Articles

1. Andersson, T.R., Hosking, J.S., Pérez-Ortiz, M. et al. Seasonal Arctic sea ice forecasting with probabilistic deep learning. Nat Commun 12, 5124 (2021). https://doi.org/10.1038/s41467-021-25257-4
2. Mayer, K. J., & Barnes, E. A. (2021). Subseasonal forecasts of opportunity identified by an explainable neural network. *Geophysical Research Letters*, 48, e2020GL092092. https://doi.org/10.1029/2020GL092092
3. Thomas Vandal, Evan Kodra, Sangram Ganguly, Andrew Michaelis, Ramakrishna Nemani, and Auroop R. Ganguly. 2017. DeepSD: Generating High Resolution Climate Change Projections through Single Image Super-Resolution. In Proceedings of the 23rd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining (KDD '17). Association for Computing Machinery, New York, NY, USA, 1663–1672. https://doi.org/10.1145/3097983.3098004
4. Evan Racah, Christopher Beckham, Tegan Maharaj, Samira Ebrahimi Kahou, Prabhat, and Christopher Pal. 2017. Extreme weather: a large-scale climate dataset for semi-supervised detection, localization, and understanding of extreme weather events. In Proceedings of the 31st International Conference on Neural Information Processing Systems (NIPS'17). Curran Associates Inc., Red Hook, NY, USA, 3405–3416.
5. Gordon, E. M., & Barnes, E. A. (2022). Incorporating uncertainty into a regression neural network enables identification of decadal state-dependent predictability in CESM2. Geophysical Research Letters, 49, e2022GL098635.

Title: Probabilistic weather forecasting with machine learning.

Authors (Year): Ilan Price et al. (2024)

Type of problem:

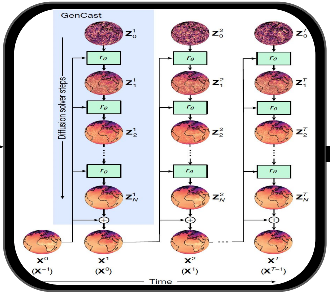
ML application: Probabilistic Machine Learning Weather Prediction, GenCast

Inputs

Training: 40 years (1979-2018), ERA5 reanalysis

Prediction Timescale

12h-15 days



Model Type

Conditional Diffusion Model w/ denoiser NN

Output

Global, 0.25° Resolution, Six surface variables, six atmospheric variables at 13 pressure levels

Title: Seasonal Arctic sea ice forecasting with probabilistic deep learning.
Authors (Year): Tom R. Andersson, J. Scott Hosking et al. (2021)
Type of problem: Classification
ML application: Seasonal Sea Ice Forecasts [IceNet]

Inputs

Monthly Average SIC
11 climate variables
Statistical SIC forecasts
Metadata

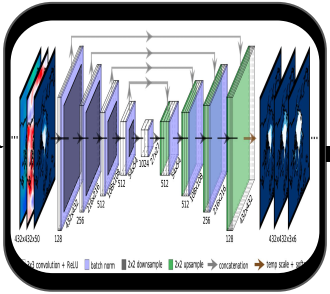
Pre-training:
CMIP6 Data, 1850-2100
[historical + 'middle of the road']

Training: Observations, OSI-SAF, 1979-2011

Validation: Obs, OSI-SAF, 2012-2017

Prediction Timescale

1-6 months



Model Type

U-Net (CNN)

Output

Monthly Average SIC Maps
Classes:
SIC < 15%
15% < SIC < 80%
SIC > 80%

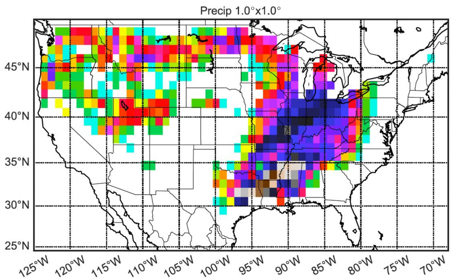
Title: DeepSD: Generating High Resolution Climate Change Projections through Single Image Super-Resolution.

Authors (Year): Thomas Vandal et al. (2017)

Type of problem: Regression

ML application: Downscaling

Inputs



Low Res + High Res Image (LR Precipitation + HR elevation & land/water mask)

Low Res = same variable as output; High Res = different variable from output

Prediction Timescale

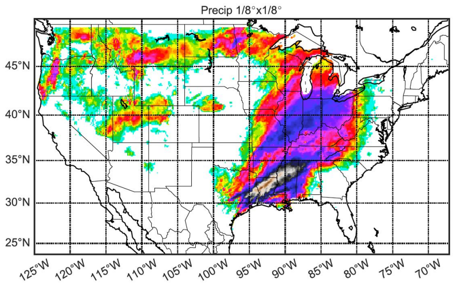
same time

machine learning model

Model Type

Super Resolution CNN (SRCNN)

