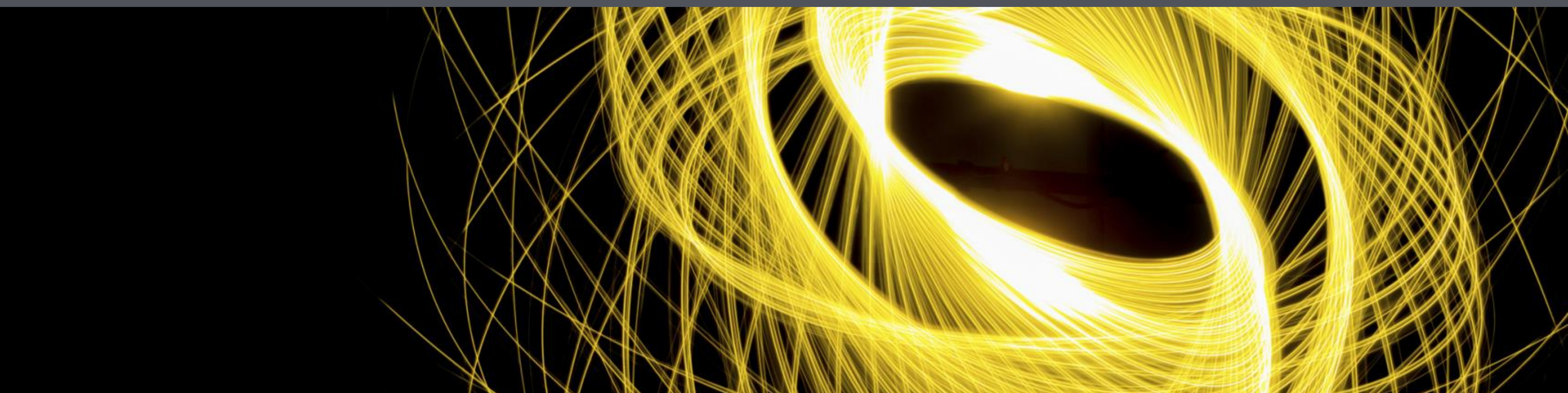
Department of Meteorology

University of Reading

Meteorological Data Filtering for Tropical Cyclones using Deep Learning



Daniel Galea, Bryan Lawrence

Scenario DOCTORAL TRAINING PARTNERSHIP

UKRI Natural Environment Research Council

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Outline

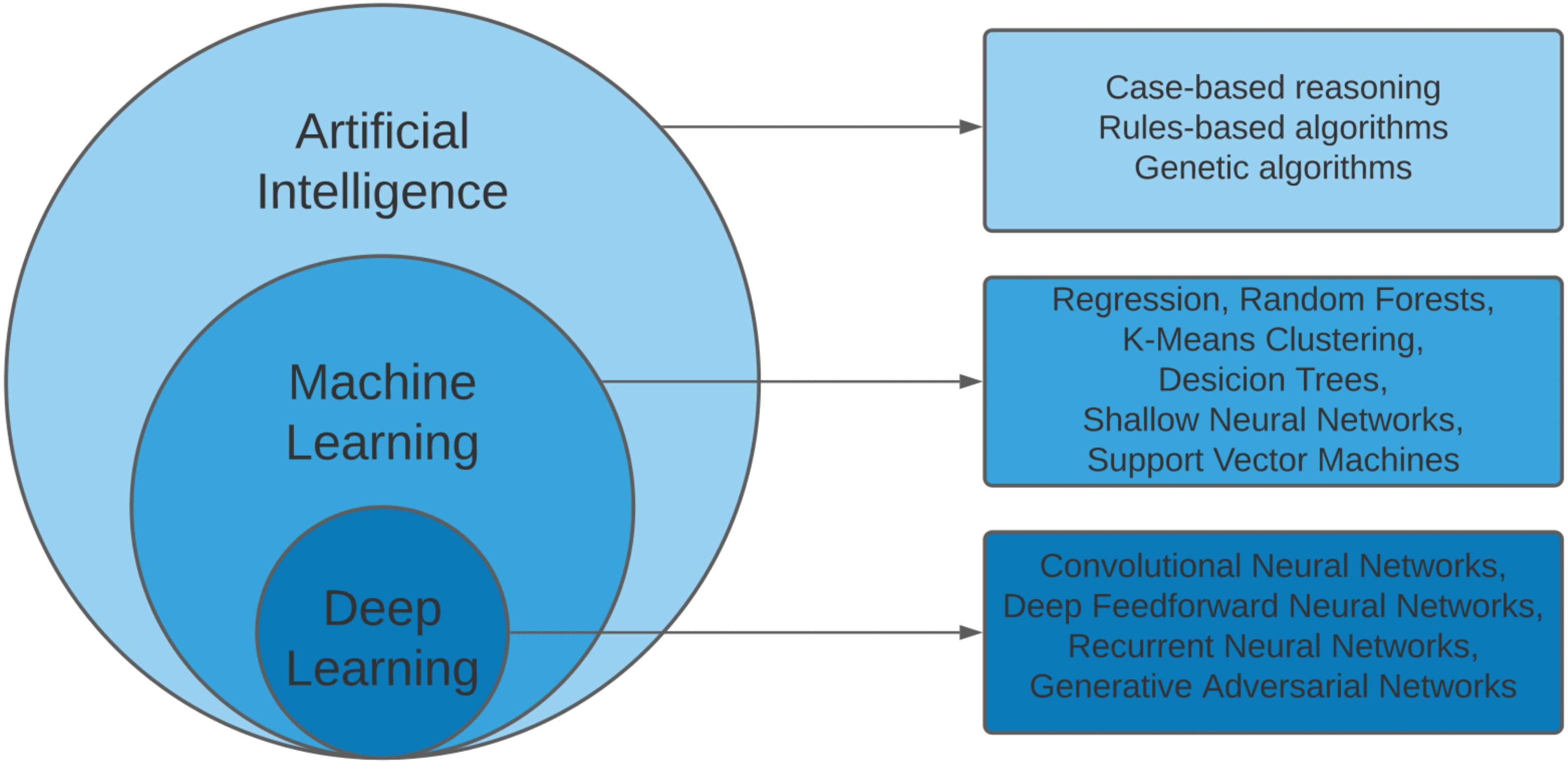
- Introduction and Aims
- Deep Learning
- Detecting Tropical Cyclones with Deep Learning
- Verification of Deep Learning algorithm
- Implementation of Deep Learning algorithm in a GCM
- Summary and Future Work

