



GENERAL-TO-SPECIFIC MODELLING OF HEMISPHERIC SEA SURFACE TEMPERATURES UNDER ANTHROPOGENIC WARMING

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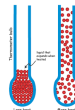
Model Invariance and Constancy in the Face of Large Shocks
University of Oslo, 17-18 June 2026

Global sea surface temperatures have been rising, along with increasing variation in seasonal patterns, which have significant impacts.

Thermal expansion leads to sea level rise.



Damage to ecosystems



Extreme weather events:
more energy for hurricanes and cyclones.



Warmer waters reduce CO_2 absorption.

Bilal and Känzig (2024) show that ocean temperatures are responsible for the majority of temperature effects on global economic activity.

Different patterns of warming in northern and southern hemisphere, but closely linked through ocean heat transport (e.g. AMOC) and atmospheric teleconnections (e.g. El Niño).

Model as a system with global greenhouse gases driving each hemisphere, allowing for interactions between hemispheres, while jointly modelling short-term seasonal and cyclical patterns.

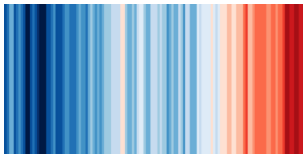
Approach

Ocean heat budget motivates initial model specification.

General-to-specific modelling framework to allow for many possible explanatory factors, non-linear relationships, outliers & breaks.

Statistical selection of main drivers while ensuring congruent model specification.

Model used to produce scenario projections of future sea surface temperatures.



- 1 **Modelling approach and data**
- 2 **Econometric model of sea surface temperatures**
- 3 **Scenario Projections**
- 4 **Conclusions**

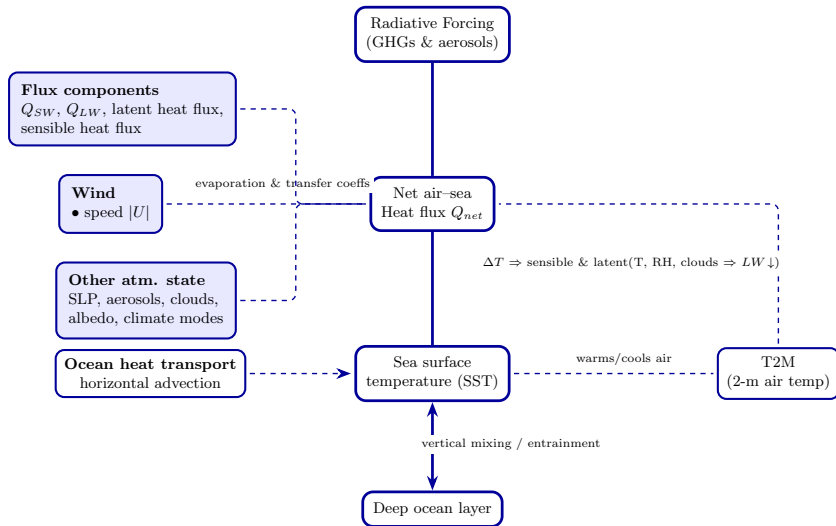
Two component energy balance model with heat budget equation

$$C_u^i \frac{dT_u^i}{dt} = F^i - \lambda^i T_u^i - \gamma (T_u^i - T_l)$$

$$C_l \frac{dT_l}{dt} = \gamma (\overline{T_u} - T_l)$$

- C_u^i/C_l : heat capacity in upper (northern and southern hemispheres) and lower (aggregated) layer
- T_u^i/T_l : temperature of upper (northern and southern hemispheres) and lower layer.
- F^i : total radiative forcing, where
 $F^i - \lambda^i T_u^i = Q_{net}^i = Q_{in}^i - Q_{out}^i$, (difference between incoming (Q_{in}^i) and outgoing heat flux (Q_{out}^i)) in each hemisphere.
- λ^i : climate feedback parameter for each hemisphere
- γ : global heat exchange coefficient.

Schematic of the modelling approach



— primary exchange — modulators/feedbacks

- Net heat flux (Q_{net}^i) drives sea surface temperatures (SST^i).
- Radiative forcing from GHGs & aerosols modifies Q_{net}^i .
- When $Q_{\text{net}}^i > 0$ ocean surface gains heat; $Q_{\text{net}}^i < 0$ it loses heat.
- Mixed layer coupled to deep ocean by vertical mixing and entrainment, buffering rapid SST^i changes.
- Feedback through $t2m^i$ (temperature 2m above ocean). Warmer SST^i warms $t2m^i$, feeds back Q_{net}^i via sensible/latent heat flux.
- Temperature, humidity, & clouds influence downwelling longwave to the surface, further modulating Q_{net}^i .
- Wind speed controls bulk transfer coefficients & evaporation rate
- Atmospheric states (sea-level pressure patterns, aerosols, clouds, albedo, and climate modes (such as ENSO)) primarily alter radiation & humidity.
- Ocean heat transport can import/export heat in mixed layer, changing SST^i even when local Q_{net}^i is small.

Map physical heat exchange model to empirical statistical model

$$\begin{pmatrix} SST_t^n \\ SST_t^s \end{pmatrix} = f(Q_{net}^i)_t + f(T_u^i - T_l)_t + f(\mathbf{Z})_t + \mathbf{u}_t$$

Direct channels include net heat flux & heat transfer to deep ocean.
Indirect channels by $f(\mathbf{Z})_t$ (physical & anthropogenic drivers).

