Using mPING Data to Generate Random Forests for Precipitation Type Forecasts

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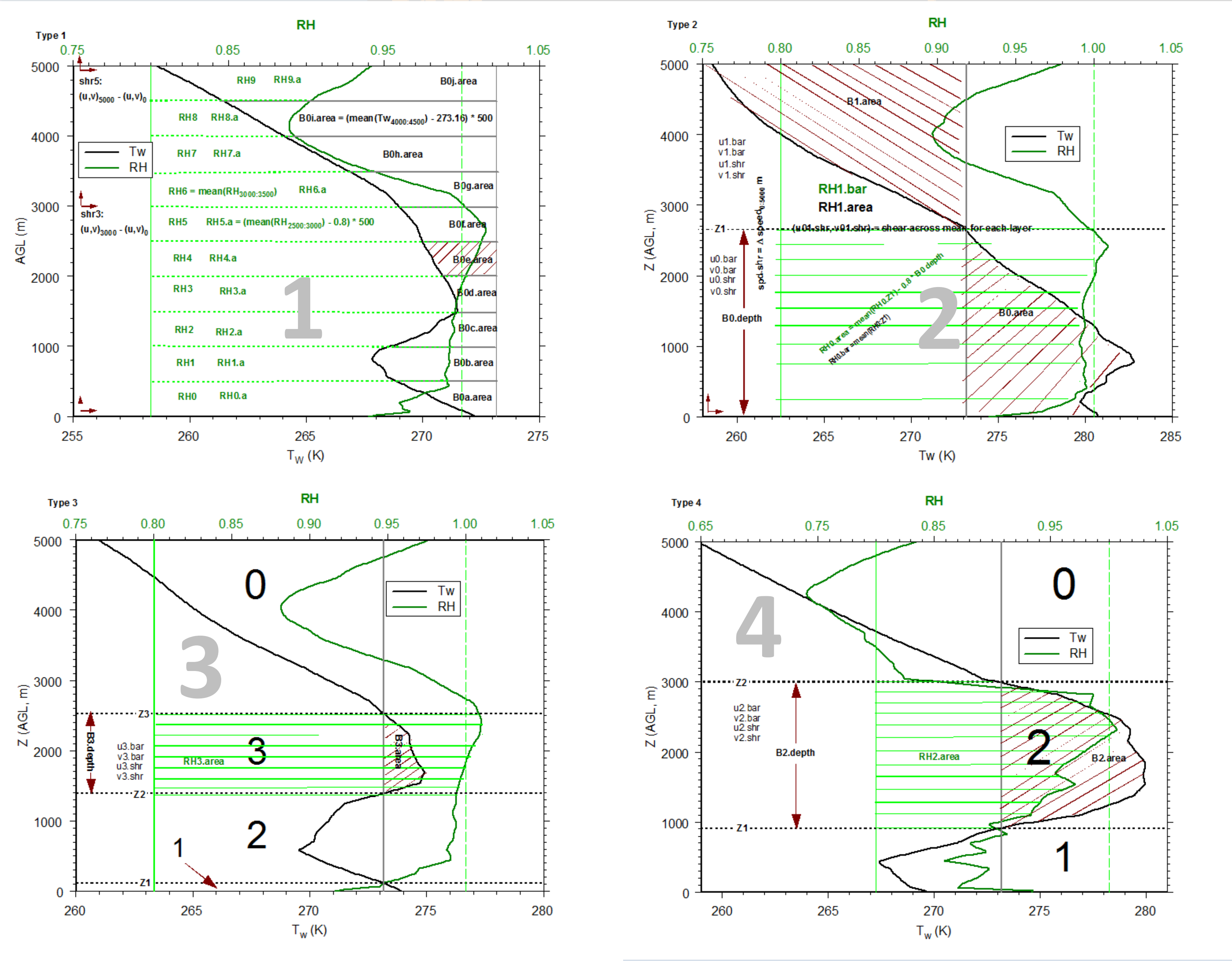
Can We Significantly Improve Forecast Ptypes Using AI Techniques?

