Atmospheric Circulation and Rainfall Patterns: Bridging Climate Science Fundamentals with Advanced Modeling Techniques

Jules Udahemuka

judahemu [at] andrew [dot] cmu [dot] edu

1 Introduction

Understanding atmospheric circulation and rainfall patterns is important in the face of global climate change. These fundamental processes not only shape our daily weather but also play a crucial role in long-term climate trends, agricultural productivity, water resource management, and the frequency and intensity of extreme weather events. As our planet continues to warm, changes in atmospheric circulation are altering precipitation patterns worldwide, with far-reaching consequences for ecosystems and human societies alike.

The complexity of these systems, however, presents significant challenges for accurate prediction and modeling. Traditional climate models, while based on sound physical principles, often struggle to capture the intricate dynamics of atmospheric circulation and precipitation, particularly at regional scales. This limitation has stimulated the development of novel approaches that combine classical climate science with advanced computational techniques.

This review paper aims to provide a comprehensive review of the fundamental principles governing atmospheric circulation and rainfall patterns, while also exploring the cutting-edge modeling approaches that promise to enhance our predictive capabilities. We will examine the basic mechanisms driving global air movements, the formation and distribution of precipitation, and the observed and projected changes in these systems due to climate change. Furthermore, we will go into the limitations of current climate models and the potential of data-driven methods, particularly physics-informed machine learning, to overcome these challenges.

As I am currently working on a Physics-Informed Neural Network (PINN) down-scaling model for regional rain prediction, I am particularly interested in the intersection of traditional climate science and advanced modeling techniques for understanding climate change at the regional level. This paper will highlight how such interdisciplinary approaches can bridge the gap between large-scale climate dynamics and local-scale precipitation patterns, potentially revolutionizing our ability to predict and prepare for future climate scenarios.

2 Fundamentals of Atmospheric Circulation

Atmospheric circulation is a key component of Earth's climate system, responsible for distributing heat, moisture, and momentum across the globe. Understanding these circulation patterns is crucial for predicting weather and climate changes, including rainfall patterns. This section explores the fundamental mechanisms driving large-scale atmospheric movements and their implications for global climate.

2.1 Atmospheric Energy Balance and Circulation

Atmospheric circulation is primarily driven by differential heating of the Earth's surface. The tropics receive more solar radiation than the poles, creating temperature and pressure gradients that drive global circulation patterns [20]. Quantitatively, net radiative heating in the tropics is about 100 W/m^2, while net cooling at high latitudes is about -100 W/m^2. This imbalance drives poleward heat transport, with the atmosphere accounting for about 78% at 35° latitude [17]. Vertical circulation is tied to moist static energy (MSE) distribution, which combines sensible heat, latent heat, and geopotential energy. Areas of high MSE (typically tropics) experience rising motion, while low MSE areas (often subtropics) experience subsidence, significantly influencing global precipitation patterns [17]. Recent research has shown that global warming is likely to intensify the global hydrological cycle, leading to a "wet-get-wetter, dry-get-drier" pattern of precipitation changes. This is partly due to the increase in atmospheric water vapor content with warming, following the Clausius-Clapeyron relation of about 7% per degree Celsius of warming [20].

2.2 Coriolis Effect and Atmospheric Movement

The Coriolis effect, resulting from Earth's rotation, significantly shapes atmospheric circulation patterns. It deflects moving air rightward in the Northern Hemisphere and leftward in the Southern Hemisphere, with its strength proportional to the sine of latitude. This effect creates easterly trade winds in the tropics and westerlies in mid-latitudes. While the Coriolis effect would turn winds parallel to isobars in isolation, pressure gradient forces, and friction also play crucial roles in the real atmosphere [20].

In mid-latitudes, the Coriolis effect and pressure gradient force create geostrophic balance, key to understanding large-scale features like jet streams. These fast-flowing upper tropospheric currents, nearly geostrophic, steer weather systems and influence precipitation patterns. In the tropics, where the Coriolis effect is weaker, convective overturning and wave dynamics dominate, including equatorial Kelvin and Rossby waves. These tropical dynamics play crucial roles in phenomena like the El Niño-Southern Oscillation (ENSO) [20].

