Title: `popClimVar`: Climatic variability and fluctuating populations
Short title: Climate and pop variability

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Project summary: Climate change is expected to alter global temperature and precipitation patterns in multiple ways, including increases in mean temperatures, more variable precipitation patterns and extreme events, and more autocorrelated climate across space and time. These multiple dimensions of shifting climate are already exhibiting large impacts on our ecosystems, and are predicted to continue affecting population and community dynamics, with implications for species extinction risk and food security. However, how climate variability will impact population and community dynamics depends on ecological sensitivity to climate drivers and species' abilities to buffer dynamics during adverse conditions. Our group will integrate climate and multiple ecological data sources to link climatic variability with population and community variability across the US, providing insight into potential ecological impacts under future climate change scenarios. In doing so, we aim to additionally provide a synthetic understanding of variability as a *measure*, bridging standard measures with more complex metrics that consider temporal autocorrelation (i.e., noise color), nonequilibrium conditions (i.e. comparing stochastic distributions through time), and spatiotemporal patterns (spatial synchrony). This will highlight the multiple dimensions of potential climate change impacts, using consistent spatiotemporal metrics that link from climate to ecological impacts.

Public summary: Environmental conditions play a key role in shaping ecological patterns, from species diversity to the variability in species abundances through time. As such, it stands to reason that climate-change driven impacts to temperature and precipitation patterns will fundamentally alter our ecosystems. However, species have developed a multitude of mechanisms that help them cope with environmental variability. As such, how current and future climate change will impact ecological variability remains an open question, critical for predicting species extinction risk, biomass production, and ecosystem stability. A highly interdisciplinary and diverse team with expertise in ecology, modeling, computer science, and climate science will tackle these questions through synthesis of big data across climates and taxa, ranging from fish to beetles to small mammals.

Introduction and goals:

How does environmental variability influence population dynamics? More variable environments should lead to more variable ecological dynamics [21, 20]. While this may seem intuitive, it is an oversimplification that often is not detected in data. For instance, species and communities may differ in their susceptibility to environmental conditions (i.e., their "response diversity"), rates of response to change, and ability to buffer during adverse times, all of which may mask the relationship between climate and ecological variability (Fig. 1A, B). Further, *variability* can be defined in a multitude of ways, depending on the underlying questions and data structure [6]. This includes considering the data distribution and standardizing the variance by the mean (i.e., the coefficient of variation), considering the actual structure of the time series (i.e., *noise color* [11] and *time series decomposition* [13, 1]). Finally, scaling across populations of the same species, or from the population to the community scale, requires that we consider *synchrony* or correlated fluctuations in environmental conditions or species abundances [15] (Fig. 1).

Variability in a changing climate Over time, environmental conditions have changed in their mean, become more temporally autocorrelated [5], and increased in their variability, leading to more extreme events [10]. These offer potentially conflicting forces on resulting population dynamics, as more temporally autocorrelated environments can stabilize population dynamics [16, 7], while more variable environments are expected to destabilize population dynamics [8].

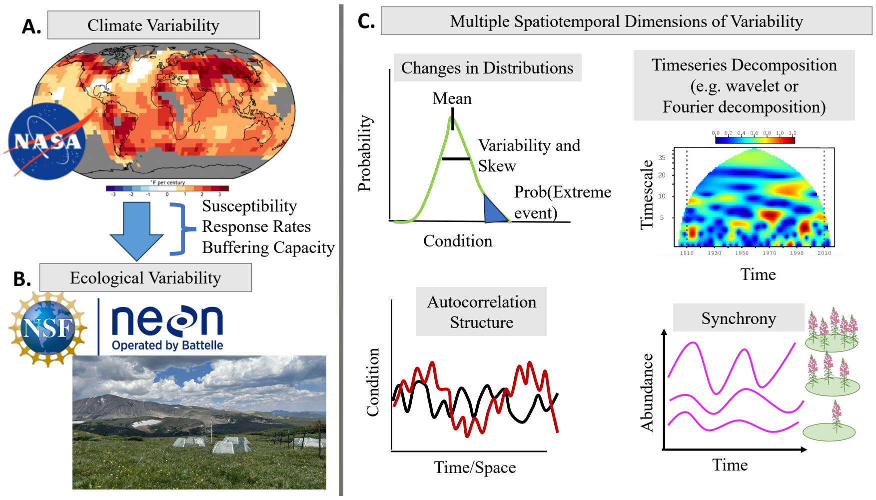

Figure 1: *Climate variability (A) is expected to alter ecological variability (B), though its effect is often masked due to the complexity of ecological systems. By exploring the multiple dimensions of variability (C) we can better understand how current and future climate variability will impact population dynamics.*

By exploring the multiple dimensions of climate and ecological variability, our interdisciplinary working group aims to synthesize across big data from atmospheric and ecological systems to address the complex relationship between climatic drivers and fluctuating populations across a breadth of geographic and taxonomic scales.

