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Improved Large-Scale Ocean Wave Dynamics Remote Monitoring Based on Big Data Analytics and Reanalyzed Remote Sensing

Subhrangshu Adhikary*† and Saikat Banerjee**
*Department of Computer Science and Engineering, Dr. B.C. Roy Engineering College, Durgapur-713206, India
**Department of Remote Sensing, WINGBOTICS, Baghajatin, Kolkata-700086, West Bengal, India
†Corresponding author: Subhrangshu Adhikary; subhrangshu.adhikary@spiraldevs.com

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ABSTRACT

Oceans and large water bodies have the potential to generate a large amount of green and renewable energy by harvesting the ocean surface properties like wind waves and tidal waves using Wave Energy Converter (WEC) devices. Although the oceans have this potential, very little ocean energy is harvested because of improper planning and implementation challenges. Besides this, monitoring ocean waves is of immense importance as several ocean-related calamities could be prevented. Also, the ocean serves as the maritime transportation route. Therefore, a need exists for remote and continuous monitoring of ocean waves and preparing strategies for different situations. Remote sensing technology could be utilized for a large scale low-cost opportunity for monitoring entire ocean bodies and extracting several important ocean surface features like wave height, wave time period, and drift velocities that can be used to estimate the ideal locations for power generation and find locations for turbulent waters so that maritime transportation hazards could be prevented. To process this large volume of data, Big Data Analytics techniques have been used to distribute the workload to worker nodes, facilitating a fast calculation of the reanalyzed remote sensing data. The experiment was conducted on Indian Coastline. The findings from the experiment show that a total of 1.86 GWh energy can be harvested from the ocean waves of the Indian Coastline, and locations of turbulent waters can be predicted in real-time to optimize maritime transportation routes.

INTRODUCTION

All renewable energy sources from the ocean are referred to as “ocean energy.” Wave, tidal, and ocean thermal energy are the three basic categories of ocean energy. The development of all marine renewable resources is still in its initial stages (Melikoglu 2018).

The energy contained within ocean waves is converted into electricity and used to generate wave energy as renewable energy (Khatri & Wang 2020). Various wave energy systems are being developed and tested to transform wave energy into electricity. The potential energy provided by the height difference between high and low tides is harvested by tidal range technology. Technologies that capture the kinetic energy of currents moving in and out of tidal zones are known as tidal streams or current technologies (such as seashores or coastal regions) (Wang et al. 2018).

ORCID details of the authors:

Subhrangshu Adhikary
https://orcid.org/0000-0003-1779-3070
Saikat Banerjee
https://orcid.org/0000-0003-0610-7266

Ocean surface observation is a necessary part of studying environmental and hydrological aspects with respect to marine renewable energy sources. Recent improvements in satellite-based optical remote sensing have booted up a new age in the field of surface water sensing (Shen et al. 2018). The phenomena also observe the current state and challenges of the ocean geothermal field, including problems with spatiotemporal scale, integration with spaceborne hydrological data, elevation data, cloud, and vegetation obscuration, and the increasing need to map and examine surface water physics on a global scale. Sensor resolutions have always been contradictory in the past. To address this inconsistency, techniques such as pixel unmixing and reconstruction, and spatiotemporal fusion, have been developed. Ocean surface water dynamics are now being predicted using remote sensing techniques and in-situ oceanographic data. Recent research has also shown that oceanographic surface physics may be predicted simply using optical remote sensing pictures, which provides useful information for hydrological studies in unmeasured areas. Cloud and vegetation obscuration has been a problem for optical sensors. Combining synthetic aperture radar data with other data is an efficient way to overcome this issue (Liang et al. 2019). Cloud/terrain shadows were also removed using digital elevation model data. The advancement of big data and cloud computing techniques has made it easier to meet the growing need for high-resolution monitoring of global and regional marine dynamics (Guillou et al. 2020).

