Spatial dynamics model of built-up area growth and mean sea level rise projection. Case study: Bandar Lampung city, Indonesia

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Abstract. The city of Bandar Lampung has a significant population growth, resulting in continuous expansion of built-up areas. This situation parallels the threat of mean sea level rise along the coast of Bandar Lampung. This study aims to project the development of built-up areas and the rise in sea level. The projection of built-up area growth is conducted through dynamic spatial modeling form data 2010-2020, while mean sea level rise forecasting is done using long short-term memory (LSTM) form data 2002-2022 to project the years 2024, 2029, 2035, 2041, 2048, and 2059. The research findings indicate that by the year 2059, the projected population growth is 4114190 people. Consequently, 90% (16543.44 hectares) of the total area will be converted into a built-up area. Bandar Lampung will face a mean sea level rise of 107 cm in 2059, which will have a significant impact, submerging a coastal area of 116.13 hectares out of the total area of Bandar Lampung City.

Key Words: built-up area, inundation, long short-term memory analysis, mean sea level rise, spatial dynamic.

Introduction. Humans have certain specifications for land to be used as space for certain needs and conveniences (Tsai et al 2018; Unal Cilek & Uslu 2022). However, some requirements are often aggregated or omitted with the limited land used (Gabriele et al 2023). For individuals or communities, this certainly provides flexibility in selecting and making choices. The action provides different avoidable problems such as landslides caused by inappropriate planning of land use change on slopes (Loche et al 2022), distance from watersheds (Mudashiru et al 2021), and settlements submerged by tidal flooding (Mudashiru et al 2021b). Poor planning is due to the aggregation of specific requirements based on land availability and other factors such as economy and accessibility (Xu et al 2019). This causes various adverse effects in the future (Sagala et al 2021).

Spatial area is a representation of the earth surface with land specifications, which tend to be unchangeable (Briassoulis 2019). The fluctuations of changes in spatial area can occur slowly. Several factors trigger spatial changes such as subduction activities of the earth's plates (Adibpour et al 2021) and natural activities including standing water capacity on the land surface, mean sea level rise (MSLR), and anthropogenic events (Mulyadi et al 2020). Bandar Lampung is an administrative city with a bay as the coastal landscape. The population density is around the city center and the coastal area is vulnerable to Mean Sea Level Rise. Historically, tidal flooding occurs during high tide time and Bandar Lampung has area of 18332.88 hectares. In 2020, the city population reached 1,116,066 with an increase of 9.83%. The increase shows that the population is higher when compared to the national population growth of 0.85% from 2019 to 2020 (Diantoro 2024).

The explosive growth in Bandar Lampung will suppress the percentage of the optimum carrying capacity of the land when built-up area is 30-70% of the total area (Tan et al 2022). Spatial availability also decreases due to MSLR. The total spatial availability decreases due to the presence of exponential MSLR variability when built-up area increases. Therefore, this research aims to estimate growth of built-up land influenced by population growth in a space with exponential reduction. Spatial modeling with dynamic system is a form of method that can provide an overview of the human population and the development of land use change to meet human needs. The method uses spatial modeling, the review of predictive land use suitability, the estimation of population growth, and the suitability for the possibility of specific natural disasters or changes (Deng et al 2009; Jamshed et al 2020; Lestari et al 2020). Spatial modeling provides information about the density of an environment due to the development of land use, current population growth patterns, and MSLR.

Material and Method

Dynamic system of built-up area and population growth. Modeling was carried out using a quantitative method through mathematical, statistical, or computer formulas described in a diagram model known as a causal loop diagram (CLD). CLD is the disclosure of a causal relationship into a specific image language to understand the behavior of the phenomenon. Based on CLD population growth model with land availability, 2 negative and 3 positive feedbacks are reported. The model validation is carried out using a simple statistical method, namely average mean error (AME) between simulation and empiric data. Figure 1 shows the CLD model.

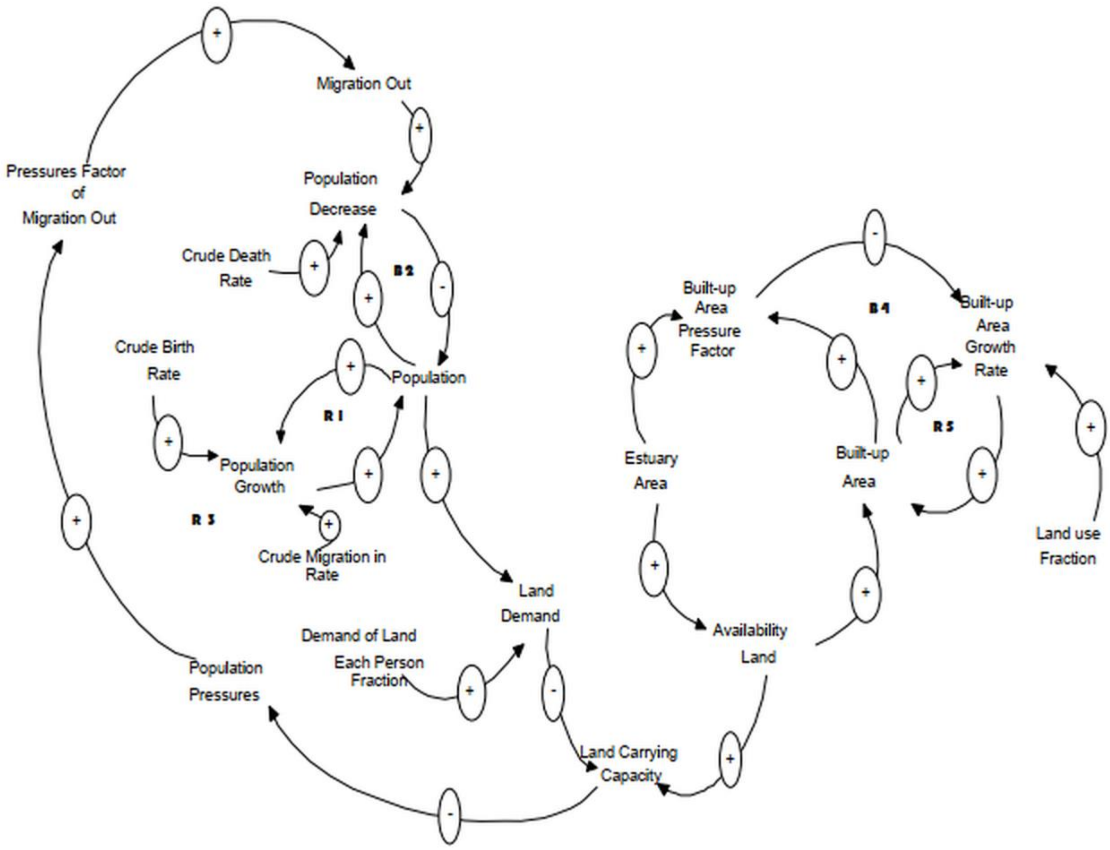


Figure 1. Causal loop diagram on modeling (Source: Lestari et al 2020).

Spatial dynamic model development was conducted by predicting the development of built-up area. Spatial dynamic development steps model was achieved by the following. First, the development of built-up area is based on built-up area dynamic system simulation results. Second, the development of built-up area is based on built-up area suitability analysis by using a grid of 100 m x 100 m (1 ha). Therefore, each existing grid has a value representing the weight of built-up area suitability. Third, built-up area was developed by following the distribution of the appropriate area (Prăvălie et al 2020). The development will continue in a place less suitable for built-up area when the suitable are packed. Buffer analyses were used to analyze the distance from the river and the map of suitability build-up area was formed from overlay analysis, scoring, and querying of physical and accessibility variables.

Mean sea level rise forecasting. A key characteristic of time series data that is often overlooked is the importance of the temporal relationships between data points in the sequence. These time-dependent patterns are crucial for understanding and forecasting future trends (Zhou et al 2021). A deep learning model is designed to process data sequences by considering the time series data set. The right model to use in modeling time series forecasting is the long-short-term memory (LSTM) algorithm (Sherstinsky 2020). LSTM is a recurrent neural network model whose modeling process is sequence-based. In the process of time series forecasting, the data can be treated as a set of sequences (Sherstinsky 2020). Therefore, different research selects the LSTM model as the main choice in forecasting. LSTM model has other advantages such as the ability to accommodate outliers and nonlinearity of data. The strengths make LSTM the main choice in modeling forecasting of MSLR. The flow in modeling using LSTM is showed in Figure 2.

