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Scaling Data Fusion Tools to Support Local Air Quality Managers in Latin America

Carl Malings

Morgan State University & GESTAR-II cooperative agreement

NASA Global Modeling and Assimilation Office

Project Team: Nathan Pavlovic, Daniel King, Bryan Duncan, Megan Damon, Sina Hasheminassab, Daniel Westervelt, Sebastián Diez, Colleen Rosales, Russ Biggs, Felipe Mandarino, Vicente Lorca

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Project Goals

- Improve city-scale forecasts for key air pollutants ($PM_{2.5}$, NO_2, O_3) for local air quality managers by integrating global model, satellite, and in-situ datasets via data fusion

- Transfer data fusion tool to sustained operation by local end-users with Google Earth Engine cloud resources

- Assist in analysis of data fusion outputs to support user-specific needs, e.g., siting new air quality monitors, preparing for MAIA mission products

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Stakeholders & Locations of Interest

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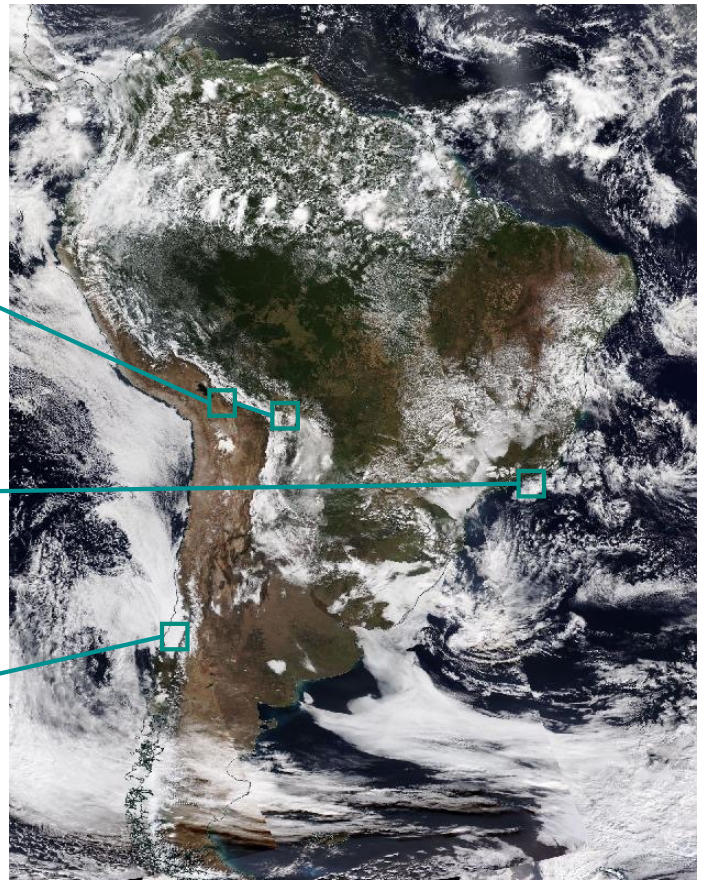
- Bolivia
  - La Paz & Santa Cruz
  - US State Department mission
- Brazil
  - Rio de Janeiro
  - Instituto Pereira Passos
- Chile
  - Maule Region
  - Maule Regional Government (GORE)



