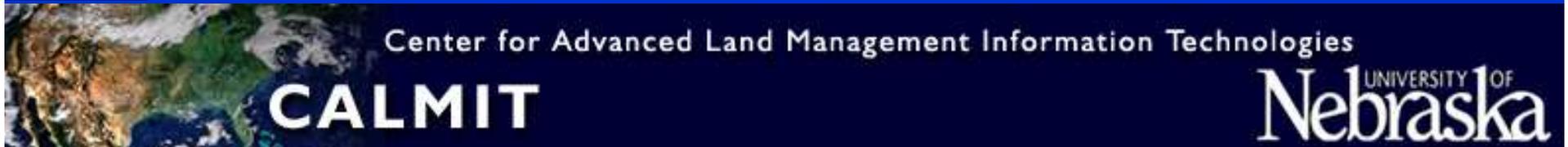
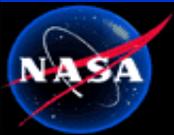


Challenges in modeling spatio-temporal variation in biogeophysical fields: examples from ecological remote sensing

Geoffrey M. Henebry, Ph.D., C.S.E.

Collaboratory for Ecological Remote Sensing, Modeling & Analysis (CERSMA)
Center for Advanced Land Management Information Technologies (CALMIT)

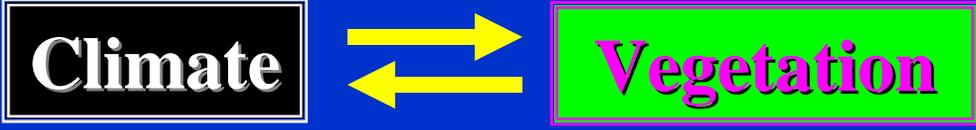
School of Natural Resources
University of Nebraska-Lincoln
ghenebry@calmit.unl.edu
<http://calmit.unl.edu/cersma/>



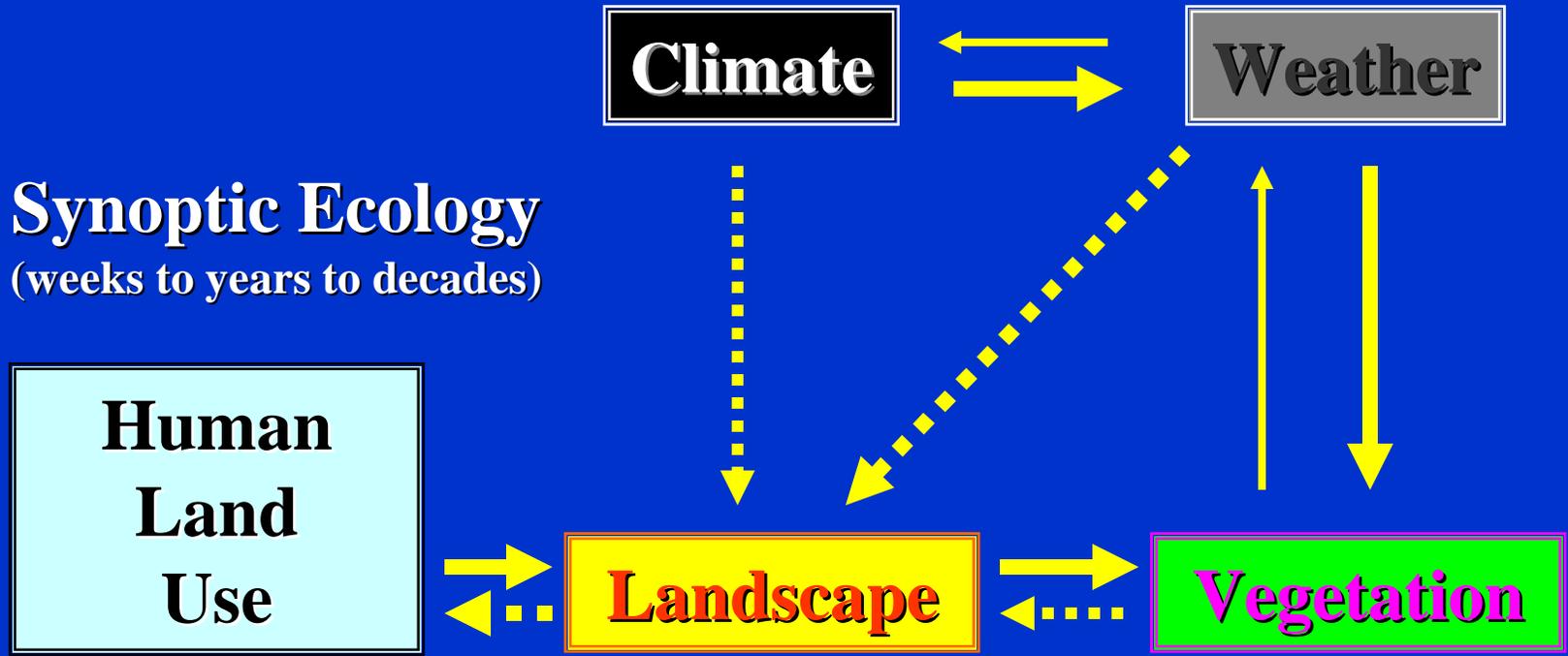
Outline of Talk

0. Synoptic ecology: remote sensing of ecological change
 1. What are the appropriate units of analysis?
 2. What constitutes appropriate baselines?
 3. How do we conduct change analysis?
4. How do uncertainties affect model reliability?
5. Slouching toward ecological forecasting...

Biogeography
(decades to millenia to eons)



Synoptic Ecology
(weeks to years to decades)



Meteorology
(seconds to hours to weeks)



0. Why Synoptic Ecology?

- A) Synoptic ecology focuses on the interface between land surface & atmosphere, where human activity greatly affects the biogeophysical & socioeconomic patterns and processes.

- B) Science requires the ability to distinguish unusual change from expected variation. This assumes a good notion of what is expected and thereby provides a foundation for modeling.

- C) Long range objective → Construction of an operational environmental monitoring & forecasting system for the land surface dynamics that interacts with other environmental monitoring & forecasting systems, e.g., the global weather network.

Remote sensing is a valuable tool for the ecologist. It permits him to extend observation of the relationships between living organisms and the environment to vast areas otherwise impossible to investigate. **Remote sensing is important to the scientist in allowing him to determine the spatial relationships of the environment by synoptic view of interaction of ecological variables** such as soil types and soil moisture with the geographical distribution of plant species.

Yost and Wenderoth 1969

THE CHALLENGE:

- We are now in an era of intensive earth observation.
- Image time series are voluminous and difficult to analyze.
- Yet, these datastreams hold the promise for environmental decision support by means of integrated modeling.