Define vectors of variables:

$$Q_{net}^i = (Q_{sw}^i, Q_{lw}^i, Q_{SH}^i, Q_{LH}^i)'.$$

$$\mathbf{X}_t^i =$$

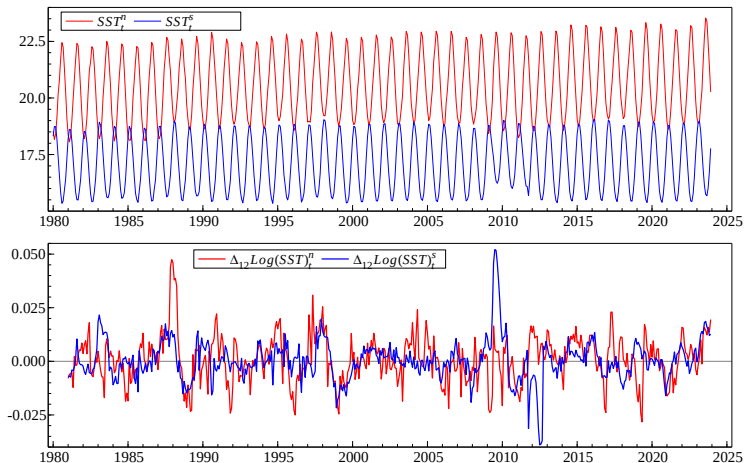
$$(t2m^i, mslp^i, wind^i, cloud^i, ghp_{500}^i, gph_{800}^i, albedo^i, AOD^i)'_t;$$

$$\mathbf{W}_t =$$

$$(GHG, Nino, AMM, NAO, PNA, OHC_{0-700}, OHC_{700-2000})'_t.$$

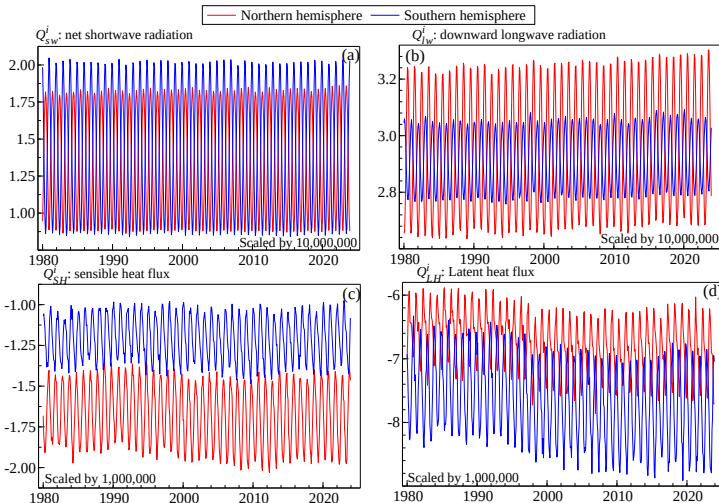
where $\mathbf{X}$ contains the disaggregate data by hemisphere and $\mathbf{W}$ includes the global measures.

Northern and Southern Hemisphere Sea Surface Temperatures



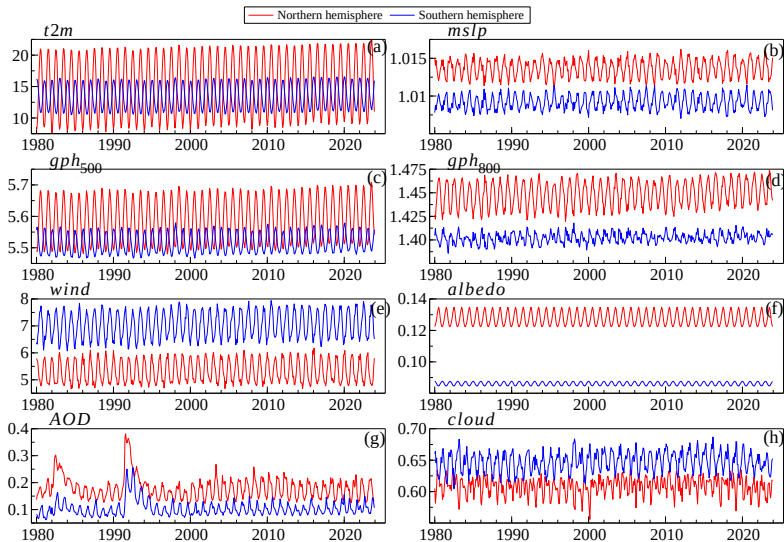
(a) monthly data in levels; (b) annual changes.

Net heat flux components



- (a) Q_{sw}^i , short wave radiation downward; (b) Q_{lw}^i , surface longwave radiation downward; (c) Q_{SH}^i , sensible heat flux; (d) Q_{LH}^i , latent heat flux.

