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TEMPORAL ANALYSIS PROJECTION OF RIVER SALINITY PATTERNS IN SUNGAI TERENGGANU: A GEOSPATIAL PERSPECTIVE

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ABSTRACT

The Malabar blood snapper (*Lutjanus malabaricus*) has become increasingly vulnerable to overfishing, driven by rising export demand. This study aimed to evaluate the exploitation status of *L. malabaricus* around Karimunjawa Islands off Central Java in Indonesia and recommend management options. Fish samples were collected from 2017 to 2022. The data analysed included length-frequency, growth and mortality parameters, exploitation rates, and Spawning Potential Ratio (SPR). The study found that the species' Total Length (TL) ranged from 19 cm to 80 cm, with an average of 43.18 ± 11.32 cm. Growth parameter estimation yielded an asymptotic length ($L\infty$) of 83.4 cm TL, a growth coefficient (K) of 0.23 year^{-1}, and a theoretical age at zero length (t0) of -0.56 years. Mortality analysis showed a total maturity rate (Z) of 0.72 year^{-1}, with estimated fishing mortality (F) and natural mortality (M) of 0.42 and 0.30 year^{-1}, respectively, resulting in an exploitation rate (E) of 0.59. The stock was considered fully exploited with an SPR of 20% only. To prevent further decline, we recommend immediate measures such as enforcing minimum catch sizes above the length at maturity (Lm), limiting vessel permits to reduce fishing pressure, and expanding protected areas to safeguard spawning habitats in Karimunjawa.

Introduction

Saltwater intrusion is when the tide brings highly saline seawater from the estuary to the upstream of rivers, causing freshwater bodies to become salty. Changes in climatic conditions, such as global warming and climate shifts, might cause abnormal saltwater rises and falls (Pereira *et al.*, 2022). The infiltration of saltwater into the river severely contaminates the water source critical for the treatment plant, affecting water quality and disrupting the efficiency of treatment processes (Moore & Joye, 2021; Hasna Ameena *et al.*, 2022). Therefore, it becomes essential to understand the dynamics and future trends of saltwater intrusion to ensure the reliability of water supply systems (Tang, 2019).

River discharge, tidal forces, runoff, seasonal variation and estuarine geometry are the main parameters determining saltwater intrusion (Li & Liu, 2020). Salinity levels that allow for agriculture and drinking purposes are lower than 1 and 0.5 PSU, respectively (Lee *et al.*, 2016). Hence, site validation using field-based measurements is important to forecast salinity changes. Saltwater intrusion is a global issue, including in Malaysia, where direct river intake for water treatment plants, such as in Sungai Terengganu faces high risks. The river is uniquely influenced by both tidal effects and seasonal monsoon rainfall, combined with the presence of water intake stations within the tidal catchment area.

Although studies on saltwater intrusion exist worldwide, limited empirical studies have been conducted on Sungai Terengganu, especially in modelling future salinity trends. Empirical modelling approaches are useful in deriving the relationship between salinity, sea level, rainfall and runoff (Yirga *et al.*, 2024). However, the extent of saltwater intrusion in Sungai Terengganu has not been thoroughly explored (Zhang *et al.*, 2023).

Therefore, the objective of this study is to derive an average river salinity model using a multiple regression approach based on in-situ data that includes salinity, tidal levels and runoff. The reliability of this model will be evaluated to ensure its suitability for predictive use. Finally, the validated model will be applied to map both present and future salinity patterns in Sungai Terengganu by integrating geospatial techniques with field-based measurements to support informed decision-making for freshwater security and water treatment operations.

Materials and Methods

Figure 1 details how this research was carried out in the Sungai Terengganu basin, which is located in Peninsular Malaysia's north-eastern coastal area, between 4°40'-5°20' north latitude and 102°30'-103°09' east longitude. The Sungai Terengganu basin, which flows from the Kenyir Lake basin into the South China Sea, is the most important river in this basin. Sungai Terengganu is approximately 17.52 km long and 250 m wide (Ferdous & Rahman, 2020a). The upper watershed of the Sungai Terengganu includes the Kenyir Dam, a hydroelectric generating freshwater reservoir, while the middle and lower catchments are involved in plantation operations and are near to the estuary flowing into the South China Sea (Yi *et al.*, 2021a).

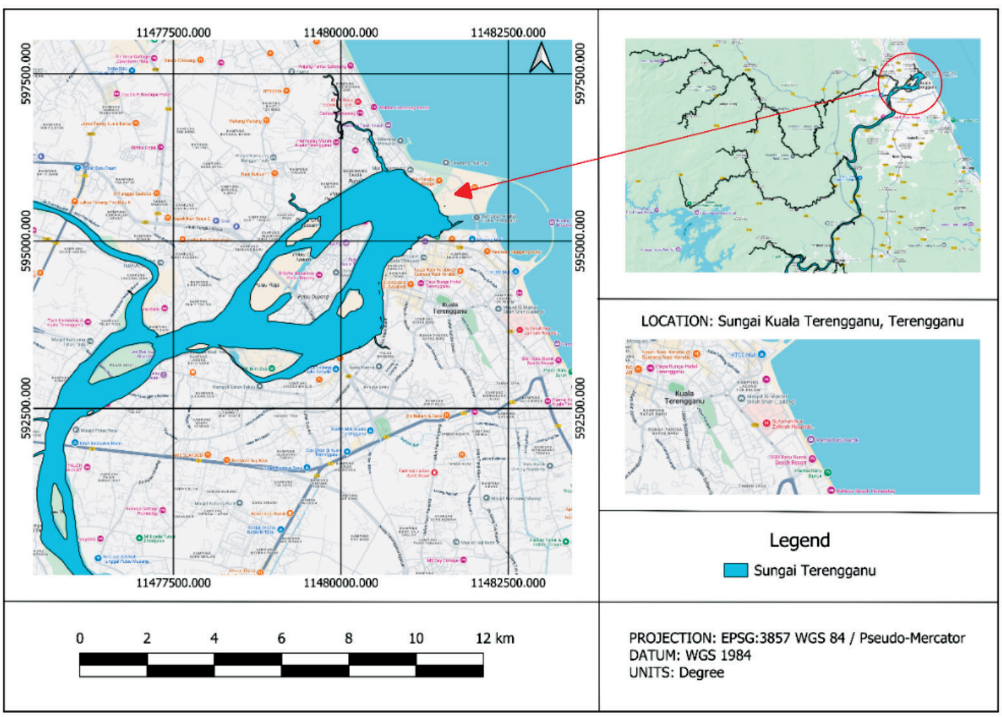

Figure 1: Sungai Terengganu basin

Higher amounts of freshwater runoff are released at the start and end of the year, with lower levels observed from June to September. During the end and early months of the year, the research site experiences the rainy season, which is related to the northeast monsoon (Siemens, 2021a). During the rainy season, the average monthly rainfall ranges from 200 to 600 mm. Average monthly rainfall ranges from 100 to 125 mm during the dry season from April to September (Mazelan & Suhaila, 2023).

The diurnal tide controls the tidal variation at the research location, with the spring and neap tidal ranges being roughly between 3.07 and 0.7 m (Ariffin, 2017). The Sungai Terengganu basin coastal position may make it prone to saltwater intrusion, making it an ideal place for researching and comprehending the causes and consequences of saltwater intrusion (Syazuani *et al.*, 2022).

The basin is also home to a range of plant and animal species that are vulnerable to saltwater intrusion and is a significant supply of freshwater to human settlements. making it an ideal location for research into the effects of saltwater intrusion on water supplies (Yi *et al.*, 2021b).

The methodology is structured into four phases as depicted in Figure 2.

Phase 1: Data Acquisition

In this phase, various datasets were collected including tidal data, rainfall, sea level, land use and in-situ salinity. Rainfall data were extracted from satellite-based climatological sources, such as Global Precipitation Measurement (GPM), for a 21-year period focusing on the dry season (May to July). Tidal values were gathered using tide gauge readings and runoff values were estimated using the Rational Method, where runoff coefficients were based on local land use and slope conditions.

