Global mean surface temperature projection constrained by historical observations

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Alternatives to Cummins et al. (2020)

- We map the two-component energy balance model (EBM) into a linear state space model (EBM-SS model) and obtain the maximum likelihood estimates of the physical parameters.
- The EBM-SS model provides alternative and extension to the linear state space framework by Cummins et al. (2020):

	EBM-SS model	Cummins et al. (2020)
Nature of datasets	observation-based	$4 \times CO_2$ experiments (CMIP5)
Measurement choice	Empirical counterparts	top-of-atmosphere (TOA) net flux
Radiative forcing	exogenous/local linear trend	red noise process
Multiple data sources	Yes	No

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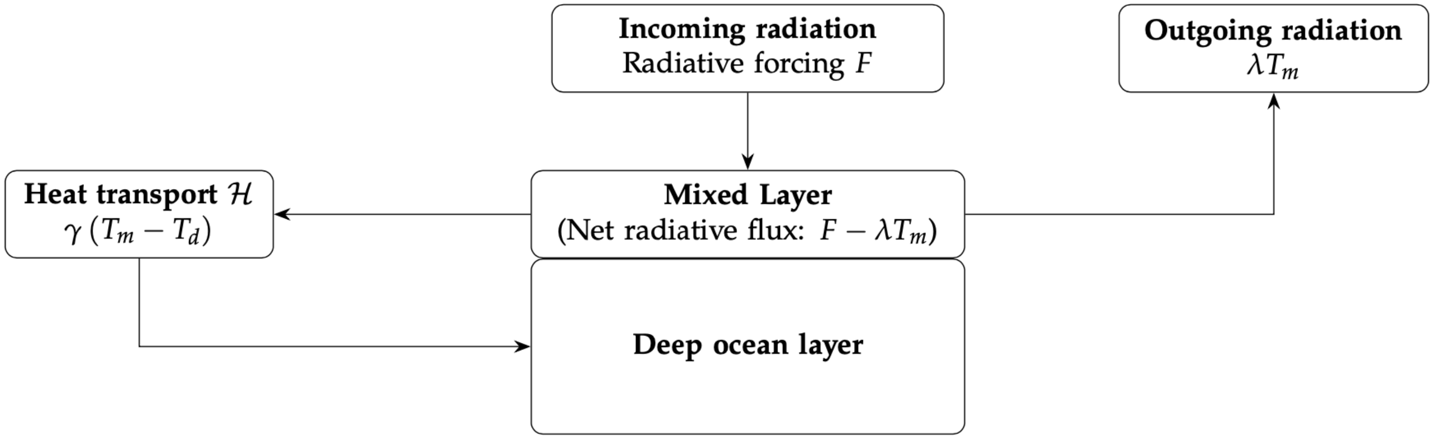
Two-component energy balance model



Notation	Description
R	radiation
$\mathcal{H}$	heat exchange
T	temperature
C	heat capacity
m	subscript for the mixed layer
d	subscript for the deep ocean layer
F	radiative forcing
λ	climate feedback parameter
γ	coefficient of heat exchange

Two-component EBM

$$\begin{aligned} C_m \frac{dT_m}{dt} &= F - \lambda T_m - \gamma\left(T_m - T_{d_1}\right) \\ C_d \frac{dT_d}{dt} &= \gamma\left(T_m - T_d\right) \end{aligned} \tag{1}$$

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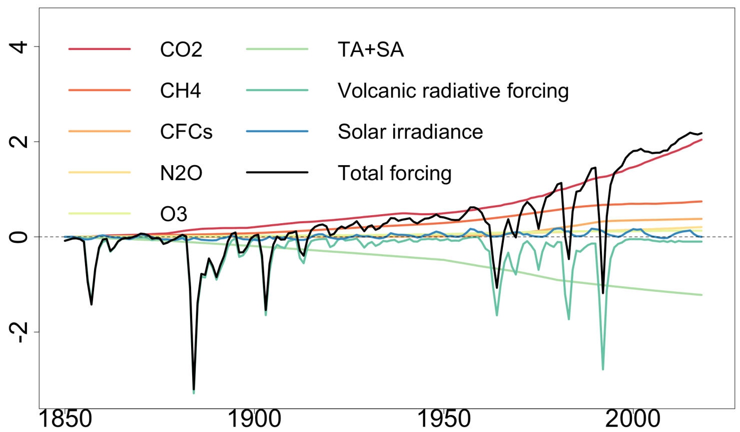
Decomposition of radiative forcing F_t

