ASSESSMENT OF RISK DUE TO CLIMATE CHANGE FOR COASTAL PELAGIC SPECIES IN THE CALIFORNIA CURRENT MARINE ECOSYSTEM

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SOUND BITE

Forage fishes in northern, nearshore areas of the California Current marine ecosystem are most exposed and most sensitive to changes in sea surface temperature and chlorophyll projected to occur by 2100.

EXECUTIVE SUMMARY

In the ocean, forage species such as squid, anchovies, and sardines play a crucial role, serving as dominant lower trophic-level consumers, targets of some of the largest fisheries in the world, and essential food for higher trophic level species like marine mammals, seabirds, and larger fishes. Contemporary climate change has already changed the distribution and abundance of some of these species, while also modifying the timing

and synchrony of important ecological and life history events. It has been challenging, however, to predict *a priori* which species, in which places and under which conditions, are most likely to be affected. Using projections of changes in oceanographic climate, we assessed risk to marine forage species in the California Current to the year 2100. On the basis of expected changes in the mean and variability of sea surface temperature and chlorophyll concentrations, and species-specific sensitivity to these changes, we ranked the relative risk to 15 species, many of which are or were valuable fisheries targets. We found that exposure to changes in oceanographic climate varied much less across the California Current than the sensitivity of individual species to those changes. By separating exposure and sensitivity components of risk to marine forage species, we provide insights into how to proactively develop climate change adaptation and mitigation strategies.

DETAILED REPORT

INTRODUCTION

Anthropogenic climate change is a major driver of ecological dynamics in terrestrial, freshwater, and marine ecosystems (Parmesan and Yohe 2003). Already, species have responded to changing climatic conditions in a variety of ways, including via altered phenology, distributional shifts, changes in synchrony with food and habitat resources, and in some cases extirpations and extinctions (Parmesan 2006, Doney et al. 2011). It has been challenging, however, to predict *a priori* which species, in which places and under which conditions, are most likely to be affected. Generating such expectations is a crucial first step to proactively developing climate change adaptation and mitigation strategies (Dawson et al. 2011).

Perhaps the most common method for assessing climate change impacts relies on species-distribution (or climate-envelope) models (Guisan and Thuiller 2005, Cheung et al. 2009). While one of the only tools for assessing the impacts of forecasted climate change on a wide range of species, alone such niche-based models may be too simplistic to resolve discrepancies between predicted and realized climate impacts (Dawson et al. 2011, Brander et al. 2013). More hopefully, recent evidence suggests that fine-scale climate data can help to improve on the predictions of species-distribution models by more accurately capturing location-specific changes in climate (Pinsky et al. 2013). However, these models are mostly projecting plastic responses of species to change and fail to consider species micro-evolutionary responses and adaptations.

For every rule related to expected climate change responses (e.g., expected poleward shifts and earlier spring blooms), there appear to be numerous exceptions. The same species can respond differently throughout its distribution, different species can respond differently in the same location, and responses to climate change clearly vary among communities and across ecosystems (Parmesan 2006, Burrows et al. 2011, Pinsky et al. 2013). While species-distribution models tend to account explicitly for the exposure of a species to changing climatic conditions, they generally make implicit assumptions about other aspects of a species' vulnerability, such as sensitivity and adaptive capacity (Turner et al. 2003, Williams et al. 2008).

Traditionally, ecological risk assessment models have considered a species' sensitivity equivalent to its response to a stressor visualized along a dose-response curve (Turner et al. 2003). This concept captures the idea that the identical stressor—whether it is nutrient limitation or human exploitation—can have dramatically different effects on different species, depending on their physiologies, prior conditioning, life histories, and behaviors (e.g., Vaquer-Sunyer and Duarte 2008; it is related in many ways to the evolutionary concept of phenotypic plasticity, Nussey et al. 2007). Similarly, a species' sensitivity to climate change is a function of many factors, including physiological tolerance limits, ecological traits (e.g., behavior, Kearney et al. 2009), and genetic diversity (Chevin et al. 2010, Phillimore et al. 2010). Whereas niche-based models project current and past understanding of a species-environment relationship (the plastic response), they fail to consider evolutionary constraints to adaptability. Under the assumption that adaptability is proportional to genetic diversity (A = S^2 * H * delta, where S is genetic diversity, H = heritability and delta is the selection gradient, akin to exposure), the variety of niches that a species occupies throughout its range is an expression of its genetic diversity, and therefore proportional to its adaptive capacity (Arnold 1992, Futuyma 2010, Hutchings 2011).

If species today are adapted to current environmental conditions, a reasonable first approximation is that species occurring in climatically consistent environments (through space or time) will be more sensitive (and less able to adapt) to climate change than species living in climatically variable environments (cf. Rapaport 1982, Gaston 2003, Gaston and Fuller 2009, Dickinson et al. unpublished). Thus, the climatic breadth of a species today may be inversely related to its sensitivity to, and adaptive capacity for, climate change in the future. Remotely-sensed data and global climate models, when coupled to information on contemporary species distributions, offer an unprecedented opportunity to estimate the sensitivity of many species to climate change based on their climatic breadths, using a rapid, uniform method.

In this paper, we bring together measures of both exposure and sensitivity to estimate risk of population change for marine forage species due to changes in oceanographic climate. By doing so we integrate our best understanding of potential evolutionary and ecological responses of forage species to climate change. Forage species play a crucial role in marine ecosystems, serving as dominant consumers, targets of some of the largest fisheries in the world (e.g., Peruvian anchoveta), and food for higher trophic level species like marine mammals, seabirds, and larger fishes (Pikitch et al. 2014). Populations of forage species are notoriously variable in size (Pinsky et al. 2011), and in many cases this variability is thought to be linked to changes in biophysical factors in the ocean such as sea surface temperature and primary productivity (e.g., Cushing 1988, Chavez et al. 2003, Baumgartner et al. 1992, Sydeman et al. 2013). Despite the widely acknowledged connections between climate and the dynamics of forage species, we are not aware of any other efforts to bring together climate forecasts, along with exposure and sensitivity estimates, for multiple forage species in any particular geographic domain. Our analysis thus provides insights into population- and community-level risk to marine forage species, with implications for fisheries, food webs, and the utility of alternative management responses in the California Current, a highly productive yet spatially and temporally variable upwelling ecosystem (Checkley and Barth 2009).

METHODS

We assessed risk due to climate change for marine forage species within the California Current ecosystem. Specifically, we focused on 10 coastal pelagic fishes and invertebrates (Table 1) that are well-sampled in long-term monitoring studies of pelagic nekton, during life stages in which they are considered forage species (Brodeur et al. 2003).