2.3 Implications for Rainfall Patterns

The global circulation patterns described above have profound implications for rainfall distribution. The ascending branches of the Hadley and Ferrel cells are associated with regions of enhanced precipitation, while the descending branches correspond to drier areas. This explains the band of heavy rainfall in the tropics (the ITCZ), the subtropical dry zones, and the mid-latitude storm tracks [8]. Moreover, the interaction of these large-scale circulation patterns with topography and land-sea contrasts leads to regional variations in rainfall. Monsoon circulations, for instance, arise from the seasonal reversal of temperature gradients between land and sea, bringing critical rainfall to many parts of the world [8].

Understanding these fundamental aspects of atmospheric circulation is crucial for predicting weather patterns and long-term climate trends. Recent research has shown that global warming may be altering these circulation patterns, with potential far-reaching consequences for regional climates. For instance, there is evidence of a weakening and poleward expansion of the Hadley circulation, which could lead to shifts in subtropical dry zones [26]. As we move towards more advanced modeling techniques, including physics-informed machine learning approaches, incorporating these fundamental principles of atmospheric circulation will be crucial for improving our ability to predict rainfall patterns and their changes under future climate scenarios.

3 Rainfall Patterns and Mechanisms

Precipitation is a crucial component of the global water cycle and plays a vital role in shaping Earth's climate and ecosystems. Understanding the types, formation processes, and patterns of precipitation is essential for predicting weather and climate changes. This section explores the fundamental aspects of rainfall, its global distribution, and its relationship to atmospheric circulation.

3.1 Types of Precipitation and Formation Processes

Precipitation occurs when water vapor in the atmosphere condenses and falls to the Earth's surface. The main types of precipitation include rain, snow, sleet, and hail. The type of precipitation that occurs depends on the temperature profile of the atmosphere and the processes that lead to condensation [9]. Rain, the most common form of precipitation, forms when water droplets grow large enough to fall from clouds. This growth occurs through two main processes:

1. **Collision-coalescence**: In warm clouds (temperatures above 0°C), small cloud droplets collide and merge to form larger raindrops. This process is particularly important in tropical regions [9].

2. **Ice crystal process (Bergeron-Findeisen process)**: In cold clouds, where temperatures are below 0°C, ice crystals grow at the expense of supercooled water droplets due to the difference in saturation vapor pressure over ice and water. As these ice crystals fall and encounter warmer air, they melt to form rain. This process is dominant in mid-latitude precipitation [9].

The formation of precipitation requires the presence of cloud condensation nuclei (CCN) or ice nuclei (IN). These are tiny particles in the atmosphere around which water vapor can condense or deposit. The concentration and properties of these nuclei can significantly influence precipitation efficiency and are an important factor in cloud seeding experiments [27].

3.2 Global Precipitation Patterns and Their Relationship to Atmospheric Circulation

The global distribution of precipitation is closely tied to atmospheric circulation patterns. On a broad scale, the patterns can be summarized as follows:

1. **Tropical regions**: High precipitation due to the Intertropical Convergence Zone (ITCZ) and monsoon circulations.

2. **Subtropical regions**: Low precipitation due to descending air in the Hadley cell.

3. **Mid-latitudes**: Moderate precipitation associated with frontal systems and the polar jet stream.

4. **Polar regions**: Generally low precipitation due to cold temperatures and limited moisture content.

The Intertropical Convergence Zone (ITCZ), a low-pressure band near the equator, is associated with the highest global precipitation rates due to deep convective clouds. Its position varies seasonally, affecting tropical rainfall patterns [19]. In contrast, the subtropics experience high pressure and low precipitation due to the descending branch of the Hadley cell, creating major deserts like the Sahara and Atacama [19]. Mid-latitude precipitation is primarily associated with frontal systems and extratropical cyclones along the polar front, influenced by the polar jet stream [20]. Orographic precipitation occurs when moist air rises over elevated terrain, creating rainfall contrasts between windward and leeward sides of mountain ranges [19].

