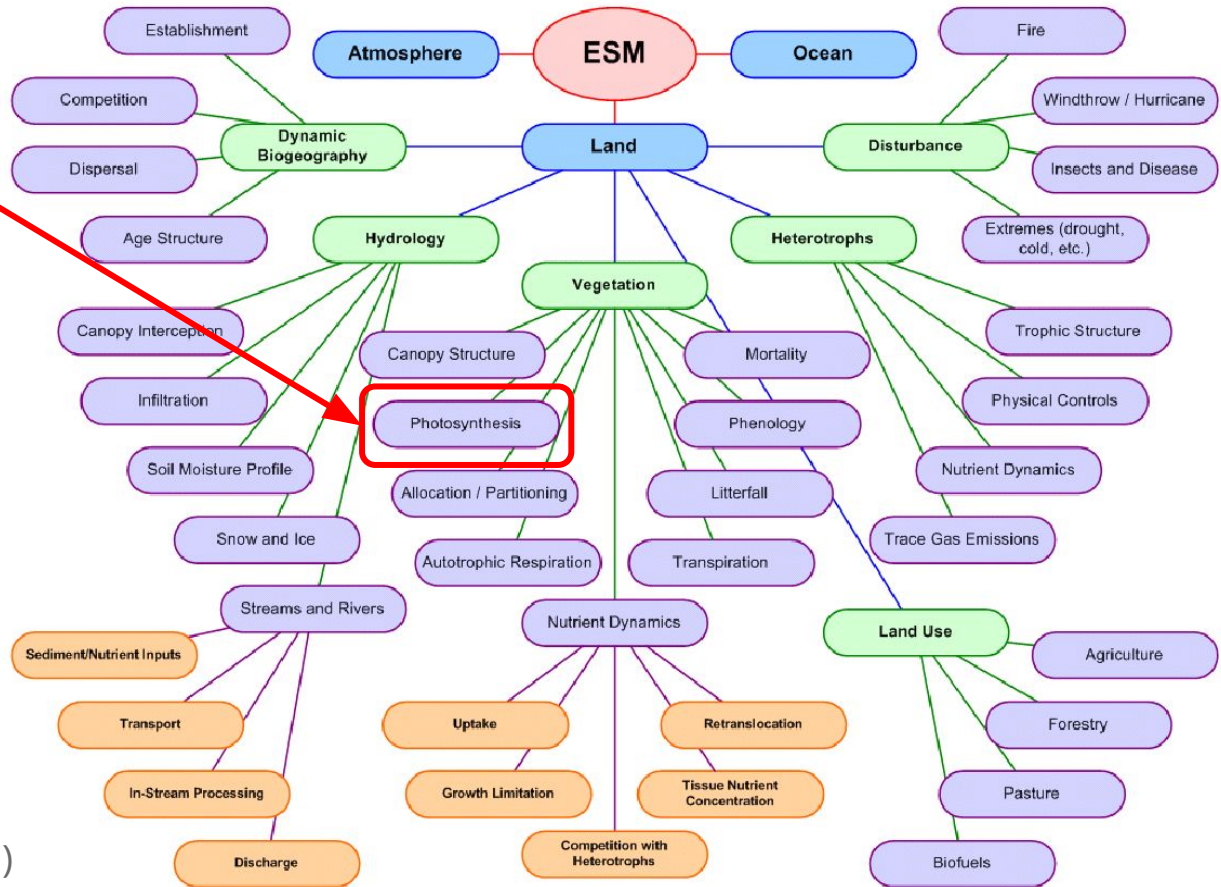


Zhu et al. (2022)

Hybrid ML/Process-based Modeling for Terrestrial Modeling

In the hierarchy of land model processes, we start with the **photosynthesis** parameterization because

