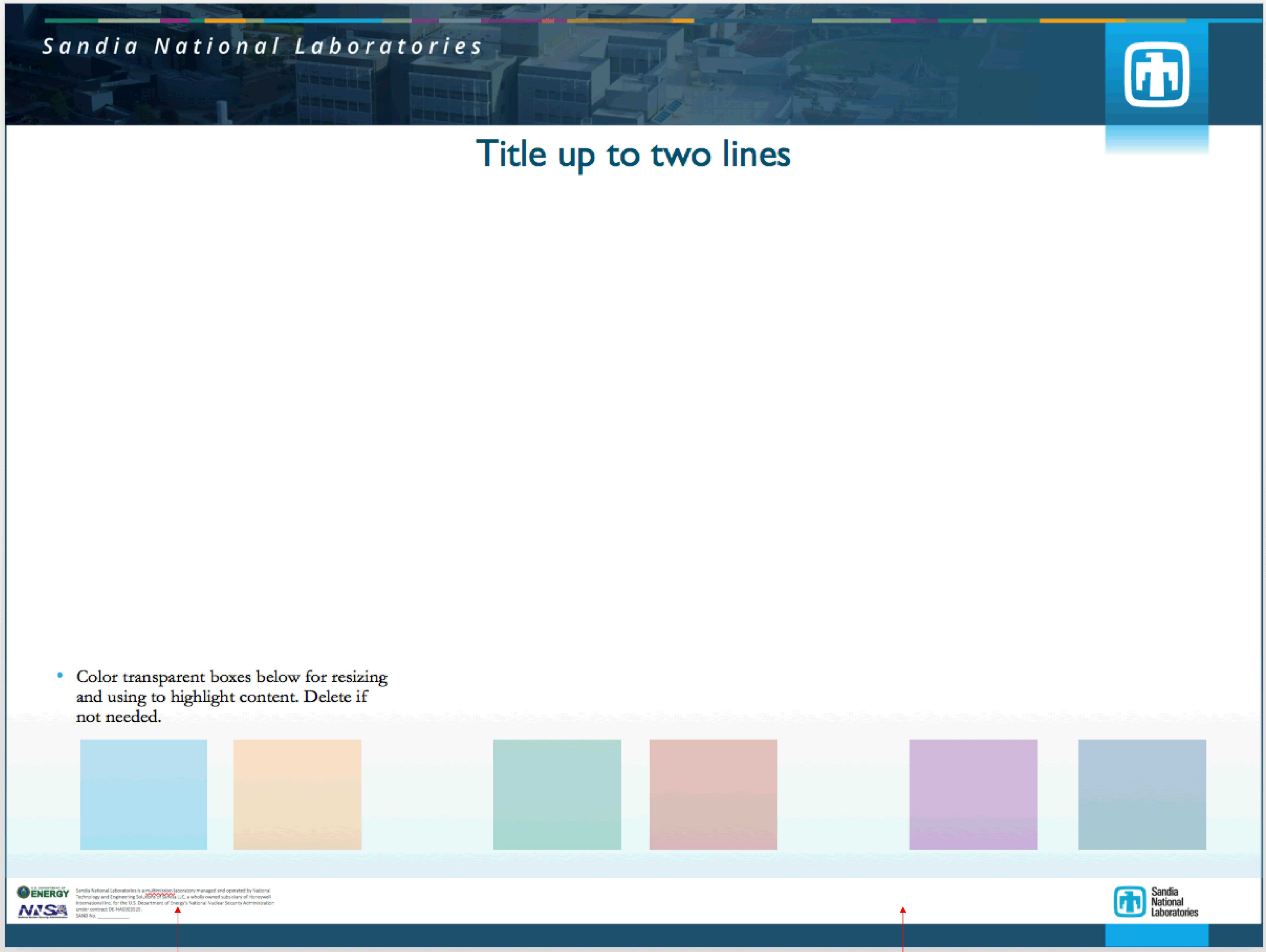
