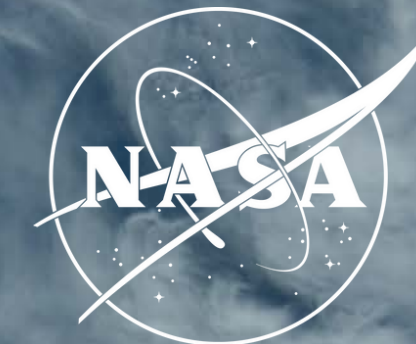




GMAO



Partner

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

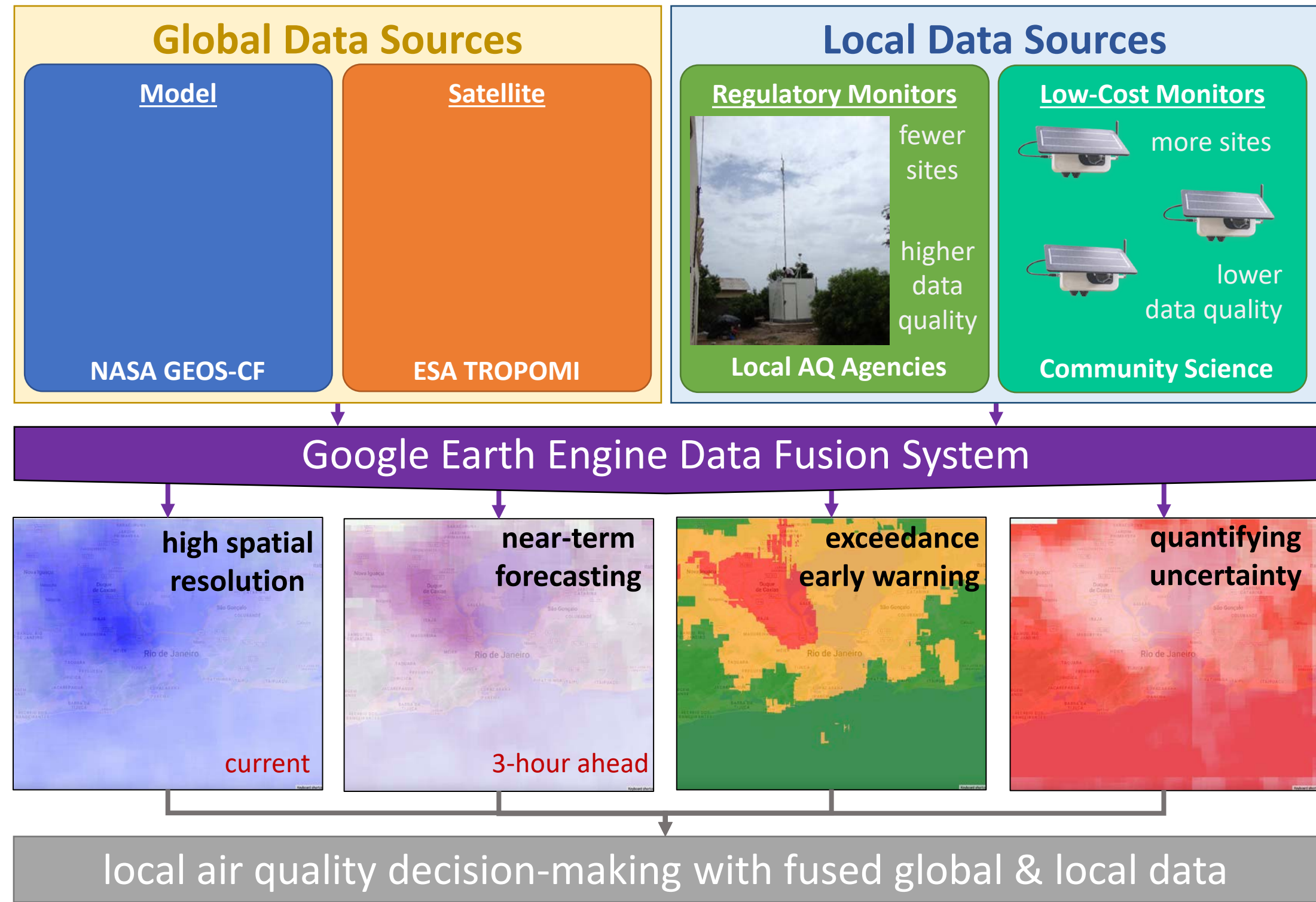
Collaborators: Sean Khan (UNEP), John White (US EPA), Dan Westervelt (LDEO), Sean Wihera (Clarity Movement Co.), Randall Martin (WUSTL)

...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.

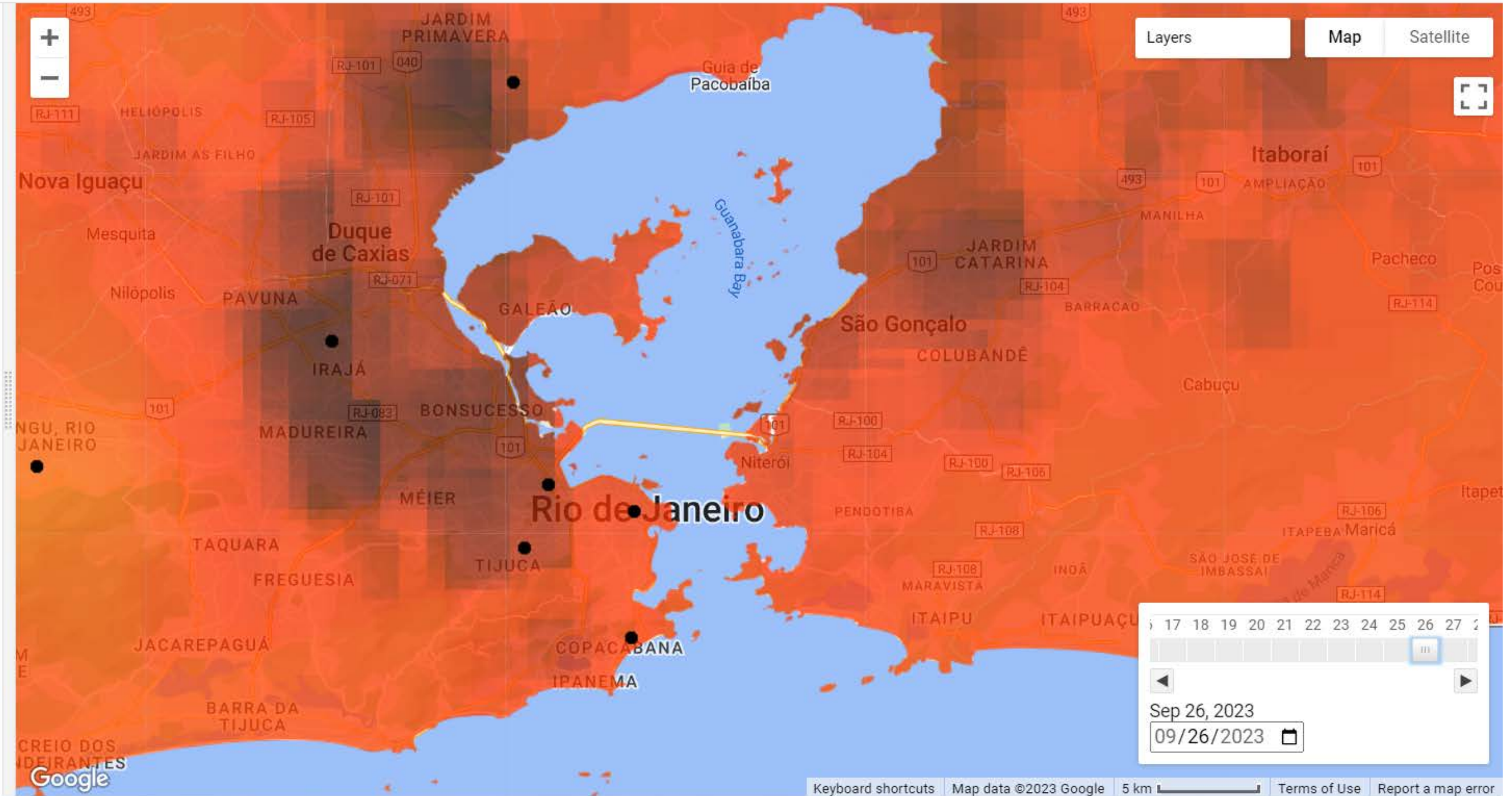
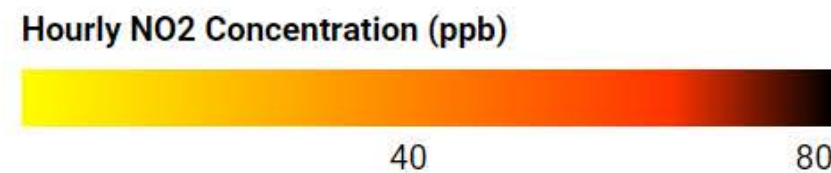
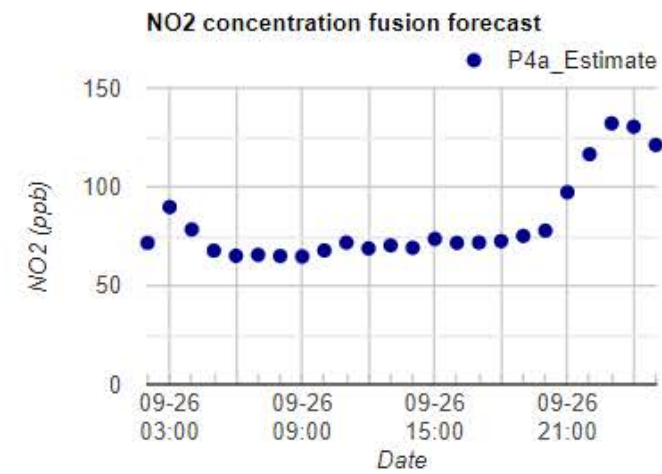


