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Impact of climate change scenario on sea level rise and future coastal flooding in major coastal cities of India

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This study evaluates the impacts of projected sea level rise (SLR) on coastal flooding across major Indian cities: Mumbai, Kolkata, Chennai, Visakhapatnam, Surat, Kochi, Thiruvananthapuram, and Mangaluru. Machine learning models, including Long Short-Term Memory (LSTM), Random Forest (RF), and Gradient Boosting (GB), has been employed to assess flood risks under four Shared Socioeconomic Pathways (SSP 126, 245, 370, and 585) emission scenarios. The research utilized these models because they demonstrate high performance in handling difficult data relationships and both temporal patterns and sophisticated environmental data. SLR projections provided by computers generate forecasts that combine with digital elevation models (DEMs) to determine coastal flooding risks and locate flood-prone areas. Results reveal that Mumbai and Kolkata face the highest flood risks, particularly under high emission scenarios, while Kochi and Mangaluru exhibit moderate exposure. Model performance is validated using residual analysis and Receiver Operating Characteristic (ROC) curves, confirming reliable predictive accuracy. These findings provide essential information for urban planners and policymakers to prioritize climate adaptation strategies in vulnerable coastal cities.

Keywords Climate adaptation, Coastal cities, Coastal flooding, Flood risk assessment, Inundation modeling, Machine learning, Sea level rise

Rising sea levels, together with coastal flooding, present a vital challenge that affects both climatic consequences and urban planning on a global scale[1,2]. Rising sea levels from climate change affect every coastal city across the world by influencing both natural environments, human-made infrastructure and human populations[3,4]. Alarming sea level changes threaten India's shoreline because of the rising sea-level and along with environmental and socio-economic impacts, major financial losses, compelling population relocation, and sustaining permanent ecological damage[5]. The risks for these areas are intensified because of increasing storm and flood frequency during extreme weather events. This investigation employs machine learning models to analyze future potential consequences of rising sea levels, which will affect major Indian coastal cities through time-based and location-specific predictions.

The need to address SLR together with coastal flooding emerges from data released by the Intergovernmental Panel on Climate Change (IPCC). The IPCC published reports state that mean sea levels increased by 20 cm during the period from 1880 until now and could increase by up to 1 m by 2100, based on which emission paths are adopted. This rise presents substantial concern for India because it has almost 7,500 km of coastal region[6]. The existence of flooding during storms and storm surges affects the major cities like Mumbai and Kolkata because these conditions will intensify in near future[7]. The research findings from Jennath and Paul[8] suggest that several million people will face threats caused by flooded waters due to rising sea levels by 2050. The present localized study becomes essential due to the significant variations in sea level projections[9].

Related studies are expanding their research about how rising sea levels affect coastal regions by linking with climate change projections. A worldwide SLR assessment performed by Church et al.[10] showed broad variations of expected increases in sea level across different regions because of ocean currents and glacial melting effects. The research by Nicholls and Cazenave[11] demonstrates that urban infrastructure, together with human settlements

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located in low-lying areas, face maximum risk during coastal flood events. The projection methodologies are shifting towards machine learning techniques such as RF and RF models to forecast SLR in various coastal areas[12,13]. Modern research about future flooding risks in Indian cities becomes scarce, especially when these studies utilize both temporal and spatial attributes with machine learning models.

Studies about SLR and flooding exist in global contexts but show restricted attention towards the particular coastal cities in India. The existing research analyzes how rising sea levels affect India's coastlines, specifically the the major coastal cities of India, which currently faces increasing tidal impact. The research methods usually apply basic projection models together with short-term prediction periods. Machine learning approaches lack integration as a method to refine both spatial and temporal characteristics of SLR in Indian territories. Through the use of LSTM alongside RF and GB models, this research enhances available informations with accurate data-based forecasts for coastal cities throughout India. Previous studies about coastal flooding remians in shadow to acknowledge social and economic along with infrastructure characteristics and fails to explain why some coastal cities are experiencing more flood damage compared to others.

The research analyzes eight primary coastal locations (cities) in India, which include Mumbai, Kolkata, Chennai, Visakhapatnam, Kochi, Surat, Thiruvananthapuram, and Mangaluru (Fig. 1). The selection of these cities is based on multiple criteria to ensure a comprehensive and representative analysis. These include the population at risk due to rising sea levels, the economic significance of the cities as major ports and industrial centers, and their geographical exposure to coastal flooding and sea-level rise. Moreover, these cities represent diverse climatic zones and socio-economic contexts across India's coastline, providing a well-rounded sample for assessing coastal vulnerability and informing targeted adaptation strategies. The research selected these urban areas since they represent different socioeconomic characteristics alongside unique weather conditions, while also being at risk from the threat of rising ocean levels and coastal floods. The extensive 7,500-kilometer coastal region of India puts its densely inhabited metropolitan areas at a major threat from adverse climate effects. The high population densities of Mumbai, Kolkata and Chennai comes under extreme risk due to their prevalent coastal locations. Rising risks of flooding and inundation await for the rapidly growing cities namely Mangaluru and Visakhapatnam, along with Surat and Kochi, throughout the upcoming decades. The main purpose of this research effort involves forecasting SLR across these cities based on various emissions pathways to analyze coastal flooding and inundation conditions. The analysis delivers meaningful knowledge to policymakers and urban planners in affected areas for developing strategies which can combat climate change effects in future.

This study focuses on how sea level will be changed across Indian coastal cities under various emission scenarios and determines the impact of these changes on coastal flooding and inundation risks. This study provides essential insights into the impacts of rising sea levels on India's coastal cities by leveraging machine learning predictions. Currently, there is a lack of detailed, city-level research on projected SLR in India, especially studies employing machine learning techniques to capture the complex interactions among climate variables. Keep on mind about the cities of Mumbai, Kolkata, and Chennai, this research addresses a significant gap in both Indian and international literature. The study applies advanced machine learning algorithms, LSTM, RF, and GB, to develop a robust predictive model that ennoble the prediction accuracy of coastal flood and inundation forecasts.

The novel aspect of this study combines cutting-edge methods to make spatial-temporal sea level forecasts targeting Indian coastal risks. The research findings will provide essential knowledge about emission-based impacts on India's coastal regions by measuringfuture climate adaptation planning and alongside minimizing the coastal flood risk.

Results

Sea level projection among major coastal cities of India

The future projection of SLR for coastal cities stands as a vital matter that involves urban planners together with environmental scientists and policymakers, because of global warming-induced climate change. The Research has been represented as a comprehensive assessment regarding the anticipated sea level rises for eight important Indian coastal cities, including Mumbai, Kolkata, Chennai, Visakhapatnam, Kochi, Surat, Thiruvananthapuram, and Mangaluru. The sea level projections have been generated by the machine learning models in this study are based on climate forcing data derived from the MIROC-ES2L model, a member of the CMIP6 ensemble. Further methodological details and rationale for selecting of this model are provided in the Materials and Method section. Figures 2, 3 and 4, and 5 present the SLR projections for eight major Indian coastal cities under four different SSPs (SSP 126, SSP 245, SSP 370, and SSP 585). Each figure compares outputs from three machine learning models—RF, GB, and LSTM—over the period 2030 to 2100. For example, under SSP 126, Mumbai's projected SLR is approximately 0.2 to 0.4 m by 2100, whereas under SSP 585, this increases drstically around 0.6 to 1.2 m. These figures illustrate both the steady long-term increases and variability captured by each model.

Each SSP scenario projects a rising trend in sea level across all the cities analyzed, with significant variations depending on the level of emissions and climate mitigation efforts. The SSP 126 scenario, representing a sustainable development pathway with low emissions, forecasts a gradual and steady increase in sea levels. This reflects the positive impact of strong climate policies and sustainable growth, resulting in slower SLR over time. Cities following this pathway are expected to experience moderate and manageable increases. In contrast, the SSP 245 scenario assumes medium-level emissions and predicts higher SLR than SSP 126, but with less volatility than the higher emission scenarios. This scenario represents a balanced approach to climate change mitigation, leading to consistent and progressive sea level increases. However, the SSP 370 and SSP 585 scenarios, characterized by high and very high emissions respectively, represents accelerated and more unpredictable SLR, particularly from mid-century onwards. SSP 370 reflects reduced effectiveness in climate mitigation, causing faster ocean warming and ice melt, intensifying SLR. SSP 585 projects the most dramatic increases, with sharp changes especially during the 2070s and 2080s, under a business-as-usual emissions scenario with minimal climate action. While

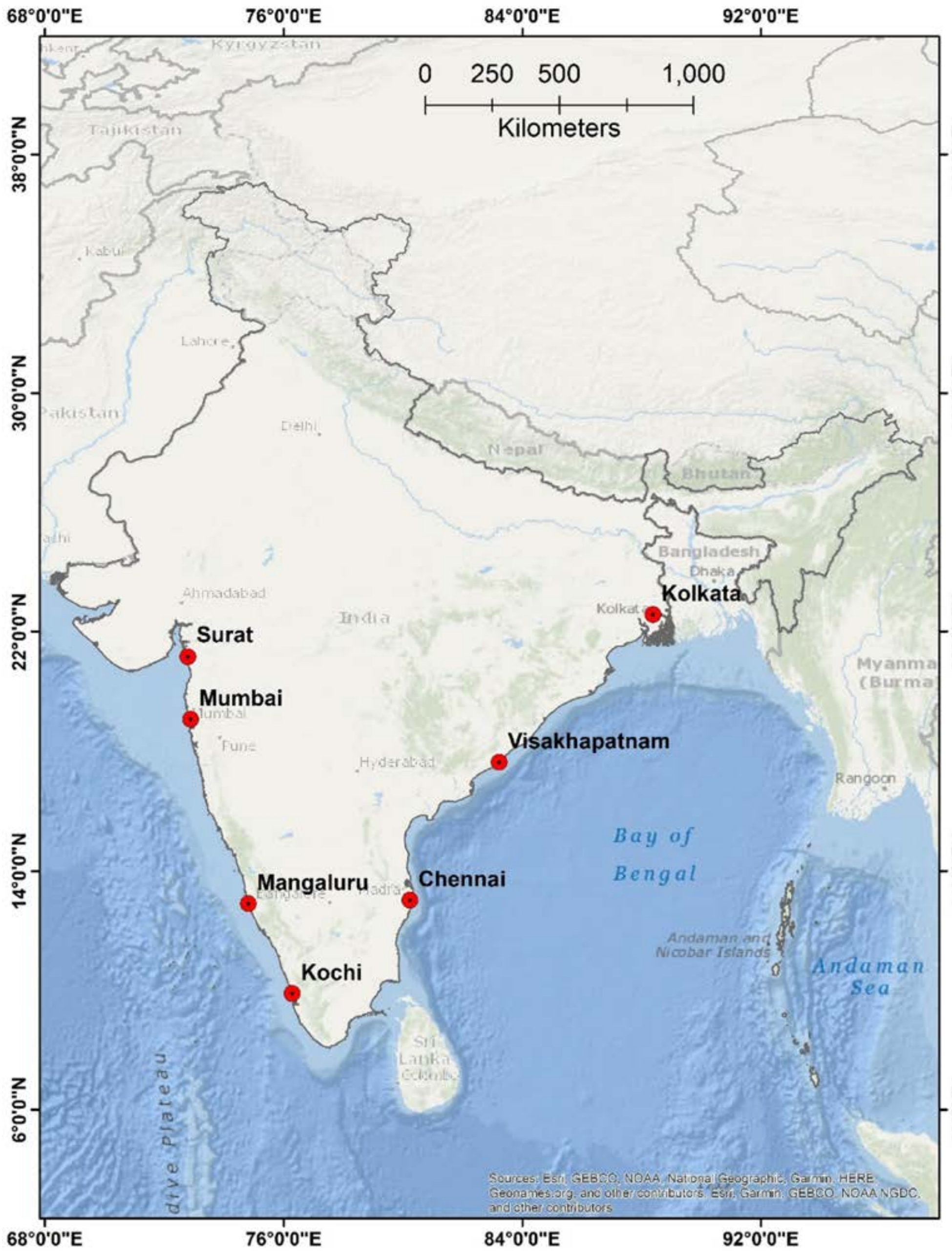

Fig. 1. Location of the study region.

the SSP scenarios indicate an overall steady increase in sea levels, the projections establishes the oscillations with amplitudes ranging from ± 0.02 to 0.1 m on interannual to decadal scales. These fluctuations arise from regional processes such as variations in ocean currents, episodic ice melt events, and atmospheric circulation patterns. The LSTM model, which captures temporal dependencies, particularly reflects these short-term variations alongside the overall upward trend. Such oscillations highlight the complex interplay of factors affecting regional sea level changes beyond the steady global warming signal.

Three different machine learning models served to produce sea level projection simulations throughout the eight cities. The predictive models show similar overall patterns, but their forecasting capabilities remain separate from each other. Model training and validation used historical sea level data from the period 1850 to 2014, against which the models achieved a high coefficient of determination (R^2 values ranging from 0.85 to 0.92). This validation confirms the models' ability to replicate observed trends and seasonal patterns, providing confidence in their future projections. Although historical data figures are not included, this process establishes a robust benchmark for assessing model performance. GB Models together with RF generate stable and uniformly smooth sea level projections for these cities. The models show sea level increases throughout time intervals while

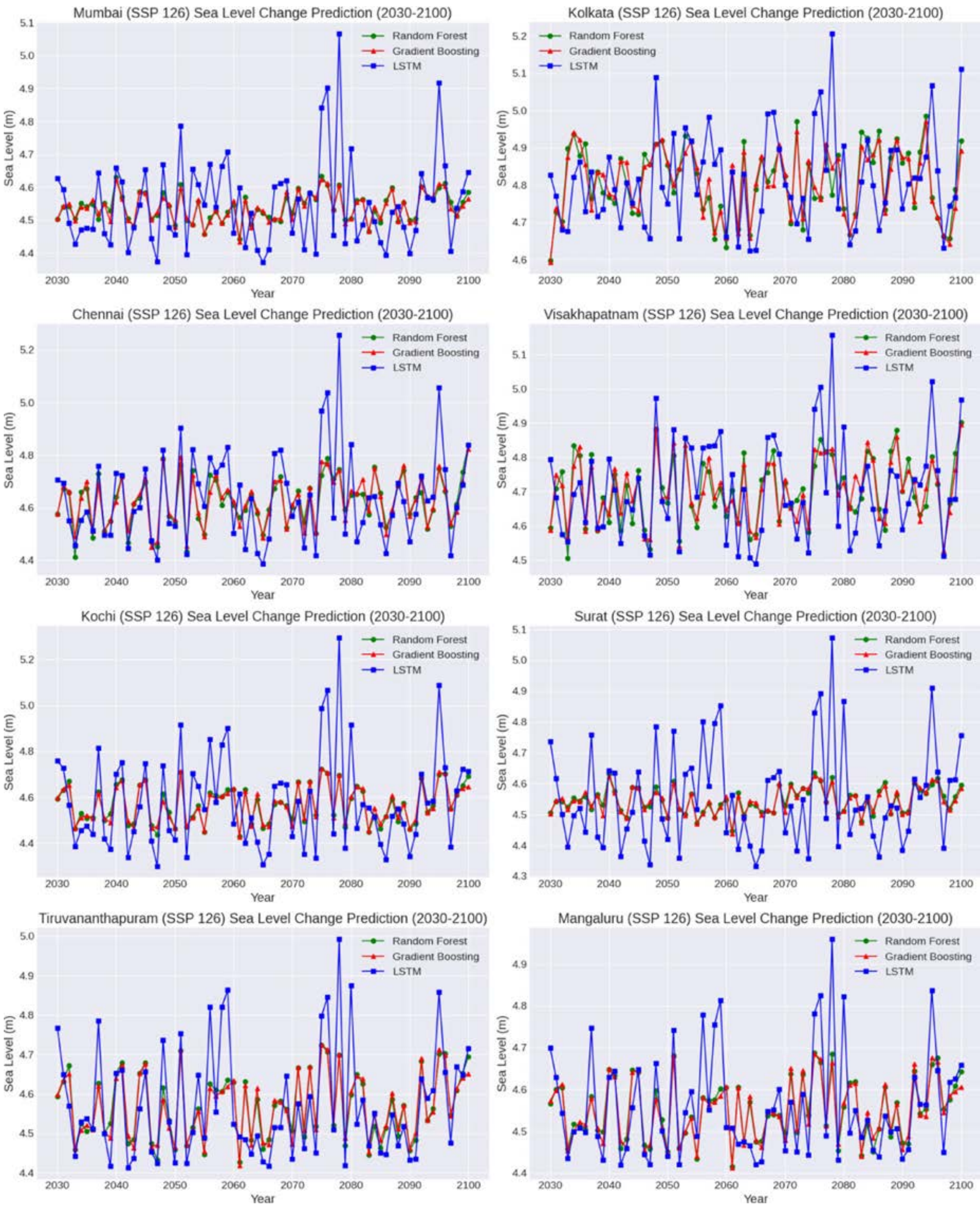

Fig. 2. Sea level changes prediction from 2030 to 2100 considering SSP 126.

