A REMOTE SENSING AND GIS APPROACH FOR MONITORING LIVELIHOOD ADAPTATION WITH CHANGE OF SOIL SALINITY IN POLDER 21 AND 22 OF SOUTHWEST BANGLADESH

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ABSTRACT

Climate change and its impact have become major concerns for ecologically fragile nations, with Bangladesh being particularly vulnerable. The country frequently faces natural disasters, leading to loss of life, infrastructure damage, and adverse livelihood effects. This is especially true for impoverished communities residing in remote and environmentally delicate areas such as river islands and cyclone-prone coastal belts. Adaptation becomes imperative to cope with climate change, although it can sometimes become a predicament. Shrimp culture was once hailed as a promising adaptation technique in the saline-prone coastal areas of Bangladesh, but it has now become a regional social and political issue blamed for land degradation. Precise monitoring is indispensable when it comes to effective adaptation or diversion strategies. This research focuses on assessing the changes in soil salinity resulting from livelihood adaptation, specifically involving shrimp culture, agriculture, and their combination. Through the utilisation of remote sensing and GIS techniques, the study examines Polder 21 and Polder 22 in southwest Bangladesh. The investigation reveals that shrimp monoculture in Polder 21 contributed to increased soil salinity, with a mean electrical conductivity (EC_e) of 14.1 dS/m in 2013, compared to the agriculture-dominant region of Polder 22, which had a lower mean EC_e of 9.2 dS/m. In 2016, a significant amount of precipitation (3161 mm) led to a slight reduction in mean EC_e to 13.5 dS/m in Polder 21. However, the relatively small change can be attributed to the prolonged exposure of Polder 21 to saline water from February to July. Conversely, Polder 22 experienced an increase in mean EC_e (10.6 dS/m) due to the rising of the groundwater table. By 2019, the salinity levels in Polder 21 escalated to 18.3 dS/m, while Polder 22 recorded 10.4 dS/m. These variations can be attributed to the continued shrimp monoculture in Polder 21 and the implementation of the Blue Gold Program, which involved the creation of freshwater reservoirs in Polder 22. However, both Polder 21 and Polder 22 witnessed a decrease in soil salinity by the year 2022. The adoption of the Shrimp-Aman crop pattern contributed to reduced soil salinity in Polder 21 (12.1 dS/m), while watermelon cultivation, which requires lighter irrigation compared to other crops, was practised in Polder 22 (8.3 dS/m). Overall, this research highlights the importance of precise monitoring and sustainable adaptation strategies to address soil salinity issues and support livelihoods in climate change-affected coastal regions. The findings underscore the significance of considering adaptive measures in conjunction with accurate monitoring using remote sensing and GIS approaches to ensure effective and resilient livelihood adaptations in the face of climate change challenges.

Keywords: *Climate Change, Soil Salinity, Remote Sensing, Geographic Information System (GIS), Polder System.*

1. INTRODUCTION

Bangladesh is considered one of the most vulnerable countries in the world to the impacts of climate change due to its geographical location and geo-morphological conditions. The Climate Risk Index 2021 report ranks Bangladesh as the seventh most vulnerable country based on data from 2000 to 2019, revealing that the nation experienced 185 extreme weather events, resulting in the loss of 11,450 lives and economic losses worth $3.72 billion during that period (Eckstein, 2021).

Climate change and its unpredictability have emerged as significant concerns, particularly for the vulnerable coastal zones of countries like Bangladesh. Bangladesh has a land area of 147,570 square kilometres, with the coastal area accounting for 20% of the total. The coastal region extends 150 kilometres inland from the coast. Approximately 30% of Bangladesh's cultivable land is situated along its coasts and islands, encompassing an area of about 0.83 million hectares out of a total of 2.85 million hectares (Hossain & Salam, 2012).

The vulnerability of this region is further exacerbated by frequent natural disasters, resulting in loss of life, damage to infrastructure and economic assets, and negative impacts on lives and livelihoods. The government has implemented coastal infrastructures such as polders and polder-like structures to mitigate the vulnerability, which initially reduced flooding and improved agricultural productivity, as shown in Figure 1. However, these measures have also led to problems such as water logging, drainage congestion, and salinity intrusion over time (Nath et al., 2019).

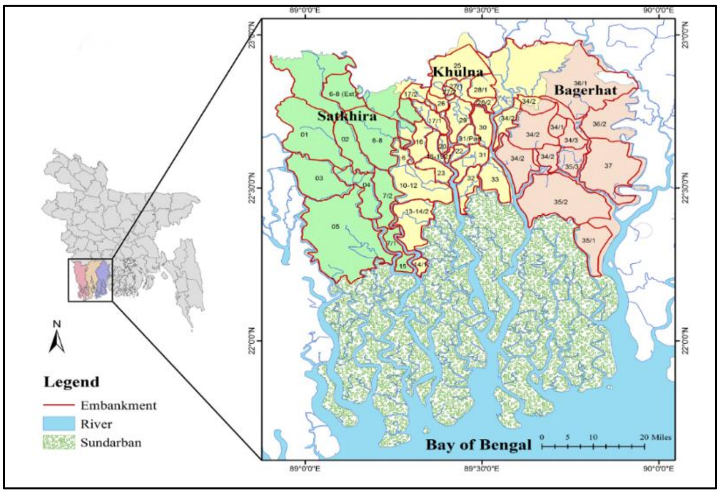

Figure 1: Coastal Polders of Southwest Regions

In response to these challenges, shrimp farming emerged as an effective and profitable adaptation strategy, encouraged by the Bangladesh Government and the World Bank. However, this shift from traditional agriculture-based livelihoods to aquaculture has increased poverty levels and the community's vulnerability. Shrimp farming has faced criticism from researchers due to its contribution to secondary soil salinity. Despite these concerns, a segment of the community engaged in shrimp farming is reluctant to abandon it, as it offers greater profitability compared to traditional agriculture (Nath et al., 2019).

