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AN INTELLIGENT NETWORK METHOD FOR ANALYZING CORPORATE CONSUMER REPURCHASE BEHAVIOR USING DEEP LEARNING NEURAL NETWORKS

QIUPING LU*

Abstract. Earth system models (ESMs) are our key tools for analyzing the planet's existing state and predicting its evolution in the next continuing human-caused events. However, the use of artificial intelligence (AI) approaches to augment or even replace conventional ESM functions has expanded in recent years, raising hopes that AI will be able to overcome some of the major difficulties in climate research. We address the advantages and disadvantages of neural ESM neurons, as well as the unsolved question of whether AI will eventually replace ESMs. Dynamic geophysical events are the foundation of Earth and environmental studies. Given the widespread acceptance of AI and the growing amount of Earth data, the geoscientific community may wish to seriously explore using artificial intelligence (AI) approaches at a much deeper level. Although it is a tall ambition to integrate hybrid physics and AI approaches from a fresh perspective, geology has yet to figure out how to make such methods feasible. This research is an important step towards realising the concept of combining physics and artificial intelligence to address problems with the Earth's system.

Key words: Earth system modelling, long short term memory, artificial intelligence, environmental sciences, geology

1. Introduction. In geosciences, applying AI approaches has a lengthy history. For instance, Abbott (1991), who coined hydro informatics 30 years ago, characterized it as combining computational hydraulics and artificial intelligence. Nonetheless, the mainstream geoscientific community is still cautious about embracing AI approaches, in large part because an AI model is believed to be a "black box," offering few mechanistic explanations beyond its capacity to fit, while some scientists have made an effort to explain black-box models, doing so instead of first developing interpretable models is likely to result in bad practices be perpetuated. With AI models, the geoscience community has increasingly considered the efficiency of the two paradigms as an appealing study area [30, 6].

AI is used to create a proxy model, identify and repair the discrepancy between physical models and observations, and other potential ways of physics-AI efficiency in geoscience were outlined. Comparatively speaking, less research has been done on the hybrid modelling method, which tries to add several physical layers to a network of neurons (NN) to make it more materially realistic. The geoscience industry has grown more interested in studying the effectiveness of the two approaches due to the relative benefits of physical procedures and AI models [12]. Given the relative benefits of biological processes and AI models, the geoscience community has grown more interested in studying the effectiveness of the two paradigms. Due to the employment of a single, integrated AI architecture throughout the process, the hybrid modelling method more closely matches the possibility of raising geoscientific awareness of AI systems [2].

Since the nineteenth century, geoscientists have extensively used ODEs to explore geosystem undercurrents, such as signal processing and global climate modelling. The proposed work is developed a innovative style is utilizing runoff simulation. The primary function of hydrology is catchment runoff modelling. Hydrology is an entire field in geosciences. In a watershed, water intake, outflow, and storage all change completed period. In this work, the LSTM layer in a DL architecture incorporates a conceptual hydrologic model, resulting in hydrology-aware DL models. Overall, our work shows that when adequately trained, AI may similarly acquire biological knowledge to humans [25].

2. Fundamentals of Earth System Modelling. Based on Navier-Stokes equivalences, which explain the atmosphere's - fluid dynamics and seas, are examples of simple physical equations of motion explicitly

*Henan Polytechnic Institute, Nanyang, Henan, 473000, China (Corresponding Author, QiupingLu9@126.com)

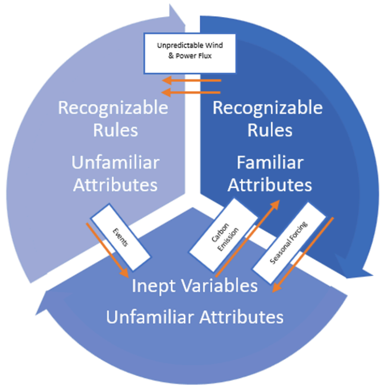

Fig. 2.1: Representation of components of earth system model

known for Earth system components (Figure 2.1). It is practically impractical to resolve all pertinent dynamics scales quantitatively. Hence approximations must be made.

The complication of the ESM makes it difficult to easily infer macroscopic occurrences from tiny scales that may or may not be understood, is primarily to blame for this. For these situations, parameterizations of potentially critical processes must also be approximated. Such parameterizations create free parameters in ESMs, regardless of the process, for which fair values must be determined empirically [26]. Modern ESMs are so large that most systematic calibration techniques, such as those based on Bayesian inference, are impractical. As a result, the models are frequently adjusted by hand.

