Artificial Neural Networks in Climate Science: Applications for Typhoon Modelling

8 January 2024

Samuel H. Baxter

MSc Climate Change, University College London

Grade: Distinction

Plain Language Summary:

This article reviews the applications of artificial neural networks (ANNs) in climate science, with a focus on typhoon modelling. ANNs are computational models that can learn complex and nonlinear relationships from data, inspired by the structure and function of biological neurons. The article discusses the history, types, and advantages of ANNs, as well as the challenges and limitations they face, such as the black box problem, data quality, and optimal network architecture. The article also presents a critical analysis of various studies that have used ANNs for different aspects of typhoon modelling, such as storm track, intensity, precipitation, and surge prediction. The article shows that ANNs can outperform traditional methods in terms of accuracy, speed, and robustness, but also require significant computing power, data, and validation. The article proposes a hybrid model framework that combines statistical methods and ANNs to exploit the strengths of both approaches and improve the transparency and validity of the model with specific reference to storm track prediction. The article concludes that ANNs are a valuable tool for climate science and typhoon forecasting, but also need further research and development to overcome their challenges and increase their utility.

1 Introduction

The artificial neural network (ANN) offers a transformative approach to data analysis, prediction, and classification. The wide literature provides many studies utilising ANNs for various environmental problems (Hsieh 2009, Gardner & Dorling 1998). However, disagreement remains between the superiority of traditional methods, such as statistical, numerical, and mechanistic methods, compared to ANNs. This review presents a critical discussion of ANNs in climate science, concentrating on typhoon modelling, and focuses on the foundational aspects of ANNs (activation functions, network topologies, and hidden layers) for a bottom-up approach. A framework for a hybrid model is also proposed by combining the strengths of both traditional and ANN methods.

2 Artificial Neural Networks

2.1 *A Brief History*

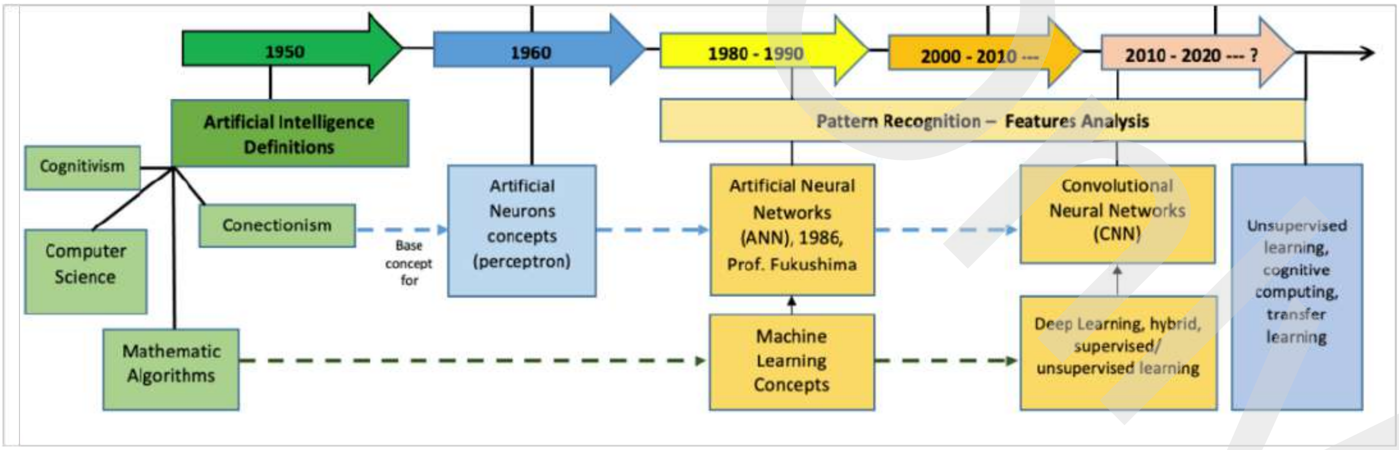

Figure 1: A simple timeline of ANN development (Castillo et al. 2021).

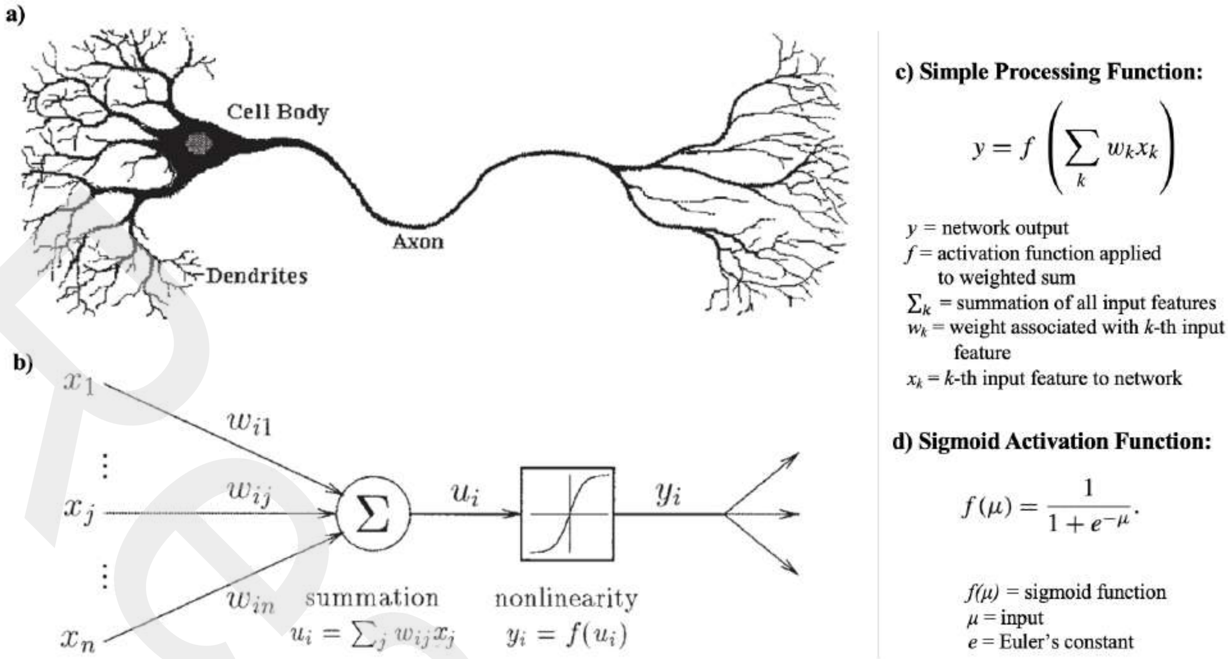

Figure 2: Adapted from (Reed & MarksII 1999). a) biological neuron in line with b) an ANN. c) simple network function (denoted as y_i). d) sigmoid function.

The first artificial neuron was proposed in the 1940s by McCulloch & Pitts (1943), inspired by the biological neuron and its unique decision-making matrix. Concepts for ANNs first emerged in the 1950s (see Figure 2) with the perceptron by translating biological operation into statistical function (Rosenblatt 1958), laying the foundation for the neural network. After a stale period, progress was revived in the 1980s by Rumelhart (1980) and Hopfield (1982) with developments in algorithmic computational learning, information retrieval, and organisation. The creation of feedback and backpropagation networks further contributed to the creation of the multi-layer perceptron (MLP), self-organising map, and Boltzmann machines, with the 1990s experiencing a maturation for ANNs (Fradkov 2020). Networks began to incorporate activation functions (see Figure 3), which mathematically transform inputs to outputs (Sharma et al. 2017), refined previous network models, and introduced further models, such as deep learning and the convolutional neural network (Hsieh 2022).

