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The Role of Lake Physical Variables and Atmospheric Forcings on the Change in Algal Biomass in North American Great Lakes

Introduction

- Observed increase in the frequency and severity of algal blooms is hypothesized to be driven by climate change[1,2,3].
- Analysis on the interaction effects of various atmospheric and lake physical forcings on changes in algae are often limited to small spatial and temporal scales due to limited data[4,5,6].
- The development of new remotely sensed chl-*a* data products allows for larger spatial and temporal analysis.
- This research utilizes a daily remotely sensed chl-*a* and LSWT data product (ESA CCI Lake version 2.0.1, 1 km grid)[7], and ERA5 hourly land reanalysis data, to determine the interaction effects of various atmospheric and lake physical forcings on algal biomass trends from 2002-2020 in five North American Great Lakes (Great Bear lake, Great Slave Lake, Lake Athabasca, Lake Winnipeg and Lake Erie) using a DBN (dbnR in R)[8].

Methods

- Daily satellite imagery pre-processed to remove outliers (Q3+(1.5*IQR)).
- Flow pathways and accumulation derived from 1 km DEM (GTOPO30)
- Daily means derived from lake basin polygons and hydrobasin level-04 regions where flow pathways intersect with each lake basin (TP, SR, and SSR).
- Daily means removed where the sum of open water pixels was <90% of the max.
- Missing values linearly interpolated.
- DBN constructed for the whole time series (all) and decomposed (stationary, non-stationary, error) lags 2-6, with daily data (natPsoho optimization), for 2002-2019 training data and 2020 for testing data. Decomposed series reconstructed.
- Performance monitored using RMSE, NRMSE, and MAE.

