

Environmental Determinants of Enteric Infectious Disease

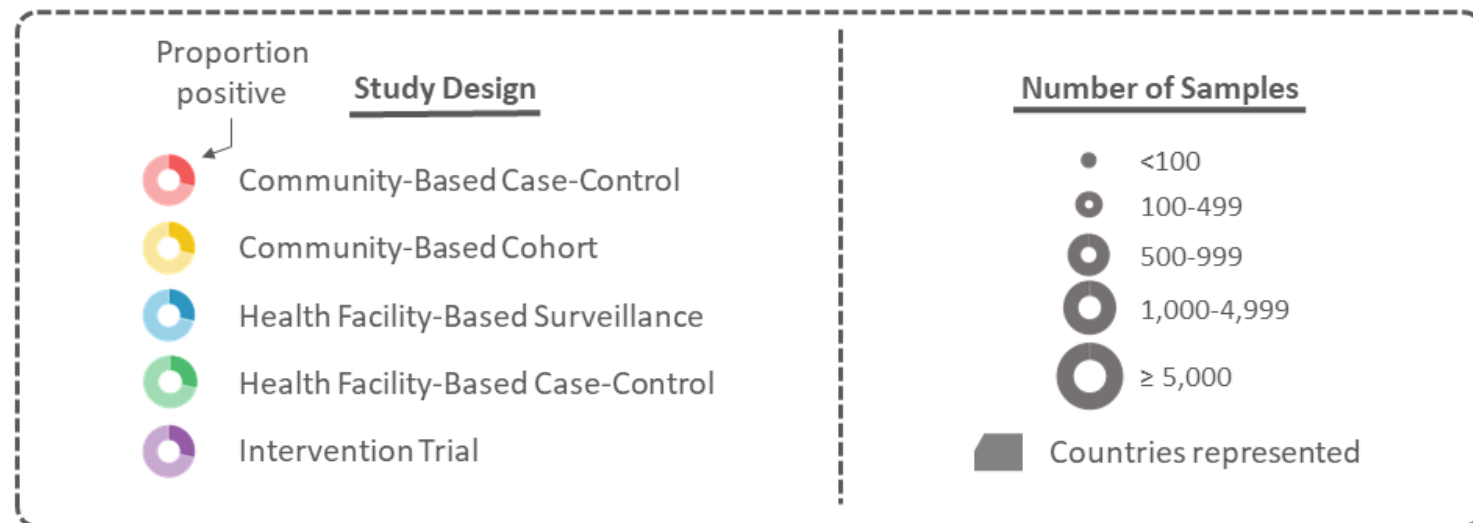
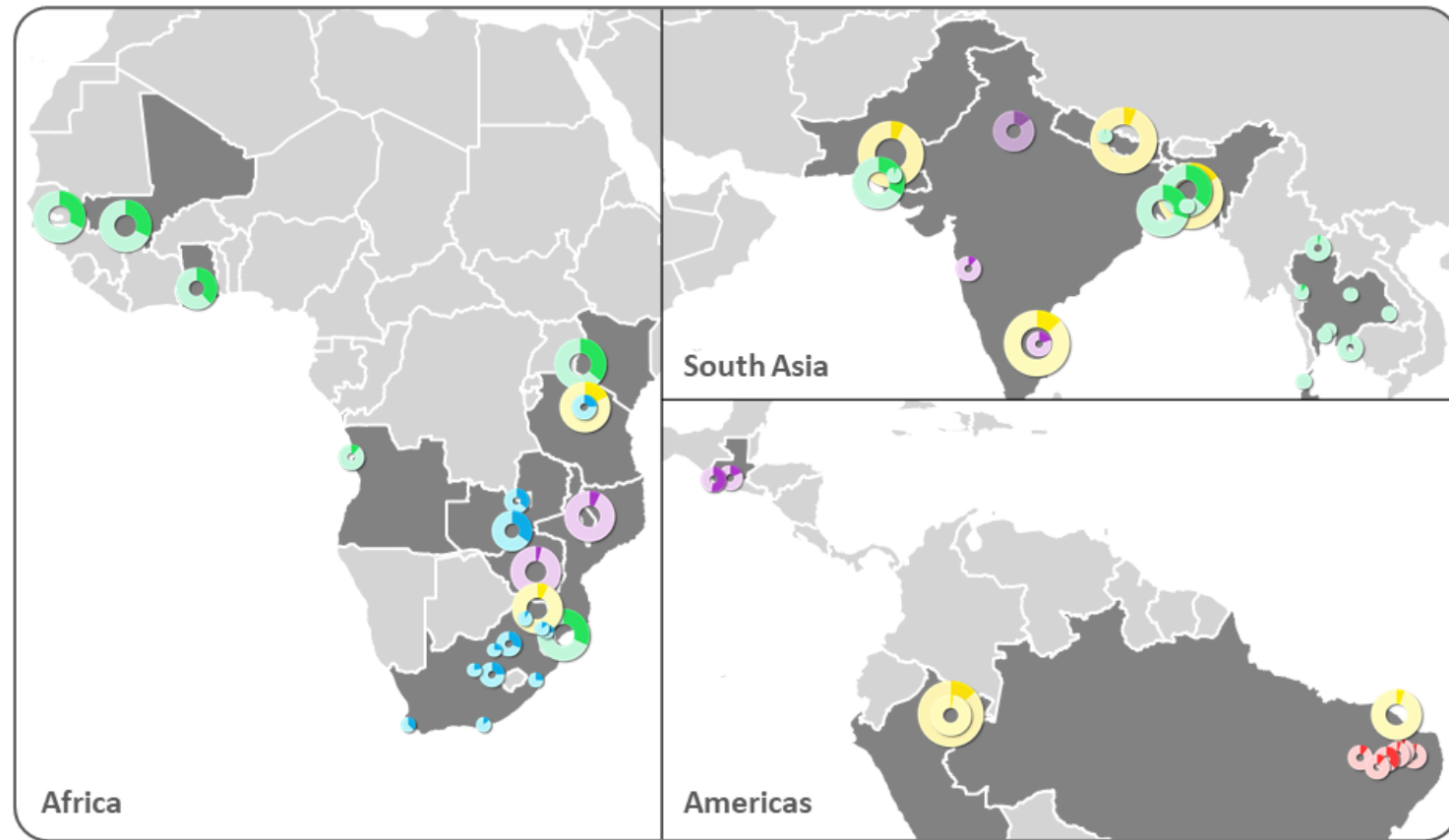
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CO-I: MARGARET KOSEK, UNIVERSITY OF VIRGINIA
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CO-I: JIM NELSON, BRIGHAM YOUNG UNIVERSITY
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Project goal

Establish the feasibility of Earth Observation-informed Enteric Infectious Disease (EID) risk mapping, monitoring, and prediction systems