In this critical situation, Bangladesh requires effective planning to address the challenges it faces. The country has implemented Adaptive Delta Management (ADM) as a long-term planning principle in the Bangladesh Delta Plan 2100 (BDP 2100), focusing on future uncertainties related to water conditions and climate change, and socio-economic development, including land use (Kulsum et al., 2021).

Monitoring plays a crucial role in planning and management. However, manual monitoring of soil salinity is a labour-intensive and expensive process. To overcome this challenge, remote sensing and Geographic Information Systems (GIS) can be utilised for soil salinity monitoring.

Therefore, this study aims to identify soil salinity using satellite imagery through remote sensing, analyse its correlation with salinity measurement, and predict soil salinity concerning land use and adaptive strategies. The objective of this research is to determine soil salinity levels and develop a regression model to establish the salinity index. This model can be used for predicting soil salinity changes using remote sensing and GIS.

The findings of this study have implications that individuals living along the coast, particularly those engaged in shrimp and crop farming, may find the results beneficial as they guide selecting the most suitable livelihood approaches. Additionally, this study is valuable for future research in the field of soil salinity detection using remote sensing and GIS.

However, there are certain limitations to this research. Firstly, due to accessibility constraints, the samples were primarily collected from areas where transportation was feasible, potentially leading to slight discrepancies between the analysed data and the entire research region. Secondly, the study was constrained by a lack of secondary data and high-quality, contemporaneous Landsat images.

2. METHODOLOGY

2.1 Geographic Location

The study focuses on two distinct polders, namely Polder 21 and Polder 22, due to the notable differences in the adaptation of livelihood strategies within these areas. Both polders are isolated islands located remotely. Polders 21 and 22 are situated in the Deluti Union, which falls within the Paikgachha Upazila of the Khulna district, shown in Figure 2. The geographical coordinates of the polders range from $22°34'34.3''N$ to $22°38'40''N$ for latitudes and $89°23'2.85''E$ to $89°28'2.20''E$ for longitudes.

Polder 21 is characterised by the extensive practice of shrimp farming, which has become ingrained in the local way of life. The embankments surrounding Polder 21 have experienced multiple breaches, resulting in the unimpeded ingress and egress of saltwater. Furthermore, the ineffectiveness of sluice gates exacerbates the intrusion of saline water into the polder.

In contrast, Polder 22 strictly prohibits saline-water farming activities. When shrimp aquaculture was introduced to the region in the 1990s, the residents of Polder 22 vehemently opposed it, leading to violent protests. Remarkably, despite numerous attempts spanning three decades, no single acre of land in Polder 22 is utilised for saline shrimp farming. The embankments of Polder 22 remain intact, preventing significant saline intrusion and minimising the impact on settlements compared to other polders in the region (Paprocki & Cons, 2014).

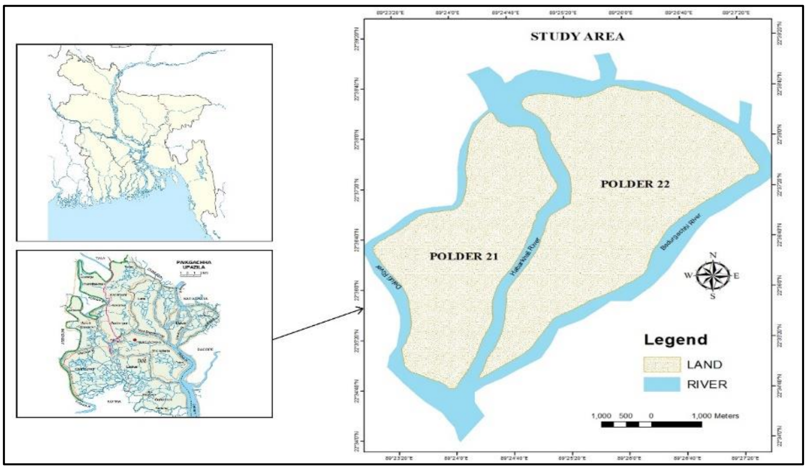

Figure 2: Location of Polder 21 and 22

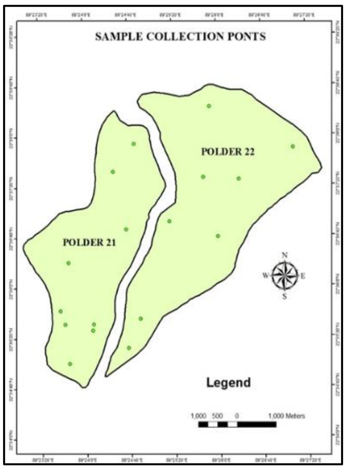

Figure 3: Soil Sample Collection Points

2.2 Climate

The study area experiences a moderate climate characterised by distinct seasonal variations. The mean maximum temperature ranges from $19.3°C$ to $30.4°C$ throughout the year, with the highest temperatures typically recorded in May. Conversely, the minimum temperature exhibits significant fluctuations, varying between $15.37°C$ and $25.2°C$. The lowest temperatures are commonly observed in January (CEGIS, 2015). For this research, rainfall data from the Paikgachha station for the period spanning 2013 to 2022 are taken into consideration. Figure 4 illustrates the annual variation in rainfall observed at Paikgachha during this period.

2.3 Groundwater Condition

Monthly fluctuations in groundwater levels from 1990 to 2010 have been plotted in Figure 5 using data from two observation wells: KHU002, located 4.5 km east of the polder in Dacope, and KHU005, situated 15 km upstream of the polder in Dumuria. The groundwater table (GWT) variation pattern for KHU002 indicates the lowest levels during April and the highest levels in September. On the other hand, KHU005 exhibits consistently low GWT values, with the lowest and highest values occurring in April and December, respectively. The lower GWT values in KHU005 can be attributed to its upstream location, where groundwater abstraction activities take place. In coastal areas downstream, groundwater recharge is expected (CEGIS, 2015).

