Deep Learning for Spatiotemporal Anomaly Forecasting: A Case Study of Marine Heatwaves

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Summary

- We proposed a PhD project on deep learning for spatiotemporal anomaly forecasting.
- We reviewed relevant latest deep learning methods (based on CNNs, GNNs, AEs, LSTMs, transfer learning) and their applications to the spatiotemporal anomaly forecasting.
- We used marine heatwaves as a case study. They are becoming more frequent and more intense as a result of climate change. Marine heatwaves have caused serious ecological and socioeconomic impacts.
- In future work, we aim to create a forecasting model that improves seasonal global and/or regional marine heatwave predictability.

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Spatiotemporal Data

1. High-dimensional
2. Limited in extent
3. Temporally correlated

Example: GODAS Dataset

Variables:

Total downward heat flux at surface

Salt Flux

Sea Surface Height Relative to Geoid

Geometric Depth Below Sea Surface

Momentum flux, u component

Momentum flux, v component

Salinity

u-component of current

v-component of current

Geometric vertical velocity (dz/dt)

Potential temperature

Years: 1980 to present

xarray.Dataset

▸ Dimensions: (**lat**: 418, **level**: 40, **lon**: 360, **time**: 12)

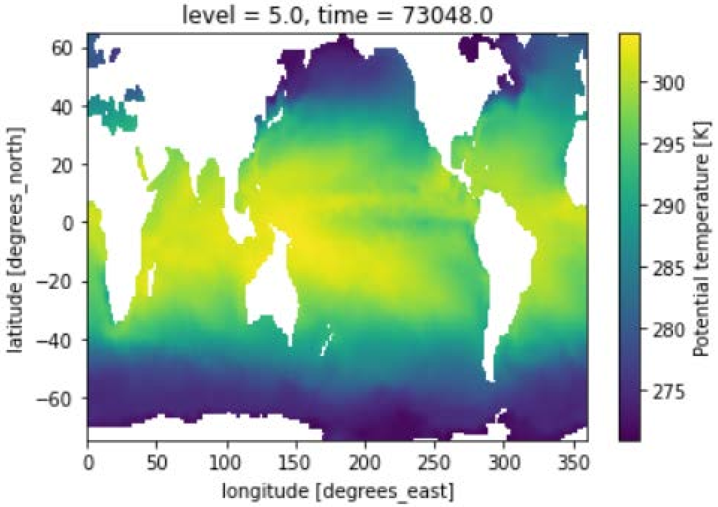
▾ Coordinates:

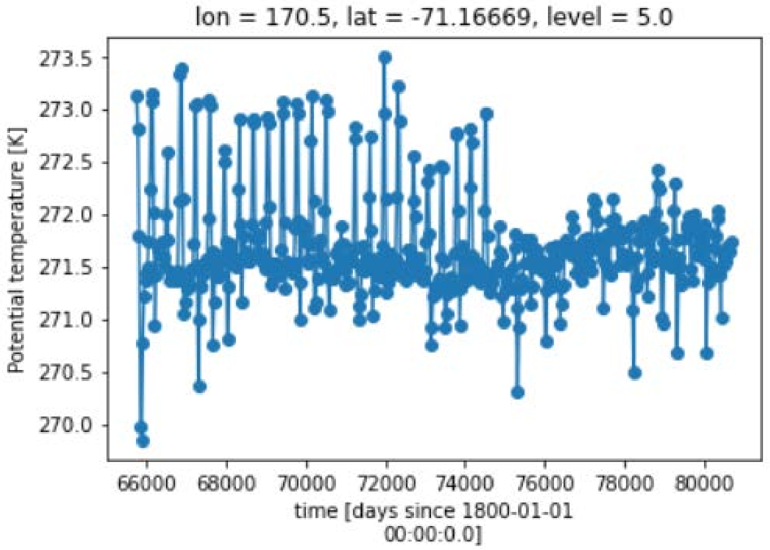
level	(level)	float32	5.0 15.0 25.0 ... 3972.0 4478.0
lon	(lon)	float32	0.5 1.5 2.5 ... 357.5 358.5 359.5
lat	(lat)	float32	-74.5 -74.16667 ... 64.16566 64.499
time	(time)	float64	6.574e+04 6.577e+04 ... 6.608e+04

▾ Data variables:

date	(time)	int32	...
timePlot	(time)	float32	...
pottmp	(time, level, lat, lon)	float32	...