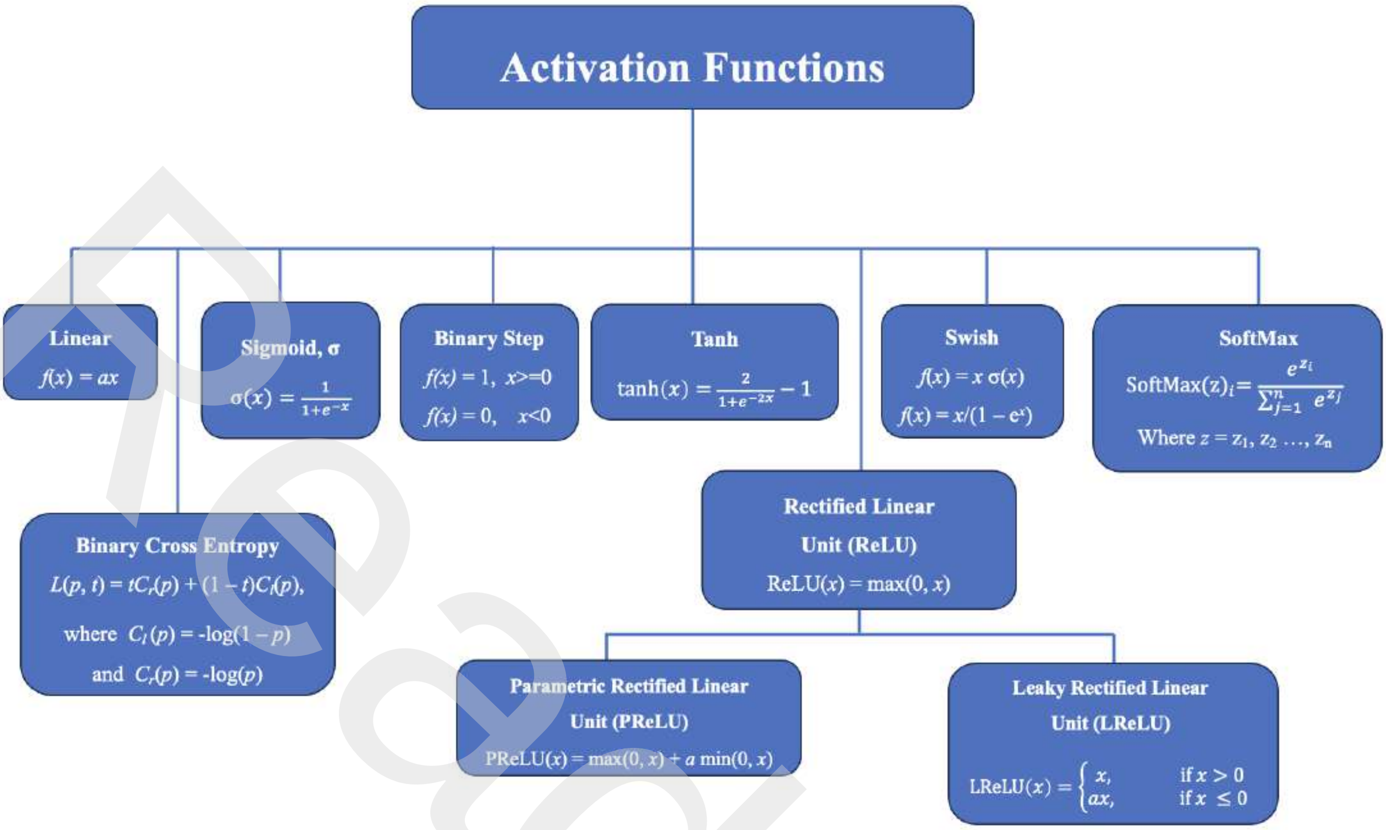

Figure 3: Common activation functions for neural networks (Sharma et al. 2017, Parhi & Nowak 2020, Asadi & Jiang 2020, Almurieb & Bhaya 2020, Ruby & Yendapalli 2020, Hurtik et al. 2022).

2.2 *Activation Functions, Network Layers, and Network Topology*

The following section provides a brief explanation of the fundamental aspects of the ANN. A basic ANN contains an input layer, hidden layer, and output layer (see Figure 4), although some ANNs may have multiple or no hidden layers (Dongare et al. 2012). The input layer variables (features) into the hidden layer, which perform unobservable computational transformations; hidden node outputs are decided upon their performance and usefulness for the final output layer (Uzair & Jamil 2020). Common network topologies are based on feed-forward and recurrent networks (see Figure 5). Feed-forward networks pass information in one direction (input to output), whereas recurrent networks have feedback connections, allowing information to flow in both directions (Fourati & Chtourou 2007). The interaction, number of network layers, hidden

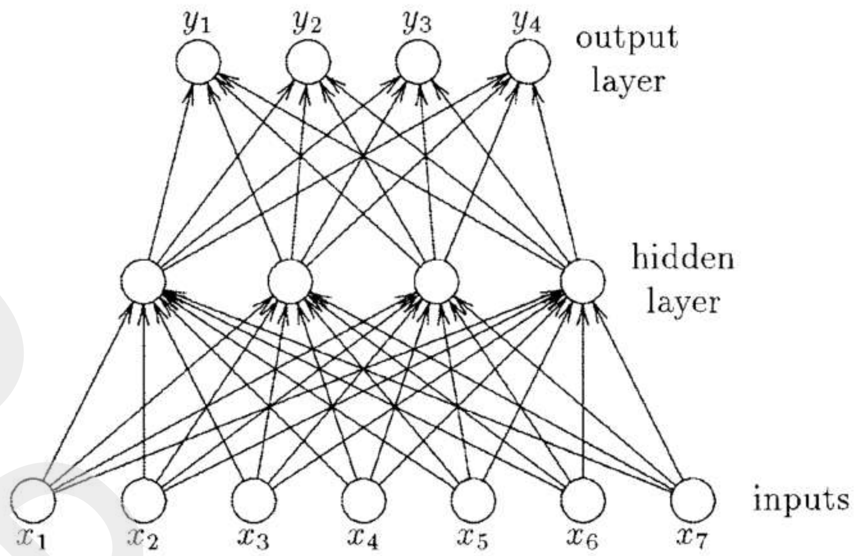

Figure 4: A basic feedforward ANN (Reed & MarksII 1999).

layers, nodes per layer, and their interconnectedness (or lack of) play a major role in determining a network's ability to generalise (Fiszelew et al. 2007). The activation function (AF) is essential to the performance of an ANN regarding the usefulness of node output. Features are inputted into a node, and the performance of node output is set against a mathematical threshold (Parhi & Nowak 2020). The functions available are indeed substantial, especially functions with slight variations, such as ReLU, PReLU, and LReLU (Sharma et al. 2017).