Figure: Forcing F_t (1850 – 2018, Wm^{-2})



- F_t is decomposed into the natural forcing (N_t) and the anthropogenic forcing (A_t):

$$F_t = N_t + A_t,$$
$$N_t = Y_{N,t}$$

Figure: Natural (N_t) and anthropogenic forcing A_t

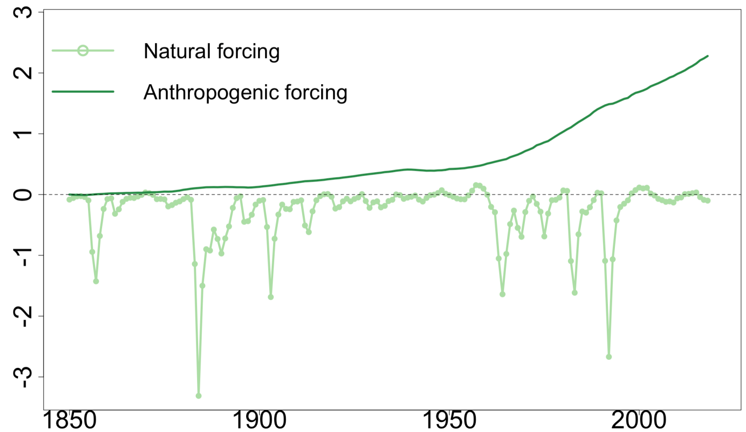
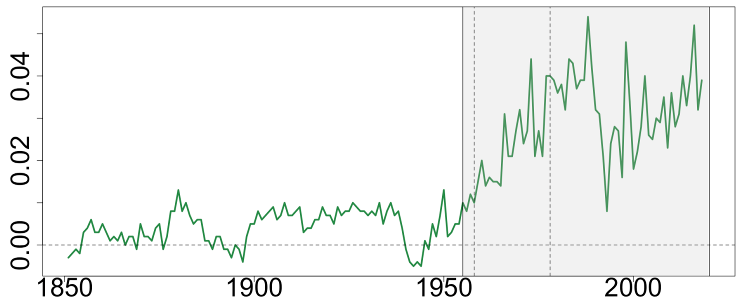


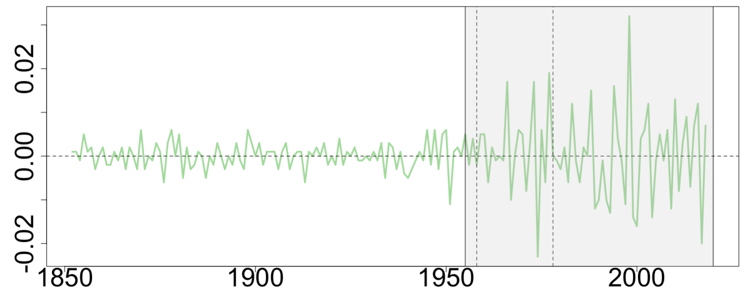
Figure: First-order difference: ΔA_t



- A_t – a local linear trend model:

$$A_t = \beta_t + A_{t-1} + \eta_{A,t}$$
$$\beta_t = \beta_{t-1} + \eta_{\beta,t}$$
$$\eta_{A,t} \sim \mathcal{N}(0, \sigma^2_{\eta_A}),$$
$$\xi_t \sim \mathcal{N}(0, \sigma^2_{\eta_\beta}).$$

Figure: Second-order difference: $\Delta(\Delta A_t)$



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EBM-State Space (EBM-SS) model

State equation: state vector $\begin{pmatrix} T_{m,t} & T_{d,t} & N_t & A_t & \beta_t \end{pmatrix}^\top$

$$
\begin{aligned}
T_{m,t} &= \left(1 - \frac{\lambda+\gamma}{C_m}\right) T_{m,t-1} + \frac{\gamma}{C_m} T_{d,t-1} + \frac{1}{C_m}\left(N_{t-1} + A_{t-1}\right) + \eta_{T_m,t}, \\
T_{d,t} &= \frac{\gamma}{C_d} T_{m,t-1} + \left(1 - \frac{\gamma}{C_d}\right) T_{d,t-1} + \eta_{T_d,t}, \\
N_t &= Y_{N,t} \\
A_t &= \beta_t + A_{t-1} + \eta_{A,t}, \\
\beta_t &= \beta_{t-1} + \eta_{\beta,t}
\end{aligned}
\tag{2}
$$