▸ Attributes: (13)



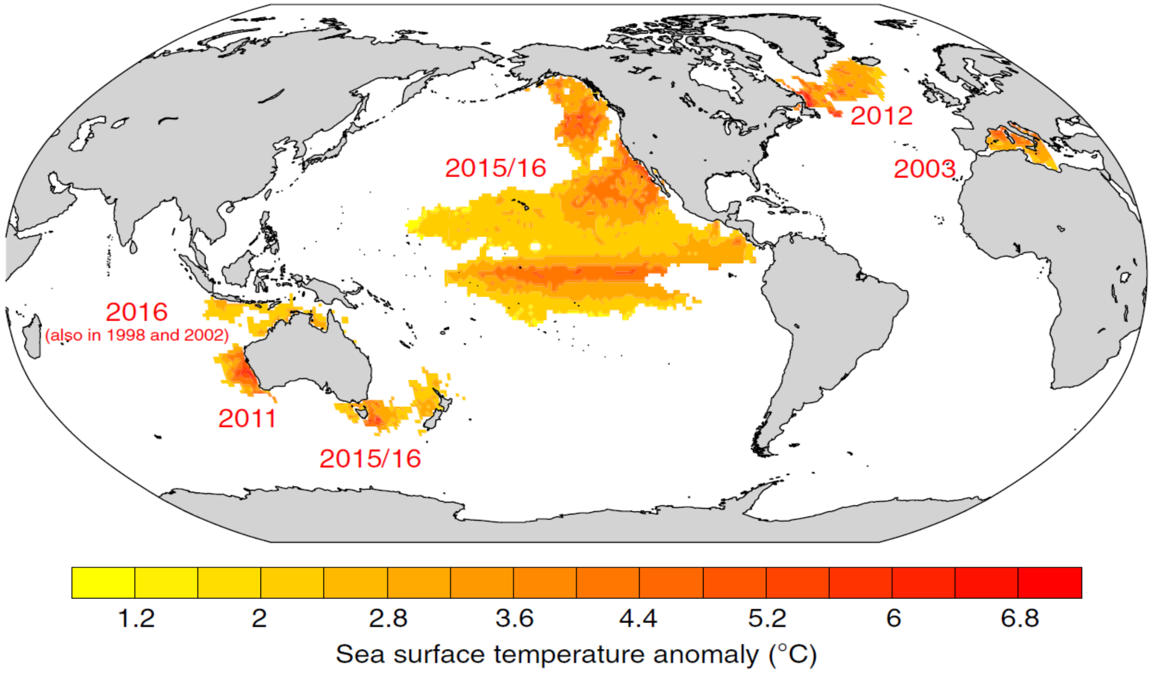


Global potential temperature in 1980, GODAS

Marine Heatwaves

Definition: a period of at least five consecutive days for which sea water temperature is warmer than the 90th percentile based on a 30-year historical baseline period (Hobday et al., 2016).

Impacts: ecological (Holbrook et al. 2020) and socioeconomic (Hobday et al., 2018)



Summary of prominent recent marine heatwaves that are documented and analyzed in the literature (Frölicher & Laufkötter, 2018)

