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Investigatory analysis of the natural hazards on the Indian coastline

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Predictive analysis, comparative analysis, and image processing can provide vital insights into understanding natural phenomena. Water bodies surround India on three sides, so natural disasters (cyclones, floods, and other related hazards) and rising water levels due to meteorological fluctuations are common occurrences. The coastal states of India, due to their diverse nature, are constantly exposed to various risks. The study focuses on the changes and disasters in the Indian Ocean surrounding the Indian shorelines. A systematic approach has been employed to examine the fluctuations in meteorological factors of nine Indian coastal states for the period of 2001–2021. The fluctuations were computed for four meteorological seasons Summer (March–May), Monsoon (June–September), Post-monsoon (October–November), and Winter (December–February). These fluctuations are studied, and trends are put forward to examine their effects on natural disasters. The results of the study focus on the correlations between the factors and disasters and their respective predictions.

Keywords: *image processing; predictive analysis; comparative analysis; meteorological factors.*

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1. Introduction

Recently, the coastal states in India have frequently been hit by natural disasters caused by changing climate patterns, including cyclones, floods, droughts, and other similar risks. The extreme vulnerability of coastal areas to hazards has been studied using site-specific indicators [1]. Global sea level changes are regularly assessed and sea level rise along the Indian coast has been projected [2,3]. Coastal hazards refer to the physical events that threaten coastal areas with property damage, loss of life, and environmental degradation. These hazards can be rapid-onset and short-lived, lasting anywhere from minutes to several days. Examples of rapid-onset hazards include intense cyclones with high winds, waves, and surges, or tsunamis caused by submarine earthquakes or landslides. Slow-onset hazards develop gradually over extended periods of time and include examples such as erosion and the gradual flooding of the land.

The spatio-temporal analysis (used in data evaluation while records are accumulated throughout both space and time. It describes a phenomenon in a certain location and time.) of the Indian Ocean is a crucial topic of research, as the changes in spatial and temporal distribution in the Indian Ocean are harming marine life. A study of yellowfin tuna's fishing activities in 2020, stresses the importance of GIS platforms for spatial statistical analysis [4]. Spatio-temporal analysis has been used to examine parts of the Indian coastline such as the Muthupet Lagoon and Bay of Bengal [5, 6]. Many marine species are suffering from thinning of population, destruction of migratory pathways, harmful changes in environmental conditions, and destruction of habitats. Climate change has been projected and the changes in Indian monsoon have been studied and simulated [8, 9]. Phenomenons such as tropical nighttime warming are also being studied [7]. Global warming is leading to a rise in water levels, frequent high tides, and damaging marine ecosystems.

Because of its extensive coastline, diverse conditions and natural hazards throughout the year, many studies have been done along the Indian coastline. Storm surges have been examined in the Bay of Bengal, and models have been created for their prediction as a safeguard against natural disasters [10, 11]. Dube and Gaur created a new disaster management model using storm surge prediction [12]. Due to the vulnerability of the coastlines, the tide gauges are a critical topic. Tide gauges have been investigated as well as other models for tide analysis such as spectroscopy [13, 14]. Tidal propagation has also been studied in the various parts of the Indian Ocean [15].

Previous studies were done by Walter and Graf (2002) to examine the concurrent variation of SST(Sea Surface Temperature) and tropospheric geopotential height and their relations to the North Atlantic Oscillation [16]. Investigations have been done on the Land Surface models [17]. Some investigations have also been carried out by Ratna et al. that suggest the IOD (Indian Ocean Dipole) influenced the monsoon rainfall in 2019 with the help of observation-based analysis [18]. Implications of extreme events, Modoki and Indian Ocean dipole as well as El NiЛњo Modoki's contributions to the sea level changes have been analysed [19, 20]. Schott et al. (2009) examined the linkages between how water moves around the Indian Ocean and climate impacts related to that ocean circulation [21]. Wang et al. studied how the frequency of El Niño and La Niña varied from decade to decade in the 1900s, using both observed data and model simulations from the IPCC AR4 report [22]. Zhang and Han (2018) examined the effects of the Ningaloo Niño, which is the primary mode of variability in sea surface temperature in the southeast Indian Ocean, on the tropical Pacific region, through the use of an atmospheric general circulation model and observational data sets [23]. The studies conducted by Agrawal et al. in 2020 and 2023 investigated correlations between meteorological factors and explored methods to derive statistical insights from weather data [24, 25]. Agrawal et al. in 2021, examined the relations between meteorological factors and land surface temperature and its investigatory methods [26].

