2018 AmeriFlux Decadal Synthesis Workshop, Lawrence Berkeley National Laboratory (LBNL)

B05: Measurement Integration for Global Scale Inference

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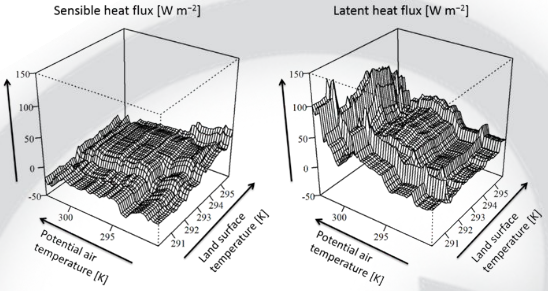
Data–Model Integration Objectives

- Inter-/Intra-network data for uncertainty quantification and scaling
  - Understanding the continental and global representativeness of AmeriFlux and Fluxnet sites and networks
  - Developing footprint, regional, and global gridded flux data products with machine learning
  - Employing remote sensing products and spectral decomposition to reduce data uncertainty
- Model–data fusion for constraining and improving models
  - Using data products to initialize, constrain, and benchmark models
  - Developing fused gridded flux data products with machine learning and environmental response functions (ERF)
  - Assimilation of flux data products with DART + CLM to constrain processes and parameters
- Accessible and machine-parsable metadata and biological data

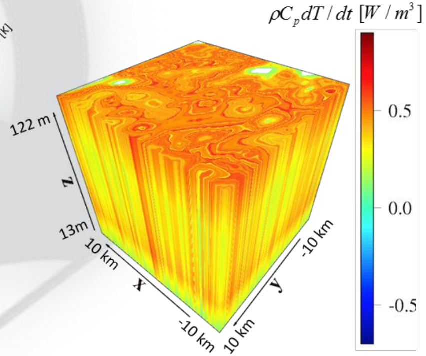
Environmental response function virtual control volume

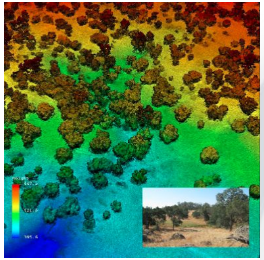
Multivariate responses of surface-atmosphere interactions

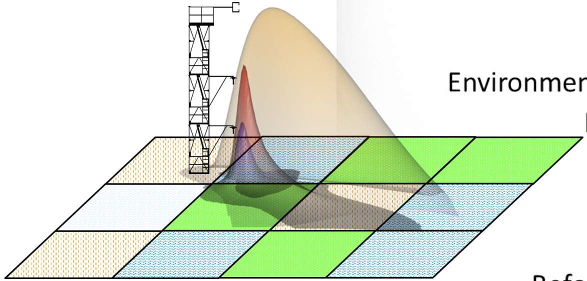


Metzger (2017)

Mapped virtual control volume



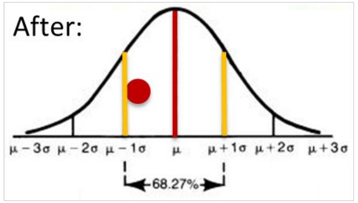




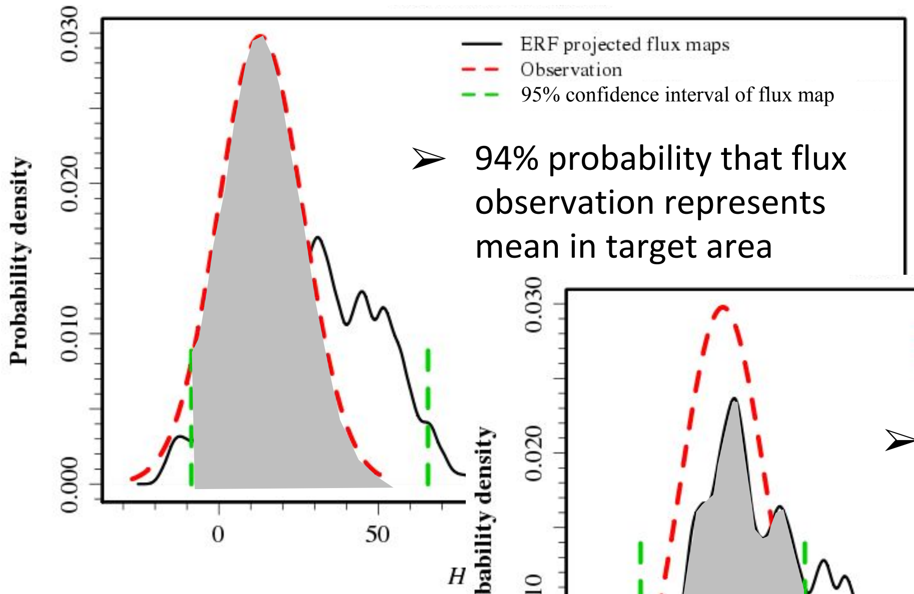
Footprint modeling over coordinated observations of drivers and responses

