Climate Vulnerability Analysis for Amphibians and Reptiles: The Devil is in the Details

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Talk objectives

- Approaches to assessing vulnerability
- Confronting the need for data quality and quantity
- Amphibians examples
- Next steps (refining models, adding complexity)
Planning for climate change

• Forecasting species responses to climate change is a necessary evil.
Planning for climate change

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**Necessary because:**

• Provide stakeholders with planning tools when developing action plans.
  • Identify species that might shift status unexpectedly.
  • Help prioritize allocation of resources, management activities, and areas.
Planning for climate change

- Forecasting species responses to climate change is a necessary evil.

**Necessary because:**
- Provide stakeholders with planning tools when developing action plans.
  - Identify species that might shift status unexpectedly.
  - Help prioritize allocation of resources, management activities, and areas.

**Evil because:**
- Fraught with assumptions and uncertainties that make forecasts challenging.
- “Alternative models can be so variable as to compromise their usefulness for guiding decisions.”
Methods for modeling species responses to climate change

- Two inter-related activities
  - Assessing vulnerabilities
    - Gauge direct and indirect effects of climate change
    - Rank species based on vulnerability
  - Forecasting future distributions
    - Estimate future expansion or contraction of species ranges
    - Estimate where species are likely to occur in the future
      - Where will species persist?
      - Where will species colonize?
      - Where do future habitats intersect with other factors?
Methods for modeling species responses to climate change

- Forecasting distribution responses
  
  **Correlative models:**
  - Phenomenological
  - Relate current distributions to environmental variables

  **Mechanistic models:**
  - Use explicit relationships between environmental variables and organismal performance
  - Estimated independently of species current distribution
Predicting the distribution of Sasquatch in western North America: anything goes with ecological niche modelling

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ABSTRACT

The availability of user-friendly software and publicly available databases has led to a rapid increase in the use of ecological niche models (ENMs) to predict species distributions. A potential source of error in ENMs that may affect the accuracy of ecological niche models is the lack of correct, is incorrect (or incomplete) taxonomic identifications of species in the dataset. Researchers of the need for careful evaluation of data and model performance, especially when the presence of cryptic species is an issue, have suggested using ecological niche models (ENMs) to predict distributions of a taxon’s potential occurrences. We present a method for predicting the potential range of Sasquatch in western North America, demonstrating that ENMs can be used to predict distributions of a taxon’s potential occurrences. The results show that ENMs can be used to predict potential distributions of Sasquatch in western North America, suggesting that ENMs can be used to predict potential distributions of other cryptic species. The results also suggest that ENMs can be used to predict potential distributions of other cryptic species, providing a new tool for studying the distribution of cryptic species in North America.

Keywords
Bigfoot, biodiversity informatics, climate change, ecological richness, Sasquatch, species distributions, Ursus americanus.

Figure 1: Map of Sasquatch occurrences from Washington, Oregon, and California used in the analysis. Points represent visual/auditory detection, and foot symbols represent coordinates where footprint data were available. Shading indicates topography, with lighter values representing lower elevations.
Predicting the distribution of Sasquatch

Ecological niche modelling with public data

Figure 2: Predicted distributions of Bigfoot constructed from all available encounter data using MaxNet (a) for the present climate and (b) under a possible climate change scenario involving a doubling of atmospheric CO₂ levels. Results are presented for logistic probabilities of occurrence ranging continuously from low (white) to high (black). Differences between (a) and (b) are shown in (c), with whiter values reflecting a decline in logistic probability of occurrence under climate change, darker values reflecting a gain, and grey reflecting no change. A predicted distribution of Ursus americanus in western North America under a present-day climate is also shown (d). White points indicate sampling localities in California, Oregon and Washington taken from GBIF (n = 113 for training, 28 for testing; compare with Fig. 1) used for the MaxNet model with shading as in (a) and (b); black points indicate additional known records not included in the model.

Figure 3: A null distribution of the ecological niche model (ENM) overlap statistic I created from MaxNet runs for 100 randomizations of localities between Bigfoot and black bear (Ursus americanus) data sets. The arrow shows the I value observed (0.849) for the actual data sets for MaxNet runs using all locality points (i.e., no test points).
Methods for modeling species responses to climate change

![Image of a lichen on a tree]

**Figure 1** Range predictions for *Salamandra salamandra* in current climates (light gray) and predicted range expansions following a uniform 3 °C increase in temperature (dark gray). Localities (○) and the atlas range polygon are shown.
Methods for modeling species responses to climate change

- Common approaches to forecasting
  - Ensemble forecasting:
    - Present a range of scenarios generated by alternative models.
  - Alternative distribution models
  - Alternative climate models
  - Varying model assumptions

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Ensemble forecasting of species distributions

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Climate change has had impacts on species distributions and has led to the use of bioclimatic modelling approaches, whereby empirical relationships between present-day distributions of species and climate variables are used to estimate distributions of species under future climate scenarios [1-4]. For several reason, alternative models may be used to explore the sensitivity of species to climate change and to inform conservation decisions. We discuss recent developments in ensemble forecasting and the potential for ensemble approaches to be a useful tool for understanding the impacts of climate change on biodiversity.

Introduction

Algorithms for ensemble forecasting of species distributions have been developed that take into account the uncertainty in climate projections and the potential for species to respond to climate change. These algorithms are based on the use of alternative climatic models and the inclusion of additional factors such as habitat suitability and environmental variables.

