Supporting Global Air Quality Management Needs with a Flexible Data Fusion Tool for Estimation and Forecasting in Google Earth Engine

Carl Malings

Morgan State University & GESTAR-II cooperative agreement

NASA Global Modeling and Assimilation Office

PROJECT TEAM

PI: K. Emma Knowland (MSU/GESTAR-II, GMAO)

Science-PIs: Carl Malings (MSU/GESTAR-II, GMAO), Nathan R. Pavlovic with Alan Chan, Justin Coughlin, and Daniel King (Sonoma Technology)

Co-Is: Christoph Keller (MSU/GESTAR-II, GMAO), Stephen Cohn (GMAO)

National/Global End-Users: United Nations Environment Programme (UNEP) & US Environmental Protection Agency (EPA)

Local End-Users: Ministry of Environment and Sustainable Development, Dakar, Senegal Instituto Pereira Passos, City Municipal Government, Rio de Janeiro, Brazil

Collaborators: Sean Khan (UNEP), John White (US EPA), Dan Westervelt (LDEO), Sean Wihera (Clarity Movement Co.), Randall Martin (WUSTL)

GESTAR II

GMAO

GODDARD EARTH SCIENCES

NASA Partner

The goal of this project is to…

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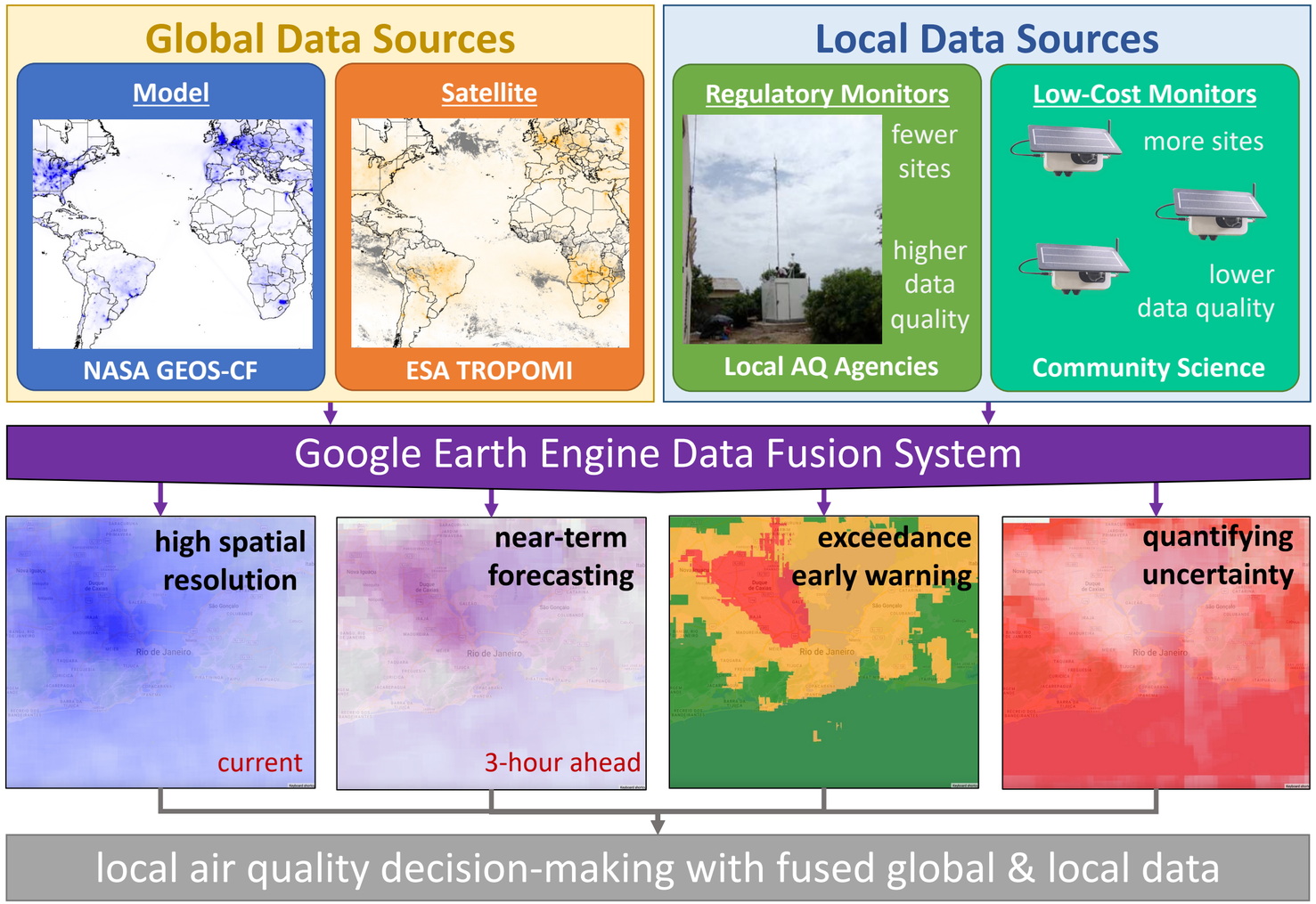
…integrate diverse **global** and **local** air quality data sources…

…using the cloud computing platform of **Google Earth Engine**…

…to provide synthesized **estimates** and **forecasts** of air quality at a **local scale** but with a **global scope**…

…freely accessible by air quality managers worldwide, facilitating their **decision-making** processes.



Presenter: Carl Malings <carl.a.malings@nasa.gov>

Data Fusion

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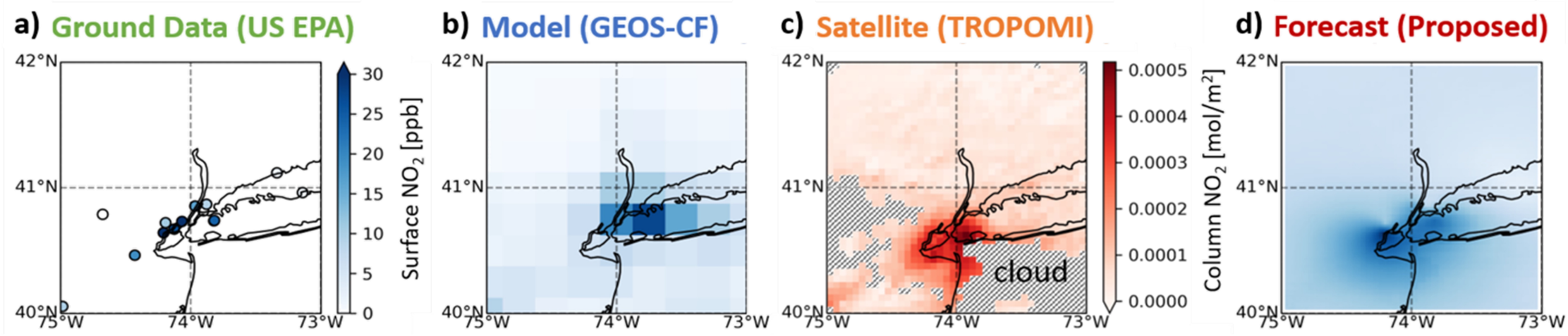

high(er) spatial resolution

fill gaps in space and time (and do forecasting)

ground-truthing with trusted “nose-level” data, identify local impacts

Source: Malings et al. (2021), “Sub-City Scale Hourly Air Quality Forecasting by Combining Models, Satellite Observations, and Ground Measurements” *Earth & Space Science.* DOI: 10.1029/2021EA001743

