Identifying coral refugia from observationally-weighted climate model ensembles

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Coral science

Data science and statistics

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Global and local stressors

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Warm-water reef-building corals face multiple mounting anthropogenic stressors

Global climate stressors:

- ocean heating
- ocean acidification
- sea level rise
- worsening cyclones

Local-scale stressors:

- nutrient pollutants
- chemical pollutants
- sedimentation
- tourism
- destructive fishing
- invasive species

Corals bleach, die in ocean heatwaves

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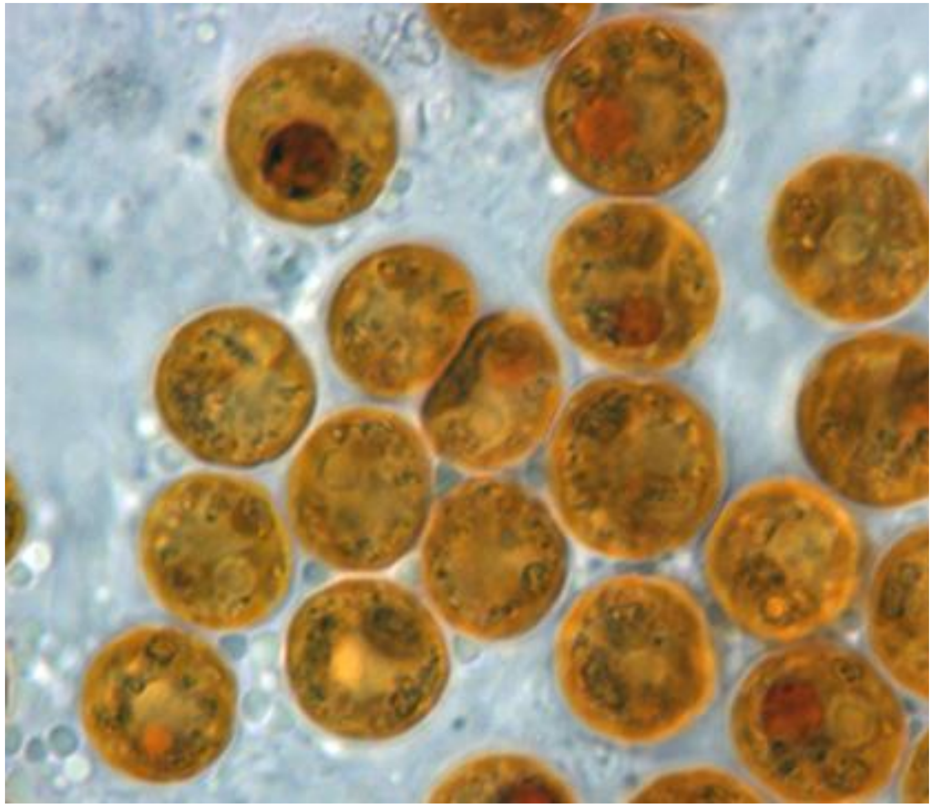
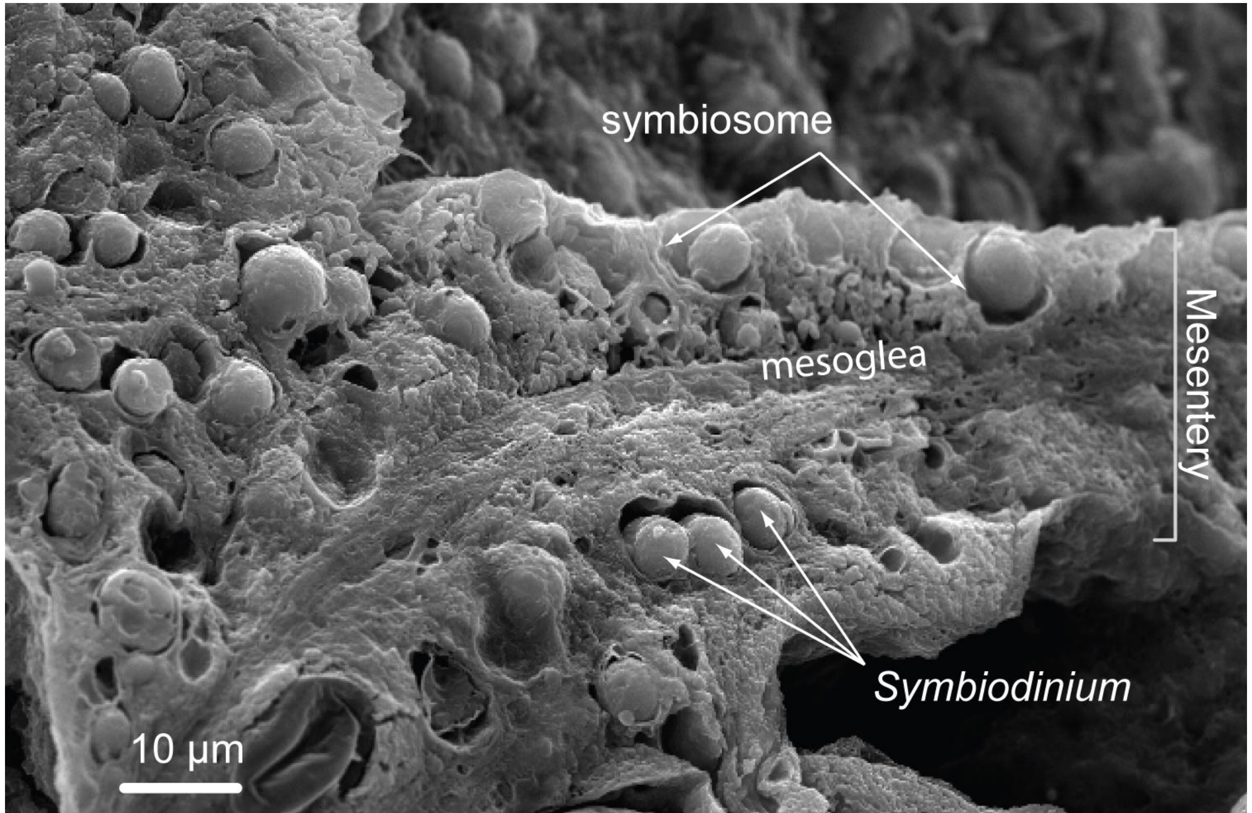
Anomalous ocean heat can cause:

- **immediate thermal death**
- **bleaching and increased disease susceptibility after recovery of symbionts**
- **bleaching and eventual starvation**

Recovery after severe bleaching requires 7+ years





Key Points:

- We project over 91 percent of coral reefs will now experience severe-bleaching-level ocean heat recurring at least once every 10 years
- We project over 99 percent of reefs will experience severe-bleaching-level ocean heat at least twice per ten years by 2036 under SSP3-7.0
- We find SSP1-2.6 to be the only scenario not consistent with near-complete global severe degradation or loss of coral reefs

Kalmus et al. (2022), Earth's Future
"Past the Precipice? Projected Coral Habitability Under Global Heating"

Data and Methods

Overview

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- 35 CMIP6 models homogenized to 1° monthly grid
- 4 climate scenarios: SSP126, SSP245, SSP370, SSP585
- We statistically downscale model ensemble means using the JPL MUR 1 km SST product
  - available 2002 - near present
- We calculate Degree Heating Weeks (DHW) from these time series
  - We calculate climatological anomaly from mean monthly maximum at each point
  - We use 3 climatological baselines: 1988, 1998, 2008 corresponding to the original CRW DHW formulation (Heron et al., 2014), an update (Liu et al., 2014), and the MUR centroid.
  - Perform 3-month running mean and multiply by 4.34 to convert from months to weeks
- We determine year after which every subsequent 5-year and 10-year period contains an ocean heat event above the 8 °C-week thermal threshold
  - Coral reefs require 7+ years to recover from severe bleaching (Johns et al., 2014)

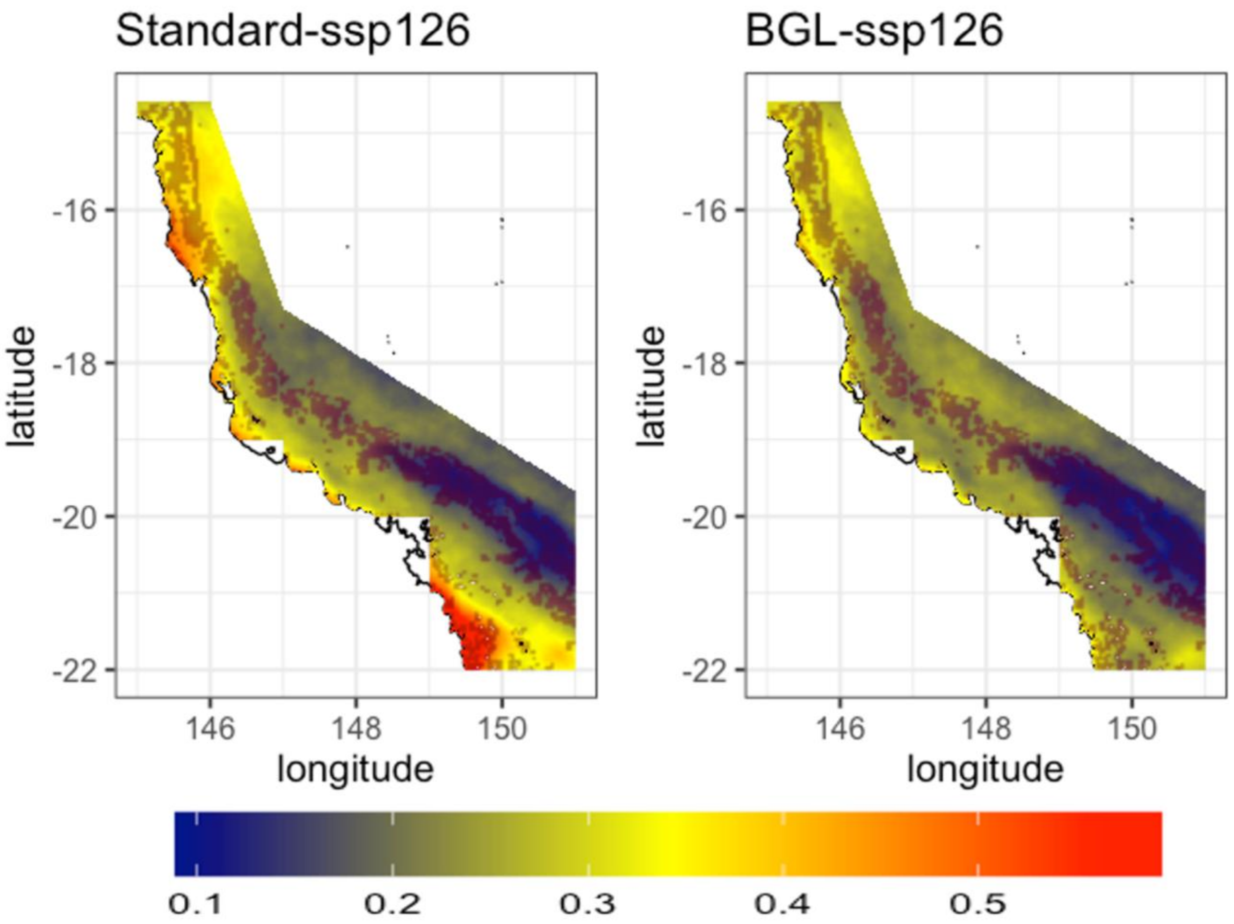
Statistical Downscaling

GCM outputs are at ~100 km scale

We downscale SST projections with 1 km JPL MUR observations

Standard downscaling (e.g. van Hooidonk et al., 2016): (1) At each coarse-scale cell time series, and for each month, subtract climatology; (2) Interpolate this coarse-scale anomaly time series onto the fine-scale grid; (3) At each fine-scale pixel, for each month, add the MUR climatology.

We developed a novel downscaling method by applying Basis Graphical Lasso (BGL, see Ekanayaka et al., 2022) which models spatial dependence structure across the coarse and fine scales.



Standard and BGL downscaling MSE (°C^2) estimated from validation against withheld 2018-2020 MUR data in the central GBR. Reefs are indicated by brown mask. Note improvement in near-coastal regions. Averaged over reefs, standard had MSE of 0.25°C^2 while BGL had MSE of 0.17°C^2, a reduction of 31%.