- Generate a Random Forest classifier that uses forecast soundings at mPING observations for each model
- Use mPING obs at closest model grid point ± 30 min from the forecast valid time to evaluate Random forests generated from the RAP, NAM and GFS every 6 h out to 18 h lead time
  - use pressure-level data (native vertical coordinate data unavailable)

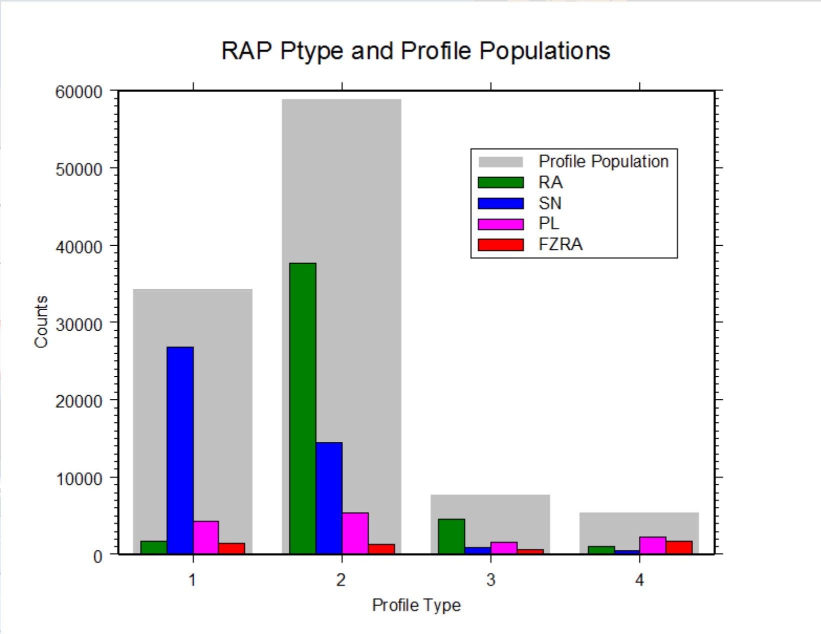
Training and Testing Data

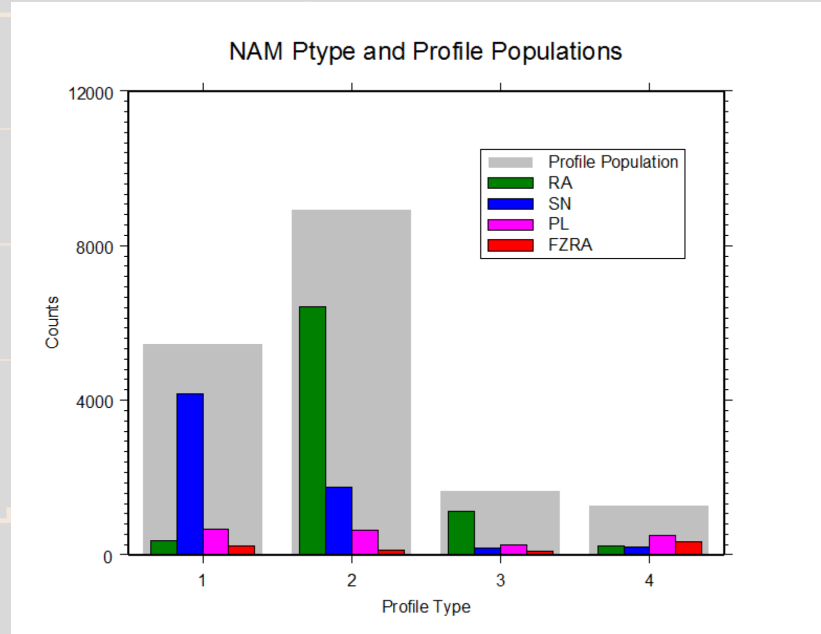
- Divide training and testing by hours with no hours common to either set
- Training data consist of 80% of the hours of available data, testing of the remaining 20%
- 6X more data from the RAP because it runs hourly to generate 6, 12 and 18 h forecasts while NAM and GFS run only every 6 h.
- Random forests “tuned” to yield Bias ~ 1 for all ptype categories