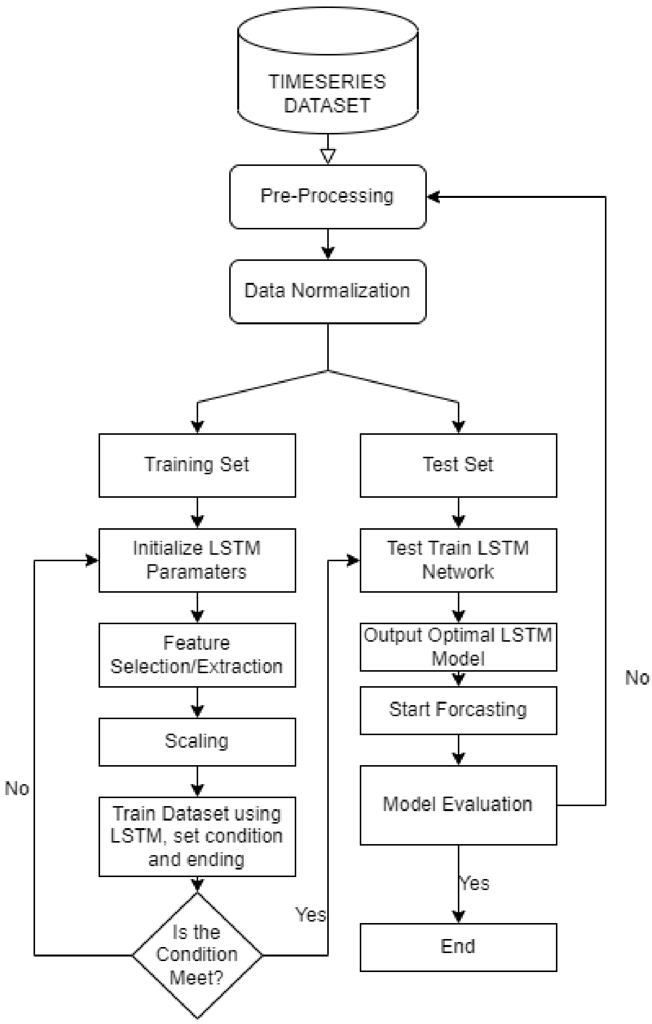


Figure 2. LSTM time series forecasting flowchart (Source: data analysis, 2022).

The method for predicting sea level rise in a region requires various variables. The three main variables that influence the prediction are global mean sea level rise (GMSL), MSLR, and temperature. Some of the data were collected from NOAA and PUSHIDROSAL or Pusat Hidro Oseanografi Angkatan Laut (the Indonesian Navy's Hydro-Oceanographic Center) with points starting from sea level rise data in early 2002 to 2022. This dataset also includes 24-hour sea level rise recording data whose distribution is generalized over a certain period. For GMSL and temperature, the distribution is equalized for one day. Before entering modeling, the transformation uses a wavelet method to maintain the time-series frequency distribution. The subsequent stage is the selection to determine the reference point in the data for determining model and level of linearity.

To accurately forecast the potential sea level rise in a given area, it is essential to identify and understand the factors that influence it. Sea level rise is caused by the increase in temperature and degradation of open land. This is directly calculated with various other supporting variables. The four main projection components are combined to predict the severity of MSLR in the Bandar Lampung area. Exploratory data analysis (EDA) is conducted on the four-time series dataset variables to determine trends, seasonality, and errors. In addition, the EDA process is useful for determining the extent of the data linearity, distribution, and errors.

The subsequent step is the stationary test. In time series forecasting, there are two important elements to determine the level of model accuracy. A dataset is stationary when it does not depend on time components such as trends, seasonal effects, as well as constant average and variance. Stationary datasets are easier to analyze and produce good output forecasting. Meanwhile, data is non-stationary when it has trends, seasonal effects, and changes over time. Statistical properties such as mean, variance and standard deviation also change over time. An augmented Dickey-Fuller (ADF) test on the input data is performed to check the properties of the given MSLR dataset. ADF is a standard unit root test used to determine the impact of trends on the data. The results are interpreted by observing the p-value of the test. The null hypothesis is rejected when the p is bigger than 0.05 known as stationary series. Meanwhile, the input data has a unit root when the p is less or equal to 0.05.

The internal mechanisms of the LSTM network must be explained before the architecture model (Figure 3). LSTM can overcome the limitations of traditional forecasting model such as ARIMA, SARIMA, Vector Autoregression, and other machine learning-based algorithms (Siami-Namini et al 2018). In the neuron LSTM design, this works by looping at different time points and continuing the output to the subsequent block to obtain comprehensive data.

LSTM is an efficient algorithm for building time series and sequential model. The basic component of the network is the memory block created to overcome the missing gradient (Sagheer & Kotb 2019). The memory block in the LSTM architecture is similar to the differential storage system of a digital system. The input gate helps in processing information using an activation function (sigmoid) with the output between 0 and 1. The reason for the sigmoid activation function is to pass a positive value to the next gate (Alhussein et al 2020). The three gates of the LSTM network are represented by the following equations:

$$JT = \text{sigmoid}\ (wJ[ht-1, kt] + bJ) \quad (1)$$
$$GT = \text{sigmoid}\ (wG[ht-1, kt] + bG) \quad (2)$$
$$PT = \text{sigmoid}\ (wP[ht-1, kt] + bP\ ) \quad (3)$$

where: JT = function of input gate;
GT = function of forget gate;
PT = function of the output gate;
Wx = coefficients of neurons at the gate (x) ;
Ht−1 = result from previous time step;
kt = input to the current function at time-step t;
bx = bias of neurons at gate (x).

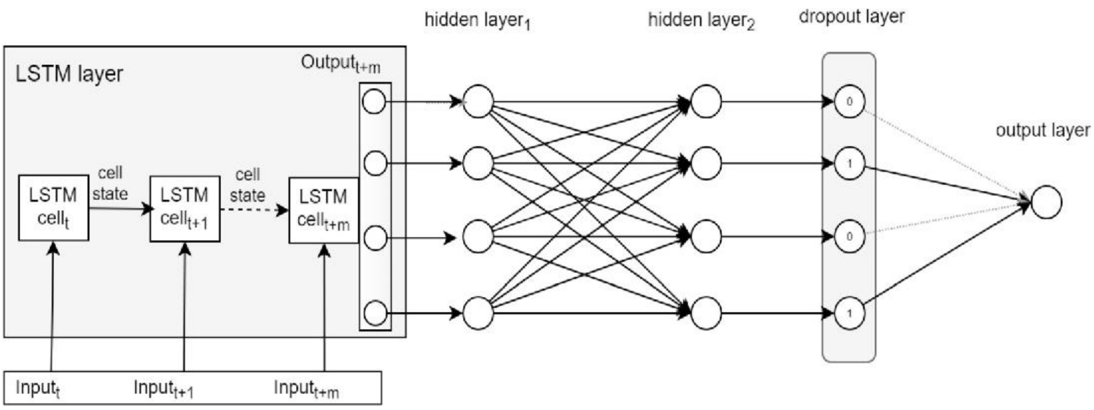


Figure 3. LSTM architecture (Source: Helmini et al 2018).

Results

The development of built-up area in Bandar Lampung. In presenting the development of built-up land periodically, this research uses Landsat 8 imagery. The observed land is classified into four classes, namely built-up, open, agricultural, and vegetation area (Figures 4 to 6). From the three maps, the land detected as built-up area continues to expand in size. Meanwhile, area detected as non-agricultural and agricultural vegetation is gradually degraded. In 2010, the highest area with a total of 10411.61 hectares was with land cover types in the form of non-agricultural vegetation. The lowest area of 2040.51 hectares was agricultural land with built-up and open area of 3475.81 and 2404.94 hectares, respectively (Figure 7).

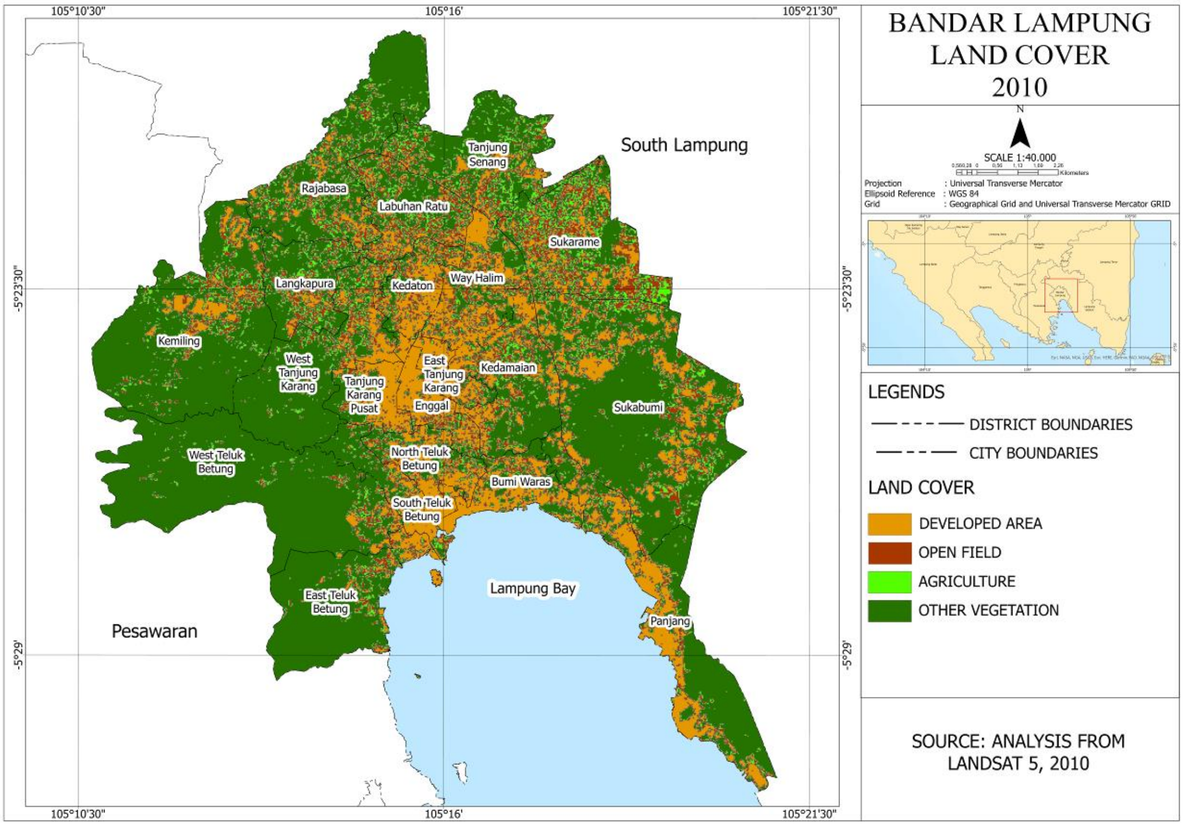


Figure 4. Bandar Lampung land cover in 2010.