Risk was defined as each species' relative exposure and sensitivity to changes in oceanographic climate expected by the year 2100. Following Dawson et al. (2011), Samhouri and Levin (2012), Foden et al. (2013), and others, those species that were highly exposed and highly sensitive were considered most at risk due to climate change. In order to quantify exposure and sensitivity, we first defined each species' current distribution and the oceanographic climate within that distribution for the recent past (1976-2005). We also defined the oceanographic climate within the historic distribution at the end of this century (to 2100).

We developed an extent of occurrence (EOO; Gaston and Fuller 2008) layer to define the current distribution of each species. This layer was based on data from IUCN (www.iucnredlist.org) and AquaMaps (www.aquamaps.org), such that all 50 km x 50 km cells with a probability of occurrence ≥0.4 were scored as present for each species. In the future, we hope to develop species distribution maps based on annual and seasonal average abundance estimates from fisheries-independent surveys.

Oceanographic climate was defined for the entire planet in each 50 km x 50 km grid cell based on four variables correlated with the abundance of marine forage species within the California Current. These variables included: mean sea surface temperature μ_{SST}, mean chlorophyll *a* μ_{CHL}, standard deviation in sea surface temperature σ_{SST}, and standard deviation in chlorophyll *a* σ_{CHL} (Brodeur et al. 2005, Emmett et al. 2005, Litz et al. 2008, Kaltenberg et al. 2010, Zwolinski et al. 2011). The historic oceanographic climate was defined based on monthly averages of the Geophysical Fluid Dynamics Laboratory's (GFDL) Earth System Model 2G (ESM2G) (Dunne et al. 2012) forced with historical estimates of atmospheric composition. Here, we selected a 30-year period from 1976-2005 as representative of the current climate. The future oceanographic climate was defined based on ESM2G monthly projections following IPCC scenario rcp 8.5 for the 30-year period 2071-2100.

The exposure of each species was estimated based on the magnitude of expected change in a multivariate climatic index, given the current observed distribution of each species within the California Current ecosystem. This approach provides a species-specific estimate of the expected "climate velocity" (Burrows et al. 2011, Pinsky et al. 2013) over this century. To derive the multivariate climatic index, we conducted a principal components analysis (PCA) on global ocean values for μ_{SST}, μ_{CHL}, σ_{SST}, and σ_{CHL} using a correlation matrix. We used outputs from a PCA, rather than estimates of change in the original climate variables, in order to account for covariance between the variables. Prior to performing the PCA, we examined the pairwise relationships among oceanographic climate variables in the historic and future periods, and determined that they were qualitatively similar. Therefore, we pooled oceanographic climate data from both time periods for the PCA. Each principal component was treated as an axis of a 4-dimensional

global climate space. Principal component scores were calculated from rescaled climate variables (centered on zero and scaled to standard normal). See the Appendix for additional details about the PCA.

We estimated exposure of the *i*th species E_i as the Euclidean distance between historic *h* and future *f* principal component scores in each of the four *j* dimensions of the global climate space within each grid cell of each species range within the California Current ecosystem (equation 1),

$$E_i = \sqrt{\sum_{j=1}^{4}(f_j - h_j)^2}\ . \qquad (1)$$

Note that this approach is agnostic as to whether increases or decreases in principal component scores are thought to have a positive or negative influence on the probability of a species' persistence. It simply assumes that larger differences between the future and historic periods (greater climate velocities) signify greater exposure to climatic change.

The sensitivity of each species to climate change was defined as the inverse of its historic climatic breadth. Following Dickinson et al. (unpublished ms), we quantified climatic breadth as the range of values of the multivariate climatic index experienced by each species during the historic period. Species with greater climatic breadth were assumed to be less sensitive to future climatic change. This approach assumes that (i) species are adapted to current climate, and (ii) species currently exposed to a broad range of climate variation will, all other things being equal, be able to withstand a greater degree of climate change than species currently exposed to a narrow range of climate.

For each of the *i* species we estimated sensitivity S_i as the inverse of the average distance between historic PC scores (in each of the four *j* dimensions of the global climate space) for the 97.5% quantile $h_{j,upper}$ and 2.5% quantile $h_{j,lower}$ of grid cells included within each species global geographic distribution (equation 2),

$$S_i = \frac{1}{\sum_{j=1}^{4}(h_{j,upper} - h_{j,lower}) / 4}\ . \qquad (2)$$

The denominator in equation 2 thus represents our estimate of climatic breadth. In the Appendix, we show that an alternative estimate of sensitivity, based simply on the geographic area of each species range, was highly correlated with climatic breadth.

The relative risk R_i to each of the *i* species was estimated as

$$R_i = \sqrt{E_i^2 + S_i^2}\ , \qquad (3)$$

implying that risk was expected to increase with Euclidean distance from the origin in the exposure-sensitivity space and that each axis received equivalent weight. Note that to ensure independence between these 2 components of risk, we first tested the rank correlation between them. Below, we report the average values of E_i, S_i, and R_i across each species' distribution.

In addition to summarizing R_i values for each species individually, we also examined geographic variation in the exposure, sensitivity, and risk due to climate change for the marine forage species community. Specifically, we mapped the exposure $E_{community}$ and sensitivity $S_{community}$ of the marine forage species community in each grid cell k as the sum of exposure and sensitivity values for each of the i species, or

$$E_{community,k} = \sum_{i=1}^{N} E_i \quad (4)$$

and

$$S_{community,k} = \sum_{i=1}^{N} S_i \,. \quad (5)$$

We estimated risk to the marine forage species community as the Euclidean distance from the origin in the summed exposure and sensitivity space,

$$R_{community,k} = \sqrt{{E_{community,k}}^2 + {S_{community,k}}^2} \,. \quad (6)$$

These community estimates allowed us to identify geographic concentrations of low and high exposure, sensitivity, and risk within the California Current ecosystem.

RESULTS

Oceanographic climate projections for the historic (Figs. 1a, c, e, g) and future (Figs. 1b, d, f, h) time periods showed substantial latitudinal clines for average and standard deviation values in sea surface temperature and chlorophyll a concentrations (Dunne et al. 2013, and references therein). Principal components analysis of pooled data from the historic and future periods distilled this multivariate variation into 4 new orthogonal axes. The first 2 principal components explained >80% of the variation (Fig. 2; Table 1), such that PC1 was positively correlated to warmer average sea surface temperatures and lower average chlorophyll a concentrations and PC2 was positively correlated to reduced variability in sea surface temperatures. The resulting global maps of historic and future oceanographic climate, plotted in principal component space (Figs. 1i-p), allowed us to derive a single exposure score (following equation 1) for each grid cell within the California Current (Fig. 3), and for each marine forage species within that geographic area (see Figs. 4a-b for an example with northern anchovy). We also estimated a globally-based sensitivity score for each species using these maps (following equation 2; Figs. 4a, c).