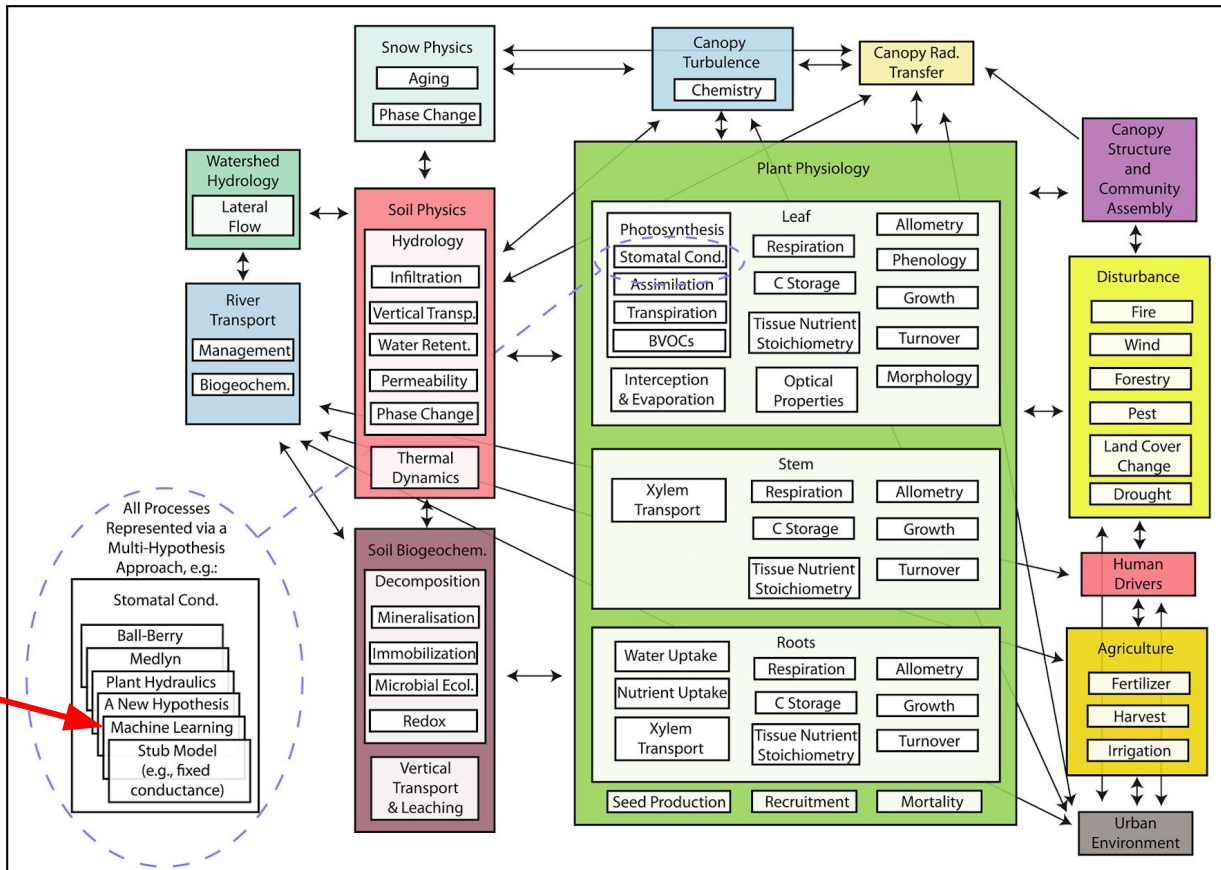
- Multiple hypotheses
- Many leaf-level measurements
- Most computationally intensive part of the land model



(Figure from P. E. Thornton)

Hybrid ML/Process-based Modeling for Terrestrial Modeling

Individual processes can be represented by a multi-hypothesis approach, and ML provides an opportunity for a data-derived hypothesis that can be further explored or used to calibrate other hypotheses, when sufficient data are available.

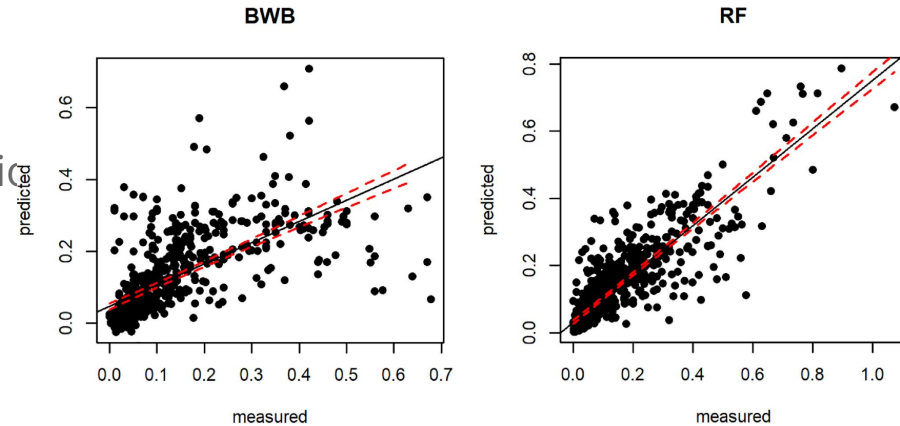


(Fisher and Koven, 2020)

