Objective 2 - To study distribution status/pattern of Molluscs on the basis of its substratum structure along South Saurashtra Coast on selected sites

Introduction:

Gujarat, India's westernmost state, boasts a uniquely diverse geographical landscape, which ranges from vast desert expanses to long, picturesque coastlines. This state is endowed with an extensive 1,600 km coastline that stretches along the Arabian Sea, encompassing a variety of coastal and marine habitats such as estuaries, mudflats, mangroves, coral reefs, and sandy and rocky shores. Diverse habitats support a rich tapestry of marine biodiversity, including a significant variety of Molluscan species (Alonso, 2008). The ecological and socio-economic fabric of Gujarat is intricately linked with its marine biodiversity, making the study of Molluscans in this region not only a subject of ecological interest but also of socio-economic necessity (Desai & Nair, 2015). Molluscans, a diverse group of invertebrates, play pivotal roles in the marine ecosystems of Gujarat (Bhatt et al., 2020). They serve as key species in maintaining the ecological balance and contribute significantly to the state's socio-economic development. Molluscan species such as clams, oysters, mussels, and squids are not just integral to the marine food web, but also form the backbone of local fisheries and aquaculture sectors (Patil et al., 2018). The fisheries sector in Gujarat is a major economic driver, supporting the livelihoods of thousands of coastal communities (Joshi et al., 2020). Molluscans, being a significant part of the catch composition, contribute to the nutritional security and economic stability of these communities (Berthou et al., 2009).

The aquaculture industry in Gujarat has also seen a substantial rise, with Molluscan aquaculture emerging as a promising sector. Species such as the Indian backwater oyster and the green mussel have been identified as suitable for commercial cultivation, providing sustainable livelihood options for coastal populations (Sekar Megarajan et al., 2018). Moreover, the Molluscan aquaculture of the state is not just limited to domestic consumption but also has a considerable export potential, contributing to the economy of the state. Beyond their direct economic value, Molluscans play crucial roles as bioindicators, serving as natural monitors of the environmental health of marine ecosystems (Markert et al., 2002). Their sensitivity to changes in water quality and habitat conditions makes them effective indicators for assessing the impacts of pollution, climate change, and anthropogenic disturbances on marine habitats (Moraitis et al., 2018). This bioindicator role is particularly valuable in a state like Gujarat, where rapid industrialization and urbanization pose significant environmental challenges to coastal and marine ecosystems (Moraitis et al., 2018).

Despite their ecological and economic significance, Molluscan populations in Gujarat face numerous threats (Gadhavi et al., 2022). Overexploitation, habitat destruction due to coastal development, pollution from industrial and domestic sources, and the impacts of climate change are some of the critical challenges (Watson & Neo, 2021). These threats not only jeopardize the survival of Molluscan species but also threaten the socio-economic fabric of coastal communities dependent on these resources (Simon, 2023). Understanding the distribution, abundance, and diversity of Molluscans is crucial for their conservation and sustainable management (Sor et al., 2020). However, comprehensive data on these aspects are often lacking, hindering effective conservation planning and management. This gap underscores the need for robust methods to predict and map the distribution of Molluscan species across diverse coastal and marine habitats of Gujarat. Species Distribution Models (SDMs) emerge as powerful tools. SDMs use species occurrence data and environmental variables to predict the potential distribution of species across geographical landscapes (Hankins, 2023). By applying SDMs, researchers can gain insights into the habitat preferences of Molluscans, identify areas of high conservation value, and predict shifts in distribution patterns in response to environmental changes (Moraitis et al., 2018). This information is invaluable for devising strategies for the conservation of Molluscan biodiversity and the sustainable management of fisheries and aquaculture sectors in Gujarat.

The socio-economic implications of Molluscan distribution patterns are profound (Gallagher & Albano, 2023). Identifying areas with high Molluscan diversity and abundance can help optimize the allocation of resources for fisheries and aquaculture, enhancing productivity and sustainability (Theuerkauf et al., 2022). Moreover, understanding the impacts of environmental changes on Molluscan distributions can inform adaptive management strategies, ensuring the resilience of coastal communities to ecological and socio-economic shifts. The threats facing these species underscore the need for a comprehensive understanding of their distribution and ecology, for which

SDMs provide an effective approach (Gutt et al., 2012). By leveraging the predictive power of SDMs, conservationists, policymakers, and stakeholders can ensure the sustainable management of Molluscan resources, safeguarding the ecological integrity of Gujarat's marine environments and the socio-economic resilience of its coastal communities.

a) Challenges in Molluscan Conservation and Management

Conserving and sustainably managing Molluscan species in Gujarat faces significant challenges, including over-exploitation, habitat destruction, and climate change impacts (Biju Kumar & Ravinesh, 2017). Over-exploitation due to high demand in fisheries leads to unsustainable harvesting, disrupting marine ecosystems and reducing species populations. Habitat destruction, driven by coastal development and pollution, further threatens Molluscan habitats such as coral reefs and mangroves, essential for their survival and biodiversity (Ryan et al., 2019). Additionally, climate change introduces stressors like rising sea temperatures and ocean acidification, adversely affecting Molluscan physiology and distribution. In Gujarat, case studies like the conservation efforts for the Indian backwater oyster (***Saccostrea cucullata***) and the green mussel ***(Perna viridis***) highlight the complexity of these challenges. For instance, the Gulf of Kutch, a biodiversity hotspot, has seen significant declines in Molluscan species due to industrial pollution and habitat degradation (Mitra et al., 2022). Efforts to restore these populations have been hampered by the lack of accurate distribution data, essential for effective conservation planning and policymaking (Borges et al., 2017).

The need for comprehensive distribution data is critical to inform conservation strategies, identify critical habitats, and assess the impacts of environmental changes (Villero et al., 2017). Recent initiatives leveraging Species Distribution Models (SDMs) analysis in Gujarat offer promising insights into Molluscan distributions, aiding in the development of targeted conservation strategies. Effective conservation policies must address these multifaceted challenges through sustainable fishing practices, habitat protection and restoration, and climate change mitigation (Riisager-Simonsen et al., 2022). Case studies in Gujarat demonstrate the importance of integrating scientific research with community engagement and adaptive management approaches, ensuring the long-term sustainability of Molluscan populations and the ecological and socio-economic benefits they provide (Mohan Joseph, 2007).

b) Overview of Machine Learning Models in SDM

Machine learning has revolutionized ecological modelling, including the prediction of species distributions through Species Distribution Models (SDMs)(Zhang et al., 2020). By leveraging complex datasets, machine learning models uncover patterns and relationships between species occurrences and environmental variables, offering nuanced insights into species habitats and potential distribution areas (Zhang et al., 2020). This method is especially useful for tackling conservation issues, as it allows for the forecasting of potential shifts in species distributions due to evolving environmental scenarios, as illustrated in Table 1 with multiple examples. Among the machine learning models applied in SDMs, **MaxEnt (Maximum Entropy)** is widely used for its effectiveness in handling presence-only data, making it ideal for species with limited occurrence records (Hankins, 2023)**. Biomod,** an ensemble forecasting package, integrates multiple models to provide more robust predictions, accounting for uncertainties inherent in ecological data (Zhang et al., 2020). **Random Forest**, an ensemble learning method, excels in classification and regression tasks, offering high accuracy and the ability to handle complex interactions between variables (Koudenoukpo et al., 2021). **Bayesian models** incorporate prior knowledge into the modelling process, enhancing predictions by integrating existing ecological theories and expert opinions (Kocot et al., 2020). The table below showcases case studies involving the application of these machine learning models in SDMs for marine invertebrates, providing a glimpse into their diverse applications:

Table 1: Machine Learning Models Utilized Species Distribution Modelling (SDM)

Marine Invertebrate	Model	Description	Reference
Endemic Brazilian coral (*Mussismilia harttii*)	MaxEnt	Predicting potential distribution under climate change scenarios.	(de Oliveira et al., 2019)
Octopus vulgaris	Random Forest	Written in ink: Elemental signatures in octopus ink successfully trace geographical origin	(Duarte et al., 2022)

Pacific oyster (*Crassostrea gigas*)	Biomod	Early detection of marine invasive species following the deployment of an artificial reef: Integrating tools to assist the decision-making process	(Castro et al., 2021)
Neon Flying Squid (*Ommastrephes bartramii*)	Bayesian models	Genralized linear Bayesian models for standardizing CPUE: an application to a squid jigging fishery in the north – west pacific ocean	(Cao et al., 2011)

These studies highlight the versatility and effectiveness of machine learning models in SDMs, providing critical insights for conservation biology and ecological research. The potential distribution of key Molluscan species, the research will identify critical habitats that necessitate conservation efforts, thereby aiding in the preservation of these vital marine resources. The findings will also illuminate the socio-economic interdependencies between local communities and Molluscan populations, highlighting the importance of sustainable management practices to support livelihoods. This complex understanding of the ecological and socio-economic dynamics at play will provide a robust foundation for informed policymaking. Policymakers can leverage the insights gained to devise regulations and initiatives that balance conservation needs with economic development, ensuring the long-term sustainability of Molluscan resources. Ultimately, this study aims to foster a symbiotic relationship between human activities and marine biodiversity, contributing to the resilience of coastal ecosystems and the communities that depend on them in Gujarat coast for their socio- economic activities.

- Methodology for Zonewise distribution of species is given in methodology chapter.
- The detail methodology for data collection and distribution modelling has been described in methodology chapter. Following flow chart shows summary of methodology used in present chapter.

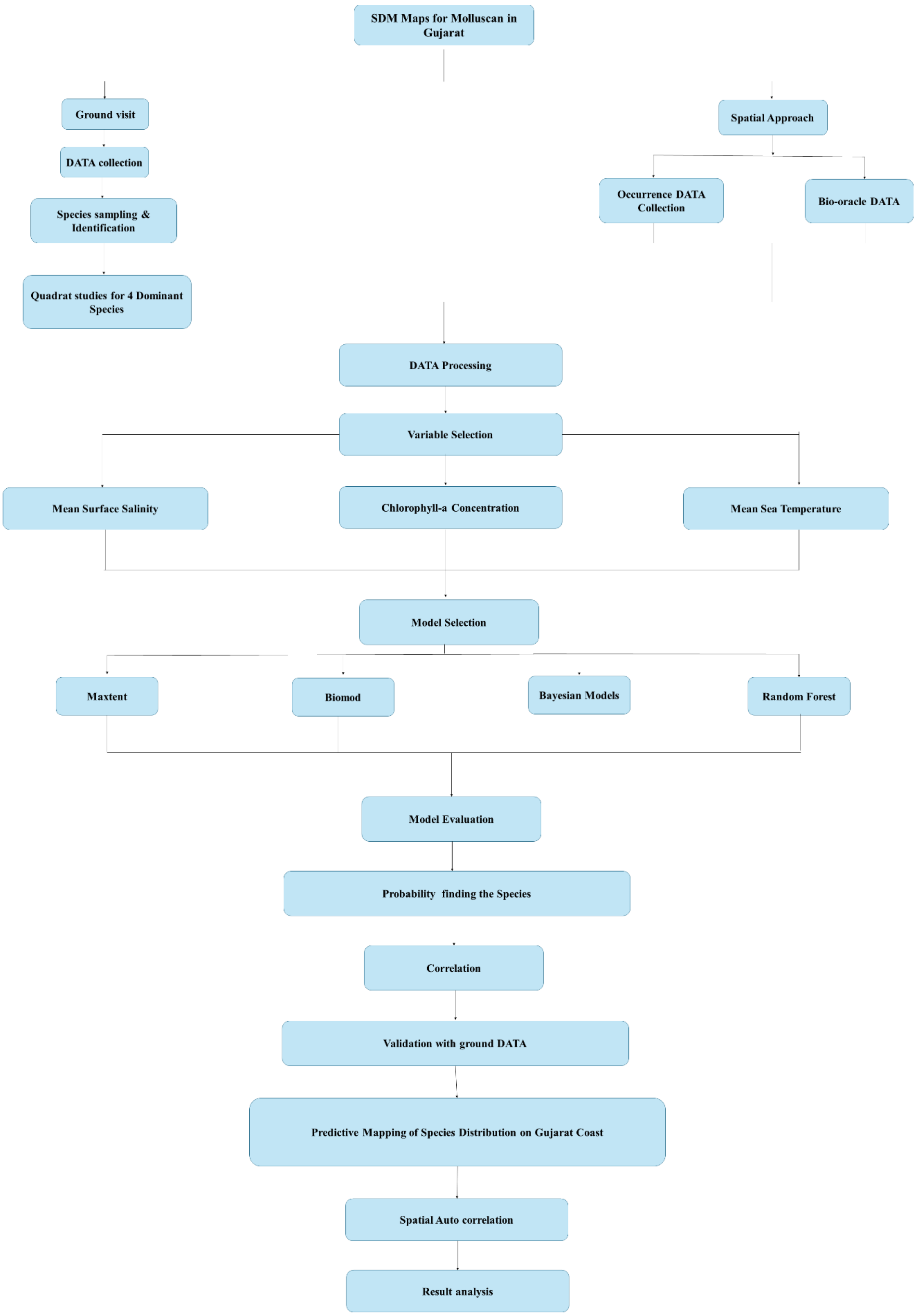

Fig 2. Methodology for Species Distribution Modelling of Mollusc

Results and Discussion:

Table : Zone wise distribution of species

SR NO	NAME OF SPECIES	ZONATION TYPE
1	*Chiton granoradiatus* Leloup,1937	U
2	*Rhyssoplax peregrina* (Thiele, 1909)	U
3	*Chiton tuberculatus* Linnaeus, 1758	U
4	*Architectonica arcana* Roding, 1798	M
5	*Dulcerana granularis* (Röding, 1798)	M
6	Gyrineum natator Röding, 1798	M
7	*Bufonaria echinata* (Link, 1807)	M
8	*Tibia insulaechorab* Röding, 1798	L,M
9	*Tibia curta* (G. B. Sowerby II, 1842)	L,M
10	*Umbonium vestiarium* Linnaeus,1758	M
11	*Trochus radiatus* Gmelin, 1791	L,M,U
12	*Monodonta australis* Lamarck, 1822	L,M
13	*Babylonia spirata* Linnaeus,1758	M
14	*Cantharus spiralis*, Gray 1839	M
15	*Pollia undosa* (Linnaeus, 1758)	M
16	*Conus capitaneus* Linnaeus, 1758	M
17	*Conus inscriptus* Reeve, 1843	M
18	*Conus miliaris* Hwass in Bruguière, 1792	M
19	*Conus locumtenens* Blumenbach, 1791	M
20	*Hexaplex cichoreum* (Gmelin, 1791)	L,M
21	*Purpura bufo* Lamarck, 1822	M,U
22	*Chicoreus ramosus* Linnaeus,1758	L,M
23	*Chicoreus brunneus* (Link, 1807)	L,M
24	*Murex tribulus* Linnaeus,1758	L
25	*Strigatella ambigua* (Swainson, 1829)	M
26	*Strigatella scutulata* (Gmelin, 1791)	M
27	*Mitra mitra* Linnaeus,1758	M
28	*Nassarius olivaceus* Bruguière, 1789	M