We are doing this through collaboration with multiple EID studies performed at sites around the world

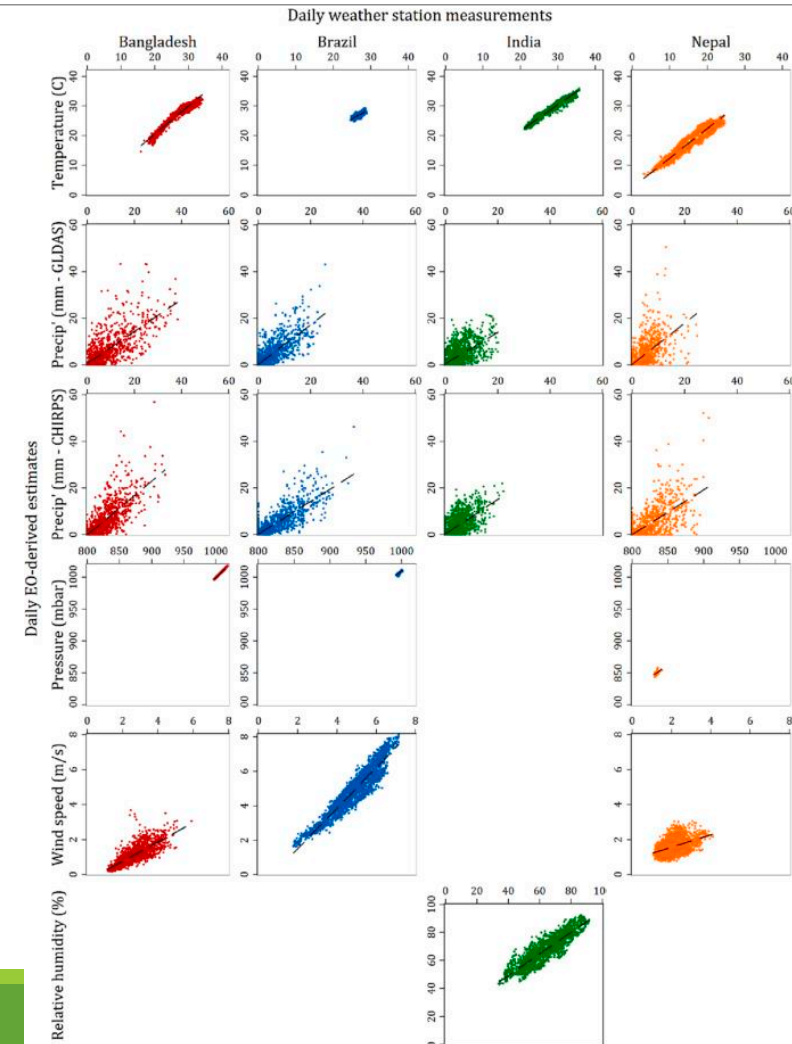
Collaborating studies



Earth Observation data

None of these infection studies included collection of data on climate or environment.

Earth Observations offer an opportunity to fill this gap.



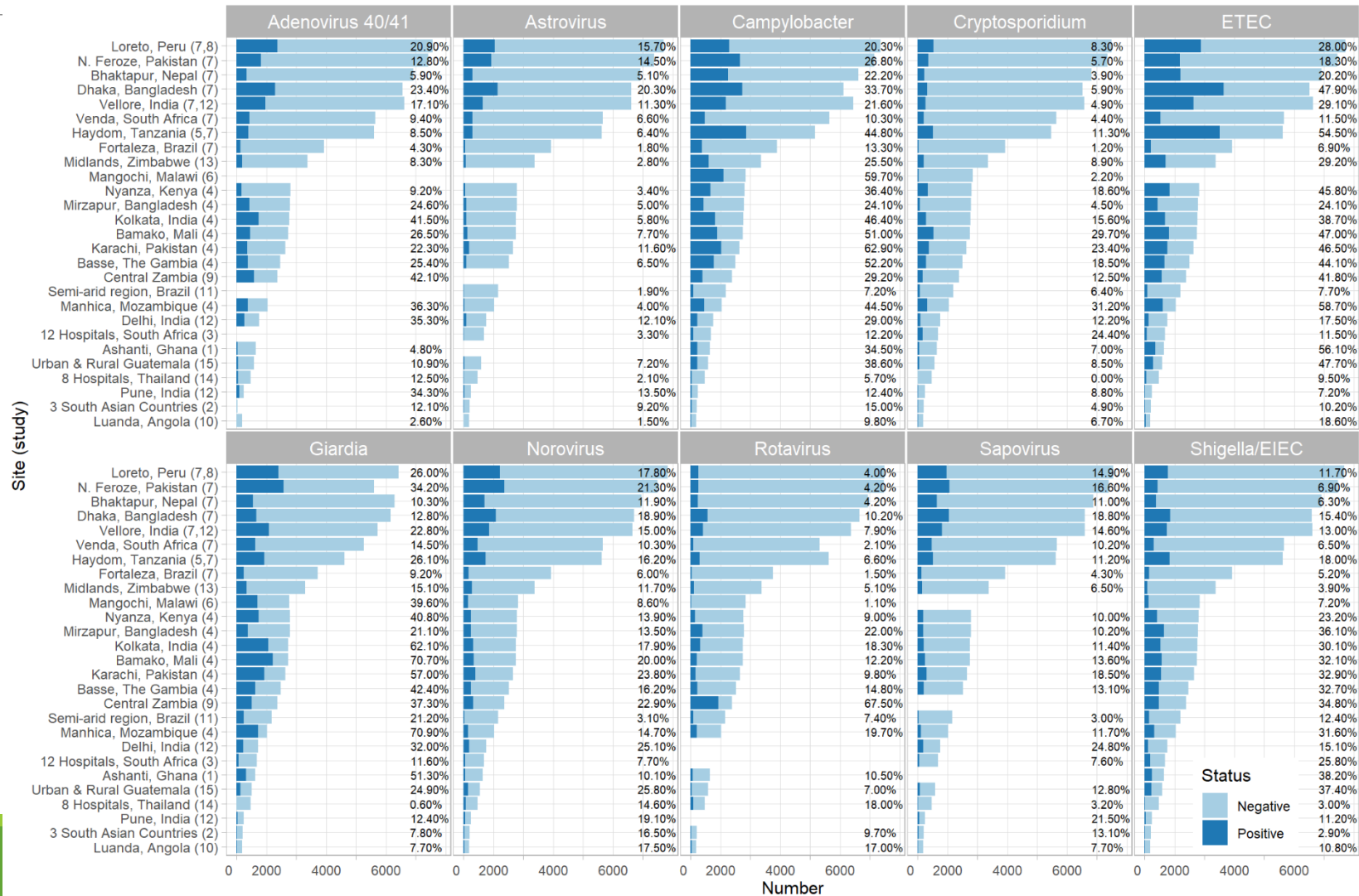
Accomplishments from previous years

1. Evaluated EO performance at MAL-ED sites, and published results collaboratively with MAL-ED site PIs (Colston et al., 2018)
2. Published the results of the rotavirus model collaboratively with site PIs (Colston et al., 2019)
3. Participated in NASA's pilot commercial data buy program
4. Performed a targeted study of ENSO influence on EID at our Peru MAL-ED site (Colston et al., 2020a)
5. Published a study of static household-level factors associated with pathogen-specific disease risk (Colston et al., 2020b)
6. Disseminated rotavirus and shigella risk to partners at study sites and health ministries
7. Piloted online visualization tool