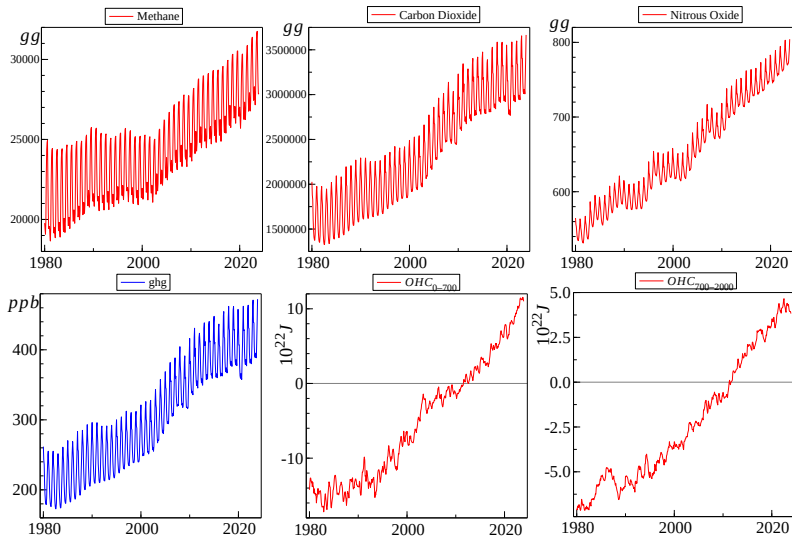
Short run seasonal SST drivers



- (a) Air temperature 2m above surface (in kelvin converted to $^{\circ}\text{C}$). Controls sensible heat flux. Impact varies over regions so universally relevant but could have different dynamics.
- (b) Mean sea level pressure (in Pa). Pressure of atmosphere at surface of Earth, i.e., weight that all air in a column vertically above a point on Earth's surface would have if point located at mean sea level. Closely linked to wind patterns influencing ocean currents and heat distribution & associated with atmospheric pressure systems which directly impact **SST**.
- (c,d) Geopotential heights at 500 hPa and 800 hPa. Height above sea level where a given atmospheric pressure is found. A measure of thickness of atmospheric layer below that pressure level and is influenced by temperature and pressure. It controls atmospheric circulation that drives surface winds which, in turn, impact **SST** through wind-induced mixing and upwelling.

- (e) Horizontal speed of wind at 10m above surface (m/s). Strong winds increase turbulence at ocean's surface causing vertical mixing. Brings cooler, deeper water to the surface (upwelling) or pushes warmer surface water down (downwelling). Wind speed also influences evaporation rates which affect latent heat flux. Wind anomalies can alter cloud cover & precipitation patterns, modulating solar radiation reaching ocean surface.
- (f) Reflectivity of Earth's surface (albedo). Indirect influence through surface energy budget & heat absorption processes. Higher albedo reflects more radiation, reducing heat absorption.
- (g) Aerosol optical depth. Aerosols scatter & absorb sunlight as it passes through atmosphere. Aerosols influence amount of solar radiation reaching ocean surface. (1992 outlier: Mount Pinatubo).
- (h) Total cloud cover. Influencing incoming solar & outgoing long-wave radiation. Greater cloud cover limits solar heating but traps outgoing radiation emitted by ocean surface, reducing loss of heat from ocean to atmosphere.

Greenhouse gas emissions & ocean heat content

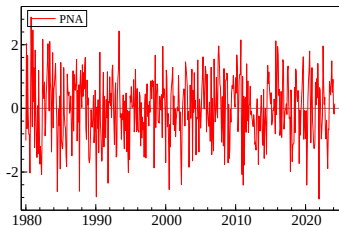
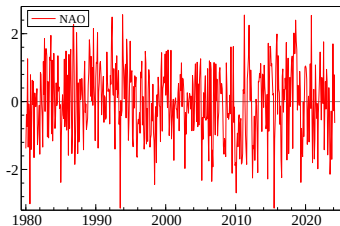
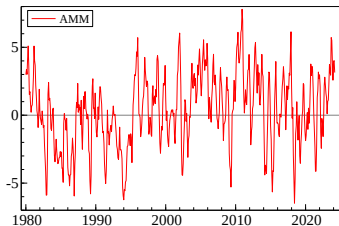
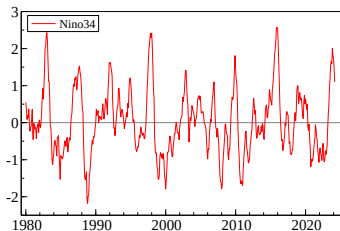


■ GHGs

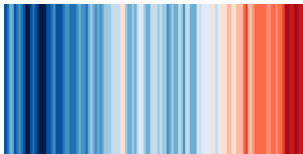
- Individual components (methane, carbon dioxide and nitrous oxide) measured as mass in gigagrams. Convert to concentrations (ppm).
- Seasonal peaks in January for CO_2 & N_2O , August for CH_4 . CO_2 trend & seasonal dominates with aggregation.
- GHGs well mixed spatially.
- Allow for transmission mechanism of GHG emissions to SST directly and via **t2m**.

■ OHC

- As sea surface temperature warms, energy transferred to deeper oceans through mixing & circulation.
- Most heat stored in upper oceans (0-700m depth)
- Slower/less variable transfer of energy to deeper oceans (700-2000m depth).
- Feedback from warming surface temperatures to atmosphere.