29	*Oliva olive* Linnaeus,1758	M
30	*Purpura persica* Linnaeus,1758	M
31	*Euplica scripta* (Lamarck, 1822)	L,M
32	*Cellana radiata* Born, 1778	U
33	*Patella vulgata* Linnaeus, 1758	U
34	*Nerita albicilla* Linnaeus,1758	M,U
35	*Siphonria laciniosa* Linnaeus,1758	U
36	*Turbo intercostalis* Menke, 1843	L,M
37	*Lunella coronata* (Gmelin, 1791)	L,M,U
38	*Mauritia depressa* (J.E. Gray, 1824)	M
39	Mauritia eglantina Duclos, 1833	M
40	*Mauritia arabica* (Linnaeus, 1758)	M
41	*Mauritia grayana* Schilder, 1930	M
42	*Clypeomorus bifasciata* (G. B. Sowerby II, 1855)	M
43	Rhinoclavis sinensis Gmelin 1791	M
44	Architectonica laevigata Lamarck, 1816	L,M
45	Littorina sp.	U
46	Aplysia Oculifera A. Adams & Reeve, 1850	L,M
47	*Astralium semicostatum* (Kiener, 1850)	M
48	*Cerithium caeruleum* G. B. Sowerby II, 1855	L,M,U
49	*Cerithium scabridum* Philippi, 1848	L,M
50	*Peronia verruculata* (Cuvier, 1830)	L,M,U
51	*Pinctada imbricata* Röding, 1798	M
52	*Purpura panama* Röding, 1798	L,M,U
53	*Pyrene flava* Bruguière, 1789	M
54	*Turritella terebra* Linnaeus, 1758	M
55	*Octopus Vulgaris*, Cuvier 1797	L
56	*Lamprohaminoea ovalis* (Pease, 1868)	M
57	*Dendrodoris fumata* [Light brown form] (Rüppell & Leuckart, 1830)	M
58	*Gafrarium dispar* (Holten, 1802)	M

59	*Gafrarium divaricatum* (Gmelin, 1791)	M

The distribution of species across these zones highlights the adaptation strategies of different species to thrive in varying environmental conditions. The extreme exposure to air in the upper intertidal zone results in species capable of withstanding desiccation and temperature extremes. In contrast, the middle intertidal zone's balanced environment supports species with moderate adaptations, while the lower intertidal zone's consistent submersion favours species adapted to constant moisture and stable temperatures. The presence of species such as *Trochus radiatus* in both the upper and lower zones indicates their versatile adaptability, whereas species like *Tibia insulaechorab*, found in the middle and lower zones, show a preference for more consistent water exposure.

The repetition of species across different intertidal zones in the study highlights the ecological adaptability and versatile nature of certain mollusc species. These species exhibit a range of physiological and behavioral adaptations that allow them to thrive in multiple environmental conditions, from the upper to the lower intertidal zones.

In the upper intertidal zone, species such as *Trochus radiatus* demonstrate significant versatility. This species can endure the harsh conditions of the upper intertidal zone through adaptations such as a strong shell to prevent desiccation and behavioural strategies to avoid the heat. In the middle intertidal zone, species like *Tibia insulaechorab*, found in both the middle and lower zones, exploit the benefits of both terrestrial and aquatic conditions. Their ability to survive in varying levels of moisture and temperature illustrates their ecological flexibility.

In the lower intertidal zone, where species are predominantly submerged, conditions are more stable with consistent moisture and reduced temperature variability. Species such as *Trochus radiatus*, also present here, indicate their ability to thrive in environments with constant submersion. The adaptations required for survival in this zone include efficient respiration in water and mechanisms to cope with wave action.

The repetition of species across different intertidal zones underscores the importance of specific adaptive traits that enable these molluscs to inhabit diverse environments. These species demonstrate a range of survival strategies that include physiological adaptations, such as tolerance to desiccation and fluctuating temperatures, and behavioural adaptations, like movement to microhabitats that offer protection from environmental stressors. The ability of certain species to inhabit multiple zones also suggests a level of ecological plasticity that could be advantageous in the face of environmental changes. This plasticity allows them to exploit a broader range of habitats and resources, enhancing their survival and reproductive success.

Understanding the factors that enable these species to thrive across different zones can provide insights into the resilience of marine ecosystems (Bernhardt & Leslie, 2013). It also highlights the need for comprehensive conservation strategies that consider the habitat requirements and adaptive capacities of key species (Beever et al., 2016).

Species Distribution Model

a) Model Evaluation

In the context of the research conducted on Species Distribution Modelling (SDM), a detailed analysis was undertaken to evaluate the comparative performance of four prevalent machine learning models, namely Maxent, BIOMOD, Bayesian models, and Random Forest. This evaluation was centred around the interpretation of Receiver Operating Characteristic (ROC) curves and the corresponding Area Under the Curve (AUC) values, which serve as critical metrics for assessing the ability of these models to accurately discriminate between species presence and absence across varied environmental conditions. The ROC curve, by plotting the True Positive Rate (TPR) against the False Positive Rate (FPR), offers a nuanced visual representation of a model's discriminative capacity at various threshold levels. This curve essentially delineates the balance a model maintains between correctly identifying locations where a species is present (sensitivity) and erroneously predicting species presence in locales where it is absent (1 - specificity)(Florkowski, 2008). Ideally, a model's ROC curve would closely align with the upper left corner of the plot, signifying optimal sensitivity and specificity levels. Upon comparative analysis of the ROC curves and AUC values across the studied models, a spectrum of discriminative capabilities was unveiled. Maxent emerged with the highest AUC value of 0.63, indicating a moderate level of discrimination that, while surpassing random chance, highlighted potential areas for enhancement. The model's

ROC curve depicted a deviation from the diagonal, suggesting a capability to distinguish between presence and absence locations to a certain extent. However, the observed moderate AUC value raised considerations regarding Maxent's ability to fully encapsulate complex ecological interactions or effectively manage data inconsistencies as depicted in Fig.3.

BIOMOD, with an AUC value of 0.53, showcased a performance closely aligned with Maxent, albeit with a marginally reduced discriminative prowess. The model's ROC curve exhibited a trajectory slightly inferior to that of Maxent, hinting at a potential compromise in sensitivity or specificity. This could be attributed to BIOMOD's ensemble approach, which amalgamates various models, potentially introducing a higher variance in predictions and a slight dip in overall efficacy(Singleton et al., 2023) as shown in Fig. 3.

In the case of Bayesian models, the AUC value further declined to 0.43, signifying a more pronounced reduction in discrimination capability relative to Maxent and BIOMOD. The ROC curve for Bayesian models indicated a greater deviation from the diagonal, reflecting lower levels of sensitivity and specificity. This suggested challenges in accurately representing species distribution patterns, possibly due to the intrinsic assumptions and constraints of the Bayesian methodology or the complexity of the ecological niches under consideration. Random Forest, with the lowest AUC value of 0.42 among the evaluated models, demonstrated the least discriminative ability. Its ROC curve approached the diagonal more closely, underscoring a marked difficulty in differentiating between presence and absence locations as illustrated in Fig. 3. This was potentially linked to the model's reliance on decision trees and its challenges in capturing intricate non-linear data relationships. Subsequent post-hoc multiple pairwise comparison tests revealed statistically significant differences in model accuracies.