maintaining moderate changes in the data. The models demonstrate excellent performance because they track worldwide patterns while avoiding random variations and temporary fluctuations. These models give credible predictions about sea level changes under various emissions, but they eliminate shorter duration changes while revealing long-term patterns. The LSTM model brings increased variations into its output projections because its functions specifically for use to track time-based patterns together with advanced temporal behaviours. The Long Short-Term Memory approach successfully detects complex patterns within sea level changes, thus producing predictions with substantial irregularities. The model visualizes occasional sensitivity to noise,

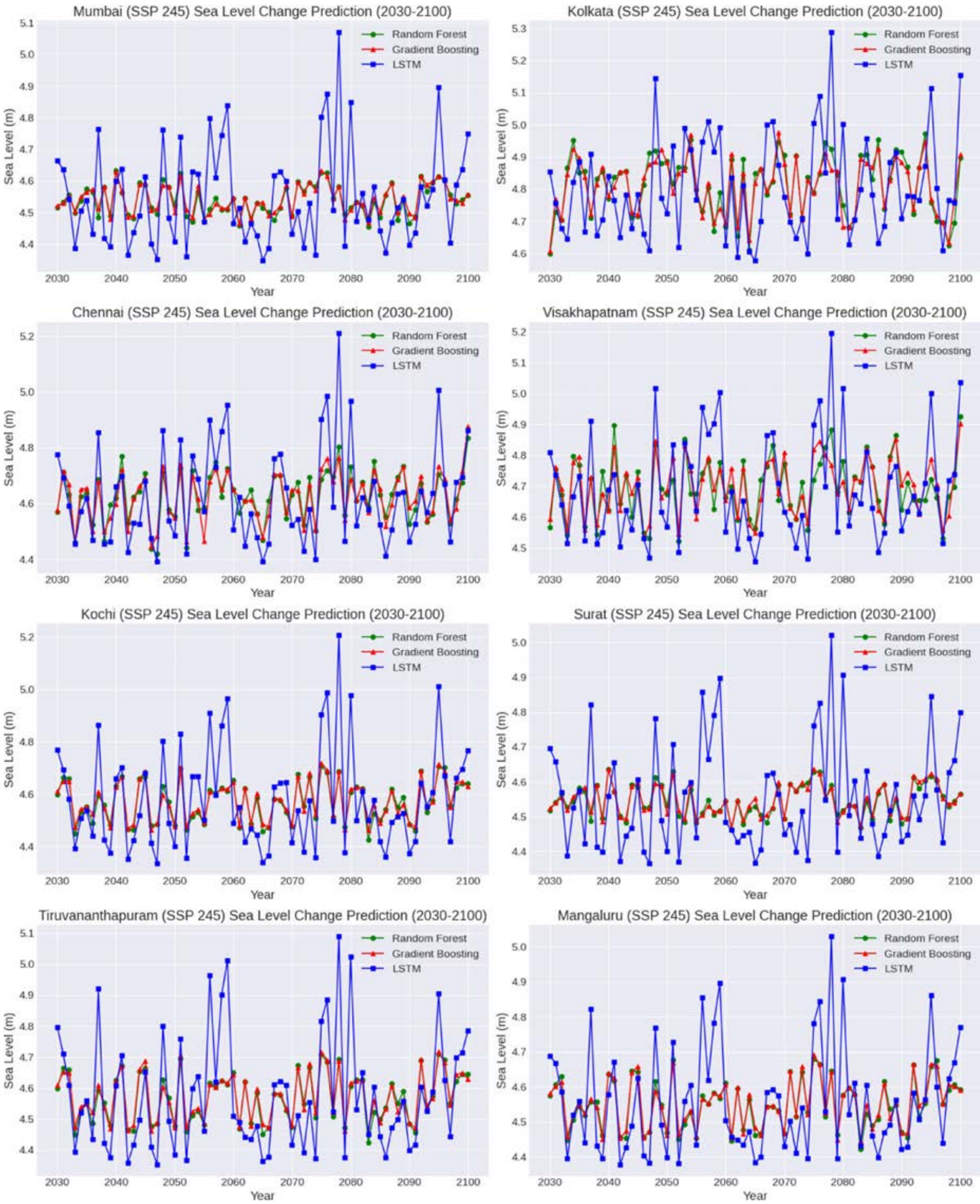

Fig. 3. Sea level changes prediction from 2030 to 2100 considering SSP 245.

which produces larger short-term fluctuations. Even though these variations occur throughout the LSTM projections, they demonstrate a consistent rising trend. The higher dispersion of predictions generated by LSTM demonstrates how important model validation should be for future implementation alongside an ensemble model combination schema.

Different cities exhibit varying ranges of projected sea level elevations because their baseline sea levels start from different reference points. Additionally, these projections differ across regions due to factors such as local geographical features, coastal topography, land subsidence, ocean currents, and regional climate dynamics, all

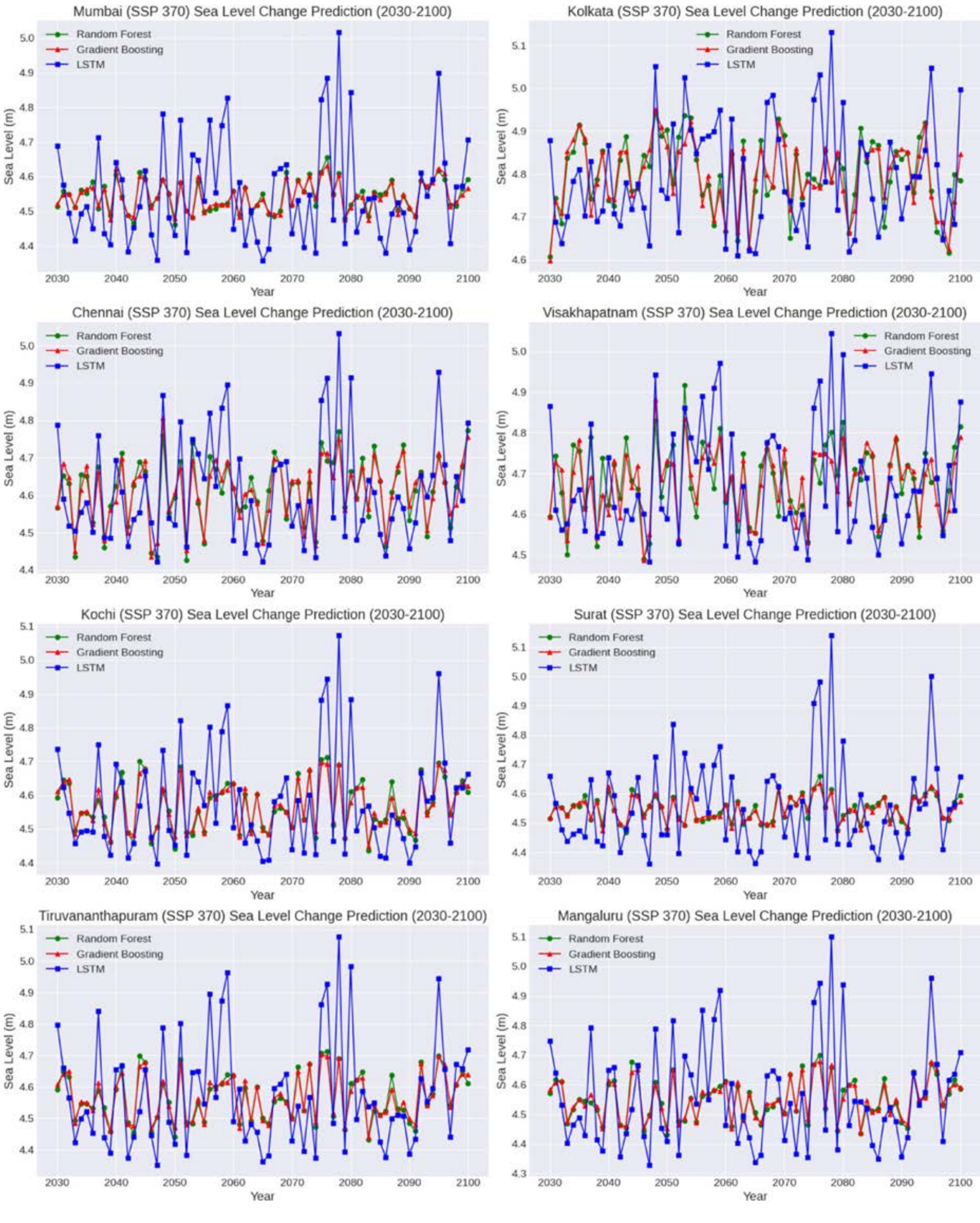

Fig. 4. Sea level changes prediction from 2030 to 2100 considering SSP 370.

of which influence how sea levels rise of specific locations. Cities situated in coastal regions, including Mumbai and Kolkata and Chennai, faced more risk due to their position below the sea level and sea height from elevated baseline. Sea levels at these locations begin higher than other regions, and their risk response escalates much more when emission scenarios reach at their peak. The study establishes that Mumbai, Kolkata and Chennai possess among the higher initial sea levels rise when compared with other locations. SSP 370 and SSP 585 emphasize their high exposure to SLR because of their vulnerable condition. The towns are expected to battle with coastal flooding problems, along with erosion issues, in addition to climate-related complications. Urgent

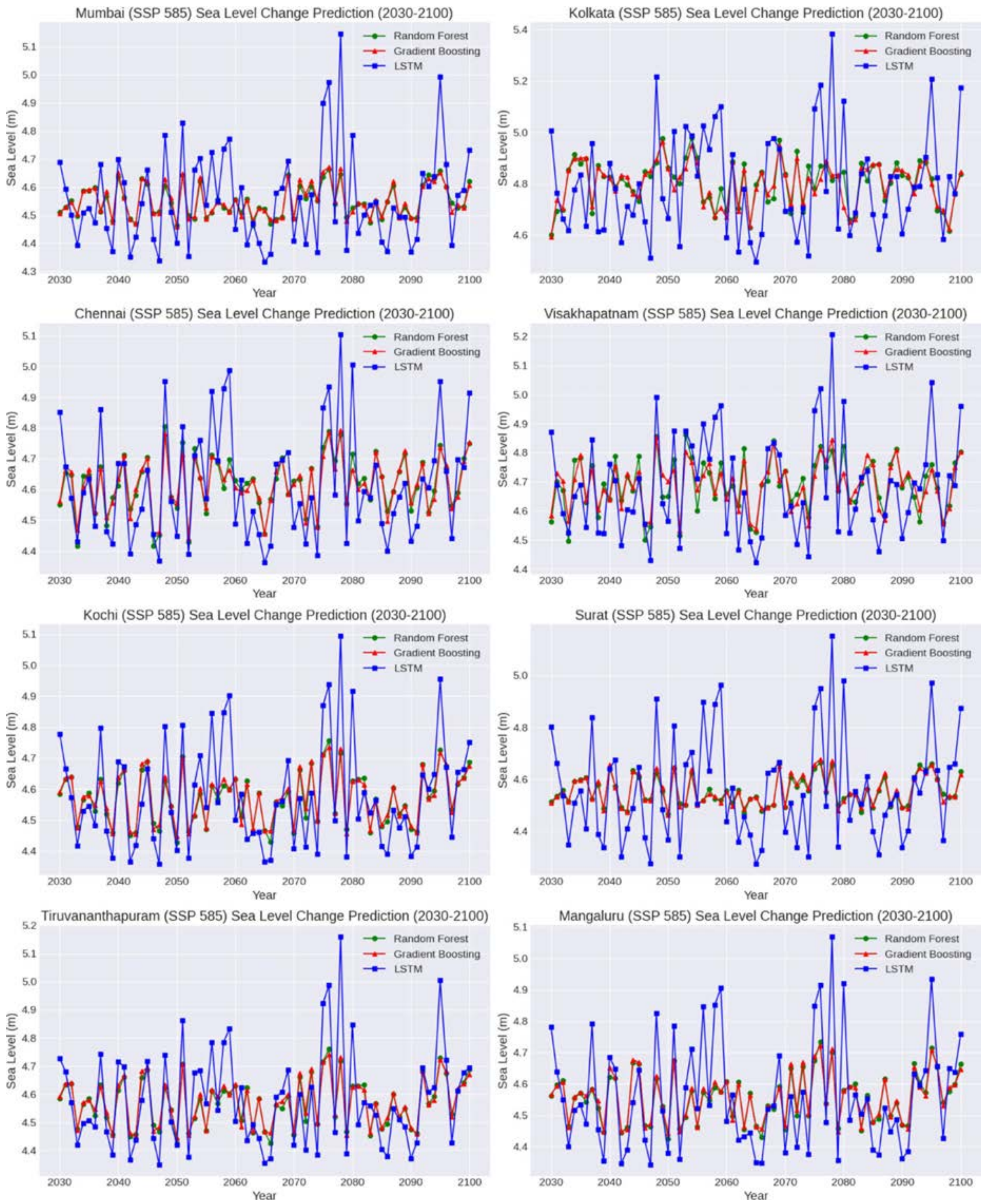

Fig. 5. Sea level changes prediction from 2030 to 2100 considering SSP 585.

actions, which involve building up harbour defences and better drainage systems, combined with complete city adaptation strategies, serve to protect these urban centers. The two cities of Kochi and Mangaluru display modest baseline sea levels rise which concomitantly with other cities under all SSPs. Although their baseline levels provides some protection at present, the cities must remain vigilant as small sea level changes will intensify their probable risks. The climate resilience strategies for both these cities need to address specific challenges due to extreme weather that will cause infrastructure damage and flooding. The models indicate moderate rising sea levels in Surat and Visakhapatnam, although these amounts differ from the chosen SSPs. These two cities stand at lower risk than Mumbai and Kolkata, yet they need to develop monitoring and adaptive measures to mitigate future risks stemming from SLR across the upcoming decades. As an economic centers in Gujarat, Surat will face dual economic and environmental challenges from rising sea levels, together with Visakhapatnam, which operates a major port facility.

Numerical data indicates that sea levels will progressively increase over the period spanning from 2030 until 2100, primarily driven by thermal expansion and the melting of polar ice sheets. The projection models display different levels of uncertainty in their predicted outcomes. SSP 370 and SSP 585 presents highly fluctuating projections throughout the second half of the century. Long-lasting high-emission activities create cascading effects in climate systems to result in intensive SLR. The emission projections in SSP 126 and SSP 245 show a steady and controlled increased pattern.