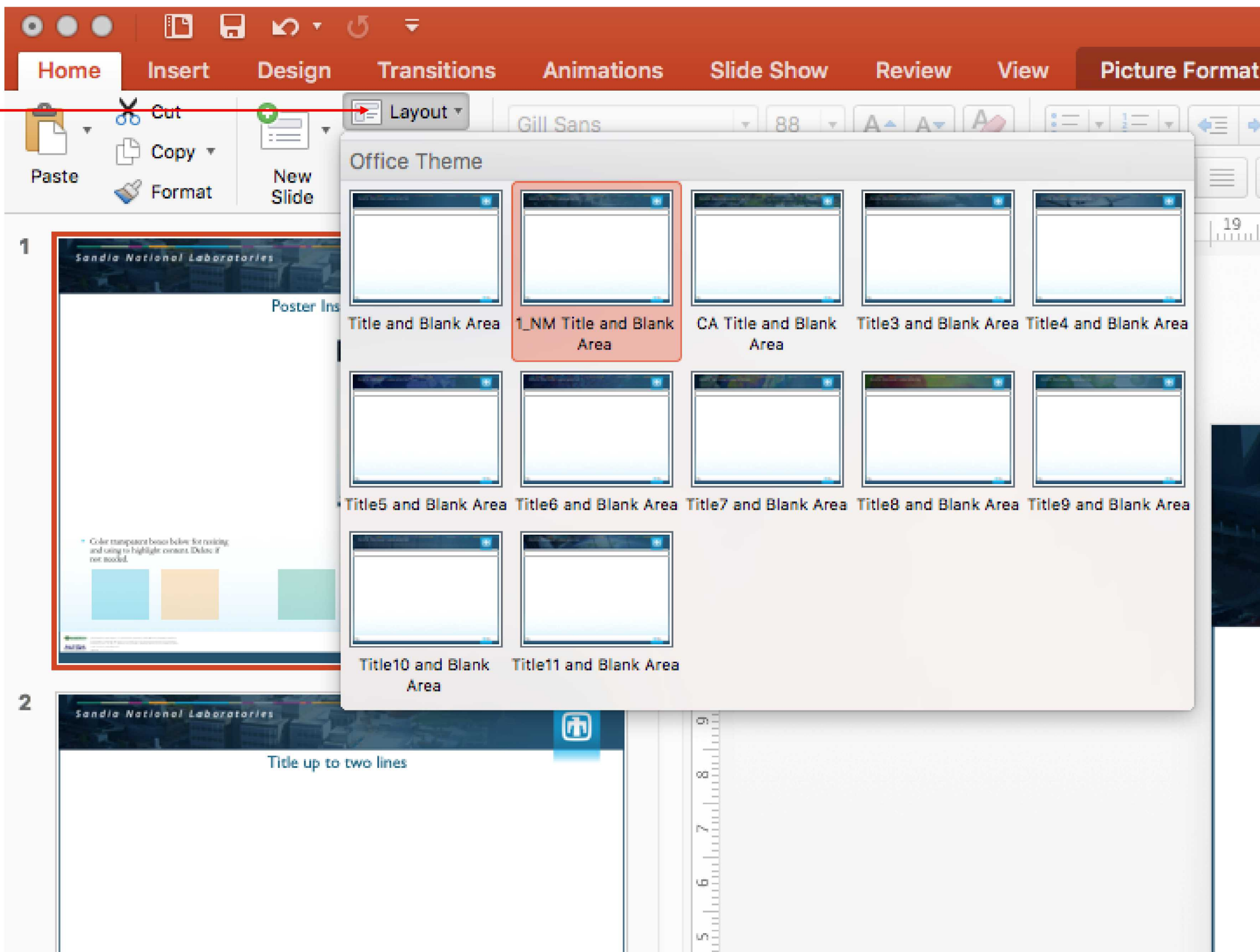