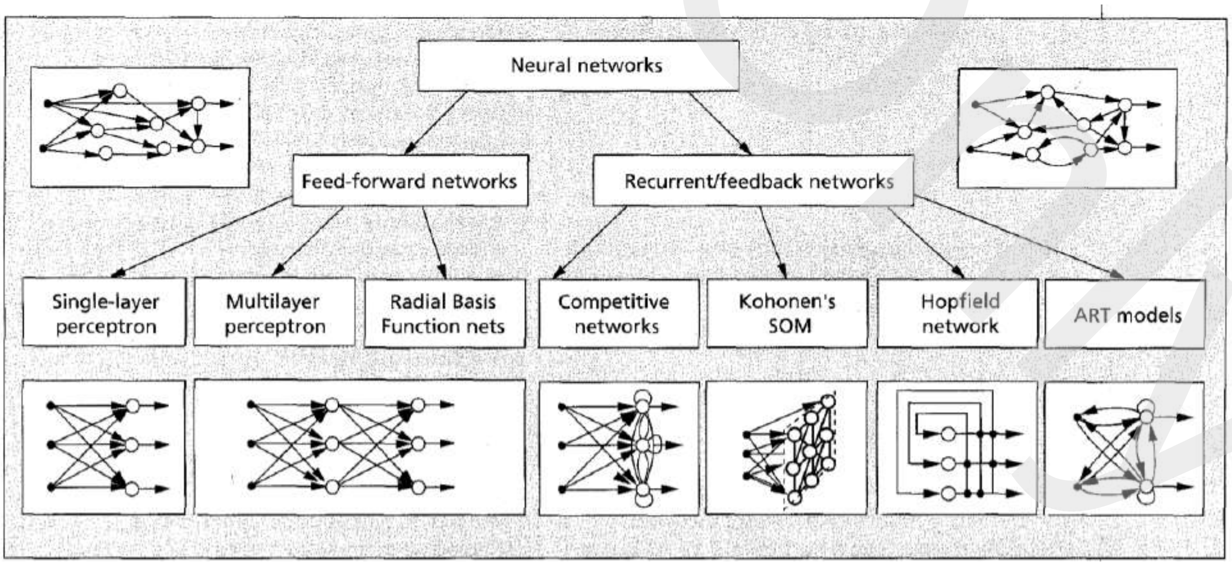

Figure 5: Many neural networks are based off the feed-forward and recurrent models (Jain et al. 1996).

2.3 *Adoption in Environmental Sciences*

Hsieh (2009) provides a comprehensive review on the substantial adoption of ANNs in environmental science, from remote sensing to ecology, and for information extraction, relevant feature retrieval, data classification, and nonlinear prediction. ANNs in environmental science have shown considerable success by expressing characteristics such as high accuracy, robustness, and speed, consistently outperforming traditional statistical (Hilbert & Ostendorf 2001) and numerical (Hashemi & Sepaskhah 2020) methods. However, the review by Haupt et al. (2022) explains ANNs are limited by their tendency to overfit and "black box" nature – where the logic of the network is hidden from observation – which hinders their transparency and can favour traditional techniques, such as general linear models (Özesmi et al. 2006).

2.4 *Neural Networks in Climate Science*

ANNs also demonstrate both a popularity and superior performance compared to traditional methods (see Figure 6) in climate science. Gardner & Dorling (1998) provide an explicit review of the MLP (see Figure 7), ranging from atmospheric prediction (surface ozone; wind speed) to classification (cloud types; convergence lines). The MLP outperformed traditional statistical and mechanistic models, especially in complex, nonlinear problems. However, the MLP was, again, limited by its "black box" nature of hidden layers, hindering its usefulness when assessing the underlying relationship between input features, and its tendency to overfit, reducing its ability to generalise on unseen data.

Author	Research Area	ANN Type	Activation Function	Problem Type	Result Summary
Mekanik *et al.* (2013)	Hydrology	MLP	Sigmoid	Prediction	ANN's ability to generalise spatial precipitation and its associated output error was lower than multiple regression.
Liu *et al.* (2016)	Atmospheric Science	CNN	RELU	Classification	CNN achieved an 89-99% accuracy detecting spatial tropical cyclones, atmospheric rivers, and weather front extreme events.
Hilbert and Ostendorf (2001)	Ecology	Feed-forward	Logistic	Classification	ANN produced higher accuracy than the generalised additive model for predicting variable vegetation distribution across different climates.
Franz *et al.* (2018)	Oceanography	CNN	ReLU	Classification	CNN argued to be more objective and robust in classifying eddy currents compared to the Okubo-Weiss dynamical model.
Sellevold and Vizcaino (2021)	Glaciology	Feed-forward	ReLU	Prediction	ANN produced similar outputs (RMSE 4.7-16.1%) compared to a regional climate model and global climate model for predicting ice sheet surface melt.
Mitsui and Boers (2022)	Palaeo-climatology	RNN	Tanh	Prediction	ANN holds higher precision when predicting key features of glacial-interglacial cycle dynamics (timing; intensity) with training data than low-dimensional glacial-cycle models (PP04; II80; SM90).

Figure 6: Compilation of various studies across different environmental fields which use ANNs as the primary tool.

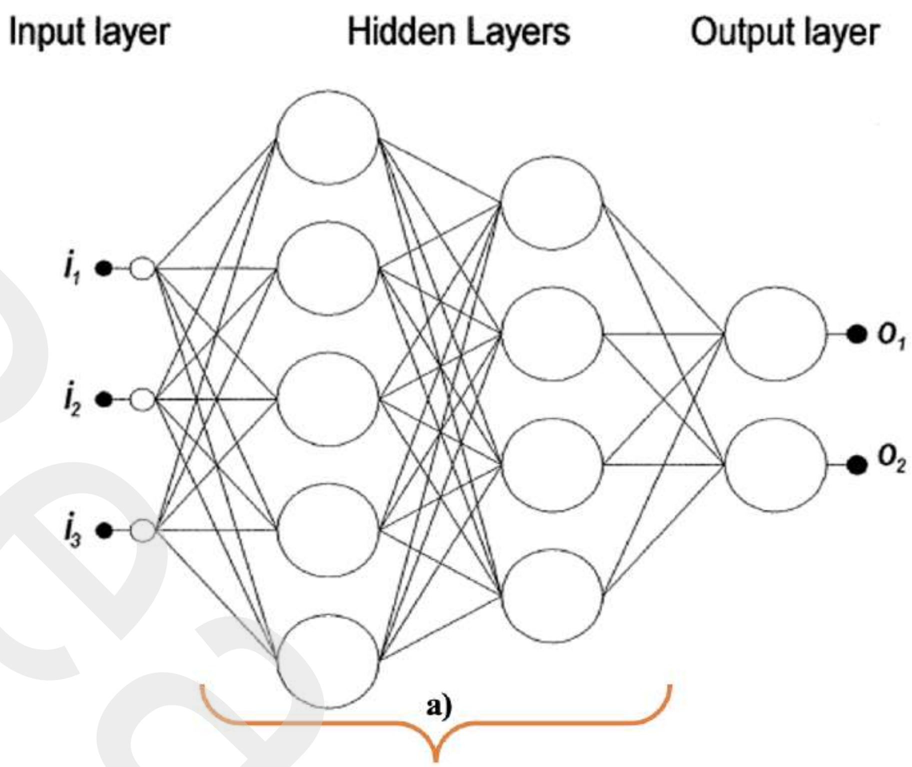

Figure 7: The Multilayer Perceptron (MLP) model structure (Gardner & Dorling 1998). a) represents the hidden layers, where the black box nature does not allow observation. The MLP contains multiple hidden layers, which can strengthen learning of complex relationships in nonlinear problems (Wagarachchi & Karunananda 2013).