Sub-city air quality forecasts

Select the region of interest to view forecasts

Rio de Janeiro, BR

P4



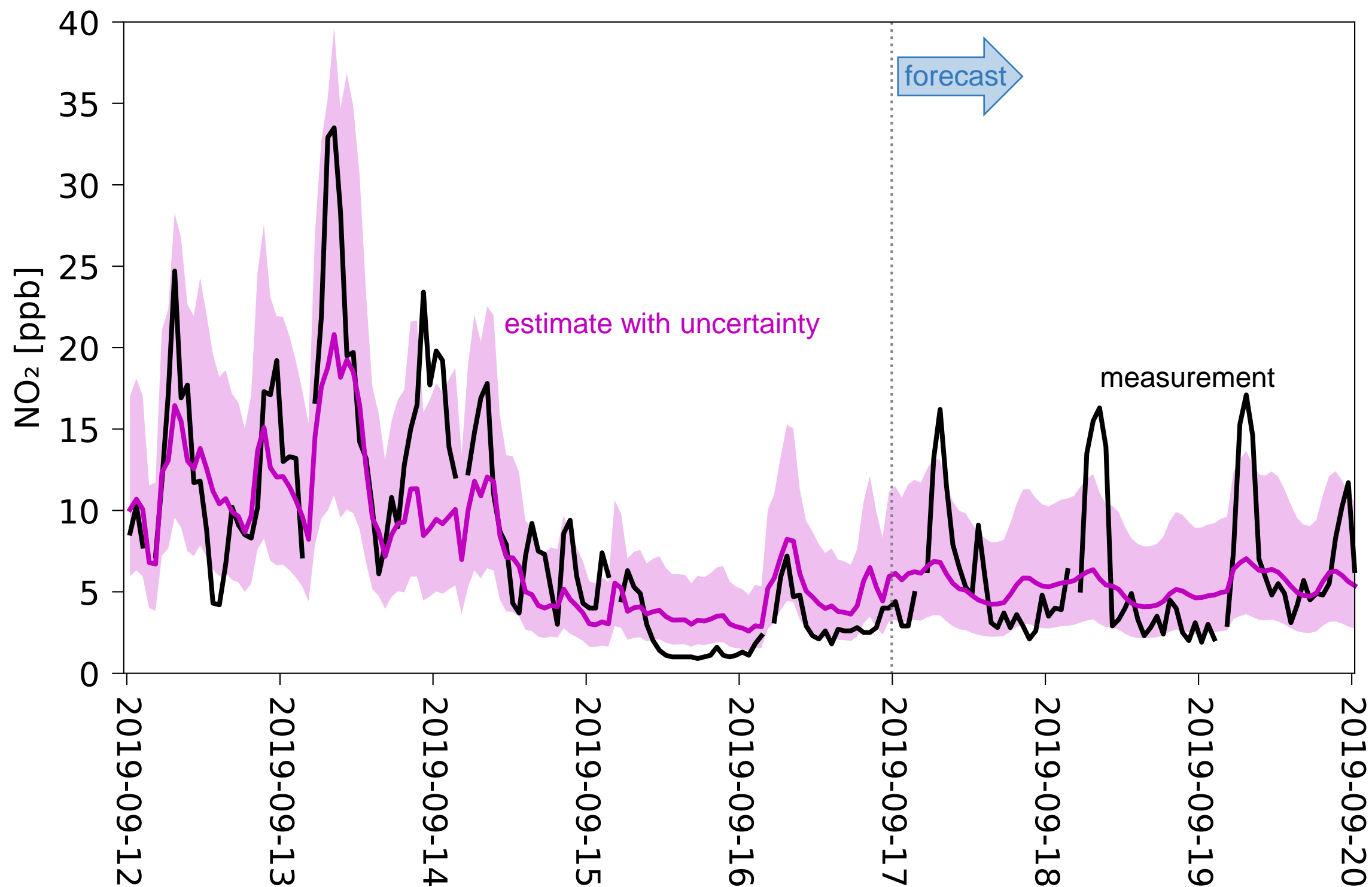
Provide a prior estimate of the relative confidence in a forecast

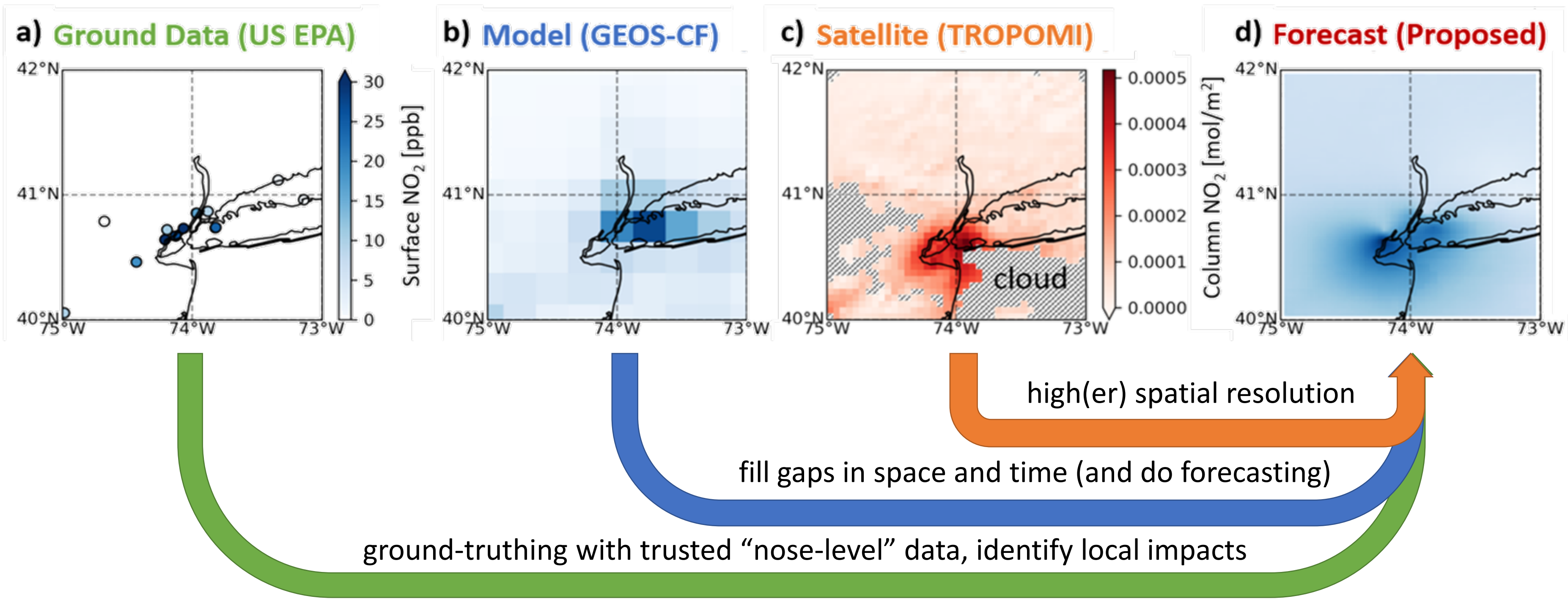
Convey probabilities of specific events, e.g., exceedance of standards

Identify a range of likely outcomes

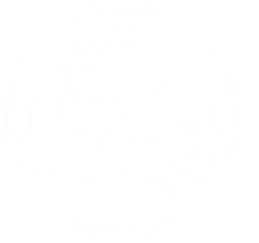
Quantify the impacts of different data sources in reducing uncertainties

Identify the potential to reduce uncertainties through additional data collection

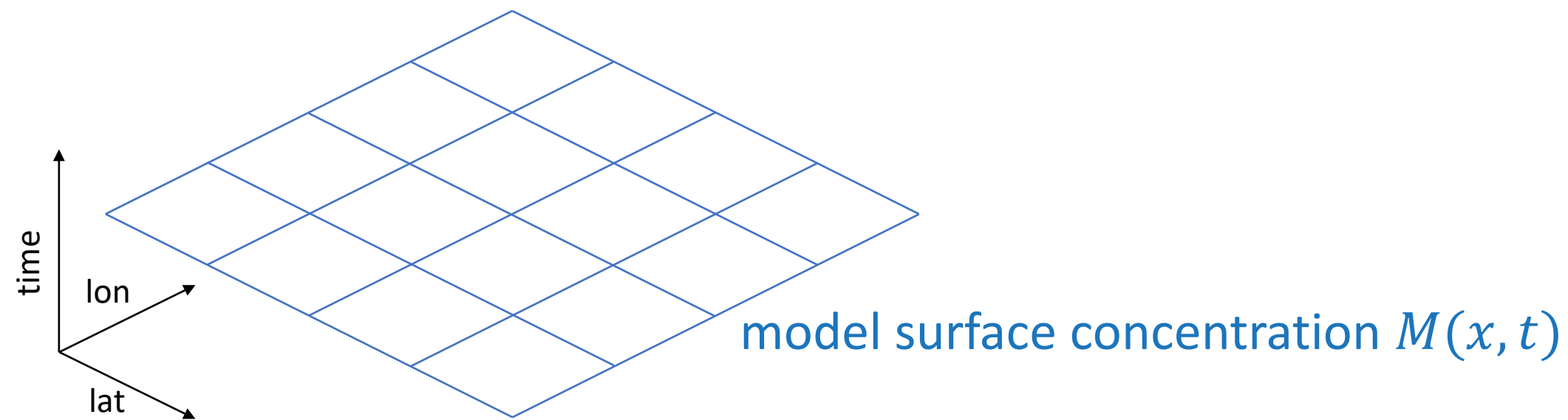


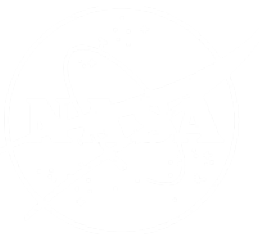


Source: Malings et al. (2021), “Sub-City Scale Hourly Air Quality Forecasting by Combining Models, Satellite Observations, and Ground Measurements” *Earth & Space Science*. [DOI: 10.1029/2021EA001743](https://doi.org/10.1029/2021EA001743)