Prototype User Interface

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Earth Engine Apps

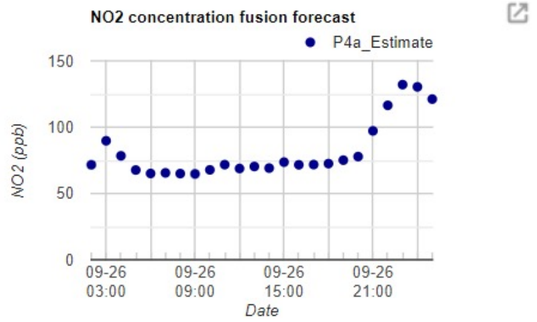
Search places

Sub-city air quality forecasts

Select the region of interest to view forecasts

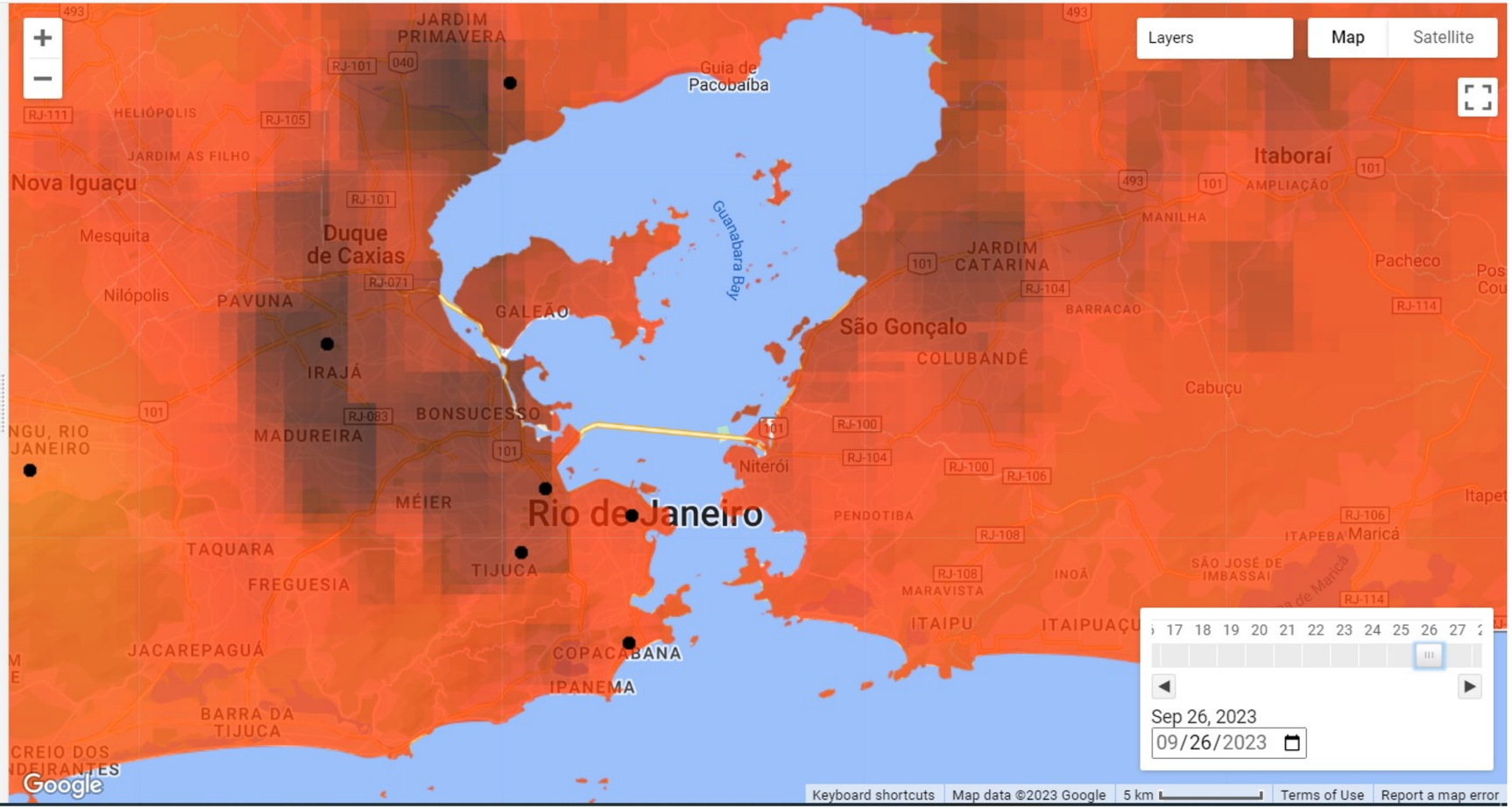
Rio de Janeiro, BR

P4



Hourly NO2 Concentration (ppb)

40 80



Why quantify uncertainty in air quality forecasting?

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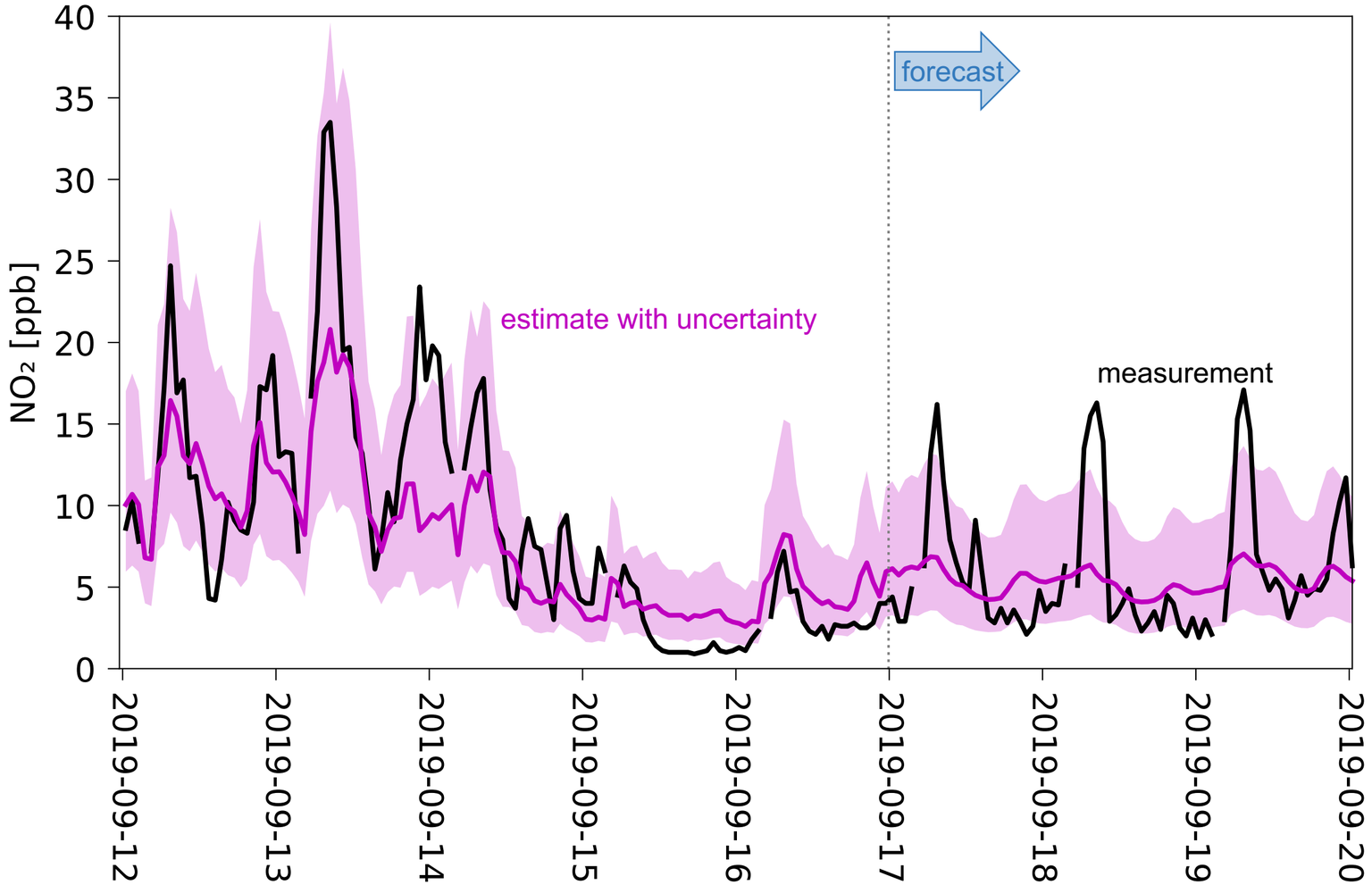
Provide a prior estimate of the relative confidence in a forecast

Convey probabilities of specific events, e.g., exceedance of standards

Identify a range of likely outcomes

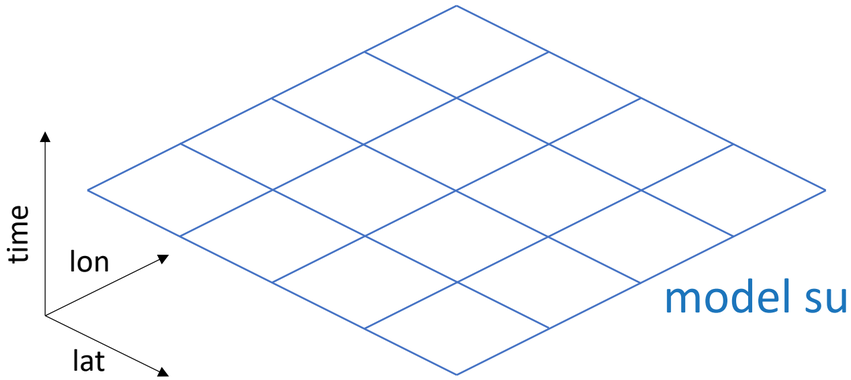
Quantify the impacts of different data sources in reducing uncertainties