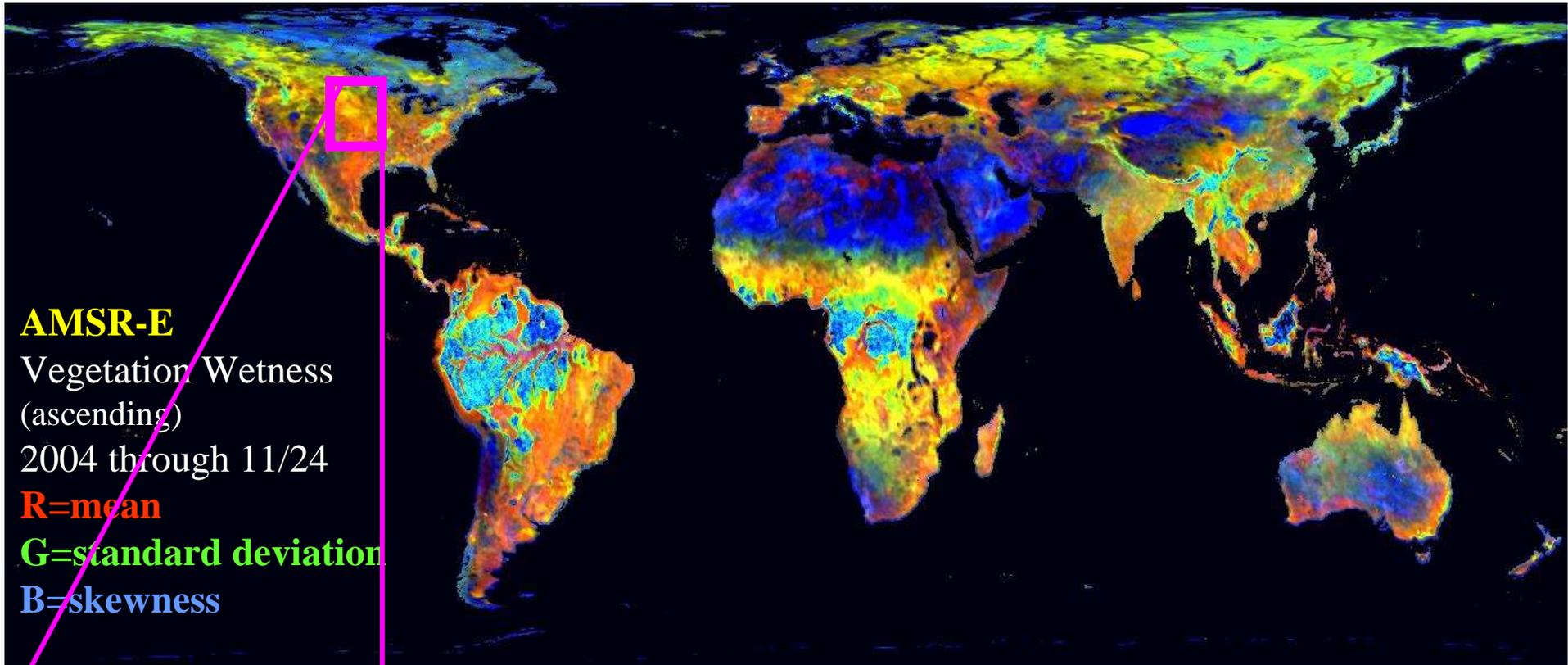
There is *critical need* for both theory & techniques to enable efficient and reliable characterization of spatio-temporal patterns latent in image time series.

A DEEP PROBLEM:

What are the appropriate units of analysis (UoA) for image time series of images of biogeophysical fields localized with spatial and temporal coordinates?

Individual pixels are neither appropriate nor sufficient!

- Fisher, P. 1997. The pixel: a snare and a delusion. *International Journal of Remote Sensing* 18:679-685.
- Cracknell, A.P. 1998. Review article. Synergy in remote sensing – what’s in a pixel? *International Journal of Remote Sensing* 19:2025-2047.
- Henebry, G.M., and J. W. Merchant. 2001. Geospatial data in time: limits and prospects for predicting species occurrences. In Predicting Species Occurrences: Issues of Scale and Accuracy, (J.M. Scott, P. J. Heglund, M.L. Morrison, J.B. Haufler, M.G. Raphael, W.A. Wall, and F.B. Samson, editors). Island Press, Covello, CA. Chapter 23. pp 291-302.



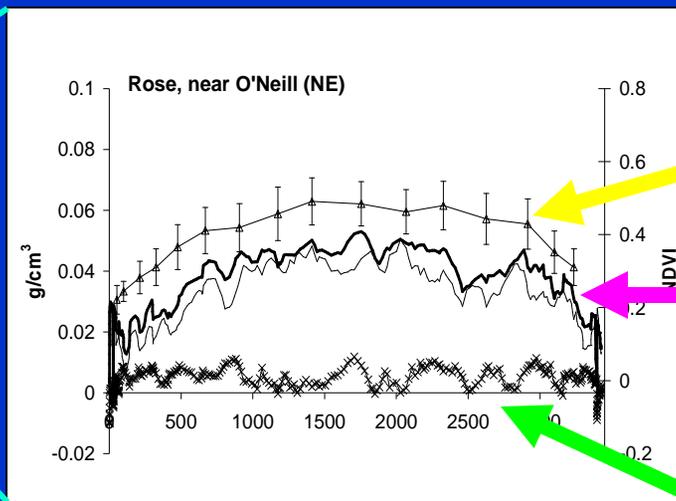
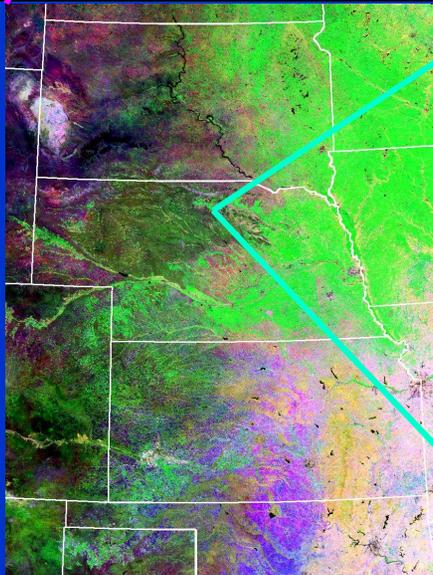
AMSR-E

Vegetation Wetness
(ascending)
2004 through 11/24

R=mean

G=standard deviation

B=skewness



MODIS NDVI + 1 SD

AMSR-E Vegetation Wetness
Descending (pre-dawn, thick line)
Ascending (afternoon, thin line)

AMSR-E Vegetation Wetness
diel variation predawn – afternoon (fuzzy line)

The UoA question involves *resolution & extent* of each dimension of measurement AND the *characteristic extents* of the thing(s) observed.

Let $R = \text{scene object extent} / \text{sensor resolution}$.

If $R < 1$, then multiple scene objects can fall within one sensor grain. **Gradients in space. Fluctuations in time.**

Summarized by measures of dependence, e.g., correlation length.

If $R > 1$, then multiple sensor grains can portray a scene object.

Contrasts in space. Seasonality in time.

Summarized by measures of heterogeneity, e.g., diversity/entropy.

•Inspired by: Strahler, A.H., C.E. Woodcock, & J.A. Smith. 1986. On the nature of models in remote sensing. *Remote Sensing of Environment* 20:121-139.

There are no natural *a priori* spatial units!

We impose units by our observational processes. Thus, delineations between patches are arbitrary and may be imprecise in location, transitory in duration, and irrelevant to underlying processes of interest.

Further, there is no *a priori* ordering of the directionality of causation in space comparable to the “arrow of time.”

While topological relationships indicate who is the neighbor of whom, additional information is required to know who are the effective neighbors. *This requires the user to inform the geospatial database about the flows of influence among spatially ordered data.*

Different processes can have different effective neighborhoods at different scales.

The related problem of partitioning space: MAUP

- ❖ Significant differences often exist between the scales of measurement and the scales at which ecological and environmental models operate.
- ❖ General problem of scale dependence has long been investigated for spatial data in geography as the Modifiable Areal Unit Problem (MAUP).
- ❖ The principal undesirable consequence of the MAUP is equivocal statistical analysis: by simply varying either data resolution through aggregation or data allocation through alternative zonations, a spectrum of correlations may be elicited from the same dataset.
- ❖ By enabling the user to define and redefine areal units, GIS can actually exacerbate the MAUP and promote discovery of spurious correlative relationships (Openshaw and Alvanides 1999).

- Arbia, G. 1989. *Spatial Data Configuration in Statistical Analysis of Regional Economic and Related Problems*. Boston: Kluwer.
- Jelinski, D.E., and J. Wu. 1996. The modifiable areal unit problem and implications for landscape ecology. *Landscape Ecology* 11:129-140.
- Openshaw, S. 1984. *The Modifiable Areal Unit Problem*. Concepts and Techniques in Modern Geography. Norwich, UK: Geo-Books.
- Openshaw, S., and S. Alvanides. 1999. Applying geocomputation to the analysis of spatial distributions. In *Geographical Information Systems. Volume 1 Principles and Technical Issues_2/e*, edited by P.A. Longley, M.F. Goodchild, D.J. Maguire, and D.W. Rhind, 267-282. New York: Wiley.