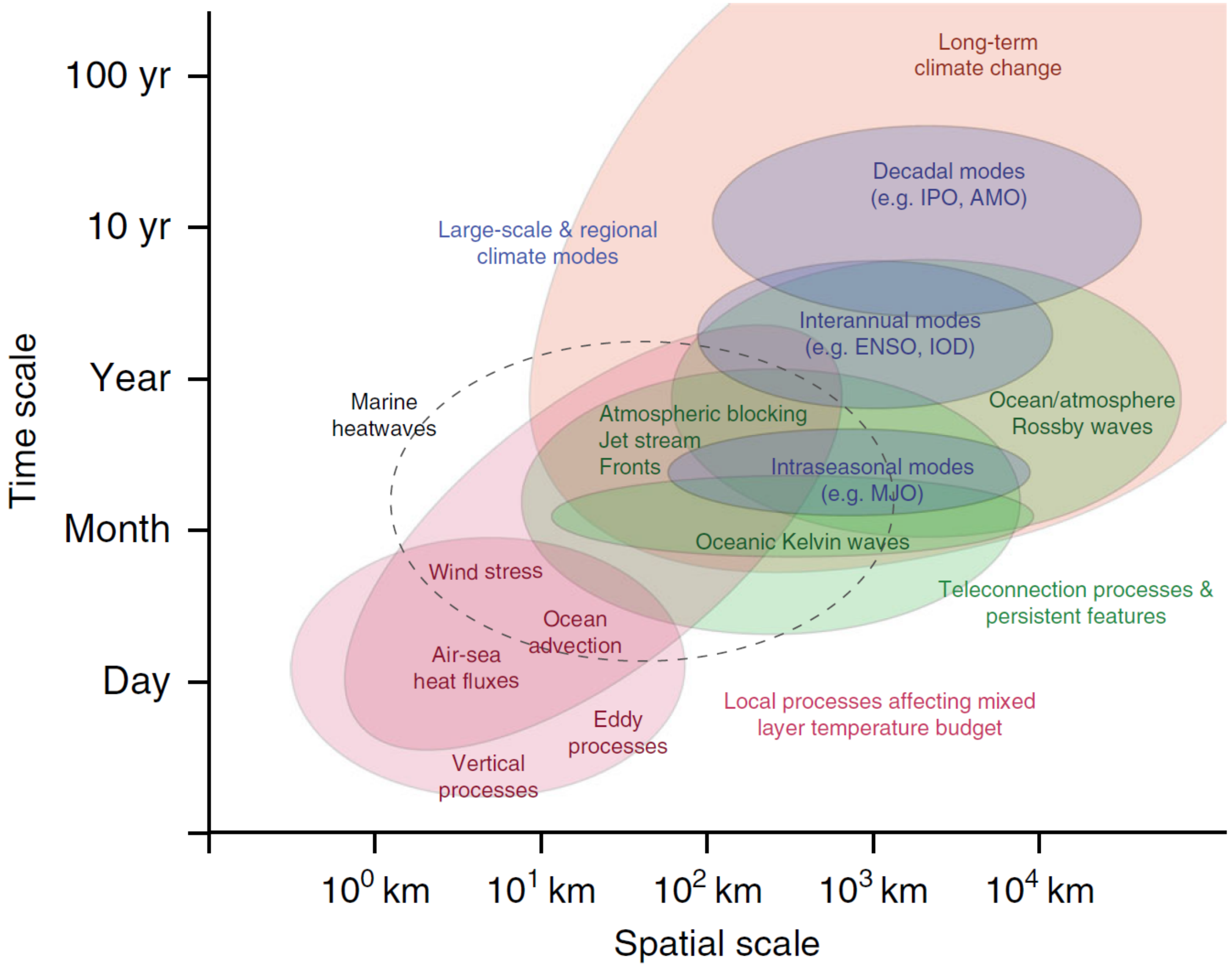
loss of foundation habitats

loss of species

damage to fisheries

Marine Heatwaves

Drivers:



Space and time scales of characteristic MHW drivers (Holbrook et al., 2019)