The population residing near the coasts suffers from frequent natural disasters such as cyclones and floods. The Indian Ocean area is one of six most prone cyclone areas in the world with five to six cyclones on average per year. Indian coastal regions with high population density, frequent cyclones and strokes, and a high rate of coastal environmental degradation lead to many disasters and extreme vulnerability for the coastal states. The environmental and industrial damage is increasing in severity with time. Therefore, a thorough study is crucial to understand how to fix our ecosystem and curb the harm done.

2. Methodology

The study will consider data for land surface temperature, air temperature (maximum, minimum, and mean), wind speed, wind direction, precipitation, precipitation cover, dew point, relative humidity, and cloud cover. The study period is between 2001–2021, with a seasonal approach to analyze different environmental conditions. For the sake of analytical clarity, the seasons are composed of four groups: Summer (March–May), Monsoon (June–September), Post-monsoon (October–November), and Winter (December–February). The cities under study are Gujrat: Ahmedabad, Kutch, Jamnagar, Surat; Maharashtra: Mumbai, Thane, Raigad, Ratnagiri, Sindhudurg; Goa: Panaji, Salcette; Karnataka: Bramhavara, Kundapur, Mangalore, Suratkal, Udupi; Kerala: Ambalappuzha, Bekal, Kanhagad, Koyilandy, Mahe, Pozhikara, Thalassery, Thumpoly, Uppala, Varkala, Vatakara; Tamil Nadu: Adyar, Cheyyur, Injambakkam, Killai, Mylapore, Nellore, Parangipettai, Tondiarpet, Triplicane; Kolkata; Odisha: Balasore, Bhadrak, Jagatsinghpur, Khedrapara, Khordha; Andhra Pradesh: Kothapatnam, Nizampatam, Tirupati, Ulavapadu, Vizianagram.

Surface temperature data will be taken through remote sensing using LANDSAT (MODO9A1 V6) and meteorological data from the national database through Visual Crossing Weather (a platform that collaborates with worldwide weather stations to document and process meteorological data).

The study analyzes and compares data from different parts of the Indian Ocean along the Indian coastline. It focuses upon the natural disasters of Cyclone Nilam (October 28th – November 1st, 2012), Cyclone Helen (November 1st – November 23rd, 2013), Cyclone Lehar (November 1st – November 28th, 2013), Cyclone Hudhud (October 7th – October 14th, 2014) and puts forward trends and relations among the influential factors.

The numerical weather data is analyzed utilizing multivariate regression and consequent predictive analytics, the data blanks are filled through mean values while being preprocessed. The surface temperature data that was fetched through remote sensing is analyzed using image processing, comparative analysis, and predictive analysis. Image processing on this data involves analyzing the temperature data captured by satellite or aerial-based sensors.

In this study, image processing is used to analyze satellite imagery obtained from LANDSAT (MOD09A1 V6). The image is first transformed into a digital form and then underwent several key steps including geometric correction, image enhancement, noise reduction, and feature extraction. The geometric correction step aimed to rectify the image and correct for any distortions. Image enhancement and noise reduction are performed to improve the quality of the image and make it easier to identify patterns in the temperature data. Feature extraction is used to identify important features in the image that could provide useful information about the temperature. The processed data is then used for applications such as monitoring climate change and analyzing land surface temperature changes over time. This study demonstrates the potential of image processing to provide valuable insights into temperature patterns and changes.

Comparative analysis is done on these processed images to gain a better understanding of the differences and similarities in the relationships between data sets. A comparative analysis involves evaluating and comparing various aspects of two or more processes, documents, data sets, or other objects. Python libraries such as skimage, matplotlib, numpy, and cv2 are used to implement this process. The images between 2001–2020 are compared using defined evaluation criteria. This criterion involves comparing images from the same location taken at different times.