There are no objective solutions to the MAUP.

But its effects can be attenuated by using domain expertise to specify meaningful ways to (dis)aggregate data.

Example of alternative partitionings of the plane:

- ❖ **Major Land Resource Areas (MLRAs) – NRCS, soils bias**
- ❖ **Bailey's ecoregions – USFS, climate-veg bias**
- ❖ **Omernik's ecoregions – EPA, watershed/LULC biases**
- ❖ **WWF ecoregions – NGO, wildlands bias(?)**
- ❖ **phenoregions of White et al. (2005) – conditional partitioning**

•White, M.A., F. Hoffman, W.W. Hargrove, and R.R. Nemani. 2005. A global framework for monitoring phenological responses to climate change. *Geophysical Research Letters* 32:L04705.

raster : vector :: field : object

People manipulate objects (but cultivate fields) → Couclelis (1992) argued that human cognition relies on both modes of spatial representation.

Thus, it is critical to embrace multiple representational modes or multi-modality in geospatial databases.

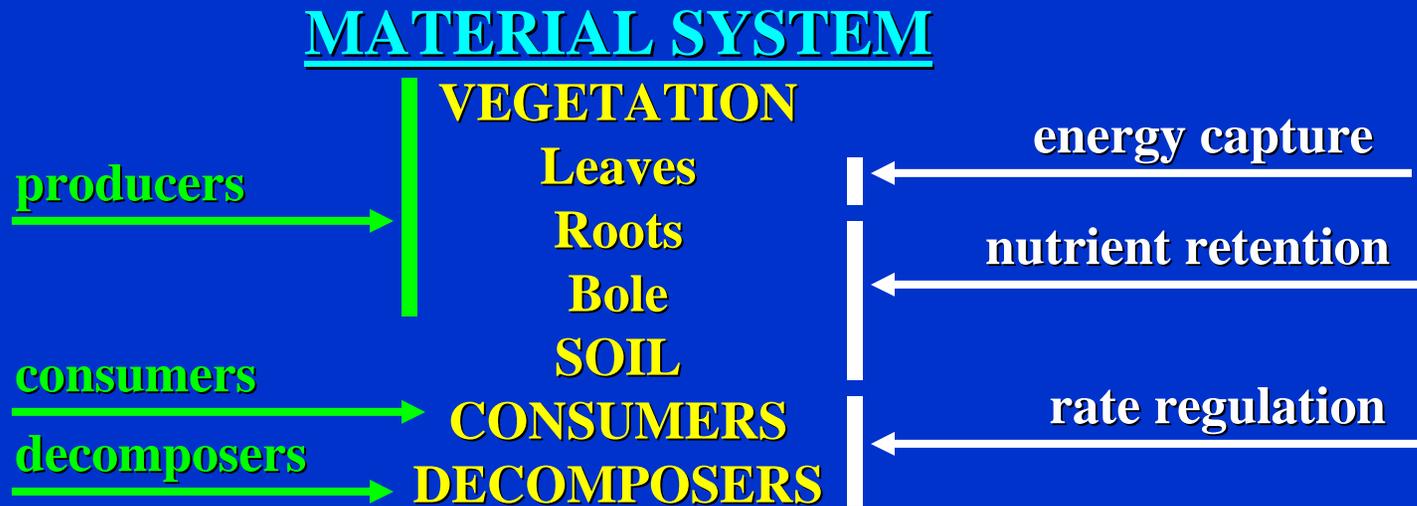
*Distinctions between field & object
are observer dependent.*

•Couclelis, H. 1992. "People manipulate objects (but cultivate fields): beyond the raster-vector debate in GIS." In *Theories and Methods of Spatio-Temporal Reasoning in Geographic Space*, edited by A.U. Frank, I. Campari, and U. Formentini, 65-77. LNCS 639. New York: Springer-Verlag.

ALTERNATIVE VALID VIEWS OF A MATERIAL SYSTEM

Biotic-Organismal
(population & community)

Process-Functional
(ecophysiology & ecosystem)



•Adapted from O'Neill et al. 1986. *A Hierarchical Concept of Ecosystems*. Princeton University Press.

Pattern searching is not the same as hypothesis testing because there is no relevant null hypothesis. This point was lost on the original quantitative geographers [during the 1970's]. ...[They] failed to develop a statistical theory of spatial analysis as distinct from providing examples of statistical methods being applied to spatial data in search for largely aspatial patterns.

The danger now is that the same mistake will be repeated 20 years later in the GIS era by a failure to appreciate that spatial patterns are themselves geographic objects that can be recognized and extracted from spatial databases.

Openshaw 1994

- Openshaw, S. 1994. A concepts-rich approach to spatial analysis, theory generation, and scientific discovery in GIS using massively parallel computing. In: (M. Worboys, ed.) Innovations in GIS. London: Taylor and Francis. pp. 123-137.

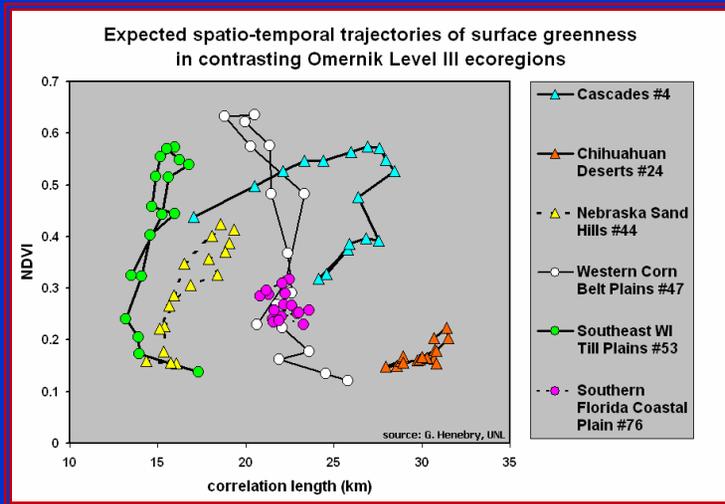
What is of scientific interest in image time series *are not the pictures themselves*, but the dynamic of pattern and process that sequences of pictures portray.

2. What constitutes appropriate baselines?

Statistical modeling of complex spatio-temporal data through local filters on neighbors (AR) and noise (MA), e.g., AR(D)MA, CAR, SAR, wavelets, harmonic/Fourier analysis, Kalman filters.

- ❖ Climatological approaches via the moments of the distribution of accumulated observations.
- ❖ Use the power of recurrent observation for identifying anomalies, the unusual, and the unique.
- ❖ Building empirical expectations sets the stage for change analysis & forecasting.

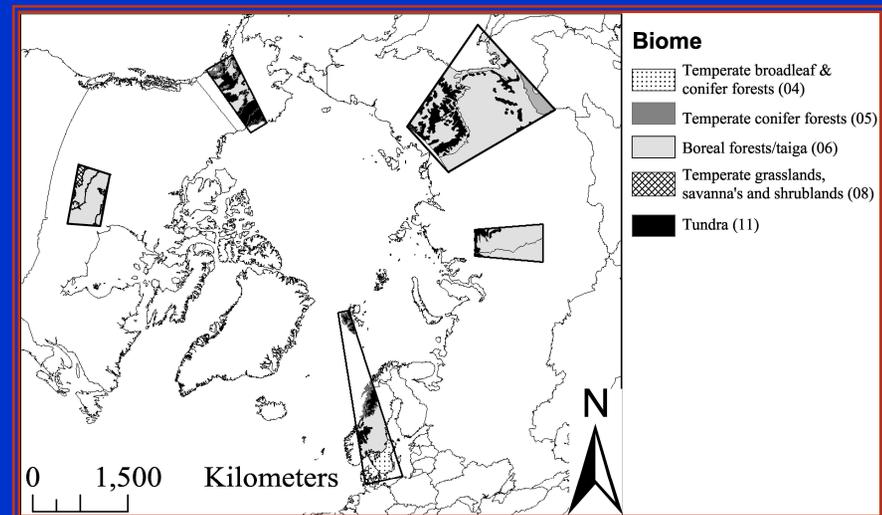
Examples of complex expectations based on prior observations



Poster on changes in high latitude phenologies by de Beurs & Henebry →

Imagine a picture of a dung beetle

← Poster on landscape trajectories by Henebry & Goodin



← Poster on tracking spatio-temporal change in tropical forests to prioritize bioindicator surveys by Aguilar-Amuchastegui & Henebry

SEEKING BASELINES—AN ANALOGY:

Consider sparsely sampling a movie by individual frames or even frame sequences.