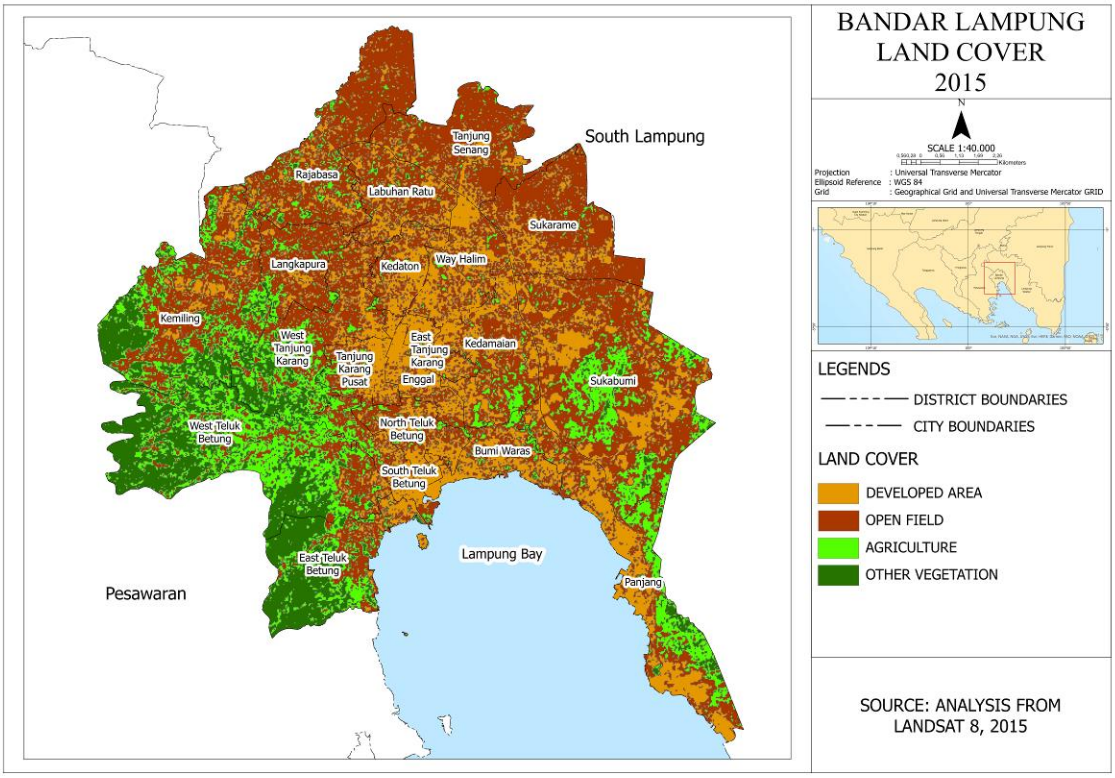


Figure 5. Bandar Lampung land cover in 2015.

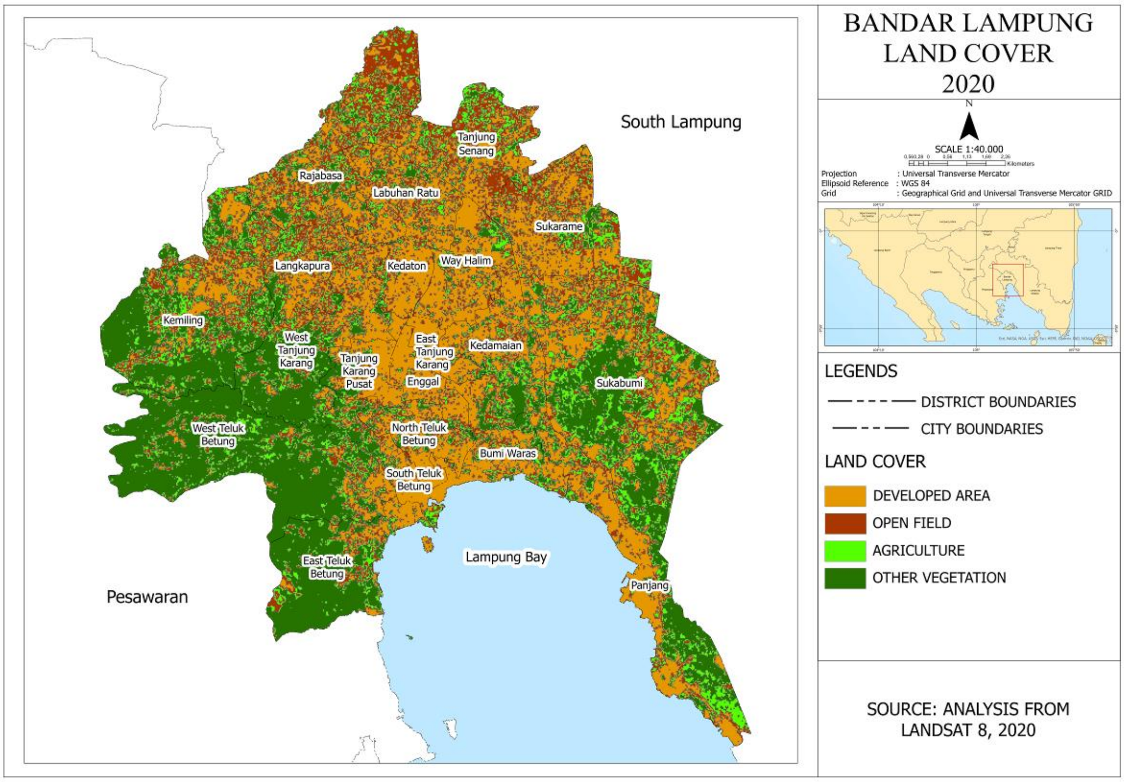


Figure 6. Bandar Lampung land cover in 2020.

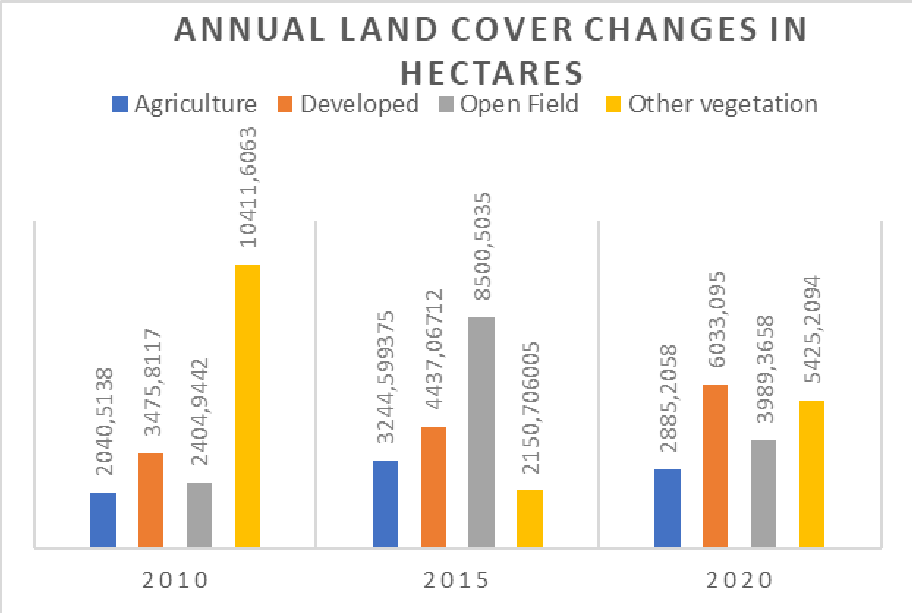


Figure 7. The annual land cover changes in Bandar Lampung.

In 2015, area of land for non-agricultural vegetation decreased significantly by 79.34% with a reduced width of 8260.90 hectares. There was an increase in the percentage of the land cover area detected as agriculture by 59% with an additional 1204.09 hectares. Built-up area increased by 27.66% with an increase of 961.66 h hectares. Meanwhile, the open area had the highest increase of 253.46% with a width of 6095.56 hectares (Figure 7). In 2020, the non-vegetation area had a very significant development with an increase of 152.25% and 3274.50 hectares wide. The agricultural area decreased by 12.46% to 359.39 hectares. Built-up area increased to 1596.03 hectares with a percentage growth of 35.97%. The open area decreased to 4511.14 hectares at a percentage of 53.07% (Figure 7).

Projection of built-up area and population growth. Land availability and population growth are two variables with different growth characteristics. This is due to the contradictory characteristics of each variable. The availability of land will decrease when population growth increases. In contrast, land availability will be high when population growth is at a minimum. This shows a negative correlation since decreased population growth does not increase land availability.

Table 1

The result of dynamic system

Year	*Total population (people)*	*Built-up area (ha)*	*Percentage*	*Land availability (ha)*
2024	1373217	7339.41	40%	10993.46
2029	1606265	9032.75	50%	9300.11
2035	1938700	11067.82	60%	7265.05
2041	2339936	12925.37	70%	5407.50
2048	2914157	14698.31	80%	3634.56
2059	4114190	16543.44	90%	1789.43

Source: data analysis, 2022.