(a) Process Schematic of a Possible Full-Complexity Configuration of a Land Surface Model

Hybrid Modeling of Photosynthesis and Ecohydrology

- Hierarchy of process-/ML-based models connecting plant community structure, hydrodynamics, physiology, and soil composition to the water cycle
- Multiple hypotheses for stomatal behavior motivate competing process-based parameterizations in land models
- Significant leaf-level and canopy-scale data are available for training ML parameterizations that may improve understanding and reduce uncertainties while also reducing computational costs of running the hybrid model
- Recent work has shown that random forests (right figure) offer improved stomatal conductance over Ball-Berry process-based model (left figure) (Saunders et al., 2021)
- Approach: Build offline implementations then prototype online modules for use in ELM
- Perform simulations to quantify sensitivity of the global carbon cycle to various ML models



Saunders et al. (2021), Figure 4, panels (a) and (d)



ARTIFICIAL INTELLIGENCE FOR EARTH SYSTEM PREDICTABILITY (AI4ESP): CHALLENGES AND OPPORTUNITIES

DOE Environmental System Science (ESS) PI Meeting

FORREST M. HOFFMAN
Oak Ridge National Laboratory

CHARULEKA VARADHARAJAN
HARUKO WAINWRIGHT
Lawrence Berkeley National
Laboratory

NICKI L. HICKMON
SCOTT M. COLLIS
Argonne National Laboratory



Artificial Intelligence for Earth System Predictability

A multi-lab initiative working with the Earth and Environmental Systems Science Division (EESSD) of the Office of Biological and Environmental Research (BER) to develop a new paradigm for Earth system predictability focused on enabling artificial intelligence across field, lab, modeling, and analysis activities.

White papers were solicited for development and application of AI methods in areas relevant to EESSD research with an emphasis on quantifying and improving Earth system predictability, particularly related to the integrative water cycle and extreme events.

How can DOE directly leverage artificial intelligence (AI) to engineer a substantial (paradigm-changing) improvement in Earth System Predictability?

156 white papers were received and read to plan the organization of the **AI4ESP Workshop on Oct 25–Dec 3, 2021**



Earth System Predictability Sessions

- Atmospheric Modeling
- Land Modeling
- Human Systems & Dynamics
- Hydrology
- Watershed Science
- Ecohydrology
- Aerosols & Clouds
- Climate Variability & Extremes
- Coastal Dynamics, Oceans & Ice

Cross-Cut Sessions

- Data Acquisition
- Neural Networks
- Surrogate models and emulators
- Knowledge-Informed Machine Learning
- Hybrid Modeling
- Explainable/Interpretable/Trustworthy AI
- Knowledge Discovery & Statistical Learning
- AI Architectures and Co-design

Workshop Report

- Chapters for each session have been written and reviewed
- Summary chapters are being written now
- Final review and approval expected soon after July 1, 2022

AMS Special Collection

- Papers to be published in *AI for the Earth Systems*

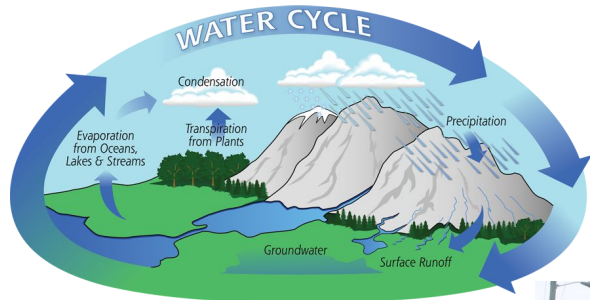




AI4ESP White Papers: Earth System Predictability Topics

● Watershed science

- Hydro-Biogeochemistry, Soil biogeochemistry
- Water quality
- Lab-to-field, field-to-regional scale analysis
- Experimental data, sensor networks (rapid responses), and experimental/network designs



