

Drought assessment in paddy rice fields using remote sensing technology towards achieving food security and SDG2

Original

Drought assessment in paddy rice fields using remote sensing technology towards achieving food security and SDG2 / Shams Esfandabadi, H.; Ghamary Asl, M.; Shams Esfandabadi, Z.; Gautam, S.; Ranjbari, M.. - In: BRITISH FOOD JOURNAL. - ISSN 0007-070X. - ELETTRONICO. - ahead-of-print:ahead-of-print(2022). [10.1108/BFJ-08-2021-0872]

Availability:

This version is available at: 11583/2968863 since: 2022-08-01T14:55:44Z

Publisher:

Emerald Group Holdings Ltd.

Published

DOI:10.1108/BFJ-08-2021-0872

Terms of use:

This article is made available under terms and conditions as specified in the corresponding bibliographic description in the repository

Publisher copyright

(Article begins on next page)

Drought assessment in paddy rice fields using remote sensing technology towards achieving food security and SDG2

Hadi Shams Esfandabadi¹, Mohsen Ghamary Asl^{1,*}, Zahra Shams Esfandabadi^{2,3}, Sneha Gautam⁴, Meisam Ranjbari^{5,6}

¹ Department of Geomatics Engineering, South Tehran Branch, Islamic Azad University, Tehran, Iran

² Department of Environment, Land and Infrastructure Engineering (DIATI), Politecnico di Torino, Torino, Italy

³ Energy Center Lab, Politecnico di Torino, Torino, Italy

⁴ Karunya Institute of Technology and Sciences, Coimbatore, Tamil Nadu, India

⁵ Department of Economics and Statistics “Cognetti de Martiis”, University of Turin, Torino, Italy

⁶ ESSCA School of Management, Lyon, France

* Corresponding author; email: m_ghamaryasl@azad.ac.ir

Abstract

Purpose

This research aims to monitor vegetation indices to assess drought in paddy rice fields in Mazandaran, Iran, and propose the best index to predict rice yield.

Design/methodology/approach

A three-step methodology is applied. First, the paddy rice fields are mapped by using three satellite-based datasets, namely SRTM DEM, Landsat8 TOA, and MYD11A2. Second, the maps of indices are extracted using MODIS. And finally, the trend of indices over rice-growing seasons is extracted and compared with the rice yield data.

Findings

Rice paddies maps and vegetation indices maps are provided. Vegetation Health Index (VHI) combining average Temperature Condition Index (TCI) and minimum Vegetation Condition

Index (VCI), and also VHI combining TCI_{min} and VCI_{min} are found to be the most proper indices to predict rice yield.

Originality/value

This study, as one of the first research assessing and mapping vegetation indices for rice paddies in northern Iran, particularly contributes to (1) extracting the map of paddy rice fields in Mazandaran Province by using satellite-based data on cloud-computing technology in the Google Earth Engine platform; (2) providing the map of VCI and TCI for the period 2010-2019 based on MODIS data; and (3) specifying the best index to describe rice yield through proposing different calculation methods for VHI.

Practical implications

The results serve as a guideline for policy-makers and practitioners in the agro-food industry to (i) support sustainable agriculture and food safety in terms of rice production; (ii) help balance the supply and demand sides of the rice market and move towards SDG2; (iii) use yield prediction in the rice supply chain management, pricing, and trade flows management; and (iv) assess drought risk in index-based insurances.

Keywords: Agro-food industry, Food security, Drought prediction, Rice yield, Sustainable agriculture, Risk assessment.

Paper type: Research paper

1. Introduction

Food security is a multifaceted concept in nature due to its various definitions by different organizations from time to time (Tanksale and Jha, 2015). However, food security is mainly built upon on the following main four pillars (Fawole *et al.*, 2016): (i) availability of sufficient quantities of food for all people, (ii) accessibility to sufficient resources to obtain appropriate foods for a nutritious diet, (iii) utilization to guarantee the appropriate use of the available and accessible food for healthy living, and (iv) sustainability of the earlier three factors for a record period in a place at a particular point in time.

Agriculture systems as the main suppliers of the global food supply chain play a vital role in ensuring food security worldwide. On one hand, the outbreak of the COVID-19 pandemic has imposed significant challenges to the food production and consumption patterns, which highlight the urgent need for rethinking the sustainability of current approaches to agriculture and the food industry (Musa and Basir, 2021; Ranjbari, Shams Esfandabadi, Zanetti, *et al.*, 2021). On the other hand, the increasing global demand for food due to the growing population of communities has imposed many challenges to the sustainability of agriculture systems, such as natural resource depletion with emphasis on deforestation (Regmi and Weber, 2000), sustaining the soil quality in agroecosystems and soil fertility management (Guilherme *et al.*, 2018), environmental pollution (Tiraieyari *et al.*, 2014), and biodiversity and the conservation of ecosystem services (Ferreira *et al.*, 2012). Moreover, over the past few decades, both the frequency and the severity of natural hazard-induced disasters have grown drastically worldwide (FAO, 2015) leading to an average economic loss of USD 250 to 300 billion per year (UN, 2015). In developing countries, approximately 22% of the total negative impact caused by natural hazards and 25% of all the losses and damages caused by climate-related disasters (e.g. floods, droughts, and tropical storms) are absorbed by the agriculture sector (FAO, 2015). Approximately 83% of the damaging effects in the wake of drought occur in the agriculture sector which leads to crop loss and lower agricultural productivity (Khan *et al.*, 2021). In this regard, more than 50% of the global rice paddy areas have been affected by water scarcity and drought which serve as one of the main constraints for rice production (Dar *et al.*, 2020).