With the growing amount of remote sensing ocean surface data, the processing capacity needs to be improved, giving rise to Big Data Analytics techniques. This replaces the requirement for developing more powerful computers by integrating multiple low-powered devices connected via the Internet to efficiently distribute the workload among them. The field of marine science is fast moving into the digital era (Amaro & Pina 2017). Escalating the opportunity and efficiency of ocean observations, as well as automated sampling and smart sensors integrated phenomenon, has resulted in rapid growth in the dataset size. Big data techniques help reduce the time requirement and cost of processing these large-scale data. This opens up new possibilities for studying and understanding the ocean through more complicated and multidisciplinary studies and inventive methods of marine resource management (Lytra et al. 2017).

This article discusses the usage of big data on reanalyzed remote sensing statistics to estimate the electricity generation capacity of the Indian Coastline. Further, the article discusses the optimal locations for harvesting electricity from ocean waves and their power generation capacities.

RELATED WORKS

In the areas of physical, biological, coastal, and satellite oceanography, remote sensing has a wide range of applications. The acquisition of oceanographic data, monitoring of coastal and oceanic dynamics, and analysis of numerous processes employing space and airborne sensors are all part of oceanographic research (Adhikary et al. 2021). Remote sensing enables large-scale monitoring of oceanographic properties at regular intervals with minimal cost. This can be utilized to detect the direction of waves, height, speed, time period, and many more ocean surface properties with reliable accuracy. This method can also observe the water viscosity and physical and chemical features. Deep learning and machine learning on remote sensing have been widely used for forecasting and predicting different properties and phenomena related to ocean surface properties. Deep learning-based image segmentation techniques on remote sensing data have been used to detect coastlines and seashores. Autonomous detection of multiple objects on the sea has also been widely implemented with this technique (Tiwari et al. 2021). The technique has further been used for automatic ocean eddy detection. The coastal risk has been estimated using remote sensing and GIS techniques. Heat captured by oceans and their global impact has been estimated with this approach.

The large volume of oceanographic data has been widely studied with different significant data approaches. IoT frameworks consisting of self-powered sensors have been implemented for ocean surface feature extraction, and big data on these have fetched reliable results much faster than the traditional method (Man et al. 2020, Vo et al. 2021). The Big Data Ocean project has studied several tactics for offshore grid-based optimization techniques leveraging wave energy and has been optimized by big data analytics techniques (Khare et al. 2020). Remote sensing techniques can be utilized to detect the temperatures of ocean bodies. Likewise, large-scale integration of this technique with the application of big data have been used to simulate ocean surface temperature for planning foreign trade through sea route. The technique has been further used for forecasting several maritime parameters based on satellites, buoy, GPS, drone and other components to build early warning systems for ocean-based natural calamities (Román-Rivera & Ellis 2019).

Limitations of the State of the Art and Motivation for the Experiment

The oceans around the world have a large potential for energy generation. Estimation of the potential reserves of energy is crucial to prepare strategies to extract electricity from ocean waves. Several approaches have been performed to estimate both the theoretical and practical limits of energy production (Hernández-Fontes et al. 2020). However, most of them have lesser accuracy as most were based on in-situ observations and other approximation techniques (Srisuwan et al. 2020). Table 1 summarizes all recent works and the limitations this article has attempted to solve. These limitations motivated us to use reanalyzed remote sensing technology and observe the entire coastline at regular intervals, estimate the energy production capacity purely based on the ocean waves, and find strategic locations of high turbulence.

MATERIALS AND METHODS

The mechanism to estimate the oceanic power generation capacity of the Indian coastline has been summarized in Fig. 1 and discussed further in the following text.

Table 1: Limitations of previously conducted related studies.

Sources	Objective	Methods	Findings	Limitations
(Thirugnana et al. 2021)	Estimation of Ocean Thermal Energy	Temperature, Salinity, Dissolved Oxygen, and Water Mass Profiling	Strategic locations for energy harvesting are depicted	In-situ observations have limited scalability
(Wahiduzzaman & Yeasmin2020)	Potential energy estimation for tropical cyclones	Remote sensing and geographically weighted regression	Correlations have been found between tropical cyclones and convective available potential energy	It cannot be used as a renewable energy source
(Hoang & Baraille 2020)	Energy estimation of ocean currents	Neural network with adaptive filtering	The possibility of oceanic current energy estimation with the method was confirmed	Simulated environment
(Nguyen & Tona 2018)	Wave excitation force estimation	Kalman filtering approach	Up to 94% accuracy	In-Situ experiment with limited scalability
(Chen et al. 2021)	Estimation of oceanic current fields using a decentralized sensor network	Kalman filtering and Monte Carlo Simulation	The model works well with fast-varying dynamics	In-Situ observations have limited scalability
(Bergamasco et al. 2021)	Real-time estimation of oceanic current energy	Point cloud estimation	10x faster processing compared to the State of the Art	Limited mobility of the setup makes it difficult for large-scale monitoring
(Choi et al. 2020)	Real-time wave height estimation from 2D and 3D images	CNN and ConvLSTM	84% classification accuracy	Camera-based monitoring limits large-scale monitoring

