DENVar: A global Dynamic Estimate of NDVI Variance

Stefano Mezzini[1,2]   Gavin L. Simpson[3]   Michael J. Noonan[1,2,4,*]

[1] Okanagan Institute for Biodiversity, Resilience, and Ecosystem Services, The University of British Columbia Okanagan, Kelowna, British Columbia, Canada.

[2] Department of Biology, The University of British Columbia Okanagan, Kelowna, British Columbia, Canada.

[3] Department of Animal & Veterinary Sciences, Aarhus University, Denmark.

[4] Department of Computer Science, Math, Physics, and Statistics, The University of British Columbia Okanagan, Kelowna, British Columbia, Canada.

[*] Correspondence: Michael J. Noonan <michael.noonan@ubc.ca>

Abstract

Since the 1980s, remote-sensing estimates of habitat productivity such as the Normalized Differnece Vegetation Index (NDVI) have helped develop and support a variety of hypotheses and inform policy and industriy-related decisions. The free availability of such data has allowed widespread access and use of well-established metrics of habitat productivity. However, historically, users tended to focus solely on (predictable) trends in productivity. In recent years, people have been recognizing the importance of envrironmental unpredictability (stochasticity), particularly as climate change and human-induced rapid environmental change transform the ecosystems species have evolved in and adapted to. We adress this gap by presenting a new global Dynamic Estimate of NDVI Variance, *DENVar*. We estimate spatiotemporal trends in mean NDVI and the variance around the mean using Hierarchical Generalized Additive Models, which provide a flexible yet transparent model structure, unlike machine learning approaches such as neural netwoks. We show that DENVar can be used as a reliable proxy of environmental stochasticity, strongly correlates with **XXX**, and can be used to test many hepotheses related to environmental stochasitcity, such as forage stochasticity, regime shifts, ... We conclude by offering some considerations around quantifying and interpreting envirnomental stochasticity, and we provide a publicly and freely available shiny app for estimating mean NDVI and the variance around it, DENVar, for given coordinates and optional dates. The app requires no knowledge of statistics or coding. Additionally, we provide a temporally static raster of mean NDVI and DENVar for the years 1981-2025 that can be used for GIS applications and does not require any knowledge of `R`.

Introduction

Since its early uses in the 1970s, the Normalized Difference Vegetation Index (NDVI) has greatly expanded our ability to quantify and monitor landscapes using remotely sensed imagery (Pettorelli *et al.*, 2005; Pettorelli *et al.*, 2011; Anyamba & Tucker, 2012). NDVI is an estimate of a landscape's greenness, and it often a good proxy of primary productivity, forage availability, and vegetative cover (Pettorelli *et al.*, 2011; Merkle *et al.*, 2016). However, as NDVI a proxy, it is not a direct measurement of such variables, and it should be interpreted carefully. NDVI is prone to loss of sensitivity in highly saturated (i.e., very green) environments (Matsushita *et al.*, 2007), and estimates can vary substantially across sensors (Huang *et al.*, 2021). Still, NDVI is often used because it is free, well-established, and available at a wide variety of spatiotemporal scales (**ref?**).

NDVI has been particularly useful when studying the movement behavior of herbivorous mammals, such as when testing the relationship between resource availability and range size (**ref?**)

NDVI has also been used to test the "green wave hypothesis", which was first developed by (**ref?**) in relation to migratory birds and states that animals will time their migration with the early green-up phases of forage growth to maximize forage nutrient content.

many people focus on changes in the mean

ability to predict and respond to changes in mean conditions (forage availability, phenology, etc.) depends on the scale of changes relative to the perception scale (Levin, 1992; Frankham & Brook, 2004; Riotte-Lambert & Matthiopoulos, 2020; Steixner-Kumar & Gläscher, 2020) and memory (Abrahms *et al.*, 2019). Consequently, environmental stochasticity is also an important driver, besides changes in the mean (Mezzini *et al.*, 2025)

scale in remote sensing and GIS: Goodchild & Quattrochi (2023)

- variance is hard to calculate, as it depends on a the estimated mean
- paper on estimating the asymptote of environmental variance globally, but variance

for a closed system must converge towards a finite value (Bachmaier & Backes, 2011;