The investigation produces critical aspects which will affect both urban planning measures as well as climate adaptation techniques designed for coastal Indian cities. The exceptional difference between projections from low-emission and high-emission scenarios represent why we need to make more efforts toward climate change mitigation strategies. The considerable increase in sea levels from both SSP 370 and SSP 585 demonstrates the dire impact of SLR due to climate change, so implementing carbon reduction plans and climate-friendly policies becomes essential as an mitigation adaptation strategies. Due to their elevated sea levels, Mumbai, Kolkata, and Chennai face intensified risks across all SSP projections. The cities require urgent short-term as well as permanent mitigation strategies regarding coastal protection alongside flood control methods, considering urban development initiatives to manage rising sea levels. The LSTM projections exhibit higher patterns of variation, model uncertainty reveals the necessity to validate models through ensemble strategies to achieve more precise predictions. Using several modeling approaches allows experts to comprehend sea-level changes in more detail. The predictions produced essential information about coastal mitigation adaptation strategies since they show the effects of SLR on cities throughout India. As a priority we should to focus on those assisting cities with the highest risk of flooding including Mumbai, Kolkata together with Kochi, Surat and Visakhapatnam despite their varying degrees of flooding scenario.

Validation of the models

Figure 6 presents the integrated methodology for projecting SLR and mapping of flood-prone coastal areas. The process begins with historical and future sea level data inputs, which undergo bias correction to ensure consistency. These corrected data sets are then subjected to data preprocessing and feature engineering, where relevant climate variables and elevation characteristics are incorporated. The processed dataset is used to train these three distinct machine learning models: LSTM for time-series pattern recognition, RF for handling multidimensional and non-linear data, and GB for enhancing the accuracy through sequential learning. Each model produces SLR projections, which are validated through residual analysis and ROC-AUC metrics. The validated outputs are then applied to spatial terrain data from DEMs for projecting and classifying the flood-prone regions. This allows for the mapping

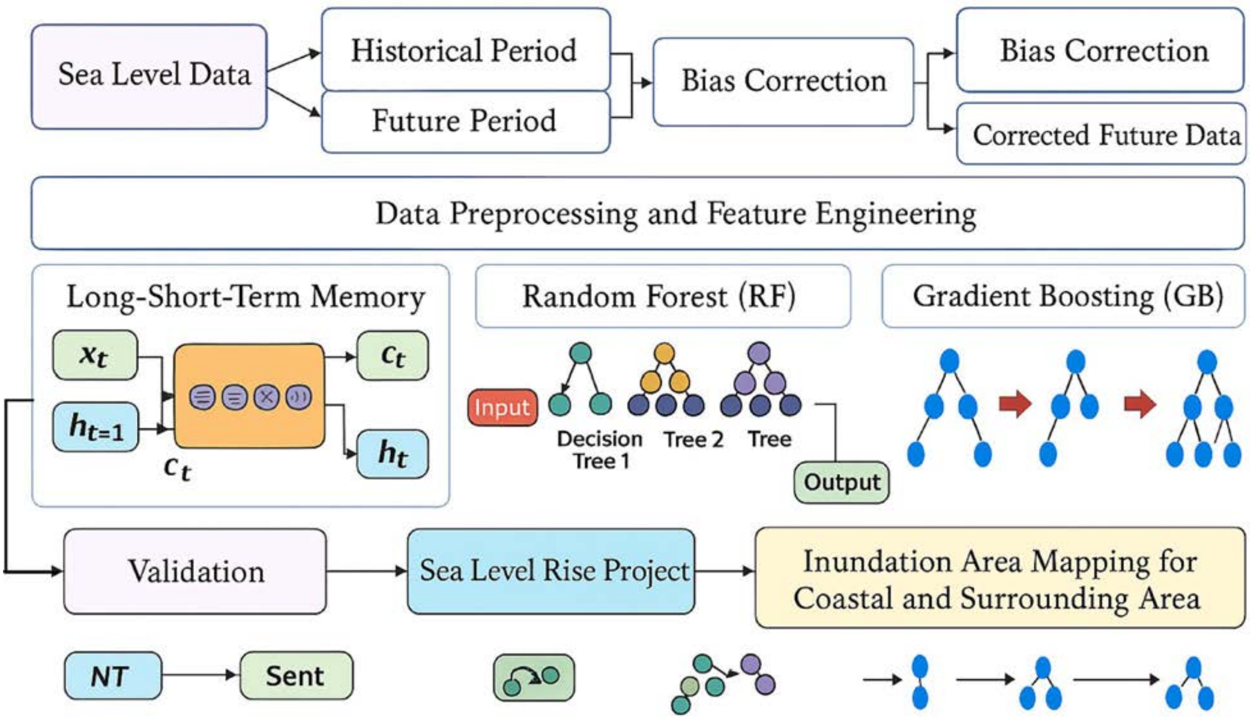

Fig. 6. Methodology flowchart.

of potential inundation areas under different Shared Socioeconomic Pathway (SSP) scenarios, offering critical spatial insights for coastal resilience planning.

The model validation was performed using historical SLR data from 1850 to 2014. This historical dataset served as a benchmark to assess the predictive accuracy of the machine learning models—RF, GB, and LSTM. Residual analysis has been employed to measure the differences between predicted and observed sea level values, while sensitivity analyses has evaluated the model robustness across various climate scenarios. Direct validation of spatial flood projections was impossible due to the lack of comprehensive observed data analysis regarding inundation or flood extent for all coastal cities. Consequently, validation focused on the models' ability to reproduce historical sea level trends rather than direct inundation mapping accuracy. Despite this limitation, the historical validation provides confidence about the model's reliablity to forecast future SLR trend under different SSPs.The residual errors for the RF and GB models were generally low, with maximum deviations of ± 0.15 m and ± 0.22 m respectively and standard deviations are 0.07 and 0.11 m. The LSTM model showed higher residual variability (up to ± 0.75 m), reflecting its sensitivity to temporal patterns but also indicating the need for further refinement to improve stability (Fig. 7). The model predictions demonstrated low bias with accuracy through this assessment. Data residuals in Mumbai alongside Chennai demonstrated minimal measurements, thus indicating the proper applicability of the RF model for citywide predictions in these specific locations. The residuals in Visakhapatnam and Surat experienced larger variations compared to other cities because random patterns or deviations made it difficult for the model to predict accurately. The RF model demonstrated reliable performance across various geographical areas even though it's initially established metrics are altered occasionally.

The GB model demonstrated more patterns in its residual values because it detected intricate relationships in the data, which resulted in marginally higher prediction errors. GB provided a maximum residual value of 0.22 while its minimum reached − 0.22, and its standard deviation amounted to 0.11 (Fig. 8). Data fluctuations showed greater effects on GB model predictions than the effects of the RF model which produced less unstable outcomes. The model had problems with unpredictable patterns in data from Kochi as well as Mangaluru because it produced elevated residual outcomes. The GB model demonstrated satisfactory prediction abilities in these areas of Mumbai and Chennai, as it produced nearly zero residuals, therefore indicating its dependency on specific regions.

The LSTM model surpassed those of the RF and GB models by a significant margin because of its capability to process sequential time-dependent input. The residual value range for LSTM reached 0.75 to -0.75 and displayed 0.27 standard deviation (Fig. 9). The LSTM model unveiled important discrepancies from the zero line through its evaluative values, suggesting that it failed to detect essential patterns within the dataset. Statistical analysis of Chennai and Surat city residuals showed high dispersion because the model struggled with these regions, possibly due to overfitting and dataset complexities. The high prediction variability of LSTM demonstrated the requirement to improve its regional generalization capability because of its capacity to manage temporal information.The Area Under Curve (AUC), along with residual analysis, was used to evaluate the models' ability to compare between correct and incorrect predictions. The RF model achieved an AUC of 0.85, indicating strong predictive performance (Figs. 8, 9 and 10). The GB model demonstrated superior capability, with an AUC of 0.87. In comparison, the LSTM model recorded an AUC of 0.78, reflecting a lower prediction capacity relative to the other models tested.

Coastal flooding and inundated area projection

The scientific predictions regarding coastal flooding and inundation due to SLR in eight major Indian cities namely Mumbai, Kolkata, Chennai, Visakhapatnam, Surat, Kochi, Thiruvananthapuram, and Mangaluru demonstrate significant differences according to four different emission scenario models (SSP 126, SSP 245, SSP 370, and SSP 585). Three machine learning models (LSTM, GB, and RF) shows that rising emissions lead to the largest extent of flooding, whereby each model produces its patterns of flooding regions.

The coastal city of Mumbai faces extensive flooding risks according to all scenarios, especially under SSP 370 and SSP 585 (Fig. 11). The flooding reaches its peak intensity across the coastal section and riverfront zones as extensive parts of the city's urban facilities area come under risk. The flooding area extends widely throughout the southern and eastern regions of these scenarios. According to the LSTM prediction, the flooded areas reach their maximum, while the GB and RF models indicate smaller flooded zones. All climate models anticipated severe coastal flooding in Mumbai at higher SSPs.

The Indian city of Kolkata faces a high risk from coastal flooding, as reported data shows extensive water submersion under SSP 370 and SSP 585 (Fig. 12). The location of Kolkata near both the Hooghly River and the Bay of Bengal leads the city to face severe flooding risks. Major flooding is predicted on riverbanks, together with coastal lowlands. Using the LSTM model reveals the greatest extent of flooding that penetrates densely populated urban areas of the city. The GB and RF models present somewhat less extent of considerable levels of flooding as opposed to the LSTM models. All simulation models demonstrate similar patterns of flooding that primarily strike the riverbanks, in addition to coastal regions. Although the flooding extent is reduced under SSP 126 and SSP 245 scenarios, coastal and riverbank regions remain at risk and continue to face significant flood threats.

Under high-emission climate scenarios, significant flooding risks are posed to the city of Chennai, including its extensive coastal infrastructure and large resident population (Fig. 13). Peak flood intensity is projected in two main areas: along the East Coast Road and within the urban waterfront region. The maximum extent of inundation is indicated by the LSTM model, which predicts deep inland flooding affected critical urban zones. Notable flooding is also forecasted by the GB and RF models, predominantly concentrated in coastal areas. Although lower flood levels are expected under low-emission scenarios, coastal regions are still projected to remain at risk. Despite variations in model projections, the overall pattern suggests that Chennai will face major flooding threats, particularly near the coast and along riverbanks.

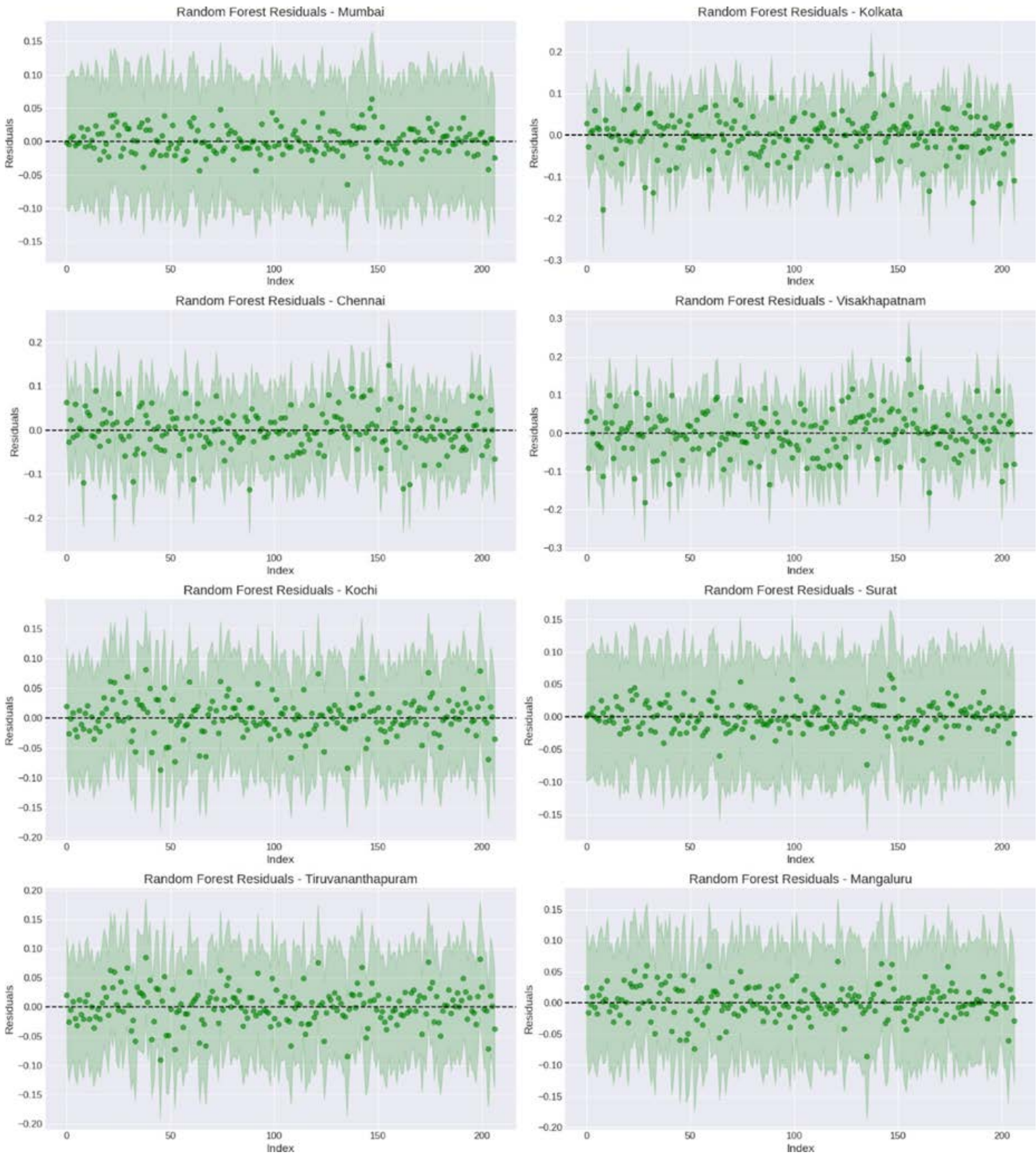

Fig. 7. Residual in RF model.

The extent of flood waters in Visakhapatnam stands between Mumbai and Kolkata in terms of severity. The coastline faces a substantial flooding threat according to model projections, especially when considering high-emitting future scenarios (SSP 370 and SSP 585) (Fig. 14). Areas closest to both the coastline and rivers show the highest risk according to LSTM modeling, but GB and RF estimate less flooding in these locations. All modeling data indicate that coastal areas of Visakhapatnam will face extreme risk from rising sea levels while flooding will spreads across urban terrain. The models demonstrate that in SSP 245 medium-emission predictions, the waterfront sections of the city will be flooded, although to a more limited degree.