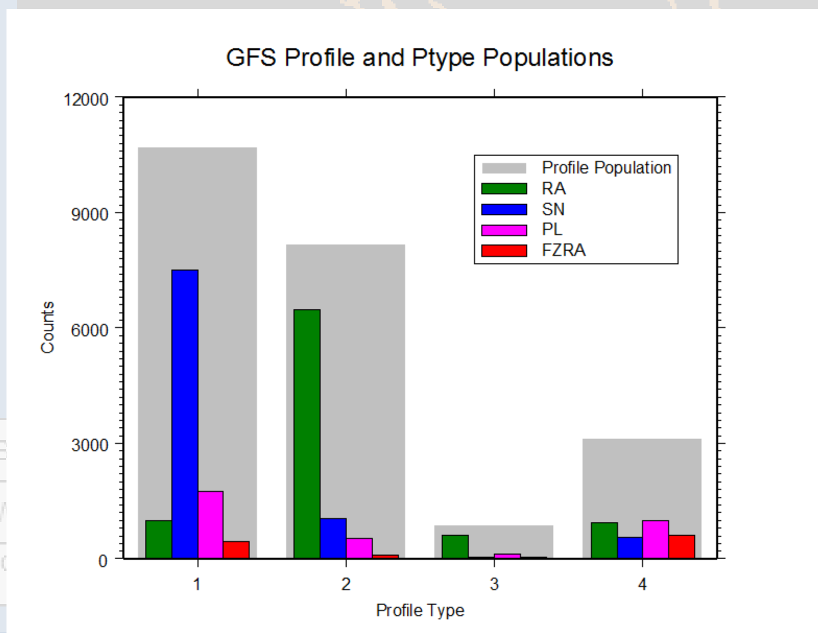
Random Forest Attributes



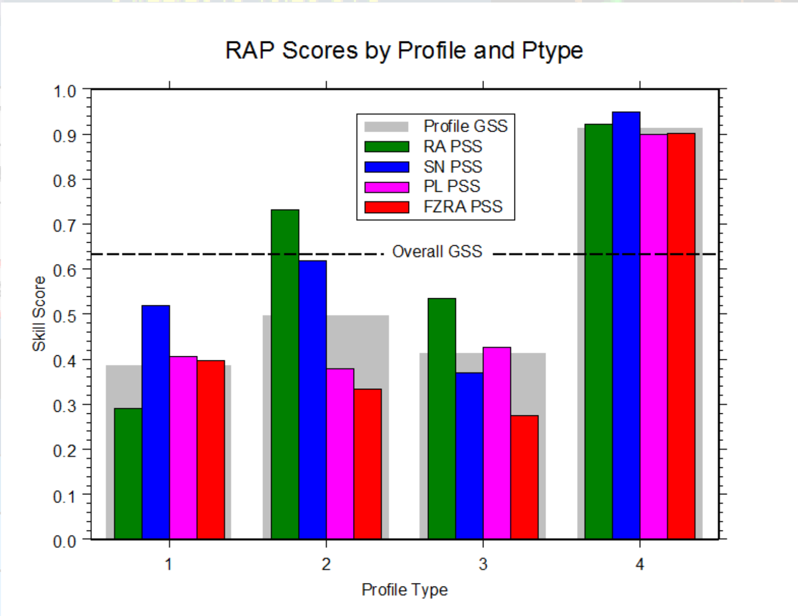