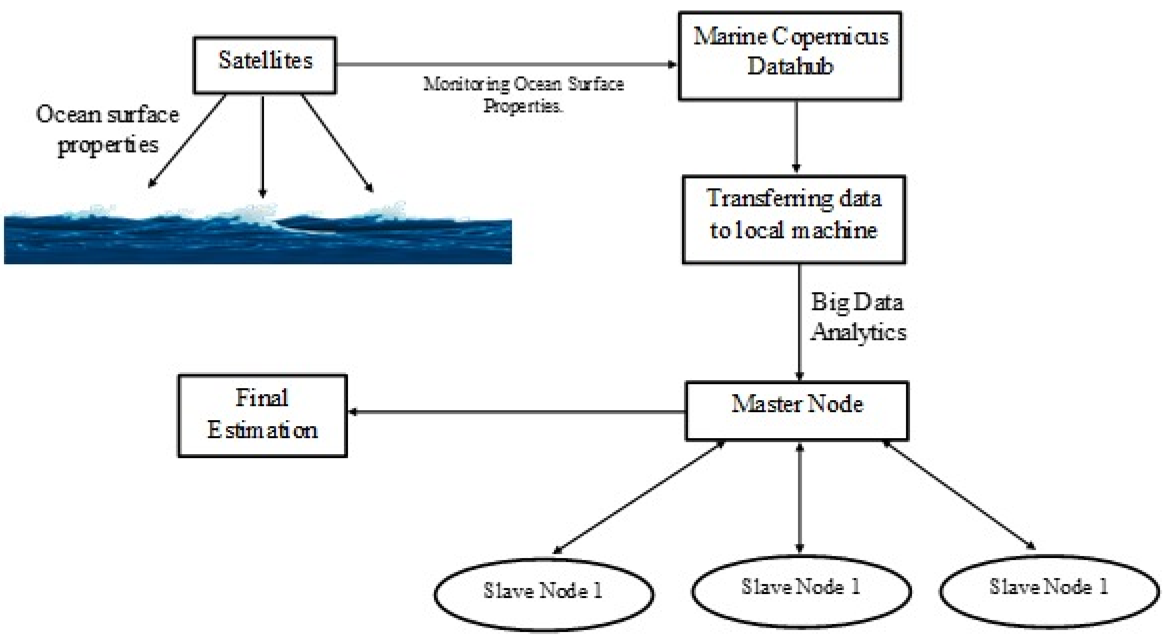

Fig. 1: The workflow diagram for the proposed mechanism to estimate oceanic power generation capacities.

Study Location and Data Availability

The experiment has been conducted on Global Ocean Waves Analysis and Forecast statistics published by the Marine Copernicus program. Remote sensing data have been processed by the agency to track several important ocean surface features (Dalphinet et al. 2020). The study location was selected as Indian Coastline is significantly long and shares three geographically important water bodies: The Bay of Bengal, the Indian Ocean, and the Arabian Sea. The coordinates of the study location include 6º to 24º N and 67º E to 98º E. The date ranges were from 8^{th} August 2021 to

8th November 2021, where 8 snapshots for each day were recorded. Each degree latitude and longitude were divided into 12 equal parts whose readings were recorded in the data. The dataset contained ocean surface features including Spectral significant wind wave height, Mean secondary swell wave direction, Mean wave direction (Mdir), Mean primary swell wave direction, Spectral moments (-1,0) wave period (Tm-10), Wave principal direction at spectral peak, Wave period at spectral peak/peak period (Tp), Spectral moments (0,2) wave period (Tm02), Spectral significant primary swell wave height, Mean wind wave direction, Spectral moments (0,1) secondary swell wave period, Stokes drift U, Spectral moments (0,1) primary swell wave period, Stokes drift V, Spectral significant wave height (Hm0), Spectral moments (0,1) wind wave period and finally Spectral significant secondary swell wave height. Table 2 contains the features along with their descriptions.

