Function of machine learning in attaining environmental sustainability

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Abstract-Sustainable development and climate change are important issues that need to be tackled right away. Because of this goal, the renewable energy (RE) sector has grown significantly, and artificial intelligence (AI) is being used to increase the sector's overall efficiency. To achieve the Sustainable Development Goals (SDGs), however, they Given its recent significant rise in popularity and growing influence on the global energy sector, more research is required to determine whether renewable energy (RE) can help us achieve our sustainable development goals. Furthermore, an evaluation of AI being carried out has the potential to help accomplish the Sustainable Development Goals. In order to achieve environmental sustainability using solar panels, we classify the radiative energy flux at the earth's surface using a machine learning model that we developed using regression rigging. A number of variables are provided as input to the model, which considers the data modelling to determine environmental sustainability. The purpose of the simulation is to evaluate the model's effectiveness in achieving environmental sustainability, and the outcomes demonstrate that it is more sustainable than alternative approaches.

1. INTRODUCTION

Resources for food, water, and energy are under increasing demand due to the world's population growth, which has already put a burden on them. Energy production processes deal with a variety of problems, such as those pertaining to cost, security, sustainability, and changes in market prices, due to the growing environmental factors.

Hence, it has also become more and more important for scientists to focus their work on creating sustainable, renewable, and alternative energy sources. Research on solar cells and biofuels has increased as a result of this, which has also drawn a lot of attention to the transition of energy systems [9–11]. The renewable energy revolution is thought to require a number of renewable energy systems, including biomass, geothermal, wind, and solar [12–14].

The anticipated global photovoltaic generation in 2023-24 is shown in Fig 1. Figure 2 illustrates how renewable energy sources contribute significantly to global energy consumption. Among the cleanest forms of electricity, solar energy emits very little greenhouse gas (GHG) into the environment. Generation that is currently accessible. Sunlight irradiation is perfect for clean energy gathering because it contains massive amounts of energy in a single minute.

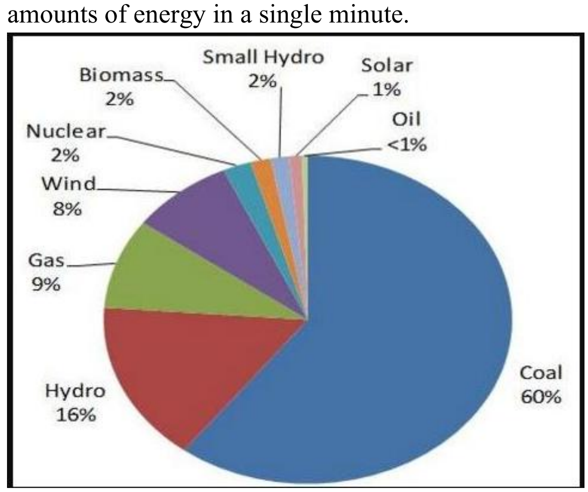


Fig 1.Global Primary Energy Generation

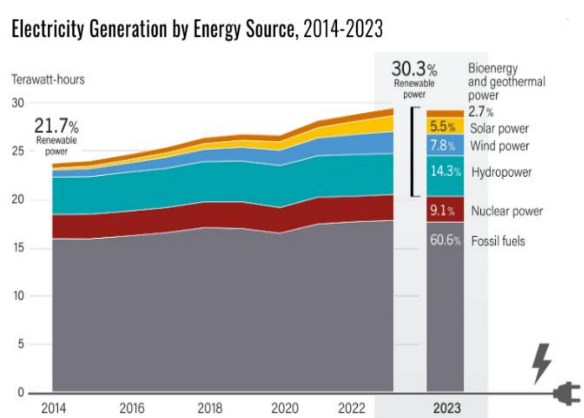


Fig 2. Capacity Installed Globally

Solar-based technologies play a unique function in the environment, filling a void left by other renewable technologies that are unable to meet the demands of the environment. For instance, because it takes up less subject matter, a micro-solar system for a single home is more realistic than a wind turbine or a biomass combustion system. It is possible to feed more power generated by a single residence into the urban areas grid.

As a result, planners and decision-makers who aspire to minimise their carbon impact are depending more and more on solar energy. Thus, it is imperative that research be done to increase solar energy harvesting efficiency while causing the least amount of damage to the environment and ecology.

A recent review of the literature states that it is crucial to evaluate the environmental impact of solar PV systems. The scientific literature states that little is now known about how various solar PV system components affect the environment. Additionally, more research is required to identify how the PV system's performance varies by elements including land use and requirements, as well as suitable distribution patterns. There is a lack of knowledge regarding the optimal design and implementation practices for photovoltaic (PV) technology and its effectiveness in minimising global greenhouse gas emissions.