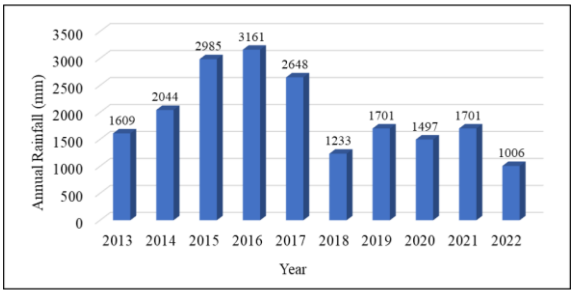

Figure 4: Annual Rainfall at Deluti Union from 2013 to 2022

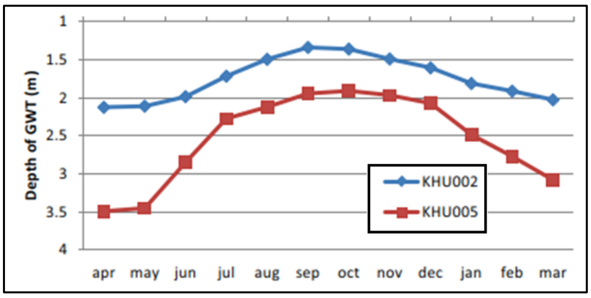

Figure 5: Average Monthly Variations of Ground Water Table

2.4 Site Investigation and Soil Sample Collection

A comprehensive field visit was conducted in Polders 21 and 22 to facilitate the collection of soil samples. The soil sampling took place on February 2, 2023, in Polder 21 and on February 11, 2023 in Polder 22. Although the sampling locations were slightly adjusted for convenient access, diligent efforts were made to ensure representativeness. Multiple soil samples, each of about 500 grams, were collected from 9 to 10 random locations within each polder (Figure 3), with a sampling depth of 0 to 30 cm. These individual samples were then combined to form composite samples for subsequent analysis.

2.5 Landsat Data Collection

A thorough acquisition of Landsat satellite images was performed using the USGS Earth Explorer website (https://www.usgs.gov/). The selected dataset covered a span of 10 years, ranging from 2013 to 2022. Landsat 8 (OLI) satellite images from Collection 2 Level 2 were obtained on February 3, 2023, and February 10, 2023, to assess the soil salinity status. A Landsat 8 image, captured on May 8, 2014, was used for validation purposes. Additionally, Landsat 8 images acquired in 2013, 2016, 2019, and 2022 were procured to predict soil salinity, as shown in Table 1. The spatial resolution of the individual bands within the Landsat images was 30 m.

During the image selection process, careful consideration was given to the maximum allowable cloud cover threshold set at 2%. Images that exhibited significant cloud coverage over the study area or possessed inadequate georeferencing were excluded from the dataset to ensure the reliability and accuracy of the analysis.

Table 1: Details of Collected Landsat Images

Extracted Date	Image Code	Use
February 10, 2023	LC08_L2SP_138044_20230210_20230217_02_T1	Model generation
February 3, 2023	LC08_L2SP_137044_20230203_20230209_02_T1	Model generation
December 24, 2022	LC08_L2SP_138044_20221224_20230103_02_T1	Prediction
December 25, 2019	LC08_L2SP_137045_20191225_20200825_02_T1	Prediction
December 23, 2016	LC08_L2SP_138044_20161223_20200905_02_T1	Prediction
May 8, 2014	LC08_L2SP_138044_20140508_20200911_02_T1	Validation
December 24, 2013	LC08_L2SP_137044_20131224_20200912_02_T1	Prediction

2.6 Soil Salinity Test

To measure the electrical conductivity (EC_e) of the soil, a 200-gram soil sample was taken and placed in a container. Distilled water was added to the sample and stirred using a spatula. The soil-water mixture was periodically consolidated by tapping the moisture box on the working table. This process continued until a saturated soil paste was obtained, characterised by a glistening appearance when reflecting light and a slight flow when the container was tipped. The sample was allowed to stand for one hour, and the criteria for saturation were rechecked. If the glistening disappeared after one hour, additional distilled water was added to prepare a saturated paste. The sample was then filtered to obtain a clear filtrate, and the extraction was stopped when air started to pass through the soil. The EC_e of the soil sample was measured by inserting an EC meter into the filtrate (Huq & Alam, 2005).

2.7 Salinity Index Calculation

Image processing and raster calculations were performed using ArcGIS 10.8 software (ESRI, Redlands, California, USA). The raster calculator functionality was utilised to calculate the Normalised Differential Salinity Index (NDSI) as part of the salinity index calculation process. The NDSI is a formula used for quantification and comparison of salinity levels in different areas based on the differences in spectral reflectance between the red and near-infrared regions (Aldakheel et al., 2005). The formula for NDSI is as follows:

$$NDSI = \frac{R-NIR}{R+NIR} \tag{1}$$

Table 2: Electrical Conductivity of Soil Saturated Paste, EC_e and Respective NDSI for the Polders

Polder No.	Serial No.	Latitude	Longitude	Electric Conductivity, $EC_e(dS/m)$	NDSI
Polder 21	1	22°35'58"N	89°24'08"E	33.7	-0.0286
	2	22°35'00"N	89°23'45"E	24.8	-0.0400
	3	22°35'31"N	89°23'41"E	18.4	-0.0768
	4	22°37'32"N	89°24'26"E	28.3	-0.0082
	5	22°35'31"N	89°24'07"E	20.0	-0.0596
	6	22°36'20"N	89°23'45"E	22.0	-0.0912
	7	22°35'42"N	89°23'37"E	24.8	-0.0411
	8	22°35'26"N	89°24'06"E	17.2	-0.0643
Polder 22	1	22°35'26"N	89°24'06"E	8.4	-0.1308
	2	22°37'25"N	89°26'19"E	9.2	-0.1237
	3	22°35'35"N	89°24'49"E	10.3	-0.1146
	4	22°36'52"N	89°25'16"E	10.3	-0.1043
	5	22°35'12"N	89°24'38"E	12.0	-0.0539
	6	22°35'05"N	89°24'35"E	9.7	-0.1145
	7	22°37'50"N	89°27'08"E	11.7	-0.1285
	8	22°38'23"N	89°25'53"E	10.2	-0.1031

In this equation, R represents the spectral reflectance measurements acquired in the visible red regions, and NIR represents the spectral reflectance measurements obtained in the near-infrared regions.