Big Data Analytics-Based Processing of Reanalyzed Remote Sensing Data

The large volume of data associated with the study is considerably challenging to process with general-purpose

Table 2: Wave features and their short description.

Features	Description
Spectral significant wind wave height	The average height of the highest one-third of all waves measured
Mean secondary swell wave direction	Mean direction of waves in the second swell partition
Mean wave direction (Mdir)	Mean direction toward which the waves and wind are propagating
Mean primary swell wave direction	Direction from which the primary swell is coming
Spectral moments (-1,0) wave period (Tm-10)	Turbulence energy spectra in the wavevector and frequency domain between subsequent waves
Wave principal direction at spectral peak	The direction of the peak of the wave spectrum
Wave period at spectral peak/peak period (Tp)	The time difference between the two peaks
Spectral moments (0,2) wave period (Tm02)	The spectral moment of the wave at 2nd order
Spectral significant primary swell wave height	Height of the primary swell wave for the wave spectrum
Mean wind wave direction	The direction of the wind blowing at the ocean/sea surface
Spectral moments (0,1) secondary swell wave period	Spectral moment of 1st order for secondary swell waves
Stokes drift U	The difference in endpoints of waves after a predefined amount of time
Spectral moments (0,1) primary swell wave period	The spectral moment at 1st order for the primary swell wave
Stokes drift V	Vertical stokes drift
Spectral significant wave height (Hm0)	Wave height of the spectral field
Spectral moments (0,1) wind wave period	1st order spectral moment for a wind wave
Spectral significant secondary swell wave height	Wave height of the secondary spectral wave

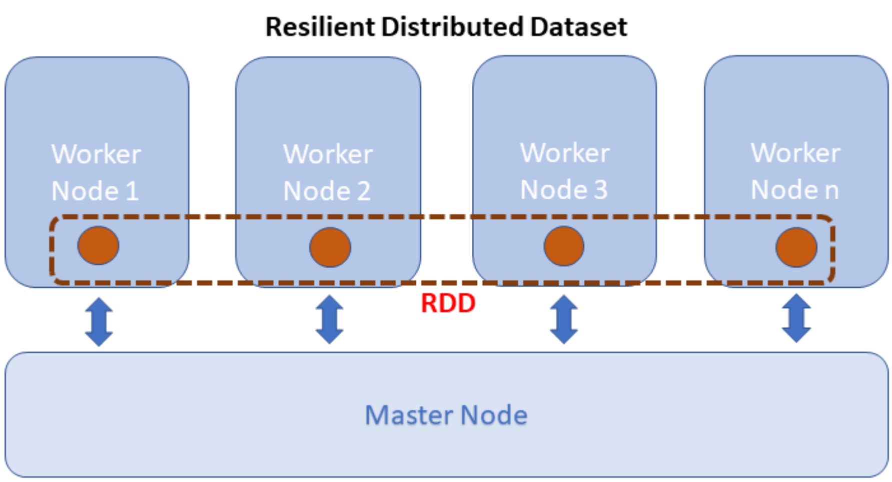

Fig. 2: Architecture of Resilient Distributed Datasets (RDD).

computers. Therefore big data analytics techniques have been implemented to distribute the workload across multiple server nodes (Qian et al. 2021). The system is controlled by a master node which splits the entire task into smaller chunks which are then processed by slave nodes and finally synchronized by the master node. The entire reanalyzed remote sensing dataset has been converted into a time series for each location pixel, and this time series has been stored with Resilient Distributed Datasets (RDD) method, which splits the entire dataset into multiple server nodes maintaining the sequence, speed, and fault tolerance (Athira & Thomas 2018). RDDs are immutable and, therefore, cannot be modified by other RDDs can be created from modifying an existing RDD. The architecture of RDD has been shown in Fig. 2. RDDs are not directly loaded into the memory for execution. First, a set of data is created to map all the functions to be executed in each row of the dataset. Therefore, because of this mapping, the immutability of RDDs can be exploited for faster and lightweight execution.