Environmental response function procedure

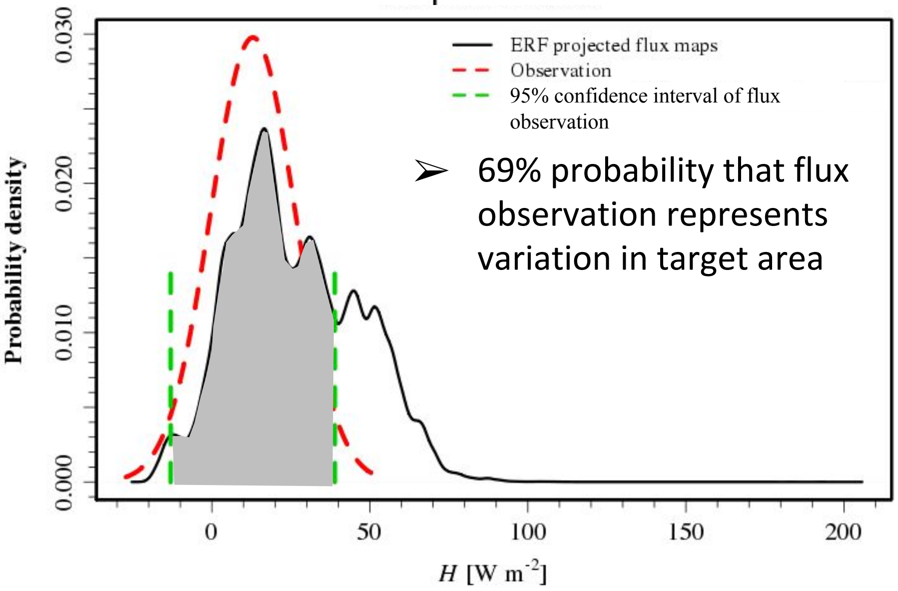
Before:



Spatial representativeness of flux observations



- 94% probability that flux observation represents mean in target area

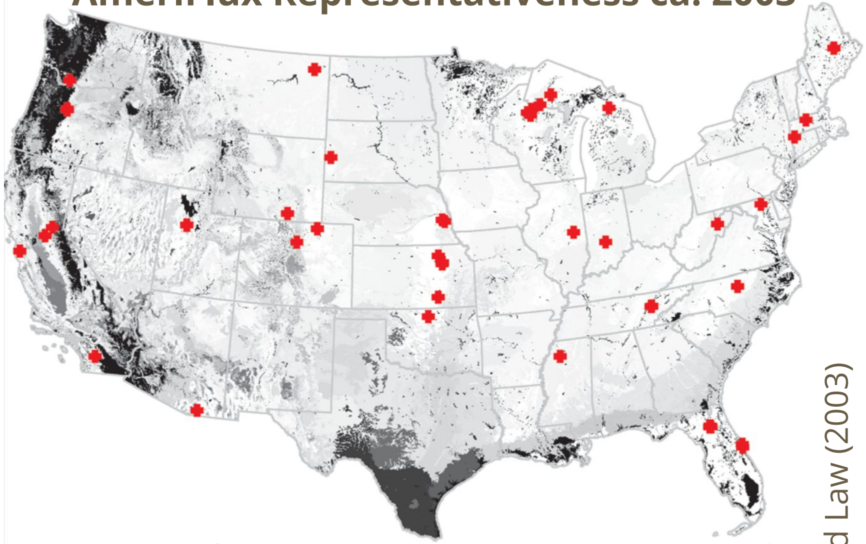


- 69% probability that flux observation represents variation in target area

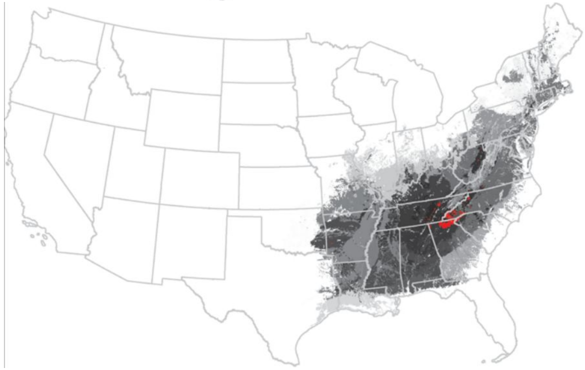
Flux Site and Network Representativeness

- Maps of AmeriFlux representativeness have been produced at least since 2003
- Light areas are well represented by the sites and dark areas are poorly represented by the sites
- Quantitative method based on climatic, physiographic, and edaphic variables
- Enables similarity analysis (e.g., maps of Smokies-ness) and provides quantitative basis for upscaling fluxes