The prediction in this study is carried out using a linear regression model. Linear regression is a statistical approach employed to model the linear connection between a dependent variable and one or multiple independent variables. The data is formatted in a way that allows for the prediction of temperature based on dew and humidity. This was accomplished by making the temperature the dependent variable meanwhile dew and humidity are the independent variables. The linear regression model is trained and tested using historical data. After the model is trained, a portion of the data is reserved for testing to evaluate the accuracy of the model's predictions. The results of the testing phase are used to determine the performance of the model and the quality of the predictions.

Meta-analysis of all the covariates was stressed due to evidence given by the previous studies [27,28]. Factors such as sea surface temperature (SST) have been investigated and links to other meteorological factors as well as other phenomena are established. SST has been linked to rainfall and El Niños is thoroughly researched [29,30]. Many models have been created to act as a safeguard against the natural hazards of the coast. The hydrodynamic models of Sahoo and Bhaskaran (2018) to simulate storm surge heights and flooding, and the work of Mandal et al. (2020) to develop early warning systems for flooding are excellent references of the existing works [31,32]. This study moves forward while stressing these points of reference.

2.1. Model (linear regression)

In our study, we used a multivariate linear regression model to examine the relationship between the dependent variable and ten independent variables. The performance of the model was evaluated using various statistical simulations, which are Multiple R, R-squared, Adjusted R-squared, and Standard

Error. The mathematics behind our linear regression model is

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_p x_p + \varepsilon, \tag{1}$$

where y is dependent variable, β_0 is y-intercept, this represents the value of y when all independent variables are 0, $\beta_1, \beta_2, \ldots, \beta_p$ are regression coefficients, $x_1, x_2, \ldots, x_p$ are independent variables, ε is error term. The regression coefficients determine the slope of the regression line. The error term captures randomness in the relationship.

The coefficients are estimated using the least squares method, which minimizes the sum of squared residuals (SSR) between predicted and actual y:

$$SSR = \sum (y - \hat{y})^2, \tag{2}$$

where $\hat{y}$ is the predicted value of y from the regression line for the given x.

Multiple R (multiple correlation coefficient) was used to study the correlation between the observed and predicted values of the dependent variable. It represents the correlation between the observed values of the dependent variable (y) and the predicted values ($\hat{y}$) based on the regression model. It is calculated as

$$R = r(y, \hat{y}), \tag{3}$$

where r is correlation coefficient between y and $\hat{y}$, y is observed dependent variable, $\hat{y}$ is predicted value from the regression line. The correlation coefficient r ranges from -1 to 1 and indicates the strength and direction of the linear relationship between y and $\hat{y}$.

R-squared (coefficient of determination) determined the variation in the dependent variable by the independent variables of our model and Adjusted R-squared adjusted the R-squared for the number of predictions in the model, and provided a more accurate measure when the model was compared across different prediction numbers. R-squared (R2) is a statistical measure that represents the proportion of variance in the dependent variable (y) that is explained by the independent variables (x) in the regression model.

R-squared was calculated as

$$R^2 = 1 - \frac{SSE}{SST}, \tag{4}$$

where SSE is sum of squares due to error, SST is total sum of squares.

R-squared ranges from 0 to 1, with higher values indicating more variance is explained by the model. Standard Error measured the standard deviation of the residuals or prediction errors and provided an estimate of the accuracy of our predictions.

The 't' statistic, fundamental in this analysis, serves to measure the individual significance of predictors within the regression model. The formula for the t statistic in linear regression is

$$t = \frac{\text{Coefficient Estimate}}{\text{Standard error of the coefficient}}. \tag{5}$$

The Analysis Of Variance (ANOVA) table provided further insight into the performance of the model using the components of Degrees of Freedom(df), Sum of Squares (SS), Mean Square (MS) and F value.

Degrees of freedom (df) represented the number of values that are free to vary in the final computation of the data. The sum of squares (SS) provided the sum of the differences in squares between each sample and its group, which in turn provided a measure of the overall variability in our data. Mean Square (MS) is the mean of the sum of squares, which took into account the variability in our data.