Fleming *et al.*, 2014)
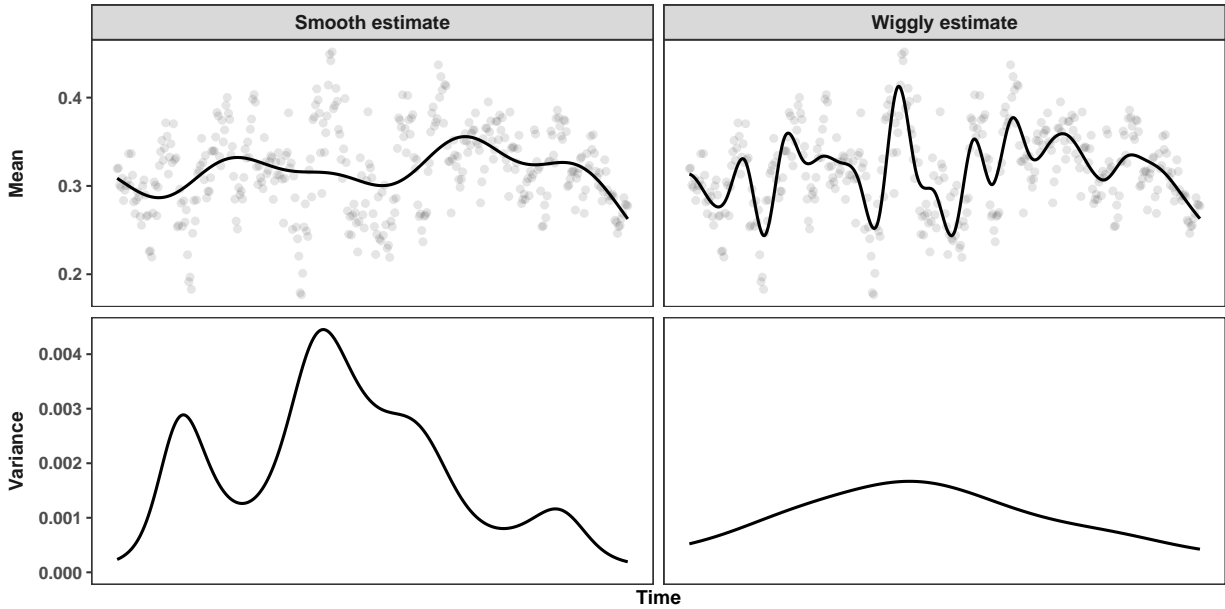
Figure 1: Examples of smooth and wiggly estimated trends in simulated NDVI data (points). Smooth estimates of the mean (top left) result in wiggly and large variance estimates (bottom left), as short-term trends in the data are assumed to be extreme events. In contrast, wiggly (i.e., flexible) estimates of the mean (top right) result in smooth and small variance estimates (bottom right), since short-term trends in the data are assumed to be trends in the mean. The data is the same in both columns.

- we present DENVar

- HGAMs are higly flexible models that allow us to estimate trends in the data without imposing preconceived expectations

- more transparent than black-box machine learning methods like neural networks, etc.

- https://www.sciencedirect.com/science/article/abs/pii/S0034425718305625

- https://silvis.forest.wisc.edu/data/dhis/

- we provide global rasters of the mean and variance in NDVI, averaged across 1981-2025

- we provide a shiny app for people to calculate mean and variance without any knowledge of `R`

Methods

Choice of color schemes

We represent NDVI using a modified version of Fabio Crameri's divergent *bukavu* palette (Crameri, 2018; Crameri, Shephard & Heron, 2020), which has high-contrast for deuteranope and protanope vision. For NDVI values between 0 and 1 (the right half of the palette), the colors also have sufficient contrast for the colors to be distinguishable by both tritanope and achomatic vision. Appendix A contains an approximate representation of the color palette for each vision type. We obtained all color palettes from the `khroma` package (v. 1.14.0, Frerebeau, 2024) for `R` (v. 4.4.1, R Core Team, 2024).

Input data

We obtained NDVI data using the image composites from the AVHRR and VIIRS sensors (Vermote & NOAA CDR Program, 2018, 2022). The code for downloading the data directly from the NOAA server is available at https://github.com/QuantitativeEcologyLab/ndvi-stochasticity/blob/main/analysis/002-download-ndvi-rasters.R. The number of non-NA land raster cells was substantially larger than the maximum data frame size in `R` ($2.28 \times 10^{10} > 2^{31} - 1 \approx 0.21 \times 10^{10}$), so we reduced the dataset size by calculating 15-day averages of NDVI (see Fig. A2) and aggregating the averaged rasters by a factor of 2×2 with `terra::aggregate(fact = 2)`. Although this resulted in a reduction in sample size, the temporal averaging also reduced signal-related noise.