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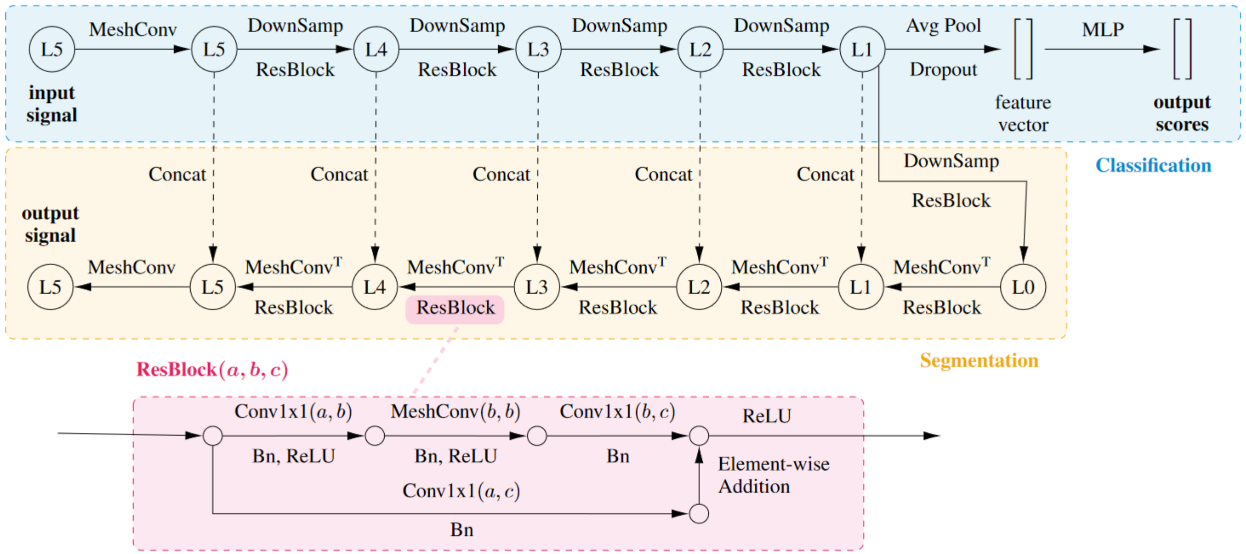
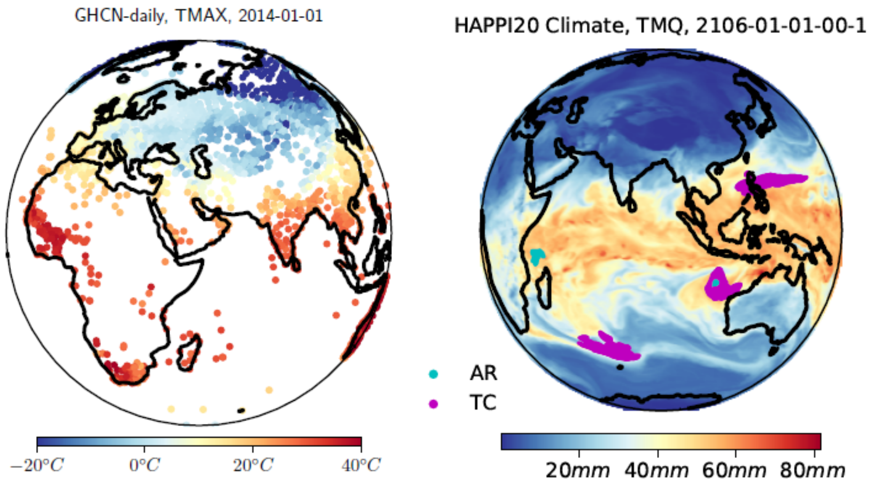
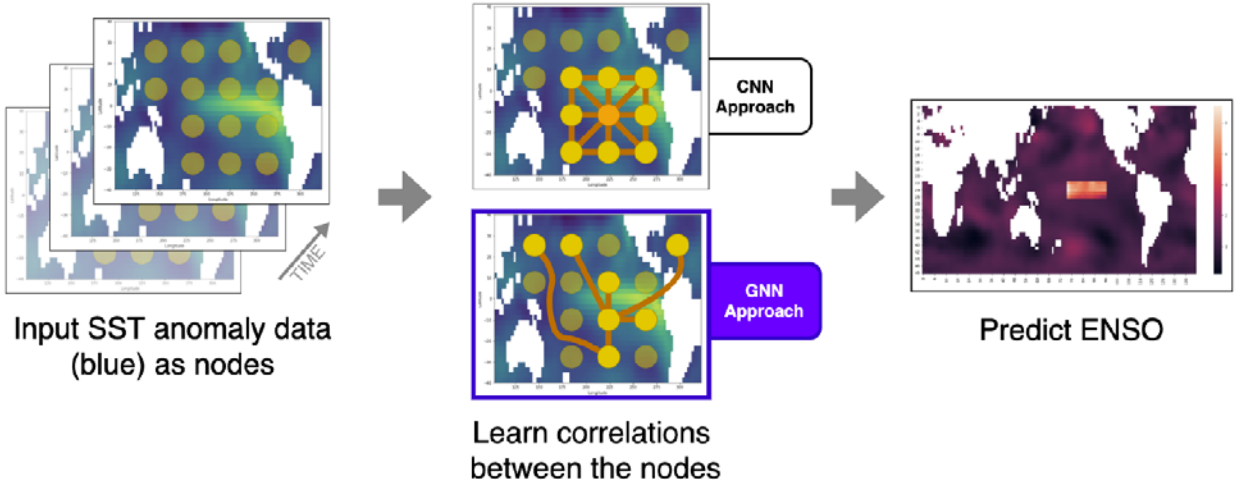
Deep Learning Applications for Spatiotemporal Anomaly Detection / Forecasting

2. Graph-based spherical CNNs for atmospheric river and tropical cyclone segmentation (Jiang et al., 2019) and spherical data (Defferrard et al., 2020)