Thermal Departure Projections

Global maps of thermal departure

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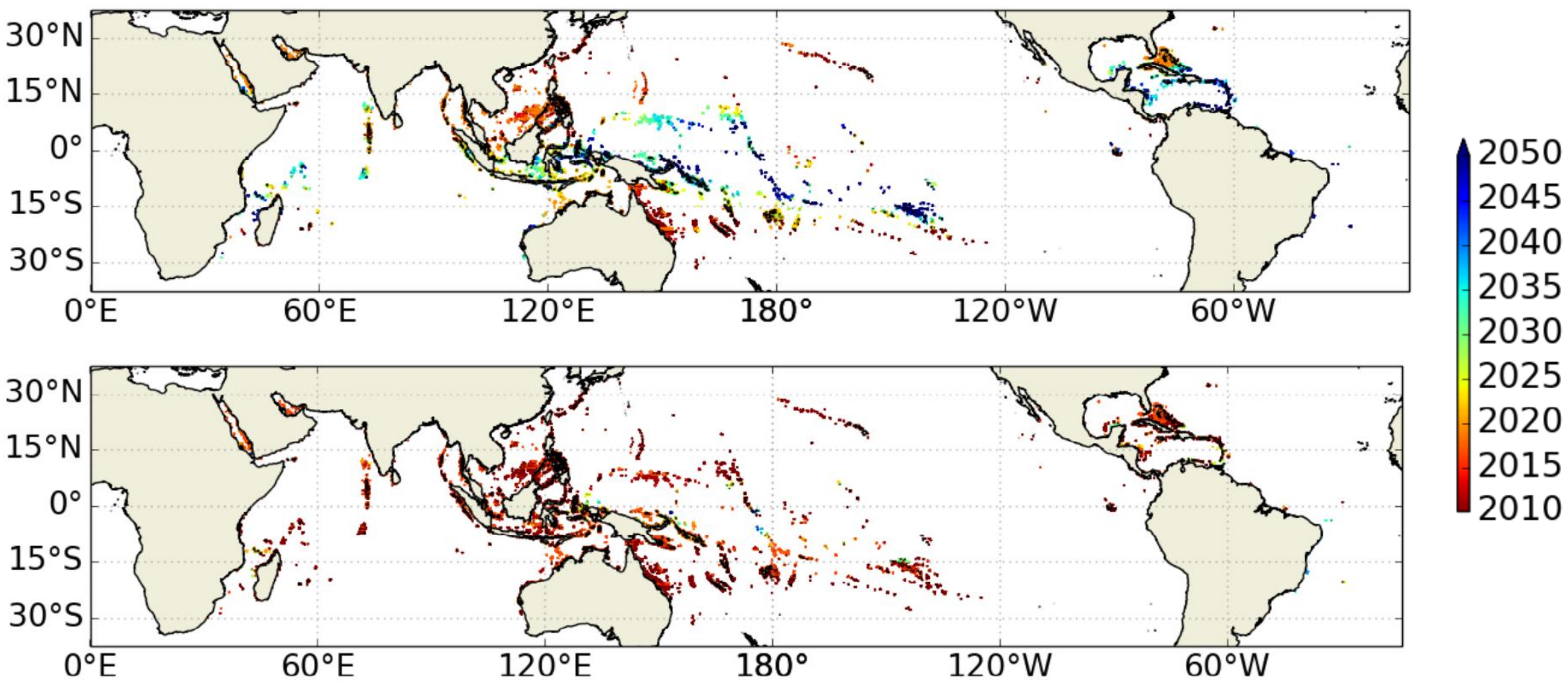
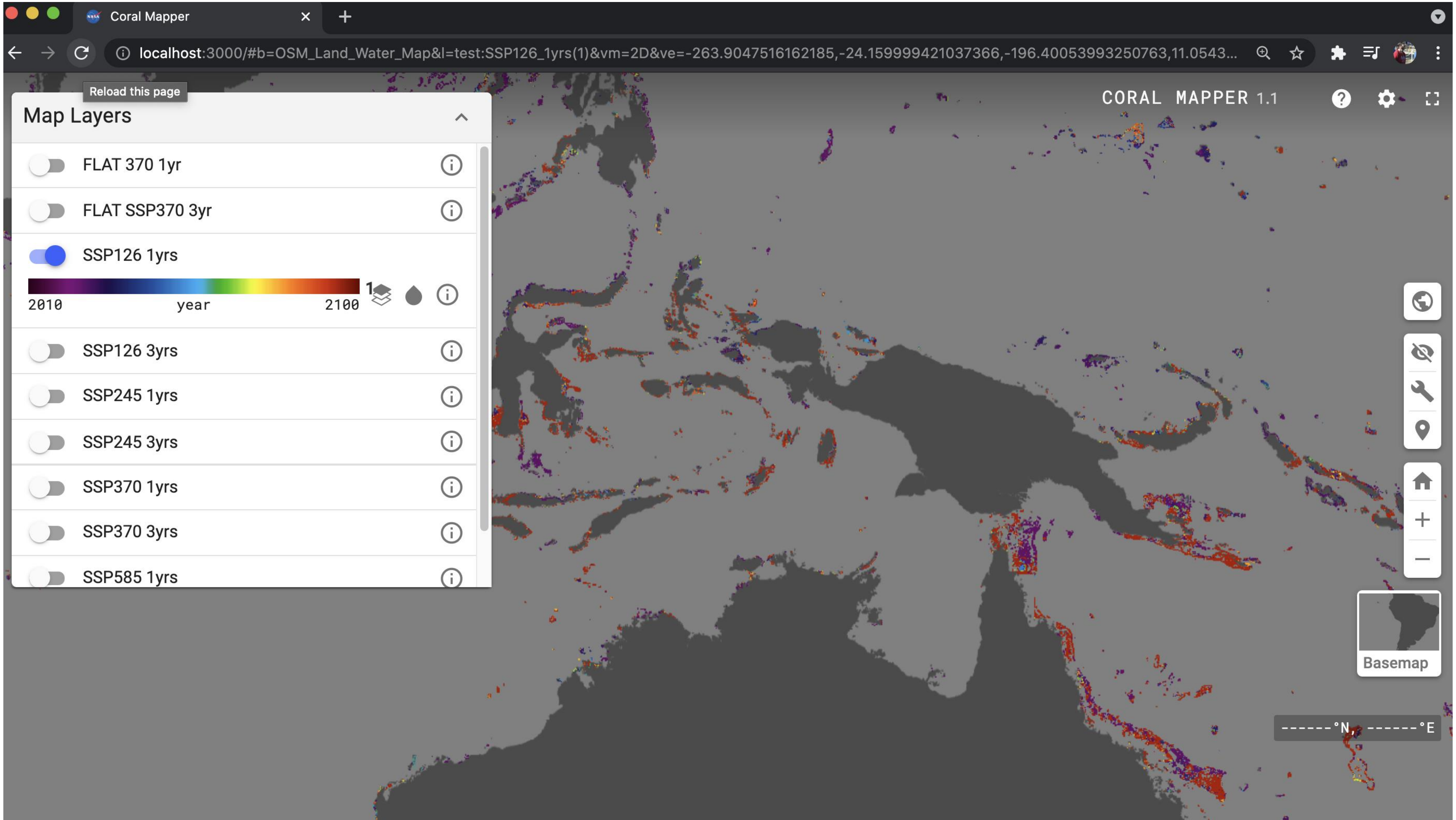


(top) The highest thermal threshold and most optimistic climate scenario: TD5Y, 8 DHW2008 threshold, and SSP126.
(bottom) The lowest thermal threshold and most pessimistic scenario: TD10Y, 8 DHW1988 threshold, and SSP585.

Global maps of thermal departure



Cumulative histograms

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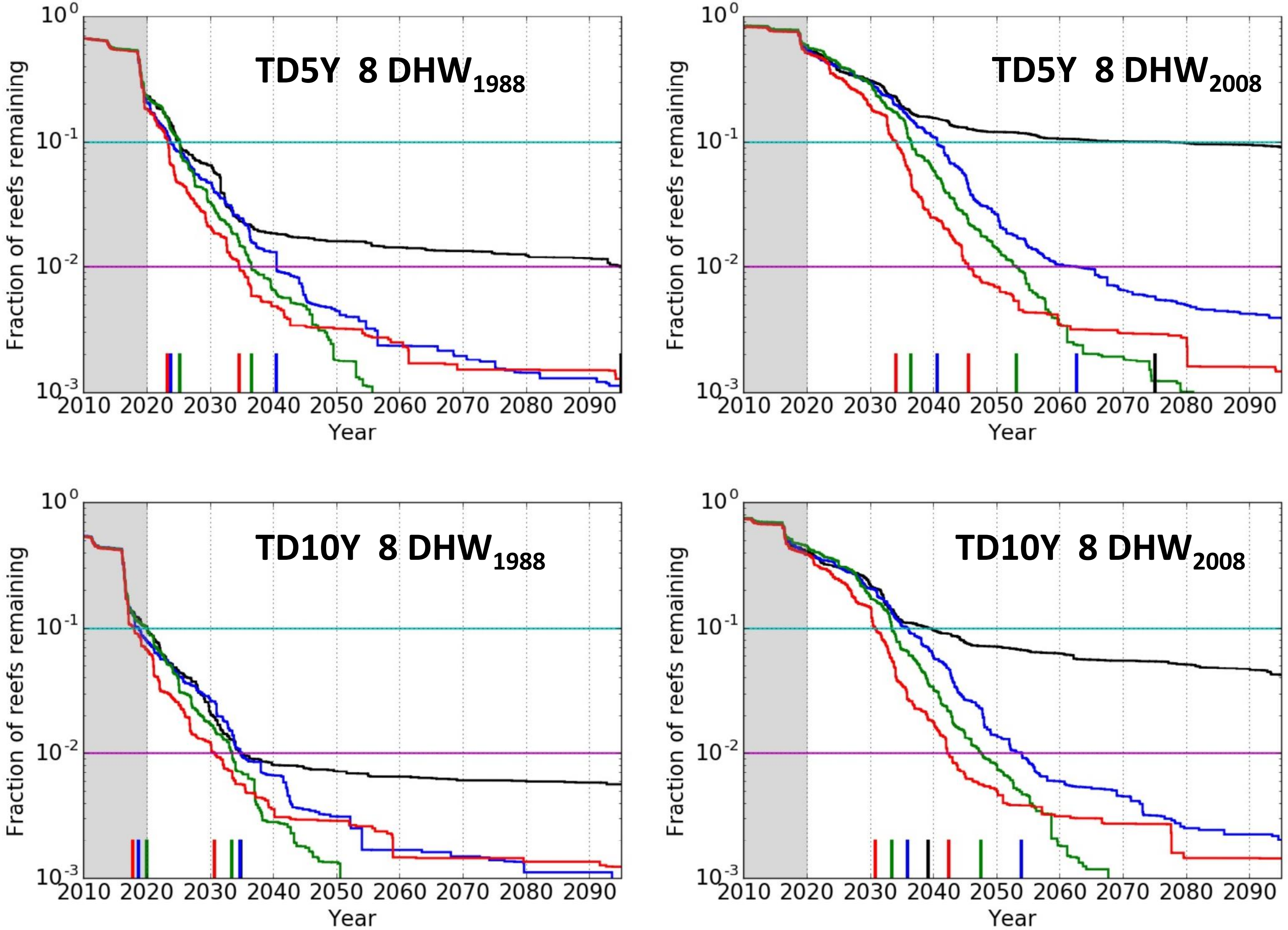

SSP126 (black)
SSP245 (blue)
SSP370 (green)
SSP585 (red)

Thermal departure milestones

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Projected years and GMSTAs after which fewer than the stated percentage of 1 km reef locations remain below the thermal thresholds, for a return timescale of 10 years

	8 DHW_{2008}			8 DHW_{1998}			8 DHW_{1988}		
	30%	10%	1%	30%	10%	1%	30%	10%	1%
Year in twenty-first century									
SSP126	25	39	—	17	29	—	16	20	34
SSP245	25	35	53	17	28	44	16	18	34
SSP370	26	33	47	19	27	39	16	19	33
SSP585	22	30	42	16	25	36	16	17	30
Global mean surface temperature anomaly (°C)									
SSP245	1.4	1.7	1.9	1.2	1.5	1.8	1.1	1.2	1.7
SSP370	1.4	1.7	1.9	1.2	1.5	1.8	1.1	1.2	1.6
SSP585	1.3	1.5	1.9	1.1	1.4	1.7	1.1	1.2	1.5

90% TD10Y by 2020

99% TD10Y by 2044
SSP126 avoids this

2°C is a hard limit

Thermal departure milestones

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Percentages and numbers of reef locations remaining below the stated thresholds, for a return timescale of 10 years

	8 DHW_{2008}			8 DHW_{1998}			8 DHW_{1988}		
	1.5°C	1.7°C	2.0°C	1.5°C	1.7°C	2.0°C	1.5°C	1.7°C	2.0°C
Percent 1 km^2 reef locations remaining below threshold									
SSP245	26%	9%	0%	11%	3%	0%	3%	1%	0%
SSP370	24%	6%	0%	9%	1%	0%	2%	1%	0%
SSP585	15%	3%	0%	5%	1%	0%	1%	0%	0%
Number of 1 km^2 reef locations remaining below threshold, out of 773K									
SSP245	201K	68K	4K	83K	21K	2K	24K	6K	729
SSP370	191K	52K	9K	73K	14K	4K	17K	5K	1233
SSP585	117K	25K	6K	40K	9K	3K	10K	4K	2265

0% (rounded) at 2°C

Small number of 1 km reefs projected to remain at all metrics

Limitations of the study

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- Using a global degree-heating-week thermal threshold for every reef
  - Using 3 climatological baselines mitigates this somewhat
  - Fully mitigating this limitation will require extensive global bleaching event dataset
- Treating all CMIP6 global models equally
  - Model-weighting “redo” of the analysis is in progress
- Does not account for potential adaptation using empirical estimates
- Does not account for different species and assemblages
- Does not account for non-thermal ecological factors (other predictive variables)

These limitations are shared by other projection studies from global models.

Future work

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Use observations to skill-weight models at 1 km locations

- Confidence for refugia projections
- Uncertainty quantification
- “Redo” of analysis with weighting is in progress

Geospatial model using bleaching remote sensing data

- Replace global DHW threshold
- Add additional predictor variables

Investigate projected thermal refugia locations with dynamical models

Apply and advance design and methods in context of other ecosystems:

- New Advanced Information Systems Technology (AIST) project: “Ecological Projection Analytic Collaborative Framework (EcoPro)” **poster**
- New Health and Air Quality (HAQ) project: “Neighborhood-Scale Extreme Humid Heat Health Impacts”

Conclusion

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- We project over 91% of coral reefs will now experience severe-bleaching-level ocean heat recurring at least once every 10 years

- We project over 99% of reefs will experience severe-bleaching-level ocean heat at least twice per ten years by 2036 under SSP3-7.0

- We find SSP1-2.6 to be the only scenario not consistent with near-complete global severe degradation or loss of coral reefs

- Without rapid cessation of fossil fuel use, coral reefs as we know them will be gone well before 2°C

Kalmus et al. (2022), AGU Earth's Future
"Past the Precipice? Projected Coral Habitability Under Global Heating"

Smithsonian

backup slides

Comparisons to prior studies

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Being explicit about the climatological baseline allows apples-to-apples comparisons:

- Schleussner et al. (2016) project a 70–90% loss at 1.5°C and 99% loss at 2°C using CMIP3 global models (no downscaling) and thermal criteria of TD5Y and 8 DHW_{1990}
  - These results were highlighted in the IPCC Special Report on 1.5°C of warming
  - Our study projects a 95-98% loss at 1.5°C and a 99.7% loss at 2°C
- Donner (2009) project 70% loss by 2025 and 90% loss by 2040 using one global model (no downscaling), criteria of TD5Y and 8 DHW_{1988} and SRES B1 (similar to SSP245)
  - Our study projects 70% and 90% loss by 2019 and 2023 under SSP245
- Frieler et al. (2013) project 90% loss at 1.5°C, and complete loss before 2°C using 19 CMIP3 models (no downscaling) and thermal criteria of TD5Y and 8 DHW_{1990}
  - Our study projects over 95% TD5Y at 8 DHW_{1988} and 1.5°C, and over 99.7% at 2°C
- Dixon et al. (2022) project a 99.8% loss at 1.5°C and 100% at 2°C using CMIP6 models and downscaling to 1 km, and thermal criteria of TD10Y and 4 DHW_{1988}
  - Our study does not use such a low thermal threshold