The predictor data for the models included: WWF biome (Olson & Dinerstein, 2002, see Fig. A3), ecoregion (the individual polygons from Olson & Dinerstein, 2002, see Fig. A4), integer day of year (1 to 366), integer year (1981 to 2025), and elevation above sea level (Fig. A5). We excluded all polygons that did not have any NDVI data (0.06% of land, 29% of the polygons, maximum area: 452 km$^2 \approx (21$ km$)^2$). We distinguished between biomes in the northern and southern hemisphere to allow for different seasonal trends between hemispheres.

84 The 15-day averages allowed us to have non-repeating values of day of year across years, since

85 15 is not a factor of 365 or 366. We downloaded the global digital elevation model using

86 the `get_elev_raster()` function from the `elevatr` package for R (v. 0.99.0, Hollister *et al.*,

87 2023) with a resolution of 0.076 degrees.

Modeling

89 We estimated spatiotemporal trends in mean NDVI using Hierarchical Generalized Ad-

90 ditive Models (HGAMs) via the `mgcv` package for R (v. 1.9-3, Wood, 2017). To reduce

91 modeling fitting times with negligible losses to model accuracy, we used the `bam()` function

92 with fast REstricted Marginal Likelihood (`method = fREML`) and covariate discretization

93 (`discrete = TRUE`). See Wood, Goude & Shaw (2015) and Wood *et al.* (2017) for more

94 information. Ideally, NDVI should be modeled using beta location-scale models (after the

95 linear transformation $Y^* = \frac{Y+1}{2}$) to account for the fact that: (1) NDVI is bounded between

96 -1 and 1, and (2) the variance in NDVI is dependent on the mean (and vice-versa), since

97 ecosystems with very low NDVI (e.g., rock, ice, or concrete) or very high NDVI (e.g., dense

98 forest) tend to have lower variance in NDVI. However, preliminary tests showed that fitting

99 times for beta models were prohibitive, especially for beta location-scale models. In contrast,

100 Gaussian models fit substantially faster and provided very similar spatialtemporal estimates

101 of mean NDVI (see the `analysis/000-sardinia-test.R` script in the GitHub repository).

102 The global model for the mean NDVI had the structure below:

```
m_mean <- bam(
  ndvi_15_day_mean ~
    biome + # to avoid intercept shrinkage
    s(poly_id, bs = 'mrf', xt = list(nb = nbs)) +
    s(doy, biome, bs = 'fs', xt = list(bs = 'cc'), k = 10) +
    s(year, biome, bs = 'fs', xt = list(bs = 'cr'), k = 10) +
    ti(doy, year, biome, bs = c('cc', 'cr', 're'), k = c(5, 5)) +
    s(elevation_m, bs = 'cr', k = 5),
  family = gaussian(),
  data = d,
  method = 'fREML',
```

7

```
  knots = list(doy = c(0.5, 366.5)),
  drop.unused.levels = TRUE,
  discrete = TRUE,
  samfrac = 0.001, # find initial guesses with a subset of the data
  nthreads = future::availableCores(logical = FALSE) - 2,
  control = gam.control(trace = TRUE))
```

Biome-specific fixed-effect intercepts allowed to account for the differences in mean NDVI throught biomes without coefficient shrinkage (i.e., reversion towards the global mean). A Markov Random Field of the ecoregions (`bs = mrf`, see page *240?* of Wood, 2017) estimated smoothed, ecoregion-specific deviations from the biome-level spatial means. Two factor-smooth interaction terms (`bs = 'fs'`) accounted for biome-specific seasonal and yearly trends. Seasonal terms were made cyclical by using cyclical cubic splines (`xt = list(bs = 'cc')`), which are continuous up to and including second derivative at the edge knots (0.5 and 366.5, which correspond to 00:00 of January 1st and 24:00 of December 31st, respectively). A tensor product interaction smooth for each biome estimated the change in seasonal trends over the years. Finally, a smooth of elevation above sea level accounted for the effect of altitude. See Pedersen *et al.* (2019) for more information on hierarchical modeling and the use and interpretation of factor smooth interaction terms.

will we subtract the average residual from each pixel?