F value test statistic provided an indication of how much the model has improved compared to a model with no prediction. Significance F is the p-value of the F statistic. A small P-value ($\leqslant 0.05$) indicated strong evidence that at least one of the regression coefficients of the predictors is not equal to zero. An 'f' value surpassing the critical threshold signifies the presence of at least one predictor variable significantly related to the dependent variable, reinforcing the model's overall relevance in capturing essential patterns within the data. The f statistic formula to assess the overall significance of the regression model is

$$f = \frac{\text{Explained Variance}}{\text{Unexplained Variance}}. \tag{6}$$

The coefficients table (Table 1) shows the coefficients for each intercept and predictor, which can be used to predict the response to given input values. This includes statistical standard errors, t-statistics, and p-values, which test the null hypothesis that the coefficient equals zero (no effect).

In conclusion, our multivariate regression model provides a powerful tool to understand the complex relationships between our dependent variable and many independent variables. High R-squared and Adjusted R-squared values indicate that our model is accountable for a highly dependent variable variance, while a low standard error indicates our predictions are precise. And the ANOVA and coefficients table provides further evidence of the model's validity and the significance of the predictors.

Fig. 1. Map of cities under study (*made using python leaflet.js florium*).

These statistical measures, added into the methodology alongside image processing techniques, comparative analysis using Python libraries like skimage, matplotlib, numpy, and cv2, and the utilization of satellite data from LANDSAT (MOD09A1 V6), converge to delineate a comprehensive understanding of the climatic factors studied. Beyond aiding prediction, these statistical tools assume a pivotal role in validating the model's accuracy against historical data, thereby enhancing the reliability and robustness of the predictive outcomes.

3. Results and discussion

From the multivariate analysis, we were able to gather that the most influential and consistent meteorological factors over the Indian coastline are air temperature, dew point, and humidity. There is a positive relationship between dew and air temperature, while humidity has a negative relationship. Precipitation is another major factor that affects the eastern coast, and meteorological factors of wind speed, cloud cover, and wind direction play a significant, consistent role in the meteorological condition of the states of West Bengal, Odisha, and Goa, respectively. The number of meteorological factors showing consistent behaviour lessens as we move from the eastern coast to the western coast. The range of numerical data of air temperature, dew point, and humidity show noticeable shrinkage with the increase in the minimum value.

Investigation in the period of months before the natural disasters of Andhra Pradesh shows an alarmingly similar shrinkage in the ranges of minimum to maximum values of the concerned meteorological factors. The shrinkage varies by $1-3$ units for the range. The multivariate analysis has provided critical evidence that dew point and humidity are vital for predictive analysis and that different factors are uniquely influential in distinct states. The meteorological factors showing consistent behaviour and significant influence on weather conditions are shown in Table 1.

3.1. Comparative analysis (image processing)

From the comparative analysis, we gathered the Structural Similarity Index Measure (SSIM) and the Mean Squared Error (MSE), which are necessary to evaluate the image quality after processing. SSIM is a quality index that measures the similarity between two images. It takes into account structural information such as luminance, contrast, and structure and returns a value between -1 and 1, where a value of 1 indicates that the two images are identical. MSE, on the other hand, is a measure of the difference between two images. It calculates the average squared difference between the pixels of the

Table 1. Significant independent variables for specific cities for predictive analysis.

Weatern coast

States/Correlation	Positive		Negative	
Gujrat	Dew point		Humidity	
Maharashtra	Dew Point		Humidity	
Goa	Dew Point	Precipitaion	Humidity	Wind direction
Karnataka	Dew Point	Precipitaion	Humidity	

Southern coast

States/Correlation	Positive		Negative	
Kerala	Dew Point	Precipitaion	Humidity	
Tamil Nadu	Dew Point		Humidity	

Eastern coast

States/Correlation	Positive		Negative	
Andhra Pradesh	Dew Point	Precipitaion	Humidity	
Odisha	Dew Point	Precipitaion	Humidity	Cloud cover
West Bengal	Dew Point	Precipitaion	Humidity	Wind speed

two images and returns a scalar value. The lower the MSE, the more similar the images are. This analysis identifies the trends and patterns in the surface temperature, such as changes in temperature patterns, increased or decreased activity in certain areas, and so on. The average similarity index of the comparative analysis of 2001 and 2020 surface temperature images is 0.40.