Thermal departure milestones

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	TD1Y			TD3Y			TD5Y		
SSP	30%	10%	1%	30%	10%	1%	30%	10%	1%
Year in twenty-first century									
126	$91^{—}_{19}$	$—^{—}_{34}$	$—^{—}_{—}$	19^{83}_{15}	$26^{—}_{19}$	$—^{—}_{20}$	18^{31}_{13}	$20^{—}_{15}$	$88^{—}_{18}$
245	32^{57}_{19}	45^{92}_{21}	$—^{—}_{41}$	19^{33}_{15}	23^{45}_{19}	38^{81}_{20}	17^{26}_{13}	19^{37}_{15}	30^{61}_{18}
370	30^{45}_{19}	38^{56}_{21}	54^{75}_{35}	19^{31}_{15}	23^{40}_{19}	35^{53}_{19}	17^{25}_{13}	19^{35}_{15}	28^{47}_{18}
585	28^{41}_{19}	35^{51}_{20}	49^{66}_{33}	19^{29}_{15}	21^{37}_{19}	31^{48}_{19}	17^{23}_{13}	19^{32}_{15}	25^{42}_{18}
Global mean surface temperature (°C)									
245	$1.6^{2.0}_{1.2}$	$1.9^{2.1}_{1.3}$	$2.1^{2.1}_{1.8}$	$1.2^{1.6}_{1.1}$	$1.4^{1.9}_{1.2}$	$1.8^{2.1}_{1.2}$	$1.2^{1.5}_{1.0}$	$1.2^{1.7}_{1.1}$	$1.6^{2.1}_{1.2}$
370	$1.6^{1.9}_{1.3}$	$1.8^{2.0}_{1.3}$	$2.0^{2.1}_{1.7}$	$1.2^{1.6}_{1.1}$	$1.3^{1.8}_{1.2}$	$1.7^{2.0}_{1.3}$	$1.2^{1.4}_{1.0}$	$1.2^{1.7}_{1.1}$	$1.5^{1.9}_{1.2}$
585	$1.5^{1.8}_{1.3}$	$1.7^{2.0}_{1.3}$	$2.0^{2.1}_{1.6}$	$1.2^{1.5}_{1.1}$	$1.3^{1.7}_{1.2}$	$1.6^{2.0}_{1.3}$	$1.2^{1.4}_{1.0}$	$1.2^{1.6}_{1.1}$	$1.4^{1.9}_{1.2}$

Table 1. Projected years in the 21st century (top four rows) and global mean surface temperatures (bottom three rows) after which fewer than the listed (30,10,1) percentage of 1 km^2 reef locations remain below the thermal thresholds. Dashes indicate that the milestone is not reached prior to 2100. Superscripts and subscripts give one standard deviation uncertainty estimates.

90% TD5Y before 2021 and TD3Y before 2026

99% TD3Y by 2031, 2035, and 2038 for SSP585, SSP370, SSP245. SSP126 avoids this.

2.1°C of GMSTA looks like a hard upper limit.

Conclusions

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- Most of the world's reefs are already in a regime of unrelenting thermal stress
- Our projections include a small number of robust thermal refugia locations
- Under TD5Y, 1% of reef locations remain at 1.5°C global heating, but none at 2.0°C
- Prospects for corals are far better under SSP126 than SSP245, suggesting that reefs face a critical crossroads today (not in the future)
- Data science methods improve precision and skill of ecological projections
- These methods can be applied widely in similar contexts

2014-17 was a deadly period for corals

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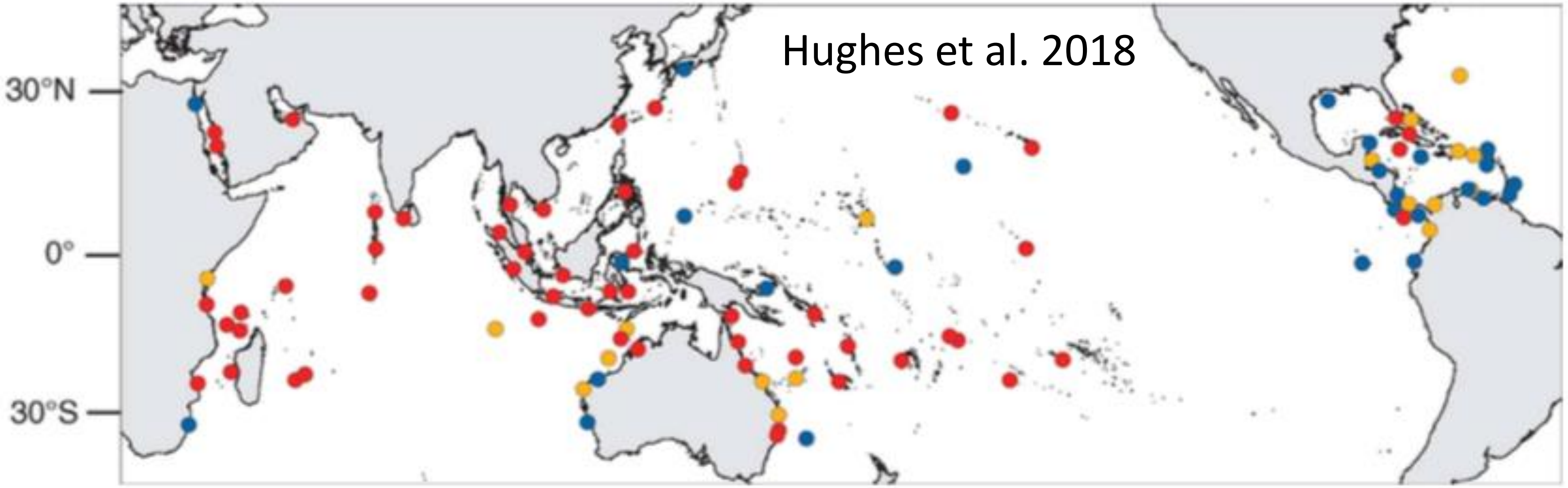
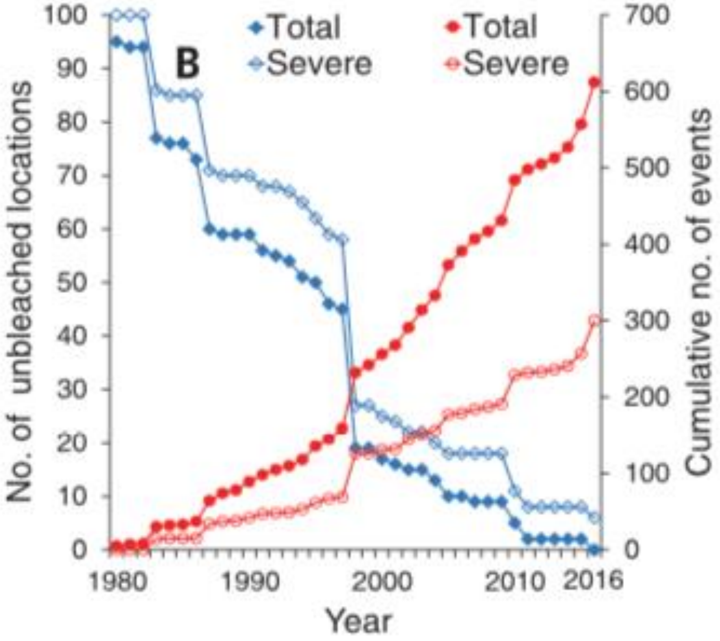
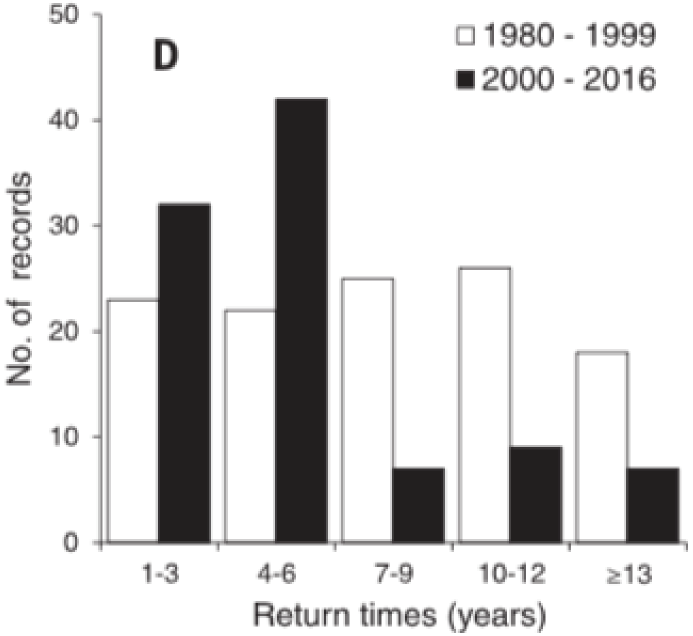


100 locations monitored

In 2015-2016
- red: > 30% bleaching
- orange: < 30% bleaching
- blue: no bleaching

Hughes et al. 2018

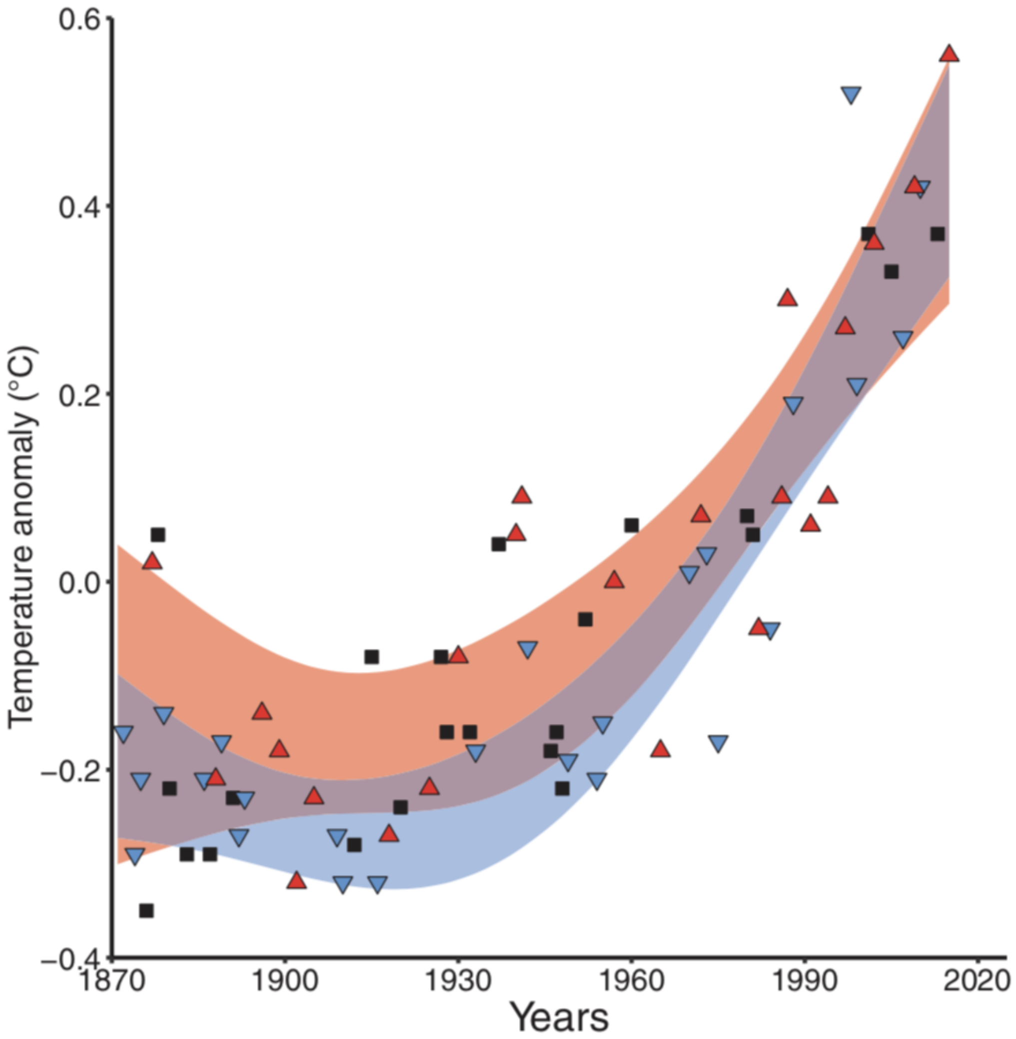




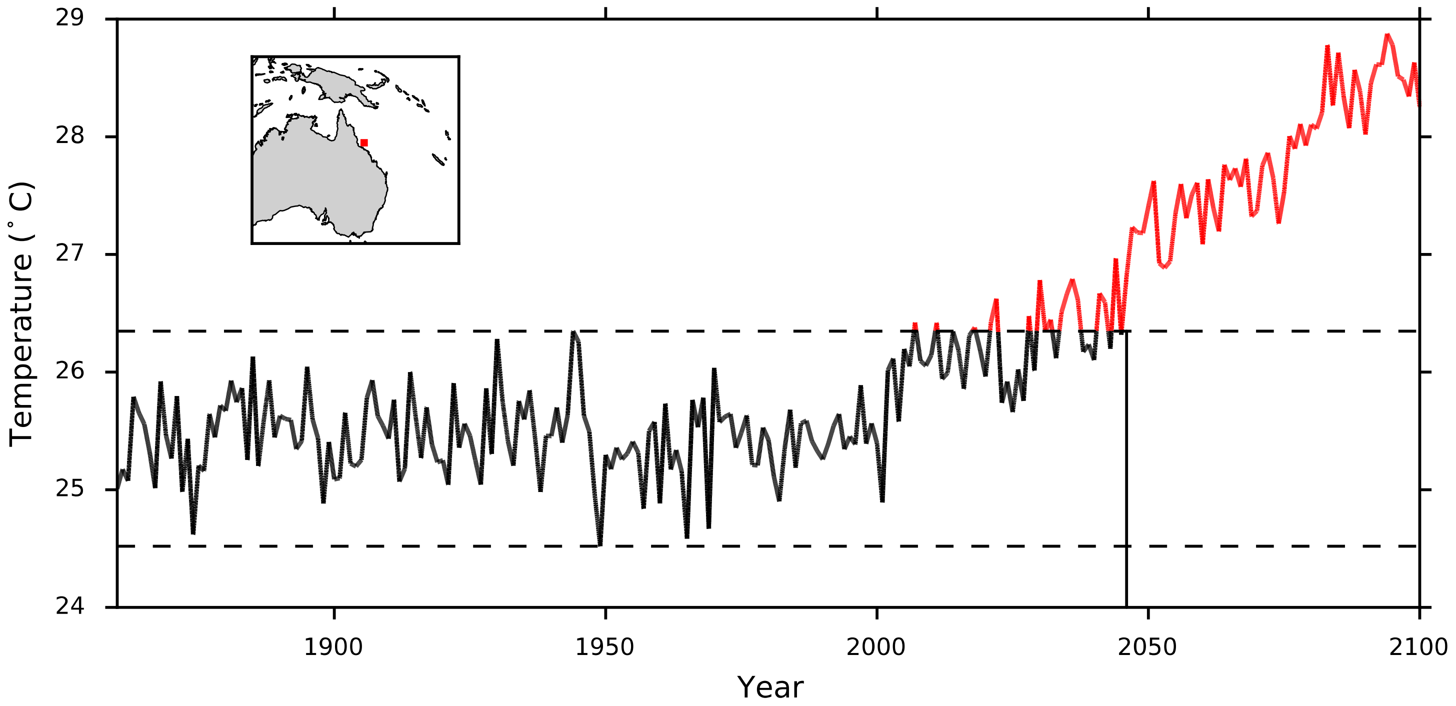
In 2014-2017:
- >75% of reef locations surpassed bleaching thresholds
- >30% severe