Maxent models were found to exhibit significantly higher accuracy compared to BIOMOD, Bayesian models, and Random Forest, with p-values less than 0.01 for both AUC and True Skill Statistics (TSS) metrics. Despite these significant disparities in accuracy, the magnitude of differences remained relatively modest. The gap between the highest (Maxent) and lowest (Random Forest) mean accuracy measures was merely 0.022 AUC points and 0.034 TSS points. Among the algorithms, all pairwise comparisons of accuracy were significantly distinct for both AUC and TSS metrics ($p<0.01$), except for the comparison involving Maxent. The sequence of mean accuracies observed was Maxent (mean AUC: 0.63; TSS: 0.777), followed by Bayesian models (mean AUC: 0.53; TSS: 0.702), BIOMOD (mean AUC: 0.49; TSS: 0.56), and Random Forest (AUC: 0.42; TSS: 0.693).

This comprehensive analysis underscored the intricate nuances and inherent challenges in accurately modelling species distributions. While Maxent and BIOMOD displayed relatively superior discriminative capacities, Bayesian models and Random Forest highlighted the complexities involved in SDM. The ROC curve and AUC metrics proved instrumental in dissecting the strengths and limitations of each model, facilitating informed decisions regarding model selection, threshold optimization, and data interpretation in the realm of ecological research and conservation endeavours.

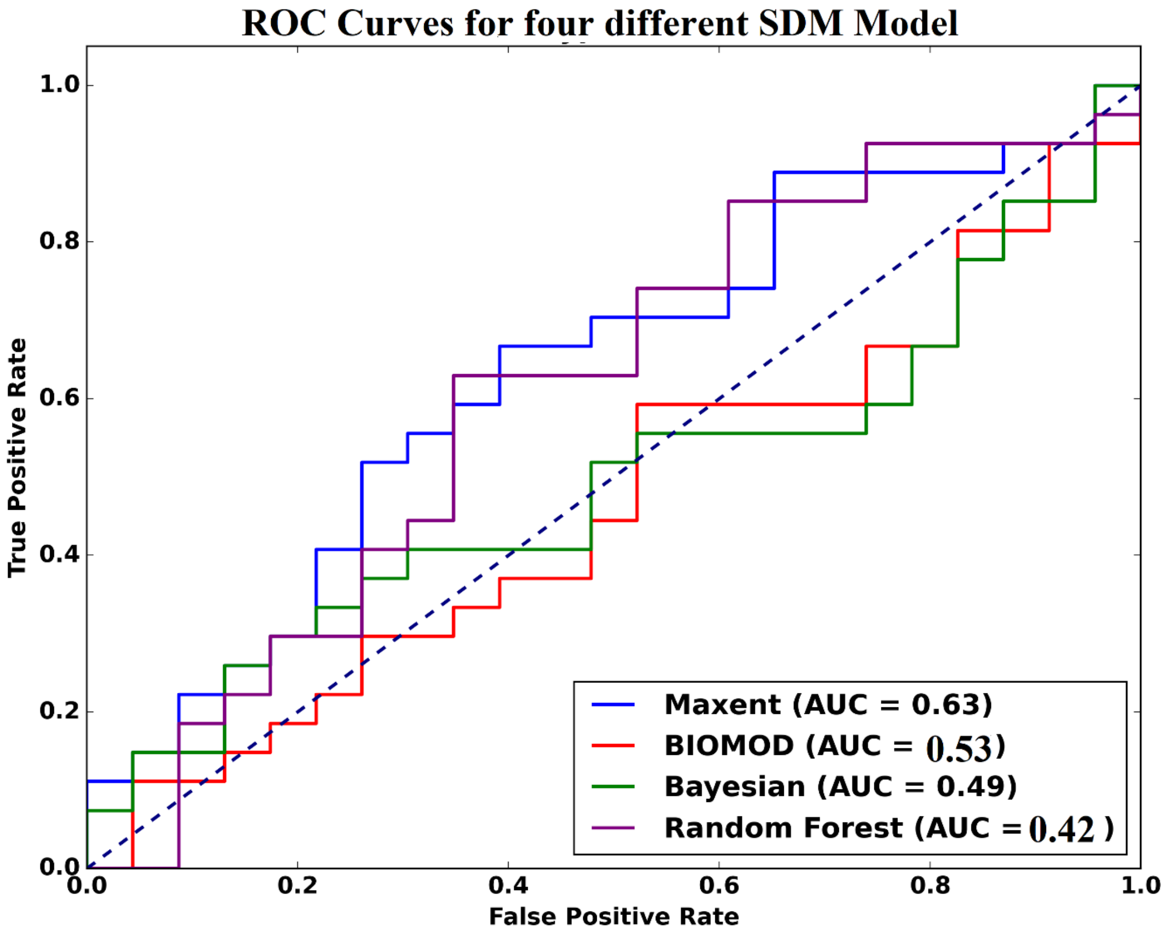

Fig 3. The ROC curve and AUC values for machine learning models for potential zone distribution of Molluscans through SDM

b) Probability of Finding the Species through Abiotic Factors

The exploration of oceanographic data revealed intricate details about the marine environment, shedding light on the dynamic interplay of ecological and physical factors.

The study commenced with an analysis of salinity, a parameter indicative of the total dissolved salt content in water, typically expressed in Practical Salinity Units (PSU). It was found that the average salinity across the observed regions stood at approximately 35.80 PSU, aligning with the general range for the world's oceans and denoting a marine environment of typical salinity levels. However, the noted variability in salinity, as evidenced by a standard deviation of 2.44 PSU, underscored the complex interplay of factors such as riverine input, precipitation, evaporation, and ocean currents, which could significantly alter local salinity levels. The observed salinity ranged from 31.60 PSU to 39.40 PSU, highlighting the diverse conditions under which marine organisms thrive as shown Fig. 4.

The investigation further delved into chlorophyll concentrations, a crucial proxy for the abundance of phytoplankton, the microscopic, plant-like organisms at the base of the marine food web. An average chlorophyll concentration of about 5.02 mg/m^3 was recorded, reflecting a healthy presence of phytoplankton essential for supporting a diverse marine life. The variability in chlorophyll levels, with a standard deviation of 2.23 mg/m^3, pointed to the varying productivity of different marine areas, influenced by factors such as nutrient availability, light penetration, and water temperature. The range of chlorophyll concentrations observed, from 0.89 mg/m^3 to 8.90 mg/m^3, indicated significant ecological variability, attributable to natural phenomena such as algal blooms and seasonal changes, or anthropogenic impacts like pollution and eutrophication. The temperature of the water bodies emerged as a critical parameter influencing numerous biological and chemical processes within aquatic ecosystems. The study noted an average temperature of 18.73°C, reflecting the temperate nature of the sampled environments. However, the considerable standard deviation of 6.07°C highlighted the wide range of temperatures to which marine organisms are exposed. The temperature span from 7.90°C to 27.90°C underscored the diversity of thermal habitats in the marine environment, each supporting unique communities of organisms. Temperature variations were found to affect metabolic rates, reproductive cycles, migration patterns, and even the solubility of gases in water, thus playing a pivotal role in shaping marine biodiversity as shown in Fig. 4.

