Exploratory Research on Global Warming and Weather Data Simulation for Increased Sustainability or Resilience to Hazards Induced by a Changing Climate

Gautam Siwach

Distinguished Data Scientist
IBM, Southbury, United states
0000-0002-9633-5328

Abstract **- This research explores the rise in global surface temperature of planet earth. This analysis combines the granular details contributing to the impact of climate change by observing the simulations for rising temperature and includes the details on other possible contributing factors like temperature against date and time, etc. To find the main cause leading to recent climate changes, it is vital to account the effects of global warming through analysis of weather data by region and season. In the planet geography, there are places where the impact is severe and rapid. this study discusses the overall implications of the climate changes on ecosystem, wildlife, and people. This study outlines the impact of natural calamities like drought, ice storms, etc. in terms of moisture loss and the anticipated impact of these continued tragedies in near future to understand complexities to build support systems, prepare and respond.**

Keywords - Climate Change, Sustainability, Weather, Machine Learning, Global Warming

I. INTRODUCTION

The meteorology of most regions depends on surface temperature. The surface temperature affects moisture loss and the anticipated impact of these continued tragedies. This study incorporates the variables impacting climate change with temperatures anomalies at Global Land and Ocean till the month of November 2022 starting from 1880 are integral part of this research.

II. WHY CLIMATE CHANGE RESEARCH IS OF IMPORTANCE

A. Variables Impacting Climate Change

In [1], Swaminathan, R., Sridharan, M., & Hayhoe, K., describes the fatal impact of ice storms on ecosystem. Authors explored the cause of Ice storm and determined that Ice storms are caused by complex mix of atmospheric conditions and is the least understood weather phenomenon, and the study of Ice storm to build support systems will require modeling and categorizing storm and related features.

A. Challenges with Humanitarian Assistance and Disaster Response (HADR)

In [2] M Weiss et al, elaborates the difficulties in collaborating for building the support systems and disaster response mechanisms due to variety in geospatial data modalities or big data while performing modeling.

B. Climate Change and Human Health Corelation Analysis

In [3], Pizzulli, V. A., Telesca, V., & Covatariu, G. quantitatively explores the correlation between climate change and human health. Authors describes the role of polluting emissions and their effects on human body through Principal component Analysis. In this study author builds a forecasting model and discusses the impact of nervous system diseases in the world on mortality.

C. Impact of Climate Change on Wildlife, Species Health and Biodiversity

In [4] Nwaerema Peace explores out impact of climate change on Insects, pest, diseases, and animal biodiversity. Author forecasts a serious attack of pests, insects and diseases on plant and crop species with changing climate based on incidents like the Epizootic ulcerative syndrome infected fish in the southern part of South Africa due to severe variation in temperature, rainfall, and other related climatic conditions. Bluetongue disease that affected cattle farmers migrated from southern Europe to the northern Europe due to change in climate. Author implies that with increasing temperatures some microbes those are beneficial to soil, crop and plant species can move from one region to other.

III. HOW TO PREPARE FOR CHANGING CLIMATE?

There are many suggestions proposed by researchers over time which focuses on addressing specific climate change challenges. Some of those observations include novel visualization techniques whereas others are strategies to reduce carbon footprint to net zero and become more sustainable.

In [5] D Mauree et al, emphasizes on energy efficient practices and carbon offset mitigation of climate change. Authors also points out the need of incorporating the carbon neutral needs into design and architectures through planners and community developers.

In this study, observations are made on rising temperatures thereby proposed a solution to harness the main constituent impacting climate change i.e., solar energy and become sustainable.

In [6], Nirupam Bidikar, Kotoju Rajitha, P. Usha Supriya talks about solar energy being a major advantage to be the most economical and clean sustainable energy sources on the planet. Authors describes unpredictable nature of the amount of energy produced through solar as one of the major hurdle.