Furthermore to building a machine learning model that use Regression Kriging to determine the radiative energy flux on Earth's surface, we expect that the installation of solar panels will help us accomplish our goal of being environmentally conscious. Numerous inputs are employed for determining environmental sustainability, including put into a model that combines statistical analysis and data modelling. The simulation outperforms other approaches when used as a test to evaluate the model's environmental sustainability, according to the results.

2. LITERATURE SURVEY

Soft computing methods have been used in several studies to calculate the amount of solar radiation that the planet receives. Rehman and Mohandes [15] created a neural network using ambient temperature and relative humidity as inputs to estimate global solar radiation, and the findings were published in a peer-reviewed journal.

Convolution neural networks (CNNs) are used in the initial step of the integrated model to extract features from the prediction variable. The model's parameters are estimated in the second stage using LSTM neural networks. Long-term and short-term memory networks were employed in the Chandola et al. [20] model to take into consideration the interdependence of daylight variables, including the normality index (NI), relative humidity (RH), dew point (DPT), and direct horizontal irradiance (DHI). Sunlight was expected to reach the Thar Desert region in four different places, the prediction said. Between 0.099 and 0.181%, there was a significant range in the RMSE and MAPE values across the four distinct locations. The model's efficacy was demonstrated by the low RMSE and MAPE values. In order to estimate solar radiation, Zang et al. [21] employed deep learning methods that applied embedding clustering and deep belief networks. The case study required the analysis of radiation data from 30 locations around China in order to verify the accuracy and viability of the suggested approach to analysis.

3. PROPOSED METHOD

Regression kriging

RK uses Kriging models to anticipate the spatial dependence of the responses and auxiliary elements (such climate, geography, and so forth) to forecast trends. A set of geographical and climatic factors are used as regressors in the RK, and the spatial dependence within the neighbourhood is described by the Kriging-fitted residuals. The following follows what the RK model predicts.

$z(x0) = m(x0)+e(x0)$ p

$\sum z(x0) =$ where k=0

$\beta k q k(x0) + n \sum i=1\ \omega i e(xi)$

m(x0)- fitted trend that involves geographical variables and climatic variation, and