Introduction and Aims

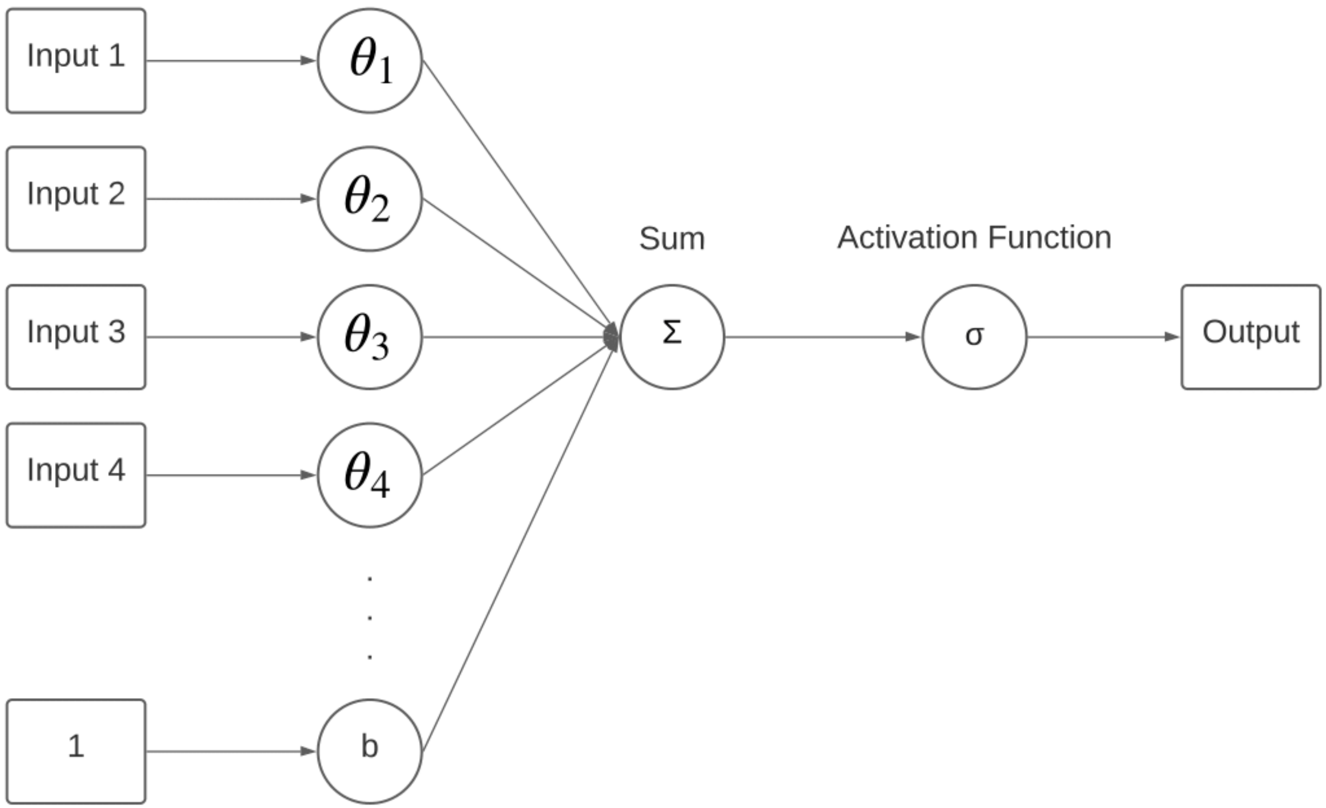
- The effects of a changing climate on multiple meteorological phenomena are being investigated by long General Circulation Model (GCM) simulations
- Each simulation produces large amounts of data which can be inefficient to store and analyse
- We created a method that scans GCM analysis data for the presence of Tropical Cyclones (TCs) and only outputs it to disk if a TC is detected

Deep Learning

What is Deep Learning?