Alternative approaches to forecasting the sensitivity of species to climate change include the use of multiple models, the use of historical data, and the use of statistical methods to estimate the potential impacts of climate change on species distributions. These approaches can be combined to provide a more comprehensive understanding of the potential impacts of climate change on biodiversity.

Alternative bioclimatic models

Alternative bioclimatic models are also used to explore the potential impacts of climate change on species distributions. These models are based on different assumptions about the relationship between climate and species distributions, and can be used to explore the sensitivity of species to climate change and the potential for species to respond to climate change.

Varying model assumptions

The use of alternative climatic models and the inclusion of additional factors such as habitat suitability and environmental variables can help to improve the accuracy of species distribution models and provide a more comprehensive understanding of the potential impacts of climate change on biodiversity.
Amphibian vulnerabilities to climate change

- Patterns of amphibian distributions and diversity show consistent, strong dependence on climate
  - Richness often related to topography, moisture, and temperature
- Diversity generally highest at mid and high elevations in montane regions
- Most species colonized those regions when the climate occurred across valley bottoms
- Many species appear strictly confined to their current climatic zone.
  - Many species exist at or near their thermal maxima.
- Dispersal limited through warm habitats
Selecting a tool for modeling

- DOMAIN, logistic regression, MaxEnt, GARP, Random Forests....
Selecting a tool for modeling

- **DOMAIN**: logistic regression, MaxEnt, GARP, Random Forests...
Creating a correlative model from presence-only data

- Species locality data collected and mapped
- Climate data matching (precipitation, temperature)
- Use ‘background points’ to match climate at other localities
- Project onto current and future climate-scapes
- Post-processing of other variables
  - Land use/land cover
  - Sea level rise
  - Focal species (i.e., longleaf pine)
- Output may be threshold-based or continuous
- Output represents probability distribution of suitable climate – not probability of presence
Creating a correlative model from presence-only data

- Species locality data collected and mapped

www.herptnet.org

www.gbif.org
Creating a correlative model from presence-only data

- Species locality data collected and mapped (HerpNet data)
Creating a correlative model from presence-only data

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Creating a correlative model from presence-only data

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Creating a correlative model from presence-only data

- Species locality data collected and mapped (HerpNet data)
Creating a correlative model from presence-only data

- Species locality data collected and mapped (HerpNet data supplemented with state-maintained EOs)
Aneides aeneus
Current habitat suitability
No TN data
Creating a correlative model

- Intersect locality data with current climatic conditions (typically 30 – 40 year average of conditions)
- Measures of climate will depend on
  - SDM algorithm, interpretability, and natural history of species
Creating a correlative model

- Use background points to match climate at other localities
- Extent of background point placement is important
  - Restrict to area around known range of species
- Use target group background localities if possible
Creating a correlative model

- Project onto current and future climate-scapes
- Availability of data at this stage progressing rapidly

**WORLDCLIM**

Future climate data download

IPCC 3rd Assessment data. Future climate projections, calibrated and statistically significant. Download projected future climate by climate model (e.g. CCCMA), emission scenario.

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<td>bio 1-9</td>
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| 2.5 arc-minutes |              |              |
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| 2050: min, max, prec | bio 1-9 | 10-18        |
| 2080: min, max, prec | bio 1-9 | 10-18        |

| 5 arc-minutes |              |              |
| 2020: min, max, prec | bio 1-9 | 10-10        |
| 2050: min, max, prec | bio 1-9 | 10-10        |
| 2080: min, max, prec | bio 1-9 | 10-10        |

| 10 arc-minutes |              |              |
| 2020: min, max, prec | bio 1-9 | 10-18        |
| 2050: min, max, prec | bio 1-9 | 10-18        |
| 2080: min, max, prec | bio 1-9 | 10-18        |

**HADCM3**

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Creating a correlative model

- Output from model may be continuous or binary
- For binary models a threshold must be chosen
Distribution

CEMs

strict CEM
assumes current distribution is strictly predicted by climate

liberal CEM
assumes species climate distribution is larger than current realized distribution

• Used regional GCMs mathematically scaled from global models.
• Each GCM run under two future CO2 scenarios [“low” and “high”]

Therefore, for each of 28 species...

2 CEMs X 2 GCMs X 2 CO2 levels = 8 model scenarios

• Model projections run out to 2020, 2050, and 2080
B) County based richness map

B) County based richness map

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Current vulnerability assessment

Funding provided by US Fish and Wildlife Service Competitive State Wildlife Grant (2009)

Model future climatic distributions of “priority” reptiles and amphibians.

- **Southeastern Pilot Study**
  - Modeling species identified with input from SE States
  - Species selected by...
    - species of greatest conservation need
    - eliminated species that were only listed by a single state if that state represented a range margin

Products

- Bracketed scenarios of shifts in climatic distributions for focal species.
- Post-processing of other variables
  - Intersections of suitable habitat with conservation management lands
  - Incorporating land use/land cover it habitat projections
- Applying to other modeling efforts:
  - Coastal habitat loss due to sea level rise
  - Habitat restoration forecasting (e.g., Longleaf pine habitat restoration)
Concluding remarks

• Need to build better biophysiological models
  • Limited (and biased) data on most species
• Need to identify factors that are not currently part of vulnerability assessments
• Species distribution models can be used cautiously as a valuable tool to forecast conservation needs and management actions.
  • Such approaches need to ensemble multiple models and provide a range of scenarios.
  • Accurate and abundant species distribution data is a limiting factor for assessing climate change vulnerability of most species.