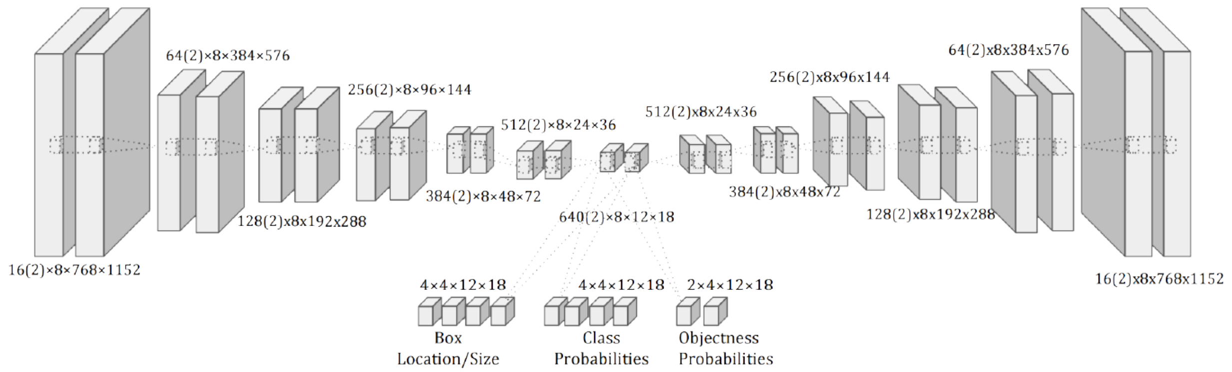


1. Graph neural networks (GNNs) for multi-month El Niño forecasting (Cachay et al., 2020)

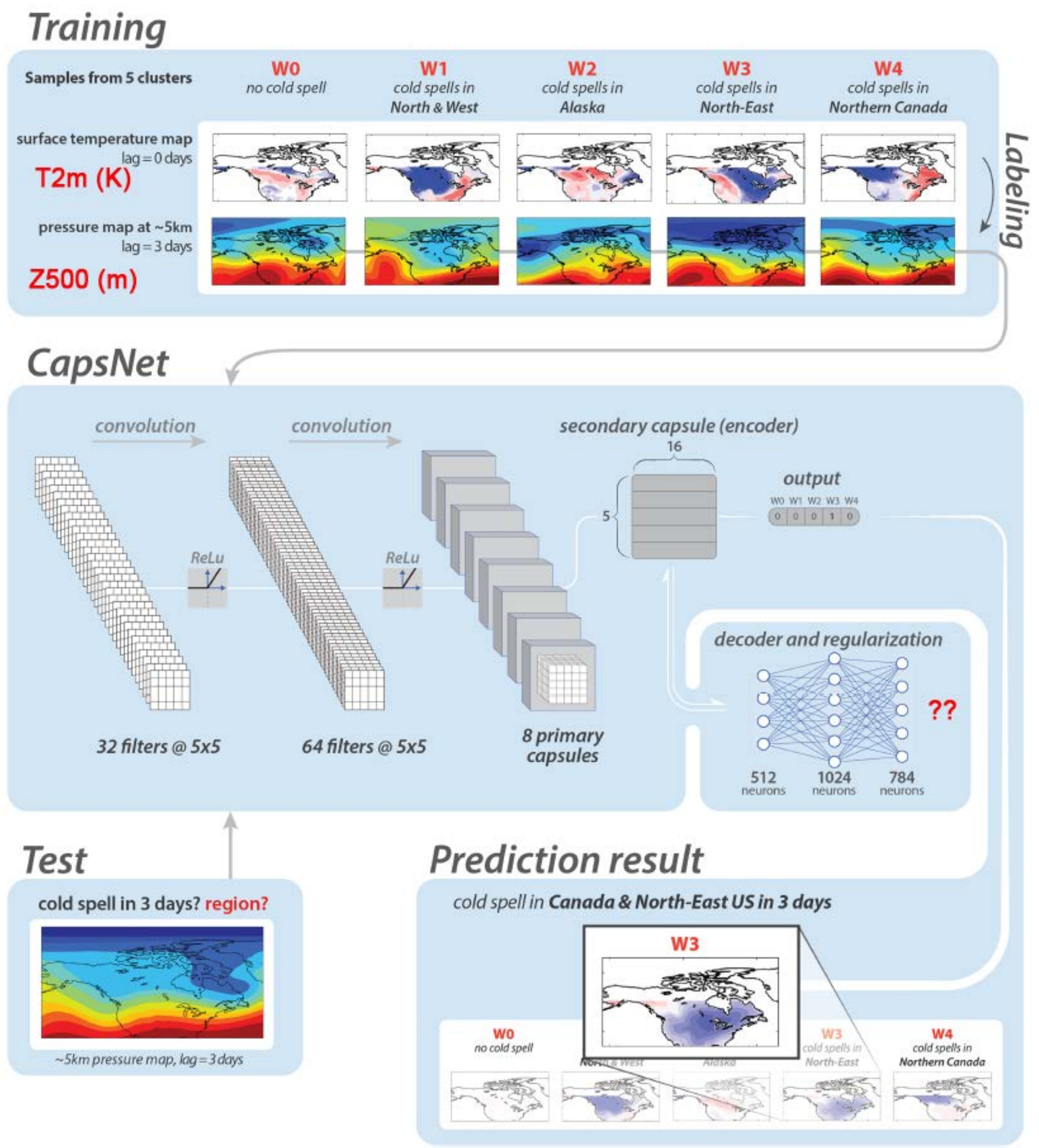


Deep Learning Applications for Spatiotemporal Anomaly Detection / Forecasting

3. CNNs combined with autoencoders (CNN-AEs) for tropical cyclone, extra tropical cyclone, tropical depression and atmospheric river detection (Racah et al., 2016)