Measurement equation with multiple data sources for T_m and T_d:

$$
\begin{aligned}
Y^1_{T_m,t} &= T_{m,t} + \varepsilon^1_{T_m,t}, \\
&\vdots \\
Y^K_{T_m,t} &= T_{m,t} + \varepsilon^K_{T_m,t}, \\
Y^1_{T_d,t} &= T_{m,t} + \varepsilon^1_{T_d,t}, \quad Y^1_{O,t} = C_d T_{d,t} + \varepsilon^1_{O,t}, \quad \mathrm{Corr}\left(\varepsilon^1_{T_d,t}, \varepsilon^1_{O,t}\right) = \rho_1 \\
&\vdots \qquad\qquad\qquad\qquad \vdots \\
Y^J_{T_d,t} &= T_{m,t} + \varepsilon^J_{T_d,t}, \quad Y^J_{O,t} = C_d T_{m,t} + \varepsilon^J_{O,t}, \quad \mathrm{Corr}\left(\varepsilon^J_{T_d,t}, \varepsilon^J_{O,t}\right) = \rho_J \\
Y_{F,t} &= N_t + A_t + \varepsilon_{F,t}.
\end{aligned}
$$

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Data – summary

Table: Summary of data series from different research groups. The last column "baseline" indicates the reference period or the year upon which the anomalies are constructed.

Variable	Acronym/Type	Institution/Authors	Coverage	Baseline
Global mean surface temperature (GMST) Anomalies	GISTEMP	NASA	1880 – 2020	1951 – 1980
	NOAAGlobalTemp	NOAA	1880 – 2019	1901 – 2000
	HadCRUT5	Met Office Hadley Center	1850 – 2020	1961 – 1990
	BEST	Berkeley Earth	1850 – 2020	1951 – 1980
	CW14	Cowtan and Way(2014)	1850 – 2020	1961 – 1990
	JMA	Japanese Meteorological Agency	1891 – 2020	1981 – 2010
	ERA-Interim	Copernicus	1970 – 2020	pre-industrial
	JRA-55	Japanese Meteorological Agency	1970 – 2019	pre-industrial
Global ocean temperature	NOAA 0-700m	NOAA	1955 – 2020	not reported
	IAP 0-700m, 0-2000m	Institute of Atmospheric Physics	1940 – 2020	1981 – 2010
Global OHC Anomalies	NOAA 0-700m	NOAA	1955 – 2020	not reported
	IAP 0-700m, 0-2000m	Institute of Atmospheric Physics	1940 – 2020	1981 – 2010
Forcing	Effective Forcing	Hansen et al. (2011)	1850 – 2018	1850

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Synchronizing anomalies relative to pre-industrial era

GMST anomalies :

- pre-industrial era: 1850 – 1900 (IPCC, 2018);
- We normalize all of the GMST series with respect to the pre-industrial period (1850 – 1900) using the method in IPCC (2018).

OHC anomalies: sparse information before 1955.

We include constants in the measurement equations of ocean temperature and OHC to offset the baseline difference between 1981 – 2020 and the pre-industrial era ($j = 1, ..., J$):

$$\begin{aligned} Y^j_{T_d,t} &= \mu^j_{T_d} + T_{d,t} + \varepsilon^j_{T_d,t} \\ Y^j_{O,t} &= C_d \mu^j_{T_d} + C_d T_{d,t} + \varepsilon^j_{O,t}. \end{aligned} \tag{3}$$

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Estimation of EBM-SS model

- The parameters to be estimated in EBM-SS model include:
  - physical parameters: $\lambda, \gamma, C_m, C_d$
  - variances of state disturbances and measurement errors + ρ
  - constants for the measurement of T_d, μ_{T_d}
- Maximum likelihood using outputs of the Kalman filter (Durbin and Koopman, 2012);
- Two settings (generated in the same simulation):
  - EBM-SS base model: one data source for each latent state
  - EBM-SS full model: eight GMST series, two pairs of ocean temperature and OHC 0-700m series (one pair of 0-2,000m series), and one radiative forcing series

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Monte Carlo simulation – results

- Equilibrium climate sensitivity (ECS): the GMST increase that follows a doubling of atmospheric CO_2;
- $\text{ECS} = \frac{F_{2\times CO_2}}{\lambda}$, where $F_{2\times CO_2} \approx 3.93\ (\pm 0.47,\ \ 5\% - 95\%\ \ \text{CI})\ \ \text{W m}^{-2}$ (Forster et al., 2021);
- Including multiple data sources helps decrease the estimation uncertainty.