Even if they are required, parameterizations can generate biases or structural model errors. Furthermore, it is envisaged that the model's representation of the Earth system will become more accurate if significant advancements are resolved plainly. Despite the huge success of ESMs, problems and uncertainty persist.

1. A large range of equilibrium climate sensitivity still exists in current ESMs. Between CMIP5 and CMIP6, the range of expected symmetric weather warmth increased from 1.9-4.5 °C to 1.5-6.6 °C. Losing such reservations is one of the key issues in developing ESMs.
2. Numerous Earth system subsystems may swiftly and gradually induce alterations, according to theoretical considerations and paleoclimate evidence. Many clear evolutions have been found in the CMIP5 models' predictions of the future after a comprehensive investigation. But due of the extremely risky events, it is still unclear if ESMs are reliable in predicting them.
3. Using the present ESMs is still necessary to assess the efficiency or environmental impact of CO2 removal methods and crucial mitigation options for putting the Paris Agreement16 into practice. ESMs also need to do a better job of capturing basic environmental processes like the carbon cycle, the availability of water and nutrients, or the connections between land use and climate [24, 10].
4. The distributions of the time series encoding the dynamics of the Earth system frequently include heavy tails. Severe weather has a very detrimental socioeconomic effect. Because human climate change is still occurring, such events are expected to get worse. There is still space for improvement when representing extremes, even though modern ESM are too competent at predicting usual climatic quantities.

3. Literature Review. Following this line of thinking, we introduce the term "Neural Earth System Modelling" (NESYM) and emphasize the need for a detail explanation forum that brings organized professionals in AI, extensive data analysis, and Earth and climate science. The possibilities and potential problems of NESYM and talk about the uncleared queries of AI is neither only permeate but ultimately replace ESM.

Process-based models were once considered vital resources for comprehending the intricate relationships between the coupled Earth system's components and predicting how the Earth system will react to human-induced weather modification. The startling idea that Earth system models (ESMs) would become obsolete when new artificial intelligence (AI) capabilities are developed has caused a gold rush-like feeling and ridicule among the scientific communities On the other hand, the majority of neural networks lack actual process knowledge and are trained for discrete applications [18]. Yet, the daily expanding Earth system observation (ESO) data streams, growing processing power, and the accessibility and availability of potent. We emphasize the need for fresh transdisciplinary cooperation between the concerned communities to address the arising problems.

It is not simply a fun exercise; it is crucial for applying AI to creating and using NESYM. Earth and climate scientists can contribute to creating uniform standards that compare the geophysical consistency of stand-alone ML and NESYM hybrid models. However, the AI community's assistance is required to tackle additional recently noted ML issues. For instance, it is creating new ways to recognize and prevent shortcut learning in NESYM hybrids.In conclusion, the evolution of neural earth system modelling will only occur through joint cooperation. The development of techniques will be further stimulated by problems unique to the Earth system, and we offer the following four leading suggestions [20].

As a result, we suggest testing the efficacy of machine learning methods using produced fictional data. It is used to assess actual data utilizing a range of dynamics that complex physical models simulate. When training data is provided and extrapolation issues are taken into account, it is crucial. Future models should employ process-driven and machine-learning methods of learning, according to our recommendation. Although data-driven machine-learning technologies will greatly improve and supplement physical modelling, it will still play a vital role in geoscientific research. Additionally, the neuro sciences will contribute to the development of reliable physically grounded linkages for machine learning research [4].

Since physics constrains the search parameter space and eliminates implausible models, hybridization has an intriguing regularization effect. Hence, physics-aware machine learning models need less training data, are simpler (sparser), and better combat overfitting to attain similar performance. Overall, the hybrid modelling framework represents a new line of inquiry that should be intensified and continued [5].

Despite its widespread success in other fields, The Transformer as a new DL architecture has yet to receive much acceptance in this one. In this study, we suggest Earth former, a space-time Transformer for predicting the behaviour of the Earth system. The concept is to apply parallel cuboid-level self-attention while decomposing the data into cuboids. A group of global vectors connect these cuboids in more detail. To test the efficacy of cuboid attention and determine the ideal architecture of Earth former, we do tests on the Movingness dataset [8].