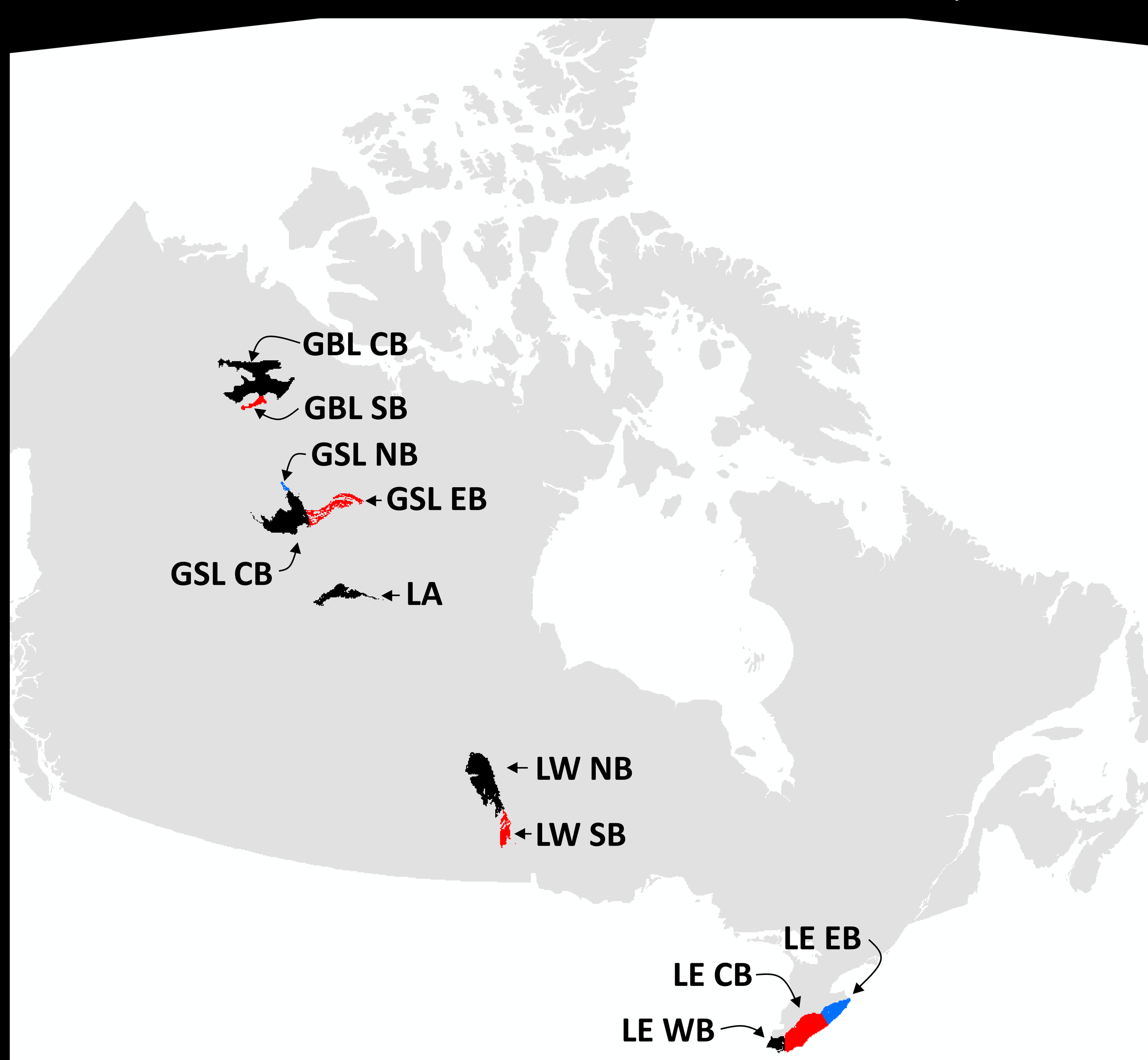


Fig 1. Study lakes and basins.