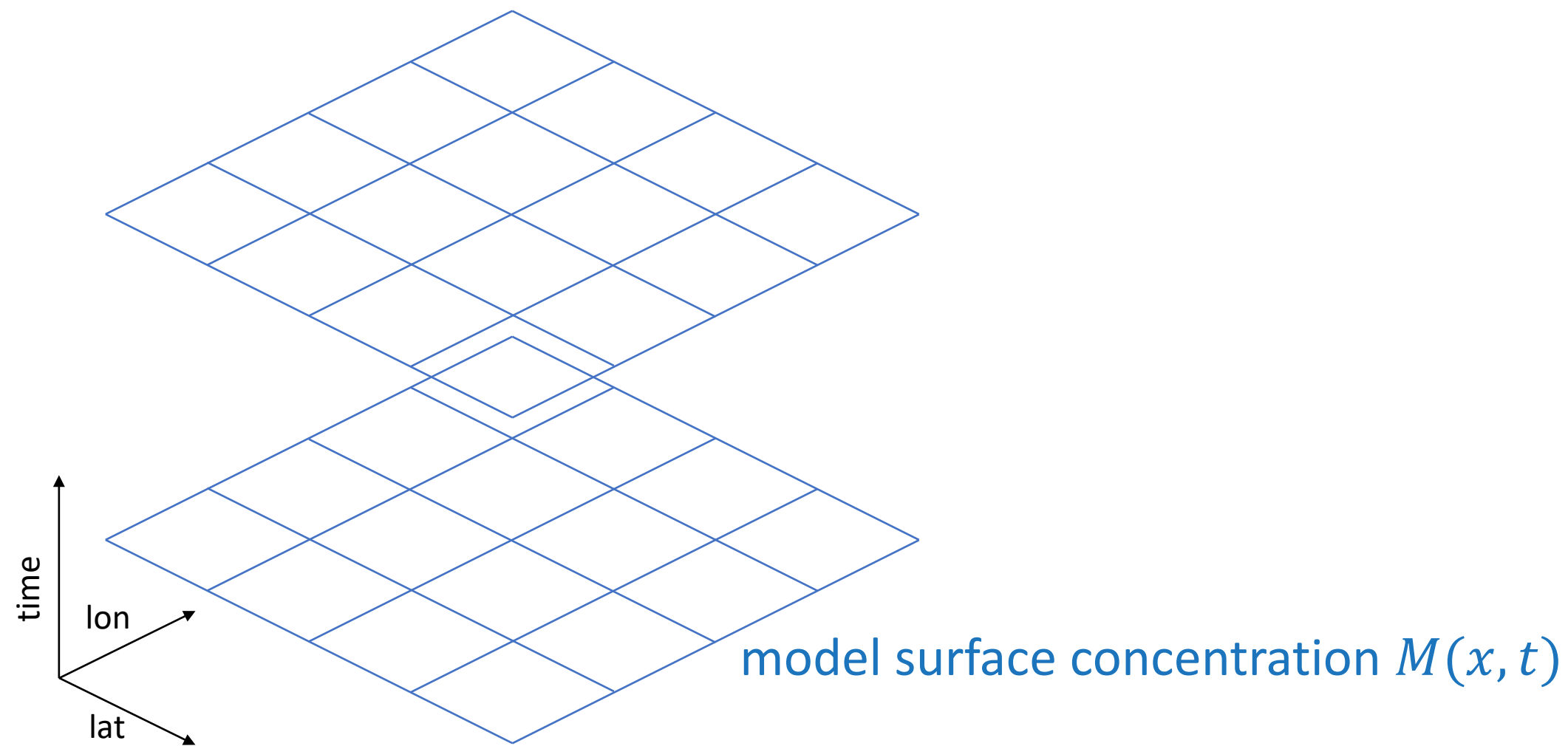


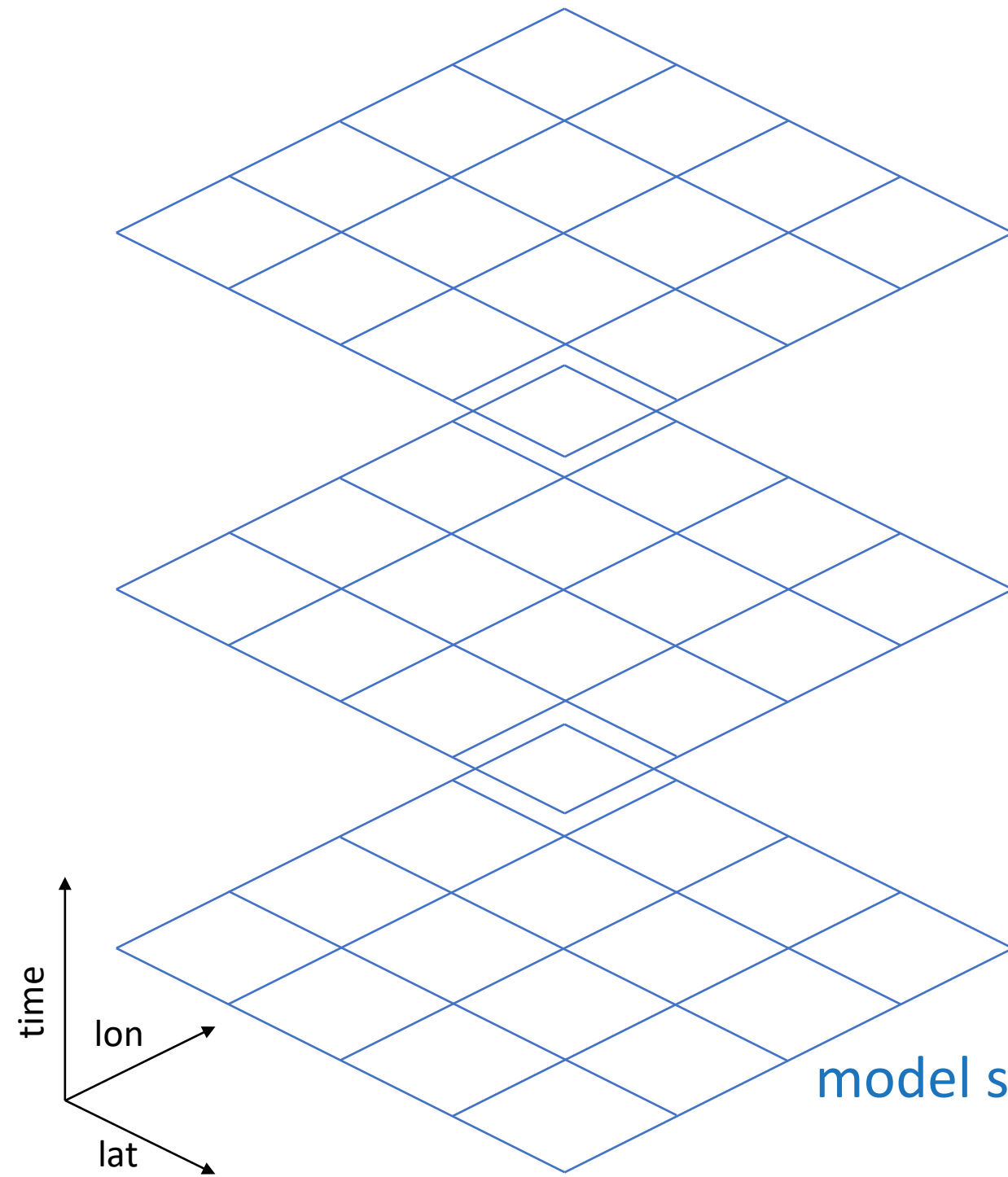
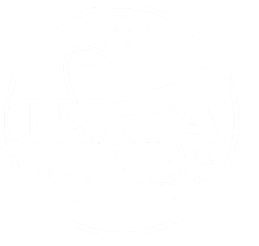
Phase	Estimate
1	forecast model (GEOS-CF)





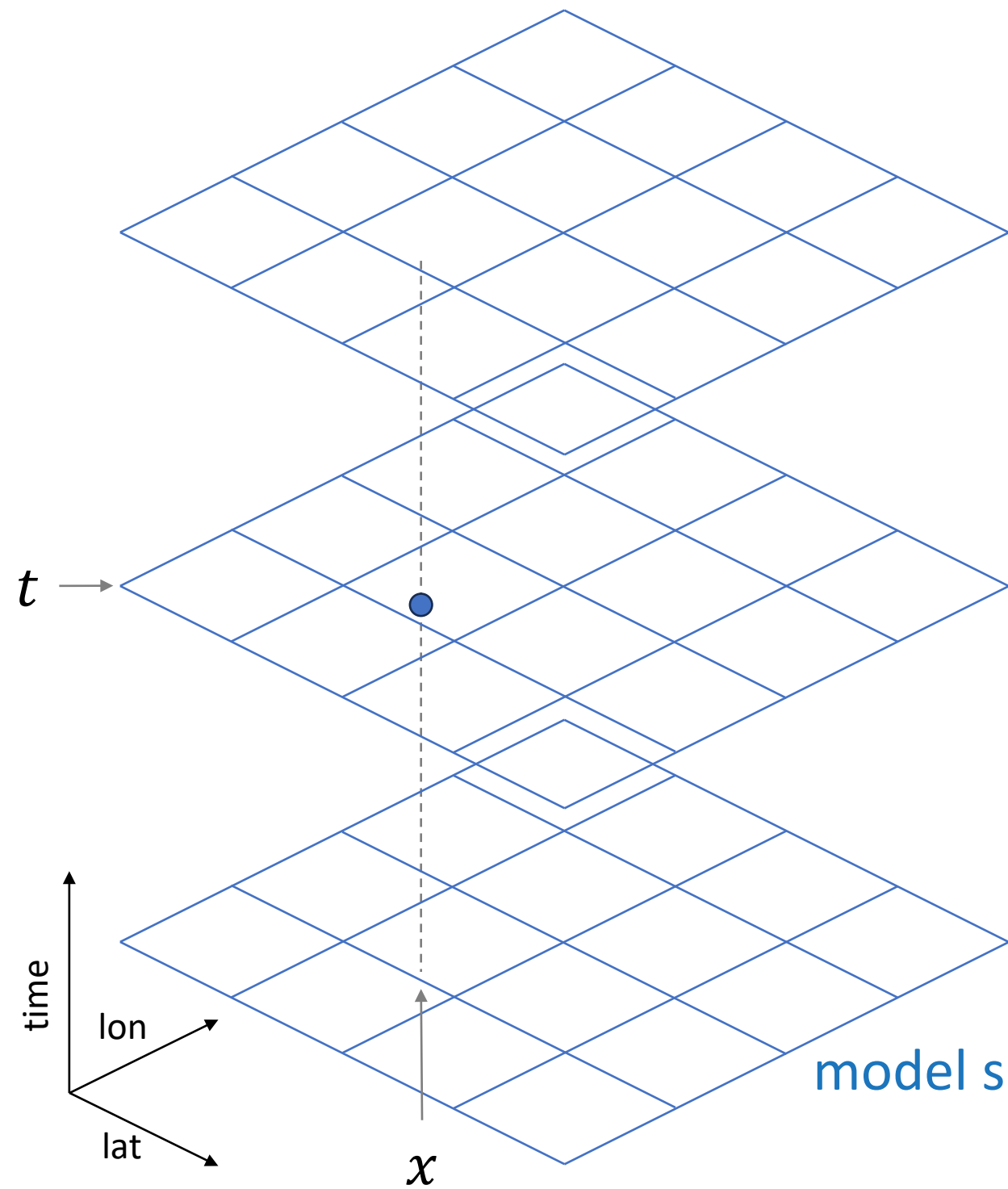
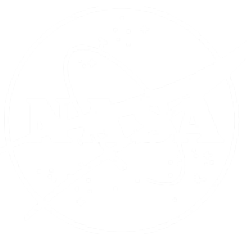
Phase	Estimate
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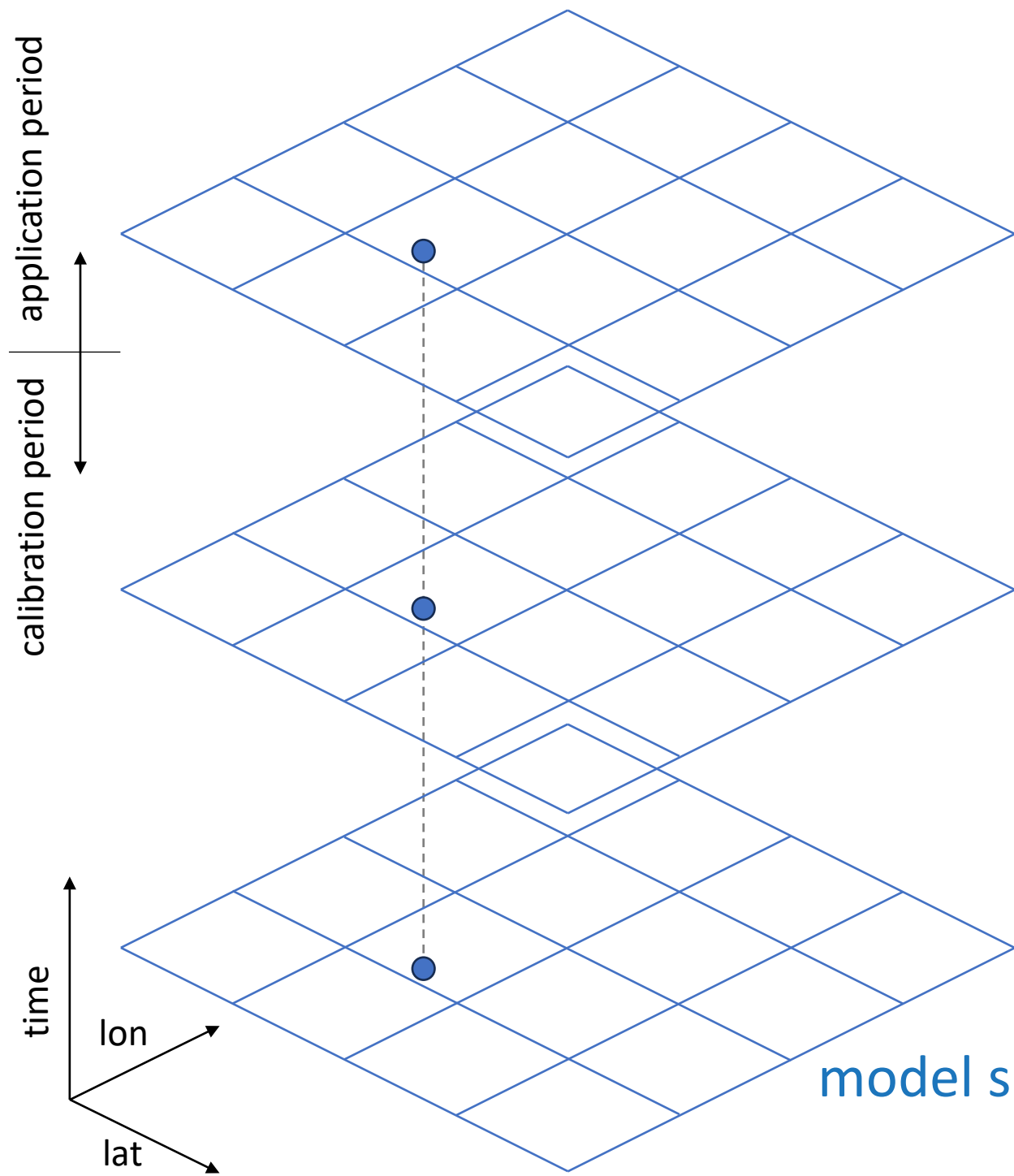