3 Artificial Neural Networks for Typhoon Modelling

3.1 *Climate Change and Typhoons*

The influence of anthropogenic forcing and consequent climate change is causing changes in typhoon frequency and intensity (Seneviratne et al. 2021). Lee et al. (2020) and Różyński et al. (2009) present evidence of exacerbated extreme typhoons, such as those over 120 knots, due to anthropogenic forcing. Future projections by Cha et al. (2020) show increases in typhoon intensity and precipitation (5% and 17%, respectively), but a 10% decrease in frequency, possibly due to warming of north-western Pacific low latitudes and central Pacific Sea surfaces (Mei et al. 2015). Furthermore, Cha et al. (2020) suggests that typhoons are not only intensifying, but also shifting poleward or eastward in the North-West Pacific Ocean, potentially impacting communities that have never experienced typhoons before. Typhoons across coastal China cause approximately US$ 1.6 billion in economic losses per year (Elliott et al. 2015), and forecasts predict 2.5% increase in future economic losses from typhoons in the Philippines (Strobl 2019). Typhoons also impact the environment with extensive salt intrusion and consequent insland salinisation (Wang et al. 2016), and can adversely influence feeding habits of local mammals, such as the Japanese macaque *(Macaca fuscata)* after Typhoon Meari in 2004 (Tsuji & Takatsuki 2008). The speed and accuracy of typhoon models is therefore vital for event warning and impact reduction, and the incorporation of ANNs have shown to be an effective tool.

3.2 *Discussion*

The literature provides satisfactory coverage of studies incorporating ANNs in typhoon modelling (see Figure 8). Firstly, there is a strong theme of ANNs consistently outperforming traditional methods including dynamical, numerical, and statistical models. In Young et al. (2017), the ANN outperforms physically-based models for storm surge modelling by correctly weighting parameters to reduce unnatural skews in the data (Krenker et al. 2011), reducing output uncertainty, alongside the ability to capture both spatial and temporal variability in precipitation. In Chao et al. (2020), the empirical, hydrodynamic, and process-based models are outperformed in terms of accuracy and efficiency, especially regarding long lead-time predictions. Lee (2009) notes that the numerical Finite Volume Method (FVM), based on the Navier-Stokes equation, holds lower precision compared to an ANN when the typhoon is not directly approaching the coastline.

Author	Geographical Focus	Typhoon Forecast Focus	Artificial Neural Network Topology	Results
Tseng *et al.* (2007)	South-west Taiwan	Storm surge	Feed-forward	Model D used 18 input factors and forecasted with the highest General Evaluation Index and coefficient of efficiency.
Lin and Chen (2005)	Northern Taiwan	Precipitation	Feed-forward	ANN1 using typhoon characteristics as inputs, and ANN2 using both typhoon characteristics and optimal spatial rainfall information. ANN2 found to have lower Root Mean Square Error (RMSE) for both typhoon testing events.
Young *et al.* (2017)	Southern Taiwan	Precipitation runoff	Backpropagation	ANN applied to predict hourly runoff discharges during seven typhoon events, and was able to predict precipitation one hour ahead with good accuracy.
Chao *et al.* (2020)	Northeastern Taiwan	Storm surge	Backpropagation	ANN for storm prediction achieved high accuracy for one-hour predictions (RMSE < 10cm), and can be accurately extended to 12-hour prediction (RMSE < 15cm).
Park *et al.* (2022)	South Korea	Storm surge	Convolutional	The convolutional ANN was used to predict tide levels and storm surge. Produced an accurate prediction with absolute relative error of less than 5% for all five locations.
Lee (2009)	Taiwan	Storm surge	Backpropagation	For storm surge prediction, the ANN predicts with higher accuracy (average RMSE 0.238m across all stations), outperforming the numerical model also used.
Lin and Wu (2009)	Northern Taiwan	Precipitation	Self-organising map & MLP	The combined ANN predicts with high accuracy forecasting (average RMSE 3.454mm across all study locations) and provides reasonable prediction for extreme typhoon.
Gao *et al.* (2018)	North China	Storm track	LSTM	The LSTM AANN can provide 6-24 hour forecasts with reasonable accuracy, but fails to contain a low error with forecasts 24-72 hours long compared to empirical and numerical models (average errors for 24-72 hour forecasts: 470.9km, 145.1km, 196.1km, respectively).
Hong *et al.* (2017)	North-West Pacific Ocean	Storm track	Convolutional	Compares simple convolutional ANN with complex CNN for typhoon eye tracking. Complex CNN with an ELU/Tanh activation achieved best prediction (RMSE 74.53km circle distance), compared to the worst performing CNN with ReLU/sigmoid activation (RMSE 362.91km).

Figure 8: Compilation of various studies across different typhoon aspects which use ANNs as their primary tool.

A CNN (see Figure 9) uses convolution operations, the merging of datasets, to extract significant features from images (Ketkar et al. 2021). The CNN is highly applicable to geospatial object detection due to its ability to produce multi-feature maps and handle imbalances regarding classification and localisation, whilst applying the ANN to learn nonlinear feature relationships (Guo et al. 2018). Park et al. (2022) and Hong et al. (2017) present evidence that CNNs are especially effective at typhoon storm track prediction by using satellite data alongside physical parameters. Statistical methods could not account for the spatial variability of storm surges (local bathymetry; coastline features), and empirical models were unable to provide timely forecasts for rapidly-developing typhoons.