Sampling of salinity was conducted at seven stations over a 48-hour period at the end of March 2023, with measurements taken every 4 hours to obtain the average salinity per station. The stations were selected using stratified sampling based on proximity to the estuary and known salinity gradient patterns. Although there was no fixed distance between stations, most were located about 2 to 5 km apart. They were chosen at central parts of the river that were accessible and suitable for capturing salinity variation along Sungai Terengganu. The resulting spatial resolution for salinity data corresponds to approximately 2 km intervals, which was later interpolated for mapping.

In this study, two different types of stations were used for data collection, which explains the difference between the numbers reported and those shown in Figure 3. There were five in-situ salinity sampling stations: Pantai Seberang Takir, Pulau Duyong, Hotel Felda Residence Kuala Terengganu, Jambatan Manir and Masjid Ibadurrahman Kuala Bekah. Direct salinity measurements were taken to represent upstream, midstream and downstream conditions. The salinity/tidal data reference stations were at Pulau Warisan, Jeti Shahbandar (Jeti Kuala Terengganu), Muzium Terengganu and Jambatan Manir, which were used mainly for recording tidal elevation and salinity fluctuations in the estuary and in upstream areas. Although Figure 3 shows eight watershed-related stations, not all were used for in-situ salinity measurement; only five were applied for direct sampling while the remaining stations served as tidal and hydrological reference points to support model development and validation. Figure 3 presents the locations of each sampling station along the river watershed stretch.

Salinity Data

Salinity data were used in this study to forecast future average river salinity (Thorslund *et al.*, 2021). By analysing historical salinity data and understanding how it is influenced by factors like rainfall, runoff and tidal forces, we can develop models that provide insights into future salinity levels.

These forecasts play a crucial role in water resource planning, allowing us to make informed decisions and take necessary actions to ensure the sustainability of our freshwater sources.

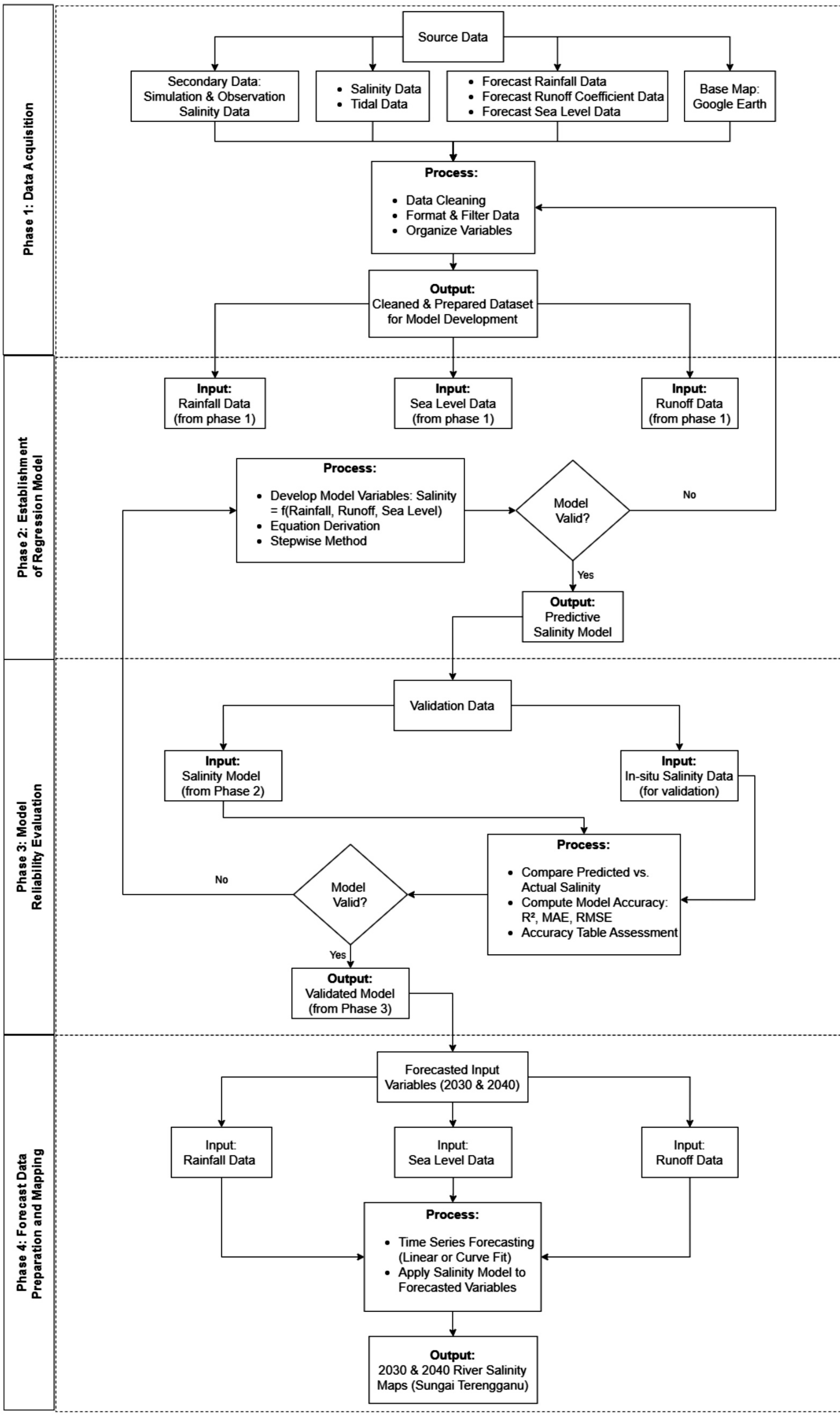

Figure 2: Framework methodology

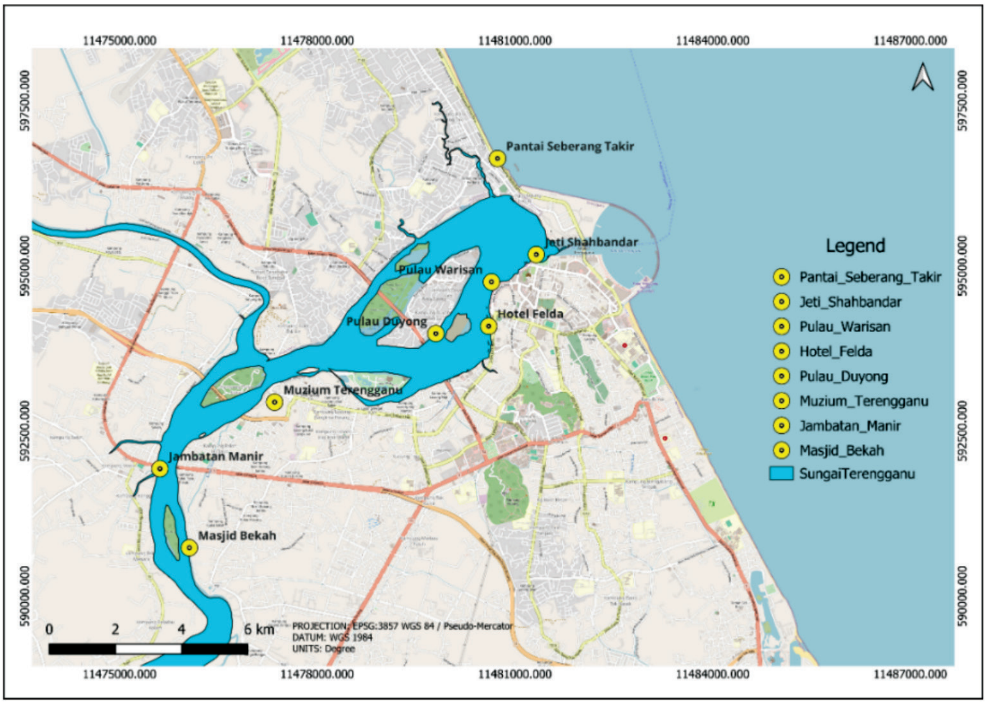

Figure 3: Sungai Terengganu watershed with station

Tidal Data

Tidal data were used in this study to forecast future river average salinity levels. The information on tidal height and timing can have a significant impact on river salinity levels (Heiss *et al.*, 2022). This data was collected over 20 days at the end of March 2022, with readings taken every 4 hours in the estuary and upstream areas. This period marks the transition to the dry season, when lower river flow allows seawater to move further inland. Collecting data during this time gives a clear picture of natural saltwater intrusion patterns and if data taken in different seasons, such as the monsoon when higher river discharge would likely reduce the extent of intrusion, produce different salinity patterns (Tomkratoke *et al.*, 2025).

