The Spatial Structure of Productivity, Trade, and Inequality: Evidence from the Global Climate

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Economic consequences of global phenomona

Global phenomena often produce heterogeneous local impacts

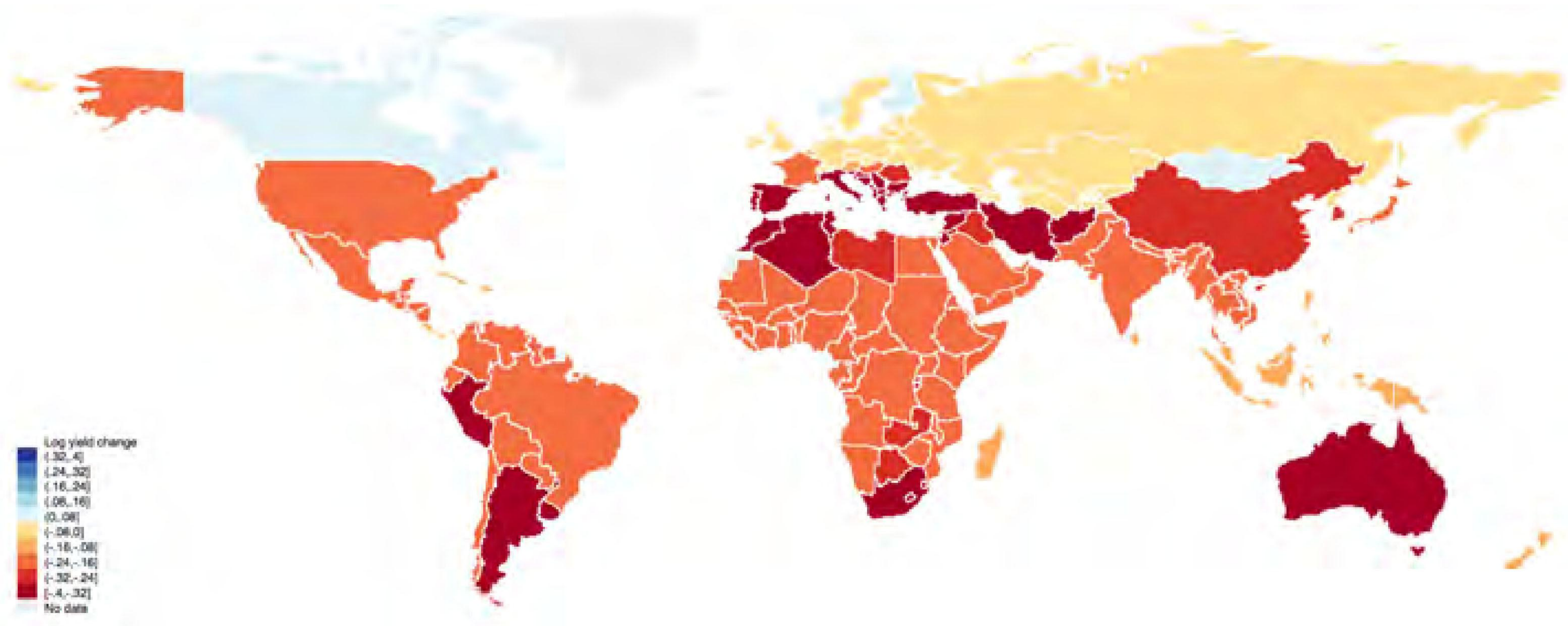
In some cases, heterogeneity exhibits spatial correlation: neighboring locations experience similar impacts

Sometimes called the "first law of geography" (Tobler, 1970)

Some spatially-correlated global events:

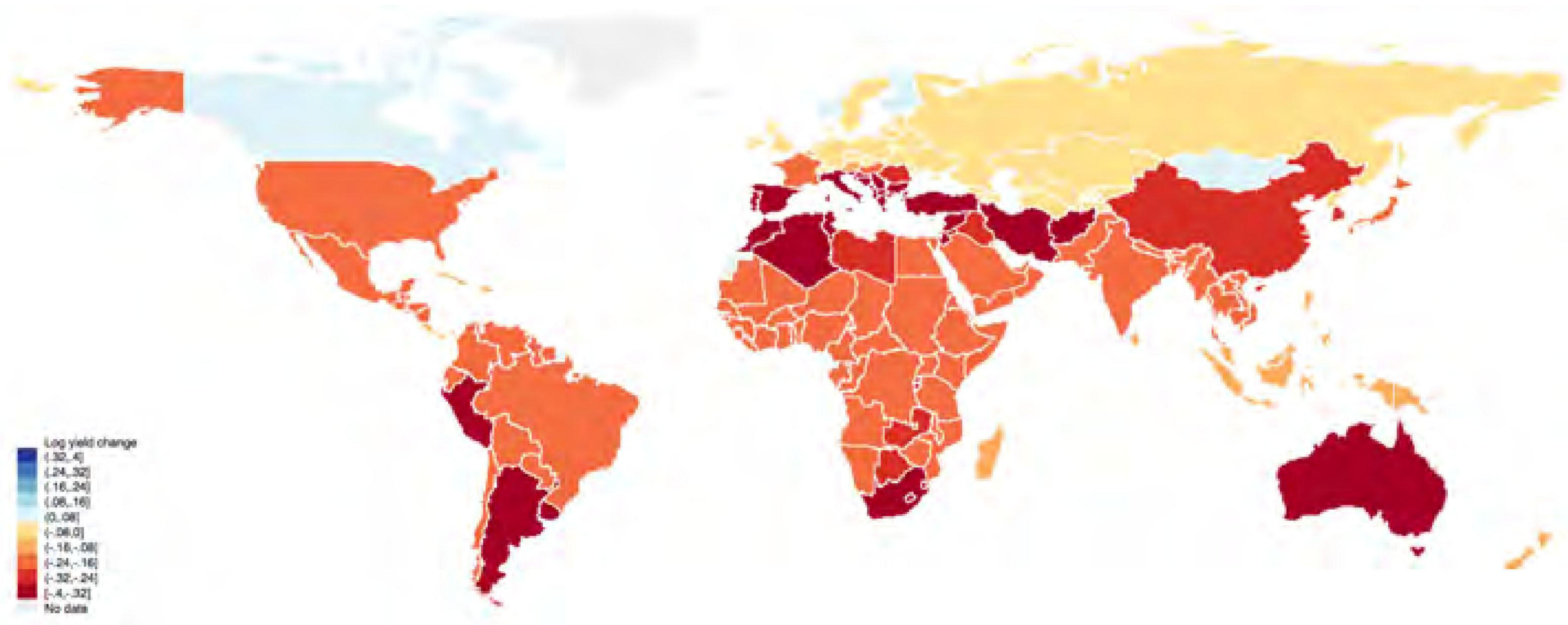
- Great Recession (Piskorski and Seru, 2018)
- Global food prices (McGuirk and Burke, 2020)
- Global pandemics (Barro et al., 2020; Dong et al., 2020)

Prime example: anthropogenic climate change



- Spatially-correlated footprint of local impacts
- Greater losses in tropics
- Smaller losses/gains in mid-latitudes

Prime example: anthropogenic climate change



A full account of global climate impacts requires estimating:

1. local productivity effects (i.e. partial equilibrium)
2. global trade effects (i.e. general equilibrium)

Current approaches

Quasi-experimental:

Quasi-experimental climate impact estimates directly relate local temperature to local outcomes, ignoring temperatures elsewhere

Projected global CC impact: sum of each location's impact under isolated warming

Like asking: what if Kenya warmed by itself, independent of concurrent warming in Congo, Sweden, or US?

Overlooks global nature of climate change

Structural:

Quantify indirect effects by imposing functional form assumptions of trade models

Our approach:

Incorporate spatial linkages in climate impact projections using quasi-experimental variation without imposing full structure of trade models

Overview: Paper in 3 parts

1. Theoretically demonstrate that increasing spatial correlation of productivities increases global welfare inequality across a trading network
2. Empirically validate general-equilibrium prediction by examining the last five decades of global agricultural trade driven by a global climatic phenomenon
3. Augment standard quasi-experimental climate impact projections to include this general equilibrium effect

Part 1: Theory

In standard trade models, a country gains more from trade when partners are

1. more productive, and
2. physically closer

Increased spatial correlation makes neighbors more similar:

- high productivity countries gain more from trade by being near other high productivity countries
- low productivity countries gain less from trade by being near other low productivity countries

Implications:

- Across a broad class of trade models, greater spatial correlation of productivities increases global welfare inequality

Part 2: Empirical validation

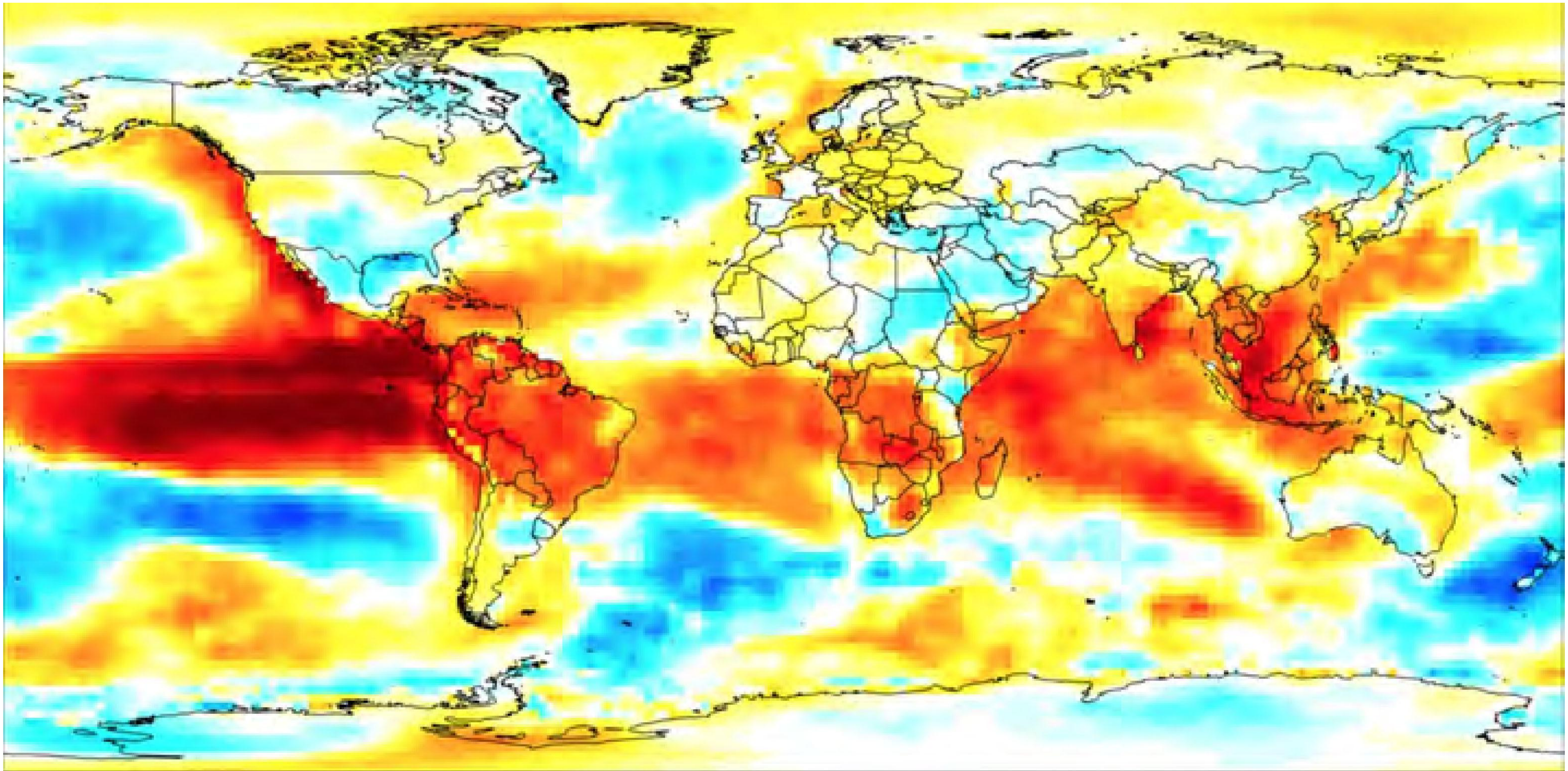
Challenges with identifying a global GE effect

- Prediction about a counterfactual for the entire global economy
- Need exogenous variation affecting spatial structure of productivities at a global scale

Our solution:

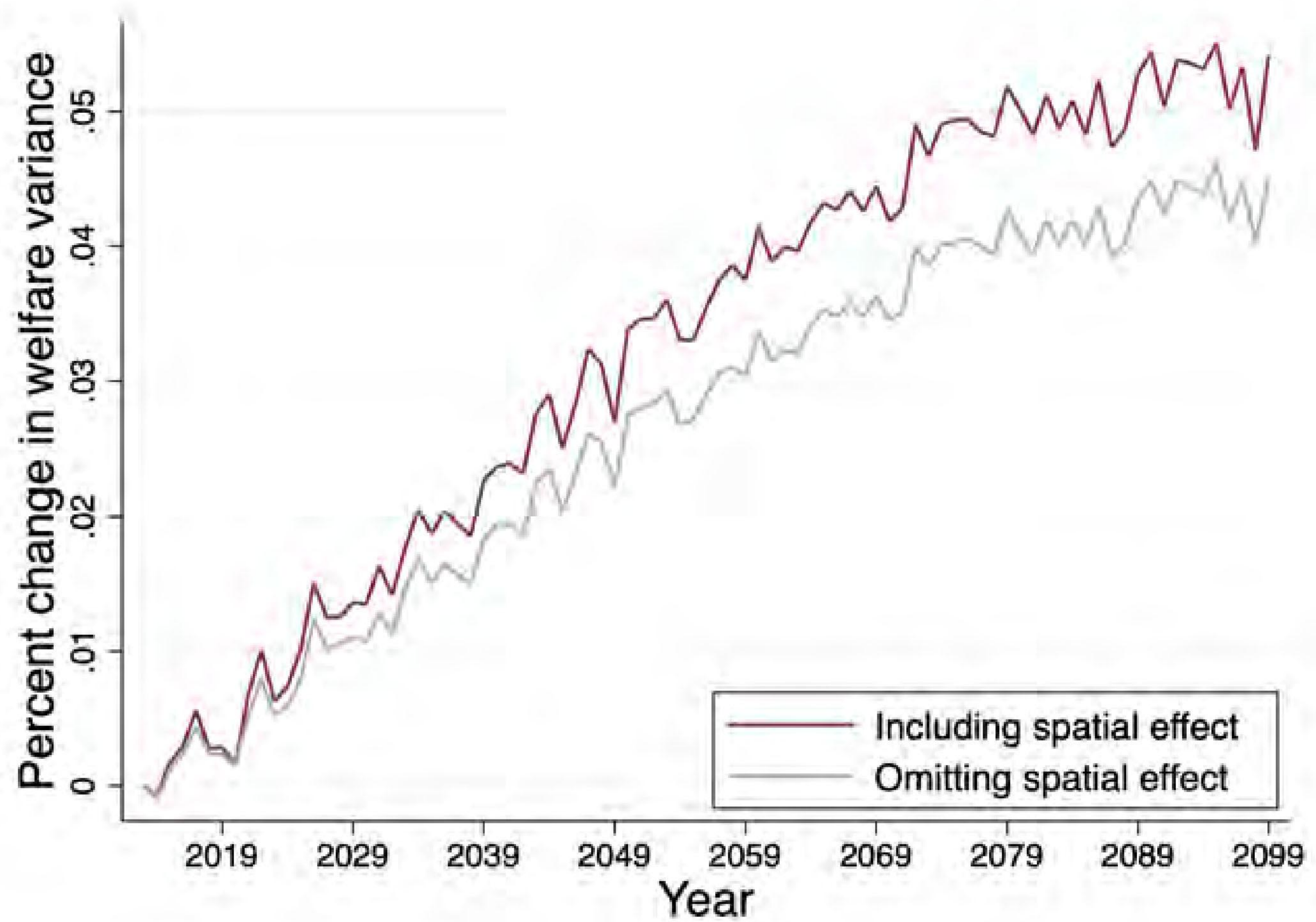
- Global natural experiment: El Niño-Southern Oscillation (ENSO)
- ENSO alters local temperatures in a way that increases global spatial correlation in agricultural productivity, holding mean and variance fixed.

Part 2: Empirical validation



- Over 1961-2013, 1 s.d. increase in spatial correlation of agricultural productivities → 2% increase in welfare variance

Part 3: Climate change application



- Incorporate GE prediction into standard quasi-experimental climate impact estimation, without imposing full structure of trade model
- 20% greater change in global welfare inequality by 2099 under climate change when including changes to spatial correlation in agricultural productivity
- Higher losses in most African countries

Related work

Geography

- Local natural resources associated with local outcomes (Sachs and Warner, 1997; Easterly and Levine, 2003), via productivity (Nordhaus, 2006; Bleakley, 2007), institutions (Nunn and Puga, 2012), investments (Burchfield et al., 2006)

International trade

- We articulate and empirically examine role of spatial correlation using Arkolakis, Costinot and Rodríguez-Clare (2012) sufficient statistic for gains from trade
- Costinot, Donaldson and Smith (2016) examine consequences of predicted shifts in comparative advantage across different crops due to climate change

Inequality under climate change

- Bring reduced-form climate impacts lit. (Dell, Jones and Olken, 2012; Burke, Hsiang and Miguel, 2015; Burgess et al., 2014; Houser et al., 2015) conceptually closer to macro/GE approaches (Brock, Engström and Xepapadeas, 2014; Desmet and Rossi-Hansberg, 2015; Krusell and Smith, 2016; Costinot, Donaldson and Smith, 2016)

1. Theoretical framework
2. The El Niño-Southern Oscillation
3. Empirics
4. Application: Inequality under future climate change
5. Conclusions

Theoretical framework

Welfare variance across a trading network

Welfare = autarky welfare + gains from trade

In a broad class of trade models (Arkolakis, Costinot and Rodríguez-Clare, 2012):

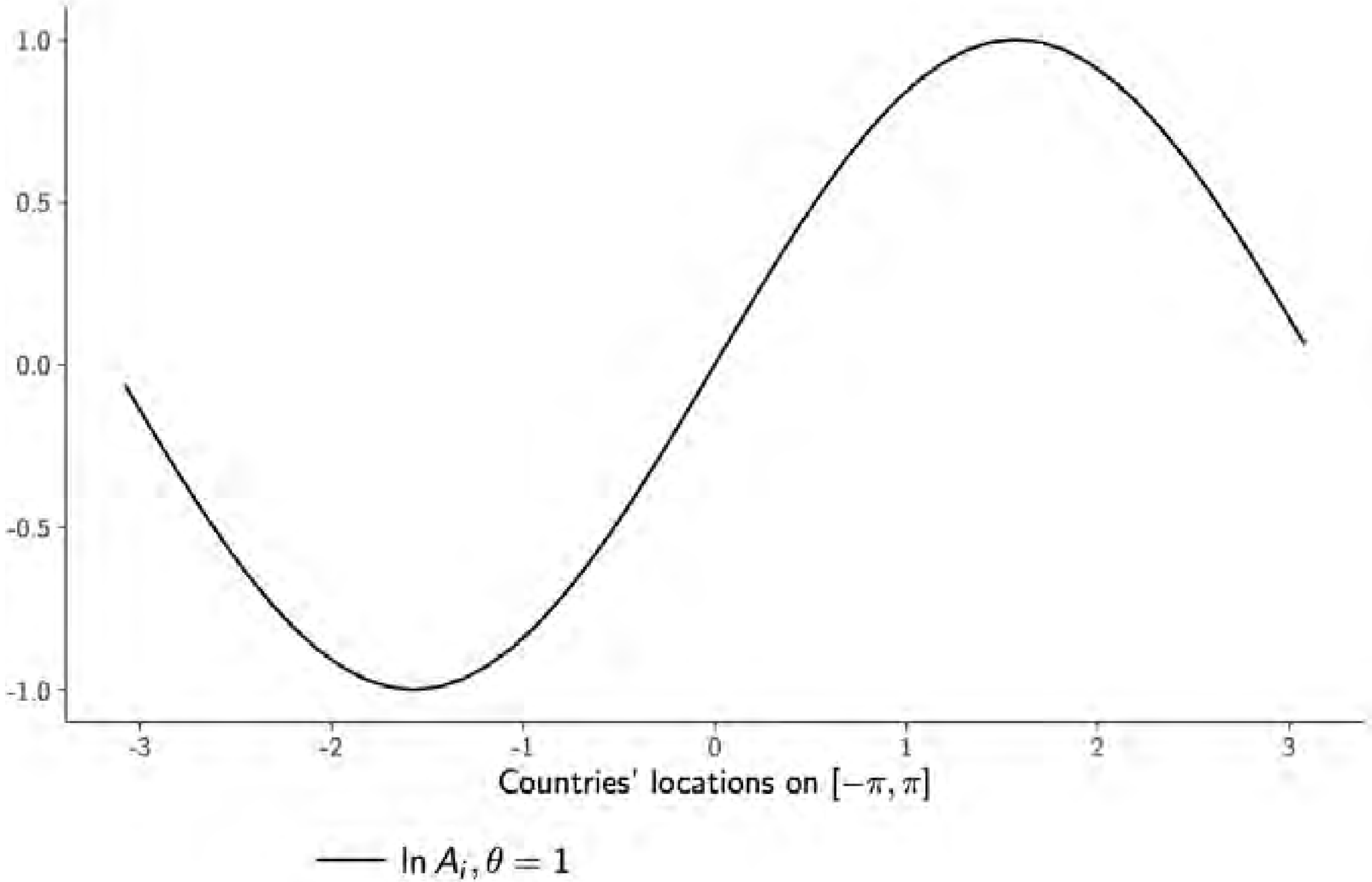
ACR primitives

$$\underbrace{\ln\left(C_i/L_i\right)}_{welfare} = \underbrace{\underbrace{\ln A_i}_{\text{productivity}} + \underbrace{\gamma}_{micro-foundation}}_{\text{autarky welfare}} \underbrace{- \underbrace{\frac{1}{\epsilon}}_{\text{trade elasticity}} \underbrace{\ln \lambda_{ii}}_{\text{domestic share}}}_{\text{gains from trade}}$$

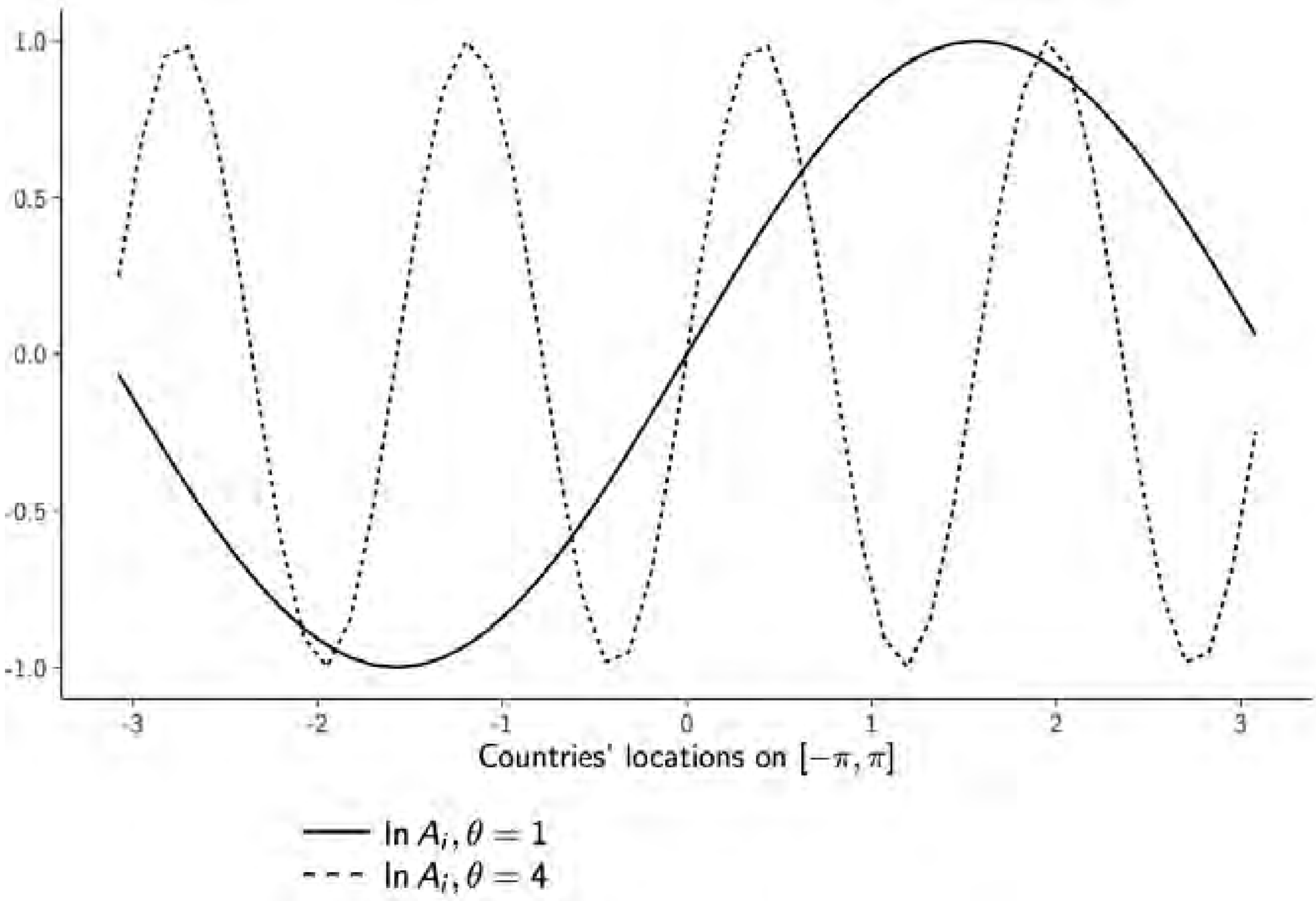
Global welfare variance across countries:

$$var\left(\ln\left(C_i/L_i\right)\right) = var\left(\ln A_i\right) + 2\, cov\left(\ln A_i, -\tfrac{1}{\epsilon}\ln \lambda_{ii}\right) + \frac{1}{\epsilon^2} var\left(\ln \lambda_{ii}\right)$$

What is spatial correlation? sine-wave circular economy



What is spatial correlation? sine-wave circular economy



Spatial correlation and gains from trade

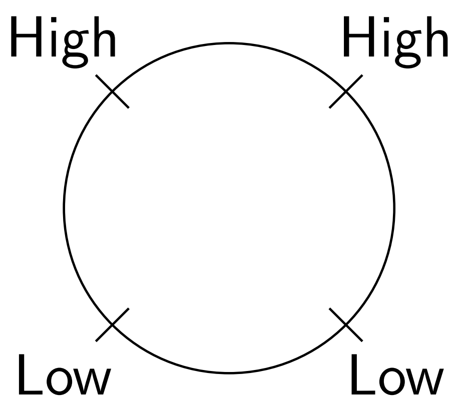
- A country gains more from trade when trading partners are more productive
- Dist.-related trade costs $\rightarrow$ larger gains with when more prod. partners closer
- Neighbors more similar under greater spatial correlation:
  - high productivity countries gain more from trade by being near other high productivity countries
  - low productivity countries gain less from trade by being near other low productivity countries
- Greater spatial correlation raises inequality by increasing $cov\left(\ln A_i, -\frac{1}{\epsilon}\ln \lambda_{ii}\right)$, or decreasing $cov\left(\ln A_i, \ln \lambda_{ii}\right)$

Standard measure of spatial correlation, Moran's I:

$$I = \frac{N}{\sum_i \sum_{j\neq i} w_{ij}} \frac{\sum_i \sum_{j\neq i} w_{ij}\left(\ln A_i - \overline{\ln A}\right)\left(\ln A_j - \overline{\ln A}\right)}{\sum_\ell \left(\ln A_\ell - \overline{\ln A}\right)^2}, \quad \frac{dw_{ij}}{d\mathrm{dist}_{ij}} < 0, \; w_{ii} = 0$$

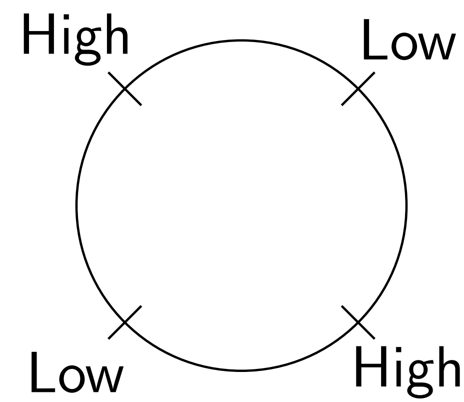
Simplest example: 4 countries on a circle, 2 states

$N = 4$, $L_i = L \ \forall i$, $\epsilon \geq 1$, productivity is high or low. Two states:



$$\tau \equiv \begin{bmatrix} 1 & d_1 & d_2 & d_1 \\ d_1 & 1 & d_1 & d_2 \\ d_2 & d_1 & 1 & d_1 \\ d_1 & d_2 & d_1 & 1 \end{bmatrix}$$

$$1 < d_1 < d_2 < d_1^2$$



Proposition (Four-country case)

Comparing productivity distributions $A_c = (\tilde{a}, \tilde{a}, 1, 1)$ *and* $A_u = (\tilde{a}, 1, \tilde{a}, 1)$, $\tilde{a} > 1$,

- $\ln A^c$ *is more spatially correlated than* $\ln A^u$ *in that* $I(\ln A^c) > I(\ln A^u)$
- $cov(\ln A_i^c, \ln \lambda_{ii}^c) < cov(\ln A_i^u, \ln \lambda_{ii}^u)$.
- *The variance of welfare across counties is greater for the more spatially correlated productivity distribution:* $var(\ln(C_i^c/L)) > var(\ln(C_i^u/L))$.

More realistic models

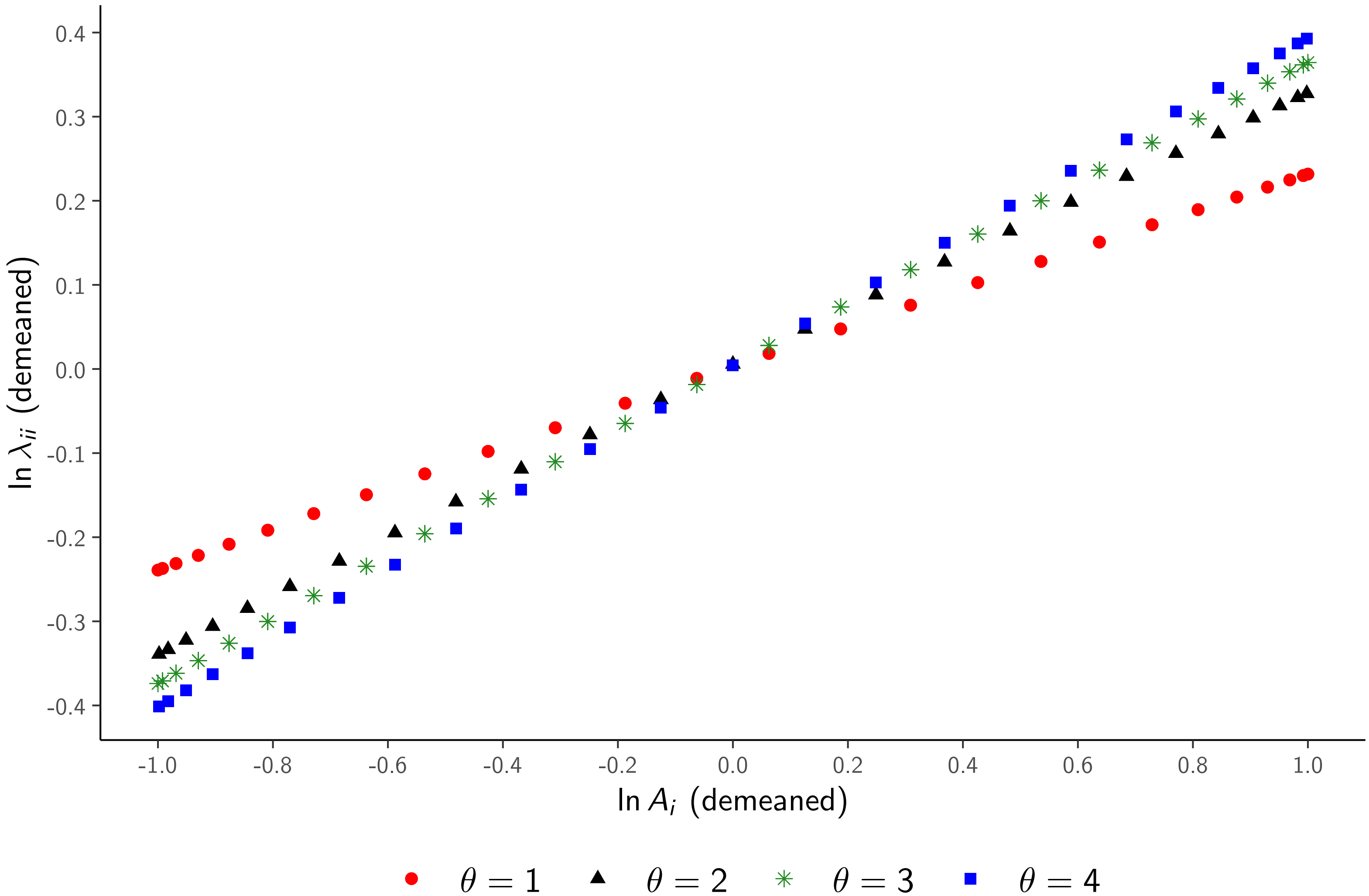
Compared to real world, 4-country, 2-state, circular example missing...

1. many countries, many states
2. heterogeneity in country size
3. arbitrary productivity distributions
4. 2-D geography with observed geography
5. multiple sectors

For each extension:

- use simulations to demonstrate that prediction holds
- discuss implications for empirical tests

Sine-wave circular economy w/ uniform countries



Mean and variance table

Implication for empirics:

$$\ln \lambda_{iit} = \beta_0 \ln A_{it} + \beta_1 \ln A_{it}\theta_t + \pi^T + \epsilon_{it}$$

More realistic models

Compared to real world, 4-country, 2-state, circular example missing...