AmeriFlux Representativeness ca. 2003

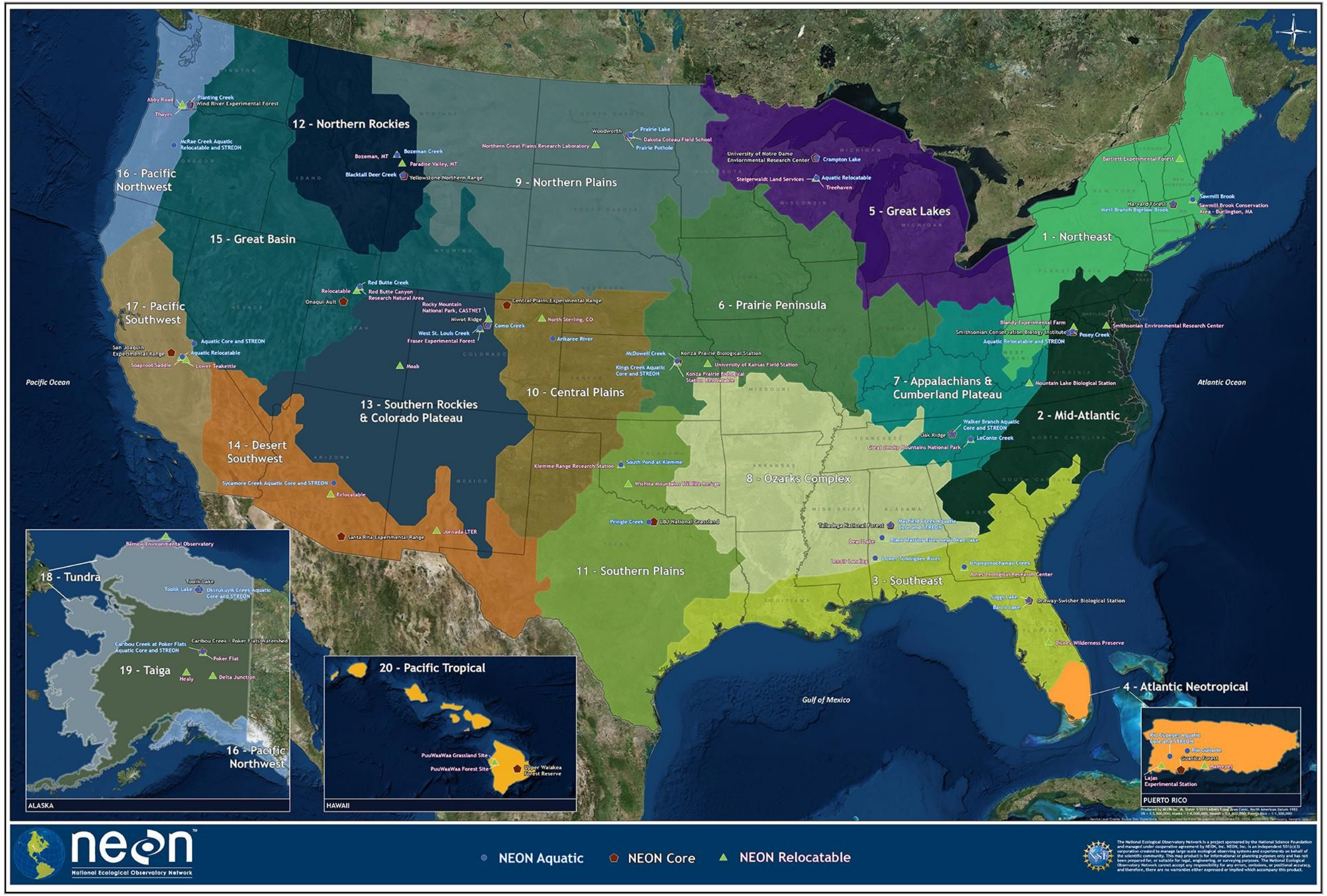


Smokies-ness



Hargrove, Hoffman, and Law (2003)

Defining the 20 NEON Domains



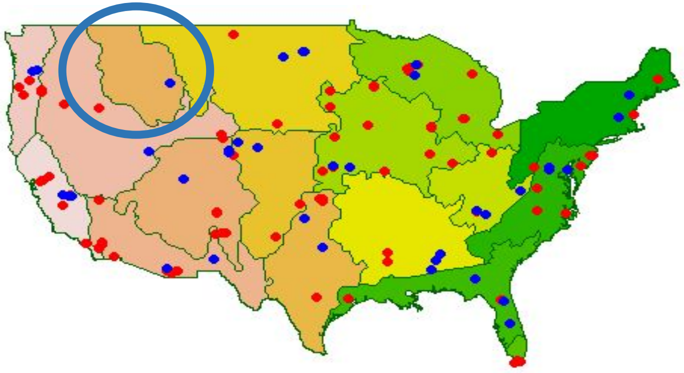
A Primer on the NEON Sampling Design

https://www.neonscience.org/observatory/observatory-blog/primer-neon-sampling-design

Schimel et al. (2007)
Keller et al. (2008)