Tidal data may be obtained using several ways, including tidal gauges. This implies that they are instruments to monitor and record the water level in a river or ocean over time. Otherwise, satellite altimetry can be used to estimate sea surface height using satellite-based radar or laser systems (Srinivasan & Tsontos, 2023).

Tidal salinity value data is a measurement of the salt content in water at a specific location during different tide stages (Atekwana *et al.*, 2022). This data helps to understand how tides affect river salinity and water flow. Tidal elevation shows the height of the tide at a given point and it can be used to analyse how changes in tide levels influence both the river water level and its salinity.

Forecasted Sea Level

Based on Figure 4, the Revised Local Reference (RLR) is subtracted by the value of the depth between the Datum 1984–1992, 1994- and Mean Sea Level (MSL 1987-03) to calculate future average river salinity.

The sea level in Kuala Terengganu is forecast from the present time to 2040 using tide gauge data (1985–2019; 21 years). By using the forecasted annual mean sea level (mm) data, the sea level value for 2030 = 7,080 mm and for 2040 = 7,090 mm.

Forecasted Rainfall

Rainfall data may also be used to forecast average river salinity. Rainfall has a considerable influence on river salinity since it may dilute saltwater while increasing freshwater content (America *et al.*, 2020a). Rain gauges, for example, can be used to gather rainfall data at a certain point over the time. Aside from that, there is also meteorological radar that detects and measures rainfall in a given area.

Hourly rainfall in 2025, 2030 and 2040 is forecast by using satellite rainfall data (1989 to 2019; 21 years) during the dry season (May to July) (Yi *et al.*, 2021d). The forecasted rainfall may be used with other data such as tidal data, river flow data and land use data to create models that predict future river average salinity levels. These models can produce more accurate estimates of future salinity levels if the link between rainfall and river salinity is comprehended.

Forecasted Runoff

Runoff data might be used to foresee potential salinity levels in rivers. Water that runs over the land surface into rivers and streams is known as runoff, and it may have a substantial influence on the salinity levels in a river (Olson, 2019). Runoff data can be collected using a variety of ways, including stream gauges, which record the flow rate and water level in a river or stream, and hydrological models, which describe the movement of water through the catchment area and can be used to estimate runoff. Runoff data was forecasted using linear time series techniques (2000 to 2035 with interval 10 years).

The Rational Method is used to estimate the peak discharge resulting from a rainfall event. The formula is expressed as:

$$Q = Cf \, . \, C \, . \, i \, . \, A \tag{1}$$

where,

Q is peak discharge (cubic feet per second, cfs),
Cf is runoff coefficient adjustment factor to account for infiltration and other losses during high-intensity storms,
C is runoff coefficient, representing the ratio of rainfall that becomes surface runoff,
i is rainfall intensity (inches per hour, in/hr), and
A is drainage area (acres, ac).

In addition, depending on rainfall increase and catchment area, the Rational Method is frequently used for estimating peak runoff or flood flow from limited drainage regions (Kencanawati *et al.*, 2021). The rational approach equation is Q = CiA, where Q is the peak discharge, C is the runoff coefficient, (I) is the increase of rainfall, and (A) is the catchment area.

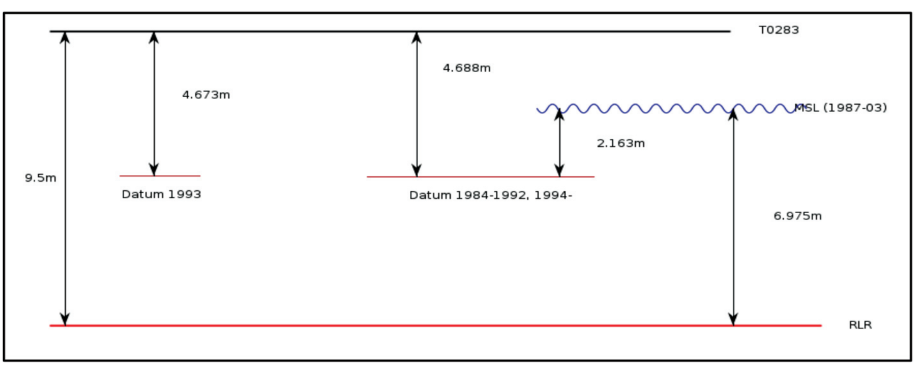

Figure 4: Mean sea level Kuala Terengganu

The runoff coefficient (C) is an empirical coefficient that takes into consideration the catchment area's hydrological features, such as soil type, land use, slope and vegetation. The coefficient values typically vary from 0.2 to 0.9, with the higher the number indicating greater runoff (Siemens, 2021b). The rainfall increase (I) is often derived from a rainfall frequency assessment and stated as a number with a particular chance of being surpassed in a given year, such as a rainfall increase with a return time of two years. The catchment area (A) is the region that supplies runoff to a certain location in the river, generally when runoff is measured or peak discharge is required.

The Rational Method runoff data may be used with other data, such as rainfall, tidal data and land use data to create models that can forecast future river salinity levels. These models can compensate for the impact of runoff on river salinity, as well as other variables, such as rainfall, tides and land use. Understanding the link between runoff and river salinity allows models to make more accurate projections of future salinity levels.

Phase 2: Establishment of Regression Model

Next, for Phase 2, the establishment of the regression model is the key parameter, where tidal data were modified and converted into sea level measurements and paired with the input average salinity data. This transformation allowed for a more direct representation of salinity-driving forces. Historical data were required and involved a number of outliers that had to be removed to improve the model's R^2 value and overall accuracy.

The regression model was designed to predict the average salinity in both current and future years in Sungai Terengganu through function-based equations. Data preparation involved the removal of missing values and outliers to ensure clean datasets. This included filtering out abnormal records, encoding categorical variables and performing data normalisation to ensure consistency in unit scale and reduce modelling bias.

The model construction used a Multiple Linear Regression (MLR) approach, where average salinity levels served as the dependent variable and the independent variables included rainfall, sea level (tides), and river runoff. Stepwise regression was applied to identify the most statistically significant predictors, which improves model performance by excluding irrelevant variables and avoiding overfitting (Chowdhury & Turin, 2020).

In this phase, the following steps were taken: historical data collection (2000 to 2020), data cleaning, variable selection, model construction and validation. The regression model was evaluated using standard metrics, such as R-squared, Mean Squared Error (MSE), and residual analysis, and further validated with an unseen dataset for consistency.

There are various approaches to forecasting salinity, including statistical, hydrological and numerical models. In this study, statistical modelling via MLR was selected due to its efficiency and suitability for the available temporal dataset (Hunter *et al.*, 2018). While hydrological models simulate river flow based on catchment characteristics and numerical models replicate physical phenomena like tides and evaporation (Lucas & Deleersnijder, 2020), they often require more extensive data and computational capacity. The final multiple regression model for forecasting salinity is represented as:

$$Salinity(t) = \beta 0 + \beta 1X1(t) + \beta 2X2(t) + ... + \beta nXn(t) + \epsilon(t) \quad (2)$$

where,

$Salinity(t)$ is the predicted average salinity at time t,

$X1(t)...Xn(t)$ are the independent variables (e.g., rainfall, sea level, runoff),

$\beta 0...\beta n$ are the regression coefficients estimated from historical data, and

$\epsilon(t)$ is the residual error at time t.