Aim 1: What is the spatial distribution of environmental variability? Using large-scale spatio-temporal environmental data from NASA, we will estimate different types of temporal variability across environmental axes (e.g., temperature, precipitation). Some sites might have increased climatic temporal variability along a rolling window when estimated as the coefficient of variation, but have decreased (or no change) in the temporal autocorrelation of climatic conditions (i.e., noise color). By disambiguating the different types of climatic variability, we aim to expose differences in environmental structuring across geographic space and habitat types (e.g., biomes) and how these measures are changing over time. Finally, our rolling window approach will enable the ability to forecast temporal variability into the future under different climate projection scenarios. Given the role of environmental variability for species' persistence, food safety, understanding how ow temporal variability in climatic conditions are changing across space and biomes represents a clear and pressing need.

Aim 2: Is temporal variability in population dynamics related to environmental variability? Uncovering geographic and temporal patterns of population and community fluctuations is critical for conservation and management of our ecosystems [4]. We aim to map temporal variability in climate to the observed variability in population and community abundances across multiple biomes and taxa using a suite of metrics (Fig. 1). For example, a seeming lack of response under common metrics, such as the coefficient of variation [19], may mask timescale specific responses in synchrony [15, 25] or changes in the autocorrelation structure of species' variability [12].

Aim 3: How do we quantify variability? While we have multiple metrics of variability, that range in complexity and disciplinary use, our final metrics of variability will be informed by the expertise of our working group and the iterative process as we apply each to climate and ecological data. Based on what we learn from this process, we aim to publish a synthesis manuscript paired with contributions to existing open-source *R* projects (e.g., `synchrony` or `codyn` packages).

Proposed activities:

Data

National Ecological Observatory Network: The NEON data will serve an essential role for exploring temporal variability in population and community dynamics across a diversity of ecological systems, and linking these to climatic variability. These data consist of species abundance and community composition across taxons and at a set of sites distributed across the United States sampled for an extended period of time (Table 1). These data are ideally-suited for explorations of temporal variability, as they consist of site-level repeated surveys of many different taxonomic groups with methodological approaches standardized across geographically widespread sites (Table 1). Many of the working group members have expertise in working with the NEON data [3, 17, 18, 2, 24], suggesting that data wrangling will be feasible fairly quickly.

Table 1: *NEON data sources, species, and density ranges (ranges of individuals per sampling area) available.*

Taxa	Sites	Species	Density range
Fish	27	94	1-116
Ground beetles	19	315	1-80
Macroinvertebrates	34	378	1-7839
Small mammals	46	120	1-69
Ticks	46	13	1-629
Zooplankton	7	80	0.002 - 6785.7

High-resolution climate data: We will use NASA Earth Exchange climatic data layers to assess temporal variability in climatic data. Data from these layers are provided as daily temperature minimum and maximums, as well as daily precipitation data [9]. Spatial resolution of many of the data products is 0.25 degrees or less (25km x 25km grid cells). IPCC climatic projections from multiple climatic scenarios derived from the general circulation model allow for the potential to explore future climatic conditions, enabling forecasts of climatic variability as well as highlighting areas where the link between species variability and climatic variability may become more pronounced. All model outputs are under the umbrella of NASA's NEX-GDDP data, allowing flexible comparisons of different climatic projection models and different representative concentration pathway (RCP) scenarios for future greenhouse gas emissions.

Data harmonization: Climatic data is at a much higher resolution than the NEON data in terms of spatial and temporal grain. We will sample climatic layers as appropriate for the questions of the working group. That is, to link climatic variability to population and community variability, we will use the representative timescale that the NEON data were sampled – which can range from sampling performed every two weeks to only a few times per year depending on taxonomic group – and representative spatial scale. Standardized sampling of NEON sites allows us to explore the relevant spatial resolution, though even the more vagile taxa in the NEON data will occupy a small number of grid cells in climatic space. A strength of leveraging both of these data resources is that some questions may only rely on one data resource, allowing us to both fully exploit the spatial and temporal scale of the climatic data using high performance computing (HPC) methods while simultaneously integrating climate and ecological data using parallel processing on the cluster to explore dimensions of variability.