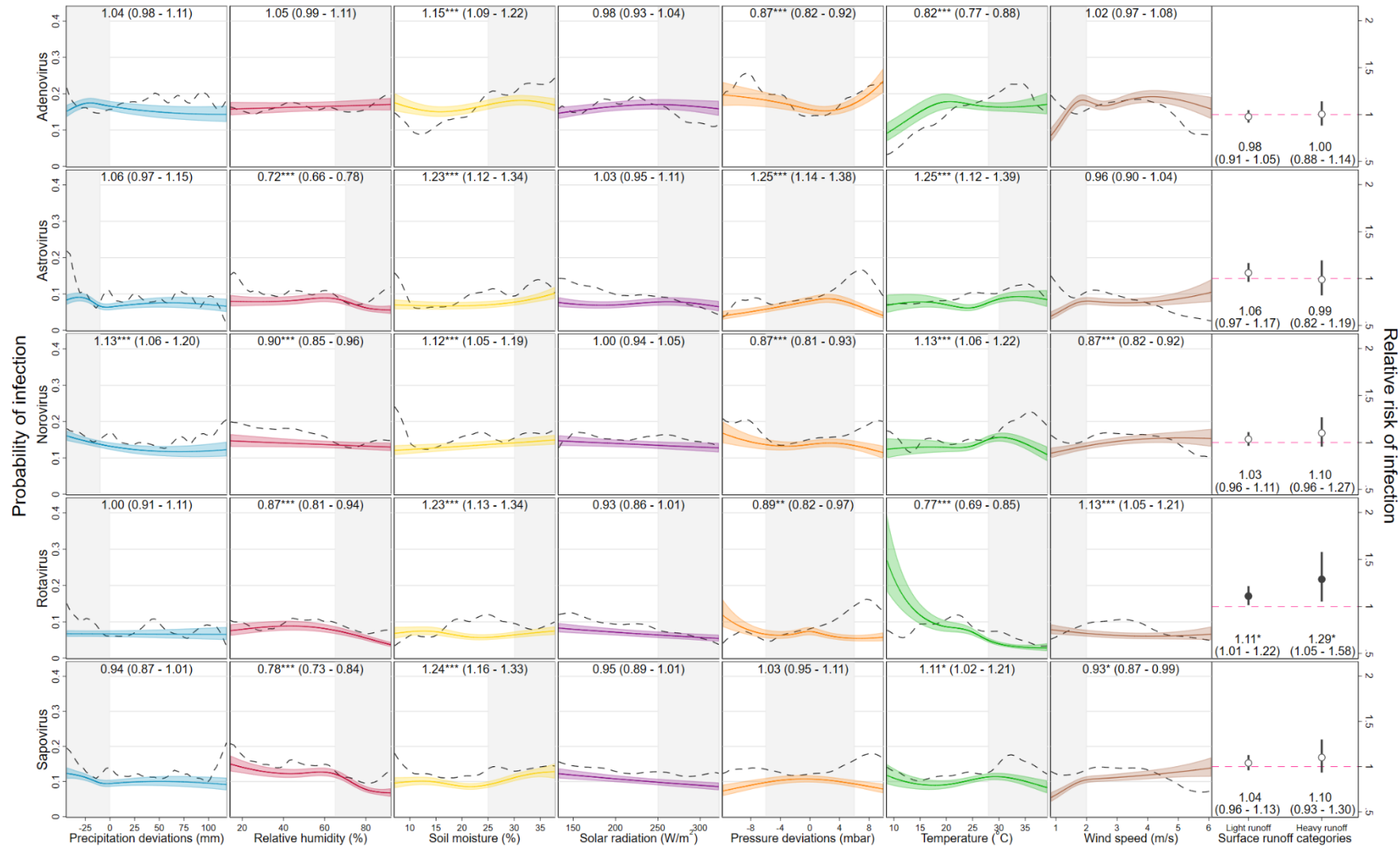
Accomplishments this year

1. Completed multi-pathogen modeling analyses (Colston et al., *In Review*)
2. Implemented optimized Bayesian predictive modeling approach and completed application to Shigella (Badr et al., *In preparation*)
3. (Nearly) finalized online visualization tool