All regression assumptions, such as linearity and normality of residuals were tested and satisfied to ensure that the model is statistically sound and reliable for forecasting salinity in Sungai Terengganu.

Phase 3: Model Reliability Evaluation

Moreover, the reliability of the model in Phase 3 was evaluated by applying the best time-series regression equation to determine the forecasted average salinity values. The assessment was done using a computational equation derived from the in-situ data compared with the input (modelled) data. The proposed techniques for forecasting included the linear regression form (y = mx + c) and the logarithmic equation (y = a(ln)(x) + b) which is particularly suited to model the relationship between river salinity and its distance from the river mouth based on observed data.

After determining the best-fit time series model, forecast probabilities were computed to produce salinity projection maps for the years 2030 and 2040 along Sungai Terengganu.

Temporal projection was conducted using linear time-based forecasting rather than Autoregressive Integrated Moving Average (ARIMA), as it offered sufficient predictive capability for environmental patterns observed in the historical dataset and required fewer assumptions.

To assess model accuracy, the predicted salinity values were compared against actual in-situ measurements taken at multiple stations (Pulau Duyong, Hotel Felda Residence Kuala Terengganu, Jambatan Manir, and Masjid Ibadurrahman Kuala Bekah). Error was calculated by subtracting modelled values from field measurements and converting them into percentages as illustrated in Table 4. The results showed a model reliability of approximately 70.33% with station-level accuracy ranging from 50% to 98.2%, which depends on proximity to the river mouth and the magnitude of salinity variation.

According to Lee *et al.* (2024), an acceptable tolerance range for salinity forecasting in estuarine systems is between ± 0.5 PSU and ± 1.0 PSU. In this study, the majority of stations fell within or close to this range, indicating that the model provides a reasonably reliable estimate of salinity distribution along Sungai Terengganu. For example, Jambatan Manir and Hotel Felda Residence Kuala Terengganu had minimal errors (1.8% and 6.8%), while Pulau Duyong and Masjid Ibadurrahman Kuala Bekah showed higher discrepancies (28.6% and 50%) due to location-specific variations and extremely low salinity values affecting proportional error calculations.

The capacity of a model to produce accurate predictions is also validated through cross-validation which separates the dataset into different subsets for training and testing. This process ensures the model performs consistently on unseen data. Alternatively, real world testing involved comparing the model's outputs with actual field values to simulate operational prediction settings (Major *et al.*, 2020).

In evaluating model performance, standard statistical indicators, such as Mean Absolute Error (MAE), MSE and R-squared (R^2) were used. These metrics quantify the difference between predicted and actual values, and serve as a benchmark for evaluating how well the model performs. A lower MAE or MSE indicates higher predictive accuracy. In this study, the R^2 value of 0.7033 supports a strong predictive relationship between variables such as tidal sea level and observed salinity.

Phase 4: Forecast Data Preparation and Mapping

The final phase (Phase 4) involves the preparation of forecast data and mapping. Using the validated regression model, future salinity values for the years 2030 and 2040 were forecasted through time-series regression analysis, which is a particularly linear trend projection based on decadal averages. These predictions were based on computed results from the average salinity model described in previous phases that specifically incorporates variables such as sea level and runoff.

The forecasted values were then processed using Quantum Geographic Information System (QGIS) to produce river salinity maps for 2023 (baseline), 2030 and 2040. The spatial resolution used in these maps was 30m, derived from landsat base imagery. Geographic Information System (GIS) software such as QGIS was utilised to import and visualise spatial and tabular data formats, including shapefiles, CSV file and raster layers. These tools allow for the generation of detailed spatial maps, overlaying multiple data layers and running spatial analyses.

Each map includes standard cartographic elements such as scale bars, north arrows, UTM coordinates and color-coded salinity legends. Figure 5 below illustrates the Peninsular Malaysia map generation workflow for the Sungai Terengganu watershed salinity map. Additionally, a conditional logic step was implemented in the modelling process, where if the forecasted error exceeded 1 PSU, the result was flagged for re-evaluation. This helped ensure the maps were both statistically valid and practically usable for interpretation by stakeholders.

The first step in creating a map is to import the data into the application or platform that we are choosing. This usually entails transforming the data into a software-readable format such as a shapefile or CSV file. The data layers are then overlaid on a base map, which can be a satellite picture or a street map. Then, using the software's built-in functions or libraries, we construct a map with a legend, labels and other graphic components. Once the map has been made, users may export it in a variety of forms, including image, PDF and online map, and share it with others. It is crucial to remember that generating a map is only one stage in the process; it is also critical to test the model and the findings before making any choices based on the model's predictions.

Results and Discussion

This study focuses on the development of an empirical model for estimating river salinity. By utilising in-situ data and empirical approaches, the aim is to derive a reliable model that can accurately predict salinity levels in rivers. The model development process involves analysing various factors such as rainfall and tidal and sea levels to understand their impact on salinity. Through this research, valuable insights into the dynamics of river salinity can be gained, which can enable better management and planning of water resources.

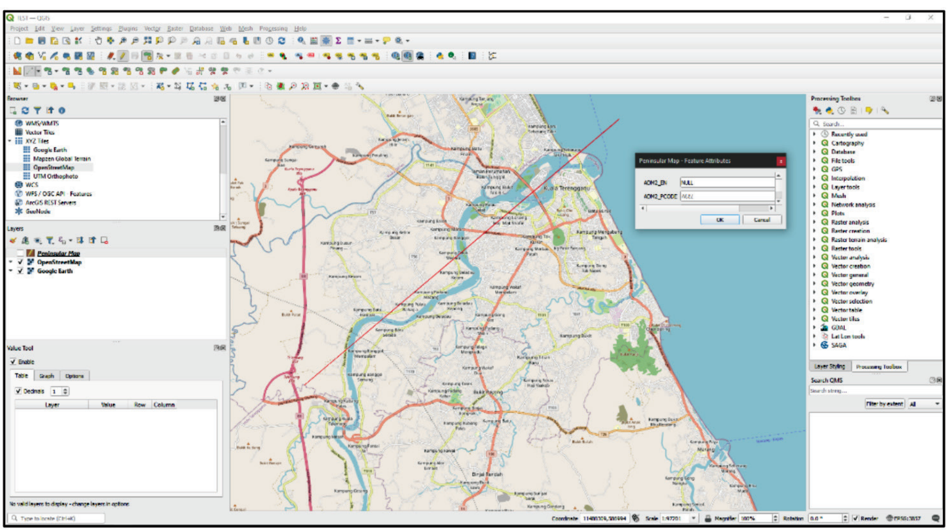

Figure 5: Preprocessing mapping in QGIS

Estimate Establish Multiple Regression Model

The model may then be evaluated using statistical metrics, such as R-squared, adjusted R-squared, RMSE and MAE, among others as represented in Tables 1, 2, and 3. In addition, the model is validated using a distinct dataset to examine if correct predictions can be made using updated data (America *et al.*, 2020c). Based on the provided multiple regression model results (Figure 6), the regression equation for the salinity (PSU) parameter is given as: y = 14.064x – 21.716, where y represents the predicted salinity value based on the sea level (x) input.

