CHAPTER 21

Planning for climate change without climate projections?

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In 2012, Yale University hosted 12 scientists from NGOs, government agencies, and academia at a workshop aimed at developing a framework for addressing climate change in conservation planning (Schmitz et al., 2015). It quickly became obvious that there was a deep divide among the attendees. Some felt models that incorporate climate projections were useful and even essential to planning for climate change. Others felt that climate forecasts are too uncertain and should be avoided. These climate model skeptics recognized that conservation planning needs to address the impending impacts of climate change, but they proposed alternative approaches that required no climate forecasts. At one point, the meeting facilitator had us line up and arrange ourselves from one end of the room to the other with the extremes representing those who thought no forecasts should be used in the planning process to those who felt forecasts were essential. The majority of the working group clustered at the "no-forecast" end of the spectrum, a few were at the pro-forecast extreme, and a small group stood somewhere near the middle.

Several "forecast-free" planning responses to climate change have been proposed. The most popular include protecting climatic refugia, increasing connectivity, and what has come to be known as "protecting nature's stage" (Game et al., 2011; Groves et al., 2012). Although all three approaches have merit, those who champion them as a substitute for climate forecasts overlook a key issue. Yes, there are known uncertainties associated with models used to project climate change and climate impacts. But all three of the forecast-free approaches also entail large uncertainties—indeed, just as much, or perhaps even more, uncertainty as found in the latest climate forecasts (Table 21.1).

In this chapter, we compare the uncertainties of climate forecasts to those inherent in planning for connectivity and protecting nature's stage, the two forecast-free approaches that currently have the most traction with conservation NGOs and funders. We ask if it makes good sense to shun climate projections because of their large uncertainties.

21.1 What we know about the uncertainty of climate projections and predicted impacts

There are well-known uncertainties associated with all models used to project climate change (GCMs) that arise from assumptions about, and parameterizations of, key mechanisms in atmospheric processes, such as cloud formation. There are additional uncertainties associated with future emissions, as well as uncertainties in finer resolution climate maps due to incomplete coverage of weather stations and differences in downscaling approaches. Finally, there are uncertainties associated with the myriad ecological models used to translate projected changes in climate into impacts on flora and fauna.

Although it is impossible to assess the accuracy of future projections without waiting for the future to arrive, there have been rigorous evaluations of the abilities of GCMs to recreate historical climatic conditions. The correlation between modeled and

Lawler, J. J. and Michalak, J., *Planning for climate change without climate projections?* In: *Effective Conservation Science: Data Not Dogma*. Edited by Peter Kareiva, Michelle Marvier, and Brian Silliman: Oxford University Press (2018).
DOI: 10.1093/oso/9780198808978.003.0021

Table 21.1 General sources of uncertainty in three approaches to addressing climate change in conservation planning.

Climate-informed biotic projections	Conserving nature's stage	Connectivity
Climate projections	Elevation data	Habitat suitability assessment
Downscaling	Soils and geology data	Landscape resistance assessment
Current species distributions or biotic conditions	Analytical approach (including variable selection)	Core-area delineation
Extrapolating to the future		Analytical approach
Analytical approach		Current species distributions
		Land-cover data

observed temperatures is roughly 99% globally with an intermodel spread of ±3°C. The correlation between modeled and observed precipitation is lower at 82% (ranging from 0.75 to 0.90), but improving as models advance (IPCC, 2013). Uncertainty regarding precipitation increases at regional scales, although observed precipitation fell within the range estimated by the most recent suites of GCMs for 21 out of 26 of the regions evaluated by the IPCC (IPCC, 2013).

Most attempts to use climate projections for conservation planning rely on downscaled climate projections, which come with a suite of errors introduced by the downscaling. For example, Klausmeyer and Shaw (2009) found the error associated with downscaling temperature projections to a 2.5-minute resolution grid at the 66% confidence level to be approximately ±26%, ±16%, and ±14% for low, moderate, and high emissions scenarios, respectively.

Applying ecological models to climate-change projections can only compound the uncertainties associated with GCMs and downscaling approaches. For example, the type of model used (e.g., logistic regression, neural network, MaxEnt) can strongly influence the projections of species distributions (Thuiller, 2004; Diniz-Filho et al., 2009). Lawler et al. (2006) found an average of only 19% overlap in projected future distributions for 100 mammal species across six different modeling approaches (agreement was measured across all six approaches—not as the average of pairwise agreement). However, the models also ranged in their ability to accurately represent current distributions, emphasizing the need to test models and select ones that perform better.