The importance of agriculture and nutrition for sustainable development has been considerably highlighted by the United Nations (UN) within the 2030 Agenda for Sustainable Development through promoting a sustainable and resilient agri-food system (Iazzi *et al.*, 2021). In this regard, assuring global food security is substantial to achieve the Sustainable Development Goal 2 (SDG2), aiming at ending hunger worldwide (UN, 2015). Food security has been under research from different points of view, such as drought, flood, crop damage, purchasing power, household income, family size, food self-sufficiency, and agricultural and horticultural land size (Ataei *et al.*, 2021; Galiev and Ahrens, 2021). However, Rezaei (2013) in a study in Iran highlighted the role of the government in achieving food security through supporting farmers by compensating

agricultural water shortage, increasing the productivity of water supply systems, and providing financial support.

Rice as one of the main food crops in the world (Gutaker *et al.*, 2020) has an important share in ensuring food security for more than half of the world population (Kumar and Ladha, 2011), especially in Asia (Inoue *et al.*, 2020). Although rice is grown in various climates, Asia is on the top in terms of production and consumption of rice (Panda *et al.*, 2021), accounting for approximately 90% of the global rice production and consumption (Bi *et al.*, 2021).

Rice has a significant share in the Iranian diet based on the nutritional and world rice trade (Kalantari *et al.*, 2020), which is ranked second in the Iranian food basket in terms of consumption with approximately 38-42 kg per capita (Seyed Raoufi *et al.*, 2018). The coastal areas of the Caspian Sea in the northern part of Iran (including Mazandaran, Guilan, and Golestan provinces) meet a huge share of the rice demand of this country. Therefore, this region has been the case of several studies regarding rice production, such as studying gender factors in rice production systems (Valiollahi Bisheh *et al.*, 2017), assessing the land suitability and sustainability of rice production (Amini *et al.*, 2020a), and studying the effect of fertilizers and inoculum density on rice diseases (Khoshkdaman *et al.*, 2021).

Monitoring the dynamics of land surface and natural resources has benefited from earth observation from space through applying remote sensing tools over the recent years (S *et al.*, 2018). Huang *et al.* (2020) used Landsat data to study the vegetation cover in China. Kukunuri *et al.* (2020) utilized Moderate Resolution Imaging Spectroradiometer (MODIS) products data for precisely classifying agriculture drought in India. MODIS data was also used by Liu *et al.* (2020) to propose three disaster monitoring models in China. Furthermore, several studies have utilized remote sensing technology to map the paddy rice fields (Dong *et al.*, 2016; Wu *et al.*, 2019) or have employed satellite-based data to monitor drought in paddy rice fields (Raksapatcharawong *et al.*, 2020) in different regions by considering different vegetation indices. Nevertheless, limited research has been conducted on mapping paddy rice fields and monitoring drought in the northern part of Iran by applying remote sensing technology. For instance, Taherparvar and Pirmoradian (2018) applied the images of Landsat 7 ETM+ sensor for the calculation of Normalized Difference Vegetation Index (NDVI) to estimate the rice evapotranspiration in the

Foomanat district located in Guilan Province. Moreover, Bahramvash Shams (2014) and Mirzapour *et al.* (S *et al.*, 2018) used Landsat 8 time-series images to map paddy rice fields in Guilan province and Amol county in Mazandaran Province, respectively, through an algorithm employing NDVI and Land Surface Water Index (LSWI).

To the best of the authors' knowledge, no study has applied the cloud computing platform of Google Earth Engine (GEE) and satellite-based data to map paddy rice fields in the whole Mazandaran Province and develop the spatial distribution map of the vegetation indices to assess drought and predict the rice yield in this province. To fill this gap, this research aims at specifying the most proper vegetation index among Vegetation Condition Index (VCI), Thermal Condition Index (TCI), and Vegetation Health Index (VHI)-based indices to describe the changes in rice yield by employing remote sensing technology over the period 2010-2019. To this end, the following research questions are addressed in this study.

RQ.1. How have VCI, TCI, and VHI changed in Mazandaran paddy rice fields over the period 2010-2019?

RQ.2. Which vegetation index best describes the trend of rice yield in Mazandaran?