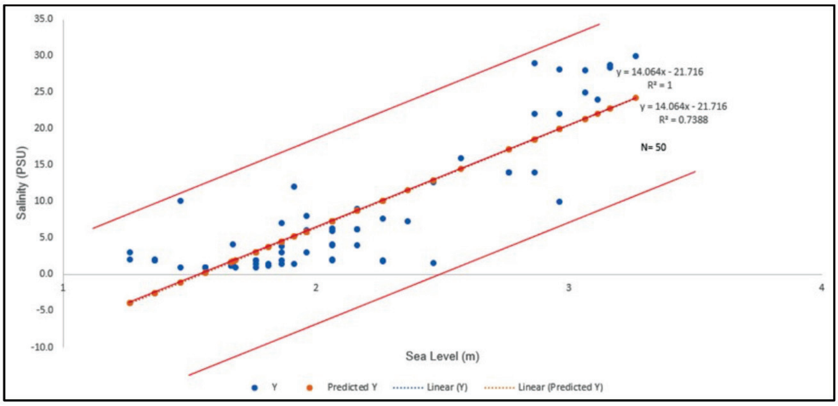

Figure 6: Salinity vs. sea level (model)

Table 1: Regression statistics

Multiple R	0.859555137
R-squared	0.738835033
Adjusted R-squared	0.73455364
Standard error	4.623626469
Observations	63

Table 2: ANOVA for regression and residual

	Df	SS	MS	F	Significance F
Regression	1	3689.163283	3689.1633	172.568846	1.93518E-19
Residual	61	1304.053225	21.377922	-	-
Total	**62**	**4993.216508**	**-**	**-**	**-**

Table 3: Statistics of intercept and X Variable 1 model

	Coefficients	Standard Error	t Stat	*p*-value	Lower 95%	Upper 95%	Lower 95.0%	Upper 95.0%
Intercept	-21.716	2.347	-9.254	3.175E-13	-26.408	-17.023	-26.408	-17.023
X Variable 1	14.064	1.071	13.137	1.935E-19	11.923	16.205	11.923	16.205

The R-squared value for this model is 1, indicating that the sea level explains 100% of the variation in salinity according to the model. This implies a strong and perfect relationship between sea level and salinity. However, it is important to note that the R-squared value of 1 raises a concern of overfitting. Overfitting occurs when the model is too complex and fits the noise or random fluctuations in the data rather than the true underlying relationship. It is advisable to assess the model's performance on independent data to validate its predictive capability.

Additionally, the R-squared value of the predicted salinity model is 0.739. This indicates that approximately 73.88% of the variation in salinity can be explained by the sea level variable. It implies a reasonably strong relationship between sea level and salinity, but there is still some unexplained variability. The descriptive analysis of the multiple regression model suggests that sea level is a significant predictor of salinity. The perfect R-squared value of 1 for the original model indicates a strong relationship, while the R-squared value of 0.7388 for the predicted model suggests a reasonably good fit. However, further analysis and validation are necessary to ensure the model's generalisability and accuracy on independent data.

Salinity Intrusion Regression Model

The findings from the river salinity observations and simulations in Sungai Terengganu, as shown in Figure 7, reveal interesting patterns. The salinity levels vary across different locations, with the highest average salinity of 8 PSU observed at Jeti Shahbandar, followed by Pulau Warisan (4.5 PSU), Muzium Terengganu (1.5 PSU) and Jambatan Manir (0 PSU). When examining the relationship between distance and salinity through a line graph, a clear decreasing trend becomes apparent.

As we move farther from the sea, the salinity decreases, indicating an inverse relationship. This finding suggests that areas closer to the river mouth have higher salinity due to the influence of saline water from the sea while upstream areas experience lower salinity levels.

The correlation between distance and salinity is supported by the statistical analysis, which shows a strong relationship with an R-squared value of 0.9937. This implies that the distance from the sea is a reliable predictor of salinity levels in Sungai Terengganu. The observed trend in salinity levels is based on the average data collected at specific locations and may not capture the full variability of salinity over time.

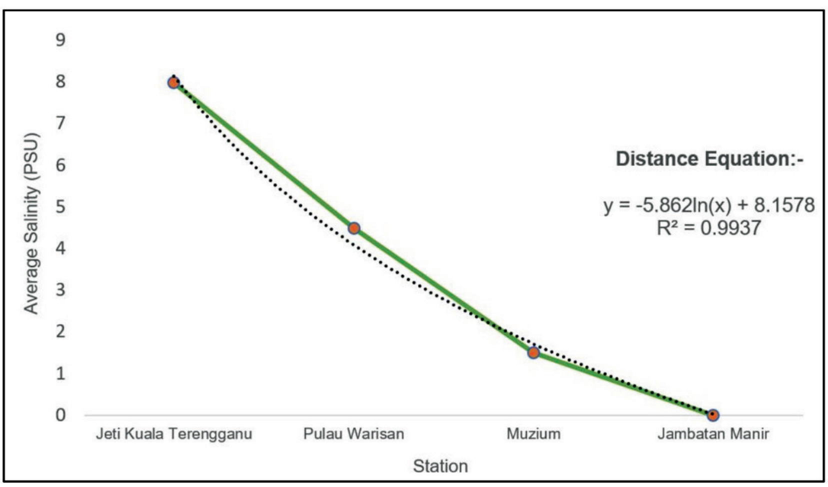

Figure 7: Salinity vs. sea level (model)

To determine the best time-series regression equation to forecast average salinity value for future, the assessment was done by computing the equation from in-situ data with input data. The proposed techniques for this forecasting were the equation intercept/straight line form, which is $y = mx + c$ and together with $y = a(\ln)(x) + b$ for the distance from river salinity observation and simulation. After testing the best time series forecasting, the probability was computed to produce a map of average salinity in Sungai Terengganu from 2030 to 2040.

These findings have important implications for water resource management and urban planning in Sungai Terengganu. They provide valuable insights into the spatial distribution of salinity and highlight areas that are more vulnerable to saltwater intrusion. Understanding these patterns can help decision-makers identify suitable locations for freshwater intake, particularly for water treatment plants. By considering the salinity levels and their spatial distribution, stakeholders can make informed decisions to ensure the sustainable use of water resources in the region.

Salinity Map 2023, 2030, and 2040

The development of salinity maps for Sungai Terengganu, covering the present year (2023) as well as future projections for 2030 and 2040 as depicted in Figures 8, 9 and 10, play a crucial role in visualising the spatial distribution of salinity data. These maps offer valuable insights into the increasing salinity levels over time, primarily resulting from saltwater intrusion caused by human activities, such as drinking water usage, agriculture and bathing. By analysing the salinity map, it becomes evident that locations nearer to the sea exhibit higher salinity, while areas farther away tend to have lower levels.

The maps were generated at a resolution of approximately 1 km² per pixel by using a consistent scale and projection (EPSG: 3857, WGS 84/Pseudo-Mercator) to ensure spatial accuracy. The coverage extends from the river estuary to midstream areas, allowing for effective comparison of salinity changes across both coastal and inland zones.

According to the salinity map for the year 2023 (Figure 8), Jeti Shahbandar records the highest average salinity at 8 PSU, followed by Pulau Warisan (4.1 PSU), Hotel Felda Residence Kuala Terengganu (3.8 PSU), Pulau Duyong (3.5 PSU), Muzium Terengganu (1.7 PSU), Jambatan Manir (1.1 PSU), and Masjid Ibadurrahman Kuala Bekah (0.5 PSU). These findings highlight specific areas within Sungai Terengganu with significant saline water content. The numbers

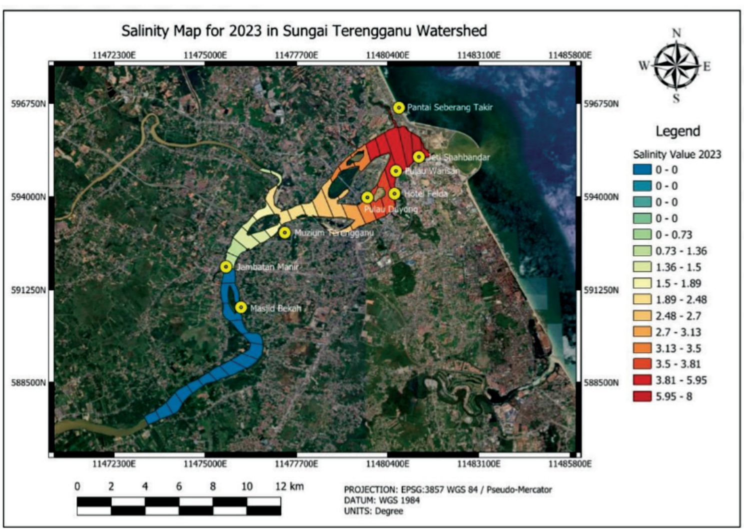

Figure 8: Salinity map for 2023 in Sungai Terengganu watershed

of salinity PSU might slightly increase over the year based on location. The map utilises a colour scheme to enhance visualisation, with red or orange representing higher salinity, white or yellow depicting intermediate salinity, and blue or green indicating areas with lower salinity or freshwater.