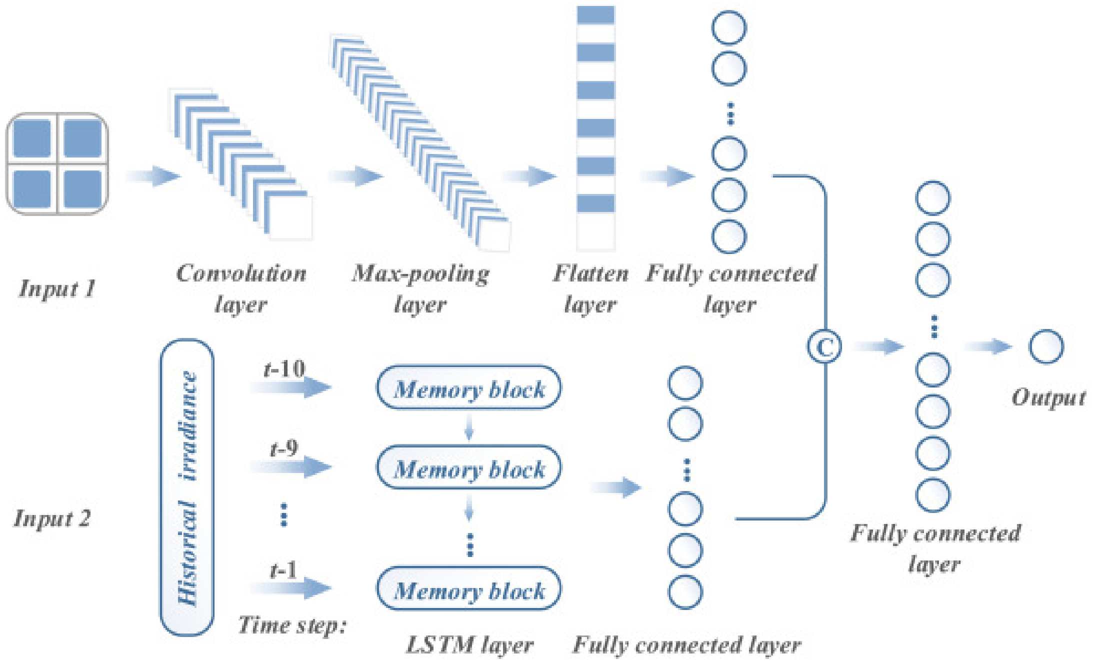


4. Capsule neural networks (CapsNets) for multi-day heat or cold wave forecasting (Chattopadhyay et al., 2017)

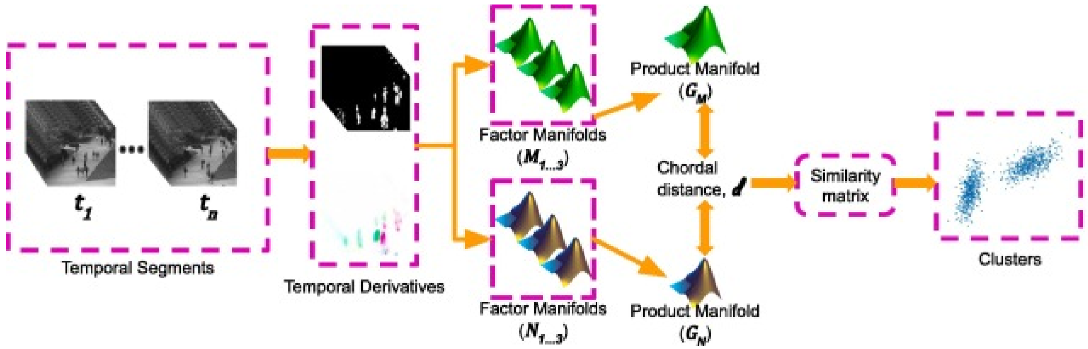


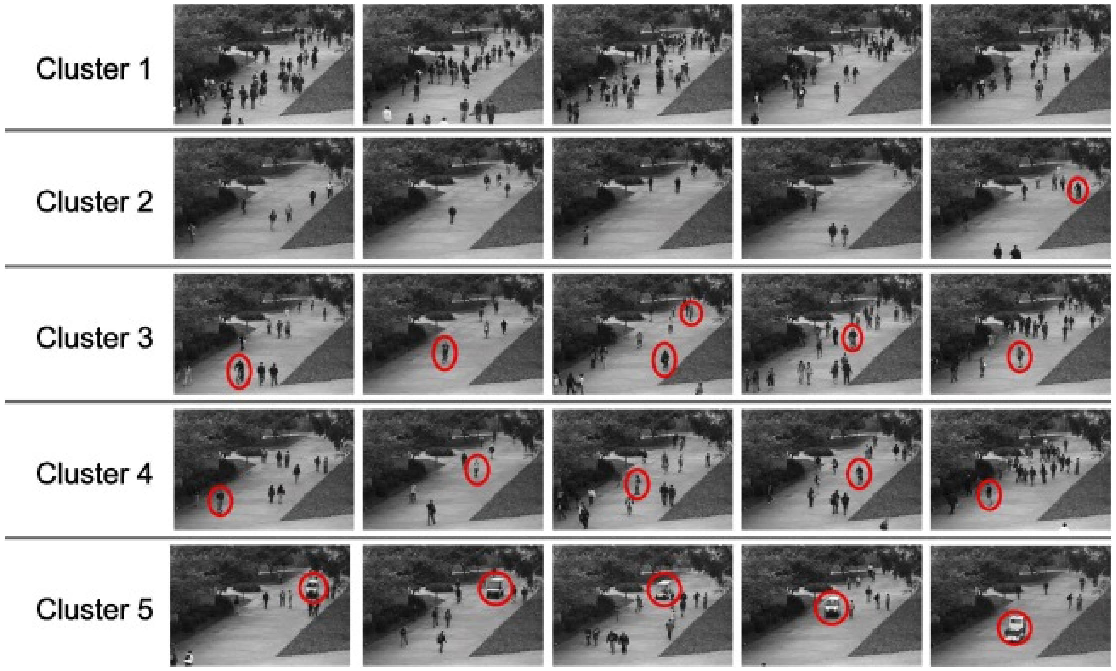
Deep Learning Applications for Spatiotemporal Anomaly Detection / Forecasting

5. CNNs combined with long short-term memory (CNN-LSTMs) for hourly solar irradiance forecasting (Zang et al., 2020)



6. Transfer learning (zero-shot learning) for offline anomaly detection (Buckchash & Raman, 2021)





Research Questions

- How to select an appropriate number of predictors for spatiotemporal forecasting, what domain knowledge is required, and whether we can make the learning semi-supervised or unsupervised.
- How to overcome geophysical data insufficiency, and whether we can use the generative models to create additional data.
- Whether transfer learning, including one-shot learning and zero-shot learning, can be used, and how to select appropriate relevant datasets and/or pre-trained models.
- How to tackle temporal correlations, and whether the video processing techniques can be used for spatiotemporal data.
- Whether we can use the reviewed deep learning methods that tackle spatial and/or temporal information, such as spherical convolutions, capsules, and graph reasoning, to improve the marine heatwave predictability.

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