model surface concentration $M(x, t)$

Phase	Estimate
1	forecast model (GEOS-CF)

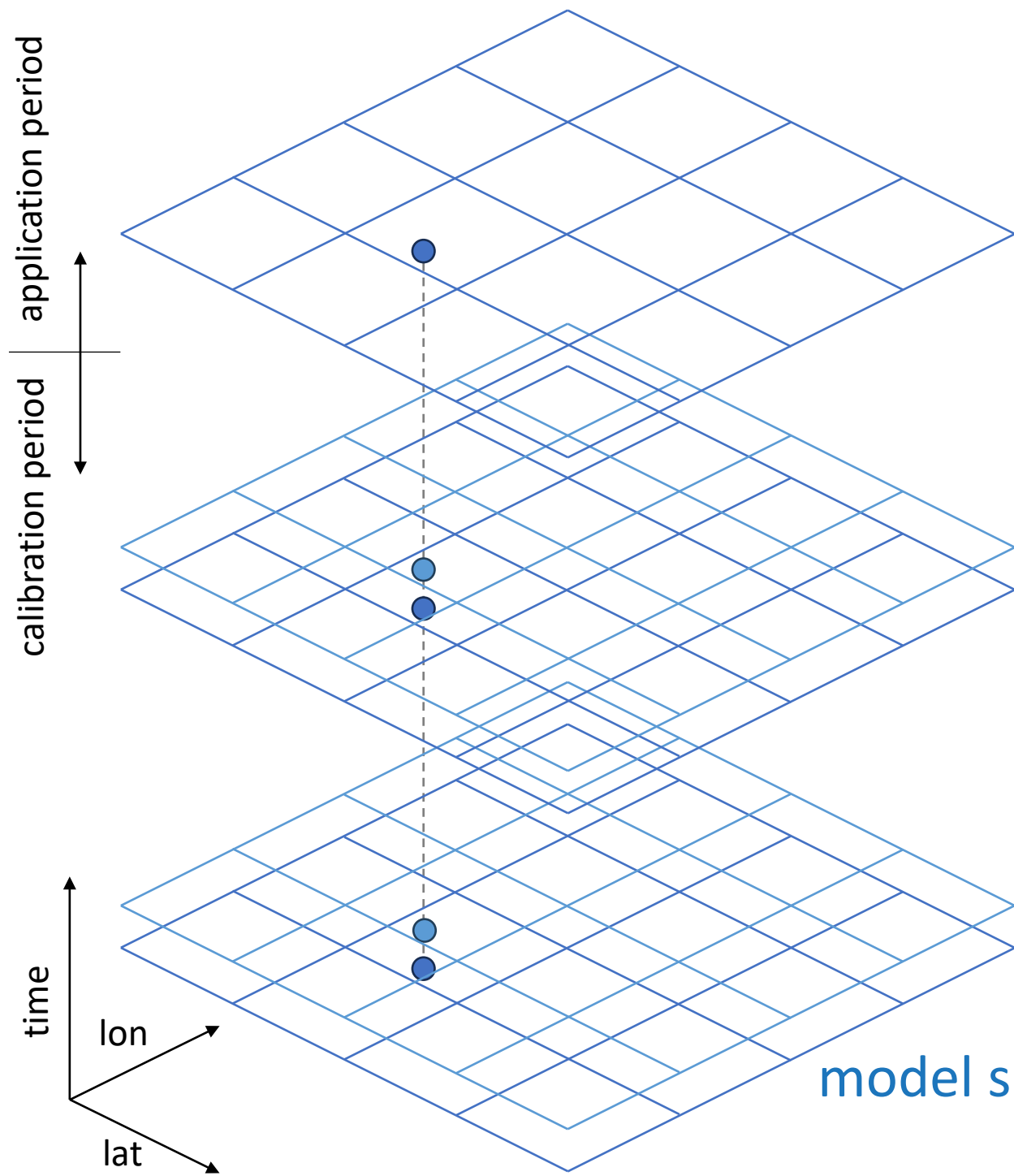


Phase	Estimate	Uncertainty
1	forecast model (GEOS-CF)	cell-to-cell variability of model



model surface concentration $M(x, t)$

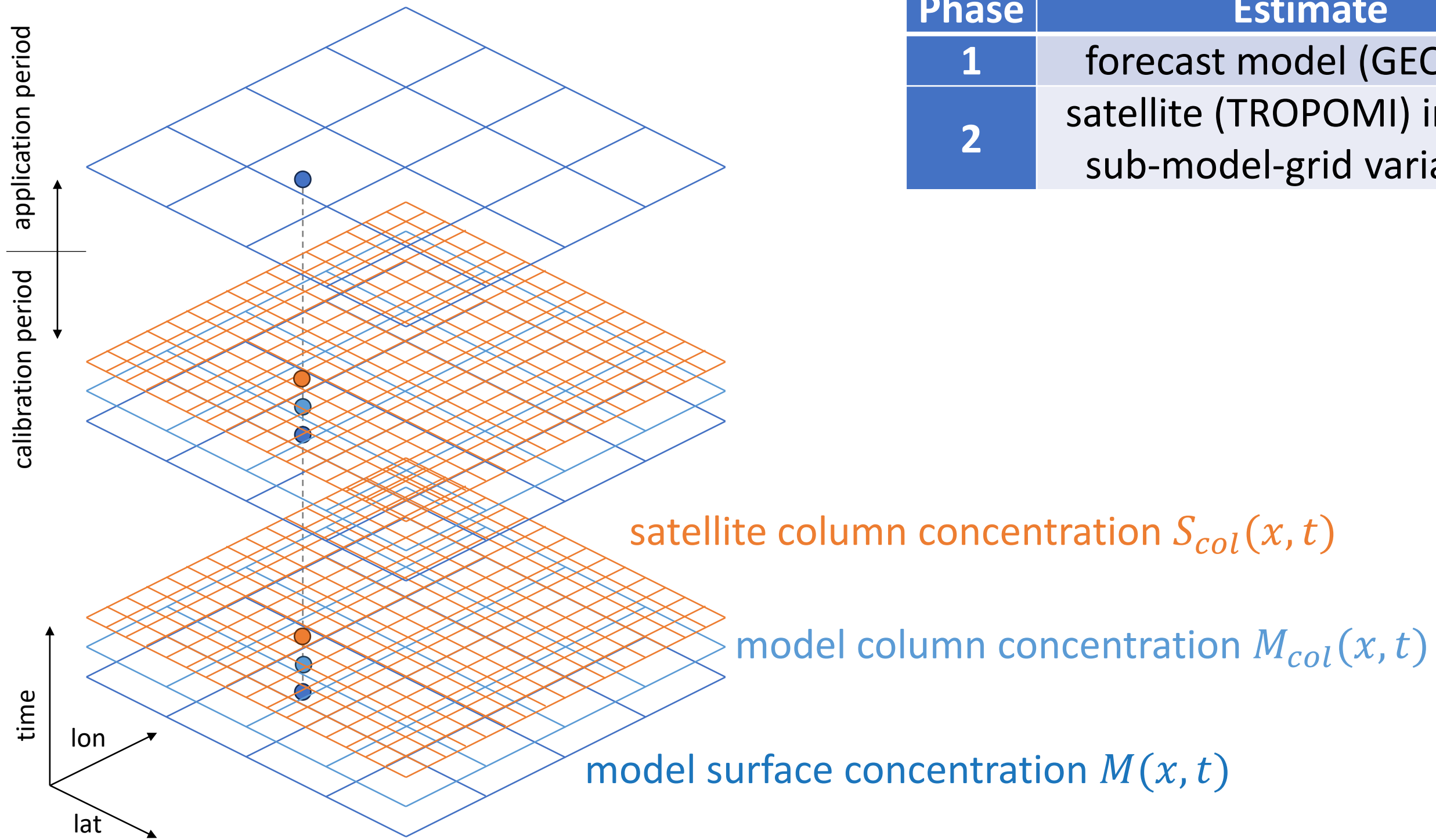
Phase	Estimate	Uncertainty
1	forecast model (GEOS-CF)	cell-to-cell variability of model
2	satellite (TROPOMI) informs sub-model-grid variability	satellite-to-model and surface-to-column ratios vary over time