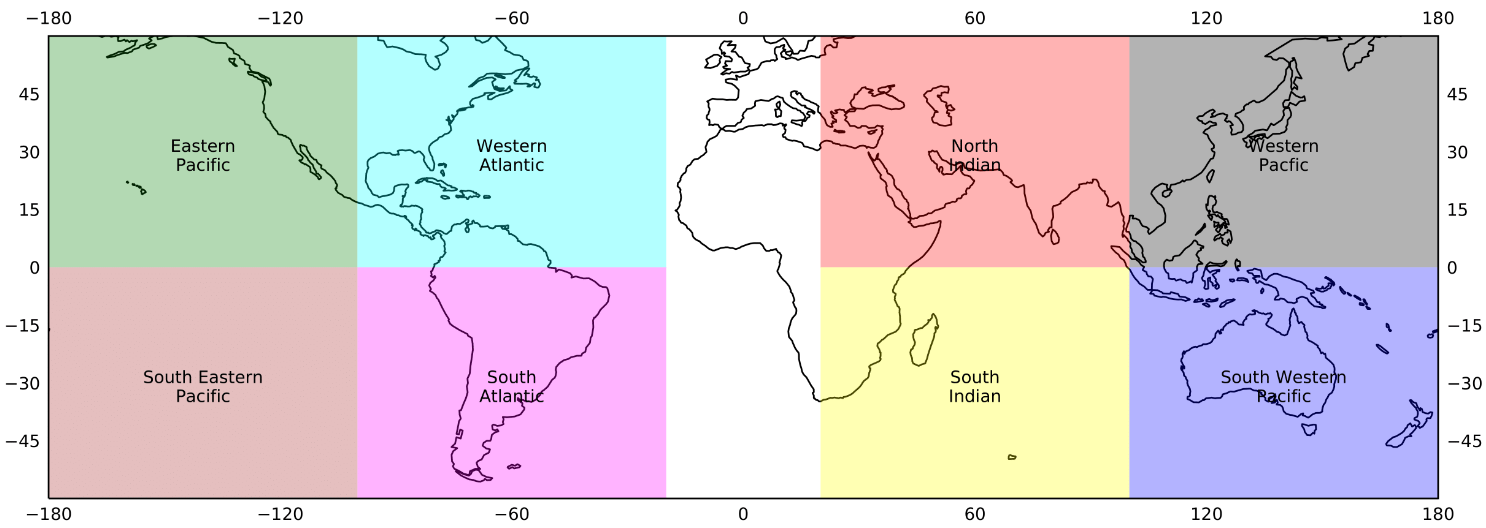
Neural Networks

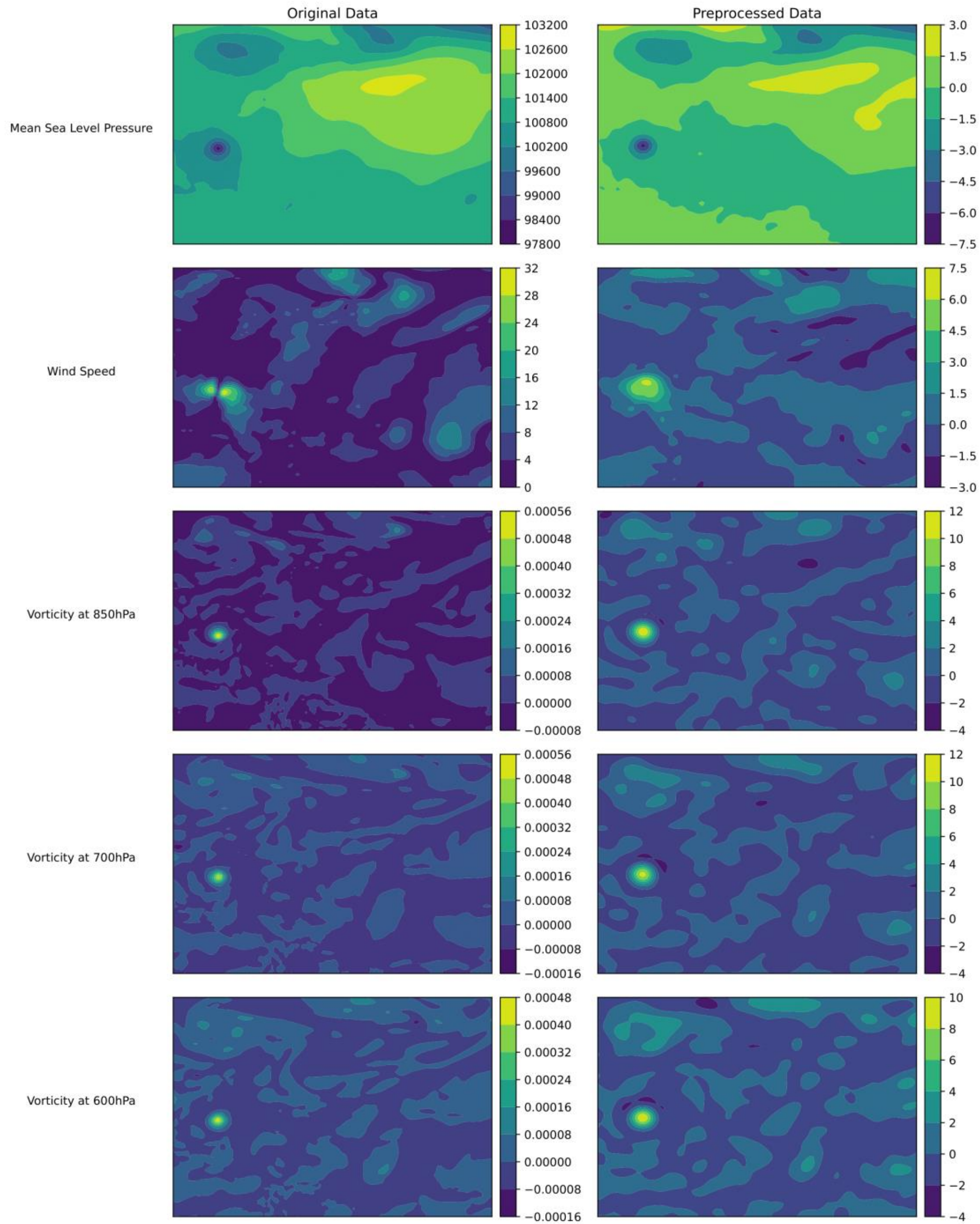


Detecting TCs with Deep Learning

Data

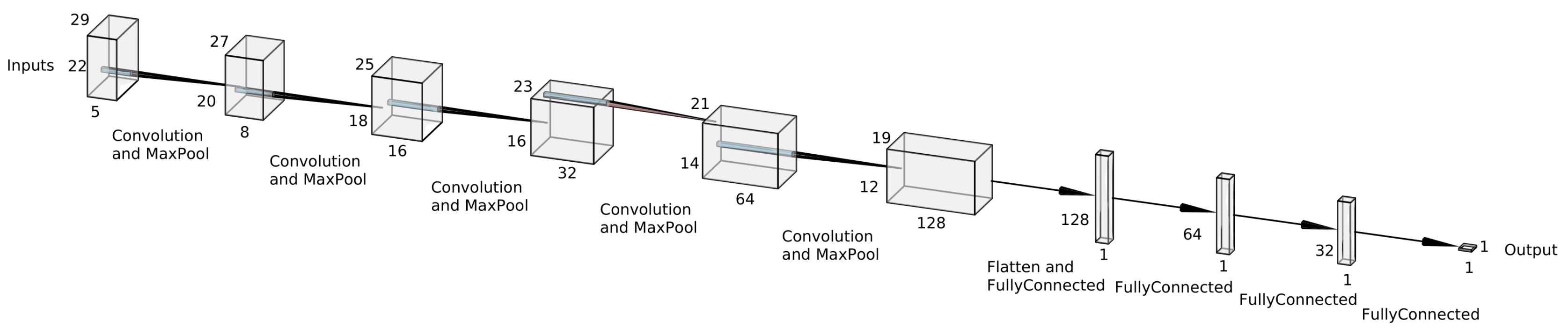
- ERA-Interim reanalyses dataset; each timestep split into 8 regions
- Fields used: 10m wind speed; MSLP; Vorticity at 850hPa, 700hPa, 600hPa at a resolution of 2.8º
- Labels obtained from the IBTrACS database
- Training Set: January 1979 – June 2017 (450912 cases)
- Testing Set: July 2017 – August 2019 (24352 cases)




Original Data
Preprocessed Data
Mean Sea Level Pressure
103200 102600 102000 101400 100800 100200 99600 99000 98400 97800
3.0 1.5 0.0 −1.5 −3.0 −4.5 −6.0 −7.5
Wind Speed
32 28 24 20 16 12 8 4 0
7.5 6.0 4.5 3.0 1.5 0.0 −1.5 −3.0
Vorticity at 850hPa
0.00056 0.00048 0.00040 0.00032 0.00024 0.00016 0.00008 0.00000 −0.00008
12 10 8 6 4 2 0 −2 −4
Vorticity at 700hPa
0.00056 0.00048 0.00040 0.00032 0.00024 0.00016 0.00008 0.00000 −0.00008 −0.00016
12 10 8 6 4 2 0 −2 −4
Vorticity at 600hPa
0.00048 0.00040 0.00032 0.00024 0.00016 0.00008 0.00000 −0.00008 −0.00016
10 8 6 4 2 0 −2 −4

Deep Learning Model: Architecture

- CNN-based classifier, termed TCDetect
- Convolutional Base: 5 blocks using 2D convolution, dropout, glorot uniform weight initialisation, ReLU activation function
- Classifier: 4-layer fully-connected network using dropout, glorot uniform weight initialisation, ReLU activation function, L2 normalisation
- Final layer uses a softmax function to output a single value



Deep Learning Model: Optimisations

- Choice of Data – Filtered Fields; 5 fields
- Early Stopping – 10 steps
- Normalisation - Standardisation
- Resolution - Sixteenth
- Dataset Balancing – Undersampling with replacement
- Loss Function – Binary Cross-Entropy
- Optimiser – Momentum
- Learning and Momentum Rates – 0.01 and 0.8
- Data Augmentation – Roll in x-direction; Random rotation; LR flip
- Dropout Position and Rate – Whole model, 10%
- L2 Position and Rate – Classifier; 0.5%
- Batch Size - 8

Results

- An accuracy of 90.65% was obtained when testing on data from July 2017 until August 2019
- 1231 out of 1342 (91.73%) positive cases were correctly classified

		Identified	
		TC Present	TC Not Present
Ground Truth	TC Present	1231	111
	TC Not Present	2166	20844

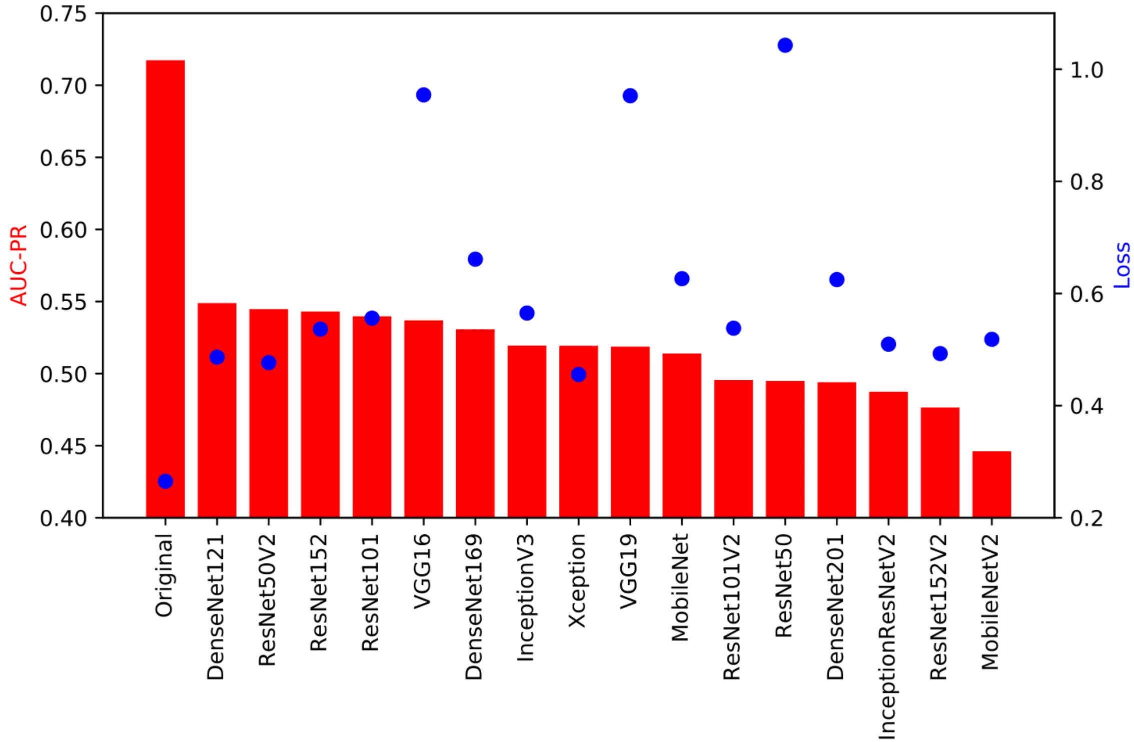
Results: TC Category

Category	Global Model
1	88.02%
2	91.53%
3	94.19%
4	94.64%
5	100.00%

- This upward trend of recall with category shows that TCs of higher categories are being identified better as they have features which are more easily identifiable