In the salinity map for 2030 (Figure 9), Jeti Shahbandar records the highest average salinity at 9.6 PSU, followed by Pulau Warisan (5.5 PSU), Hotel Felda Residence Kuala Terengganu (5.3 PSU), Pulau Duyong (4.9 PSU), Muzium Terengganu (3.2 PSU), Jambatan Manir (1.5 PSU) and Masjid Ibadurrahman Kuala Bekah (1.2 PSU). For 2040 (Figure 10), Jeti Shahbandar records the highest average salinity at 10.5 PSU, followed by Pulau Warisan (6.4 PSU), Hotel Felda Residence Kuala Terengganu (6.2 PSU), Pulau Duyong (5.8 PSU), Muzium Terengganu (4.1 PSU), Jambatan Manir (2.4 PSU) and Masjid Ibadurrahman Kuala Bekah (2.1 PSU). The 2030 and 2040 maps show only slight differences because salinity change in Sungai Terengganu is gradual and strongly influenced by seasonal and tidal cycles. The

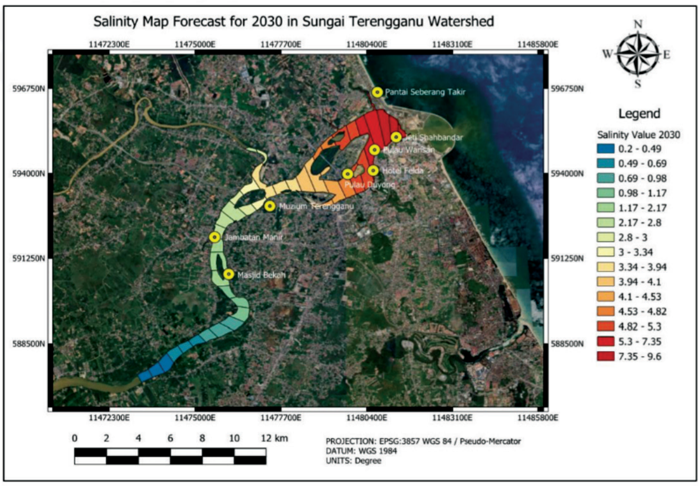

Figure 9: Salinity map forecast for 2030 in Sungai Terengganu watershed

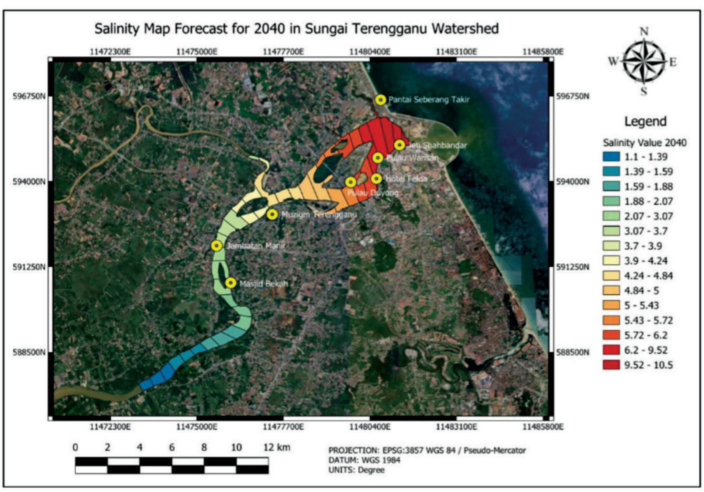

Figure 10: Salinity map forecast for 2040 in Sungai Terengganu watershed

model captures this slow progression, where major shifts are expected only over a longer time horizon beyond 2040.

Both forecasting year salinity maps can provide insights into future projections, allowing us to anticipate potential impacts, resulting from continued saltwater intrusion. These maps demonstrate a gradual increase in salinity while underscoring the need for effective monitoring and management of freshwater resources to mitigate the risks of rising salinity levels.

The salinity maps are essential tools for policymakers, water resource managers and other stakeholders in Kuala Terengganu. They offer valuable insights and actionable information for addressing the escalating salinity levels. By visualising the data, individuals can gain a better understanding of the spatial distribution of salinity and take appropriate actions to tackle the issue of saltwater intrusion. These maps raise awareness among the local population regarding the consequences of increasing salinity and encourage proactive measures to safeguard freshwater resources.

Accuracy Assessment Salinity

The reliability and accuracy of the derived salinity model and the predicted salinity maps were assessed to determine the agreement between the model predictions and the in-situ measurements. The accuracy assessment focused on several key variables, including river discharge, river salinity and river level. These variables were measured using flow meter devices in one of the Sungai Terengganu tributaries. The accuracy of the model predictions was evaluated by comparing them with the measured values. According to the Figure 11 and Table 4, the accuracy assessment compares the salinity input data with the in-situ measurements taken at four stations: Pulau Duyong, Hotel Felda Residence Kuala Terengganu, Jambatan Manir and Masjid Ibadurrahman Kuala Bekah.

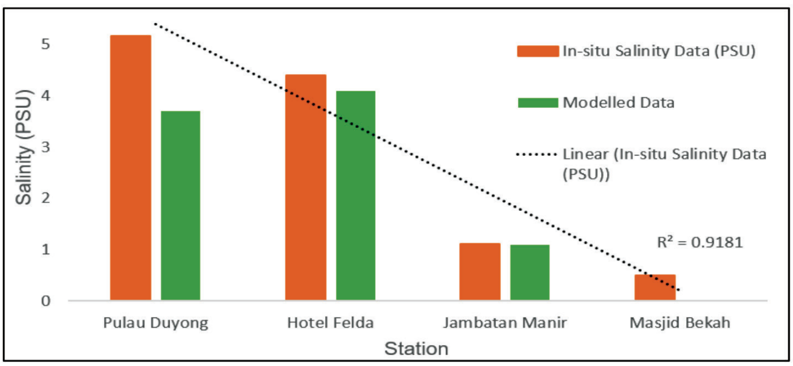

Figure 11: Graph comparison salinity input and in-situ data

Table 4: Accuracy assessment and errors for input and in-situ data

Stations	In-situ Salinity Data (PSU)	Input Data (PSU)	Errors (%)	Accuracy Assessment (%)
Pulau Duyong	5.18	3.7	28.6	71.4
Hotel Felda Residence Kuala Terengganu	4.4	4.1	6.8	93.2
Jambatan Manir	1.12	1.1	1.8	98.2
Masjid Ibadurrahman Kuala Bekah	0.5	0	50	50

Field Measurement Results

This assessment helps to evaluate the reliability of estimated salinity values with the actual salinity that were taken independently. At Pulau Duyong, the salinity input data was 3.7 PSU, while the in-situ measurements showed 5.18 PSU. This means there was an error of 28.6% and an accuracy of 71.4%. These results indicate a significant difference between the estimated and actual salinity values at this station. On the other hand, at Hotel Felda Residence Kuala Terengganu, the salinity input data was 4.1 PSU, and the in-situ measurements recorded 4.4 PSU. Here, the error was only 6.8%, and the accuracy was 93.2%. This suggests a better agreement between the estimated and measured salinity values, indicating a higher level of accuracy.

The Jambatan Manir station exhibited minimal errors, with a salinity input data of 1.1 PSU and in-situ measurements of 1.12 PSU. The error was just 1.8%, and the accuracy was 98.2%. These findings showed a strong agreement between the estimated and measured salinity values, indicating a reliable estimation for this station. At Masjid Ibadurrahman Kuala Bekah station, the salinity input data was 0 PSU, while the in-situ measurements revealed a salinity of 0.5 PSU. Since both values are the same, the error and accuracy are also both 50%. This means the estimated salinity value matched the measured value, but there was a significant deviation.