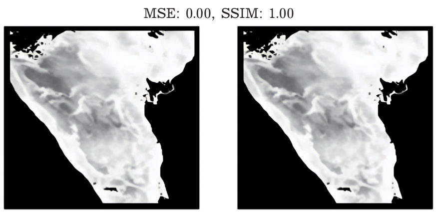

Fig. 2. Comparative Analysis of Day 1 of 2001 and 2020.

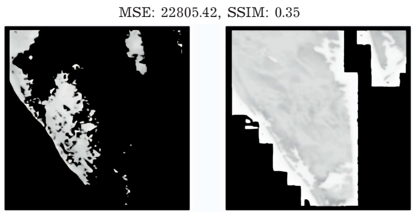

Fig. 3. Comparative Analysis of Day 2 of 2001 and 2020.

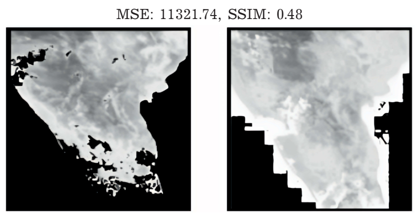

Fig. 4. Comparative Analysis of Day 3 of 2001 and 2020.

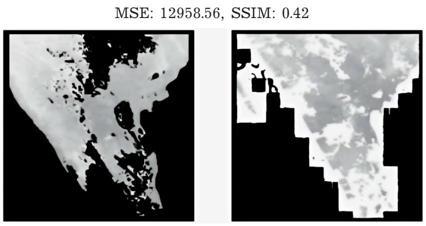

Fig. 5. Comparative Analysis of Night 1 of 2001 and 2020.

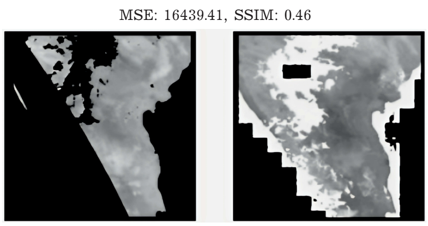

Fig. 6. Comparative Analysis of Night 2 of 2001 and 2020.

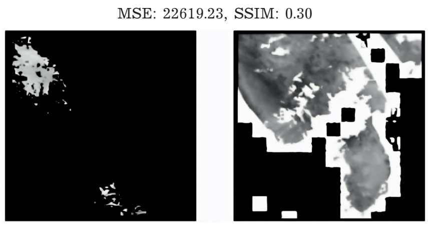

Fig. 7. Comparative Analysis of Night 3 of 2001 and 2020.

The analysis of the 2001–2005 period has two phases: the first phase, where the SSIM value increases, which suggests a similarity of temperature, and the second phase, where the SSIM value decreases and a temperature shift is seen. The comparison between 2001 and 2010 starts with a 0.58 SSIM value and ends with a 0.65 SSIM value. It implies an increasing similarity in the temperature pattern.

Similarly, the comparison between 2001 and 2015 also suggests increasing temperature pattern similarity, as it starts with a 0.40 SSIM value and ends with a 0.60 SSIM value. As we compare daily values between 2001 and 2020, the SSIM value decreases. This implies a shift in the temperature pattern. The following figure shows the comparison between 2001 and 2020.

3.2. Predictive analysis

Predictive analysis is performed using a linear regression model to predict the temperature for a specific region. Linear regression is a widely used statistical method for modeling the relationship between a dependent variable and one or more independent variables. In this case, the dependent variable is the temperature, and the independent variables are dew point and humidity. The linear regression model is trained on historical data. The historical data is used to train a model, which is then tested on the test dataset to evaluate its performance in making accurate predictions. The relationship between the variables is estimated using a best-fit line. This line is then used to make predictions about the temperature based on the values of dew point and humidity.

A predictive analysis is performed to predict the temperature for the year 2021 for various cities in the states of Maharashtra, Gujarat, Andhra Pradesh, Odisha, and Tamil Nadu. The mean actual temperature for the city of Cheyyur, TN for the year 2021 was found to be 28.70934°C, while the mean predicted temperature based on the linear regression model is 28.72145°C. The actual temperature was found to have a standard deviation of 2.172194°C, while the predicted temperature has a standard deviation of 2.234673°C.