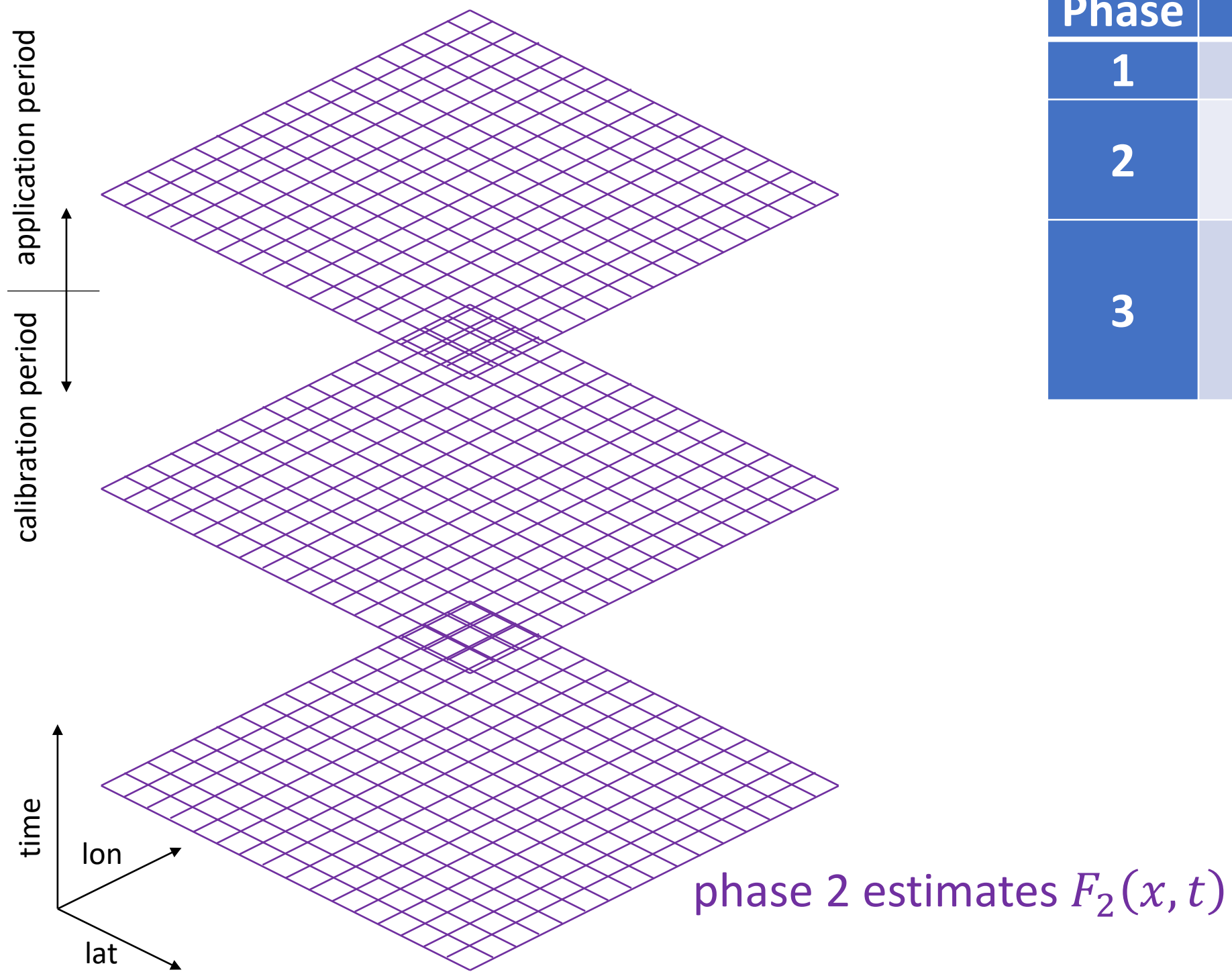
model column concentration $M_{col}(x, t)$

model surface concentration $M(x, t)$

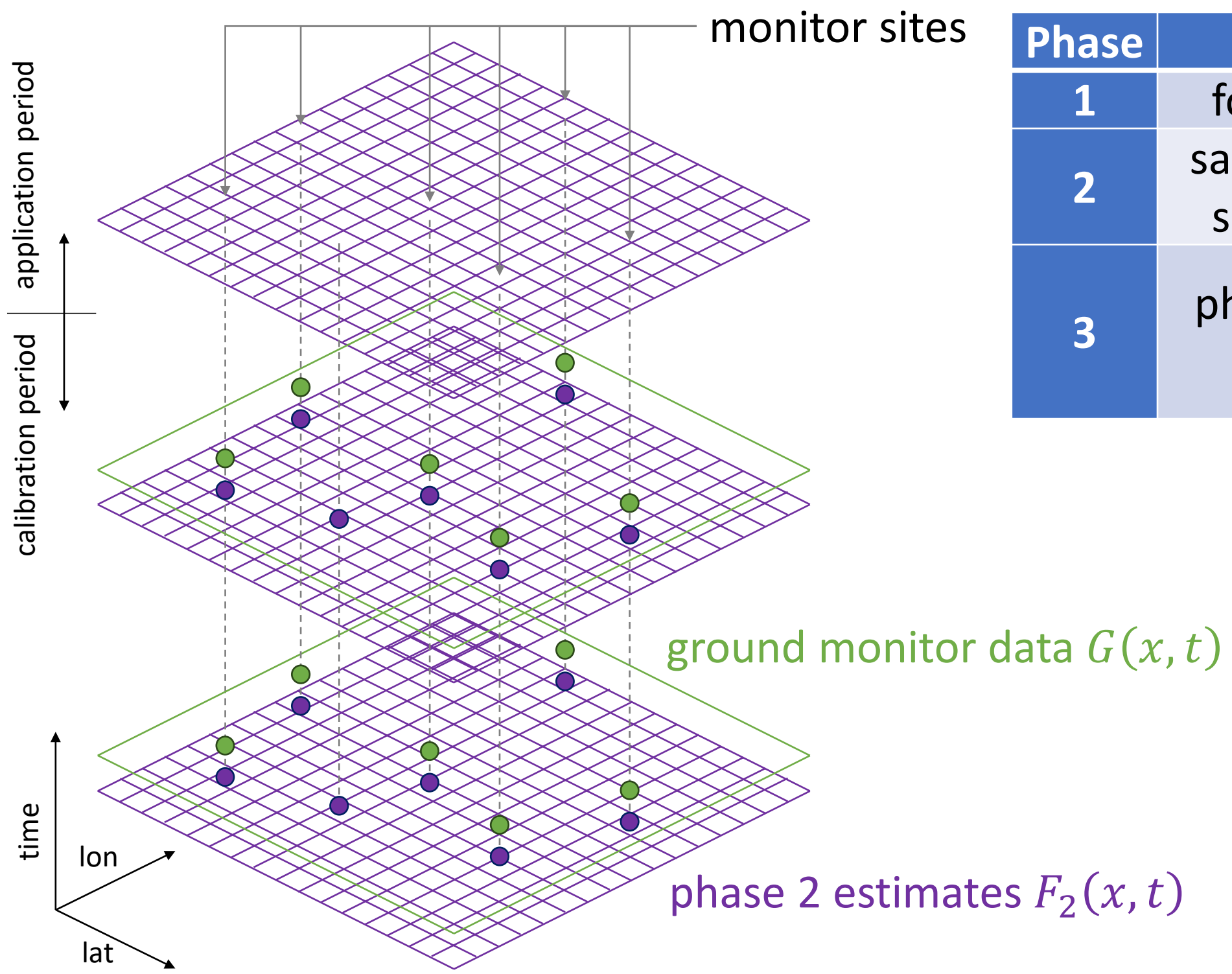
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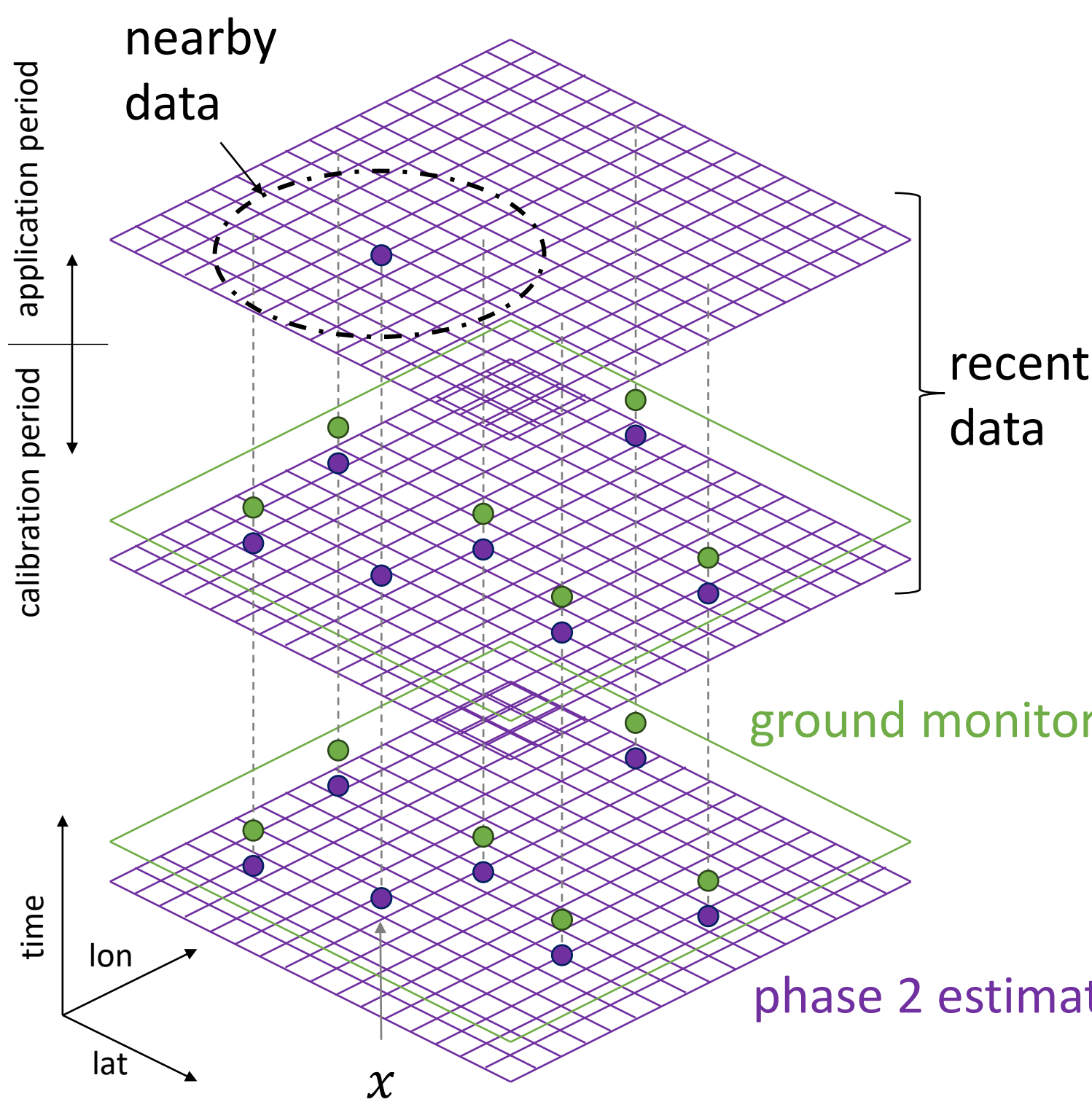
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3	phase 2 corrected to match surface monitor data	uncertain regression parameters between phase 2 output and surface monitor data



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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 Details