● Hydrology

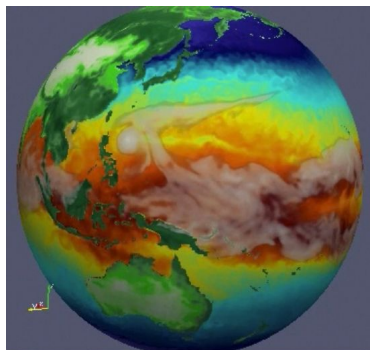
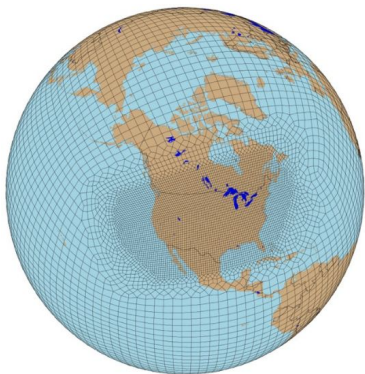
- Water resources ess.science.energy.gov
- Precipitation-induced hazards (floods etc)
- Weather/hydrological monitoring
- Groundwater to surface water models
- Mountain hydrology
- Regional to continental scale



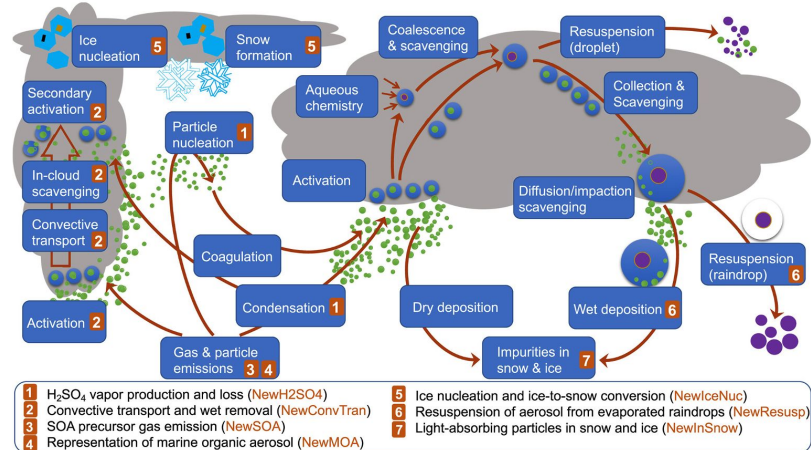
AI4ESP White Papers: Earth System Predictability Topics

● Atmospheric Modeling

- Convection and turbulence
- Surface Fluxes
- Radiation
- Model Tuning
- General concepts that can be generalized to other ESMs components



e3sm.org



e3sm.org

● Aerosols and Clouds

- Cloud Classification
- Aerosol cloud interactions



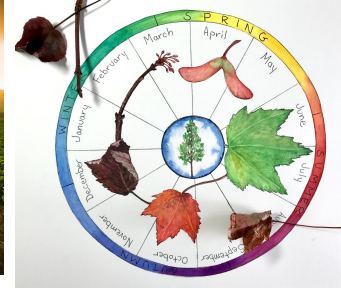
AI4ESP White Papers: Earth System Predictability Topics

● Land Modeling

- Agriculture / Crops
- Leaf Phenology
- Streamflow / Water Availability
- Wildfire
- Satellite Data Assimilation



Getty Images



Adkins Arboretum



wallpaperbetter.com

● Ecohydrology

- Stomatal Conductance / Photosynthesis
- Plant Hydraulics and Growth
- Evapotranspiration
- Soil Moisture
- Soil Hydrology