The accuracy assessment graph, based on the simulated trendline using the in-situ data, achieved an R-square value of 0.8348. This indicates a reasonably good fit between the estimated and measured salinity values. The results of the accuracy assessment revealed a reasonably good level of accuracy in predicting the mentioned variables, indicating that the geospatial approach and empirical model utilised in this study can effectively predict and map the present and future river salinity of Sungai Terengganu.

The error was quantified as the absolute difference between the modelled (input) salinity and the in-situ (observed) salinity divided by the observed salinity and multiplied by 100 to give a percentage error. This value was then subtracted from 100% to calculate the accuracy percentage as shown in Table 4.

According to previous studies, the acceptable prediction tolerance for river salinity typically ranges from 0.5 PSU (ideal threshold) to 1.0 PSU (upper acceptable limit) (Lee *et al.*, 2024). In this study, the model produced a MAE of 0.43 PSU and a RMSE of 0.55 PSU. Based on this analysis, three out of four stations (Hotel Felda Residence Kuala Terengganu, Jambatan Manir, and Pulau Duyong) produced salinity predictions within the acceptable range, while two stations (Hotel Felda Residence Kuala Terengganu and Jambatan Manir) met the ideal 0.5 PSU threshold.

These results suggest that the regression-based salinity predictions are statistically reliable and meet the standards required for supporting freshwater management decisions. The accuracy assessment through in-situ data sampling using river flow meter devices at specific locations enhances the reliability and validity of the model. It ensures that the predicted salinity values align with the actual measured values, validating the suitability of the multiple regression model for predicting salinity based on sea level input.

The in-situ data collected from different locations along the Sungai Terengganu watershed further supports the findings. The salinity measurements reveal a decreasing trend as the distance from the sea increases. According to the Figure 12, Pantai Seberang Takir has the highest average salinity of 22.879 PSU, followed by Pulau Duyong (5.18 PSU), Hotel Felda Residence Kuala Terengganu (4.4 PSU), Jambatan Manir (1.12 PSU) and Masjid Ibadurrahman Kuala Bekah (0.5 PSU). This pattern aligns with the distance-salinity relationship observed in the line graph, where salinity decreases as we move farther from the river mouth. The trendline equation derived

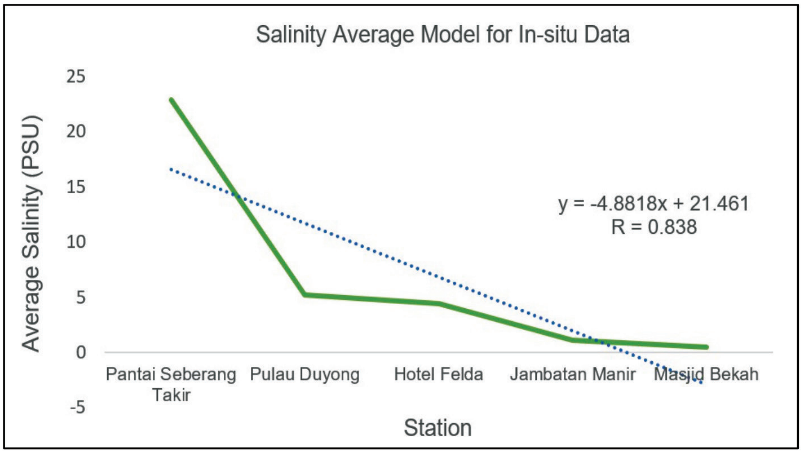

Figure 12: Salinity average model of in-situ data

from the in-situ data, y = -4.8818x + 21.461, demonstrates a reasonably strong negative relationship between sea level and salinity.

Based on Table 4, the model achieved varying levels of accuracy across stations. Hotel Felda Residence Kuala Terengganu and Jambatan Manir demonstrated high predictive accuracy with 93.2% and 98.2%, respectively, while Pulau Duyong showed moderate performance (71.4%) and Masjid Ibadurrahman Kuala Bekah recorded lower accuracy (50%). The overall model performance was derived from averaging these values, resulting in an approximate model accuracy of 78.2%.

Therefore, the previously stated 70% accuracy appears to be an underestimation. The refined benchmark of 78.2% reflects a stronger and more representative model performance. However, variation in performance among stations suggests that local conditions such as proximity to the estuary, hydrodynamic complexity and sampling limitations may influence predictive strength.

The R-squared value of 0.7033 indicates that approximately 70.33% of the variation in salinity can be explained by the sea level variable, leaving some unexplained variability. This suggests that factors other than sea level may also influence salinity levels in the Sungai Terengganu watershed. The accuracy assessment through in-situ data sampling using river flow meter devices at five locations enhances the reliability and validity of the model. It ensures that the predicted salinity values align with the actual measured values, validating the suitability of the multiple regression model for predicting salinity based on sea level input. The findings from the accuracy assessment or validation of the multiple regression model using in-situ data, support the strong relationship between sea level and salinity in Sungai Terengganu. The model provides reliable predictions of salinity based on sea level input, with a high level of explained variability. Future changes in the river course or morphology may influence salinity patterns and could affect the accuracy of the projections. This study is based on current river conditions so significant physical changes in the river may require model recalibration and updated forecasts.

Conclusions

This study mapped the present and future salinity of Sungai Terengganu using a geospatial and regression-based approach. A multiple regression model was developed with in-situ salinity, rainfall, runoff and sea level data, achieving an accuracy of about 78%. The projections for 2030 and 2040 showed a gradual increase in salinity, especially during dry periods, with higher salinity zones shifting further inland. These findings highlight the growing risk of saltwater intrusion and its potential impact on freshwater supply for treatment plants. The salinity maps produced in this study provide useful guidance for the Department of Irrigation and Drainage (DID) and other agencies in managing water resources and planning adaptation measures. While the model proved reliable, further validation through longer-term monitoring, seasonal data collection, and inclusion of land use and groundwater factors is recommended to improve accuracy and support long-term freshwater security.

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Conflict of Interest Statement

The authors declare that they have no conflict of interest.

References

Alenezi, A., & Alabaiadly, Y. (2025). Emerging technologies in water desalination: A review and future outlook. *Energy Nexus*, *17*, 100373. https://doi.org/10.1016/j.nexus.2025.100373

Ariffin, E. H. (2017). *Effect of monsoons on beach morphodynamics in the east coast of Peninsular Malaysia: Examples from Kuala Terengganu coast* [Doctoral dissertation, Université de Bretagne-Sud]. https://theses.hal.science/tel-01795143v1/file/2017theseBin_Ariffin_EH.pdf

Atekwana, E. A., Ramatlapeng, G. J., Ali, H. N., Njilah, I. K., & Ndondo, G. R. N. (2022). Tide–salinity patterns reveal seawater–freshwater mixing behavior at a river mouth and tidal creeks in a tropical mangrove estuary. *Journal of African Earth Sciences*, *196*, 104684. Https://doi.org/10.1016/j.jafrearsci.2022.104684

Basack, S., Loganathan, M. K., Goswami, G., & Khabbaz, H. (2022). Saltwater intrusion into coastal aquifers and associated risk management: Critical review and research directives. *Journal of Coastal Research*, *38*(3), 654–672. https://doi.org/10.2112/JCOASTRES-D-21-00116.1

Chowdhury, M. Z. I., & Turin, T. C. (2020). Variable selection strategies and its importance in clinical prediction modelling. *Family Medicine and Community Health*, *8*(1), e000262. https://doi.org/10.1136/fmch-2019-000262

Ferdous, J., & Rahman, M. T. U. (2020). Developing an empirical model from Landsat data series for monitoring water salinity in coastal Bangladesh. *Journal of Environmental Management*, *255*, 109861. https://doi.org/10.1016/j.jenvman.2019.109861

Hasna Ameena, P. O., Varughese, A., Gilsha Bai, E. B., & Sajeena, S. (2022). Assessment of salt water intrusion from Ponnani to Tavanur along the banks of River Bharathapuzha in Kerala. *Journal of the Indian Society of Coastal Agricultural Research*, *40*(2), 33–47. https://doi.org/10.54894/JISCAR.40.2.2022.128473