Source: NASA Worldview

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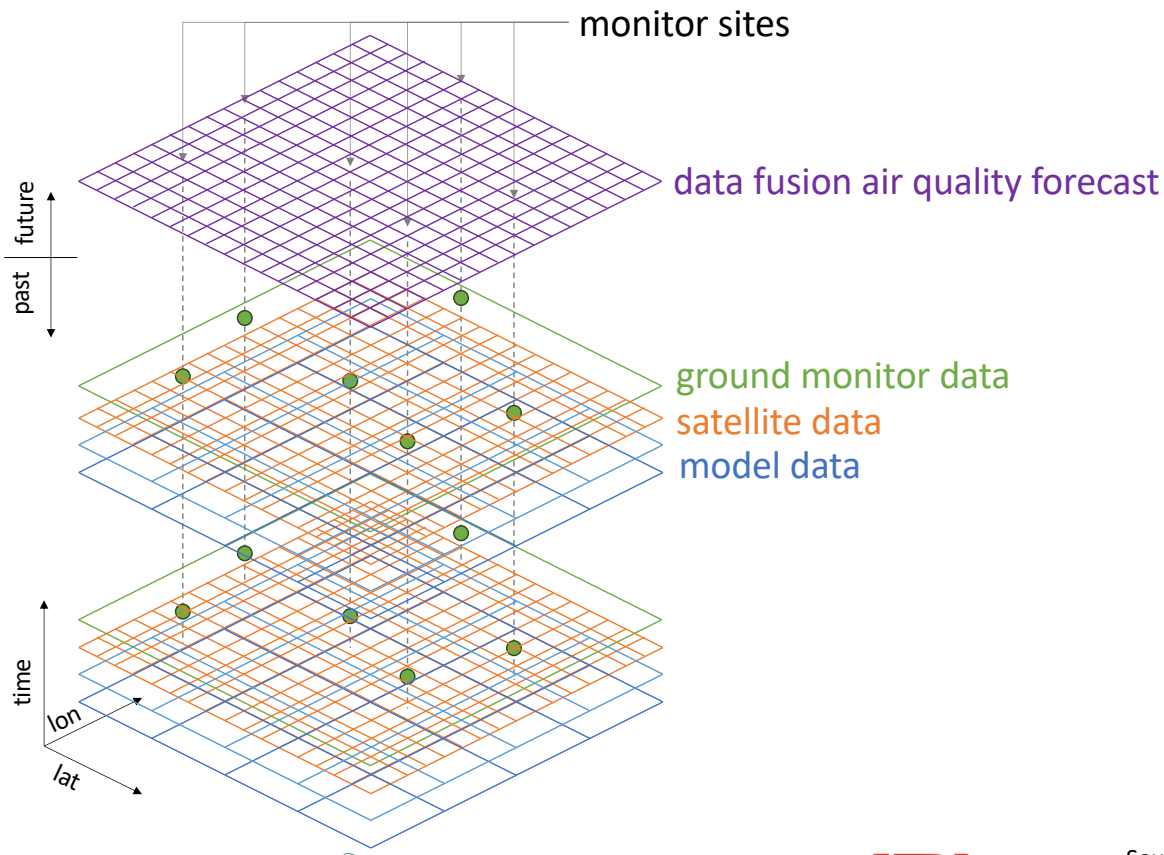
Air Quality Data Fusion – Methodology



Combine model (NASA GEOS-CF), satellite (TROPOMI, MODIS, VIIRS), and local air quality monitor data to produce regional air quality forecasts using uncertainty-aware data fusion

- Spatially complete (fill in gaps in monitor networks)
- High temporal resolution (hourly)
- Higher spatial resolution (1-5 km) than model (25km)
- Forecasting (~3 days ahead)
- Include quantifications of uncertainty

Applications

- Early warning of poor air quality
- Region-specific pollution exposure estimates
- Analysis of sources of forecast uncertainty
- Guidance for ground monitor network expansion

Source: Malings et al., 2024

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Performance for Rio de Janeiro

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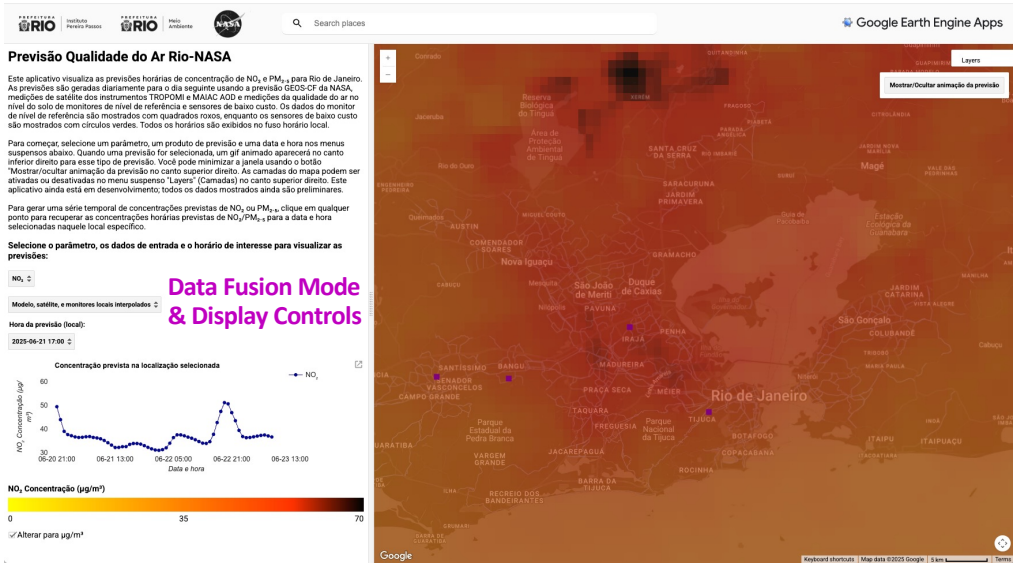
Rio's customized user interface (Portuguese version)