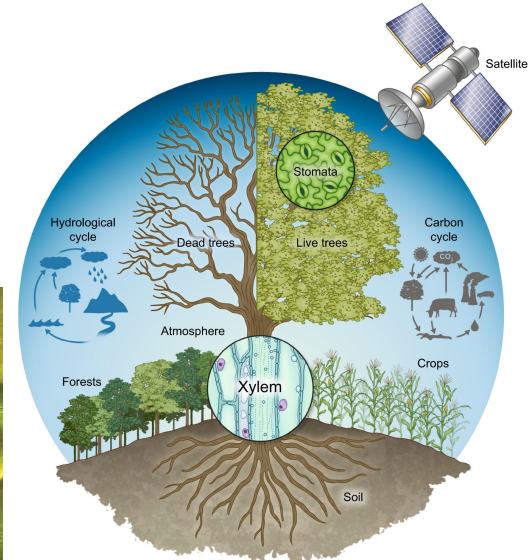
ABC7 News



drought.gov



Nature



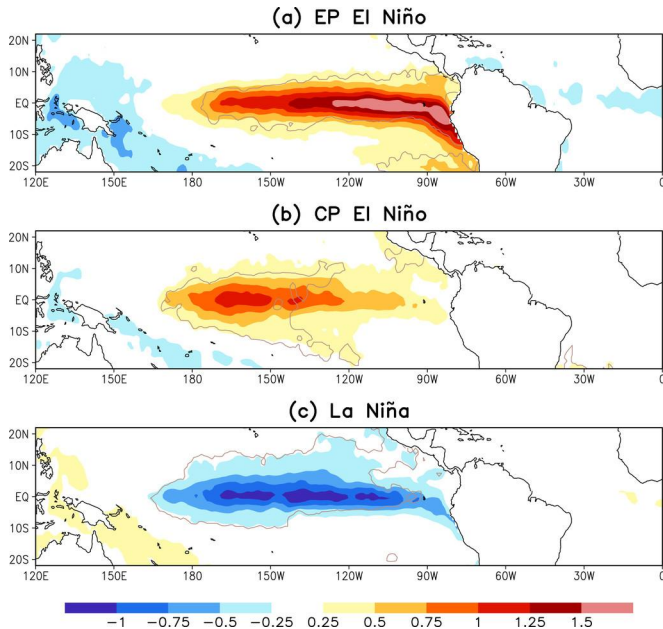
McDowell et al. (2019)



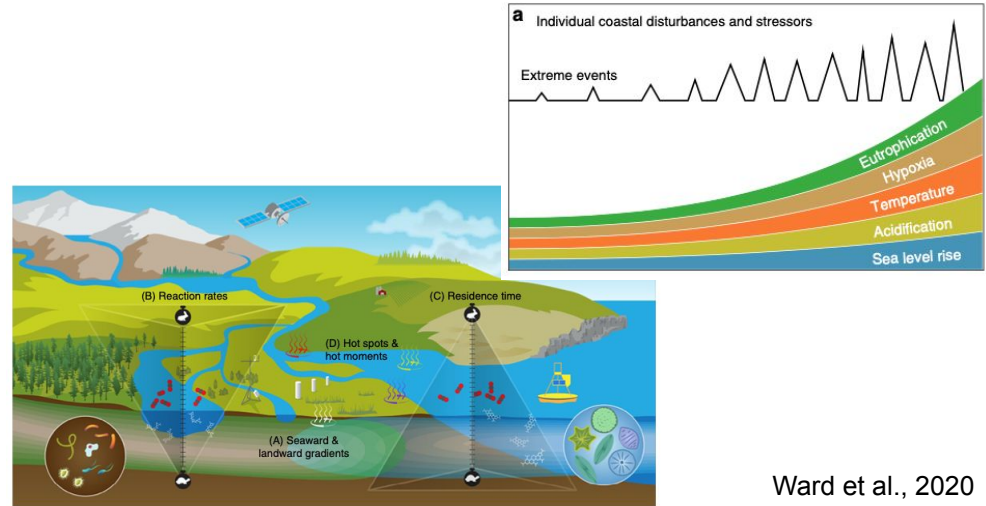
AI4ESP White Papers: Earth System Predictability Topics

● Climate variability and Extremes

- TCs, ARs, Compound/Cascading events
- Predictability
- Circulation/climate variability (ENSO, NAO etc)
- Telecommunication