Estimates of exposure varied by ~20% among species, whereas sensitivity estimates spanned an order of magnitude more variation (~200%; Fig. 5). Exposure and sensitivity scores were not significantly correlated across species (Spearman rank correlation = -0.125, p = 0.66). Overall, risk due to climate change for each of the 10 marine forage species varied widely, with *Scomber japonicus* exhibiting the lowest risk and *Allosmerus elongatus* the highest risk (Fig. 5).

Community exposure, sensitivity, and risk showed similar geographic gradients (Fig. 6). In general, forage species were more exposed, sensitive, and at risk in northern, coastal

areas of the California Current than they were in southern, offshore areas. This cline was somewhat stronger for sensitivity estimates than it was for exposure and risk, as highly exposed and at risk communities extended further offshore than did highly sensitive communities.

DISCUSSION

Climate change is expected to have major effects on the viability of populations on land and in the sea. Understanding their risk of decline due to climatic change is key to predicting the consequences for biodiversity, and for people that rely on some of these species for food directly and indirectly. Indeed, this risk analysis can be viewed both as an assessment of risk to the forage species themselves, and to the fisheries and predators that rely on them.

Risk has been assessed in multiple ways, including via climate envelope models and through vulnerability frameworks that separate exposure from sensitivity. There are pros and cons of assessing risk each way. Ensembles of approaches are best, and there is a real need to balance the vast climate envelope modeling literature with other approaches. A vulnerability framework (*sensu* Turner et al. 2003), like the one presented here, provides a convenient method for predicting climate change impacts by integrating exposure and sensitivity estimates. A species that is highly exposed but not very sensitive may have the same predicted overall vulnerability to climate change as a species that is highly sensitive but not very exposed, yet very different management actions may be warranted for these alternative scenarios (Dawson et al. 2011).

For highly sensitive species, in order to reduce the probability of a population decline, one appropriate management response may be to reduce the magnitude of non-climate stressors (eg harvest rates) on them. Doing so may mitigate negative impacts of changes in climate. Similarly, for highly exposed species, it may make sense to redistribute non-climate stressors in areas of lower exposure, where possible. Furthermore, it may make sense to displace fishing effort away from marine forage species that are highly exposed or highly sensitive to climate change, by encouraging alternative, less exposed and less sensitive target species.

A major limitation of this risk assessment, as applied here, relates to the spatial resolution of the global climate model. The model has a spatial resolution that precludes great representation of the coastal upwelling domain. It has upwelling, but not to the right magnitude; kind of smearing it out over the first grid points (hundred of km) rather than right along the coast. So it is most appropriate for asking broad-scale questions, but not necessarily for resolving different types of habitat within the upwelling system. For spatial domains like the California Current Large Marine Ecosystem, it may mean that the model cannot project the right spatial gradient in the magnitude of change in the mean and variability of SST and chlorophyll, even qualitatively. However, scientists at NOAA GFDL are in the process of developing a downscaled model for the California Current that will better capture nearshore oceanographic features. The approach presented here will be best applied when that model is ready.

Among the many caveats here is the assumption that species ranges do not change nor expand in the future. This is a very coarse assumption for mobile, pelagic species such as sardine and mackerel. For instance, King et al. (2011) considered conceptual pathways linking climate change to Pacific sardine, and suggested that in the future we may expect higher abundances of sardine off Vancouver Island, and potentially even resident populations. Such details of life history and ocean condition are not captured by the risk assessment methods here.

In a thoughtful and comprehensive chapter, Freon et al. (2009) consider potential effects of climate change on small pelagic fishes in the California Current and other systems. These authors discuss key physical processes (beyond simple warming) such as changes in stratification, upwelling, and intensity of the California Current. These processes in turn may lead to changes in temperature and primary production, but also shifts in the zooplankton food web, altered advection of fish larvae, and changes to phenology essential for successful recruitment. However, beyond recognizing the role of these processes, precise predictions of these complex interactions are not possible, given the resolution of the current generation of models such as ESM2G (50km grid scale) and the limits of present ecological knowledge. Thus we offer the present framework as a first step toward prioritizing species and regions that are most at risk, based on expected deviations of future conditions from the present.

In future risk assessments related to expected changes in climate within the California Current, it will be interesting to:

- Pair the analyses presented here with information on non-climate stressors, e.g. levels of harvesting of individual species.
- Examine changes in estimates of risk based on alternative species distribution data, beyond AquaMaps.
- Relax the assumption, implicit in our analysis, that species that occupy the same grid cell have the same climate sensitivity, regardless of differences in life history or other characteristics.
- Investigate alternative measures of community risk, including one that weights risk according to the abundance or biomass of each species.
- Determine whether greater community risk in more northern, nearshore areas is simply a consequence of more species co-occurring in that region than in southern and/or offshore areas.
- Limit or expand the analysis to the spawning period of the life-cycle for each species, in order to avoid underestimating risk for highly migratory species (e.g., sardine and hake).

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TABLES

Table 1. Marine forage species considered in the risk assessment. These species are commonly sampled in the BPA survey (Brodeur et al. 2003).

Scientific name	Common name
Allosmerus elongatus	Whitebait smelt
Clupea pallasii	Pacific herring
Cololabis saira	Pacific saury
Engraulis mordax	Northern anchovy
Hypomesus pretiosus	Surf smelt
Loligo. opalescens	Market squid
Merluccius productus	Pacific hake
Scomber japonicas	Pacific mackerel
Sardinops sagax	Pacific sardine
Trachurus symmetricus	Jack mackerel

Table 2. Results of principal components analysis on pooled output from historic and future projections of the GFDL model.

CORRELATION MATRIX FOR POOLED HISTORIC AND FUTURE DATA				
	sst_mean	sst_sd	chl_mean	chl_sd
sst_mean	1	-0.0773	-0.5156	-0.6810
sst_sd	-0.0773	1	0.1724	-0.1315
chl_mean	-0.5156	0.1724	1	0.6314
chl_sd	-0.6810	-0.1315	0.6314	1
EIGENVECTOR LOADINGS				
	PC1	PC2	PC3	PC4
sst_mean	0.5717	-0.0014	0.6910	0.4423
sst_sd	-0.0501	-0.9544	-0.1295	0.2641
chl_mean	-0.5573	-0.1755	0.7111	-0.3912
chl_sd	-0.6001	0.2414	0.0088	0.7626
PERCENT OF VARIATION EXPLAINED BY EACH PC				
	PC1	PC2	PC3	PC4
	55.6046	26.6206	11.8835	5.8914

FIGURES

Figure 1. (a-h) Maps of GFDL Earth System Model 2G global hindcasts (historic: 1976-2005) and forecasts (following IPCC scenario rcp 8.5, future: 2071-2100) of mean and standard deviation in sea surface temperature (SST) and chlorophyll a (CHL). (i-p) Maps of principal component scores based on principal component analysis of GFDL model output (see Methods for details).

Figure 2. Results of principal component analysis of GFDL Earth System Model 2G global hindcasts (historic: 1976-2005; black symbols) and forecasts (following IPCC scenario rcp 8.5, future: 2071-2100; blue symbols) of mean and standard deviation in sea surface temperature and chlorophyll a.