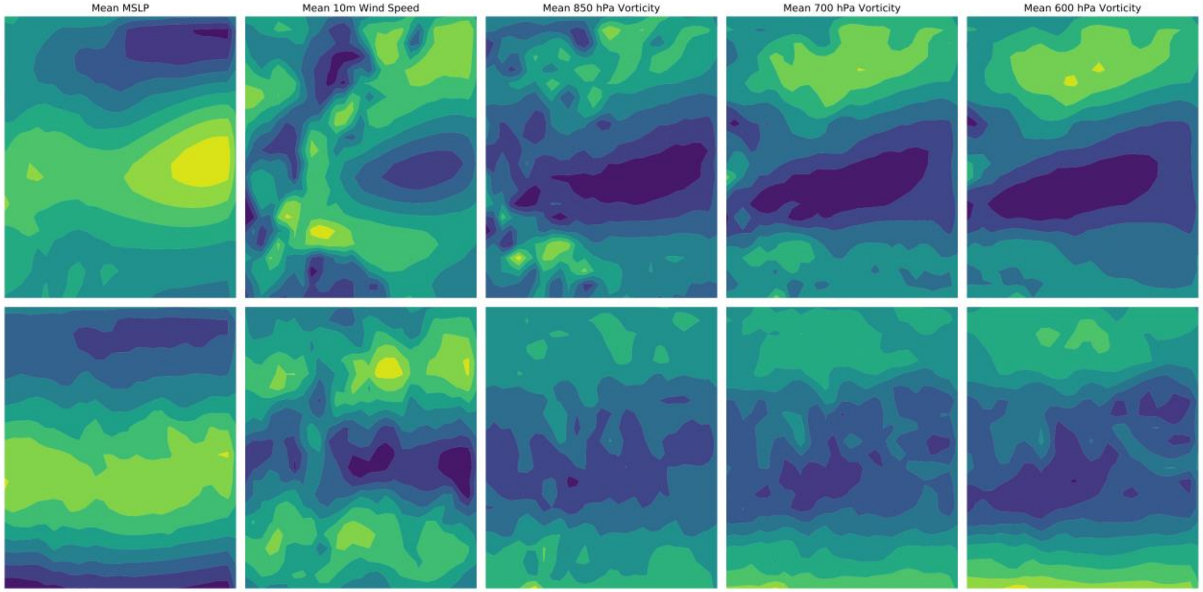
Results: Standard Models

- The model developed was compared with some standard models. It did not obtain the best accuracy, but did get the best loss



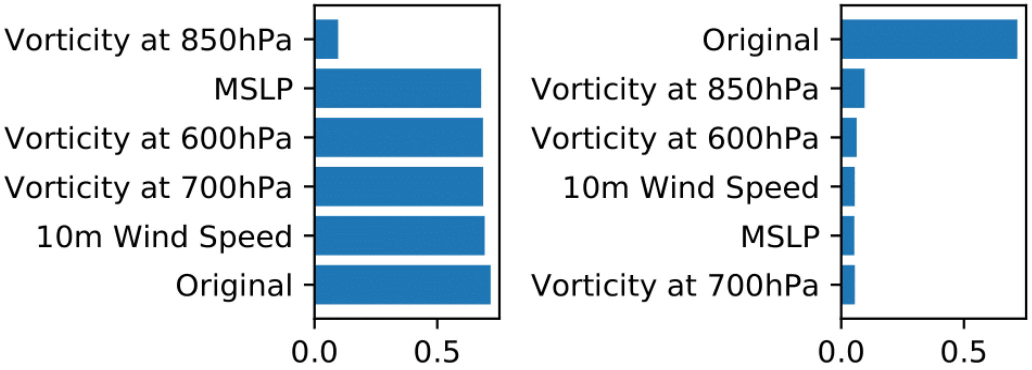
Results: Different Training Areas

Model	Training Region	Testing Region	AUC-PR
WAWP	WAWP	WAWP	0.7884
WAWP	WAWP	Global	0.6491
Global	Global	Global	0.7173

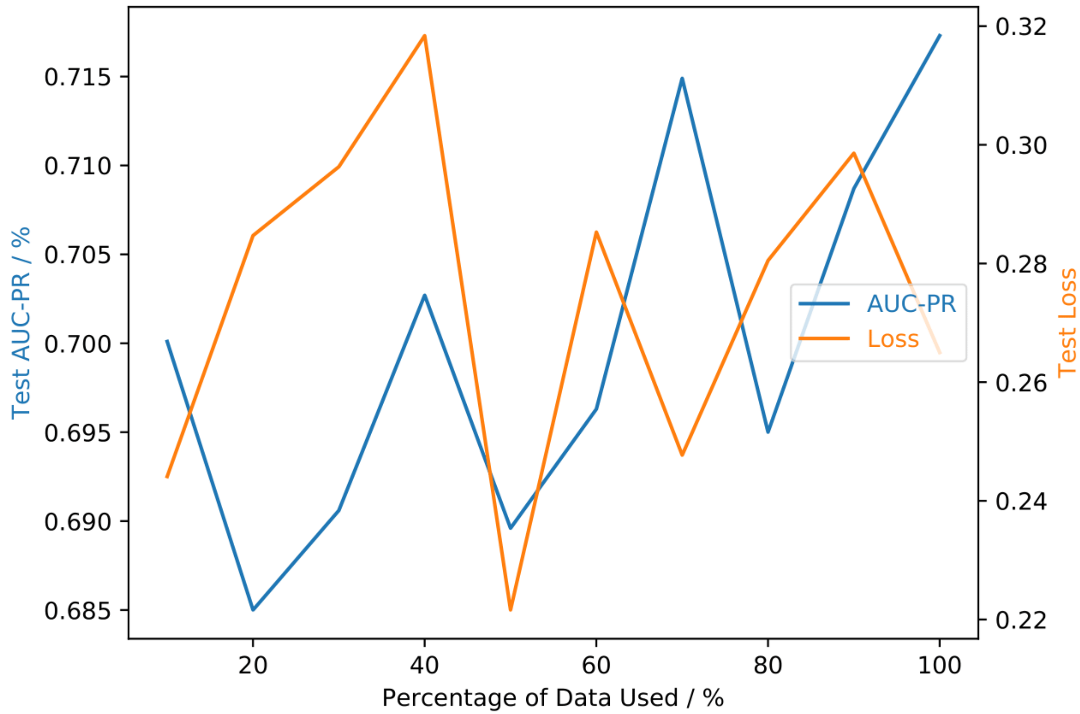


Results: Feature Importance

- Breiman Method:
  - Each field is permuted across all testing cases
  - If performance decreases from original, the field is important for the model
  - The larger the decrease, the more important the field
- Lakshamanan Method:
  - Each field is permuted across all testing cases
  - Most important is kept permuted, while the next important is found
  - Keep on going until all fields are permuted



Results: Dataset Size



Verification

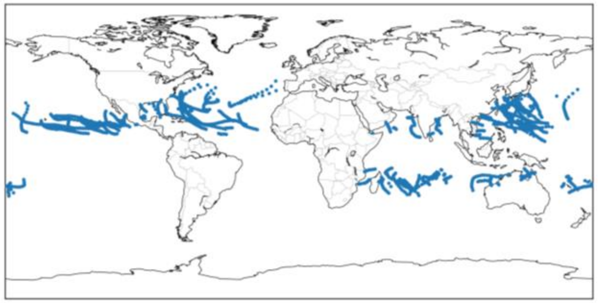
Verification:

- Compare outputs from DL model to an algorithm and observations
- Algorithm: TRACK by Dr Kevin Hodges
  - Uses vorticity and other fields to track all TCs
  - Outputs are tracks of TC centres (lats/lons)
  - We use only hurricane portion of track, T-TRACK
- Observations: IBTrACS
  - Positions of major storms including category on Saffir-Simpson scale