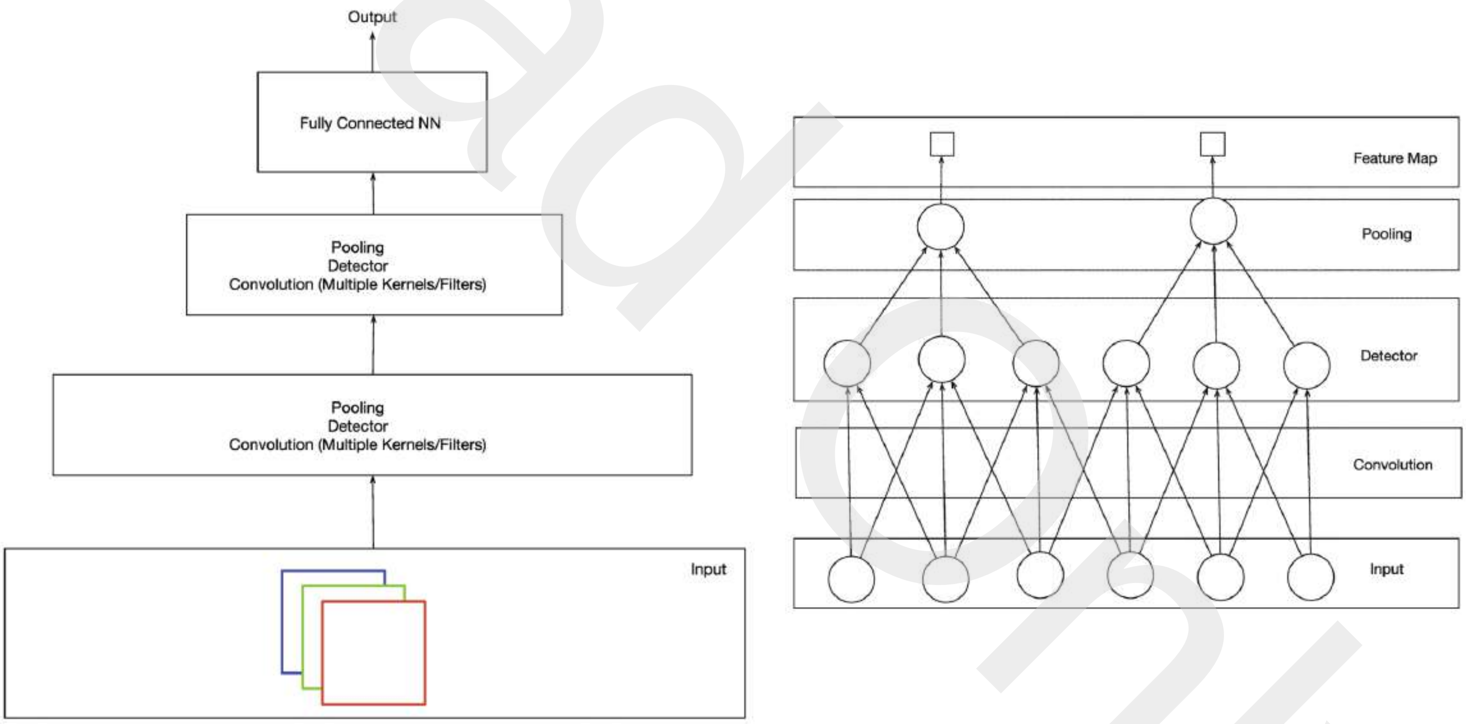

Figure 9: Left: A complete CNN framework, where multiple CNNs are used. Convolutions extract significant features from images to increase performance.
Right: One CNN network (Ketkar et al. 2021).

The performance of the long-short term memory ANN (LANN) is contested. In Gao et al. (2018), empirical and numerical models outperformed the LANN for typhoon storm track forecasts longer than 24 hours, suggesting the LANN is only suited for short forecasts.

Furthermore, Wei (2020) suggests numerical models are more consistent in weather forecasts than LANNs. However, Cha et al. (2020) forecasted temperature using both image and numerical data, and the LANN outperformed all three numerical models provided by the Korean Meteorological Agency with lower bias and model error. This suggests that LANNs may not be suitable for multi-feature prediction.

There is inconsistency in the studies in Figure 9 regarding computational speed and computational cost. Chao et al. (2020) compared the efficiency of a backpropagation ANN to a hydrodynamic model and determined the ANN was faster and required less data whilst maintaining a higher robustness in model output. In Hong et al. (2017), the CNN was described as being less computationally-intense compared to large numerical weather prediction models whilst producing accurate results. Jain & Deo (2006) explain that ANNs speed up calculations by parameterising nonlinear relationships and providing simpler alternatives to complex numerical models, thus decreasing computational load. Conversely, the emphasis of computational cost of using ANNs (Lin & Chen 2005, Gao et al. 2018, Hong et al. 2017) may originate from the fact that the ANNs are able to run at high speeds due to stronger hardware. This is difficult to validate in the study comparison as only Gao et al. (2018) explicitly details the hardware used; a 2.6 GHz central processing unit (CPU) and a NVIDIA Tesla 12GB graphics processing unit (GPU). However, when looking to the wider literature, ANNs do indeed require significant computing power, particularly during the training phase (Wang et al. 2014), but parallel computing, where calculations are computed simultaneously, can considerably increase overall computational efficiency for training and testing (Topping et al. 1998).

In addition, the selection of backpropagation as a learning method is popular in typhoon modelling. Backpropagation ANNs offer the ability to model complex relationships in nonlinear systems (Goh 1995) with easy implementation (Rumelhart et al. 1995). In Lin & Chen

(2005), backpropagation with spatial data effectively lowered RMSE for typhoon precipitation. However, these studies also experienced a range of challenges regarding the application of ANNs (see Figure 10), most commonly concerning the black box problem, data quality, and determining optimal network architecture.

Firstly, the black box problem, where the reasoning for network logic and output is hidden from observation (Benítez et al. 1997), is mentioned most. The black box presents a lack of interpretability, such as evaluating casual relationships between input features (Wieland et al. 2002), lack of trust for assessing model uncertainty (Cawley et al. 2007), and the inability to conduct effective improvements on the network (Dayhoff & DeLeo 2001). Opening the black box of ANNs has proven difficult. Setiono et al. (2000) created a rule-extracting algorithm, resulting in useful knowledge retrieval regarding problem domain and network structure, but the algorithm would be impractical in typhoon modelling due to its inability to perform under nonlinear problems. Olden & Jackson (2002) created a randomisation technique which eliminates insignificant weights to understanding contributing input features, but results showed equivalent outputs could be achieved with different network weights, underscoring uncertainty.

Secondly, the importance of data quality is highlighted, especially regarding ANN performance. Amongst those studies, prediction is the most common; high quality data enables better understanding of feature relationships and prevents overfitting, and can be improved through data transformation, cleaning, splitting, and reduction of especially noisy datasets (Bejou et al. 1996). The role of high-quality data is similar in classification, and can be improved using feature selection, which selects a subset of the most relevant features (Morán-Fernández et al. 2022).

A number of studies in the literature (Özesmi et al. 2006, Lee 2009, Lin & Wu 2009) emphasise the lack of standard frameworks for determining optimal network architecture, which

Author	Challenges					
	Black Box	Data Quality	Network Architecture	Over-fitting	Computational Cost	Input Parameters
Tseng *et al.* (2007)		■	■	■		
Lin and Chen (2005)	■	■	■		■	
Young *et al.* (2017)	■		■	■		
Chao *et al.* (2020)	■	■				■
Park *et al.* (2022)	■		■			
Lee (2009)	■	■	■			
Lin and Wu (2009)	■			■		■
Gao *et al.* (2018)	■			■	■	
Hong *et al.* (2017)		■			■	

Figure 10: Studies from Figure 8 and their common challenges in using ANNs.

is clearly apparent in Figure 11. Outlined in Ibnu et al. (2019), determining the optimal network topology is a major challenge. The interaction and number of network layers, and their interconnectedness (or lack of) can have a significant impact on a network's ability to generalise (Fiszelew et al. 2007). Adamu (2020) calls for a more systematic approach for selecting activation functions due to their critical nature in network training and overall performance (Ramachandran et al. 2017). Traditional methods for choosing optimal AFs usually only entails trial-and-error (Ertuğrul 2018). Regarding hidden layers, Uzair & Jamil (2020) note that optimum performance could be met with only three hidden layers, and could provide an unofficial framework for determining the number of hidden layers. Genetic algorithms, commonly used for hyperparameter tuning for finding optimal ANN settings (Asadi & Jiang 2020), have shown success in determining ideal network topologies (Mattioli et al. 2019), especially in noisy environments (Stepniewski & Keane 1996). However, given the solutions available, the wide range of network characteristics conveys uncertainty into the reproducibility and comparability of ANNs across studies.

4 A Hybrid Model Framework

4.1 *Statistical-Neural Network Models in Environmental Science*

A hybrid model, whereby statistical and ANN are used in unison, could offer the advantages of both. Application of hybrid statistical-neural networks (HSNNs) in the environmental sciences is limited. Gómez Miranda et al. (2021), a HSNN was used to predicted greenhouse gases by using multilinear regression and a feedforward ANN. The HSNN was able to explain model 64% of output variance, but the model was limited by its linearity and requirement of large amounts of data to prevent overfitting. Additionally, Isiyaka et al. (2019) used multivariate statistics to simplify datasets and reveal underlying patterns for sources of water pollution, and then applied an ANN to learn relationships of the most relevant features for accurate prediction.