Eakin et al. 2018

Ocean heatwaves are worsening



Hughes et al. 2018



Example: one model (HadGEM2-ES) projection at one point on GBR

Projected robust thermal refugia

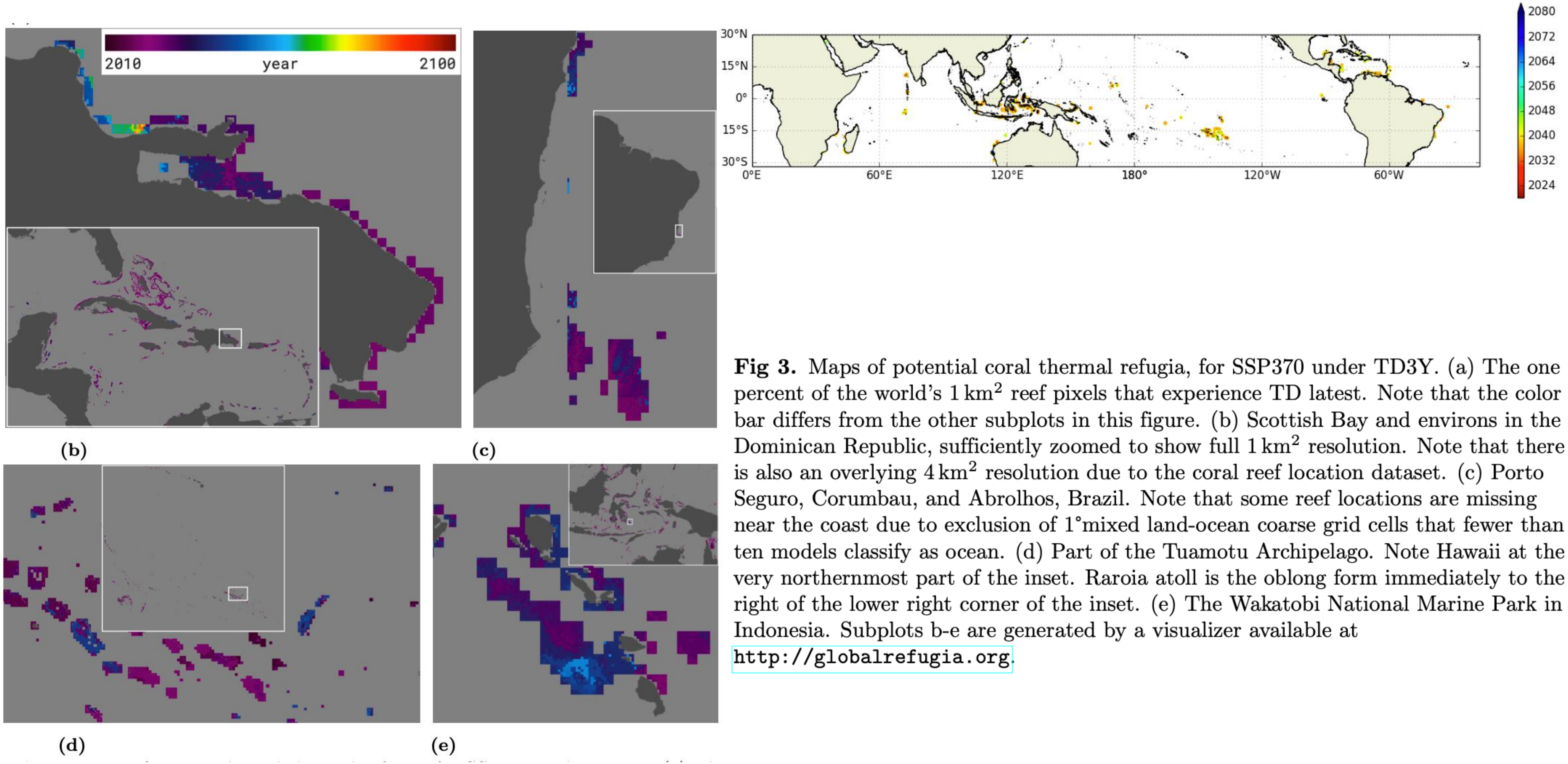
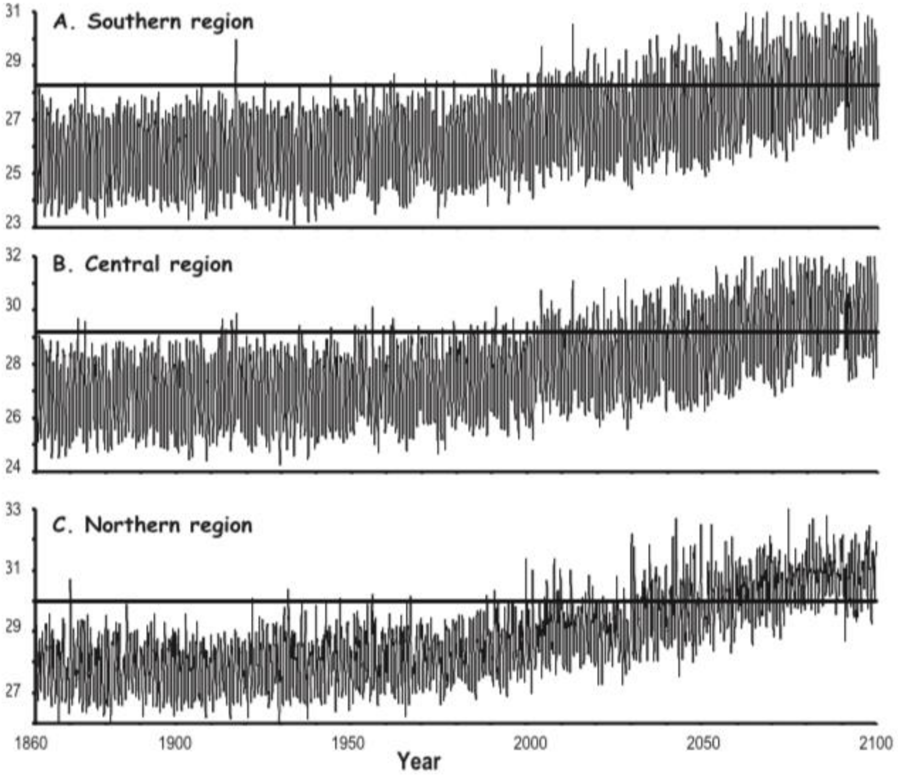
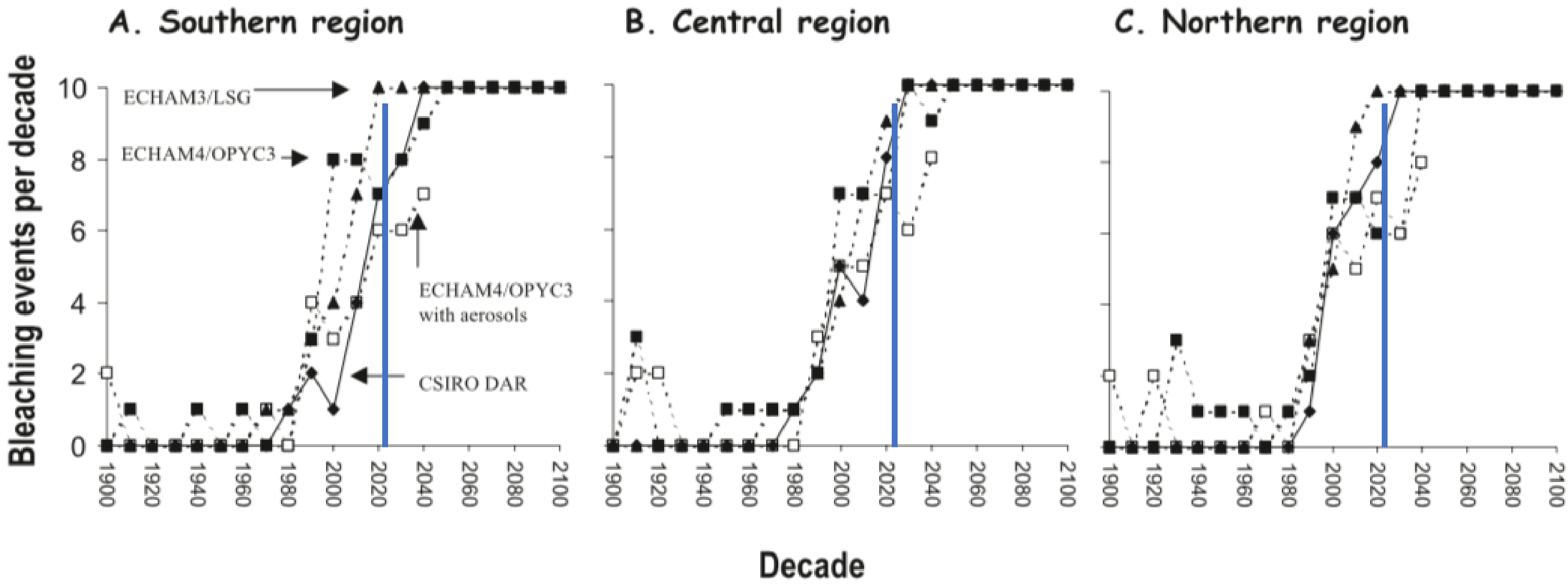


Fig 3. Maps of potential coral thermal refugia, for SSP370 under TD3Y. (a) The one percent of the world's 1 km^2 reef pixels that experience TD latest. Note that the color bar differs from the other subplots in this figure. (b) Scottish Bay and environs in the Dominican Republic, sufficiently zoomed to show full 1 km^2 resolution. Note that there is also an overlying 4 km^2 resolution due to the coral reef location dataset. (c) Porto Seguro, Corumbau, and Abrolhos, Brazil. Note that some reef locations are missing near the coast due to exclusion of 1°mixed land-ocean coarse grid cells that fewer than ten models classify as ocean. (d) Part of the Tuamotu Archipelago. Note Hawaii at the very northernmost part of the inset. Raroia atoll is the oblong form immediately to the right of the lower right corner of the inset. (e) The Wakatobi National Marine Park in Indonesia. Subplots b-e are generated by a visualizer available at `http://globalrefugia.org`.

Projections of coral bleaching and mortality





Hoegh-Guldberg 1999

- **IPCC SR1.5: 70-90% mortality at 1.5°C of global heating, 99% mortality at 2°C**

Bayesian Ensemble Optimization (BEO)

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- This part of the analysis was led by Elias Massoud
- Assign skill-based weights to model projections
  - Historical GCM model runs (hindcasts) compared to observation SST records (HadISST)
  - We do this on a maximum-annual DHW basis to match analysis metric
  - BEO uses Bayesian inference to estimate model weights to maximize log-likelihood function
  - BEO handles model dependence by preferring independent models, allowing us to avoid arbitrary selection of model instances (e.g. r18i2p1f1)

Massoud et al. 2020

Bayesian Ensemble Optimization (BEO)