Identify the potential to reduce uncertainties through additional data collection



Phase 1: Model Only

Phase	Estimate
1	forecast model (GEOS-CF)



model surface concentration $M(x,t)$

Phase 1: Model Only

Phase	Estimate
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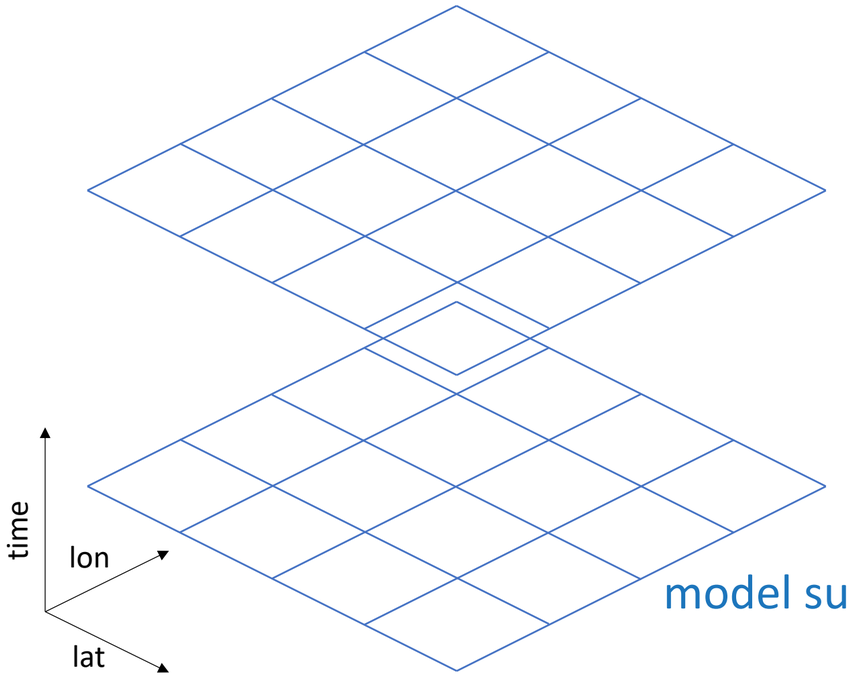

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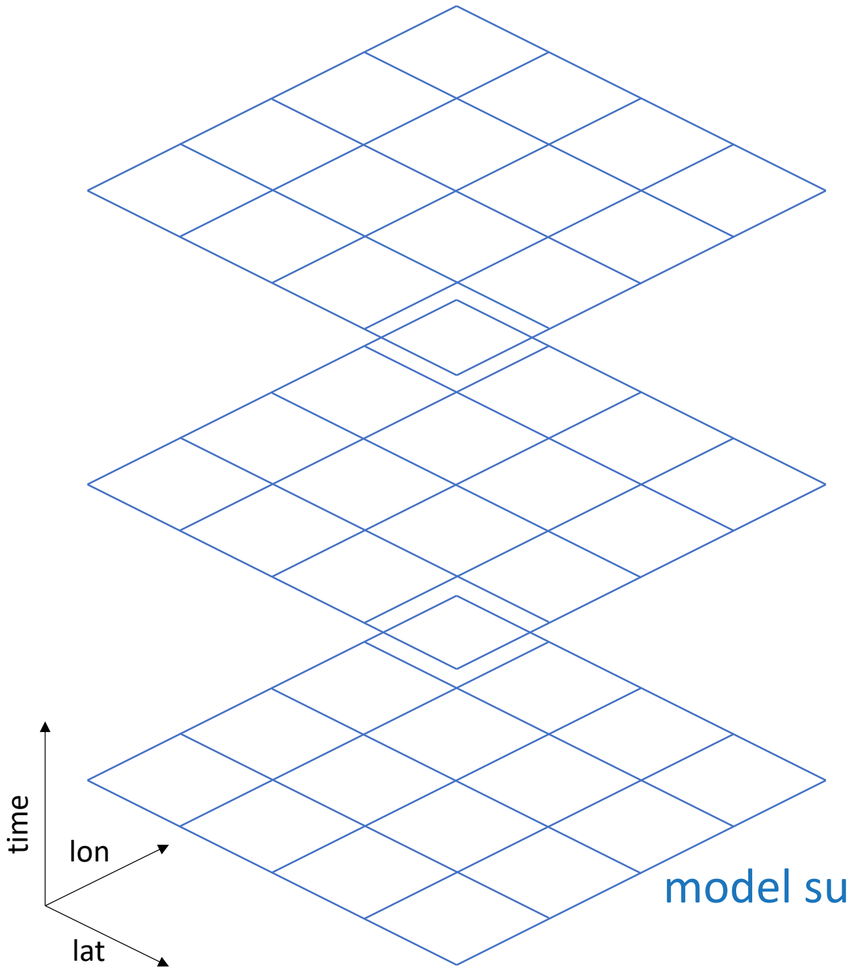

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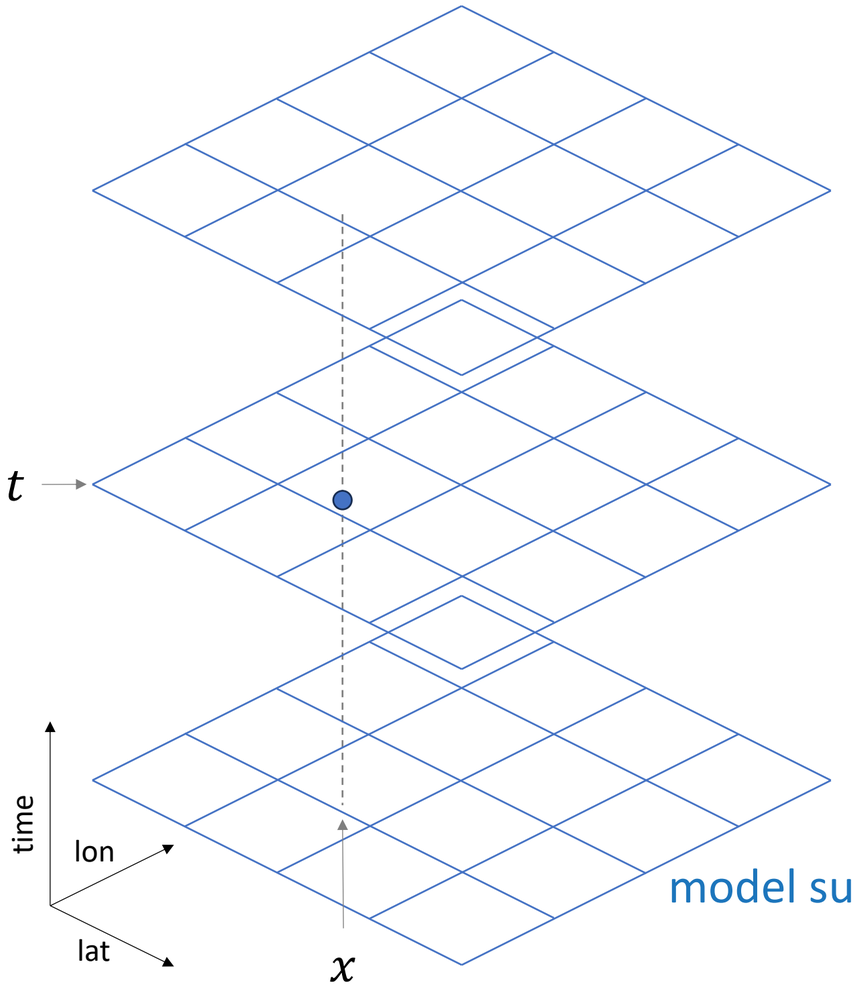
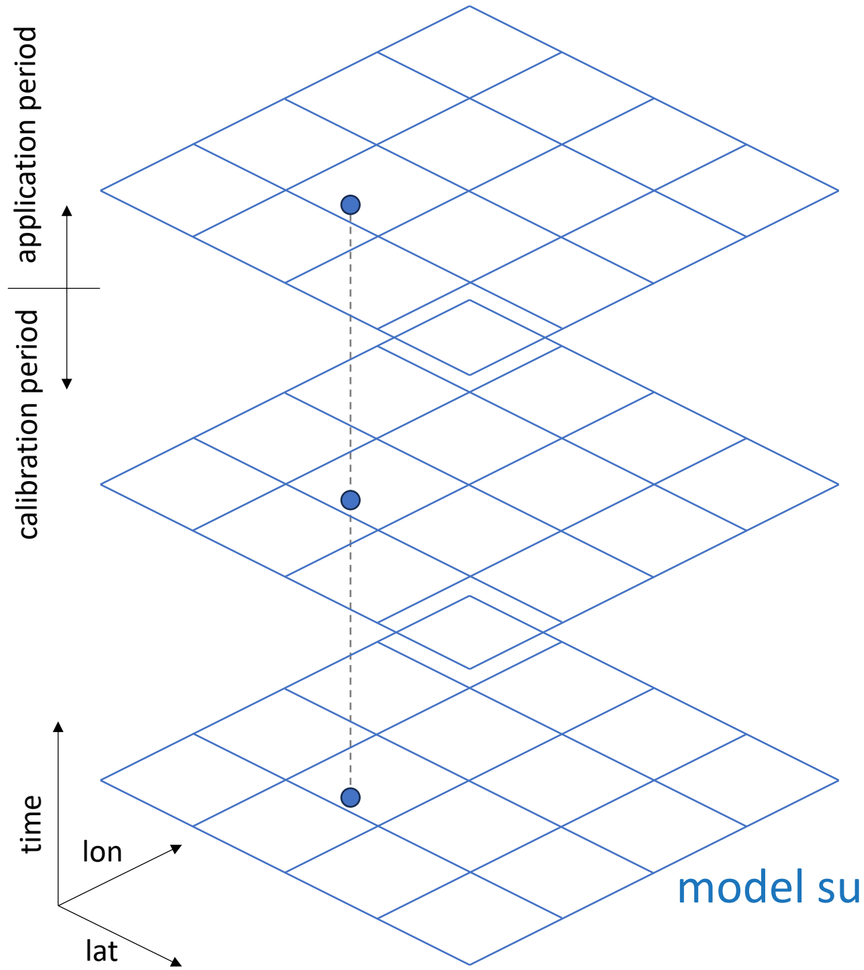