4.2 *A Hybrid Model Framework for Typhoon Storm Tracking*

The incorporation of a statistical-hybrid model in typhoon modelling is seldom seen. To illustrate how a HSNN may be used in climate science, specifically typhoon forecasting, Figure 12 presents a framework on how statistical methods and ANNs can be combined to exploit the advantages of both methods. The example of a typhoon storm track offers an opportunity to use both statistical methods, where typhoon features can be analysed with full transparency and validity, which can then be displayed geospatially using a CNN. The CNN is suggested due to its higher performance in geospatial prediction and typhoon storm track forecasting (Guo et al. 2018, Park et al. 2022, Hong et al. 2017). Additional features that statistical methods may struggle with, such as local bathymetry and coastline features, could also be used for the HSNN, further enhancing the predictability of the output, whilst maintaining a certain level of model transparency and validity.

5 Trusting in Innovation

The ANN is shown as a highly versatile and valuable tool for analysis in climate science. Organisations such as the Met Office (2022) and NOAA (2020) have recently produced extensive document for the incorporation of ANNs and artificial intelligence for numerical weather predictions in the near future. This review presents ANNs as especially effective for typhoon forecasting, with their ability to produce more accurate predictions quicker than traditional methods. However, the black box hinders ANN transparency, and the lack of universal frameworks available can lead to difficulty for both reproducibility and comparison across studies of similar natures. When looking forward to the future, processes for validating neural network output, and creation of standardised frameworks, should be of utmost importance to researchers in the field. Nevertheless, at present, determining the utility that ANNs provide could perhaps be a balance of exploiting its advantages whilst trusting in the hidden workings of the model.

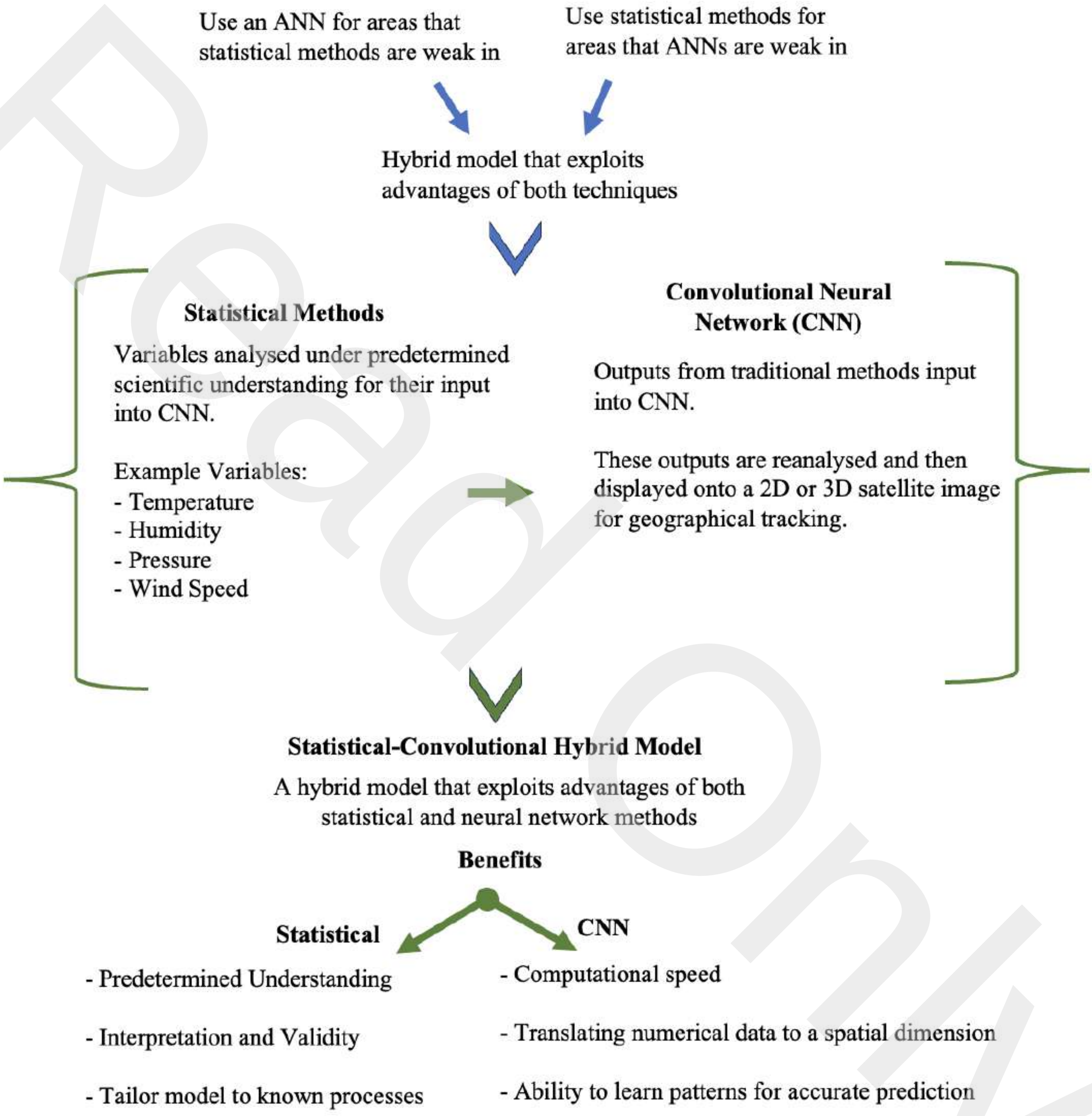

Figure 11: A simplified framework for a statistical-neural network model, inspired by De Veaux et al. (1999) and Gonzalez-Carrasco et al. (2014).

References

Adamu, J. A. (2020), Insight, limitations, criticism, and interpretability of the use of activation functions in deep learning artificial neural networks, *in* 'Emerging Topics in Artificial Intelligence 2020', Vol. 11469, SPIE, p. 114691K.

Almurieb, H. A. & Bhaya, E. S. (2020), Softmax neural best approximation, *in* 'IOP Conference Series: Materials Science and Engineering', Vol. 871, IOP Publishing, p. 012040.

Asadi, B. & Jiang, H. (2020), 'On approximation capabilities of relu activation and softmax output layer in neural networks', *arXiv preprint arXiv:2002.04060* .

Bejou, D., Wray, B. & Ingram, T. N. (1996), 'Determinants of relationship quality: an artificial neural network analysis', *Journal of business research* **36**(2), 137–143.

Benítez, J. M., Castro, J. L. & Requena, I. (1997), 'Are artificial neural networks black boxes?', *IEEE Transactions on neural networks* **8**(5), 1156–1164.

Castillo, D., Lakshminarayanan, V. & Rodriguez-Alvarez, M. J. (2021), 'Mr images, brain lesions, and deep learning', *Applied Sciences* **11**(4), 1675.

Cawley, G. C., Janacek, G. J., Haylock, M. R. & Dorling, S. R. (2007), 'Predictive uncertainty in environmental modelling', *Neural networks* **20**(4), 537–549.