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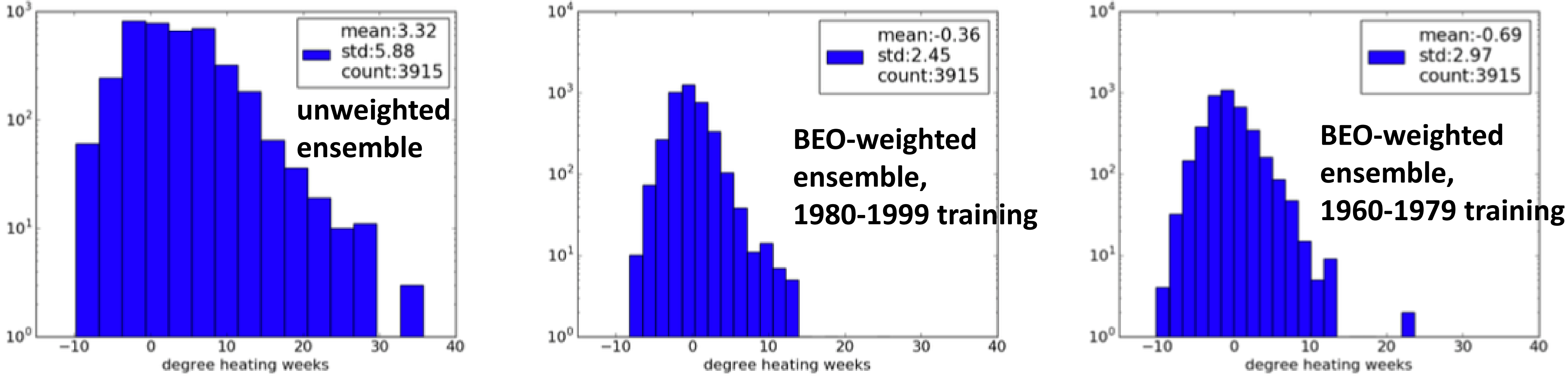
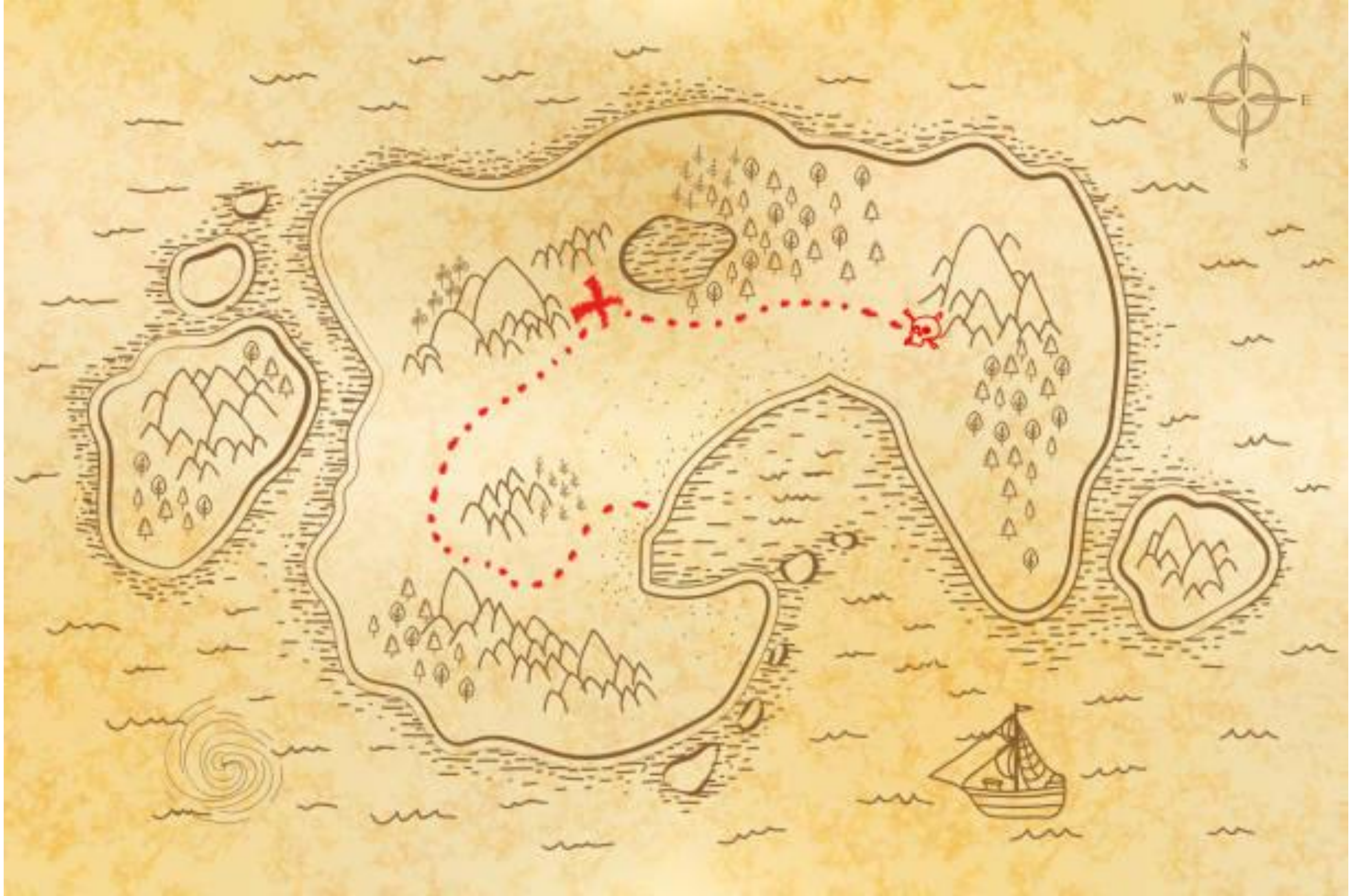
Histograms of differences between truth and projections of mean of annual maxima of DHW for 2005-2014 for 1° pixels



- BEO improves RMSE by 63% compared to unweighted ensemble, even for hindcast projections four decades in the future
- In an identical analysis without BEO (unweighted), every robust refugia location disappears
- We conclude that analyses without skill-weighting incorrectly identify refugia


N
W
E
S

Some locations may provide temporary refuge

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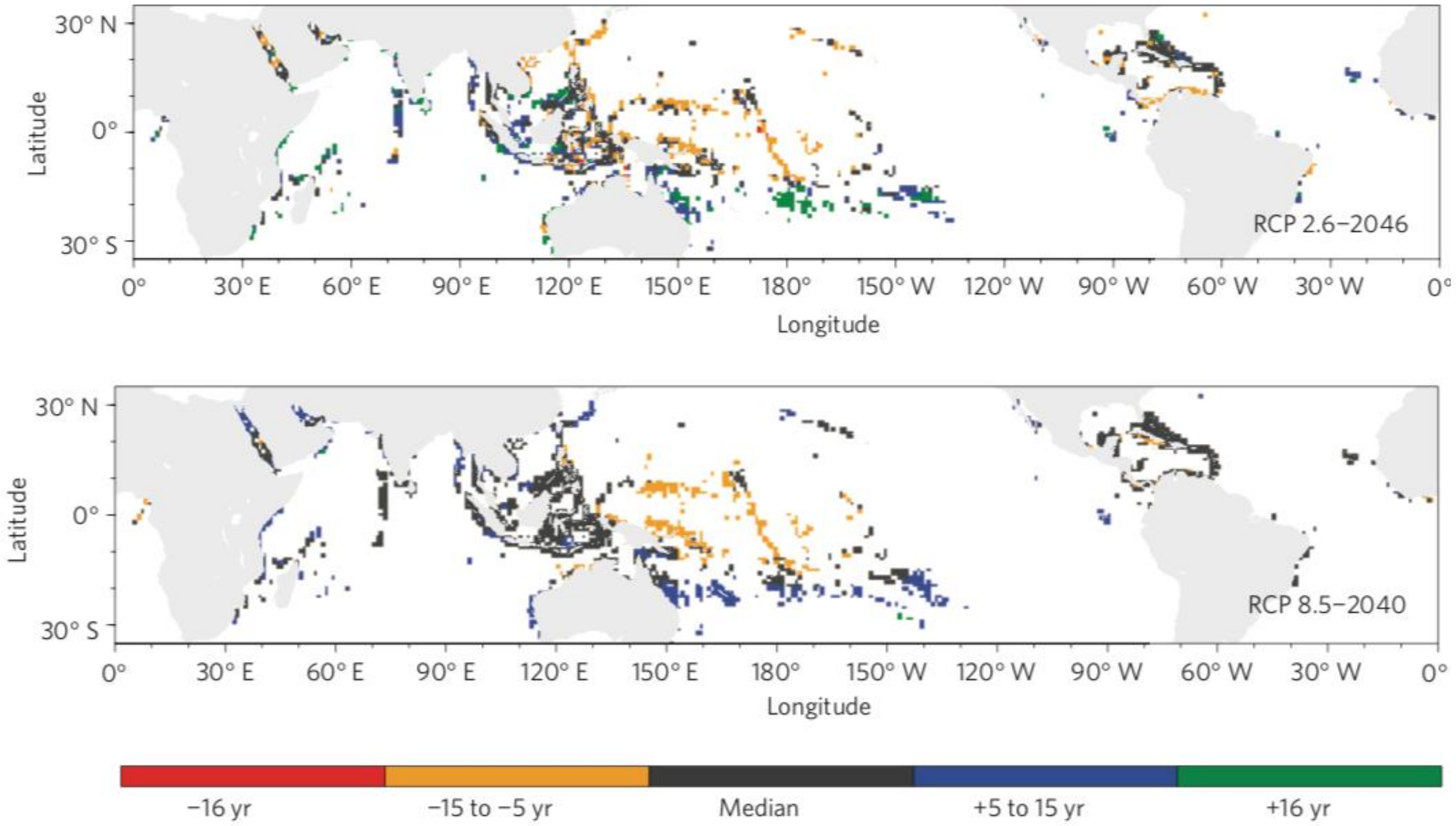

van Hooidonk et al. 2013

Projections are confounding
- disease
- other stressors
- depth DHW(z)
- new current regimes
- species diversity
- individual diversity
- adaptation

Bayesian hierarchical model

Combines model weights and statistical downscaling in one integrated model

Produces monthly SST projection PDFs on 1 km grid

The hierarchical model contains components to describe:

- spatial and spatio-temporal variation in fine-scale SST
- how a GCM grid cell is related to the fine-scale SST
- model departure by incorporating model weights in a prior distribution

The hierarchical model propagates uncertainty in an integrated way but is more computationally expensive than the Gaussian process model.

Data

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- **GCM averages from 6/2002 to 12/2100**
  - **Flat means of the following models:**
- **MUR data from 6/2002 to 12/2019**

ACCESS-CM2 r1i1p1f1	MIROC-ES2L r1i1p1f2
ACCESS-ESM1-5 r1i1p1f1	MIROC6 r1i1p1f1
BCC-CSM2-MR r1i1p1f1	MPI-ESM1-2-HR r1i1p1f1
CNRM-CM6-1 r1i1p1f2	UKESM1-0-LL r1i1p1f2
CNRM-ESM2-1 r1i1p1f2	CESM2 r1i1p1f1 gr
CanESM5 r10i1p1f1	CESM2-WACCM r1i1p1f1 gr
CanESM5-CanOE r1i1p2f1	INM-CM4-8 r1i1p1f1 gr1
EC-Earth3-Veg r1i1p1f1	INM-CM5-0 r1i1p1f1 gr1
IPSL-CM6A-LR r4i1p1f1	MRI-ESM2-0 r1i1p1f1 gr
MCM-UA-1-0 r1i1p1f2	

Trend

- **Modeled in two steps**
  - **Averaged annual cycle**
    - Averaged annual cycle at MUR pixels is calculated by taking the average of monthly SSTs over the years.
    - Averaged annual cycle at model pixels is calculated by aggregating MUR averages into model pixels.
  - **Interpolation**
    - Detrend model data by subtracting annual cycle and perform bivariate interpolation .

- **NOTES**

  - Bilinear interpolation requires 4 neighbors which form a rectangular grid. Does not work here!
  - Bivariate interpolation works when neighbors are irregularly spaced. It is a spline interpolation

- **Trend = annual cycle + interpolated values**

Interpolation-12/2019

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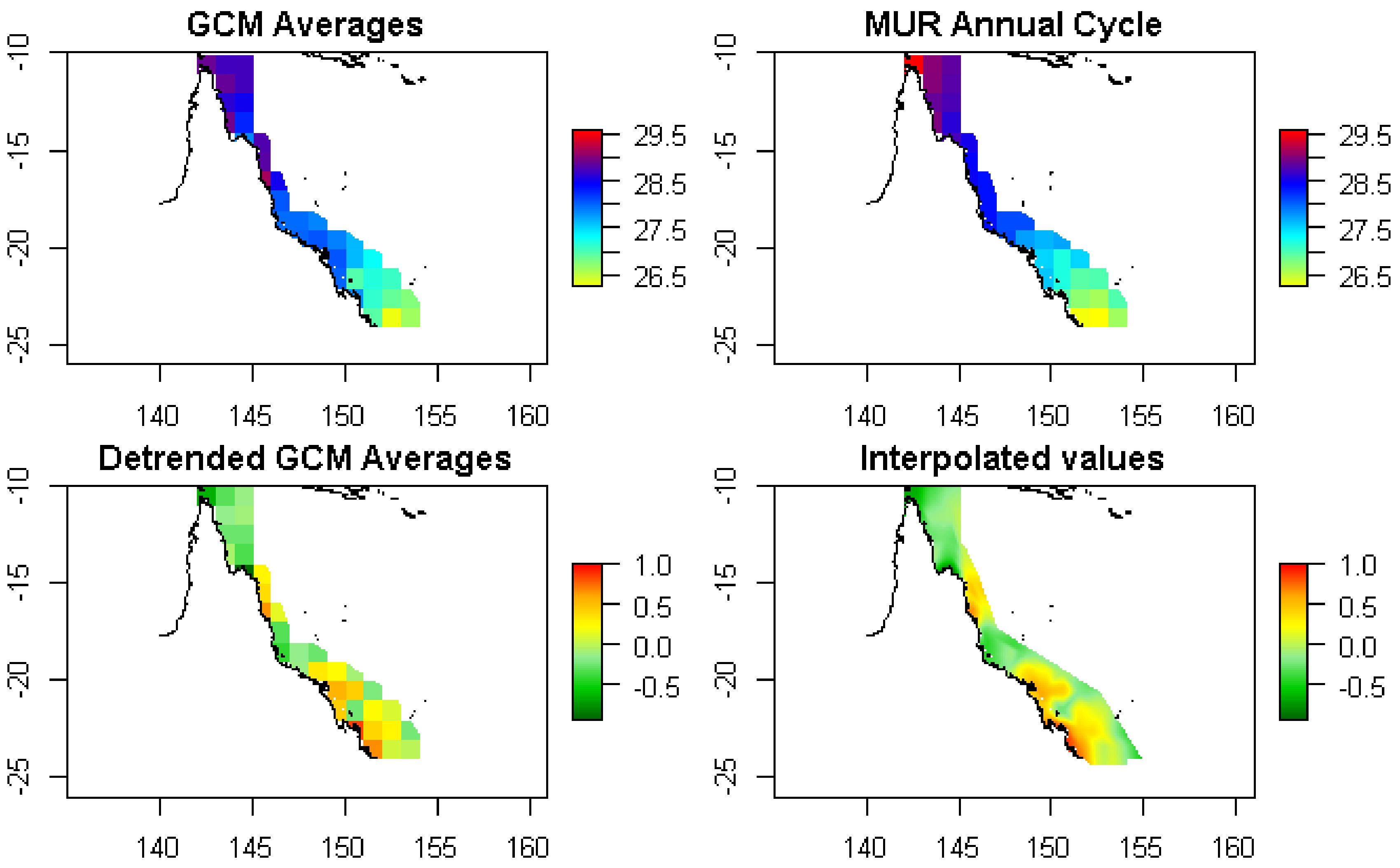