Title font: Gill Sans MT

# Poster Instructions

Choose from different headers by selecting the “Layout” option in the “Home” tab

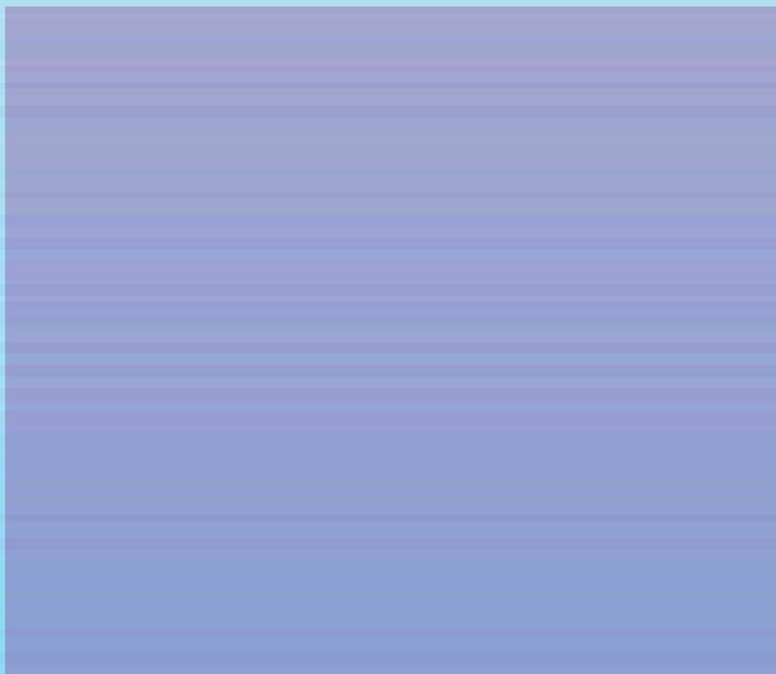
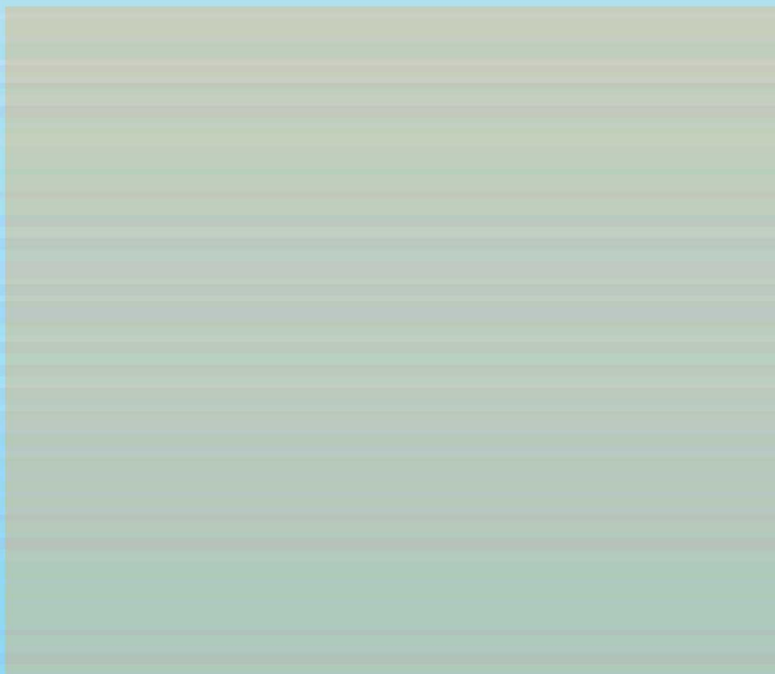


Body text/ support font: Garamond MT

Add Sand Number to the funding statement within the Master Title slide

Additional program/partner logos can be added here

- Color transparent boxes below are for resizing and using to highlight content. Delete if not needed.