A second HGAM estimated the variance in NDVI around the mean estimated by the model above. The model had an identical structure to the model for the mean, with the exception that (1) the response variable was the squared residual from the first model, such that the model estimated the mean squared residual (i.e., the variance) for a given point in time and space, and (2) a smooth term of the estimated mean NDVI. The model is available below:

```
#' *CHANGE TO SOS BASIS*
m_var <- bam(
  e_2 ~
    biome +
    s(poly_id, bs = 'mrf', xt = list(nb = nbs)) +
    s(doy, biome, bs = 'fs', xt = list(bs = 'cc'), k = 10) +
    s(year, biome, bs = 'fs', xt = list(bs = 'cr'), k = 10) +
    ti(doy, year, biome, bs = c('cc', 'cr', 're'), k = c(5, 5)) +
```

```
  s(elevation_m, bs = 'cr', k = 5) +
  s(mu_hat, bs = 'cr', k = 5),
family = gaussian(),
data = d,
method = 'fREML',
knots = list(doy = c(0.5, 366.5)),
drop.unused.levels = TRUE,
discrete = TRUE,
samfrac = 0.001,
nthreads = future::availableCores(logical = FALSE) - 2,
control = gam.control(trace = TRUE))
```

Results

figures:

- plot grid of mean over space, `s(year)`, `s(doy)`, `s(elev)`

- plot grid of DENVar over space, `s(year)`, `s(doy)`, `s(elev)`, `s(mean)`

- histograms of DENVar around flat map of biomes (change colors)

- hex plots of DENVAr with other variables (add temperature, annual precip, extreme weather events, fires, invasive species, max body size, disease occurrence, . . .)

General results

- two Orthographic projections of DENVar: Northern and southern hemispheres on spring solstice

Correlations with other metrics

- temperature

- seasonal temperature range

- precip

- seasonal temperature range

- spp diversity

- gross primary productivity

- max animal weight

9
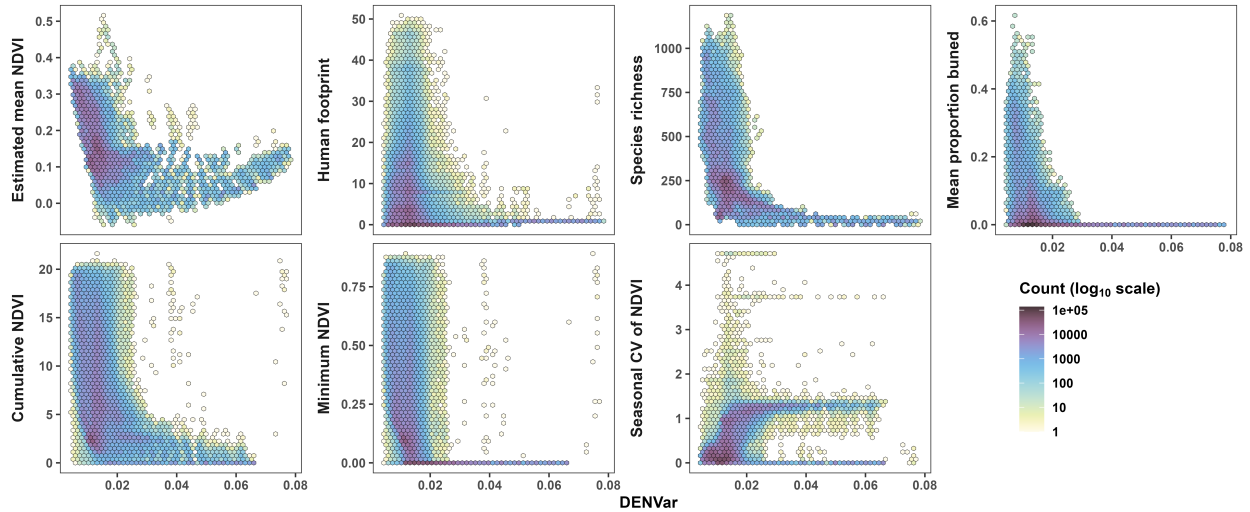
Figure 2: Hex plots of the relationship between the global Dynamic Estimate of NDVI Variance (DENVar) and common ecological metrics. The fill of the hexagonal cells represents the log-10-transformed number of points within the cell. Rowwise, the variables are: mean NDVI (as estimated in this manuscript); the machine-learning Human Footprint Index (ml-HFI) of Keys, Barnes & Carter (2021); the 2015 cumulative, minimum, and seasonal range in the Dynamic Habitat Index of XXX, (F).