Table 2 shows the Electrical Conductivity of the soil sample (EC_e) and coordinates of their collection point with calculated respective Normalised Differential Salinity Index (NDSI) for Polders 21 and 22.

2.8 Regression Model Generation

To develop a regression equation that best represents the Electrical Conductivity of the Saturation Paste Extract of Soil (EC_e) and the soil salinity, Ordinary Least Squares (OLS) regression models were employed, as shown in Figure 6. The OLS regression analysis was conducted to establish the relationship between the variables and generate a predictive equation as follows:

$$EC_e = 32.127e^{8.8251 \times NDSI} \tag{2}$$

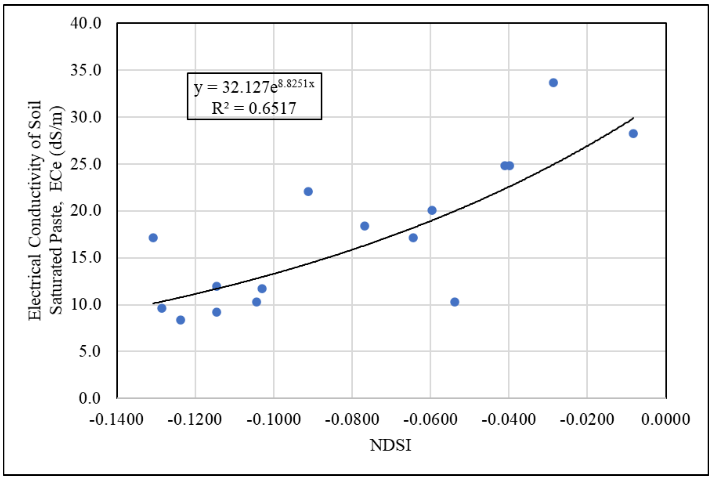

Figure 6: Regression Model to find Electrical Conductivity of the Saturation Paste Extract of Soil (EC_e)

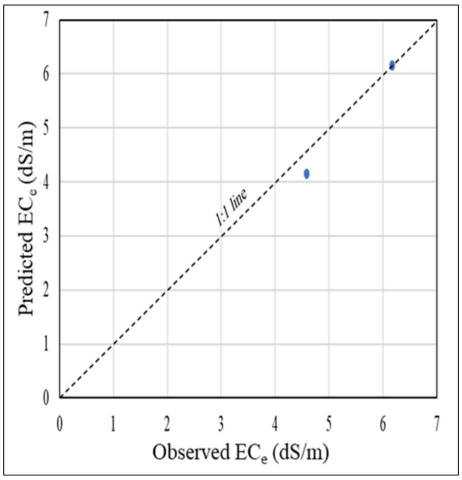

Figure 7: Predicted EC_e vs Observed EC_e

2.9 Model Validation

Since salinity is a slow-changing soil property and limited data were available within the timeframe of the study, data provided in the Environmental Impact Assessment (EIA) report on the Rehabilitation of Polder 22 under the BLUE GOLD PROGRAM, were utilised for model validation, as shown in Table 3. These data are expected to provide relevant information for assessing the performance of the regression model.

Two metrics were calculated to validate the generated regression model: average error and Nash-Sutcliffe Efficiency (NSE). The NSE is a widely used performance measure that assesses the relative magnitude of the predicted data variance compared to the measured data variance. It has been recommended as a performance measure by ASCE (1993) and Legates and McCabe (1999). The NSE is calculated using the formula:

$$NSE = 1 - \left[\frac{\sum_{i=1}^{n}(Z_i^{obs} - Z_i^{*})^2}{\sum_{i=1}^{n}(Z_i^{obs} - Z)^2}\right] \tag{3}$$

Where, Z_i^{obs} represents the i^{th} observation for the constituent being evaluated, Z_i^{*} is the i^{th} predicted value for the constituent, Z is the mean of the observed data for the constituent, and n is the total number of observations.

The NSE values range between $-\infty$ and 1, with an NSE of 1 indicating optimal model performance. Values between 0 and 1 are generally considered acceptable, while values less than 0 suggest that the mean observed value is a better predictor than the simulated value, indicating unacceptable performance (Garcia & Eldeiry, 2020). The value of Nash-Sutcliffe Efficiency (NSE) for the model was found to be

0.85, as in Figure 7, indicating that the model's performance is acceptable for prediction. This value falls closer to 1, indicating a better match between the predicted and observed data.

Table 3: Error Calculation of Soil Salinity Data

Location	Latitude	Longitude	Observed $EC_e(dS/m)$	Remarks	Predicted $EC_e(dS/m)$	Errors (%)	Average Error (%)
Noaibeel	22°35'33"N	89°24'50"E	6.17	-	6.15	0.32%	4.83%
Hatbaria	22°38'09"N	89°26'17"E	4.58	-	4.152	9.34%	
Telikhali	22°39'32"N	89°36'07"E	5.50	Improper Ordinates	-	-	

3. RESULTS AND DISCUSSIONS

3.1 General

The soil salinity assessment in Polders 21 and 22 was conducted using remote sensing and GIS techniques. This section focuses on the predicted soil salinity and the spatial distribution of salt-affected soil, as well as the interpretation of soil data concerning changes and their underlying causes.

A regression model and satellite images from 2013, 2016, 2019, and 2022 were employed to classify the study area based on soil salinity. Table 5 provides an overview of the distribution of soil salinity levels in Polder 21 and Polder 22 during the mentioned years.