Phase	Estimate	Uncertainty
1	forecast model (GEOS-CF)	cell-to-cell variability of model

model surface concentration $M(x, t)$

Phase 2: Model & Satellite



model surface concentration $M(x,t)$

Phase	Estimate	Uncertainty
1	forecast model (GEOS-CF)	cell-to-cell variability of model
2	satellite (TROPOMI) informs sub-model-grid variability	satellite-to-model and surface-to-column ratios vary over time

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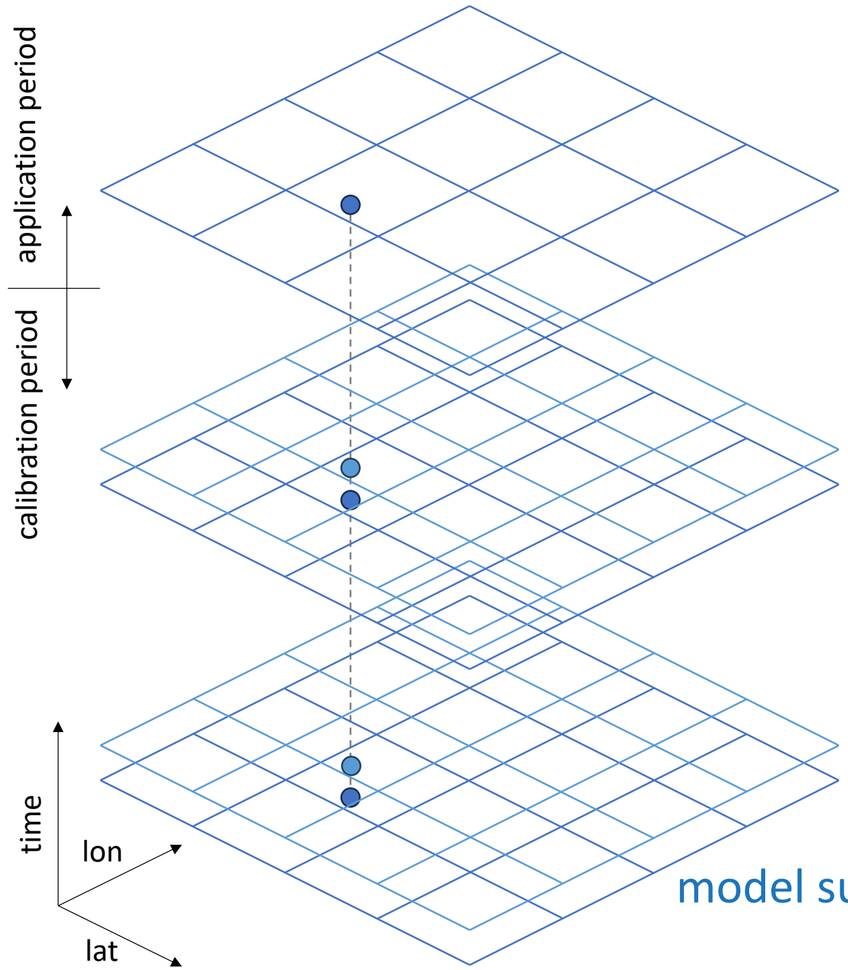

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model column concentration $M_{col}(x,t)$

model surface concentration $M(x,t)$

Phase 2: Model & Satellite

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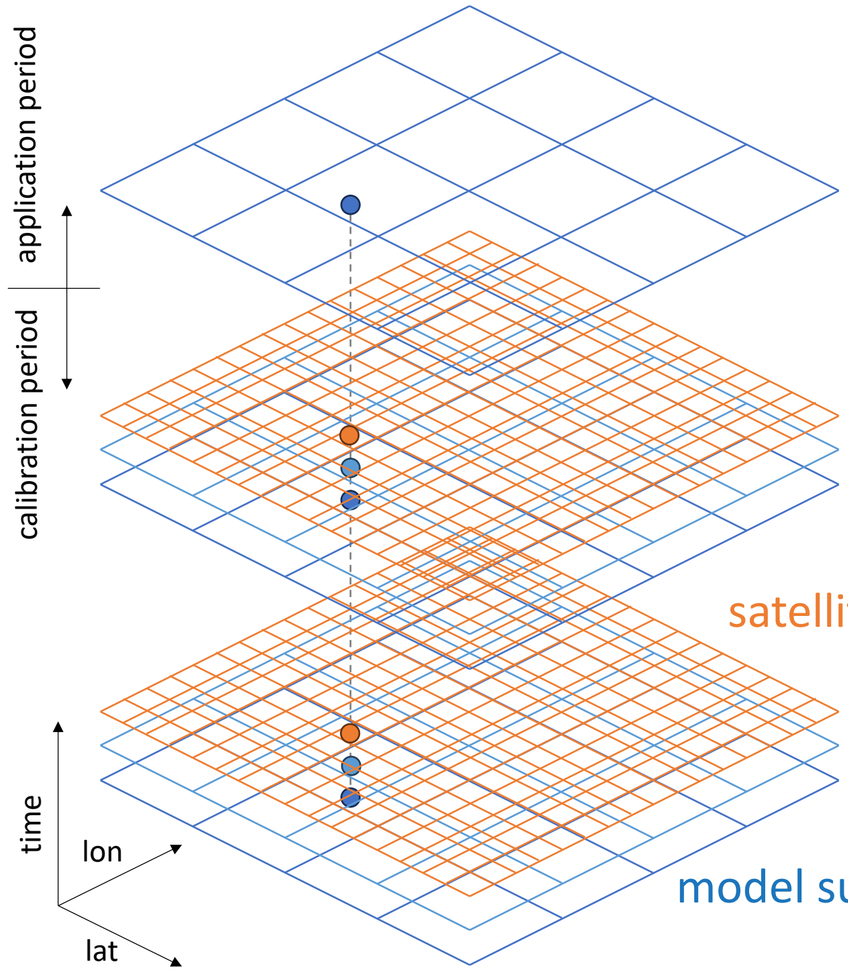
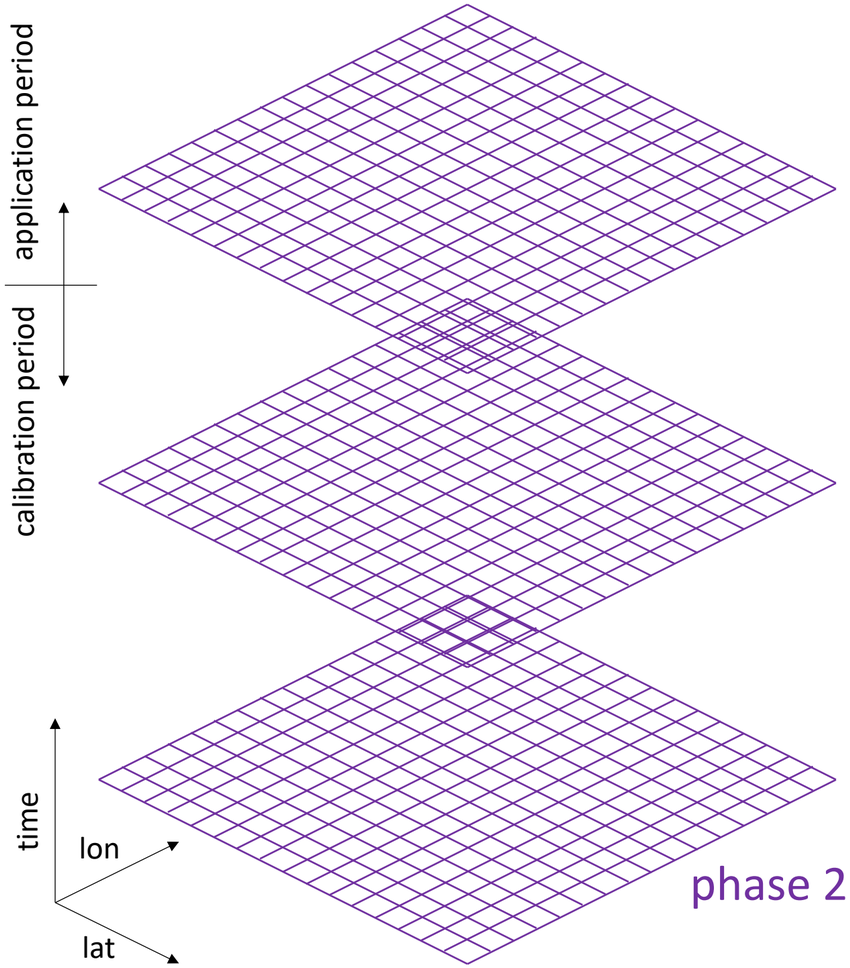