Figure 3. Exposure, the magnitude of expected change in a multivariate climatic index within the US California Current ecosystem.

Figure 4. Example (a) species distribution, and calculation of (b) exposure and (c) sensitivity for *Engraulis mordax*. We estimated exposure as the Euclidean distance between historic and future principal component scores in each of the four dimensions of the global climate space within each grid cell of each species range within the US California Current ecosystem (see equation 1). We estimated sensitivity as the inverse of the average distance between historic PC scores (in each of the four dimensions of the global climate space) for the upper 97.5% and lower 2.5 of grid cells included within each species global geographic distribution (see equation 2).

Figure 5. Preliminary risk scores.

Figure 6. Preliminary community exposure, sensitivity, and risk scores.

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Figures

Figure 1. (a-h) Maps of GFDL Earth System Model 2G global hindcasts (historic: 1976-2005) and forecasts (following IPCC scenario rcp 8.5, future: 2071-2100) of mean and standard deviation in sea surface temperature (SST) and chlorophyll a (CHL). (i-p) Maps of principal component scores based on principal component analysis of GFDL model output (see Methods for details).

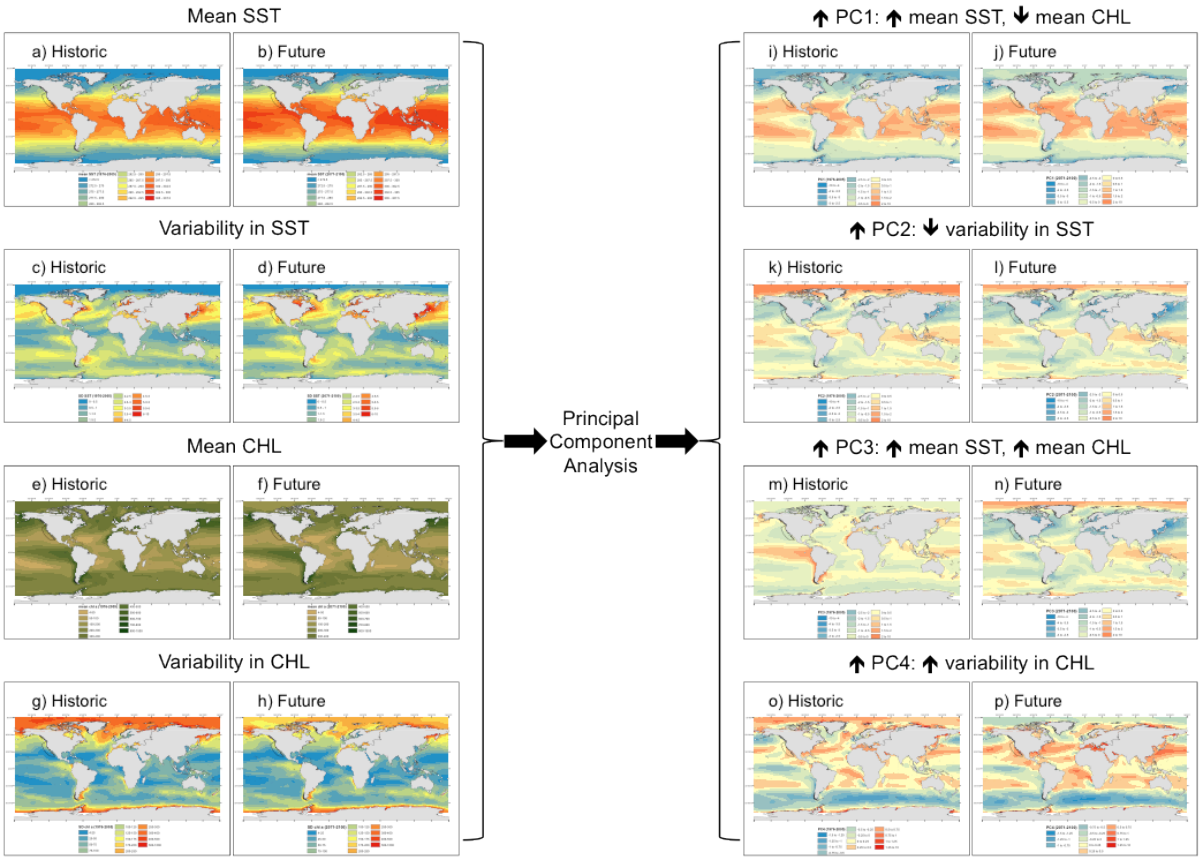
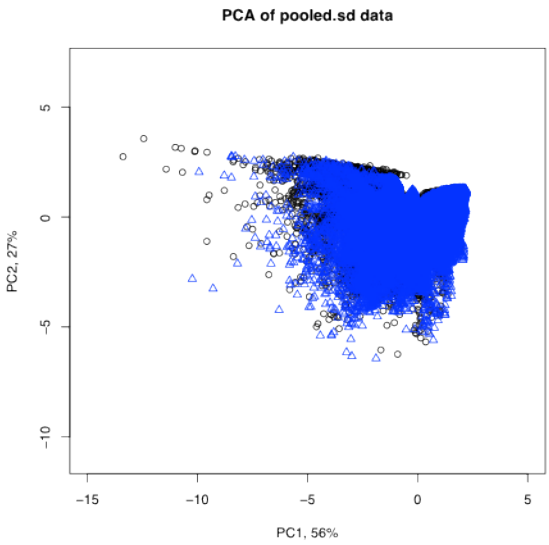
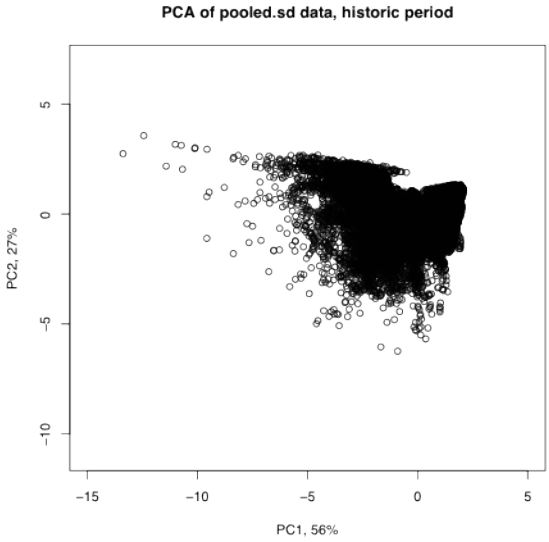


Figure 2. Results of principal component analysis of GFDL Earth System Model 2G global hindcasts (historic: 1976-2005) and forecasts (following IPCC scenario rcp 8.5, future: 2071-2100) of mean and standard deviation in sea surface temperature and chlorophyll a.