Among several other challenges like predicting exact amount of watts/m2 at a specific location, there are other challenges for e.g., " The biggest challenge with energy generated from the solar is of the 'energy storage'". Calculating solar radiance based on historical data at a zip code level, for e.g., 10001, NYC using statistical modeling will help in predicting the amount of energy generated through renewables for upcoming years which can then be compared to offset the global rise in temperature or to calculate the impact of harnessing the solar power.

In this research, Table I shows the solar radiance from sun captured on a zip code level to obtain the exact amount of energy generated from the solar panels.

TABLE I. WEATHER DATA ELEMENTS

Weather Data for a specific Zip code	**Weather Data by Zip Code, New York City EST Zone**			
	Date	**Mean Temp (F)**	**Humidity %**	**Downward Solar radiance W/m2 (Watts per square meter)**
10001	12/27/22	32.1	0.06	2269
10001	12/28/22	40.4	0.12	2214
10001	12/29/22	44.6	1.27	227
10001	12/30/22	49	0.88	304
10001	12/31/22	47	0.001	3026

Conceptually, an integration of gids can harness the solar power after sunset at EST (Eastern Standard Time) zone and store the energy in the batteries connected to solar panels from PST (Pacific Standard Time) zone where it's still sunlight. Another key point to consider is of electricity usage in peak hours when integrating grids. Battery units in EST zone at a loss of sunlight readily starts to provide for appliances being in peak hours, it will allow more room for power storage due to high consumption and no charging. This gap and required energy for recharge can be served by integrated Solar energy infrastructure in PST zone.

In [7] Derrick Effah, Chunguang Bai, Matthew Quayson, explored on how exactly AI and innovation will reduce impact of extreme weather events on sustainable production. Using AI and machine learning concepts, they build predictive models and trained on publicly available data sets via Delphi best worst method. Authors concluded with a scope for future research that, the AI and Machine Learning are best used in aiding decision makers for devising strategies and rules for sustainable production due to their predictive ability.

In [8] Fausto A. Canales, Jakub Jurasz, Alexandre Beluco, Alexander Kies explores combine use of different energy sources considering for wind, solar, and hydro as partial solutions. In their study authors discusses the dependencies of weather on renewable energy sources, and how the weather hinders integration of national grids as well.

In [9] Bradford J. Foley and Andrew J. Smye discusses the conditions for habitability of rocky planets using CO2 cycling, thermal evolutions, and other mechanisms. This study draws out modeling for maintaining volcanic outgassing rates for a planet and underlying conditions.

The goal is to draw the focus on using a combination of different ideas and proposed solutions with grid infrastructure through national integration for supplying power back and forth from solar panels in different time zones. To harness solar energy at this scale will have solid implications and at the end we have a chance to converting the solar energy relating to global warming to our biggest advantage.

In [10] Geunyeong Byeon, Pascal Van Hentenryck, Russell Bent, Harsha Nagarajan discusses the importance of remote management and designing distribution and communication systems for smart grid. To make distribution grids more resilient authors performed variety of test cases with varying disaster intensities and network topologies.

In [11] Christoph Bergmeir et al, worked on predicting and optimizing challenges in renewable energy. Authors explored building the most accurate forecast using gradient-booted tree and random forest models and optimization using mixed integer linear and quadratic programming.

In [12] SW McIntosh, RJ Leamon discusses the solar magnetism and outer atmosphere of sun. Author studies the slow decay in radiative and particulate forcing of our atmosphere and that it may be driven by a downturn in the Sun's global magnetism. Basically, activity related to sun and our limited and recent knowledge in the field.

In [13] Biswarup Bhattacharya, Abhishek Sinha proposed deep learning-based system for optimal placement of power sources or generators in order to do contingency planning. Authors explored the ability to embed machine learning to build fault tolerant systems and address other uncertainties in generating sustainable electric power.

In [14] Tom Kimpson et al, describes the deep learning application for water bodies specifically freshwater lakes categories using neural network regression model trained to simulate satellite observed surface skin temperatures.