One level of analysis might aim at reconstructing motion, but a more sophisticated analysis would aim at *reconstructing the plot*.

Intelligent (and informed) knowledge discovery in scientific databases must aim at

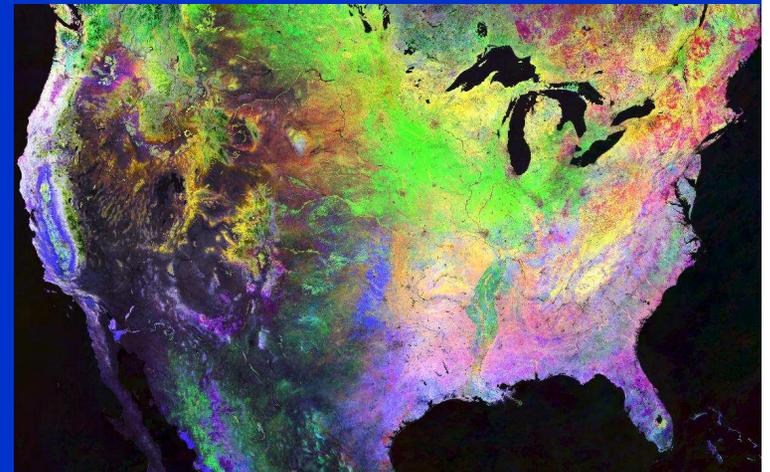
- * reconstructing plots,
- * comparing plots,
 - * identifying unusual plots, and
 - * interesting deviations from typical plots.

Some relevant ecological “plots” include:

- **Succession in ecological communities/ecosystem structure**
- **Growth and development of urban areas**
- **Disaster recovery**
- **Invasive species/disease outbreak & spread**
- **Land surface phenology (both reflected and emitted light)**

Land Surface Phenology: the what and the why

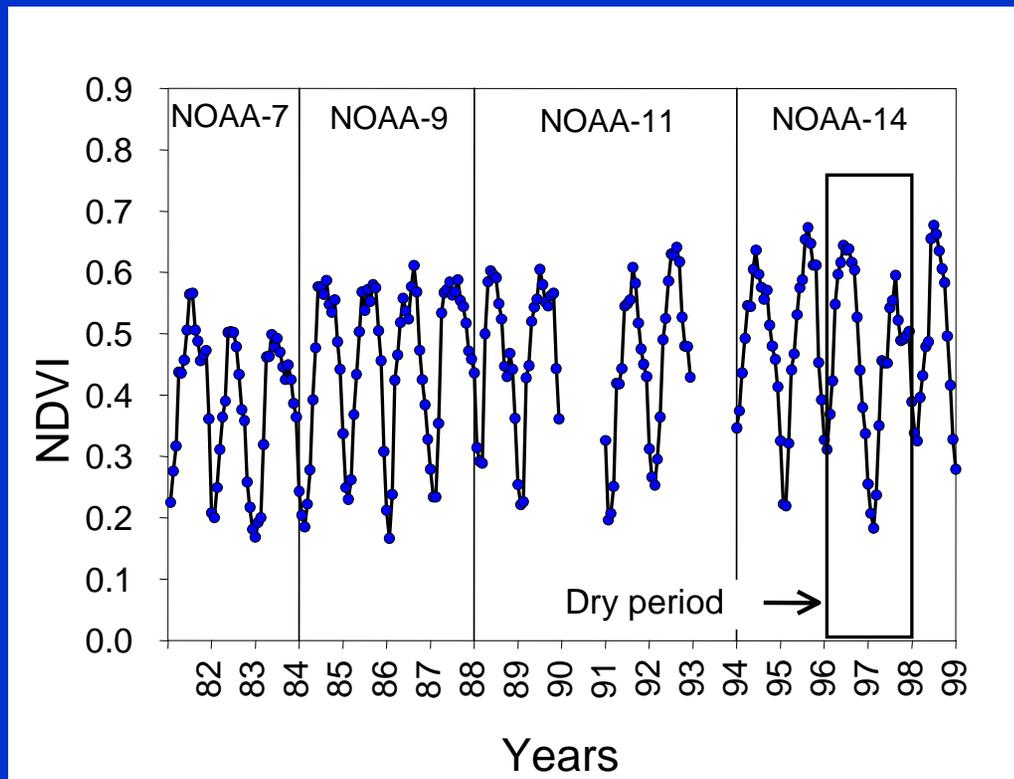
- ❖ ***Land Surface Phenology*** is defined as the spatio-temporal development of the vegetated land surface as revealed by synoptic sensors (e.g., AVHRR, MODIS, VEGETATION, MERIS, VIIRS, etc.).
- ❖ ***Land Surface Phenology*** deals with mixtures of land covers; it is distinct from the phenology of particular species. Linked to seasonality of aboveground net primary production (ANPP).
- ❖ Need to understand dynamics of ***Land Surface Phenology*** to model carbon, water, energy exchanges in the biosphere.



3. How do we conduct change analysis?

- 1. Change detection – perceiving the differences**
- 2. Change quantification – measuring the magnitudes of differences**
- 3. Change assessment – determining the significances of differences**
- 4. Change attribution – identifying/infering the proximate causes**
- 5. Consequences of changes – ancillary data, modeling, domain expertise**

Are there significant changes in land surface phenology?