The percentage of the carrying capacity of the land is a value representing the ability of the environment to provide services to living things. Various lives face degradation in terms of quality and quantity when this ability is degraded and the optimal bearing capacity of built-up area is 30 to 70% (Tan et al 2022). In projection model, this research provides a different perspective on the percentage of built-up land. In Bandar

Lampung, the optimal value limit showing a good environmental carrying capacity of 70% is in 2041. Meanwhile, the maximum carrying capacity of 90% is predicted to be in 2059 (Table 1).

The suitability of built-up area. Physical and accessibility factors are used to determine the suitable area. The physical factors include slope, distance from river, and distance from protected area. Accessibility factors are the distance from the road network and distance from the center of economic activity. In the visualization of the suitability distribution, the most suitable area are spread from the central to the northern part and the bay coast of the administrative area. Area with non-conformities are spread over the eastern and western area of the administrative area. The pattern shown by the suitability area is determined by the land suitability variable. From 18332.88 hectares of Bandar Lampung, the unsuitable, less suitable, and suitable area has a percentage of 9.61%, 16.29%, and 74.1%, respectively. Projection of spatial dynamic model is conducted by developing built-up area and following the distribution. Built-up area is assumed to develop into less suitable and unsuitable land when the availability is full. The distribution of built-up areas suitability is shown in Figure 8.

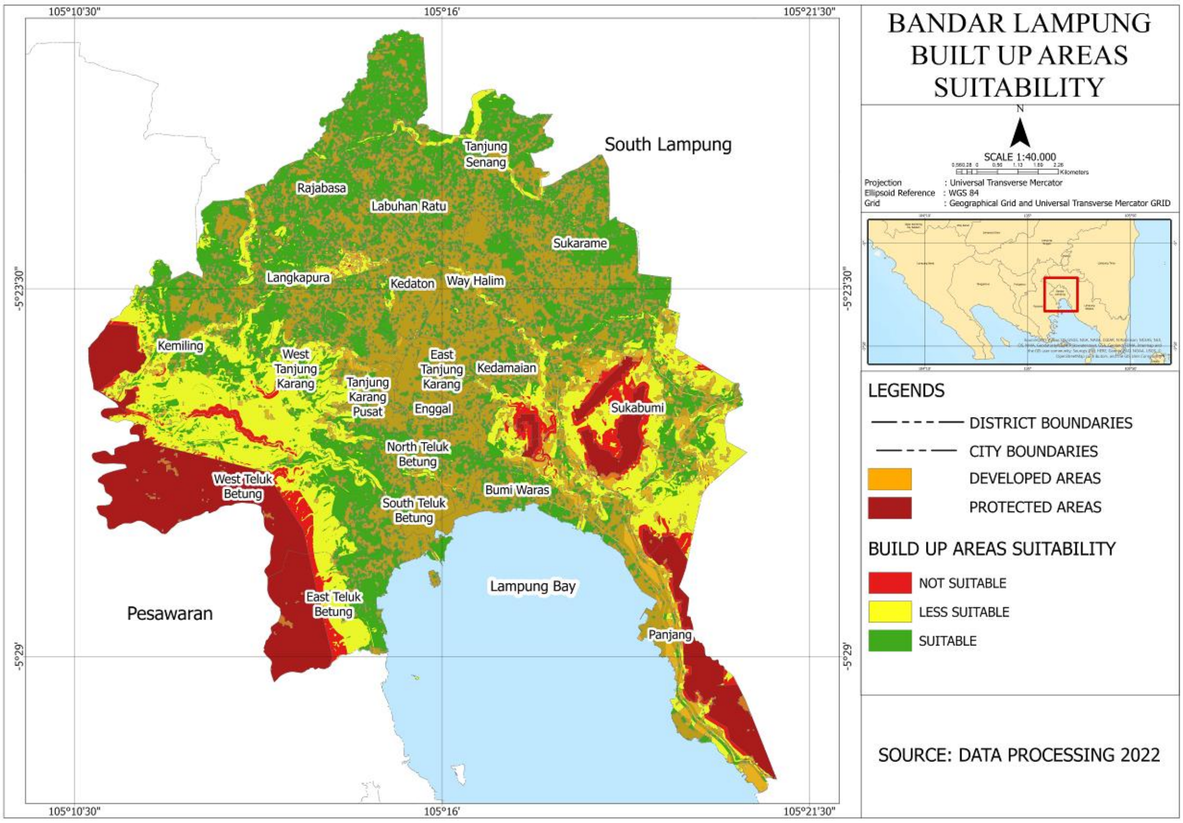


Figure 8. Built-up area suitability of Bandar Lampung (Source: data analysis, 2022).

Mean sea level rise forecasting in Bandar Lampung city. The output of modeling is determined by using decomposition method. MSLR in the Bandar Lampung area for 39 years is relatively the same due to decomposition. Therefore, the data used as a point of reference in the future experiences regular period. This is because the influence between variables that exist linearly is not strong. However, the property value of trends and seasonality can change at any time. The effect on the final value of the forecasting can be projected after determining the strength of the trends and seasonality influence (Figure 9). This can happen because the decomposition process is the foundation of every time series modeling.

In the process of modeling, a scenario with an LSTM hidden layer configuration of 100 neurons was used. This is combined with one output neuron used as a point in predicting MSLR. The loss function of mean absolute error (MAE) is used to evaluate gradient descent. In determining the iteration cycle of each sequence, 70 training epochs with a side batch of 200 iterations are used. From the scenario, a predictive model was produced with a high level of accuracy. As visualized in Figure 10, MSLR is 1.07 meters over a period of 39 years. This increase occurs because the trend of data distribution and the parameters have a strong influence on each other. The influence is formed through a temporal sequence accommodating the scenario of MSLR in Bandar Lampung. The increase of 1.07 meters ignores the value of lower confidence or the value of the minimum. The change depends on dynamic of nature around the Bandar Lampung area. In addition, the influence of land subsidence can worsen the condition of MSLR.

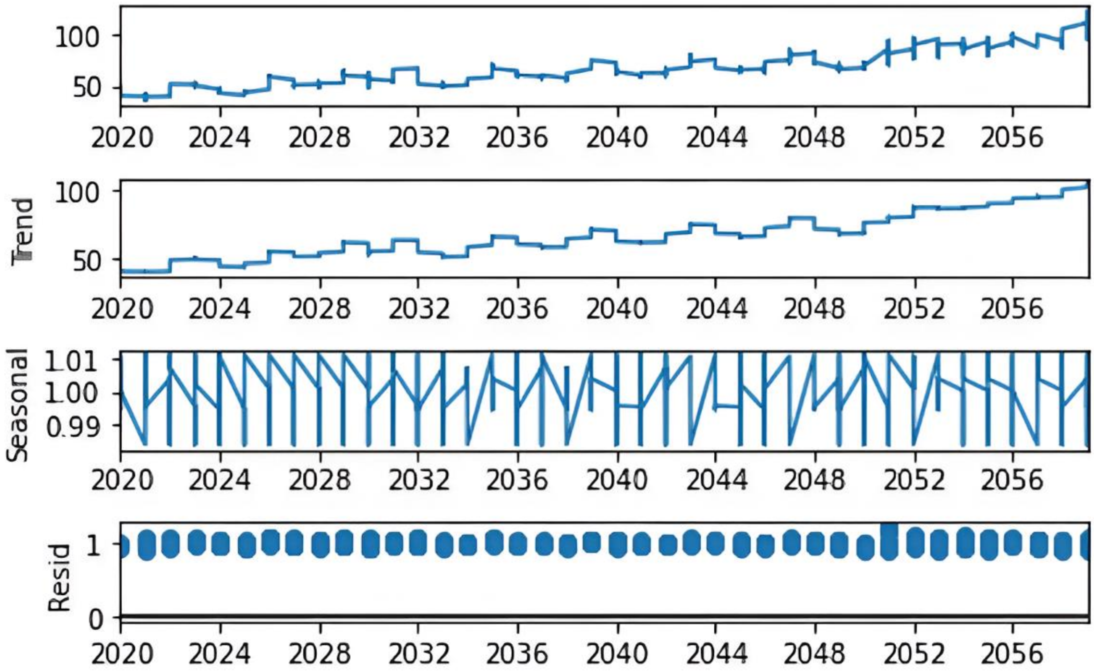


Figure 9. Mean sea level rise of Bandar Lampung city (Source: data analysis, 2022).