Results

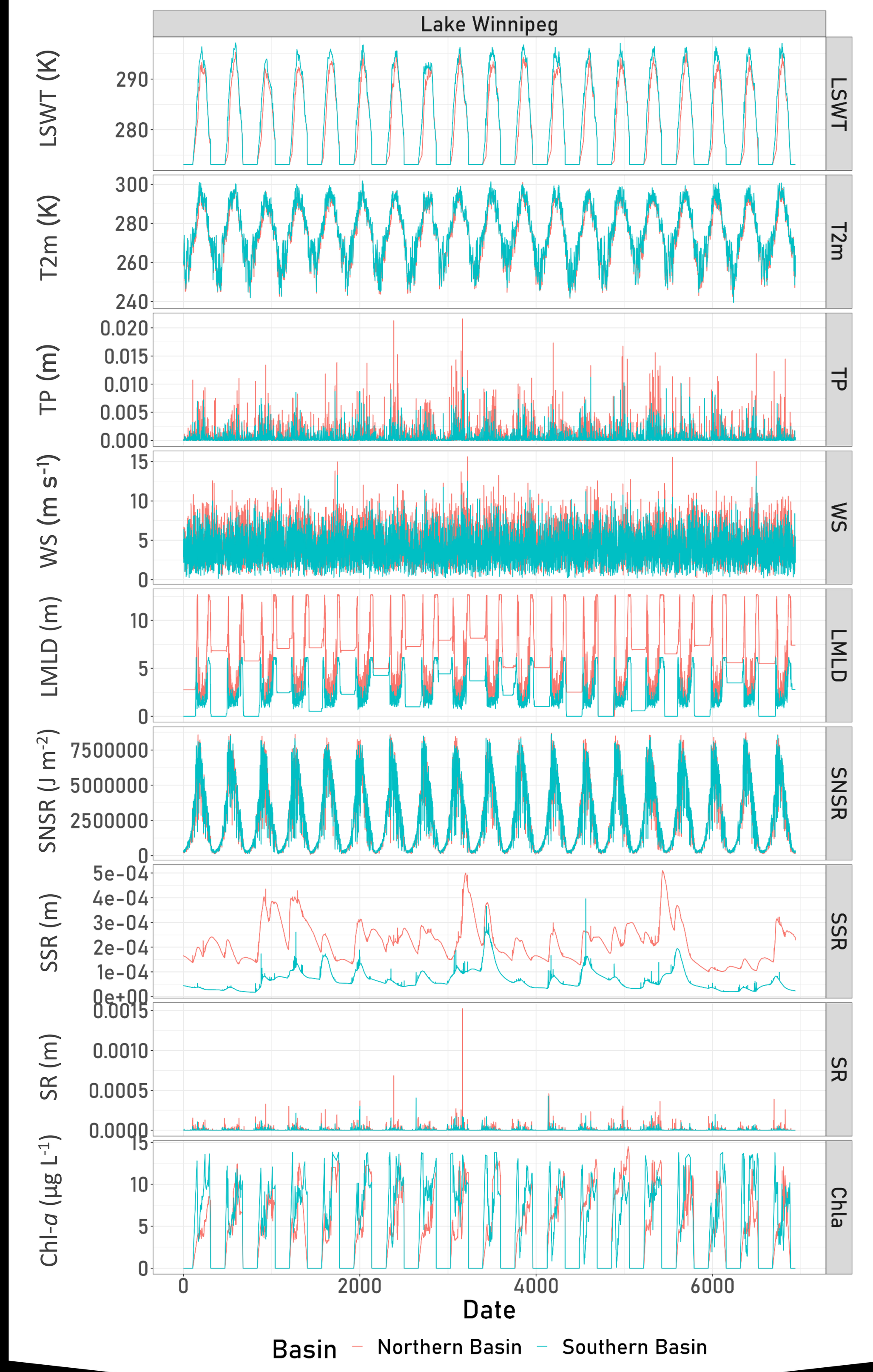


Fig 2. Time series of atmospheric and lake physical parameters for Lake Winnipeg.

