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Promising subseasonal forecasting results based on machine learning

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Short summary

- LASSO regression and ensembling was used to forecast 2-weekly temperature and precipitation in Tropics and Northern Extratropics
- The method requires minimal amount of tuning and is effective in finding the most relevant predictors
- The achieved skill was high and comparable to the skill of the state-of-the-art dynamical model of ECMWF



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Background

- Recently, machine learning methodology has been proposed as an alternative paradigm for making S2S predictions (Cohen et al., 2019) in addition to the traditional dynamical methods
- Kämäräinen et al. (2019) used skillfully LASSO* regression, PCA*, predictor lagging, and bagging* of predictor data to forecast seasonal temperatures in Europe based on reanalyses

Glossary*

LASSO	least absolute shrinkage a	and selection operator
PCA	principal component analysis	
Bagging	bootstrap	aggregating

≈ random

sampling

References

Cohen, J. et al., 2019: S2S reboot: An argument for greater inclusion of machine learning in subseasonal to seasonal forecasts. Wiley Interdiscip. Rev. Clim. Chang., 10, 1–15, doi:10.1002/wcc.567.

Kämäräinen, M. et al., 2019: Statistical Learning Methods as a Basis for Skillful Seasonal Temperature Forecasts in Europe. J. Clim., 32, 5363-5379, doi:10.1175/JCLI-D-18-0765.1.









Method

- Here the earlier method was revised to forecast the subseasonal time scale over the land areas of Tropics and Northern Extratropics
 - Variables (SST, Z, ...) from the 20CRv2c and NCEPv1 reanalyses were decomposed into their leading principal components to be used as predictor variables

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(†)

- 2-week means of temperature (T2M) and precipitation rate (PRAT) were the target variables
- Each season, grid cell, and lead time was predicted using a separate LASSO ensemble with 50 members
 - Predictor selection and weighting in each ensemble member is automated and based on the internal cross-validation of LASSO
- The output was bias-corrected with ERA-5 reanalysis



Validation metrics



- Persistence, climatology, and reforecasts from the ECMWF dynamical model were used as reference forecasts
- ERA-5 was used as observations
- Anomaly correlation coefficient (ACC) and root mean squared error (RMS) were calculated from the LASSO model output, and from the reference forecasts
- ACC and RMS values were transformed to skill scores:

$$egin{aligned} ACCS &= rac{ACC_{fcs}+1}{ACC_{ref}+1} - 1 \ RMSS &= 1 - rac{RMS_{fcs}}{RMS_{ref}} \end{aligned}$$



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(†



Results: grid aggregations

ACC

- Out of all references, only climatology • is slightly better than the mean of LASSO ensemble after 2-4 weeks in the RMS sense
- Otherwise LASSO ensemble performs • better or similarly than the reference forecasts

0.6

0.5

0.4

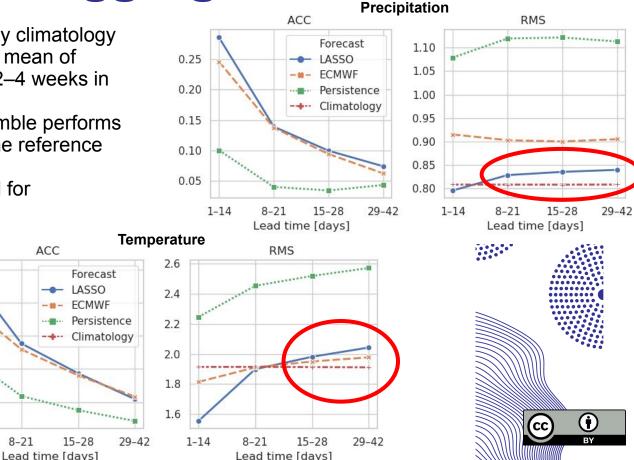
0.3

0.2

1 - 14

8-21

Note: ACC is not defined for climatology



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Results: T2M spatial



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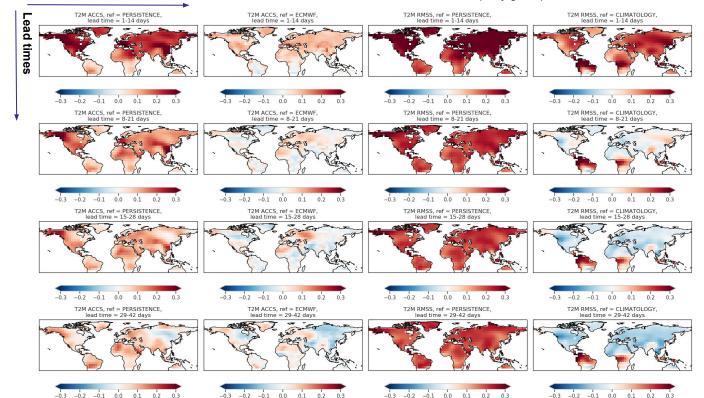
- Skill scores for temperature indicate that the LASSO ensemble works well in many regions of Tropics
- In Extratropics LASSO ensemble skill surpasses the ECMWF model skill eg. in Europe





References/scores

Red shades = LASSO ensemble outperforms the reference **Blue shades** = Reference outperforms the LASSO ensemble **Near-white shades** = equally good performance

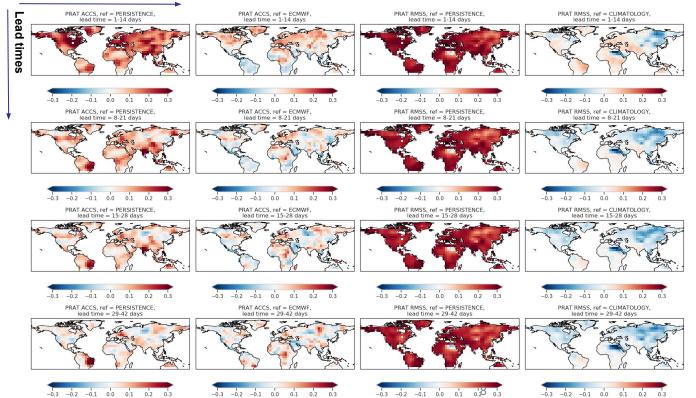


Results: PRAT spatial

References/scores



 Qualitatively similar results for precipitation **Red shades** = LASSO ensemble outperforms the reference **Blue shades** = Reference outperforms the LASSO ensemble **Near-white shades** = equally good performance





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Conclusion

- **KONE FOUNDATION**
- Machine learning should be used in subseasonal forecasting