satellite column concentration $S_{col}(x,t)$

model column concentration $M_{col}(x,t)$

model surface concentration $M(x,t)$

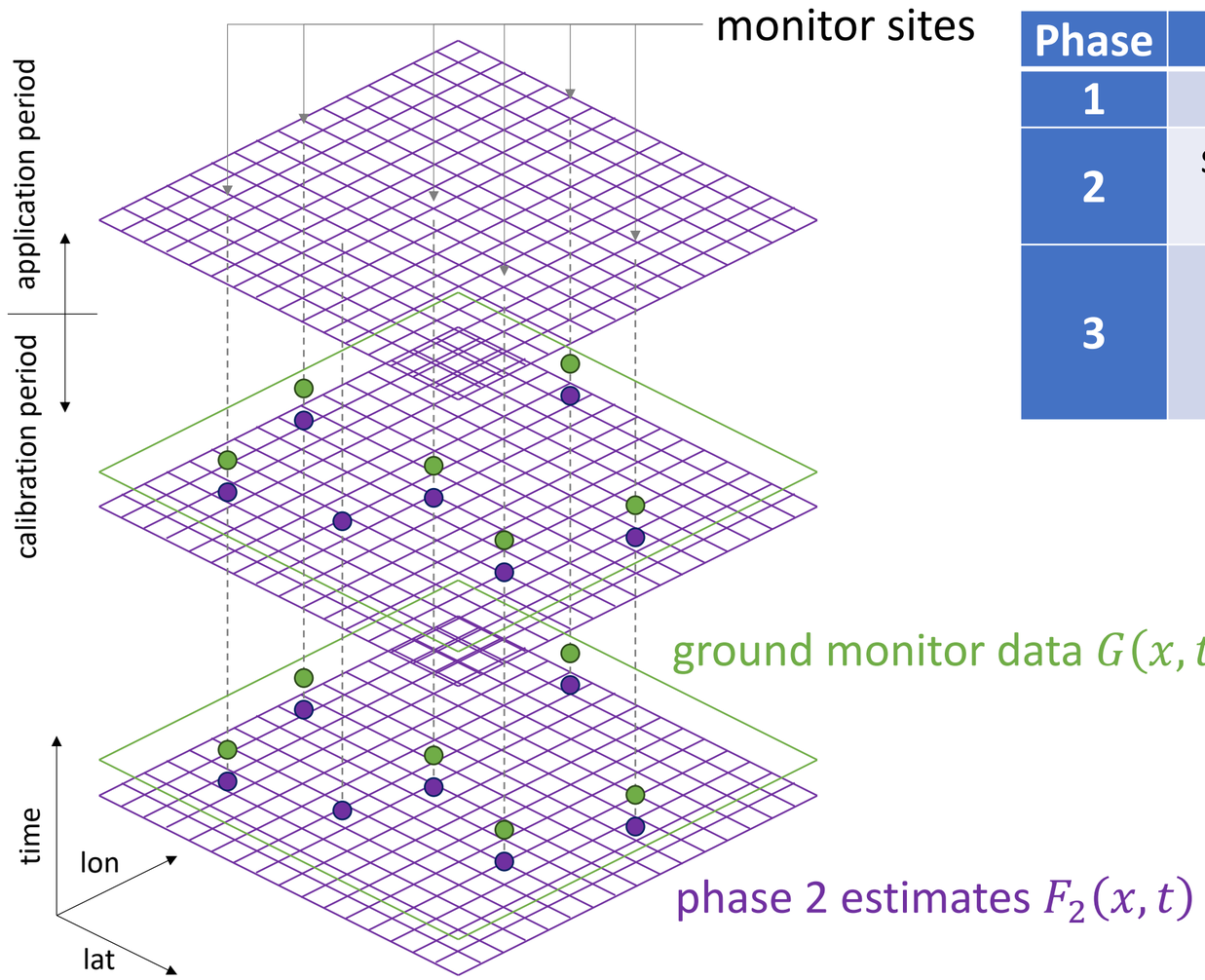
Phase 3: Model & Satellite & Ground



phase 2 estimates $F_2(x,t)$

Phase	Estimate	Uncertainty
1	forecast model (GEOS-CF)	cell-to-cell variability of model
2	satellite (TROPOMI) informs sub-model-grid variability	satellite-to-model and surface-to-column ratios vary over time
3	phase 2 corrected to match surface monitor data	uncertain regression parameters between phase 2 output and surface monitor data

Phase 3: Model & Satellite & Ground



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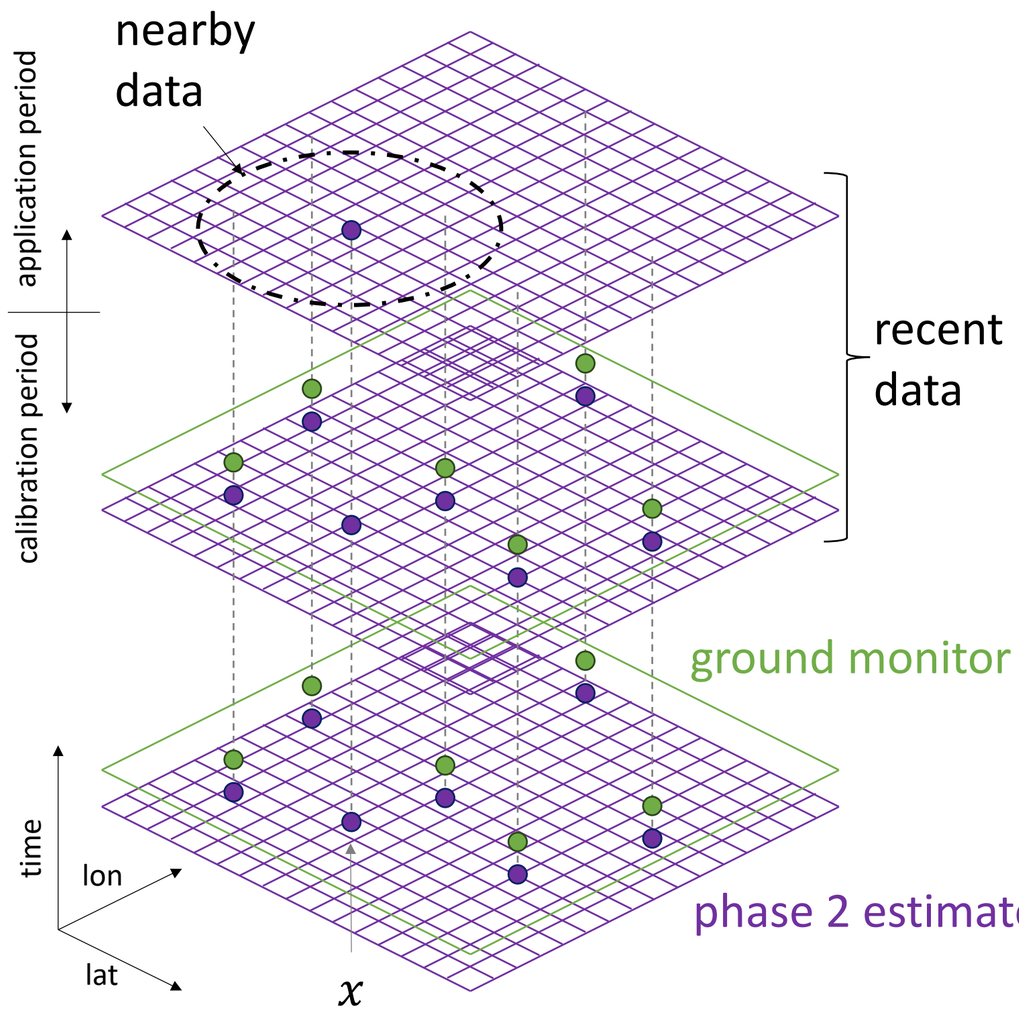
Phase 4: Residual Kriging