e(x0)- interpolated residual of neighbours

p– total auxiliary variables,

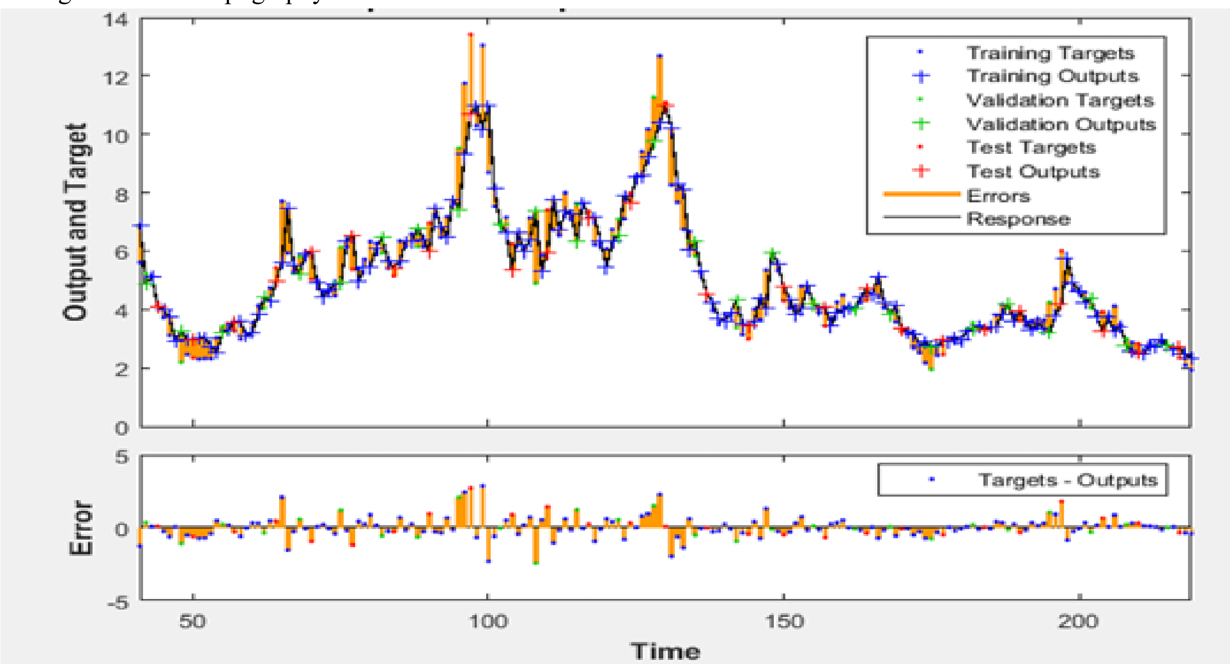
βk- estimated regression coefficients,

q0(x0) = constant term, where it is fixed as unity and

ωi- Kriging weights.

4. RESULTS AND DISCUSSIONS

This section assesses the model's validity using the Climate Research Unit (CRU)-TS 4.04 climate data collection. All of the world's landmasses' data can be downloaded for free from the CRU website, with the exception of Antarctica. This model's spatial resolution is obtained by using Grid cells of 0.5◦ x 0.5◦ each. CRU-TS observations are used to derive the climatic variables, which include We undertake model testing because the topography and climate of different continents vary, and in some situations, are completely opposite. A static cross-sectional map, which allows for one observation per distinct site, is the sole way to train the research model. In contrast, There isn't another way. As a result, Kriging data is regularly used for testing and training.



A monthly 10-fold CV is used to feed regression residuals from regression models into OK, which uses the residuals to provide SSR residual forecasts based on spatial dependence. Our final predictions are derived using a Kriging residual. The three regression models that were tested—Ordinary Kriging, Suggested Regression Kriging, and Random Forest Model—all produced statistically significant differences in errors, as illustrated in Fig., with Random Forest and Random Forest generating the smallest errors and Ordinary Kriging producing the largest errors, respectively.

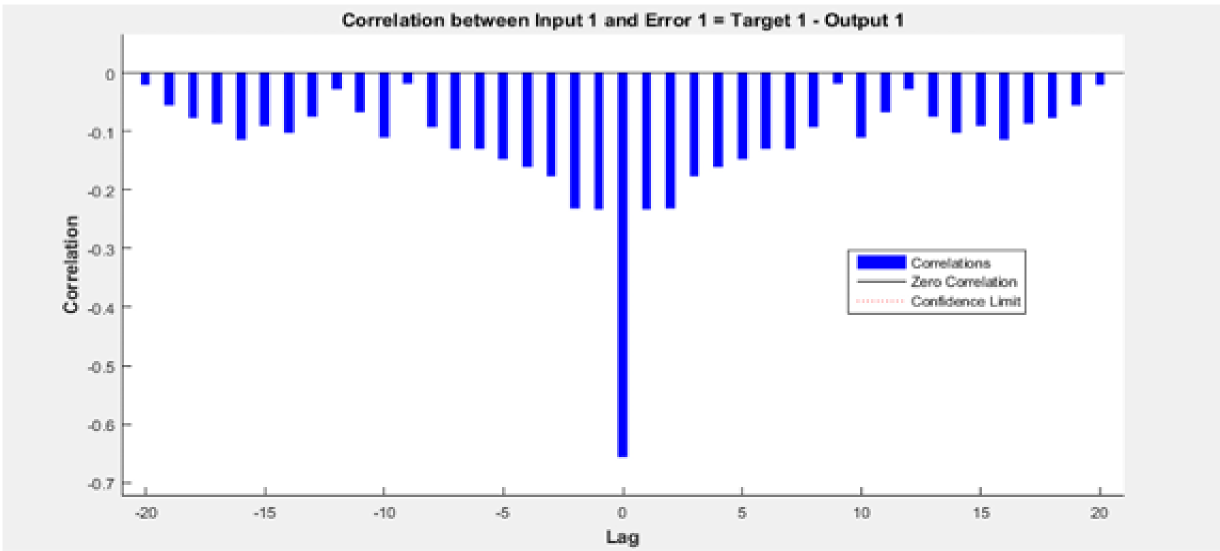
The higher number of mistakes produced by standard Kriging indicates that a more specialised method is required and that using the month variable as a standard numerical variable is insufficient. The study found that the results were positively impacted by high polynomial terms and varying treatment quantities for each month. The standard Kriging method is not more effective than regression. Furthermore, standard Kriging is less successful in South America than it is in North America due to the more subtle nature of the error.