Trend (Annual cycle + Interpolated values) - 12/2019

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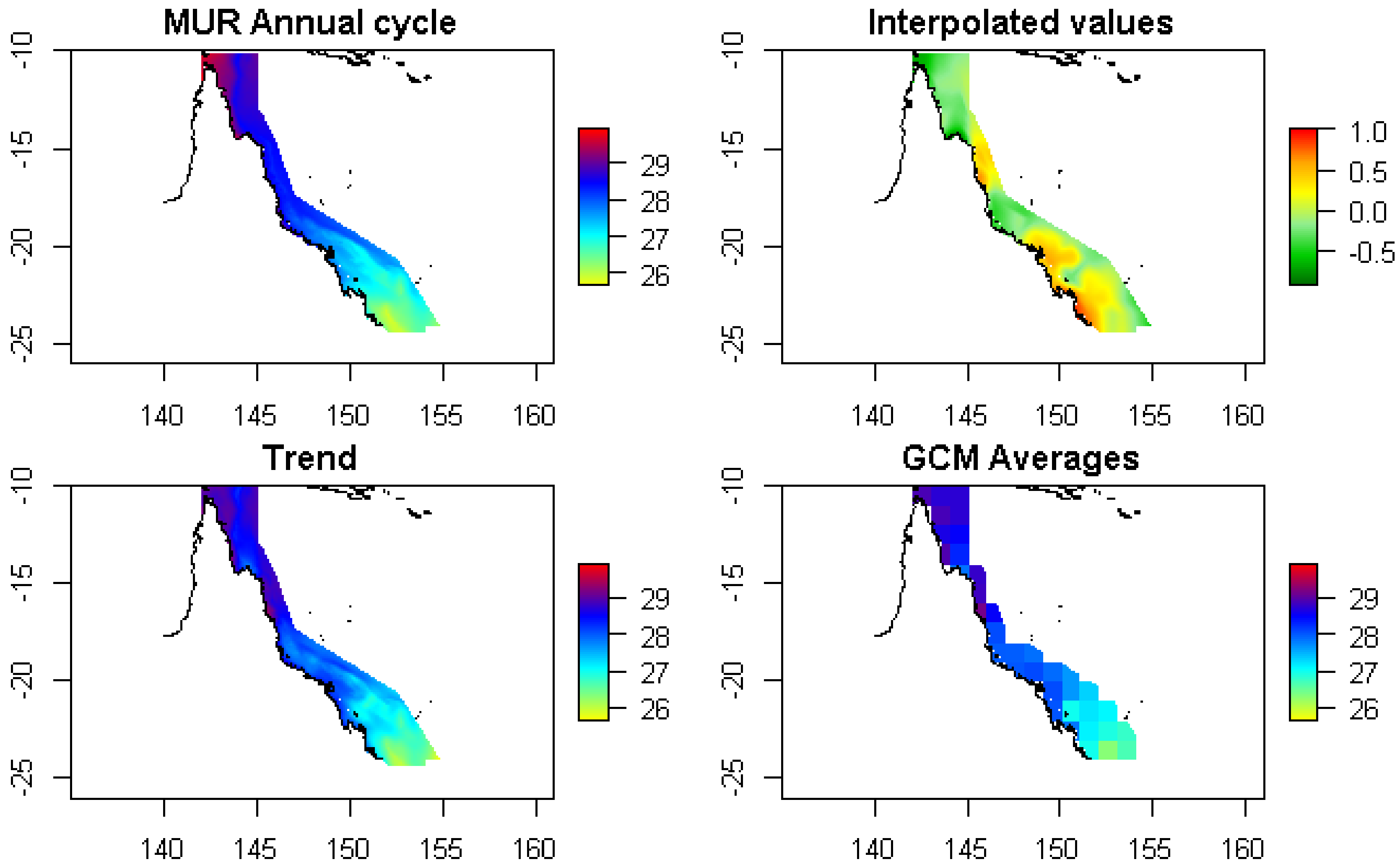

Interpolation-12/2100

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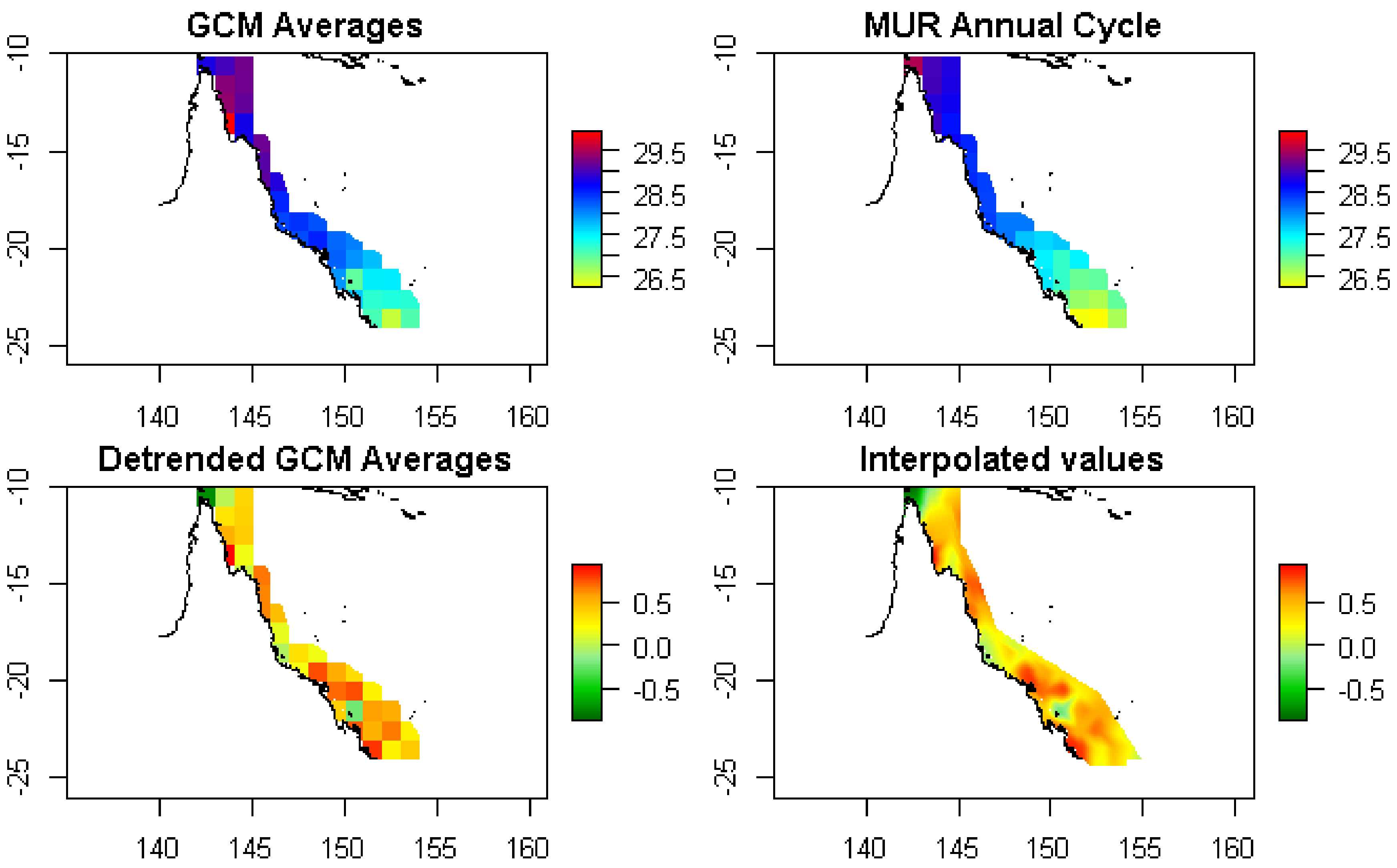

Trend (Annual cycle + Interpolated values) – 12/2100

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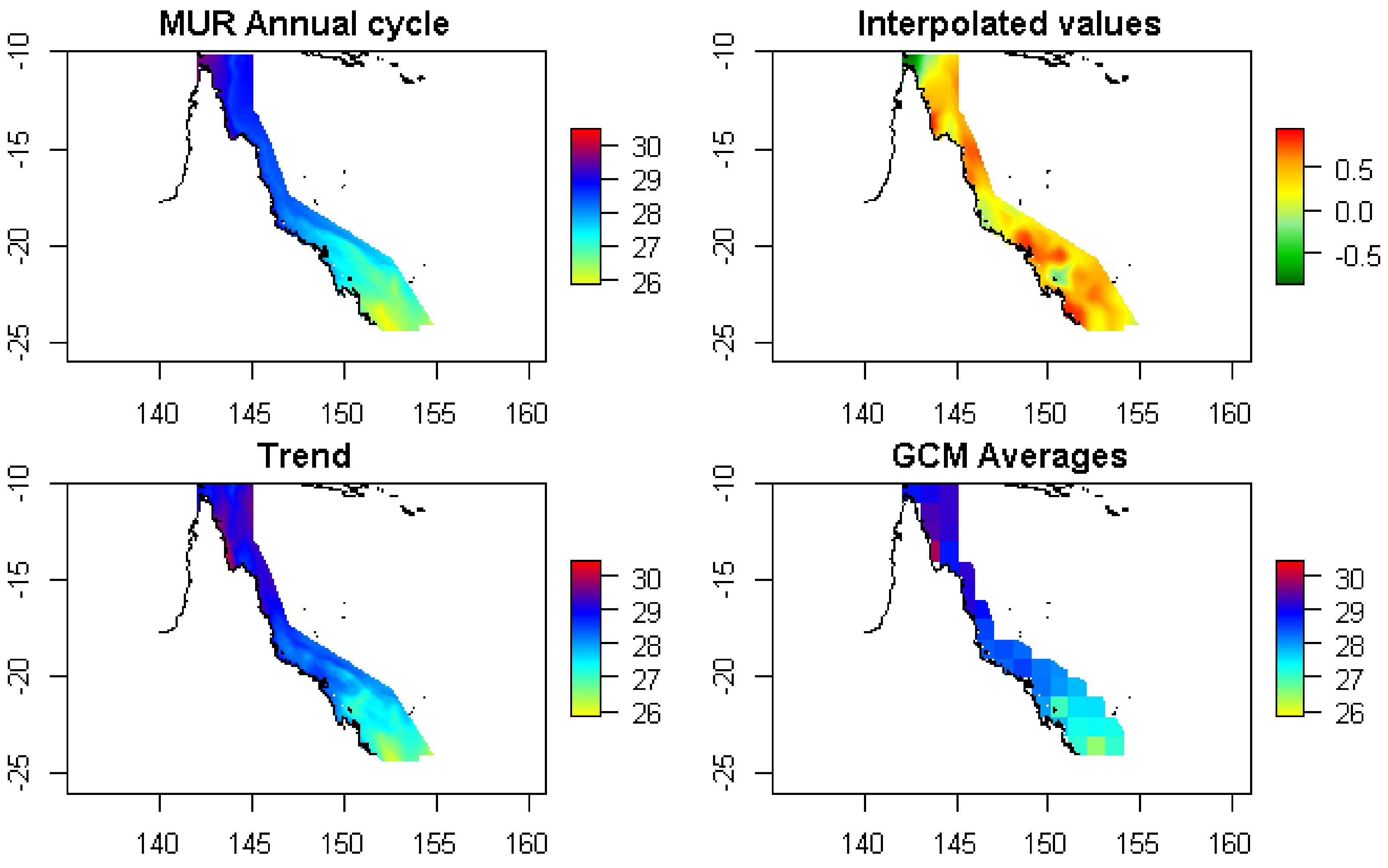
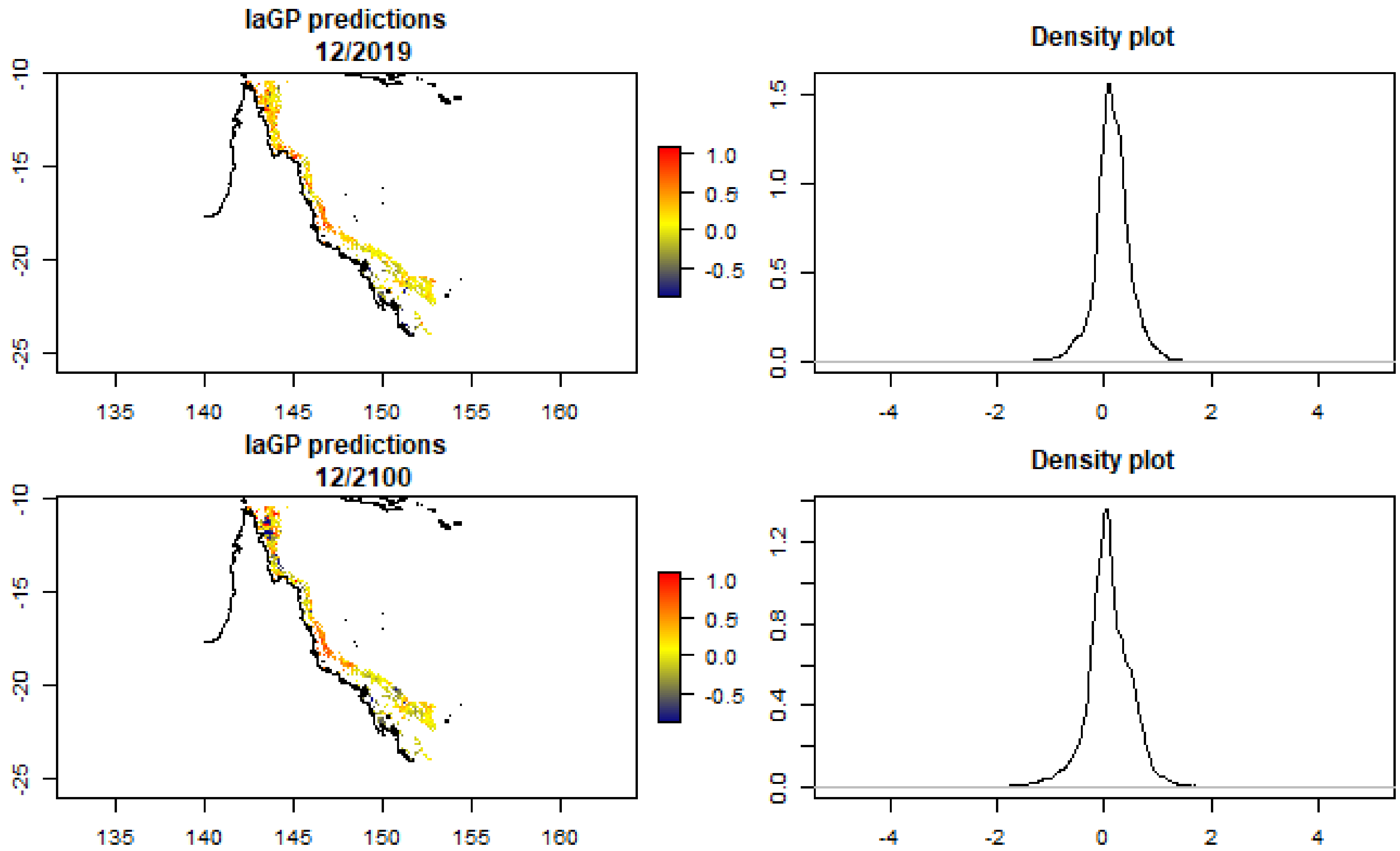