The present research contributes to the extant studies within the literature by (1) paddy rice mapping in Mazandaran Province by using satellite-based data to compute LSWI, NDVI, and Enhanced Vegetation Index (EVI) in the GEE platform; (2) providing the spatial distribution map of VCI, TCI, and VHI for the period 2010-2019 based on the data obtained from MODIS; (3) specifying the best vegetation index among VCI, TCI, and various VHI-based indices to describe drought and predict the rice yield through mapping the trends of the indices and the rice yield during the growing season of rice.

The remainder of the paper is structured as follows. Section 2 presents the research design, including the study area and the method adopted to map rice paddies and calculate vegetation indices. The main results of the research consisting of the extracted map of the rice paddies and vegetation indices for drought assessment in the study area, as well as the practical implications of this research, are analyzed and discussed in Section 3. Finally, section 4 concludes the research and provides the research limitations and future directions for further developments.

2. Materials and Methods

2.1. Study area

In this research, Mazandaran province in the northern part of Iran is considered as the study area and its paddy fields are monitored. Mazandaran is on the southern coast of the Caspian Sea and is surrounded by the central Alborz mountain chains from the south. It is a neighbor to Golestan province from the east and Guilan province from the west and is located between 35°46'- 36°58' N latitude and between 50°21'- 54°08' E longitude. Mazandaran has a total area of 23,833 km², enjoys an average annual temperature of 15.87 °C, and benefits from approximately 2000 hours of sunshine per year. The annual average precipitation in this area is 960 mm, 21% of which takes place in the rice-growing season (Amini *et al.*, 2020b). More than 80% of the total Iranian paddy is produced in the Mazandaran, Guilan, and Golestan provinces (Rezaei *et al.*, 2021), and among these top rice producers, Mazandaran is ranked first by producing more than 950,000 tons of rice, i.e. approximately 42% of the total rice produced in the country (Alipour Amir *et al.*, 2020).

2.2. Research design

To select the index that better predicts the change in the rice yield, a three-step method as illustrated in Figure 1 is applied. First, the paddy rice areas are selected by extracting the paddy rice map of Mazandaran. Second, the spatial distributions of the considered vegetation indices are extracted and shown on maps. Third, the available statistical data is used to illustrate the rice yield trend and select the most proper index to predict the rice yield. The maps extracted in the first step are used to select sample polygons in the index maps of the second step. Therefore, when making the comparisons in the third step, it is ensured that the selected index values refer to a paddy rice field. These steps are discussed in detail in the following sub-sections.

2.2.1. Mapping rice paddies

Changes in the rice land coverage during its lifecycle can be used to identify paddies within an area (S *et al.*, 2018). The dominance of water in the vegetation phase, the coverage of plant canopies on the water surface in the productive phase, and lessening the vegetation signature

during the ripening phase of the rice canopy development play key roles in mapping rice paddies (Bridhikitti and Overcamp, 2012). Information regarding the flooding and lodging area of paddy fields can be captured through remote sensing technology (Wu *et al.*, 2019). To map rice paddies in this research, three datasets including MODIS/Aqua Land Surface Temperature (MYD11A2), United States Geological Survey (USGS) Landsat 8 Collection 1 Tier 1 calibrated top-of-atmosphere (TOA) reflectance, and NASA Shuttle Radar Topography Mission (SRTM) 90m Digital elevation models (DEM) digital elevation database are called from the GEE.

MYD11A2.006, the latest MODIS LST version, provides an average 8-day per pixel Land Surface Temperature and Emissivity (LST&E) with a 1Km spatial resolution from Aqua-MODIS. Since temperature is a dominant factor in vegetation growth and cropping (Dong *et al.*, 2016), the nighttime LST time series data for the study area in the year 2020 is taken from MYD11A2.006 to determine the period of rice transplanting and growing season.

USGS Landsat 8 Collection 1 Tier 1 TOA Reflectance provides time-series data from Landsat 8 satellite, on which radiometric corrections have been made (Roy *et al.*, 2016). Landsat sensors measure electromagnetic radiation from the sun that is reflected by the objects on the earth's surface. Many factors including cloud cover, atmospheric interactions, and spectral properties of the objects affect the proportion of radiation received by the sensors (Gautam and Brema, 2020). Considering our study period and location, spatial and temporal filtering are applied to this data and the cloud cover is neglected according to the Landsat 8 quality assessment band (Dong *et al.*, 2016; Roy *et al.*, 2016). Recognizing transplanting signals through remote sensing technology play a vital role in identifying the rice paddies. In this regard, the relationship between LSWI and NDVI or the relationship between LSWI and EVI are of high importance in the identification of transplanting signals (Gautam *et al.*, 2020; Xiao *et al.*, 2006). Therefore, LSWI, NDVI, and EVI are calculated by applying the time series of Landsat TOA image collection based on equations 1, 2, and 3 (Dong *et al.*, 2016) to map the paddy rice fields.