a) PCA showing historic and future periods together



b) PCA showing historic period



c) PCA showing future period

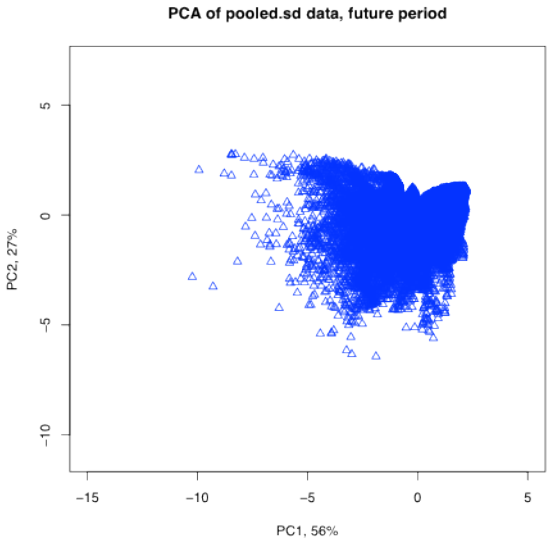

PCA of pooled.sd data, future period
PC2, 27%
PC1, 56%
5
0
−5
−10
−15
−10
−5
0
5

Figure 3. Exposure or climate velocity, the magnitude of expected change in a multivariate climatic index within the California Current ecosystem.

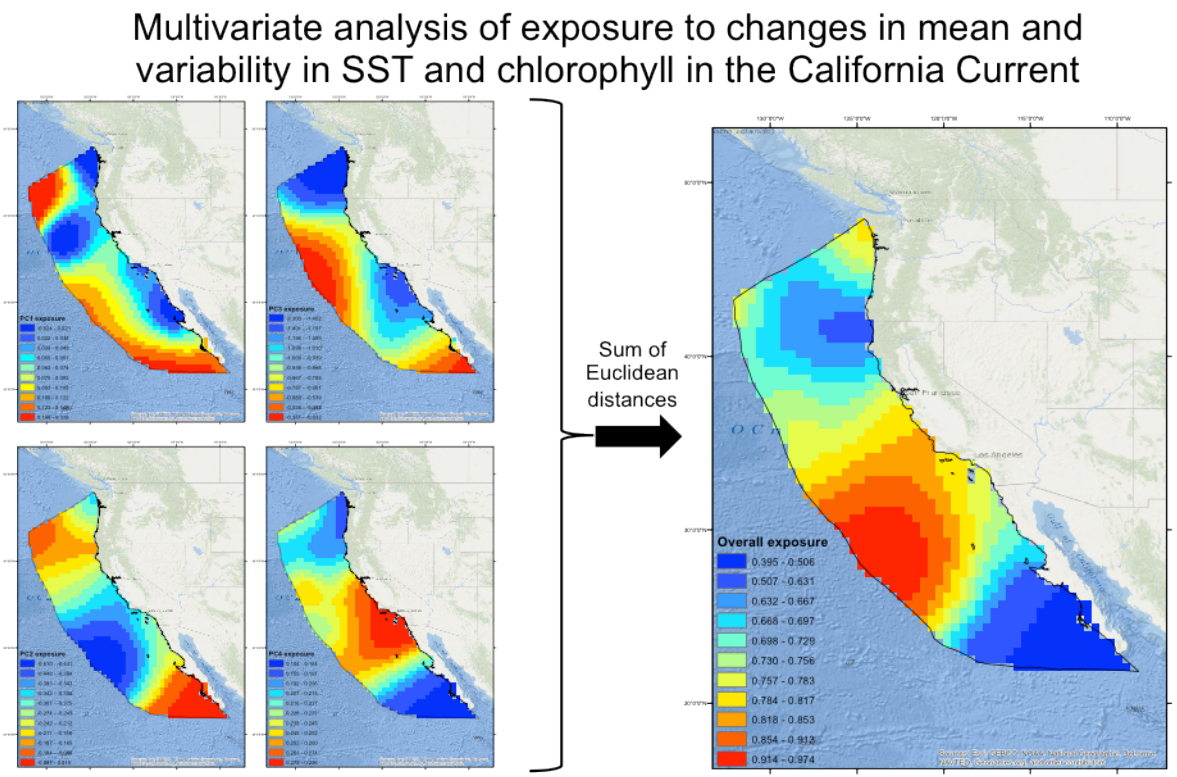


Figure 4. Example (a) species distribution, and calculation of (b) exposure and (c) sensitivity for *Engraulis mordax*. We estimated exposure as the Euclidean distance between historic and future principal component scores in each of the four dimensions of the global climate space within each grid cell of each species range within the US California Current ecosystem (see equation 1). We estimated sensitivity as the inverse of the average distance between historic PC scores (in each of the four dimensions of the global climate space) for the upper 97.5% and lower 2.5 of grid cells included within each species global geographic distribution (see equation 2).

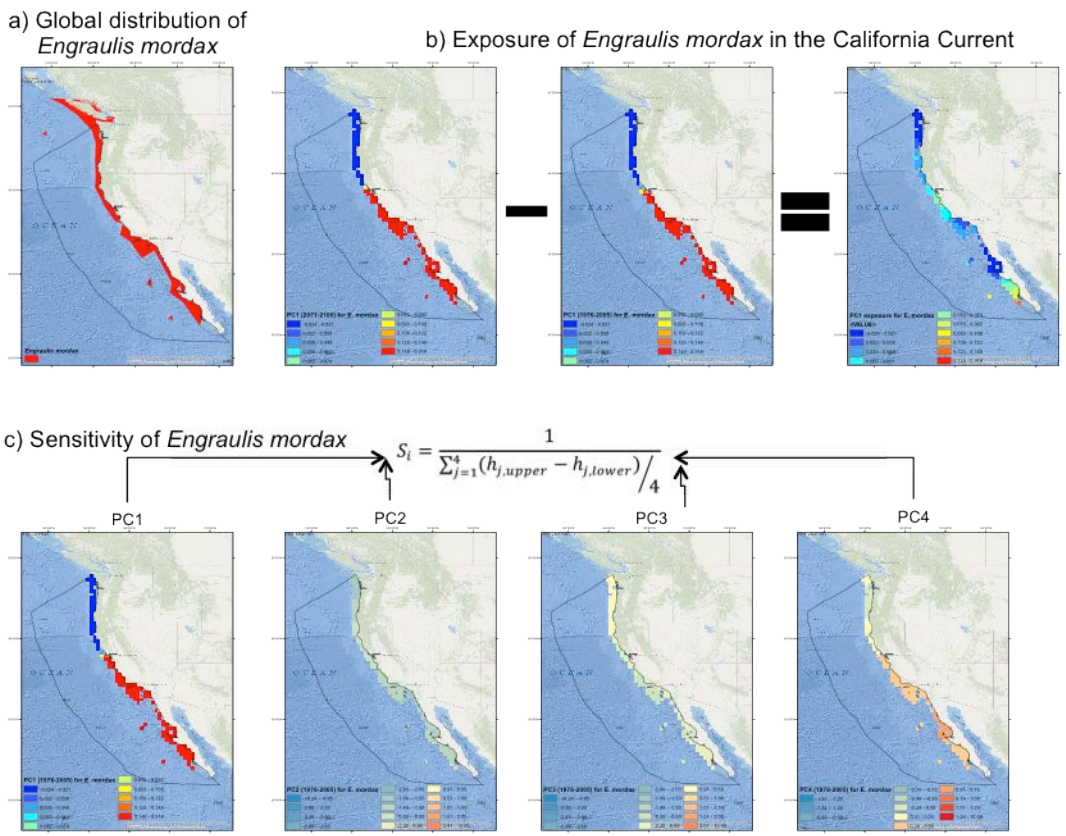


Figure 5. Preliminary risk scores.