All scenarios in Surat predict moderate flooding, but SSP 370 and SSP 585 produce maximum water inundation in the industrial Gujarat city (Fig. 15). Surat experiences the majority of flooding events that affect the city near to its coastlines and riverbanks. The LSTM model detects the most significant flooding extent, while the GB and RF models display restricted predictions. Surat will suffer from some flooding, even though the risk

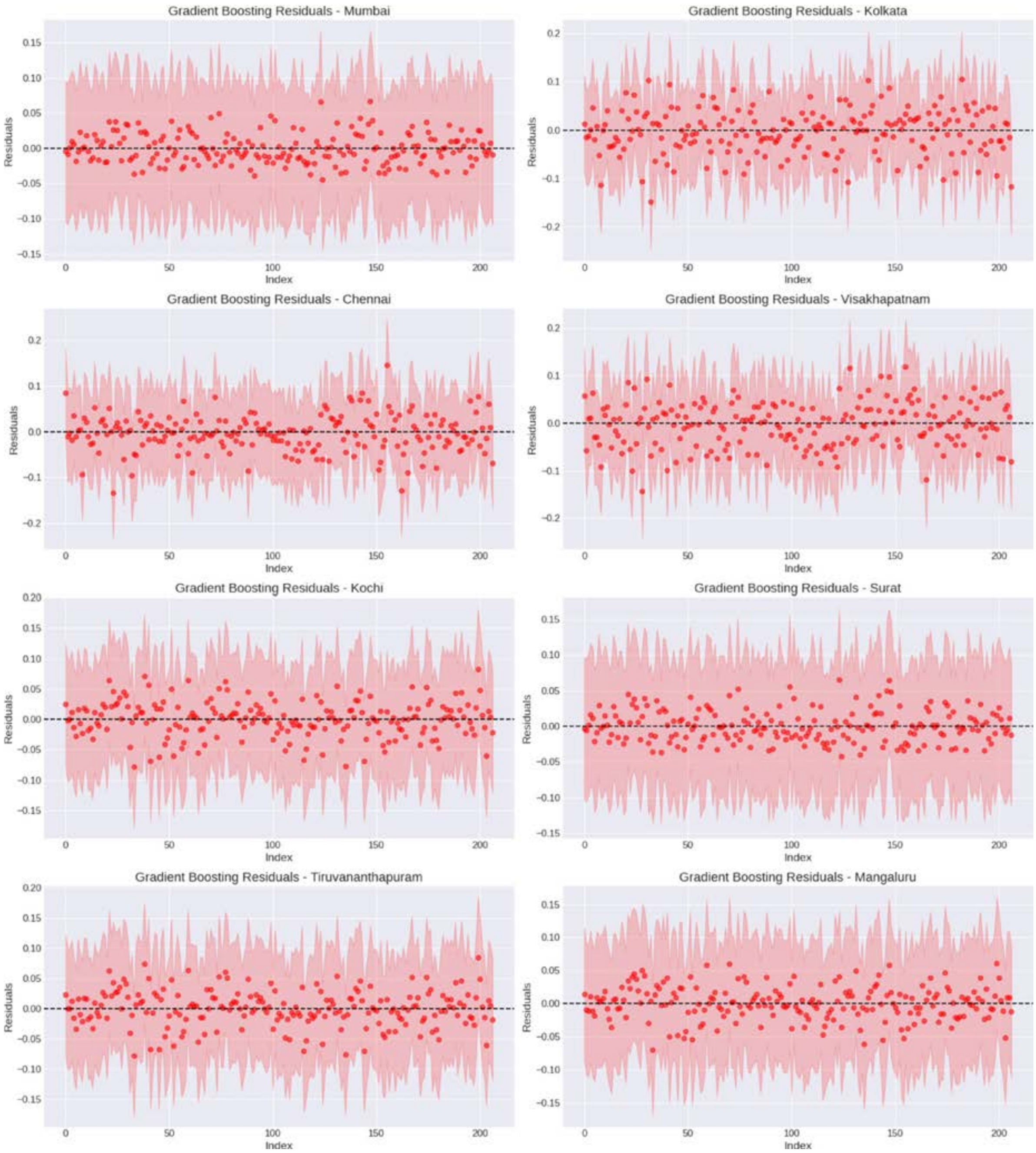

Fig. 8. Residuals in GB model.

rises according to SSP 126 and SSP 245 lower-emission scenarios. Surface flooding exposures that threaten the city require rapid implementation of flood-resistant management protocols and protective coastal measures.

SLR significantly threatens Kochi because this city possesses substantial port infrastructure. Coastal regions will experience the worst consequences based on operational projections that will become more pronounced during high-emission conditions (Fig. 16). Under high-emission climate scenarios, Chennai faces significant flooding risks that threaten its extensive coastal infrastructure and large population. The highest flood intensities are projected in two key areas: along the East Coast Road and the urban waterfront region. The LSTM model indicates the greatest extent of inundation, predicting deep inland flooding that impacts critical urban zones. Flooding is also forecasted by the GB and RF models, primarily concentrated in coastal areas. While lower flood levels are anticipated under low-emission scenarios, coastal regions are still expected to remain vulnerable. Despite differences among model projections, the overall consensus indicates that Chennai will experience severe flooding threats, especially near the coast and along riverbanks.

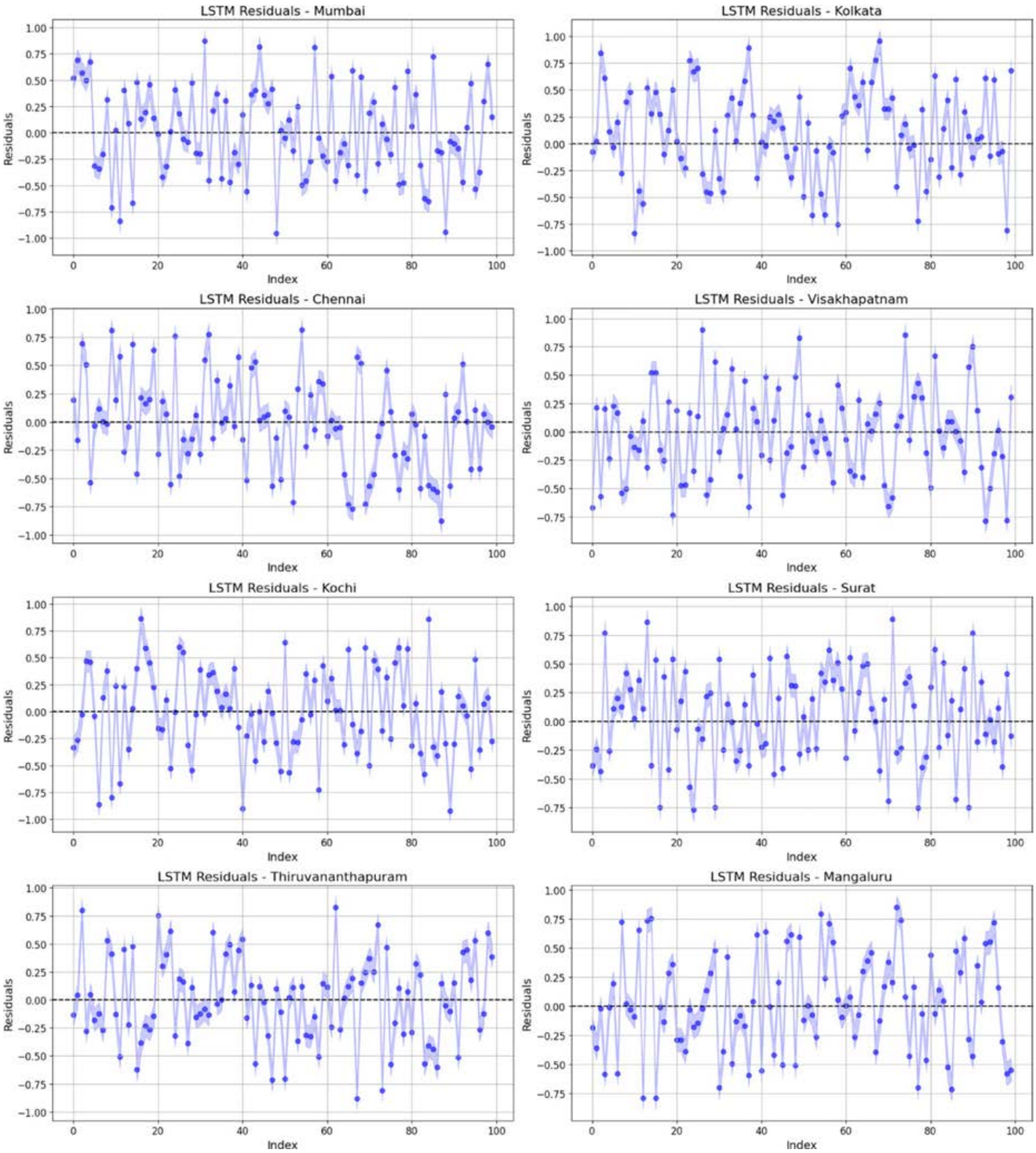

Fig. 9. Residuals in LSTM model.

As the southernmost city in India, Thiruvananthapuram exhibits average vulnerability to flooding. With higher emissions, the coastal and low-lying regions will be become completely flooded according to the LSTM model predictions, which shows the greatest extent of floodwater (Fig. 17). The GB and RF analysis predicts low but meaningful flood risks in addition to present vulnerabilities in the coastal areas. The Thiruvananthapuram region faces limited flooding risks under lower-emission scenarios; however, these risks still exceed what would occur in the absence of climate change. Protection efforts must be targeted to the vulnerable coastal regions because the city remains at high risk.

Flooding in Mangaluru presents a moderate risk because the coastal city of Karnataka experiences less flooding than Mumbai and Kolkata. The future projections warn of considerable flood threats even though the models provide the most severe vulnerabilities in the highest emission scenarios (Fig. 18). The LSTM model determines the maximum flood extents across coastal areas and river openings with more pronounced predictions than the GB and RF models. Mangaluru comes under potential flooding even under lower emission

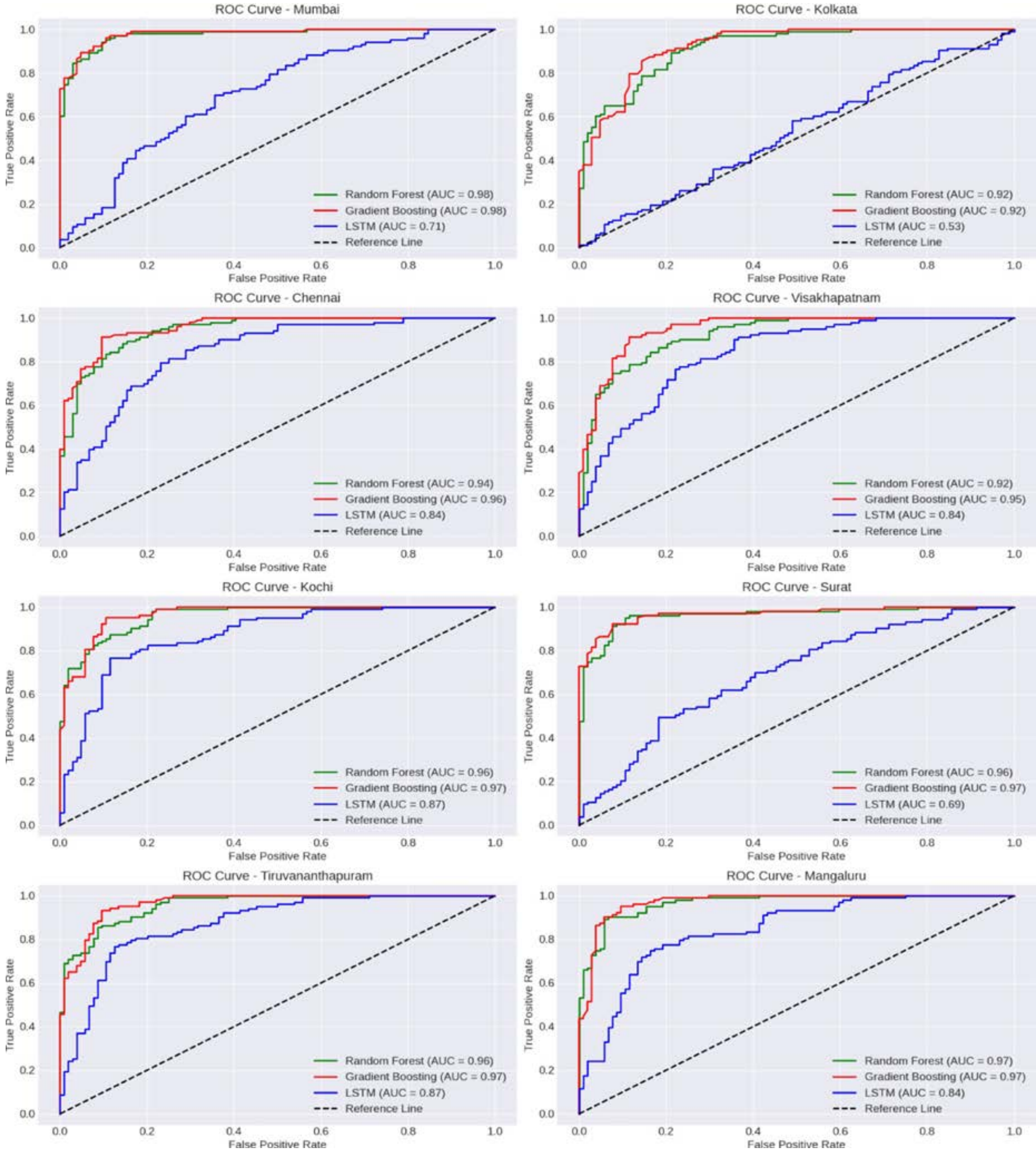

Fig. 10. Validation of the predicted models using AUC.

scenarios, as increasing emissions will elevate the risk. The city requires sustainable, long-term flood resilience planning and infrastructure improvements to safeguard its coastal areas from flooding and inundation.

Discussion

This study presents critical insights into the impacts of rising sea levels on eight major Indian coastal cities—Mumbai, Kolkata, Chennai, Visakhapatnam, Surat, Kochi, Thiruvananthapuram, and Mangaluru—which are vital hubs of economic activity and dense populations. Utilizing RF, GB, and LSTM models, we projected flooding patterns up to 2100 across different SSPs, ranging from low (SSP 126) to high (SSP 585) emissions scenarios. These projections deepen understanding of the spatially varied coastal flood risks driven by climate change.

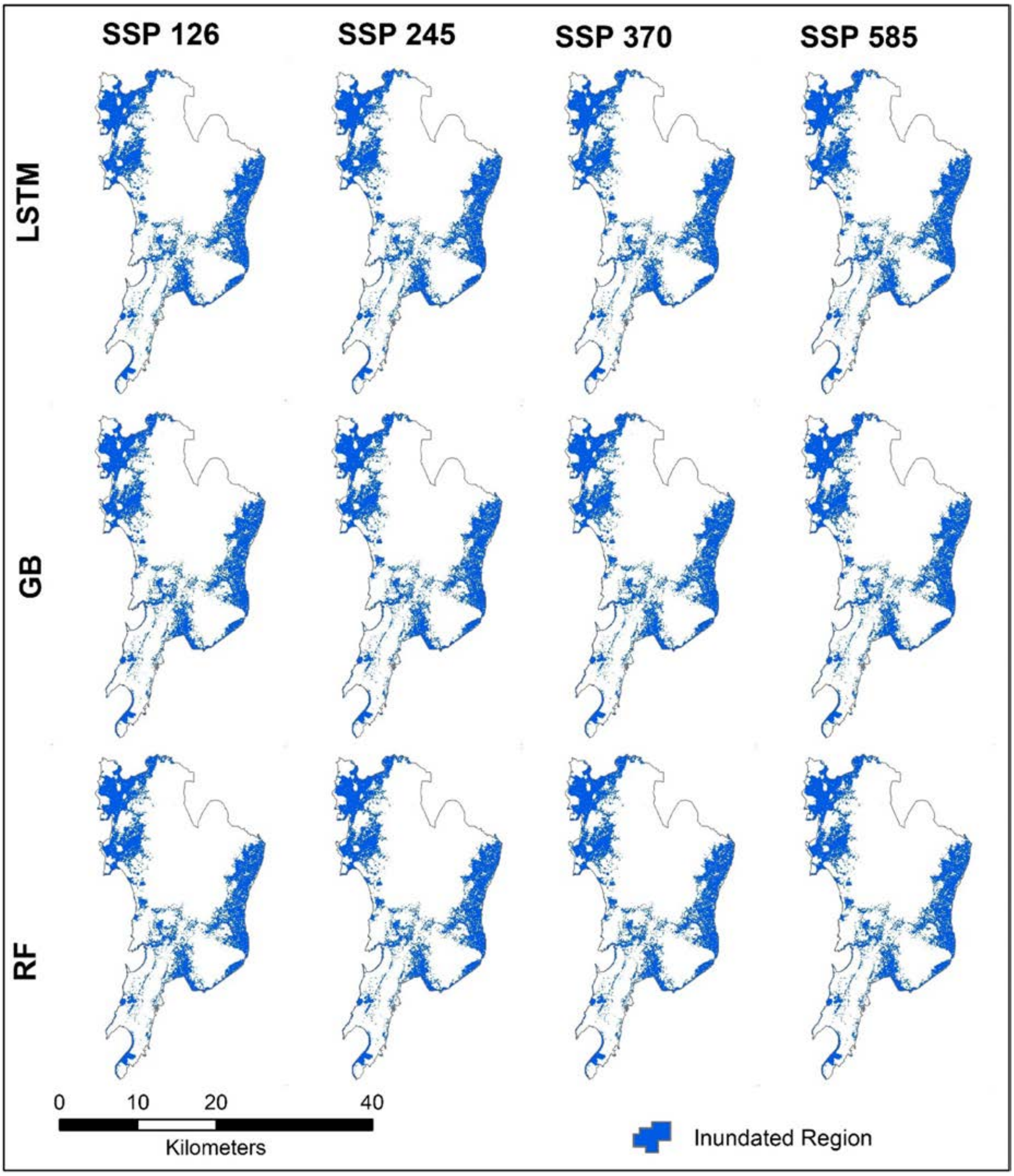

Fig. 11. Coastal flooding and inundation from SLR in the 2100s for Mumbai.