Heiss, J. W., Mase, B., & Shen, C. (2022). Effects of future increases in tidal flooding on salinity and groundwater dynamics in coastal aquifers. *Water Resources Research*, *58*, e2022WR033195. https://doi.org/10.1029/2022WR033195

Hunter, J. M., Maier, H. R., Gibbs, M. S., Foale, E. R., Grosvenor, N. A., Harders, N. P., & Kikuchi-Miller, T. C. (2018). Framework for developing hybrid process-driven, artificial neural network and regression models for salinity prediction in river systems. *Hydrology and Earth System Sciences*, *22*(5), 2987–3006. https://doi.org/10.5194/hess-22-2987-2018

Kaushal, S. S., Likens, G. E., Pace, M. L., Reimer, J. E., Maas, C. M., Galella, J. G., Utz, R. M., Duan, S., Kryger, J. R., Yaculak, A. M., Boger, W. L., Bailey, N. W., Haq, S., Wood, K. L., Wessel, B. M., Park, C. E., Collison, D. C., Aisin, B. Y. I., Gedeon, T. M., … Woglo, S. A. (2021). Freshwater salinisation syndrome: From emerging global problem to managing risks. *Biogeochemistry*, *154*, 255-292. https://doi.org/10.1007/s10533-021-00784-w

Kencanawati, M., Anwar, N., & Maulana, M. A. (2021). Modification of basic hydrology formulation based on an approach of the rational method at field measurement. *IOP Conference Series: Earth and Environmental Science*, *930*(1), 012051. https://doi.org/10.1088/1755-1315/930/1/012051

Kolathayar, S., Sitharam, T. G., & Yang, S. (2019). Coastal reservoir strategy to enhance India's freshwater storage by impounding river flood waters: A detailed overview. *Water Science and Technology: Water Supply*, *19*(3), 703–717. https://doi.org/10.2166/ws.2018.140

Lee, G., Park, J., Jung, C., & An, Y. (2024). Assessing salinity reduction by environmental restoration in the Seomjin River estuary (South Korea): A numerical model approach for *Corbicula* habitat conservation. *Sustainability*, *16*(13), 5653. https://doi.org/10.3390/su16135653

Lee, H. L., Tangang, F., Hamid, M. R., Benson, Y., & Razali, M. R. (2016). Modeling the influence of river flow and salt water intrusion in the Terengganu estuary, Malaysia. *IOP Conference Series: Materials Science and Engineering*, *136*(1), 012076. https://doi.org/10.1088/1757-899X/136/1/012076

Li, Y., & Liu, J. (2020). Salt intrusion and its controls in the macro-tidal Oujiang River estuary, China. *Ocean Dynamics*, *70*(11), 1409–1420. https://doi.org/10.1007/s10236-020-01405-0

Lucas, L. V., & Deleersnijder, E. (2020). Timescale methods for simplifying, understanding and modeling biophysical and water quality processes in coastal aquatic ecosystems: A review. *Water*, *12*(10), 2717. https://doi.org/10.3390/w12102717

Major, V. J., Jethani, N., & Aphinyanaphongs, Y. (2020). Estimating real-world performance of a predictive model: A case study in predicting mortality. *JAMIA Open*, *3*(2), 243–251. https://doi.org/10.1093/jamiaopen/ooaa008

Mazelan, N. A., & Suhaila, J. (2023). Exploring rainfall variabilities using statistical functional data analysis. *IOP Conference Series: Earth and Environmental Science*, *1167*(1), 012007. https://doi.org/10.1088/1755-1315/1167/1/012007

Melesse, A. M., Khosravi, K., Tiefenbacher, J. P., Heddam, S., Kim, S., Mosavi, A., & Pham, B. T. (2020). River water salinity prediction using hybrid machine learning models. *Water*, *12*(10), 2951. https://doi.org/10.3390/w12102951

Moore, W. S., & Joye, S. B. (2021). Saltwater intrusion and submarine groundwater discharge: Acceleration of biogeochemical reactions in changing coastal aquifers. *Frontiers in Earth Science*, *9*, 600710. https://doi.org/10.3389/feart.2021.600710

Olson, J. R. (2019). Predicting combined effects of land use and climate change on river and stream salinity. *Philosophical Transactions of the Royal Society B: Biological Sciences*, *374*(1764), 20180005. https://doi.org/10.1098/rstb.2018.0005

Pereira, H., Sousa, M. C., Vieira, L. R., Morgado, R., & Dias, J. M. (2022). Modelling salt intrusion and estuarine plumes under climate change scenarios in two transitional ecosystems from the NW Atlantic coast. *Journal of Marine Science and Engineering*, *10*(2), 262. https://doi.org/10.3390/jmse10020262

Raschka, S. (2018). *Model evaluation, model selection, and algorithm selection in machine learning*. arXiv preprint. https://doi.org/10.48550/arXiv.1811.12808

Salman, H. H., & Jazaa, H. S. (2023). Shatt Al-Arab River and the seawater intrusion: Causes and solutions. *Al-Bahir*, *2*(1), 6. https://doi.org/10.55810/2313-0083.1018.

Siemens, R. W. (2021). *Efficient modelling of ecomorphology in estuaries to evaluate salt-intrusion solutions: Literature report*.

Srinivasan, M., & Tsontos, V. (2023). Satellite altimetry for ocean and coastal applications: A review. *Remote Sensing*, *15*(16), 3939. https://doi.org/10.3390/rs15163939

Sriratana, L., & Bisalyaputra, K. (2019). Reconnaissance study on saltwater intrusion control at main raw water pumping station of Metropolitan Waterworks Authority (Thailand). *International Journal of Engineering & Technology*, *11*, 33–38. https://doi.org/10.7763/IJET.2019.V11.1119

Syazuani, M. S., Edlic, S., Mohd Sofiyan, S., & Jamilah, M. S. (2022). Preventing saltwater intrusion in the coastal of Terengganu: Can BRIS soil system help? *IOP Conference Series: Earth and Environmental Science*, *1019*(1), 012008. https://doi.org/10.1088/1755-1315/1019/1/012008

Tang, K. H. D. (2019). Climate change in Malaysia: Trends, contributors, impacts, mitigation, and adaptations. *Science of the Total Environment*, *650*, 1858–1871. https://doi.org/10.1016/j.scitotenv.2018.09.316

Thorslund, J., Bierkens, M. F. P., Essink, G. H. P. O., Sutunudjaja, E. H., & van Vliet, M. T. H. (2021). Common irrigation drivers of freshwater salinisation in river basins worldwide. *Nature Communications*, *12*, 4232. https://doi.org/10.1038/s41467-021-24281-8

Tomkratoke, S., Kongkulsiri, S., Narenpitak, P., & Sirisup, S. (2025). *Drought and salinity intrusion in the lower Chao Phraya River: Variability analysis and modeling mitigation approaches*. EGUsphere. https://doi.org/10.5194/egusphere-2024-4052

Yi, T. J., Mahmud, M. R., Reba, M. N. M., Hashim, M., Norman, M., & Jaafar, W. S. W. M. (2021). Forecasting the near future of rainfall in humid tropics using high-resolution satellite precipitation data. *Physics and Chemistry of the Earth*, *124*, 103069.

Yirga, H., Urge, M., Goetsch, A. L., Tolera, A., Puchala, R., & Patra, A. K. (2024). Effects of salinity levels of drinking water on water intake and loss, feed utilization, body weight, thermoregulatory traits, and blood constituents in growing and mature Blackhead Ogaden sheep and Somali goats. *Animals*, *14*(11), 1565. https://doi.org/10.3390/ani14111565

Zhang, B., Zheng, T., Zheng, X., Jiang, S., Cao, M., Walther, M., & Lu, C. (2023). Dynamics of upstream saltwater intrusion driven by tidal river in coastal aquifers. *Science of the Total Environment*, *877*, 162857. https://doi.org/10.1016/j.scitotenv.2023.162857