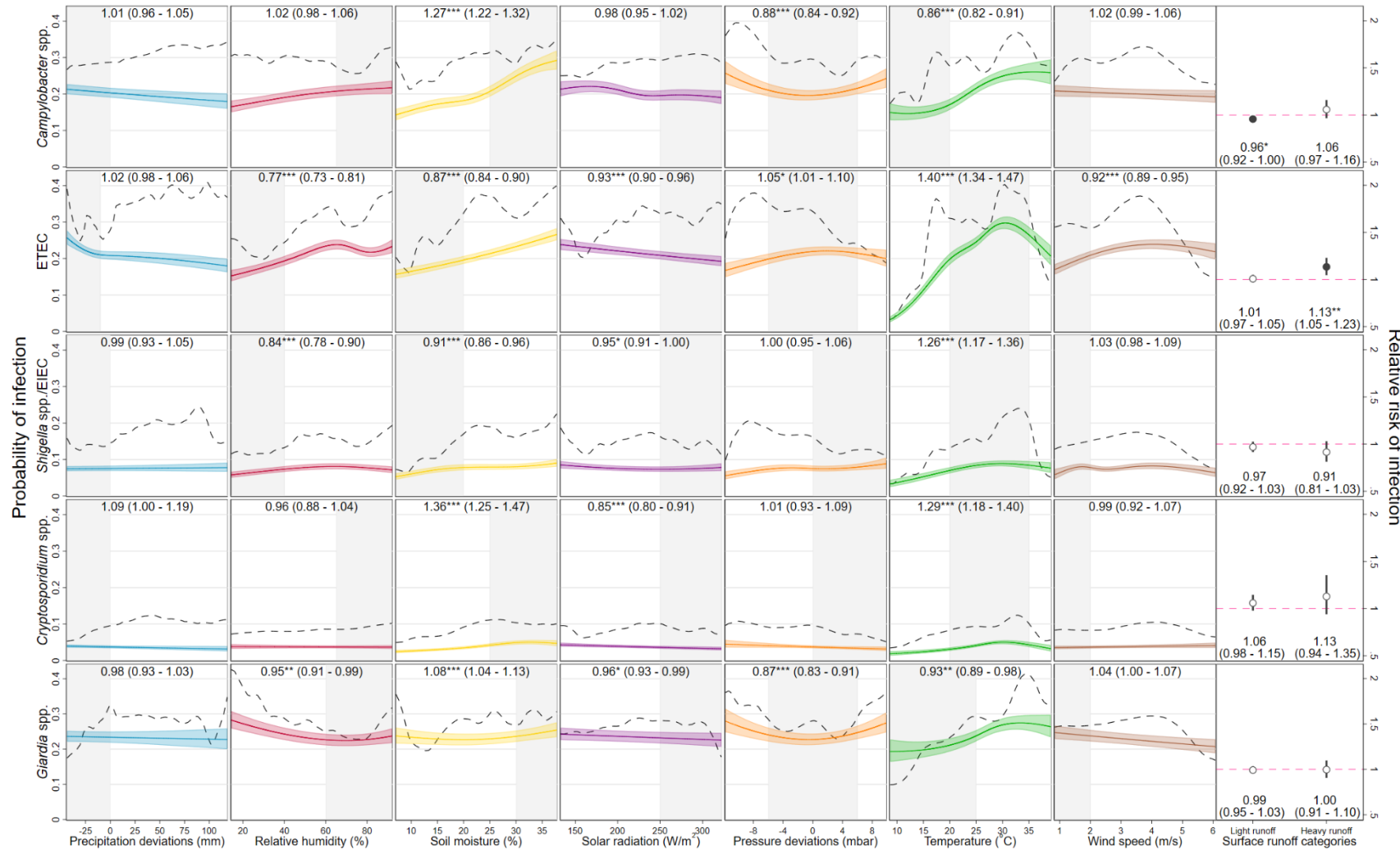
Multi-pathogen modeling



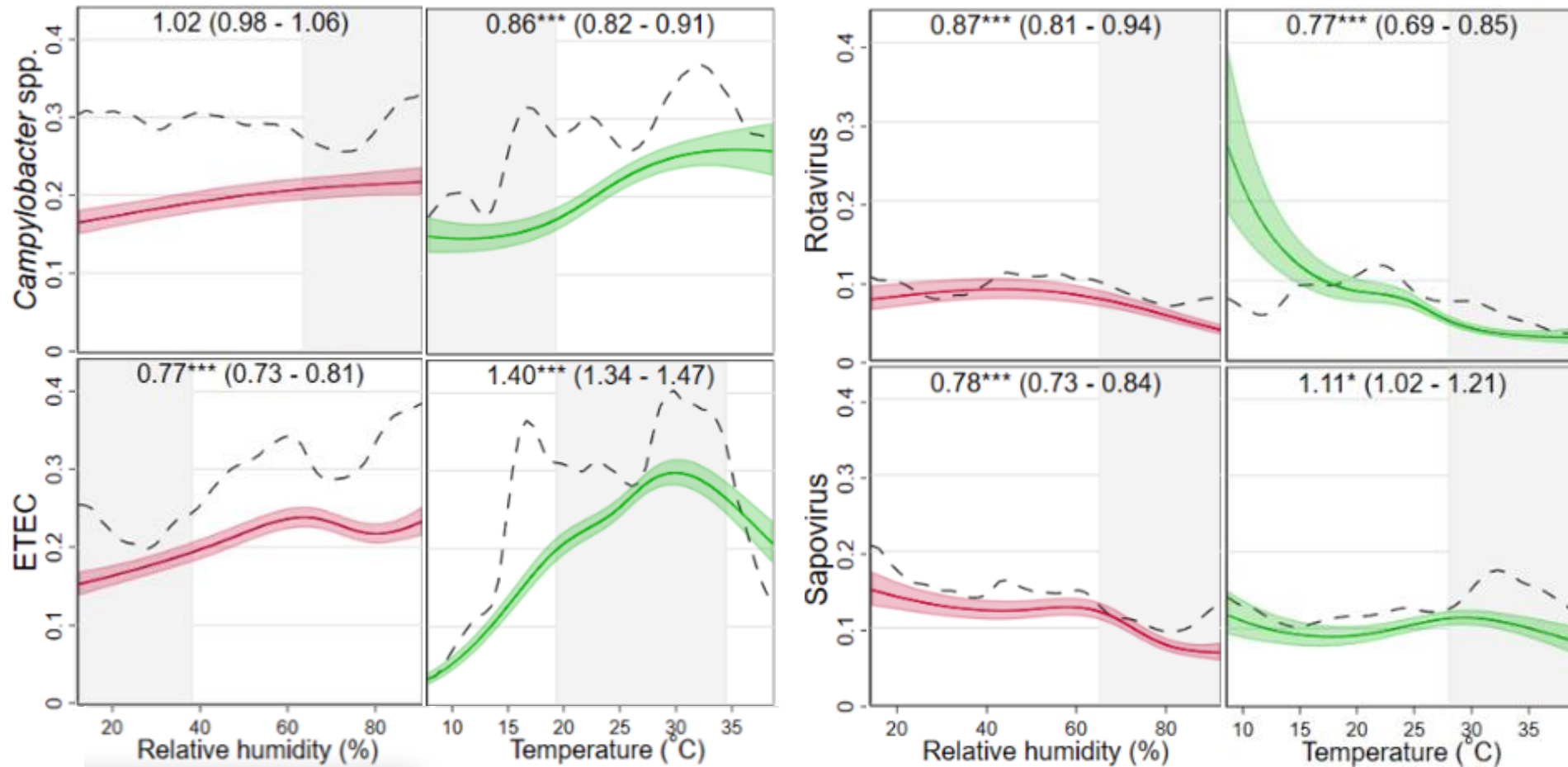
Multi-pathogen modeling



Multi-pathogen modeling

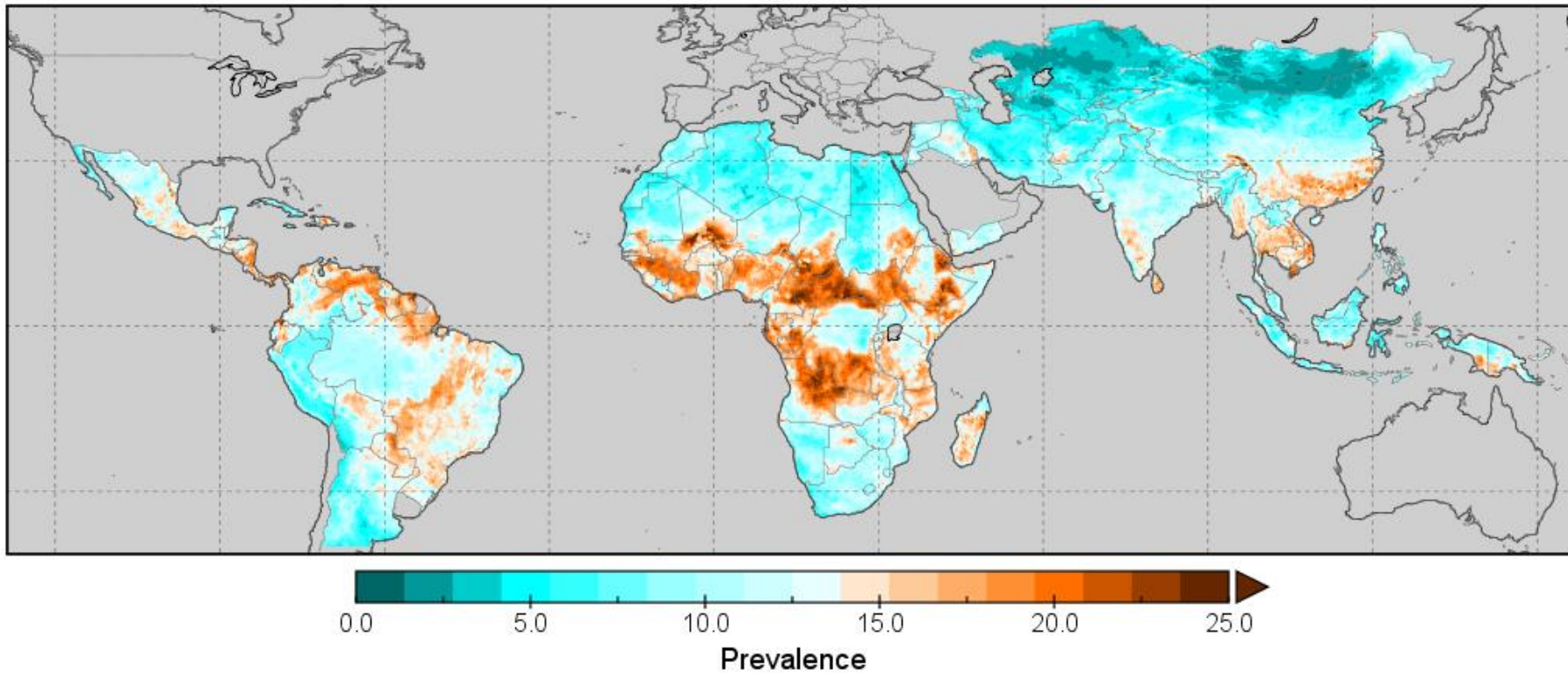


Differing sensitivities