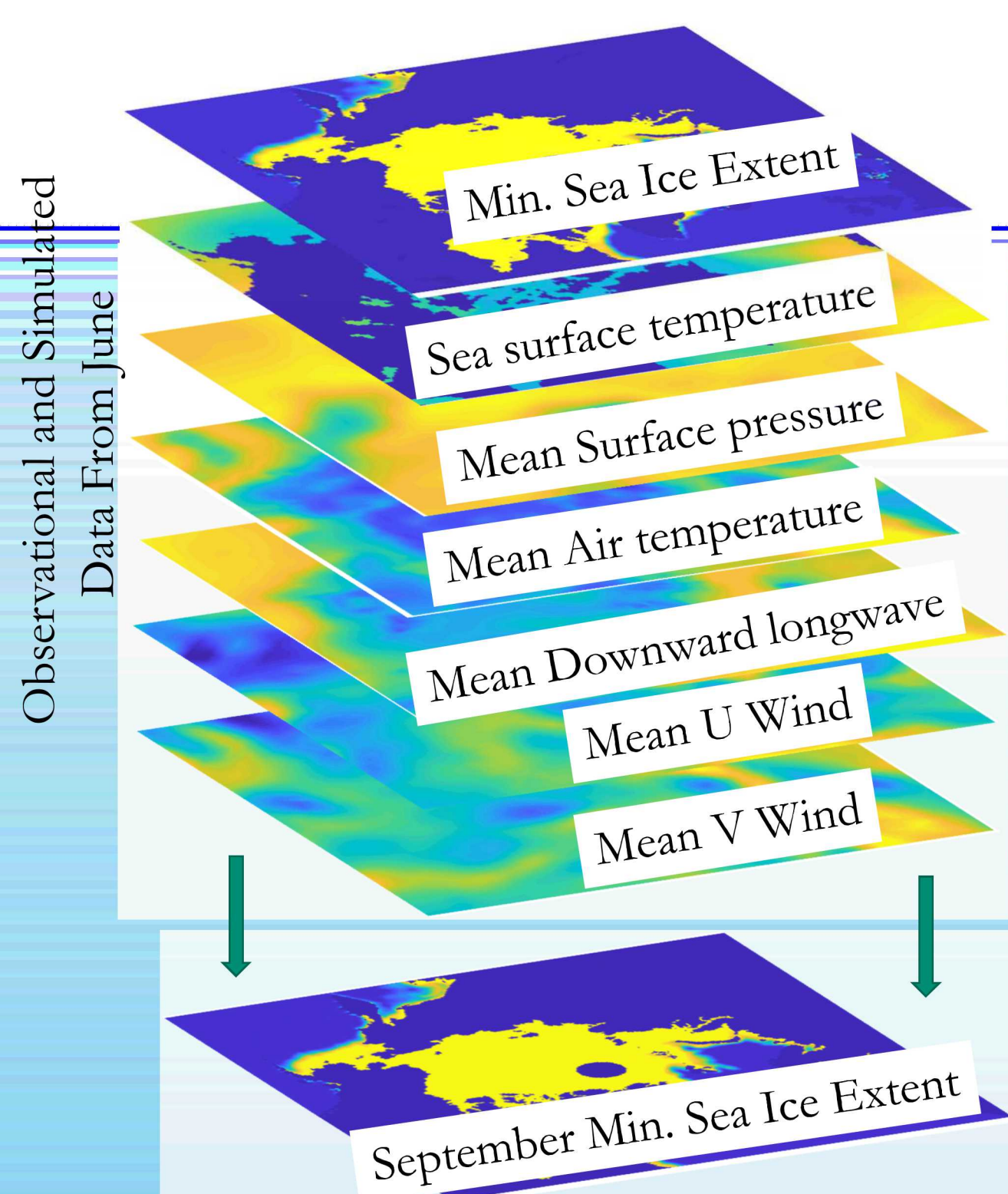
# FEATURE COMPARISON OF ARCTIC OBSERVATIONS AND CLIMATE MODELS

## Problem

- Since the advent of the satellite era we have observed declining sea ice in the Arctic across all seasons [3].
- Rosenblum and colleagues found that of 118 CMIP5 models, only 11 were within a standard deviation of observed sea ice extent trends. This amounts to an underestimate of at least 150,000 km<sup>2</sup> per decade [2].
- Data driven methods may be able to highlight areas where traditional models are biased.