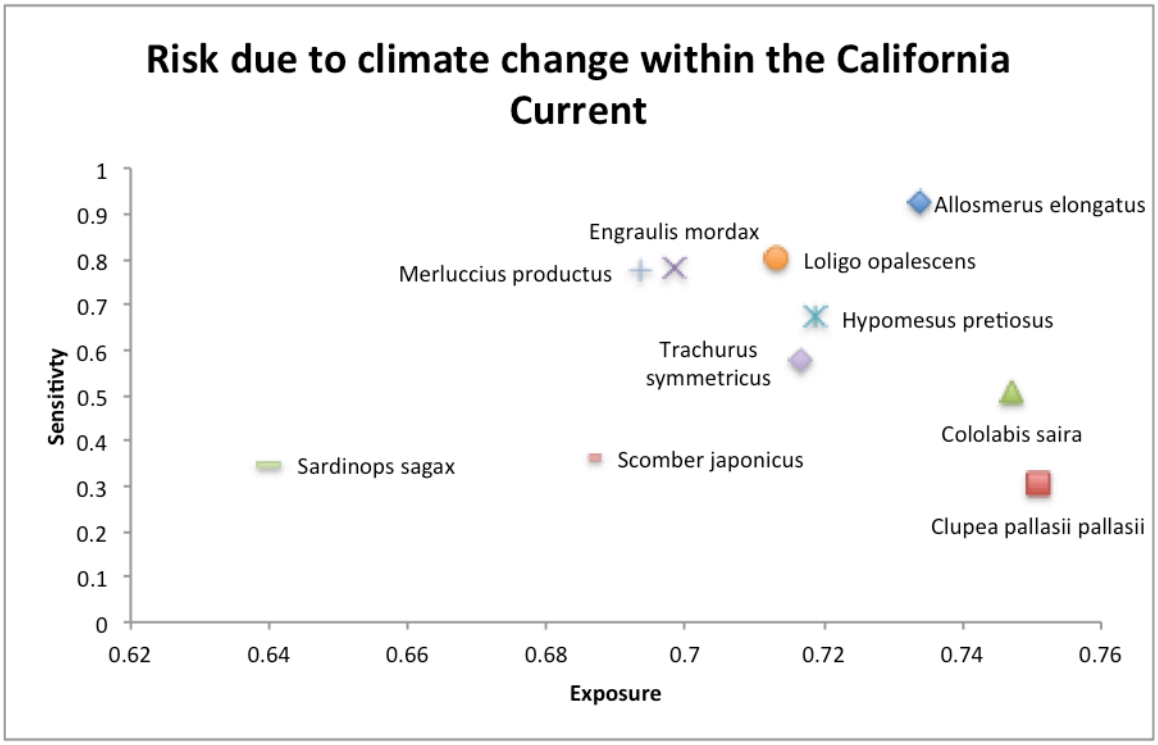
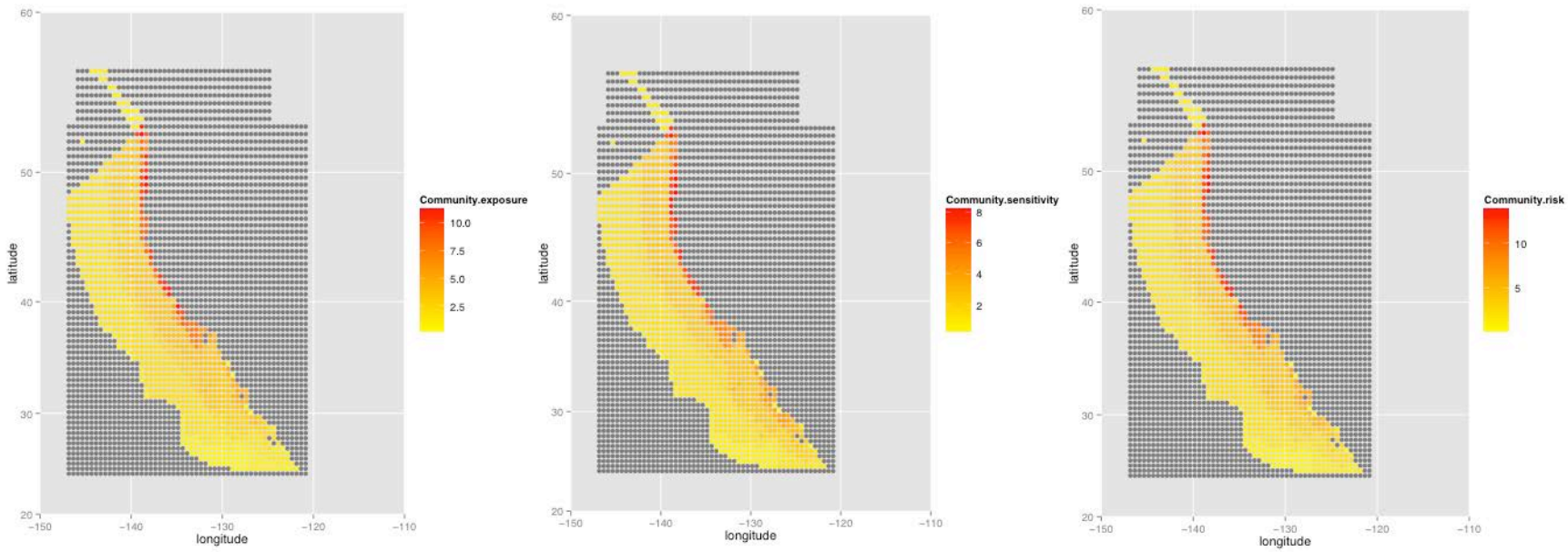


Figure 6. Preliminary community exposure, sensitivity, and risk scores.