$$LSWI = \frac{\rho_{NIR} - \rho_{SWIR}}{\rho_{NIR} + \rho_{SWIR}} \quad \text{Equation (1)}$$

$$NDVI = \frac{\rho_{NIR} - \rho_{Red}}{\rho_{NIR} + \rho_{Red}} \quad \text{Equation (2)}$$

$$EVI = 2.5 \times \left(\frac{\rho_{NIR} - \rho_{Red}}{\rho_{NIR} + 6\rho_{Red} - 7.5\rho_{Blue} + 1} \right) \quad \text{Equation (3)}$$

where ρ_{NIR} , ρ_{SWIR} , ρ_{Red} , and ρ_{Blue} are the values of the surface reflectance for the near-infrared band (0.76–0.90 mm), the shortwave infrared band (1.55–1.75 mm), red band (0.63–0.69 mm), and blue band (0.45–0.52 mm), respectively. Maximum EVI smaller than 0.6 during the thermal growing season above 5 °C and maximum EVI larger than 0.4 before the start of the thermal growing season above 10 °C are considered to apply sparse vegetation mask and natural vegetation mask, respectively.

SRTM 90m DEM Digital Elevation Database version 4 provided by NASA is now the highest quality SRTM dataset available (SRTM, 2018), generating an integrated remote sensing image (Ibrahim *et al.*, 2020). The data in this database have a resolution of 90m at the equator and are presented in 5×5 degree tiles (SRTM, 2018). Since rice has a high flooding demand at the transplanting phase, it cannot be planted in sloping lands (Dong *et al.*, 2016). Therefore, SRTM DEM data is used in this research with a sloping land mask to remove the areas with a slope larger than 3°.

Finally, putting the computed indices in equation 4 (Dong *et al.*, 2016), we specify the map of the paddy rice fields. Based on this equation, where $Flood = 1$ the area is a paddy rice field.

$$Flood = \begin{cases} 1 & (LSWI_{T_i} > EVI \text{ or } LSWI_{T_i} > NDVI) \\ 0 & (LSWI_{T_i} \geq EVI \text{ and } LSWI_{T_i} \geq NDVI) \end{cases} \quad (SOT < T_i < EOT) \quad \text{Equation (4)}$$

where SOT and EOT are the starting and ending of the transplanting phase and T_i is the observation time.

2.2.2. Vegetation indices calculation

Three indices including VCI, TCI, and VHI are used in this research, which are discussed in the following sub-sections.

2.2.2.1. Vegetation condition index (VCI)

VCI is used to estimate the impact of weather on vegetation by applying long-term NDVI (Kukunuri *et al.*, 2020). Through VCI, the short-term weather-related NDVI fluctuations are separated from the long-term ecosystem changes, and therefore, the relative changes in the moisture condition are revealed (Bhuiyan, 2008). VCI is calculated based on equation 5 (Kogan, 1997).

$$VCI_{ijk} = \frac{NDVI_{ijk} - NDVI_{i,min}}{NDVI_{i,max} - NDVI_{i,min}} \quad \text{Equation (5)}$$

where i is the pixel, j is the month, and k represents the year for which the index is calculated. Besides, $NDVI_{ijk}$ is the value of the NDVI index in pixel i of the image corresponding to the month j and year k . The terms $NDVI_{i,min}$ and $NDVI_{i,max}$ are the minimum and maximum values of NDVI for each desired pixel over a long period (in this research, 10 years), respectively.

MOD13Q1.006 Terra Vegetation Indices 16-Day Global 250m has been applied to calculate NDVI and VCI to analyze the drought. Spatial and temporal filtering are applied to the data to specify it for our study area from 2010 to 2019.

2.2.2.2. Temperature condition index (TCI)

TCI is calculated based on LST values as in equation 6 (Kogan, 1997) and characterizes drought considering the thermal conditions of the vegetation (Kukunuri *et al.*, 2020). High LST and thermal stress with low soil moisture and vice versa are considered in TCI to denote the probability of drought severity (Danodia *et al.*, 2021).

$$TCI_{ijk} = \frac{(LST_{i,max} - LST_{ijk})}{(LST_{i,max} - LST_{i,min})} \quad \text{Equation (6)}$$

where i stands for the pixel, j is the month, and k represents the year for which the index is calculated. $LST_{i,min}$ and $LST_{i,max}$ are minimum and maximum LST in pixel i in a long period (in this research, 10 years).

MOD11A2.006 Terra LST&E 8-Day Global 1km data in the GEE is used to calculate daytime LST and consequently, TCI. Besides the spatial and temporal filtering, data is masked based on a function that removes the null values.

2.2.2.3. Vegetation health index (VHI)

VHI combines thermal and moisture stresses presented in TCI and VCI through equation 7 (Kogan *et al.*, 2004) to capture the overall health status of the vegetation.

$$VHI_{ijk} = \alpha VCI_{ijk} + (1 - \alpha)TCI_{ijk} \quad \text{Equation (7)}$$

where α quantifies the relative contribution of VCI and TCI to VHI. Due to a lack of sufficient information about the value of α , it is usually considered equal to 0.5. Therefore, $\alpha = 1 - \alpha = 0.5$.