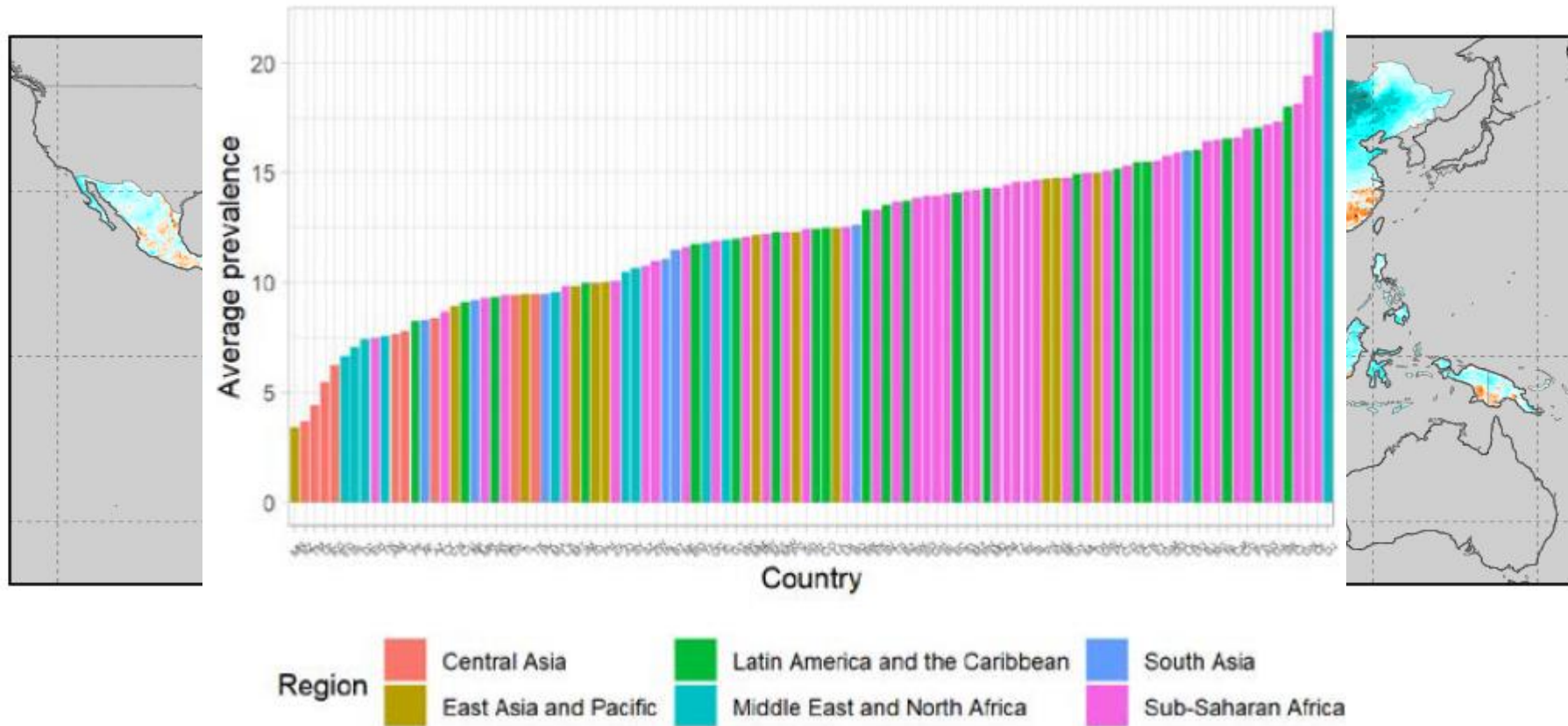
Shigella modeling

Estimated annual average prevalence of Shigella infection in children age 12 - 23 months



Shigella modeling

Estimated annual average prevalence of Shigella infection in children age 12 - 23 months