The examination of probability values associated with the observations offered a lens through which the reliability and confidence in the data could be assessed. An average probability of 0.85 signified a high level of confidence in the observations or the predictions made by the model, with a relatively low standard deviation of 0.06 indicating a consistent level of reliability across the dataset. The range of probabilities, from 0.74 to 0.96, though not exceedingly wide, reflected a degree of variability in the confidence levels associated with different observations as illustrated in Fig. 4 .

The derived model for the multiple linear regression analysis further illuminated the relationships between the parameters:

$$\text{Probability} = 0.69\text{-}0.01\times \text{Salinity}\text{-}0.01\times \text{chlorophyll}+0.01\times \text{Temperature}$$

This equation suggested that temperature exerted a positive effect on probability, with a coefficient of 0.01, implying a slight increase in probability with rising temperatures. The coefficients for salinity and chlorophyll were found to be negligible, indicating a minimal direct effect on probability within this linear framework. The intercept of the equation, set at 0.69, represented the baseline probability when all independent variables were held constant at zero. It was noted that the small coefficients for salinity and chlorophyll might not necessarily signify an absence of relationship but could indicate that the relationship might not be linear or could be influenced by interactions between variables not captured by this simple linear model.

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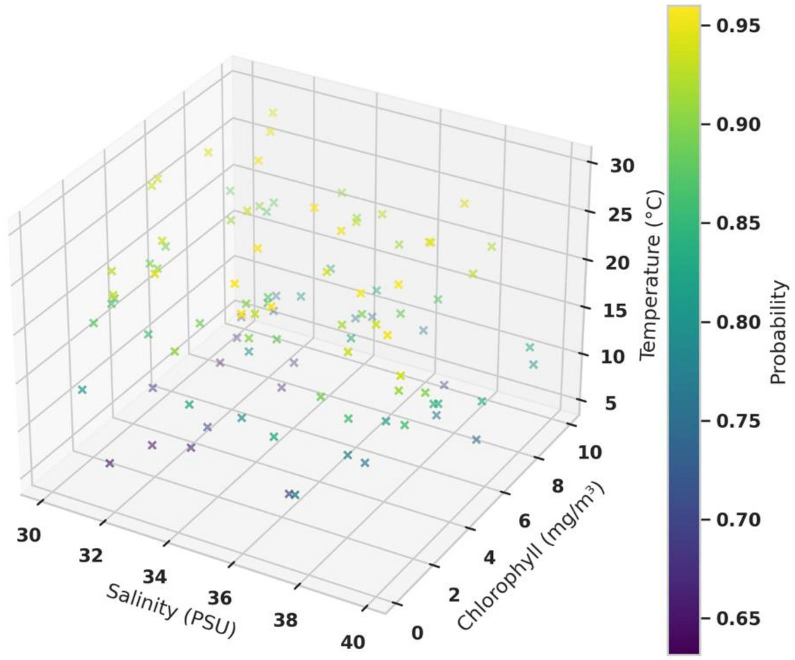


Fig 4. The Fig. illustrating the likelihood of locating the species in relation to abiotic factors such as salinity, chlorophyll content, and temperature

The growth probabilities of Molluscan species ***Cerithium caeruleum, Lunella coronata, Peronia verruculata, and Trochus radiatus*** were analyzed against environmental factors such as salinity, chlorophyll concentration, and water temperature through Pearson correlation analysis. The findings revealed a strong negative correlation between salinity and growth probability (-0.84), suggesting that higher salinity levels might inhibit growth across these species, possibly due to osmotic stress affecting physiological processes. Chlorophyll concentration showed a high correlation (0.78) with growth probability, indicating that the abundance of phytoplankton, as inferred from chlorophyll levels, might directly impact the growth of these species, possibly due to varied diets or the overriding influence of other environmental or ecological factors as shown in Fig. 5 . Conversely, a very strong positive correlation (0.98) was observed between water temperature and growth probability, highlighting temperature's critical role in promoting growth, likely due to its influence on metabolic rates and physiological functions in these ectothermic organisms. These insights emphasize the importance of monitoring and managing salinity and temperature within the habitats of these species to support their growth and conservation, while also suggesting that factors beyond primary food availability, such as food quality and ecological interactions, might be significant for their growth as shown in Fig. 5.

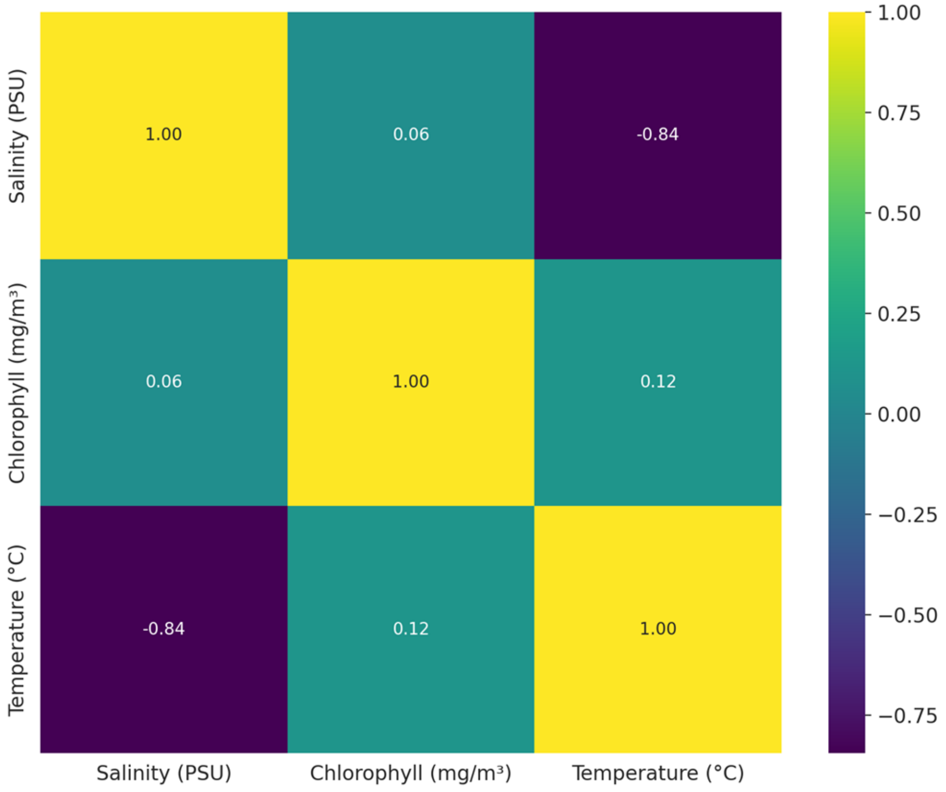


Fig 5. Figure illustrates a correlation plot with various Bio-ORACLE data types

c) Projection onto the Gujarat Coast:

In the assessment of potential habitats for the Molluscan species *Cerithium caeruleum, Lunella coronata, Peronia verruculata,* and *Trochus radiatus* along the Gujarat coast, the Maximum Entropy (MaxEnt) modelling technique was utilized to delineate their prospective distributions. Employed extensively in ecological modelling for predicting species distributions, MaxEnt capitalizes on presence-only data coupled with environmental variables to approximate the likelihood of species occurrences across varied landscapes. This approach has been demonstrated to be particularly efficacious in forecasting species distributions under both existing and future environmental conditions, thereby offering invaluable insights for the formulation of conservation strategies and resource management plans.