Comparison with global literature

The study confirms international research about coastal cities facing increased exposure to SLR, which impacts facilities and residential districts as well as economic activities. Mumbai, along with Kolkata and Chennai will face high risks due to its low elevation and heavy population concentrations[14–16]. The study confirms previous concerns by presenting projected extensive flooding in these cities under high-emission conditions. Research at a global scale demonstrates the present and ongoing boost of sea levels is affecting coastal cities, which sometimes receives additional pressure from subsidence, together with intense weather events[17,18]. The global sea levels could be elevated by 1 m under high-emission conditions by the year 2100, thus will cause substantial harm to infrastructure networks and human settlements[19]. The analysis of Mumbai, Kolkata, and Chennai matches research evidence which demonstrates that merging coastal erosion with urban development tasks, the

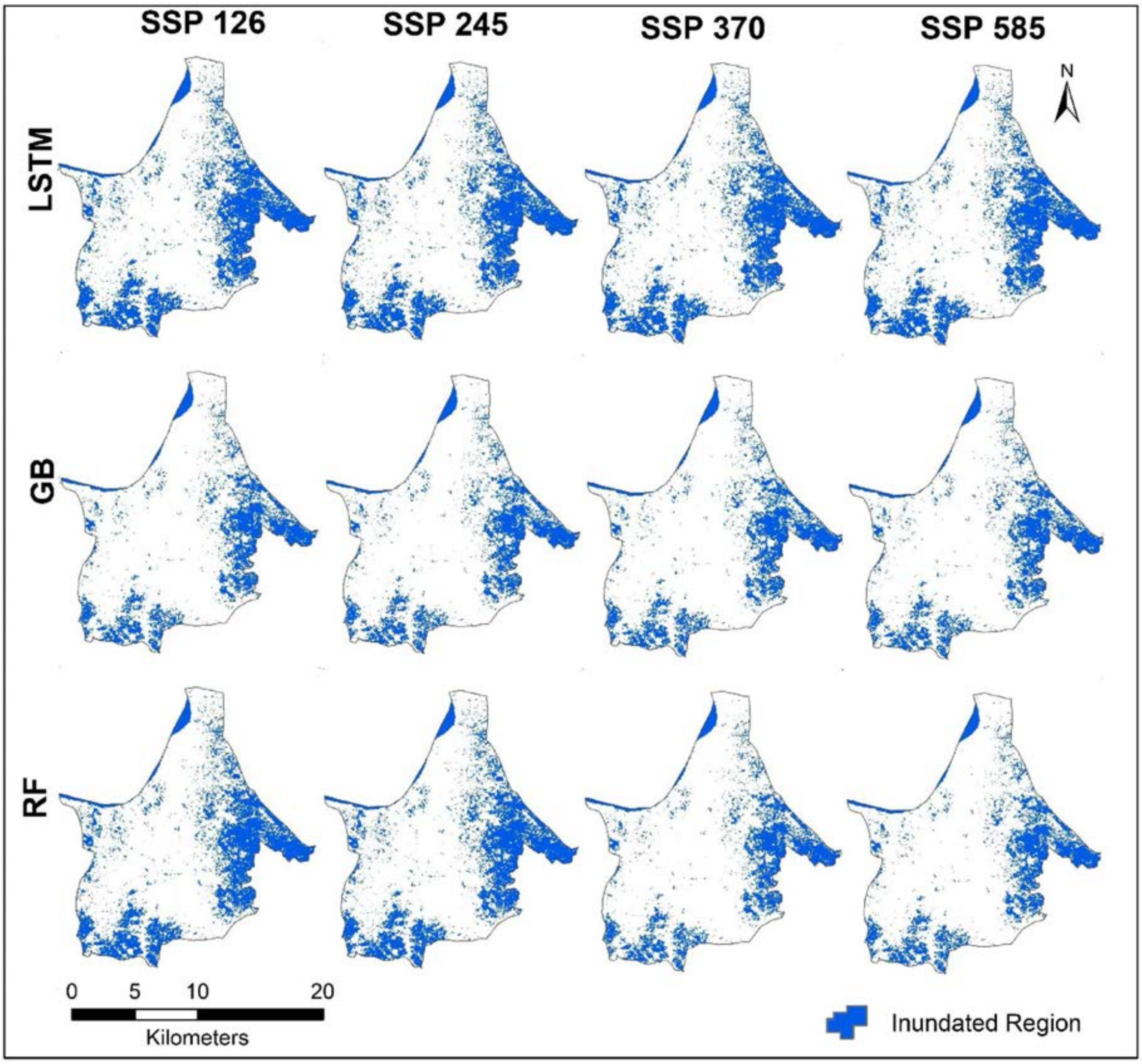

Fig. 12. Coastal flooding and inundation from SLR in the 2100s for Kolkata.

inhabitants and infrastructure situated in oceanic zones with grave identified as threats. The East Side Coastal Resiliency (ESCR) project undertaken by New York City demonstrates how active climate resilience planning must be included the flood barriers combined with green infrastructure. This finding aligns with global research indicating that low-lying coastal megacities face increasing risks from SLR, which threaten infrastructure, residential areas, and economic sectors[20,21]. Cities such as Mumbai, Kolkata, and Chennai—characterized by low elevations and dense populations—are particularly vulnerable in situations, with projected extensive flooding under high emission scenarios, confirming global trends[22–25]. The necessity for climate resilience measures, including flood barriers and green infrastructure, as exemplified by the New York City ESCR project[26] is strongly supported by our results. The projections show that flood risks escalate with higher emissions, emphasizing the urgency of mitigation efforts. The 'sponge city' initiative by China has evolved the design of urban city that can absorb and manage rainwater, reducing the flood risk and mitigating the impacts of SLR to the urban facilities[27,28]. Singapore is taking the initiative to protect the low-lying coastal area by investing in offshore barrier island, elevated buildings and in other flood defences measure[29]. Maldives has taken the initiatives by utilizing land reclamations for creating artificial islands and trying to raise the exixting ones to higher elevation as a key strategy to reduce the impact of SLR[30]. Netherlands is known for its sophisticated system for constructing dykes, dams, storm surge barriers and its investment in nature based solutions and climate based urban planning became famous in worldwide[31]. Bangaldesh is keeping attention on coastal embankment buildings, encouraging the reforestation of mangrove and also implementing the early warning system to restrict the impact of SLR[32]. India is now shifting towards adaptation strategies over mitigation. As mitigation India folows up transitioning to low carbon energy sources, uses carbon capture technologies, protecting forest and oceans as carbon sinksand promoting sustainable behaviour[33]. But now adopting SLR defences, diversifying crops for changing climate and protecting infrastructure from extreme weather for adjusting to climate change effects to minimize harm.

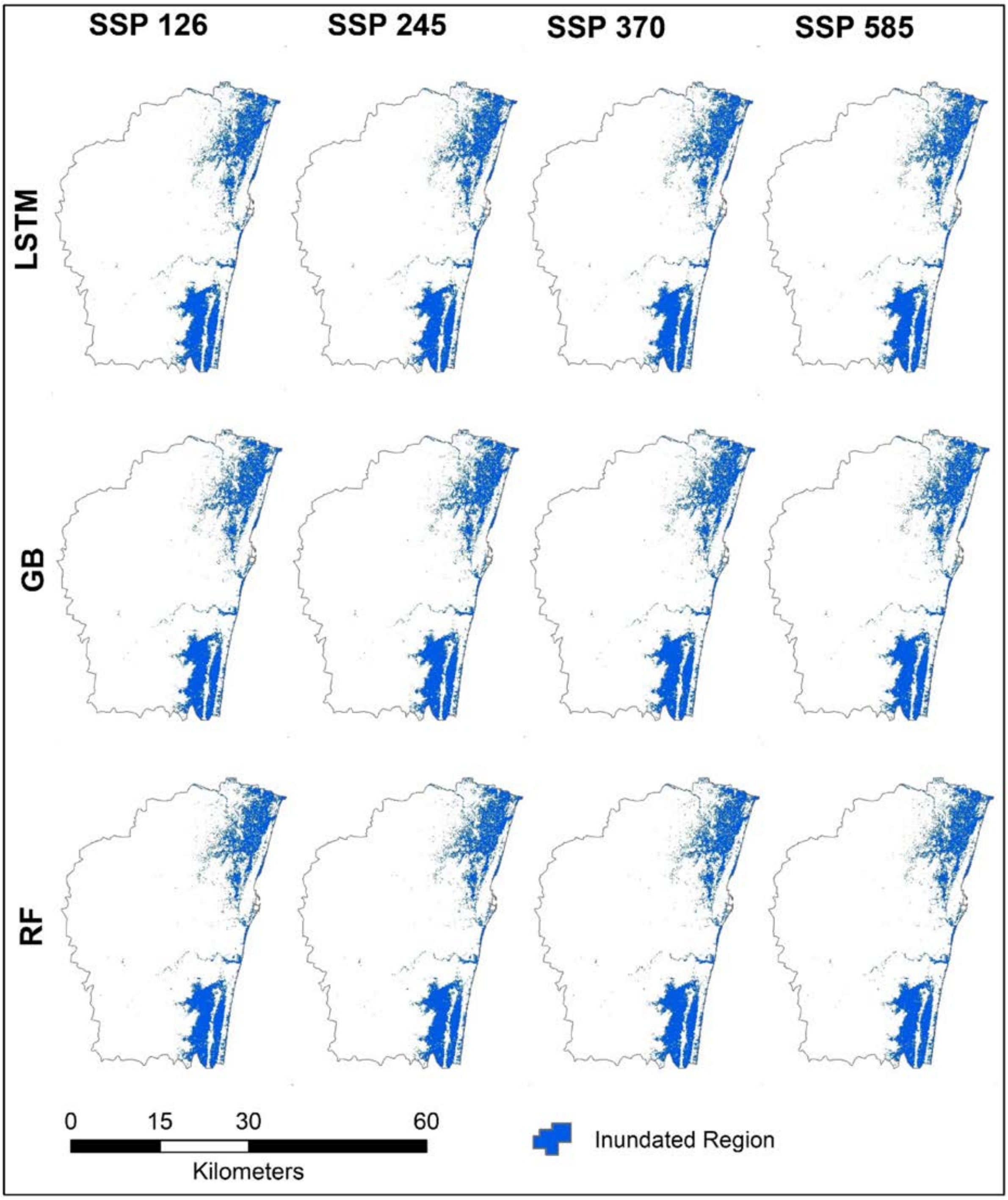

Fig. 13. Coastal flooding and inundation from SLR in the 2100s for Chennai.

As a resilience programme India developing an early warning system, increasing urban green spaces for flood absorption and also encouraging to afforestation to mitigate the effect of urban heat island.

The research data indicates that Mumbai and other cities require immediate installation of flood measures alongside complete climate adaptation plans. Many international studies show that the implementation of different emission scenarios creates significant impacts on future floods. According to IPCC, the effects become more serious as the emission levels increase from SSP 370 to SSP 585 [34]. The research demonstrates that Mumbai, Kolkata, and Chennai experience their largest flooding conditions when emissions reach to higher levels, thus supporting international data on rising flood risks will help to take mitigation action for minimizing the affects.

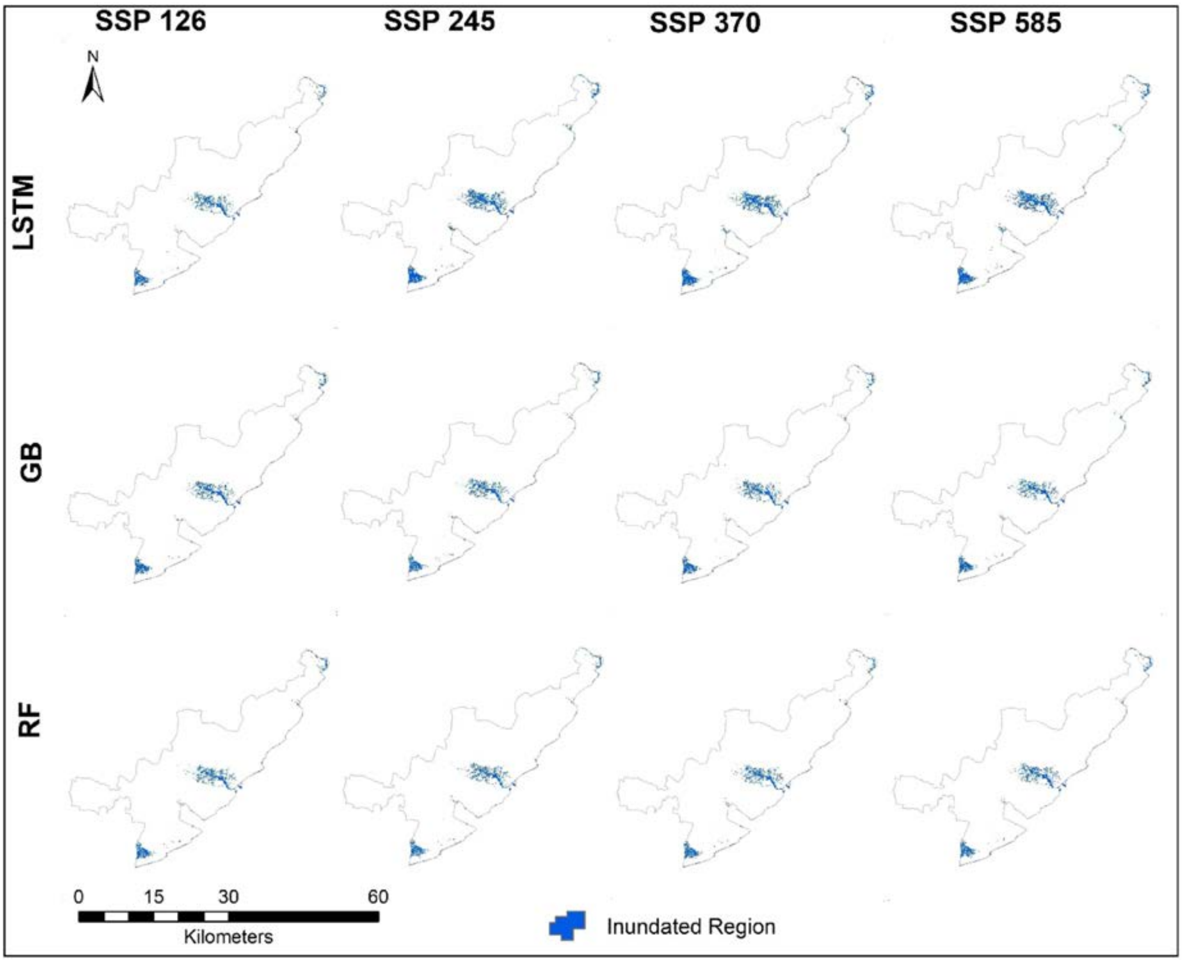

Fig. 14. Coastal flooding and inundation from SLR in the 2100s for Vishakapatnam.