Coastal areas often have enhanced precipitation due to land-sea breeze interactions and abundant ocean moisture, while continental interiors tend to be drier. Global precipitation patterns can shift in response to large-scale phenomena like the El Niño-Southern Oscillation (ENSO), causing regional variations in rainfall [7]. These diverse precipitation mechanisms and their interactions create complex global rainfall patterns that vary both spatially and temporally.

3.3 Seasonal Variations in Rainfall

Seasonal rainfall variations are driven by factors including ITCZ migration, monsoon circulations, and changes in mid-latitude storm tracks. The ITCZ shifts north during boreal summer and south during winter, causing wet and dry seasons in tropical regions like the Sahel [18]. Monsoon systems, such as the Asian monsoon, bring dramatic seasonal rainfall variations. These are driven by seasonal temperature and pressure gradient reversals between land and sea, with factors like ENSO and the Indian Ocean Dipole influencing their strength and timing [18].

In mid-latitudes, rainfall variations often relate to storm track shifts. Winter's greater equator-pole temperature contrast strengthens the jet stream and intensifies storms, increasing precipitation in regions like the Mediterranean. Some equatorial areas, such as parts of the Amazon and Indonesia, experience a double rainfall peak due to the ITCZ's twice-yearly passage. These diverse seasonal patterns highlight the complex interplay of global and regional climate mechanisms in determining rainfall distributions [18].

3.4 Implications for Rainfall Prediction and Modeling

Understanding rainfall patterns and mechanisms is crucial for accurate prediction and modeling. Traditional numerical weather prediction models, while fundamental, struggle with sub-grid scale processes like cloud microphysics and convection [1]. Recent advances in machine learning, particularly physics-informed neural networks, offer promising avenues for improving rainfall predictions by capturing complex, non-linear relationships while respecting physical constraints. Convolutional neural networks have shown success in short-term precipitation forecasting, while LSTM networks have demonstrated skill in predicting seasonal variations [16].

Challenges remain in integrating data-driven approaches with a physical understanding of atmospheric processes. Future improvements will likely come from hybrid models combining physical models and machine-learning techniques [16]. As climate change alters global temperature patterns and atmospheric circulation, understanding rainfall mechanisms becomes increasingly crucial. These changes may intensify precipitation extremes like droughts and floods. Continued research into rainfall patterns and mechanisms, coupled with advances in modeling techniques, is essential for adapting to and mitigating these impacts.

4 Climate Change and Its Impact on Circulation and Rainfall

As the Earth's climate continues to warm due to anthropogenic greenhouse gas emissions, significant changes are occurring in atmospheric circulation patterns and precipitation regimes. Understanding these changes is crucial for predicting future climate scenarios and developing effective adaptation strategies. This section explores the observed changes in atmospheric circulation, shifts in precipitation patterns, and projected future changes based on climate models.

4.1 Observed Changes in Atmospheric Circulation Due to Global Warming

Global warming has led to observable changes in atmospheric circulation patterns, driven by uneven surface warming. Key changes include poleward expansion of the Hadley cell by 0.5-1° latitude per decade since 1979 [10], increased meandering of the polar jet stream [5], and alterations in monsoon systems [13]. These changes have significant implications for regional climates, including potential increased aridity in subtropical zones and more persistent weather patterns.

These observed changes are complex and interconnected, involving feedback that can amplify or dampen global warming effects. For instance, jet stream changes influence storm tracks, affecting heat and moisture transport and further impacting circulation patterns. While natural variability and data limitations pose challenges in quantifying these changes, advanced statistical techniques, improved satellite observations, and reanalysis products have increased confidence in identifying long-term circulation trends.

4.2 Shifts in Precipitation Patterns and Extreme Rainfall Events

Climate change has led to significant shifts in global precipitation patterns, characterized by an intensification of the hydrological cycle. As the atmosphere warms, it can hold more water vapor, leading to more intense precipitation events globally [23]. Observations show an increase in the frequency and intensity of extreme precipitation events in many regions. Simultaneously, the poleward expansion of the Hadley cell has expanded subtropical dry zones, increasing aridity in regions like the Mediterranean, southern Africa, and parts of Australia [20]. Extreme rainfall events have shown changes. In the contiguous United States, for instance, the amount of rainfall in the heaviest 1% of rain events increased by 55% in the Northeast, 42% in the Midwest, and 27% in the Southeast between 1958 and 2016 [24].