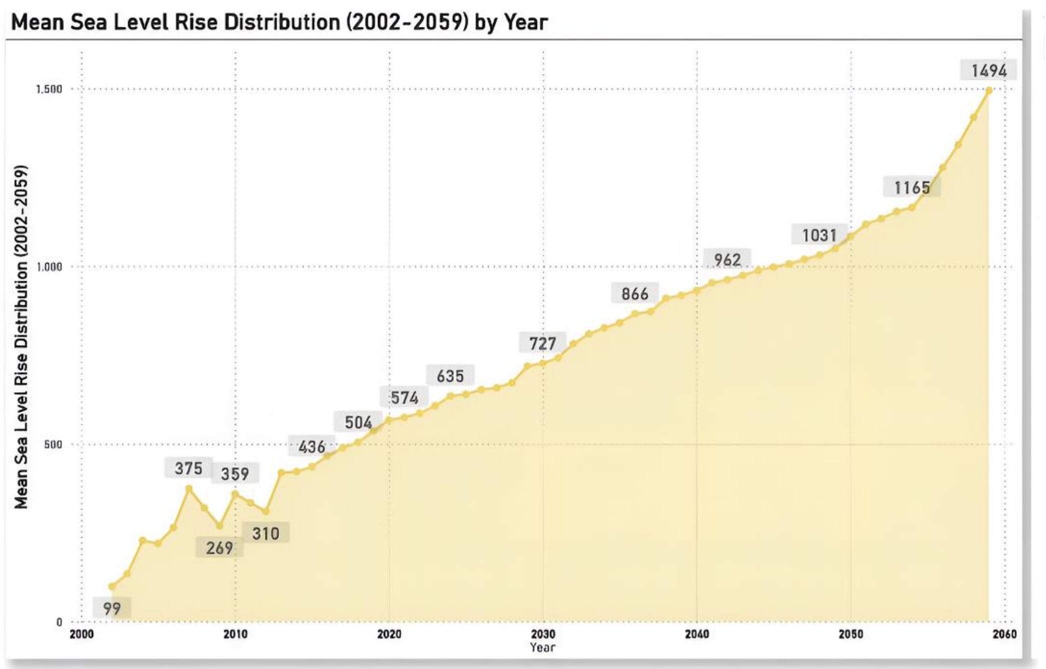
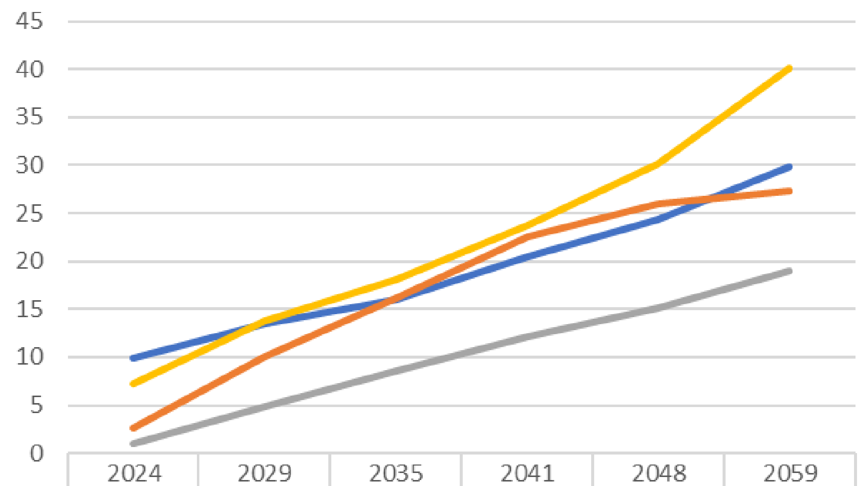


Figure 10. Sea level forecasting rise of Bandar Lampung (Source: data analysis, 2022).

Numerical and temporal modeling is divided into five scenarios of time. This division is conducted to determine MSLR. The research combines the decrease in sea level to determine the availability of land in the Bandar Lampung area until 2059. Projection has various fluctuations in value and occurs exponentially. The most affected administrative area is the Panjang Sub-district and the submerged area is predicted to reach 40.06 hectares in 2059. Meanwhile, the submerged area with the lowest occurs in Bumi Waras Sub-district (Figure 11). In 2059, the predicted submerged area in the Sub-district covers area of 18.57 hectares.



	2024	2029	2035	2041	2048	2059
East Teluk Betung	9.91	13.44	15.94	20.52	24.31	29.83
South Teluk Betung	2.6	10.08	16.2	22.57	25.91	27.26
Bumi Waras	1.05	4.81	8.56	12.12	15.16	18.97
Panjang	7.16	13.82	18.06	23.78	30.11	40.06

Figure 11. The graph of increased area affected by mean sea level rise (Source: data analysis, 2022).

Dynamic spatial model of built-up area growth, land availability, and mean sea level rise projection in 2024. The development of built-up land in 2024 will reach 40% of Bandar Lampung with a population development of 1373217 people. Built-up and total land area of 7339.41 and 18332.88 hectares, respectively. Growth distribution of built-up land is still in suitable and unsuitable area. The overall growth occurs in the northern, western, southern, and central parts of Bandar Lampung. In 2024, sea level will reach 65 mm since a coastal area of 20.72 hectares will be submerged and cannot be used as built-up land (Figure 12). Modeling of MSLR shows that the predicted value is relatively close to the actual value (Figure 13). Based on the distribution output model can accommodate the non-linear nature of projection data with scenarios up to 2024. Meanwhile, timestamps starting from 0 can be used to determine the extent of MSLR. The timestamp is a yearly Projection suitable to the character of the dataset with mean value.

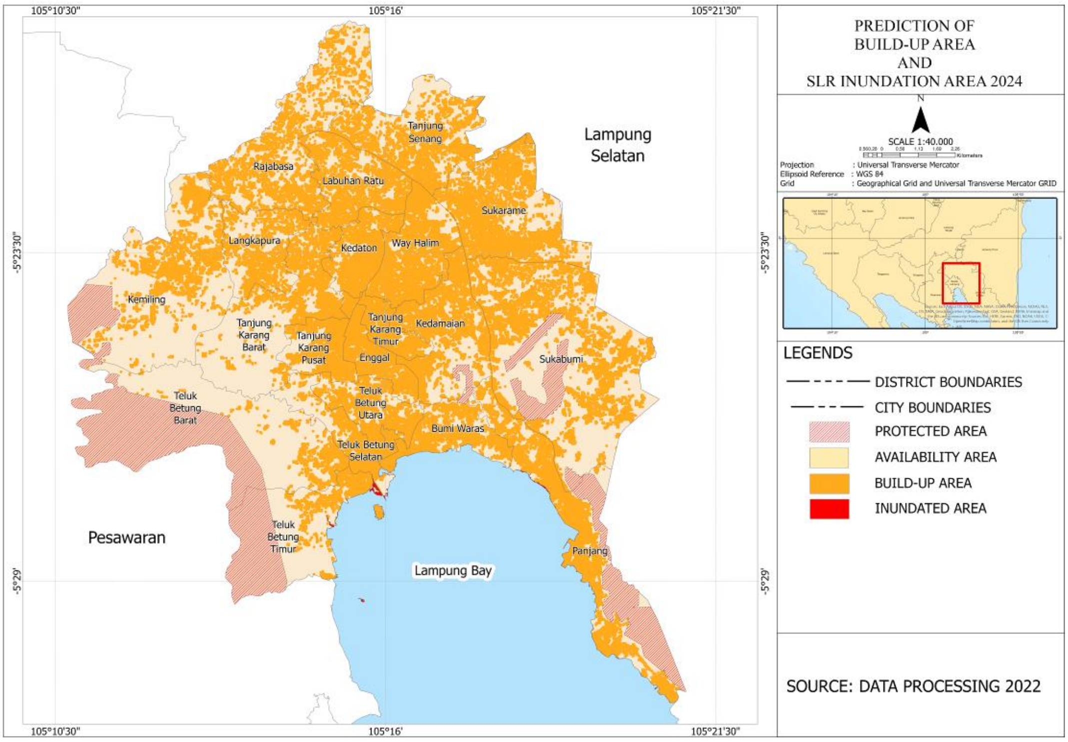


Figure 12. Projection of build-up area and mean sea level rise inundation in 2024.

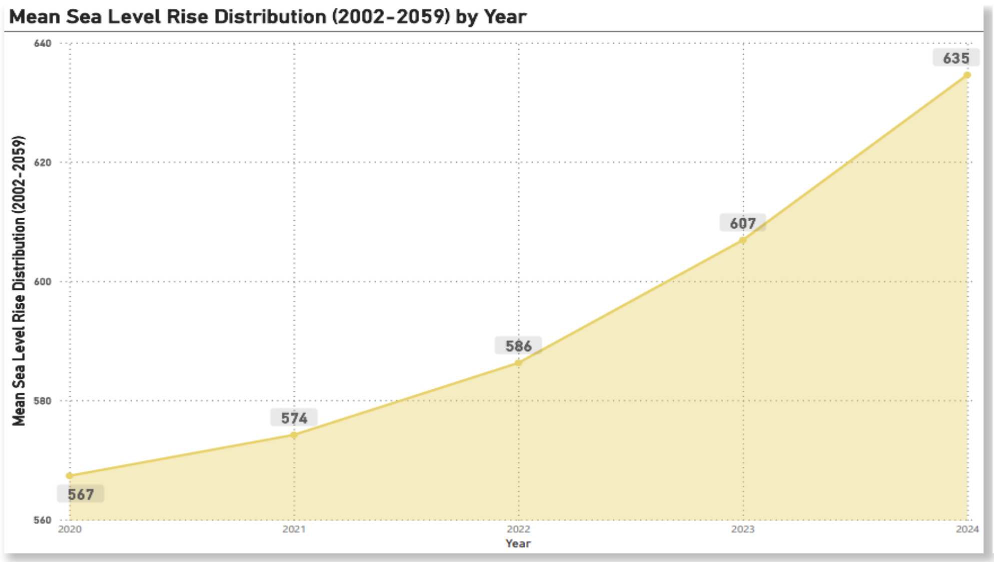


Figure 13. The forecasting of mean sea level rise in Bandar Lampung in 2024.

