Exploring the landscape of brain-behavior predictions by leveraging dynamic connectivity information from resting-state fMRI

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Poster # 27

INTRODUCTION

- A primary goal of cognitive neuroscience is to develop a deeper understanding of how to link brain activity with behavior using predictive models.
- Researchers often rely on resting-state fMRI data, reported in the form of static functional connectivity (FC) matrices, where each entry in the matrix corresponds to the correlation between the activity over the complete duration of a scan for a pair of regions of interests (ROIs or nodes)[1].
- This approach has been crucial to many findings in the neuroimaging field[2], yet it ignores time-varying changes of connectivity that might help boost prediction accuracy.
- Here, we applied a novel network neuroscience technique[3] to explore how multiple alternative summary measures that capture aspects of this time-varying behavior perform at predicting subject's phenotypes.

METHODS

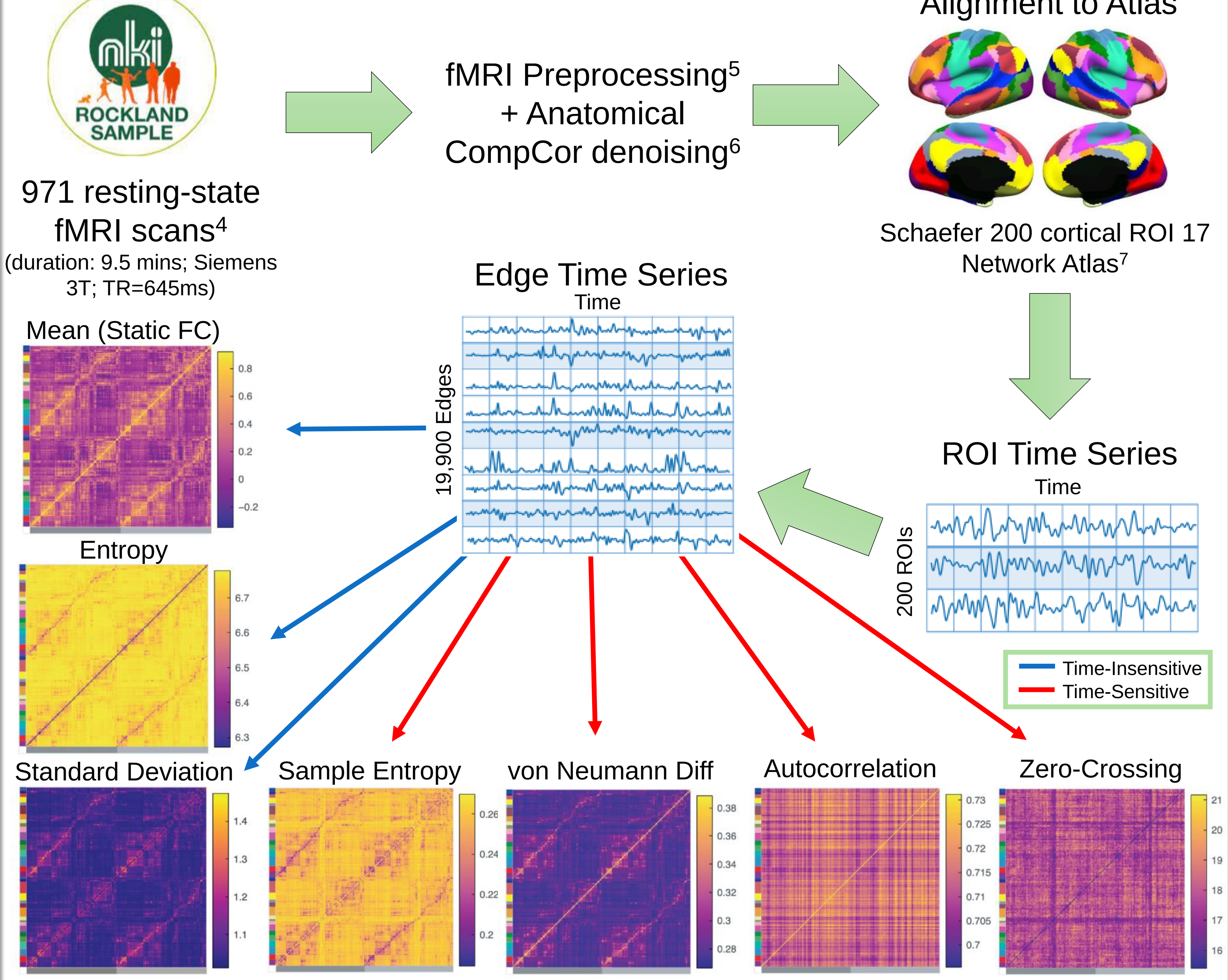

Figure 1. ROI x ROI matrices each containing a different summary metric of resting-state fMRI edge time series. Each plot shows the average across the dataset. Blue arrows indicate time-insensitive summary metrics, whereas red arrows indicate time-sensitive summary metrics

Calculated multiple summary measures of edge time series for all subjects

- Sample Entropy: conditional property that two windows of size 10 will remain similar to the next window, with a shift of 1 TR[8]
- von Neumann Difference: standard deviation of the successive differences[9]
- Autocorrelation: computed with a lag of 3 TRs (approx. 2s)[8]
- Zero-Crossing: zero-crossing of the autocorrelation function[8]

Feature matrices as input to a brain-behavior modeling framework known as Connectome-Based Predictive Modeling (CPM)[10,11] to predict subject phenotypes

