Incorporating extremes into climate envelope models for Florida threatened and endangered vertebrates

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Introduction

Climate envelope models (CEMs) are a subset of species distribution models (SDM) which attempt to define a species' climate "niche." CEMs correlate species presence locations to a set of climatic variables, which are commonly derived from mean monthly values of temperature and precipitation over a specified historic period (generally 30 years or more). Mean variables smooth out the variability in the climate record, ignoring potentially deterministic factors such as rainfall events, droughts, hurricanes, and high/low temperature events. Despite generally occurring on a short time scale, extreme weather/climate events can impact many aspects of a species' biology, including individual fitness, morphology, timing of activity, and distribution; certain extreme events (such as droughts and hurricanes) can even lead to extinctions of entire populations.[1] Recent historical evidence points to an increase in extreme climate (Figure 1), generally associated with ongoing climate change.

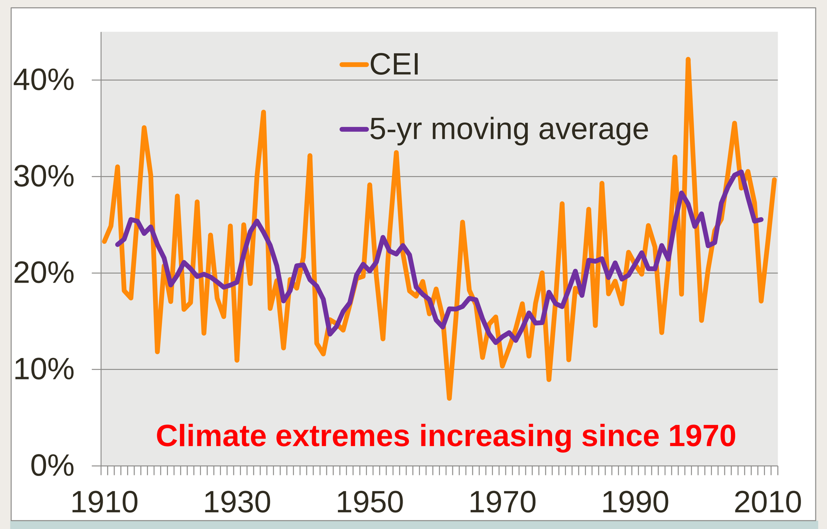


Figure 1. Percentage of contiguous U.S. area affected by climate extremes as measured by NCDC's Climate Extreme Index, 1910-2011[2]

In this study, CEMs were built for 16 threatened and endangered (T&E) vertebrate species or subspecies occurring in peninsular Florida and the Keys. To identify the impact of extreme variables in CEMs, two models were built for each species. The first set of models ("means") were built using eight bioclimatic variables derived from monthly means for the 30-year period 1981-2010. The second, ("means + extremes") added eight extreme variables to the predictor pool (listed in *Materials and Methods* diagram).

Table 1. Species (or subspecies) for which models were created

Common name	presences
Birds	
Cape Sable seaside sparrow[a]	54
Florida grasshopper sparrow[a]	43
Florida scrub jay	424
Audubon's crested caracara[a]	425
Everglades snail kite[a]	184
Mammals	
Florida bonneted bat	10
Key deer[a]	9
Silver rice rat[a]	12
Key Largo cotton mouse[a]	8
Southeastern beach mouse[a]	26
Anastasia Island beach mouse[a]	14
Florida panther[a]	784
Lower Keys marsh rabbit[a]	11
Reptiles	
American crocodile	74
Bluetail mole skink[a]	16
Sand skink	28

[a] subspecies

Results

Three metrics were used to evaluate model performance - area under the receiver operating characteristic curve (AUC), Cohen's kappa, and the True Skill Statistic (TSS). For all species together, there were no significant one-way changes in average model performance according to these metrics, with only small changes for individual species.