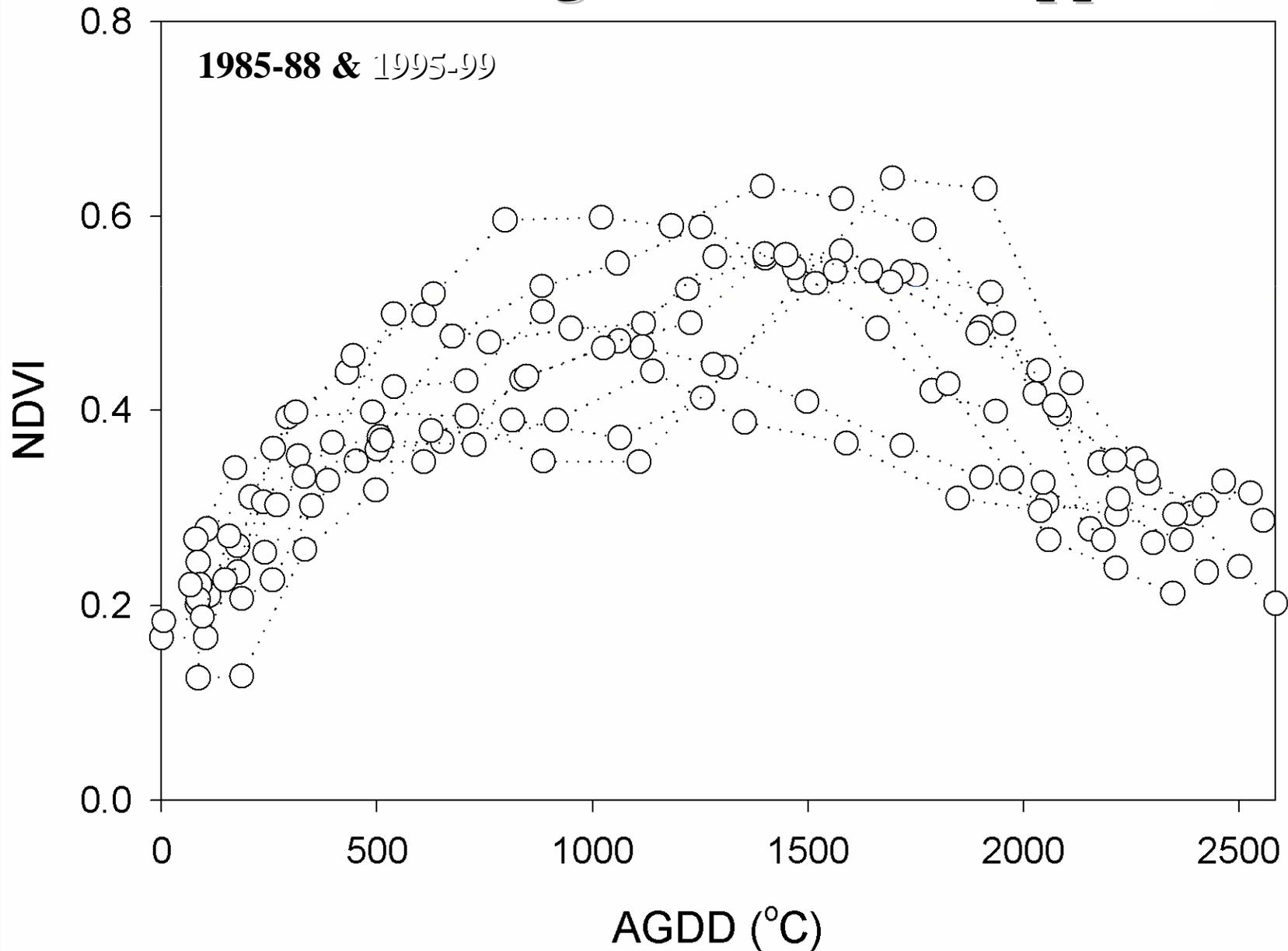


Apparent changes in vegetated land surface can result from:

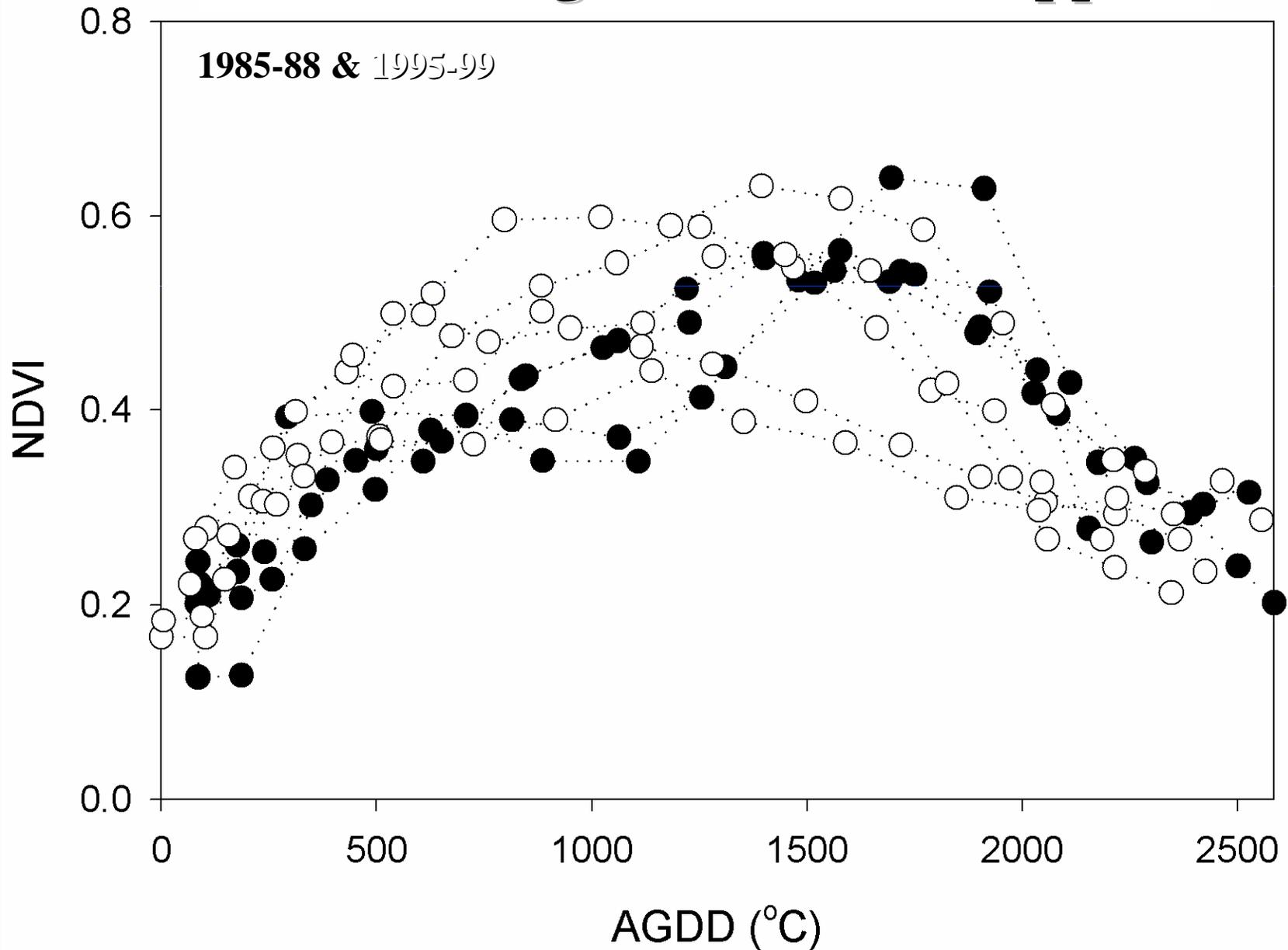
- Sensor changes
- Seasonal variability
- Interannual variability
- Anthropogenic changes

How do we distinguish between these types of variation?