	EBM-SS base model					EBM-SS full model				
	λ	γ	C_m	C_d	ECS	λ	γ	C_m	C_d	ECS
data-generating value	1.0828	1.3027	9.6376	98.4886	3.6294	1.0828	1.3027	9.6376	98.4886	3.6294
sample mean bias	0.0131	0.0343	0.1785	−0.0276	0.1943	0.0280	−0.0133	−0.179	−0.0032	0.1216
standard deviation	0.2700	0.2616	2.3388	0.8449	1.0408	0.2650	0.2485	2.1049	0.2048	0.9557
RMSE	0.2702	0.2637	2.3444	0.8450	1.0583	0.2663	0.2487	2.1114	0.2047	0.9629

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Empirical estimates

Table: Comparison of estimates for the physical parameters between EBM-SS full model and other frameworks. The standard errors of the estimates are reported in the parentheses.

A. evaluation of the two-component EBM using historical data					
model	$\hat{\lambda}$	$\hat{\gamma}$	$\hat{C}_m$	$\hat{C}_d$	$\widehat{ECS}$
EBM-SS full, 0-700m ocean data (NOAA & IAP)	1.08 (0.25)	1.30 (0.34)	9.64 (2.86)	98.49 (0.26)	3.63 (0.89)
EBM-SS full, 0-2,000m ocean data (IAP)	0.66 (0.31)	1.82 (0.45)	9.35 (2.61)	269.30 (0.42)	5.91 (2.77)
B. evaluation of the two-component EBM using $4\times CO_2$ experiment data					
model	$\hat{\lambda}$	$\hat{\gamma}$	$\hat{C}_m$	$\hat{C}_d$	$\widehat{ECS}$
CMIP6 means (Smith et al., 2021)	0.84 (0.38)	0.64 (0.13)	8.1 (1.0)	110 (63)	3.0
CMIP5 means (Cummins et al., 2020)	1.21	0.77	6.88	97.18	3.41
C. estimates of ECS using different datasets and methods					
model and data	$\hat{\lambda}$	$\hat{\gamma}$	$\hat{C}_m$	$\hat{C}_d$	$\widehat{ECS}$
Instrumental records (Forster et al., 2021)	-	-	-	-	2.5 – 3.5
CMIP6 means (Schlund et al., 2020; Smith et al., 2021)	-	-	-	-	3.78 (1.08)
CMIP5 means (Schlund et al., 2020; Smith et al., 2021)	-	-	-	-	3.28 (0.74)

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Empirical evidence for estimation uncertainty reduction by using multiple data sources

- EBM-SS base model: 16 combinations (0-700m) and 8 combinations (0-2,000m).
- A measure for relative estimation uncertainty – coefficient of variation (CV):

$$\frac{\text{standard error of the parameter}}{\text{estimate of the mean of the parameter}}.$$

Table: "% CV ≥ (*)" reports the percentage where the individual CV of EBM-SS base model is not smaller than the CV of the EBM-SS-full model (denoted as $*$).

Model		NOAA / IAP 0-700m					IAP 0-2,000m				
		$\hat{\lambda}$	$\hat{\gamma}$	$\hat{C}_m$	$\hat{C}_d$	ECS	$\hat{\lambda}$	$\hat{\gamma}$	$\hat{C}_m$	$\hat{C}_d$	ECS
EBM-SS-full	**CV (*)**	0.23	0.26	0.30	0.003	0.25	0.46	0.25	0.28	0.002	0.47
EBM-SS-base	**median of CVs**	0.39	0.22	0.37	0.01	0.40	1.20	0.19	0.36	0.002	1.21
	% CV ≥ *	93.8%	62.5%	93.8%	50%	93.8%	100%	0	87.5%	100%	100%

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RCP scenarios and GMST projection

- Representative Concentration Pathways (RCPs) represent different possible GHG concentration trajectories until 2100.
- RCP 2.6, RCP 4.5, RCP 6, and RCP 8.5 denote different radiative forcing levels (Wm^{-2}) 2.6, 4.5, 6, and 8.5, respectively, in 2100.
- Assume the physical parameter vector follows a multivariate normal distribution $\mathcal{N}\left(\hat{\theta}, \hat{\Sigma}\right)$, where $\hat{\theta}$ and $\hat{\Sigma}$ are estimated empirically.
- Draw 10,000 sets of physical parameters from $\mathcal{N}\left(\hat{\theta}, \hat{\Sigma}\right)$, while fixing other parameters at their empirical estimates.
- EBM-SS model produces point predictions of GMST at $T + h$ (T = 2020, and h = 1, 2, ..., 80) under the four RCP scenarios.