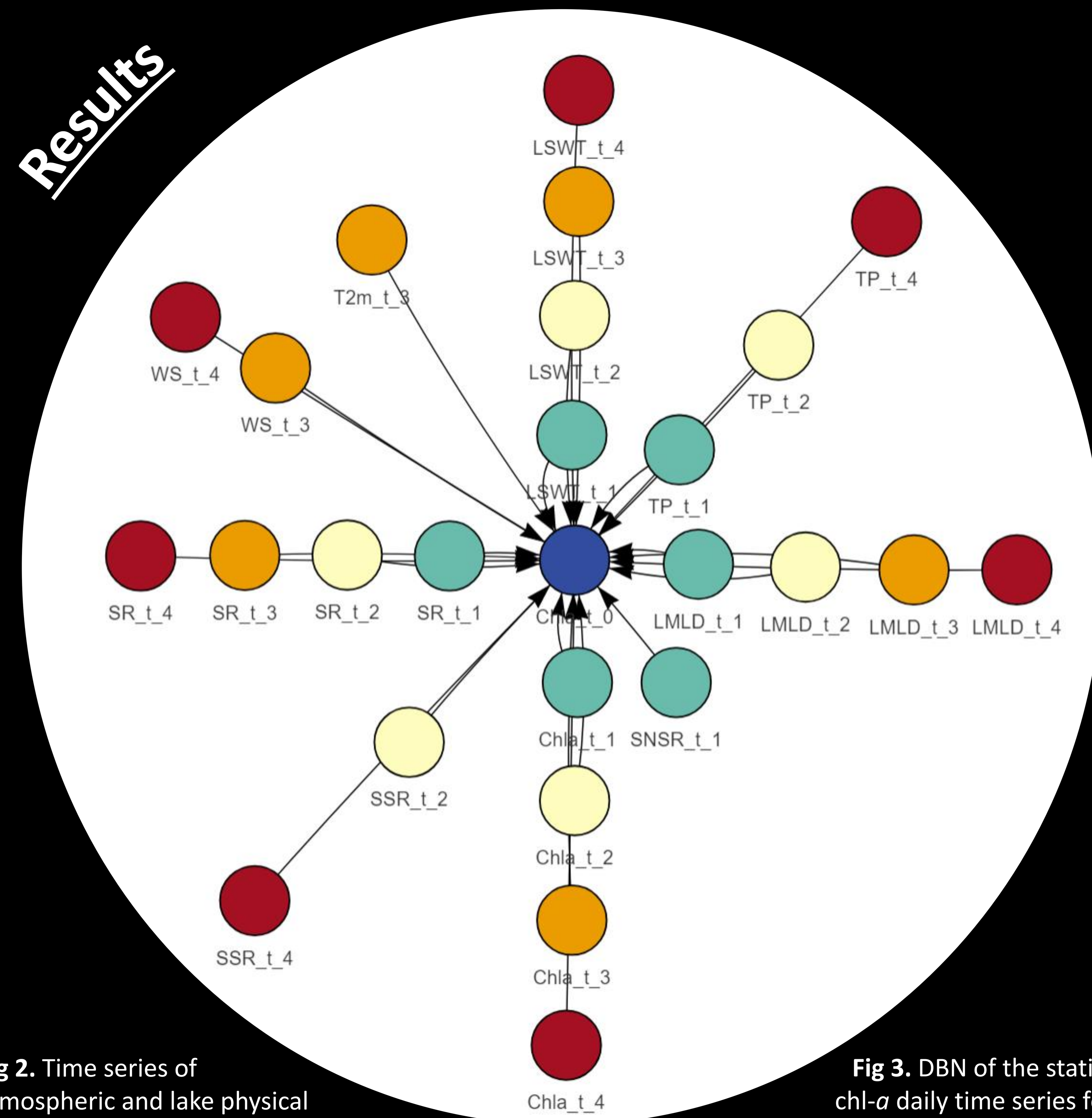


Fig 3. DBN of the stationary chl-*a* daily time series for the south basin of Lake Winnipeg.