The MaxEnt model, integrating pivotal environmental predictors such as salinity, chlorophyll concentration, and water temperature—parameters previously identified to exert significant influences on the growth and survivability of these Molluscan entities—generated intricate distribution maps for each species across the Gujarat coastline. The projections derived from the model indicated distinctive habitat preferences among the species, mirroring their unique ecological niches and tolerance levels to the environmental variables under consideration. For ***Cerithium caeruleum*** and ***Trochus radiatus***, the model delineated potential habitats within regions characterized by comparatively moderate salinity levels, corroborating prior findings that elevated salinity could adversely affect these species. Conversely, the projections for ***Lunella coronata and Peronia verruculata*** suggested a more expansive distribution along the coastal stretch, indicative of a heightened tolerance to fluctuating salinity levels, potentially attributable to their adaptive osmoregulatory capacities.

Furthermore, the model incorporated the variable of chlorophyll concentration, reflecting a strong correlation with growth probability, to signify the availability of food resources. These highlighted areas endowed with ample primary productivity as potential focal points for these Molluscan species as shown in Fig. 6,7,8,9. This aspect accentuates the necessity of acknowledging not merely the direct impacts of environmental factors on species growth but also their indirect ramifications through the dynamics of the food web. The initial analysis, revealing a pronounced positive impact of water temperature on Molluscan growth, was reaffirmed by the MaxEnt projections Fig. 6,7,8,9. Zones featuring optimal temperature ranges were identified as potential high-probability locales for the occurrence of all four Molluscan species. This observation holds pertinence in the context of climate change, wherein rising temperatures may instigate shifts or expansions in the suitable habitats for these species along the Gujarat coast.

The projections formulated by the MaxEnt model provide a holistic overview of the potential distribution patterns of ***Cerithium caeruleum, Lunella coronata, Peronia verruculata,*** and ***Trochus radiatus*** within the Gujarat region, encapsulating the critical environmental determinants pivotal to Molluscan habitat suitability. These insights are imperative for the conservation and management of these species, particularly in the wake of ongoing environmental alterations and anthropogenic activities that may modify their natural habitats. Moreover, this study underscores the complexity inherent in species-environment interactions, highlighting the imperative for an integrated approach that encompasses multiple environmental variables and their potential synergistic effects on species distribution. The observed variability in habitat preferences among the examined species underscores the significance of devising species-specific conservation strategies, underpinned by rigorous ecological modeling and a comprehensive understanding of each species' ecological niche Fig 6,7,8,9.

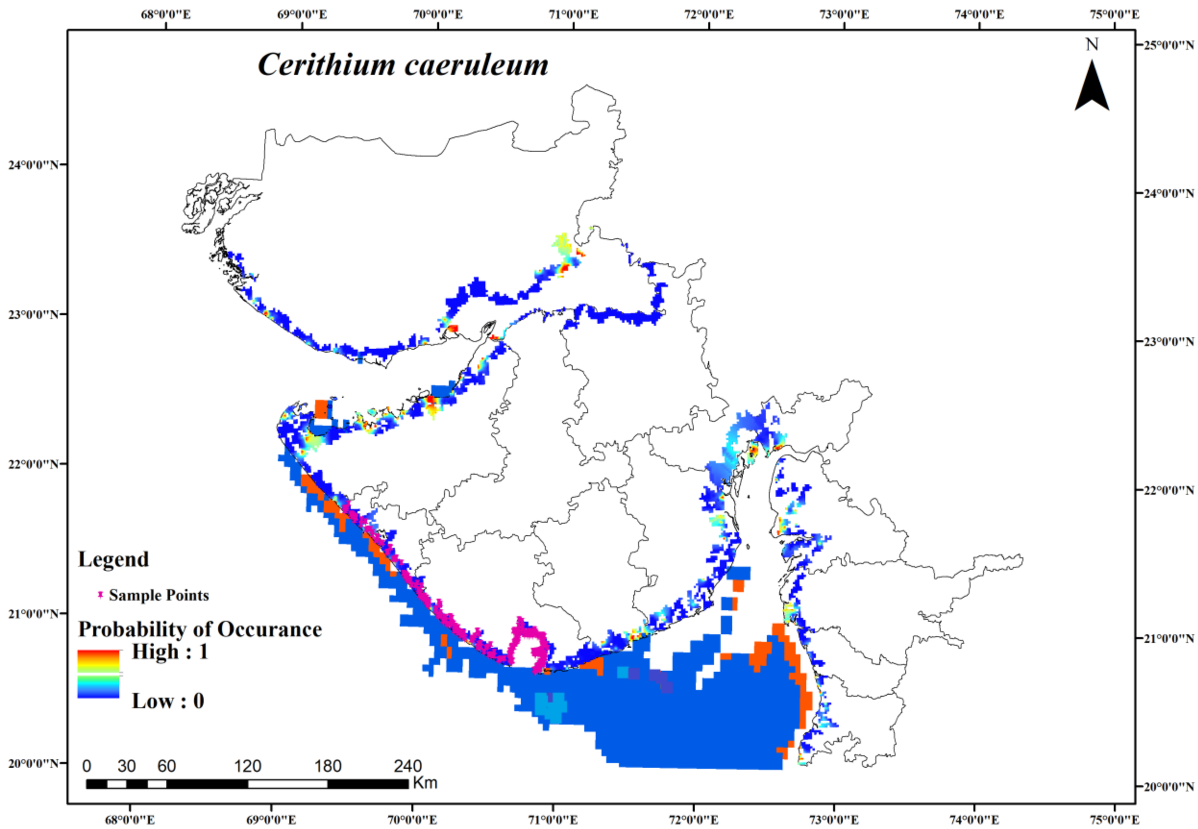


Fig 6. Projection for the species distribution model for *Cerithium caeruleum* using MaxEnt modelling

