December 18, 2023 Theory Working Group Call

Attendees: Cole Brookson, Caleb Robbins, Abby Lewis, Jonathan Borrelli, Freya Olsson, Jody Peters, Hassan Moustahfid, Bilgecan Sen, Shubhi Sharma

Agenda:

1. Poll for scheduling calls for January to May

2. December European EFI Chapter Seminar was by Frank Pennekamp (U of Zurich) on "Advancing forecasts with ecological theory" which had a nice shout-out to the Lewis et al. 2022 Methods in Ecology and Evolution paper. Frank shared 3 case studies from his research
   a. Constraining empirical dynamic modelling with the Metabolic theory of Ecology
   b. Informing species interactions with trait data in a theoretical model
   c. Moving beyond pairwise interactions to model community dynamics.
   d. You can find the recording and details here.

3. Code Review Updates
   a. Recent blog post from SORTEE (Society for Open, Reliable, and Transparent Ecology and Evolutionary Biology) "Setting the Record Straight: How data and code transparency caught and error and how I fixed it"
   b. Honest description of providing code and data for a journal article and having an error caught a year after it was published
   c. Includes 6 lessons learned,
      i. Interesting that for point 3 the author isn't sure if someone would've caught the error with a code review.
      ii. Point 6 - science works!
   d. From Cole's experience - stop writing your own code and start reusing other code that is available
      i. Ecosphere is commissioning a special issue about issues in code review.
   e. Education call had discussed AI and one of the points that came up was that in the future people may just use AI to create code instead of writing their own code so this may lead to not needing to write
   f. Has anyone used GitHub Copilot?
      i. Abby has. Thinks it encourages bad coding practices. Would recommend using it if you have coding experience. It has reduce the time slightly. It is nifty and is seamlessly integrated into R Studio. Abby doesn't pay for it.
      ii. Put in "Make a simple shiny app" and it developed a basic Shiny app which was impressive

g. Cole's experience with chatGPT - really good at pointing you to a general solution to a problem. But if you give it a specific problem, it can't handle that.
h. Abby - Students like plugging code in and asking what the code is doing to get the context

4. Manuscript Outline - Uncertainty analysis that decomposes different uncertainties and ties that to intrinsic predictability which would have some analyses from the Challenge forecasts. Simulations confronted with some data. (Shubhi and Cole)
    a. Shared conceptual figure - want the whole thing to be connected by a simulation framework
        i. Trying to connect Mike's uncertainty framework with the predictability matrix
        ii. Still working on the math
        iii. Show 2 cases
        iv. 1st panel: A variable and a time series
        v. 2nd panel: 2 predictability metrics - permutation entropy used to calculate intrinsic predictability. REalized predictability was estimated by the forecast to the null model.
        vi. Intrinsic predictability - the closer it is to x axis the more predictable
        vii. Realized predictability is flipped from intrinsic predictability. The higher it is the more predictable
        viii. 3rd panel: Variance decomposition - can see where there is the most uncertainty and then can use that know how increase predictability
        ix. Use this to know how to improve your model.
        x. Can get similar values for realized/intrinsic predictability with different models, but will have different variance decompositions
        xi. For predictability:
            1. Is it possible to adjust so that they are both going in the same direction
            2. Realized predictable is 0-100 with 0 = chaos
            3. Intrinsic predictability is at 0-1 with 1 = chaos
            4. Could use standardized error (a non-entropy metric)
            5. Can use standardization but it needs to be meaningful
            6. May differ on a case by case basis where 0.8 for one species may not be the same for other species
            7. Different error types may influence the predictability. Currently, the 3 panels are not connected mathematically
        xii. At end of paper want to provide guidelines and then apply it to the NEON CHallenge forecast
        xiii. Bilgecan's example - 2 penguin communities. When you look at the time series they both looked equally noisy and messy. Have high level of observation error. When you compare the counts of expert counters vs novice counters or to drone measurements. Not fitting observation error

independently in their state space model. Include the observation error in the model.