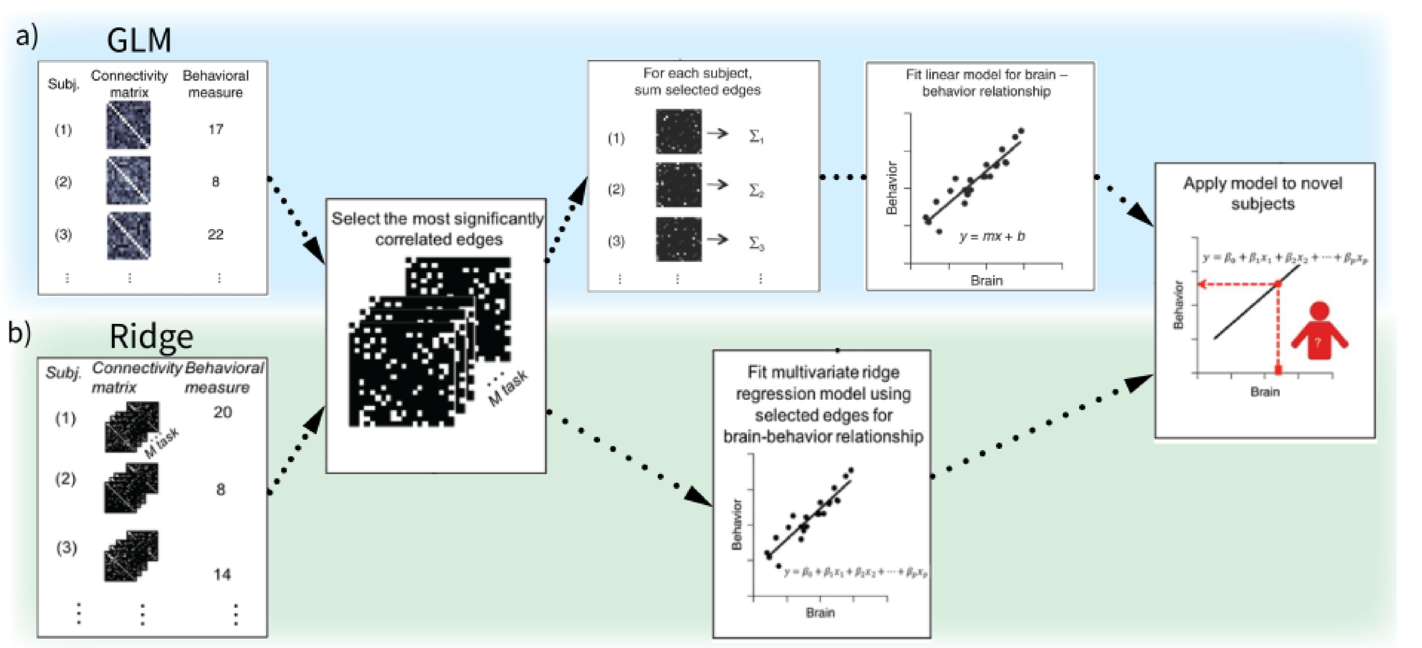

Figure 2. Description of Connectome-Based Predictive Modeling (figure adapted from Shen et al. 2017 & Gao et al. 2019) a) Description of CPM using a general linear model to compute behavioral predictions from one fMRI scan per subject. B) Description of CPM using a ridge regression to compute behavioral predictions using multiple representations of fMRI data per subject. Note that shared steps are indicated by being placed in between the blue (panel a) and green (panel b) shaded backgrounds

RESULTS

*** p < 0.001
** p < 0.01
* p < 0.01

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- We used CPM to build predictions of subject phenotypes and evaluated prediction accuracy by computing the correlation between observed and predicted scores.
- We were able to significantly predict intelligence scores (Figure 3) using all three **time-insensitive** metrics (all permutation-based p-values < 0.01).
- Mean of edge time series (equal to FC) consistently performs best.
  - We replicated this pattern of results when predicting measures of attention, as well.