After this, multiple worker nodes are initiated for the execution by distributing the workload by the master node. Following this, each row is then separately processed by the assigned worker node fetching a limited row at a time only when necessary. This reduces the requirement for unnecessary ram usage and enables the processing of a very large volume of data efficiently without lagging. The data within the RDDs are replicated into copies spread across multiple worker nodes to make them resilient. This way, no data are lost even if there are issues with a few worker nodes, as the replicas can be processed if necessary. Following this, Map-Reduce-based operations have been performed to map each point in the RDD and create a new reduced RDD with applied conditions to get the final result. Reduce is performed to combine multiple rows of an RDD based on different conditions, and the resulting output creates another RDD. By this method, a total of 12942771x22 elements have been processed. The data are then visualized based on a different time to check for the variation of the ocean waves at different points of the day and seasonal variation. Following this, the ocean wave properties are further calculated to estimate the energy generation capacity, as discussed later. The map reduction process has been implemented to combine multiple rows of the primary RDD according to the equation conditions. The work has been conducted on 3 virtual private servers of 4GB RAM, and 2 CPU cores where one node was used as master and two other nodes were used as worker nodes.

RESULTS AND DISCUSSION

The experimental results show that Indian Coastline potentially has a large reserve of energy production capacity based on mechanical properties like waves and tides, which can be utilized to extract electricity. Fig. 3 shows the ocean surface properties of the Indian Coastline that helps in estimating the energy generation capacities. The study reveals that the spectral significant wind wave height is maximum at the conjunction between the Bay of Bengal and the Indian Ocean. The wave heights in these areas rise above 0.8 m, which can be effectively utilized for energy production. The wave directions from the figure show the direction of waves' movement where the waves travel according to the wind movements. The waves mostly travel from the southeast and far south of the Indian subcontinent and mix with the Bay of Bengal. Further, the spectral moment wave time periods reveal that the waves at the Indian Ocean at the base of the Bay of Bengal are much longer than the waters of the Bay of Bengal. This indicates a steady near-laminar flow of water waves in this region. However, the wave time periods near the Bay of Bengal and the Arabian Sea are much shorter, more vigorous, and more turbulent. This observation indicates that both the wave height and time period of the wave are higher near the conjunction between the Indian Ocean and the Bay of Bengal, making it the ideal location for energy harvesting. The steadier flow in these regions would ensure ease of electricity generation. Similarly, the method can be utilized to find locations of high turbulence in real-time where maritime transportation could be hazardous. Therefore, routes of lower turbulence could be used for safer transportation.

The energy generation capacity has been measured by conditionally combining multiple ocean surface properties. Theoretically, any wave with kinetic energy can be harvested to produce energy in this method, but practically waves should be large enough to feasibly harvest the energy. Firstly, discussing the theoretical limits, any wave with a height greater than zero has been considered. This leaves us with 10005015x22 elements to filter from. The drift velocity of the wave for horizontal (ξ_x) and vertical (ξ_z) components of Lagrangian position (ξ) and amplitude a and wave number k is given by,

$$u_S = u_{x(\xi,t)} - u_{x(x,t)}$$

$$= [u_{x(x,t)} + (\xi_x - x)\frac{\partial u_x(x,t)}{\partial x} + (\xi_z - z)\frac{\partial u_x(x,t)}{\partial z} + \cdots] - u_x(x,t) \quad ...(1)$$

$$\approx (\xi_x - x)\frac{\partial^2 \xi_x}{\partial x \partial t} + (\xi_z - z)\frac{\partial^2 \xi_x}{\partial z \partial t}$$

$$= \left[-ae^{\{kz\}}\sin(kx-\omega t)\right]\left[-\omega kae^{\{kz\}}\sin(kx-\omega t)\right]$$

$$+\left[ae^{\{kz\}}\cos(kx-\omega t)\right][\omega kae^{\{kz\}}\cos(kx-\omega t]$$