Phase	Estimate	Uncertainty
1	forecast model (GEOS-CF)	cell-to-cell variability of model
2	satellite (TROPOMI) informs sub-model-grid variability	satellite-to-model and surface-to-column ratios vary over time
3	phase 2 corrected to match surface monitor data	uncertain regression parameters between phase 2 output and surface monitor data
4	update phase 3 based on recent surface monitor data	uncertainty reduction via updating with nearby & recent data (kriging)

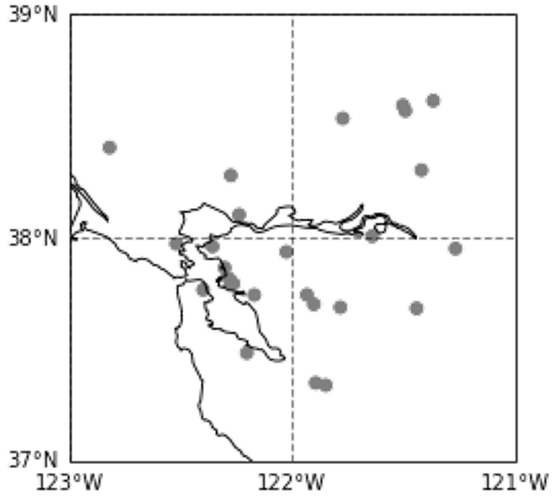
Case Study Results

Partner

Case Study Details

San Francisco
September 2019
Surface NO_2
Lognormal distribution
Cross-validation test
25 ground monitors

Ground Sites



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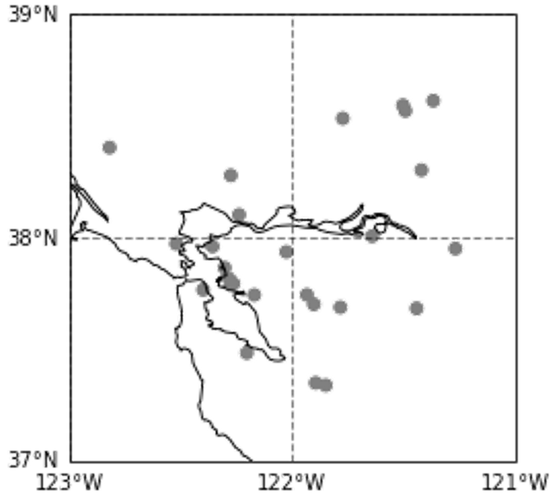
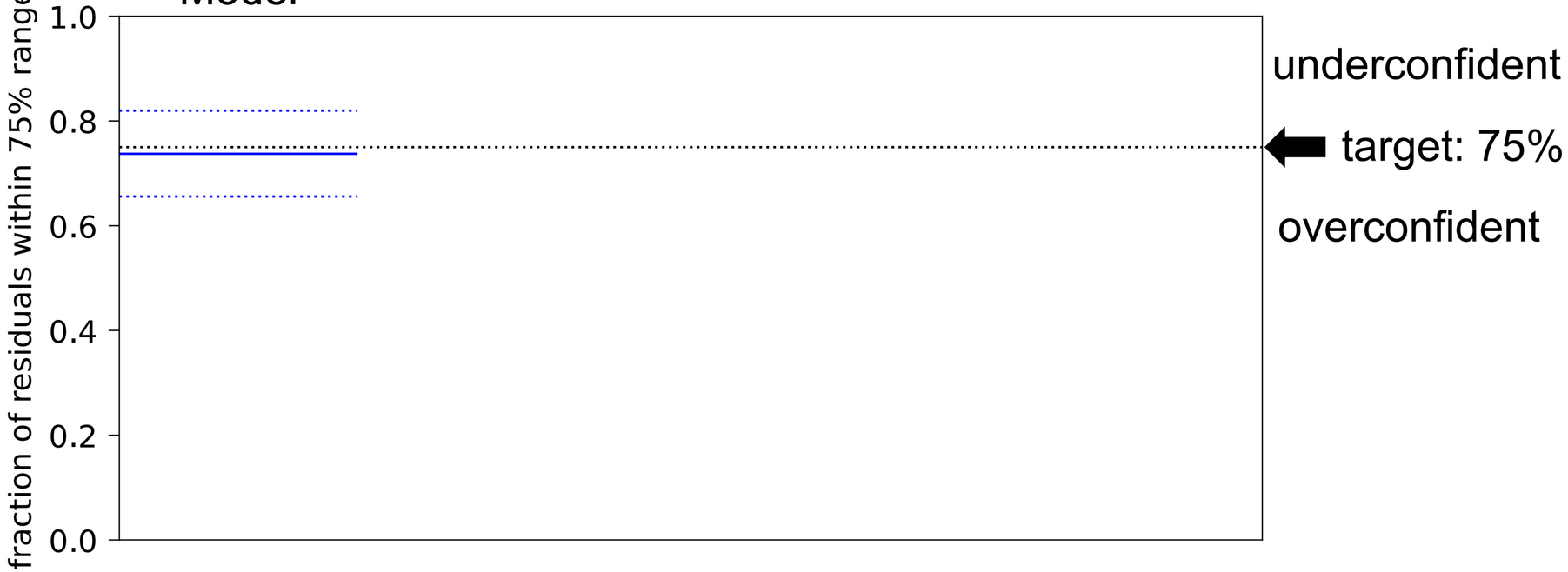


Phase 1

Model



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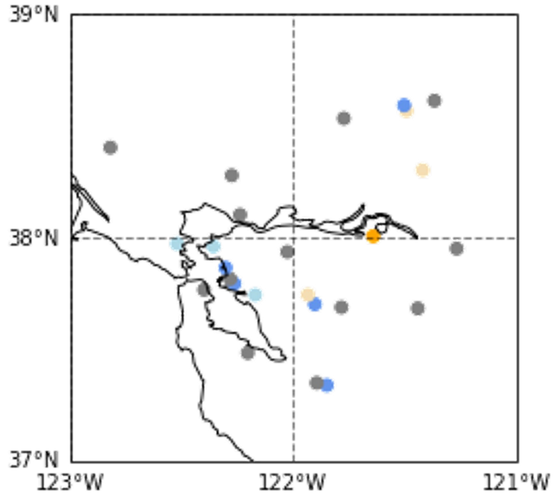