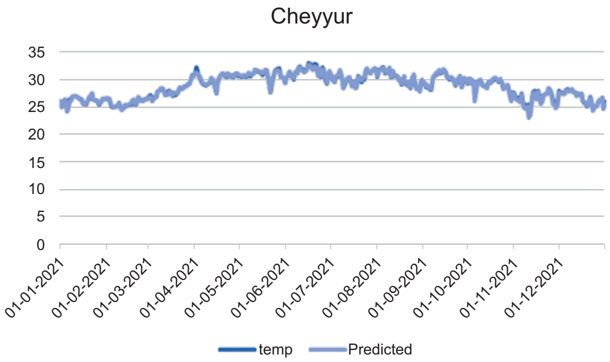

Fig. 8. Predictive Analysis for Cheyyur, TN in 2021.

The mean actual temperature for the city of Khordha, Odisha for the year 2021 was found to be 27.12055°C, while the mean predicted temperature based on the linear regression model is 26.98039°C. The actual temperature was found to have a standard deviation of 3.187008°C, while the predicted temperature has a standard deviation of 3.139459°C with a Mean Square Error of 0.013375.

The mean actual temperature for the city of Khedrapara for the year 2021 was found to be 27.07068°C, while the mean predicted temperature based on the linear regression model is 27.00704°C. The actual temperature was found to have a standard deviation of 3.188318°C, while the predicted temperature has a standard deviation of 3.182789°C with a Mean Square Error of 0.028929.

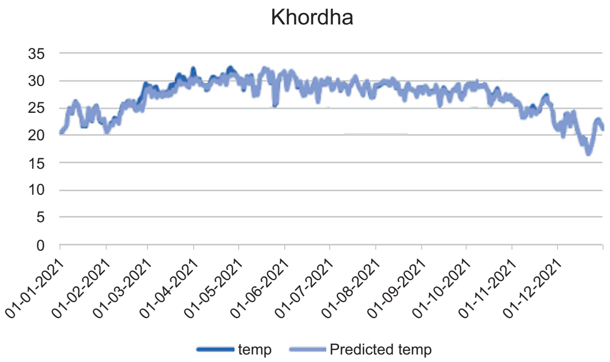

Fig. 9. Predictive Analysis for Khordha, Odisha in 2021.

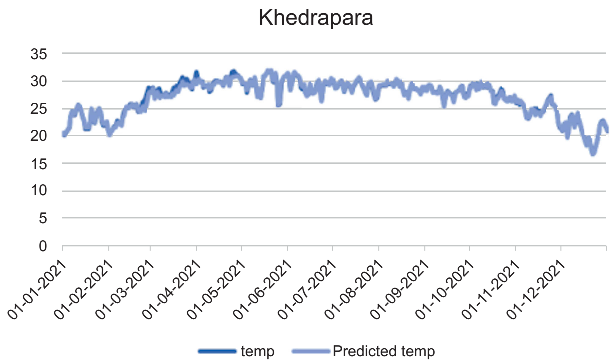

Fig. 10. Predictive Analysis for Khedrapara in 2021.

The mean actual temperature for the city of Jamnagar, Gujarat for the year 2021 was found to be 26.93644°C, while the mean predicted temperature based on the linear regression model is 27.11744°C. The actual temperature was found to have a standard deviation of 4.212744°C, while the predicted temperature has a standard deviation of 2.250523°C with a Mean Square Error of 35.65933.

The mean actual temperature for the city of Jagatsinghpur for the year 2021 was found to be 23.6189°C, while the mean predicted temperature based on the linear regression model is 23.85716°C. The actual temperature was found to have a standard deviation of 5.399847°C, while the predicted temperature has a standard deviation of 5.572265°C with a Mean Square Error of 0.252039.

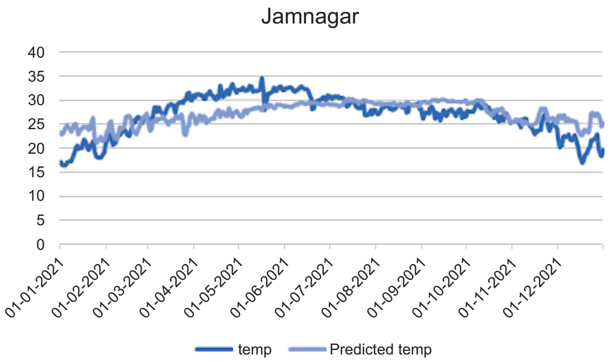

Fig. 11. Predictive Analysis for Jamnagar, GU in 2021.