Appendix

PCA details

Correlation matrix for mean and SD historic data:

	sst_mean	sst_sd	chl_mean	chl_sd
sst_mean	1	0.005853084	-0.554346	-0.701783
sst_sd	0.005853084	1	0.0899618	-0.292243
chl_mean	-0.55434549	0.089961798	1	0.6478051
chl_sd	-0.70178284	-0.29224314	0.6478051	1

Correlation matrix for mean and SD future data:

	sst_mean	sst_sd	chl_mean	chl_sd
sst_mean	1	-0.1703871	-0.474776	-0.6747135
sst_sd	-0.170387	1	0.2705106	0.09804175
chl_mean	-0.474776	0.27051064	1	0.62167702
chl_sd	-0.674714	0.09804175	0.621677	1

Figure A1. Draftsman plot for mean and SD historic data

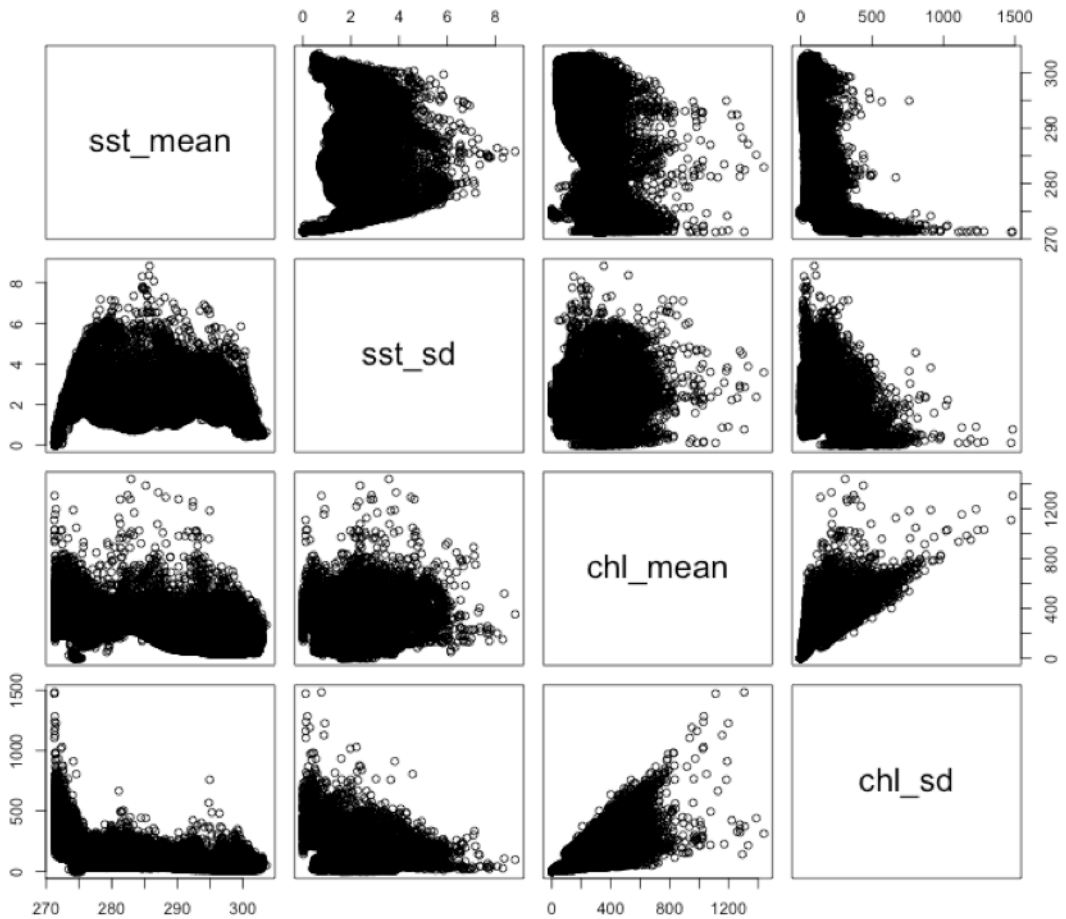
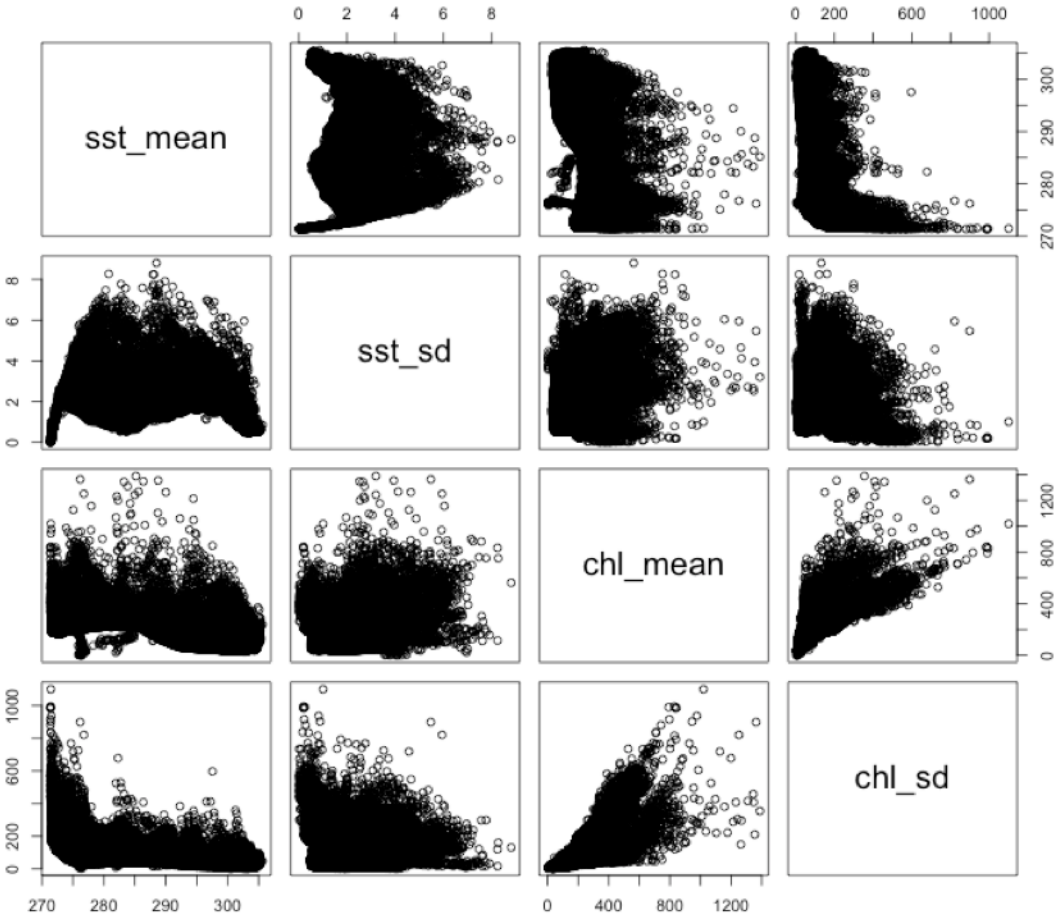


Figure A2. Draftsman plot for mean and SD future data



Sensitivity estimates

The inverse of the geographic area of a species range provides a simple, alternative estimate of sensitivity to climate change (Gaston 2003, Gaston and Fuller 2009). It is also independent of the climate forecast data we used to estimate exposure. We estimated the geographic area of each species range based on the maximum convex polygon characterizing the outermost points of its extent of occurrence layer (see *Methods*). The inverse of this estimate of range size was highly correlated with the sensitivity measure described in Equation 2 (Spearmans rank correlation = 0.71, p = 0.004; Fig. A3). Indeed, risk scores for the California Current marine forage species were qualitatively similar whether we used the inverse of climatic breadth or range size as our estimate of sensitivity (Fig. A4).