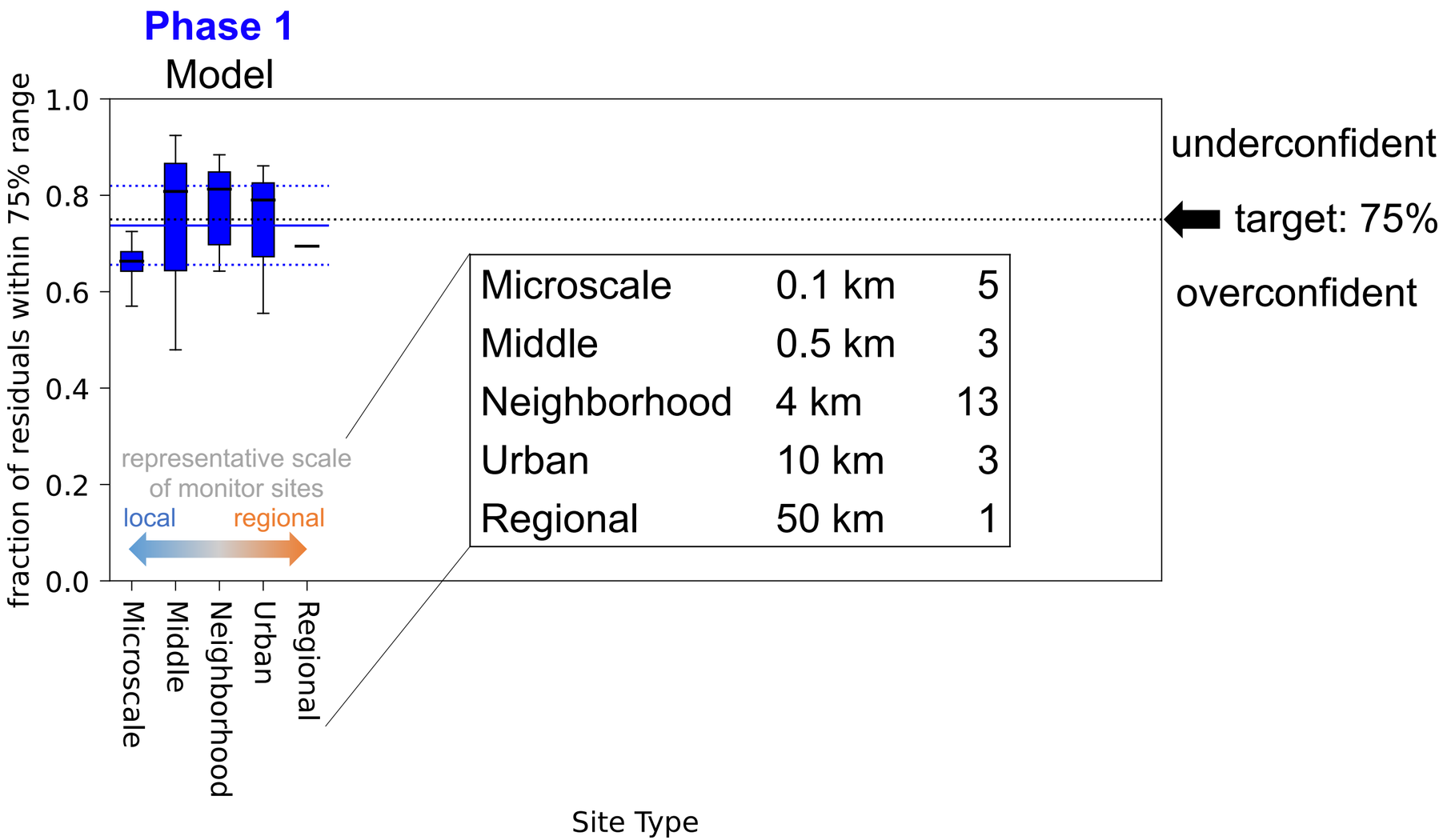

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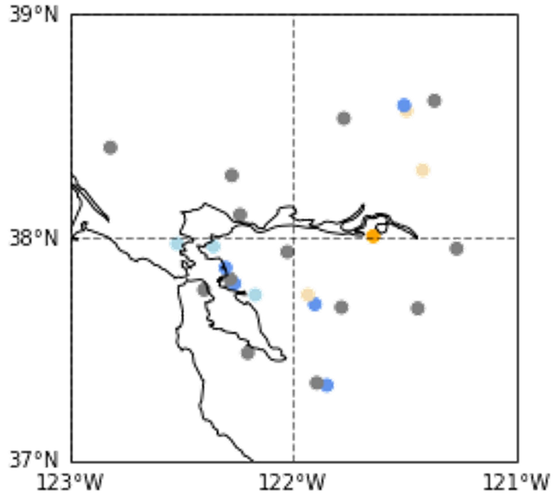

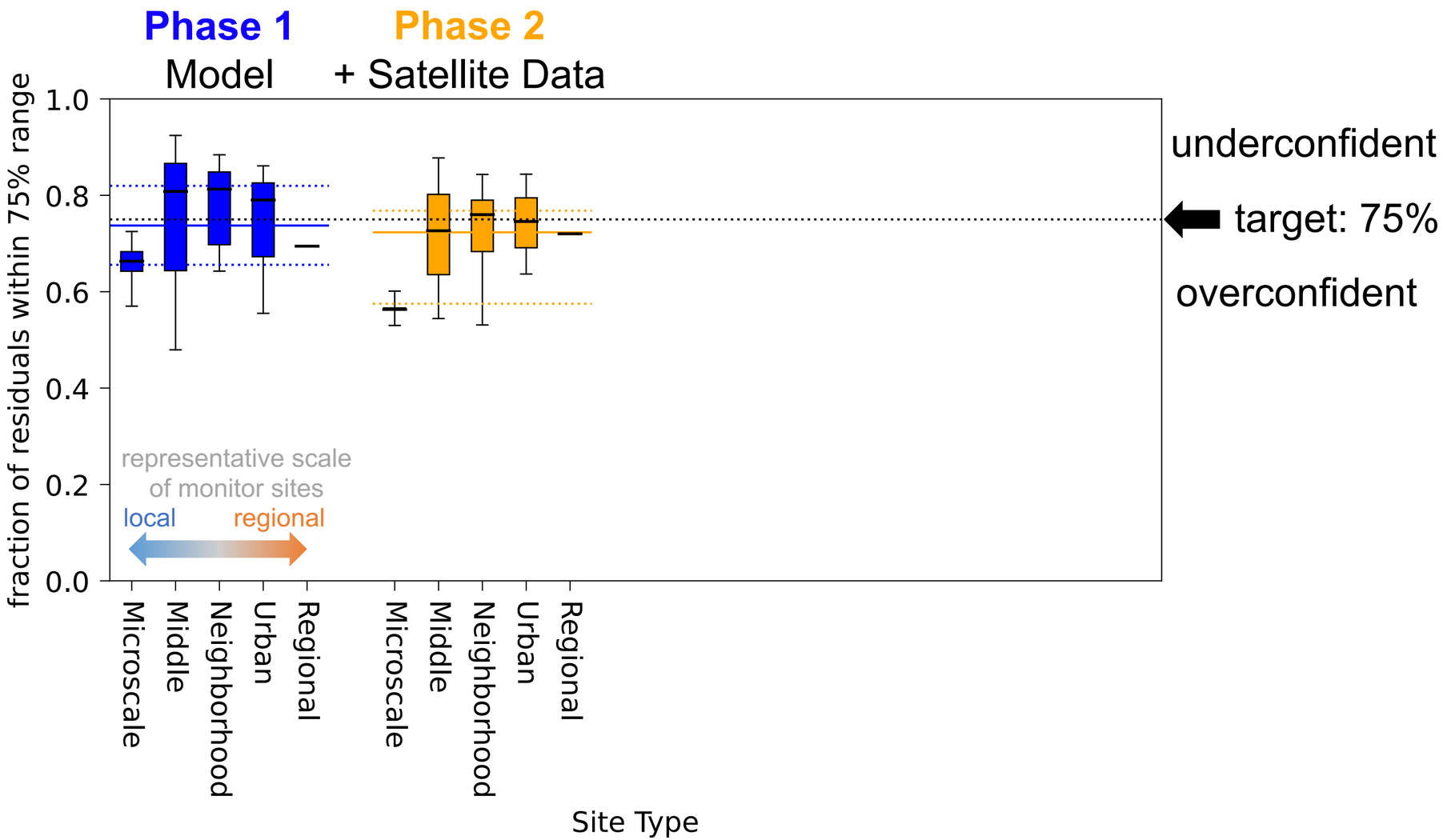

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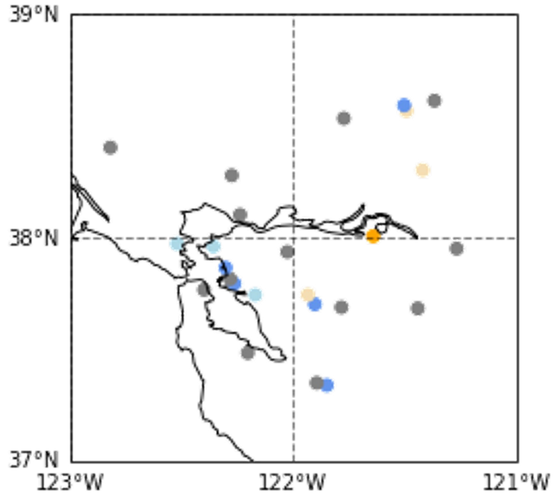