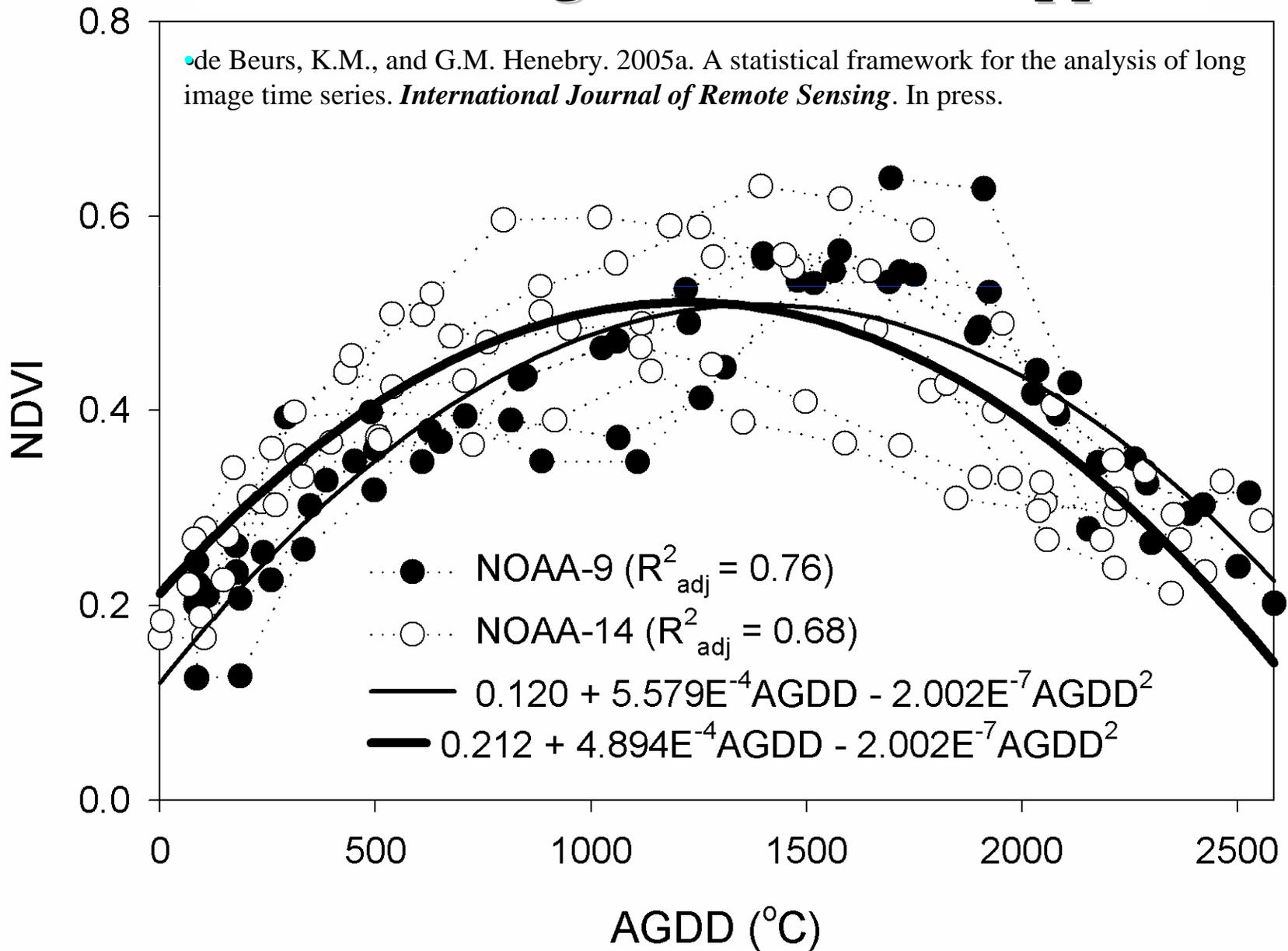
WWF ecoregion: Kazakh Steppe



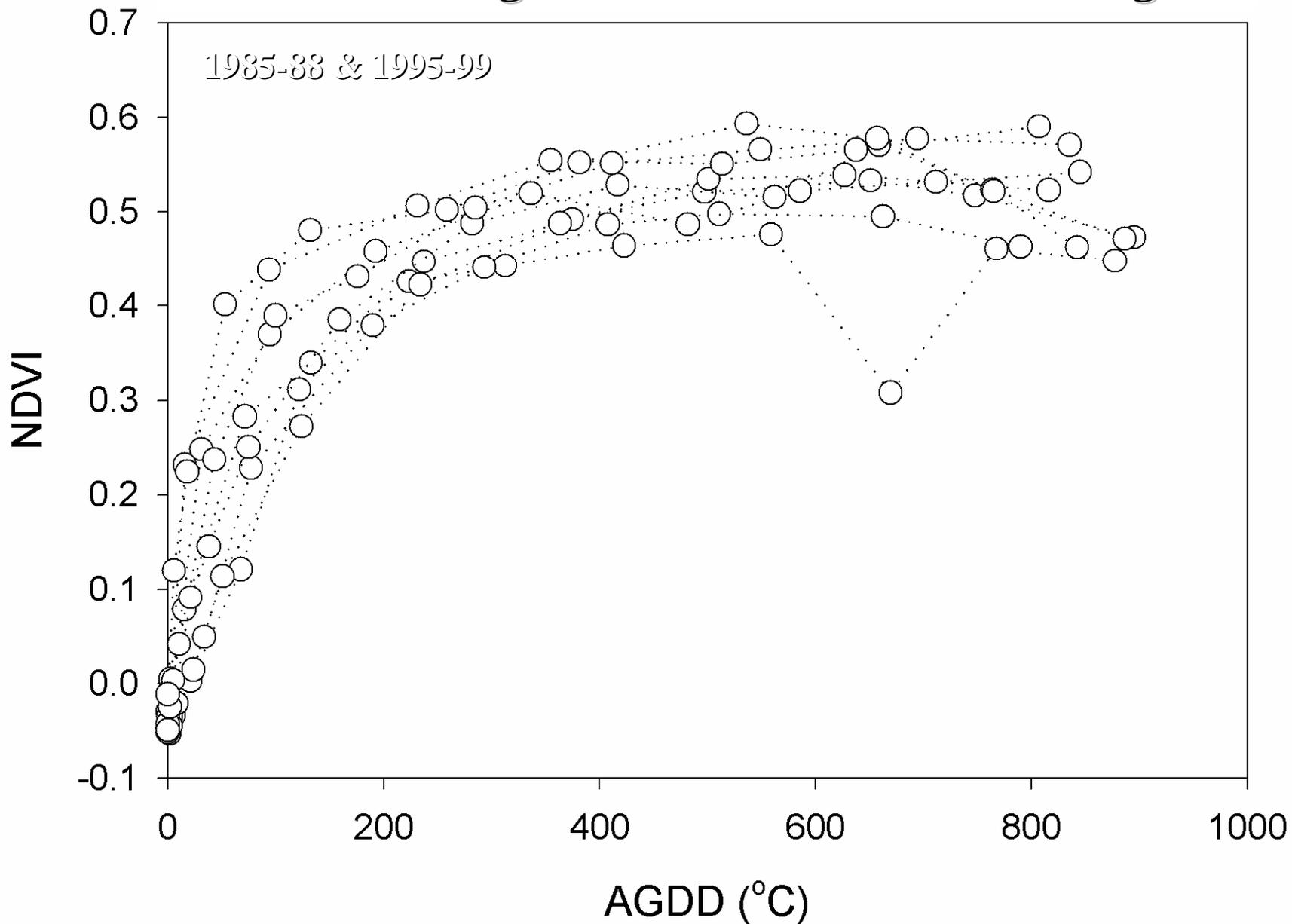
WWF ecoregion: Kazakh Steppe



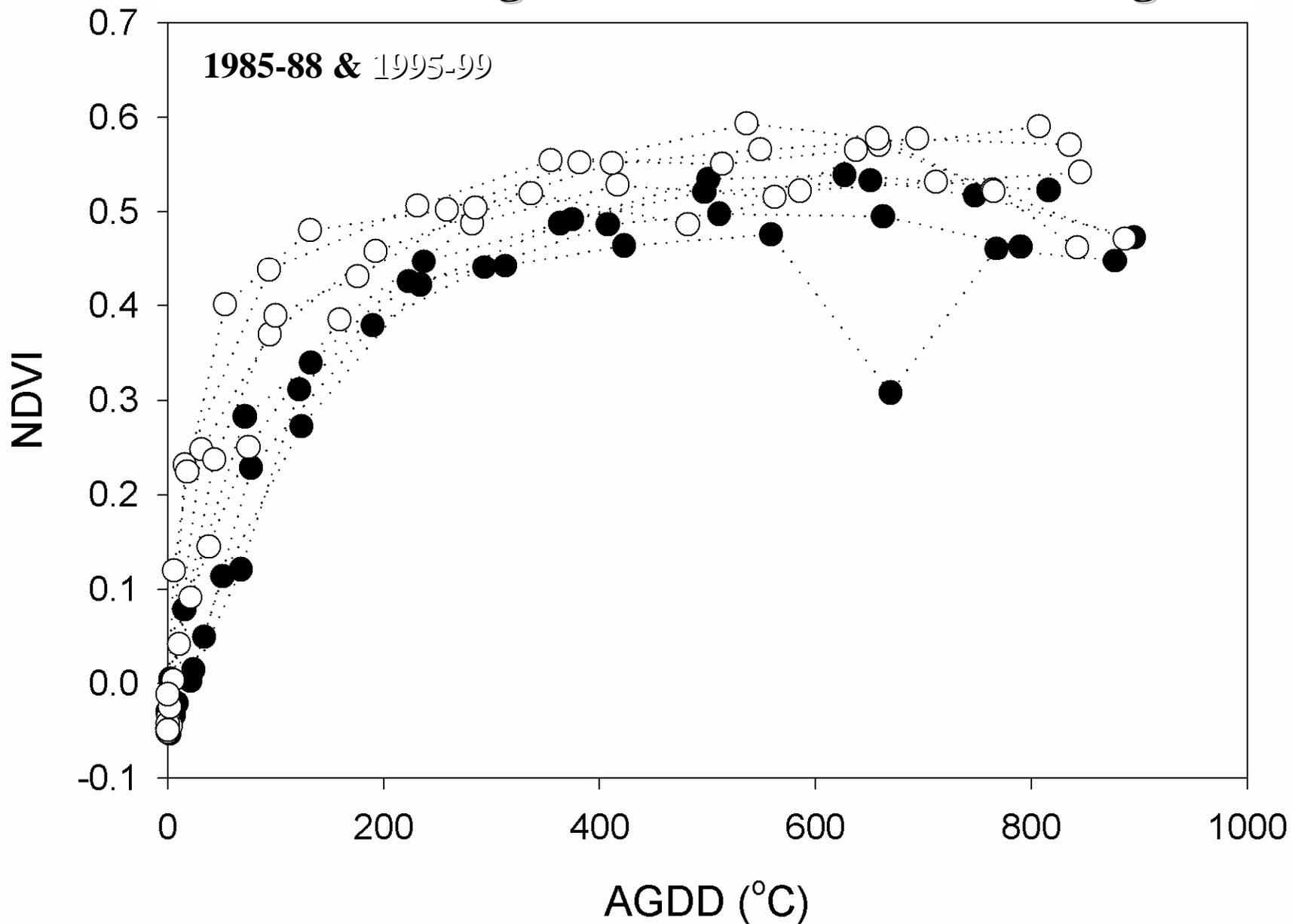
WWF ecoregion: Kazakh Steppe



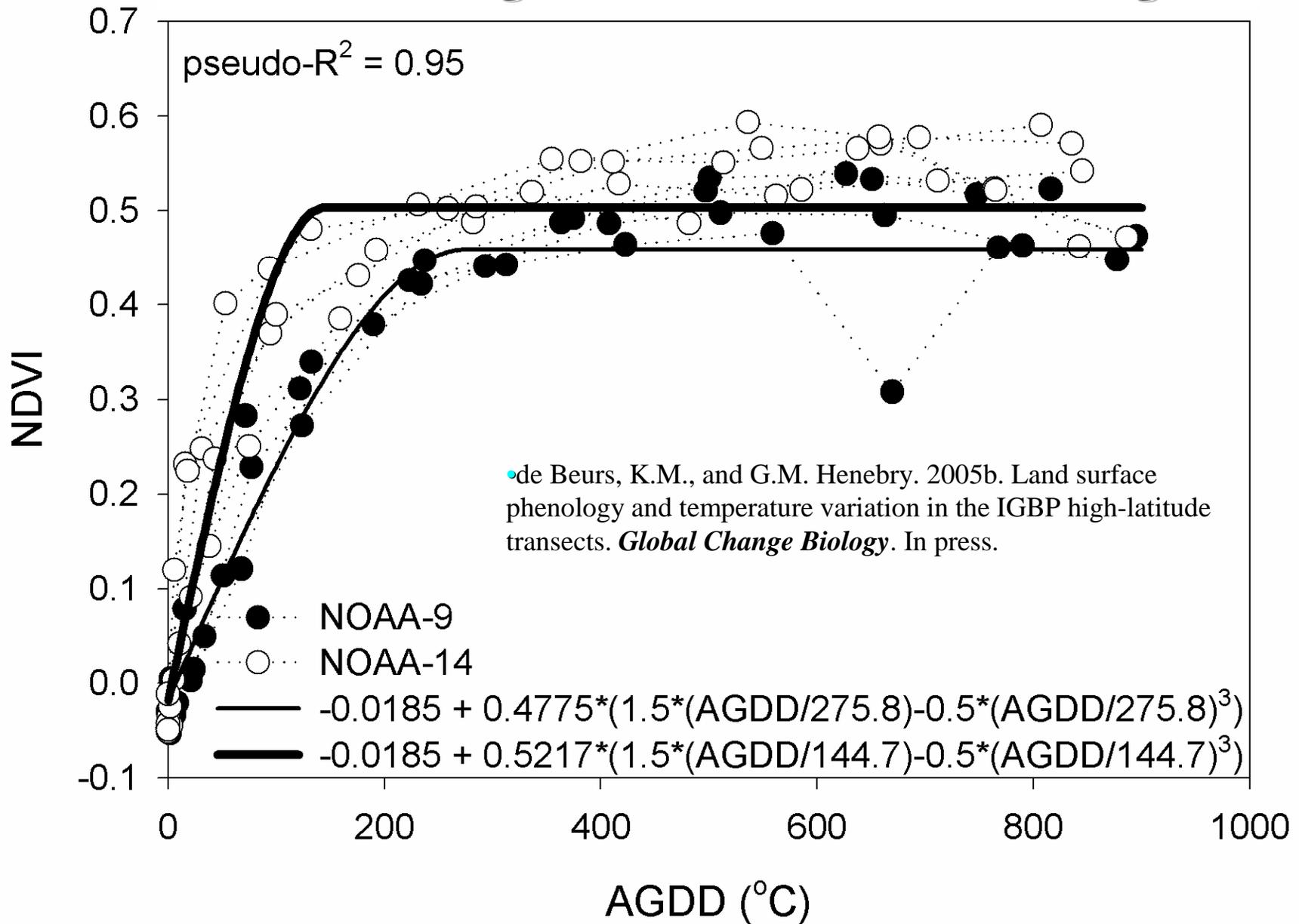
WWF ecoregion: Northeast Siberian Taiga

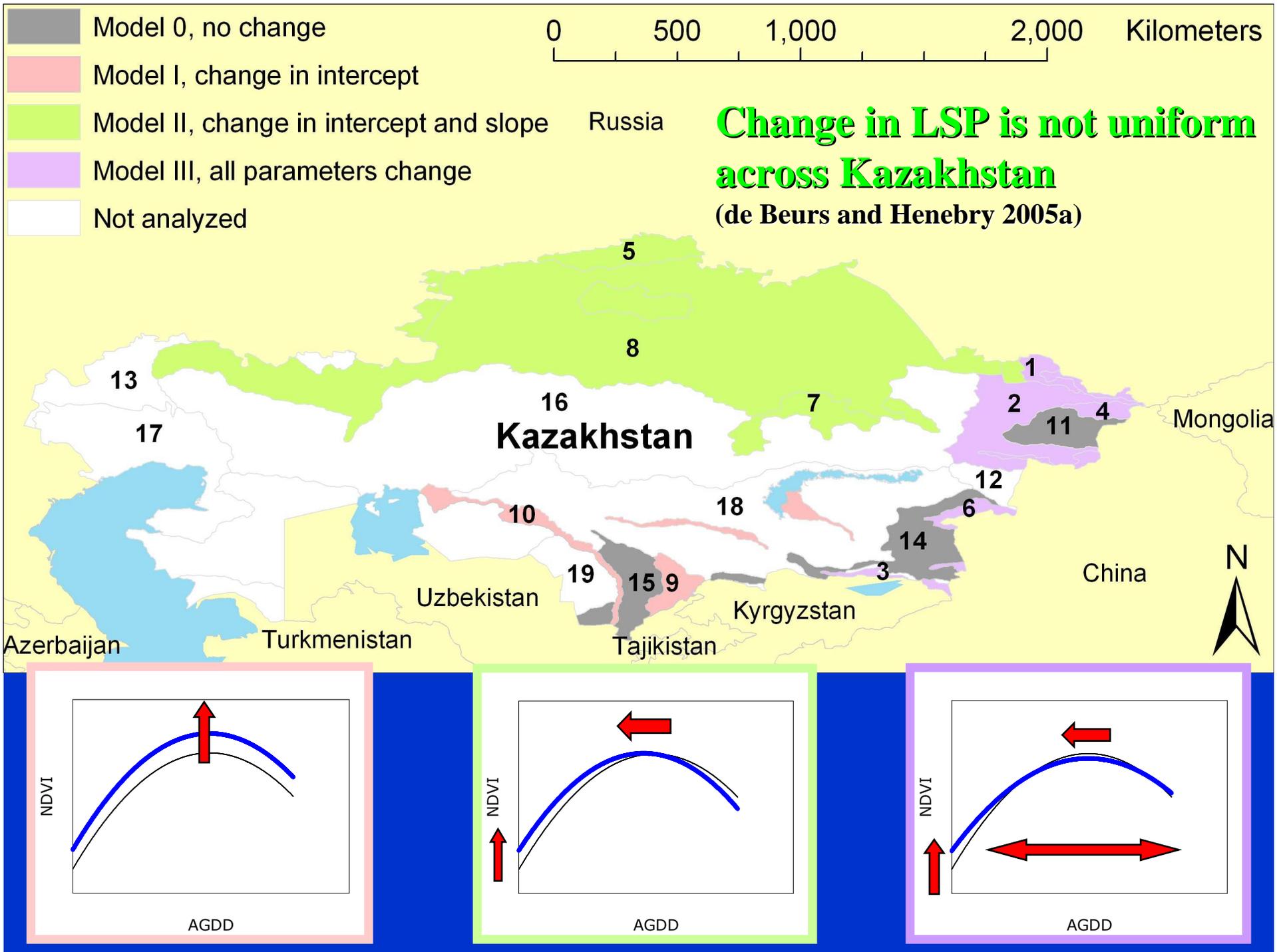


WWF ecoregion: Northeast Siberian Taiga



WWF ecoregion: Northeast Siberian Taiga





4. How do uncertainties affect model reliability?

Model Reliability is the probability that a calibrated model will correctly predict to within a predetermined level of accuracy (Warwick and Cale 1987, Henebry 1995).

Computationally intensive model error analyses using Monte Carlo methods enable wide-ranging explorations of a model's parameter space to estimate the model reliability.

The model reliability approach imposes a decision-making framework on assessment of model performance. The reliability of a model is estimated by the frequency with which Monte Carlo predictions fall within a user-designated accuracy interval at some specified time and/or location.

- Henebry, G.M. 1995. Spatial model error analysis using autocorrelation indices. *Ecological Modelling* 82:75-91.
- Warwick, J.J., and W.G. Cale. 1987. Determining the likelihood of obtaining a reliable model. *Journal of Environmental Engineering* 113:1102-1119.