This paper proposes an Earth former, a space-time transformer, to forecast how the Earth system would behave. Cuboid Awareness is a flexible and useful construction material that forms the basis of the Earth. We obtained SOTA on Movingness, our recently proposed N-body MNIST, SEVIR, and ICAR-ENSO. There are certain limitations to the job we do. Initially, the Earth model is a mechanical version without an uncertainty model. By forecasting the average of all potential futures, the model can deliver foggy forecasts with poor perceptual quality and require additional beneficial small-scale characteristics. More suitable methods must be taken to evaluate the uncertainty in Earth system forecasting models. Extending Earth's historical forecasting model to a probabilistic one represents an exciting future direction. We plan to investigate ways to include biological data into Earth's past atmosphere in the future. [22, 9].

4. Materials and Methods.

4.1. LSTM Architecture. A unique variety of recurrent neural networks (RNN), known as the LSTM architecture, was created to address the typical RNN's inability to learn long-term dependencies. The typical RNN can only remember sequence 10, as Bengio et al. (1994) demonstrated. It would indicate that for daily streamflow modelling, we could only utilize the past ten days (about one and a half weeks)' worth of input taken from climatological data to forecast.

We unfold the network's recurrence into a directed acyclic graph to illustrate how the RNN and the LSTM function. The input $m = m_1, m_2, \cdots, m_n$ consists of the preceding n repeated period stages of self-determining variable star and is processed sequentially to forecast the output at a particular period. The internal processes of the recurrent cell, and these processes distinguish the LSTM from a standard RNN.Old RNN cells have single internal state, l_t, which is recalculated at each time step using the equation below.

$$l_t = s(Vm_t + Yi_{t-1} + bias) \tag{4.1}$$

Also, the input gate of the second gate computes which (and to what extent) information effect is utilized. The current time step's cell state should be updated:

$$i_t = \sigma(Vi_{xt} + Yi_{ht-1} + bias) \tag{4.2}$$

The following equation updates the cell state c_t.

$$c_t = f_t(c_{t-1} + i_t c_t) \tag{4.3}$$

where denotes multiplication by elements. Eq. (4.1) applies because both entries in the vectors f_t are in the range (0, 1). Like that, it determines which newly stored infect information will be discarded. (The value of it of approx. 0).

Output gate calculation:

$$o_t = \sigma(VWx_t + Yoh_{t=1} + b_0) \tag{4.4}$$

V_0,Y_0 and b_0 are a set of learnable parameters defined for the problem, and ot is a vector with values between (0, 1) output control. It is determined from this vector (4.5)

$$h_t = \tanh(c_t)o_t \tag{4.5}$$

It can maintain the integrity of the information stored across many time steps because of its straightforward linear interactions with the remaining LSTM cell. This property assists in preventing the issue of exploding or disappearing gradients during training. The final discharge prediction is computed by a single output neuron conventional dense layer. The following equation provides the viscous layer calculation:

$$y = V_d h_n + bias \tag{4.6}$$

V_d is the weight matrix, bias is the bias term, h_n is the output of the final layer in LSTM at the previous time step, and y is the final discharge, all derived from Eq. (4.6).

Finally, Algorithm 1 displays the complete LSTM layer's pseudocode. When there are numerous stacked LSTM layers, the output $h = [h_1, h_2, \cdots, h_n]$ of the first layer serves as the input for the subsequent layer. Eq. (4.6) is then used to determine the discharge, the final output, where ht is the final output of the last LSTM layer [11, 13, 3, 15, 19].

4.2. LSTM Layers Description. The standardization process had comprised a predetermined number of recapitulations in which the full calibration period is reproduced using a particular set of model parameters. The network's adaptable (or learnable) parameters, including its weights and biases, are altered when an LSTM is trained based on the particular loss function of each iteration step. As a result, the gradient loss function including the network metrics may was evaluated .

Figure 4.1 depicts the LSTM training and standardization process for one iteration phase graphically. A batch or mini batch of the available training data is typically used for one iteration of LSTM training. A hyperparameter is anything preset, such the 512 samples per batch. One discharge value from a certain day plus weather information from the n days before that day make up each sample. The loss function is computed as the average of the MSE of the simulated and real runoff for each of 512 samples in each iteration step [14]. Each piece inside a batch can be made up of randomly selected time steps, which are unnecessary to be ordered chronologically because the discharge of a certain time step is just a function of the meteorological inputs of the prior n days. Convergence can be hastened even with random samples included in the batch [23].