Uncertainty reduction through optimal site placement

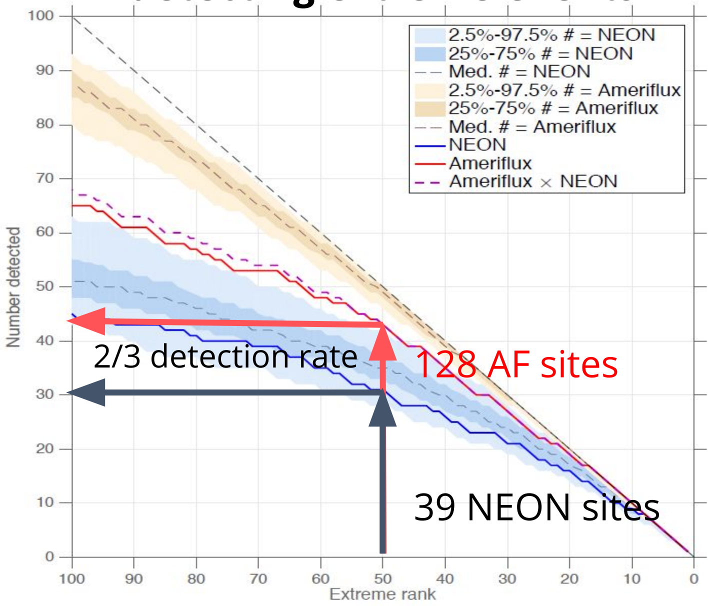
sites across eco-climatic regions



- AmeriFlux
- NEON

Hargrove and Hoffman, 1999 & 2004

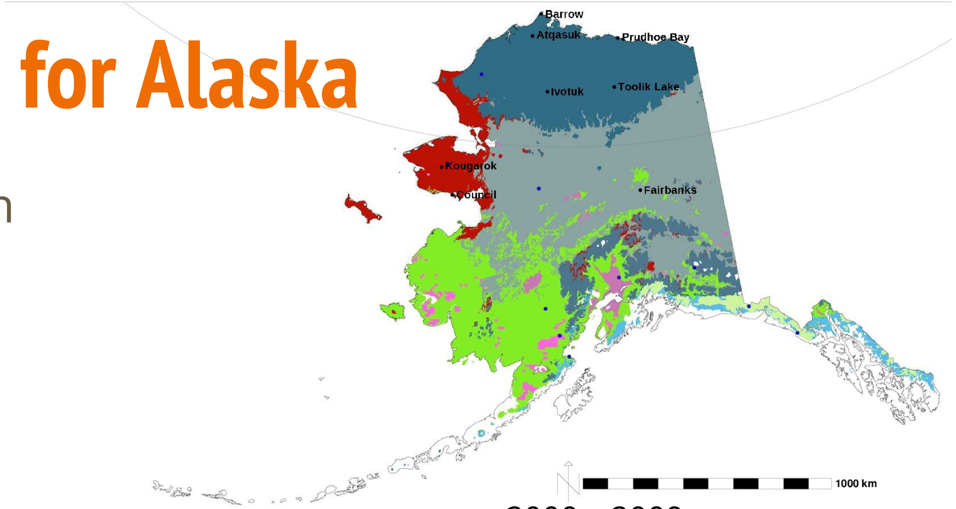
detecting extreme events



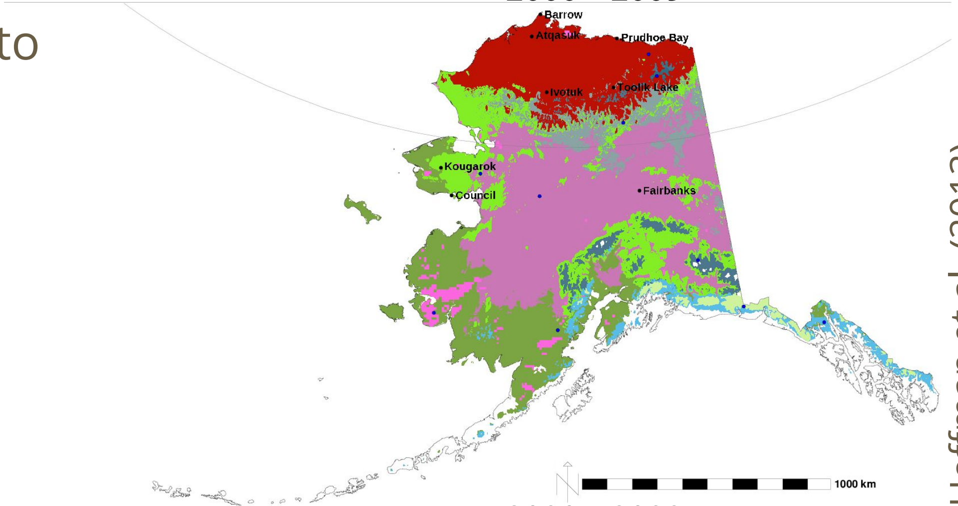
Mahecha et al., 2017

Sampling Network Design for Alaska

- Quantitative methodology based on multivariate clustering for
  - Stratifying sampling domains
  - Informing site selection
  - Determining the representativeness of measurement sites and networks
- Provides model-inspired insights into optimal sampling strategies
- Offers framework for up-scaling measurements
- Provides downscaling approach for integration of models and measurements