140   • https://silvis.forest.wisc.edu/globalwui/

141   • https://silvis.forest.wisc.edu/data/dhis/: NDVI16 (Normalized Difference Vegetation

142   Index), EVI16 (Enhanced Vegetation Index), FPAR8 (Fraction absorbed Photosyn-

143   thetically Active Radiation), LAI8 (Leaf Area Index), GPP8 (Gross Primary Produc-

144   tivity)

145 **How to obtain the data**

146 **Static rasters of mean and variance (1981-2025)**

147   • for GIS users (tif)

148 **Shiny app for obtaining values**

149   • get values for specific coordinates: 1981-2025 average

150   • get values for specific coordinates and dates (upload as a CSV, download as a CSV)

151   • screenshot of the shiny app

Discussion

We have presented a new spatiotemporally dynamic metric of environmental stochasticity, which we have called the Dynamic Estimate of NDVI Variance, DENVar. In this section, we discuss the interpretation of DENVar in greater depth, and we argue the advantages and limitations of the statistical methods used. We conclude by suggsting some use cases of DENVar within animal movement ecology, landscape ecology, and phenology, but we invite readers to consider how DENVar may be of use in their field and adjacent disciplines.

Why use complicated statistics instead of machine learning?

Admittedly, the title of this section is misleading for two reasons. Firstly, some may argue that Generalized Additive Models are a form of machine-learning (here abbreviated as ML), but we intend to contrast GAMs with more "black-box" types of machine learning, such as neural networks and random forests. The second reason for which the title is misleading is that it implies that machine learning is not complicated, or at least that it is less complicated than the models we used. However, we argue that while traditional statistical models may seem more intimidating to some, their complexity is what allows analysts to produce interpretable results and measures of uncertainty (Wood, 2017). And while the theoretical basis for GAMs can discouraging for those who do not a strong background in mathematics or statistics, outputs from GAMs can be presented in an accessible manner even to those without a strong quantitative background through the use of well-designed figures, especially in a Bayesian context (when the aim is to estimate a parameter). In contrast, while ML methods will often give understandable results, it may not be possible to discern *why* such results were "chosen" by the model. Instead, GAMs produce flexible yet interpretable estimated effects that can be represented with relatively simple figures, even if the mathematical formula(e) for the model may be complicated.

Ideally, a model should estimate or explore the relationships among variables such that

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results can be interpreted in a transparent and unambiguous manner, such that readers can scrutinize the underlying assumptions, methods, and decisions. We recognize that the assessing GAMs requires a certain level of expertise, but we hope the readers can appreciate the option to assess the GAMs more easily than a series of consecutive, weighted regressions (as in the case of neural networks). In contrast, GAMs learn from data with no initial starting assumptions other than user-imposed limitations of wiggliness, which are clearly outlined in each basis size of the models' terms. The structure and wuggliness of GAMS can thus be grossly designed based on the system's complexity and structure while allowing the data to inform the model trends, wiggliness, and coefficient size.

Interpreting DENVar: the importance of scale

- smoothness of mean impacts smoothness and size of variance: depends on scale of interest (e.g., animals' ability to respond to, learn, and predict changes in the mean). Changes not attributed to trends in the mean are stochastic
- DENVar is a good metric as long as the spatiotemporal scale of interest is similar or larger to that of DENVar. May not work well for small-scale processes such as the movement dynamics of a small rodent, the phenology of a small orchard when spatiotemporal heterogeneity is finer than DENVar's resolution

Environmental stochasticity and animal movement ecology

The field of animal movement ecology has long shown that animals alter their movement in response to resource abundance or availability (Burt, 1943; Charnov, 1976; Southwood, 1977; Broekman *et al.*, 2024). More recently, movement ecologists have started focusing more on resource stochasticity (e.g., Stephens & Charnov, 1982; Rizzuto *et al.*, 2021), but it is worth distinguishing between resource stochasticity and seasonality (Nilsen, Herfindal & Linnell, 2005). Seasonality is generally best interpreted as a cyclical change in the mean that many animals can learn to predict, as in the case of green-wave surfing (Middleton *et al.*,