Given an optimization procedure without a convergence condition, the number of iteration steps affects the overall number of model runs performed during calibration for conventional hydrological models. Neural networks are referred to as epochs. Epochs are the intervals at which a training sample updates a model parameter. If the data set included 1000 training samples and the batch size was 10, an epoch would have 100 iteration steps (the quantity of training samples divided by the quantity of samples per batch). In each iteration step, 10 of the 1000 samples are taken without a replacement, continuing until all 1000 samples have been used. The discharge time series of the training data is accurately replicated once [16].

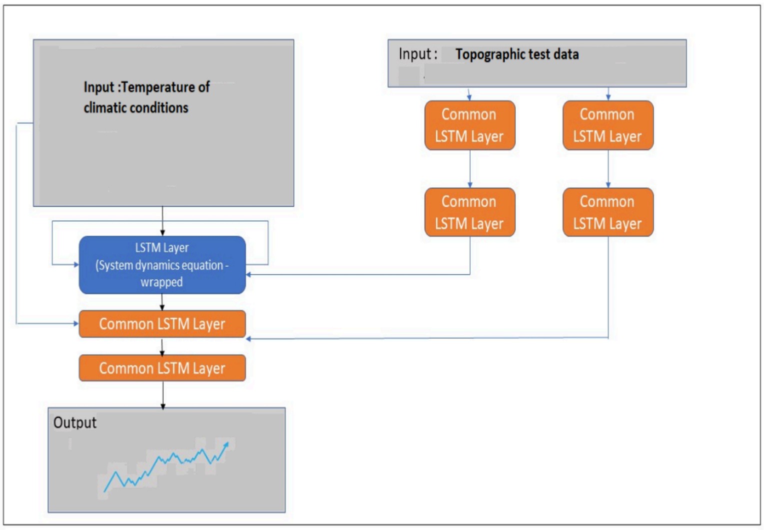

Fig. 4.1: LSTM architecture based on earth system modelling

For a conventional hydrological model, it is comparable to one calibration iteration, with the crucial difference being that each sample is generated independently of the others. The LSTM's learning process throughout several training epochs. Despite having to learn the complete rainfall-runoff relation from scratch for each period, the network may better capture the discharge dynamics (grey line of random weights).

5. Experimentation and Results.

5.1. Dataset. The GSDE is created using a variety of regional and national soil databases or soil maps, as well as the 1:5 million scale Digital Soil Map of the World (DSMW), which serves as a fundamental soil map. In the accompanying information, specifics regarding the data sources are provided. One or more components make up the soil mapping units in the soil maps. Each element takes up a specific portion of the mapping unit, although it is not evident where they are. In most cases, the components share the same soil type or a mix of soil type and additional taxonomy data, such as land use and texture class. The FAO-74 legend is used to construct the DSMW. Europe and northern Eurasia are covered by the 1:1 million ESDB, which uses FAO-90 soil categorization data. Using the soil polygon linkage approach and the Genetic Soil Classification of China (GSCC), the soil database for the land surface modelling in China was created [Shangguan et al., 2013]. To fill in the gaps in the SOTER attribute data at scales between 1:250,000 and 1:5 million, the soil attributes of the SOTWIS are based on the FAO-90 categorization [1, 17, 27, 28].

5.2. Results and Discussion. The State Soil Geography (STATSGO) dataset was replaced by the GSM of the U.S. at a scale of 1:250,000 using the Soil Taxonomy (S.T.) [Soil Survey Staff, 1999]. However, the available properties are significantly diverse and only partially cover the soil maps. These two profile databases were integrated into a single data structure. Ten thousand two hundred fifty-three profiles containing FAO-74 and FAO-90 legends were stored in WISE 5.1, released in 2005. Around 1900 of the 81,218 profiles in the NCSS were gathered outside of the United States. The NCSS uses the ST to refer to dirt. After deleting soil profiles lacking soil classification or soil property measurement, 71 339 profiles remain. Using an LSTM approach, Figure 5.1 shows the dataset's mean, median, and mode [21, 29, 7]. Geospatial data is present in 60,638 of the 89,592 profiles in the WISE and NCSS. Local soils are typically more accurately represented in soil profiles with greater density. Multiple techniques were employed in the lab and throughout time to measure the soil properties in WISE and NCSS. The accuracy of the information of the NCSS is greater because the soil investigations in the NCSS adhered to established protocols. In contrast, soil analyses in the WISE were carried out in at least 190 laboratories worldwide using a variety of approaches. [Batjes, 2008a]. For deep soils,