Wang et al., 2014



● Coastal dynamics, Ocean/Ice

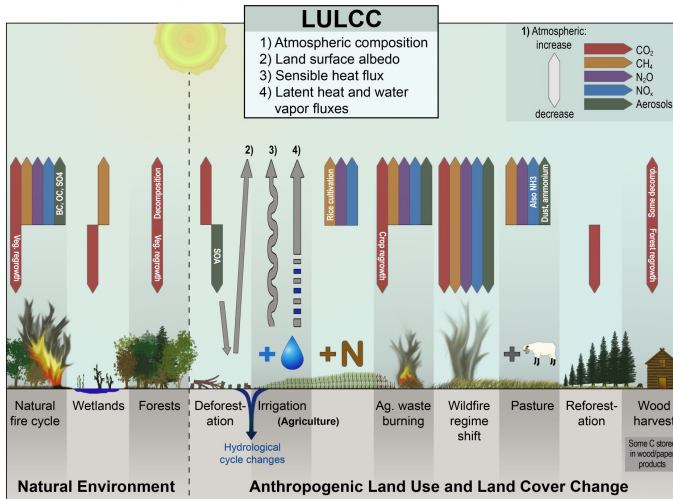
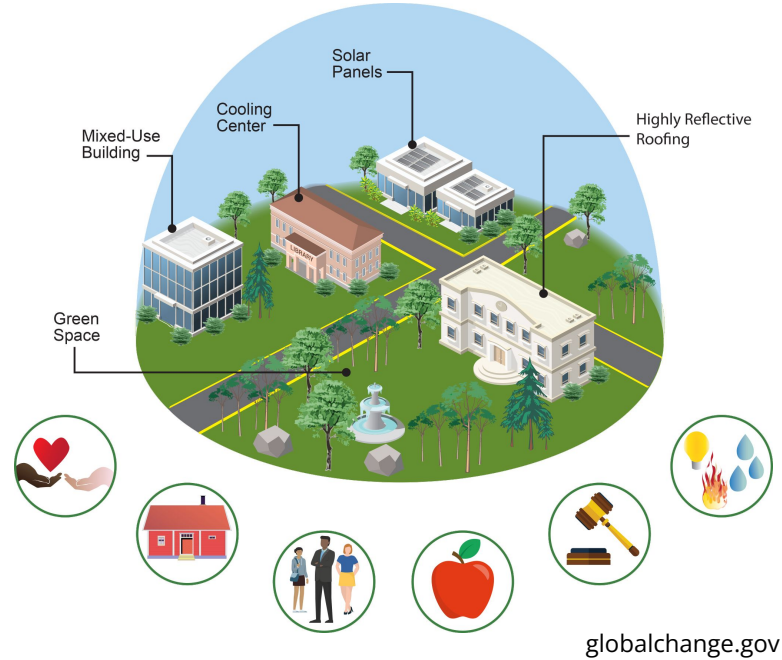
- Ocean/land/ice interface
- Sea-level rise, storm surge
- Coastal ecosystem/carbon cycling



AI4ESP White Papers: Earth System Predictability Topics

● Human Systems and Dynamics

- Human activities/population
- Energy-water-land nexus
- Agriculture
- Urban environment
- Land use/cover changes



AI4ESP: Cross-cutting Topics

- Data Acquisition to Distribution
- Neural Networks
- Surrogate Models and Emulators
- Knowledge-Informed Machine Learning
- Hybrid Modeling
- Explainable and Trustworthy AI
- Knowledge Discovery & Statistical Learning
- AI Architectures and Co-design

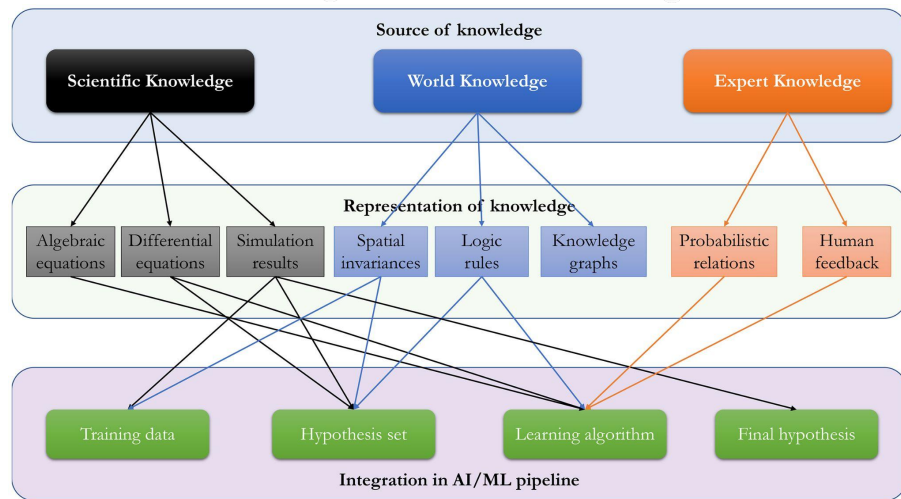
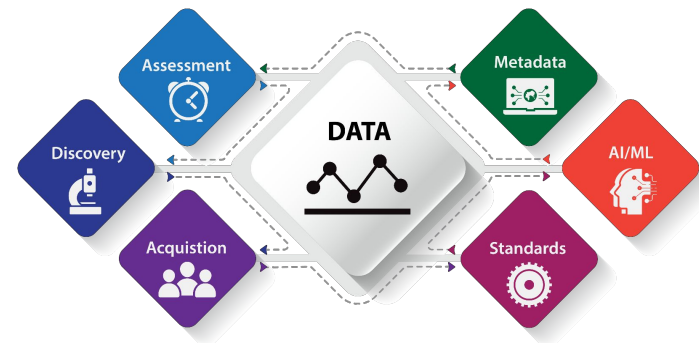