Data Set Size

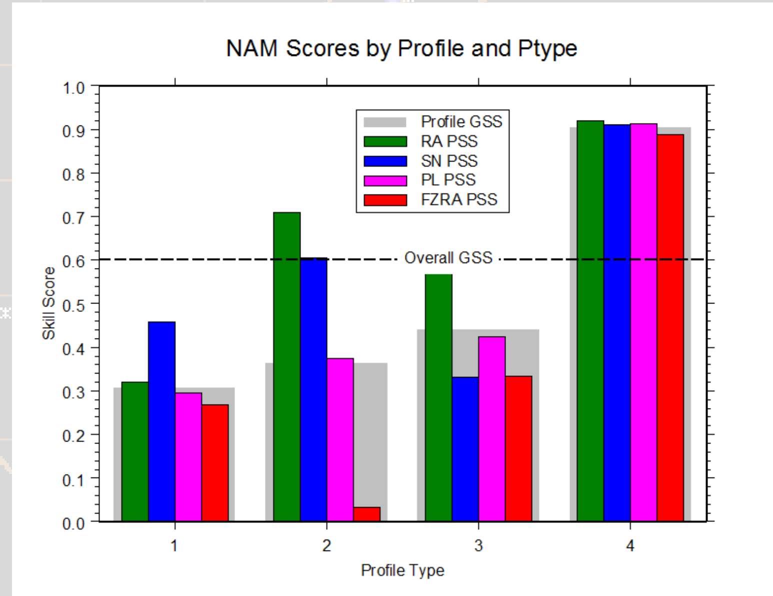


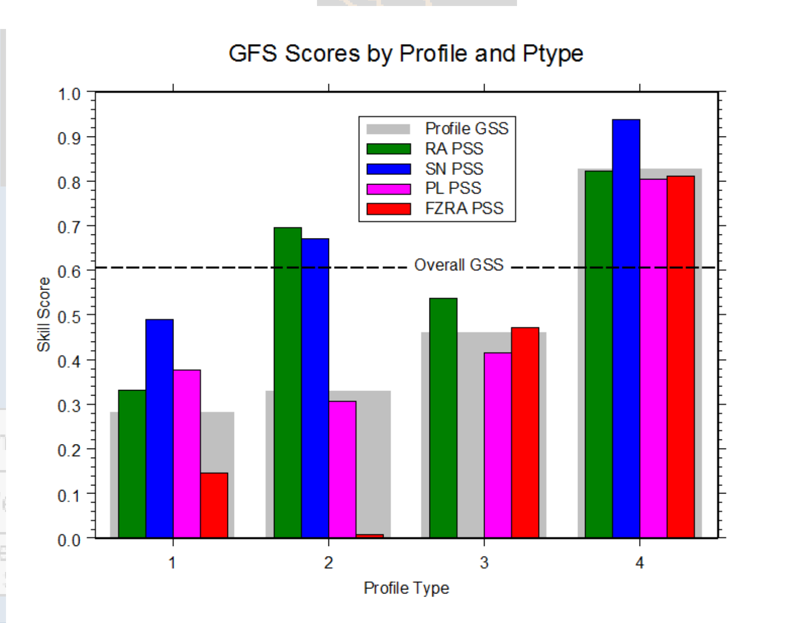