1. many countries, many states
2. **heterogeneity in country size**

   Implication: country fixed effects
3. **arbitrary productivity distributions**

   Implication: Spatial correlation captured by Moran's I
4. **2-D geography with observed geography**

   Implication: Effect is linear in Moran's I
5. **multiple sectors**

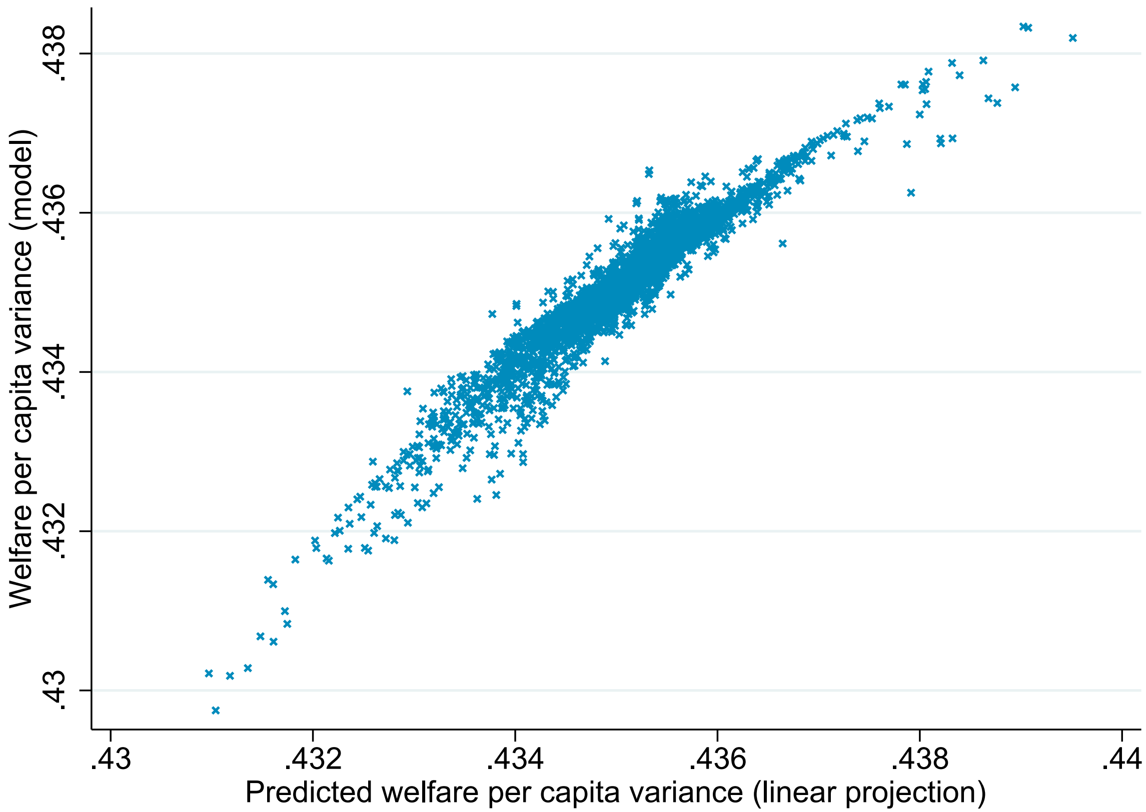
   Implication: Sufficient to look at 1 sector provided productivity are not strongly anti-correlated. 1-sector effect is upper bound on total wefare effect

From theory to empirics

Theory-implied estimating equation:

$$\ln \lambda_{iit} = \beta_0 \ln A_{it} + \beta_1 \ln A_{it} I_t + \pi_i^I + \pi_t^T + \epsilon_{it}$$

- Reduced-form eqn. captures 93% of welfare variance from quant. trade model
- Enables reduced-form empirical test without imposing trade model structure
- **Interpretation:** $\widehat{\beta}_1 < 0 \iff var\left(\ln\left(C_i^c / L_i\right)\right) - var\left(\ln\left(C_i^u / L_i\right)\right)$



From theory to empirics

Remaining identification challenge

- Productivity may still be endogenous to expenditure shares if unobserved:
  1. trade cost shocks affect imported intermediate goods
  2. demand shocks elicit supply responses
- Ideal (impossible) experiment: exogenously reshuffle global productivities to alter its spatial correlation

Solution: a global natural experiment

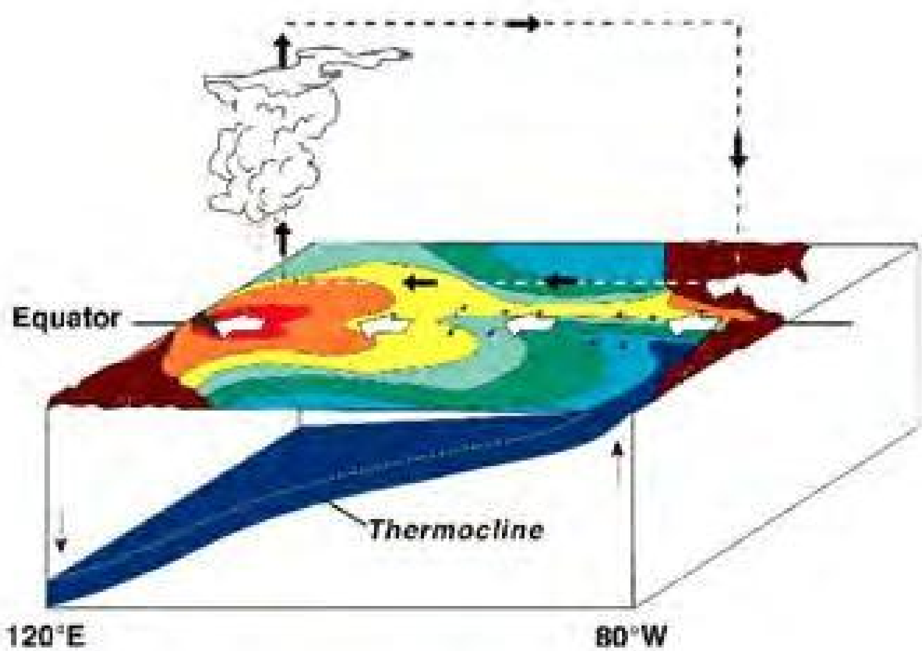
- El Niño-Southern Oscillation (ENSO)

The El Niño-Southern Oscillation (ENSO)

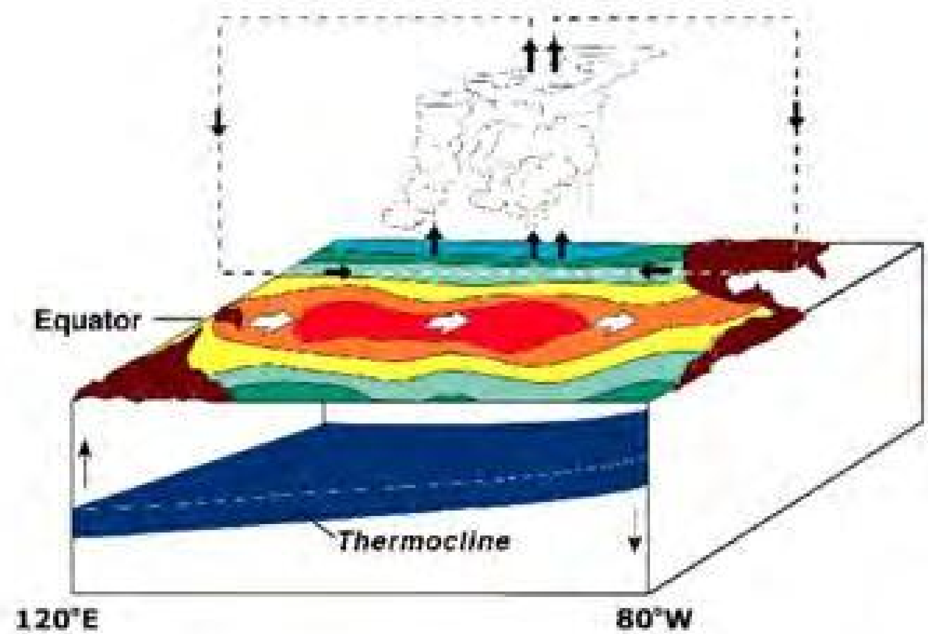
What is ENSO?

Dominant natural year-to-year driver of the global climate

Quasi-periodic (3-7 years) release of heat from the tropical Pacific driven by instabilities in the coupled ocean-atmosphere circulation



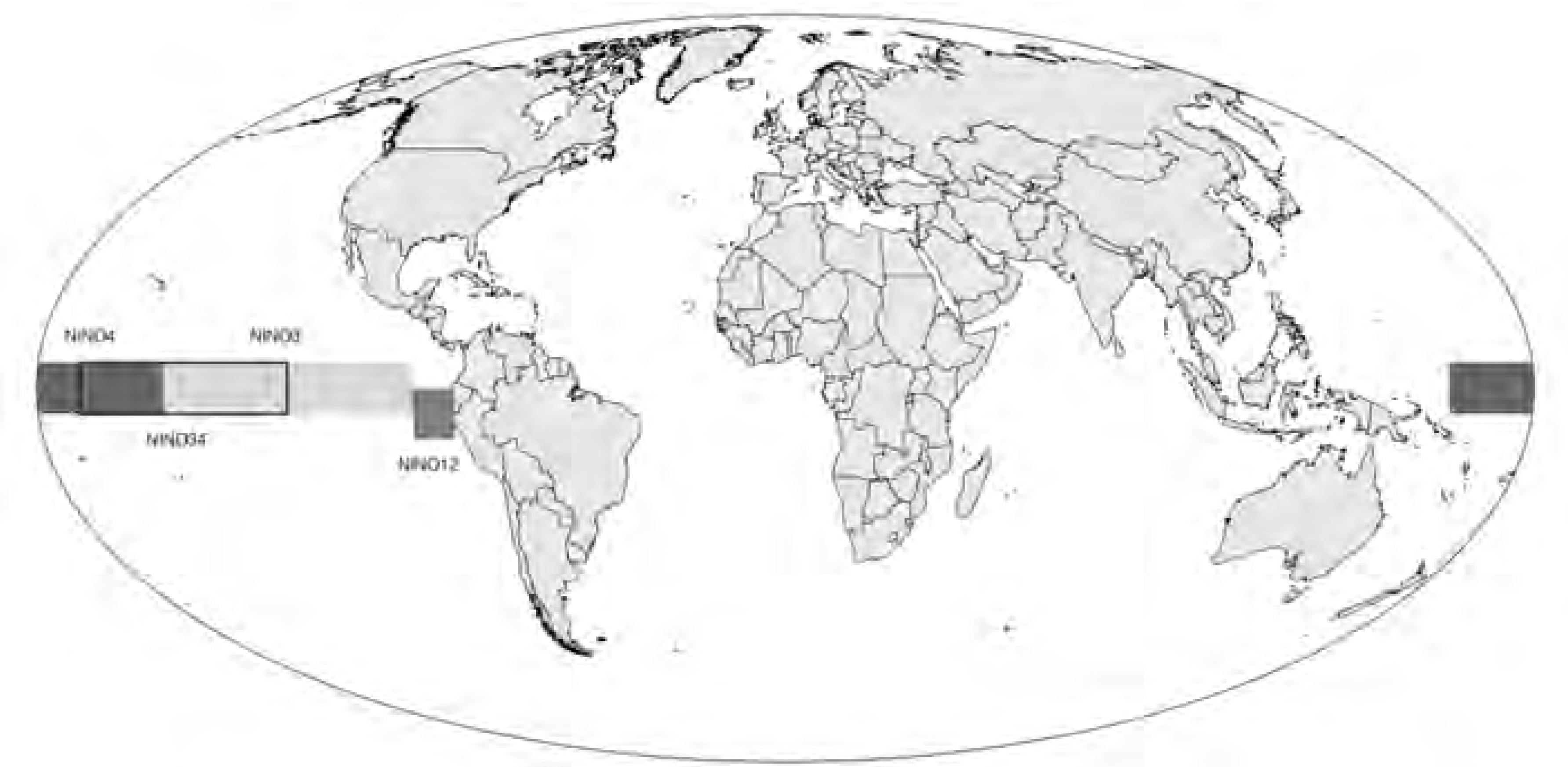
La Niña



El Niño

ENSO index

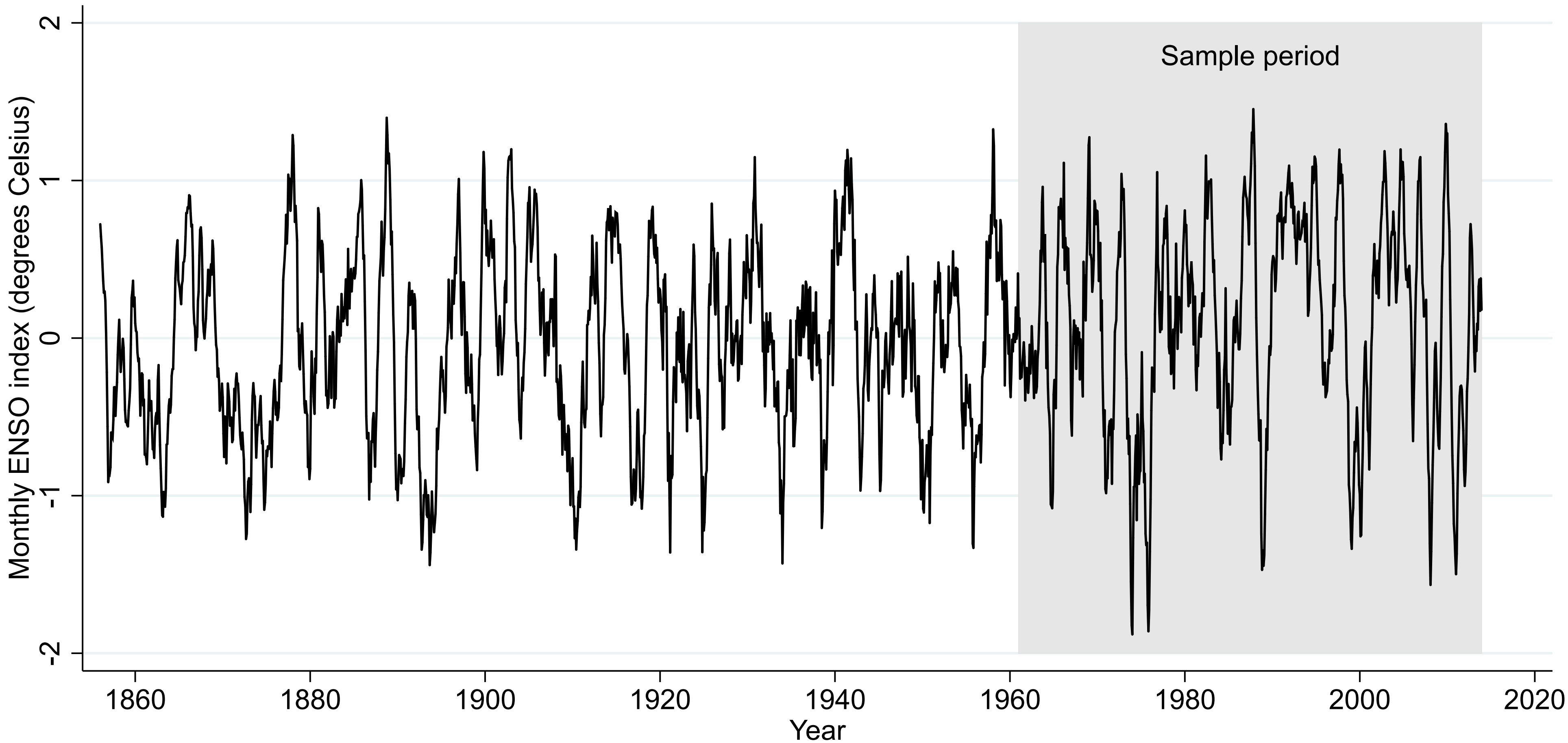
Summarized by average sea surface temperatures in the tropical Pacific Ocean.



Key features:

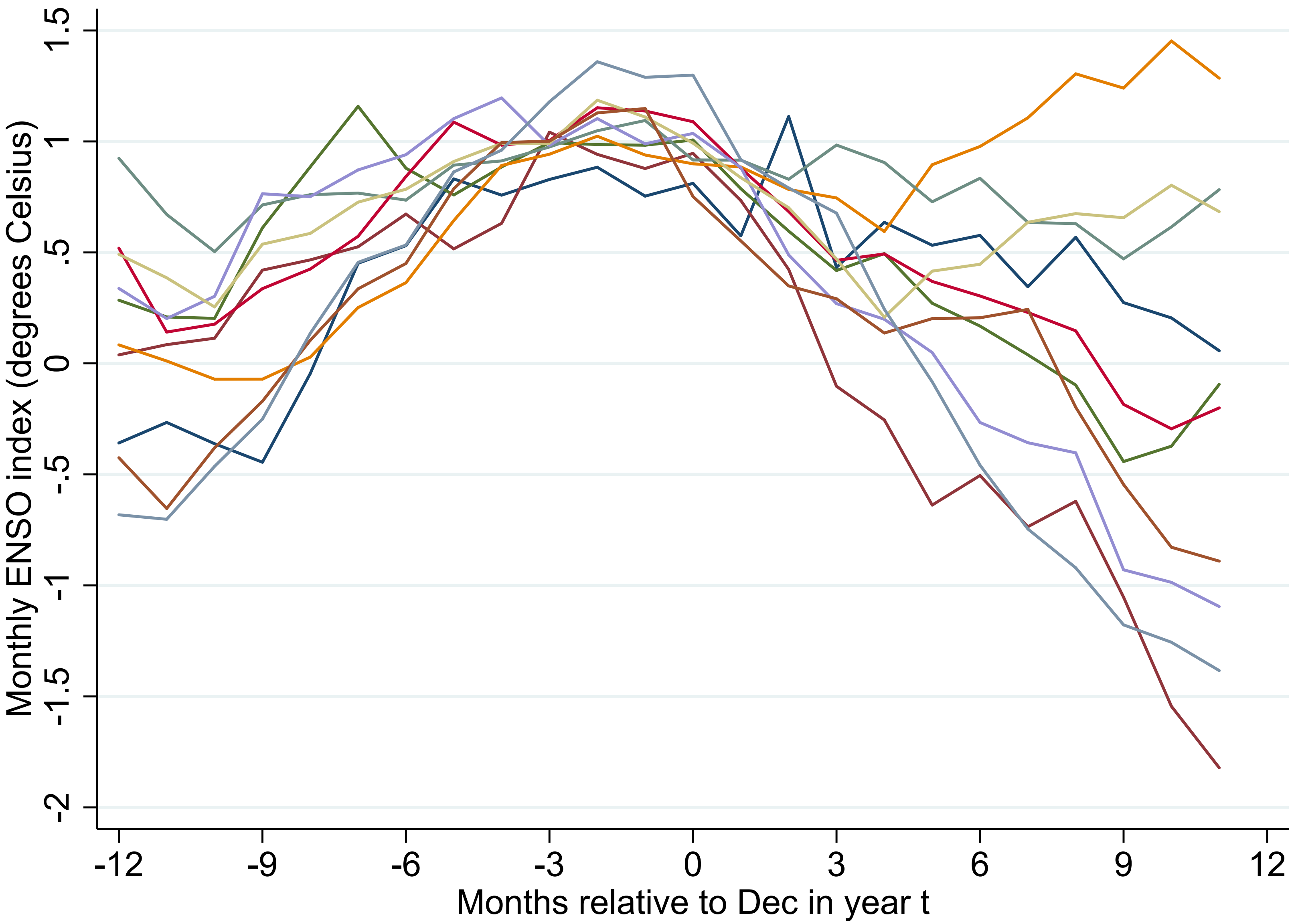
- Cleanest annual measure is ENSO index in December
- ENSO local temperature impacts spans May to May “tropical year”
- Increases global spatial correlation of agricultural prod., not mean or variance

ENSO index time series (1856-2013)



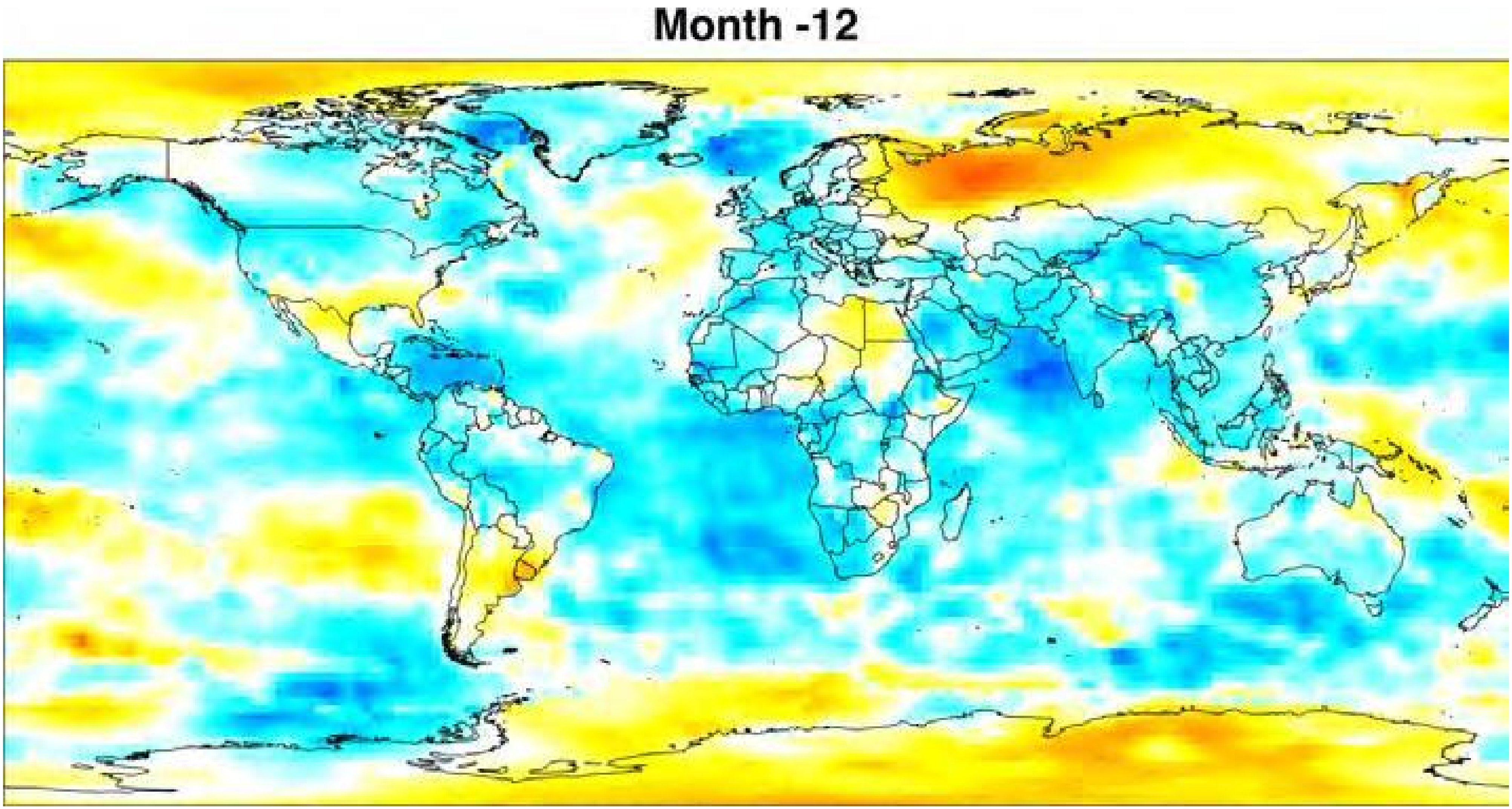
NOTES: Monthly ENSO index (NINO4) during 1856-2013. Shaded area shows sample period of analysis covering 1961-2013.

Monthly ENSO index for top 10 positive events



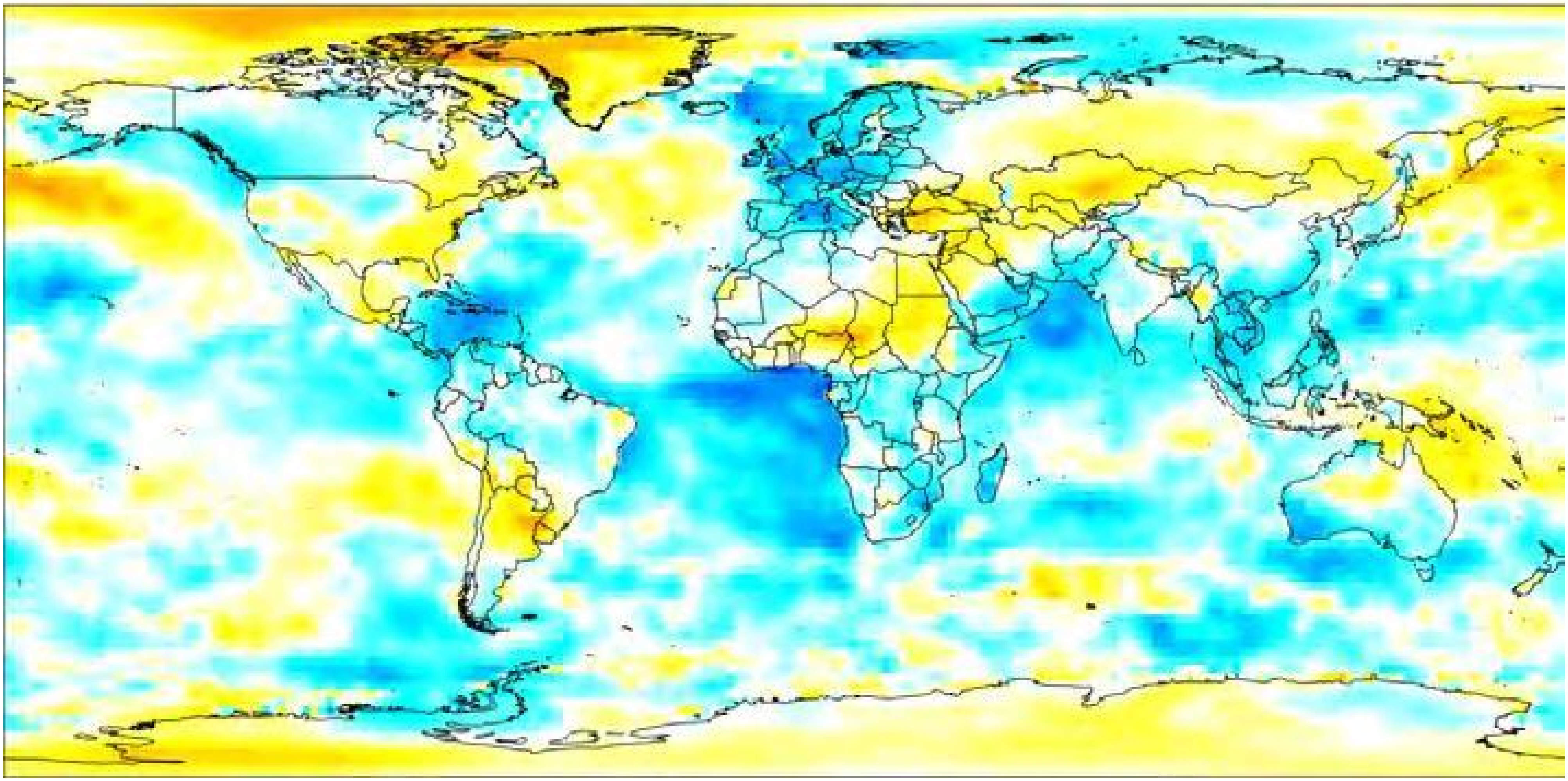
NOTES: Monthly evolution of ENSO index 12 months before and after the 10 most positive ENSO events over 1961-2013. ENSO events during the winters of 1965, 1972, 1982, 1986, 1991, 1994, 1997, 2002, 2006, and 2009.

Timing of ENSO's local temperature effects



Timing of ENSO's local temperature effects

Month -11



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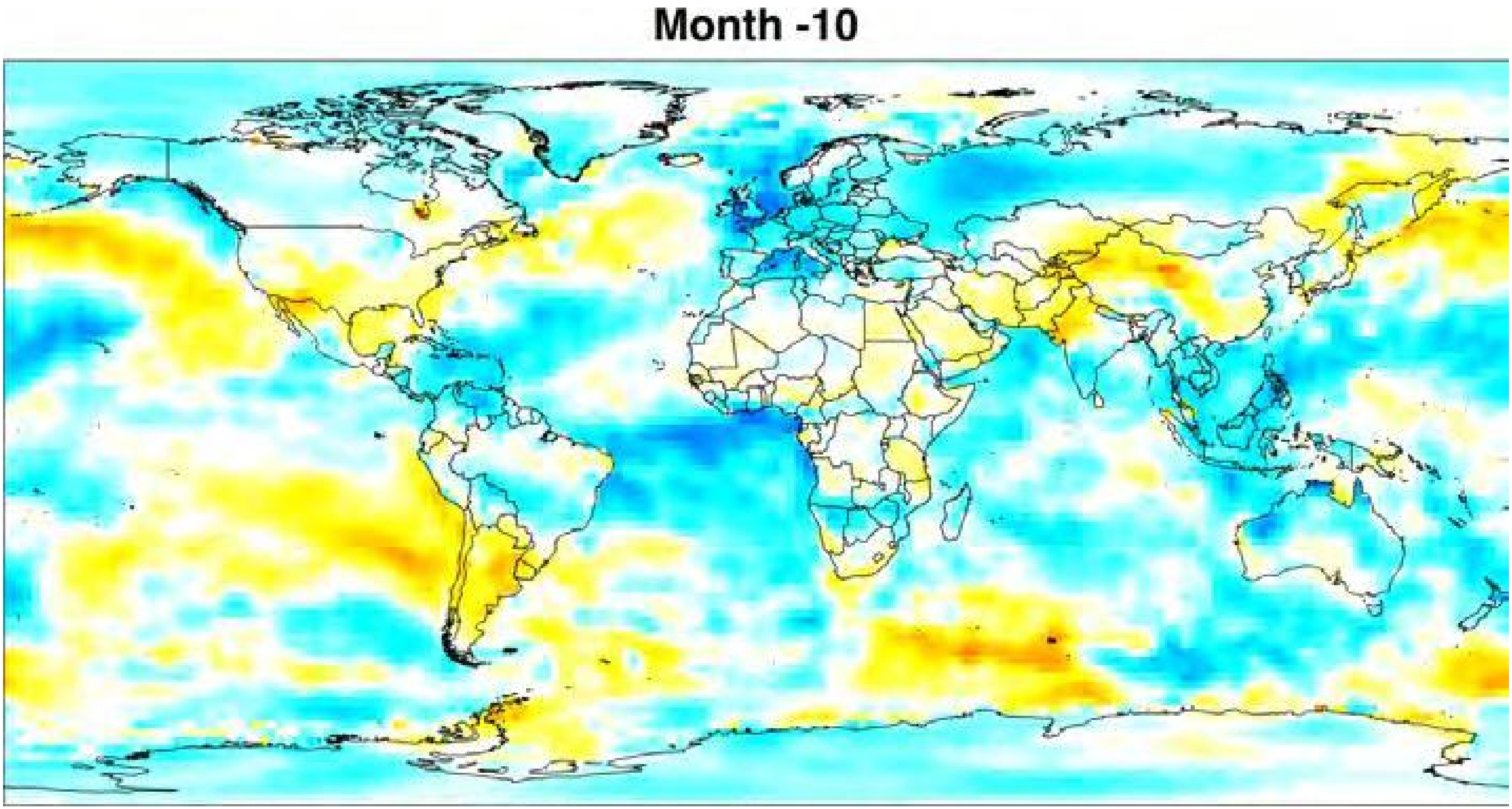

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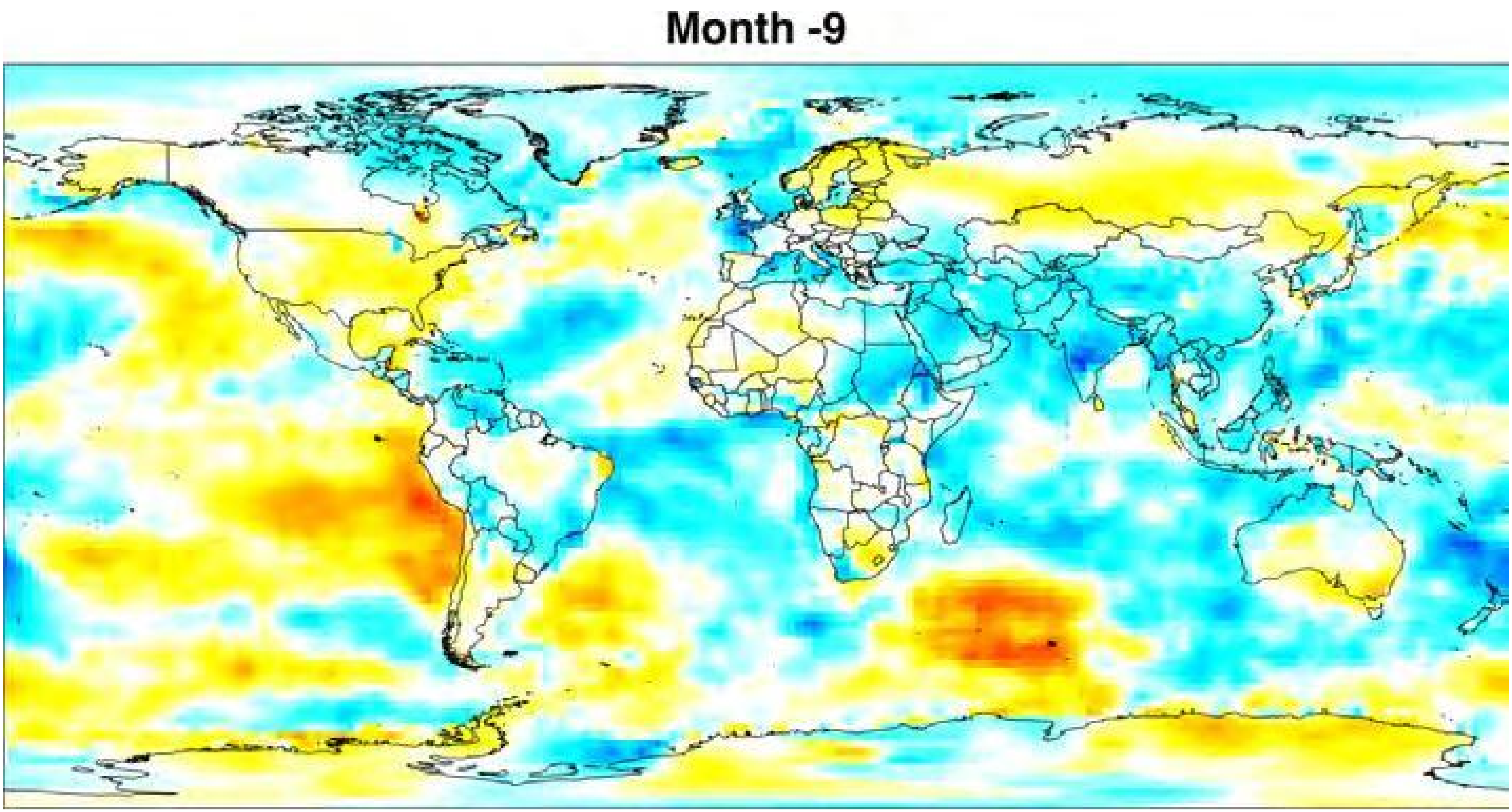