Figure adapted from Von Reuden et al. (2021)

Highlights Across All Sessions

Science

- AI/ML can accelerate next-generation integrated models to support decision-making that incorporate complex natural and human processes at sufficient resolutions
- Broad consensus on need for deep integration of process-based and ML models (hybrid models)
- Challenges: scaling, sub-grid representation, model calibration/UQ, extreme events, human systems
- Data gaps are vast – more observations informed by model needs, AI-ready products
- Results must be robust, explainable, & trustworthy

Data, Software, Infrastructure

- Need benchmark data and model intercomparison approaches
- Computational infrastructure for integration of process & ML models, data assimilation and synthesis
- Use ML to accelerate data-model and model-observation pipelines

Culture

- Workforce development across domain and computational scientists
- Interdisciplinary research centers focused on AI4ESP

AI-Constrained Ecohydrology for Improving Earth System Predictions

Collaboration among ORNL, LANL, Penn State, et al.

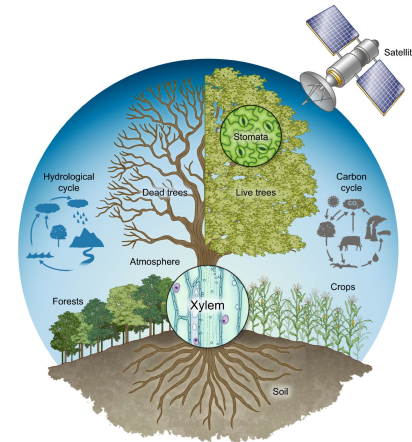
Contact: Forrest M. Hoffman

Project to prototype machine learning-based parameterizations for stomatal conductance and photosynthesis

- Photosynthesis is a computationally expensive part of land models and leaf-level flux and phenology data are available
- Use combinations of leaf-level and plant hydrodynamics data to build ML models of C_3 , C_4 , and CAM vegetation
- Investigate ML approaches for scaling to canopies and watersheds
- Prototype hybrid ML-/process-based components within the E3SM Land Model (ELM)
- Future efforts:
 - Conduct regional and global simulations to benchmark different combinations of process-based and ML modules
 - Explore approaches for building hybrid modeling interfaces within ELM



Nature



McDowell et al. (2019)

The Future is Bright for AI/ML in Earth System Science

A Convergence of New Technology, Explosive Data Growth, and Free Tools

- High performance computing (exascale in big centers and commercial cloud)
- Large data storage resources (commercial and on-premise cloud)
- High speed networks (e.g., ESnet) and data movement technologies (Globus)
- Satellites (shoebox CubeSats) and airborne (drones) platforms
- Cheap (free!) and easy-to-use ML tools (PyTorch, Keras, Scikit-Learn)

Future Applications Could Revolutionize Our Understanding and Ability to Predict

- Poorly understood processes and mechanisms can be mimicked with adequate amounts of data and advanced ML techniques
- Explainable AI and systematic approaches to modeling could lead to new scientific discoveries and improved understanding of the Earth system
- Predictions of complex, nonlinear, large-scale phenomena and natural hazards could be predicted with increasing accuracy



THANK YOU