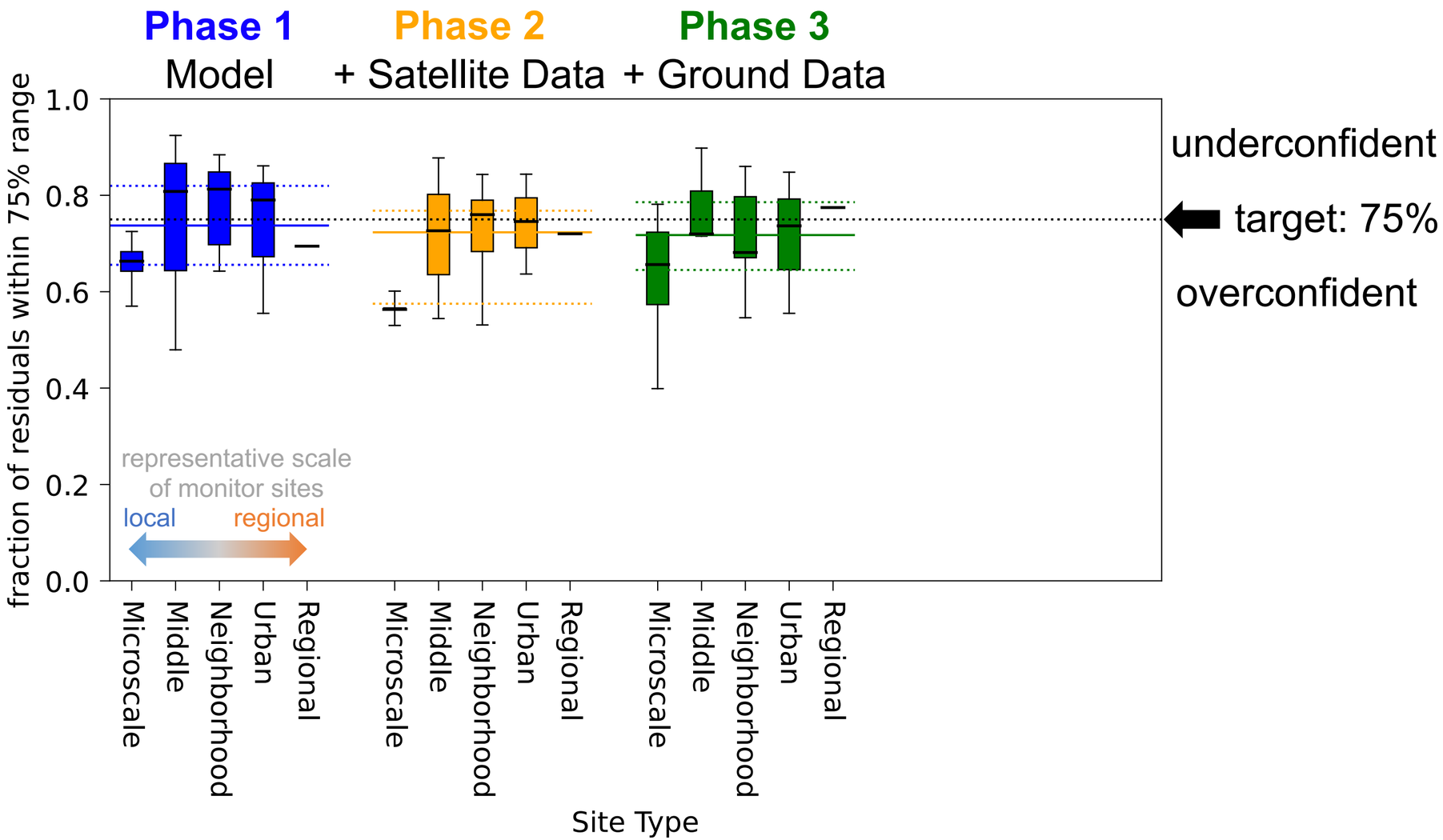

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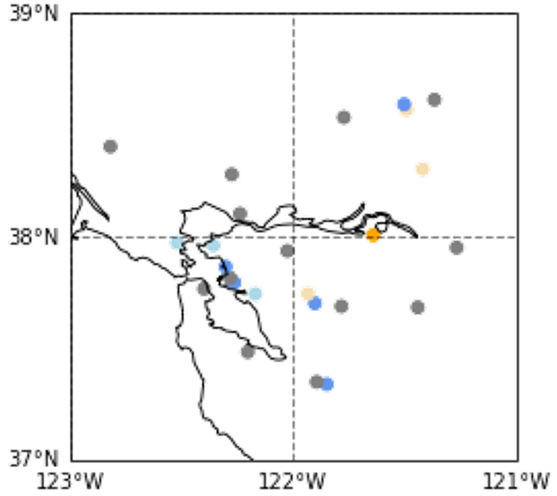

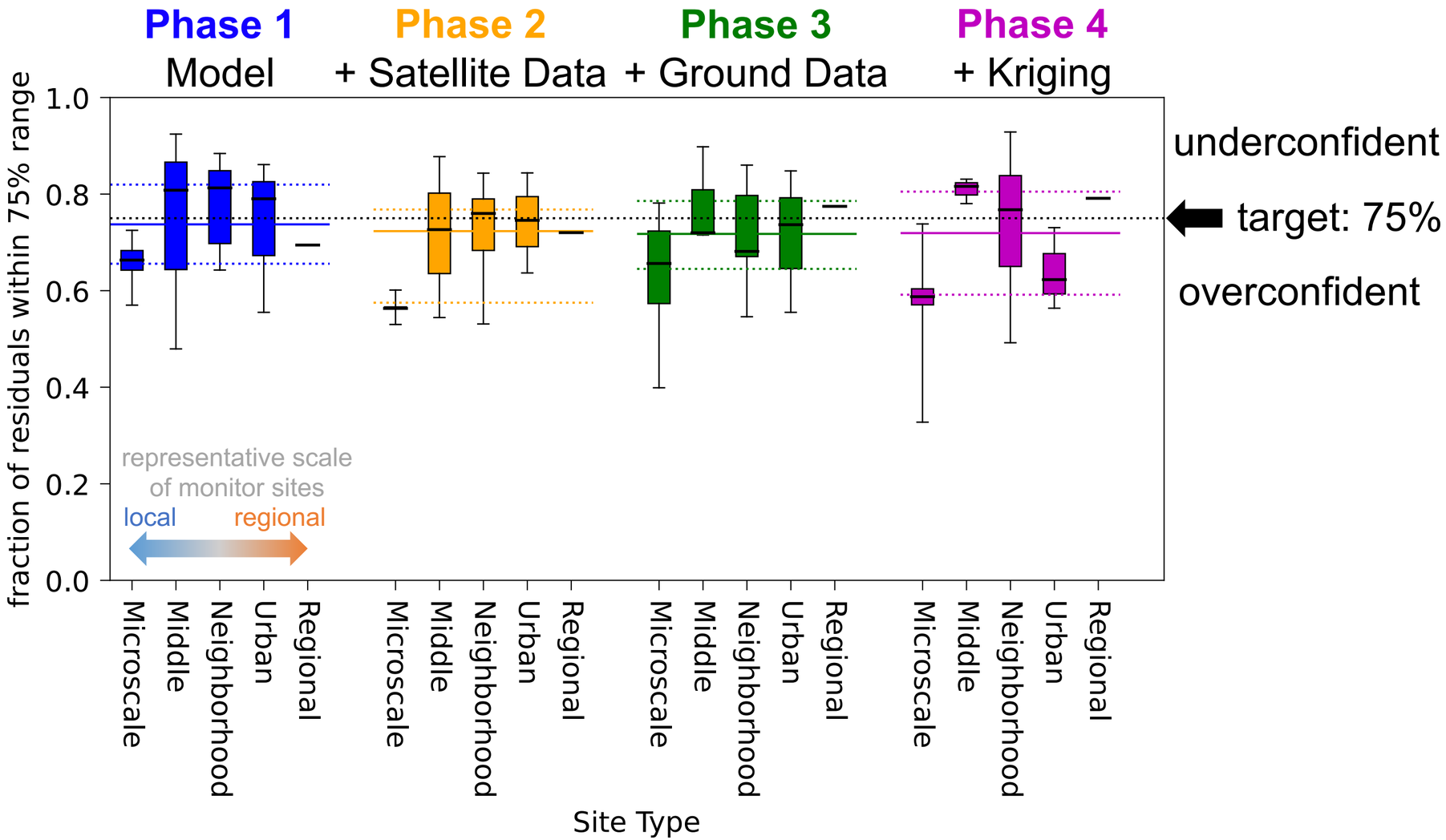

Thank you!

Questions?

This material is based upon work supported by the National Aeronautics and Space Administration (NASA) under Grants 80NSSC22K1473 and WBS 389018.02.09.02.72 issued through the NASA Health and Air Quality Applied Sciences Program.

This research is supported by the GESTAR II Cooperative Agreement with NASA Goddard Space Flight Center. For more information about GESTAR II, scan the QR code provided.