$$= \omega ka^2e^{\{2kz\}}[\sin^2(kx-\omega t)+\cos^2(kx-\omega t)$$

$$= \omega ka^2e^{\{2kz\}} \quad ...(2)$$

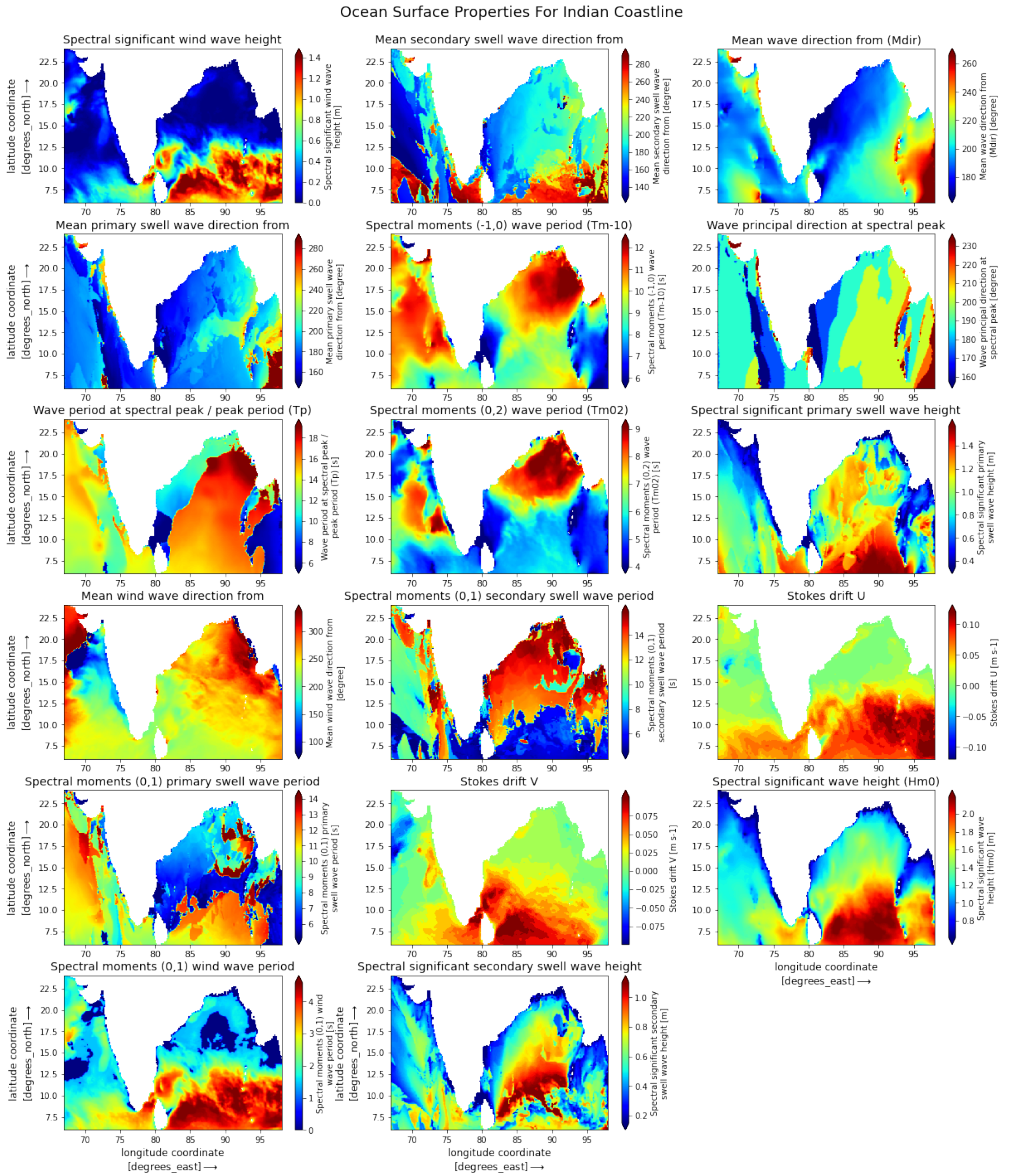

Fig. 3: Visualization of different ocean surface properties for the Indian coastline. The x-axis represents longitude, the y-axis represents latitude, and the color bar represents the magnitude of the points.

