Temporal NDVI analysis to detect the effects of seawater intrusion on rice growth in coastal areas

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Abstract
As population size grows over time, staple food production also needs to keep up with increased annual demands. In Indonesia, the agricultural sector applies intensification and extensification to maximize rice productivity. However, farm extensification can instead decline productivity, should it sprawl into marginal lands like the study area that has been affected by sea-level rise impact, i.e., surface saltwater intrusion. Therefore, this study set out to differentiate paddies into segments affected and unaffected by salinity based on discernible variation in rice growth stages. These stages were determined using a vegetation index, NDVI (Normalized Difference Vegetation Index), calculated from time-series Sentinel-2 L2A+B image data from 2015 until 2020. The resulting temporal NDVI showed two cropping patterns year-round but with different planting times. In salinity-unaffected paddy segments, farmers began the inundation-transplanting stage in late March and ended the cropping season with fallow in August. Meanwhile, in salinity-affected segments, the cropping stages were the opposite: inundation in early April and fallow in early September. The measurable impact of salinity was apparent at the vegetative-generative stage, where salinity-affected paddies had the highest NDVI of 0.64–0.65, whereas those unaffected had the highest NDVI of 0.7–0.75. These index values indicate an impaired rice growth rate due to salinity effects. Compared with the field-measured data, the NDVI showed 85% accuracy, with a Kappa coefficient of 0.87. Meanwhile, the NDVI-EC correlation test produced R-values of 63–85%. Overall, this research has confirmed that remote sensing image and technology can acquire variable data that explain salinity effects on coastal paddies.

Keywords: salinization, NDVI, crop growth, Sentinel-2, coastal

1. Introduction
Rice is the staple food of most Indonesian population. In 2018, there were up to 14.7 million hectares of paddies nationwide, producing around 78.8 million tons of rice. Paddies on Java, the most densely populated island in the country, comprise of 44.5% of the total paddies by area and supplies 49% of national rice production [1]. Most coastal regions provide a suitable environment for rice growth and have become the centers for production. However, there has been a downward trend in rice yields, especially along the northern coast of Java Island, where the influence of seawater intrusion is profound.
[2]. Saline water in irrigation channels delays rice planting [3], and soil salinization is an environmental stress factor that causes wilting and leads to poor growth.

Salinization, or sea salt accumulation in soils, can occur naturally or from human activities. Excess salt can come from marine sediments, which naturally have high salinity, or seawater invading river channels during low flows. It is often the result of land clearing, deforestation, erosion, unorganized irrigation systems, and groundwater overdraft in coastal zones, all of which can increase salt concentrations in the soil [4]. Salinity can affect plant growth depending on (1) plant resistance to salinity, (2) soil characteristics (especially soil texture), (3) salt content in groundwater, and (4) salt composition [5]. Agricultural land in coastal areas is irrigated all year round and is, therefore, at high risk of salinization. Distance to shoreline, topography, and irrigation network density determine salinity levels along the irrigation canals [3]. Temporal monitoring of soil and water salinity in coastal areas is necessary for immediately adopting measures to tolerate and reduce the adverse effects of excess salt levels. Salinity occurs when salt elements, such as chloride (Cl⁻), carbonate (CO₃²⁻), sodium (Na⁺), calcium (Ca²⁺), and magnesium (Mg²⁺), are present in soil and water at high concentrations. It is often measured using electrical conductivity (EC) and expressed as dS/cm. EC is obtained through field measurements, and because of many limitations associated with this data collection technique, paddy salinity maps are rare. Therefore, the use of technology like remote sensing is highly recommended for identifying temporal variation in salinization.

Remote sensing can capture information without direct contact with the observed object at varying spatial and temporal scales, and this substantially contributes to enabling regular salinization monitoring [6]. Plants under salinity stress suffer a water loss syntax, impairing their growth stage [7]. Therefore, vegetation responses, quantifiable by vegetation index, can show the temporal and spatial dynamics of salinity. The time-series vegetation index extracted from satellite imagery plays a crucial part in land cover monitoring and classification because it provides details on vegetation characteristics at various growth stages [8].