These changes in precipitation patterns have significant implications for water resources management, agriculture, and natural ecosystems. They also pose challenges for infrastructure designed based on historical climate data, as the frequency and intensity of extreme events exceed previous expectations. Many regions are experiencing changes in the timing and distribution of seasonal precipitation, with some areas seeing an earlier onset of spring rains, while others experience more concentrated rainfall in shorter periods.

4.3 Implications for Rainfall Prediction and Modeling

The projected changes pose significant challenges for rainfall prediction and modeling. Traditional statistical methods based on historical data may become less reliable as the climate system moves into states not observed in the recent past, and the fact that they tend to converge toward the mean makes them less applicable in these situations. This highlights the need for physics-based models that can capture the fundamental processes driving these changes. However, even complex global climate models have limitations, particularly in representing small-scale processes like convection that are crucial for precipitation. This is where advanced techniques like physics-informed machine learning could play a crucial role. By combining data-driven approaches with physical constraints, these methods could potentially improve our ability to model and predict changes in circulation and rainfall patterns [16].

For instance, machine learning models could be trained on high-resolution simulation data to emulate complex physical processes, improving the representation of these processes in larger-scale models. Neural networks could also be used to downscale global model projections to provide more localized precipitation predictions [25]. As climate change continues to alter atmospheric circulation and precipitation patterns, the integration of traditional physical modeling with advanced machine-learning techniques will be crucial for improving our understanding and predictive capabilities. This interdisciplinary approach, combining climate science with data science, offers promising avenues for addressing one of the most pressing challenges of our time.

5 Modeling Atmospheric Circulation and Rainfall

Accurate modeling of atmospheric circulation and rainfall is crucial for weather forecasting, climate projections, and understanding of the Earth's climate system. As our understanding of atmospheric processes has grown and computational capabilities have advanced, modeling approaches have evolved significantly. This section explores current climate models, their limitations, the emergence of data-driven approaches, and the potential of physics-informed machine learning in improving these models.

5.1 Overview of Current Climate Models and Their Limitations

Current climate models, often referred to as General Circulation Models (GCMs), are based on fundamental physical principles including conservation of mass, energy, and momentum. These models discretize the atmosphere, ocean, and land surface into three-dimensional grids and solve complex systems of differential equations to simulate the Earth's climate [15].

Key components of modern climate models include:

1. **Atmospheric component**: Simulates atmospheric dynamics, thermodynamics, and composition.
2. **Ocean component**: Models ocean circulation, heat transport, and biogeochemistry.
3. **Land surface component**: Represents processes like vegetation dynamics, hydrology, and soil properties.
4. **Sea ice component**: Simulates the formation, movement, and melting of sea ice.
5. **Atmospheric chemistry component**: Models the chemical composition of the atmosphere and its interactions with climate.

These models have become increasingly sophisticated, with higher spatial resolution, improved representation of physical processes, and the inclusion of more Earth system components. For instance, the latest models used in the Coupled Model Intercomparison Project Phase 6

(CMIP6) have typical atmospheric resolutions of about 100 km, with some models achieving resolutions as fine as 25 km [4].

Despite their sophistication, current climate models face several limitations. Computational constraints restrict spatial resolution and simulation length. Many important sub-grid processes, like cloud formation and convection, must be parameterized, introducing uncertainties [2]. Complex feedback loops involving clouds, aerosols, and biogeochemical cycles are challenging to represent accurately [2]. Initial and boundary condition uncertainties, structural differences between models, and bias propagation further complicate simulations.

These limitations are particularly evident in rainfall modeling, where precipitation processes involve complex interactions across various spatial and temporal scales. Consequently, rainfall predictions from climate models often show significant biases and uncertainties, especially at regional scales [22]. Quantitatively, a study by Mehran et al. [12] found that CMIP5 models had a high mean absolute percent error in simulating annual precipitation over various global regions. Temperature simulations generally performed better, with errors often less than 2°C. These findings highlight the ongoing challenges in accurately modeling precipitation patterns within current climate models.