2.2.3. Statistical data on rice yield

To identify the best describing index for the drought in paddy rice fields in Mazandaran, the trend of the rice yield in this region is compared with the trend of the calculated vegetation indices. The required statistical data is taken from the yearbooks published by the Statistical Center of Iran for the years 2010-2019 (Statistical Center of Iran, 2020) to calculate the average rice yield in Section 3.3. The average rice yield shows the mean of produced rice in each hectare of paddy field in Mazandaran regardless of the rice cultivar. According to Statistical Center of Iran (2020), the amount of fertilizer per hectare of paddy rice and also the pesticides are almost constant over the years, and the change in the rice cultivars are not significant in this region. Therefore, fertilizers, pesticides, and rice cultivars may not be the causes of fluctuations in the rice yield over the studied period (as in Figure 4). Instead, drought parameters should be studied more in depth in this regard.

3. Results and discussion

3.1. Map of the rice paddies in the study area

The preliminary map of the paddy rice fields is developed for the year 2019 as illustrated in Figure 2(a). To remove the green fields on the map, which do not refer to rice paddies, the sparse vegetation mask is created to mask the areas with sparse vegetation or no cover of vegetation (Figure 2(b)), and the natural vegetation mask is created to separate rice paddies from other green areas (Figure 2(c)). Furthermore, the sloping land mask is formed as shown in part (d) of Figure 2 to remove the pieces of land with a slope larger than 3° on which rice cannot be transplanted. Finally, these three masks are applied on the preliminary map to present the final paddy rice fields map, as shown in Figure 2e. In the final map, the white areas are the fields where rice is cultivated.

3.2. Map of vegetation indices

To show the drought severity, the values of VCI and TCI for the period 2010-2019 are shown in parts (a) and (b) of Figure 3, respectively. The map for VHI is not presented as different combinations of VCI and TCI for its calculation is used in this research. In Figure 3, the areas with the low value of the vegetation indices, corresponding to dry areas are shown in red, while the areas with the high value of vegetation indices, corresponding to wet areas are shown in blue. Therefore, where the red color has more density, the severity of drought based on the considered vegetation index is higher.

3.3. The relationship between the indices and rice yield

To construct an empirical relationship between the indices and the rice yield, the trends of the calculated VCI, TCI, and VHI indices are compared with the trend of rice yield over 2010-2019. Besides, different combinations of VCI and TCI minimum, average, and maximum values are used to build new VHI-related indices. To do so, a paddy rice field is selected based on the map of rice paddies in Figure 2(e), and minimum, average, and maximum values of VCI, TCI, and VHI are extracted for this polygon based on Figure 3. Considering the average period of transplanting and growth of rice in Mazandaran, the value of the indices for the period March 5 to September 17 in each year is selected. This period is confirmed by the LST trend extracted from MODIS and is also in line with Dong *et al.* (2016). Since VCI and TCI characterize weather-related vegetation changes based on moisture and temperature conditions, respectively, the maximum VCI and the average TCI, as well as the maximum VHI in the selected period in

each year, are utilized as the base for comparison during the studied period, as shown in Figure 4 (a). Besides, for more in-depth analysis, VHI is computed based on different combinations of minimum, average, and maximum values of VCI and TCI for the studied period and compared with the rice yield as in Figure 4(b). The average rice yield in Mazandaran province is shown with the thick blue line in Figure 4.

Several variables can be considered to increase the correlation between the indices and rice yield (Hochrainer-Stigler *et al.*, 2014). However, the focus of this study is on finding a satisfactory relationship between the indices and the rice yield, not the best fitting trend. Therefore, to evaluate the relationship between the considered indices and the rice yield, regression analysis has been conducted, and the obtained R^2 values are reported in Table 1. As can be seen in this table, the VHI built by considering $TCI_{average}$ and VCI_{min} has the highest value of R^2 equal to 0.625, showing that more rice yield values can be predicted by using the defined this proposed VHI. The VHI comprising of TCI_{min} and VCI_{min} with the R^2 value of 0.617 is the next satisfying index to describe and predict rice yield. Although VCI, $VHI(TCI_{average}, VCI_{max})$, $VHI(TCI_{min}, VCI_{max})$, and $VHI(TCI_{max}, VCI_{max})$ are in the next ranks, their R^2 , which are between 0.47 and 0.38, do not indicate an adequate prediction capability for this indices. As a result, fluctuations in the rice yield can be better described by using the proposed vegetation health indices, including $VHI(TCI_{average}, VCI_{min})$ and $VHI(TCI_{min}, VCI_{min})$ rather than the other studied indices.

3.4. Practical implications

The findings of this study have several important managerial and practical implications for authorities and practitioners in the agro-food industry, and policy implications for decision-makers involved within the food supply chain, risk assessment, and its applications in the agriculture-related insurance industry as the following.