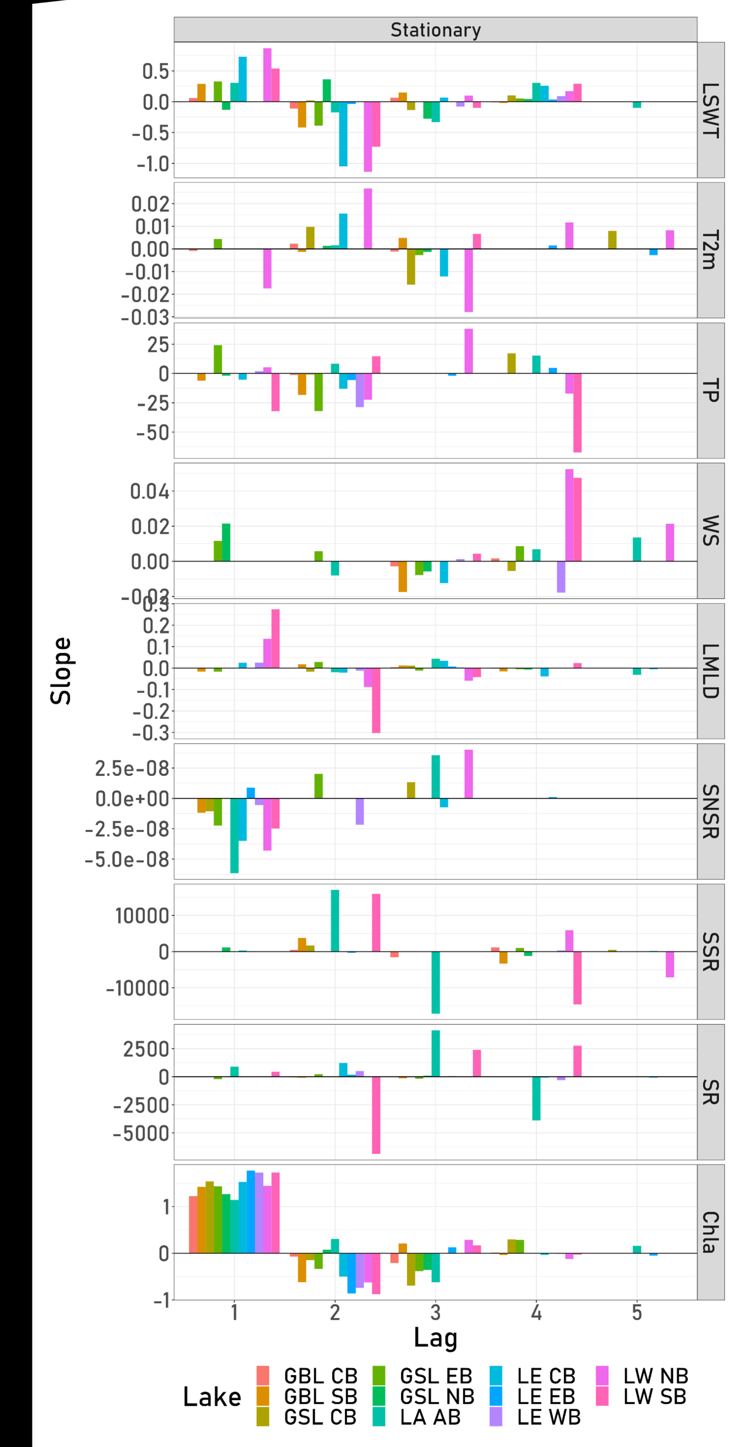
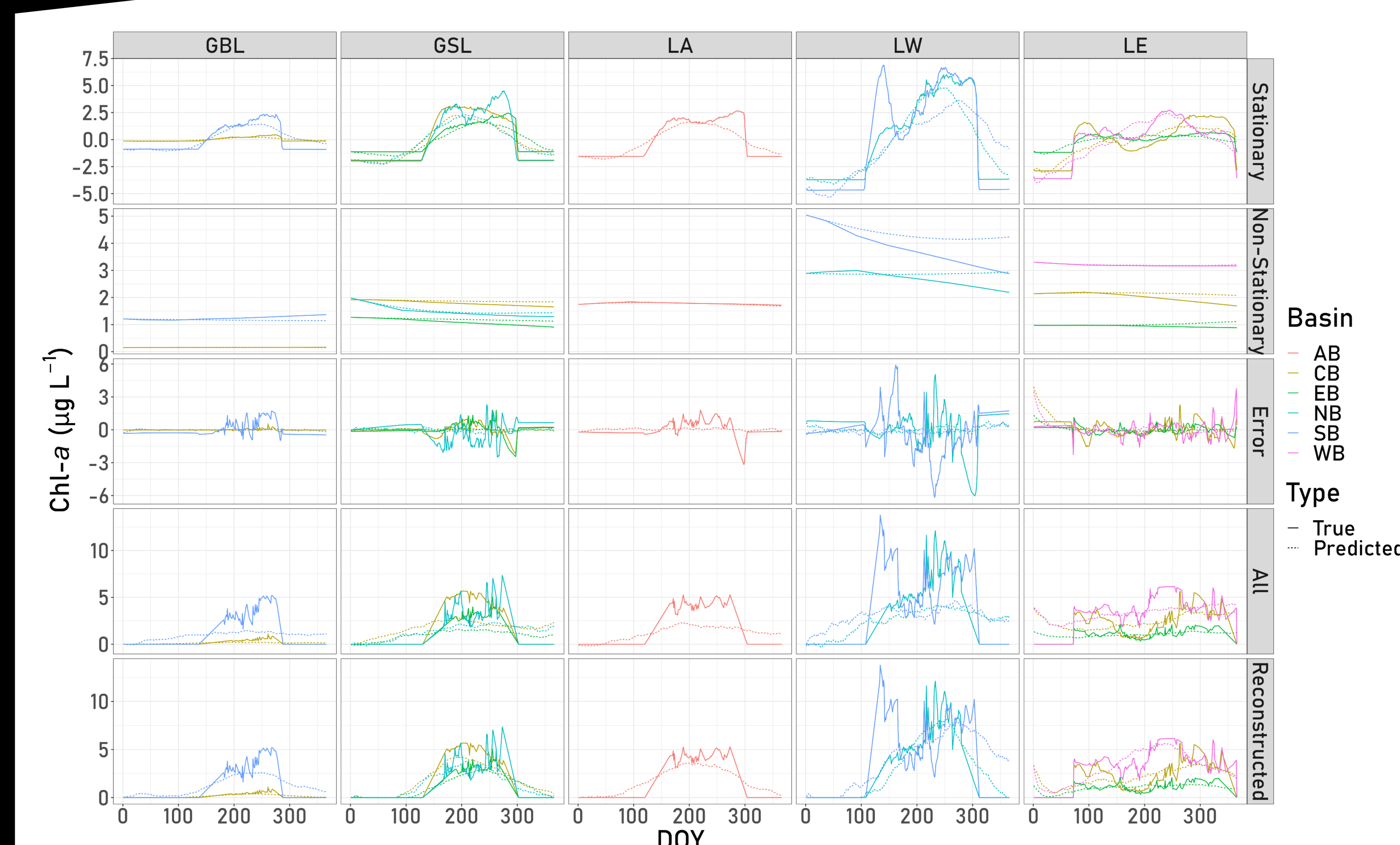