2. Previous work

The research location is Demak Regency, Central Java Province. It is a coastal region mainly utilized for rice farming, which has shown a rapid increase in area from 99,884 ha (in 2017) to 113,876 ha (in 2018) [8]. Prior scholars found seawater intrusion reaching more than four and seven km upward Demangan and Tuntang Lama Rivers, respectively, because of the flat coastal morphology formed by fluvial material deposition [9]. Consequently, the groundwater hydrogeochemical type is Na(K)HCO₃, showing an evolution from CaHCO₃ to MgCl₂ (brackish) and Na(K)Cl (brine) [10]. Inadequate irrigation channels, in terms of quality and quantity, can exacerbate the impact of natural salinization on food crop farmland. Normalized Difference Vegetation Index (NDVI), Soil-Adjusted Vegetation Index (SAVI), and Enhanced Vegetation Index (EVI) obtained from Landsat 8 OLI imagery confirmed that salinity had significant effects [11].

Currently, remote sensing technology has been developing rapidly, especially in providing free-access satellite image data. The launch of the Sentinel-2A (S2) makes collective mapping of paddies over a broad area possible as it has wide satellite coverage and high spatiotemporal resolution. S2 has a repeat cycle of five days with a relatively high spatial resolution, suitable for mapping crops at the field level and providing time-series data [12][13]. A cloud-based computing platform like www.sepal.io, designed by the Food and Agriculture Organization (FAO), is based on the Google Earth Engine and can access satellite imagery (Landsat and Sentinel-2), detect, and classify land cover changes. This technology can process S2 images to identify the impact of salinity on rice growth on a temporal basis.

3. Objectives

This study was intended to determine differences in rice growth stages as indications of salinity impacts. It used the vegetation index, NDVI, extracted from Sentinel-2 images spanning from 2015 to
2020 to identify and differentiate paddies into salinity-affected and unaffected segments. There were three aspects considered in this segmentation: distance to the irrigation channel, distance to the coastline, and land use type.

4. Materials and Methods

4.1. Study Area

Paddies are agricultural plots divided by bunds and sometimes irrigation channels and mostly planted with rice. Demak Regency is geographically located between 6°43’26” and 7°09’43”S and between 110°27’58” and 110°48’47”E, with elevations ranging from 0 to 6 masl (meters above sea level). Tides inundate areas lower than the mean sea level every year. Apart from the vast paddies (with technical and simple irrigations), the regency is also utilized for ponds, dry land, plantations, and settlements. Because of the monsoonal effects, its climate has two seasons: rainy (November–April) and dry (May–October), with annual rainfall in the range of 346–2944 mm/year.

4.2. Data Collection and Preparation

This study used Sentinel-2 level-2A and level-2B image data products obtained from https://sepal.io/ (a cloud-computing platform that can access Sentinel Hub Access online) from December 2015 to August 2020. These products have been geometrically and radiometrically-corrected and have TOA and BOA-corrected reflectance values. Satellite data processing and accuracy testing of the confusion matrix were processed on the https://sepal.io platform.

Tide data, obtained from http://tides.big.go.id/, and topographic data were used to determine the location of the training area. Supporting data for map visualization in the QGIS program were extracted from the base map, RBI-containing layers of administrative boundaries, rivers, land use types-and high-resolution imagery in vector data format (*.shp) accessible at https://portal.ina-sdi.or.id/.

4.3. Selection of The Training Area

Differences in rice plant growth, arising from salinity effects in the coastal area of Demak Regency, are necessary to identify to build ROI (Region of Interest) as the training area. For this reason, there were three aspects considered in the selection of training area: the conditions of river and irrigation channels [9], distance to coastline [3], and differences in land-use types. As a first step, this research used the RBI land use map and high-resolution satellite imagery (Google Earth) as references and Sentinel-2 images in false color formats to distinguish between areas that were always inundated and those that were not.

The next step was to determine paddies located within the coastal area by creating a 7-km buffer zone from the coastline according to the farthest reach of seawater intrusion identified in a previous study [9]. Two locations with highly contrasting conditions due to salinity were selected: (1) ponds that were influenced continuously by seawater and (2) paddies that were far from the coastline but within a coastal or riverine system.