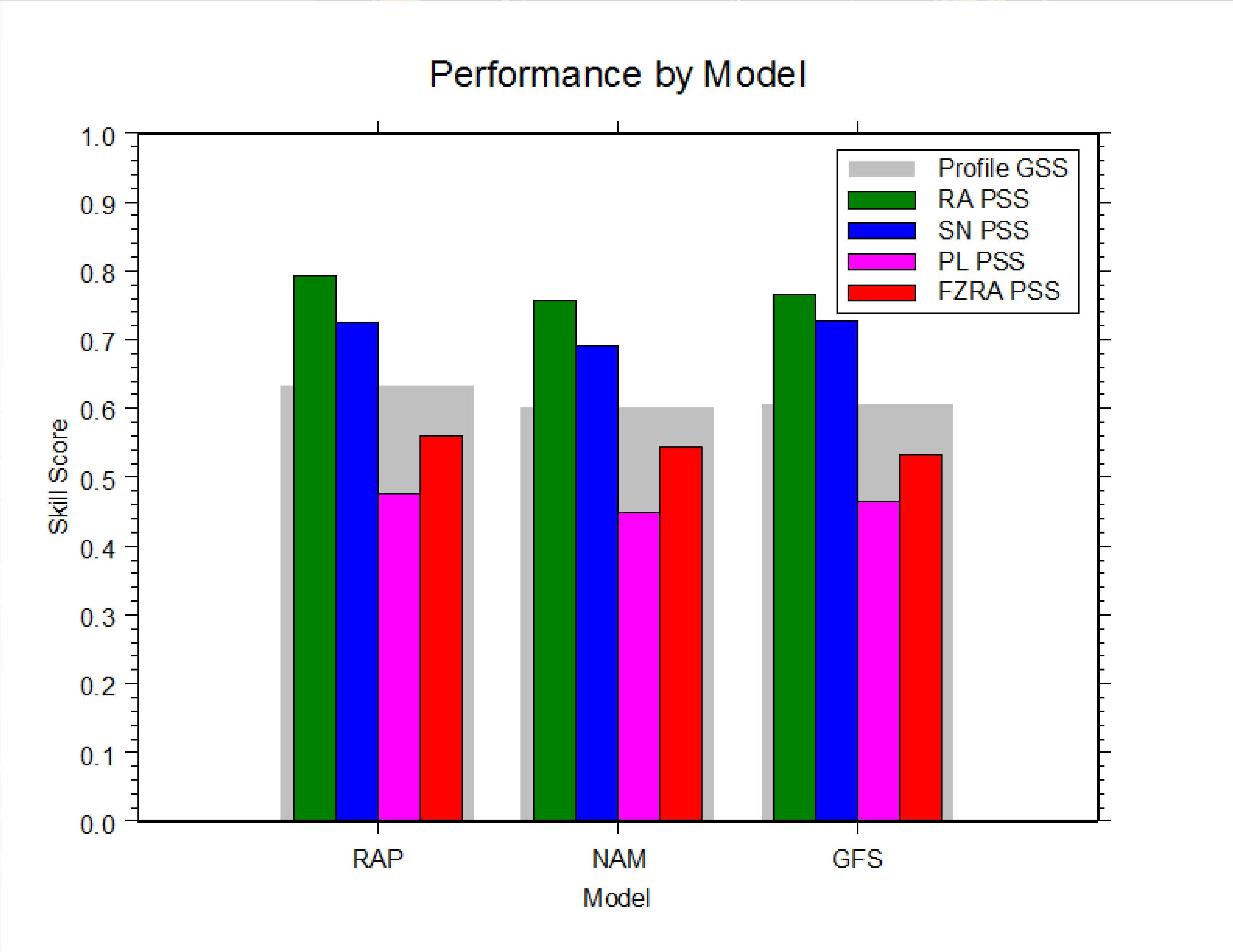
How Well do Random Forests Perform?