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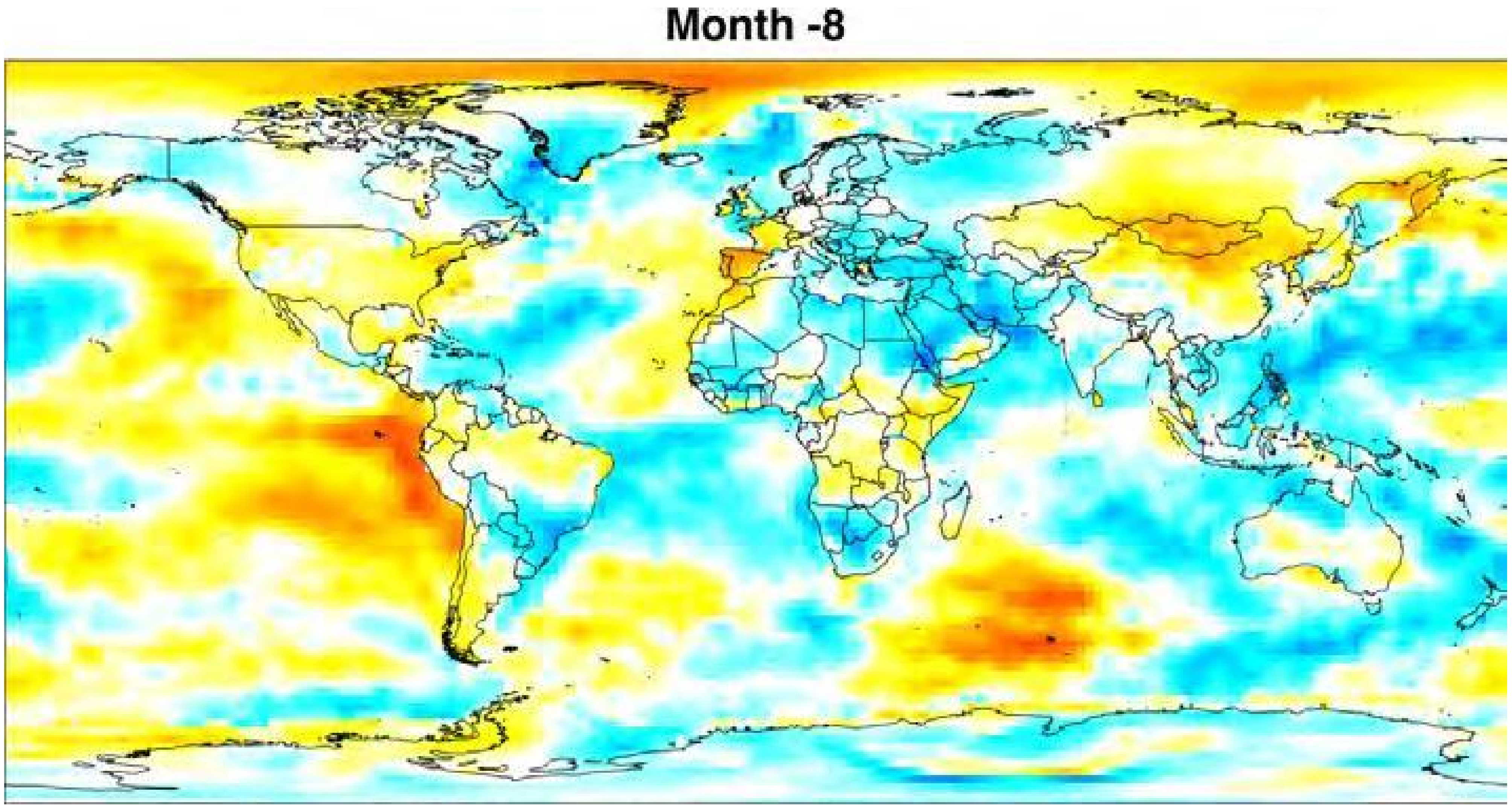

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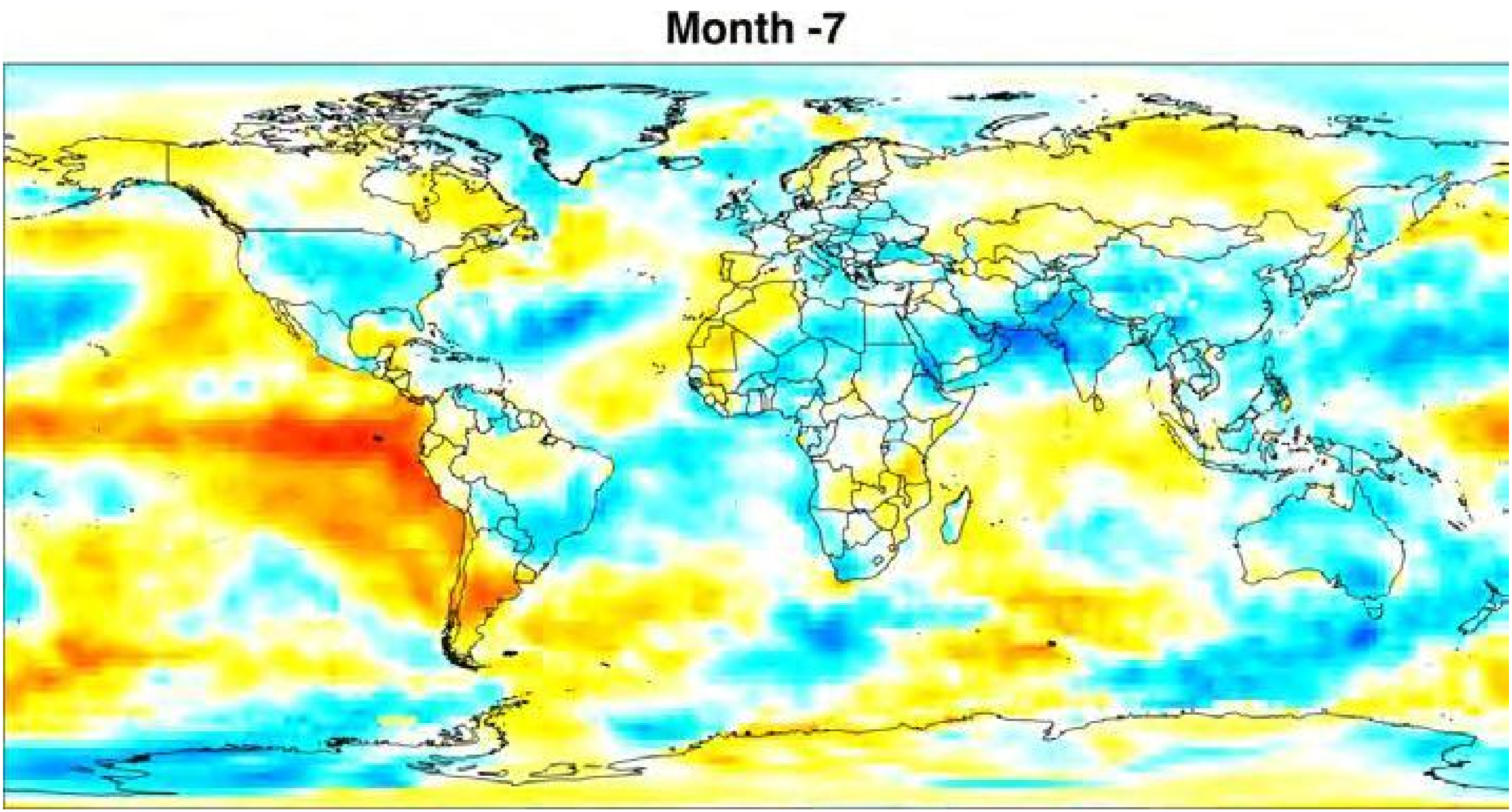

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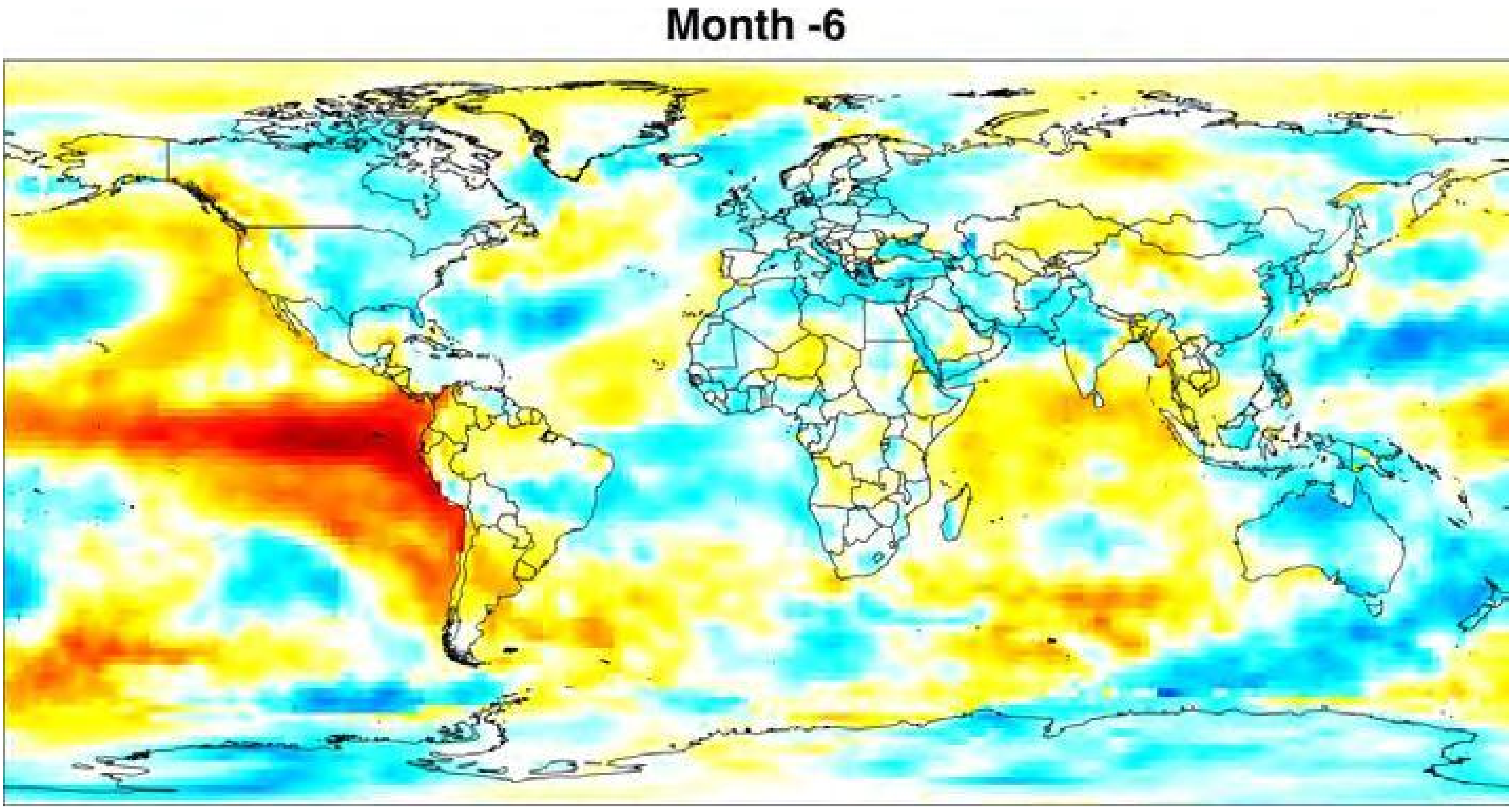

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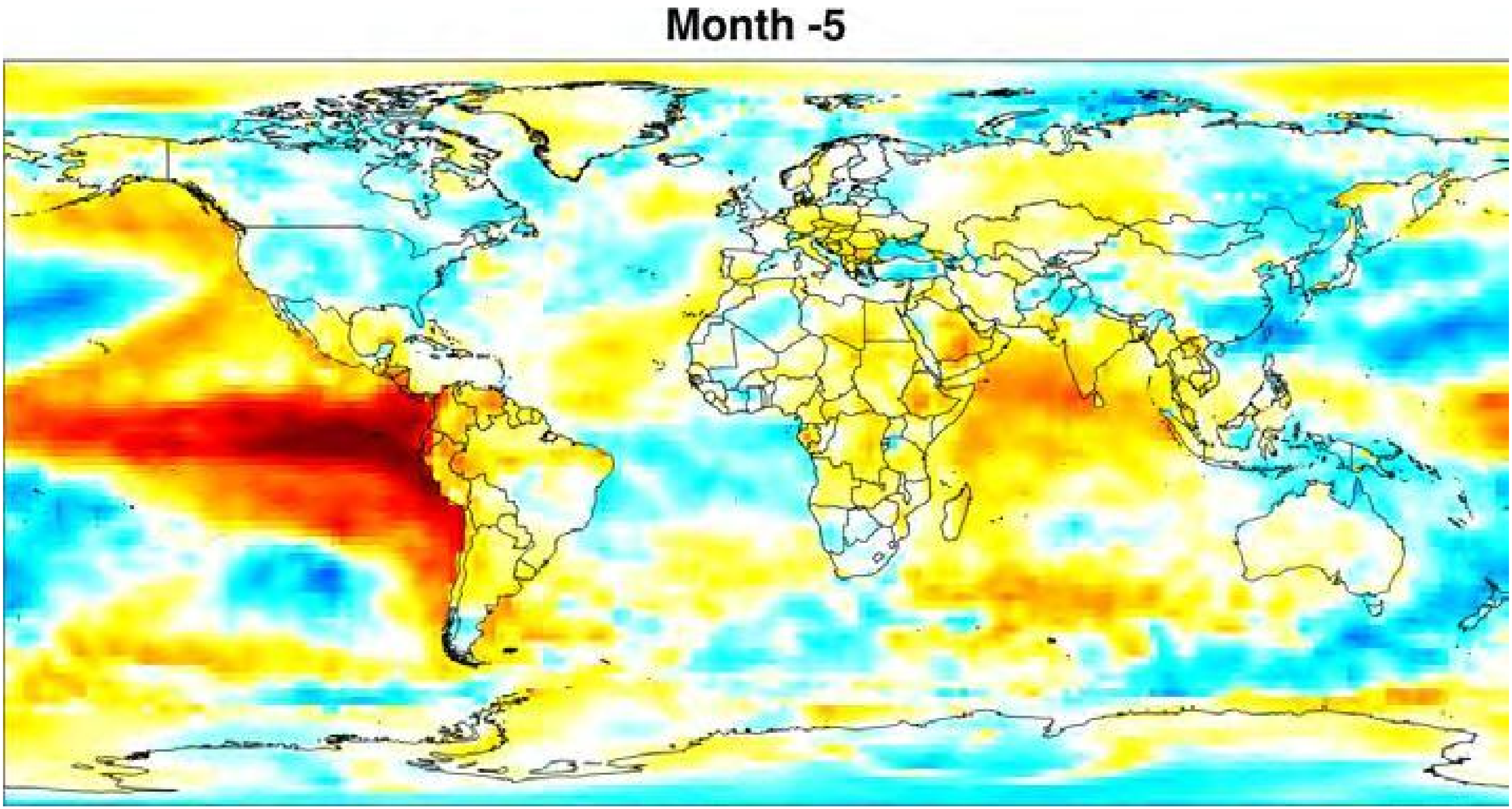

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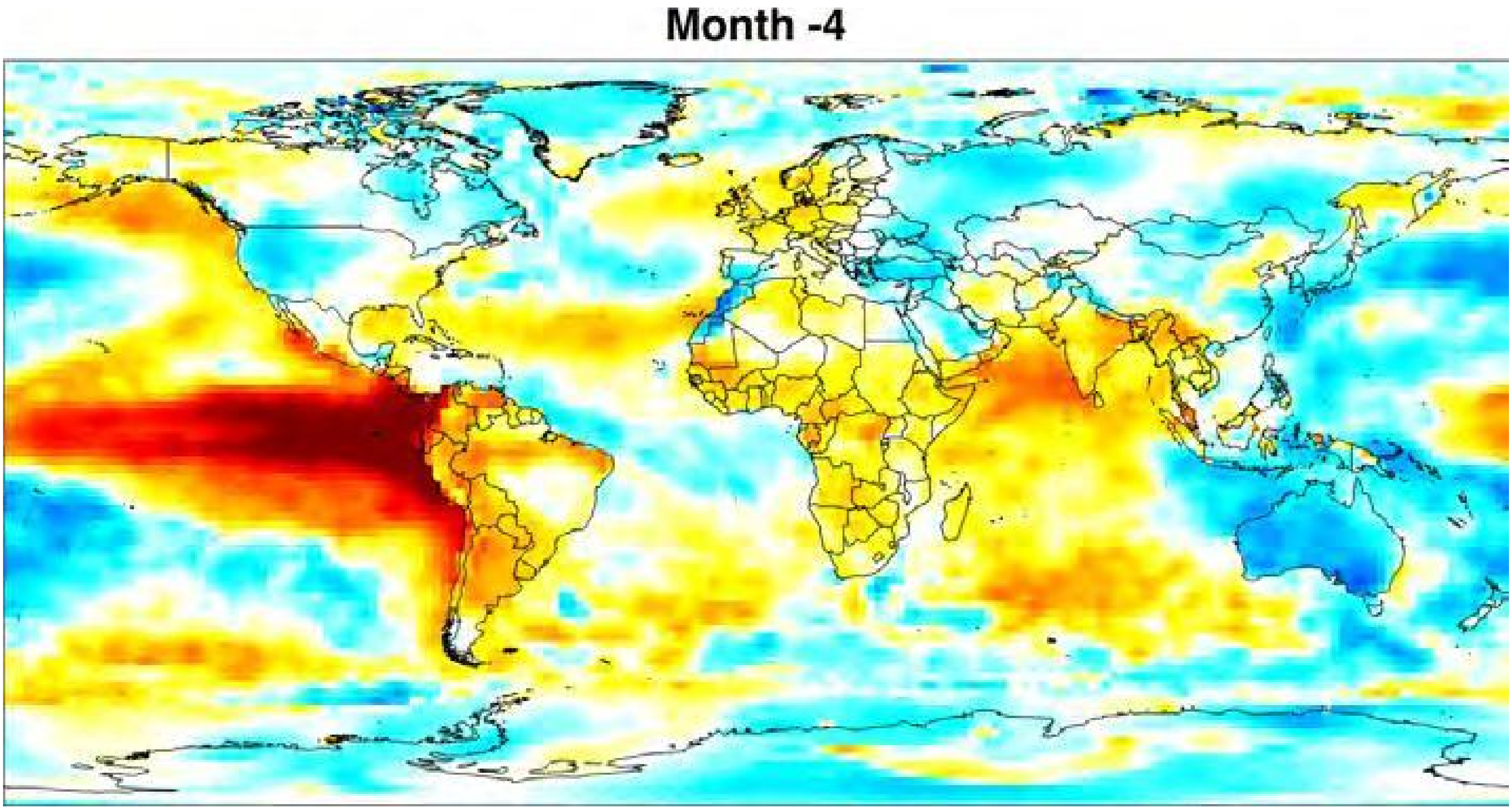

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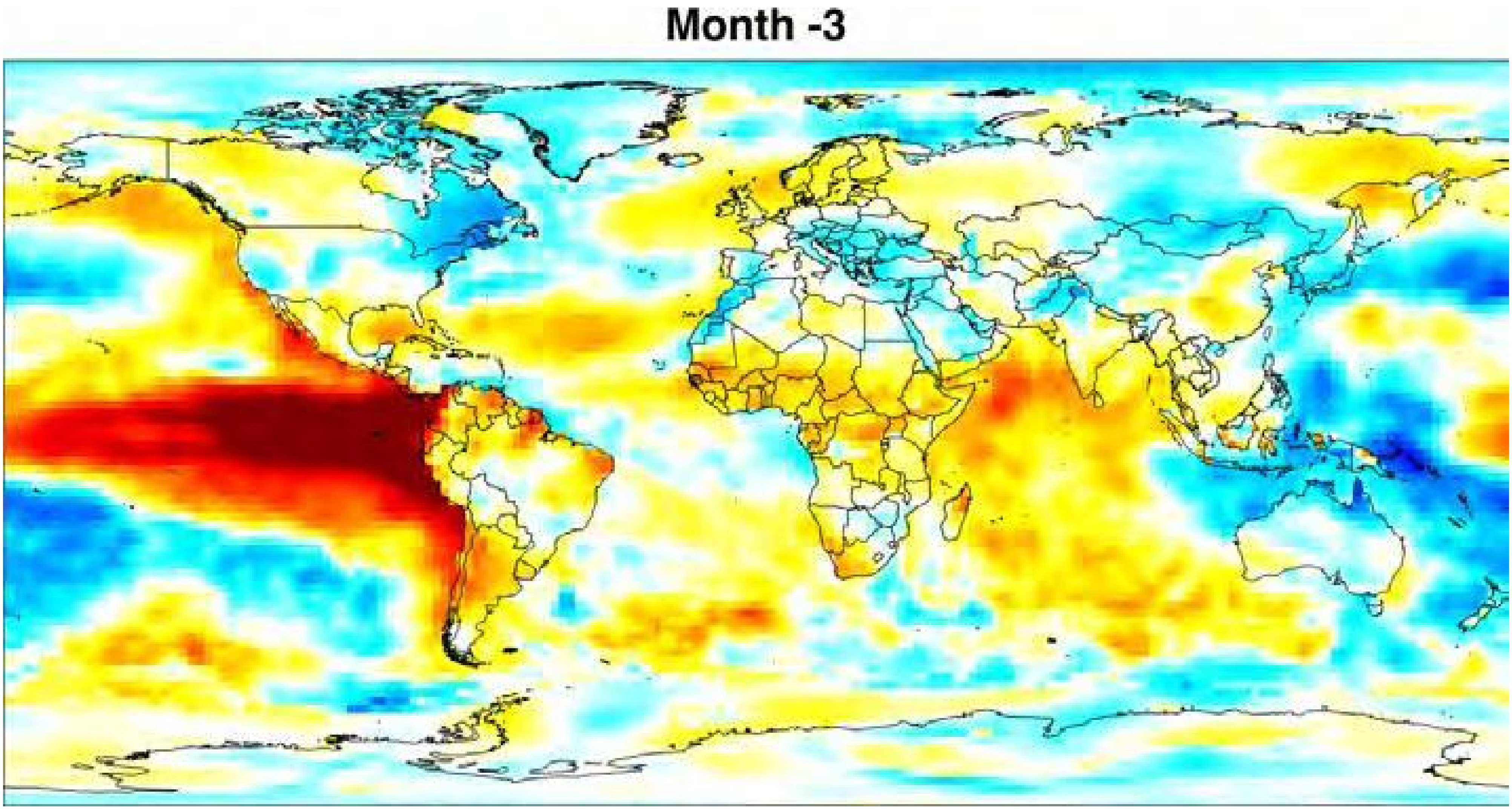

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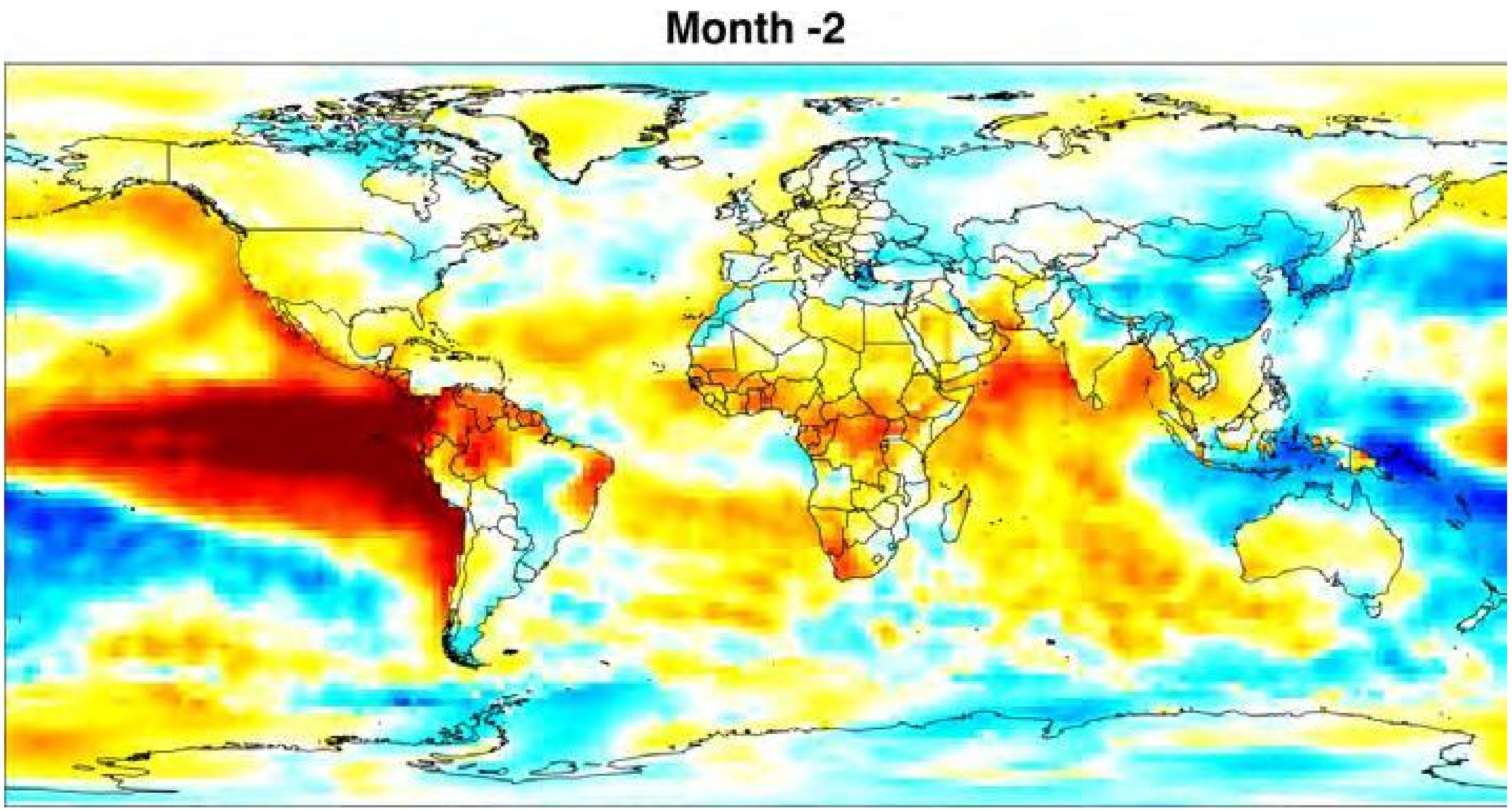

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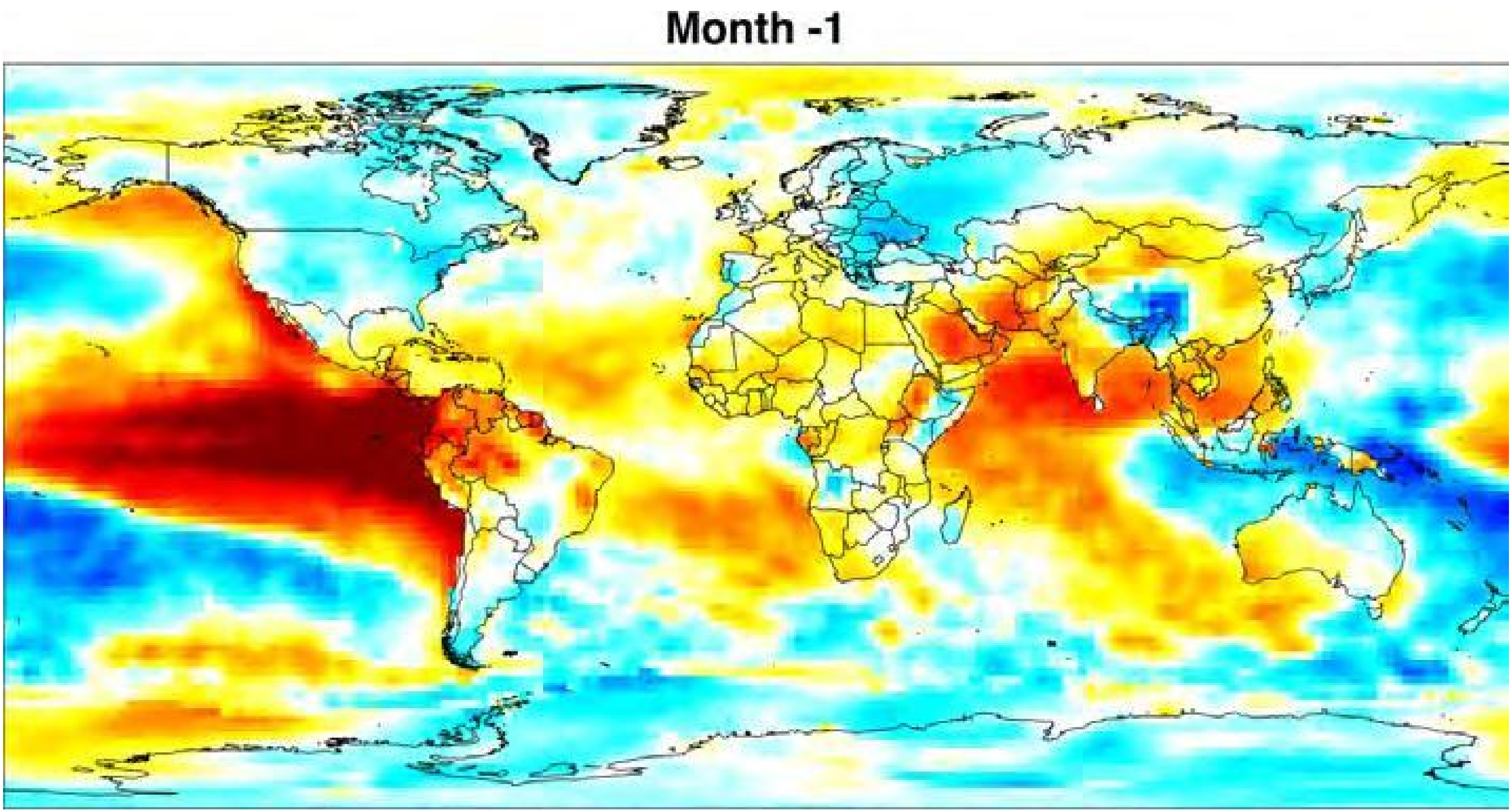

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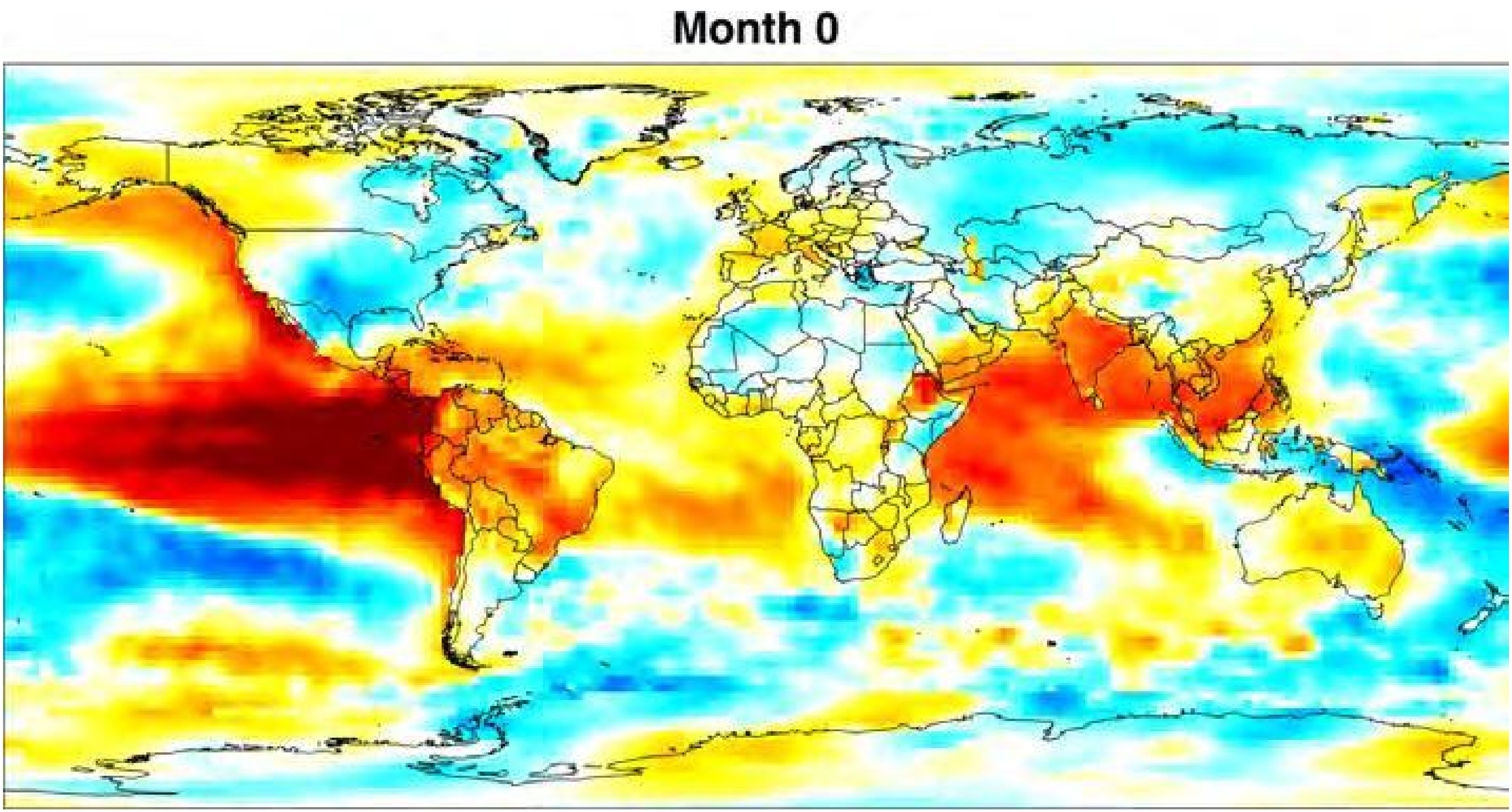