Table 4: Soil Salinity Condition of Polder 21 and 22 for Years 2013, 2016, 2019 and 2022

Year	Polder	Mean Soil Salinity, EC_e (dS/m)	Soil Salinity Class						
			Area Measure	Very Slightly Saline	Slightly Saline	Moderate	Strongly Saline	Very Strongly Saline	Total
2013	Polder 21	14.1	Area (Ha)	7.8	341.9	308.7	136.5	354.9	**1149.8**
			%	0.7	29.7	26.8	11.9	30.9	**100.0**
	Polder 22	9.2	Area (Ha)	55.2	444.6	972.3	116.7	48.0	**1636.8**
			%	3.4	27.2	59.4	7.1	2.9	**100.0**
2016	Polder 21	13.5	Area (Ha)	0.2	211.7	428.2	206.6	300.4	**1147.1**
			%	0.0	18.5	37.3	18.0	26.2	**100.0**
	Polder 22	10.6	Area (Ha)	1.2	314.9	970.7	250.6	95.6	**1633.0**
			%	0.1	19.3	59.4	15.3	5.9	**100.0**
2019	Polder 21	18.3	Area (Ha)	0.1	44.4	239.9	362.7	502.8	**1149.9**
			%	0.0	3.9	20.9	31.5	43.7	**100.0**
	Polder 22	10.4	Area (Ha)	43.3	344.4	846.5	317.3	85.1	**1636.6**
			%	2.6	21.0	51.7	19.4	5.2	**100.0**
2022	Polder 21	12.1	Area (Ha)	87.0	475.8	249.3	106.1	228.8	**1147.0**
			%	7.6	41.5	21.7	9.3	19.9	**100.0**
	Polder 22	8.3	Area (Ha)	89.4	820.4	563.0	78.7	81.6	**1633.1**
			%	5.5	50.2	34.5	4.8	5.0	**100.0**

Figure 8 depicts a comparison of the areas affected by soil salinity in Polder 21 and Polder 22 across the years 2013, 2016, 2019, and 2022. Furthermore, Figure 9 illustrates a comparison of the mean soil salinity in Polder 21 and Polder 22 for the same periods.

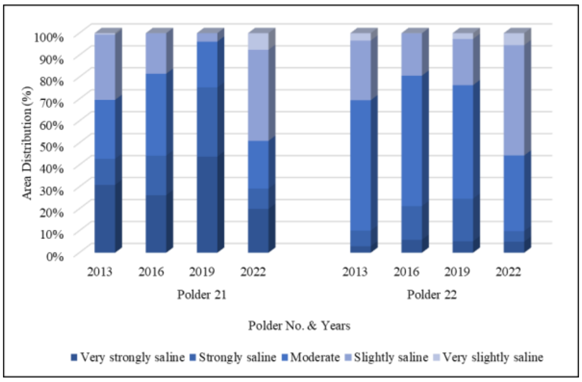

Figure 8: Comparison of Soil Salinity Affected Areas of Polder 21 & 22 in Different Years

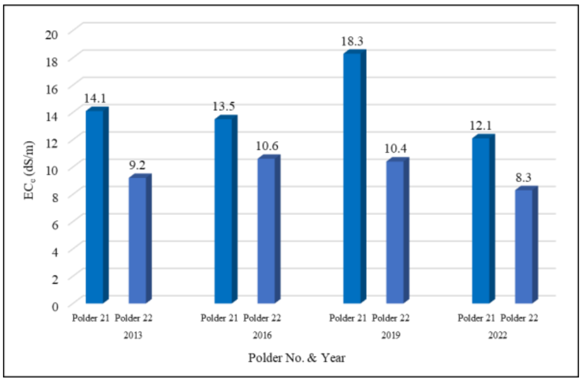

Figure 9: Comparison of Mean Soil Salinity of Polder 21 & 22 in Different Years

Subsequently, the regression model was utilised to determine the soil salinity levels for Polders 21 and 22 using satellite images from 2013, 2016, 2019, and 2022. Based on the resulting data, salinity maps were generated, shown in Figures 10 to 17.

3.2 Soil Salinity Condition In 2013

Table 4 illustrates the distribution of soil salinity levels in Polder 21 and Polder 22 in the year 2013. The findings reveal that a significant portion of Polder 21, covering 354.9 hectares (30.9%), exhibited a very strong salinity level. Moreover, 136.5 hectares (11.9%) were classified as strongly saline, 308.7 hectares (26.8%) as moderately saline, 341.9 hectares (29.7%) as slightly saline, and a small area of 7.8 hectares (0.7%) showed very slight salinity. The mean electrical conductivity in Polder 21 was recorded at 14.1 dS/m. Conversely, the distribution of soil salinity levels in Polder 22, as shown in the table, indicates that only 48.0 hectares (2.9%) of the land exhibited a very strong salinity level. The percentages of strongly, moderately, slightly, and very slightly saline soil in Polder 22 were 116.7 hectares (7.1%), 972.3 hectares (59.4%), 444.6 hectares (27.2%), and 55.2 hectares (3.4%), respectively. The mean electrical conductivity in Polder 22 was determined to be 9.2 dS/m.

For visual comparison, Figures 10 and 11 present an overview of the areas affected by soil salinity in Polder 21 and Polder 22 in 2013. Shrimp monoculture emerges as the primary driver behind the elevated soil salinity levels in the region. The intrusion of salinity resulting from shrimp farming activities significantly contributes to the escalation of soil salinity levels.