Data Fusion Mode & Display Controls

Point-specific time forecast series

Time-specific forecast map

Lessons Learned from Rio de Janeiro Application

Implementation

- Iterative testing of forecast algorithms
- Co-development of Google Earth Engine user interface
- Google Earth Engine provides both advantages and challenges for sustained operation of forecast systems

Source: https://aq-rionasa.projects.earthengine.app/view/aqrionasa

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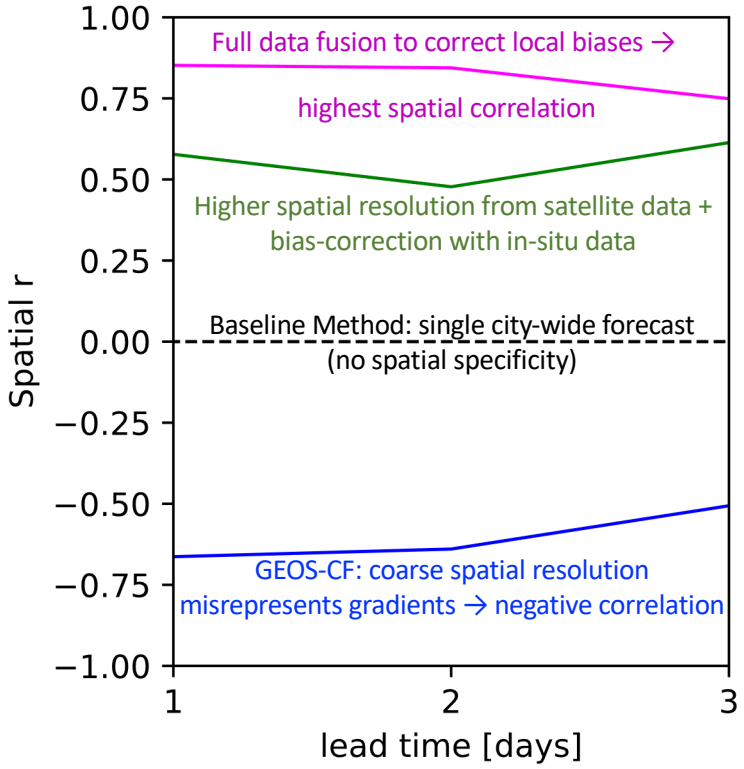
NO_2 forecasts: spatial correlation



Lessons Learned from Rio de Janeiro Application

Implementation

- Iterative testing of forecast algorithms
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NO_2 Forecasting

- Data fusion improves spatial specificity of forecasts
- Able to produce realistic intra-urban gradients
- Relatively stable performance out to 3 days forecast lead time