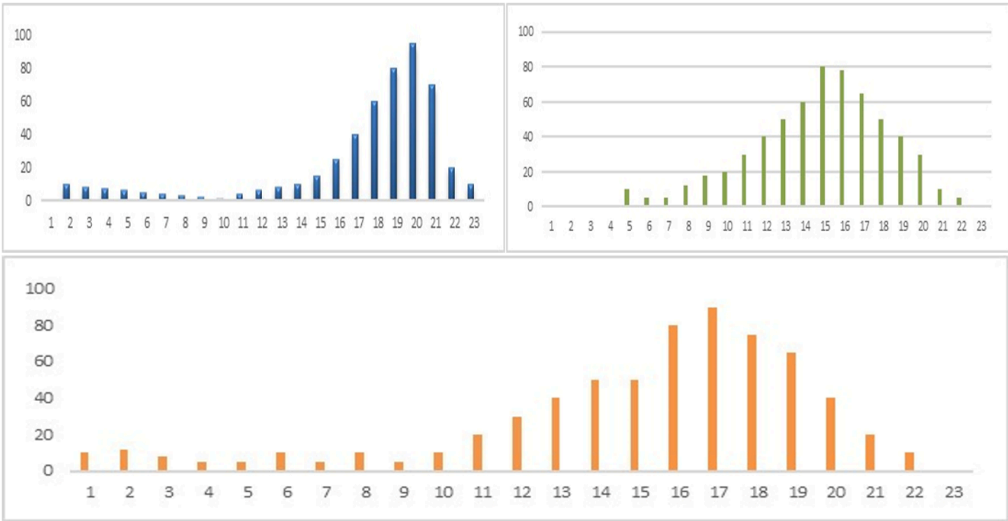

Fig. 5.1: Determination of mean, median and mode of LSTM in ESM

in particular, the characteristics of a soil profile are only sometimes known for each horizon. Regarding soil properties, different soil classes are represented differently.

The two pipelines, in this instance, are used for runoff modelling and its parameterization, respectively, in the generic design. As required by the LSTM, the climatic forcing variables P, T, and Lday, shortwave downward radiation SRad and vapour pressure VP are the leading pipeline's inputs. A two-layer standard NN block is supplied with the five input variables and a preliminary runoff estimation Q* from the model-wrapped LSTM(Feng et al., 2019). Conv1D layer has been used in research for data-based hydrologic modelling because it can handle the lagged impact through a one-direction convolution operation. Through the Conv1D layers, the physical approach's approximation errors are fixed, and the final runoff Q is achieved. Like the main pipeline architecture, the "hybrid DL model" blends physical principles (represented by the LSTM) with data-driven components (i.e., Conv1D layers). Although there are many potential traps and dead ends in this research field, a significant amount of risk is involved. The promise that artificial intelligence (AI) will assist in resolving the main problems in Earth and climatic sciences is now required. Some of these challenges were highlighted at the beginning of this Viewpoint. In addition, it is unlikely that AI will be able to solve the issue of climate prediction on its own at this time. Therefore, the science of the Earth system will be able to advance through AI, transcending the current uproar. The chance of the next evolutionary step will, however, improve if we can create interpretable and geophysical consistent AI technology and find solutions to the limitations mentioned above. The goal of Reichstein et al. (2019) to use hybrid physics and AI methodologies to address Earth system challenges has been advanced by this study.

Moreover, the parameterization pipeline provides the main pipeline's catchment awareness, which has dual blocks of completely associated layers that supply for the LSTM layer and N for the Conv1D layers. The parameterization pipeline allows to change with physiographic features across many catchments. Figure 5.2 shows yearly based data of ESM analysis.

6. Conclusion. Our Perspective is a reaction to the recent request for cooperation from the AI community as well as the description of a workable scientific approach to better comprehend the present and future conditions of the Earth. The artificial neural network framework suggested in this study can correctly infer information about occurrences that are not experienced, as demonstrated via runoff modelling. The revolutionary design provides a practical method for appropriately guiding AI using geoscientific data. We foresee future studies that will extend the developed framework to accommodate the deployment of increasingly sophisticated AI systems to advance geoscience research and apply it in a variety of geoscientific situations.