In [15] Dattaraj B. Dhuri, Shamik Bhattacharjee1, Shravan M. Hanasoge, and Sashi Kiran Mahapatra discusses solar magnetic activity and provide means to improving space weather forecasting models and gaining new insights about solar activity.

In [16] David S. Gutzler studies a specific region for climate change and impacts and correlates the cause to human-caused increases in greenhouse gases. Author forecasts the simulations from climate change and thereby demonstrates the modifications and effects caused in atmosphere.

In [17] Thorsten Kurth et al, extracted pixel-level make of extreme weather patterns using neural networks. Authors also used summit systems for climate analytics and explored the precision rate. Also, this study outlines the importance of using accelerated infrastructure for building better climate analytics and models.

In [18] Swati Sharma, Aditi Partap, Maria Angels de Luis Balaguer, Sara Malvar, Ranveer Chandra puts agriculture using artificial intelligence at the heart of solving the sustainability challenges. Authors discusses Precision Agriculture (PA), as a management strategy combined with Geographical Information System (GIS), remote sensing, and machine learning to make better decisions for increasing yield, crop production, and to optimize soil health thereby minimize environmental impact.

In [19] C.-C. JayKuoAzad M.Madni talks about reducing the complexities of deep learning models for becoming more sustainable. Authors raises concerns on high carbon footprint yielded by very large deep learning models. As a solution they propose using green learning that encompasses use of lightweight models and a significant lower carbon footprint.

In [20] Siwach, G., & Esmailpour, A. demonstrates the architecture for using unstructured data securely with clusters or modern containers. Authors evaluates different architectures to enable private search options and encoding techniques used in analyzing different formats of data securely.

In [21] Swapna Thorve et al, digs dipper at energy consumption at household level and through bottom-up frameworks. Authors use surveys and applies modeling on the input received to report the energy usage. Author proposes having better insights into energy usage will result in efficient energy consumption to achieve sustainable energy goal.

In [22] Longfei Wei, Arif I. Sarwat advocates smart grids, and hybrid integration especially for grid distribution networks, for e.g., using weather parameters integration with artificial intelligence enabled neural networks at the grid level for minimizing power disruptions. In [23] Siwach, G., & Esmailpour, A. investigates the security vulnerabilities for LTE (Long Term Evolution) networks and proposes a secure solution through encryption techniques to be embedded into the communications systems through algorithmic enhancements.

In [24] Chaitanya Poolla; Abraham K. Ishihara proposes leveraging weather data from local and global forecasts due to trend for net zero sustainability for commercial buildings and importance if integration of photovoltaic assets.

In [25] J.K. Berry, J.A. Detgado, R. Khosla, and F.J. Pierce discusses the impact of growing population on natural resources. Authors warn about the dangers of climate change, and the impact on soil and water quality. Authors propose introducing new practices and the use of technology for sustainability.

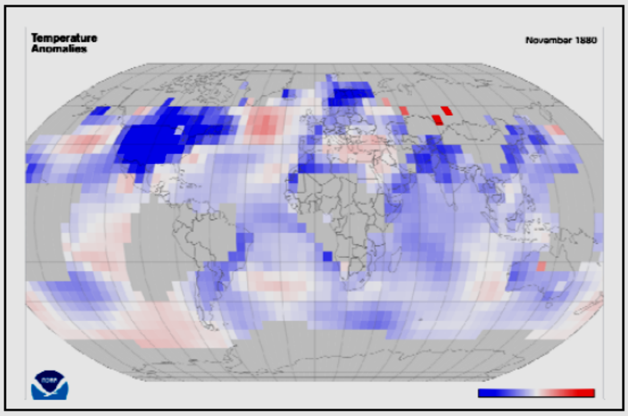

Figure 1. Blue color denominates the global temperature for (-5 degrees) and the red (+5 degrees) in Celsius for November 1880.