4.4. Indirect Indicators

Vegetation Index (VI) is proven effective in monitoring vegetative biomass and vegetation health [14]. NDVI is an example of VI that has been successfully used for soil salinity mapping [15-17] and can reduce spectral disturbances caused by certain illumination conditions, topographic variations, or cloud shading [18]. NDVI ranges between +1 and -1, and it is defined as follows:

\[
NDVI = \frac{(NIR - RED)}{(NIR + RED)}
\]

where \(NIR\) is near-infrared-band reflectance and \(R\) is red-band reflectance.
Figure 1. The coastal area of Demak Regency (Source: Google Earth image and S2 LA captured on May 14, 2018, in 49MDN)

Rice plants grow in three stages [19]: vegetative, reproductive, and ripening. The vegetative stage starts with transplanting rice seedlings into paddies, tillering (seedlings begin to grow lateral shoots), and stem elongation (seedlings grow in height and develop leaves). The reproductive stage is characterized by the bulging of leaf stems that conceal panicles (‘booting’ stage), the full appearance of panicles (‘heading’), and flowering. The ripening stage can be subdivided into milky grain, dough grain, and maturity. However, detecting rice growth with this classification using the NDVI is challenging, if not undoable. Therefore, using the NDVI calculated from Sentinel-2 image data, [20] proposes different rice growth stage indicators (Table 1).

In the field, the growth stage appears as follows. (i) The transplanting stage involves moving seedlings from seedbeds to water-inundated paddies, which marks the early phase of rice plant growth. (ii) At the vegetative stage, paddies turn green as rice leaves start to thicken and cover the entire fields. (iii) The reproductive stage is marked by leaves turning into yellow rice grains. (iv) The fallow stage is where the land is left dormant or unplanted for a certain period.

4.5. Field Data Collection

The field survey was conducted in 2019, and the time of observation was adjusted to the rice growth stage and was approximately 3–7 days after the Sentinel-2 image recording date. A consumer quadcopter equipped with a built-in camera (20 mm lens, FOV 94°, CMOS 1/2.3” 12 M) was installed at 50 m above ground level (constant height) to take vertical photos and measure rice plant density in the field. Several photos were combined to produce vegetation density values in 100 m² and then analyzed with the image analysis program to determine the vegetation density.

Table 1. The NDVI value range for rice growth stage based on S2 image data products

| Rice growth stage     | NDVI value range | Planting period (days) |
|-----------------------|------------------|------------------------|
| Inundation+transplantation | < 0.174         | -                      |
| Vegetative            | 0.174–0.783      | 0–35                   |
| Reproductive          | 0.783–0.1929     | 35–100                 |
| Fallow                | 0.144–0.277      | > 100                  |

Source: [20]

Soil salinity was measured indirectly using a proxy, electrical conductivity (EC). Soil texture and moisture are two known factors of apparent electrical conductivity (ECa), i.e., EC values collected through actual measurements in the field. To get a standard saturated extract (ECf), the relationship between ECa and soil texture is by multiplying the factor coefficient from the correlation formula [21] describe bellow (2). Table 2 shows the salinity levels (ECa) based on soil texture and their equivalence to ECf. Soil samples were collected at a root depth of rice plants, about 0, 20 cm, and at the selected
sample location several measurements were taken to adjust the grid size of 10x10 m² according to the pixel resolution of S2 products.

$$EC_f = (5.26 \times EC_a) - 0.94$$ (2)

| Textures          | Low      | Moderate | High     | Very high |
|-------------------|----------|----------|----------|-----------|
| Clay sand         | 0.4      | 0.4-0.7  | 0.7-1.3  | >1.3      |
| Clay              | 0.4      | 0.7-1.1  | 1.1-1.9  | >1.9      |
| Clay - light clay | <1.0     | 1.0-1.5  | 1.5-2.5  | >2.5      |
| Medium - heavy clay | <1.25  | 1.25-1.9 | 1.9-3.0  | >3.0      |

Notes: Low is equivalent to \(EC_f < 2\) dS/m; Moderate is equivalent to \(2 \leq EC_f \leq 4\) dS/m; High is equivalent to \(4 \leq EC_f \leq 8\) dS/m; Very High is equivalent to \(EC_f > 8\) dS/m. Source: Rhoades et al (1989) [21]

5. Results and Discussion

5.1. Selected training area

Rice farmlands between the Tuntang Lama and Demangan Rivers were determined as the training areas. Only paddies with technical or simple irrigation systems were selected to estimate the effects of salinity or seawater intrusion into rivers and irrigation channels. As a comparison, ponds were used as a land-use type with high salinity. A 7-km buffer zone from the coastline was created to determine which paddies were located within the coastal areas; this process also assumed that the river profile located 7 km upstream still received the influence of seawater and high salinity [9], which is in line with the tidal fluctuation data in the period of 2015-2020 (Figure 2).