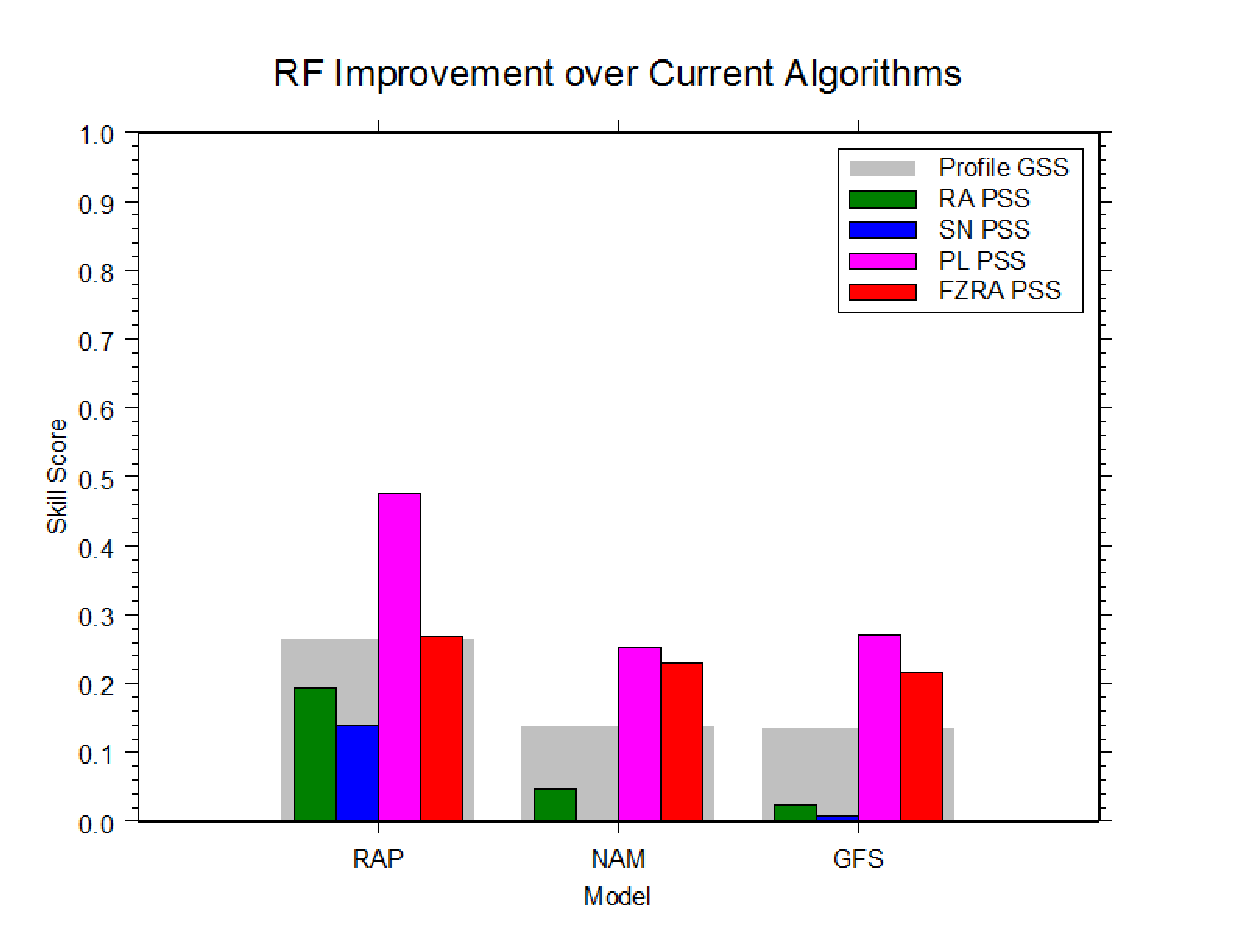




Aggregate Random Forest Performance



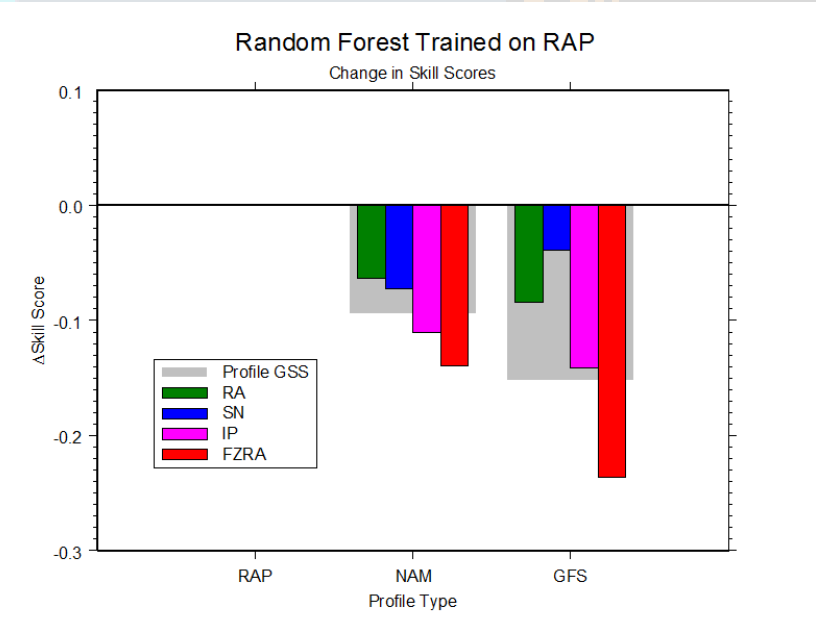
Random Forest Improvement

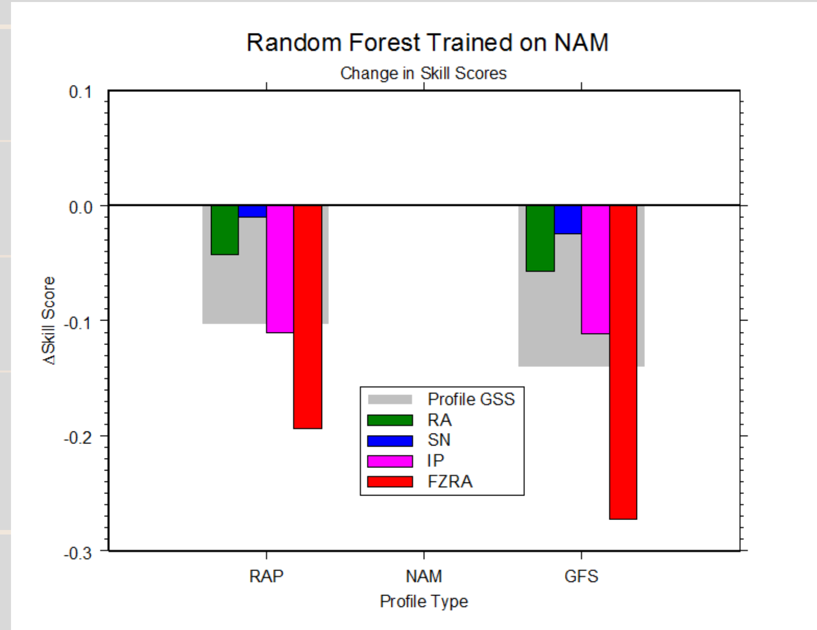


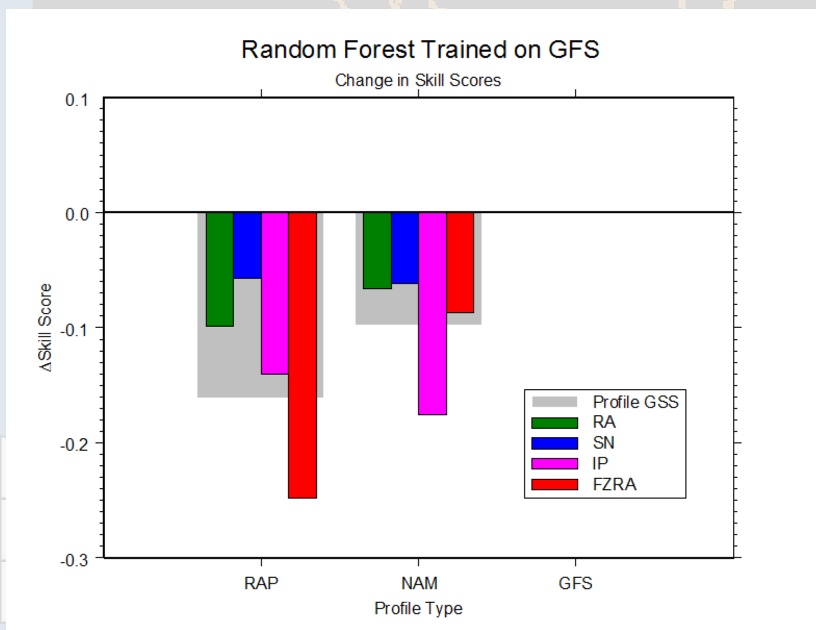
Not Much Difference Between Models!

- How can we tell if we actually have different random forests?
- Feed attributes from a model different from that used to train the forest
  - If there’s no difference between the forests, performance should be independent of the source model used to generate attributes because similar forests should result from similar attributes.
- Judge the difference by how the scores behave

