June 17, 2025 Theory Working Group Call

Attendees: Bilgecan Sen, Jonathan Borrelli, Jody Peters, Hassan Moustahfid, Caleb Robbins, Mark Urban, Freya Olsson, Shubhi Sharma, Abby Lewis, Rania Adouim

Agenda:

1. Update from Abby and Caleb - have been meeting and making progress on creating models and synthesizing them across the NEON forecasting challenge
    a. Abby has been working on adding new models for the challenges and getting those new models caught up with the historical forecasts. Will check in again in August

2. Debrief from EFI2025 Conference Predictability of Nature Working Group
    a. EFI 2025 - Predictability Working Group
    b. Agenda and Reading List
    c. Predictability manuscript
    d. Debrief - Had >20 people on Thursday and probably more on Tuesday. Many people were interested in being involved in the paper
        i. Main products: 3 conceptual figures for the paper
            1. Predictability workflow - help people contextualize what it means to do predictability research vs the iterative forecasting cycle
                a. Develop forecasts
                b. Compare forecasts
                c. Develop hypotheses
                    i. Testing hypothesis & Generating hypothesis
            2. How the hypotheses and modeling building, collecting data, etc come together to affect predictability
            3. Research and data gaps people focusing on predictability research should be thinking about going forward
        ii. After conference - subgroup have been fleshing out the figures. Working to flesh out
        iii. Will have a spreadsheet to keep track of who is participating on the paper and what they have done (see folder in 1c)
    e. Goal for today: talk about hypothesis figure
        i. Scale and novelty are hypotheses
        ii. Horizon is another hypothesis that could affect realized predictability
        iii. Complexity affects intrinsic predictability
        iv. Scale affects data, model, and intrinsic predictability
        v. This figure will help - question: do you expect tropics to be more predictable than temperate or arctic systems
            1. Less data in tropics = less predictable

2. More diversity, more complexity = more predictable
3. Higher temp, higher variable rates = less predictable

vi. Take the hypothesis figure and map on different examples

vii. Complexity and non-linearity - small changes in initial conditions lead to big differences in outcomes

viii. Goal is to break down the aspects of complexity can increase or decrease predictability
1. Hard to work in complex ecosystem since knowledge requirements are higher

ix. What the reponse is - expect will also influence what is predictable (e.g., biomass vs diversity)

x. Scale - both spatial and temporal

xi. Goal - for any hypothesis mentioned, want to mention all the potential ways to think about each hypothesis
1. Then will recommend, create forecasts to

xii. Is temporal scale and horizon the same?
1. Bilgecan thinks of scale as daily or annual prediction. Minimum resolution

xiii. Arrow from intrinsic to realized - may want to separate them
1. Intrinsic - the maximum achievable predictability
2. Realized - how close your data/model can you get to realized predictability

xiv. The arrows in this figure change depending on the relationship.
1. Still working on how to visually show what we want to show.
2. If the arrow means different things (if they do not mean dependencies), then need to think about how to depict or define the arrows
3. A variable with higher intrinsic predictability than expected will have higher realized predictability
4. Point of the diagram is not causal relationships but what things influence predictability

xv. From Hassan: I also come across a recent research, particularly in fields like finance and specific machine learning applications, suggests that highly complex models (often with more parameters than observations, in a carefully managed way) can sometimes outperform simpler models in prediction.
1. This is often achieved through techniques like regularization that prevent overfitting, allowing complex models to learn subtle, non-linear relationships in data that simpler models would miss
2. Simply adding more stuff (variables, parameters) to a model often decreases predictability due to overfitting or amplifying

chaos. However, adding the right kind of complexity , complexity that accurately reflects the underlying mechanisms and interactions of a real-world complex system may be essential for achieving meaningful predictability, especially for short forecasts or for understanding emergent patterns and probabilistic outcomes.

3. The challenge lies in discerning what type of complexity is truly explanatory and predictive versus what is just noise or unmanageable chaos. This is where ecological forecasting theory comes in, by providing frameworks for model selection, uncertainty quantification, and iterative model improvement.

xvi. Novelty was on first slide, but not on second slide
   1. Can put it on the second slide and think about how to incorporate it into the second slide

xvii. Acknowledge that these three (scale, complexity, horizon) are not the only things to consider that there are other things influencing predictability

f. What is the longer-term goal of the paper? Is it to set up a structure for people to use to help think about the different axes of what to compare across forecasts (e.g., scale, horizon, complexity)?

g. General message - we aren't focusing on our favorite study system and working in isolation. Goal is to create forecasts across systems so we can compare across systems which will allow us to make better forecasts. Focus on the hypotheses so we can compare across forecasts

h. Will use some figures to explain what the group means and then as discussions continue then the group will develop specific hypotheses
   i. Scale, horizon, novelty and expect others will come up from the group - could be a table or could be a list of outstanding questions

3. Other papers previously shared that Jody is including here for reference
   a. Discussed on 10-7-24 call. Nonlinear population dynamics - https://www.nature.com/articles/s41559-019-1052-6
      i. See notes from the call here
   b. Discussed on 11-4-24 call. Basic principles of temporal dynamics
   c. The intrinsic predictability of ecological time series and its potential to guide forecasting; https://esajournals.onlinelibrary.wiley.com/doi/10.1002/ecm.1359
   d. Prediction in ecology: a first-principles framework; https://esajournals.onlinelibrary.wiley.com/doi/full/10.1002/eap.1589
   e. Fishing down the food web - https://www.science.org/doi/10.1126/science.279.5352.860
   f. Discussed on 1-14-25 call. Error metrics - the choice of error metrics can influence your overall conclusions. Ideas in this paper could feed into the

synthesis and what metrics to use. Not relevant for forecasting specifically, but useful frameworks
https://www.sciencedirect.com/science/article/pii/S0304380023002922?via%3Dihub

g. EDM paper - https://www.pnas.org/doi/pdf/10.1073/pnas.1417063112
h. Pennekamp paper with weighted permutation entropy: https://esajournals.onlinelibrary.wiley.com/doi/10.1002/ecm.1359
i. Came up in the 11-4-24 call. Temporal ecology in the Anthropocene https://onlinelibrary.wiley.com/doi/10.1111/ele.12353
j. Came up in the 11-4-24 call. Forecasting phytoplankton blooms https://esajournals.onlinelibrary.wiley.com/doi/10.1002/fee.2376
    i. Here is the Supplemental Table with the specific example: https://esajournals-onlinelibrary-wiley-com.libproxy.rpi.edu/action/downloadSupplement?doi=10.1002%2Ffee.2376&file=fee2376-sup-0003-TableS3.pdf