A test of spatial correlation (r) revealed how similar the testing/training models (n=100) were relative to the "default" model run with 100% of occurrence data (n=1). On average, models including extremes had significantly higher spatial correlation (paired t-test, n=16, mean = +0.014, $p<0.05$). This effect was primarily evident for the species with higher prevalence and larger ranges. Spatial correlation *between* "default" models with and without extremes was generally high, ranging from 0.87 (Bluetail mole skink) to 0.99 (Lower Keys marsh rabbit). Model output and metrics for 8 species are shown in Figure 2.

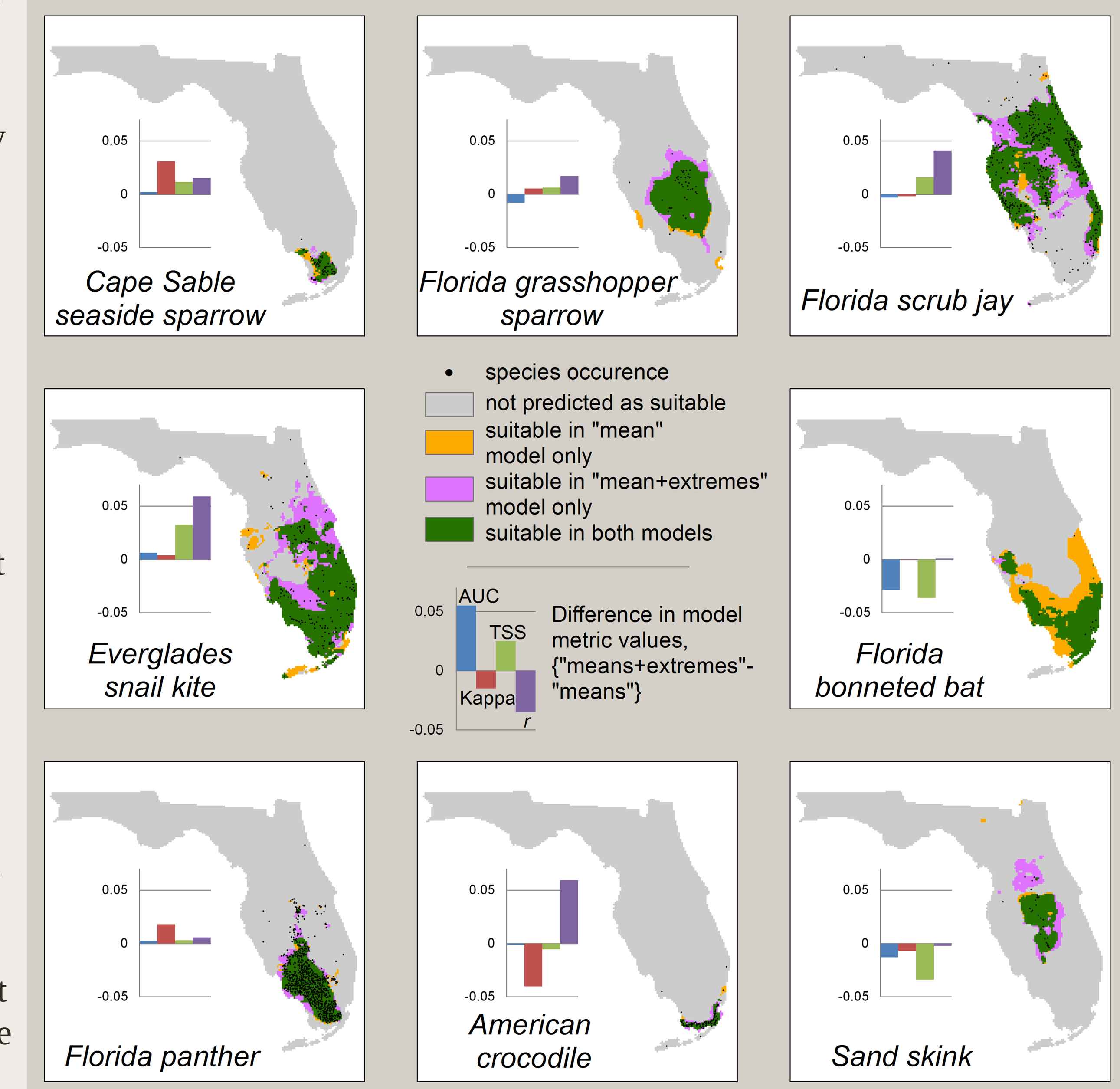


Figure 2. Model spatial predictions ("default" model, threshold at 10% occurrence probability value, metrics (calculated as mean value for 100 model runs with 75/25 training/testing split), and occurrences for eight species