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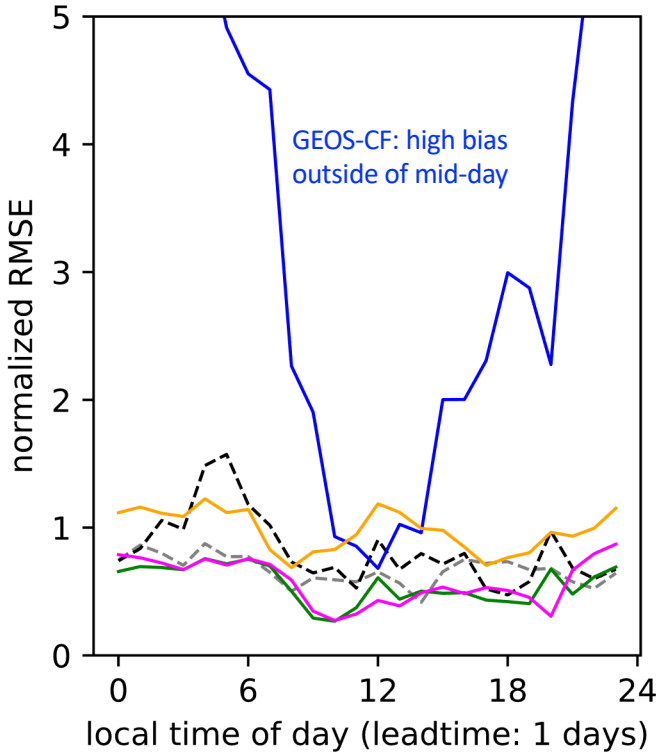
Performance for Rio de Janeiro

$PM_{2.5}$ forecasts: accuracy by time-of-day



Incorporating satellite AOD drastically reduces bias, even outside of overpass times

Full data fusion has highest accuracy at most times of day

Lessons Learned from Rio de Janeiro Application

Implementation

- Iterative testing of forecast algorithms
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NO_2 Forecasting

- Data fusion improves spatial specificity of forecasts
- Able to produce realistic intra-urban gradients
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$PM_{2.5}$ Forecasting

- Incorporating satellite data greatly reduces regional bias, even without ground-based data
- Important consideration: there is only one regulatory PM2.5 monitor currently operating
- Opportunities for future improvement: use PM2.5 data from newly deployed low-cost sensor systems

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Priorities and Next Steps

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- Continue collaboration with Rio, focusing on robust integration of low-cost air quality sensor data
- Begin deployment of system for Maule Region, Chile, delivering local data in anticipation of MAIA mission
- Identify new local users in Bolivia as supplement or replacement for US State Department mission personnel

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References & Sources

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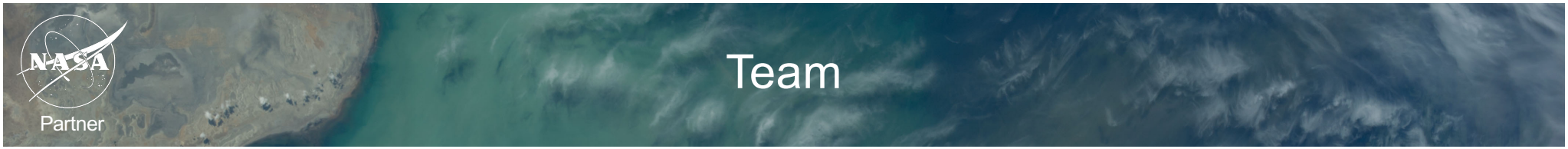
Thank you!

Questions?



Team

Role	Name	Affiliation	Tasks
PI	Carl Malings	Morgan State University	Project leadership, data analysis, capacity building
Co-I	Nathan Pavlovic	Sonoma Technology, Inc.	Project leadership, Google Earth Engine tool development
Co-I	Daniel King	Sonoma Technology, Inc.	Google Earth Engine tool development, data analysis
Co-I	Bryan Duncan	NASA Goddard Space Flight Center	Project leadership, atmospheric science expert
Collaborator	Megan Damon	Science Systems and Applications, Inc.	GEOS-CF model expert, project representation
Collaborator	Sina Hasheminassab	NASA Jet Propulsion Laboratory	MAIA mission expert
Collaborator	Daniel Westervelt	Columbia University	Air quality measurement expert, capacity building
Collaborator	Felipe Mandarino	Insituto Pereira Passos	Brazil/Rio stakeholder representative
Collaborator	Sebastián Diez	Univerisidad del Desarrollo	Chile/Maule stakeholder representative
Collaborator	Vicente Lorca	Univerisidad del Desarrollo	Chile/Maule stakeholder representative
Collaborator	TBD	TBD	Bolivia stakeholder representative
Collaborator	Colleen Rosales	OpenAQ	Air quality data sharing expert
Collaborator	Russ Biggs	OpenAQ	Air quality data sharing expert