First, the provided map of indices in the present research shows that a huge part of Mazandaran province is prone to drought, which can immensely affect the whole food supply chain and food security of this area. This is in line with the research conducted by Karimi et al. (2018) showing that almost 85% of Iran is facing frequent droughts and significant water shortages, which highly relies on groundwater resources. Cultivation of five rice cultivars is common in Mazandaran

province, out of which four are sensitive and one is slightly sensitive to water stress (Amini *et al.*, 2020b). Therefore, to support achieving the SDG2 and ensuring food safety in terms of rice production in the region and also to make the agriculture system more sustainable, aerobic rice should be considered as an alternative for the current rice cultivars (Sabouri *et al.*, 2018). Aerobic rice cultivars grow in soil, which is kept below water saturation (Silwal *et al.*, 2020), since they require less water and have been developed for drought-prone regions (Sabouri *et al.*, 2020). Hence, proper decisions made by the authorities and decision-makers in this regard can save water resources while keeping rice production activities in the region.

Second, in view of the findings of this research, fluctuations in the average rice yield shown in Figure 4 highlight the importance of proper decisions and actions to support sustainable agriculture and ensure food security. Besides, the supply and demand sides of the market must be taken into account while planning for the management of the whole system. In this regard, not only producing or importing agricultural products but also the population and consumer rice consumption preferences (Suwannaporn *et al.*, 2008) play key roles in decision making. However, this would cover only a part of the requirements to achieve “food for all” and partially supports moving towards SDG2. Thus, other proper actions must be taken to reach food security and provide safe food to all people (Rehber, 2012) in a system thinking framework (Ranjbari *et al.*, 2019).

Third, computing the VHI index at the rice-growing season, when the chlorophyll content increases, can be used to predict the rice yield at the end of the season. This prediction plays a vital role in planning for the management of the rice supply chain, pricing the products, and managing the trade flows (i.e., rice import and export). The management of food systems post COVID-19 has faced more challenges than before (Ranjbari, Shams Esfandabadi, Zanetti, *et al.*, 2021; Zolin *et al.*, 2021) and the sustainable development goals, mainly SDG1 and SDG2 that deal with poverty and hunger, have been seriously affected in Iran (Ranjbari, Shams Esfandabadi, Scagnelli, *et al.*, 2021). In such a situation, any probable future natural hazards that negatively affect agricultural products would intensify these challenges. Therefore, for Iran, as a developing country in which rice has a considerable share in the household food basket, timely prediction of the changes in crop yield would support decision-makers in better managing the food system and organizing the supply side of the market.

Finally, the prediction of rice yield is a key factor in the risk assessment in index-based insurances, and this study showed that applying VHI in the prediction of drought would be helpful in this regard. This finding is in line with the research conducted by Hochrainer-Stigler *et al.* (2014), who used VHI to predict crop yield in order to assess the risk in index-based insurance in Ethiopia. Through proper risk assessment by applying modern technologies, such as remote sensing, insurance companies can economically support farmers, who form the backbone of food security (Tey *et al.*, 2020), for probable losses and enable them to continue farming in the next years if they face a natural disaster and lose their agricultural products.

4. Conclusion

Natural hazard-induced disasters, such as droughts can immensely affect the sustainability of agriculture systems and food security worldwide. Therefore, a proper mechanism to monitor drought trends is vital to assure the productivity of agricultural products and prevent food insecurity. This research as an attempt to map the paddy rice fields and vegetation indices in northern Iran was conducted by applying remote sensing technology. Consequently, drought intensity trends for three vegetation indices, including VCI, TCI, and VHI, and also VHI with different combinations of VCI and TCI values were assessed for the period 2010 to 2019. Regression analysis on the trends of the studied indices and the average rice yield in the study area revealed that $VHI(TCI_{average}, VCI_{min})$ is the most proper index followed by the $VHI(TCI_{min}, VCI_{min})$ to predict rice yield considering the changes in drought level in paddy rice fields in Mazandaran. The provided maps of paddy rice fields and vegetation indices, and the identified trends of the vegetation indices and the rice yield in the period 2010-2019 can serve as a guideline for policy-makers and practitioners involved in the agro-food industry to (i) support sustainable agriculture and food safety in terms of rice production, which is a main component of the global diet; (ii) help balancing the supply and demand side of the rice market and moving towards SDG2; (iii) use rice yield prediction in the rice supply chain management, rice pricing, and the rice trade flows management; and (iv) assess drought risk in index-based insurances.

4.1. Limitations and future directions for research

This study had some limitations which deserve to be addressed by scholars for further developments in future research. First, the MODIS sensor was used in this research to calculate

the main vegetation indices. Using other sensors with higher spatial accuracy as well as other vegetation indices and accordingly, comparing the results with our findings are recommended for future studies. Second, the focus of the present research was on drought as one of the most frequent natural hazard-induced disasters. Applying the same method considering other disasters, such as floods and severe storms could be a potential direction for further investigations in different geographical areas. Third, in this research, LST was studied and the vegetation indices were computed to estimate the rice yield. However, besides temperature, cumulative precipitation is suggested to be studied in future research to increase the accuracy of the results. And finally, in this research, all rice cultivars were considered equal and an average yield and average time interval for their growth were considered regardless of their differences. Conducting more detailed research considering different rice cultivars separately is recommended for more precise analyses according to different rice yields performance.