Dynamic spatial model of built-up area growth, land availability, and mean sea level rise projection in 2029. The development of built-up land in 2029 will be 50% or 9032.76 hectares in Bandar Lampung. This is driven by the increase in population growth reaching 1606265 people and triggering the expansion of built-up area. The percentage of land conversion into built-up area is 50%. The unsuitable area are converted significantly to built-up land. The condition happens in some unsuitable area of Bandar Lampung (Figure 14). Area of MSLR reaches 42.15 hectares with MSLR of 84 mm. In 2029, model recognizes patterns and predicts the output with a loss function of 0.85. Therefore, model can recognize the pattern of sequences in the data and the influence between variables. The value of MSLR has increased significantly by 84 millimeters (2024-2029) from the final periodization of the calculation. This is affected by the increasing value of sea surface temperature causing an increase in GMSL and sea level rise (Figure 15).

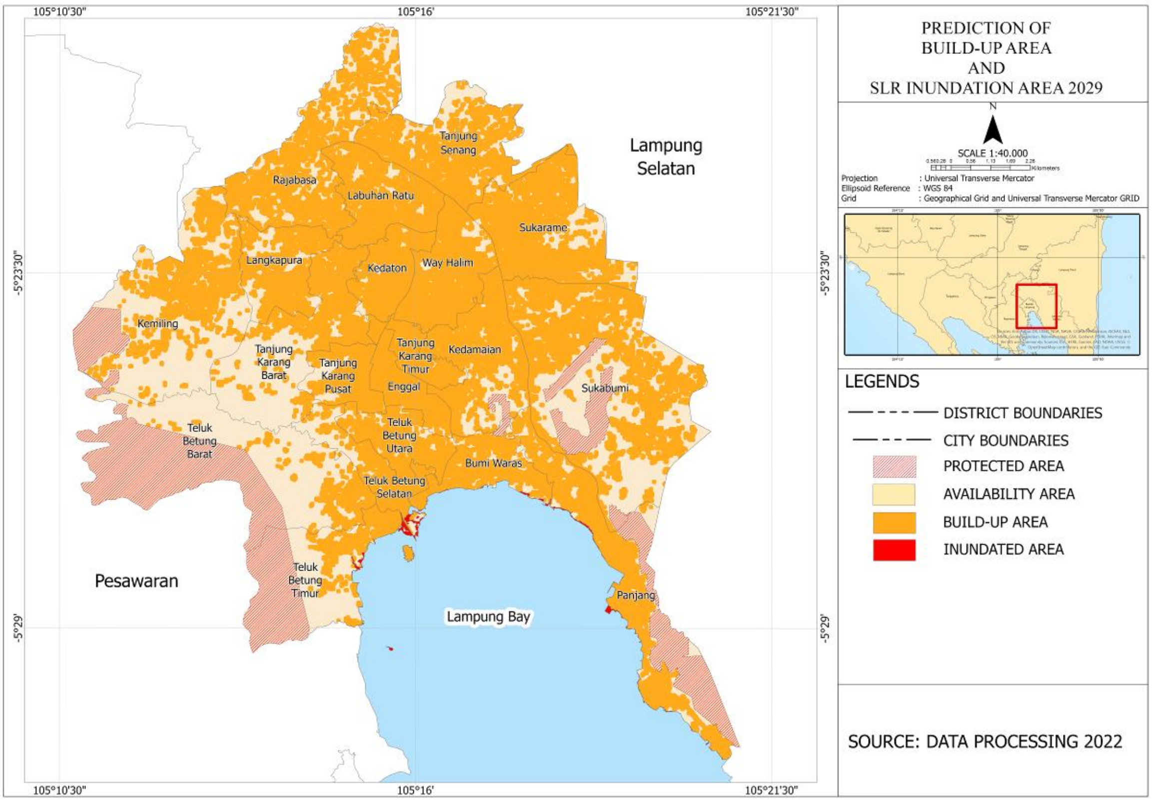


Figure 14. Projection of build-up area and mean sea level rise inundation in 2029.

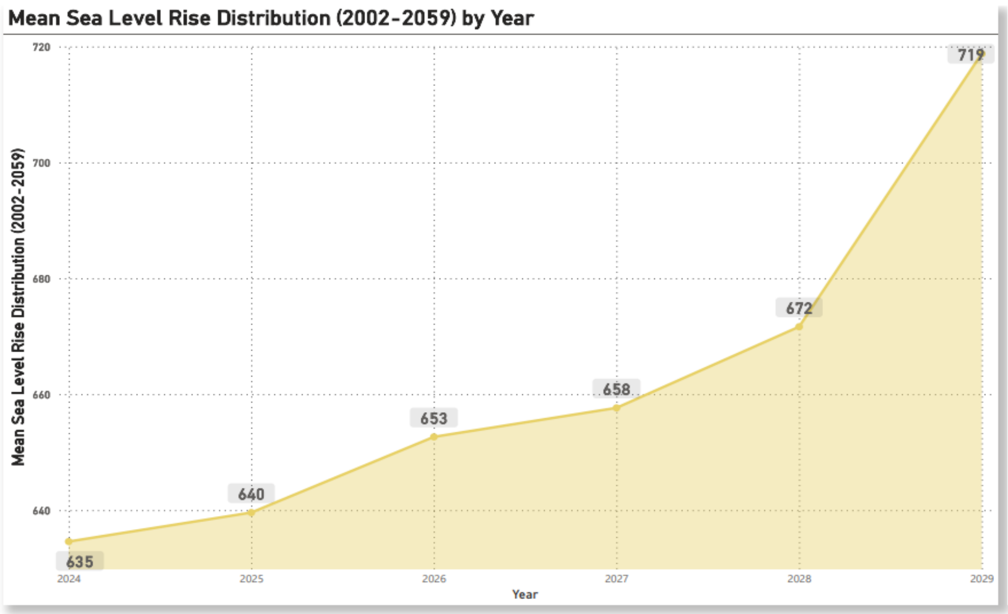


Figure 15. The forecasting of mean sea level rise in Bandar Lampung in 2029.

Dynamic spatial model of built-up area growth, land availability, and mean sea level rise projection in 2035. The development of built-up land will reach 60% at 11067.82 hectares of Bandar Lampung in 2035. This development is triggered by the population increasing to 1938700 people and triggering the increase in the need for land. Therefore, the empty area is converted into built-up land since the density has increased in the downtown area and city center. The unsuitable area in the eastern part is converted into built-up land (Figure 16). In 2035, area submerged by MSLR is estimated to be 58.76 hectares and model predicts the actual value. This is proven by the loss function mean square error of 80.05 and the temporal sequence dynamic modeling is very good. In this scenario, MSLR is projected to increase by 122 millimeters between 2029 and 2035, with the upward trend continuing in subsequent periods. The increase shows a significant rise as supported by the upper and lower confidence intervals. Additionally, the influence of seasonality and long-term trends reinforces the probability of a continued increase in sea level (Figure 17).

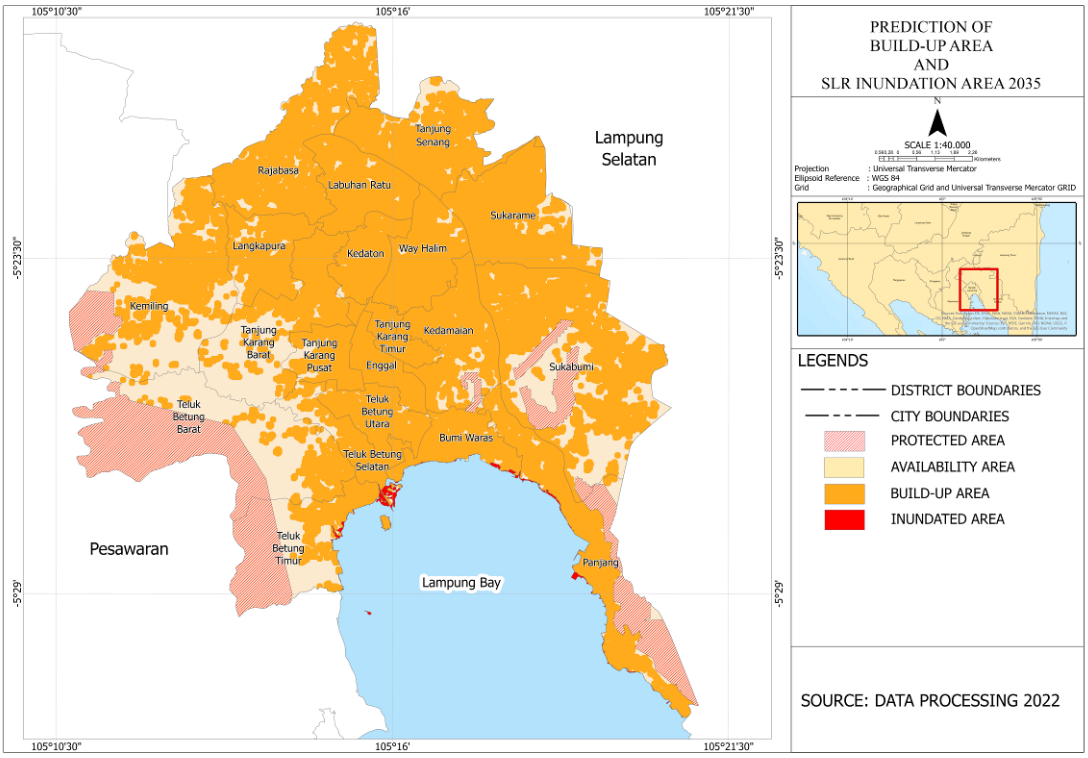


Figure 16. Projection of build-up area and mean sea level rise inundation in 2035.