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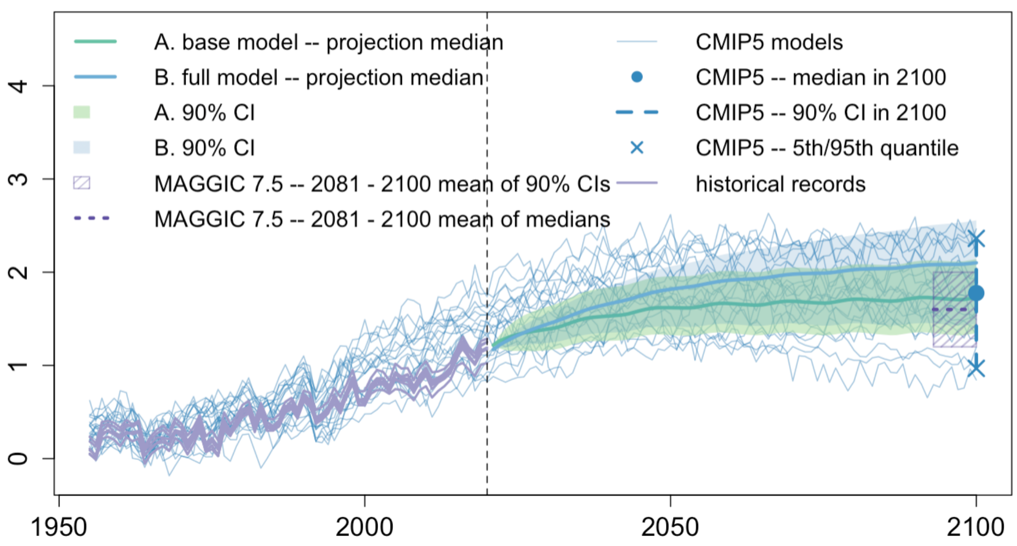
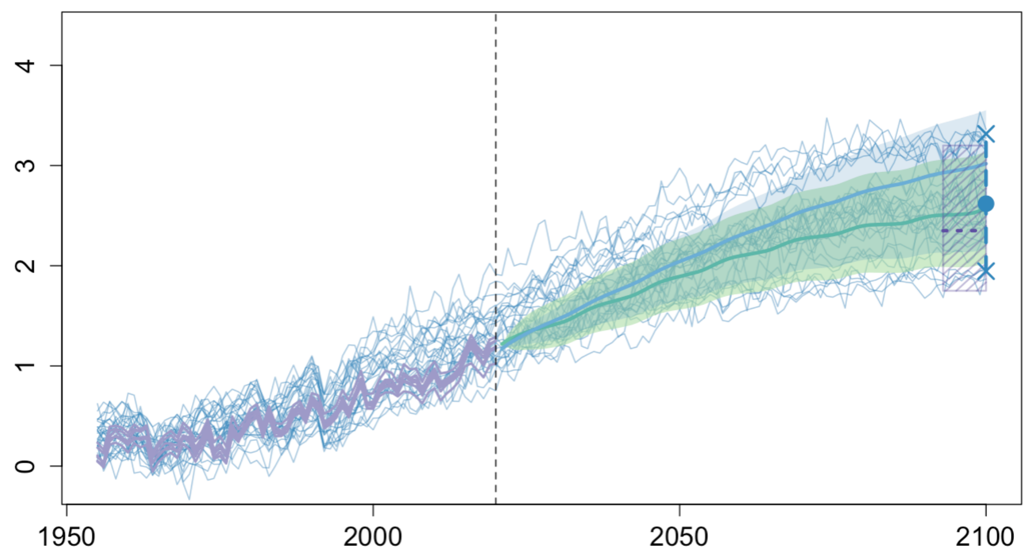
GMST projections – 0-700m ocean data