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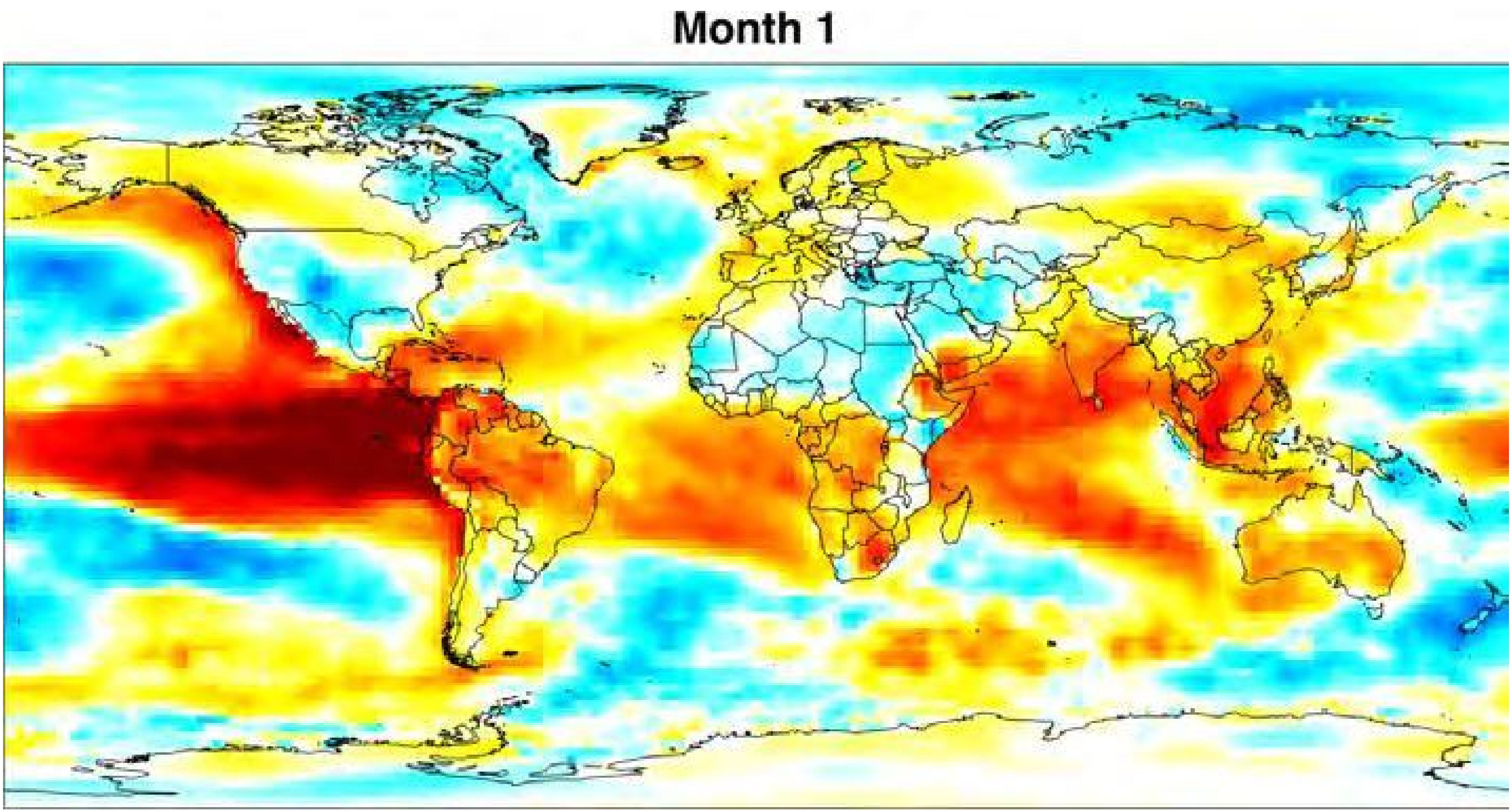

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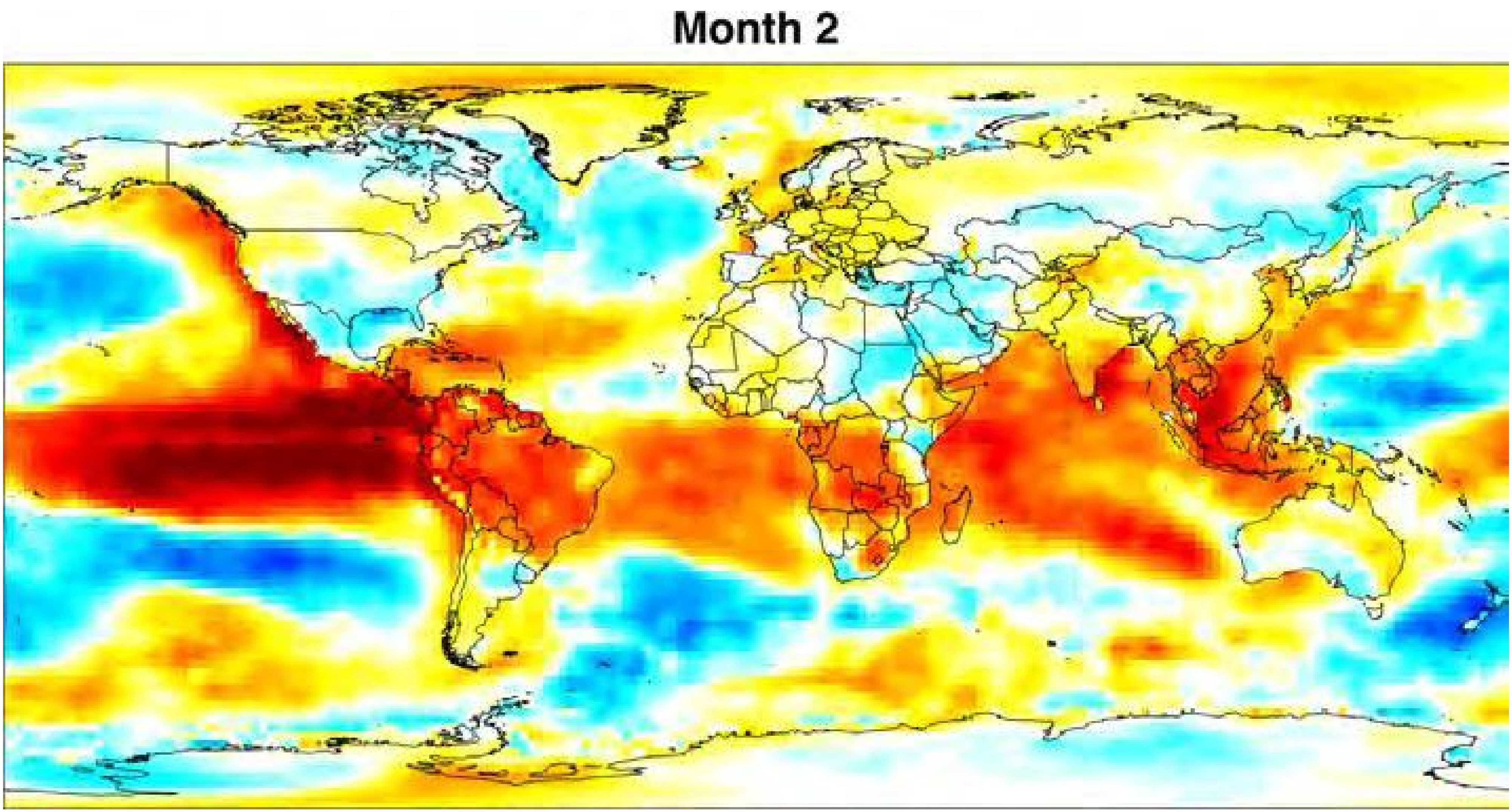

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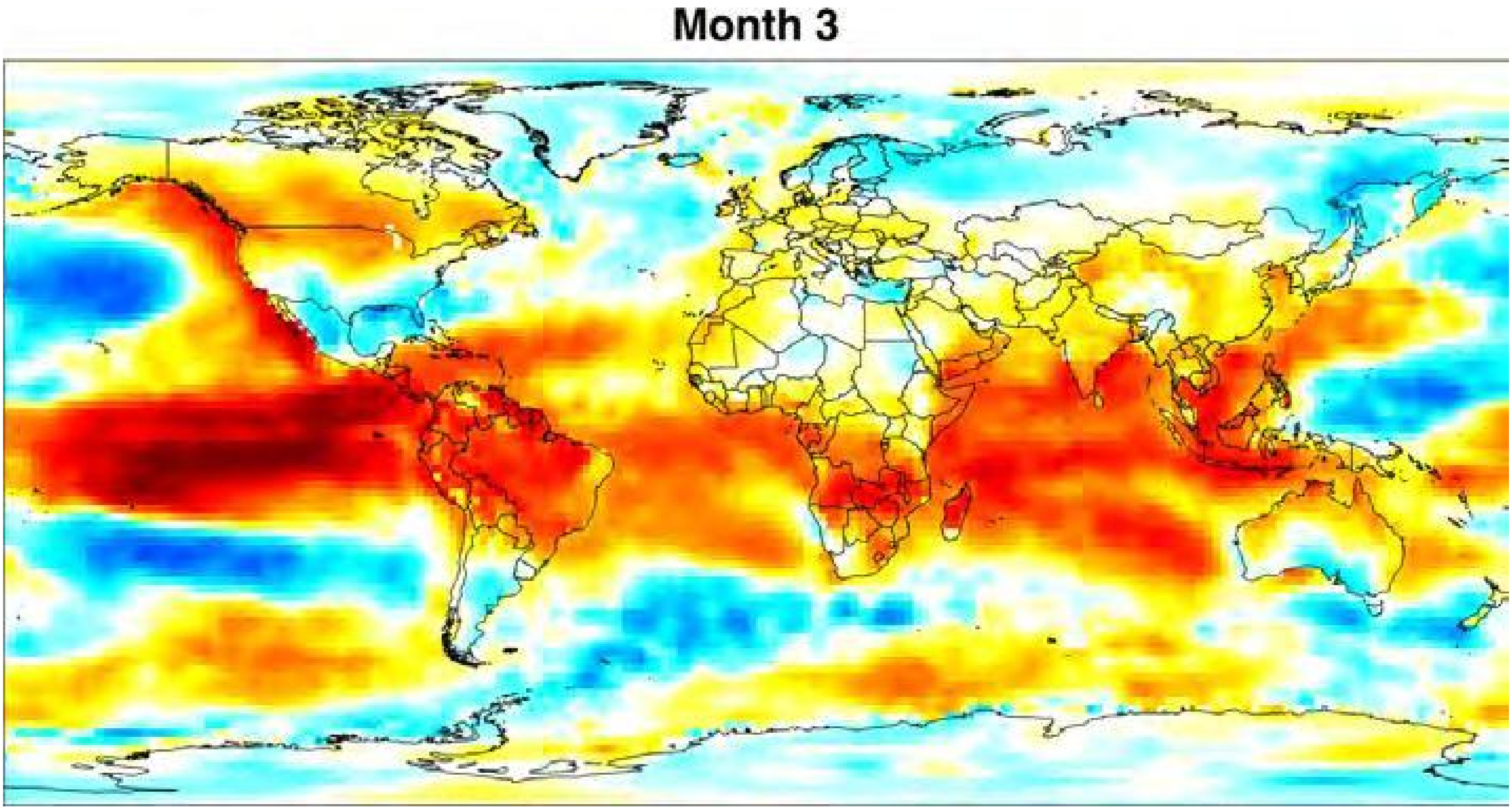

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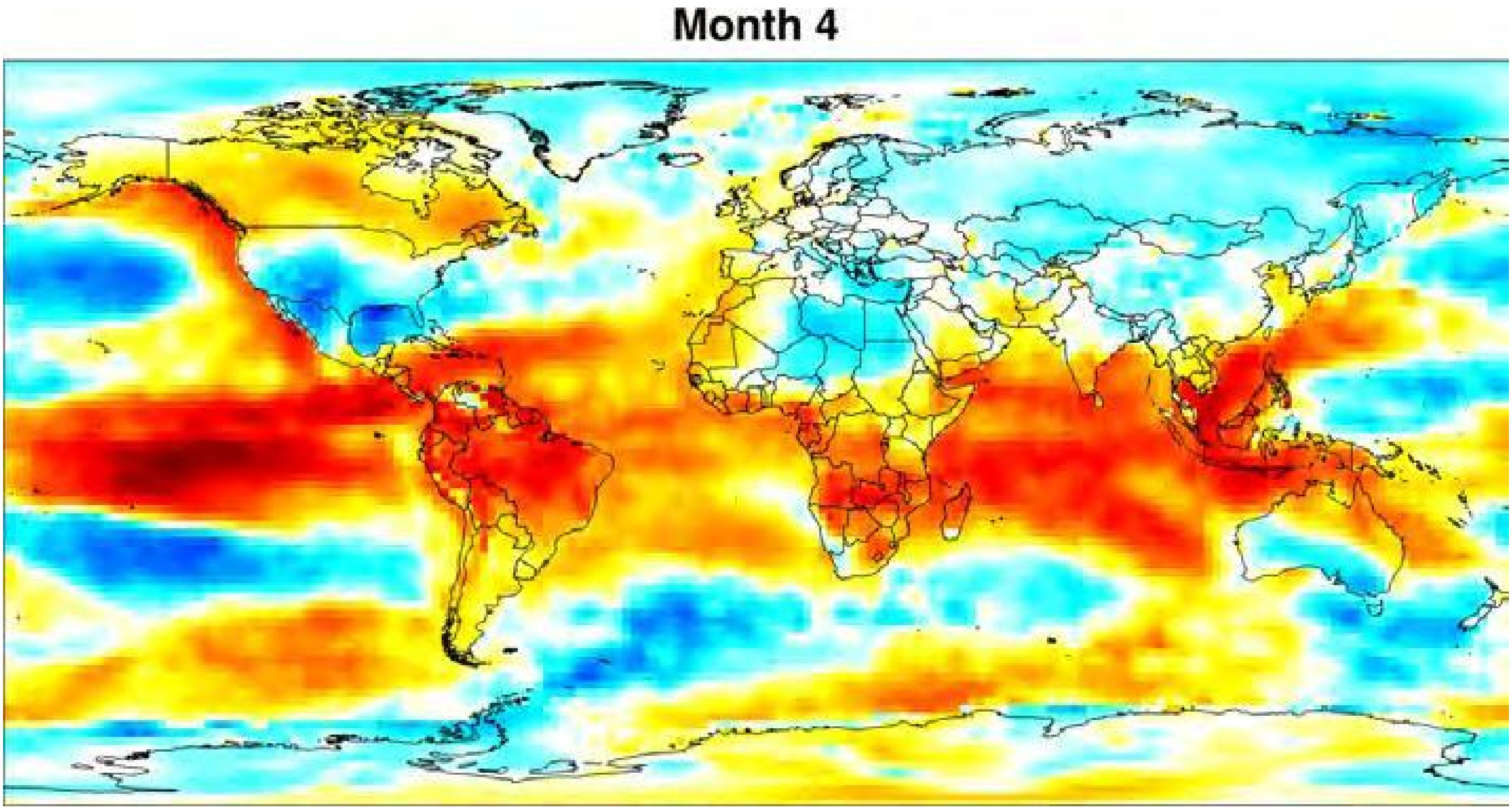

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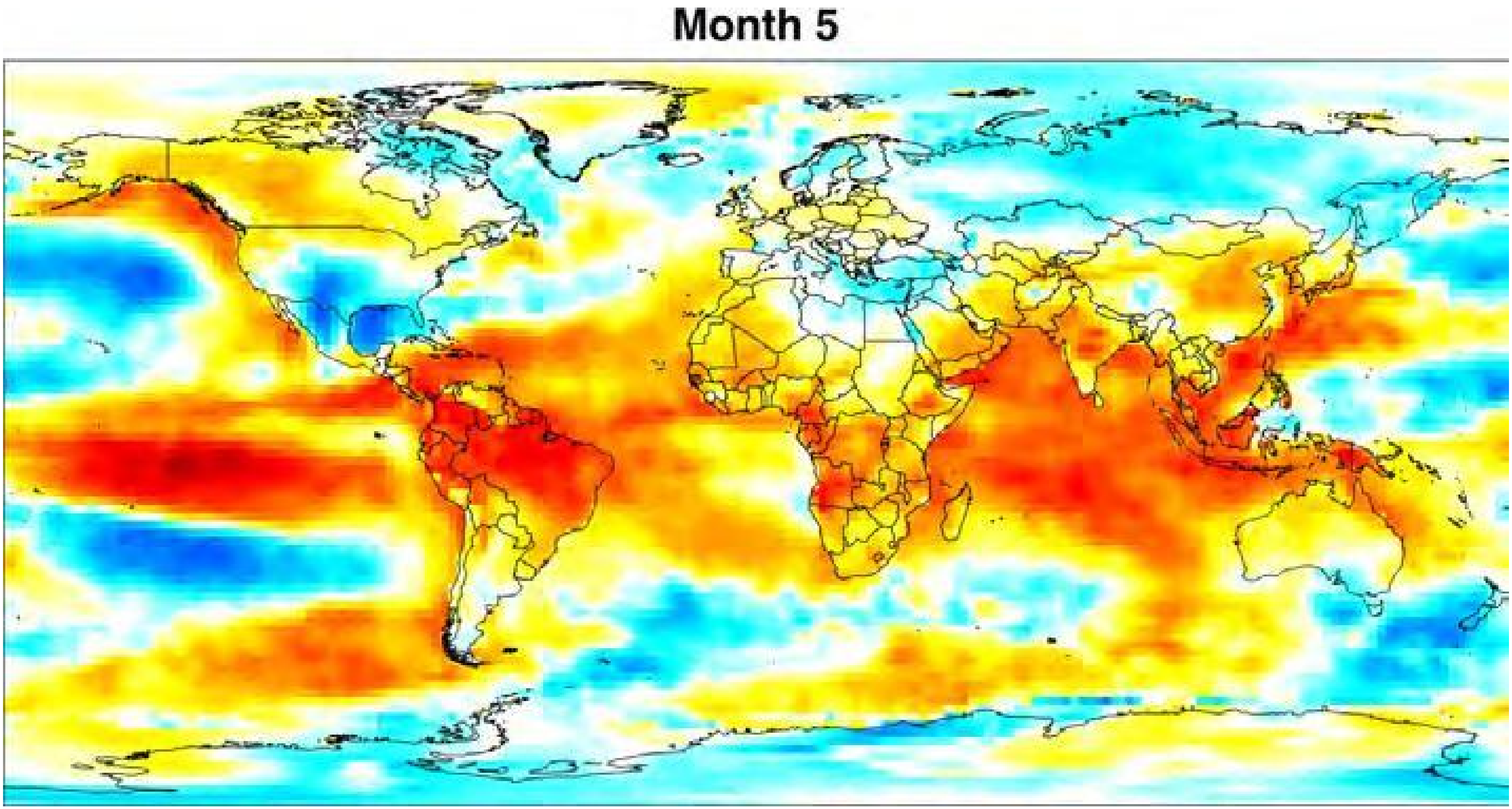

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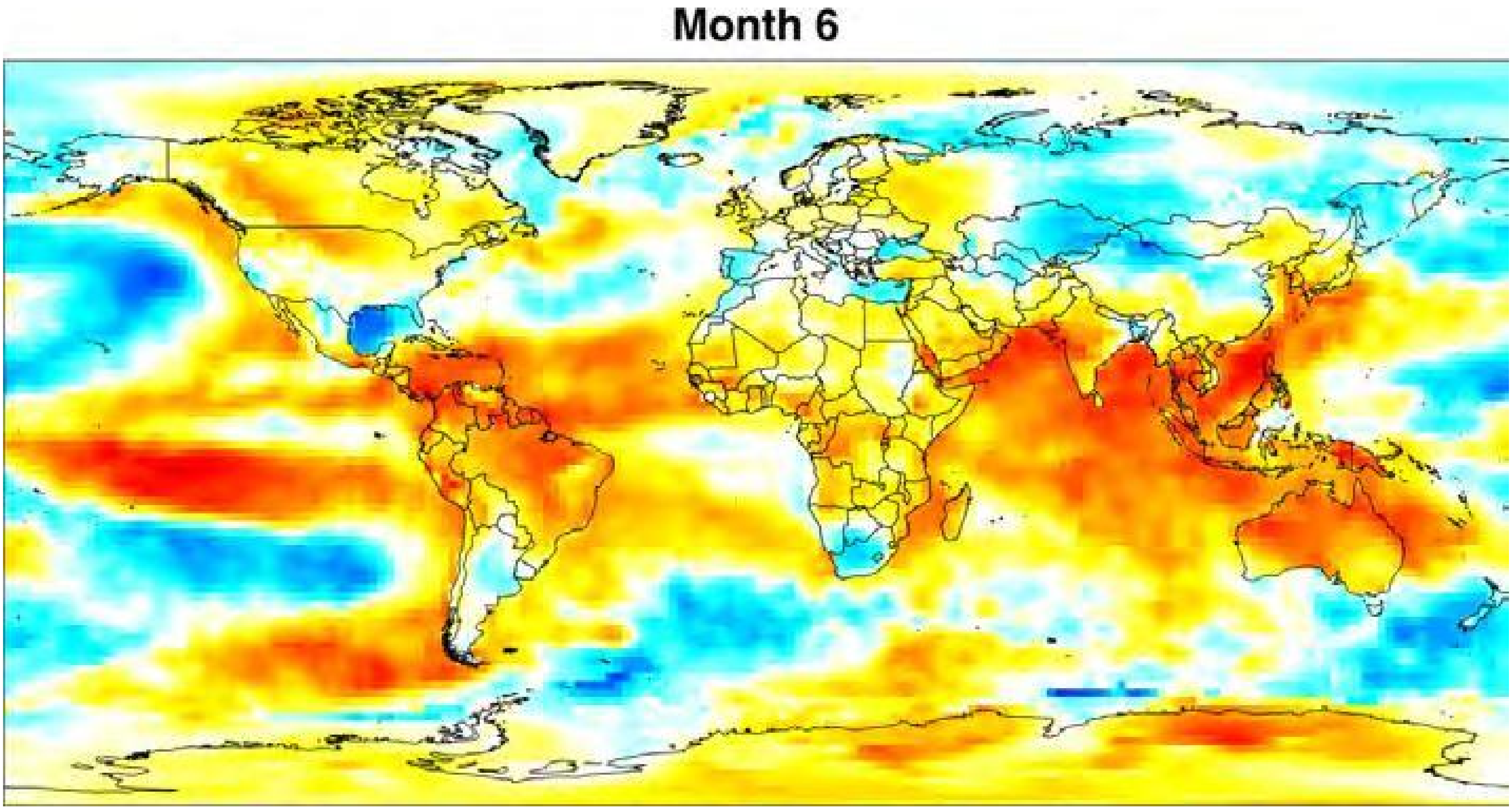

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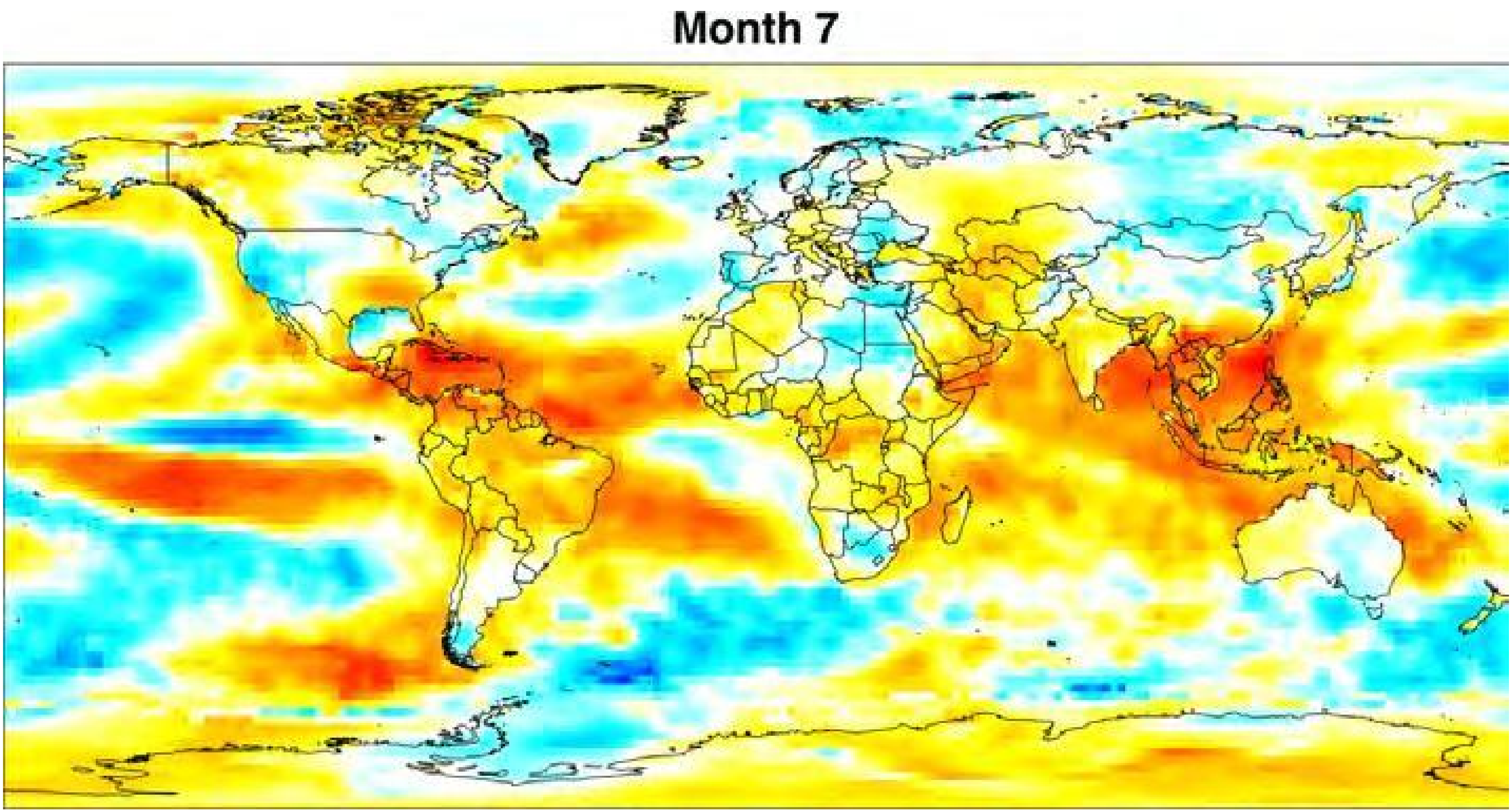

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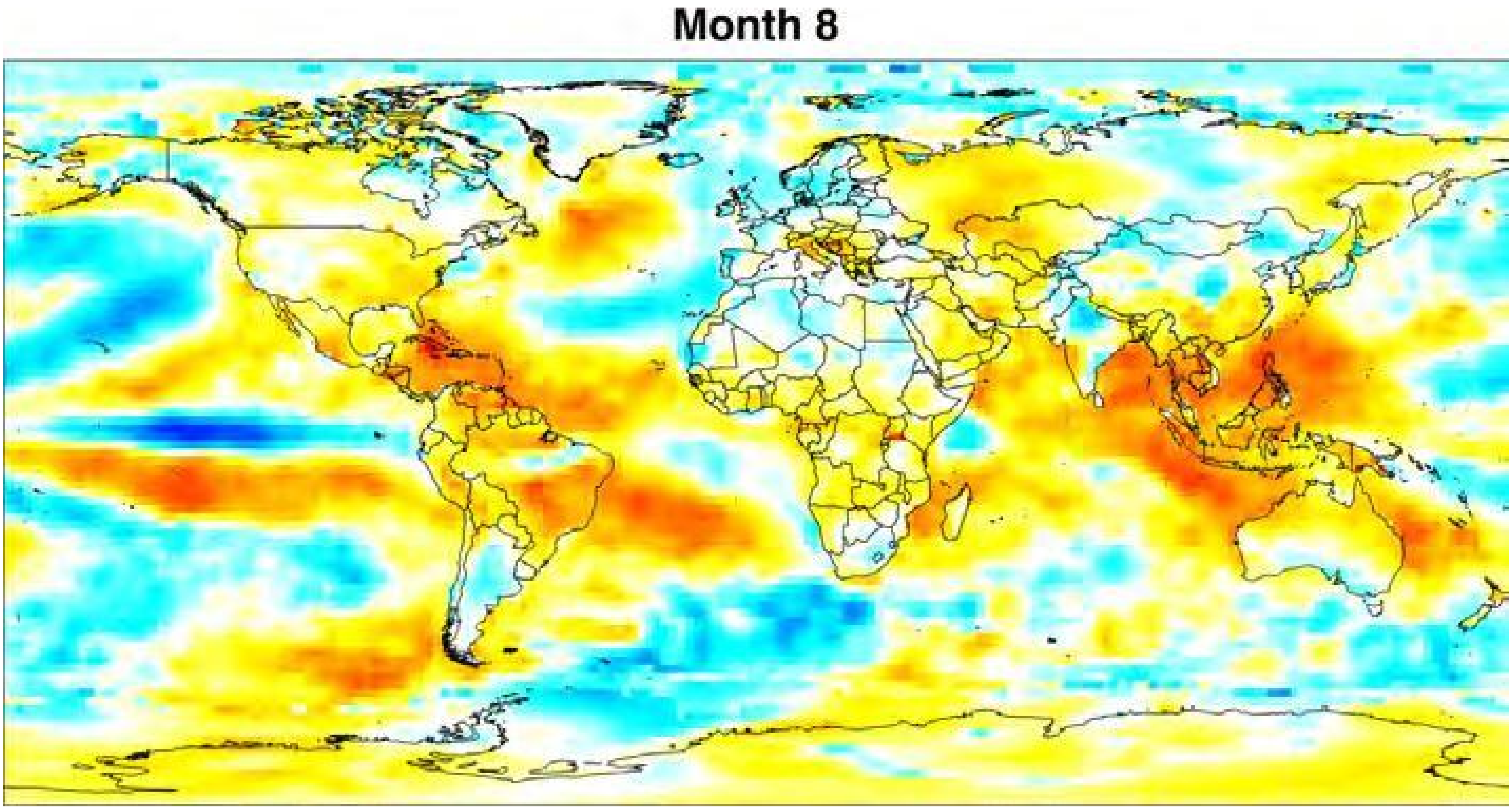

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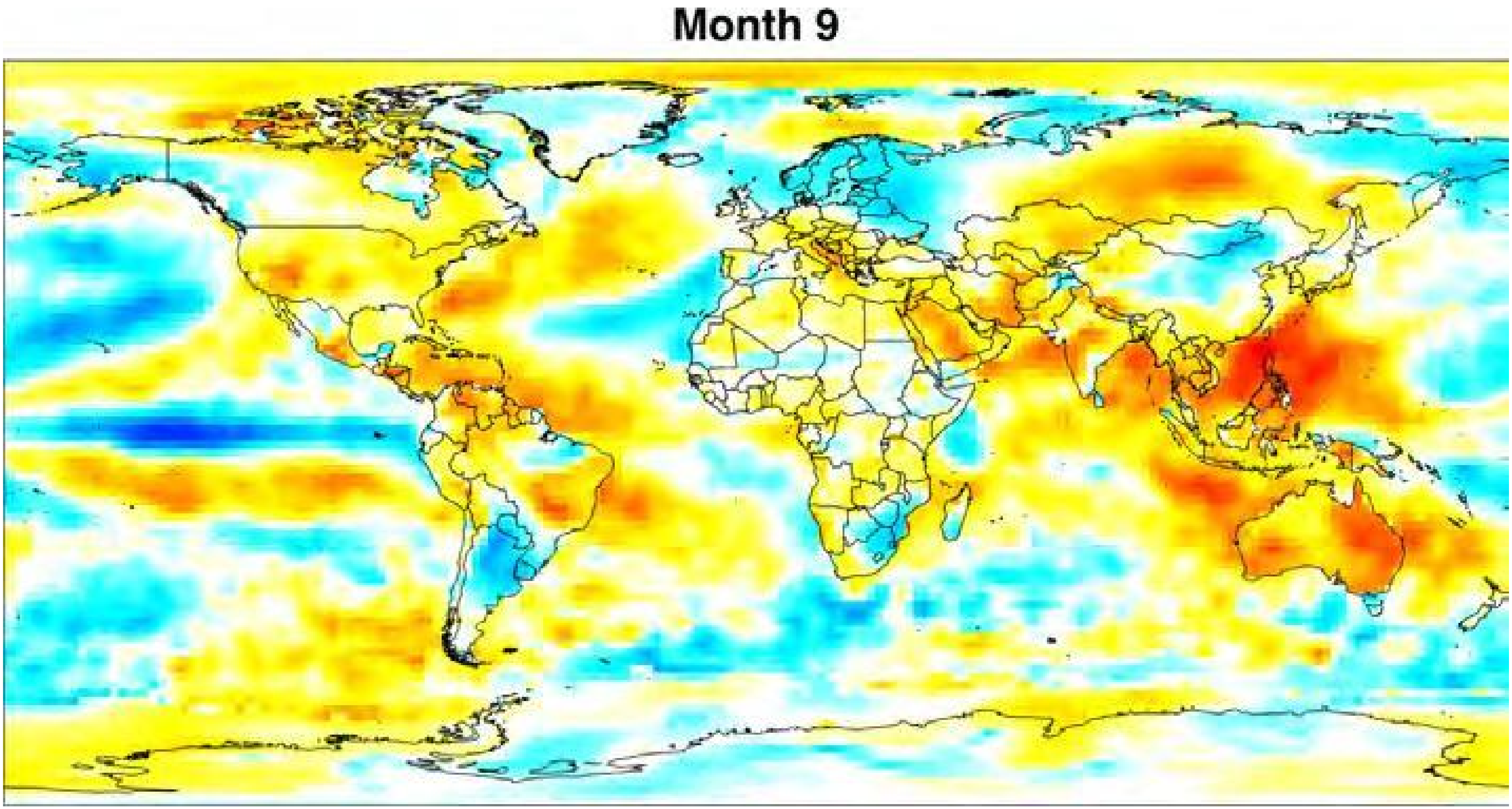