Regional variability in sea level rise projections

The fundamental aspect of this research work depicts how the effects of SLR influnces coastal cities area associated with future trends throuh the different emmisions scenerio ofdifferent geographical regions. Coastal urban areas will face varying levels of susceptibility because they possess different geographic positions, together with densities of human inhabitants alongwith infrastructure facilities. Cities such as Mumbai, Kolkata and Chennai located in low-lying lands together with dense populations, will encounter major floods under high-emission scenarios. The cities comes under major flood risks through the projection of SSP 370 and SSP 585 because their principal infrastructure hubs and residential districts and industrial establishments will face a high probability of submersion. Analysis indicates Kochi and Thiruvananthapuram, together with Mangaluru will not experience extreme levels of flooding while facing the same emission conditions. The topographical configuration of each city plays a vital role in determining its risk levels because of its elevated locations, together with urban features spread across larger distances, make cities less prone to flooding. Kochi, together with Thiruvananthapuram, benefits from larger coastal protection areas which integrate natural mangroves and coastal wetlands systems and this feature grants additional flood-resilience against the impacts experienced by Mumbai and Kolkata because their landscapes were extensively modified by land reclamation and industrial activities. The research demonstrates that Kochi and Mangaluru, along with other cities, face substantial flooding risks, although they are designated as less vulnerable areas, especially when emissions levels increase. The necessity of implementing early prevention measures stands clear among experts because such measures should enhance coastal zone management as well as drainage systems and will protect natural flood barriers such as mangroves and coral reefs. This research indicates global consensus about coastal cities becoming more at risk due to increasing sea levels, yet the extent of this threat depends directly on the way land conditions influence the city environment, including geographic position and infrastructure development and response preparedness. The significant contribution of this study is the detailed assessment of regional variability in SLR impacts. Cities with lower elevations and dense urbanization, such as Mumbai and Kolkata will face far greater flood exposure than higher-elevation cities like Kochi and Thiruvananthapuram. Natural coastal features, including mangroves and wetlands, contribute to resilience in some areas, but urban expansion and land

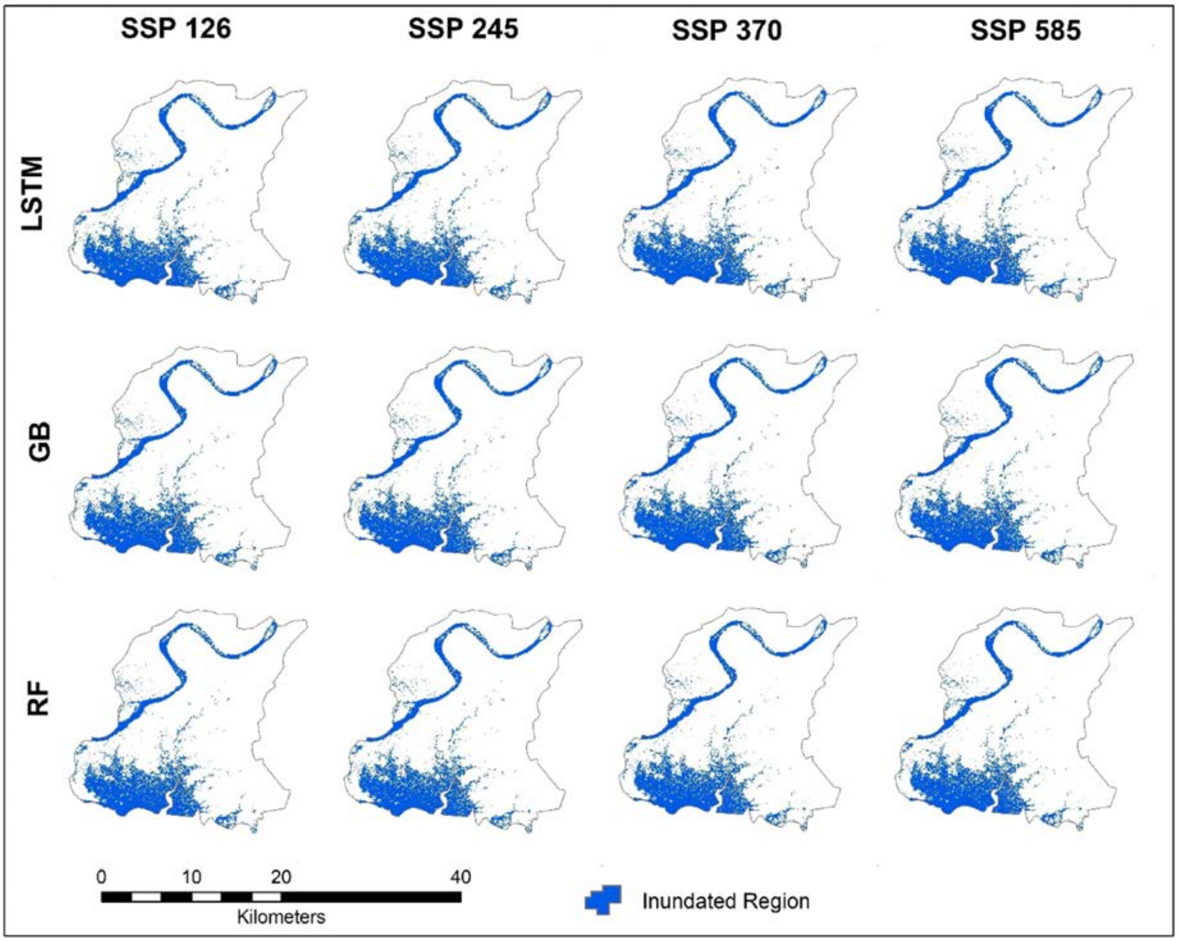

Fig. 15. Coastal flooding and inundation from SLR in the 2100s for Surat.

reclamation have increased vulnerability of the low elevated city areas. This spatial heterogeneity aligns with global observations (UN-Habitat, 2020) and highlights the need for tailored, location-specific adaptation strategies.

Machine learning models and their application in coastal flooding projections

Research on climate change is benefitted greatly from advanced SLR predictions enabled by machine learning models. The three applied models, i.e., RF, GB, and LSTM, each demonstrate unique strengths and limitations when handling complex datasets that encompass SLR, climate variability, and local flood patterns. RF consistently delivered reliable predictions across the study locations, as evidenced by its stable residual patterns. This model excels at processing diverse variables, producing dependable results even from noisy or imperfect data. The complex relationships between SLR, urban development, and environmental changes pose challenges for traditional modeling approaches, particularly in cities like Mumbai and Chennai.

The RF model is proved as a stable tool that delivers generalized predictions because it works effectively in regions with regular data patterns. GB produced higher levels of residual variation, especially in Kochi and Mangaluru cities, showing intricate situations in flood conditions. GB demonstrates superior ability in managing complex non-linear relationships arising from the interplay of unpredictable tidal events, storm surges, and varying rainfall conditions.

The benefit of heightened sensitivity in the model leads to predict instability in volatile data environments. LSTM performs poorly at modeling time-dependent data in Chennai and Surat because these cities face changing environmental conditions and rapid urbanization, which result in unpredictable flood risks. The use of machine learning models offers an advanced predictive capabilities but also highlights challenges. RF models provide stable, generalized predictions even in noisy datasets, while GB models are more sensitive in complex local interactions but sometimes it is less stable. LSTM models excel at capturing temporal dynamics but show higher variability and lower reliability in rapidly changing urban contexts like Chennai and Surat. These model differences suggest that combined approaches may improve overall predictive performance and will support dynamic flood risk management.

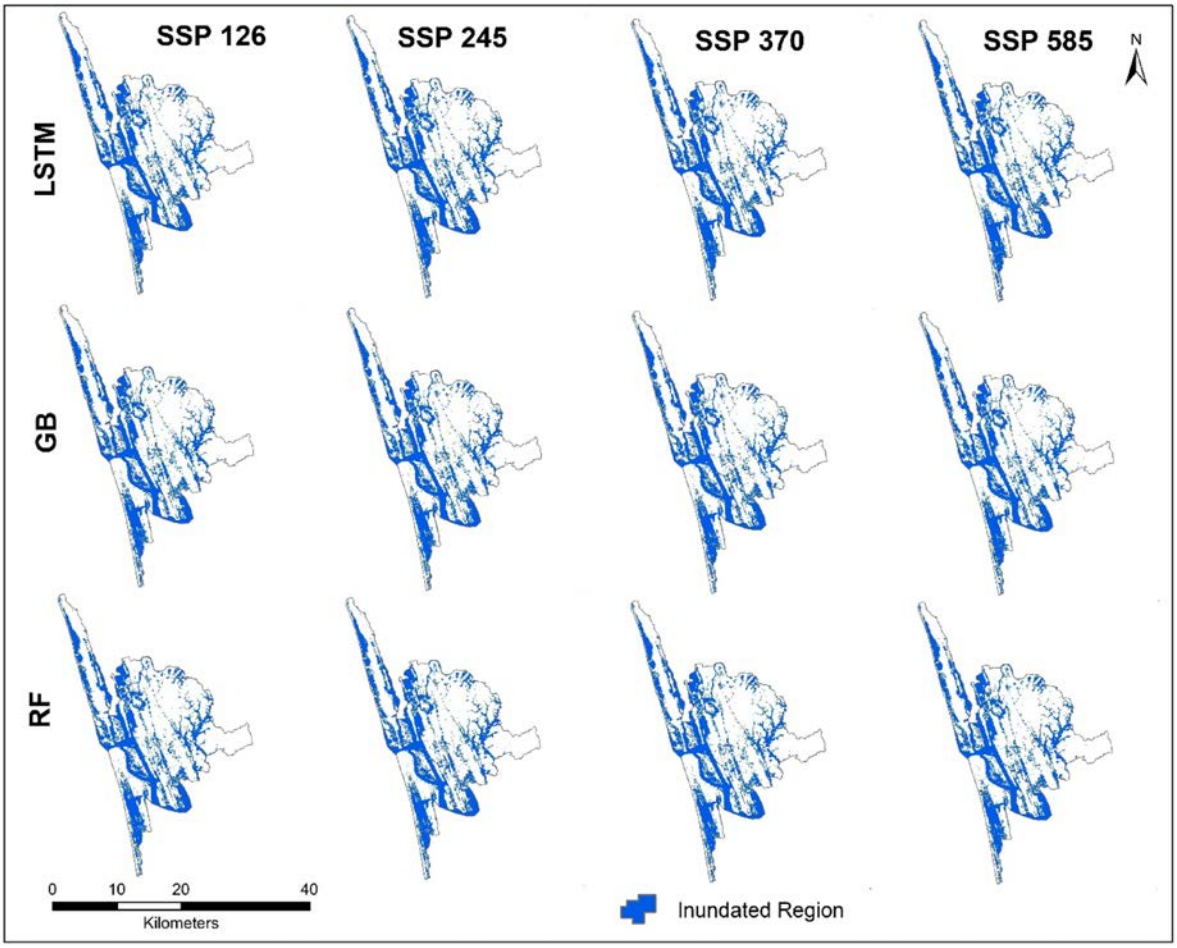

Fig. 16. Coastal flooding and inundation from SLR in the 2100s for Kochi.

Implications for policy measures and adaptation strategies

This research demonstrates that Indian coastal cities require immediate adaptation strategies designed for specific locations. Future flooding hazards targeting Mumbai and Kolkata require immediate implementation of flood barriers along with seawalls and storm surge protection systems because such coastal defences is already proven an effective measurement in London and New York. Since these cities encounter major risks, it is crucial to embed climate-resilient infrastructure into their long-term urban planning systems as a defence against SLR, together with extreme weather events. Mumbai, along with Kolkata, should adopt sustainable urbanization policies to stop people from rapid building construction in coastal zones where high risks exist. The priorities for Kochi and Mangaluru should include building stronger flood alert systems, together with expanding green infrastructure and protecting natural flood protection areas to counter the rising sea level.

Recent studies have shown that land subsidence rates along the Indian Coast are a major concern due to SLR[5]. In India, SLR puts about 40 million people at risk of coastal flooding[35]. To withstand increasing sea levels and more frequent storm surges, the Bandra-Worli Sea Link in Mumbai is being built[36]. Conservation and rehabilitation of mangroves are major initiatives in Gujarat's Gulf of Kutch Marine National Park. Management of coastal zones is crucial to addressing SLR and its effects, according to the National Action Plan on Climate Change (NAPCC). India advocates for effective international action by taking part in the talks of the United Nations Framework Convention on Climate Change (UNFCCC). Climate-resilient design elements are incorporated into the Chennai Metro Rail project to accommodate extreme weather events and SLR[37]. Guidelines for the initial design parameters of appropriate coastal protection projects for various coastline segments were released by the Central Water Commission in 2020[38]. The Coastal Vulnerability Index (CVI) for the Indian coastline has been assessed by the Indian National Centre for Ocean Information Services[39]. It is the result of the combined effects of seven coastal parameters: tidal range, elevation, slope, significant wave height, coastline change rate, sea-level change rate, and coastal geomorphology. Resettlement of displaced individuals impacted by erosion is allocated Rs. 1000 crore under the 15th Finance Commission's recovery and reconstruction window of the National Disaster Response Force (NDRF)[40]. Notification of the Coastal Regulation Zone, 2019 to preserve and safeguard maritime areas and coastal stretches, as well as to provide the security of livelihood for fishermen and other local populations, the Ministry of Environment, Forests, and Climate Change issued this notification[41].

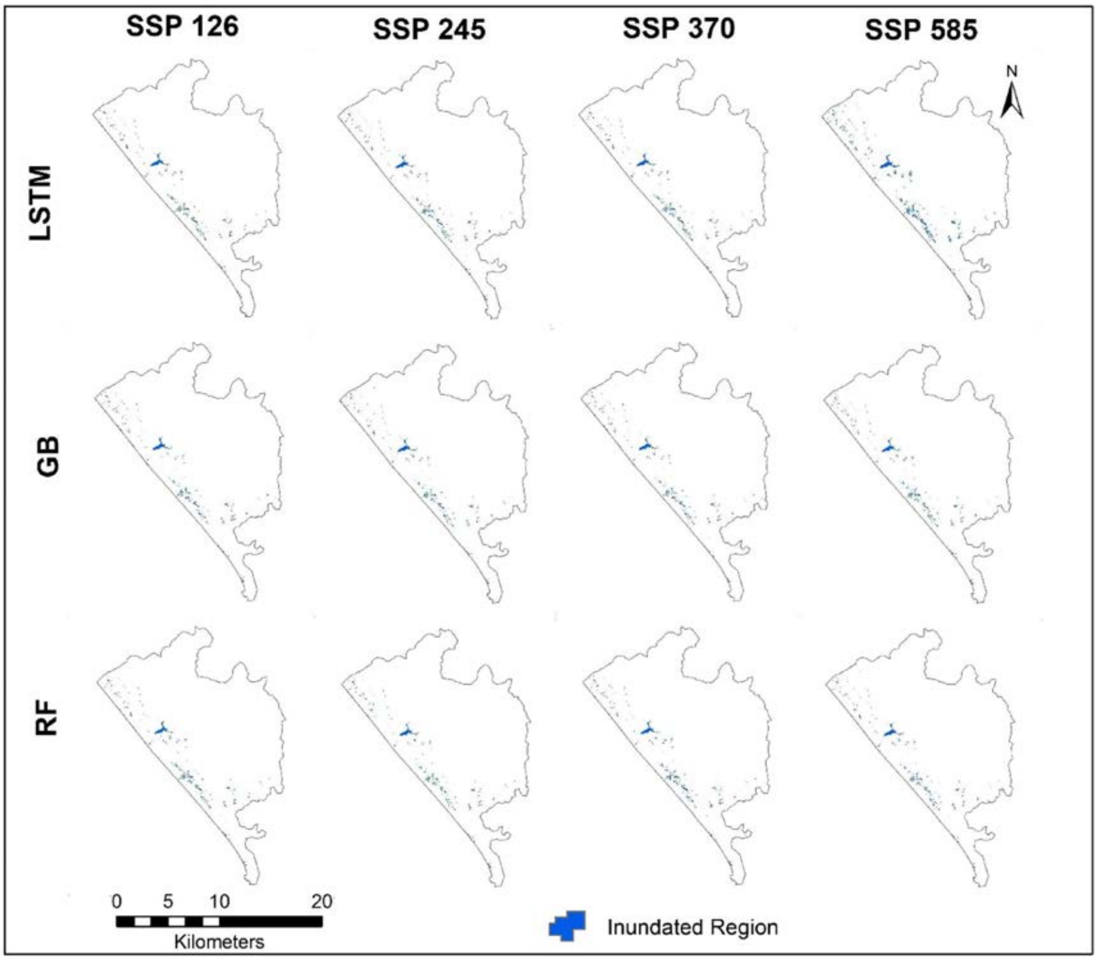

Fig. 17. Coastal flooding and inundation from SLR in the 2100s for Thiruvananthapuram.