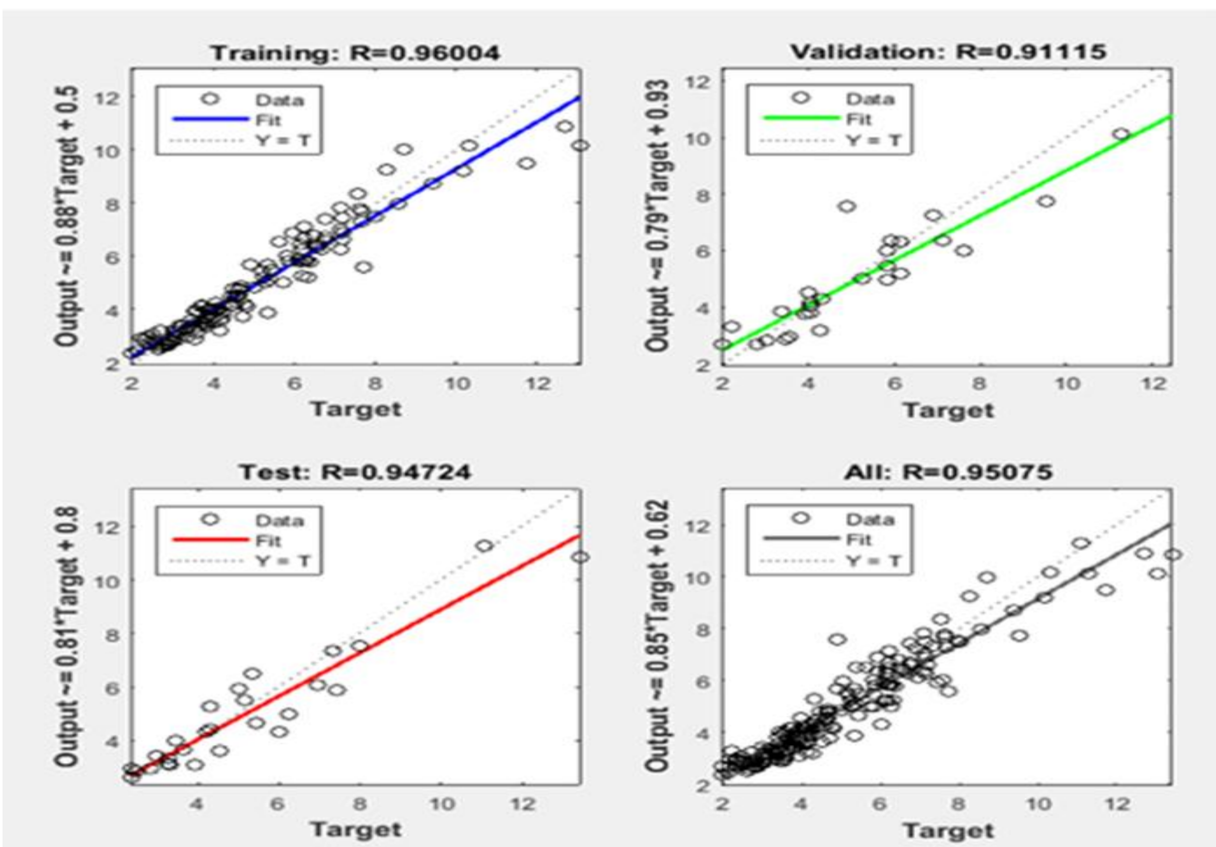
However, as compared to that, the performance of regular Kriging in Europe differs significantly. Regression in RK approaches adds a residual component to the trend forecast to increase accuracy by accounting for geographical dependence. This method's efficiency is demonstrated by its lower error measure when compared to conventional regression processes. Figure show the predicted and actual values for the four top-performing models in Europe. More than 95% of the variation in the response can be accurately predicted by the model when the R2 value is more than 95%. The RF model's high accuracy is demonstrated by the fact that there are very few points on either side of the regression line.

5. CONCLUSION

In addition to building a machine learning model that use Regression Kriging to calculate the radiative energy flux on Earth's surface, we expect that the installation of solar panels will help us accomplish our goal of environmental sustainability. Several inputs are used to assess environmental sustainability, including put into a model that combines statistical analysis and data modelling. The simulation outperforms other approaches when used as a test to evaluate the model's environmental sustainability, according to the results. The results indicate that while the RE has a negative effect on 15.97% of the global agenda targets, it has a positive effect on 44.3% of the SDGs.

According to the Environmental Protection Agency, it is responsible for 37% of environmental goals not being completed. When artificial intelligence (AI) is used in renewable energy (RE) applications, it is possible to achieve 23%, 28%, and 22% of these objectives.





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