MaxEnt's output includes variable contribution and permutation importance metrics for each model run. Across all species, temperature seasonality (Figure 3a) contributed the most to the models, with maximum diurnal temperature range contributing the most among extremes (and 2nd most overall). Temperature seasonality was also the most important variable; however, 1-year return extreme minimum temperature (Figure 3b) was the most important extreme climate variable (but only 4th most overall). Variables representing tropical storms (Figure 3c) and hurricanes generally contributed little to the models and had low importance scores.

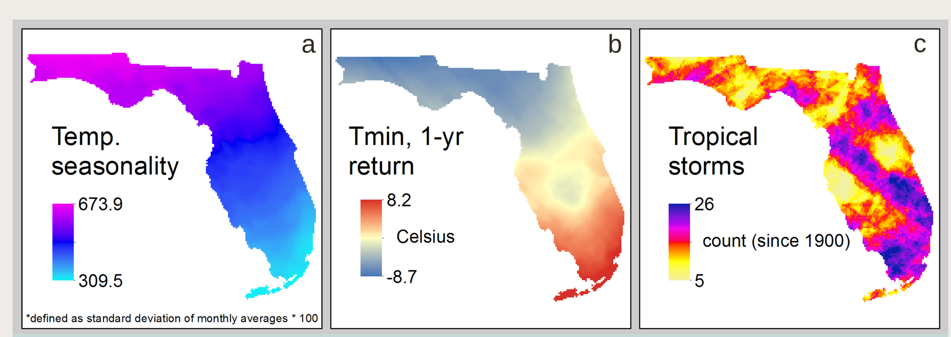


Figure 3a,b,c. Three study variables

Discussion

Because of the lack of conclusive improvement in model metrics and high spatial correlation between models with/without extremes, this study provides little support for universal addition of extreme variables to CEMs. Several factors may have contributed to this:

- **Correlation** - extreme temperature and precipitation variables created for this study were all highly correlated with at least one "mean" climate variable (r > 0.84), limiting the amount of novel information they could provide
- **Temporal correspondence** - due to scarcity of occurrence data for most species, some occurrences from outside the temporal domain were used; this may be more relevant to extreme climate due to its short-term impact
- **Spatial scale** - while climate undoubtedly plays a role in species distributions, it is possibly a more appropriate determinant at courser scales and across a wider geographic domain than used in this study
- **Applicability for some study species** – many T&E species are inherently range-limited, possibly not fulfilling their full abiotic niche. Extremes play a more important role at species' range edges[1]; as such, many T&E species have already had their ranges reduced by non-climatic factors (anthropogenic effects, habitat loss/change, competition, etc.).

There was some evidence that adding extremes was beneficial for the *most* prevalent species - TSS and spatial correlation were improved for the four species with the most occurrences. The overall significant improvement in spatial correlation does not indicate that models including extremes were "better" - just more similar to the "default" model.

Addition of extremes will probably be most beneficial is cases where there are empirically-derived physiological limits or well-documented responses to climate/weather events, allowing for hypothesis testing and better predictions into future climates. In this study, the Bluetail mole skink showed the greatest improvement with the addition of extremes (Figure 4). Looking just at extreme temperatures, the envelope of daily minimums and maximums are fairly small (between -3.8^0 – -2.7^0 C and 36.7^0– 36.9^0 C, respectively), with the minimum likely near the ectotherm's limit. This may currently deter range expansion, but increases in minimum temperatures may allow for expansion, provided habitat is available.