Followed by this, for wavelength L, height H, and time period T, the energy per unit area is calculated by,

$$E = \frac{\rho g H^2}{8} \quad \text{...(3)}$$

Therefore from eqn. and eqn 3, we have the wave energy transmission rate or wave power defined by,

$$P = \frac{\rho g H^2 c}{16}\left(1 + \frac{2kh}{\sin(h\, 2kh)}\right) = E c_g \quad \text{...(4)}$$

Where group celerity is given by,

$$c_g = \frac{c}{2}\left(1 + \frac{2kh}{\sin(h\, 2kh)}\right) \quad \text{...(5)}$$

The wave heights multiplied by the horizontal width of the waves, the drift velocity, and the wave's time period give us the waves' total volume, and multiplying that with water density gives us the total mass of the ocean waves, which is found to be 67 MT. With the usage of the big data distributed computing framework, the calculation was performed within 632 s as computed by 2 worker nodes and one master node of specification as described in an earlier section. Considering the drift velocity for waves of each location, the total power of the waves according to eqn. 4 has been estimated to be 1.86 GigaWatts (GWh). Although this is a theoretical limit, the energy could be logically harvested at a large scale if the ocean wave heights are over 1m. This condition leaves us with 1021415x22 elements, and repeating the calculation, we find 1.35 GWh power capacity in an ideal scenario. Considering 90% efficiency, 1.21 GWh could be effectively harvested. Following this, the waves could be harvested cost-effectively in case the waves are very large. Considering 2 m wave heights, 80233x22 elements of the dataset have been tested, resulting in 0.19 GWh power generation capacities with practically efficiency rates, 0.17 GWh could be harvested.

Comparison With the State-of-the-Art Methods

The proposed ocean wave monitoring and power estimation model is better in multiple aspects than the state of the Art methods. The work conducted by Thirugnana et al. (2021), Nguyen & Tona (2018), and Chen et al. (2021) were in-situ observations. These works were conducted locally at the study location; therefore, they are immobile models making it difficult for large-scale monitoring. However, the proposed model uses remote sensing satellite technologies, enabling large-scale, low-cost remote, and continuous monitoring. Wahiduzzaman & Yeasmin (2020) showed an interesting model for the power estimation of tropical cyclones. Still, this energy cannot be harvested with state-of-the-art technology, but electricity can be harvested from ocean waves using WEC machines which have been the basis of the proposed work. Hoang & Baraille (2020) conducted the experiment for energy estimation of ocean currents using a simulated environment. Still, the proposed method uses large-scale data from real environments, making it more robust in the long run. Finally, Bergamasco et al. (2021) and Choi et al. (2020) used 2D and 3D images of the waves and estimated their power. This model has limited usage for large-scale continuous monitoring as this would require a large number of cameras at different locations, and a good amount of computational complexity is required for synchronizing all footage. But the proposed method doesn't require much cost and complexity as only one satellite combined with a cloud server can deploy the model.

CONCLUSION

Oceans worldwide are potential sources of harvesting large amounts of renewable and green energy. Steady growth has been made to utilize this resource; however, a large amount of energy could be harvested from this abundant resource. Therefore, proper resource planning is required to use this large amount of resources. Remote sensing techniques could be utilized for remote regular monitoring of the ocean surface properties, and with the help of Big Data Analytics techniques, the processing could be accelerated. The paper presents a method to use reanalyzed remote sensing data with big data analytics techniques to estimate the total potential reserved energy generation capacity of the Indian Coastline using ocean and sea waves. The presented method is more precise than previously estimated results, mostly in-situ observations and approximations.

The experiment revealed that the conjunction area between the Indian Ocean and the Bay of Bengal shows promising areas to harvest the ocean wave energy. The theoretical limit for power generation capacity by ocean waves of the Indian Coastline was found to be 1.86 GWh. However, practically the waves should be large enough to be harvested, and therefore 1.35 GWh could be practically generated. Considering only the most promising areas for power harvesting, 0.19 GWh could be produced, ensuring lower implementation costs. The method can be used to find optimal maritime transportation routes based on the turbulence of the oceanic waters. The model could be used to set up proper strategies to implement WEC machines, ensuring maximum efficiency. Further, the model could be improved by increasing the resolution and considering other techniques to produce electricity from ocean waves.

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