3.3 Soil Salinity Condition In 2016

According to Table 4, the distribution of saline areas in Polder 21 consisted of 300.4 hectares (26.2%) as very strongly saline, 206.6 hectares (18.0%) as strongly saline, 428.2 hectares (37.3%) as moderately saline, 211.7 hectares (18.5%) as slightly saline, and 0.12 hectares (0.0%) as very slightly saline. The mean electrical conductivity of Polder 21 was measured at 13.5 dS/m. In the case of Polder 22, the area classified as very strongly saline was 95.6 hectares (5.9%), strongly saline was 250.6 hectares (15.3%), moderately saline was 970.7 hectares (59.4%), slightly saline was 314.9 hectares (19.3%), and very slightly saline was 1.2 hectares (0.1%). The mean electrical conductivity of Polder 22 was recorded as 10.6 dS/m.

Figures 12 and 13 display a comparison of the areas affected by soil salinity in Polder 21 and Polder 22 in 2016. Surprisingly, the salinity effect had increased despite recording high rainfall during that year. The study areas, located only 75 kilometres away from the Bay of Bengal, are greatly influenced by tidal effects, which significantly impact the salinity of groundwater. However, the heavy rainfall resulted in a rise in the water table, and a shallow water table promotes the capillary action of saline water, consequently increasing soil salinity.