From 2015 until 2020, the tides fluctuated between -0.5 m (lowest) and 0.4 m (highest). High tides are most likely to submerge paddies located relatively lower than river channels. Based on the river profile, the water stage varied from 0 to 3.6 masl, while paddies were at 0.3-3.4 masl. There were three training areas (Figure 3): Krajanbogo (KR) represents rice fields inside the 7 km buffer zone, Turitempel (TU) is paddies located >13 km from the coastline and unaffected by salinity, and Gebang (GB) is a coastal pond area.

![Figure 2](http://tides.big.go.id/pasut/index.html)

**Figure 2.** Seawater tides along the coast of Demak Regency from 2015 until 2020 (Source: [Link](http://tides.big.go.id/pasut/index.html))

![Figure 3](http://s2.google.com/tile/truecolor/49MDN)

**Figure 3.** The training areas in the coastal area of Demak Regency: (a) Gebang (GB), (b) Krajanbogo (KR), and (c) Turitempel (TU) (Source: S2 LA, true color B321, recorded on May 14, 2018, in 49MDN)
5.2. Temporal NDVI patterns as indicators of rice growth stage

The training areas (GB, KR, TU) were set as ROI on the cloud-computing platform https://sepal.io. Furthermore, from the ROI delineation, the time-series NDVI analysis of Sentinel-2 images was carried out, from December 2015 to August 2020. During this period, there were 99 scenes of S2 level-2A and level-2B image data products. The NDVI algorithm was used to calculate the NDVI of not only rice plants but also other land-use types. Because the NDVI ranges between 0 and 1, the filtering process omitted outliers, i.e., NDVI ranging between -1 and 0. This process left only data with NDVI of 0–1, where 0 indicates water-inundated paddies, while 1 shows very high vegetation density.

The NDVI values at the three ROIs (Figure 5) showed three temporal patterns: cropping pattern, rice growth stage in salinity-unaffected paddies, and rice growth stage in salinity-affected paddies. The cropping pattern was planting rice twice a year, according to the cropping calendar. However, rice planting started differently depending on weather conditions and the distribution system of the irrigation water. In general, rice plants take about 120 days to complete the transplanting and vegetative stage (90 days) and the reproductive stage (30 days), not including the inundation period that can last two weeks. The first rice cropping pattern starts with the inundation/transplantation stage in mid to late February (NDVI=0.1), continues to the vegetative phase in March-May (NDVI= 0.1–0.75), and ends with the reproductive stage in May-June (NDVI= 0.6–0.4). Afterward, the second rice cropping pattern starts with the inundation/transplantation stage in November (NDVI < 0.1), continues with the vegetative phase until mid-January (NDVI= 0.2–0.6), and ends with the reproductive stage in February. In-between is a fallow period (October-November), where the paddies are not cultivated.

Multi-temporal NDVI graphs (Figure 4) show contrasting values between ponds (GB) and paddies (KR and TU). The NDVI of ponds fluctuated between 0 and a maximum of 0.2 (similar to the NDVI range of water bodies), while that of paddies varied between 0.1 and 0.75 (within the NDVI range of rice plants at the vegetative stage). The NDVI graph also presents indications of impaired rice plant growth due to salinization. Seawater intrusion into irrigation channels potentially occurs after the inundation stage. The NDVI of paddies in TU and KR showed the widest difference during the vegetative phase, indicating that seawater intrusion into river and irrigation channels has occurred, caused salinity stress, and led to impaired rice growth in KR (close to the ponds).

![Figure 4](https://sepal.io)

**Figure 4.** The Sentinel-2 NDVI values from December 2015 through August 2020, GB: Gebang, coastal ponds; KR: Krajanbogo, paddies close to the coastline; TU: Turitempel, paddies from the coastline
(Source: NDVI calculation of multitemporal Sentinel-2 level-2A and level-2B image data products)