## Data

- The years 1979 to 2014 are considered because these are the years observational satellite data and model data overlap.
- Data is preprocessed by taking minimums and means for each feature, over all grid cells in the Arctic for a given month.
- 5 ensembles of data from the DOE's Energy Exascale Earth Systems Model (E3SM) [1].
- Each ensemble is 35 years of results from separate E3SM runs of 165-year coupled global simulations.
- Because the physical equations of the ocean and atmosphere are chaotic, small differences in initial conditions have large impacts on long-term results. Though, average behavior between each ensemble should be consistent.



### Sea ice extent

Arctic 25 km resolution  
Daily, 1979-present

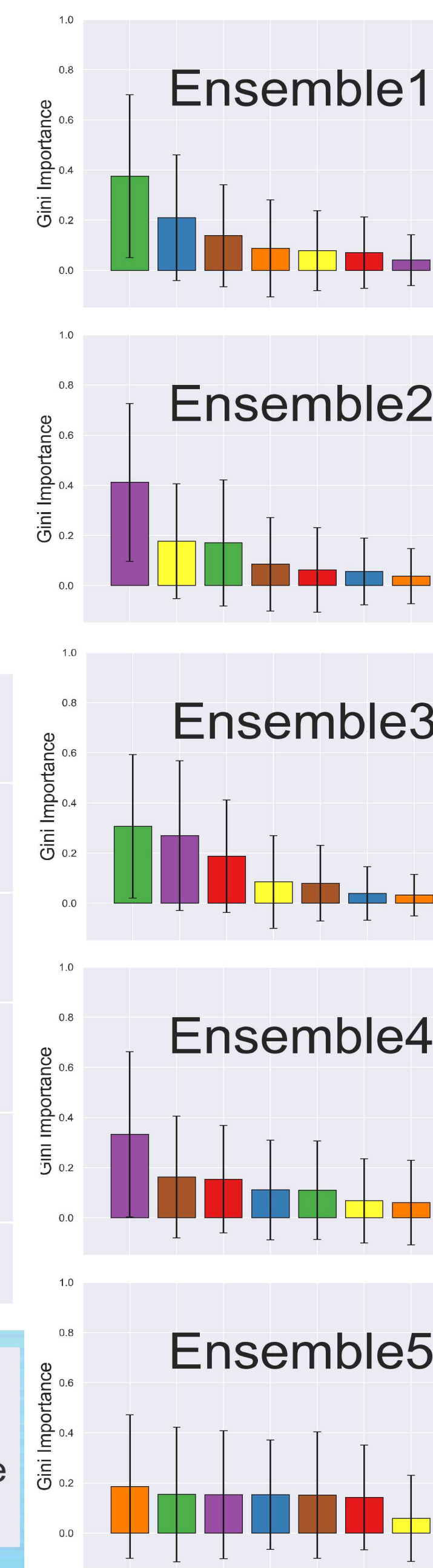
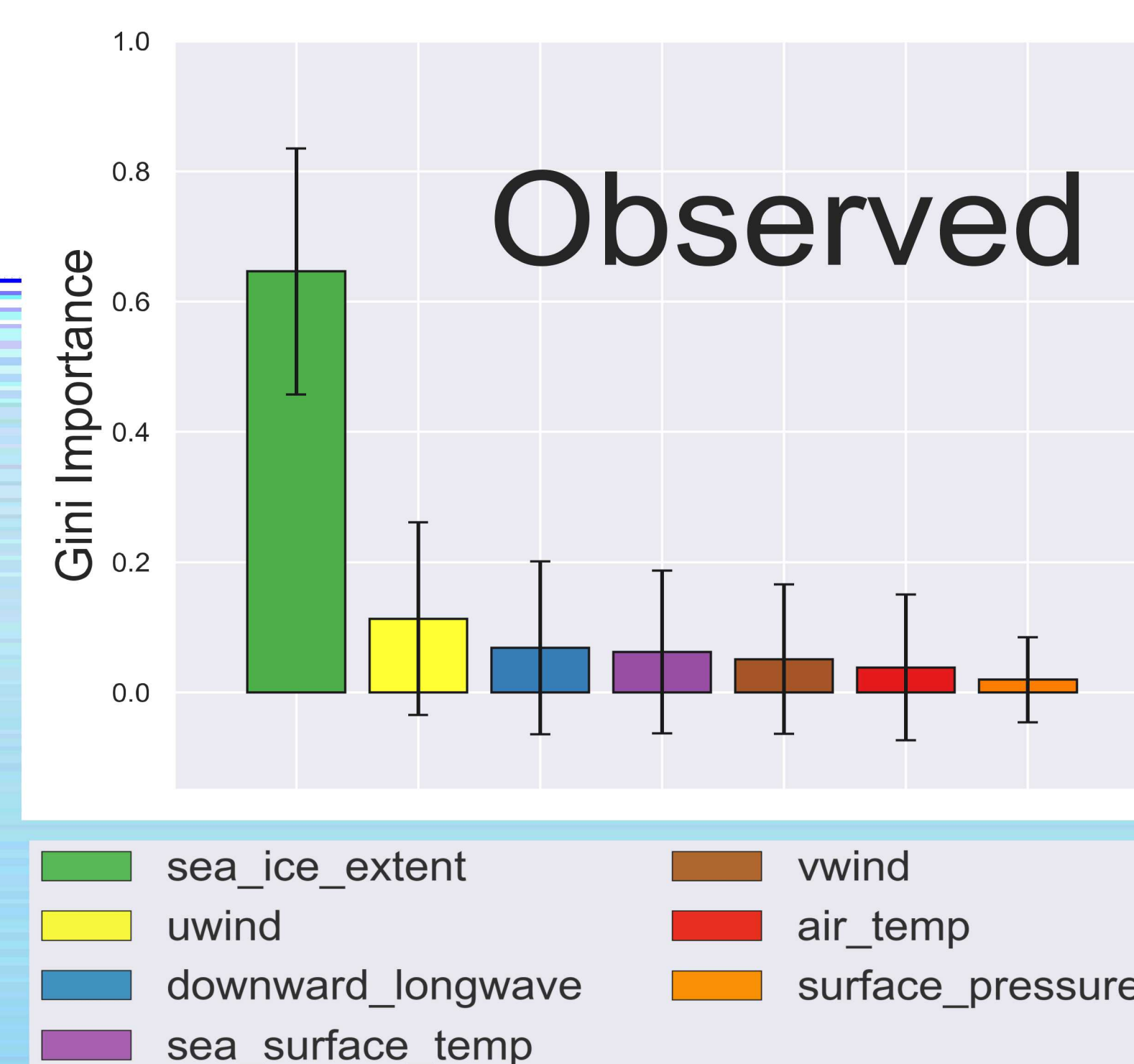
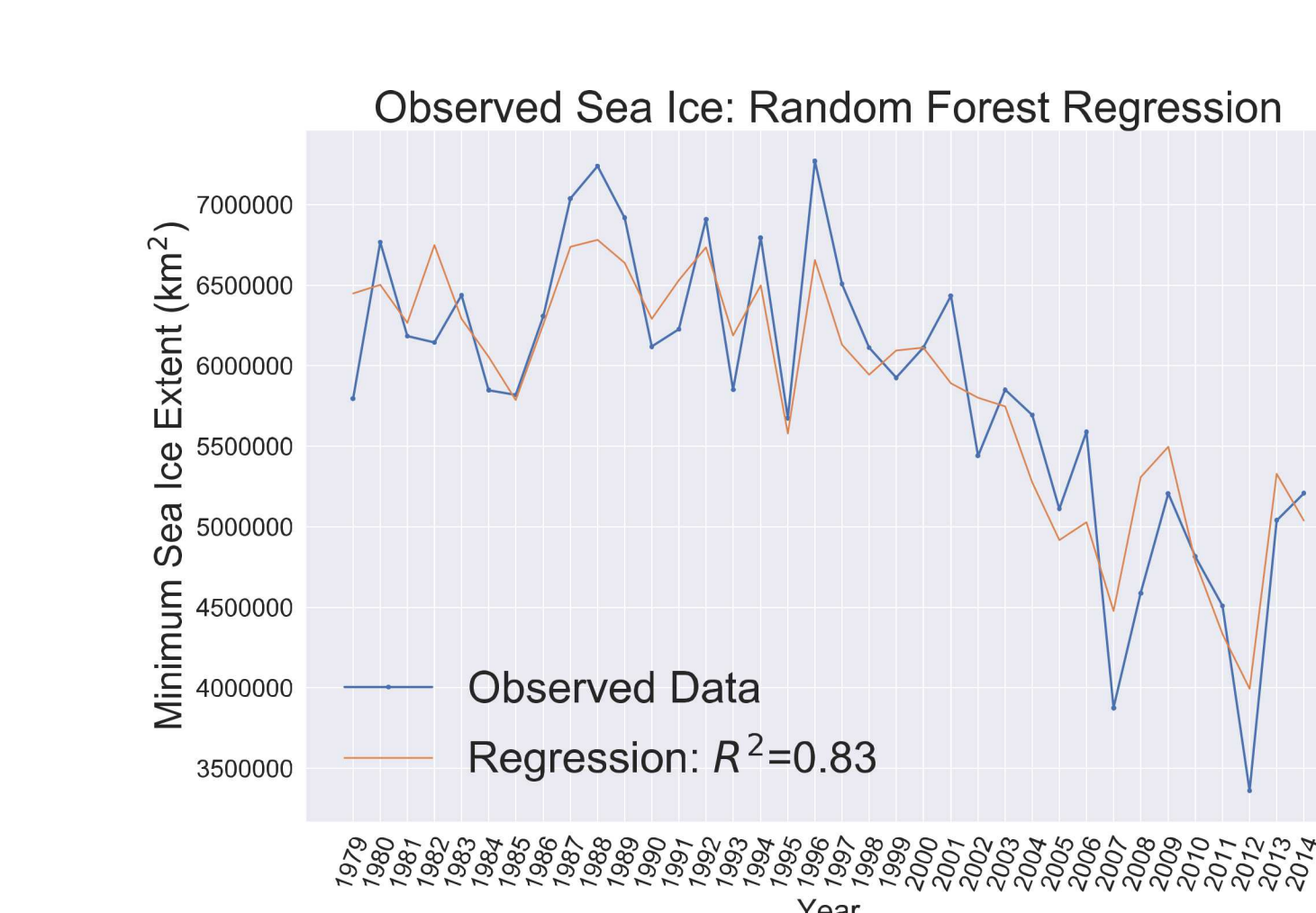
### Atmospheric reanalysis