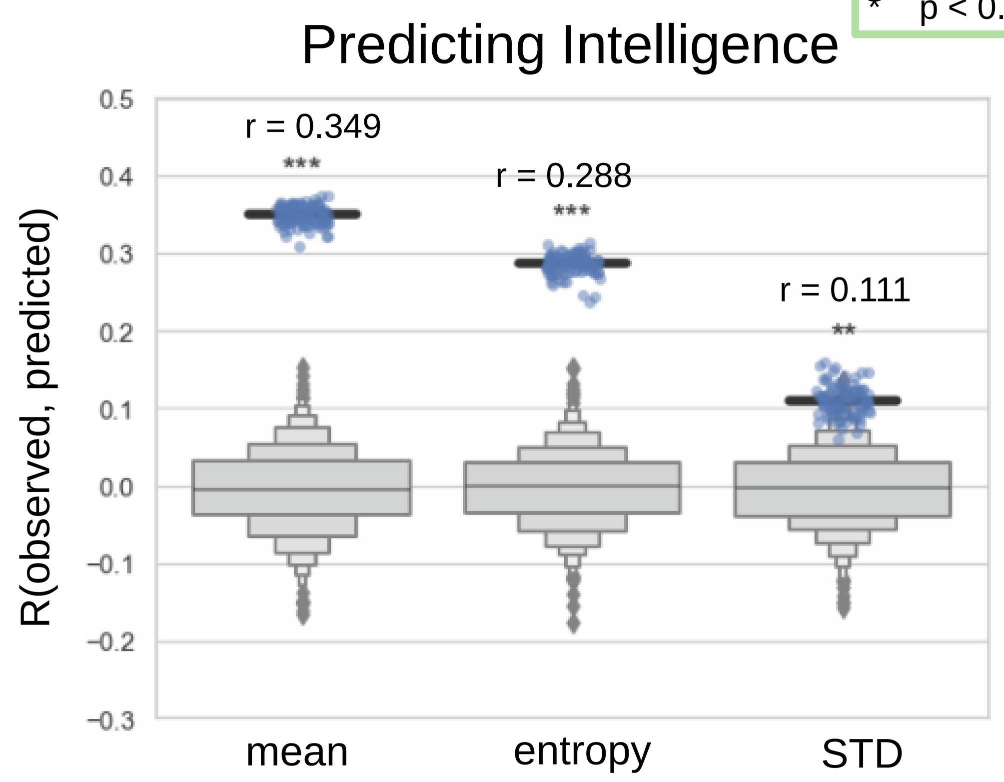

Figure 3. Connectome-Based Predictive Modeling results for predicting WASI-II Scores. Blue dots show results of 100 iterations of 10-fold cross-validation using true data, while gray boxen plots show distribution of results from 1,000 iterations using randomized data. Black lines indicate the median accuracy for true models.

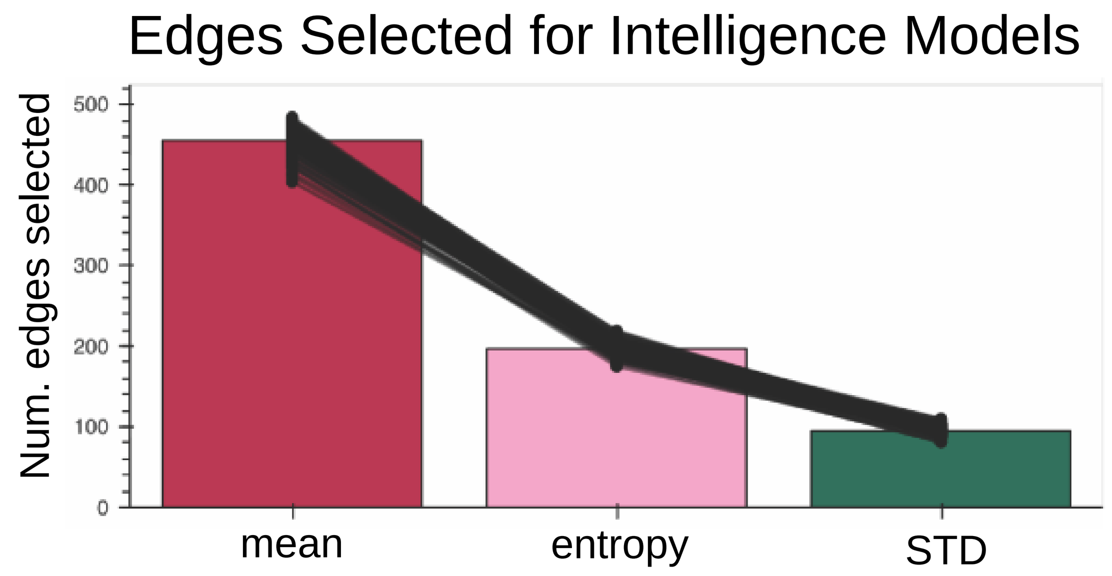

Figure 4. Bar and line plots showing the number of edges selected as being significantly (p < 0.01) correlated with WASI-II Scores within each metric when all three representations of the data were given to the model at once. Ridge regression was run 100 times. Bars depict the average number of significant edges per summary metric across all iterations, while the lines show the number of edges selected per summary metric in each iteration. Results were consistent across iterations.

Ridge Regression

- Prediction performance improved when using all three **time-insensitive** metrics together as input to ridge regression (r = 0.43; p<0.0001).
- Across fitting iterations, the model framework repeatedly selected the mean in building these predictions (Figure 4), suggesting the mean (or FC) is the most informative statistic.
  - This pattern was replicated with attention.

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- Finally, we computed predictions using several **time-sensitive** summary metrics (Figure 5). Their predictive power never reached significance.
  - A similar pattern was found when analyzing predictions for attention from temporally sensitive summary metrics.