(a) El Niño 3.4 anomalies index; (b) Atlantic Meridional Mode, (c) North Atlantic Oscillation, (d) Pacific-North American Pattern



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GUM with s lags

$$\begin{pmatrix} SST_t^n \\ SST_t^s \end{pmatrix} = \begin{bmatrix} \beta_0^n \\ \beta_0^s \end{bmatrix} + \sum_{j=1}^p \begin{pmatrix} \lambda_j^n & \lambda_j^{ns} \\ \lambda_j^{sn} & \lambda_j^s \end{pmatrix} \begin{pmatrix} SST_{t-j}^n \\ SST_{t-j}^s \end{pmatrix} + \begin{pmatrix} \gamma_j^n & \gamma_j^s \end{pmatrix} \begin{pmatrix} \tilde{Q}_{net,t}^n \\ \tilde{Q}_{net,t}^s \end{pmatrix} \\ + \sum_{j=0}^p \begin{pmatrix} \kappa_j^n & \kappa_j^{ns} \\ \kappa_j^{sn} & \kappa_j^s \end{pmatrix} \begin{pmatrix} \mathbf{x}_{t-j}^n \\ \mathbf{x}_{t-j}^s \end{pmatrix} + \sum_{j=0}^p \begin{pmatrix} \psi_j^n & \psi_j^{ns} \\ \psi_j^{sn} & \psi_j^s \end{pmatrix} \begin{pmatrix} \mathbf{x}_{t-j}^n{}' \mathbf{x}_{t-j}^n \\ \mathbf{x}_{t-j}^s{}' \mathbf{x}_{t-j}^s \end{pmatrix} \\ + \sum_{j=0}^p \begin{pmatrix} \delta_j^n & \delta_j^s \end{pmatrix} \mathbf{w}_{t-j} + \begin{pmatrix} \mu^n & \mu^s \end{pmatrix} \begin{pmatrix} D_{peak,t} \\ D_{trough,t} \end{pmatrix} \\ + \sum_{i=1}^T \begin{pmatrix} \theta_i^n \\ \theta_i^s \end{pmatrix} 1_{\{t=i\}} + \sum_{i=2}^{T-1} \begin{pmatrix} \tau_i^n \\ \tau_i^s \end{pmatrix} 1_{\{t < i\}} + \begin{pmatrix} \epsilon_t^n \\ \epsilon_t^s \end{pmatrix}$$

where $\begin{pmatrix} \epsilon_t^n \\ \epsilon_t^s \end{pmatrix} \sim N[\mathbf{0}, \mathbf{\Omega}]$.

Components include:

- intercept [square brackets indicate selection not applied]
- $1_{\{t=i\}}$: impulse indicator = 1 for t , 0 otherwise. $1_{\{t < i\}}$: step indicator = 1 for $i = 1, \dots, t$, 0 otherwise. Saturation detects outliers, measurement errors, structural breaks.
- Dynamics & regressors in each hemisphere can influence SST in the other hemisphere (λ and κ matrices) but restrict components of net heat flux to influence given hemisphere contemporaneously (γ).
- Allow for non-linear & interaction effects within hemisphere through $X'X$ matrix. Physical theory suggests interactions between cloud cover, wind speed and geopotential heights so allow for interactions between all exogenous atmospheric regressors.
- Seasonality modelled by $D_{\text{peak},t}$ (= 1 in August, 0 otherwise) & $D_{\text{trough},t}$ (= 1 in February, 0 otherwise).

Apply Frisch-Waugh-Lovell theorem to vector Q_{net}^i to orthogonalise drivers with respect to net heat flux, estimating equation by equation where $j = lw; sw; LH; SH$:

$$Q_{j,t}^i = \gamma GHG_t + \Gamma' X_t^i + \tilde{Q}_{j,t}^i$$

to obtain vector of orthogonalised residuals,

$$\tilde{Q}_t^i = \left(\tilde{Q}_{lw}^i, \tilde{Q}_{sw}^i, \tilde{Q}_{LH}^i, \tilde{Q}_{SH}^i \right)'_t, \text{ for each hemisphere.}$$

Exclude cyclical oscillation data and ocean heat content in orthogonalisation regression as unrelated to net heat flux.

Number of free parameters = 6044.

Selection conducted at $\alpha = 0.0001$.

- Under $H_0 \approx 60\%$ probability of retaining just 1 regressor if all were irrelevant, so little risk of overfitting. If a regressor is retained it will be highly significant ($\psi > 3.7$).
- Model reduction undertaken using tree search algorithm that ensures model is congruent at every reduction stage: Autometrics (Doornik, 2009) applied to unrestricted system.
- Expanding & contracting blocks used to search for relevant regressors, where expanding blocks ensure relevant regressors not eliminated if insignificant within a block but significant if correlated with regressors in other blocks.
- Mis-specification tests to ensure congruency.
- After reduction applied to unrestricted system, estimate simultaneous equation model, applying further reductions equation by equation at $\alpha = 0.01$.

Specification of GUM crucial to identifying well-specified model. Local data generating process (LDGP) must be nested within GUM to select a congruent model.

Implies all potentially relevant variables, non-linearities, interaction terms, breaks and outliers must be included at the outset.

Includes **seasonal fluctuations** (surface temperature, windspeed, latent heat, solar radiation, geopotential heights, downwards thermal, heat flux, cloud cover, albedo) and **cyclical variables** (El Niño, North Atlantic Oscillation, Atlantic Meridional Mode, Pacific-North American Pattern) capturing short run drivers of changes in SST, & **longer term anthropogenic trends in GHGs** (CO₂, nitrous oxide, methane) which feed through to increases in SST via air temperature and **adjustments through ocean heat content** from shallow oceans (0-700m depth) and deep oceans (700-2000m depth).