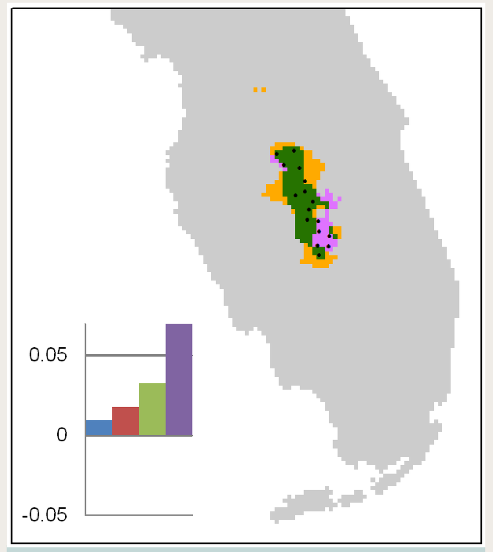
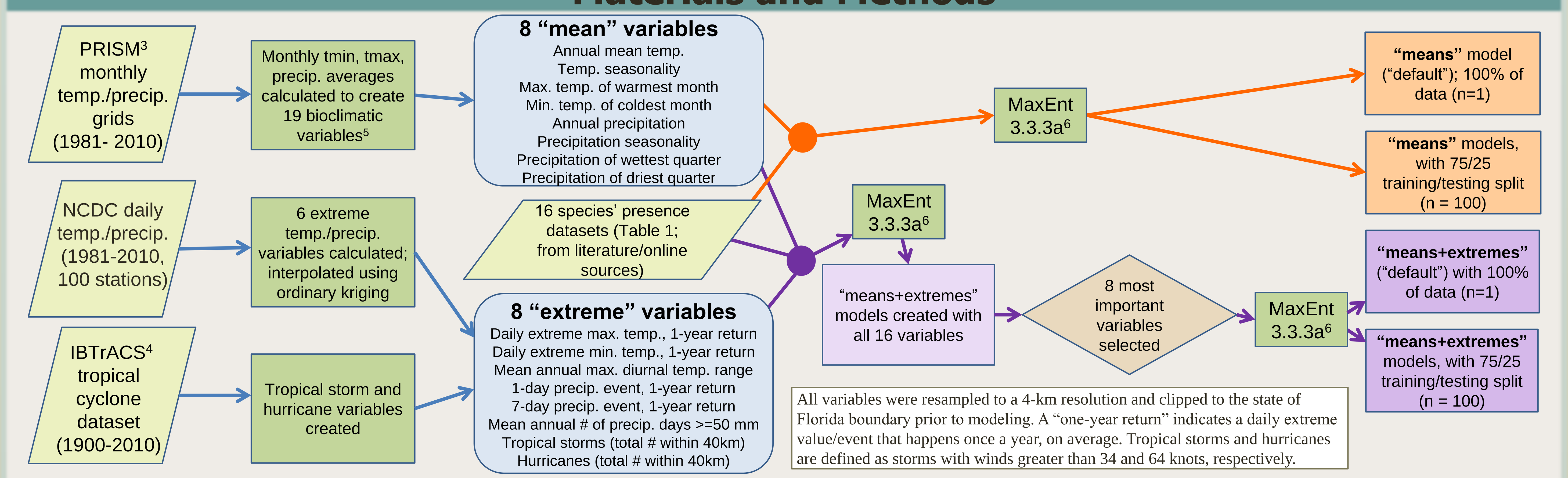


Figure 4. Model predictions for the Bluetail mole skink (following Figure 2)

While climate changes' effect on extreme precipitation events are uncertain, extreme temperatures are expected to increase with some certainty.[7] For wide-ranging species, or those with populations near known physiological limits, CEMs with the addition of extreme temperatures alone could provide valuable information for conservation managers planning for climate change.

Materials and Methods



All variables were resampled to a 4-km resolution and clipped to the state of Florida boundary prior to modeling. A "one-year return" indicates a daily extreme value/event that happens once a year, on average. Tropical storms and hurricanes are defined as storms with winds greater than 34 and 64 knots, respectively.

References

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Please contact *david.bucklin@gmail.com* for more information on this project. More information on the climate envelope modeling project at UF-FLREC can be found at http://crocdoc.ifas.ufl.edu/projects/climateenvelopemodeling/.