Cha, E. J., Knutson, T. R., Lee, T.-C., Ying, M. & Nakaegawa, T. (2020), 'Third assessment on impacts of climate change on tropical cyclones in the typhoon committee region–part ii: Future projections', *Tropical Cyclone Research and Review* **9**(2), 75–86.

Chao, W.-T., Young, C.-C., Hsu, T.-W., Liu, W.-C. & Liu, C.-Y. (2020), 'Long-lead-time prediction of storm surge using artificial neural networks and effective typhoon parameters: Revisit and deeper insight', *Water* **12**(9), 2394.

Dayhoff, J. E. & DeLeo, J. M. (2001), ‘Artificial neural networks: opening the black box’, *Cancer: Interdisciplinary International Journal of the American Cancer Society* **91**(S8), 1615–1635.

De Veaux, R. D., Bain, R. & Ungar, L. H. (1999), ‘Hybrid neural network models for environmental process control (the 1998 hunter lecture)’, *Environmetrics: The official journal of the International Environmetrics Society* **10**(3), 225–236.

Dongare, A., Kharde, R., Kachare, A. D. et al. (2012), ‘Introduction to artificial neural network’, *International Journal of Engineering and Innovative Technology (IJEIT)* **2**(1), 189–194.

Elliott, R. J., Strobl, E. & Sun, P. (2015), ‘The local impact of typhoons on economic activity in china: A view from outer space’, *Journal of Urban Economics* **88**, 50–66.

Ertuğrul, Ö. F. (2018), ‘A novel type of activation function in artificial neural networks: Trained activation function’, *Neural Networks* **99**, 148–157.

Fiszelew, A., Britos, P., Ochoa, A., Merlino, H., Fernández, E. & García-Martínez, R. (2007), ‘Finding optimal neural network architecture using genetic algorithms’, *Advances in computer science and engineering research in computing science* **27**, 15–24.

Fourati, F. & Chtourou, M. (2007), ‘A greenhouse control with feed-forward and recurrent neural networks’, *Simulation modelling practice and theory* **15**(8), 1016–1028.

Fradkov, A. L. (2020), ‘Early history of machine learning’, *IFAC-PapersOnLine* **53**(2), 1385–1390.

Franz, K., Roscher, R., Milioto, A., Wenzel, S. & Kusche, J. (2018), Ocean eddy identification and tracking using neural networks, *in* ‘Igarss 2018-2018 IEEE international geoscience and remote sensing symposium’, IEEE, pp. 6887–6890.

Gao, S., Zhao, P., Pan, B., Li, Y., Zhou, M., Xu, J., Zhong, S. & Shi, Z. (2018), ‘A nowcasting model for the prediction of typhoon tracks based on a long short term memory neural network’, *Acta Oceanologica Sinica* **37**, 8–12.

Gardner, M. W. & Dorling, S. (1998), 'Artificial neural networks (the multilayer perceptron)—a review of applications in the atmospheric sciences', *Atmospheric environment* **32**(14-15), 2627–2636.

Goh, A. T. (1995), 'Back-propagation neural networks for modeling complex systems', *Artificial intelligence in engineering* **9**(3), 143–151.

Gómez Miranda, I., Fernández Jaramillo, J. & Peñuela M, G. (2021), 'Hybrid multivariate statistical and neural network model to predict greenhouse gas emissions', *Arabian Journal for Science and Engineering* **46**(10), 10113–10123.

Gonzalez-Carrasco, I., Garcia-Crespo, A., Ruiz-Mezcua, B., Lopez-Cuadrado, J. L. & Colomo-Palacios, R. (2014), 'Towards a framework for multiple artificial neural network topologies validation by means of statistics', *Expert Systems* **31**(1), 20–36.

Guo, W., Yang, W., Zhang, H. & Hua, G. (2018), 'Geospatial object detection in high resolution satellite images based on multi-scale convolutional neural network', *Remote Sensing* **10**(1), 131.

Hashemi, M. & Sepaskhah, A. R. (2020), 'Evaluation of artificial neural network and penman–monteith equation for the prediction of barley standard evapotranspiration in a semi-arid region', *Theoretical and Applied Climatology* **139**, 275–285.

Haupt, S. E., Gagne, D. J., Hsieh, W. W., Krasnopolsky, V., McGovern, A., Marzban, C., Moninger, W., Lakshmanan, V., Tissot, P. & Williams, J. K. (2022), 'The history and practice of ai in the environmental sciences', *Bulletin of the American Meteorological Society* **103**(5), E1351–E1370.

Hilbert, D. W. & Ostendorf, B. (2001), 'The utility of artificial neural networks for modelling the distribution of vegetation in past, present and future climates', *Ecological modelling* **146**(1-3), 311–327.

Hong, S., Kim, S., Joh, M. & Song, S.-k. (2017), 'Globenet: Convolutional neural networks for typhoon eye tracking from remote sensing imagery', *arXiv preprint arXiv:1708.03417* .

Hopfield, J. J. (1982), ‘Neural networks and physical systems with emergent collective computational abilities.’, *Proceedings of the national academy of sciences* **79**(8), 2554–2558.

Hsieh, W. W. (2009), *Machine learning methods in the environmental sciences: Neural networks and kernels*, Cambridge university press.

Hsieh, W. W. (2022), ‘Evolution of machine learning in environmental science—a perspective’, *Environmental Data Science* **1**, e3.

Hurtik, P., Tomasiello, S., Hula, J. & Hynar, D. (2022), ‘Binary cross-entropy with dynamical clipping’, *Neural Computing and Applications* **34**(14), 12029–12041.

Ibnu, C. R. M., Santoso, J. & Surendro, K. (2019), Determining the neural network topology: A review, *in* ‘Proceedings of the 2019 8th International Conference on Software and Computer Applications’, pp. 357–362.

Isiyaka, H., Mustapha, A., Juahir, H. & Phil-Eze, P. (2019), ‘Water quality modelling using artificial neural network and multivariate statistical techniques’, *Model. Earth Syst. Environ.* **5**, 583–593.

Jain, A. K., Mao, J. & Mohiuddin, K. M. (1996), ‘Artificial neural networks: A tutorial’, *Computer* **29**(3), 31–44.

Jain, P. & Deo, M. (2006), ‘Neural networks in ocean engineering’, *Ships and offshore structures* **1**(1), 25.

Ketkar, N., Moolayil, J., Ketkar, N. & Moolayil, J. (2021), ‘Convolutional neural networks’, *Deep Learning with Python: Learn Best Practices of Deep Learning Models with PyTorch* pp. 197–242.

Krenker, A., Bešter, J. & Kos, A. (2011), ‘Introduction to the artificial neural networks’, *Artificial Neural Networks: Methodological Advances and Biomedical Applications. InTech* pp. 1–18.

Lee, T.-C., Knutson, T. R., Nakaegawa, T., Ying, M. & Cha, E. J. (2020), ‘Third assessment on impacts of climate change on tropical cyclones in the typhoon committee region–part i: Observed changes, detection and attribution’, *Tropical Cyclone Research and Review* **9**(1), 1–22.

Lee, T.-L. (2009), 'Predictions of typhoon storm surge in taiwan using artificial neural networks', *Advances in Engineering Software* **40**(11), 1200–1206.

Lin, G.-F. & Chen, L.-H. (2005), 'Application of an artificial neural network to typhoon rainfall forecasting', *Hydrological Processes* **19**(9), 1825–1837.