Visualization tool

☰ Shigella Risk Assessment Tool
📊 Log In ✕

Select data layer

Timeseries Results

Shigella Probability v Time

Distribution of Modeled Risk Values

Save Chart as CSV

Close

Open Street Maps
 Drawings
 Shigella Layer

▶ ▶ ⏪ ⏩
2018-12-01T07:00:00.000Z
2fps

Leaflet | © OpenStreetMap contributors

Timeline

	PY1				PY2				PY3			
	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4
Objective 1												
✓ Perform and evaluate retrospective LDAS simulations	█											
✓ Create unified database of EID predictors			█									
✓ Develop and evaluate statistical EID models	█				█							
Objective 2												
✗ Perform EID-specific regionalization			█		█							
✗ Characterize regionalization uncertainty						█						
Objective 3												
✓ Generate maps of EID potential by disease and season						█						
✓ Implement monitoring/warning systems for selected EID									█			
✗ Produce projections of future EID potential										█		
Objective 4												
✓ Create Tethys app for display and analysis of EID database	█											
✓ Integrate HiClimR to Tethys				█	█							
✓ Present preliminary system to MAL-ED community							█					
✓ Refine and operationalize system								█	█			

ARL

Current: ARL 6

Expectation: ARL 7 at our next partner feedback session

Goal: ARL 7

COVID-19

BEN ZAITCHIK, HAMADA BADR, LAUREN GARDNER, JUSTIN LESSLER – JHU
MARGARET KOSEK, JOSH COLSTON - UVA

Why have studies of environmental sensitivity of COVID-19 been so mixed?

A short and unreliable COVID-19 data record

Inconsistent and sometimes inappropriate definition of response variable

Inconsistent and sometimes inappropriate scales of analysis

Difficulty of accounting for non-meteorological predictors: behavior, policy, demographics, cultural practices, etc.

Differences between climate zones

Diverse and sometimes questionable methodologies

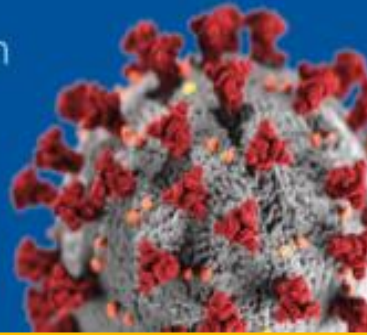
Challenge of isolating climate influence early in the pandemic

4-6 August 2020

Climatological, Meteorological and Environmental factors in the COVID-19 pandemic



An international virtual symposium
on drivers, predictability and
actionable information



<https://public.wmo.int/en/events/meetings/covid-19-symposium>



COMMENT

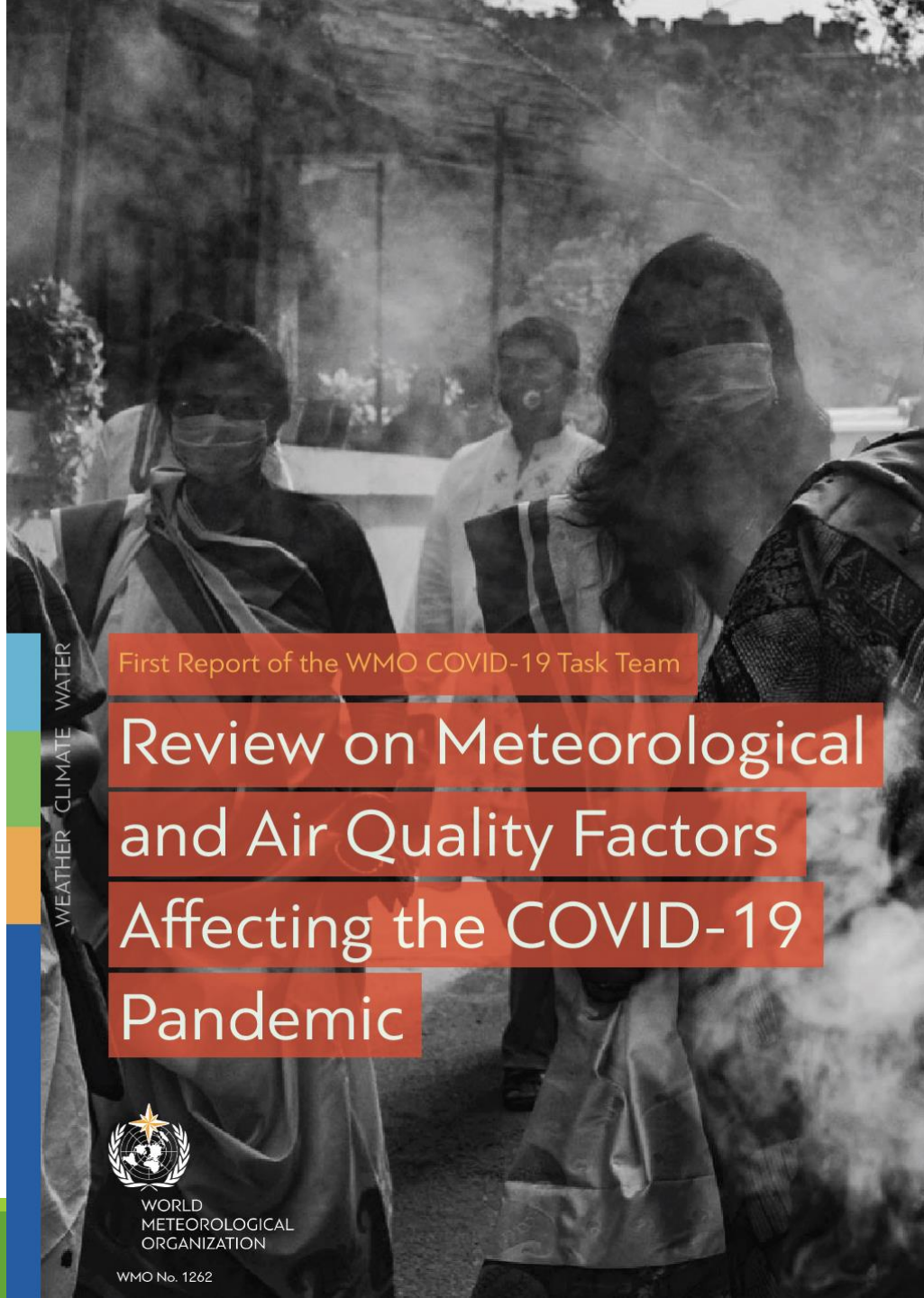
<https://doi.org/10.1038/s41467-020-19546-7>

OPEN

A framework for research linking weather, climate and COVID-19

Benjamin F. Zaitchik¹, Neville Sweijd², Joy Shumake-Guillemot³,
Andy Morse⁴, Chris Gordon⁵, Aileen Marty⁶, Juli Trtanj⁷, Juerg Luterbacher⁸,
Joel Botai⁹, Swadhin Behera¹⁰, Yonglong Lu¹¹, Jane Olwoch¹²,
Ken Takahashi¹³, Jennifer D. Stowell¹⁴ & Xavier Rodó¹⁵