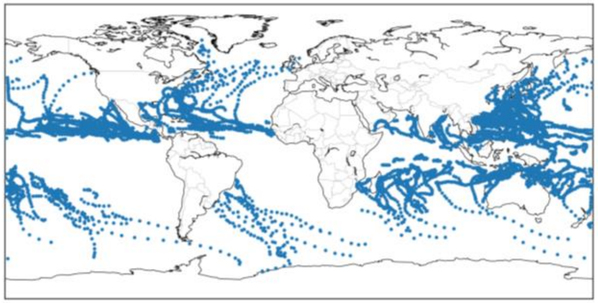
Verification: TC Centres

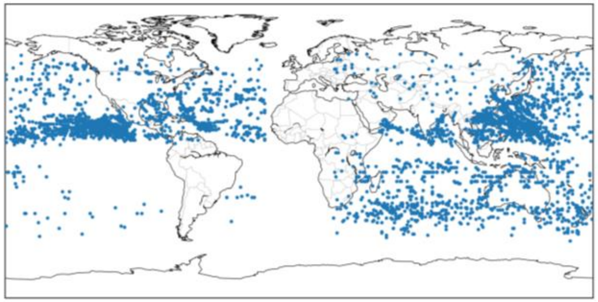
- Compare outputs from DL model to T-TRACK, observations