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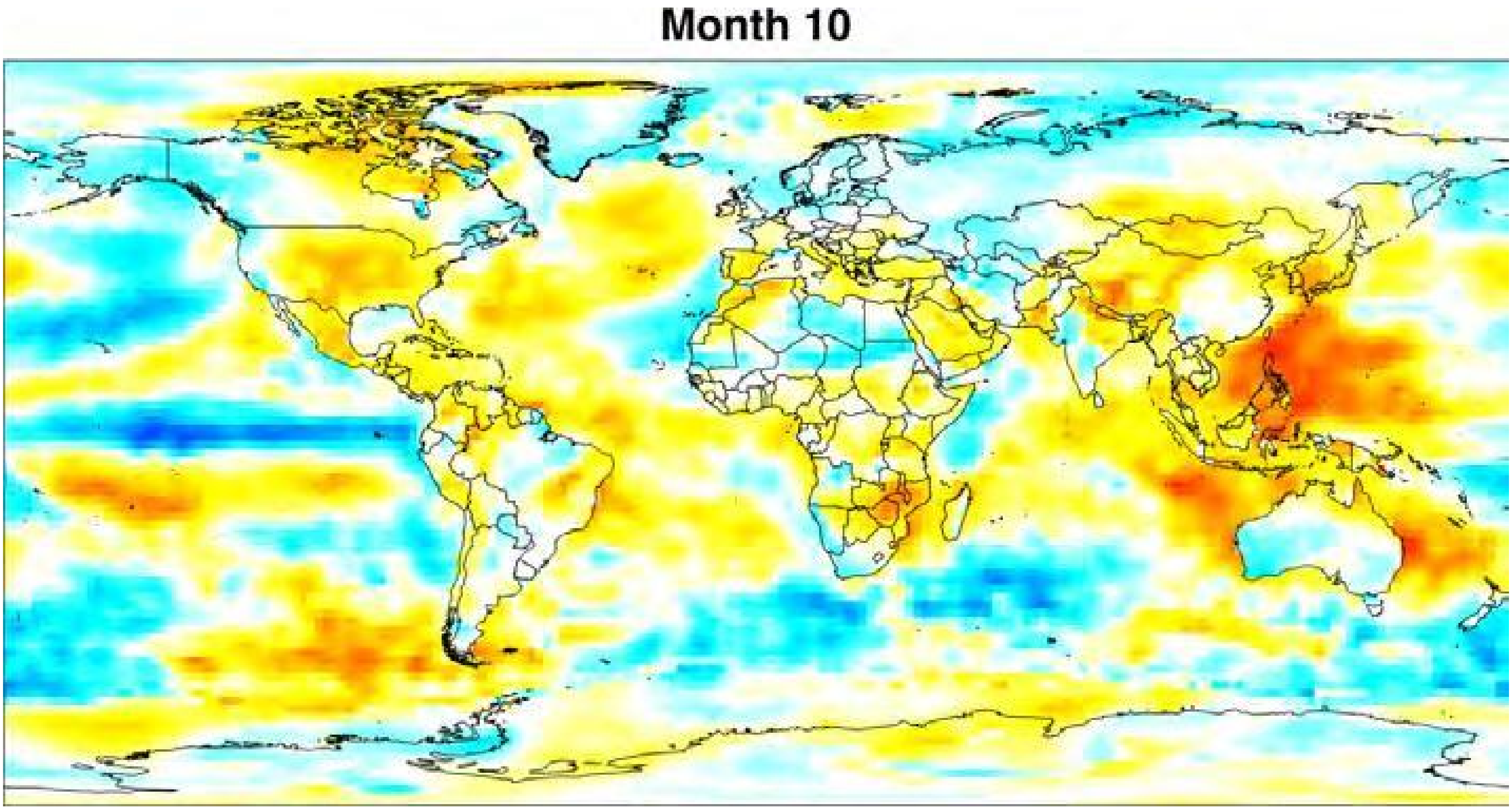

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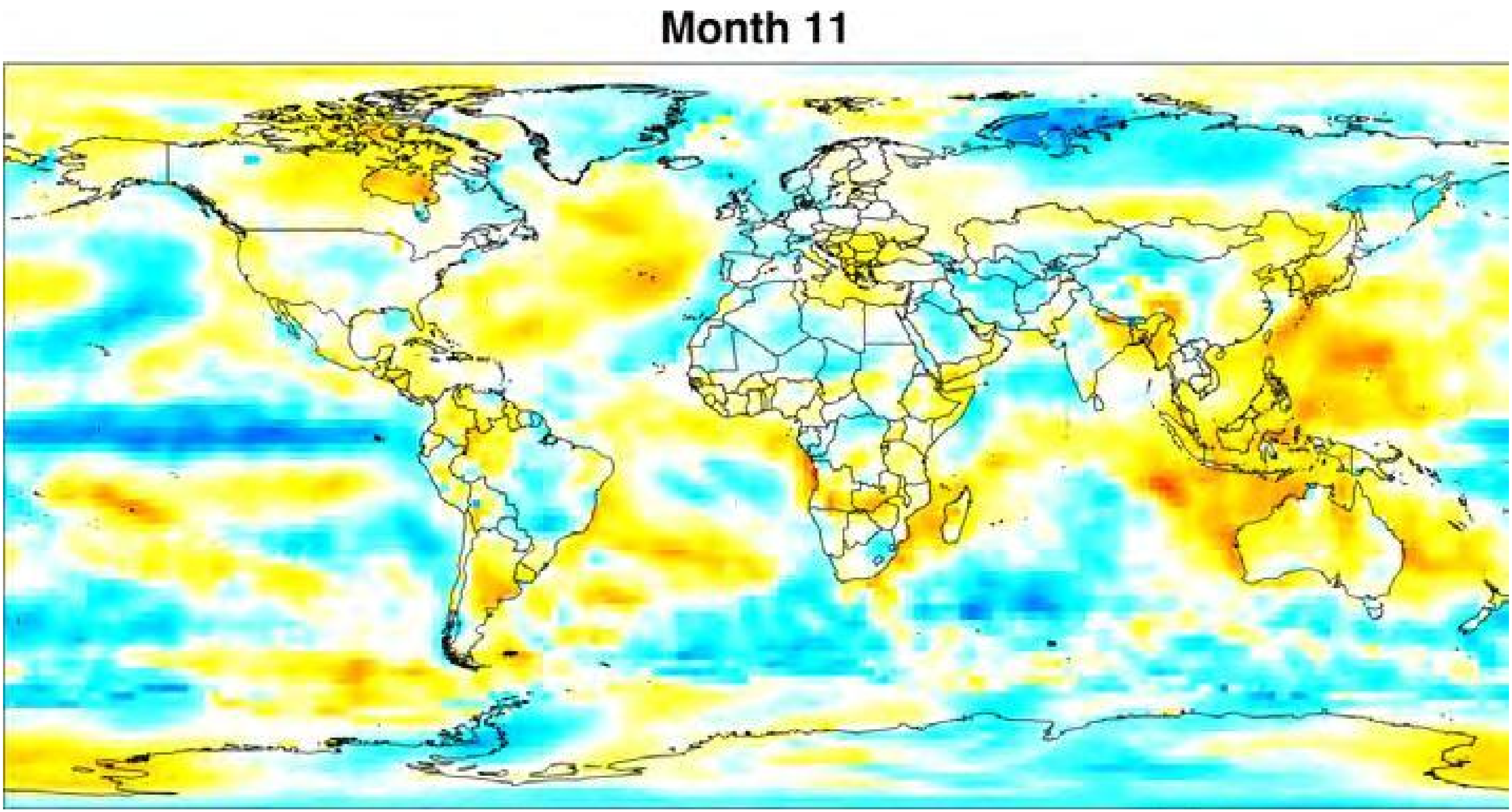

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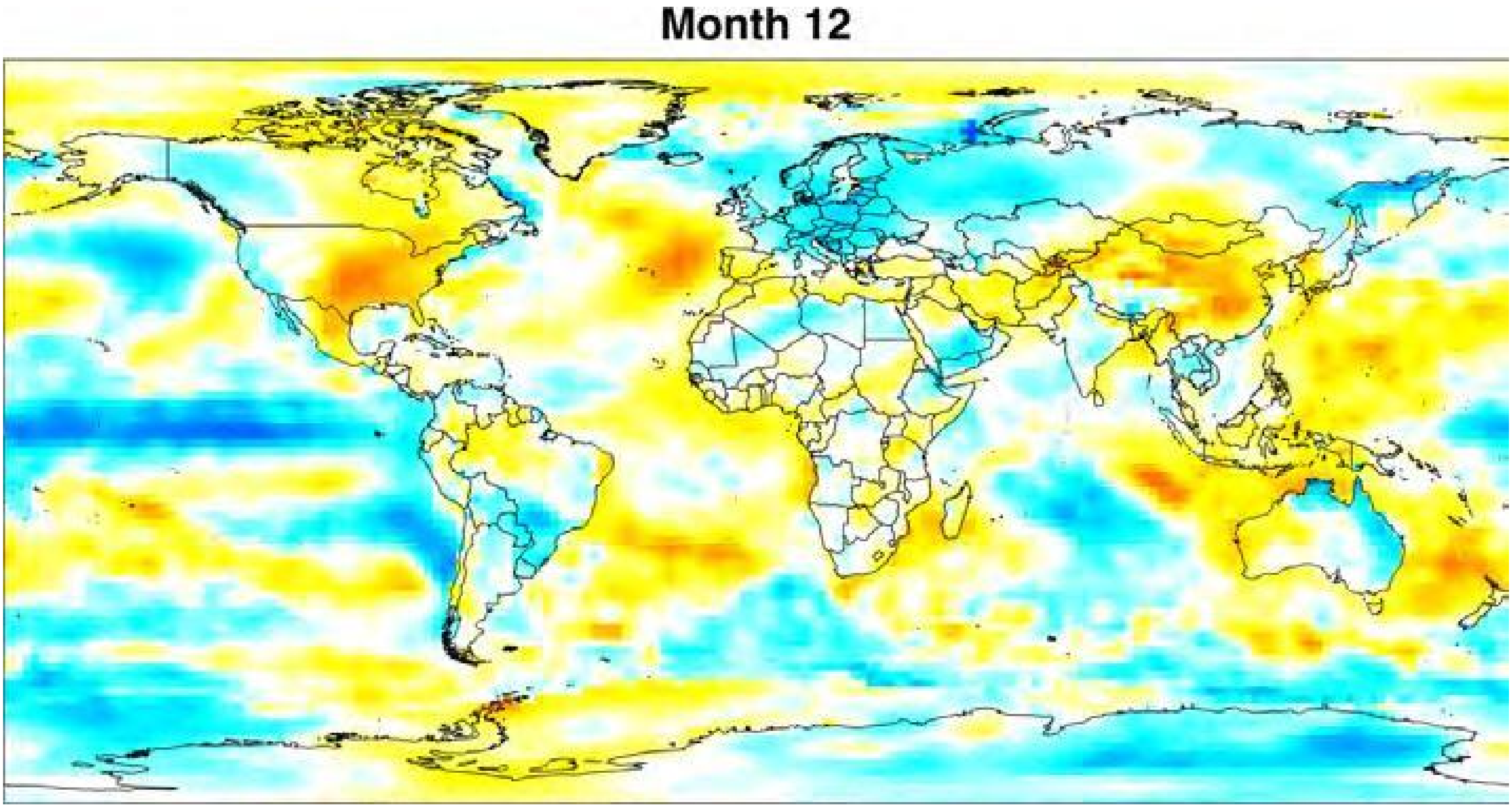
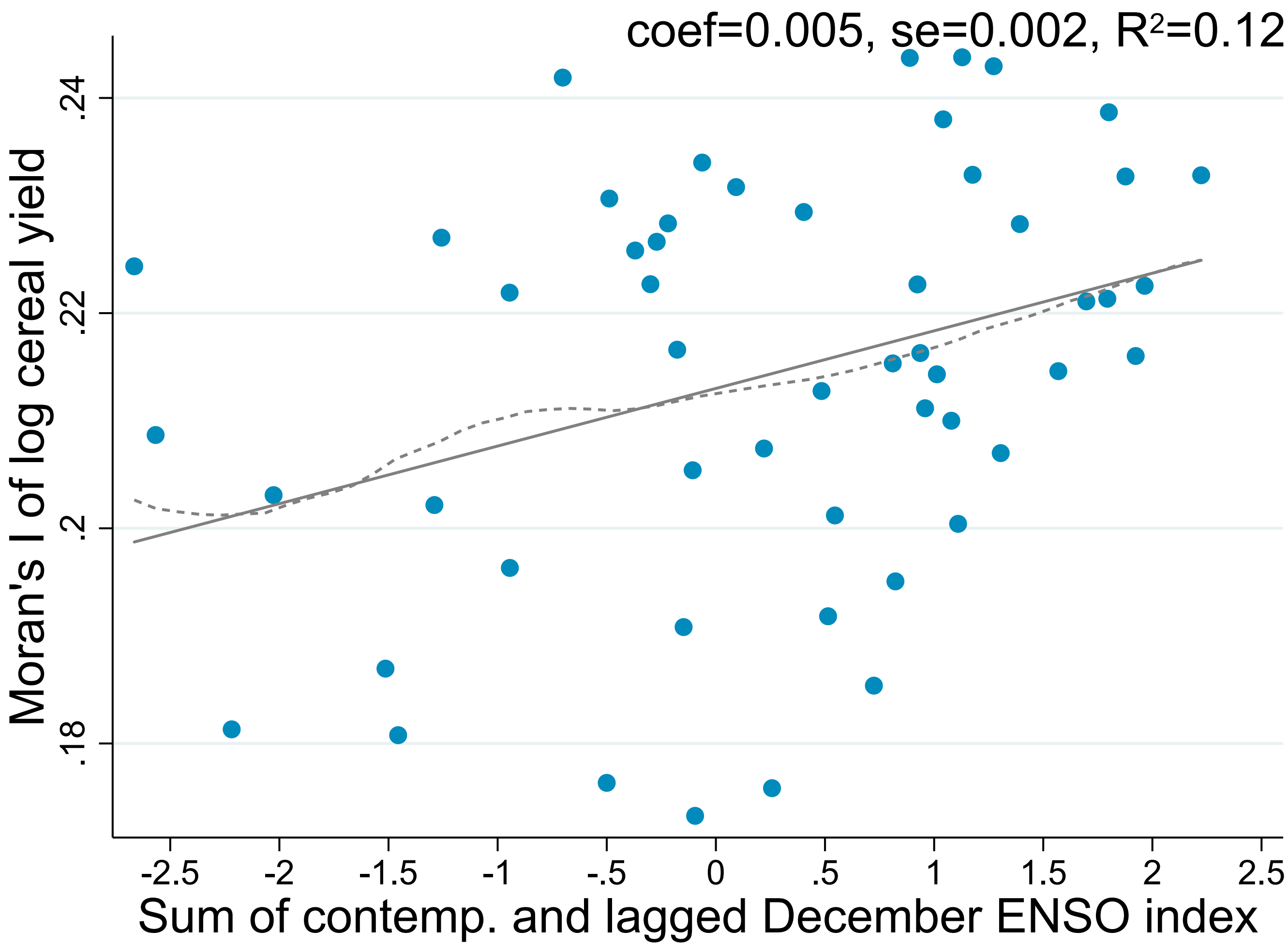


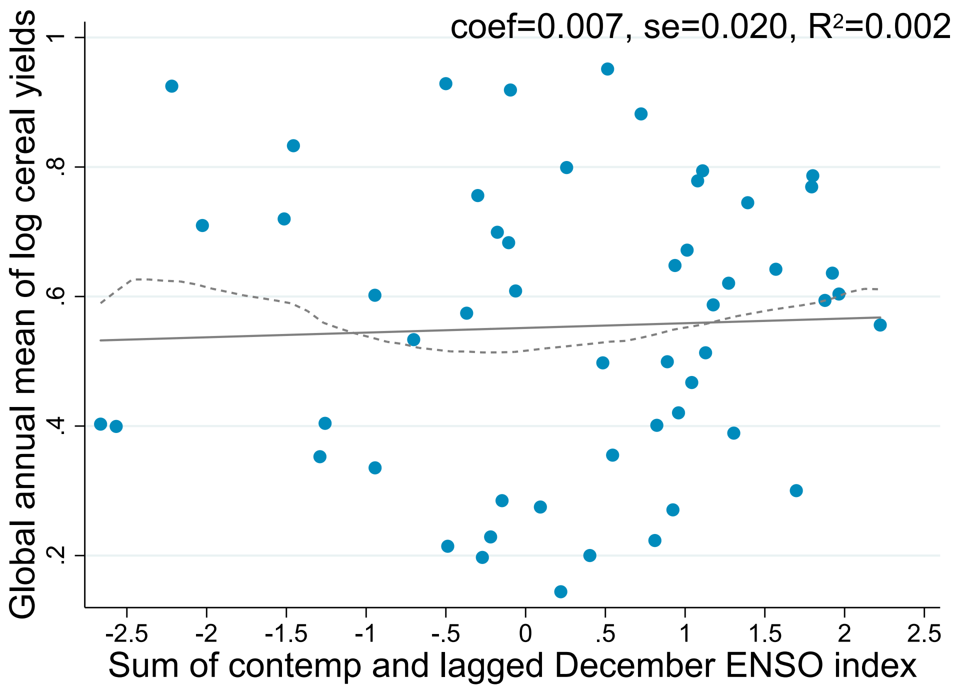
ENSO and Moran's *I* for cereal yields

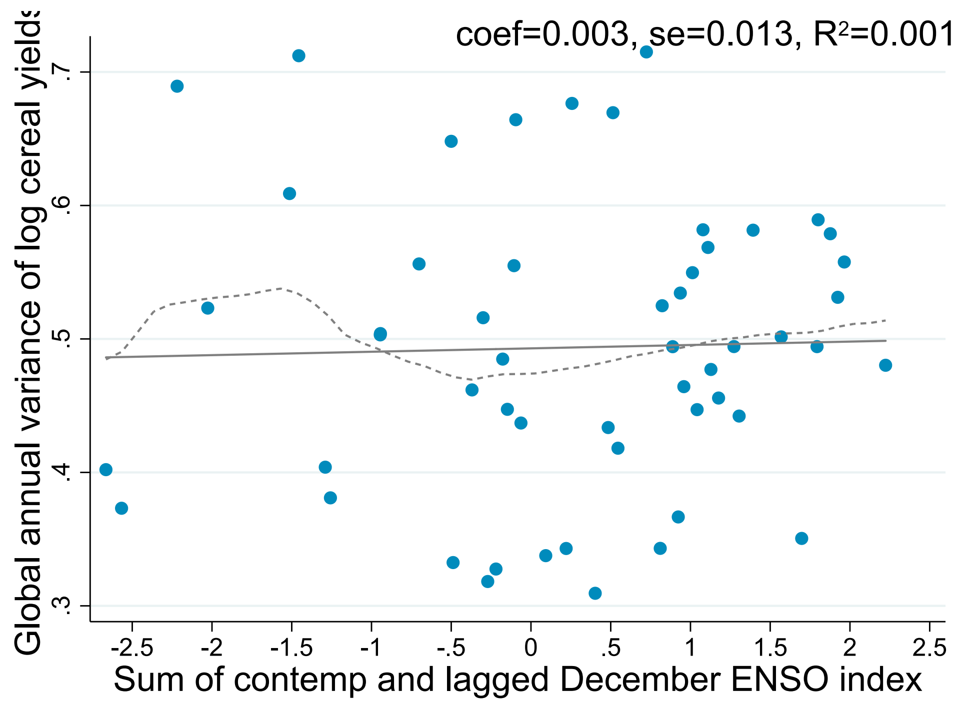


ENSO functional form:

- Both December $ENSO_t$ and $ENSO_{t-1}$ are informative
- Most parsimonious way to model nonlinear effects is to estimate effects of $(ENSO_t + ENSO_{t-1})$ and $(ENSO_t + ENSO_{t-1})^2$

ENSO and cross-sectional moments of cereal yields





Empirical results

Estimating the effect of spatial correlation

Relationship of interest:

$$\ln \lambda_{iit} = \beta_0 \ln A_{it} + \beta_1 \ln A_{it} I_t + \Pi' \mathbb{Z}_{it} + \mu_{it}$$

- Panel over country i (158) and year t (1961-2013)
- λ_{iit}: FAOStat (cereal consumption [output minus export] $\times$ export unit value)
- A_{it}: FAOStat (cereals yield in metric tons per hectare)
- $\mathbb{Z}_{it}$: Country FE, time FE, and i-specific linear trend
- μ_{it}: year clustered

Prediction: Variance of welfare increases when $\beta_1 < 0$

Endogeneity concern: Need instruments for $\ln A_{it}$ and $\ln A_{it} I_t$

Instrumental-variables strategy

IV approach:

- Drive local yields using country crop area-weighted annual temperature, T_{it}
- Drive global spatial correlation of yields using $ENSO_t$ and $ENSO_{t-1}$

Two first stage equations:

$$\ln A_{it} = \alpha_{11} f(T_{it}) + \alpha_{12} f(T_{it}) g(ENSO_t + ENSO_{t-1}) + \Gamma_1' \mathbb{Z}_{it} + \upsilon_{1it}$$

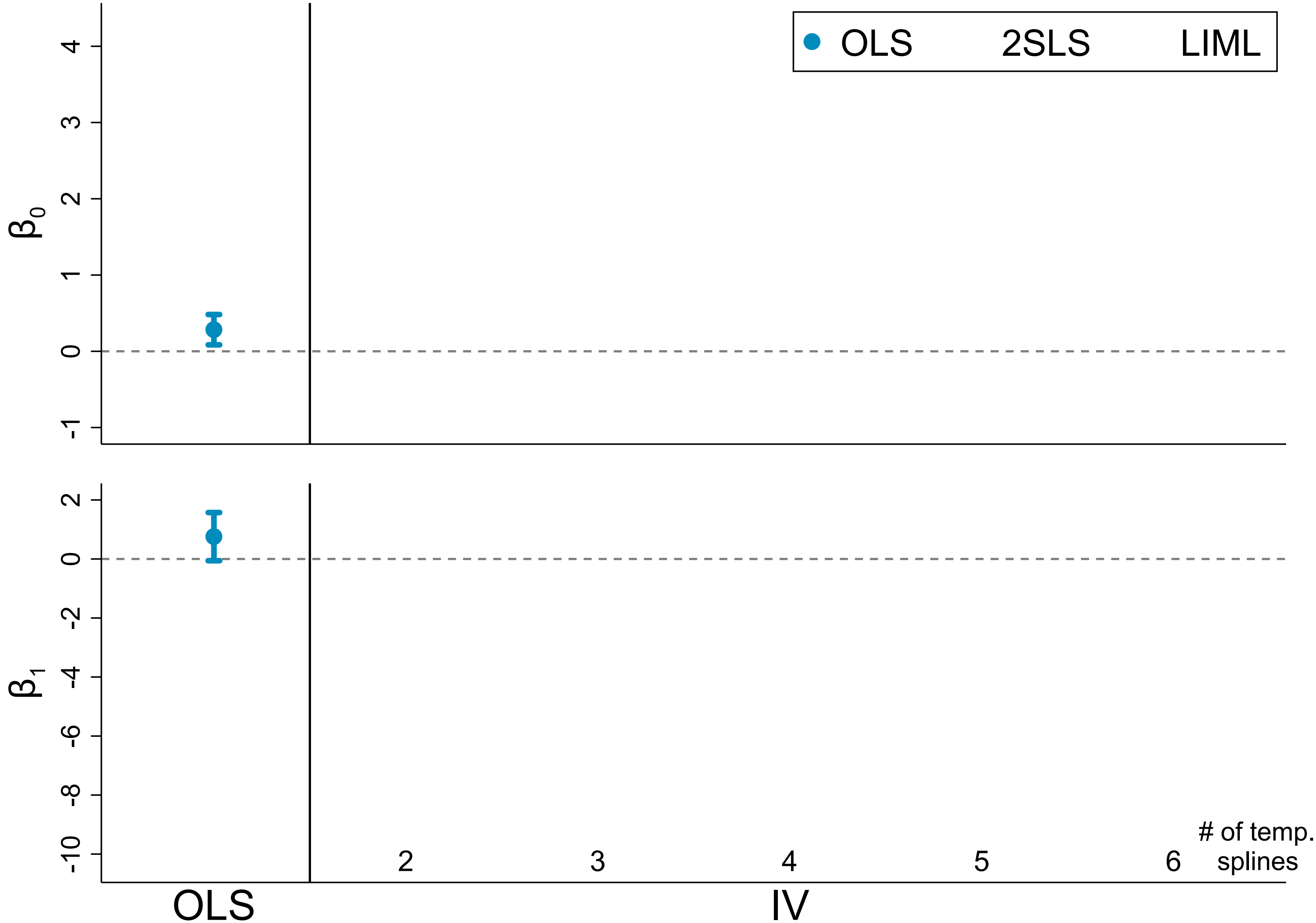
$$\ln A_{it} I_t = \alpha_{21} f(T_{it}) + \alpha_{22} f(T_{it}) g(ENSO_t + ENSO_{t-1}) + \Gamma_2' \mathbb{Z}_{it} + \upsilon_{2it}$$

- $f()$: restricted cubic spline function (Schlenker & Roberts, '09; Schlenker & Lobell, '10; Welch et al., '10, Moore & Lobell, '10)
- $g()$: quadratic function

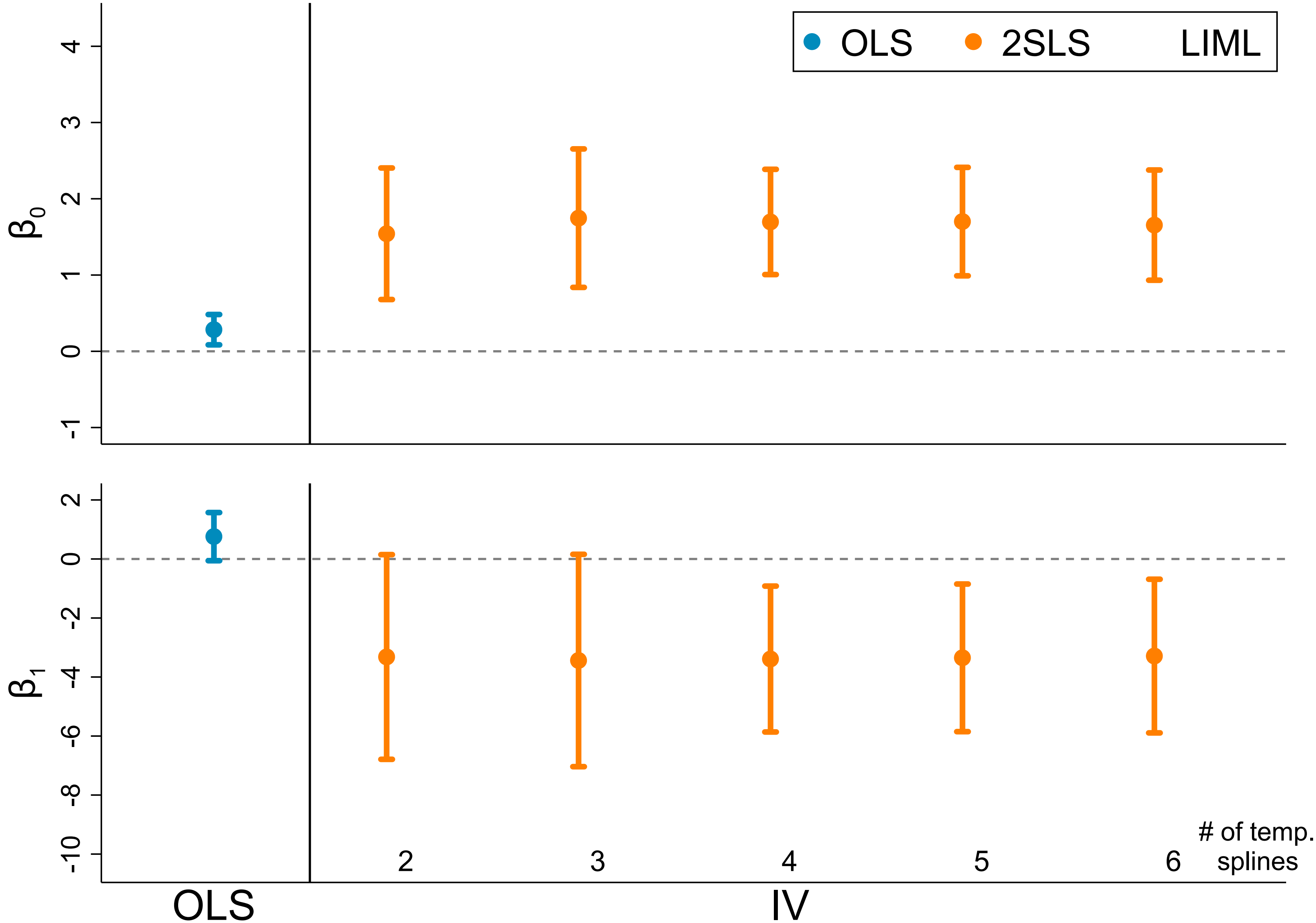
Potential concern about weak instruments:

1. Compare OLS vs. 2SLS vs. LIML estimates
2. Conduct weak-IV diagnostics
3. Conduct weak-IV robust inference

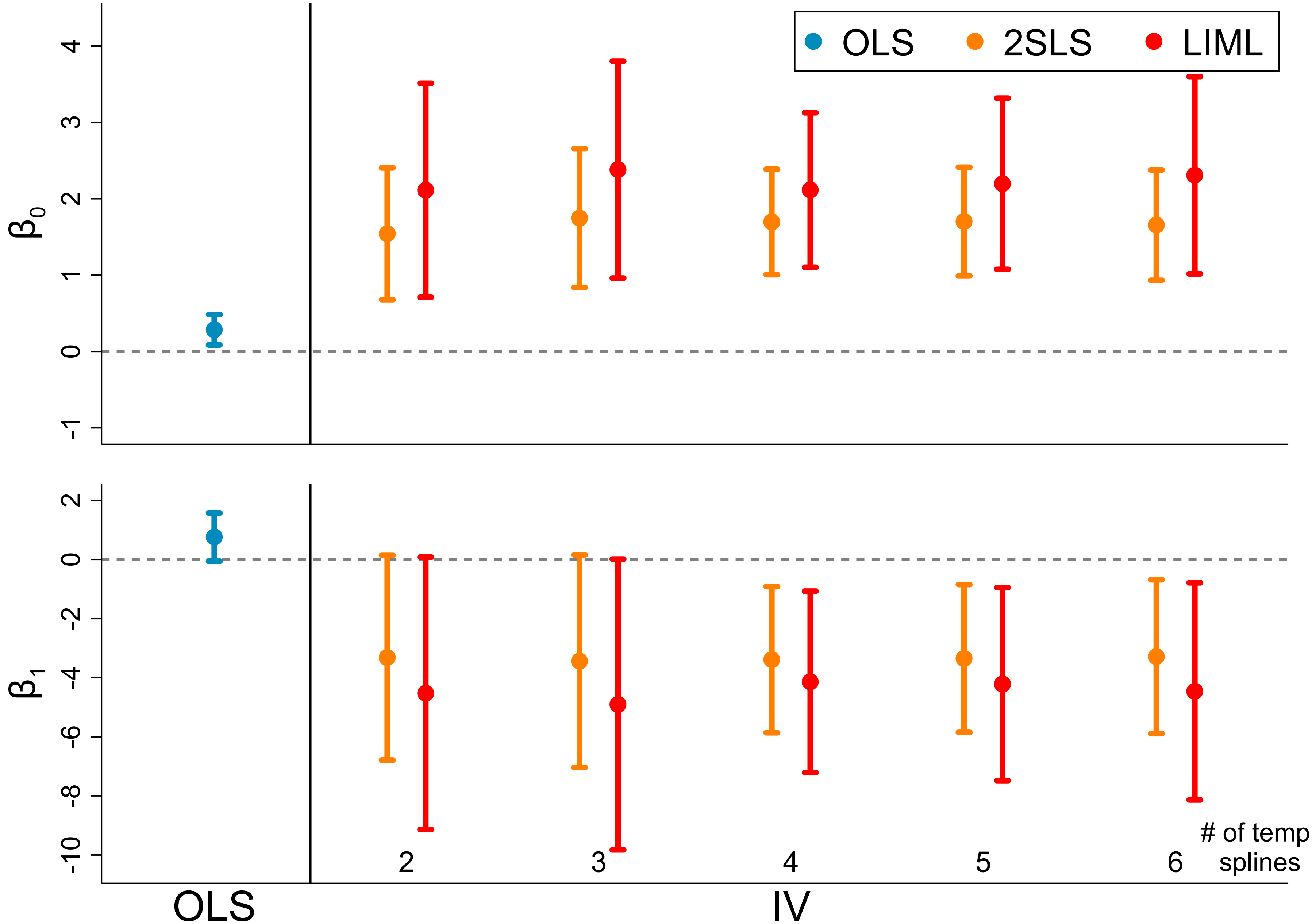
OLS shows no relationship



2SLS: Higher spatial correlation lowers $cov(\ln \lambda_{ii}, \ln A_i)$



LIML: Higher spatial correlation lowers $cov(\ln \lambda_{ii}, \ln A_i)$



First stage coefs. F-stat A-R test Spline selection

Magnitude: 2% increase in global inequality

1 std dev increase relative to historical average Moran's I

Use reduced-form coefficients $\widehat{\beta}_0$, $\widehat{\beta}_1$ and $\epsilon = 8.59$ (Caliendo and Parro, 2015) to calculate pct. change in welfare variance ▸ Welfare calculation

Outcome is log domestic share of expenditure

	(1)	(2)	(3)	(4)	(5)
$\ln A_{it}$ (β_0)	2.110**	2.380***	2.114***	2.196***	2.308***
	(0.837)	(0.847)	(0.604)	(0.669)	(0.771)
$\ln A_{it} \times I_t$ (β_1)	-4.530	-4.907	-4.144**	-4.218**	-4.463**
	(2.752)	(2.937)	(1.834)	(1.949)	(2.194)
Pct. change in welfare variance	2.091	2.264	1.914**	1.948*	2.060*
from 1 s.d. increase in I_t	(1.407)	(1.497)	(0.954)	(1.035)	(1.191)
Number of temperature splines in f()	2	3	4	5	6

NOTES: 5452 observations. All models include country fixed effects, year fixed effects, and country linear trends as excluded instruments. Year-clustered standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Other robustness checks

Statistical assumptions

- Randomization inference
- Alternative std errors: clustering and Bekker (1994) LIML adjustment
- Controls for time-varying trade costs
- Sample split by time

Structural interpretation

- Exclude large economies
- ENSO anticipation, storage, and other dynamic effects
- Terms of trade