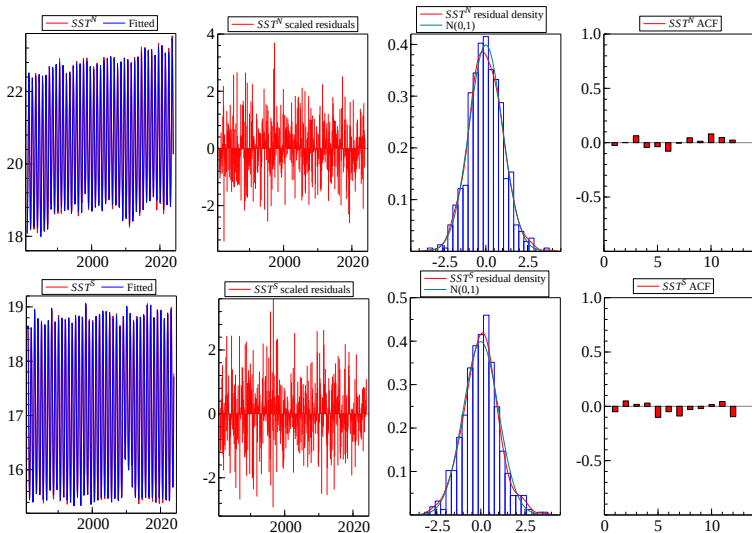
$$\begin{aligned}\widehat{SST}_t^N = & 71.2 + 0.65 SST_{t-1}^N + 0.23 SST_{t-12}^N - 0.09 SST_{t-4}^S + 1.76 \tilde{Q}_{sw,t}^N + 0.08 GHG_{t-8} \\ & - 0.07 \Delta_2 OHC_{700-2000,t-1} + 0.11 t_2 m_t^N - 18.3 gph_{500,t}^N + 254 albedo_t^N \\ & - 33.2 cloud_t^N + 23.9 (wind^N \times gph_{850}^N)_t + 0.03 Nino34_t + 0.007 AMM_t \\ & + 0.26 D_{peak} + 0.47 I_{1987(11)} - 0.35 I_{2009(2)} + 0.40 I_{2009(6)} \\ & (10.3) \quad (0.04) \quad (0.03) \quad (0.04) \quad (0.20) \quad (0.01) \\ & (0.03) \quad (0.01) \quad (2.41) \quad (23.1) \\ & (6.4) \quad (4.65) \quad (0.01) \quad (0.002) \\ & (0.02) \quad (0.03) \quad (0.01) \quad (0.02)\end{aligned}$$

$$\hat{\sigma}^N = 0.114$$

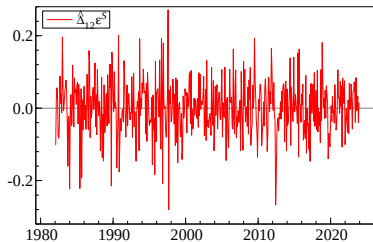
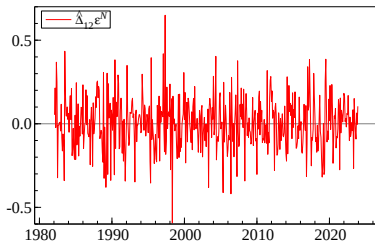
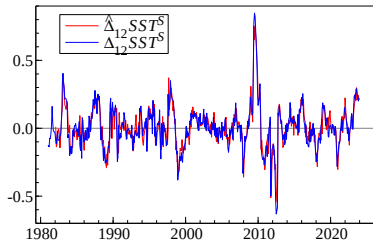
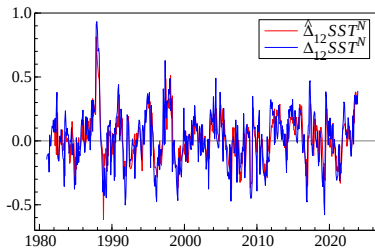
$$\begin{aligned}\widehat{SST}_t^S = & -15.1 + 0.83 SST_{t-1}^S + 0.07 SST_{t-11}^S - 0.04 SST_{t-5}^N + 0.25 \Delta SST_{t-12}^S \\ & - 0.14 \tilde{Q}_{LH,t}^S + 0.63 \tilde{Q}_{sw,t}^S + 0.03 GHG_t - 0.06 \Delta_2 OHC_{700-2000,t-1} + 0.10 t_2 m_t^S \\ & + 356 albedo_t^S - 206 cloud_t^S + 18.5 (wind^S \times mslp^S)_t + 2.84 (wind^S \times cloud^S)_t \\ & - 3.74 (wind^S \times gph_{500}^S)_t + 39.3 (cloud^S \times gph_{500}^S)_t - 22.1 (cloud^S \times gph_{850}^S)_t \\ & + 0.24 I_{1985(10)} + 0.10 D_{Nino} \\ & (4.20) \quad (0.02) \quad (0.03) \quad (0.01) \quad (0.04) \\ & (0.03) \quad (0.12) \quad (0.01) \quad (0.01) \quad (0.02) \\ & (28.7) \quad (22.4) \quad (1.59) \quad (0.77) \\ & (0.34) \quad (3.96) \quad (3.05) \\ & (0.01) \quad (0.002)\end{aligned}$$

$$\hat{\sigma}^S = 0.052; \quad ll = 1202; \quad \chi^2(33) = 46.2[0.06]; \quad T = 1981(2) - 2023(12). \quad (1)$$