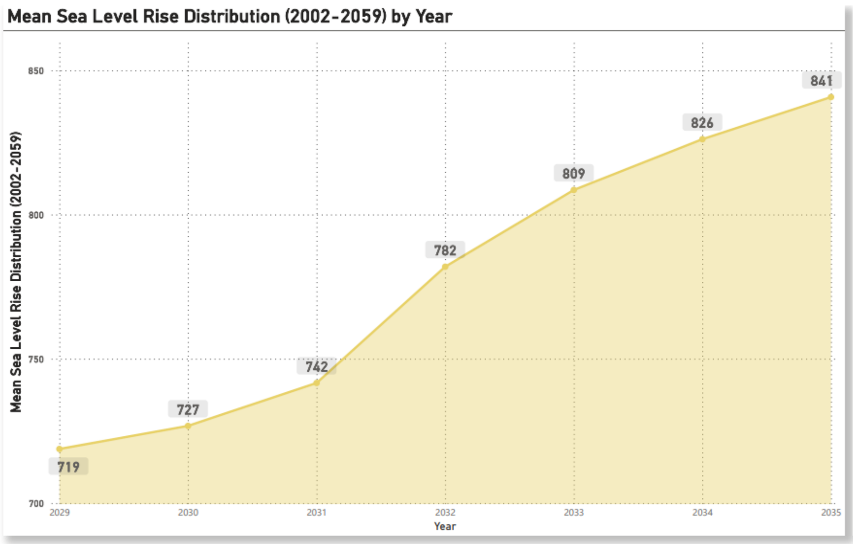


Figure 17. The forecasting of mean seal rise in Bandar Lampung in 2035.

Dynamic spatial model of built-up area growth, land availability, and mean sea level rise projection in 2041. In 2041, population growth is predicted to reach

2339936 people. Growth of built-up land will be 12925.37 hectares or 70% of Bandar Lampung city. This is the maximum limit of the comparison between built-up and other area with a good and optimal carrying capacity for the community. Several unsuitable available area are converted into built-up (Figure 18). In 2041, MSLR will have a minimum impact on Bandar Lampung city since the affected area is 78.98 hectares. Model predicts the actual value with a loss function of 0.87 apart from several outliers acting as the representation of several points. Meanwhile, there is a significant increase in MSLR by 112 millimeters in 2035-2041 (Figure 19). This occurs because of seasonal phenomena causing a decrease in the coefficient of GMSL and sea level rise values. Considering the patterns of data distribution, there has been a large reduction in numbers due to several factors affecting the value of the supporting variables.

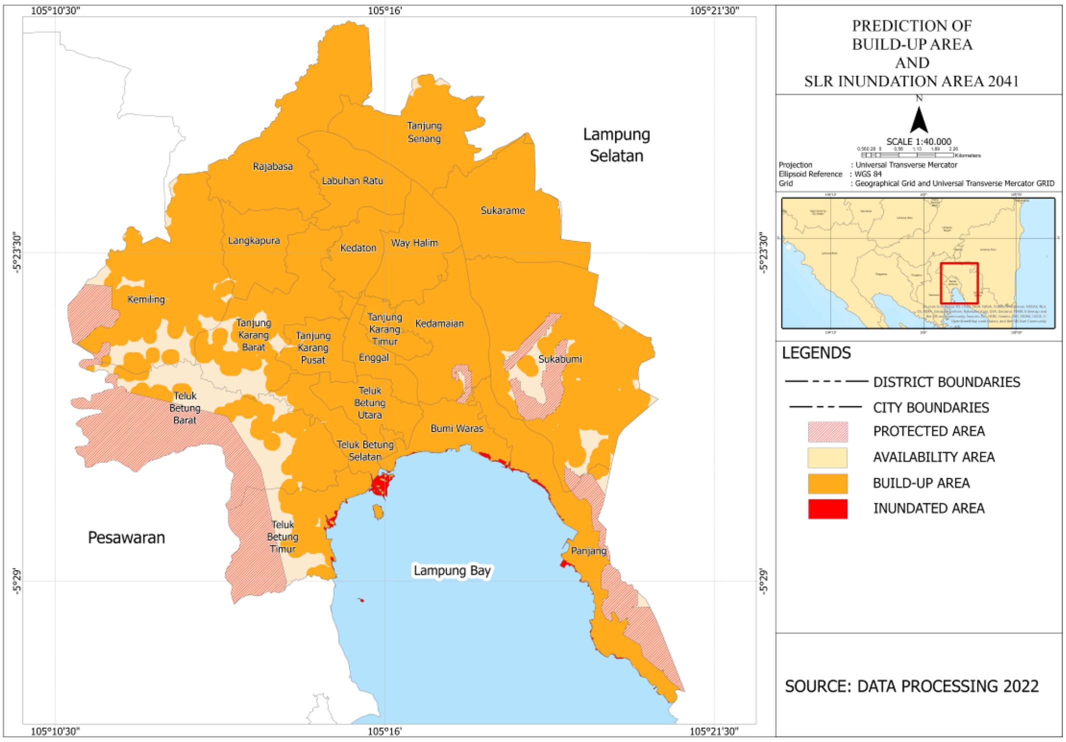


Figure 18. Projection of build-up area and mean sea level rise inundation in 2041.

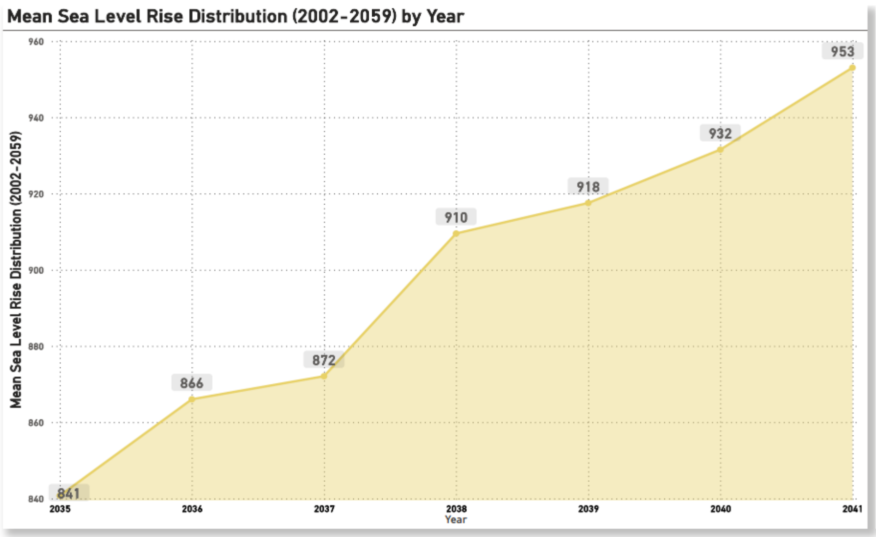


Figure 19. The forecasting of mean sea level rise in Bandar Lampung in 2041.

Dynamic spatial model of built-up area growth, land availability, and mean sea level rise projection in 2048. In 2048, the development of built-up land is predicted to reach 80% or 14698.31 hectares of Bandar Lampung city with a population growth of 2914157 people. The high population suppresses the space previously found in parts of the city. There is no space in the downtown area, consisting of built-up land. The only remaining area is the availability of land in the eastern and western parts of Bandar Lampung (Figure 20). In 2048, MSLR has the highest impact, and the submerged area is predicted to reach 95.48 hectares. Additionally, dynamic distribution of data prevents model from predicting the actual value of MSLR with the loss function in the range of 0.74 MAE. The value of the water level rise is at 78 millimeters (2041-2048) and has distinctive characteristics affected by trends and the value of seasonality (Figure 21).

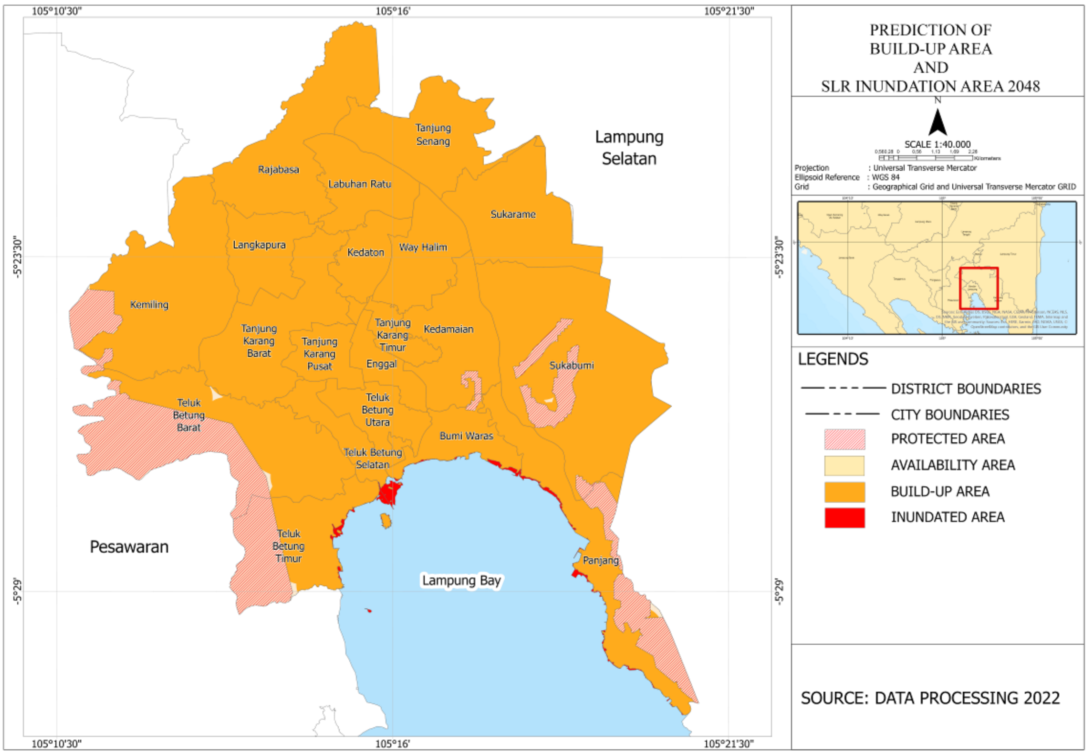


Figure 20. Projection of build-up area and mean sea level rise inundation in 2048.