<https://www.nature.com/articles/s41467-020-19546-7>



First Report of the WMO COVID-19 Task Team

Review on Meteorological
and Air Quality Factors
Affecting the COVID-19
Pandemic



WMO No. 1262

https://library.wmo.int/index.php?lvl=notice_display&id=21857#.YNmy7i2w3UI

Create a unified, reliable data record

United States:

US	36	061	10476
Admin 0	Admin 1	Admin 2	Admin 3
Country	State	County	District
ISO 3166 1 2 letters	FIPS + 2 digits	FIPS + 3 digits	ZCTA + 5 digits

Europe:

DE	2	1	H
Admin 0	Admin 1	Admin 2	Admin 3
Country	State*	County**	District
ISO 3166 1 2 letters	NUTS 1 + 1 digit/letter	NUTS 2 + 1 digit/letter	NUTS 3 + 1 digit/letter

Global:

AU	ACT		
Admin 0	Admin 1	Admin 2	Admin 3
Country	Province/State	County	District
ISO 3166 1 2 letters	ISO 3166 2 principal divisions	Local 2 country specific	Local 3 country specific

- Maps all geospatial units globally into a unique standardized ID.
- Standardizes administrative names and codes at all levels.
- Standardizes dates, data types, and formats.
- Unifies variable names, types, and categories.
- Merges data from all credible sources at all levels.
- Cleans the data and fixing confusing entries.
- Integrates hydrometeorological variables at all levels.
- Optimizes the data for machine learning applications.

<https://github.com/hsbadr/COVID-19>

<https://www.medrxiv.org/content/10.1101/2021.05.05.21256712v1>

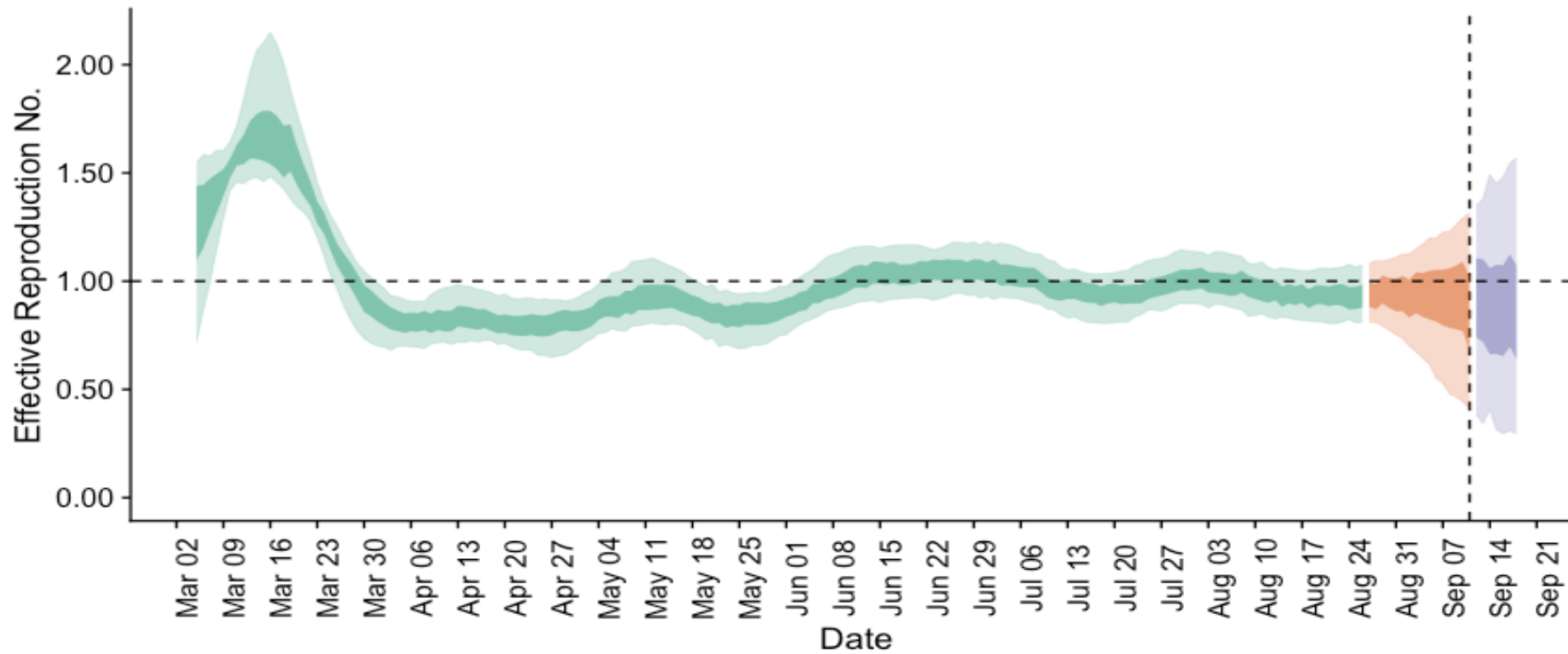
* NUTS 1 level represents groups of subregions (or equivalent) for some European countries (e.g., Italy).