A few studies have attempted to assess the accuracy of these species distribution models by forecasting present-day distributions using historical data. Using a 20-year span in bird species distribution data, Araújo et al. (2005) found that niche models did a decent job of capturing modern ranges when they were built with historical data. Martínez-Meyer et al. (2004) found that models seeded with Pleistocene distributions significantly predicted current distributions for 18 of 23 mammal species. Kharouba et al. (2009) found that for the majority of butterfly species they analyzed, species distribution models corresponded with species' observed responses over a 60-year period (mean autoregressive $R^2 = 0.70$).

The key message is that although the uncertainties associated with using climate projections are substantial, they are widely recognized and can be rigorously quantified. This kind of scrutiny helps to drive model improvement and a transparent understanding of model strengths and limitations.

21.2 The devil (and uncertainty) is in the details of increasing connectivity

Conservationists have long used connectivity as a strategy to counteract the negative impacts of habitat loss and fragmentation. More recently, increasing connectivity has risen to prominence as the most often cited adaptation approach for conserving biodiversity in a changing climate (Heller and Zavaleta, 2009). This approach is sensible but fraught with its own, often overlooked, sources of error.

Perhaps the largest uncertainties in connectivity modeling arise from decisions about habitat suitability and landscape resistance (i.e., how difficult it is for a given species to move across the landscape). Thirty-four percent of connectivity studies from 2000 to 2013 relied on expert opinion to parameterize some aspect of the connectivity-mapping process (Correa Ayram et al., 2016). There is ample evidence that expert opinion, although often the only available information, may be far from accurate. For example, the optimal or most effective corridors can be identified if one has a geospatial representation of resistance to movement—or a "resistance layer." This resistance layer can come from expert opinion, genetic data, tracking data, or other sources. Sawyer et al. (2011) compared the movement corridors for bighorn sheep identified with resistance based on genetic data, to the corridors based on expert-opinion-derived resistance assessments. There was no overlap between the two sets of corridors.

The foundation of any corridor planning is an apt depiction of habitat suitability. Unfortunately, habitat suitability models suffer from many of the same uncertainties (e.g., differences in predictions across approaches used) as the species distribution or niche models used to project climate-driven range shifts. Indeed, often the very same types of models are used for both purposes. Additionally, these models rely heavily on land-cover datasets, which in the USA have accuracies that range from 60% to 80% for a 16-category classification (Yang et al., 2001; Wickham et al., 2013). Estimates of accuracy in some regions within the USA can be much lower, ranging from 38% to 70% (Wickham et al., 2004) and land-cover datasets with more finely resolved land-use categories are even less accurate.

Just as GCMs differ in their climate forecasts, so do connectivity models differ in their identification of corridors. Carroll et al. (2012) explored the relationships between outputs of three connectivity-mapping approaches and found correlations of 0.45, 0.58, and 0.85 for the three pairs of approaches. Most existing regional connectivity plans rely on a single, relatively simple connectivity modeling approach—least-cost corridor analysis (e.g., Spencer et al., 2010). In addition, most plans use expert opinion to define habitat suitability and resistance. It is not clear then why combining uncertain habitat suitability models with connectivity modeling warrants greater confidence than using climate projections to help with planning.

21.3 Protecting nature's stage assumes we know more about the stage than we do

Perhaps the most emblematic approach to avoiding the uncertainties of model projections, is "protecting nature's stage." The key idea behind this approach is that protecting a diversity of geophysical settings will also protect a diversity of species and ecosystems. Furthermore, these locations should continue to support a diversity of species and systems in the future, regardless of how the climate changes and how species' ranges shift. This is because, even as species move in response to climate change, a greater diversity of species is expected to settle into these geophysically diverse areas. How could we go wrong by simply protecting a collection of sites that span a wide range of elevations, soil types, exposures, and so on? We could go wrong because this approach relies on several assumptions.

The first assumption is that geophysical settings are representative of today's biodiversity. However, the evidence that abiotic conditions are an adequate surrogate for today's biodiversity is weak. Beier et al. (2015) reviewed 622 evaluations of abiotic surrogates for conservation planning and found that in only 43% of the evaluations did abiotic surrogates perform better than sites selected at random—and those that did, on average, were an improvement over randomly selected sites by only 8%.