San Francisco

September 2019

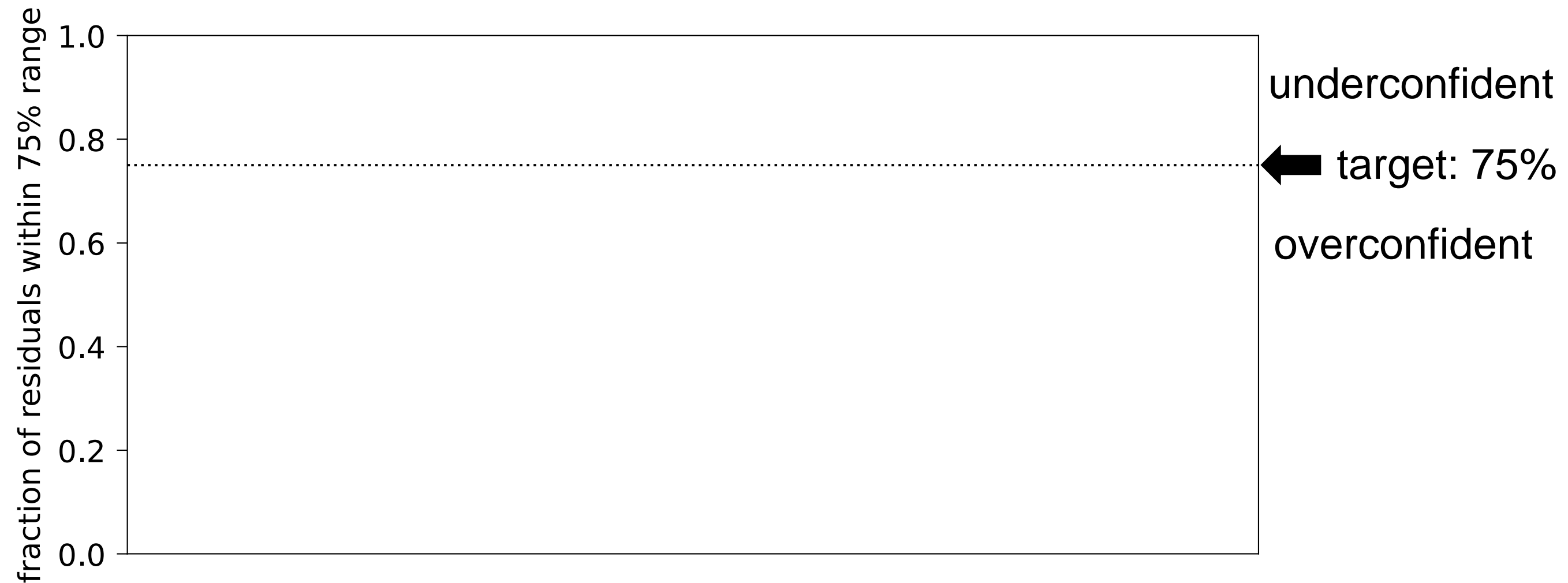
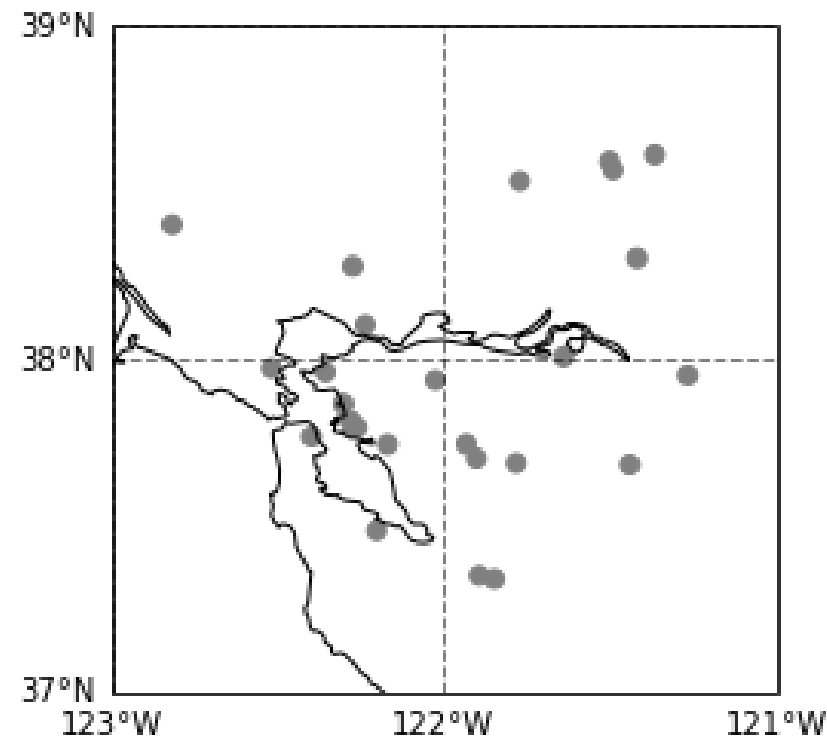
Surface NO₂

Lognormal distribution

Cross-validation test

25 ground monitors

Ground Sites



Case Study Details

San Francisco

September 2019

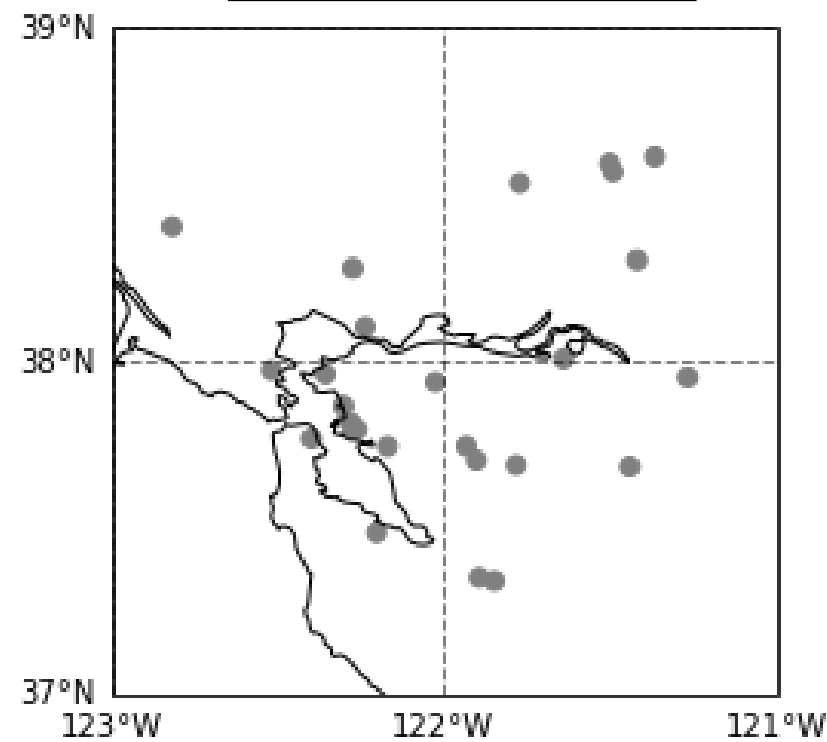
Surface NO₂

Lognormal distribution

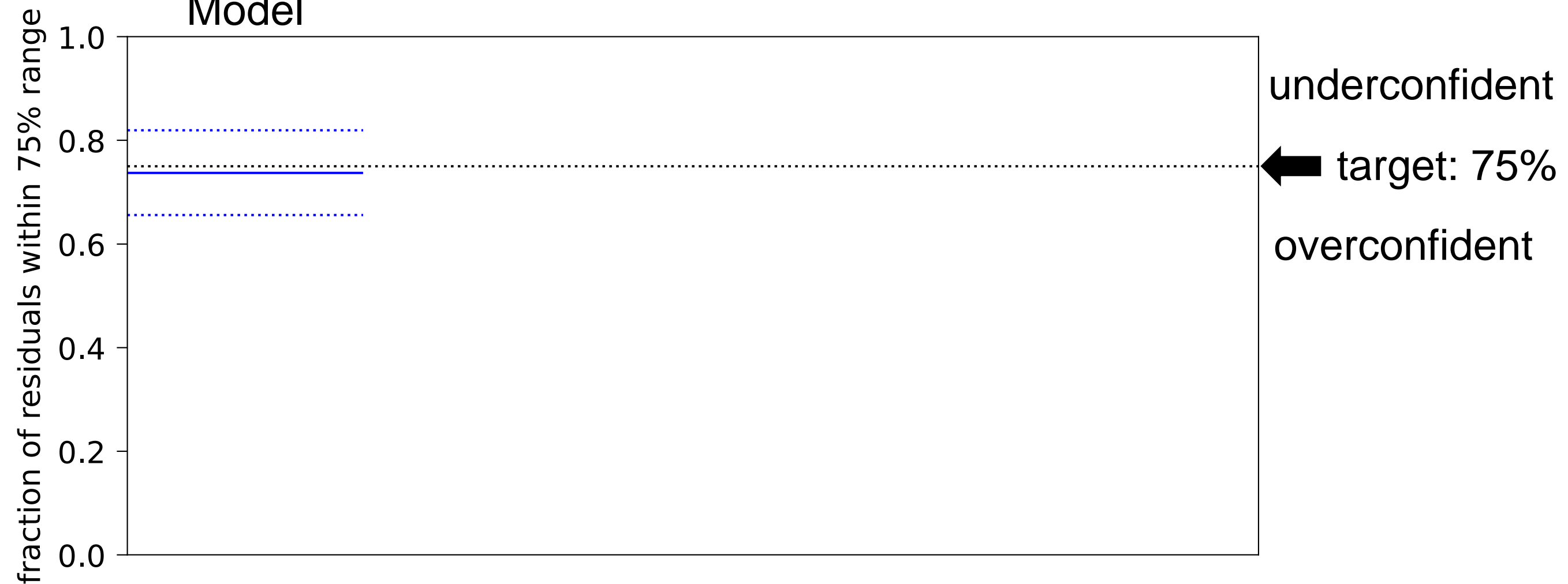
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Phase 1 Model