References

- Alipour Amir, N., Abbasi, E. and Bijani, M. (2020), “Paddy Farmers’ Pro-environmental Behavior Based on Virtue-Ethical Perspective”, *Agricultural Research*, available at:<https://doi.org/10.1007/s40003-020-00512-0>.
- Amini, S., Rohani, A., Aghkhani, M.H., Abbaspour-Fard, M.H. and Asgharipour, M.R. (2020a), “Assessment of land suitability and agricultural production sustainability using a combined approach (Fuzzy-AHP-GIS): A case study of Mazandaran province, Iran”, *Information Processing in Agriculture*, Vol. 7 No. 3, pp. 384–402.
- Amini, S., Rohani, A., Aghkhani, M.H., Abbaspour-Fard, M.H. and Asgharipour, M.R. (2020b), “Sustainability assessment of rice production systems in Mazandaran Province, Iran with emergy analysis and fuzzy logic”, *Sustainable Energy Technologies and Assessments*, Vol. 40 No. May, p. 100744.
- Ataei, P., Sadighi, H. and Izadi, N. (2021), “Major challenges to achieving food security in rural, Iran”, *Rural Society*, Vol. 30 No. 1, pp. 15–31.
- Bahramvash Shams, S. (2014), “Automatic Paddy Rice Mapping Interface Using Arcengine and Landsat 8 Imagery (Case Study in North Part of Iran)”, *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, Vol. XL-2/W3 No. 2W3, pp. 79–83.
- Bhuiyan, C. (2008), “Desert vegetation during droughts: Response and sensitivity”, *The International*

- Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, No. 8, pp. 907–912.
- Bi, J., Hou, D., Zhang, X., Tan, J., Bi, Q., Zhang, K., Liu, Y., *et al.* (2021), “A novel water-saving and drought-resistance rice variety promotes phosphorus absorption through root secreting organic acid compounds to stabilize yield under water-saving condition”, *Journal of Cleaner Production*, Vol. 315 No. 2901, p. 127992.
- Bridhikitti, A. and Overcamp, T.J. (2012), “Estimation of Southeast Asian rice paddy areas with different ecosystems from moderate-resolution satellite imagery”, *Agriculture, Ecosystems & Environment*, Vol. 146 No. 1, pp. 113–120.
- Danodia, A., Kushwaha, A. and Patel, N.R. (2021), “Remote sensing - derived combined index for agricultural drought assessment of rabi pulse crops in Bundelkhand”, *Environment, Development and Sustainability*, No. 0123456789, available at:<https://doi.org/10.1007/s10668-021-01305-3>.
- Dar, M.H., Waza, S.A., Shukla, S., Zaidi, N.W., Nayak, S., Hossain, M., Kumar, A., *et al.* (2020), “Drought Tolerant Rice for Ensuring Food Security in Eastern India”, *Sustainability*, Vol. 12 No. 6, p. 2214.
- Dong, J., Xiao, X., Menarguez, M.A., Zhang, G., Qin, Y., Thau, D., Biradar, C., *et al.* (2016), “Mapping paddy rice planting area in northeastern Asia with Landsat 8 images, phenology-based algorithm and Google Earth Engine”, *Remote Sensing of Environment*, Vol. 185, pp. 142–154.
- FAO. (2015), “The impact of natural hazards and disasters on agriculture, food security and nutrition”, *FAO Report*.
- Fawole, W.O., Ozkan, B. and Ayanrinde, F.A. (2016), “Measuring food security status among households in Osun State, Nigeria”, *British Food Journal*, Vol. 118 No. 7, pp. 1554–1567.
- Ferreira, J., Pardini, R., Metzger, J.P., Fonseca, C.R., Pompeu, P.S., Sparovek, G. and Louzada, J. (2012), “Towards environmentally sustainable agriculture in Brazil: challenges and opportunities for applied ecological research”, *Journal of Applied Ecology*, Vol. 49 No. 3, p. no-no.
- Galiev, R.R. and Ahrens, H.D. (2021), “Determinants of Food Self-sufficiency in Russia and Food Security”, *Studies on Russian Economic Development*, Vol. 32 No. 3, pp. 254–262.
- Gautam, S. and Brema, J. (2020), “Spatio-temporal variation in the concentration of atmospheric particulate matter: A study in fourth largest urban agglomeration in India”, *Environmental Technology & Innovation*, Vol. 17, p. 100546.
- Gautam, S., J., B., R., D., Brema, J. and Dhasarathan, R. (2020), “Spatio-temporal estimates of solid