5.3. NDVI segmentation using K-means clustering for each stage of rice growth

K-means clustering was used to classify the NDVI values, specifically in Krajanbogo (KR) and Turitempel (TU)—training areas selected to identify the effects of salinity on the rice growth stage in coastal paddies. Changes in the NDVI values were categorized into four stages of rice growth: (i) NDVI changes occurring between February and March 2019, indicating inundation to transplantation, (ii) NDVI changes between March and May 2020, transplantation to vegetative phase, (iii) NDVI changes in May-June 2020, the vegetative to reproductive stage, and (iv) NDVI changes in October-November 2020, indicating the fallow phase.
Changes in the NDVI values in Krajanbogo (KR) and Turitempel (TU) depict different stages of rice growth (Figures 5 and 6). Based on the phenomenon approach [22], the effects of salinity are most identifiable at the inundation-transplantation and reproductive-harvest stages. The inundation-transplantation process in Krajanbogo (Figure 5a) took a longer time than in Turitempel (Figure 6a), as evident from the area percentages in the 0.2–0.3 class (Table 3 and Table 4). Meanwhile, the vegetative to reproductive stages in both locations lasted for almost the same length of time. At the reproductive-harvest stage, the rice in Turitempel was harvested about a week faster (Figure 7c) than in Krajanbogo (Figure 6c). These results indicate that saline soils and water can lead to a longer growing time.

![Figure 5. K-means classification analysis results of NDVI values showing the rice growth stage in Krajanbogo (KR). Changes in NDVI (a) from February 23 until March 10, 2019, indicating inundation-transplantation stage, (b) from March 10 until May 4, 2019, transplantation-vegetative stage, (c) from May 4 until July 8, 2019, vegetative-reproductive stage, and (d) from October 5 until November 8, 2019, fallow stage.](image)

| Table 3 | The spatial distribution of rice growth stages using K-means clustering in Krajanbogo |
|---------|-------------------------------------------------------------------------------------|
| Class NDVI | Inundation-Transplantation Stage Feb–Mar ’19 | Transplantation-Vegetative Stage Mar–May ’19 | Reproductive-Harvest Stage May–Jul ’19 | Fallow Stage Oct–Nov ’19 |
| (K-means) | Area in km² | Area in km² | Area in km² | Area in km² |
| >0.5 | 0.3 (0.87%) | 9.24 (26.77%) | 5.4 (14.56%) | 0.3 (0.1%) |
| 0.4 - 0.5 | 11.11 (3.22%) | 7.09 (20.53%) | 4.13 (11.94%) | 0.99 (2.88%) |
| 0.3 - 0.4 | 13.65 (39.52%) | 10.34 (29.95%) | 8.99 (25.99%) | 31.87 (92.18%) |
| 0.2 - 0.3 | 14.45 (41.78%) | 3.89 (11.27%) | 9.05 (26.18%) | 1.65 (4.77%) |
| <0.2 | 5.05 (14.62%) | 3.97 (11.49%) | 7.37 (21.32%) | 0.3 (0.1%) |

| Table 4 | The spatial distribution of rice growth stages using K-means clustering in Turitempel |
|---------|-------------------------------------------------------------------------------------|
| Class NDVI | Inundation-Transplantation Stage Feb–Mar ’19 | Transplantation-Vegetative Stage Mar–May ’19 | Reproductive-Harvest Stage May–Jul ’19 | Fallow Stage Oct–Nov ’19 |
| (K-means) | Area in km² | Area in km² | Area in km² | Area in km² |
| >0.5 | 0.72 (0.87%) | 35.49 (42.91%) | 5.69 (6.88%) | 0.98 (1.2%) |
| 0.4 - 0.5 | 4.5 (5.44%) | 13.46 (16.28%) | 8.75 (10.58%) | 3.55 (4.3%) |
| 0.3 - 0.4 | 27.81 (33.61%) | 14.93 (18.04%) | 3.66 (4.42%) |
| 0.2 - 0.3 | 28.20 (46.18%) | 7.38 (8.92%) | 25.46 (30.78%) | 74.43 (89.97%) |
| <0.2 | 11.49 (13.89%) | 7.25 (3.3%) | 27.9 (33.72%) | 0.11 (0.13%) |
Figure 6. K-means classification analysis results of NDVI values showing different stages of rice growth in Turitempel (TU). Changes in NDVI (a) from February 23 until March 10, 2019, indicating the inundation-transplantation stage, (b) from March 10 until May 4, 2019, transplanting-vegetative stage, (c) from May 4 until July 8, 2019, vegetative-reproductive stage, and (d) from October 5 until November 8, 2019, fallow stage.

5.4. Model and field-measured data accuracy

In the field, the data were collected at 56 sampling points distributed across 3 ROIs (Figure 8): 8 samples in GB, 19 samples in KR, and 29 samples in TU. The homogeneity of the classification results of paddies in KR and TU represents salinity effects on rice plant growth, while that of paddies in GB indicates that, throughout the research duration, there was no change in land use other than ponds. Each sampling point was reviewed four times to obtain an overview of the rice plant growth stages: inundation-transplantation, vegetative, reproductive, and fallow.