In [26] Jared Dunnmon, Swetava Ganguli, Darren Hau, Brooke Husic demonstrates the use of social media data for communication among agriculture practitioners to gain insights on crop harvest, crop production, report reconciliation and sentiment analysis. Authors uses CNN (Convolutional Neural Networks) along with tensor flow for analyzing information exchange.

In [27] V. S. Airapetian et al, explores the roadmap along-with progress made in the detection of terrestrial-type exoplanets, and exoplanetary atmospheres. Authors emphasizes on specific the conditions favorable for the origin of life. Authors studies the NASA's funded workshop 'Exoplanetary Space Weather, Climate and Habitability' and importance of future development in this emerging field.

In [28] Dmitriy Zakharov, Elena Magaril and Elena Cristina Rada suggests approaches for sustainability for urban transport system and the impact of weather on transport infrastructure. Authors proposes a reconstruction and the results obtained upon recovery of weather impacts.

In [29] Elena Antarciuc et al, studies the enablers for sustainable venture capital investments in Saudi Arabia and investigates their causal and effect interconnections towards sustainability. Authors concludes with the commitment of the venture capitalists to sustainability and their deep understanding of sustainable business models are the most influential enablers.

In [30] Lindsey, R., & Dahlman, L. Highlighted that earth's temperature has risen by 0.14° Fahrenheit (0.08° Celsius) per decade since 1880. And that 2021 was the sixth-warmest year on record based on NOAA's temperature data. This data from NOAA has been further utilized in this research to explore the increase in global temperature. In [31] Abrahms, B. climate change is intensifying human-wildlife interaction leads to biodiversity loss. Author emphasizes the need for researching the

DOI 10.5013/IJSSST.a.24.02.04 ISSN: 1473-804x online, 1473-8031 print

complex connections among ecological dynamics, climate dynamics, and social dynamics in this regard. In [32] Zhongming, Z., Linong, L., Xiaona, Y., Wangqiang, Z., & Wei, L. Studies NASA's assessment of Earth's long-term temperature rises and finds it accurate. As per NASA's data the years 2014-2018, were the warmest years.

IV. OBSERVATIONS AND SIMULATIONS FOR RISE IN GLOBAL TEMPERATURE AT A FIX POINT IN TIME OVER A CENTURY

Plotting the gridded temperature anomalies based on 1991-2020 mean. The data derived from, In [33] NOAA National Centers for Environmental information.

In Figure 1, temperature anomalies from 1880 are displayed for the month of November. The plot shows the temperature range f -5 degree Celsius to 5 degrees Celsius. In the “Fig. 2”, temperature anomalies from 2022 are displayed for the month of November. The plot shows the temperature range f -5 degree Celsius to 5 degrees Celsius.

Fig. 1. Blue color denominates the global temperature for (-5 degrees) and the red (+5 degrees) in Celsius for November 1880.

Annual mean temperature is maximum in the years 2020 and 2021 in the New York region when compared to that in past 20 years with a difference ranging from 1–3-degree Fahrenheit.

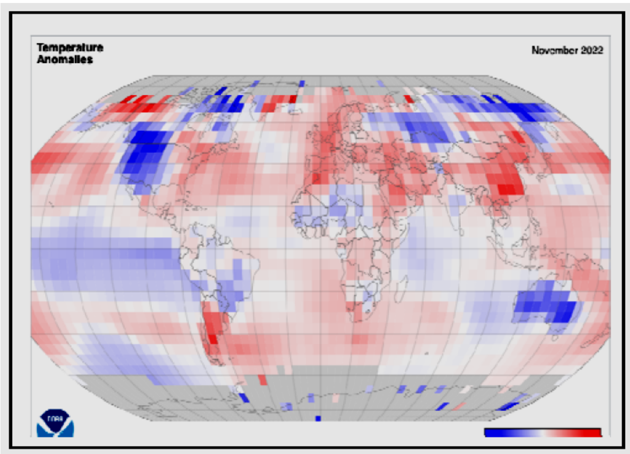

Figure 2. Blue color denominates the global temperature for (-5 degrees) and the red (+5 degrees) in Celsius for November 2022.