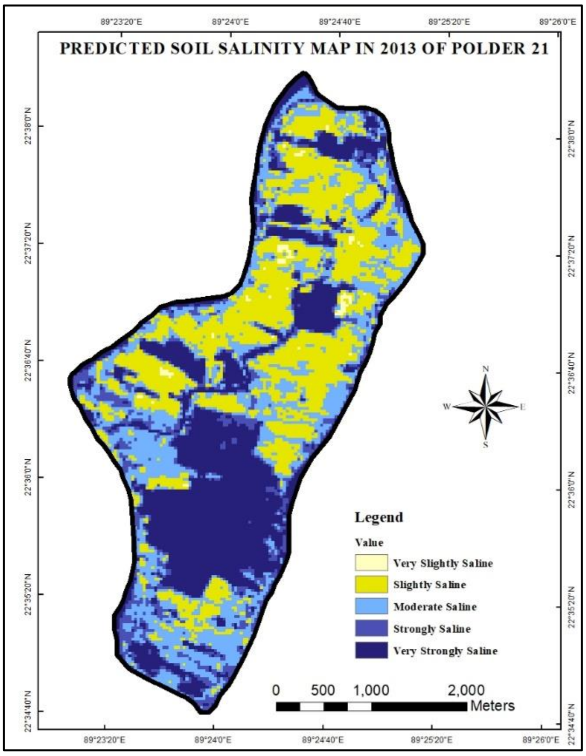

Figure 10: Spatial Distribution of Salt-affected Soil in 2013 of Polder 21

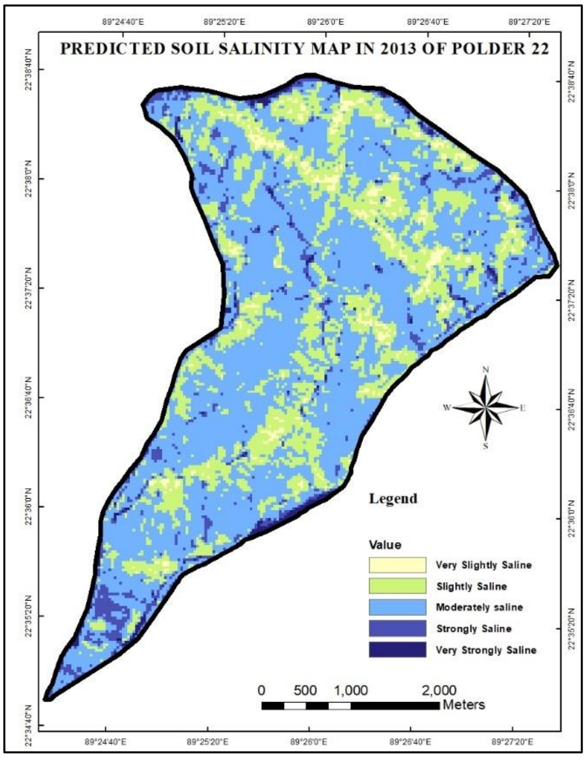

Figure 11: Spatial Distribution of Salt-Affected Soil in 2013 of Polder 22

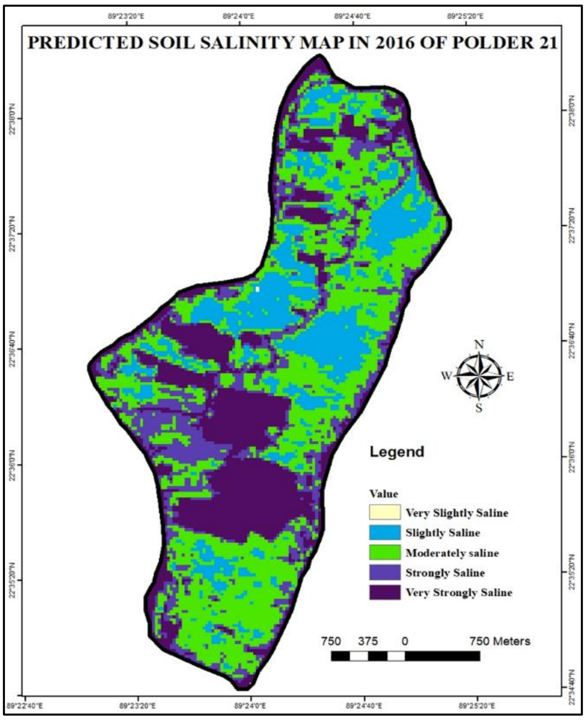

Figure 12: Spatial Distribution of Salt-affected Soil in 2016 of Polder 21

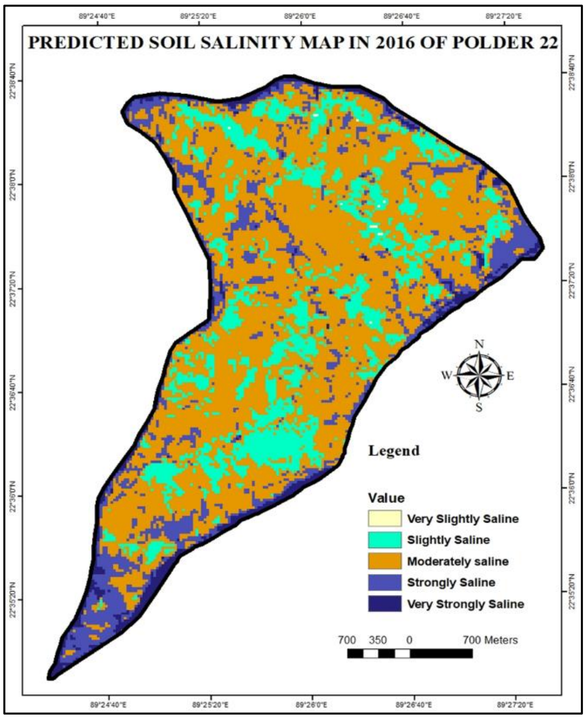

Figure 13: Spatial Distribution of Salt-affected Soil in 2016 of Polder 22.