Output



High Res Image (HR Precipitation)

Title: Subseasonal Forecasts of Opportunity Identified by an Explainable Neural Network

Authors (Year): Mayer and Barnes (2021)

Type of problem: Classification

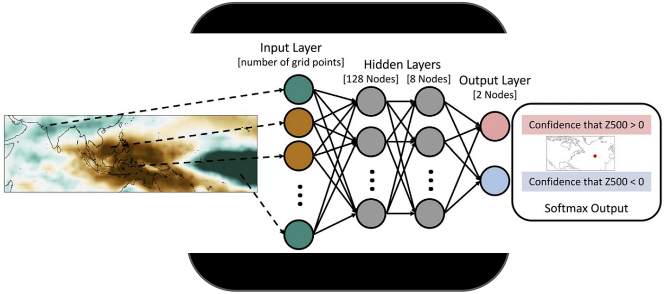
ML application: Sources of predictability /Modes of variability / teleconnections

Inputs

Tropical outgoing longwave radiation (OLR) anomalies; NCAR/NOAA; daily mean, 1979-2019; November-February

Prediction Timescale

22 days



Model Type

Artificial NN (ANN)

+

eXplainable AI (XAI, LRP)

Output

Sign of geopotential height (z500) anomalies in North Atlantic; daily mean; ERA-Interim

XAI output identifies known MJO-line OLR patterns in input

Title: ExtremeWeather: A large-scale climate dataset for semi-supervised detection, localization, and understanding of extreme weather events

Authors (Year): Racah et al. (2017)

Type of problem: classification

ML application: Feature Detection

Prediction Timescale

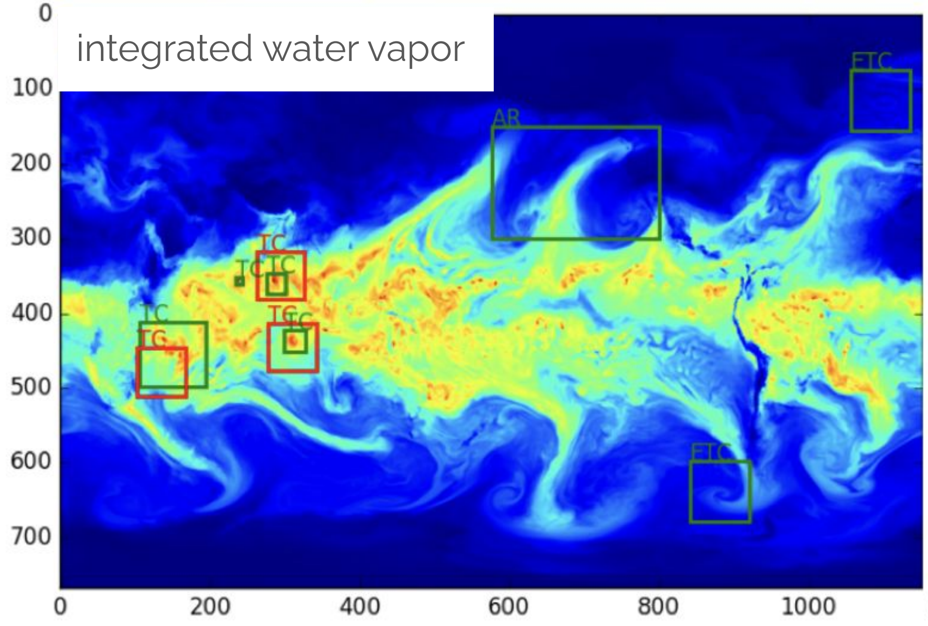
same time

machine learning model

Model Type

3D CNN encoder-decoder

Output



TC: tropical cyclone; AR: atmospheric river ; ETC: extratropical cyclone; ground truth; prediction

Title: Incorporating uncertainty into a regression neural network enables identification of decadal state-dependent predictability in CESM2.

Authors (Year): Gordon and Barnes (2022)

Type of problem: Regression

ML application: investigate state-dependent predictability; how the initial state can make a system more

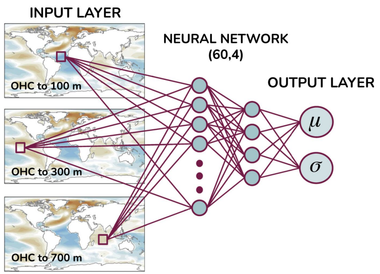
Inputs

Maps of ocean heat content (OHC) at 100, 300 and 700m depth

De-seasonalized, smoothed, detrended, standardized

Prediction Timescale

1. 12-72 months
2. 36-96 months



Model Type

Artificial neural network (ANN)

Output

SST anomaly (mean over 60 months)

10 models for each SST gridpoint