Confusion matrices were used to compare the NDVI-based land cover classification results (producer’s accuracy, PA) and field-measured data (user’s accuracy, UA) to classify rice growth stages. The multi-temporal NDVI results showed higher than 85% PA and UA (based on field check) in distinguishing the rice conditions at every growth stage, from inundation-transplantation to fallow. There were several difficulties while identifying NDVI at the inundation-transplantation stage. Different
sensitivity in the NDVI results is apparent from the open land conditions: inundated or still dry, because
of different soil moisture conditions at this stage [13]. In this case, NDSI and LSWI respond better to
soil spectral reflectance scattering [22]. Despite such limitation, the temporal resolution still allows S2
L2A + B images to record different rice growth stages.

Table 5. Accuracy of comparison of field measurement data and NDVI value of rice growth phase

| Stage                  | User Acc | Prod. Acc | Kappa Coef | Overall accuracy |
|------------------------|----------|-----------|------------|-----------------|
| Inundation-Transplantation Stage | 88.42%   | 87.5%     | 0.87       | 87.3%           |
| Vegetative Stage       | 90.3 %   | 86.1%     | 0.87       | 86.2%           |
| Reproductive Stage     | 92.2 %   | 91.2%     | 0.90       | 90.6%           |
| Fallow Stage           | 98.0 %   | 97%       | 0.95       | 95 %            |

Paddies in the study area have different crop rotations because the rice planting season did not start
at the same time. During the fieldwork, it was found that the water irrigation system and fertilizer
application were responsible for such crop rotations. Also, different asset ownerships among paddy
farmers to provide seeds and labor for land cultivation cause different timings in the rice growth stage.

EC is the main parameter that distinguishes salinity effects on paddies. Detecting salt accumulation
can be challenging, especially if it occurs in small plots, <100 m², which are more detailed than S2
spatial resolution and will affect K-means segmentation of pixel values. Another challenge may arise
during fieldwork, namely in the direct measurement of soil EC during the inundation stage. Therefore,
EC is best measured after soil sampling so as to minimize potential errors.

Soil moisture and texture influence salt content in the soil. Most paddies have clay soils. The
measurement results at all sampling points showed different variations in EC. The largest EC value was
located in GB, which was mainly used for aquaculture ponds. The fish pond rotation includes draining
the water, creating an object that looks like empty land with moist soil. During the measurement period,
EC values showed an increasing trend because of the paddy inundation process in the dry season. Also,
in this season, paddies in the entire KR were left uncultivated, whereas some paddies in TU were still
planted with rice or nuts.

Elevated EC at the inundation phase (Table 6) is believed to be the result of increased salt content in
the irrigation water, caused by previous high tides in 2019 that had spread into the paddies. Therefore,
salt levels also increased during the vegetative phase but decreased at the generative phase as soil
moisture content lowered. Meanwhile, at the fallow stage, the paddies were left unsown until the next
planting season.

Table 6. Correlation of NDVI and EC results at all measurement sample points

| Stage            | NDVI min | NDVI max | EC (ECf in dS/cm) min | EC (ECf in dS/cm) max | R    |
|------------------|----------|----------|-----------------------|-----------------------|------|
| Inundation-Transplantation Stage | 0.10     | 0.11     | 0.13                  | 6.1                   | 0.63 |
| Vegetative Stage | 0.18     | 0.74     | 0.22                  | 6.5                   | 0.67 |
| Reproductive Stage | 0.12     | 0.55     | 0.16                  | 6.3                   | 0.71 |
| Fallow Stage     | 0.03     | 0.16     | 0.20                  | 6.1                   | 0.86 |

6. Conclusion

The temporal analysis of NDVI calculated from Sentinel-2 image data products has successfully
identified the effects of salinity on rice plant growth in coastal paddies. The temporal variation shows
the cropping pattern in the study area, with two rice cultivation periods but different starting times.
Paddy segments unaffected by salinity begin the inundation and transplantation phases in late March
and end with fallow in August, while those affected by salinity are the opposite: inundation-
transplantation in early April and fallow in early September. The effects of salinity on rice growth are
most visible during the vegetative-generative phase.
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