IBTrACS



T-TRACK

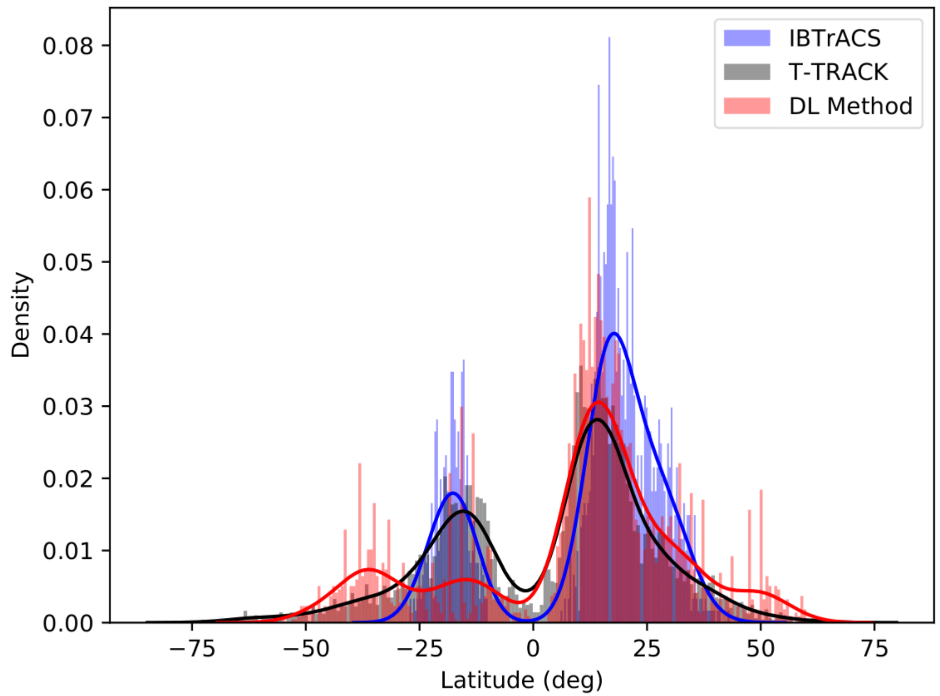




TCDetect

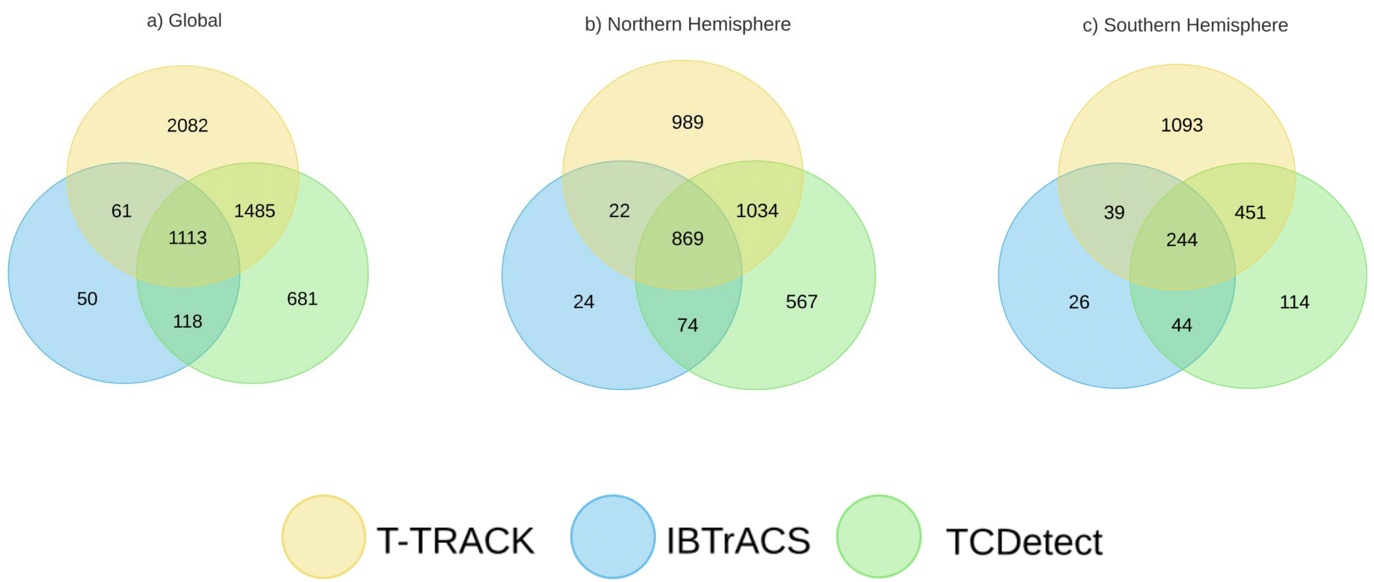
Verification: TC Centres

- Compare outputs from DL model to T-TRACK, observations

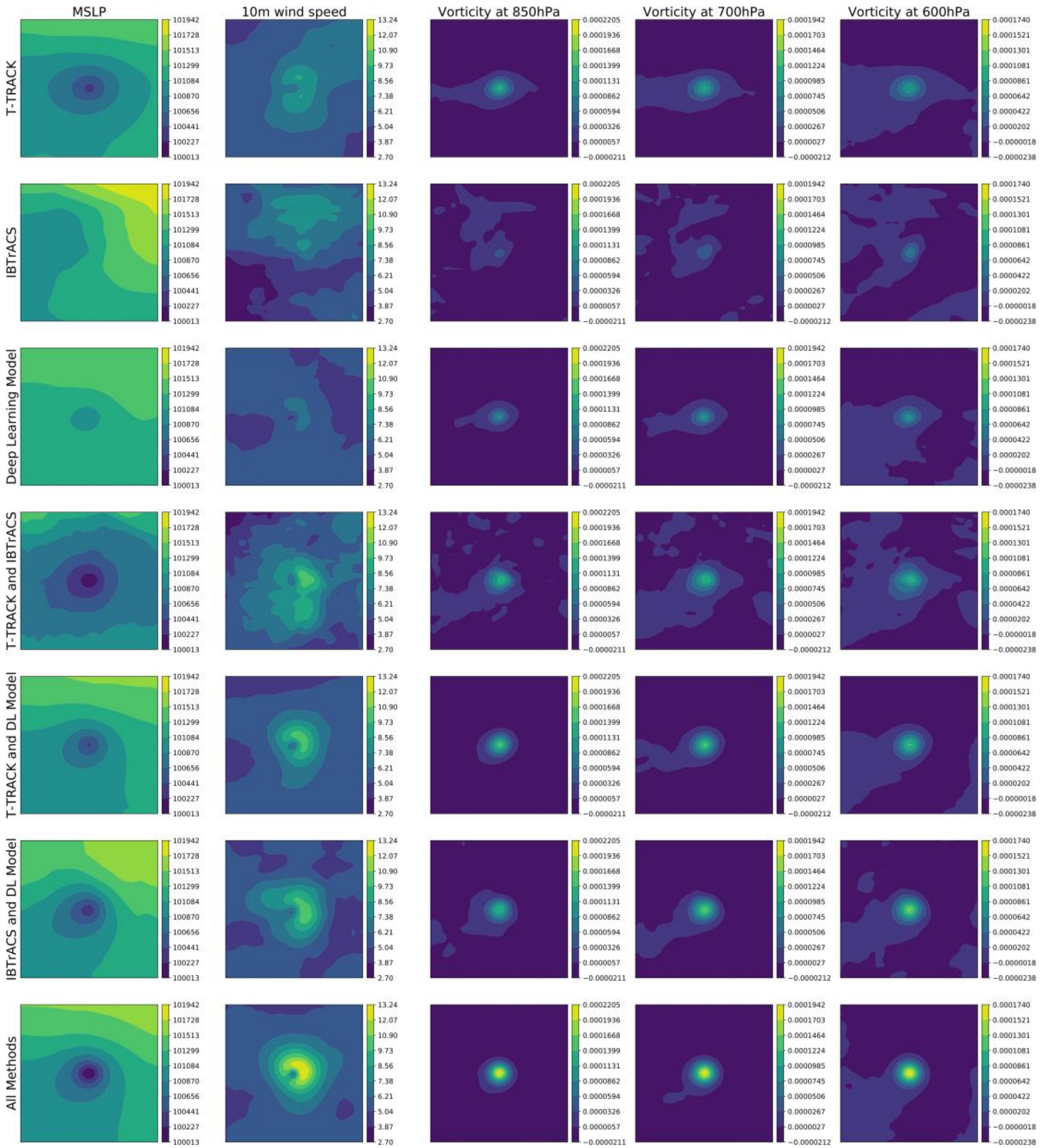


Verification: TC Matches

- Compare outputs from DL model to T-TRACK, observations



Verification: TC Matches



Verification: TC Matches

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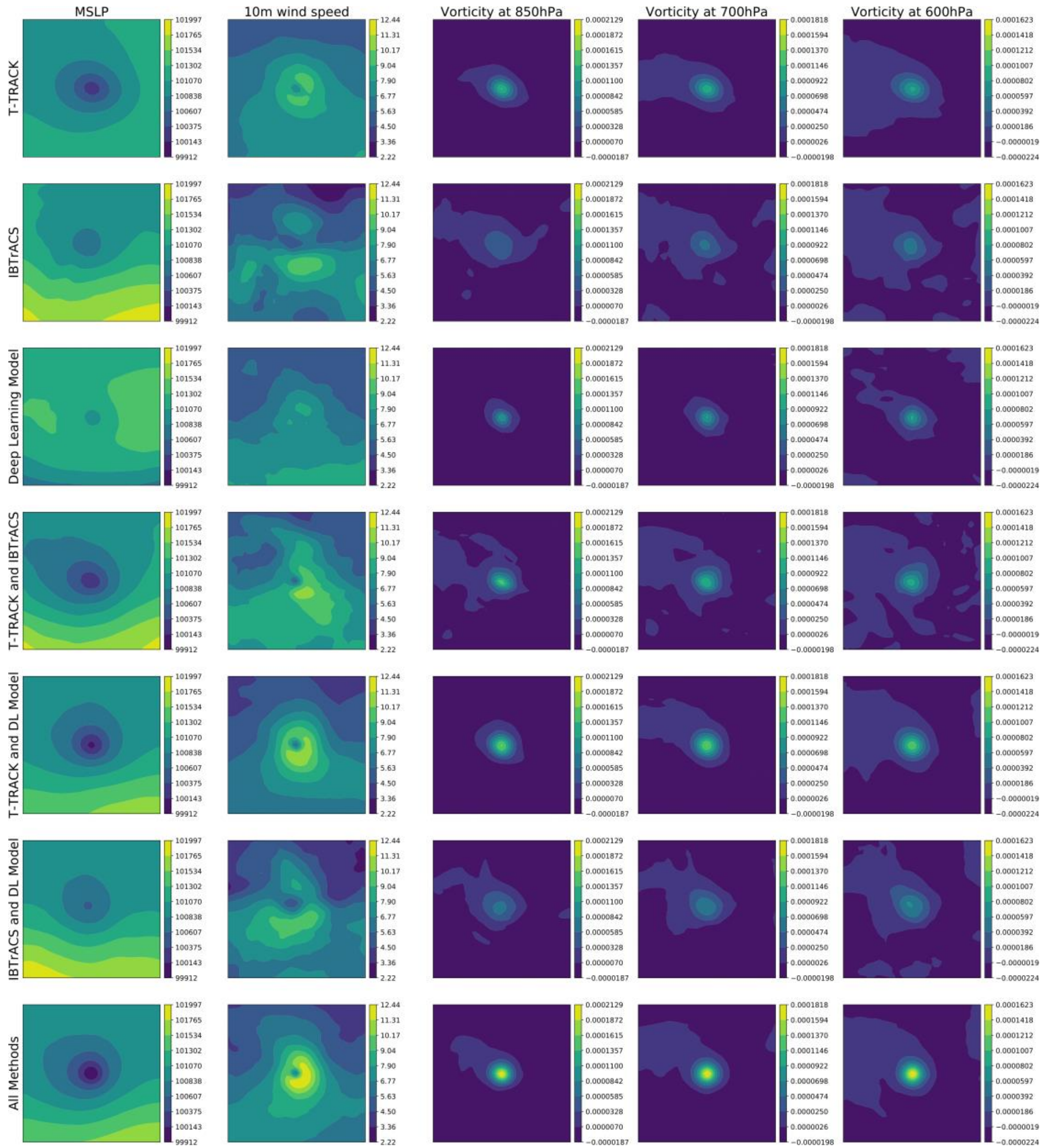
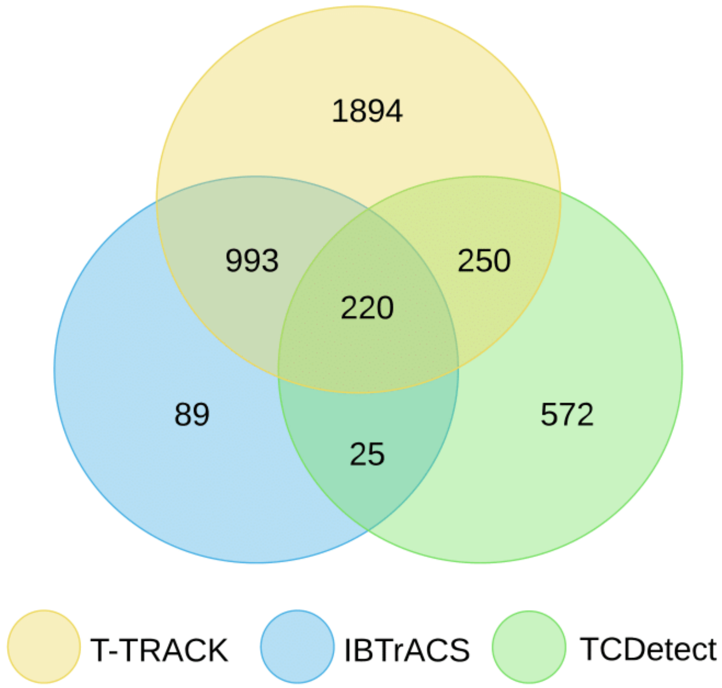
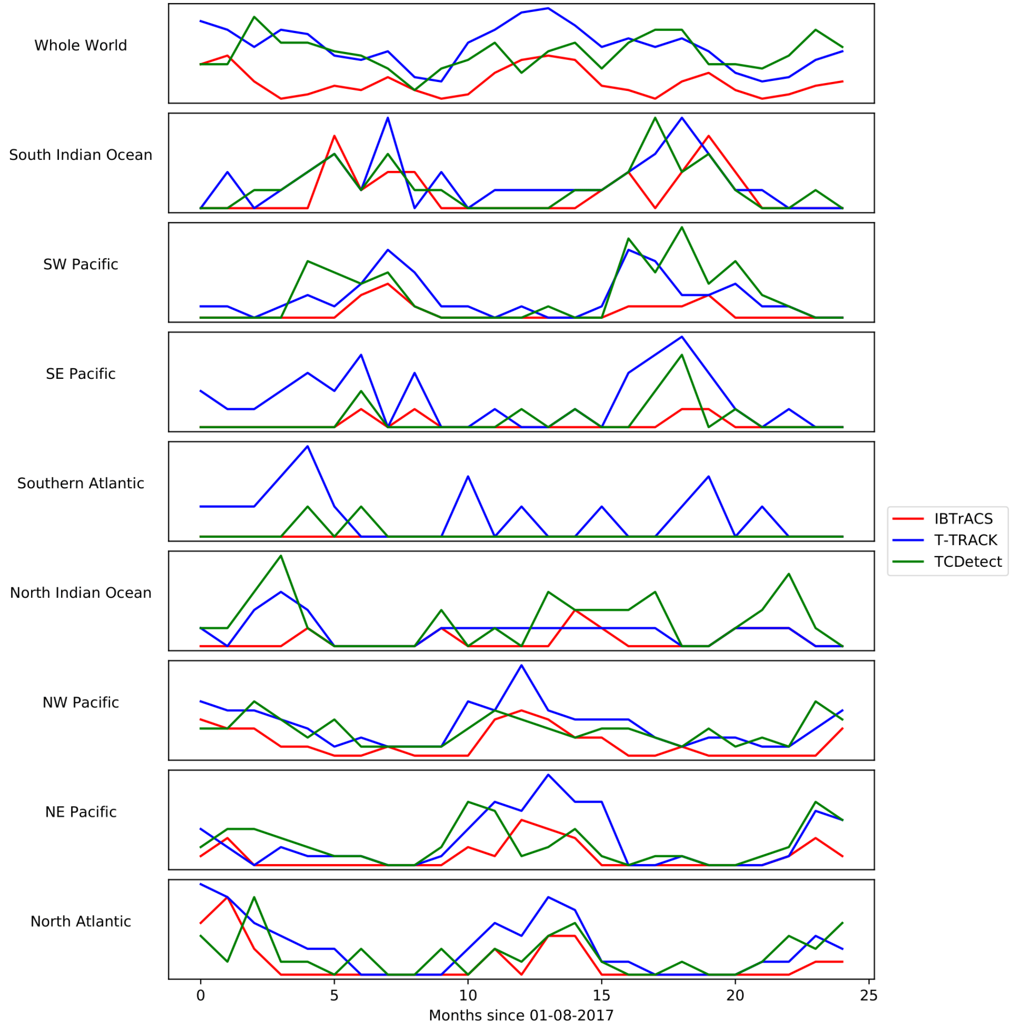