Advancing DEI: The assembled working group includes participants from highly diverse backgrounds, with expertise in ecology, coupled human-environmental systems, computer science, complex science, and mathematics. We span career stages, including four graduate researchers, a postdoctoral researcher, and a mix of assistant, associate, and full professors. The proposed project is led by two assistant professors, thus supporting early-career development. Further, our group has a balanced gender ratio, with 8 out of 15 participants identifying as female scientists. We have confirmed participants from the U.S., China, and Canada, and from varied underrepresented backgrounds, including gender identity and disability status. Further, we believe that the working group's strong *open science* approach, outreach activities, and *R* package contributions will be inclusive to a variety of researchers. Public-facing output from the working group will be available throughout project development, and our products and methods will be usable by environmental data scientists broadly.

Rationale for ESIIL support: The proposed working group leverages the strengths of ESIIL in support of the four-pronged mission of ESIIL. We aim to do *transformative science* through the integration of fine-scale climatic big data and cross-system, standardized biotic community sampling, leveraging CyVerse and other computational tools for collaborative data-driven science, developing analytical workflows collaboratively with an emphasis on FAIR data practices and open science, and publishing high-impact scientific manuscripts alongside of documented and versioned code and data products.

Several of the proposed working group members were previously members of a highly-productive National Ecological Synthesis Center (NCEAS) working group centered on synchrony of ecological systems, demonstrating their capability to produce high-quality science as part of a team as well as their expertise in the proposed research area [14, 15, 23, 22]. The addition of participants from UC Boulder, in addition to the inclusion of early career scientists (graduate students and postdoctoral researchers), will allow this team to do high-impact science while also expanding collaborative networks of early career researchers and providing an example of effective team-based science.

Collaborations with other ESIIL activities: Several of the working group participants have previously attended ESIIL events, including the 2023 ESIIL Summit (Dallas and Melbourne). A funded working group would not only bring our team to CU Boulder to interact with researchers from the broader ESIIL community, but would encourage team members to participate in ESIIL-sponsored events such as the virtual Hackathon activities and future summit meetings. Many team members have experience with hackathon style events (e.g., Dallas ran numerous funded hackathons at Louisiana State University). If appropriate, we would be excited to interface with the ESIIL STARS program, such as by hosting a data science workshop or having a students' internship experience be in collaboration with with working group.

Anticipated IT needs: Handling large spatial data and coordinating collaborative coding will necessitate the use of CyVerse. We will lean heavily on compute clusters and the ability to parallelize analyses, given the scale of analyses and data. The shared focus of CyVerse and many of the working group participants' previous experience with cluster computing, open science, and version-controlled data/analysis suggests that the activation energy required will be fairly minimal. Further, the multiple participants who attended the ESIIL 2023 summit received initial training on CyVerse and JupyterHub. All code and data generated from this project will be versioned and openly available, including this grant proposal. We do not require long-term maintenance of a public database given all datasets are maintained on open access platforms, and our curated data will be published alongside each manuscript.

Proposed timetable: We will plan to meet in Boulder, Colorado in May or June of 2025 and 2026 for 4 days each meeting, and virtually in early 2026 to wrap up existing projects and plan for future directions of the group (e.g., gauge interest in applying for an NSF research coordination network or other funding). The first meeting will focus on identifying key tractable questions and organizing small core-teams that will lead each aim of the project. The second meeting will focus on analyses and collaborative writing of manuscripts drafts. Between each meeting, we will foster asynchronous collaboration – enhanced through the creation of a GitHub organization – and regular small group meetings. We will additionally hold a half day virtual meeting fall and spring semester to ensure full group collaboration and maintain momentum towards project milestones between meetings.

Outcomes: We expect that this working group will result in a minimum of three peer-reviewed publications—one per aim—although anticipate that multiple additional publications will result from Aim 2 that dive into specific cascading effects of environmental variability. Additionally, in year 3 of the working group, we will organize a Symposium at the *Ecological Society of America's Annual Meeting*, allowing us to disseminate our results broadly and network with ecologists and environmental scientists in similar fields.

We additionally expect that the working group will promote further collaborations which will result in submission of NSF grants, targeting opportunities such as the Macrosystems and NEON-enabled Science call (NSF 22-504) or the *Emerging Mathematics in Biology* program (NSF 23-537) through both standard grants and research coordination networks (RCNs). The standard grant pathway would be used to support collaborative research stemming from work initiated during the working group, while the RCN pathway would be useful to further support (post)graduate scholars through a formalized working group structure.

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