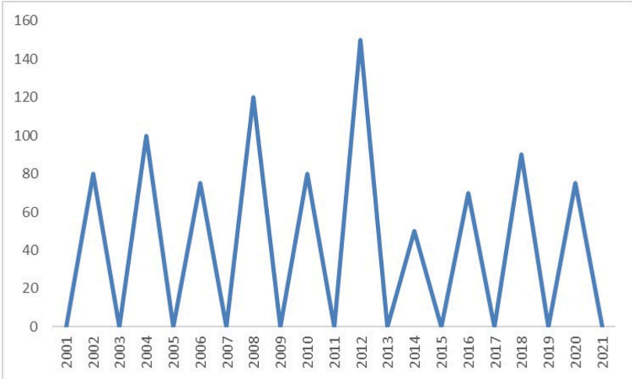

Fig. 5.2: Yearly based ESM analysis

REFERENCES

[1] *Chapter 12: Zonal Energy Budget*, pp. 141–157.

[2] A. Agapiou, *Remote sensing heritage in a petabyte-scale: satellite data and heritage earth engine© applications*, International Journal of Digital Earth, 10 (2017), pp. 85–102.

[3] P. Ajay, B. Nagaraj, R. A. Kumar, R. Huang, and P. Ananthi, *Unsupervised hyperspectral microscopic image segmentation using deep embedded clustering algorithm*, Scanning, 2022 (2022).

[4] M. Alvarez, D. Luengo, and N. D. Lawrence, *Latent force models*, in Artificial Intelligence and Statistics, PMLR, 2009, pp. 9–16.

[5] A. C. Antoulas, *Approximation of large-scale dynamical systems*, SIAM, 2005.

[6] P. Bauer, A. Thorpe, and G. Brunet, *The quiet revolution of numerical weather prediction*, Nature, 525 (2015), pp. 47–55.

[7] T. Brown, B. Mann, N. Ryder, M. Subbiah, J. D. Kaplan, P. Dhariwal, A. Neelakantan, P. Shyam, G. Sastry, A. Askell, et al., *Language models are few-shot learners*, Advances in Neural Information Processing Systems, 33 (2020), pp. 1877–1901.

[8] S. L. Brunton, J. L. Proctor, and J. N. Kutz, *Discovering governing equations from data by sparse identification of nonlinear dynamical systems*, Proceedings of the National Academy of Sciences, 113 (2016), pp. 3932–3937.

[9] G. Camps-Valls, L. Martino, D. H. Svendsen, M. Campos-Taberner, J. Muñoz-Marí, V. Laparra, D. Luengo, and F. J. García-Haro, *Physics-aware gaussian processes in remote sensing*, Applied Soft Computing, 68 (2018), pp. 69–82.

[10] V. Eyring, S. Bony, G. A. Meehl, C. A. Senior, B. Stevens, R. J. Stouffer, and K. E. Taylor, *Overview of the coupled model intercomparison project phase 6 (cmip6) experimental design and organization*, Geoscientific Model Development, 9 (2016), pp. 1937–1958.

[11] K. Han, A. Xiao, E. Wu, J. Guo, C. Xu, and Y. Wang, *Transformer in transformer*, Advances in Neural Information Processing Systems, 34 (2021), pp. 15908–15919.

[12] S. Hantson, A. Arneth, S. P. Harrison, D. I. Kelley, I. C. Prentice, S. S. Rabin, S. Archibald, F. Mouillot, S. R. Arnold, P. Artaxo, et al., *The status and challenge of global fire modelling*, Biogeosciences, 13 (2016), pp. 3359–3375.

[13] W. H. Heiss, D. L. McGrew, and D. Sirmans, *Nexrad: next generation weather radar (wsr-88d)*, Microwave Journal, 33 (1990), pp. 79–89.

[14] J. Herman, P. Reed, and T. Wagener, *Time-varying sensitivity analysis clarifies the effects of watershed model formulation on model behavior*, Water Resources Research, 49 (2013), pp. 1400–1414.

[15] J. Ho, N. Kalchbrenner, D. Weissenborn, and T. Salimans, *Axial attention in multidimensional transformers*, arXiv preprint arXiv:1912.12180, (2019).