Figure A3. Relationship between 2 alternative sensitivity measures, one based on the inverse of a species range size and the other based on the inverse of its climatic breadth (see Equation 2, main text).

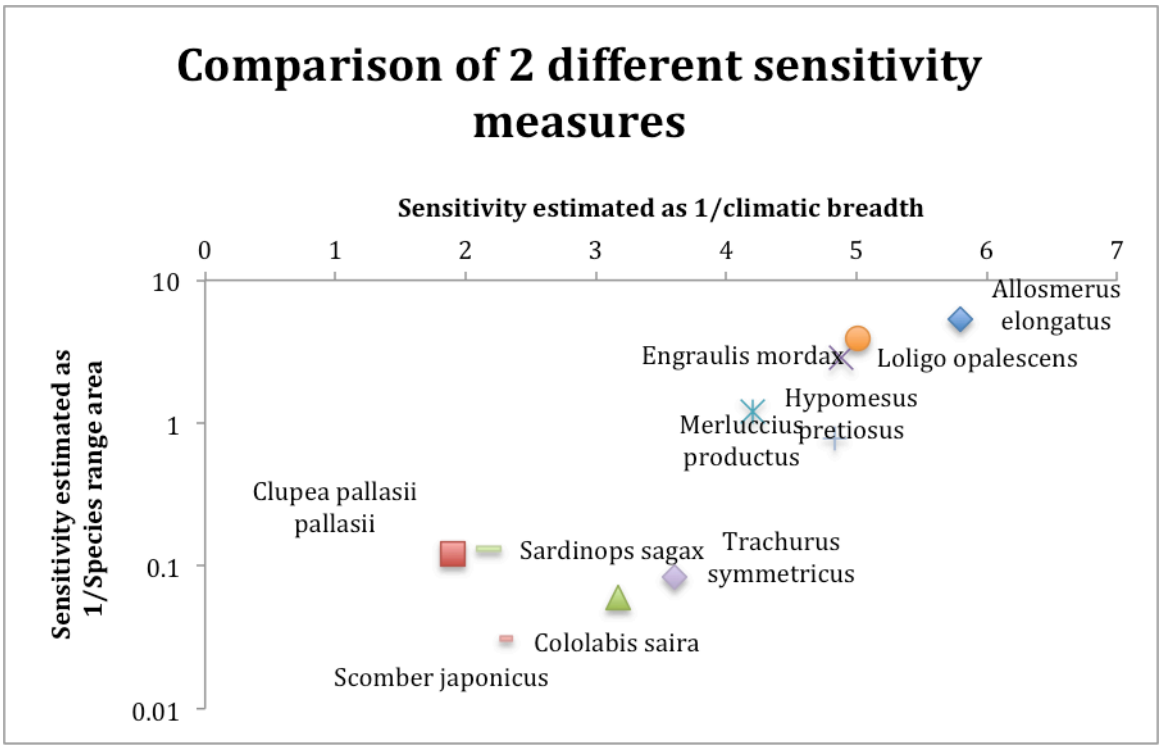
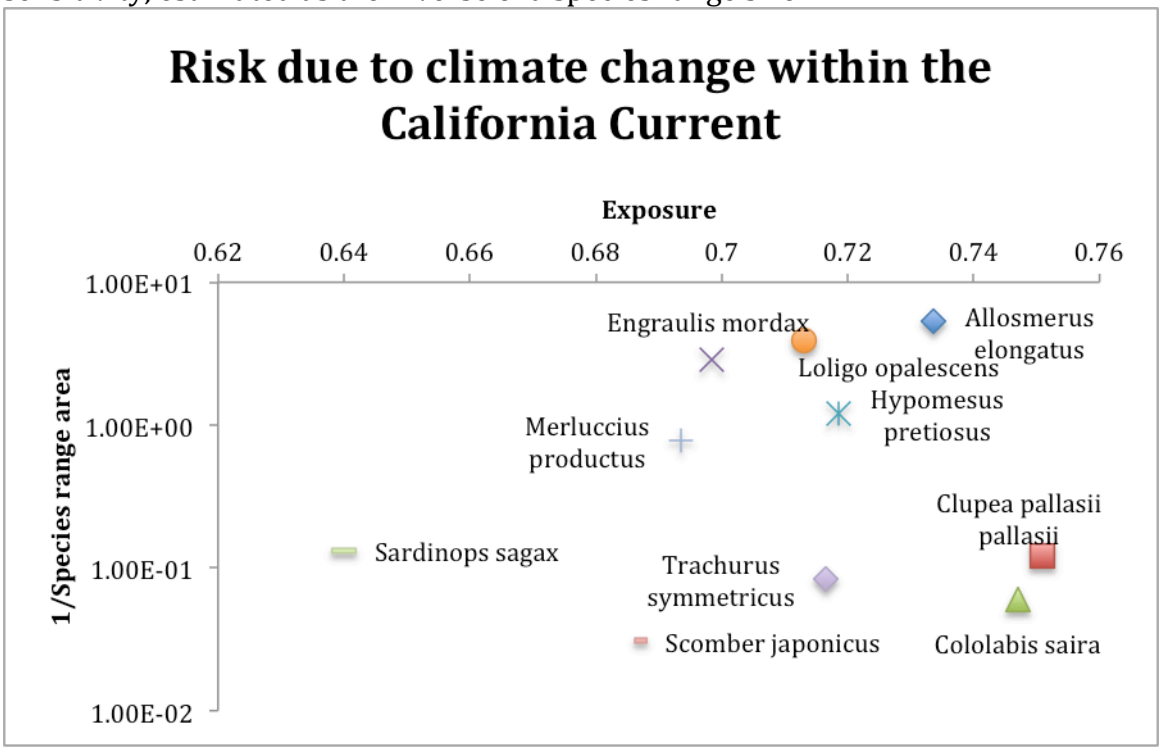



Figure A4. Preliminary risk scores based on exposure (as defined in Equation 1) and sensitivity, estimated as the inverse of a species range size.