In [34], Campbell, M. discusses using R for statistical modeling and simulations, In the Code snippet 1, there is the ggplotly function that helps in calculating the drastic changes that occurred in past 140 years on the plot with green area. The labels show the Year and Value X and Y axis respectively.

```
> install.packages("ggplot2")
> library(ggplot2)
> install.packages("dplyr")
> library(dplyr)
> install.packages("plotly")
> library(plotly)
> install.packages("hrbrthemes")
> library(hrbrthemes)
data <- read.csv("~/Desktop/Global Land and Ocean Temperature Anomalies.csv", stringsAsFactors=TRUE)
data$Year <- as.Date(data$Year)
p <- data %>%
ggplot( aes(x=Year, y=Value)) +
geom_area(fill="#69b3a2", alpha=0.5) +
geom_line(color="#69b3a2") +
ylab("Temperatures Degree Celsius  (C)") +
theme_ipsum()
# Turn it interactive with ggplotly
p <- ggplotly(p)
p
```

Code Snippet 1, Weather Data Analysis in R programming, code showing the libraries, and required packages with data frame for plotting Year and Value from Global Land and Ocean Temperature Anomalies.

Among other observations, another prominent one was that analyzing from past 20 years, New York has recorded the maximum snowfall in year 2003 and 2010 i.e., 54.4 inches and 55.6 inches respectively. There is a major down trend of total snowfall in past 5 years starting from 2017 - 2022 in the New York city region. An overall rise in temperature is observed based on the data, mostly shifts are prominent in past 20-40 years. In Figure 3, Global Land and Ocean Temperature Anomalies are plotted on a time series graph using R code and modelling feature