Temperature, velocity, surface pressure, downward longwave  
Global 1 degree resolution  
Every 6 hours

### Ocean reanalysis

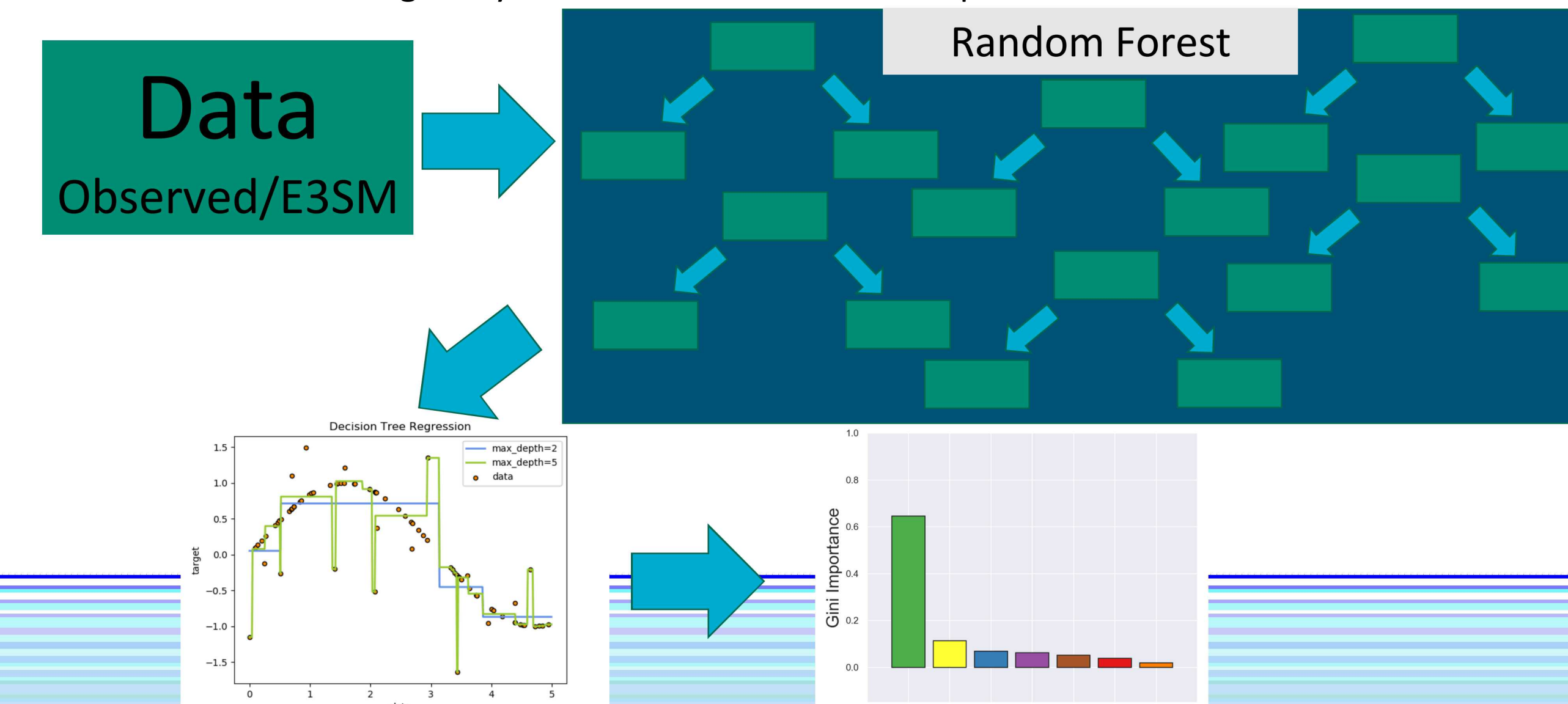
Sea surface temperature, monthly

- The random forest regression fit all datasets well, with  $R^2 > 0.8$  in all cases.
- Observational data output that sea ice extent is the most importance feature. Though the error bars for all importances are wide, observational sea ice extent's error does not overlap with any other features.
- Ensemble feature importances are surprisingly inconsistent.
- Only ensembles 1 and 3 rank sea ice extent as the most important but ranked the other features differently.
- Ensemble 5 is the most different. The error indicates that almost all features are as predictive as any others.



## Approach

- Coupled climate models are parameterized and given initial conditions when they start. These may lead to some data and physical processes being weighed too heavily, and others too lightly.
- To improve climate models and our understanding of the Earth's Arctic climate system, we want to characterize and explain the disagreement between model data and observed data. To do this we can train machine learning (ML) models on observed data and data output from simulation models.
- Random forests fit multiple decision trees to subsets of data and uses averaging to improve the model's predictability and accuracy. A random forest can minimize over-fitting by limiting the trees' depth.
- Decision trees output Gini importance for each feature as it is built. These can be averaged in the whole forest to find a good estimate of feature importance.
- Comparing feature importances between models trained on observed data and models trained on the E3SM ensembles, we can start getting an idea of what factors may be differentiating the datasets. We make comparisons between ML models trained on both data sources using analysis of the models' feature importances.



## Discussion

- The climate modelers on our team found the E3SM feature importances surprising. They expected them to be at least similar between each other, even if they disagreed with the observational data's feature importances.
- If we find that different features are important to the different models, then we can improve climate models and make more accurate predictions, develop a better understanding of the Arctic climate system, and be better prepared for future outcomes.
- Our next steps are to apply this and similar methods to develop predictive data-driven models of Arctic sea ice extent. We hope this can further inform the tuning and development of the E3SM model.