1. For one colony had expert counters while in the other colony had more novice counters so all the error and noise was accounted for by the process
2. The colony with the low observation error had very extreme and chaotic conditions
3. While the colony with higher observation error had less chaotic or extreme conditions
4. For this project, can think about having conditions with high observation error vs low observation error
5. For example with Beetle Challenge - get extremely noisy data. Biological aggregation is working to reduce the noise. Could train the model to forecast individual species and total species and see how the observation parameter changes

xiv. Cole talked to Mike about using the error partitioning as a model selection tool

1. Use the model with the lowest process model
2. For the penguin example, is there a reasonable consensus on what the best process model is? Think there can be a solid process model
3. Think penguins is like beetles and ticks
4. On the other end of the spectrum is the aquatic or terrestrial challenge
5. Would people attempt to use a process model for penguins?
6. For penguins for a process model think it would be a stage matrix - probability of coming back to breed and probability of dying or living. It can be linked to the environment, but doesn't include exactly how it is connected to the environment.
    a. There are well established matrix models for both species that are published. The parameters for those models are coming from a single colony so not sure if the parameters are applicable across Antarctica
7. Hassan - sees chaos in short lived (<1 year) species which are harder to predict in marine systems.
8. Ecology and life history traits will result in different forecast errors which is our question - by doing these analyses comparatively then we can learn were variance errors are more common

xv. Do you have a plan for how to quantify/create priors for observation uncertainty for each of the forecasting challenge targets?

1. Think this is an approachable challenge
2. When Cole was playing around with some state space models, put on wide/uninformative priors on

3. For the Challenge, go to the design teams who set up the Challenge themes to get priors
    a. If they are not standardized across models for different themes will it affect the analyses?
    b. There are statistical ways that people parameterized prior.
    c. Think it will be good to keep similar priors across themes
    d. If you can include info from the sensor calibration it will be helpful for partitioning uncertainty for a specific theme.
    e. This could be a way to do validation
    f. Sensor based info is used to set up observation error for real-world examples
    g. Mike's paper talks about (but doesn't implement) breaking down the different components. For parameters uncertainty, he suggests a way to partition your parameter uncertainty for different parameters
    h. Think you could also do it for observation error as well - sensor observation error vs something else.
    i. Is there error that would not be included in the observation error?
        i. Have uncertainty because the data going in is not at the same resolution as the model (data going in is capturing mid-day measurements, but model is modeling all day measurements

xvi. Plots: Cole trying to do a sanity check on entropy measures using autocorrelation approach.
1. Terrestrial - mean autocorrelation across sites (and then averaged)
    a. If the line on a given lag (daily for terrestrial) goes above the red line it is significantly autocorrelated
    b. There is a different autocorrlation patter between latent heat flux vs NEE
        i. Heat flux is autocorrelated throughout, but NEE is only at the beginning
    c. Same for beetles - abundance is correlated on weeks, richness is autocorrelated on a longer time scale
    d. What time scale is relevant for the autocorrelation for, for example beetles vs latent heat flux
    e. Next step - do the same analysis, but aggregate on different time scales
        i. Heat flux at daily vs weekly vs monthly - how quickly does the autocorrelation get reduced?
2. Hourly aquatics plots follow a sinusoidal pattern which you would expect with a daily change in

xvii. Intrinsic predictability captures autocorrelation

xviii. Bilgecan shared plots about autocorrelation for a paper in review
1. Looked at simulated data and autocorrelation vs WVPE
   a. If you have periodic autocorrelation and you have a long enough time period you will find a negative relationship
   b. If you look at chaotic there is a stronger negative relationship
   c. White noise - where you see a lot of autocorrelation and chaos. Autocorrelation and WVPE are not correlated.
2. This may be useful for Cole's analyses
3. There are better measurements to use that permutation entropy, but it is really hard to calculate
4. Hassan has been dealing with something similar for predator-prey analyses from marine systems

5. Manuscript Outline - using the NEON Forecasting Challenge to explore predictability across variables and scales (Caleb) - Didn't get to this on this call
   a. On the November call we talked about looking at plot with a summary of R2 vs Forecast Horizon overall (vs by month like Caleb showed in November)
   b. On November call also talked about looking at the dashboard to see the forecast and raw data patterns to help give direction for analyses
   c. Repo where Caleb is working on this: https://github.com/robbinscalebj/NeonPredictability

6. GitHub repos
   a. GitHub repo: eco4cast/predictability - comparative analysis of predictability
   b. GitHub repo: Forecast_submissions - forecasts submitted to the Challenge

7. Model Development for the NEON Challenge
   a. GitHub repo: eco4cast/Forecast_submissions
      b. New model descriptions document