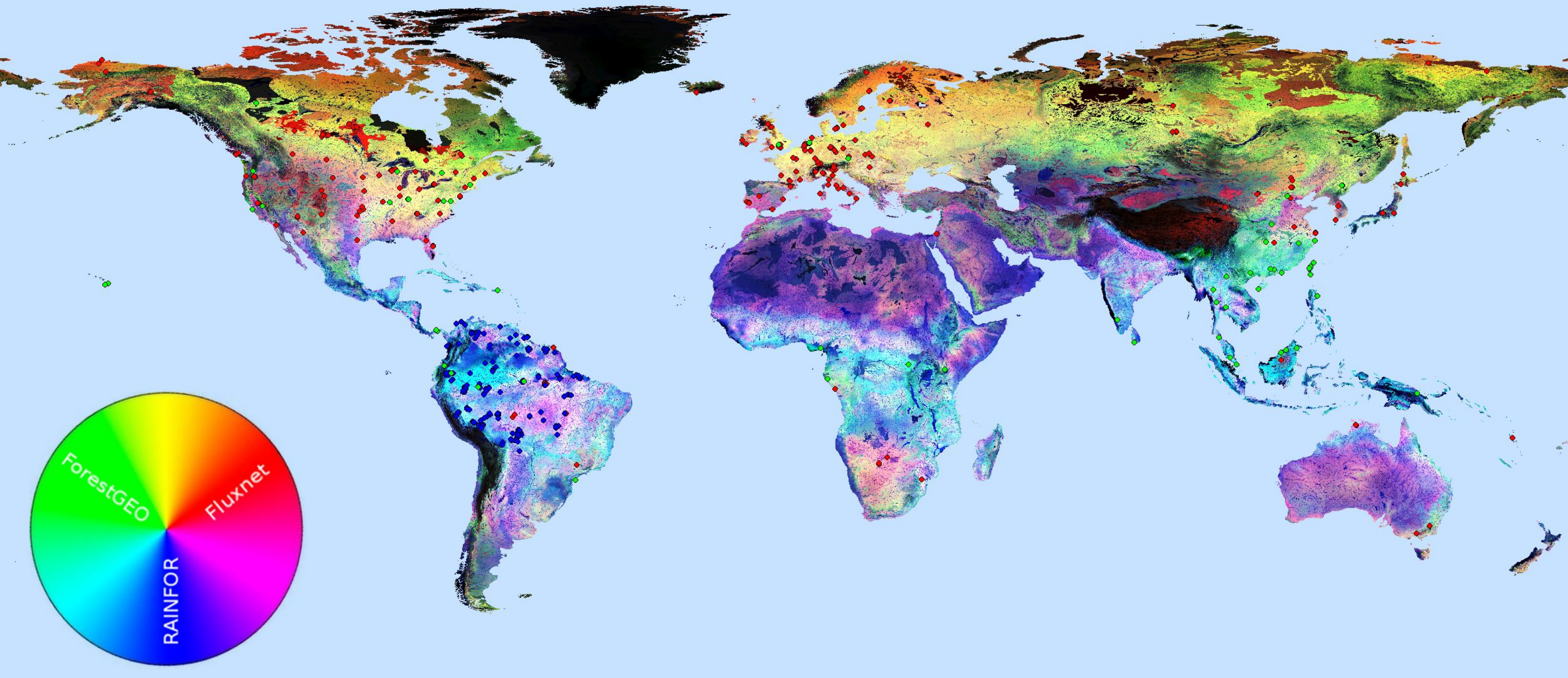
2000—2009



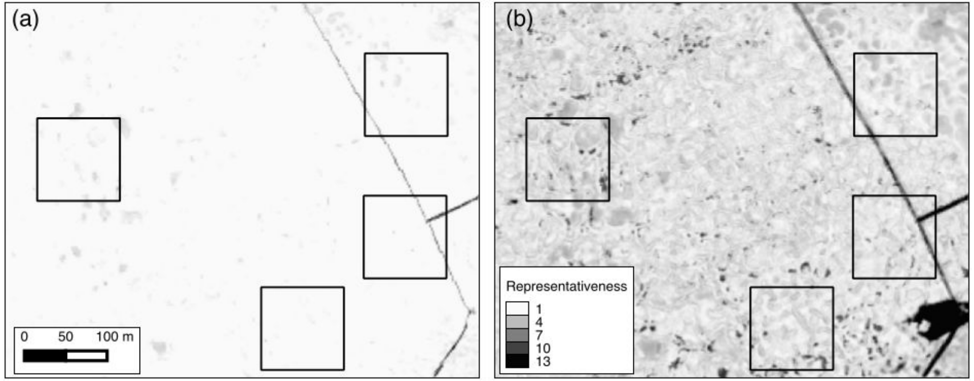
2090—2099

Hoffman et al. (2013)