2018; Geremia *et al.*, 2019). In contrast, environmental stochasticity refers to unpredictable changes, such as forest fires (**ref?**), sudden snow storms (Aikens *et al.*, 2025), and unusual phenology (**ref?**). Animals also respond to stochastic changes (Mezzini *et al.*, 2025), but their ability to adapt depends on behavioral plasticity (Rickbeil *et al.*, 2019; Steixner-Kumar & Gläscher, 2020), and memory (Polansky, Kilian & Wittemyer, 2015; Abrahms *et al.*, 2019; Riotte-Lambert & Matthiopoulos, 2020; Falcón-Cortés *et al.*, 2021; Ranc, Cagnacci & Moorcroft, 2022).

Botero *et al.* (2015) tipping points

Polazzo *et al.* (2024)

extreme events, black swans (Logares & Nuñez, 2012; Anderson *et al.*, 2017)

- migration routes are key habitat (Ortega et al., in prep), especially in stochastic environments
- can fail to adapt to changes in conditions Sawyer *et al.* (2019)
- https://www.sciencedirect.com/science/article/pii/S0960982220308484
- https://onlinelibrary.wiley.com/doi/full/10.1111/gcb.15169
- industrial development affects animals' ability to respond to both predictable and unpredictable change (https://www.nature.com/articles/s41559-022-01887-9)
- effects of sudden deep snow in red desert on proghorn (https://www.sciencedirect.com/science/article/abs/pii/S0960982225002957)
- https://www.nature.com/articles/s41467-023-37750-z
- https://esajournals.onlinelibrary.wiley.com/doi/full/10.1002/ecy.4238
- detecting regime shifts (in lakes: Bjorndahl *et al.*, 2022)

Environmental stochasticity and population dynamics

read Lande (1993)

Environmental stochasticity reduces habitats' energetic balance and carrying capacity (Chevin, Lande & Mace, 2010) as individuals struggle to rely on unpredictable resources

and increase the instability of populations and communities (Lande, 1993). Additionally, stochastic environments reduce the ability of specialist species to adapt and evolve while selecting for more generalist species (Levins, 1974). Consequently, stochastic environments tend to have lower species diversity (**marcus?**).

Environmental stochasticity and fire ecology

Recent work by (**devries?**) has suggested that NDVI stochasticity is an important metric for evaluating forest recovery after large fires, while (**collinson?**) has suggested that variance in NDVI is an important predictor of the occurrence of forest fires due to ignition by lightning.

Environmental stochasticity and phenology

- Jonzén *et al.* (2006)
- effects can be compounded by cumulative effects (e.g., loss of species diversity, see Wolf, Zavaleta & Selmants (2017))
- climate change affects plant phenology, but changes in situ may not match experimental estimates (Wolkovich *et al.*, 2012)
- reproduction of painted lady butterfly (Stefanescu, Ubach & Wiklund, 2021)
- Wessling *et al.* (2018)

Useful references

- Keith *et al.* (2008)
- Chevin *et al.* (2010)
- Rickbeil *et al.* (2019)
- Mueller *et al.* (2008)
- Pettorelli *et al.* (2005)
- Keys, Barnes & Carter (2021)
- Nilsen *et al.* (2005)
- Merkle *et al.* (2016)
- Tian *et al.* (2015)
- Huang *et al.* (2021)
- Fan & Liu (2016)
- Wang *et al.* (2019)
- Pease (2024)
- Xu *et al.* (2021)
- Mezzini *et al.* (2025)

TO READ: * Site fidelity as a maladaptive behavior in the Anthropocene: https://esajournals.onlinelibrary.wiley.com/doi/full/10.1002/fee.2456 * Pettorelli N., Vik J.O., Mysterud A., Gaillard J.-M., Tucker C.J. & Stenseth N.Chr. (2005). Using the satellite-derived NDVI to assess ecological responses to environmental change. Trends in Ecology & Evolution 20, 503–510. https://doi.org/10.1016/j.tree.2005.05.011

₂₆₅ supplementary material:

- ₂₆₆ hex plots of pred vs obs for mean and var
- ₂₆₇ histograms of mean around flat map of biomes (change colors)

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