5.2 Introduction to Data-Driven Approaches in Climate Science

The limitations of traditional climate models, combined with the exponential growth in available climate data from satellites, weather stations, and other sources, have led to increased interest in data-driven approaches in climate science. These approaches, often based on machine learning techniques, aim to leverage large datasets to improve our understanding of climate processes and enhance predictive capabilities.

Key data-driven approaches in climate science include statistical downscaling for high-resolution projections [25], pattern recognition to identify dominant climate patterns [11], extreme event attribution [3], parameterization improvement using neural networks [6], and climate model emulation for rapid parameter space exploration [21].

These approaches offer advantages such as capturing complex, non-linear relationships in climate data, computational efficiency, and potential for new scientific insights. They can handle relationships difficult to represent in traditional physics-based models and allow for rapid predictions once trained. However, data-driven approaches face challenges. They often require large amounts of high-quality training data, which may not always be available. Extrapolation beyond the training data range can be problematic, especially for climate change projections. Additionally, the "black box" nature of some machine learning models can hinder the physically meaningful interpretation of results.

5.3 Potential Applications of Physics-Informed Machine Learning in Improving Circulation and Rainfall Models

Physics-informed machine learning (PIML) represents a promising approach to combine the strengths of traditional physics-based modeling with the power of data-driven techniques. In PIML, machine learning models are constrained or guided by physical principles, helping to ensure that their predictions are physically consistent and interpretable. Several potential applications of PIML in improving circulation and rainfall models include:

1. **Hybrid Modeling**: PIML can be used to create hybrid models that combine physics-based equations with data-driven components. For example, Ramadhan et al. [14] developed a hybrid ocean model where certain terms in the Navier-Stokes equations were learned from data, improving the model's accuracy while maintaining physical consistency.

2. **Parameterization Improvement**: PIML can be used to develop improved parameterizations for sub-grid scale processes. For instance, Gentine et al. [6] used neural networks to parameterize sub-grid convection in climate models, showing potential for improving precipitation predictions.

3. **Super-Resolution Modeling**: PIML techniques can be used to enhance the resolution of climate model outputs while ensuring physical consistency. This could be particularly useful for improving regional-scale rainfall predictions [25].

4. **Uncertainty Quantification**: PIML models can be designed to provide probabilistic predictions, helping to quantify uncertainties in circulation and rainfall projections [28].

5. **Process Understanding**: By combining data-driven insights with physical constraints, PIML could help identify and characterize important processes governing atmospheric

circulation and rainfall, potentially leading to improved process representations in climate models.

Early applications of Physics-Informed Machine Learning (PIML) in climate science have shown promising results. Gentine et al. [6] reduced biases in precipitation predictions significantly using neural network parameterization of convection, while Ramadhan et al. [14] decreased errors in ocean temperature and salinity predictions with a hybrid ocean model. These improvements demonstrate PIML's potential to enhance climate modeling accuracy.

However, PIML application to atmospheric circulation and rainfall modeling is still in its early stages, facing challenges such as ensuring long-term stability, incorporating physical constraints into machine learning architectures, balancing model complexity with interpretability and efficiency, and addressing overfitting risks. Despite these challenges, PIML's ability to combine physics-based modeling strengths with machine learning power offers a promising path for addressing key climate science challenges, likely playing an increasingly important role in improving atmospheric circulation and rainfall modeling and prediction.

6 Conclusion and Future Directions

This review has explored the fundamental aspects of atmospheric circulation and rainfall patterns, their changes due to global warming, and the evolving landscape of climate modeling techniques. Several key points emerge from this comprehensive examination:

1. Atmospheric circulation patterns, driven by differential heating and the Coriolis effect, play a crucial role in global rainfall distribution.

2. Climate change is altering these circulation patterns, leading to shifts in precipitation regimes, including more frequent extreme events and expansion of subtropical dry zones.

3. While traditional climate models have improved our understanding of these systems, they face limitations in accurately representing sub-grid processes and regional-scale precipitation patterns which make it hard for scientists to understand the impact of climate changes at the regional level.