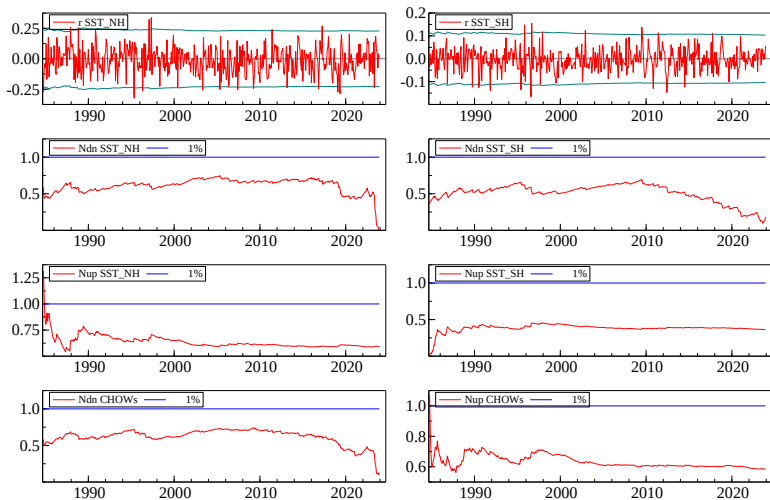
Model fit, residuals, residual density and residual autocorrelation function



Fitted model mapped to annual changes



Recursive parameter estimates



Disaggregating data by hemisphere is important as models differ: both depend on own hemisphere dynamics with small but negative feedback effects from other hemisphere.

Impact of GHGs on SST

GHGs positive & significant in both hemispheres.

Cannot impose constraint that impact of GHGs is same in both hemispheres ($\chi^2(34) = 72[0.0001]**$).

Enter contemporaneously in SH but with 8-month lag in NH.

Direct effect of emissions on SST rather than effect channelled via air temperature at 2m above surface.

Higher weight on **GHG** in NH where most emissions located, suggesting local effects of emissions on **SST** warming before mixing.

Radiative efficiency varies across gases: a 1 ppb increase in **GHG** implies 0.0008°C increase in **SSTⁿ** and 0.0003°C increase in **SST^s**.

Short-run impact is large and equilibrium response larger (for NH the static long-run coefficient is $0.69(0.28)$).

Northern hemisphere

Persistence drives SST with some moderation from SH.

Net shortwave radiation & albedo captures most seasonality.

Circulation via geopotential heights & clouds drive short-run impacts.

Non-linearity matters (circulation interacts with wind).

Cyclical remote modes also matter.

Warmer temperatures above the ocean drive warming oceans, which are somewhat moderated by deep ocean heat content which can absorb some of the additional energy via a difference term.

Peak temperatures are warmer than drivers imply & lead to higher variability.

Southern hemisphere

Model differs in short-run drivers but main determinants are common. Dynamics are highly significant (entering in levels and changes) with some moderation from northern hemisphere.

Latent heat flux & shortwave radiation, along with albedo drive short-run seasonality.

Wind and cloud interact with circulation in a non-linear specification.

Temperature above the ocean warms the ocean, with similar magnitude to that of NH.

Ocean heat content moderates rising surface temperature via a difference term, with similar magnitude to NH.

1-step ahead forecasts, 2020(1)-2023(12)

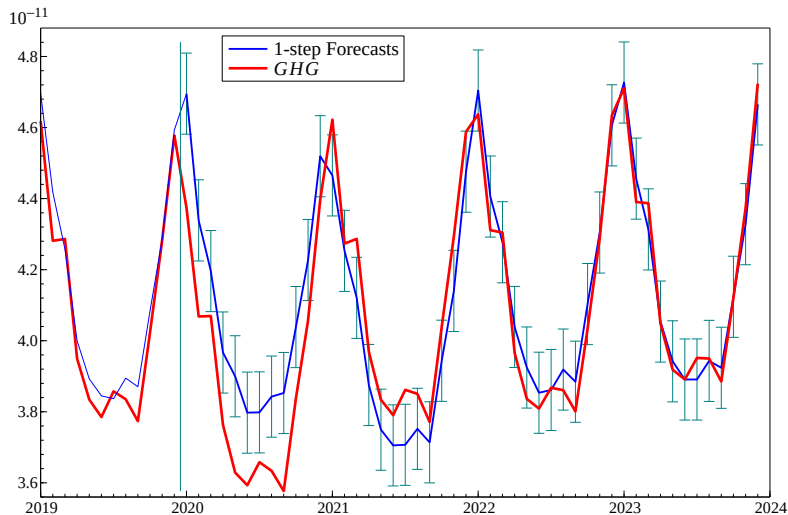


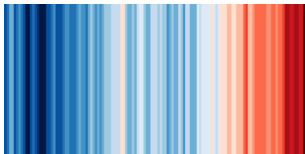
	Eq.(1)	$\widehat{\text{Eq.}(1)}$	SRW	SAR(1)	AR(12)	UC
			$SST_{T+j+1 T+j}^n$			
MAE	0.08	<i>0.09</i>	0.15	<i>0.09</i>	0.11	0.18
MAPE	0.40	0.44	0.73	<i>0.42</i>	0.55	0.89
RMSFE	0.10	<i>0.12</i>	0.19	0.13	0.14	0.21
			$SST_{T+j+1 T+j}^s$			
MAE	0.03	0.07	0.10	<i>0.04</i>	0.06	0.13
MAPE	0.18	0.41	0.59	<i>0.25</i>	0.35	0.77
RMSFE	0.04	0.09	0.14	<i>0.05</i>	0.08	0.15

Table: Bold indicates smallest value, and italic second smallest value.