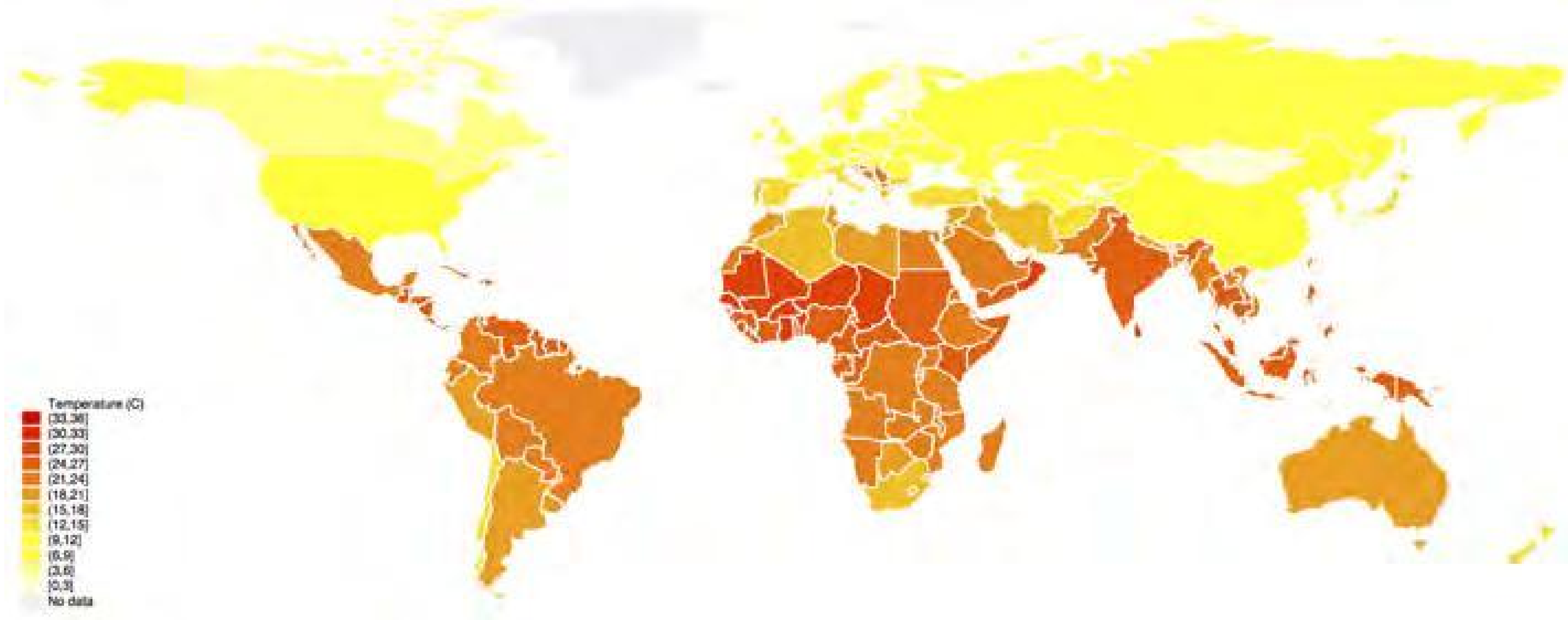
Data construction

- Alternative ENSO and temperature definitions
- Temperature-driven yields
- Domestic expenditure share construction

Inequality under future climate change

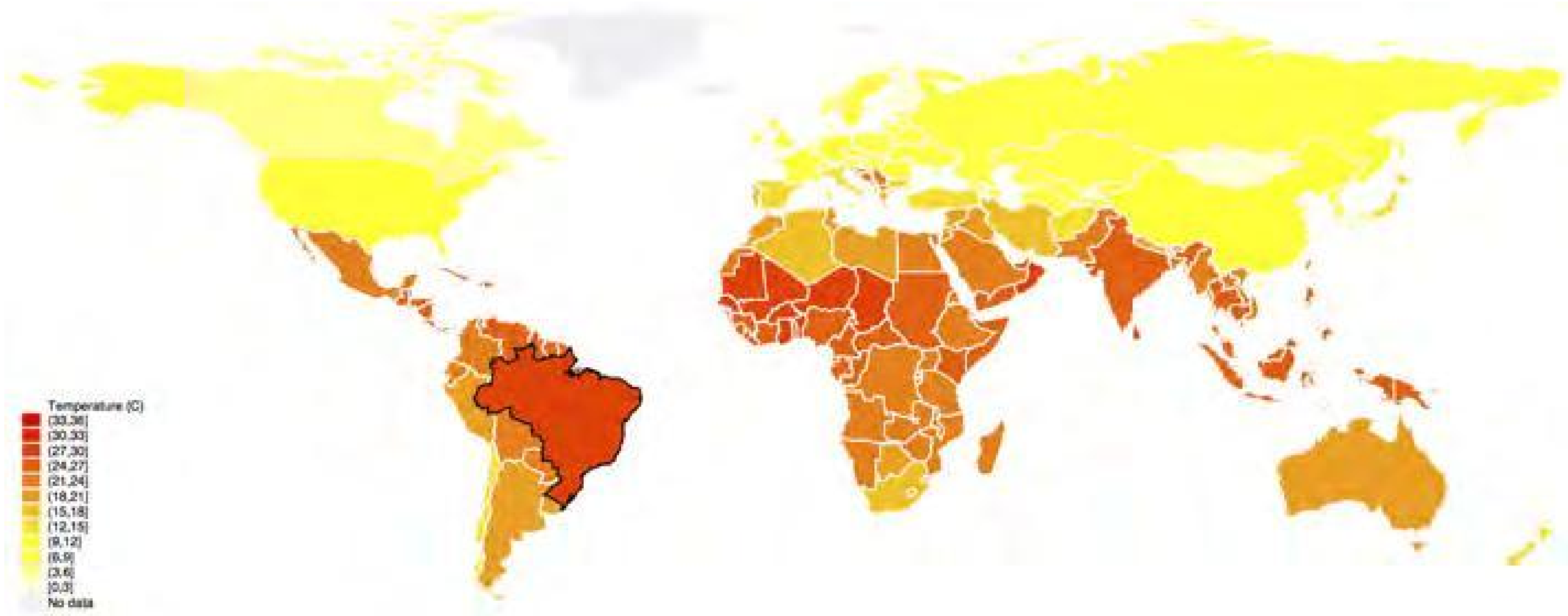
Climate change projection

2013 Climate



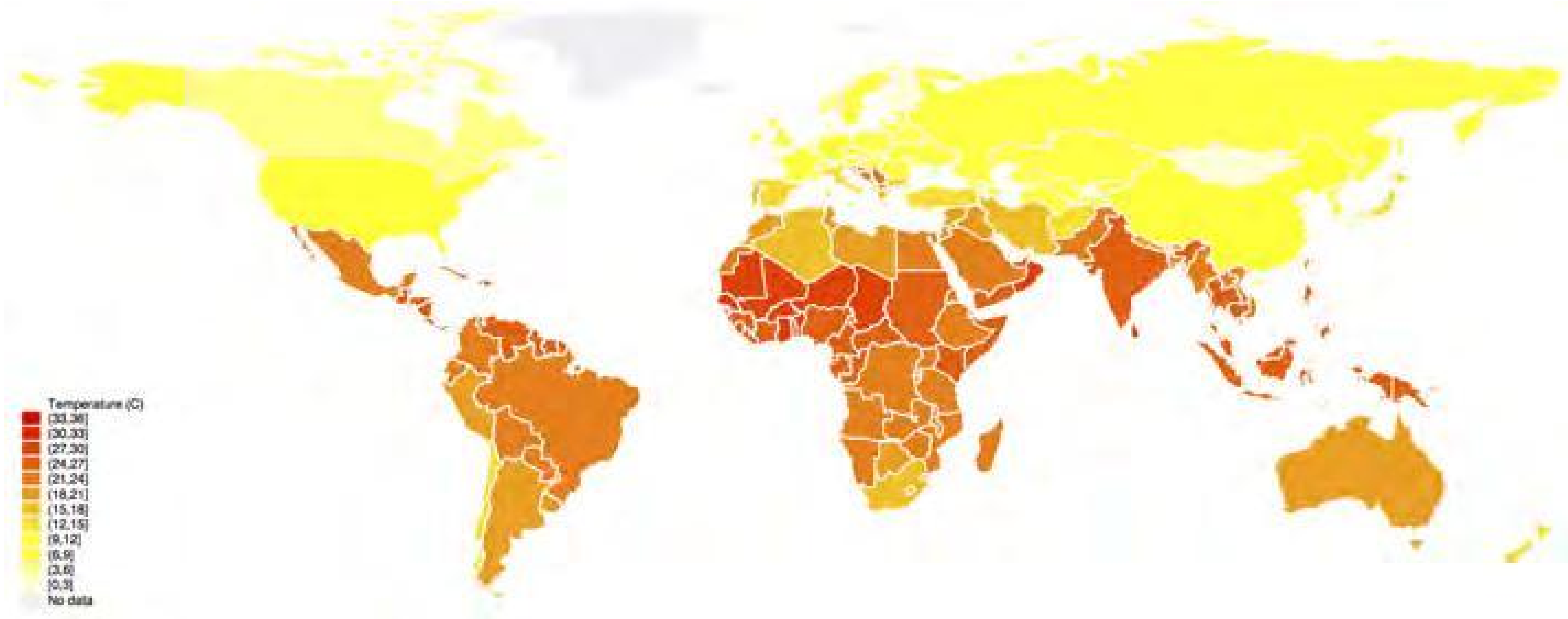
Climate change projection

2099 Temperature for Brazil + 2013 Climate



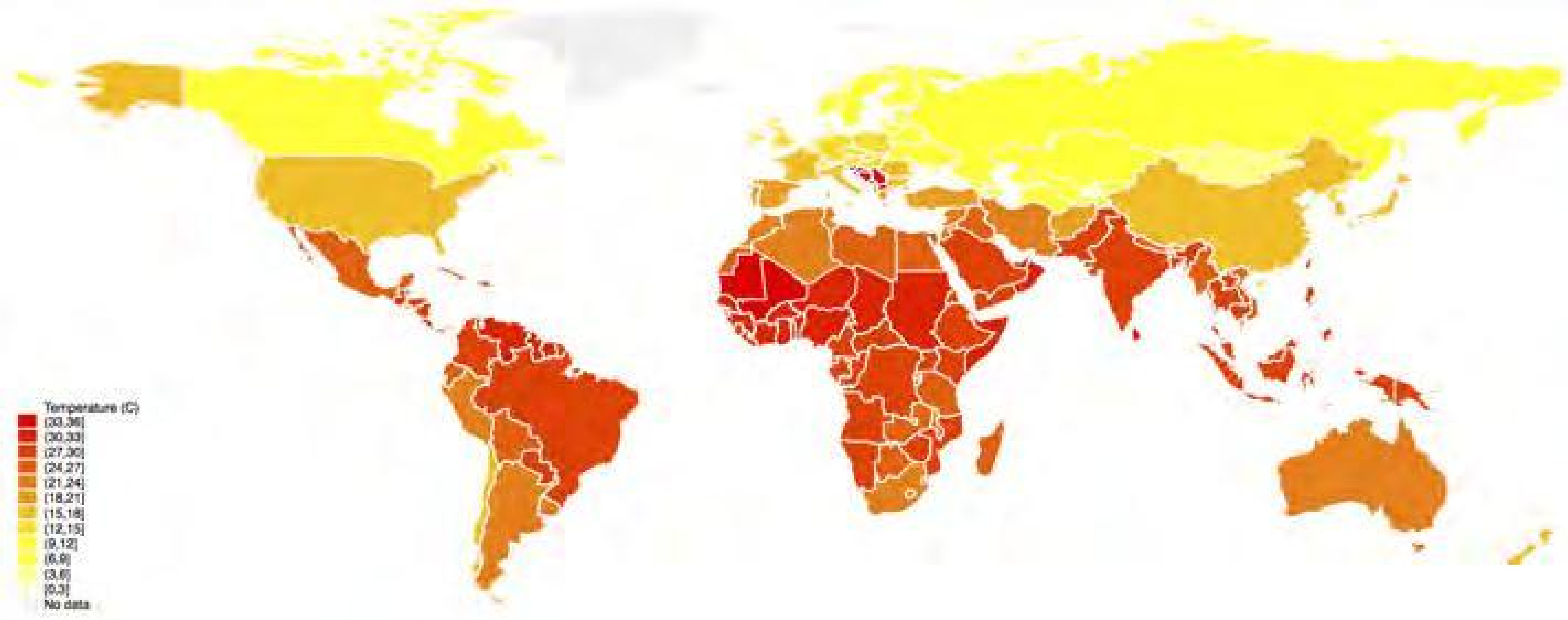
Climate change projection

2013 Climate



Climate change projection

2099 Climate



Agricultural productivity under climate change

Objectives:

- Project welfare variance under climate change
- Show global consequence of changing spatial correlation
- Show country-level consequences of changing spatial correlation

(Usual) projection caveats:

- Ceteris paribus besides climate-driven agricultural productivity
- No role for expectations
- No other GE effects (i.e. factor reallocation, crop choice)

Agricultural productivity under climate change

1. Estimate cereal yield response function during period, $t \in [\underline{t}, \bar{t}]$:

$$\ln A_{it} = k(T_{it}) + \mathbb{X}_{it}\Psi + \nu_{it}$$

   where $k()$ is a restricted cubic spline with four terms; $\mathbb{X}_{it}$ includes country FE, year FE, country quadratic trends

2. Forecast agricultural productivities through 2099 under business-as-usual climate scenario, holding everything else fixed at $\bar{t}$:

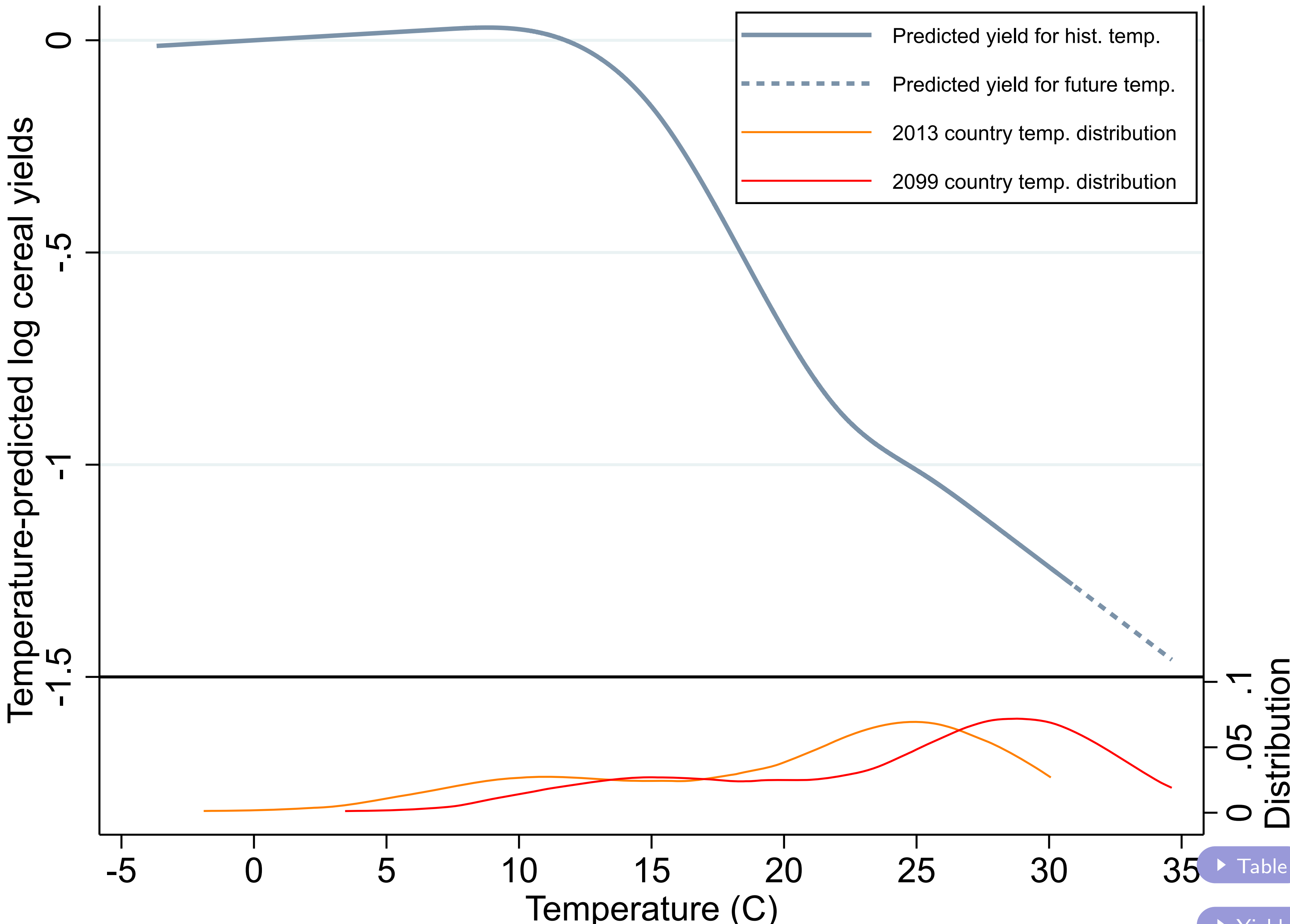
$$\widehat{\ln A}_{it} = \widehat{k}(\widehat{T}_{it}) + \mathbb{X}_{i\bar{t}}\widehat{\Psi} + \widehat{\nu}_{i\bar{t}}$$

3. Obtain welfare with and without change in spatial correlation

$$\widehat{\ln \lambda}^{s}_{iit} = (\widehat{\beta}_0 + \widehat{\beta}_1 \widehat{I}_t)\widehat{\ln A}_{it} + \widehat{\Pi}'\mathbb{Z}_{i\bar{t}} + \widehat{\mu}_{i\bar{t}}$$
$$\widehat{\ln \lambda}^{n}_{iit} = (\widehat{\beta}_0 + \widehat{\beta}_1 I_{\bar{t}})\widehat{\ln A}_{it} + \widehat{\Pi}'\mathbb{Z}_{i\bar{t}} + \widehat{\mu}_{i\bar{t}}$$

4. Calculate variance and spatial correlation of welfare under both scenarios

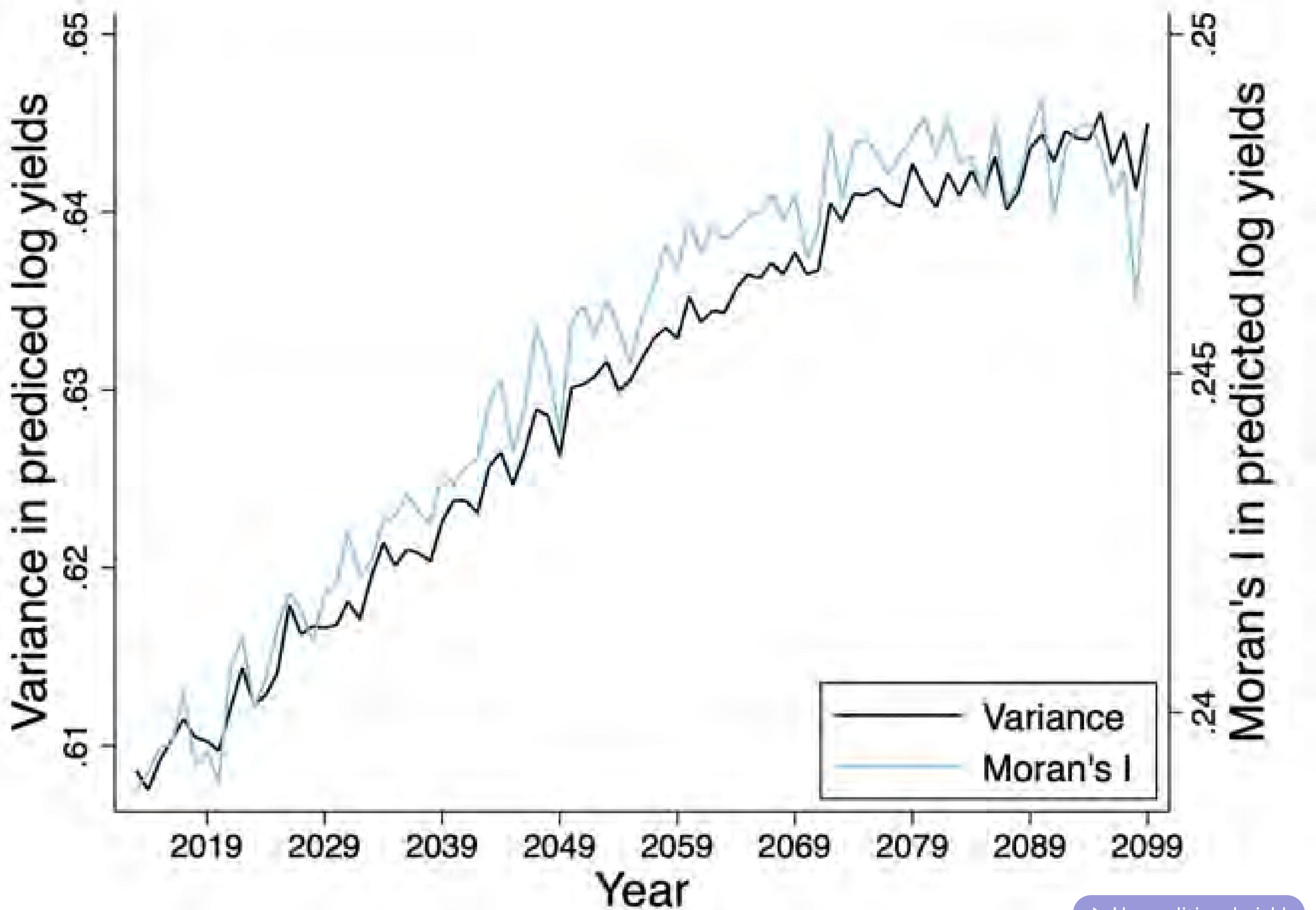
Estimated log cereal yield temperature relationship



▸ Table

▸ Yield map

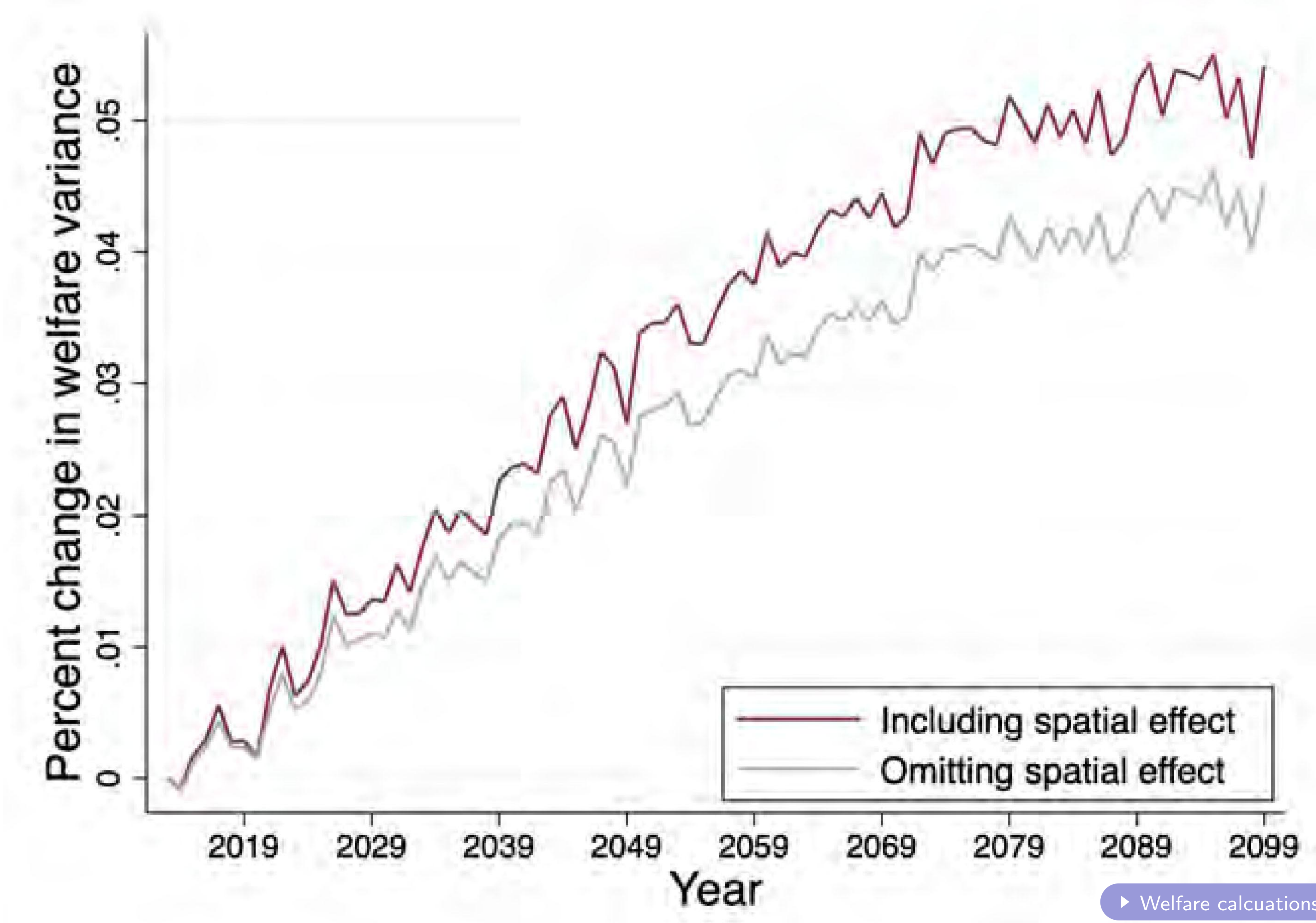
Climate-driven cereal yield variance and spatial correlation



Unconditional yield

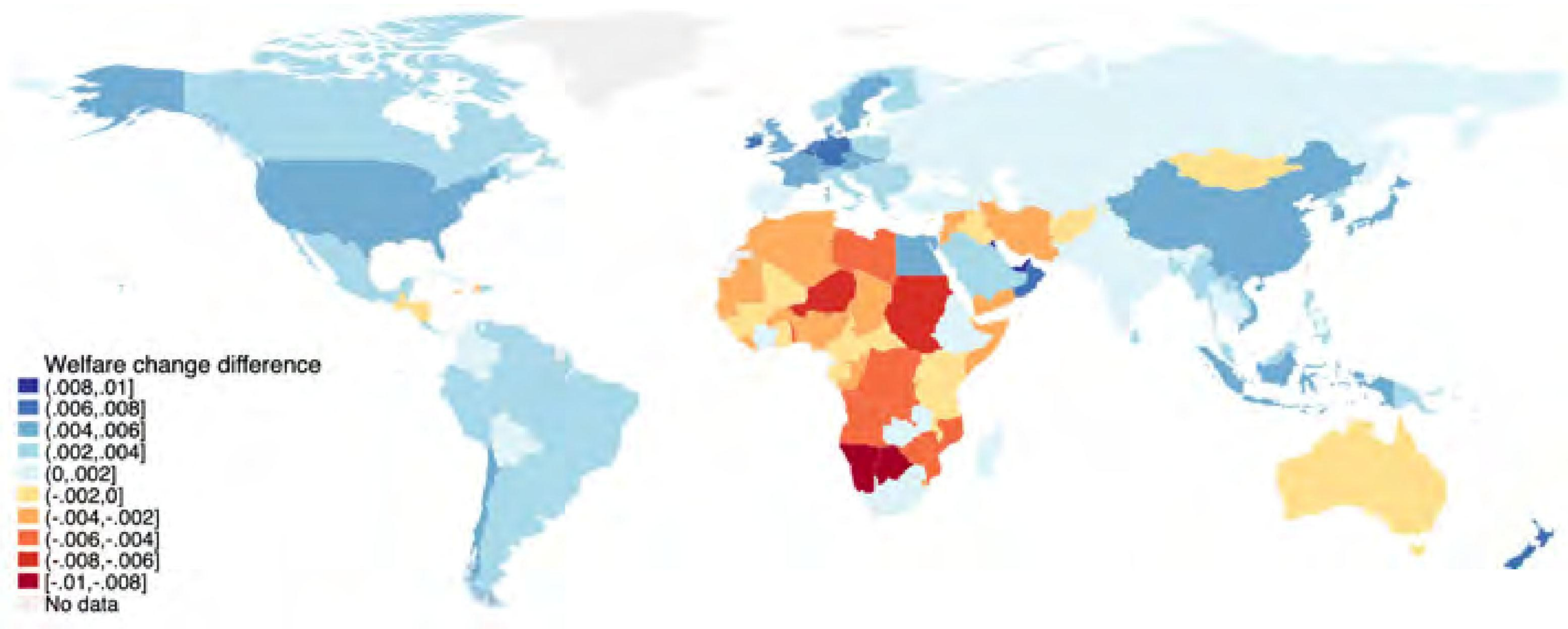
Climate-driven welfare variance

20% larger change in global welfare inequality when including spatial effects

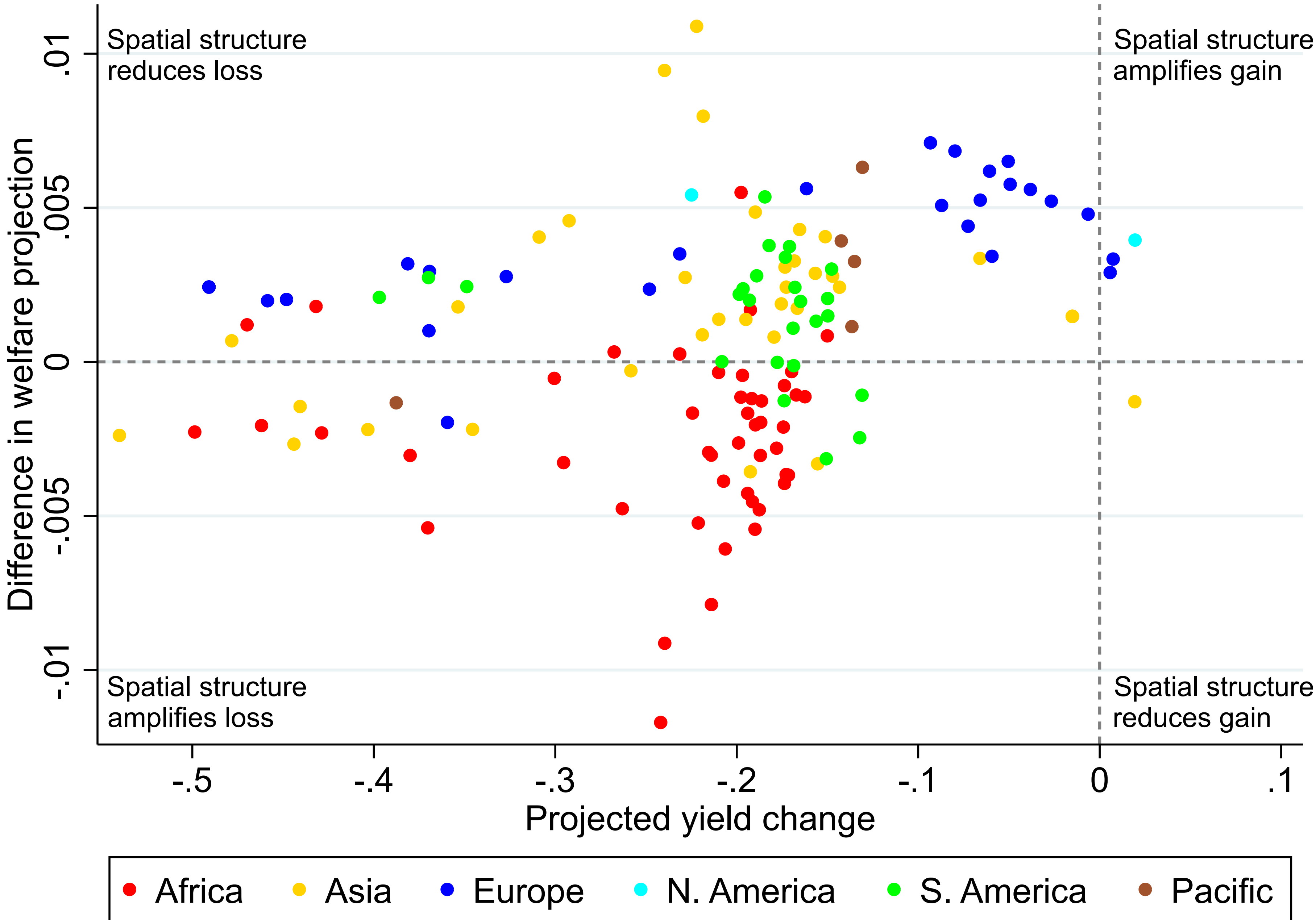


▸ Welfare calcuations

Cntry differences in projected welfare due to spatial effects



Cntry differences in projected welfare due to spatial effects



By country

Conclusions

- The *spatial correlation* of productivities influences global inequality because trade costs scale with distance
- Natural experiment exploiting exogenous reshuffling of agricultural productivity across global trade network
- Accounting for climate change-driven rise in spatial correlation increases end-of-century global inequality by 20%
- Broader implications as many natural resources exhibit substantial spatial correlation:
    1. relocation of existing resources (e.g. wildlife stocks)
    2. discovery of new uses for existing resources (e.g. solar and wind resources)
    3. discovery of new resources (e.g. shale gas deposits)

Thank you

kylemeng.com

Economic environment

Elements in Arkolakis, Costinot and Rodríguez-Clare (2012) class of models:

- $j = 1, \ldots, N$ countries populated by consumers with identical CES preferences
- One factor of production with inelastic supply L_j and productivity A_j employed under perfect competition at factor price w_j
- Iceberg trade costs $\tau_{ij} \geq 1, \tau_{ii} = 1$
- Gravity equation with trade elasticity ϵ:

$$\lambda_{ij} = \frac{X_{ij}}{X_j} = \frac{\chi_i \left(\tau_{ij} w_i\right)^{-\epsilon}}{\sum_{l=1}^{N} \chi_l \left(\tau_{lj} w_l\right)^{-\epsilon}}$$

- Equilibrium: $w_i L_i = \sum_j \lambda_{ij} w_j L_j$
- Each model differs in micro-foundations for γ:
  - Perfect competition, exogenous goods (i.e. Armington)
  - Perfect competition, endogenous goods (Eaton and Kortum, 2002)
  - Monopolistic competition (Krugman, 1980)

back

Gravity regression for cereal trade

Outcome is log import value

	(1)
ln distance$_{ij}$	-1.519***
	(0.100)
R-squared	0.545
Country-level intra-industry trade share	0.614
Bilateral intra-industry trade share	0.236
Observations	59927