Case Study Details

San Francisco

September 2019

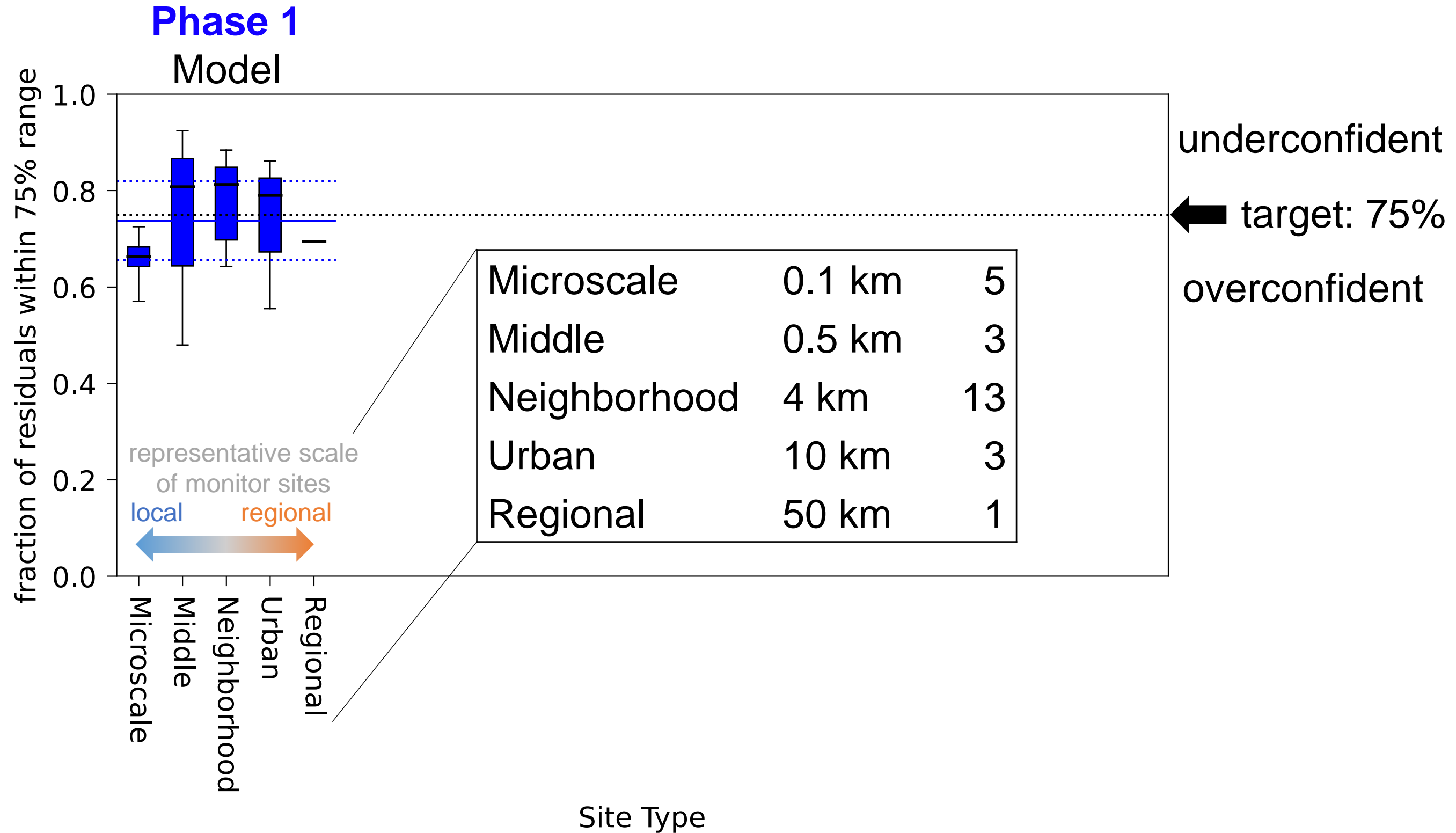
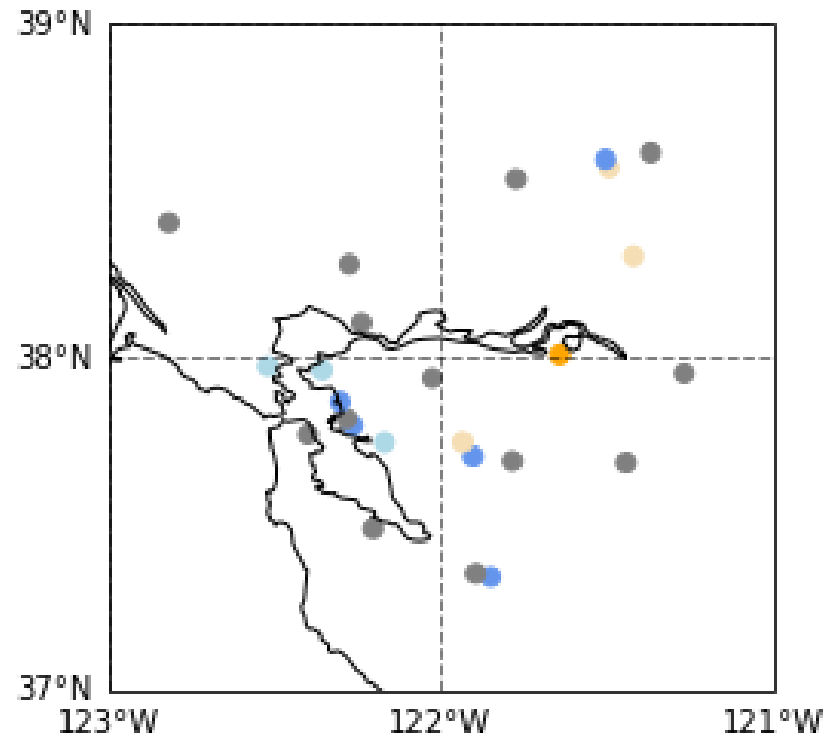
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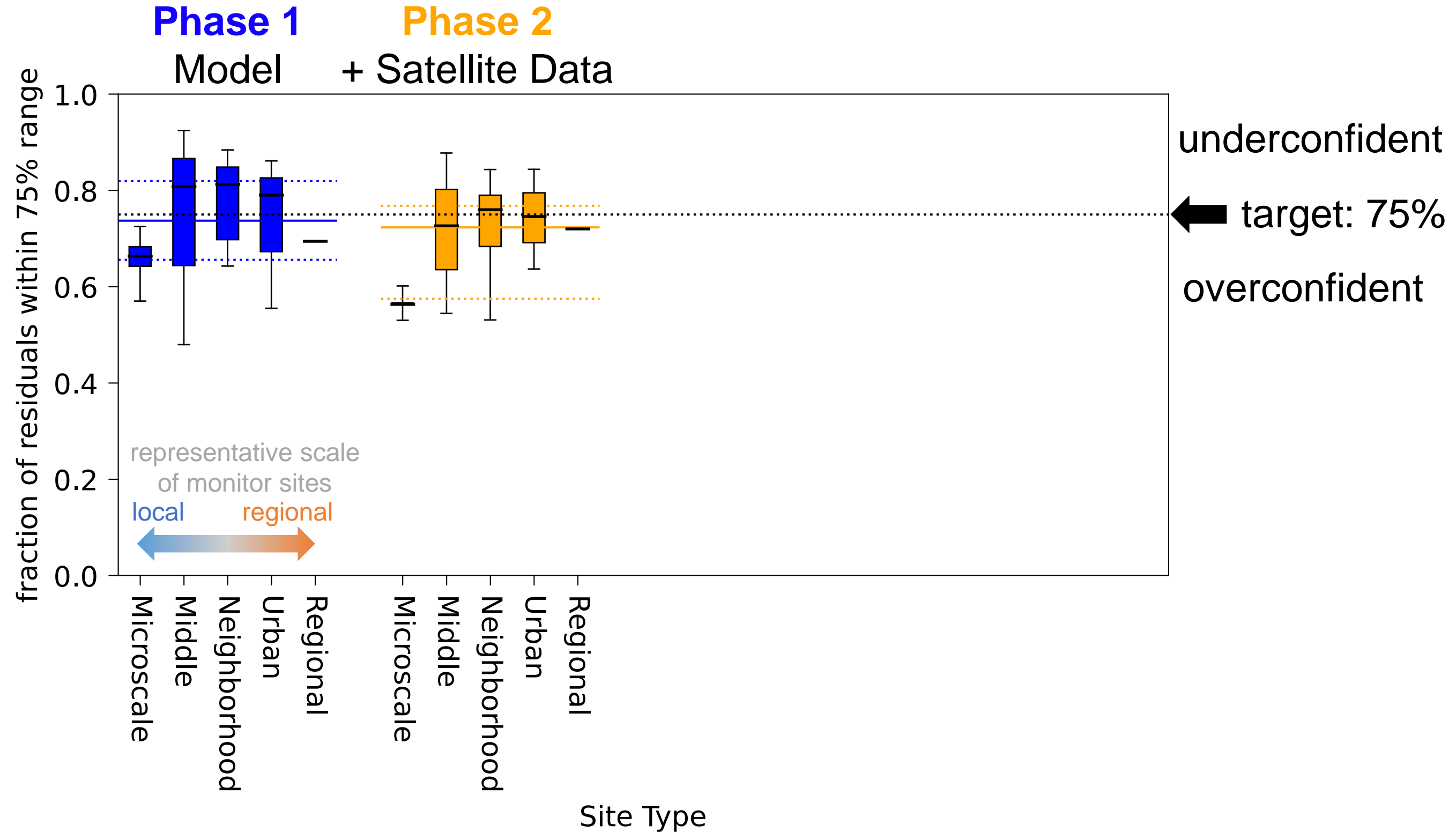
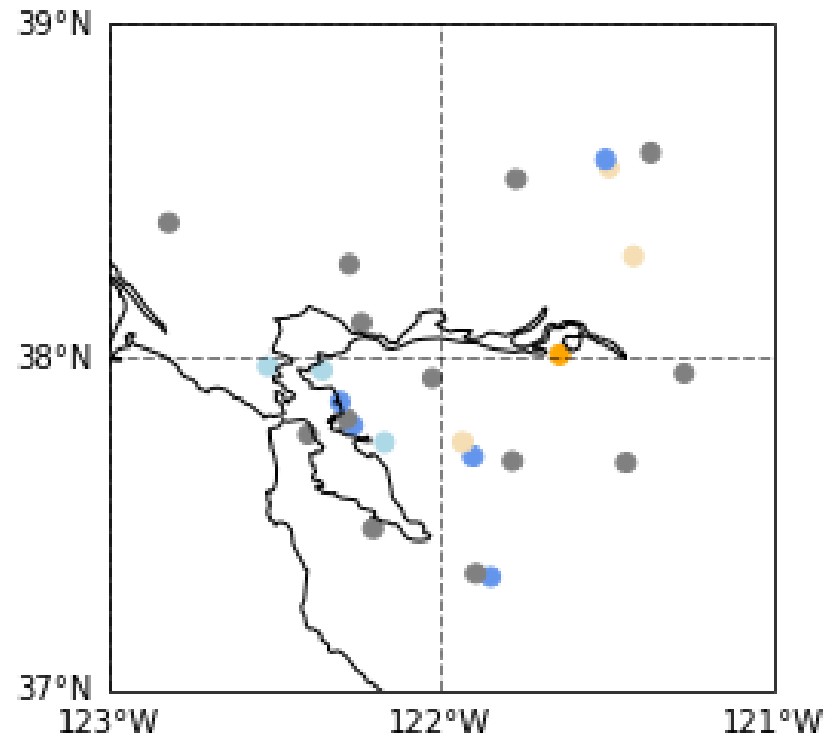
Ground Sites



Case Study Details

San Francisco
 September 2019
 Surface NO₂
 Lognormal distribution
 Cross-validation test
 25 ground monitors