Eq.(1) includes t -dated stochastic regressors. $\widehat{\text{Eq.}(1)}$: all t -dated variables forecast using an AR(12) model. For SH, need to forecast GHG. Poor forecasts over covid worsen $\widehat{\text{Eq.}(1)}$. Excluding 2020 and 2021, $\widehat{\text{Eq.}(1)}$ outperforms all univariate models.

1-step ahead forecasts for GHG using AR(12) model

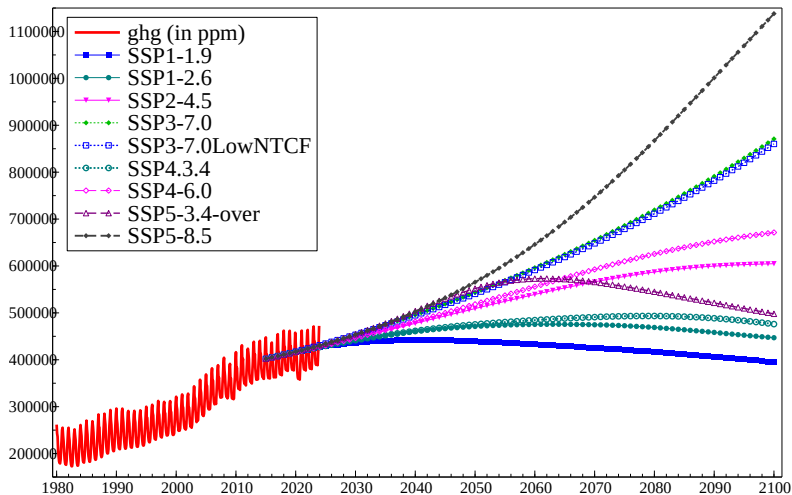




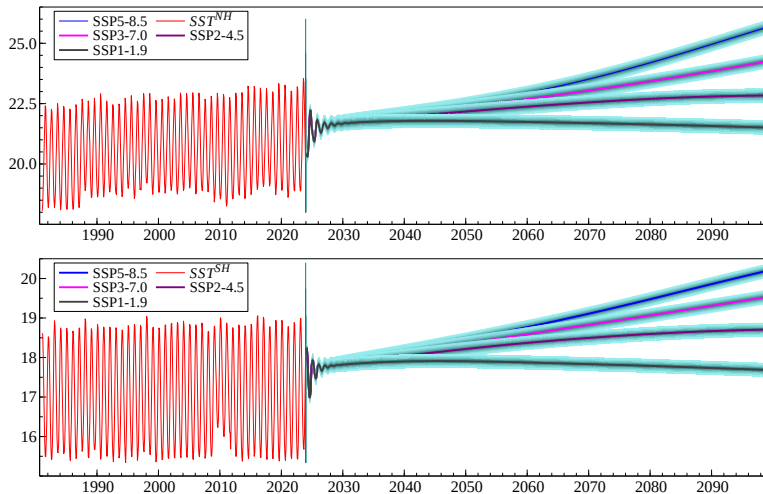
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- Condition on scenarios by imposing projections of carbon dioxide, methane and nitrous oxide from [Meinshausen et al. \(2020\)](#) which correspond to various SSPs.
- For long-run forecasts, seasonal & cyclical patterns less important, notwithstanding likely changes in seasonality & cyclicity as oceans warm. Set seasonal variables to 0 and cyclical variables to mean over last 4 years.
- Estimate model to 2023(12) & forecast 913 monthly observations to 2100.
- In SH, ΔSST_{t-12}^S estimated by including SST_{t-12}^S and SST_{t-13}^S and imposing constraint to ensure the difference term is endogenous and projected within the system.
- $t2m$ is based on the equivalent projections for surface air temperature as under the relevant SSP for GHG.

Combined emissions with projections from Meinshausen et al. (2020)



SSP projections to 2100



SSP projections to 2100 (°C)



		Central	+2SE	-2SE	Peak	Trough
1980	NH	20.2			22.4	18.2
1980	SH	17.0			18.7	15.3
2023	NH	21.0			23.5	18.9
2023	SH	17.3			19.0	15.7
2050						
SSP5-8.5	NH	22.5	22.8	22.1	25.0	20.3
	SH	18.5	18.7	18.2	20.2	16.8
SSP3-7.0	NH	22.4	22.7	22.0	24.9	20.2
	SH	18.4	18.6	18.1	20.1	16.7
SSP2-4.5	NH	22.2	22.5	21.8	24.7	20.0
	SH	18.2	18.4	18.0	20.0	16.6
SSP1-1.9	NH	21.8	22.1	21.4	24.3	19.6
	SH	17.9	18.1	17.7	19.7	16.2
2099						
SSP5-8.5	NH	25.7	26.0	25.3	28.2	23.5
	SH	20.2	20.4	20.0	22.0	18.5
SSP3-7.0	NH	24.3	24.6	23.9	26.8	22.1
	SH	19.5	19.7	19.3	21.3	17.9
SSP2-4.5	NH	22.8	23.2	22.5	25.4	20.7
	SH	18.7	18.9	18.5	20.5	17.0
SSP1-1.9	NH	21.5	21.9	21.2	24.0	19.4
	SH	17.7	17.9	17.5	19.5	16.0