[16] C. Hulbert, B. Rouet-Leduc, P. A. Johnson, C. X. Ren, J. Rivière, D. C. Bolton, and C. Marone, *Similarity of fast and slow earthquakes illuminated by machine learning*, Nature Geoscience, 12 (2019), pp. 69–74.

[17] A. Karpatne, G. Atluri, J. H. Faghmous, M. Steinbach, A. Banerjee, A. Ganguly, S. Shekhar, N. Samatova, and V. Kumar, *Theory-guided data science: A new paradigm for scientific discovery from data*, IEEE Transactions on Knowledge and Data Engineering, 29 (2017), pp. 2318–2331.

[18] R. Knutti, M. A. Rugenstein, and G. C. Hegerl, *Beyond equilibrium climate sensitivity*, Nature Geoscience, 10 (2017), pp. 727–736.

[19] A. Krishnapriyan, A. Gholami, S. Zhe, R. Kirby, and M. W. Mahoney, *Characterizing possible failure modes in physics-informed neural networks*, Advances in Neural Information Processing Systems, 34 (2021), pp. 26548–26560.

[20] G. A. Meehl, C. A. Senior, V. Eyring, G. Flato, J.-F. Lamarque, R. J. Stouffer, K. E. Taylor, and M. Schlund, *Context for interpreting equilibrium climate sensitivity and transient climate response from the cmip6 earth system models*, Science Advances, 6 (2020), p. eaba1981.

[21] S. Penny, E. Bach, K. Bhargava, C.-C. Chang, C. Da, L. Sun, and T. Yoshida, *Strongly coupled data assimilation in*

multiscale media: Experiments using a quasi-geostrophic coupled model, Journal of Advances in Modeling Earth Systems, 11 (2019), pp. 1803–1829.

[22] A. Rajendran, N. Balakrishnan, and P. Ajay, *Deep embedded median clustering for routing misbehaviour and attacks detection in ad-hoc networks*, Ad Hoc Networks, 126 (2022), p. 102757.

[23] A. Sharma, D. Gowda, A. Sharma, S. Kumaraswamy, M. Arun, et al., *Priority queueing model-based iot middleware for load balancing*, in Proceedings of the 6th International Conference on Intelligent Computing and Control Systems (ICICCS), Madurai, India, 2022, IEEE, pp. 425–430.

[24] T. F. Stocker, D. Qin, G.-K. Plattner, M. M. Tignor, S. K. Allen, J. Boschung, A. Nauels, Y. Xia, V. Bex, and P. M. Midgley, *Climate change 2013: The physical science basis. contribution of working group i to the fifth assessment report of ipcc the intergovernmental panel on climate change*, (2014).

[25] M. Stockhause and M. Lautenschlager, *Cmip6 data citation of evolving data*, Data Science Journal, 16 (2017), pp. 30–30.

[26] K. E. Taylor, R. J. Stouffer, and G. A. Meehl, *An overview of cmip5 and the experiment design*, Bulletin of the American Meteorological Society, 93 (2012), pp. 485–498.

[27] P. J. Van Leeuwen, H. R. Künsch, L. Nerger, R. Potthast, and S. Reich, *Particle filters for high-dimensional geoscience applications: A review*, Quarterly Journal of the Royal Meteorological Society, 145 (2019), pp. 2335–2365.

[28] S. Vetra-Carvalho, P. J. Van Leeuwen, L. Nerger, A. Barth, M. U. Altaf, P. Brasseur, P. Kirchgessner, and J.-M. Beckers, *State-of-the-art stochastic data assimilation methods for high-dimensional non-gaussian problems*, Tellus A: Dynamic Meteorology and Oceanography, 70 (2018), pp. 1–43.

[29] A. Voulodimos, N. Doulamis, A. Doulamis, E. Protopapadakis, et al., *Deep learning for computer vision: A brief review*, Computational Intelligence and Neuroscience, 2018 (2018).

[30] N. Wiener, J. von Neumann, M. . Mead, G. Bateson, W. S. McCulloch, W. Pitts, K. I. Lewin, F. S. C. Northrop, M. R. Harrower, L. S. Kubie, R. A. Bjork, and W. E. Bijker, *Predicting the future, leo howe and alan wain. cambridge university press, new york, ny. 208 pages. isbn: 0-521-41323-0. $29.95*, Bulletin of Science, Technology & Society, 14 (1994), pp. 240 – 240.

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