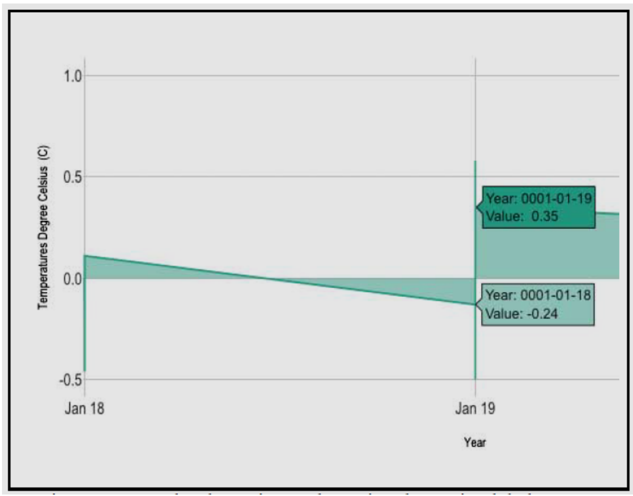

Figure 3. Green color denominates the major change in global temperature in degrees Celsius for December 2018 vs January 2019.

```
> x <- Year
> y <- value
> x <- runif(300, min=-10, max=10)
> y <- 0.1*x^3 - 0.5 * x^2 - x + 10 + rnorm(length(x),0,8)
> # Plotting x and y
> plot(x,y,col=rgb(0.4,0.4,0.8,0.6),pch=16 , cex=1.3)

> #Model with Ploynome function
> model <- lm(y ~ x + I(x^2) + I(x^3))

> # Features of the Model
> summary(model)

Call:
lm(formula = y ~ x + I(x^2) + I(x^3))

Residuals:
    Min      1Q  Median      3Q     Max
-18.2473 -5.3012  0.0589  6.1132  23.0003

Coefficients:
            Estimate Std. Error t value          Pr(>|t|)
(Intercept) 10.665220   0.685603  15.556 < 0.0000000000000002 ***
x           -1.256558   0.211880  -5.931   0.00000000841 ***
I(x^2)      -0.513341   0.016547 -31.024 < 0.0000000000000002 ***
I(x^3)       0.105596   0.003437  30.721 < 0.0000000000000002 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
Residual standard error: 8.07 on 296 degrees of freedom
Multiple R-squared:  0.9463,    Adjusted R-squared:  0.9458
F-statistic:  1739 on 3 and 296 DF,  p-value: < 0.00000000000000022
> model$coefficients
(Intercept)          x     I(x^2)     I(x^3)
 10.6652204 -1.2565576 -0.5133406  0.1055964
> summary(model)$adj.r.squared
[1] 0.9457619
> # For each value of x, getting the value of y estimated by the model, and adding it to the current plot !
> Pattern <- predict( model )
> ix <- sort(x,index.return=T)$ix
> lines(x[ix], Pattern[ix], col=2, lwd=2 )
> # Adding plot features
> coeff <- round(model$coefficients , 2)
> text(3, -70 , paste("Model : ",coeff[1] , " + " , coeff[2] , "*x"  , "+" , coeff[3] , "*x^2" , "+" , coeff[4] , "*x^3" , "\n\n"  ,  "P-value  adjusted  = ",round(summary(model)$adj.r.squared,2)))
```

Code Snippet 2: Statistical model that fits in Polynome function with summary and adjusted r squared value of the coefficients.

Furthermore, in Code Snippet 2, built a statistical model that fits in Polynome function to statistically infer the feasibility in predicting the pattern of temperature from the existing temperature rise anomalies ranges or from the differences in the earth’s temperature observed over the years scientifically, ‘Temperature Value’ over ‘Time’.

In figure 4, the built model is published to predict the temperature rise with increasing time using the predict function and plotting it with line based on the given data of global land and ocean temperature.

For each value of x as 'year', got the value of y as 'rise in temperature anomaly' estimated by the model, and added it to the existing plot also added the features of the model to the plot.

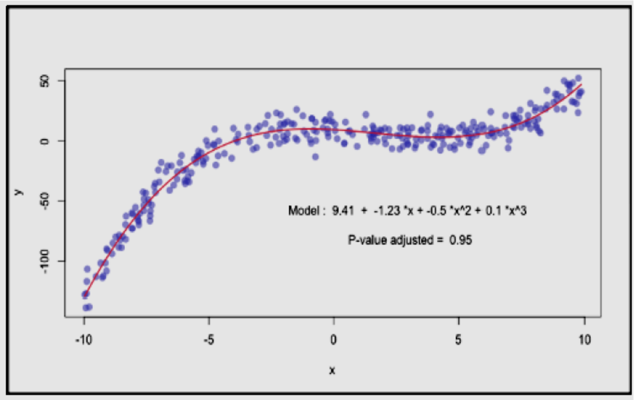

Figure 4. Scatterplot built using R, and a polynomial model is fitted into the model with lm() function.

A model is built on the variables from existing earth’s surface temperature from over a century and outputs an adjusted P-Value equal to 0.95. There are no significant outliers observed on the scatterplot when reading for the value of temperature rise anomalies.

V. CONCLUSION

There are rising temperature observed globally, be it land or ocean. A pattern is predicted from global land and ocean temperature anomalies data for years 1880 to present.

The probability test conducted for the hypothesis to plot values of years versus the temperature anomaly in Celsius which yields the p-value>=0.95 confirming that there is strong 95% probability for accurately predicting the rise of temperature in upcoming years.

Furthermore, the energy generation capability from advanced fusion generators is a work in progress and needs more time, study, and refinement. Finally, this study concludes on the future scope of research on solar energy infrastructure integration, by far solar seems to be the most economical, clean, and sustainable form of energy source on earth.

ACKNOWLEDGMENT

In this research paper the gratitude and acknowledgement go to many climate champions who are continuously expanding the awareness in the weather domain. A special acknowledgement to the 'Weather Company' to be providing insights to public to plan and mitigate several weather-related events. Notable acknowledgement for Lloyd Treinish IBM Distinguished Engineer; Chief Scientist Environmental Modeling, Climate, Weather and Deep Thunder, and John Ernst Technical BUE zStack FSM Market at IBM whose immense support drove to the completion of this successful study.