Verification: TC Track Matches

- Constraints:
  - mean separation distance between all overlapping points between tracks is less than 5 deg (geodesic)
  - tracks need to overlap for at least 10% of the base track's lifetime
  - the track with the least mean separation distance is chosen if multiple matching tracks exist



Verification: TC Frequencies

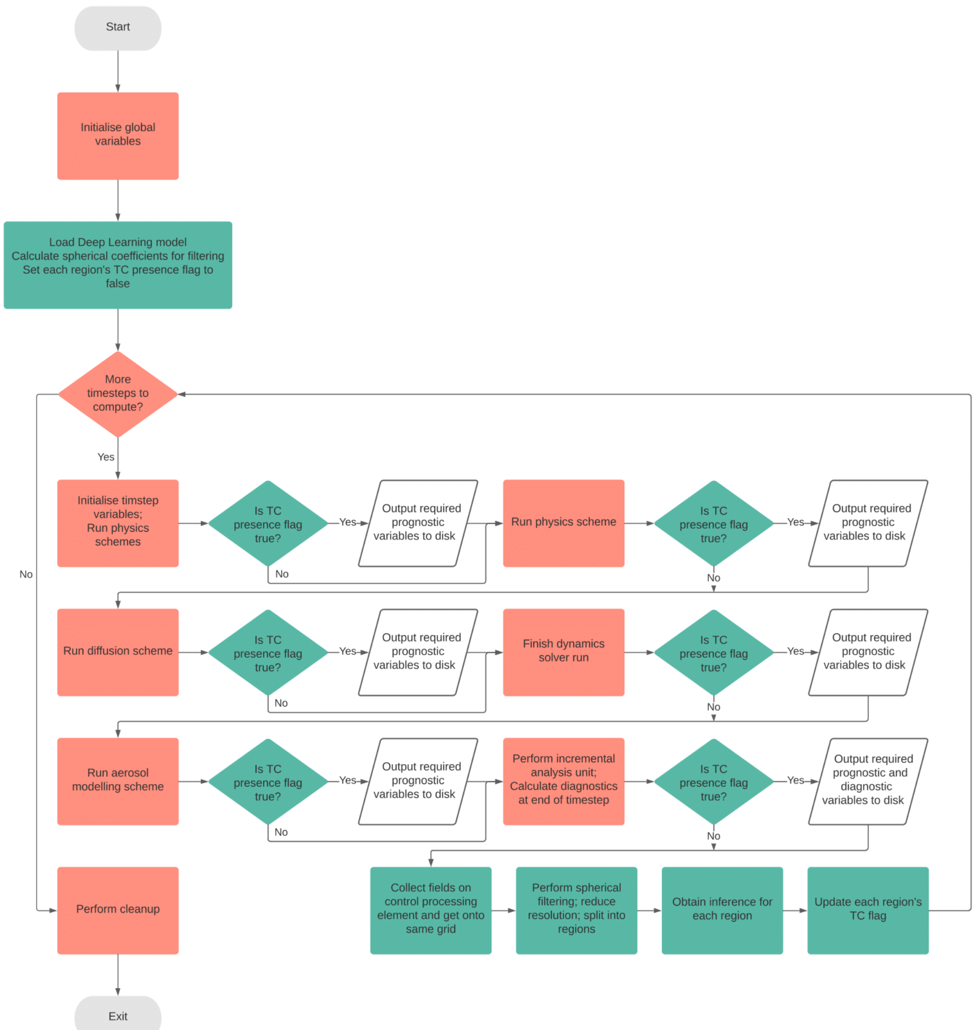


Implementation

Implementation

- TCDetect was trained in Python
- We wanted to have a climate model use it to decide whether to output data to disk
  - We chose the UK Met Office's Unified Model (UM)
  - This is based in FORTRAN
- We needed a way to use the Python-trained TCDetect in the FORTRAN-based UM
  - We use a C++ package, `frugally-deep`, to load and use TCDetect in FORTRAN

Implementation



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Results: Overview

- Wanted to check ability of TCDetect to be applied to different data sources, horizontal resolutions and climates
- Utilize 6 different datasets to run the following analysis:

Dataset	Labelling Method	Horizontal Resolution
ERA-Interim	IBTrACS	~79km
ERA-Interim	T-TRACK	~79km
UM N96	T-TRACK	~135km
UM N512	T-TRACK	~25km
Hist1950	T-TRACK	~25km
Future	T-TRACK	~25km

