THE ROLE OF BAYESIAN PROBABILISTIC INFERENCE IN ASSESSING HUMAN DIMENSIONS IN COUPLED SOCIAL-ECOLOGICAL SYSTEMS (SES)

Kostas Alexandridis, PhD
Center for Marine and Environmental Sciences (CMES) and
Department of Computational Sciences
College of Science and Mathematics
University of the Virgin Islands, USA

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Simple, **Complex** or Complicated?

How we value the simple...? Or, complicated?
Dimensions of challenges

• Contemporary environmental challenges
  – Increasing realization of the need for deeper understanding of coupled human-nature system interactions and especially of the role of human dimensions in sustainability and resilience transformations.
  – The tractability of the transformation trajectories: more often than not, ecologically desirable states correspond to socially dysfunctional states and vice versa.
  – Judgmental heuristics: true social-ecological states is subject to shifting interpretations and the irrationality of decision and policy judgments.
  – Perceptual fallacies play a key role on guiding systemic SES dynamics.
Hidden complexity

• Issues of cross-scale and cross-system interactions
• Deviation from the traditional way that humans and DMs perceive our world around us.
• Simplification through our perceptual sensory systems – cognitive and social psychology paradoxes
• Growing evidence on our social and institutional (in)abilities:
  – Social intentionality (Allen and Strathern, 2005)
  – Black swans (Taleb, 2007)
Understanding Social-Ecological Systems (SES)

Adapted from: Chapin et al (2009)
Deep uncertainty

- Endogenous deep uncertainty and incomplete information are neither linear nor linearized processes
- Scale-sensitivities
- Multiple sensitivities to initial conditions
- Predictable unpredictability or unpredictable predictability?
  - E.g., multiple thresholds, phase transitions, tipping points, complex attractors, emergence, etc.
Is our knowledge a product of social engineering?
Or, do we need a **paradigm shift** on our thinking?
Integrated systemic assessment
An integrated Knowledge-To-Action framework

Selected, Tailor, Implement Interventions

Monitor Knowledge Use

Evaluate Outcomes

Sustain Knowledge Use

Adapt Knowledge to Local Context

Identify Problem

Identify, Review, Select Knowledge

Tailoring Knowledge

Knowledge Synthesis

Assess Barriers to Knowledge Use

Adapted from Graham (2006)
Participatory co-research

Kenya, Massai elders and scientists

Credit: B. Pijanowski, 2004
Participatory co-research

East African Land Adjudication RPG

Credit: Washington Camille-Ottombre, 2006
Participatory co-research

Alice Springs, Northern Territory, Australia

Credit: K. Alexandridis, 2008
Participatory co-research

Alice Springs, Northern Territory, Australia

Credit: J. Davies, 2008
Example of self-defined Livelihood elements

Credit: K. Alexandridis, 2008
Participatory co-research

Zote Melanesian Tribe, Kia, St. Isabel Island, Solomon Islands

Credit: K. Alexandridis & S. Foale, 2009
Participatory co-research

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Credit: K. Alexandridis & S. Foale, 2009
Participatory co-research

Mitchell River, North QLD, Australia, TRaCK Visioning

Credit: K. Alexandridis, 2007
Participatory co-research

WeGrowFood Rastafarian Farmers Coop Visioning Group, Bordeaux, St. Thomas, US Virgin Islands

Credit: K. Alexandridis, 2012
Increasing inferential complexity

Participatory methods
- Discourse methods and focus groups
- Qualitative interviews (e.g., snowballing)
- Quantitative instruments (e.g., psychometric, attitudinal/belief assessments)
- Participatory GIS mapping

Qualitative knowledge narratives
- Transcribed verbatim qualitative open-ended data
- Geo-locational data
- Quantitative data
- Secondary data

Natural language processing
- Latent semantic analysis
- Semi- and un-supervised semantic classification
- Stemming and E-M clustering

Network structural learning using mining models
- Multi-modal assessment and estimation of priors
- From linear to non-linear structural models based on associative rules/inference

Bayesian probability learning
- Data mining and machine learning Bayesian inference
Complexity of interactions

Example: Estimating alternative \textit{structural learning models}
Complexity of interactions
Estimating alternative structural learning models

Model learning results:
- Complex models perform better on estimating ZS
- Unsupervised algorithms performed better: simpler TANB and complex 2SPC

<table>
<thead>
<tr>
<th>Supervision Level</th>
<th>Normal</th>
<th>Relaxed</th>
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<tbody>
<tr>
<td>CNB</td>
<td>CNPC</td>
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<tr>
<td>2SNB</td>
<td>2SNPC</td>
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<tr>
<td>TANB</td>
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</tbody>
</table>