REFERENCES

[1] Swaminathan, R., Sridharan, M., & Hayhoe, K. (2018). A computational framework for modelling and analyzing ice storms. *arXiv preprint arXiv:1805.04907*.

[2] Weiss, M., Rahaman, N., Träuble, F., Locatello, F., Lacoste, A., Bengio, Y., ... & Pal, C. A General-Purpose Neural Architecture for Geospatial Systems.

[3] Pizzulli, V. A., Telesca, V., & Covatariu, G. (2021, January). Analysis of Correlation between Climate Change and Human Health Based on a Machine Learning Approach. In Healthcare (Vol. 9, No. 1, p. 86). MDPI.

[4] Peace, N. (2020). Impact of climate change on insects, pest, diseases and animal biodiversity. *Int. J. Environ. Sci. Nat. Res. Rev*.

[5] Mauree, D., Coccolo, S., Perera, A. T. D., Nik, V., Scartezzini, J. L., & Naboni, E. (2018). A new framework to evaluate urban design using urban microclimatic modeling in future climatic conditions. *Sustainability*, *10*(4), 1134.

[6] Bidikar, N., Rajitha, K., & Supriya, P. U. (2019). A Novel Universal Solar Energy Predictor. *arXiv preprint arXiv:1902.06660*.

[7] Effah, D., Bai, C., & Quayson, M. (2022). Artificial Intelligence and Innovation to Reduce the Impact of Extreme Weather Events on Sustainable Production. *arXiv preprint arXiv:2210.08962*.

[8] Canales, F. A., Jurasz, J., Beluco, A., & Kies, A. (2019). Assessing temporal complementarity between three variable energy sources by means of correlation and compromise programming. *arXiv preprint arXiv:1905.00117*.

[9] Foley, B. J., & Smye, A. J. (2018). Carbon cycling and habitability of Earth-sized stagnant lid planets. *Astrobiology*, *18*(7), 873-896.

[10] Byeon, G., Van Hentenryck, P., Bent, R., & Nagarajan, H. (2020). Communication-constrained expansion planning for resilient distribution systems. *INFORMS Journal on Computing*, *32*(4), 968-985.

[11] Bergmeir, C., de Nijs, F., Sriramulu, A., Abolghasemi, M., Bean, R., Betts, J., ... & Yuan, R. (2022). Comparison and Evaluation of Methods for a Predict+ Optimize Problem in Renewable Energy. *arXiv preprint arXiv:2212.10723*.

[12] McIntosh, S. W., & Leamon, R. J. (2015). Deciphering solar magnetic activity: On grand minima in solar activity. *Frontiers in Astronomy and Space Sciences*, *2*, 2.

[13] Bhattacharya, B., & Sinha, A. (2017). Deep fault analysis and subset selection in solar power grids. *arXiv preprint arXiv:1711.02810*.

[14] Kimpson, T., Choulga, M., Chantry, M., Balsamo, G., Boussetta, S., Dueben, P., & Palmer, T. (2022). Deep Learning for Verification of Earth-System Parametrisation of Water Bodies. *arXiv preprint arXiv:2210.16746*.

[15] Dhuri, D. B., Bhattacharjee, S., Hanasoge, S. M., & Mahapatra, S. K. (2022). Deep-learning Reconstruction of Sunspot Vector Magnetic Fields for Forecasting Solar Storms. *The Astrophysical Journal*, *939*(2), 64.

[16] Gutzler, D. S. (2013). Regional climatic considerations for borderlands sustainability. *Ecosphere*, *4*(1), 1-12.