Multi-Network Representativeness



Site Characterization: Clustering and Neural Networks



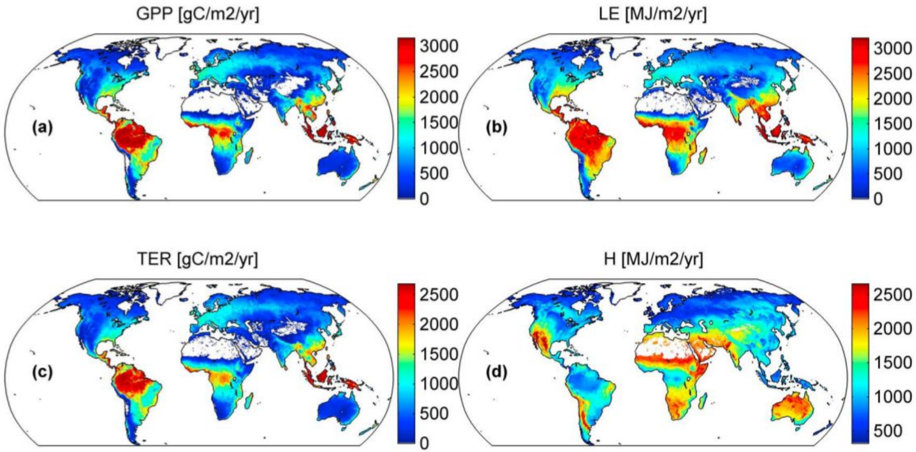
Langford et al. (2016)

Representativeness of vegetation samples across BEO study region (a) without phenology (single snapshot) and (b) with phenology (multiple snapshots).

Convolutional neural network (CNN) approach for mapping Arctic vegetation using multi-sensor remote sensing fusion.

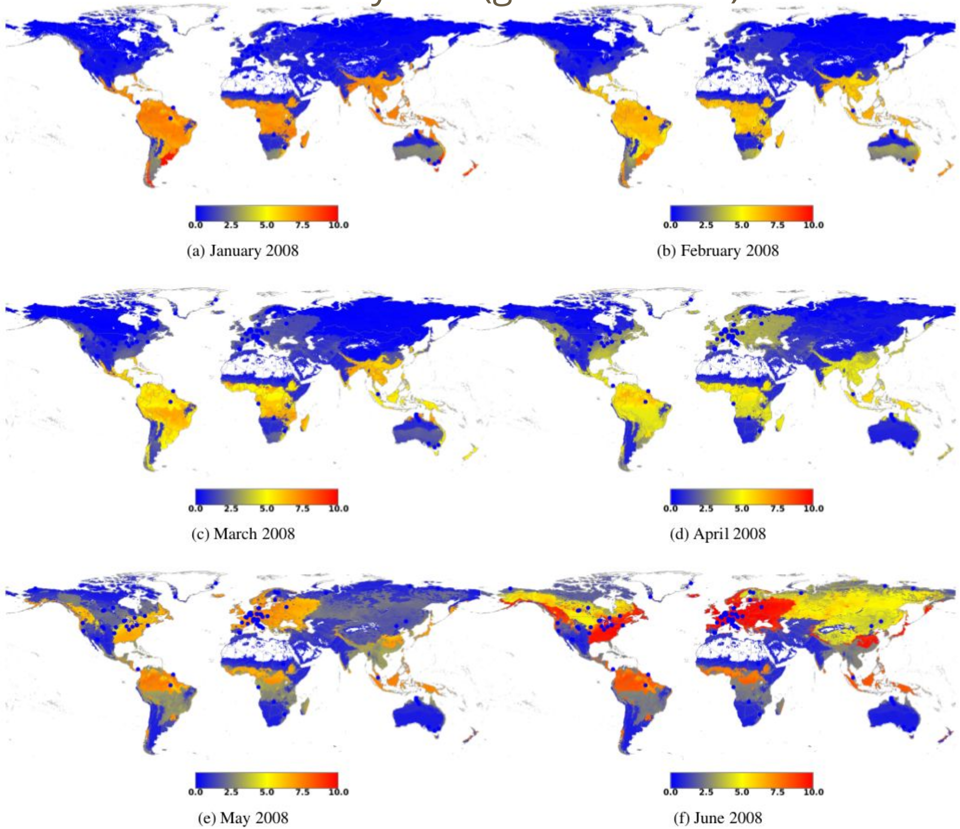
Langford et al. (2017)