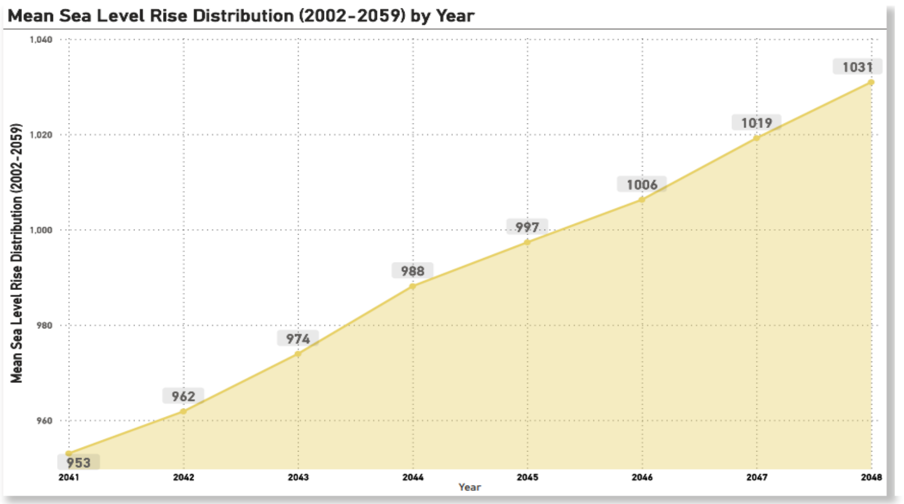


Figure 21. The forecasting of mean sea level rise in Bandar Lampung in 2048.

Dynamic spatial model of built-up area growth, land availability, and mean sea level rise projection in 2059. In 2059, the built area is expected to reach 90% of the total area of Bandar Lampung, or 16543.44 hectares with a population growth of 4114190 people. The city has a protected area in the south and east of 2337.20 hectares or 12.75%. MSLR reaches 116.13 hectares (Figure 22) and the latest scenario measured from the last period until 2059 shows 46 centimeters (2048-2059). The value of sea level is affected specifically the total built area of 90% with a longer projection. Projection from 2020-2059 temporarily and numerically shows an increase of 1.4 meters. This is the predictive value of lower confidence since there is a minimum MSLR in Bandar Lampung (Figure 23).

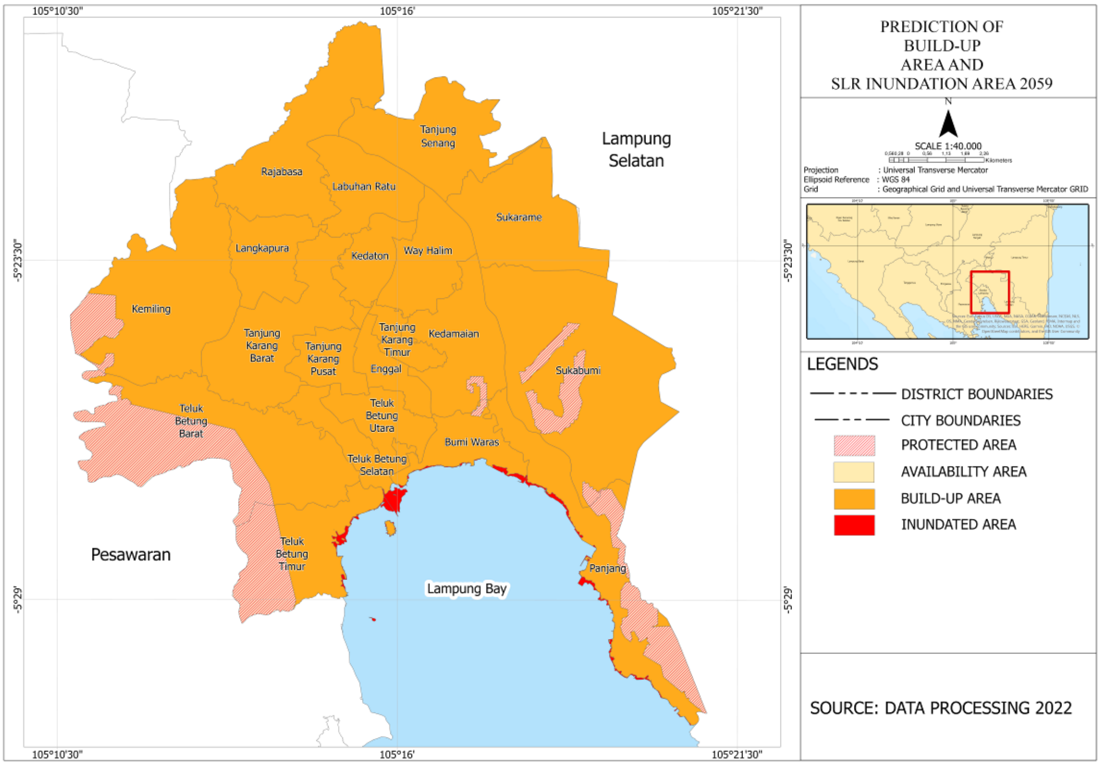


Figure 22. Projection of build-up area and mean sea level rise inundation in 2059.

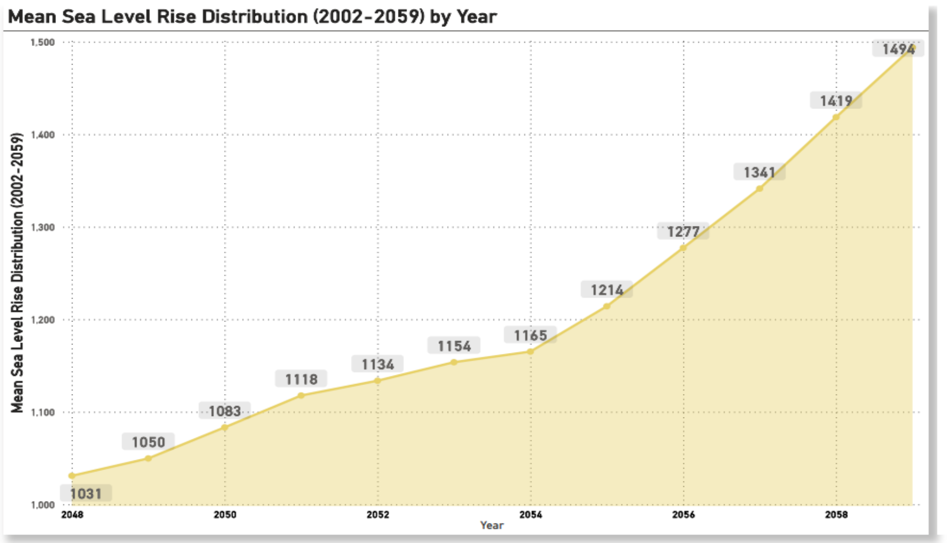


Figure 23. The forecasting of mean sea level rise in Bandar Lampung in 2059.

Conclusions. The implementation of dynamic model provided a predictive image of the complexity of population development and built-up area. The entire area could only be maximized up to 87.25% due to the limitation of the protected area. From 2010 to 2020, the development showed an increased built-up area, reducing open, agricultural, and vegetation land. In 2020, Bandar Lampung had good land suitability but certainly decreased over time where population growth would put pressure on converting land into built-up area. In 2024 and 2059, population growth is predicted to reach 1.373.217 and 4114190 people respectively with 1.4 meters of mean sea level rise. Therefore, the land area converted into a built area was 90% of Bandar Lampung. The threat of mean sea level rise had a significant impact inundating 116.13 hectares in 2059, specifically with a value of 1.4 meters. The most affected administrative area was the Panjang Sub-district. In the region, the affected area would reach 40.06 hectares in 2059. This could certainly be influenced by geographical conditions dominated by various slopes and the oblique nature of earth surface. However, there were also administrative area with stagnant land in the predictive period of 2024-2059. These included Sukarame, West Teluk Betung, Rajabasa, Kemiling, Tanjong Senang, and Sukabumi Sub-district. In Panjang, Bumi Waras, South Teluk Betung, and East Teluk Betung Sub-districts increased significantly. Even though the highest inundation scenario in 2059 would only submerge 0.6% of the total, the real affected area could be higher. This was because of the difficulty in building at a height of 0.00 m above sea level, specifically in coastal settlements dominated by fishing communities and other professions.

Conflict of interest. The authors declare that there is no conflict of interest.

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