NOTES: OLS estimates of gravity model for bilateral (importer-reported) trade value during 1986-2013. All models include importer-year and exporter-year fixed effects. Intraindustry trade shares are fraction of country-year and country-pair-year observations with positive exports and imports, conditional on positive exports or imports. Standard errors clustered at the importer and exporter levels in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

back

Focus on $cov\left(\ln A_i, \ln \lambda_{ii}\right)$

$$var\left(\ln\left(C_i^c/L_i\right)\right) - var\left(\ln\left(C_i^u/L_i\right)\right) = -\frac{2}{\epsilon}\left[cov\left(\ln A_i^c, \ln \lambda_{ii}^c\right) - cov\left(\ln A_i^u, \ln \lambda_{ii}^u\right)\right] + \frac{1}{\epsilon^2}\left[var\left(\ln \lambda_{ii}^c\right) - var\left(\ln \lambda_{ii}^u\right)\right]$$

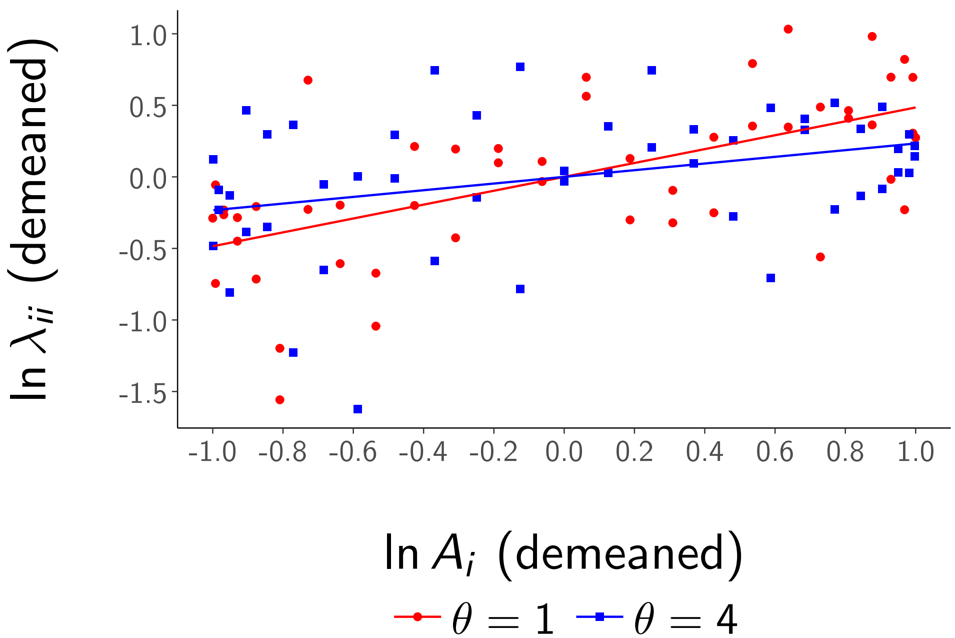
- $\frac{1}{\epsilon^2}$ is an order of magnitude smaller than $\frac{2}{\epsilon}$ for $\epsilon \geq 5$, Caliendo and Parro (2015) estimate ϵ for agriculture between 8 and 16
- Is $var\left(\ln \lambda_{ii}\right)$ the same order of magnitude as $cov\left(\ln A_i, \ln \lambda_{ii}\right)$?
- With symmetric trade costs $\tau_{ij} = \tau_{ji}$,
  $var(\ln \lambda_{ii}) = \frac{\epsilon}{\epsilon+1} cov(\ln A_i, \ln \lambda_{ii}) - \frac{1+2\epsilon}{1+\epsilon} cov(\ln \Phi_i, \ln \lambda_{ii})$
- Latter term is second-order, since Φ_i is a price-index term that is a weighted sum of all other countries' prices
- Thus, $\frac{1}{\epsilon^2}\left[var\left(\ln \lambda_{ii}^c\right) - var\left(\ln \lambda_{ii}^u\right)\right]$ is second-order

back

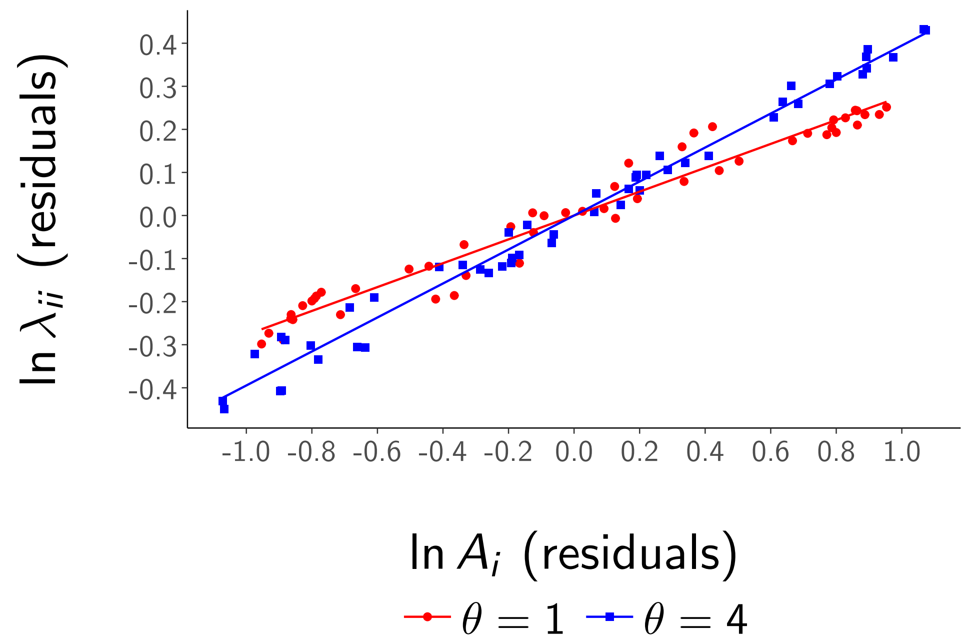
Ext. #2: heterogeneity in country size

Country size L_i may be heterogeneous

Omitted variable bias if L_i is correlated with productivity



Unconditional relationship

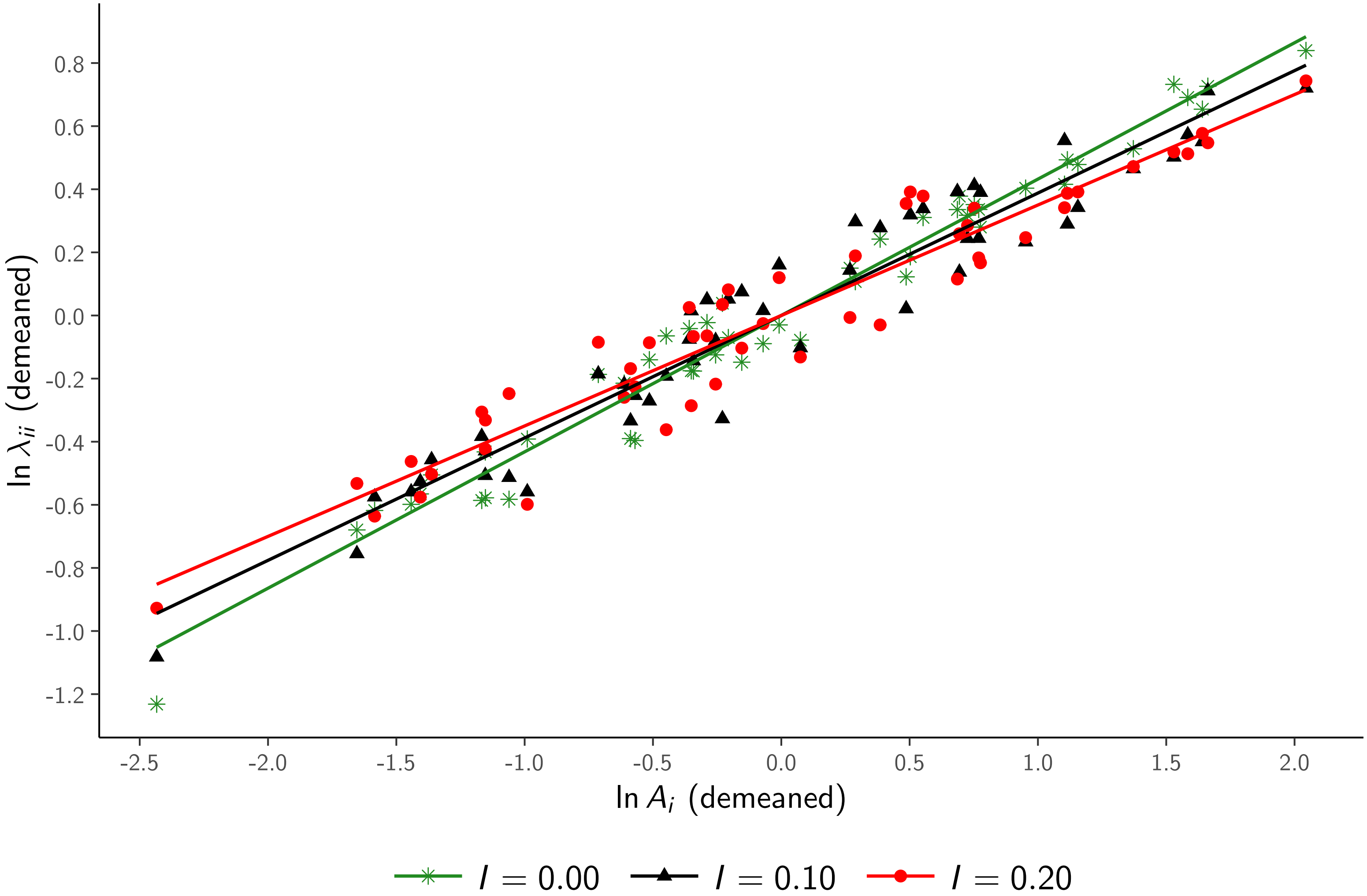


Relationship conditional on fixed effects

Implication for empirics:

$$\ln \lambda_{iit} = \beta_0 \ln A_{it} + \beta_1 \ln A_{it}\theta_t + \pi^T + \pi^I + \epsilon_{it}$$

Ext. #3: arbitrary productivity distributions



Estimation implication:

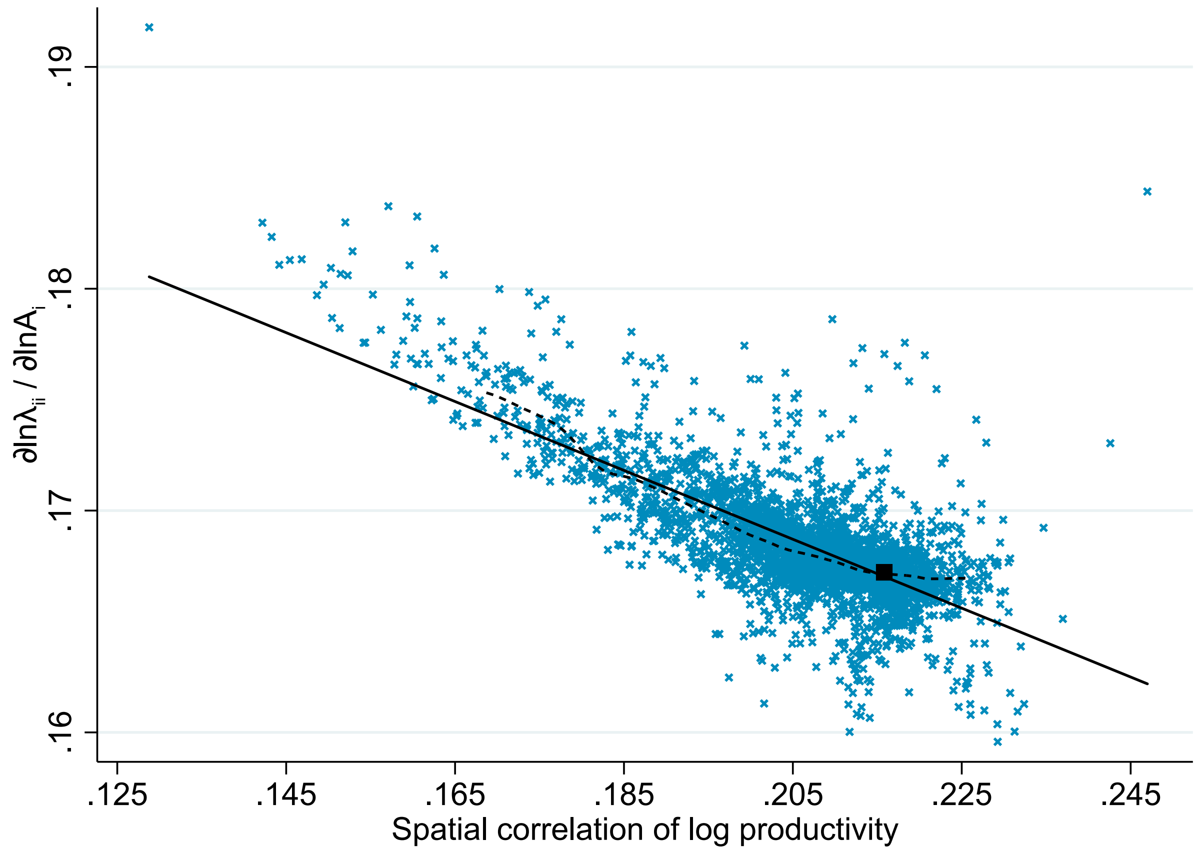
$$\ln \lambda_{iit} = \beta_0 \ln A_{it} + \beta_1 \ln A_{it} I_t + \pi^T + \pi^I + \epsilon_{it}$$

back

Ext. #4: 2-D geography with random locations

Annually reshuffle countries' lat. and long. coordinates randomly

Estimate $\ln \lambda_{iit} = \beta_t \ln A_{it} + \pi_i^I + \pi_t^T + \epsilon_{it}$, plot $\hat{\beta}_t$ against I_t

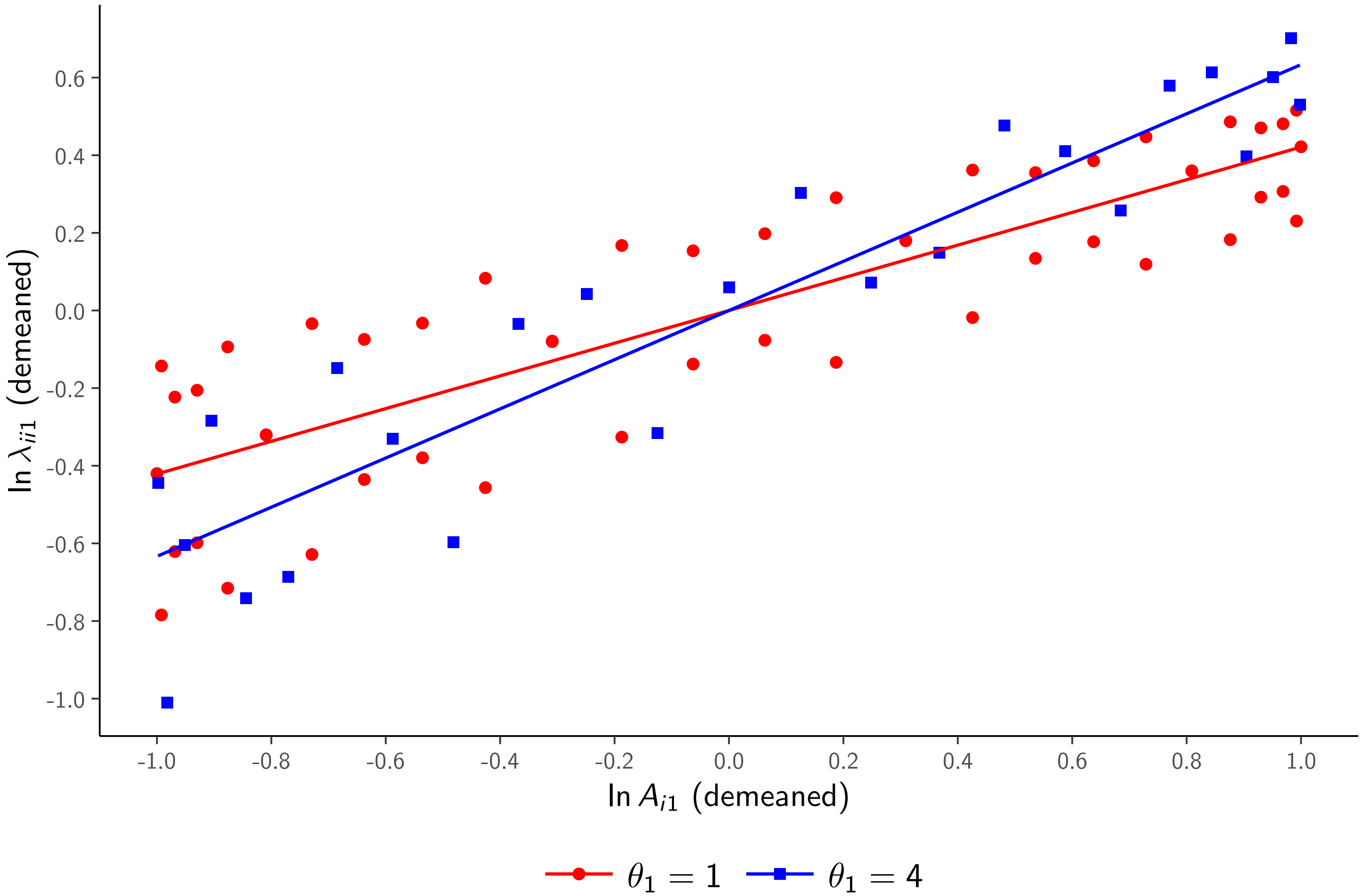


Implication for empirics:

$$\ln \lambda_{iit} = \beta_0 \ln A_{it} + \beta_1 \ln A_{it} I_t + \pi^T + \pi^I + \epsilon_{it}$$

back

Ext. #5: multiple-sector economy



Formal multi-sector expressions Mean and variance table

Implication for empirics:

- Sufficient to look at 1 sector provided prod. are not strongly anti-correlated
- 1-sector welfare effect provides upper bound on total wefare effect

back

Welfare mean and variance: one-sector sine-wave economy

Frequency of $\ln A$ sine wave (θ)	1	2	3	4
Autarky welfare ($\ln A$) mean	10	10	10	10
Autarky welfare ($\ln A$) variance	0.510204	0.510204	0.510204	0.510204
Trading-equilbrium welfare ($\ln C/L$) mean	12.2654	12.2769	12.2807	12.2836
Trading-equilbrium welfare ($\ln C/L$) variance	0.298203	0.226274	0.203006	0.184882

back

Multiple-sector case

- Assume Cobb-Douglas preferences with expenditure shares α_s, $s = 1, \ldots, S$
- Real consumption per capita in this environment is

$$\ln\left(C_j/L_j\right) = \sum_{s=1}^{S} \alpha_s \left(\ln A_{js} + \gamma_s - \frac{1}{\epsilon_s} \ln \lambda_{jjs} \right)$$

- Compare distributions c and u with $var\left(\sum_s \alpha_s \ln A_{js}^c\right) = var\left(\sum_s \alpha_s \ln A_{js}^u\right)$:

$$\begin{aligned} & var\left(\ln\left(C_j^c/L_j\right)\right) - var\left(\ln\left(C_j^u/L_j\right)\right) \\ & = 2\sum_{s=1}^{S}\sum_{s'=1}^{S} \frac{\alpha_s \alpha_{s'}}{\epsilon_{s'}} \left\{ cov\left(\ln A_{js}^u, \ln \lambda_{jjs'}^u\right) - cov\left(\ln A_{js}^c, \ln \lambda_{jjs'}^c\right) \right\} \\ & - \sum_{s=1}^{S}\sum_{s'=1}^{S} \frac{\alpha_s \alpha_{s'}}{\epsilon_s \epsilon_{s'}} \left\{ cov\left(\ln \lambda_{jjs}^u, \ln \lambda_{jjs'}^u\right) - cov\left(\ln \lambda_{jjs}^c, \ln \lambda_{jjs'}^c\right) \right\} \end{aligned}$$

- Perfectly correlated productivities are similar to one-sector case
- Perfectly anti-correlated productivities can generate offsetting effects

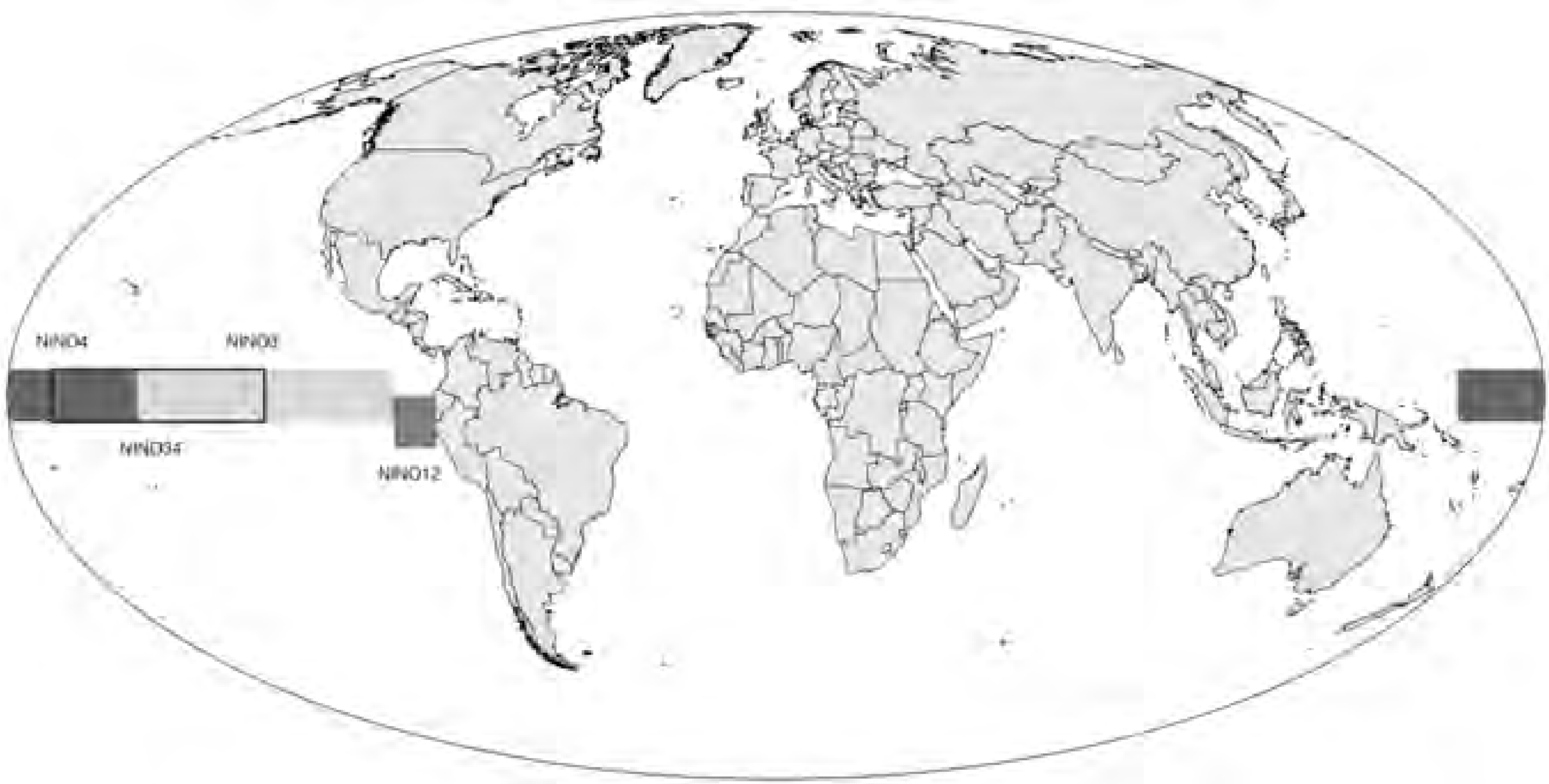
back

Welfare mean and variance: multi-sector sine-wave economy

Frequency of $\ln A_1$ sine wave (θ_1)	1	2	3	4
Autarky welfare ($\frac{1}{2}\ln A_1 + \frac{1}{2}\ln A_2$) mean	10	10	10	10
Autarky welfare ($\frac{1}{2}\ln A_1 + \frac{1}{2}\ln A_2$) variance	0.255102	0.255102	0.255102	0.255102
Trading-equilbrium welfare ($\ln C/L$) mean	12.3610	12.3699	12.3721	12.3736
Trading-equilbrium welfare ($\ln C/L$) variance	0.114255	0.097649	0.092189	0.087935

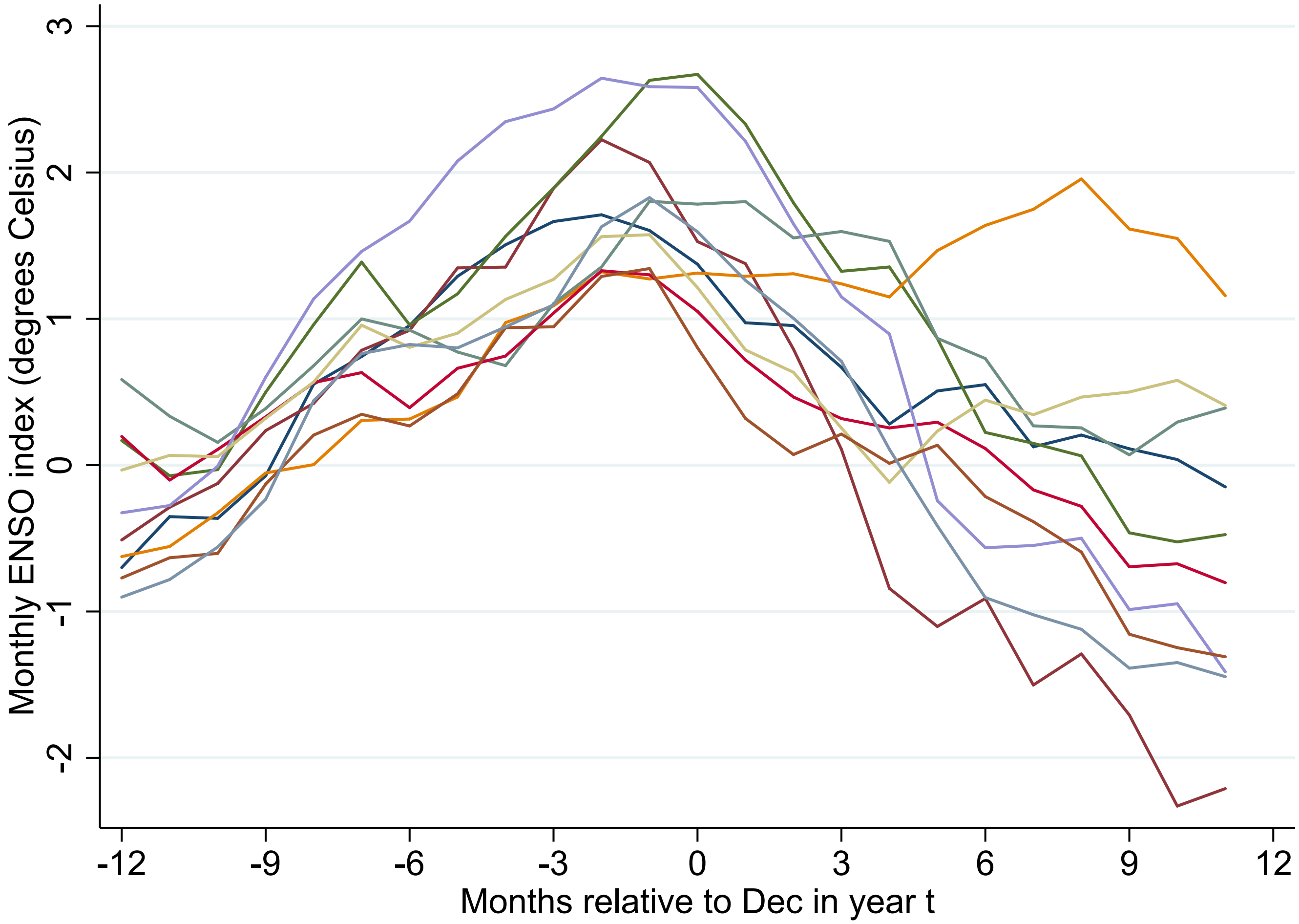
back

Location of ENSO measurements



◀ back

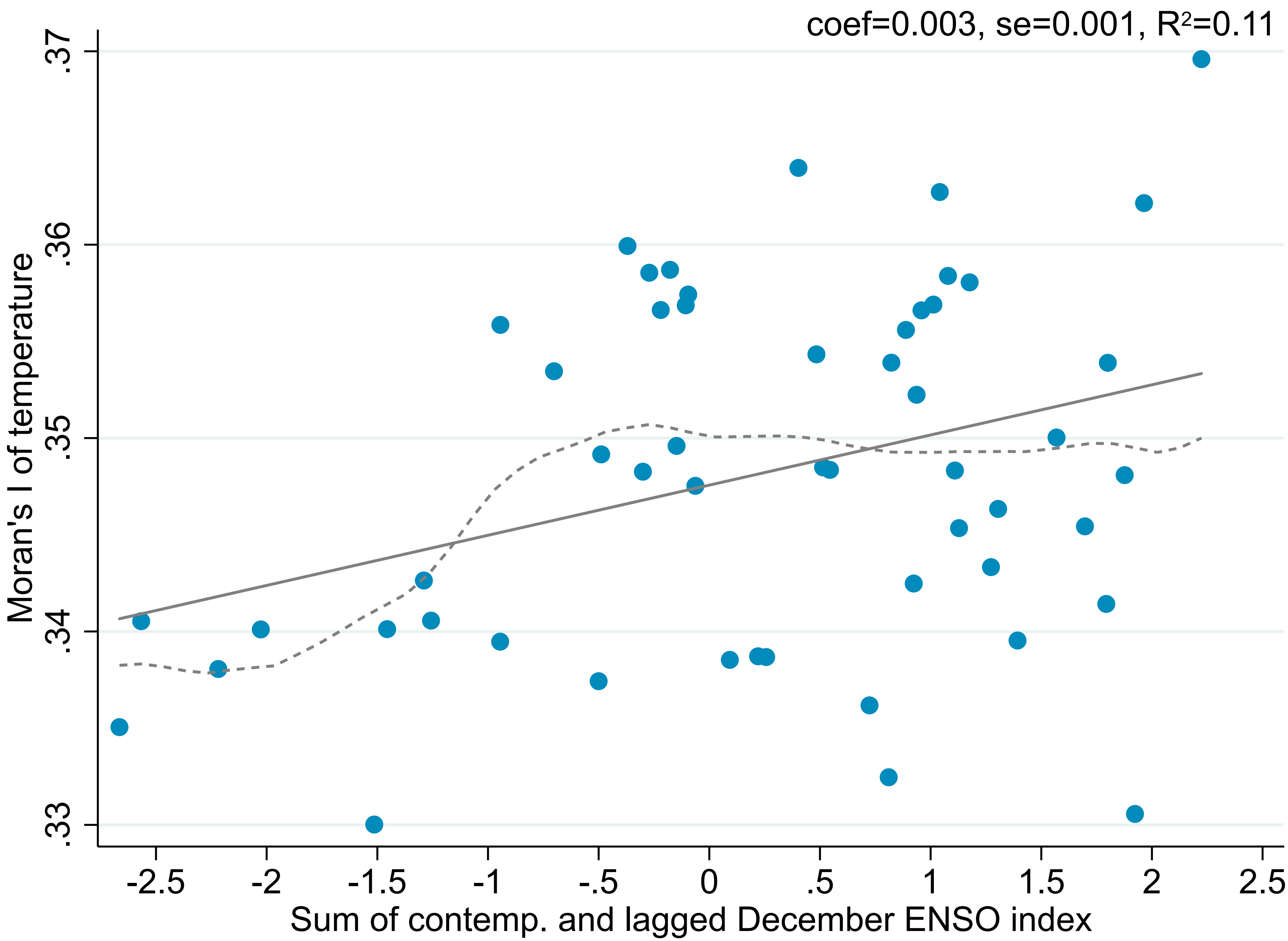
Monthly ENSO index for top 10 positive events



NOTES: Monthly evolution of ENSO index 12 months before and after the 10 most positive ENSO events over 1961-2013. ENSO events occur during the winters of 1965, 1972, , 1982, 1986, 1991, 1994, 1997, 2002, 2006, and 2009.