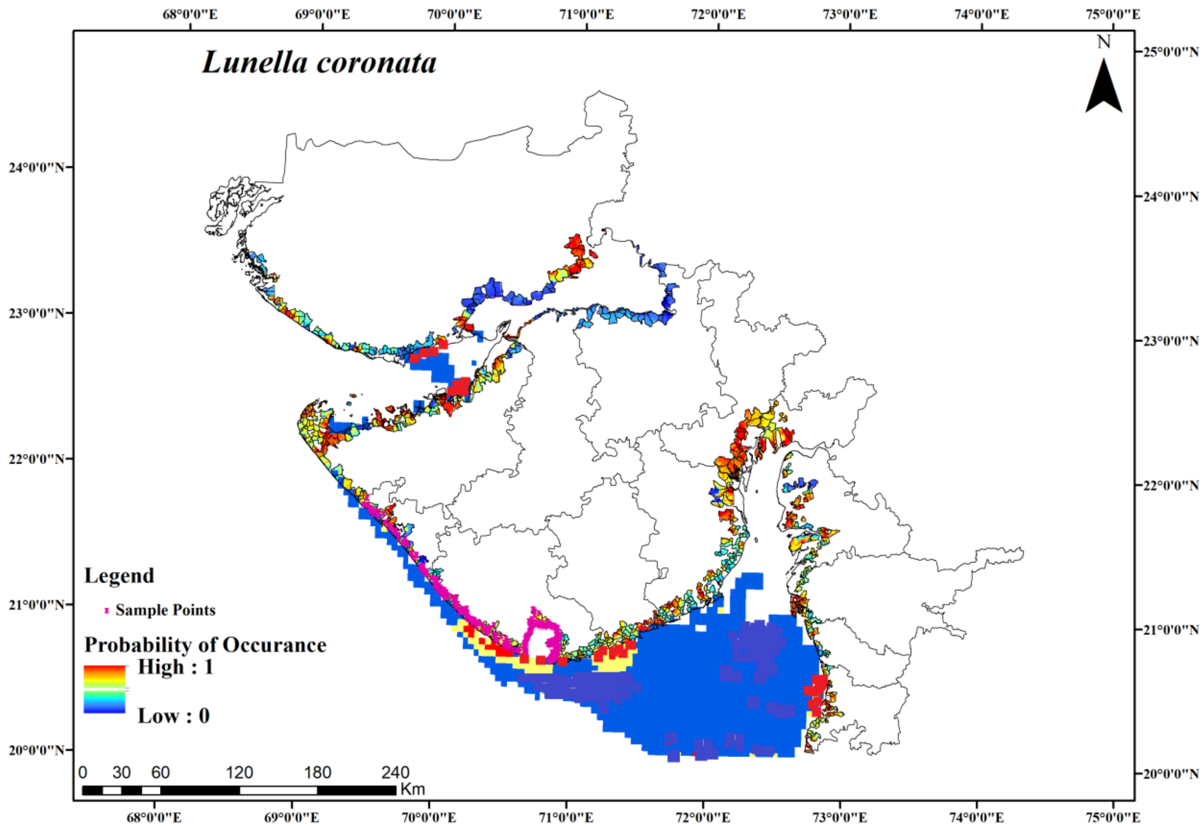


Fig 7. Projection for the species distribution model for *Lunella coronata* using MaxEnt modelling.

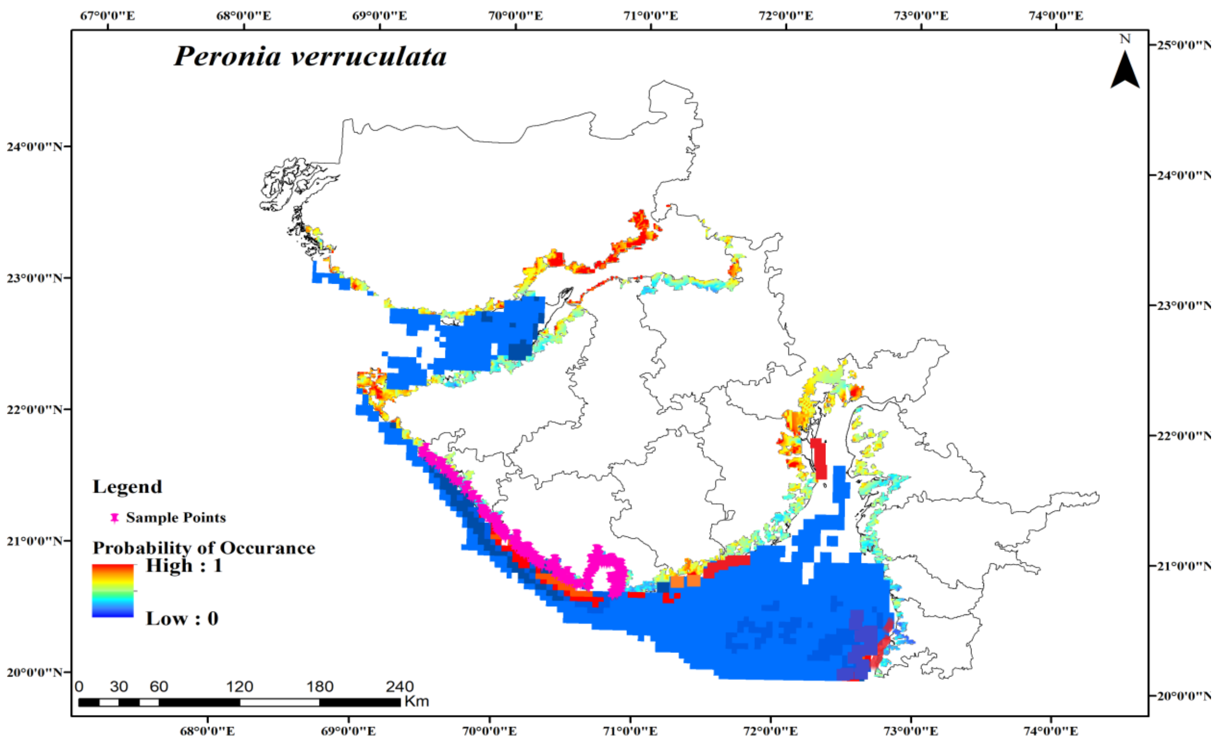


Fig 8. Projection for the species distribution model for *Peronia verruculata* using MaxEnt modelling