[17] Kurth, T., Treichler, S., Romero, J., Mudigonda, M., Luehr, N., Phillips, E., ... & Houston, M. (2018, November). Exascale deep learning for climate analytics. In *SC18: International Conference for High Performance Computing, Networking, Storage and Analysis* (pp. 649-660). IEEE.

[18] Sharma, S., Partap, A., Balaguer, M. A. D. L., Malvar, S., & Chandra, R. (2022). DeepG2P: Fusing Multi-Modal Data to Improve Crop Production. *arXiv preprint arXiv:2211.05986*.

[19] Kuo, C. C. J., & Madni, A. M. (2022). Green learning: Introduction, examples and outlook. *Journal of Visual Communication and Image Representation*, 103685.

[20] Siwach, G., & Esmailpour, A. (2014, April). Encrypted Search & Cluster Formation in Big Data. In *ASEE 2014 Zone I Conference* (pp. 1-4).

[21] Thorve, S., Baek, Y. Y., Swarup, S., Mortveit, H., Marathe, A., Vullikanti, A., & Marathe, M. (2022). High-resolution synthetic residential energy use profiles for the United States. *arXiv preprint arXiv:2210.08103*.

[22] Wei, L., & Sarwat, A. I. (2018). Hybrid integration of multilayer perceptrons and parametric models for reliability forecasting in the smart grid. *arXiv preprint arXiv:1810.05004*.

[23] Siwach, G., & Esmailpour, A. (2014, May). LTE Security potential vulnerability and algorithm enhancements. In 2014 IEEE 27th Canadian Conference on Electrical and Computer Engineering (CCECE) (pp. 1-7). IEEE.

[24] Poolla, C., & Ishihara, A. K. (2018, June). Localized solar power prediction based on weather data from local history and global forecasts. In *2018 IEEE 7th World Conference on Photovoltaic Energy Conversion (WCPEC)(A Joint Conference of 45th IEEE PVSC, 28th PVSEC & 34th EU PVSEC)* (pp. 2341-2345). IEEE.

[25] Berry, J. K., Detgado, J. A., Khosla, R., & Pierce, F. J. (2003). Precision conservation for environmental sustainability. *Journal of Soil and Water Conservation*, *58*(6), 332-339.

[26] Dunnmon, J., Ganguli, S., Hau, D., & Husic, B. (2017). Predicting State-Level Agricultural Sentiment with Tweets from Farming Communities. *Final report for research project conducted as part of the Sustainability and Artificial Intelligence Laboratory (SAIL), Stanford University*.

[27] Airapetian, V. S., Barnes, R., Cohen, O., Collinson, G. A., Danchi, W. C., Dong, C. F., ... & Yamashiki, Y. (2020). Impact of space weather on climate and habitability of terrestrial-type exoplanets. *International Journal of Astrobiology*, *19*(2), 136-194.

[28] Zakharov, D., Magaril, E., & Rada, E. C. (2018). Sustainability of the urban transport system under changes in weather and road conditions affecting vehicle operation. *Sustainability*, *10*(6), 2052.

[29] Antarciuc, E., Zhu, Q., Almarri, J., Zhao, S., Feng, Y., & Agyemang, M. (2018). Sustainable venture capital investments: An enabler investigation. *Sustainability*, *10*(4), 1204.

[30] Lindsey, R., & Dahlman, L. (2020). Climate change: Global temperature. *Available online: climate. gov (accessed on 22 March 2021)*.

[31] Abrahms, B. (2021). Human-wildlife conflict under climate change. *Science*, *373*(6554), 484-485.

[32] Merzdorf, J. (2019). New Studies Increase Confidence in NASA's Measure of Earth's Temperature.

[33] NOAA National Centers for Environmental information, Climate at a Glance: Global Time Series, published December 2022, retrieved on December 30, 2022 from https://www.ncei.noaa.gov/access/monitoring/climate-at-a-glance/global/time-series

[34] Campbell, M. (2019). R Markdown. In Learn RStudio IDE (pp. 87-97). Apress, Berkeley, CA.