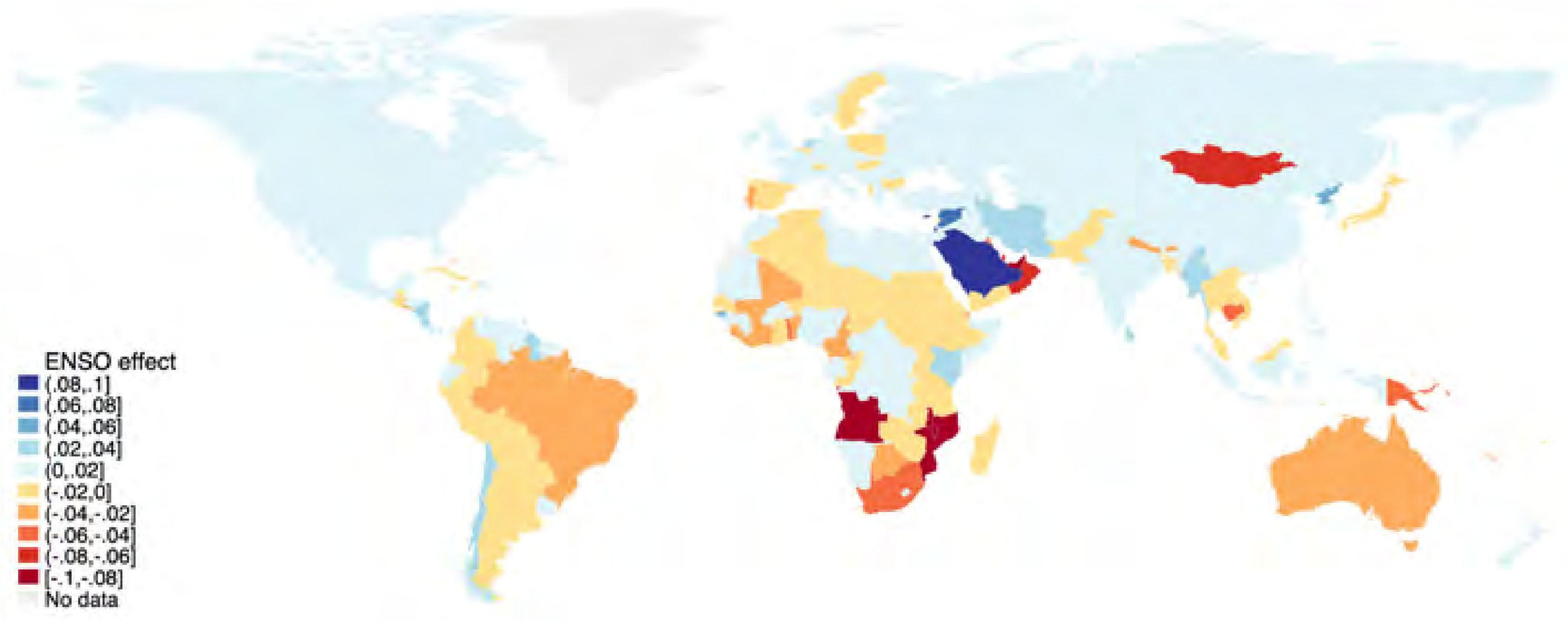
back

ENSO and Moran's *I* for temperature



Back

ENSO's effects on country cereal yields



Back

ENSO and Moran's I in log cereal yields

Outcome is Moran-I in log cereal yields

	(1)	(2)	(3)	(4)
$ENSO_t$	0.008***	0.008***		
	(0.002)	(0.002)		
$ENSO_{t-1}$	0.003	0.005***		
	(0.002)	(0.002)		
$ENSO_t \times ENSO_{t-1}$		0.004		
		(0.003)		
$ENSO_t^2$		-0.001		
		(0.002)		
$ENSO_{t-1}^2$		0.004		
		(0.003)		
$(ENSO_t + ENSO_{t-1})$			0.006***	
			(0.001)	
$(ENSO_t + ENSO_{t-1})^2$			0.002*	
			(0.001)	
$I_t(T_{it})$				0.541***
				(0.163)
BIC	-275.84	-267.21	-276.63	-272.95
Observations	53	53	53	53

NOTES: Time-series regressions of Moran's I in log cereal yields on nonlinear functions of contemporaneous and lagged December ENSO. All models include a linear time trend. Serial correlation and heteroscedasticity robust Newey-West standard errors with optimal bandwidth in parentheses (Newey and West, 1987). *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

back

Gravity regression results

Outcome is log import value

	(1)	(2)
$\ln \text{distance}_{ij}$	-1.460***	-1.477***
	(0.046)	(0.066)
$\ln \text{distance}_{ij} \times (ENSO_t + ENSO_{t-1})$		0.037
		(0.037)
$\ln \text{distance}_{ij} \times (ENSO_t + ENSO_{t-1})^2$		0.004
		(0.029)
Observations	102,787	102,787
R-squared	0.556	0.557
Country-level intra-industry trade share	0.628	0.628
Bilateral intra-industry trade share	0.185	0.185

NOTES: The dependent variable is log annual bilateral (importer-reported) cereal trade value from Comtrade. The data cover 1962-2013. All models include importer-year and exporter-year fixed effects. Intraindustry trade shares are fraction of country-year and country-pair-year observations with positive exports and imports, conditional on positive exports or imports. Standard errors clustered at year levels in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

back

LIML: Instruments do not appear to be weak

	(1)	(2)	(3)	(4)	(5)
α'_{11} joint F-stat p-value	0.022	0.007	0.011	0.011	0.008
α'_{12} joint F-stat p-value	0.006	0.038	0.097	0.178	0.218
α'_{21} joint F-stat p-value	0.071	0.004	0.007	0.006	0.003
α'_{22} joint F-stat p-value	0.041	0.062	0.028	0.041	0.071
Number of temperature splines in $f()$	2	3	4	5	6
Observations	5452	5452	5452	5452	5452

NOTES: 5452 observations. All models include country fixed effects, year fixed effects, and country linear trends as excluded instruments. Standard errors clustered at year levels in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

back

LIML: Instruments do not appear to be weak

Outcome is log domestic share of expenditure

	(1)	(2)	(3)	(4)	(5)
$\ln A_{it}$ (β_0)	2.110**	2.380***	2.114***	2.196***	2.308***
	(0.837)	(0.847)	(0.604)	(0.669)	(0.771)
$\ln A_{it} \times I_t$ (β_1)	-4.530	-4.907	-4.144**	-4.218**	-4.463**
	(2.752)	(2.937)	(1.834)	(1.949)	(2.194)
Number of temperature splines in f()	2	3	4	5	6
Number of instruments	6	9	12	15	18
Cragg-Donald F-stat	7.052	5.832	5.174	4.324	3.801
Kleibergen-Paap F-stat	6.100	5.664	3.963	3.332	3.069
Stock-Yogo crit. value: 10% max LIML size	4.060	3.700	3.580	3.540	3.560
Anderson-Rubin weak-id robust joint p-value	0.000	0.000	0.000	0.000	0.000

NOTES: 5452 observations. All models include country fixed effects, year fixed effects, and country linear trends as excluded instruments. Standard errors clustered at year levels in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

back

LIML: Instruments do not appear to be weak

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	(1)	(2)	(3)	(4)	(5)
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ln $A_{it} \times I_t$ (β_1)	-4.530	-4.907	-4.144**	-4.218**	-4.463**
	(2.752)	(2.937)	(1.834)	(1.949)	(2.194)
Number of temperature splines in f()	2	3	4	5	6
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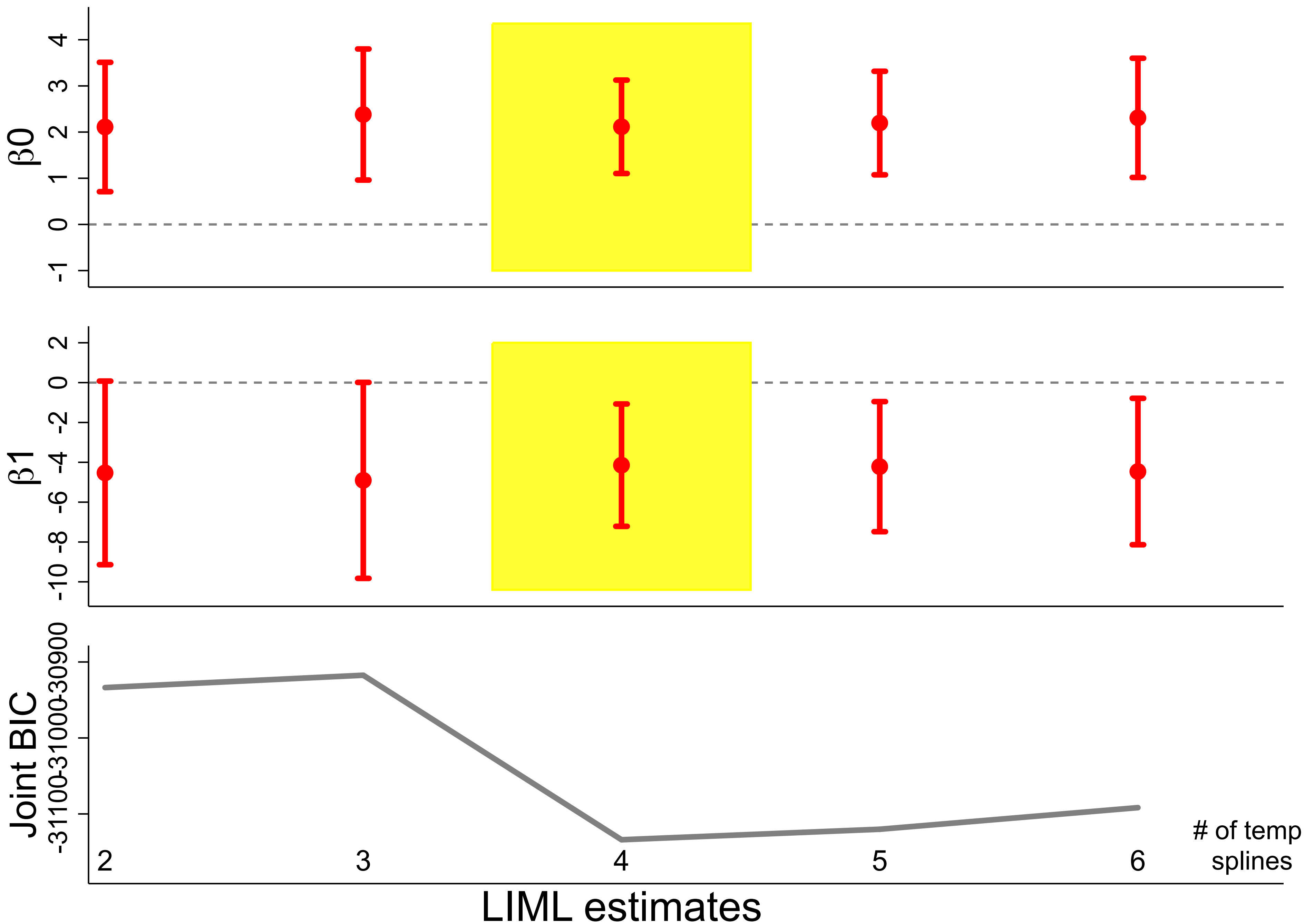
Stock-Yogo crit. value: 10% max LIML size	4.060	3.700	3.580	3.540	3.560
Anderson-Rubin weak-id robust joint p-value	0.000	0.000	0.000	0.000	0.000

NOTES: All models include country fixed effects, year fixed effects, and country linear trends as excluded instruments. Standard errors clustered at year levels in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

back

LIML: BIC selects four splines for $f()$



Welfare implication

Recall from theory:

$$var\left(\ln\left(C_i^c/L_i\right)\right) - var\left(\ln\left(C_i^u/L_i\right)\right) = -\tfrac{2}{\epsilon}\left[cov\left(\ln A_i^c, \ln\lambda_{ii}^c\right) - cov\left(\ln A_i^u, \ln\lambda_{ii}^u\right)\right] + \frac{1}{\epsilon^2}\left[var\left(\ln\lambda_{ii}^c\right) - var\left(\ln\lambda_{ii}^u\right)\right]$$

Thought experiment:

1 std dev increase relative to historical average Moran's I.

Using reduced-form coefficients $\widehat{\beta}_0$, $\widehat{\beta}_1$ and $\epsilon = 8.59$ (Caliendo and Parro, 2015):

$$cov(\ln A_i^u, \ln\lambda_{ii}^u) \equiv E_t[cov_i(\ln A_{it}, \ln\lambda_{iit}|t)]$$

$$cov(\ln A_i^c, \ln\lambda_{ii}^c) \equiv (\widehat{\beta}_0 + \widehat{\beta}_1(\bar{I} + \sigma_I))E_t[var_i(\ln A_{it}|t)] + E_t[cov_i(\ln A_{it}, \mathbb{Z}_{it}\widehat{\Pi}|t)] + E_t[cov_i(\ln A_{it}, \widehat{\mu}_{it}|t)]$$

Pct change in per capita consumption variance for 1 std dev higher Moran's I:

$$\frac{var(\ln(C_i^c/L_i)) - var(\ln(C_i^u/L_i))}{var(\ln(C_i^u/L_i))}$$

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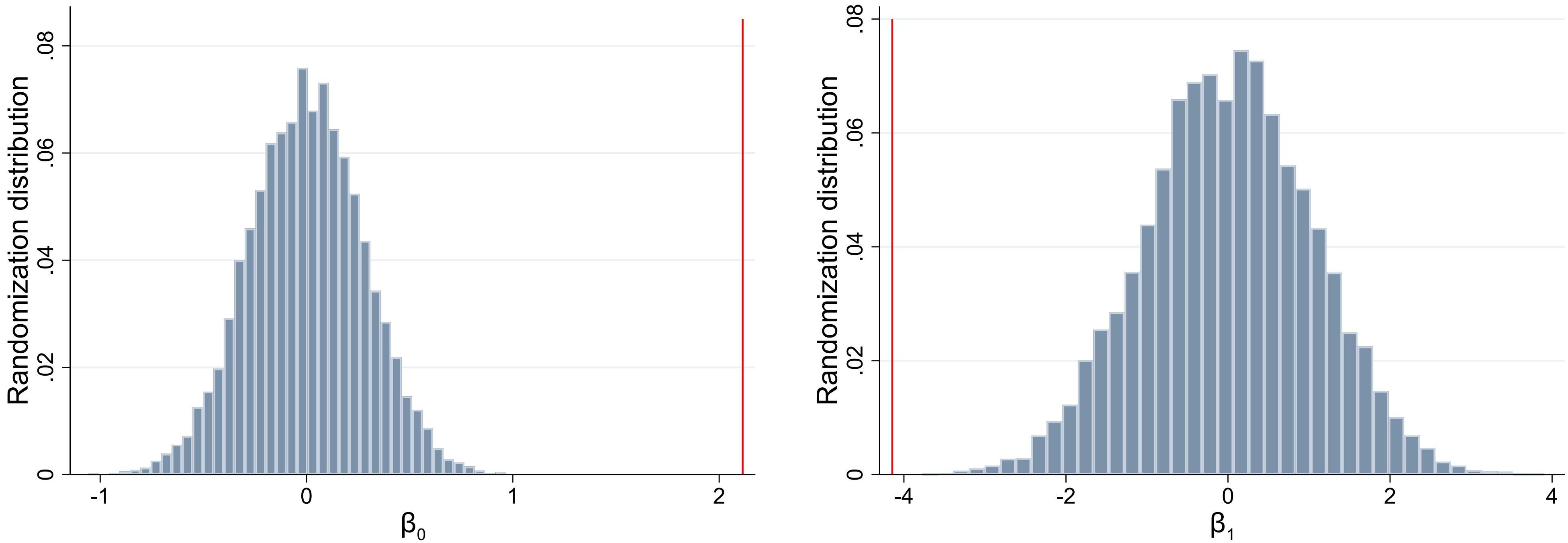
Randomization inference



NOTES: Empirical distributions of β_0 (left panel) and β_1 (right panel) from 10,000 random assignments of years. Vertical lines show estimates of β_0 and β_1 from observed data using benchmark model.

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Robustness: Standard errors

Outcome is log domestic share of expenditure				
	(1)	(2)	(3)	(4)
$\ln A_{it}$ (β_0)	2.114***	2.114***	2.114**	2.114***
	(0.604)	(0.665)	(0.830)	(0.698)
$\ln A_{it} \times I_t$ (β_1)	-4.144**	-4.144**	-4.144*	-4.144**
	(1.834)	(1.910)	(2.157)	(1.939)
Clustering	year cluster	year cluster and 20 year HAC	year cluster and cntry cluster	year cluster
Bekker adjustment	No	No	No	Yes

NOTES: 5452 observations. All models include country fixed effects, year fixed effects, and country linear trends as excluded instruments. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

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Robustness: Controlling for time-varying trade costs

Outcome is log domestic share of expenditure

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$\ln A_{it}$ (β_0)	2.114***	2.178***	2.163***	2.492***	2.297***	2.115***	2.270***
	(0.604)	(0.612)	(0.593)	(0.737)	(0.641)	(0.604)	(0.796)
$\ln A_{it} \times I_t$ (β_1)	-4.144**	-4.254**	-4.189**	-4.748**	-4.227**	-4.145**	-4.281**
	(1.834)	(1.865)	(1.825)	(2.095)	(1.844)	(1.833)	(1.985)
ln oil price $\times$ average ln λ_{ii}		Yes					
ln oil price $\times$ centrality			Yes				
Year FE $\times$ average ln λ_{ii}				Yes			
Year FE $\times$ centrality					Yes		
Export restrictions						Yes	
Precipitation							Yes
Observations	5452	5452	5452	5452	5452	5452	5452

NOTES: 5452 observations. All models include country fixed effects, year fixed effects, and country linear trends as excluded instruments. Standard errors clustered at year levels in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

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Robustness: Time-varying parameters

Outcome is log domestic share of expenditure

	(1)	(2)	(3)	(4)
$\ln A_{it}$ (β_0)	2.114***	2.152***	1.845	1.692***
	(0.604)	(0.595)	(2.807)	(0.511)
$\ln A_{it} \times I_t$ (β_1)	-4.144**	-4.226**	-4.639	-2.708
	(1.834)	(1.925)	(12.564)	(1.627)
Include large producers?	No	Yes	No	No
Sample period	1961-2013	1961-2013	1961-1987	1988-2013
Observations	5452	4952	2655	2793

NOTES: All models include country fixed effects, year fixed effects, and country linear trends as excluded instruments. Standard errors clustered at year levels in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

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Robustness: Dynamic effects

Outcome is log domestic share of expenditure

	(1)	(2)	(3)	(4)
$\ln A_{it}$	2.217***			1.326**
	(0.651)			(0.634)
$\ln A_{it} \times I_t$	-4.152**			-3.233**
	(1.874)			(1.590)
$\ln A_{it+1}$		0.724		
		(0.503)		
$\ln A_{it+1} \times I_{t+1}$		-0.830		
		(1.642)		
$\ln A_{it-1}$			0.851	
			(0.526)	
$\ln A_{it-1} \times I_{t-1}$			-2.039	
			(1.354)	
2nd stage sample period	1962-2012	1962-2012	1962-2012	1961-2013
Include stored cereals?	No	No	No	Yes
Observations	5237	5236	5235	5191

NOTES: All models include country fixed effects, year fixed effects, and country linear trends as excluded instruments. Standard errors clustered at year levels in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

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Robustness: Terms of trade

Outcome is asinh(change in terms of trade)		
	(1)	(2)
	Cereals	Food
$\Delta \ln A_{it}$ (ς_0)	-1.886*	-1.354
	(1.015)	(1.273)
$\Delta \ln A_{it} \times I_t$ (ς_1)	8.756*	6.625
	(5.058)	(6.643)
Cragg-Donald F-stat	10.054	10.054
Stock-Yogo crit. value: 10% max LIML size	3.580	3.580
Kleibergen-Paap F-stat	3.347	3.347
Observations	5747	5747

NOTES: Outcome is change in terms of trade. Models include country and year fixed effect as excluded instruments. Standard errors clustered at year levels in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

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Robustness: ENSO and local temperature definitions

Outcome is log domestic share of expenditure

	(1)	(2)	(3)	(4)
Panel A: Crop-area-weighted country temperature				
$\ln A_{it}$ (β_0)	2.114***	2.108***	2.084***	2.722***
	(0.604)	(0.715)	(0.706)	(0.987)
$\ln A_{it} \times I_t$ (β_1)	-4.144**	-4.064*	-4.465*	-6.026*
	(1.834)	(2.414)	(2.406)	(3.127)
Panel B: Total-area-weighted country temperature				
$\ln A_{it}$ (β_0)	1.632***	1.722***	1.562**	1.871**
	(0.500)	(0.626)	(0.597)	(0.729)
$\ln A_{it} \times I_t$ (β_1)	-3.960**	-4.125*	-4.155*	-4.517*
	(1.617)	(2.155)	(2.071)	(2.331)
ENSO index	4	3	34	12

NOTES: Top (bottom) panel has 5452 (5605) observations. All models include country fixed effects, year fixed effects, and country linear trends as excluded instruments. Standard errors clustered at year levels in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

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Robustness: using only local temperature variation

Outcome is log domestic share of expenditure

	(1)	(2)	(3)	(4)	(5)
$\ln A_{it}$ (β_0)	2.486*	2.540**	1.918***	1.647**	1.686***
	(1.310)	(1.182)	(0.600)	(0.618)	(0.624)
$\ln A_{it} \times I_t$ (β_1)	-5.044	-5.135	-3.092	-2.348	-2.394
	(4.173)	(4.011)	(1.884)	(1.943)	(2.021)
Percentage change in welfare variance	2.326	2.368	1.430	1.087	1.109
from 1 s.d. increase in I_t	[2.219]	[2.091]	[0.939]	[0.953]	[0.987]
	[0.294]	[0.257]	[0.128]	[0.254]	[0.261]
Number of temperature splines in f	2	3	4	5	6
Temperature Moran's I polynomial order in g	1	1	1	1	1
Number of instruments	4	6	8	10	12
Observations	5452	5452	5452	5452	5452

NOTES: All models include country fixed effects, year fixed effects, and country linear trends as excluded instruments. Standard errors clustered at year levels in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

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Robustness: domestic expenditure construction

Outcome is log domestic share of expenditure

	(1)	(2)	(3)	(4)	(5)	(6)
ln A_{it} (β_0)	2.114***	1.365***	1.825***	1.568***	1.606***	1.867***
	(0.604)	(0.397)	(0.559)	(0.432)	(0.567)	(0.536)
ln $A_{it} \times I_t$ (β_1)	-4.144**	-3.068**	-3.622**	-2.835**	-3.899**	-3.520**
	(1.834)	(1.423)	(1.585)	(1.337)	(1.568)	(1.549)
Price data	FAO	FAO	FAO	FAO	Comtrade	FAO
Price imputation	average export	export+producer	lowest export	highest export	average export	average export
Drop outliers?	No	No	No	No	No	1$
Observations	5452	2918	5452	5452	5696	5366

NOTES: All models include country fixed effects, year fixed effects, and country linear trends as excluded instruments. Standard errors clustered at year levels in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

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Robustness: Temperature-yield response function

Outcome is log cereal yields						
	(1)	(2)	(3)	(4)	(5)	(6)
Temperature 1st term	0.004	0.004	0.005	0.005	0.007	0.005
	(0.009)	(0.009)	(0.010)	(0.010)	(0.011)	(0.011)
Temperature 2nd term	-0.183	-0.165***	-0.222	-0.203***	-0.126	-0.100*
	(0.041)	(0.040)	(0.071)	(0.071)	(0.060)	(0.059)
Temperature 3rd term	0.650	0.599***	0.418	0.393*	0.020	-0.031
	(0.160)	(0.159)	(0.196)	(0.196)	(0.212)	(0.205)
Temperature 4th term	-1.162	-1.100**	0.356	0.248	1.320	1.394**
	(0.533)	(0.539)	(0.649)	(0.644)	(0.674)	(0.658)
Temperature 5th term			-2.204	-1.801	-2.895	-3.370*
			(1.775)	(1.760)	(1.880)	(1.864)
Temperature 6th term					1.830	3.213
					(3.814)	(3.791)
Precipitation		0.003***		0.003***		0.003***
		(0.001)		(0.001)		(0.001)
Precipitation squared		-0.000***		-0.000***		-0.000***
		(0.000)		(0.000)		(0.000)
Precipitation	No	Yes	No	Yes	No	Yes
Temp. joint p-value	0.0004	0.0014	0.0009	0.0030	0.0015	0.0049
Optimal temp.	8.81	8.91	8.87	8.94	7.80	7.70

NOTES: Estimates of cubic spline terms. All models include country fixed effects, year fixed effects, and quadratic linear trends. Standard errors clustered at year levels in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

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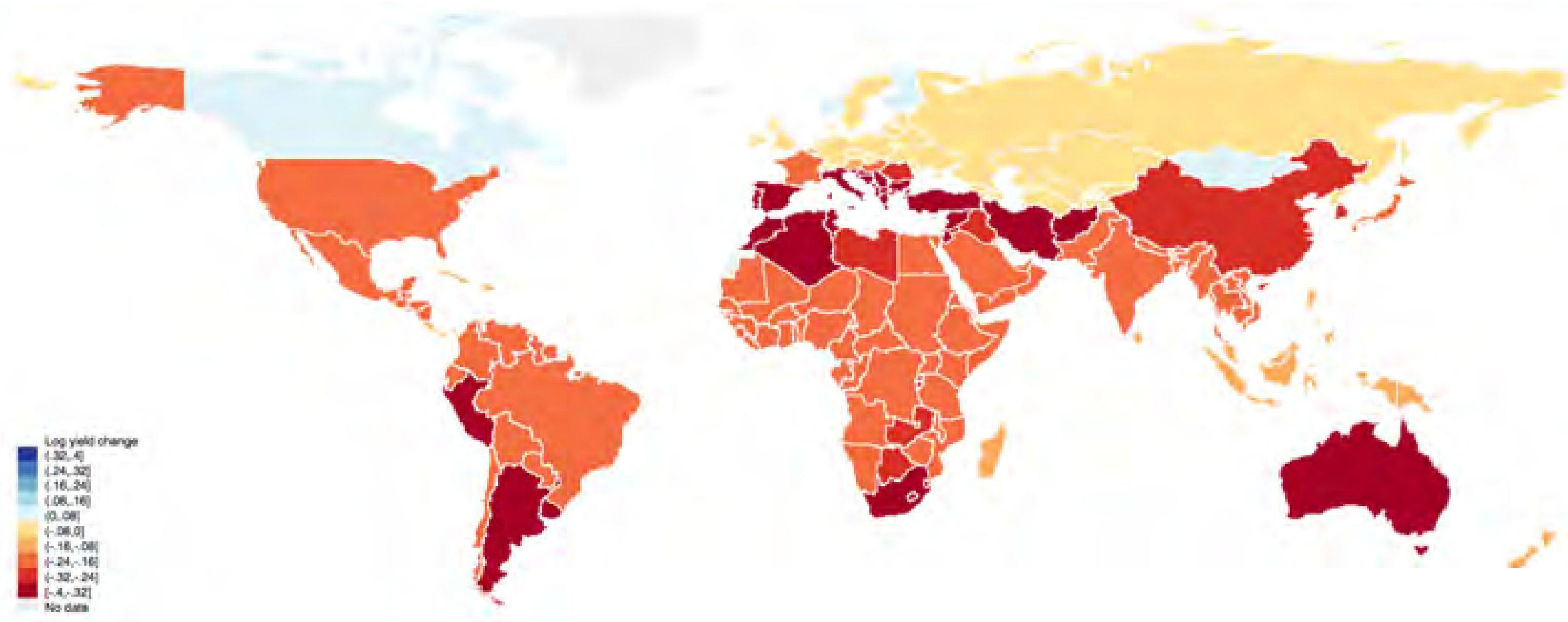
Change in log cereal yields under climate change



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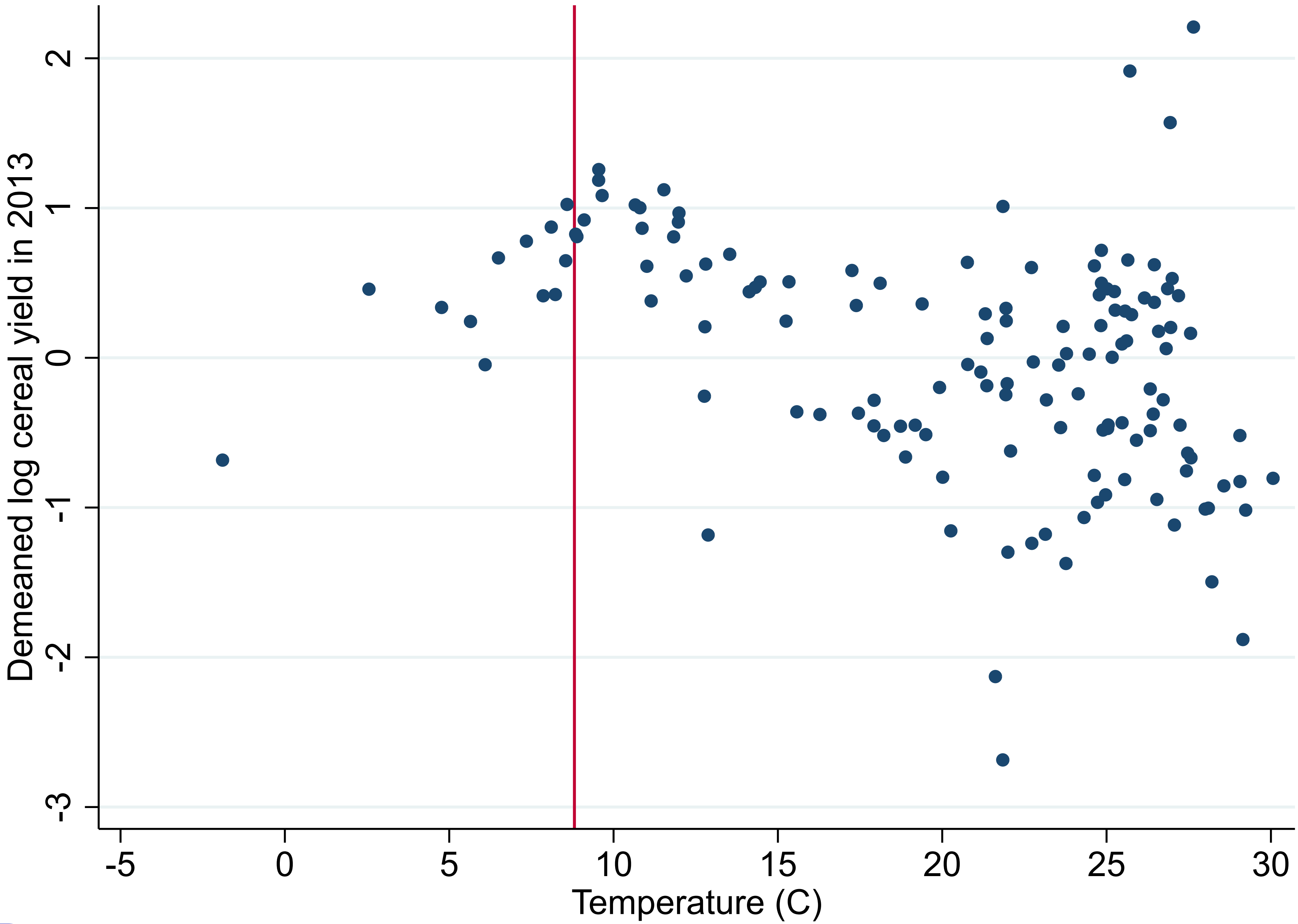
Observed log cereal yields and temperature in 2013



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Incorporating spatial structure into climate forecasts

Gains from trade holding spatial correlation fixed

$$\widehat{\ln \lambda}^{n}_{iit} = (\widehat{\beta}_0 + \widehat{\beta}_1 I_{\bar{t}})\widehat{\ln A}_{it} + \mathbb{Z}_{i\bar{t}}\widehat{\Pi} + \widehat{\mu}_{i\bar{t}}$$

Gains from trade including changes in spatial correlation:

$$\widehat{\ln \lambda}^{s}_{iit} = (\widehat{\beta}_0 + \widehat{\beta}_1 \widehat{I}_{t})\widehat{\ln A}_{it} + \mathbb{Z}_{i\bar{t}}\widehat{\Pi} + \widehat{\mu}_{i\bar{t}}$$

Percentage difference in welfare variance change across projections:

$$\frac{var\left(\ln\left(C^{s}_{i,2099}/L^{s}_{i,2099}\right)\right) - var\left(\ln\left(C_{i,2013}/L_{i,2013}\right)\right)}{var\left(\ln\left(\left(C^{n}_{i,2099}/L^{n}_{i,2099}\right)\right)\right) - var\left(\ln\left(\left(C_{i,2013}/L_{i,2013}\right)\right)\right)} - 1$$

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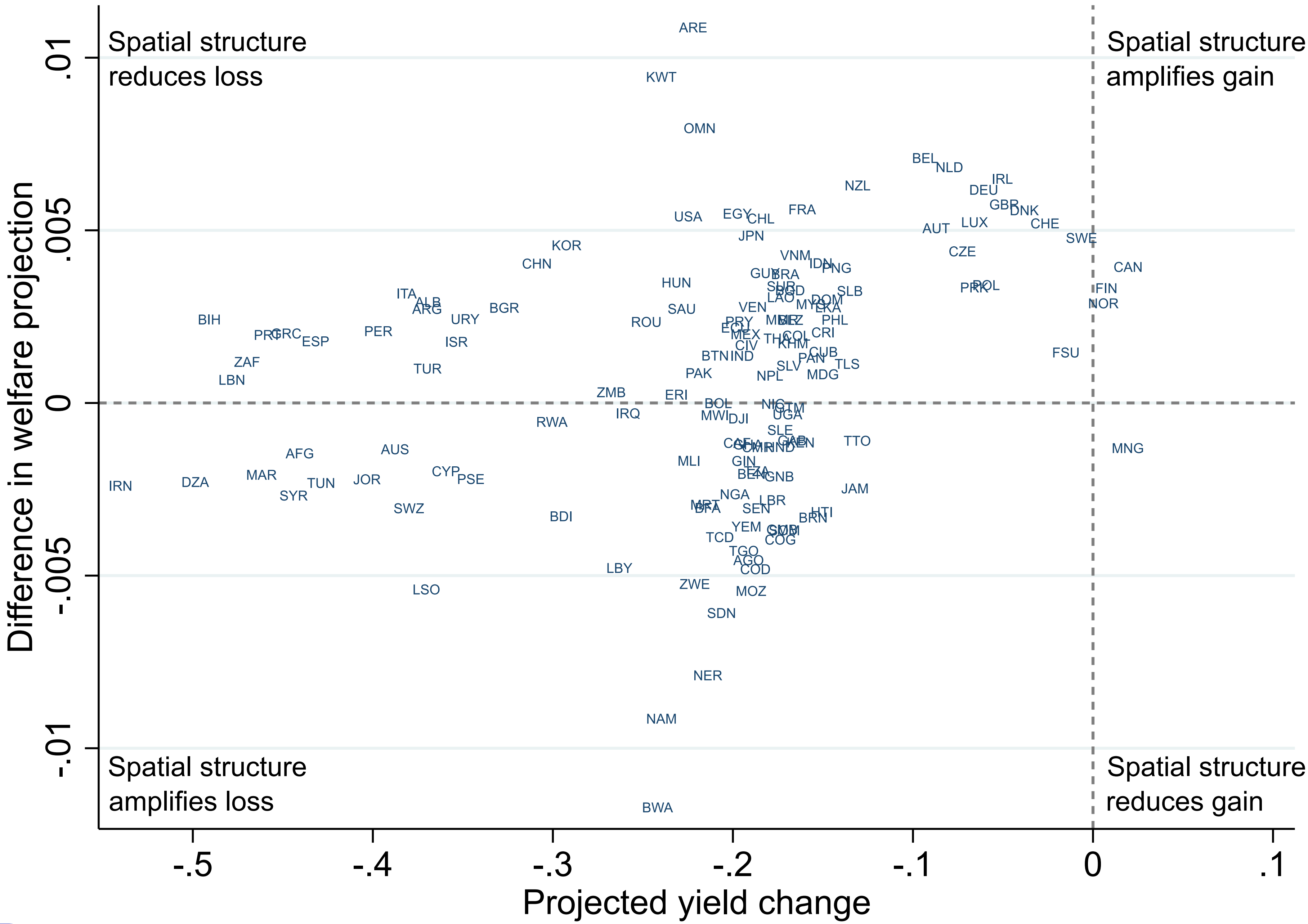
Differences in projected welfare due to spatial effects



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