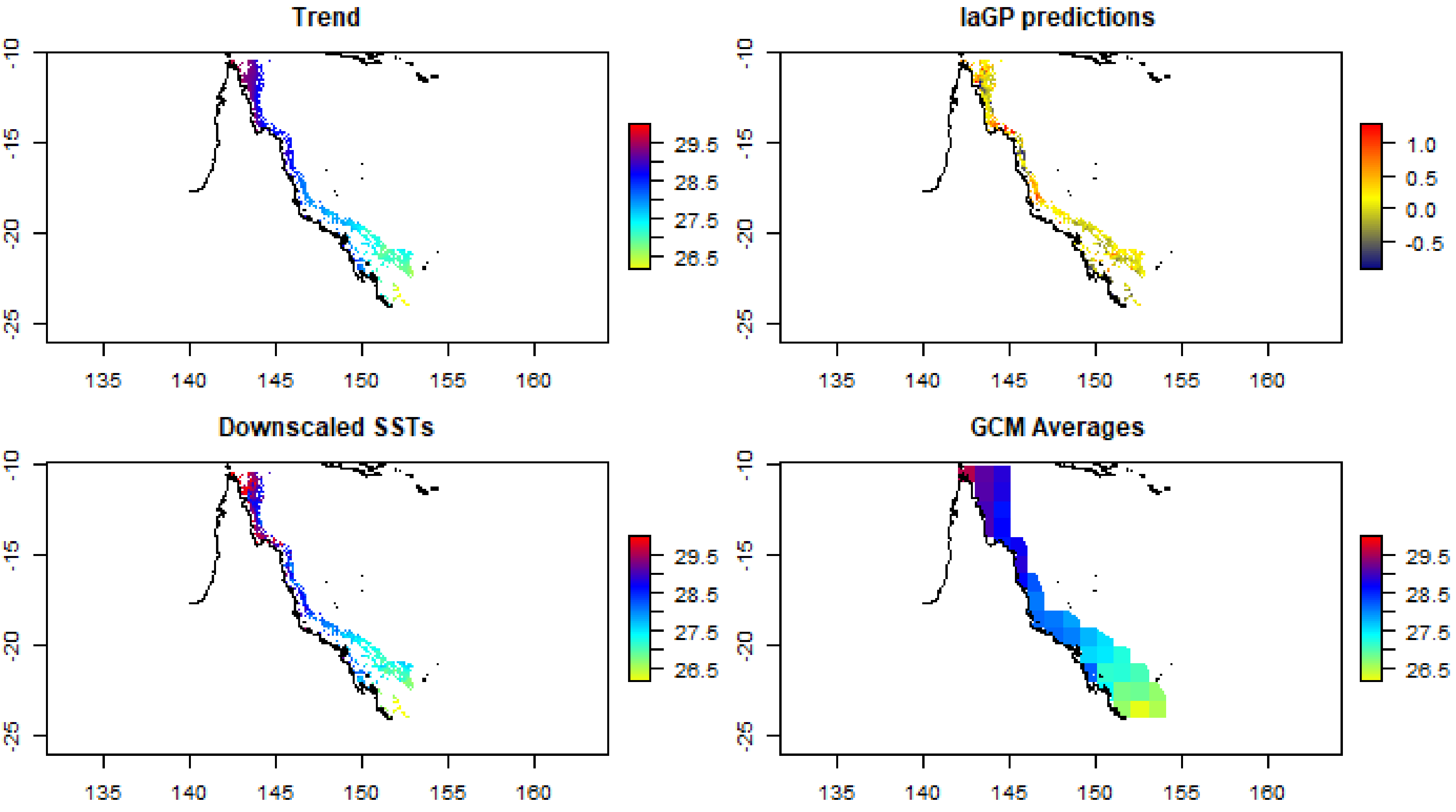
Next steps

- **Find residuals by subtracting the trend from observed MUR SSTs.**
- **Use laGP to model “residuals” with three input variables.**
  - **Longitude**
  - **Latitude**
  - **GCM – trend (fine scale)**

laGP predictions



Trend+Residuals – 12/2019



Observed SSTs , GCM averages and Downscaled SSTs – 12/2019

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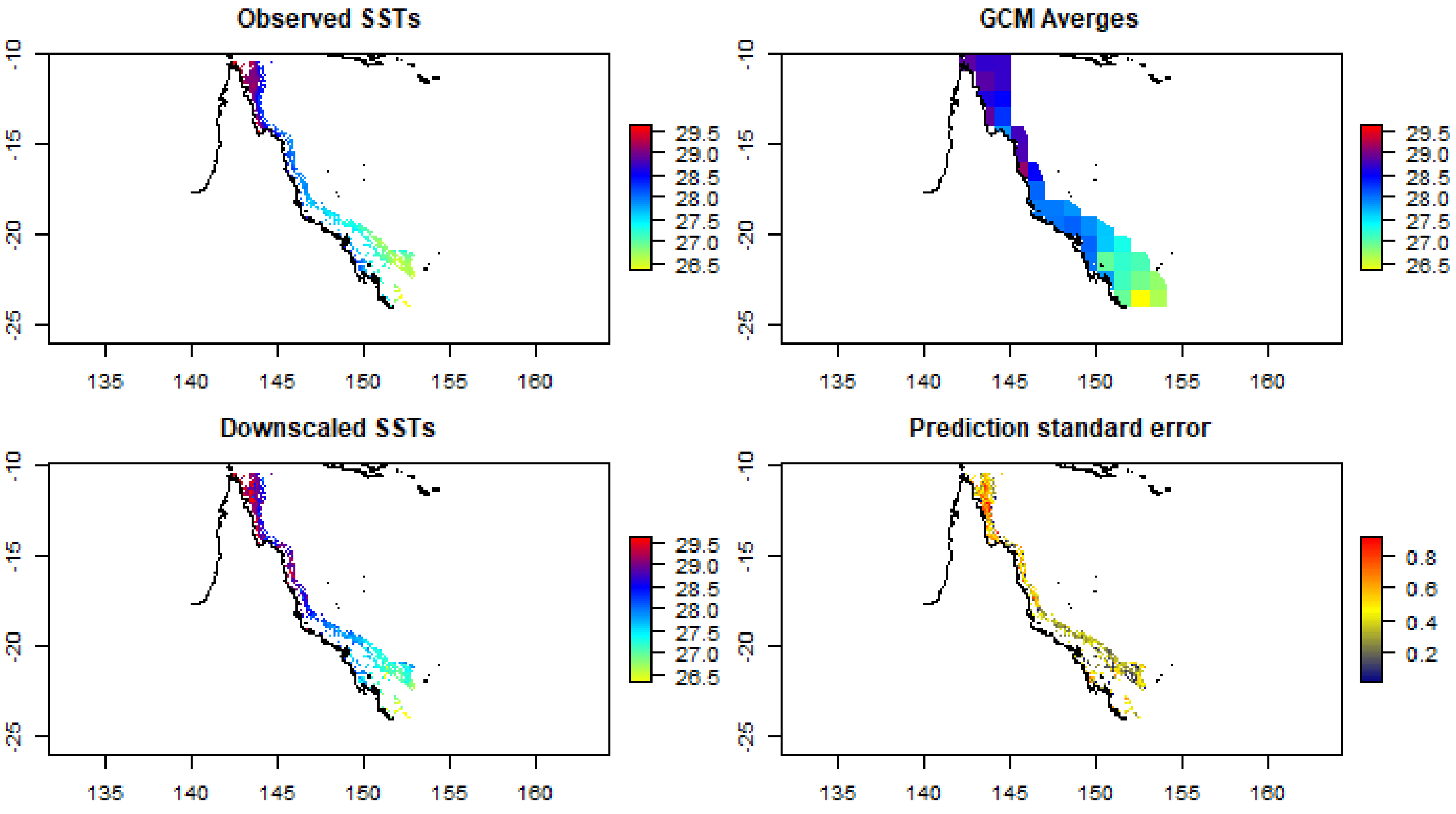
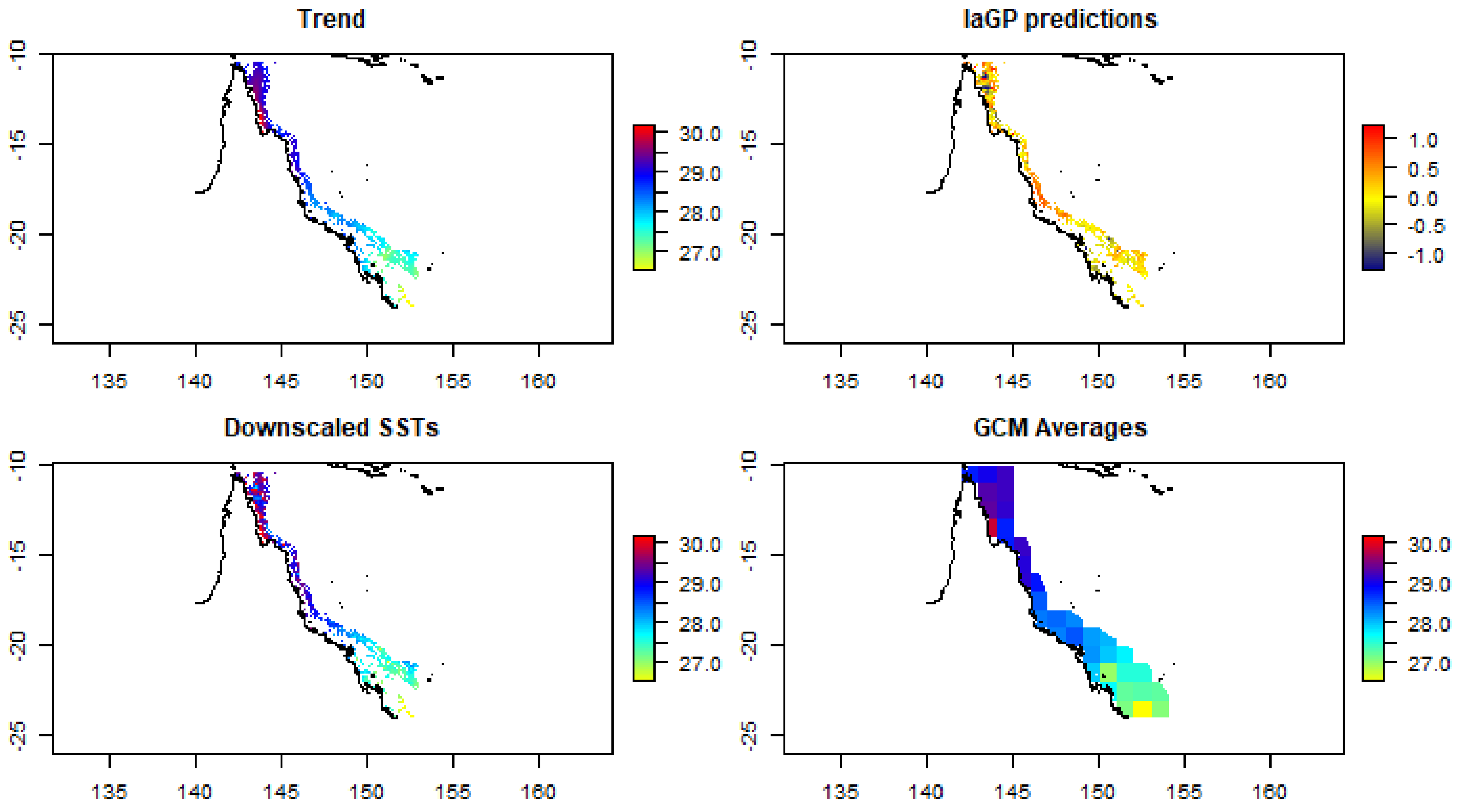