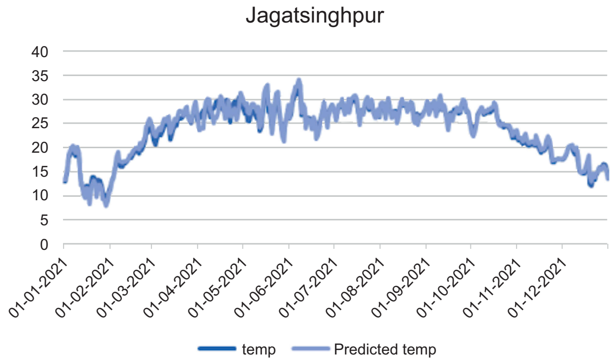

Fig. 12. Predictive Analysis for Jagatsinghpur, OD in 2021.

This comparison between the actual and predicted temperatures highlights the accuracy and reliability of the predictive model. The close agreement between the actual and predicted temperatures suggests that the linear regression model was able to capture the relationship between temperature dew point and humidity effectively.

4. Conclusion

This study focuses on the impact of natural hazards on the Indian coastline, taking into account meteorological factors such as air temperature, precipitation, dew point, humidity, wind speed, moon phase, sea level pressure, visibility, wind direction, and cloud cover. The discussion centers around the trends and changes in weather patterns, with a specific focus on the meteorological factors of dew point, humidity, and air temperature. These factors are considered crucial for understanding the impact of natural hazards on the Indian coastline. The study analyzes the fluctuations in these meteorological factors and their relationship with natural hazards, providing insights into how changes in weather patterns may affect coastal communities in the future.

In image processing, several operations are performed to prepare images for further analysis. These operations include dimension correction, noise reduction, filtering, and converting the images to grayscale. The analysis conducted in this study indicates that dew point and humidity are important indicators for predicting natural hazards on the Indian coastline. The dataset was formatted for prediction by using dew point and humidity as factors to predict temperature. The predictions were made using historical data, which was divided into training and testing datasets. This approach provides a basis for understanding how dew point and humidity may impact temperature and how these relationships can be used for predictive purposes. The use of historical data for training and testing highlights the importance of continuous monitoring and analysis of meteorological factors for predicting natural hazards. The analysis also shows that pre-disaster weather conditions are becoming more frequent, with an increase in the spread of high-temperature zones along the coastline. The findings of the study emphasize the need for continuous monitoring and analysis of weather patterns and meteorological factors in the coastal region to predict and mitigate the effects of natural hazards. The analysis shows a trend of the range between minimum and maximum temperatures shrinking and an increase in minimum temperatures along the coastline. This suggests that weather patterns are becoming more consistent and less variable in these areas. The shrinking range between minimum and maximum temperatures may have implications for the intensity and frequency of natural hazards, and the increase in minimum temperatures may lead to new weather-related challenges for coastal communities.

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Дослідницький аналіз природних небезпек на узбережжі Індії

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Прогнозний аналіз, порівняльний аналіз і обробка зображень можуть дати життєво важливе розуміння природних явищ. Водні об'єкти оточують Індію з трьох боків, тому стихійні лиха (циклони, повені та інші пов'язані небезпеки) і підвищення рівня води через метеорологічні коливання є звичайним явищем. Прибережні штати Індії через свою різноманітну природу постійно піддаються різноманітним ризикам. Дослідження зосереджено на змінах і катастрофах в Індійському океані, що оточує індійські берегові лінії. Для вивчення коливань метеорологічних факторів дев'яти прибережних штатів Індії за період 2001–2021 років застосовано системний підхід. Коливання були розраховані для чотирьох метеорологічних сезонів: літо (березень–травень), мусон (червень–вересень), постмусон (жовтень–листопад) і зима (грудень–лютий). Ці коливання вивчаються та висуваються тенденції для вивчення їх впливу на стихійні лиха. Результати дослідження зосереджені на кореляції між факторами та катастрофами та їх відповідними прогнозами.

Ключові слова: *обробка зображень; прогнозний аналіз; порівняльний аналіз; метеорологічні фактори.*