The second assumption is that geophysical settings are discrete features that can be identified and mapped with a high degree of certainty. Yet uncertainty and variability also enter into the process of mapping geophysical settings. Although digital elevation models (DEMs) have a high degree of accuracy (95% confidence interval of 4.57 m) (Gesch, 2007), data for soils and lithology have major uncertainties. Correlations between SSURGO (Soil Survey Geographic Database produced by the National Resources Conservation Service) estimates and measured soil characteristics important for tree growth ranged from 0.26 to 0.56 (Littke et al., 2014). In addition, maps of geophysical settings differ dramatically depending on which variables (soils vs. geology, slope vs. landforms, etc.) are included, how many variables are used, and how each continuous variable is classified into discrete categories.

Still, identifying the same specific geophysical settings may not be that important if the real goal is to simply identify locations with a high *diversity* of settings. Although different input variables may lead to different maps of geophysical settings, it would not matter if there were at least agreement on the location of "high diversity areas." To test this

Table 21.2 Correlations between geophysical diversity assessed from three different datasets within two neighborhood sizes (540 m and 5 km).

		Michalak	Buttrick	Theobald	Michalak	Buttrick	Theobald	Topo-complexity
Source	Neighborhood	540 m	540 m	540 m	5 km	5 km	5 km	5 km
Michalak et al. (2015)[1]	540 m	1.00	0.27	0.30	0.62	0.30	0.23	0.27
Buttrick et al. (2015)[2]	540 m		1.00	0.41	0.36	0.64	0.45	0.53
Theobald et al. (2015)[3]	540 m			1.00	0.21	0.39	0.54	0.52
Michalak et al. (2015)	5 km				1.00	0.49	0.35	0.43
Buttrick et al. (2015)	5 km					1.00	0.60	0.73
Theobald et al. (2015)	5 km						1.00	0.68
Topo-complexity	5 km							1.00

[1]Landforms, elevation, heat load index, soil order (Harmonized World Soils Data)
[2]Elevation, slope, soil order (SSURGO)
[3]Landforms, heat load index, lithology (USGS)

hypothesis, we compared scores of geophysical diversity using three different mapped portfolios of geophysical data across the Pacific Northwestern USA (see Table 21.2). We calculated diversity in the immediate neighborhood of each 270-m grid cell (i.e., within 540 m and in a larger, 5-km, circular neighborhood). We then calculated correlation coefficients for all pairs of datasets. We also compared the three maps of geophysical diversity to a layer representing topographic complexity. The correlation in geophysical diversity across the three examples ranged from 35% to 60% based on the 5-km window and between 27% and 41% for the 540-m window (Table 21.2).

In sum, identifying sites that capture a high diversity of geophysical traits is not as straightforward as it might at first seem. So, once again, what seemed like a foolproof, simple approach is far more tenuous than it first appeared.

21.4 Uncertainty does not mean we have to be paralyzed

Planning for an unknown future ecological state is a daunting task. The most important message to take from this chapter is that there are large uncertainties associated with *all* proposed approaches to addressing climate change in conservation planning—not just in approaches that rely on climate-change projections. If anything, it appears that the uncertainties associated with forecasting the future climate have been better explored, documented, and addressed than the uncertainties associated with connectivity planning and protecting nature's stage.

We need more studies that directly compare different approaches to conservation planning for climate change. One recent study compared the relative success of hypothetical ice age conservation planning for modern biodiversity based on protecting climatically and geographically diverse sites versus protecting projected future tree species distributions (Williams et al., 2013). In this case, conservation priorities based on projected species distributions were somewhat correlated with modern priorities (r = 0.45) but priorities based on abiotic diversity were not at all (or even negatively) correlated with modern priorities. This study is the kind of creative comparison that is needed if we are to move beyond a theoretical debate about which approach is better.

Given the complexity of Earth's ecosystems, no model or rule of thumb will be able to perfectly identify future conservation priority areas. Furthermore, we suspect we will find that there is no single best approach. Once we accept the inevitability of large uncertainty, we can stop trying to find an approach with no uncertainty, and instead work with uncertainty to identify robust, good decisions and robust, bad decisions.

In conclusion, it was not our intention to convince you, the reader, that one approach to addressing climate change is better than any other. Nor did we set out to paint a landscape of impassable mountains of uncertainty. Instead, we hope we have dispelled the myth that forecast-free approaches are a panacea to the uncertainty inherent in future projections. There is a tendency to be suspicious of models and model uncertainty, while not appreciating the uncertainty associated with descriptive and expert-opinion based approaches. Because there are large uncertainties in all approaches, it is the task of conservation planners and researchers to creatively conduct meaningful planning in spite of these uncertainties.

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