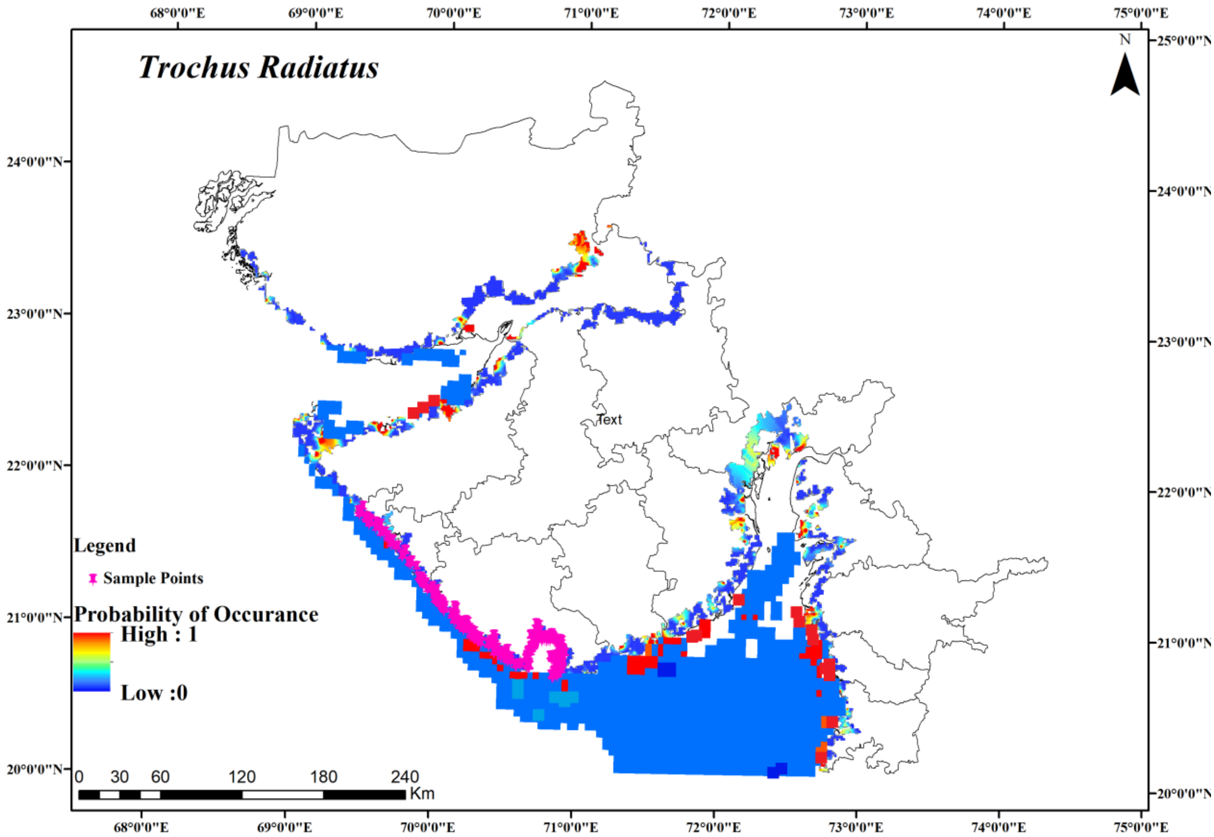
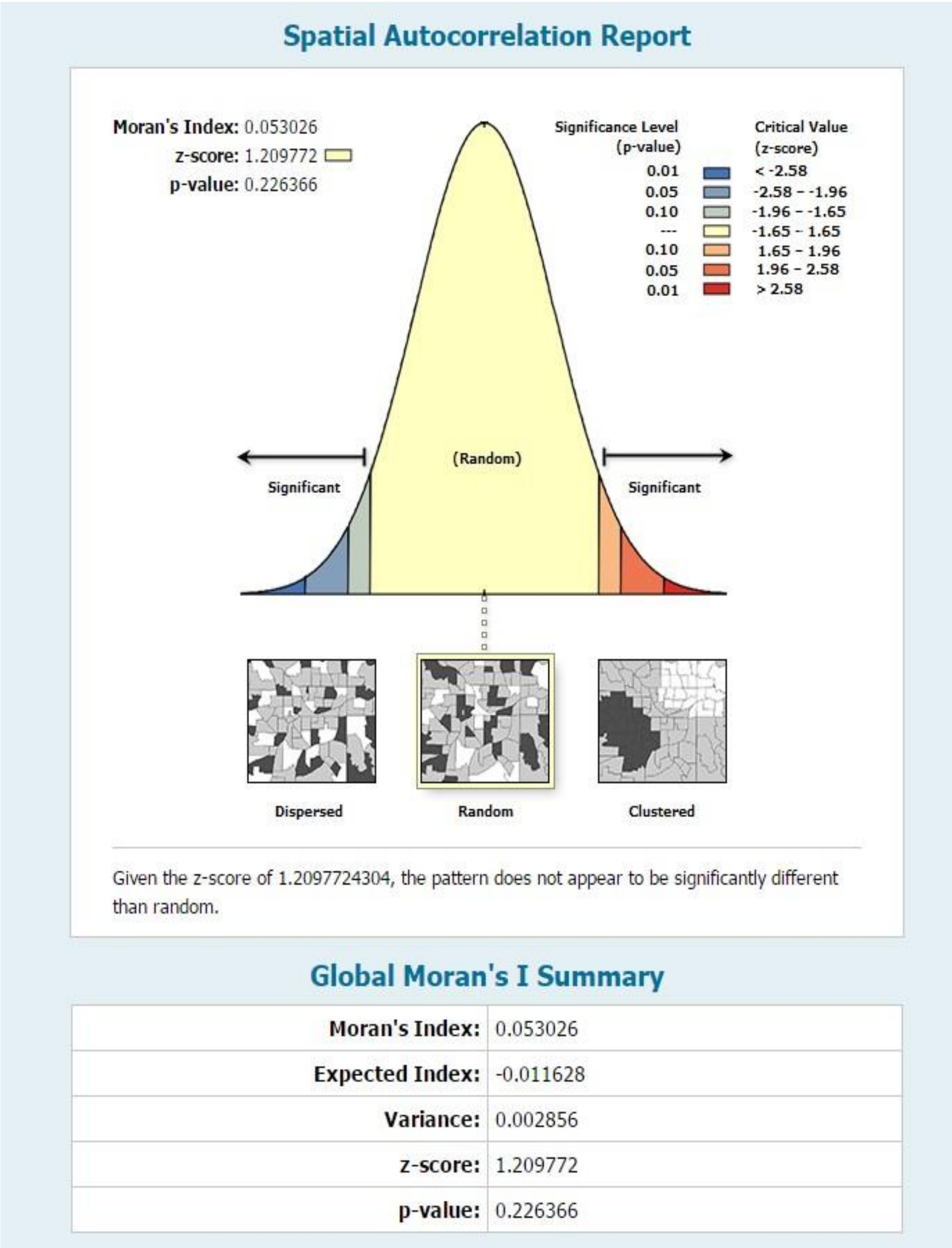


Fig 9. Projection for the species distribution model for *Peronia verruculata* using MaxEnt modelling.

d) Spatial Auto-correlation

In the conducted research, Species Distribution Modelling (SDM) was performed for four marine taxa: ***Cerithium caeruleum, Lunella coronatus, Peronia verruculata,* and *Trochus radiatus.*** Subsequent analysis for spatial autocorrelation was undertaken, yielding the following metrics: Moran's I coefficient was determined to be 0.053, diverging from the anticipated index of -0.0116. The variance of Moran's I was computed at 0.0028, and the statistical significance was evaluated through a Z-score of 1.2097, with an associated p-value of 0.226. In the executed study, Species Distribution Modelling (SDM) was applied to four marine taxa: ***Cerithium caeruleum, Lunella coronatus, Peronia verruculata, and Trochus radiatus***, with the aim of elucidating their spatial dispersion patterns. To quantify the degree of spatial autocorrelation and ascertain whether the distribution of these taxa was clustered, random, or dispersed, Moran's I statistic was employed. The computed Moran's I index stood at 0.053, marginally surpassing the hypothesized mean of -0.0116. This positive Moran's I index intim ated a slight propensity towards a clustered disposition; however, its proximity to zero suggested that the clustering was not pronounced. The expected index, inherently negative for spatial datasets, represents the Moran's I value under the null hypothesis of a stochastic spatial distribution as shown in Fig. 10.

The ascertained variance for Moran's I was recorded at 0.0028, providing insight into the dispersion of the index values and facilitating the derivation of the Z-score. The resultant Z-score was calculated to be 1.2097, serving as an indicator of the statistical significance of Moran's I as shown in Fig. 10. Within this context, the Z-score elucidates the deviation, measured in standard units, of the observed Moran's I from the expected value under the null hypothesis. The derived p-value, corresponding to this Z-score, was 0.226, surpassing the conventional alpha level of 0.05. This elevated p-value suggests that the observed spatial pattern does not significantly deviate from a random distribution, leading to the non-rejection of the null hypothesis that postulates a random spatial arrangement. Therefore, it was inferred that the spatial distribution of ***Cerithium caeruleum, Lunella coronatus, Peronia verruculata*, and *Trochus radiatus*** did not exhibit significant spatial autocorrelation. The marginally positive Moran's I index, the absence of statistical significance, as evidenced by the p-value, led to the inference that the spatial distribution of the aforementioned taxa is characterized by randomness within the study area. This outcome implies that the spatial dispersion of these taxa might be governed by variables not encapsulated in the current model or that their distribution patterns are inherently stochastic. Future investigations may benefit from exploring additional environmental or biological factors that could potentially influence the spatial distribution patterns of these taxa.



Moran's Index:	0.053026
Expected Index:	-0.011628
Variance:	0.002856
z-score:	1.209772
p-value:	0.226366

Fig 10. Generation of Spatial Autocorrelation Matrix for the study area