Over the following five years, beginning in FY 2023–2024, the Mangrove Initiative for Shoreline Habitats and Tangible Incomes (MISHTI) plan aims to establish 540 square kilometers of mangrove forests in 11 states and 2 union territories[42].The implementation of integrated coastal zone management that combines development with environmental stewardship would be beneficial to Thiruvananthapuram due to its low flood risk level. Effective flood risk management requires a data-driven approach that involves continual refinement of models such as RF, GB, and LSTM to enhance their performance and adaptability over time. Planning entities must recognize how social factors affect exposure to flooding through their assessment of different population groups, including informal settlement communities. Climate policies associated with effectiveness will have to integrate climate justice principles for making sure for equal protection of every resident of cities. The study indicates the urgent need for differentiated climate adaptation strategies. High-risk cities like Mumbai and Kolkata require immediate investment in flood defences, sustainable urban planning, and climate-resilient infrastructure. Medium-risk cities such as Kochi and Mangaluru should focus on strengthening natural flood barriers and early warning systems. Inclusive policies addressing social vulnerabilities and climate justice will be beneficial to ensure equitable protection across urban populations.

Limitations and future research directions

This study provides a valuable contribution but is subject to certain limitations. The analysis relies on historical records and current climate projections, which may not fully capture sudden environmental changes or unforeseen events. Furthermore, the coastal inundation modeling approach used in this study employs a simplified method, which assumes, all areas below a given water level or low elevated area will be flooded. This method overlooks an important physical processes such as bottom friction, flood duration, and the effects of existing flood protection infrastructure like levees and seawalls. Consequently, the approach may overestimate the spatial extent of inundation associated with socioeconomic damages. Future research should focus on developing dynamic predictive models that will integrate real-time data from coastal monitoring stations with ensemble forecasting techniques across multiple models to improve accuracy. In particular, future work should incorporate hydrodynamic flood models that simulate water flow and interaction with physical barriers to provide more realistic and localized flood risk

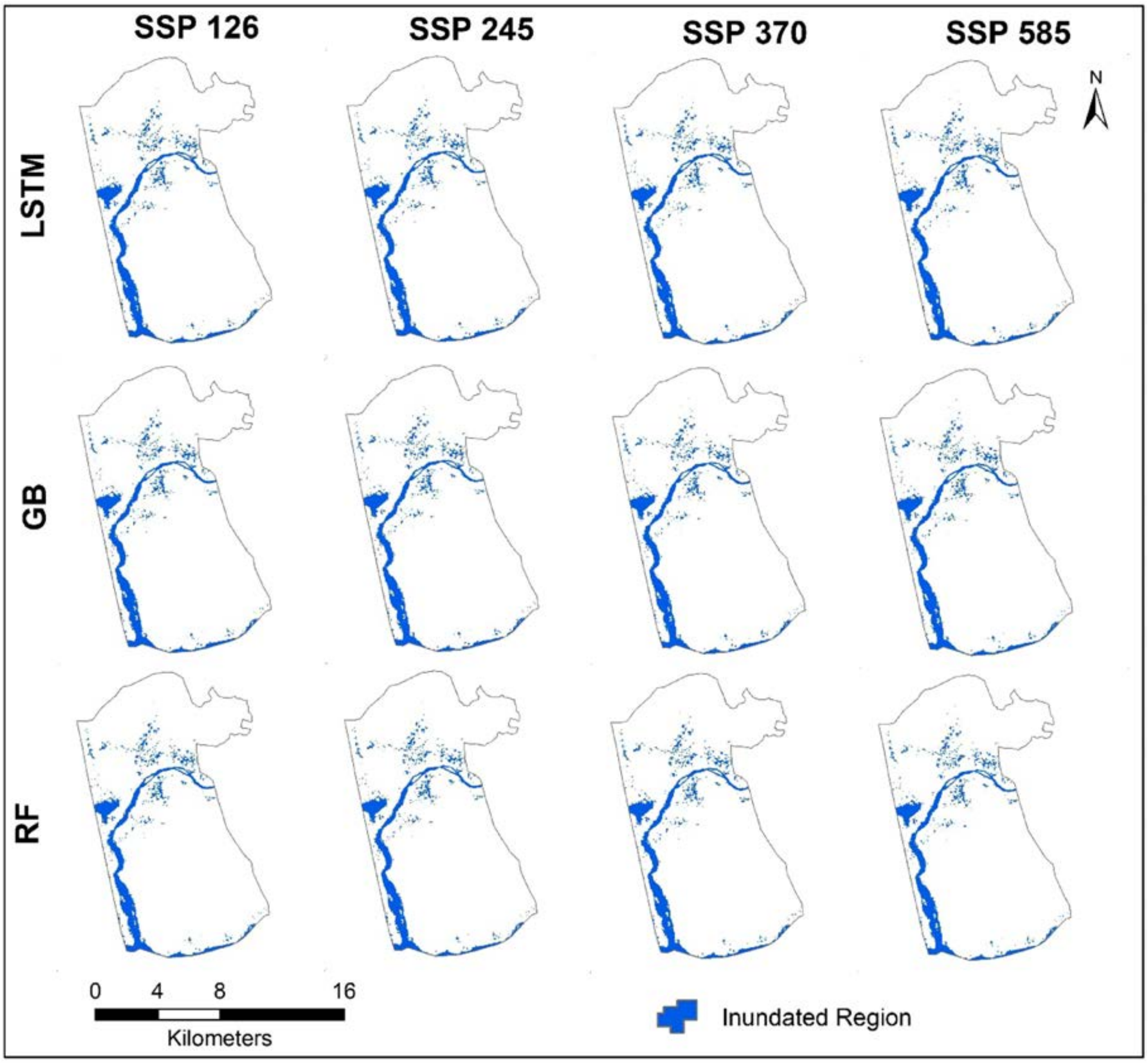

Fig. 18. Coastal flooding and inundation from SLR in the 2100s for Mangaluru.

assessments.Additionally, this study does not address the economic and social impacts resulting from SLR, which should be explored in subsequent investigations.

Future study needs to develop economic models that will determine the cost of flooding, together with quantifying the financial advantages of implementing climate adaptation measures. The implementation of research which evaluates stakeholder participation and flood risk public perception and also allows policymakers to develop localized solutions for increased community disaster readiness. Despite the valuable insights, this study has limitations. At the situations of sudden environmental changes or extreme events, the reliance on historical and modeled data may not be fully captured. The lack of observed inundation data constrained direct validation of flood extent projections. Future research should integrate real-time coastal monitoring, ensemble modeling, and socio-economic impact assessments. Additionally, incorporating stakeholder engagement and local perceptions will improve the relevance and effectiveness of adaptation planning. Scientists should develop complete computational models involving storm surge hazards and weather system extremes, and soil depression to create a widespread comprehension of climate change impacts affecting coastal metropolitan areas.

Materials and methods

Database

Existing data for this study is sourced from three principal domains: climate change projections provided by the IPCC and supported by advanced regional climate models; official socio-economic records obtained from international governmental and climate databases; and high-resolution geospatial data capturing urban topography. The topographic data for this study are derived from high-resolution DEMs obtained from the Shuttle Radar Topography Mission (SRTM), providing precise elevation profiles with a spatial resolution of approximately 30 m. While SRTM DEMs offer valuable terrain detail, they are subject to vertical accuracy limitations that can affect the identification of low-lying and flood-prone areas. The analysis utilizes four SSPs—SSP 126, SSP 245, SSP 370, and SSP 585—as frameworks for future projections, each representing different trajectories of socio-economic development and greenhouse gas emission levels. Following the latest IPCC Sixth Assessment Report (AR6) guidance, this study employs four SSPs—SSP126, SSP245, SSP370, and SSP585—to represent a wide range of potential future socio-economic and emission trajectories. SSP126 corresponds to a low-emissions scenario with strong mitigation efforts, while SSP585 reflects a high-emissions pathway with limited climate policies. The intermediate scenarios, SSP245 and SSP370, capture moderate socioeconomic development and emission levels. These scenarios were selected to provide comprehensive coverage of plausible futures, enabling robust projections of SLR and coastal flooding risks under varying climate and socio-economic conditions. Among multiple available climate models, the MIROC-ES2L model is selected as the primary tool for SLR projections due to its comprehensive coverage of all four SSP scenarios and its extensive temporal range encompassing historical data (1850–2014) and future projections (2015–2100). Although Table 1 indicates that all selected climate models offer comprehensive coverage of SSP scenarios and temporal ranges, the MIROC-ES2L model was chosen as the primary tool for SLR projections due to its superior spatial resolution and proven reliability in simulating regional climate dynamics. MIROC-ES2L has been widely employed in previous sea level and coastal impact studies, consistently providing accurate and spatially detailed projections essential for city-level vulnerability assessments. Moreover, its output integrates seamlessly with our machine learning framework, enhancing the precision of flood risk forecasts. Input data uncertainties influence the precision of SLR and flood risk projections. Vertical measurement errors in the SRTM DEMs can impact the accuracy of floodplain delineation and vulnerability assessments. Additionally, inherent uncertainties in climate model projections—due to varying emission scenarios and model structural assumptions—affect the range of possible outcomes. To address these factors, sensitivity analyses were performed, and model outputs were validated against available historical observations. This ensures that the projections capture a plausible range of futures, strengthening the robustness of the study's risk assessments. (Fig. 19) highlights these comparative advantages, emphasizing MIROC-ES2L's suitability for the present study. MIROC-ES2L is distinguished from other models such as CESM2, GFDL-ESM4, HadGEM3-GC31-LL, and IPSL-CM6A-LR by its robust capacity to generate reliable and spatially detailed sea level change data critical for regional-scale analysis (Fig. 19). The database of this study integrates historical sea level measurements with detailed urban topographical information derived from DEMs, which provide precise elevation profiles critical for evaluating vulnerability to coastal flooding and inundation. DEMs enable the identification of low-lying and flood-prone areas by offering high-resolution terrain data that, when combined with projected sea level changes, reveal spatially explicit risk patterns. Together, these diverse data sources form a comprehensive multimodal database essential for training accurate machine

Model	Scenario	Experiment	Realization	Grid	Period
MIROC-ES2L	Historical	r10i1p1f2	1	gr1	185001–201412
MIROC-ES2L	SSP 126	r10i1p1f2	1	gr1	201501–210012
MIROC-ES2L	SSP 245	r10i1p1f2	1	gr1	201501–210012
MIROC-ES2L	SSP 370	r10i1p1f2	1	gr1	201501–210012
MIROC-ES2L	SSP 585	r10i1p1f2	1	gr1	201501–210012
CESM2	Historical	r1i1p1f1	1	gr1	185001–201412
CESM2	SSP 126	r1i1p1f1	1	gr1	201501–210012
CESM2	SSP 245	r1i1p1f1	1	gr1	201501–210012
CESM2	SSP 370	r1i1p1f1	1	gr1	201501–210012
CESM2	SSP 585	r1i1p1f1	1	gr1	201501–210012
GFDL-ESM4	Historical	r1i1p1f1	1	gr1	185,001–201,412
GFDL-ESM4	SSP 126	r1i1p1f1	1	gr1	201501–210012
GFDL-ESM4	SSP 245	r1i1p1f1	1	gr1	201501–210012
GFDL-ESM4	SSP 370	r1i1p1f1	1	gr1	201501–210012
GFDL-ESM4	SSP 585	r1i1p1f1	1	gr1	201501–210012
HadGEM3-GC31-LL	Historical	r1i1p1f1	1	gr1	185001–201412
HadGEM3-GC31-LL	SSP 126	r1i1p1f1	1	gr1	201501–210012
HadGEM3-GC31-LL	SSP 245	r1i1p1f1	1	gr1	201501–210012
HadGEM3-GC31-LL	SSP 370	r1i1p1f1	1	gr1	201501–210012
HadGEM3-GC31-LL	SSP 585	r1i1p1f1	1	gr1	201501–210012
IPSL-CM6A-LR	Historical	r1i1p1f1	1	gr1	185001–201412
IPSL-CM6A-LR	SSP 126	r1i1p1f1	1	gr1	201501–210012
IPSL-CM6A-LR	SSP 245	r1i1p1f1	1	gr1	201501–210012
IPSL-CM6A-LR	SSP 370	r1i1p1f1	1	gr1	201501–210012
IPSL-CM6A-LR	SSP 585	r1i1p1f1	1	gr1	201501–210012

Table 1. Different model scenarios considered in this research.

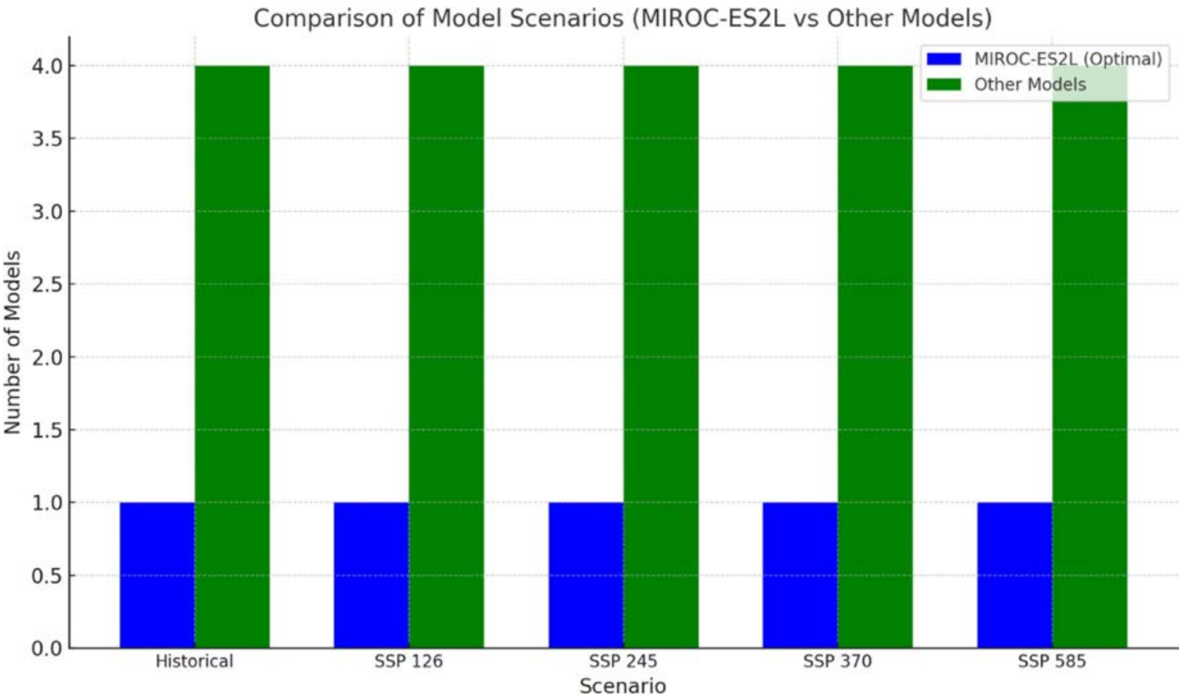

Fig. 19. Comparison of the model scenarios used in this research.

learning models. The spatial data, coupled with reliable sea level projections, allow the models to generate precise forecasts of SLR and its associated flooding risks from 2020 to 2100.

Methodology

In this research the LSTM as well as RF and GB has been implemented for performing future SLR assessments and associated coastal flooding. These models fit requirements to address non-linear connections and both time-dependent functions while processing complex environmental parameters. This study follows three main procedures which include Data Preprocessing and Feature Engineering and Model Training and Validation and Flood Risk Assessment and Inundation Modeling.