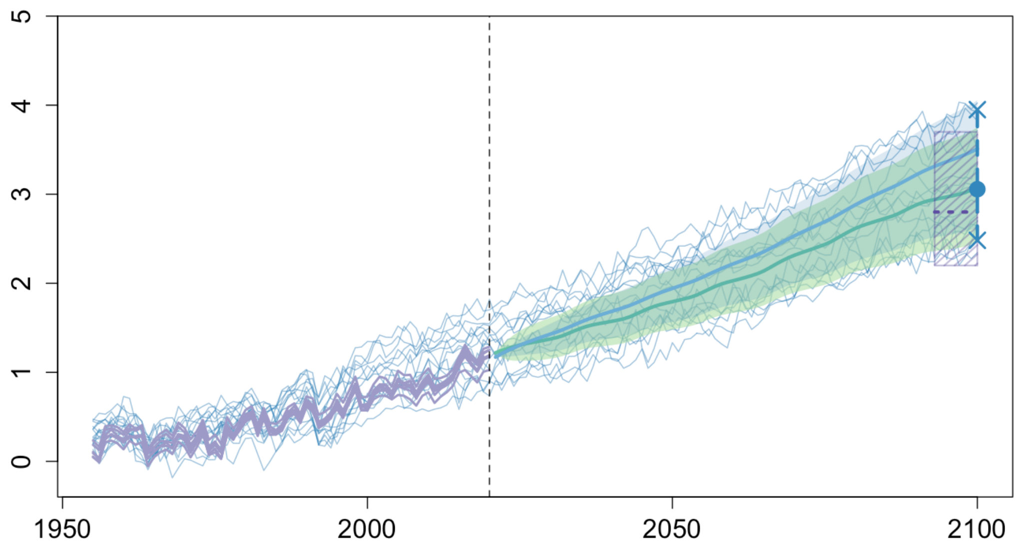
(a) RCP 2.6



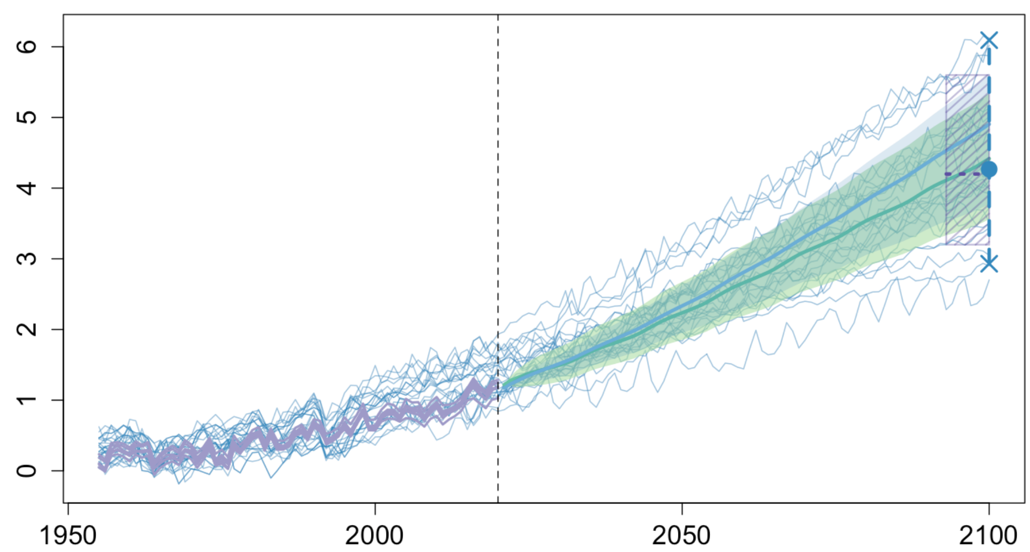
(b) RCP 4.5



(c) RCP 6



(d) RCP 8.5



Concluding Remarks

We have established a statistical climate model (EBM-SS model), which is a linear state space representation of the two-component EBM.

The EBM-SS model:

- allows to incorporate multiple data sources for the latent states, which reduce estimation uncertainty of the parameters;
- produces projections for GMSTs that are comparable to those of CMIP5 and MAGGIC 7.5 for the RCP scenarios.

Our statistical model exclusively use historical observational data, and our results corroborate earlier findings both from complex climate models and from reduced complexity models.

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