Ground Sites



Case Study Details

San Francisco

September 2019

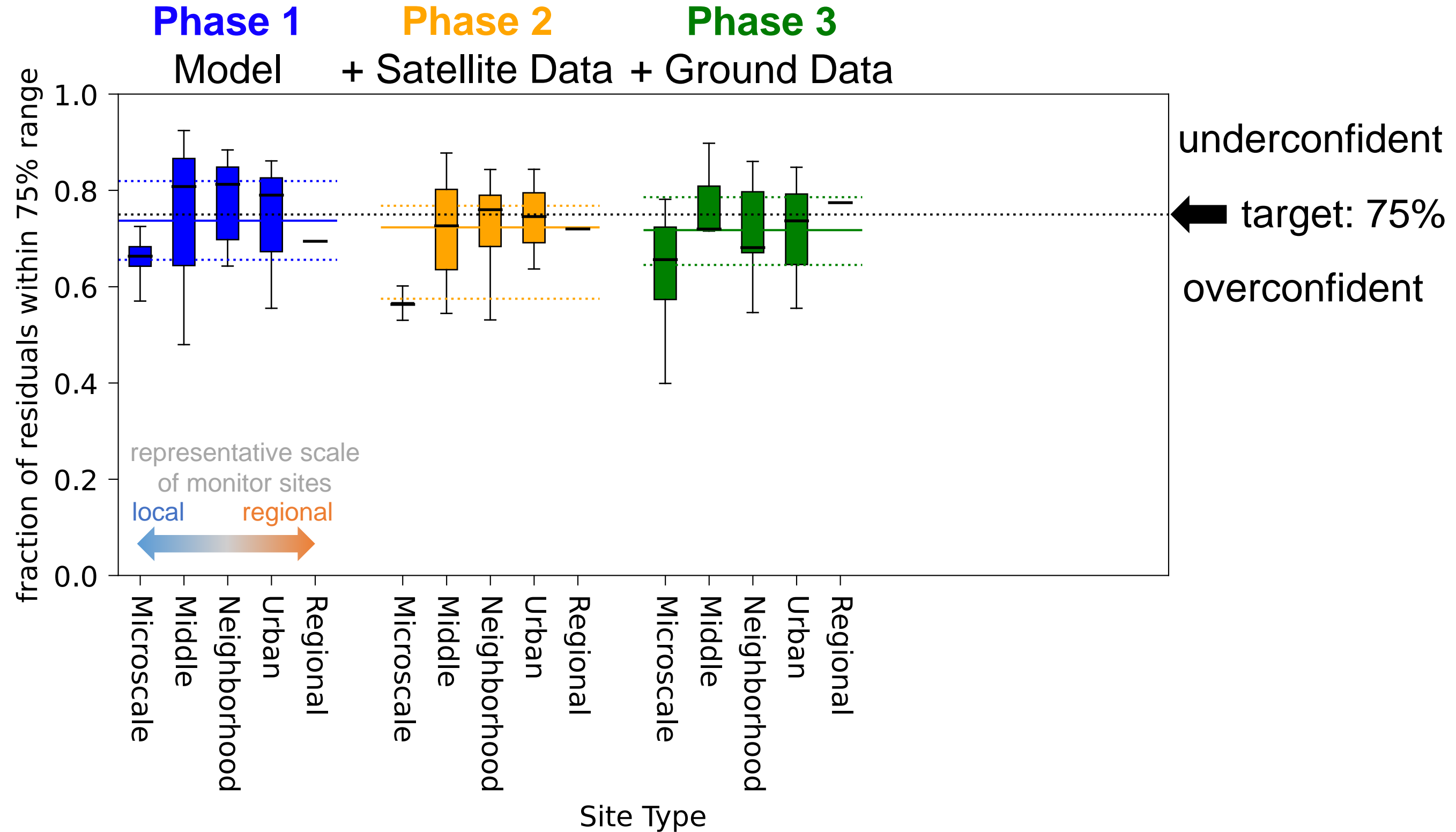
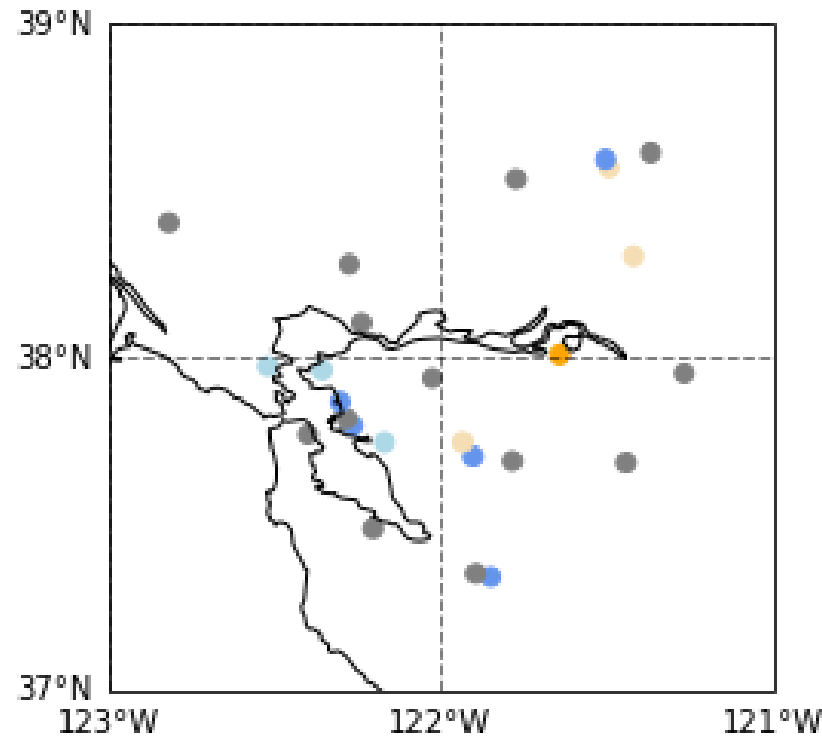
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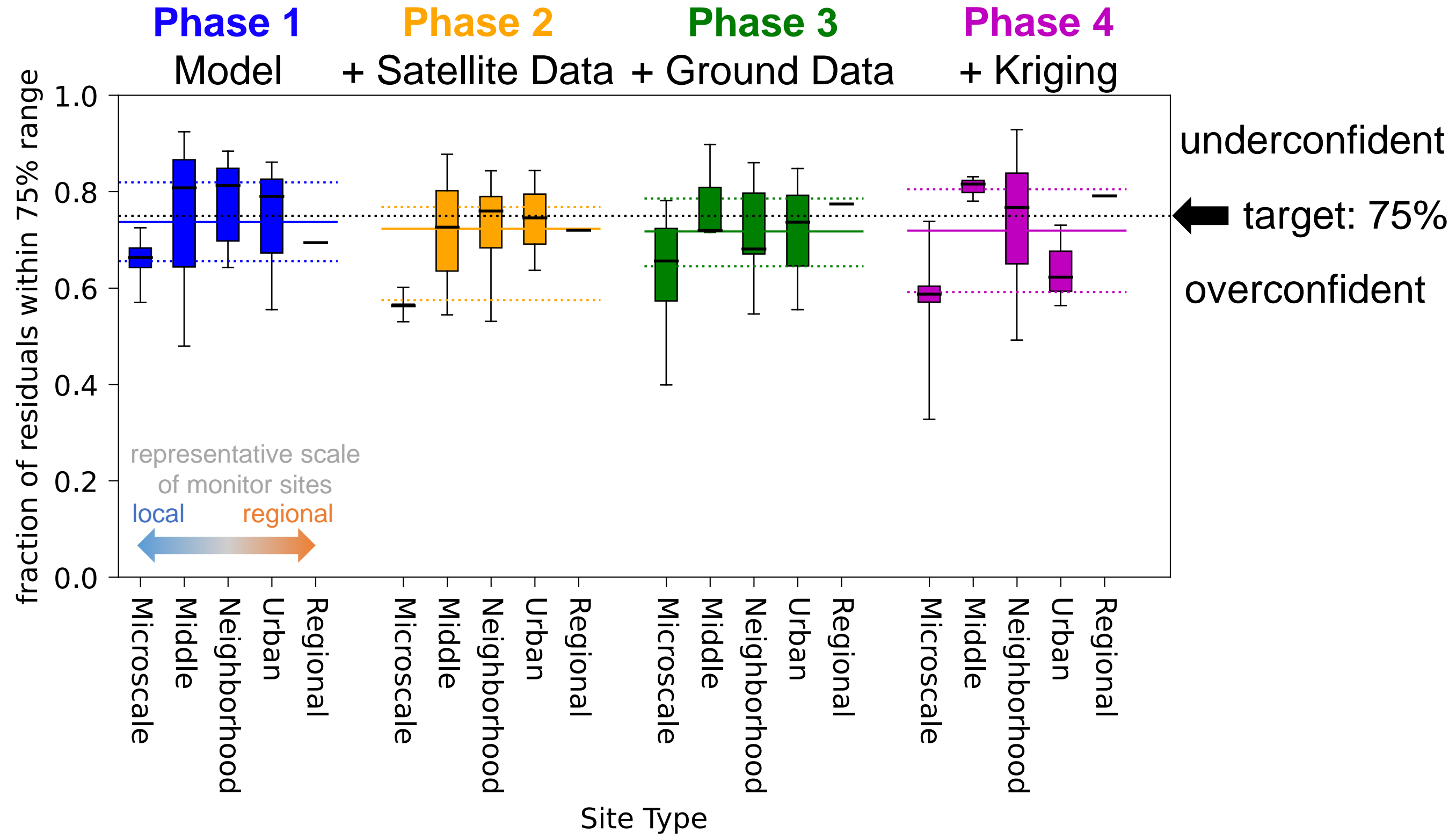
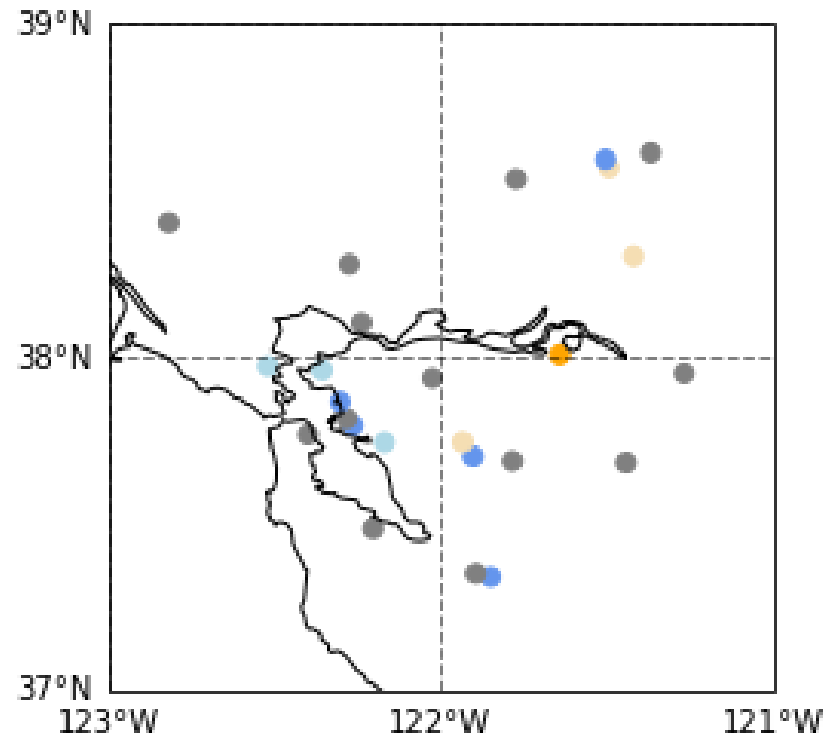
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Ground Sites



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.