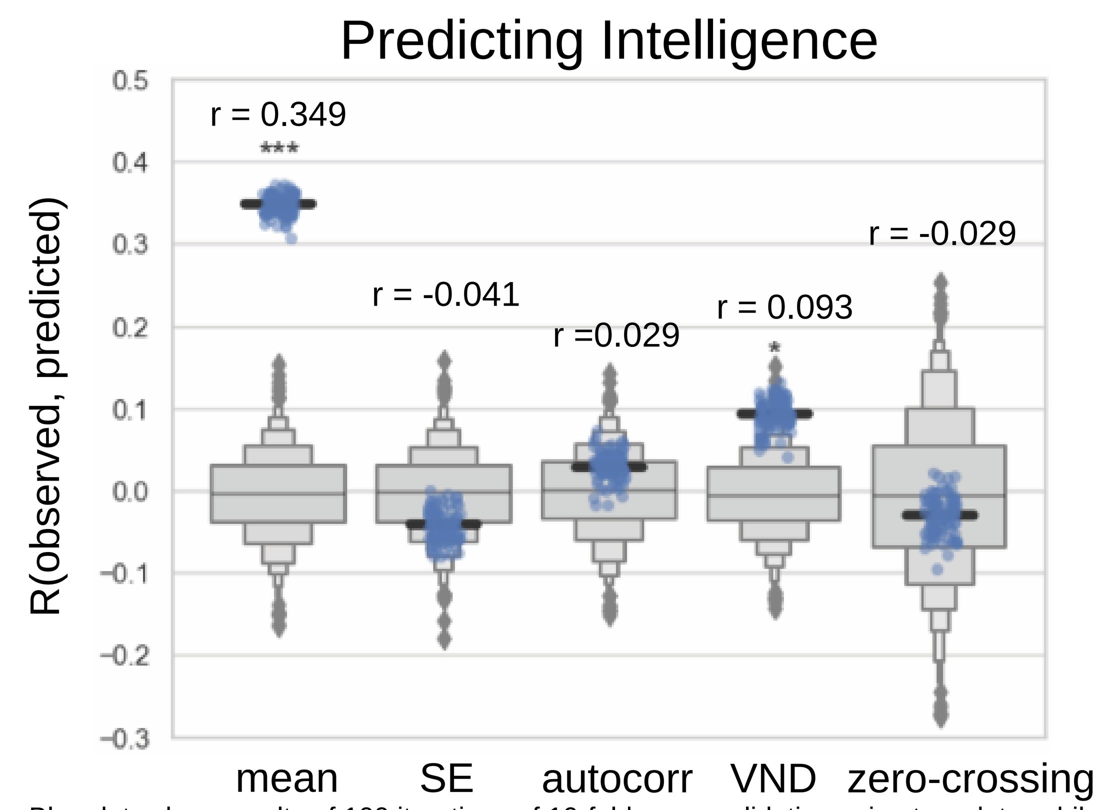

Figure 5. Connectome-Based Predictive Modeling results for predicting WASI-II Scores. Blue dots show results of 100 iterations of 10-fold cross-validation using true data, while gray boxen plots show distribution of results from 1,000 iterations using randomized data. Black lines indicate the median accuracy for true models.

CONCLUSIONS

- Our results demonstrated that static functional connectivity showed significant predictive power that was unmatched compared to a variety of other summary statistics.
- This suggests that what the brain is engaging in over 10-minute periods is perhaps more predictive of traits than the specific dynamics of how it changes from moment to moment.
- Future work will focus on exploring spatial and temporal aspects of these alternative dynamic representations of brain activity, in the hopes that other avenues of analysis will give us additional insight about the brain. In addition, we plan to apply these techniques to other datasets to attempt to push the boundaries of brain-behavior predictions.

REFERENCES

(1) Craddock 2013 (2) Finn 2015 (3) Zamani Esfahlani 2020 (4) Nooner 2012 (5) Esteban 2019 (6) Behazdi 2007 (7) Schaefer 2018 (8) Makowski 2011 (9) Baracchini 2021 (10) Shen 2017 (11) Gao 2019

ACKNOWLEDGEMENTS

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