Trend+Residuals – 12/2100



GCM averages and Downscaled SSTs - 12/2100

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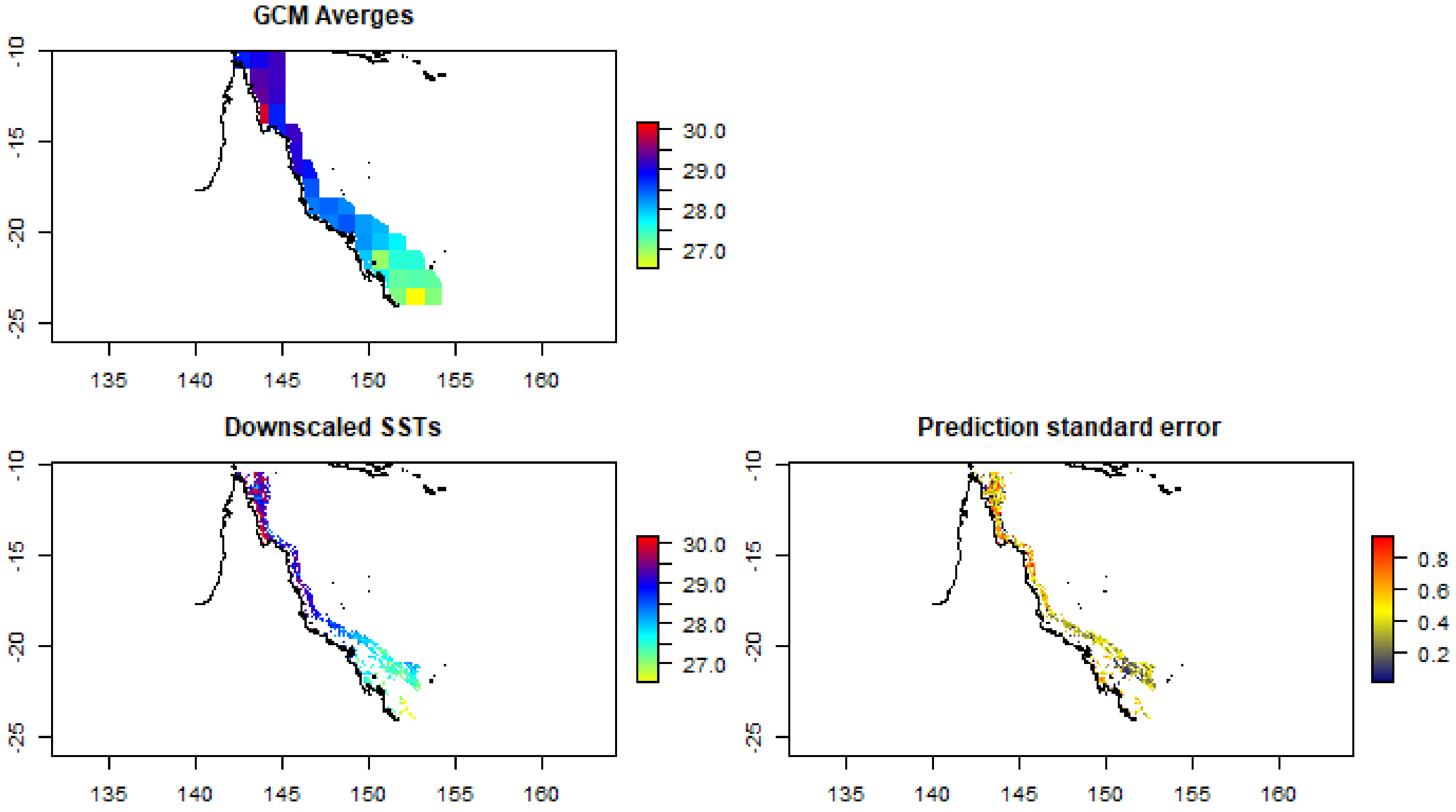

Downscaled SSTs for 12/2019 vs 12/2100

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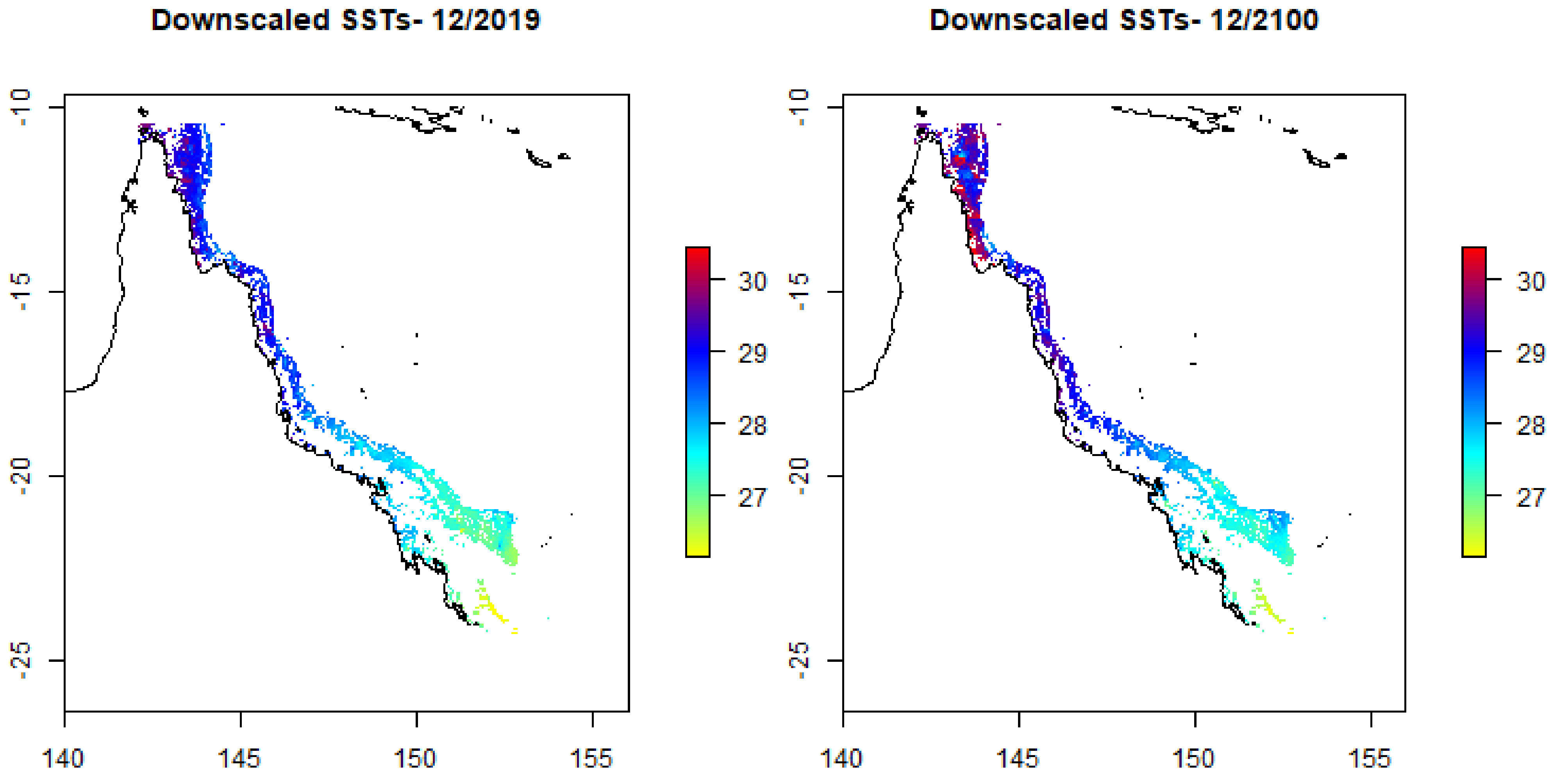
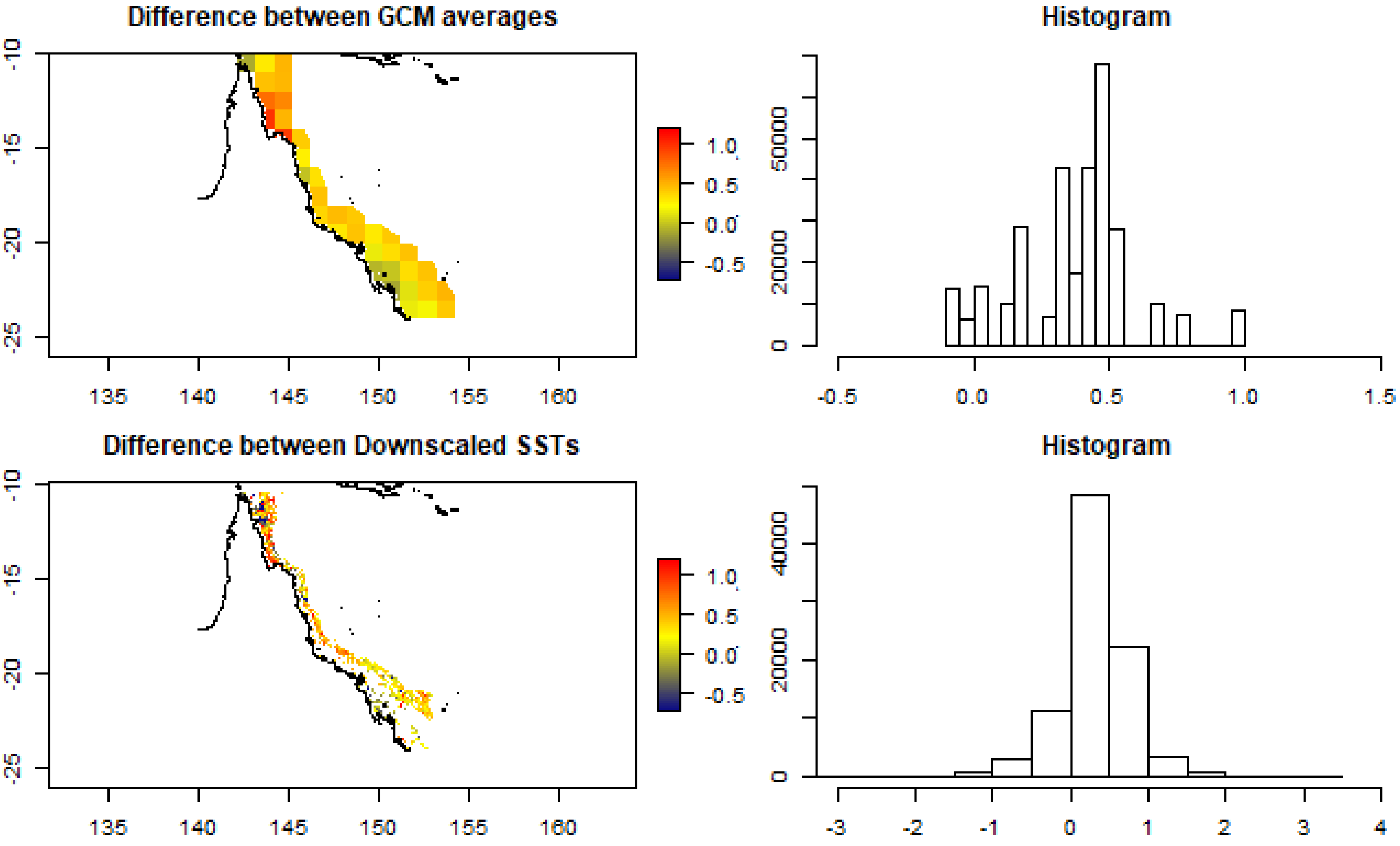


Temperature difference between 12/2019 and 12/2100



Computation

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- Data size: 36 coarse grids and 347,686 MUR pixels
  - Predictions are made only at 89,292 MUR coral pixels.
- Total number of future months: 961
  - From 1/2020 to 12/2100
- Computation time for one month: 6 hours
- Total number of coral pixels over the globe: 989,936
- About a week per SSP scenario on Pleiades

Summary

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- **We have shown preliminary results for coarse-gridded (1°x1°) GCM projections**
- **We have implemented observational model weighting**
- **We have implemented LaGP downscaling**
- **We are beginning work on a point process model to set spatially-specific thresholds**
- **We have plans to implement a Bayesian hierarchical model**

Identifying coral refugia from observationally weighted climate model ensembles

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Bayesian hierarchical model

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- **Combines model weights and statistical downscaling in one integrated model**
- **Produces monthly SST projection PDFs on 1 km grid**
- **Solve with MCMC, implemented in R**

- **SST denoted:** $Y(\mathbf{s}, t)$, for $\mathbf{s} \in \mathcal{D}$ and $t = 1, 2, \ldots$
- **MUR 1 km data:** $Y(\mathbf{s}_i, t)$ for $i = 1, \ldots, n_t$, and $t = 1, \ldots, T_{current}$
- **K ESMs, M grid cells:** $X_i(B_j, t)$

$$t = 1, \ldots, T_{current}, T_{current}+1, \ldots, T_{future}$$

$$j = 1, \ldots, M$$

$$i = 1, \ldots, K$$

Data model

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- **ESM output:** $X_i(B_j,t) = \frac{1}{|B_j|}\int_{\mathbf{s}\in B_j} Y(s,t)ds + d_i(B_j,t) + \epsilon_{X,i}(B_j,t)$ (1)
- relates fine scale to ESM scale   bias of ESM   Gaussian noise, $\sigma^2_{X,\epsilon,i}$
- **SST:** $Y(\mathbf{s},t) = \mathbf{T}(\mathbf{s},t)'\boldsymbol{\alpha}_t + w(\mathbf{s},t) + \epsilon_Y(\mathbf{s},t)$ (2)
- trend/regression term   process model TBD   Gaussian noise, τ^2
- **Apportion N areal units at fine res:** $\mathbf{Y}_t \equiv (Y(\mathbf{s}_1,t),\ldots,Y(\mathbf{s}_N,t))',\quad t=1,\ldots,T_{current}$
- **(2) becomes:** $\mathbf{Y}_t = \mathbf{T}_t,\boldsymbol{\alpha}_t + \mathbf{w}_t + \boldsymbol{\varepsilon}_{Y,t}; t = 1,\ldots,T_{current},$
- **similarly let:** $\mathbf{X}_{i,t} = (X_i(B_1,t),\ldots,X_i(B_M,t))'$
- **(1) becomes:** $\mathbf{X}_{i,t} = \mathbf{A}\mathbf{Y}_t + \mathbf{d}_{i,t} + \boldsymbol{\varepsilon}_{X,i}$
  -

Process Model

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- **Specifies distribution of spatial-temporal process, and the model bias.**
- **Incorporates the observational model weights.**

- **Assume** $w(\mathbf{s}, t)$ **to be Gaussian process w/ spatio-temporal covariance** $C(\cdot, \cdot; \boldsymbol{\theta})$
- **Assume additive approx. Gaussian process (see e.g. Ma, Konomi, and Kang 2018)**

- **Assume** $\mathbf{d}_{i,t} \sim \mathcal{N}_M((1-\omega_i)\boldsymbol{\gamma}_i, \sigma_{d,i}^2 \mathbf{I})$

scaling factors (unknown)

Parameter model (priors)

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We'll first try:

$\{\boldsymbol{\alpha}_t\}$ $\{\boldsymbol{\gamma}_i\}$ **Gaussian prior with zero mean, multiple of the identity prior covariance matrix with large variance**

$\boldsymbol{\theta}$ $\sigma^2_{X,\epsilon,i}$, τ^2, and $\sigma^2_{d,i}$ **standard conjugate inverse gamma priors**