State Value:
- Lowest rating (-2)
- Low rating (-1)
- Neutral rating (0)
- High rating (+1)
- Highest rating (+2)
Estimating alternative structural learning models

2SNPC
Estimating alternative structural learning models
Estimating alternative structural learning models
Estimating alternative **structural learning models**

**Model learning results:**
- Complex models perform better on estimating ZS
- Unsupervised algorithms performed better: simpler TANB and complex 2SPC
Performing **Sensitivity Analysis**
Performing Sensitivity Analysis
Performing Sensitivity Analysis

What-if scenario

Total Gain in ZS+: 27.75% (from 0.699 to 0.9675% )
Performing Sensitivity Analysis

**What-if scenario**

**Loss in ZS-**: -35.77% (from 0.413 to 0.643%)

Example: Comparing cropland abandonment patterns in post-socialist Albania - Romania

<table>
<thead>
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<th></th>
<th>1990-1995</th>
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<tr>
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<td>N</td>
<td>Mean</td>
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<td>Input intensity</td>
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<tr>
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<td>Fragmentation</td>
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<tr>
<td>Abandonment</td>
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</tr>
</tbody>
</table>

Note: Values in the same row and subtable not sharing the same subscript (highlighted) are significantly different at \( p < 0.05 \) in the two-sided test of equality for column means. Tests assume equal variances.\(^1\)

1. Tests are adjusted for all pairwise comparisons within a row of each innermost subtable using the Bonferroni correction.
Example: Comparing cropland abandonment patterns in post-socialist Albania - Romania
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Example: Comparing *cropland abandonment patterns* in post-socialist Albania - Romania

Test Result Variable(s): Predicted Abandonment

<table>
<thead>
<tr>
<th>Area (AROC)</th>
<th>Std. Error(^a)</th>
<th>Asymptotic Sig.(^b)</th>
<th>Asymptotic 95% Confidence Interval</th>
</tr>
</thead>
<tbody>
<tr>
<td>.782</td>
<td>.003</td>
<td>.000</td>
<td>.776</td>
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<tr>
<td></td>
<td></td>
<td></td>
<td>.788</td>
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</tbody>
</table>

- a. Under the nonparametric assumption
- b. Null hypothesis: true area = 0.5

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![](chart.png)

Legend:
- Blue: Percentile
- Green: Ideal Model
- Orange: Naïve Bayes Model

Graph: Sensitivity vs. 1 - Specificity
Connectivism and Bayesian Inference

• Bayesian probabilistic assessments allow for **important methodological and theoretical contributions** in applied and advanced inference especially in the areas of data mining and computational methods.

• Bayesian methodologies enable **integration across multiple network inferential mechanisms**, including physical networks (e.g., geographic/geocomputational), social and graph-theoretic networks (through structural learning and network analyses), semantic, cognitive and computational linguistic networks (through latent semantic analyses and natural language processing algorithms), and belief networks (learning and assessing state transitional probabilities for associative inference).
Connectivism and Bayesian Inference

- Many advanced and applied multi-modeling and multi-assessment methods are utilizing associative Bayesian inference to address the increasing levels of:
  - Real-world complexity and factor interactions
  - Deep uncertainty and previously unobserved directions of social-ecological transformations
  - Cross-scale and non-monotonic nature of associations
Challenges and Opportunities

• Key challenges:
  – Need to align methodological inferences across interdisciplinary domains, and especially across the qualitative-quantitative spectrum and the social-physical sciences divide.
  – Challenges in coupling statistical inferences across mathematical and probabilistic formulae, for example information-theoretic (entropy) and subjective probabilistic estimates. Information-based Bayesian priors often are at par with collective knowledge estimates from real-world observations and inferential emergence.
  – Computational intensity – new algorithms are needed especially in converging associational Bayesian prior estimates in large networks (especially in NxN large associative network matrices).
Challenges and Opportunities

- Key opportunities:
  - Integrating Bayesian inference closely into graph and network sciences including structural estimation, normative priors and Bayesian-based objective functions for evolving network optimization.
  - Advancing nonparametric Bayesian MCMC and bootstrapping methodologies to complement field and empirical measures requiring generalizability support (especially critical for cognitive, social and decision sciences coupling with physical and mathematical sciences).
  - Exploring parameter spaces in large associative data structures, especially in modeling ensembles and SES resilience estimates.
Acknowledgments:

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Thank you!

Dr. Kostas Alexandridis
McLean Center for Marine & Environmental Studies (CMES),
University of the Virgin Islands
2 John Brewer’s Bay, St. Thomas VI 00802
Tel: +1 (340) 693-1381 | Fax: +1 (340) 693-1385