** NUTS 2 level represents subregions (or equivalent) for some European countries (e.g., Italy).

Generate a response variable

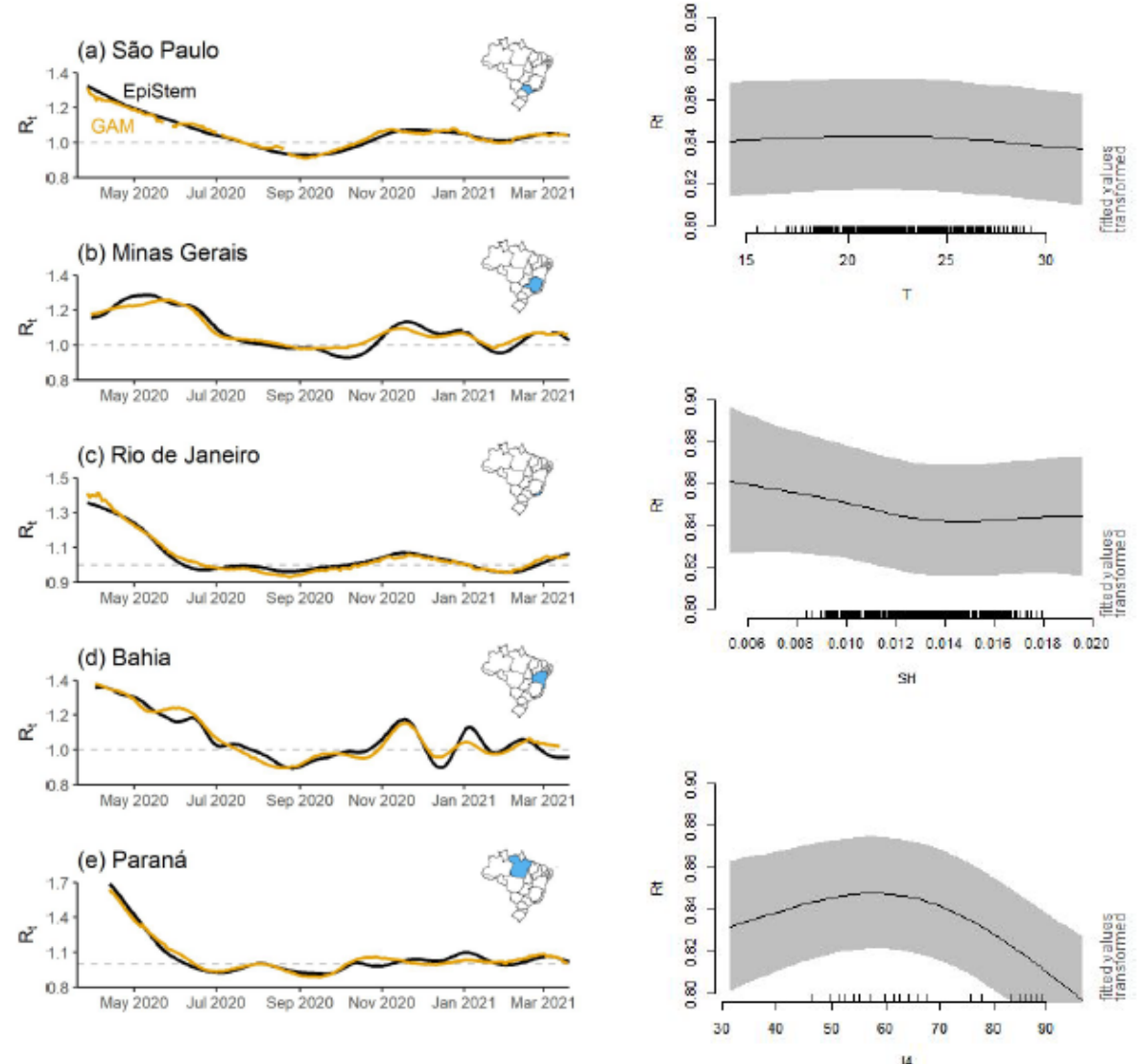
EpiNow2

New York City, NY



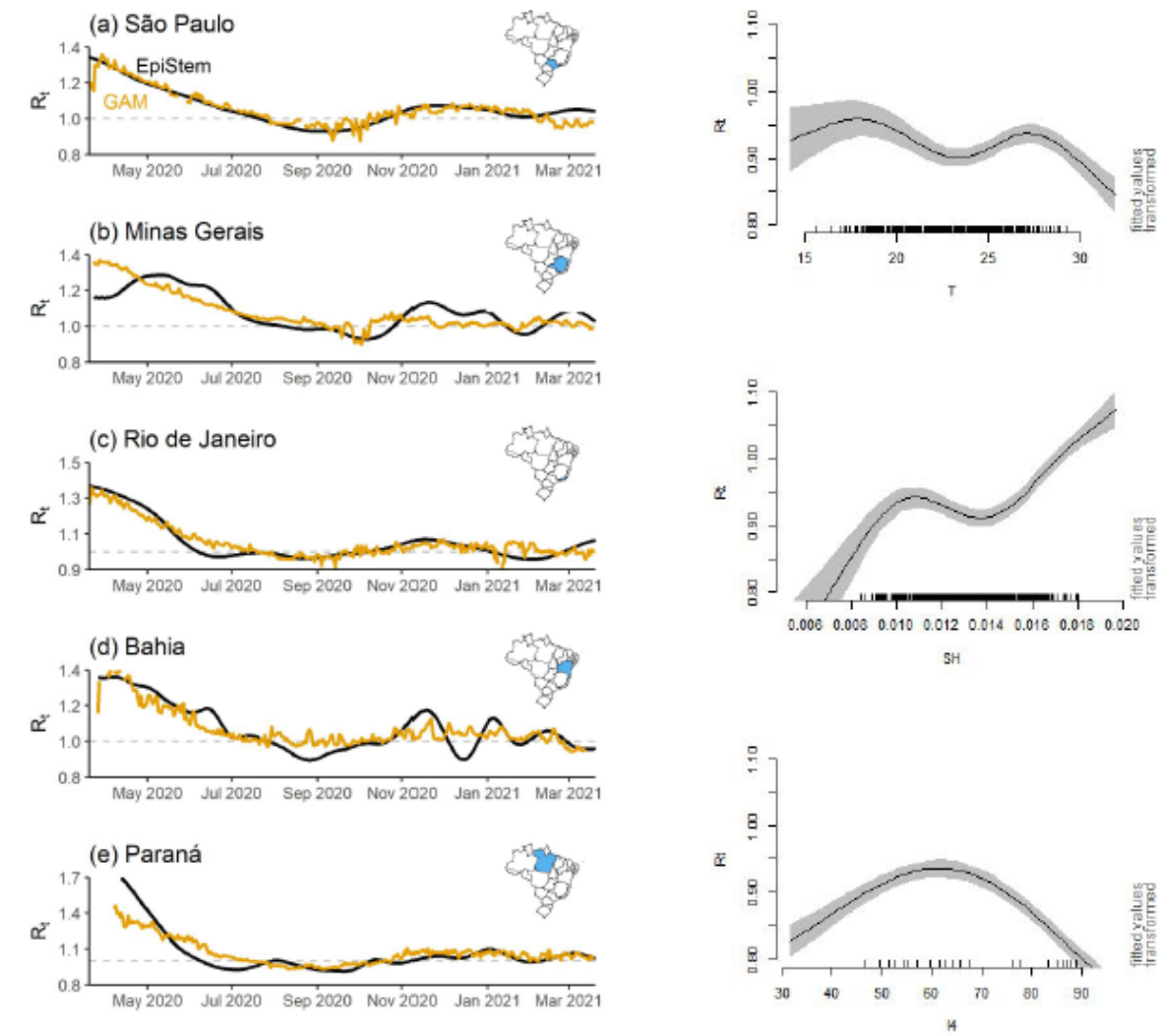
Type Estimate Estimate based on partial data Forecast

$$R_t \sim s(T) + s(SH) + s(I4) + ti(Tstatestd, SH)^* + ti(I4, Date) + ti(T, SH) + te(Date, Latitude, Longitude)** + s(state)$$



Left plot in each panel: example of predicted R_t
 Right plot: smooth terms

$$R_t \sim s(T) + s(SH) + s(I4) + ti(Tstatestd, SH) + ti(I4, Date) + ti(T, SH) + s(state)$$



Thank You