SSP projections to 2100 (°C)

		Central	+2SE	-2SE	Peak	Trough
1980	NH	20.2			22.4	18.2
1980	SH	17.0			18.7	15.3
2023	NH	21.0			23.5	18.9
2023	SH	17.3			19.0	15.7
2050						
SSP5-8.5	NH	22.5	22.8	22.1	25.0	20.3
	SH	18.5	18.7	18.2	20.2	16.8
SSP3-7.0	NH	22.4	22.7	22.0	24.9	20.2
	SH	18.4	18.6	18.1	20.1	16.7
SSP2-4.5	NH	22.2	22.5	21.8	24.7	20.0
	SH	18.2	18.4	18.0	20.0	16.6
SSP1-1.9	NH	21.8	22.1	21.4	24.3	19.6
	SH	17.9	18.1	17.7	19.7	16.2
2099						
SSP5-8.5	NH	25.7	26.0	25.3	28.2	23.5
	SH	20.2	20.4	20.0	22.0	18.5
SSP3-7.0	NH	24.3	24.6	23.9	26.8	22.1
	SH	19.5	19.7	19.3	21.3	17.9
SSP2-4.5	NH	22.8	23.2	22.5	25.4	20.7
	SH	18.7	18.9	18.5	20.5	17.0
SSP1-1.9	NH	21.5	21.9	21.2	24.0	19.4
	SH	17.7	17.9	17.5	19.5	16.0

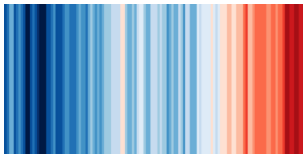
SSP projections to 2100 (°C)

		Central	+2SE	-2SE	Peak	Trough
1980	NH	20.2			22.4	18.2
1980	SH	17.0			18.7	15.3
2023	NH	21.0			23.5	18.9
2023	SH	17.3			19.0	15.7
2050						
SSP5-8.5	NH	22.5	22.8	22.1	25.0	20.3
	SH	18.5	18.7	18.2	20.2	16.8
SSP3-7.0	NH	22.4	22.7	22.0	24.9	20.2
	SH	18.4	18.6	18.1	20.1	16.7
SSP2-4.5	NH	22.2	22.5	21.8	24.7	20.0
	SH	18.2	18.4	18.0	20.0	16.6
SSP1-1.9	NH	21.8	22.1	21.4	24.3	19.6
	SH	17.9	18.1	17.7	19.7	16.2
2099						
SSP5-8.5	NH	25.7	26.0	25.3	28.2	23.5
	SH	20.2	20.4	20.0	22.0	18.5
SSP3-7.0	NH	24.3	24.6	23.9	26.8	22.1
	SH	19.5	19.7	19.3	21.3	17.9
SSP2-4.5	NH	22.8	23.2	22.5	25.4	20.7
	SH	18.7	18.9	18.5	20.5	17.0
SSP1-1.9	NH	21.5	21.9	21.2	24.0	19.4
	SH	17.7	17.9	17.5	19.5	16.0

Caveats to long-run projections imply uncertainty is much wider than error variance bands imply:

- Model accounts for non-stationarities within sample but extrapolate model assuming it is constant over next 77 years.
- Non-linearities over forecast horizon such as unmodelled tipping points add uncertainty.
- Deep ocean heat uptake needs careful modelling over very long time horizons, which may change redistribution.
- Sea ice will be a key factor in SH, as it is currently in NH, and will affect surface albedo.
- Potential weakening or shifting of currents and cloud feedbacks could also be non-linear.

While such long-run forecasts are highly uncertain, they point to the direct effect of GHG emissions on increasing sea surface temperatures.



- 1 Modelling approach and data
- 2 Econometric model of sea surface temperatures
- 3 Scenario Projections
- 4 **Conclusions**

Approach to modelling SST allows for all possible explanatory variables motivated by physical theory of heat exchange, including seasonal, cyclical and long-run drivers.

Clear and direct effect of GHGs on rising SSTs, by applying FWL to orthogonalise net heat flux and isolate GHGs.

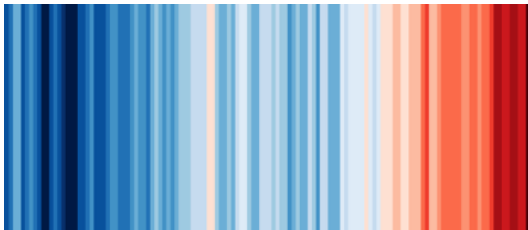
Emissions have stronger effect on SST in northern hemisphere.

Bivariate modelling allows for different dynamics and drivers across the two hemispheres while addressing their interactions.

Ex post forecasts demonstrate importance of conditional variables in predicting monthly sea surface temperatures.

Longer run projections highlight degree of persistence in rising temperatures. Averaging across the two hemispheres, the model SSP projections are close to the IPCC projections of a 0.86°C rise in under SSP1-2.6 and a 2.89°C rise in SST under SSP5-8.5 compared to the benchmark 1995-2014.

Thank You!



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