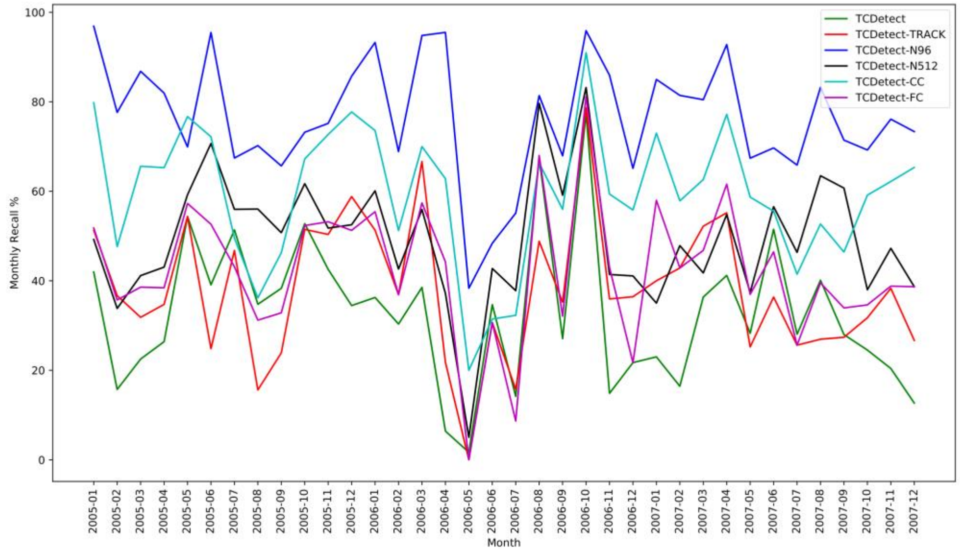
Results

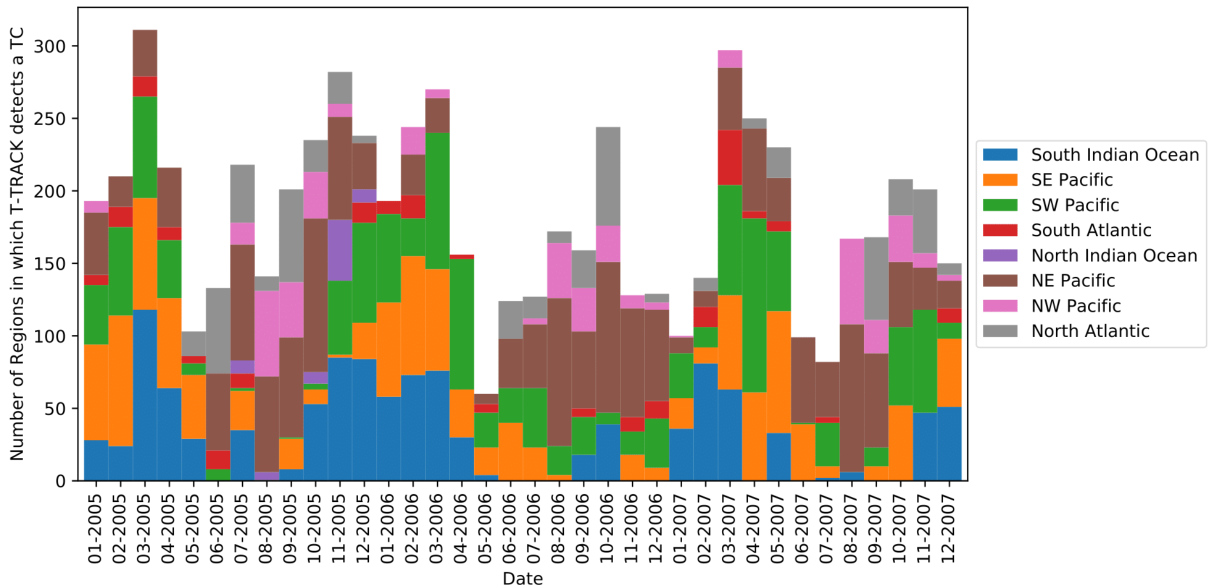
Data Source	Label Source	TCDetect	TCDetect -TRACK	TCDetect -N96	TCDetect -N512	TCDetect -CC	TCDetect -FC
ERAI	IBTrACS	92%	85%	97%	91%	93%	89%
ERAI	T-TRACK	59%	62%	76%	70%	73%	62%
UM N96	T-TRACK	34%	41%	78%	50%	62%	44%
UM N512	T-TRACK	58%	58%	71%	72%	77%	60%
Hist1950	T-TRACK	60%	58%	73%	73%	77%	64%
Future	T-TRACK	62%	62%	74%	74%	79%	66%

Results

- Model trained on the dataset being tested obtained superior recall to most others
- Different sources:
  - Models trained on UM data, except TCDetect-FC, obtain better recall than models trained on ERA-Interim data
- Different resolutions:
  - TCDetect-N96 performed better on N512 data. Not vice-versa
- Different climates:
  - All models are close when testing on the Hist1950 and Future datasets

Results: Variability





Implementation: Data Volume

	ERA-Interim			UM N96		UM N512	
	IBTrACS	T-TRACK	TCDetect	T-TRACK	TCDetect	T-TRACK	TCDetect
NI	72 (2%)	277 (9%)	239 (8%)	74 (2%)	105 (2%)	157 (11%)	197 (14%)
NWP	400 (13%)	1222 (40%)	933 (31%)	1674 (39%)	2617 (61%)	956 (67%)	920 (64%)
NEP	267 (9%)	712 (23%)	875 (29%)	442 (11%)	689 (16%)	524 (37%)	714 (50%)
NA	250 (8%)	703 (23%)	497 (16%)	559 (13%)	999 (23%)	431 (30%)	683 (48%)
SI	214 (7%)	646 (21%)	406 (13%)	913 (31%)	1596 (37%)	234 (16%)	552 (38%)
SWP	113 (4%)	740 (24%)	399 (13%)	874 (20%)	1436 (33%)	154 (11%)	374 (26%)
SEP	26 (1%)	322 (11%)	35 (1%)	1096 (25%)	1945 (45%)	149 (10%)	370 (26%)
SA	0 (0%)	119 (4%)	119 (4%)	167 (4%)	362 (8%)	28 (2%)	97 (7%)

Implementation: Computational Performance

Function	Times Applied	N96 Timings / sec	N512 Timings / sec
Collect data	1	4.64 $\times 10^{-4}$	2.99$\times 10^{-3}$
Interpolate MSLP	1	3.15 $\times 10^{-4}$	0.35
Resize field	5	9.1$\times 10^{-3}$	3.67$\times 10^{-2}$
Calculate Vorticity	3	1.16 $\times 10^{-3}$	2.28$\times 10^{-3}$
Spherical filtering	5	0.68	1.36
Standardisation	5	4.13 $\times 10^{-5}$	6.64$\times 10^{-5}$
Data formatting	8	1.63$\times 10^{-5}$	3.66 $\times 10^{-5}$
DL inference	8	0.19	0.37
Full Method		4.96	10.22
Full Timestep		6.15	15.64
Full Simulation		23%	5%

Summary

Summary

- Data volumes from GCMs is large; we want to reduce it
- We have developed a DL algorithm that infers the presence of a Tropical Cyclone in a set of data
- It achieves a recall rate of 91% over the test dataset
- This was compared to a SOTA non-ML algorithm and was found to be mostly comparable in performance
- The DL algorithm was used in a running GCM (the UM) to decide whether to output data from a region to disk
  - Data volume was reduced by ~70%
  - The DL algorithm does not affect the GCM runtime too much

Possible Future Work

- Better DL model
- Change filtering techniques to be done inside DL model; hopefully producing computationally less expensive method
- Replicate method for other phenomena

Acknowledgements

- This work was supported by NVIDIA and Oracle
- It was funded by Natural Environment Research Council (NERC) as part of the UK Government Department for Business, Energy and Industrial Strategy (BEIS) National Productivity Investment Fund (NPIF), grant number NE/R008868/1
- UM work was aided by members of the NCAS-CMS team