Data preprocessing and feature engineering

Machine learning algorithms need raw data preprocessing for quality improvement before they can predict SLR. The initial important process revolves around managing missing information. Real-world data collection often leads to data gaps that stem from either faulty sensors or incorrect data measurements, or any other operational problems. The absence of values within the dataset significantly impacts the operational quality of machine learning models when used with advanced systems like LSTM networks and RF, and GB. The implementation of different imputation approaches exists to handle the problem. The selection of imputation techniques for numerical features depends on the data type, so analysts use either mean, median or mode imputation methods. Experts remove rows or columns from the dataset as a measure to preserve its structure when missing data becomes excessively frequent or when an unreliable value cannot be estimated. The model remains unaffected to unreliable data through these measures to prevent both inaccurate and biased predictions.

An important step in the preprocessing stage is outlier removal. The impact of outliers on model predictions is particularly significant for LSTM, RF, and GB models, as these algorithms are sensitive to data points that consistently deviate from the norm. To identify outliers, statistical methods such as the Z-score and Interquartile Range (IQR) analyses are employed. The Z-score detects values that lie far from the mean, while the IQR method identifies data points outside the established quartile range. Removing outliers improves model accuracy by preventing extreme values from distorting the underlying patterns present under normal conditions.

Feature scaling is applied as the next step to normalize the input features. Machine learning algorithms such as GB and RF produce optimal results when input features possess similar scales because extreme differences in feature values can result in performance bias. The temperature feature, which uses degrees Celsius, faces a different scaling range than sea level data represented in meters. Min-max scaling or standardization (z-score normalization) serves as a solution to normalize features into equivalent scales. Standardization transforms features to possess a mean value of zero and a standard deviation of one because it benefits LSTM algorithms and others that react to input data magnitude. During the transformation process, features maintain equivalent impact on model training, allowing features with smaller numerical values to avoid dominating the learning process.

Feature engineering serves as one of the core methods which improve the predictive capabilities of machine learning systems. Research into SLR prediction requires the development of time-sensitive variables. Historical sea level measurements alongside climate factors, including temperature, precipitation and atmospheric pressure, act as inputs for generating seasonal and multi-year trend recognition. Long-term climate fluctuations and yearly wave patterns in sea level become more identifiable through these temporal pattern features. LSTM models require lag features to recognize time-based data relationships and dependencies in the available information. The forecasting model requires lag features because they teach the model to extract information from past data points, which it uses to generate future prediction results.

Geospatial features accompany temporal features in the dataset to analyze coastal city topography. DEMs help determine both elevation heights and slope gradients in endangered flood areas. Geospatial features enable the model to assess vulnerable low-lying coastal areas so it can identify areas most at risk from rising sea levels. The integration of spatial data enhances the precision of risk assessments, enabling cities and regions to develop effective adaptation plans and flood protection strategies in response to projected sea level changes.

Model training and validation

The data processing stage is followed by the training of machine learning models. The prepared dataset is used to train a combination of LSTM, RF, and GB models. These models are well-suited for capturing complex non-linear relationships as well as temporal patterns, which are essential for analyzing the effects of SLR on coastal regions. Model evaluation is conducted using cross-validation techniques, where the dataset is divided into multiple subsets. In each iteration, the model is trained on all but one subset, which is reserved for testing, ensuring robust performance assessment. The ability to assess model generalization is improved through cross-validation, along with the prevention of overfitting, which results in consistent model performance across multiple partitions of data. Residual analysis helps establish the predictive capability of the developed models. The comparison between actual and predicted observations results in residuals. Calculations for maximum and minimum values, along with the standard deviation of residuals, help determine how well each model fits the gathered data. A model achieves better predictive accuracy when it produces residuals that are small in size. The models' distinction between inundated and non-inundated zones based on sea level change forecasts is evaluated through the AUC measure ROC assessments.

Flood risk assessment and inundation modeling

The generated SLR projections produced by machine learning models need additional analysis to identify zones at risk of coastal flooding through modeling potential flooded areas. Topographic data, including DEMs, helps accomplish this step through which the projections integrate with the fundamental elevation data about the landscape. DEMs prove indispensable since they allow the identification of regions situated at low elevations that face high flood risks. Projected SLR results from the models are mapped onto topographic data using DEMs for detailed impact assessment in each city area. The integration of these projections with DEMs provides a comprehensive understanding of future sea level changes and allows for precise elevation-based identification of at-risk zones. This combined data analysis enhances the development of models that effectively recognize flood vulnerabilities and accurately map regions likely to experience flooding in coastal metropolitan areas.

The risk classification system monitors flooding extent through threshold criteria. The risk assessment strategy divides regions according to their predicted exposure to increasing sea levels through a specific threshold ranging from a minimum of 1 m to higher. The evaluation considers the impact of SLR on cities through SSP 126 (low emissions) and SSP 245 (moderate emissions) and SSP 370 (high emissions), and SSP 585 (very high emissions) during the year 2100. Places projected to reach SLR which reach or exceed set thresholds become designated as Inundated Areas. The areas susceptible to high flooding need immediate flood adaptation solutions, including seawall constructions and flood barrier implementations, along with alternative mitigation methods. The zones below the SLR threshold are identified as Non-Inundated Areas because they do not experience rising water levels. The non-inundated regions show good resistance to flooding, which suggests these areas need limited flood control operations at present.

The classification process assists flood modellers in determining how much land faces potential flooding by helping identify the areas at risk. The analysis enables essential urban planning decisions by separating regions into zones which will be affected by flood and those that will remain safe from inundation. A straightforward threshold classification method identifies specific locations which need urgent flood protection measures or ones that will not face flooding, so authorities can provide strategic countermeasures in the most vulnerable areas.

After classification, the resulting flood risk maps visually depict the spatial extent of projected inundation areas. These maps serve as essential tools for planners, environmental managers, and policymakers by identifying regions most vulnerable to SLR. They support informed decision-making for the development of coastal defence infrastructure, flood mitigation strategies, and climate adaptation plans. By clearly showing which zones are most at risk, these visual tools help public authorities prioritize interventions and allocate resources effectively for long-term coastal resilience.

Sea level projection

In this study, the RF, GB, and LSTM models were selected for sea-level rise projections due to their strengths in handling complex climate data. RF is well-suited for managing high-dimensional datasets with diverse variables, such as temperature, precipitation, and elevation, offering robust and interpretable predictions by aggregating results from multiple decision trees. GB improves accuracy by sequentially correcting errors from earlier models, making it effective in capturing non-linear relationships among environmental factors influencing sea level. LSTM, a deep learning model designed for sequence prediction, is particularly advantageous for analyzing long-term temporal dependencies, trends, and seasonal patterns in historical sea level data. The combination of these models provides a comprehensive framework that captures spatial, non-linear, and time-dependent dynamics, resulting in more accurate and reliable sea-level rise and flood risk projections.

Long short-term memory

The LSTM network operates as an improved version of Recurrent Neural Networks (RNNs) to solve their chief weaknesses in handling long-term relationships in sequential information[43,44]. The model provides valuable insight into future prediction challenges because it relies on past time sequences for making accurate sea-level rise forecasts. The memory cell in LSTMs serves as an information storage unit, while the gates regulate the memory inputs and outputs. Through these gates, the LSTM can track extended dependencies within the data while discarding unnecessary details. An LSTM network carries out its mathematical operations through these specific steps:

$$f_t = \sigma\left(W_f\ \left[h_{t-1}\ x_t\right] + b_f\right) \tag{1}$$

where f_t is the forget, h_{t-1} is the previous hidden state, x_t is the input data at time t, and W_f and b_f are the weights and bias of the forget gate.

$$i_t = \sigma\left(W_f\ \left[h_{t-1}\ x_t\right] + b_i\right) \tag{2}$$

where i_t is the memory gate

$$C_t = f_t\ C_{t-1} + i_t\ \tanh(W_c\ \left[h_{t-1}\ x_t\right] + b_C) \tag{3}$$

where C_t is the cell state, and tanh is the hyperbolic tangent activation function.

$$o_t = \sigma\left(W_f\ \left[h_{t-1}\ x_t\right] + b_o\right) \tag{4}$$

where o_t is the output gate

$$h_t = o_t\ \tanh\left(C_t\right) \tag{5}$$

where h_t is the hidden state, which represents the output of the LSTM model[45]. The hidden state serves as a summary of both the current input and the learned context from previous time steps. It is updated dynamically at each step based on the internal gating mechanisms, allowing the model to retain and propagate important temporal patterns.

Random forest

The RF functions as one of the leading ensemble learning techniques that enables both regression and classification research[46]. RF creates a group of decision trees, each using a randomly selected subset of data for construction[47]. The RF model maintains its strength through ensemble operation, which uses aggregated predictions of all decision trees to create a final robust output[48]. The aggregation technique reduces the overfitting occurrences typical in single decision trees.

RF starts with selecting random data subsets using bootstrapping as its methodology[49]. The model develops its components from independently trained decision trees made using the selected subsets of data[50]. During the training phase, RF performs two forms of randomness by sampling the data portions and choosing random feature sets for each decision tree[51]. The algorithm creates diverse decorated trees because the methodology selects random subsets to reduce the link between separate trees during training. The proposed prediction emerges from averaging the output values of separate trees in an RF model when utilized for regression tasks or minority vote calculations when used for classification.

RF effectively handles overfitting problems in data analysis, especially when working with sets that contain many features or contain high levels of noise. The model possesses competence in handling continuous data as well as categorical information, making it suitable for analyzing diverse complex patterns in datasets. RF presents a dependable solution for modeling nonlinear relationships between climate variables and increased sea levels across different coastal cities when predicting sea-level rise. The method has achieved successful deployment throughout environmental studies, including climate change modeling, because it retains stability during sophisticated dependency modeling.

The mathematical expression for the RF model appears as follows:

$$f\left(x\right) = \frac{1}{N}\sum\ {}_{i=1}^{N} T_i\left(x\right) \tag{6}$$

where $f\left(x\right)$ represents the predicted output for a given input, N is the number of trees in the forest, $T_i\left(x\right)$ is the prediction from the i-th tree[52].

Gradient boosting

GB functions as an efficient ensemble learning method, which differentiates from RF through its specific implementation process[53]. RF operates independently to build trees before predicting them, while GB makes trees one after another[54]. The trees GB processes work toward reducing errors that previously emerged in the sequential order of trees[55]. The progressive addition of new trees through this process helps decrease residual errors, therefore making the model highly effective at predicting outcomes accurately[56]. The GB algorithm executes its first operation by using a starting prediction based on the mean value of the target al.ongside residual error measurements between actual and predicted results. A system follows with a decision tree prediction of these residual values before updating the model through predicted outcomes from this new tree. A weight factor adjusts the new prediction, which determines the extent each new tree impacts the model outcome. The process runs multiple times or until the remaining errors reach their minimum threshold.

GB excels at targeting problem predictions through its weighting system, which gives more importance to data points with large residual values. The model connects a larger weight to as well as learn from problematic regions identified by earlier trees, thus producing more precise outcome predictions. What makes GB stand out is its widespread usage across multiple applications, which also includes environmental forecasting of sea-level rise and coastal city impact.

The iterative mathematical structure of GB during iteration m appears as follows:

$$f_m(x) = f_{m-1}(x) + \eta \ h_m(x) \tag{7}$$

where $f_m(x)$ is the updated prediction after the m-th iteration, $f_{m-1}(x)$ is the prediction from the previous iteration, $h_m(x)$ is the decision tree that predicts the residual errors, η is the learning rate.

The analysis utilizes SSPs to project future SLR and assess its potential impact on coastal flooding across major Indian cities. These SSP-based projections, derived from climate models, are combined with high-resolution DEMs and topographic data to evaluate spatial vulnerability. This integration enables the identification of low-lying urban areas that are likely to be inundated as sea levels rise under varying emissions scenarios. The core of the inundation modeling approach involves comparing projected mean sea level elevations to the ground surface elevation at each point across the urban landscape. Areas where projected sea levels exceed the local elevation are identified as inundation-prone. This process accounts for natural terrain variability and urban topography, enabling the detection of vulnerable flood zones even within complex coastal city environments. Flood risk estimation is operationalized through a classification scheme that groups areas based on their exposure to SLR. Rather than relying on preset elevation thresholds, the model dynamically assesses risk by determining whether the future sea level, as predicted under each SSP scenario, will surpass the elevation at each specific location. This produces a binary classification: inundated areas (where projected sea level exceeds ground elevation) and non-inundated areas (where elevation remains higher than sea level). To quantify city-level vulnerability, the total land area of each city is divided into these two categories. The proportion of land projected to be inundated relative to the city's total surface area is then calculated, offering a clear, quantitative measure of flood exposure. This percentage-based metric reflects both the severity and spatial extent of flooding risks for each city under different climate scenarios. The resulting data are used to produce detailed spatial flood risk maps. These maps visually depict projected inundation zones and serve as critical tools for urban planners, infrastructure developers, and policymakers. They allow decision-makers to identify high-risk neighbourhoods, prioritize areas for adaptation measures, and allocate resources more effectively. By understanding where and how SLR is likely to impact urban infrastructure—such as roads, housing, utilities, and transportation corridors—cities can implement targeted interventions, including coastal defences, zoning changes, flood-resilient infrastructure, and early warning systems.

Conclusion

This research provides essential findings about how increasing sea levels and coastal flooding will affect the major Indian coastal cities, i.e., Mumbai, Kolkata, Chennai, Visakhapatnam, Surat, Kochi, Thiruvananthapuram and Mangaluru. Here RF and GB algorithms and LSTM networks hase been considered to evaluate flood levels according to the SSP 126, SSP 245, SSP 370, and SSP 585 emission projections which generated essential projections regarding future coastal destruction.Research results demonstrate that across Indian cities, Mumbai, together with Kolkata and Chennai, experience the greatest flood risks because they have low elevations as well as dense settlements and essential infrastructure. Kochi, Thiruvananthapuram and Mangaluru cities experience moderate flooding perils but should still implement proactive coastal protection initiatives. Studies results we must urgently pursue climate adaptation and mitigation solutions alongside coastal safeguards, the establishment of warning systems, and urban resilience development. This research provides critical information to tackle distinct flood severities that threaten local communities, particularly in vulnerable locations such as Mumbai and Kolkata. Flood protection systems should be integrated with green infrastructure and emergency preparedness strategies to safeguard local communities from rising sea levels and increasingly severe extreme weather events. The research adds to present climate resilience discussions while setting the groundwork for subsequent studies to enhance SLR projections through better machine learning approaches for flood risk evaluation. This intervention demands that climate adaptation requires professionals from two or more disciplines to link environmental science and urban planning with sociological considerations for creating equitable and effective climate response programs. The research has certain weaknesses because it uses current climate models together with limited information available for small coastal communities. Additional research associated with compact procedures will be helpful to predict storm surges with time-based data monitoring, together with economic assessments to improve the adaptive abilities of India's coastal cities during climate change events. Results from this study will provide essential information to policymakers, urban planners, government administrators, and stakeholders, enabling them to collaborate effectively with city developers and industry experts to promote sustainable municipal development and build climate-resilient infrastructure. This knowledge supports informed decision-making will address rising sea levels and associated risks in vulnerable coastal cities. Furthermore, policy frameworks should be updated to embed climate projections and socio-economic considerations, ensuring that urban development plans are robust against future SLR and associated hazards. These actions are needed to safeguarding communities and fostering sustainable coastal urban growth in the face of climate change. Research results demonstrate that among Indian cities, Mumbai, Kolkata, and Chennai will face the greatest flood risks due to their low elevations, dense settlements, and the presence of essential infrastructure, such as transportation networks, flood protection systems, and urban utilities that are important for city functioning but still remain vulnerable to inundation.

Data availability

"The datasets used and/or analysed during the current study available from the corresponding author on reasonable request."

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Author contributions
RC and TA designed the experiments, analyzed the results, run the models, wrote, and reviewed the entire manuscript. SA, PR and CBP wrote the initial manuscript and revised the updated version accordingly.

Declarations

Competing interests
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