❖ Operations on the empirical distribution of model outputs form the basis for decision statistics.

❖ Say a model correctly predict species occurrences within a 1 km radius 60% of the time, given input data with 15% uncertainty. But reducing the input uncertainty to 10% might increase the model reliability to 75%.

❖ For models with multiple variables, the joint reliability is usually not simply the product of the individual reliabilities, because the variables are typically not independent.

❖ For the decision-maker the utility of a model comes from its ease of interpretation and the degree of confidence that can be placed in its predictions. Reliability is an attractive decision statistic because it is easier to grasp than error measures based on sum of squares.

❖ Mapping model performance onto a binomial variable leaves no gray areas: either the model performed up to the decision-maker's standards or it did not.

• Henebry, G.M., and J. W. Merchant. 2001. Geospatial data in time: limits and prospects for predicting species occurrences. In Predicting Species Occurrences: Issues of Scale and Accuracy, (J.M. Scott, P. J. Heglund, M.L. Morrison, J.B. Haufler, M.G. Raphael, W.A. Wall, and F.B. Samson, editors). Island Press, Covello, CA. Chapter 23. pp 291-302.

5. Slouching toward ecological forecasting...

“[Ecological forecasting is] the process of predicting the state of ecosystems, ecosystem services, and natural capital, with fully specified uncertainties.”