Global extrapolation of fluxes



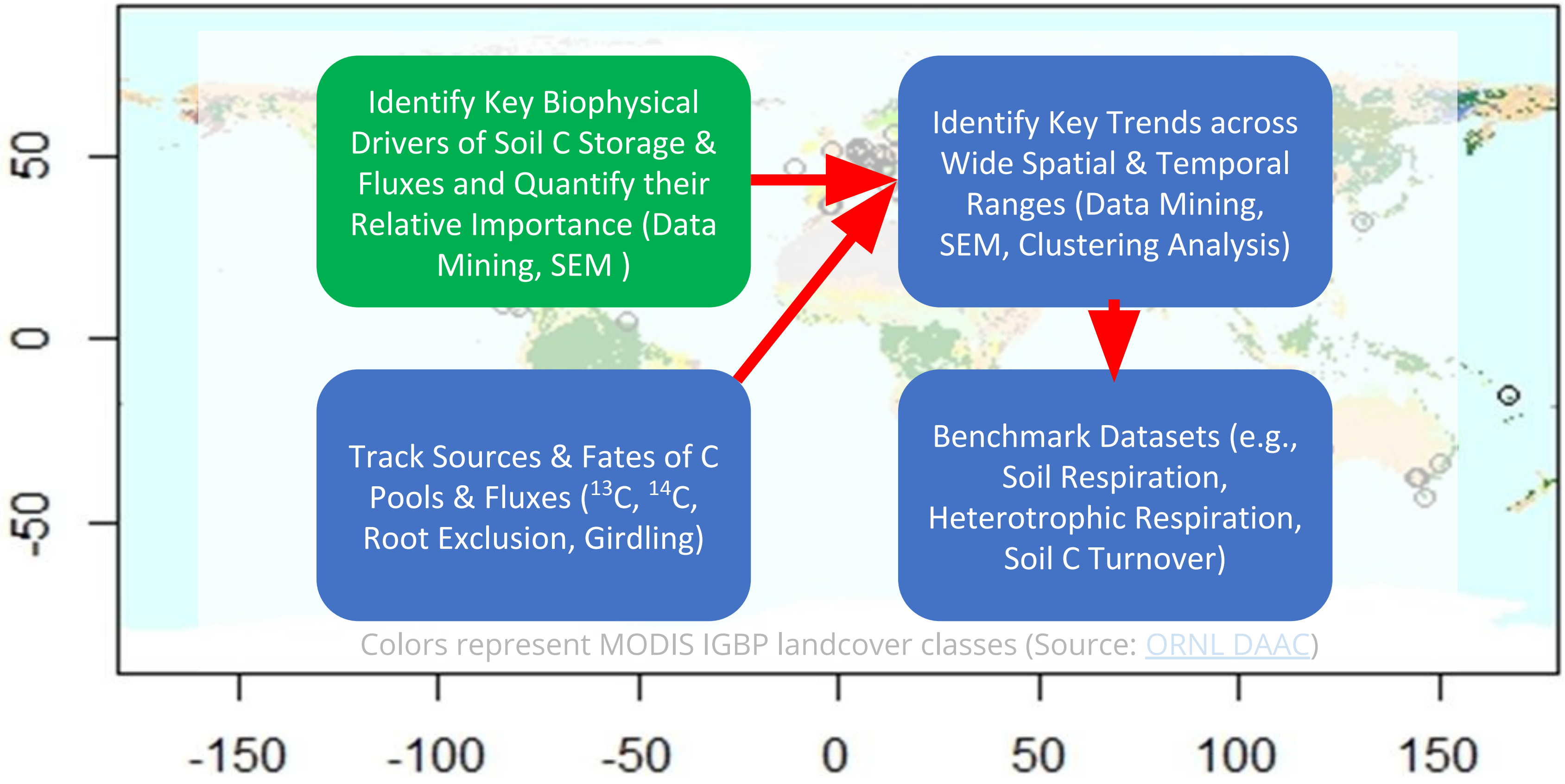
Jung et al. (2011)

Monthly GPP (gC/m^2/month)



Kumar et al. (2016)

Representativeness of Belowground Processes & Global Land C Cycle



Courtesy of Debjani Sihi and Junyi Liang

Data and metadata standards for data assimilation