Fig 4. Stationary DBN coefficients (slope) at each lag interval for all study lakes and basins.



	Metric	GBL – LE
Stationary	RMSE	0.10-3.21
	NRMSE	0.40-0.60
	MAE	0.07-2.46
Non-Stationary	RMSE	0.00-0.67
	NRMSE	0.40-3.19
	MAE	0.00-0.55
Error	RMSE	0.06-1.71
	NRMSE	0.93-1.16
	MAE	0.03-1.18
All	RMSE	0.20-3.46
	NRMSE	0.78-0.95
	MAE	0.14-2.89
Recon.	RMSE	0.13-3.26
	NRMSE	0.41-0.82
	MAE	0.08-2.26

Fig 5. DBN Chl-*a* prediction for the year 2020 across all lakes and basins.

Implications/Conclusions

- Reconstructed time series returned lower predictive error compared to all.
- Daily scaled data returned the highest predictive error while monthly returned the lowest.
- Stationary models improved at higher lag orders, while non-stationary models did not.
- Each lake displayed a unique response to changes in climatic and atmospheric forcings.
- LSWT and LMLD were the most frequently featured parameters (daily), with both positive and negative effects? (lake dependent).
- Network interactions of atmospheric and lake physical parameters show predictive performance and play a significant role in the algal biomass response over time.

GBL: Great Bear Lake
GSL: Great Slave Lake
LA: Lake Athabasca
LE: Lake Erie
CB: Central Basin
EB: East Basin
WB: West Basin
NB: North Basin
SB: South Basin
RMSE: Root Mean Squared Error
NRMSE: Normalized RMSE
MAE: Mean Absolute Error
Chl-a: Chlorophyll-*a*
Recon: Reconstructed
LSWT: Lake Surface Water Temperature
T2m: 2m Air Temperature
TP: Total Precipitation
WS: Wind Speed
LMLD: Lake Mixing Level Depth
SNSR: Surface Net Solar Radiation
SSR: Subsurface Runoff
SR: Surface Runoff
DBN: Dynamic Bayesian Network
NatPsoho: Natural Particle Swarm

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