“[EF] is contingent on explicit scenarios for climate, land use, human population, technologies, and economic activity.”

J.S. Clark et al., Science 293:657-660, 27 July 2001

To make ecological forecasting an operational possibility, we need the capability to establish and to update *complex spatio-temporal baselines* that will enable prediction of the usual and the detection, quantification, & assessment of the unusual.

Take Home Points

1. What are the appropriate units of analysis?

It is very much depends on the question at hand and the available measurements, but they're unlikely to be pixels.

2. What constitutes appropriate baselines?

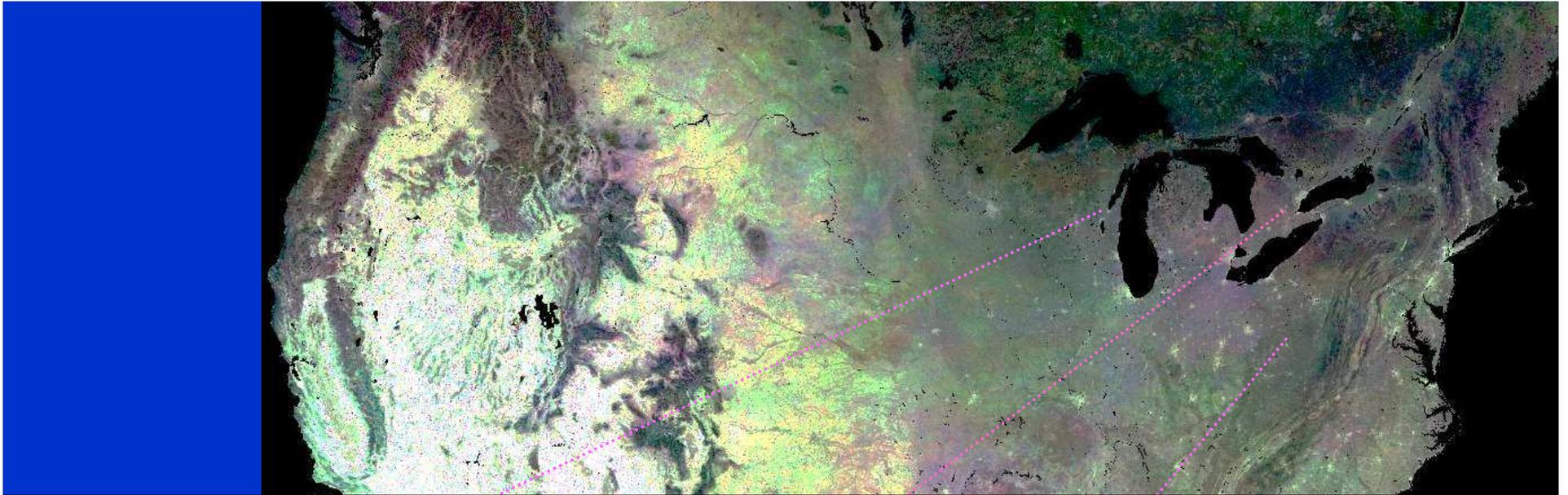
Climate analogy: expectations based on prior observations.

3. How do we conduct change analysis?

i. Detection ii. Quantification iii. Assessment iv. Attribution

4. How do uncertainties affect model reliability?

Model predictions need explicit treatment of uncertainties but simple performance metrics like model reliability may work better for decision support.



Tuning the *macroscope* of remote sensing to support ecological inference requires an integrated and sustained approach to technology and theory.



**Portrait of CONUS using AVHRR MIR (band 3)
Settlements & transportation networks appear appear
as white patches and lines contrasted against the
vegetated matrix.**