4. Data-driven approaches, particularly machine learning techniques, offer promising avenues for enhancing our predictive capabilities in climate science.

5. Physics-informed machine learning (PIML) represents a frontier in climate modeling, potentially bridging the gap between traditional physics-based models and purely data-driven approaches.

The integration of traditional climate science with advanced modeling techniques is not just beneficial, but essential for advancing our understanding and predictive capabilities in atmospheric and rainfall dynamics. As we face unprecedented changes in our climate system, the synergy between physical understanding and computational power becomes increasingly crucial. Traditional models provide foundational physics and large-scale dynamics, while advanced techniques like machine learning can capture complex, non-linear relationships and improve the representation of sub-grid processes.

In my current work on a Physics-Informed Neural Network (PINN) down-scaling model for regional rain prediction, I am witnessing firsthand the potential of these integrated approaches especially in developing countries where weather stations are relatively low in numbers and scale of the data points that they gather. By incorporating physical constraints into neural network architectures, we can generate high-resolution precipitation forecasts that are both data-driven and physically consistent. This approach shows promise in addressing one of the persistent challenges in climate modeling: accurate regional-scale precipitation prediction.

Looking forward, several exciting research directions emerge:

1. Further development of hybrid models that seamlessly integrate physics-based and data-driven components.

2. Exploration of novel neural network architectures specifically designed for atmospheric and climate applications.

3. Improvement of uncertainty quantification in machine learning-based climate predictions.

4. Application of PIML techniques to other challenging areas in climate science, such as cloud physics and aerosol-cloud interactions.

As we continue to push the boundaries of climate science and modeling, the convergence of traditional physical understanding with cutting-edge computational techniques offers a powerful pathway for addressing one of the most pressing challenges of our time: predicting and adapting to a changing climate. The future of atmospheric and rainfall prediction lies in this interdisciplinary approach, where the rigorous physics of climate science meets the flexible, data-driven power of advanced machine learning techniques.

References

[1] Peter Bauer, Alan Thorpe, and Gilbert Brunet. The quiet revolution of numerical weather prediction. *Nature*, 525(7567):47–55, 2015.

[2] Sandrine Bony, Bjorn Stevens, Dargan M. W. Frierson, Christian Jakob, Masa Kageyama, Robert Pincus, Theodore G. Shepherd, Steven C. Sherwood, A. Pier Siebesma, Adam H. Sobel, Masahiro Watanabe, and Mark J. Webb. Clouds, circulation and climate sensitivity. *Nature Geoscience*, 8(4):261–268, 2015.

[3] Noah S. Diffenbaugh, Deepti Singh, Justin S. Mankin, Daniel E. Horton, Daniel L. Swain, Danielle Touma, Allison Charland, Yunjie Liu, Mark Haugen, Michael Tsiang, and Bala Rajaratnam. Quantifying the influence of global warming on unprecedented extreme climate events. *Proceedings of the National Academy of Sciences of the United States of America*, 114(19):4881–4886, 2017.

[4] Veronika Eyring, Sandrine Bony, Gerald A. Meehl, Catherine A. Senior, Bjorn Stevens, Ronald J. Stouffer, and Karl E. Taylor. Overview of the coupled model intercomparison project phase 6 (cmip6) experimental design and organization. *Geoscientific Model Development*, 9(5):1937–1958, 2016.

[5] Jennifer A. Francis and Stephen J. Vavrus. Evidence linking arctic amplification to extreme weather in mid-latitudes. *Geophysical Research Letters*, 39(6), 2012.

[6] Pierre Gentine, Mike Pritchard, Stephan Rasp, Giulia Reinaudi, and George Yacalis. Could machine learning break the convection parameterization deadlock? *Geophysical Research Letters*, 45(11):5742–5751, 2018.

[7] Dennis L. Hartmann. *Global physical climatology*. Academic Press, 1994.

[8] Isaac M. Held and Brian J. Soden. Robust responses of the hydrological cycle to global warming. 2006.

[9] J. G. Lockwood. *The Earth's Climates*, pages 59–89. John Wiley & Sons, Ltd, 2003.

