October 16, 2023 Theory Working Group Call

Attendees: Bilgecan Sen, Jody Peters, Alyssa Willson, Abby Lewis, Hassan Moustahfid, Cole Brookson

Agenda:

1. Any thoughts for proposing workshops, panels, short courses, socials, etc for the EFI 2024 Conference?
    a. Deadline is November 1; Use this short feedback form
        i. Education group had talked about code review and developing standards. There is a recent paper that came out with some standards that would be good to discuss as a community
            1. Paper: https://onlinelibrary.wiley.com/doi/full/10.1111/jeb.14230
            2. Effectively reviewing forecasting code is hard, so would be good to discuss
            3. Good to have a larger community discussion to talk about what others are doing (e.g., dockers) or tools or connect with computer scientists that have processes put in place because they do this regularly
            4. Are any journals moving toward having specific editors, not necessarily AEs or SMEs to review code? A quality specialist?
                a. Have heard of journals starting to have open science reviewers, but I think that's more on the side of data publication than code
            5. Abby will reach out to the group about rubrics for code review
                a. Cole TA'd this summer that Mike helped instruct had a code review component so happy to talk
                b. Alyssa with the McLachlan lab has mandatory code review but still developing protocols for that

2. Manuscript Outlines
    a. Caleb - Using the NEON Forecasting Challenge to focus on the realized predictability with reference to calculations of intrinsic predictability which is a small portion of the work that Shubhi and Cole have done. Realized predictability confronted with some intrinsic predictability
        i. Questions for the group to figure out how to move forward
        ii. How does the rate of decline and forecastability change through time? Take model agnostic ML approach to look at predictability
        iii. Goals:
            1. use a variable agnostic approach
            2. Bench forecasts - there is a need for this

3. Compare across variables and levels of aggregation across the forecasting challenge to make generalizations about ecological predictability

iv. Not focused on variability within a Challenge theme (that is more of the work that Kathryn and Freya have/are doing with the Phenology and Aquatics themes)

v. Can we estimate of intrinsic predictability across all Challenge variables without stepping on Shubhi/Cole's toes?
    1. Analysis on ML learning and look at predictability across time scales
    2. From Shubhi/Cole: Yes, think that is a possibility. Not a problematic overlap
    3. Shubhi wants to take intrinsic/realized predictability and put them in a framework with uncertainty decomposition to see what is driving low predictability
        a. This is harder to do with ML because uncertainty partitioning isn't there yet. So planning to do it analytically
        b. Shubhi/Cole - have code that can be modified for Caleb's analysis. Have done it for all the NEON data.
        c. Computed intrinsic predictability for all the challenges data. Cole put that into a targets format so it gets updated as new data come in
        d. Think it would be easy to add in the intrinsic predictability so with new forecasts/models can see if there is change through time.
        e. This connects well with the Unconference work of thinking about the visualizations on the Forecasting Challenge dashboard. Whatever gets developed for the manuscript can be migrated to the Dashboard.

vi. Analysis question - what is going to drive the analysis and forecastability scale
    1. What is the R-squared, RSME, etc of different variables with a certain modeling approach
    2. What is the average rate of decline for each variable and how does it compare across variables?
    3. What kind of variability dominates the uncertainty in the average forecast decline? Site to site or variable specific or monthly forecast (some aggregation)
    4. Looking at the average shape of predictability through time. Not planning to do anything with the underlying uncertainty
    5. Bilgecan suggestion - in recent paper tried to connect predictability with space Take the realized predictability of one colony and see if/how it applies to other colonies. The predictability declined with space.

a. Didn't have long enough time series for that paper.
b. Is intrinsic predictability related to realized predictability in general or do you get more information. Will realize profitability decline faster as you move away from your point of forecast. Or does it not matter, are there some places that are always bad
c. Think it would be straightforward to do

6. Abby: I'm also quite curious about whether declines will be linear or non-linear. My expectation would be ~linear up to a threshold of no skill. The "intercept" of those declines is also interesting
   a. Caleb's expectation is that it will be non-linear, or should use a method that does allow for non-linear analysis.
   b. Want a global smoother for decline.
   c. Won't have to pick a specific horizon, but let the GAM pick
7. What is the response variable?
   a. Caleb is leaning toward R-squared value. What level to aggregate? A week? A month? Compare to historical mean or random walk?
      i. Bilgecan - found no relationship with intrinsic predictability and R-squared. So had used RSME instead of R-squared. But standarize RSME with null models.
      ii. Some people normalize RSME with average or max, min of their time series
      iii. Lit review from ecological forecasts. R-squared is imperfect because it is biased.
         1. Mike recommends using R-squared to 1:1 line rather than the absolute location. Abby hasn't explored this yet so not sure about the practicalities. Not sure if the units would be comparable across variable. Shubhi looked into this. It is a matter of changing what your baseline is. Seems to make sense.
         2. Abby thinks this might be in a chapter of Mike's text book, so will look for it
         3. Nice that it doesn't require a choice of a null model
   b. 2 approaches
      i. Normalized RSME relative to null model
      ii. Or R-squared relative to something

vii. Caleb has a few examples of ML in aquatic ecosystems that he will share
   1. Examples of ML for forecasting from Hassan

a. https://www.ecmwf.int/en/elibrary/81207-machine-learning-ecmwf-roadmap-next-10-years
b. https://www.ecmwf.int/en/about/media-centre/science-blog/2021/assimilating-soil-moisture-scatterometer-data-using-neural

viii. Next steps - Caleb will continue to work on this and will share what he develops

b. Shubhi and Cole - 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.
    i. Shubhi and Cole have an outline
        1. Getting stuck on which simulations will be most useful for the whole community

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

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