Lin, G.-F. & Wu, M.-C. (2009), 'A hybrid neural network model for typhoon-rainfall forecasting', *Journal of Hydrology* **375**(3-4), 450–458.

Liu, Y., Racah, E., Correa, J., Khosrowshahi, A., Lavers, D., Kunkel, K., Wehner, M., Collins, W. et al. (2016), 'Application of deep convolutional neural networks for detecting extreme weather in climate datasets', *arXiv preprint arXiv:1605.01156* .

Mattioli, F., Caetano, D., Cardoso, A., Naves, E., Lamounier, E. et al. (2019), 'An experiment on the use of genetic algorithms for topology selection in deep learning', *Journal of Electrical and Computer Engineering* **2019**.

McCulloch, W. S. & Pitts, W. (1943), 'A logical calculus of the ideas immanent in nervous activity', *The bulletin of mathematical biophysics* **5**, 115–133.

Mei, W., Xie, S.-P., Primeau, F., McWilliams, J. C. & Pasquero, C. (2015), 'Northwestern pacific typhoon intensity controlled by changes in ocean temperatures', *Science advances* **1**(4), e1500014.

Mekanik, F., Imteaz, M., Gato-Trinidad, S. & Elmahdi, A. (2013), 'Multiple regression and artificial neural network for long-term rainfall forecasting using large scale climate modes', *Journal of Hydrology* **503**, 11–21.

Met Office (2022), 'Embedding machine learning and artificial intelligence in weather and climate science and services: a framework for data science in the met office'.

Mitsui, T. & Boers, N. (2022), 'Machine learning approach reveals strong link between obliquity amplitude increase and the mid-brunhes transition', *Quaternary Science Reviews* **277**, 107344.

Morán-Fernández, L., Bólon-Canedo, V. & Alonso-Betanzos, A. (2022), 'How important is data quality? best classifiers vs best features', *Neurocomputing* **470**, 365–375.

NOAA (2020), 'Noaa artificial intelligence strategic plan 2021—2025'.

Olden, J. D. & Jackson, D. A. (2002), 'Illuminating the "black box": a randomization approach for understanding variable contributions in artificial neural networks', *Ecological modelling* **154**(1-2), 135–150.

Özesmi, S. L., Tan, C. O. & Özesmi, U. (2006), 'Methodological issues in building, training, and testing artificial neural networks in ecological applications', *Ecological Modelling* **195**(1-2), 83–93.

Parhi, R. & Nowak, R. D. (2020), 'The role of neural network activation functions', *IEEE Signal Processing Letters* **27**, 1779–1783.

Park, Y., Kim, E., Choi, Y., Seo, G., Kim, Y. & Kim, H. (2022), 'Storm surge forecasting along korea strait using artificial neural network', *Journal of Marine Science and Engineering* **10**(4), 535.

Ramachandran, P., Zoph, B. & Le, Q. V. (2017), 'Searching for activation functions', *arXiv preprint arXiv:1710.05941* .

Reed, R. & MarksII, R. J. (1999), *Neural smithing: supervised learning in feedforward artificial neural networks*, Mit Press.

Rosenblatt, F. (1958), 'The perceptron: a probabilistic model for information storage and organization in the brain.', *Psychological review* **65**(6), 386.

Różyński, G., Hung, N. M. & OSTROWSKI, R. (2009), 'Climate change related rise of extreme typhoon power and duration over south-east asia seas', *Coastal Engineering Journal* **51**(03), 205–222.

Ruby, U. & Yendapalli, V. (2020), 'Binary cross entropy with deep learning technique for image classification', *Int. J. Adv. Trends Comput. Sci. Eng* **9**(10).

Rumelhart, D., Durbin, R., Golden, R. & Chauvin, Y. (1995), 'Backpropagation: The basic theory 1–34', *L. Erlbaum Associates Inc., USA* .

Rumelhart, D. E. (1980), Schemata: The building blocks of cognition, *in* 'Theoretical issues in reading comprehension', Routledge, pp. 33–58.

Sellevold, R. & Vizcaino, M. (2021), 'First application of artificial neural networks to estimate 21st century greenland ice sheet surface melt', *Geophysical Research Letters* **48**(16), e2021GL092449.

Seneviratne, S. I., Zhang, X., Adnan, M., Badi, W., Dereczynski, C., Di Luca, A., Ghosh, S., Iskander, I., Kossin, J., Lewis, S. et al. (2021), 'Weather and climate extreme events in a changing climate (chapter 11)'.

Setiono, R., Leow, W.-K. & Thong, J. (2000), 'Opening the neural network black box: an algorithm for extracting rules from function approximating artificial neural networks', *ICIS 2000 Proceedings* p. 17.

Sharma, S., Sharma, S. & Athaiya, A. (2017), 'Activation functions in neural networks', *Towards Data Sci* **6**(12), 310–316.

Stepniewski, S. W. & Keane, A. J. (1996), Topology design of feedforward neural networks by genetic algorithms, *in* 'International Conference on Parallel Problem Solving from Nature', Springer, pp. 771–780.

Strobl, E. (2019), 'The impact of typhoons on economic activity in the philippines: Evidence from nightlight intensity', *Asian Development Bank Economics Working Paper Series* (589).

Topping, B. H. V., Sziveri, J., Bahreinejad, A., Leite, J. & Cheng, B. (1998), 'Parallel processing, neural networks and genetic algorithms', *Advances in Engineering Software* **29**(10), 763–786.

Tseng, C.-M., Jan, C.-D., Wang, J.-S. & Wang, C. (2007), 'Application of artificial neural networks in typhoon surge forecasting', *Ocean Engineering* **34**(11-12), 1757–1768.

Tsuji, Y. & Takatsuki, S. (2008), 'Effects of a typhoon on foraging behavior and foraging success of macaca fuscata on kinkazan island, northern japan', *International Journal of Primatology* **29**, 1203–1217.

Uzair, M. & Jamil, N. (2020), Effects of hidden layers on the efficiency of neural networks, *in* '2020 IEEE 23rd international multitopic conference (INMIC)', IEEE, pp. 1–6.

Wagarachchi, N. & Karunananda, A. (2013), Optimization of multi-layer artificial neural networks using delta values of hidden layers, *in* '2013 IEEE Symposium on Computational Intelligence, Cognitive Algorithms, Mind, and Brain (CCMB)', IEEE, pp. 80–86.

Wang, X., Wang, W. & Tong, C. (2016), 'A review on impact of typhoons and hurricanes on coastal wetland ecosystems', *Acta Ecologica Sinica* **36**(1), 23–29.

Wang, Y., Li, B., Luo, R., Chen, Y., Xu, N. & Yang, H. (2014), Energy efficient neural networks for big data analytics, *in* '2014 Design, Automation & Test in Europe Conference & Exhibition (DATE)', IEEE, pp. 1–2.

Wei, C.-C. (2020), 'Development of stacked long short-term memory neural networks with numerical solutions for wind velocity predictions', *Advances in Meteorology* .
URL: *https://api.semanticscholar.org/CorpusID:225500018*

Wieland, D., Wotawa, F. & Wotawa, G. (2002), 'From neural networks to qualitative models in environmental engineering', *Computer-Aided Civil and Infrastructure Engineering* **17**(2), 104–118.

Young, C.-C., Liu, W.-C. & Wu, M.-C. (2017), 'A physically based and machine learning hybrid approach for accurate rainfall-runoff modeling during extreme typhoon events', *Applied Soft Computing* **53**, 205–216.