[10] Jian Lu, Gabriel Vecchi, and Thomas Reichler. Expansion of the hadley cell under global warming. *Geophysical Research Letters*, 34, 2007.

[11] João P. Matos, Thibault Cohen Liechti, Dinis Juízo, Maria M. Portela, and Anton J. Schleiss. Can satellite based pattern-oriented memory improve the interpolation of sparse historical rainfall records? *Journal of Hydrology*, 492:102–116, 2013.

[12] Ali Mehran, Amir AghaKouchak, and Thomas J. Phillips. Evaluation of cmip5 continental precipitation simulations relative to satellite-based gauge-adjusted observations. *Journal of Geophysical Research (Atmospheres)*, 119:1695–1707, 2014.

[13] Seonju Moon and Kyung-Ja Ha. Future changes in monsoon duration and precipitation using cmip6. *Npj Climate and Atmospheric Science*, 3(1):1–7, 2020.

[14] Ali Ramadhan, John Marshall, Andre Souza, Xiang K. Lee, Uzi Piterbarg, Andrew Hillier, Gregory L. Wagner, Christopher Rackauckas, Chris Hill, Jean-Michel Campin, and Raffaele Ferrari. Capturing missing physics in climate model parameterizations using neural differential equations. *arXiv preprint arXiv:2010.12559*, 2023.

[15] David Randall, Marat Khairoutdinov, Akio Arakawa, and Wojciech Grabowski. Breaking the cloud parameterization deadlock. 2003.

[16] Markus Reichstein, Gustau Camps-Valls, Bjorn Stevens, Martin Jung, Joachim Denzler, Nuno Carvalhais, and Prabhat. Deep learning and process understanding for data-driven earth system science. *Nature*, 566(7743):195–204, 2019.

[17] Robert V. Rohli and Anthony J. Vega. *Climatology*. Jones & Bartlett Learning, 2017.

[18] Tapio Schneider, Tobias Bischoff, and Gerald H. Haug. Migrations and dynamics of the intertropical convergence zone. *Nature*, 513(7516):45–53, 2014.

[19] R. Serpolay. A short course in cloud physics: By r.r. rogers and m.k. yau, 3rd edition, 1989. pergamon press, oxford, 290. *Atmospheric Research*, 26(2):181, 1991.

[20] Jason Smerdon. *Climate Change: The Science of Global Warming and Our Energy Future*. Columbia University Press, 2018.

[21] Michael Stein, Elisabeth J. Moyer, Stefano Castruccio, David J. McInerney, Feng Liu, William G. Wilder, and Robert L. Jacob. Statistical emulation of climate model projections based on precomputed gcm runs (invited), 2013.

[22] Graeme L. Stephens, Tristan L'Ecuyer, Richard Forbes, Andrew Gettelmen, Jean-Christophe Golaz, Alejandro Bodas-Salcedo, Kentaroh Suzuki, Peter Gabriel, and John Haynes. Dreary state of precipitation in global models. *Journal of Geophysical Research: Atmospheres*, 115(D24):2010JD014532, 2010.

[23] Kevin Trenberth, Aiguo Dai, Roy Rasmussen, and David Parsons. The changing character of precipitation. *Bulletin of the American Meteorological Society*, 84:1205–1217, 2003.

[24] USGCRP. Fourth national climate assessment. Technical report, U.S. Global Change Research Program, Washington, DC, 2018.

[25] Thomas Vandal, Evan Kodra, Sangram Ganguly, Andrew Michaelis, Ramakrishna Nemani, and Auroop R. Ganguly. 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*, pages 1663–1672, 2017.

[26] Gabriel A. Vecchi and Brian J. Soden. Global warming and the weakening of the tropical circulation. *Journal of Climate*, 20(17):4316–4340, 2007.

[27] John M. Wallace and Peter V. Hobbs. *Atmospheric Science: An Introductory Survey*. Academic Press, 2nd edition, 2006.

[28] Yinhao Zhu, Nicholas Zabaras, Phaedon-Stelios Koutsourelakis, and Paris Perdikaris. Physics-constrained deep learning for high-dimensional surrogate modeling and uncertainty quantification without labeled data. *arXiv preprint arXiv:1901.06314*, 2019.