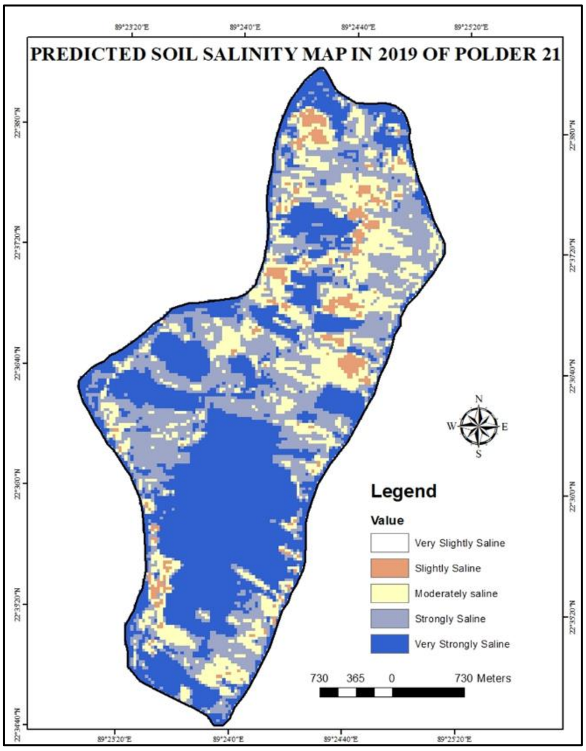

Figure 14: Spatial Distribution of Salt-affected Soil in 2019 of Polder 21

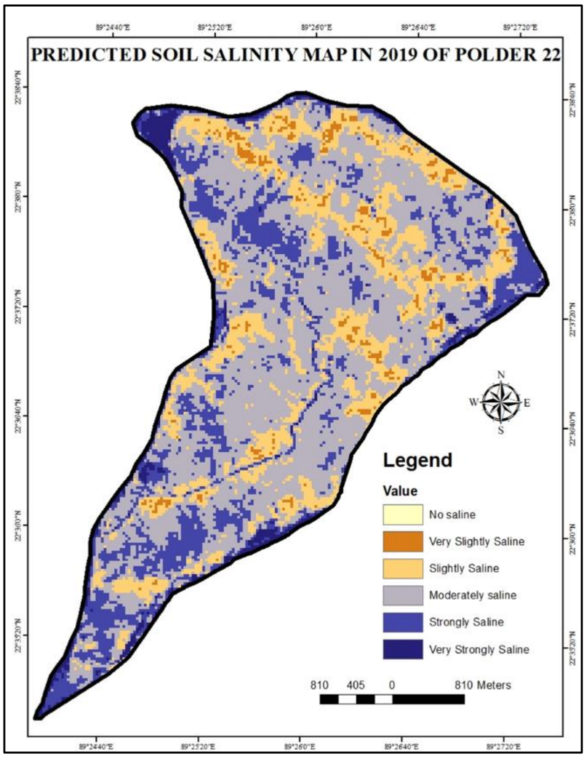

Figure 15: Spatial Distribution of Salt-affected Soil in 2019 of Polder 22

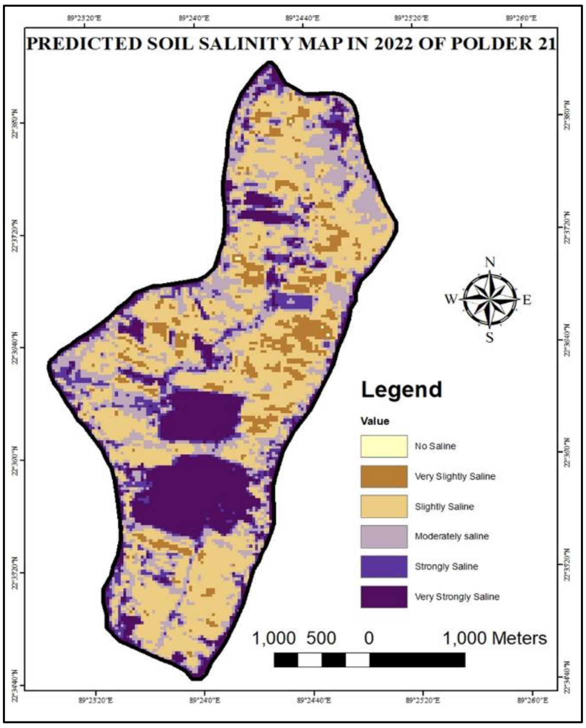

Figure 16: Spatial Distribution of Salt-affected Soil in 2022 of Polder 21

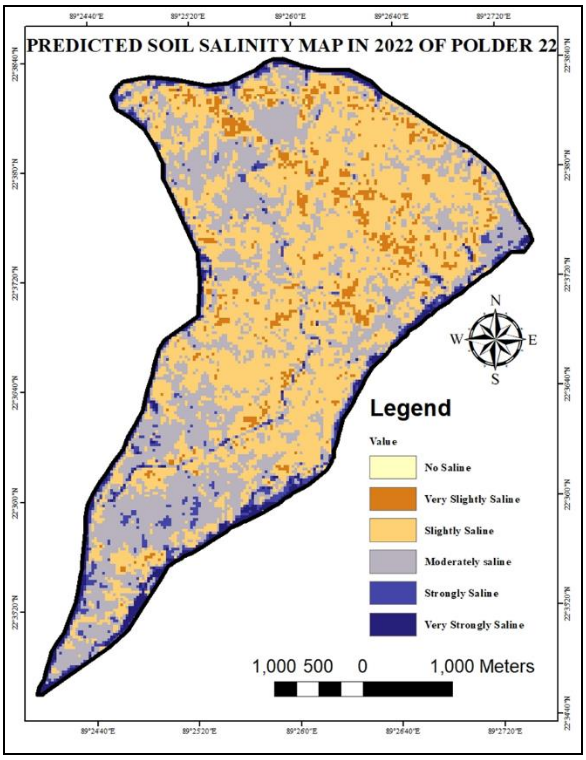

Figure 17: Spatial Distribution of Salt-affected Soil in 2022 of Polder 22

3.4 Soil Salinity Condition In 2019

In 2019, Table 4 reveals that Polder 21 experienced significant changes in the distribution of soil salinity levels. The area occupied by very strongly saline soil was 502.8 hectares (43.7%), followed by strongly saline soil covering 362.7 hectares (31.5%), moderately saline soil occupying 239.9 hectares (20.9%), and slightly saline soil covering 44.4 hectares (3.9%). The mean electrical conductivity in Polder 21 was measured at 18.3 dS/m. Notably, despite heavy rainfall, the salt-affected area in Polder 21 witnessed a substantial increase compared to 2016. The persistent shrimp monoculture practices and low rainfall were identified as key factors contributing to this rise.

Conversely, according to the table, Polder 22 displayed a different trend in 2019. The area of very strongly saline soil was 85.1 hectares (5.2%), strongly saline soil covered 317.3 hectares (19.4%), moderately saline soil occupied 846.5 hectares (51.7%), slightly saline soil encompassed 344.4 hectares (21.0%), and very slightly saline soil accounted for 43.3 hectares (2.6%). The mean electrical conductivity in Polder 22 was recorded as 10.4 dS/m. Notably, Polder 22 experienced a reduction in soil salinity attributed to the implementation of the Blue Gold Program. This program focused on water resource management and included initiatives such as the excavation of Khal, which replenishes freshwater during the dry season. As a result, the dependency on saline groundwater was minimised, leading to a decrease in soil salinity in Polder 22.

3.5 Soil Salinity Condition In 2022

Table 4 also provides an overview of the distribution of soil salinity levels in Polder 21 for the year 2022. The results indicate that the area covered by very strongly saline soil was 228.8 hectares (19.9%), strongly saline soil occupied 106.1 hectares (9.3%), moderately saline soil covered 249.3 hectares (21.7%), slightly saline soil encompassed 475.8 hectares (41.5%), and very slightly saline soil accounted for 87.0 hectares (7.6%). The mean electrical conductivity in Polder 21 was recorded as 12.1 dS/m. Similarly, the table displays the distribution of soil salinity levels in Polder 22. In 2022, the area covered by very strongly saline soil was 81.6 hectares (5.0%), strongly saline soil occupied 78.7 hectares (4.8%), moderately saline soil covered 563.0 hectares (34.5%), slightly saline soil encompassed 820.4 hectares (50.2%), and very slightly saline soil accounted for 89.04 hectares (5.5%). The mean electrical conductivity in Polder 22 was determined to be 8.3 dS/m.

It is evident that in 2022, there was a decrease in soil salinity levels in both Polder 21 and Polder 22. This reduction in Polder 21 can be attributed to a shift from shrimp monoculture to shrimp-Aman rice cultivation. In recent years, the Bangladesh Government has prioritised rice cultivation under the Rise Intensification program to ensure food security. In Polder 22, soil salinity also decreased. In addition to the Blue Gold program, the cultivation of watermelon during the dry season played a significant role as it requires low irrigation.

4. CONCLUSIONS

Based on the study's findings, several conclusions can be drawn.

- The primary objective of this study was to determine the level of soil salinity and to generate a regression model correlating with the salinity index. To achieve this, the electrical conductivity of the soil samples was first determined, followed by the development of a non-linear regression model that correlated with the salinity index.

- The second objective was to predict soil salinity changes using remote sensing and GIS. The developed regression model was utilised to predict the soil salinity levels. In the case of polder 21, the mean electrical conductivity was 14.11 dS/m, 13.52 dS/m, 18.28 dS/m, and 12.08 dS/m in the years 2013, 2016, 2019, and 2022 respectively. On the other hand, in the case of polder 22, the mean electrical conductivity was 9.23 dS/m, 10.64 dS/m, 10.42 dS/m, 8.33 dS/m in the years 2013, 2016, 2019, and 2022 respectively.

- The study revealed that shrimp culture significantly contributes to the increase in soil salinity levels. In addition, high precipitation in saline zones may also lead to an increase in soil salinity. The Blue Gold program has been found to be an effective measure in controlling soil salinity levels. Finally, the adoption of a new Shrimp-Aman crop pattern has been identified as a good adaptation measure that is more effective in controlling soil salinity levels than shrimp monoculture.

The findings of the study on the assessment of soil salinity change in polders 21 and 22 of southwest Bangladesh using remote sensing and GIS have led to some recommendations. It is highly recommended that similar studies be conducted that encompass a broader range of areas, including different polders in the coastal regions of Bangladesh with varying hydrological regimes. Relevant organisations and institutions need to establish and maintain a comprehensive database that includes yearly updates on soil salinity levels.

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