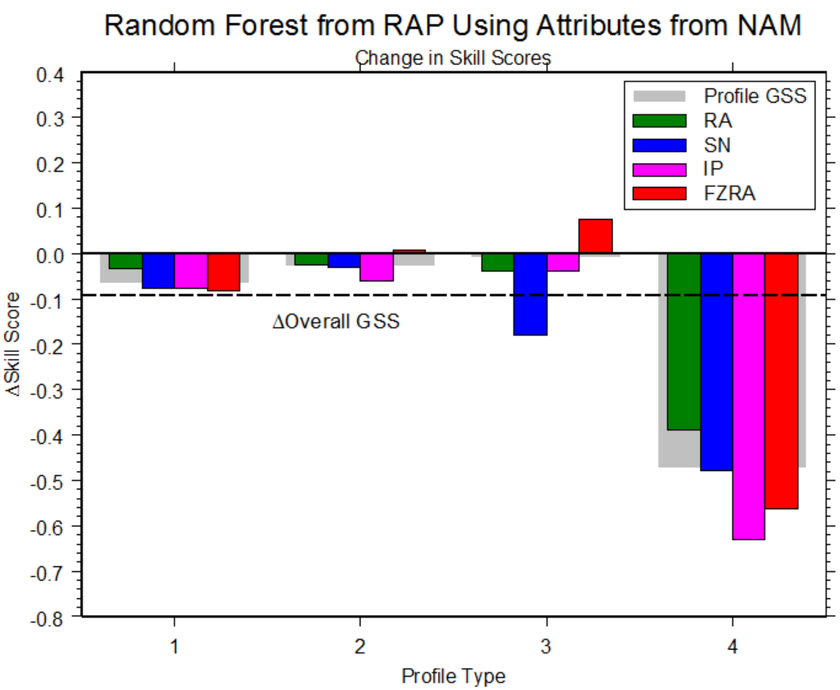
And Results show...

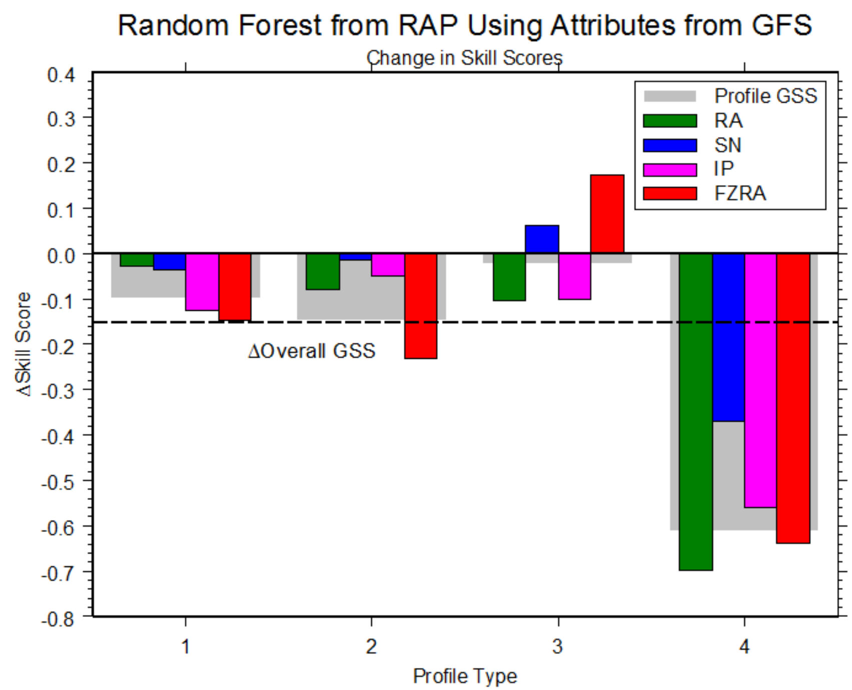






Details of Degradation





Conclusions

- **Random forests applied to forecast soundings are effective at generating skillful forecasts of surface ptype**
- **Random forests are able to extract essentially equivalent information from different forecast models**
  - **The random forest for each model, and each profile type is unique to the particular forecast model**
  - **Random forests developed using a particular model suffer significant degradation when given attributes derived from a different model**
  - **Implies that no single algorithm can perform well across all forecast models**
- **Random forests extract information unavailable to “physically based” methods because the physical information in the models does not appear as we expect**
- **Ptype results from the classic “warm nose” (Type 4) profile are most sensitive to the forecast model, but this profile is also the one for which random forests are most skillful**
- **What’s next? Ptype probabilities!**