- waste disposal in an urban city of India: A remote sensing and GIS approach”, *Environmental Technology and Innovation*, Elsevier B.V., Vol. 18, p. 100650.
- Guilherme, L.R.G., Lopes, A.S. and Corguinha, A.P. (2018), “Challenges and opportunities for a sustainable agriculture in Brazil”, *Acta Horticulturae*, No. 1224, pp. 1–6.
- Gutaker, R.M., Groen, S.C., Bellis, E.S., Choi, J.Y., Pires, I.S., Bocinsky, R.K., Slayton, E.R., *et al.* (2020), “Genomic history and ecology of the geographic spread of rice”, *Nature Plants*, Vol. 6 No. 5, pp. 492–502.
- Hochrainer-Stigler, S., van der Velde, M., Fritz, S. and Pflug, G. (2014), “Remote sensing data for managing climate risks: Index-based insurance and growth related applications for smallhold-farmers in Ethiopia”, *Climate Risk Management*, Vol. 6, pp. 27–38.
- Huang, C., Yang, Q., Guo, Y., Zhang, Y. and Guo, L. (2020), “The pattern, change and driven factors of vegetation cover in the Qin Mountains region”, *Scientific Reports*, Vol. 10 No. 1, pp. 1–11.
- Iazzi, A., Ligorio, L., Vrontis, D. and Trio, O. (2021), “Sustainable Development Goals and healthy foods: perspective from the food system”, *British Food Journal*, available at:<https://doi.org/10.1108/BFJ-02-2021-0197>.
- Ibrahim, M., Al-Mashaqbah, A., Koch, B. and Datta, P. (2020), “An evaluation of available digital elevation models (DEMs) for geomorphological feature analysis”, *Environmental Earth Sciences*, Vol. 79 No. 13, p. 336.
- Inoue, S., Ito, A. and Yonezawa, C. (2020), “Mapping Paddy fields in Japan by using a Sentinel-1 SAR time series supplemented by Sentinel-2 images on Google Earth Engine”, *Remote Sensing*, Vol. 12 No. 10, available at:<https://doi.org/10.3390/rs12101622>.
- Kalantari, H., Khodayar, M.J., Shirani, K. and Shirani, M. (2020), “Mycotoxin Contamination of Consumed Rice in Iran: A Review”, *Jundishapur Journal of Natural Pharmaceutical Products*, Vol. 15 No. 4, available at:<https://doi.org/10.5812/jjnpp.94663>.
- Karimi, V., Karami, E. and Keshavarz, M. (2018), “Climate change and agriculture: Impacts and adaptive responses in Iran”, *Journal of Integrative Agriculture*, Vol. 17 No. 1, pp. 1–15.
- Khan, M.I.R., Palakolanu, S.R., Chopra, P., Rajurkar, A.B., Gupta, R., Iqbal, N. and Maheshwari, C. (2021), “Improving drought tolerance in rice: Ensuring food security through multi-dimensional approaches”, *Physiologia Plantarum*, Vol. 172 No. 2, pp. 645–668.
- Khoshkdaman, M., Mousanejad, S., Elahinia, S.A., Ebadi, A.A. and Padasht-Dehkaei, F. (2021), “Sheath blight development and yield loss on rice in different epidemiological conditions”, *Journal of Plant*

- Pathology*, Vol. 103 No. 1, pp. 87–96.
- Kogan, F., Stark, R., Gitelson, A., Jargalsaikhan, L., Dugrajav, C. and Tsooj, S. (2004), “Derivation of pasture biomass in Mongolia from AVHRR-based vegetation health indices”, *International Journal of Remote Sensing*, Vol. 25 No. 14, pp. 2889–2896.
- Kogan, F.N. (1997), “Global Drought Watch from Space”, *Bulletin of the American Meteorological Society*, Vol. 78 No. 4, pp. 621–636.
- Kukunuri, A.N.J., Murugan, D. and Singh, D. (2020), “Variance based fusion of VCI and TCI for efficient classification of agriculture drought using MODIS data”, *Geocarto International*, available at:<https://doi.org/10.1080/10106049.2020.1837256>.
- Kumar, V. and Ladha, J.K. (2011), “Direct Seeding of Rice”, *Advances in Agronomy*, 1st ed., Vol. 111, pp. 297–413.
- Liu, Z., Liu, H., Luo, C., Yang, H., Meng, X., Ju, Y. and Guo, D. (2020), “Rapid extraction of regional-scale agricultural disasters by the standardized monitoring model based on google earth engine”, *Sustainability (Switzerland)*, Vol. 12 No. 16, available at:<https://doi.org/10.3390/su12166497>.
- Musa, S.F.P.D. and Basir, K.H. (2021), “Smart farming: towards a sustainable agri-food system”, *British Food Journal*, Vol. 123 No. 9, pp. 3085–3099.
- Panda, D., Mishra, S.S. and Behera, P.K. (2021), “Drought Tolerance in Rice: Focus on Recent Mechanisms and Approaches”, *Rice Science*, Vol. 28 No. 2, pp. 119–132.
- Raksapatcharawong, M., Veerakachen, W., Homma, K., Maki, M. and Oki, K. (2020), “Satellite-Based Drought Impact Assessment on Rice Yield in Thailand with SIMRIW–RS”, *Remote Sensing*, Vol. 12 No. 13, p. 2099.
- Ranjbari, M., Morales-Alonso, G., Shams Esfandabadi, Z. and Carrasco-Gallego, R. (2019), “Sustainability and the Sharing Economy: Modelling the Interconnections”, *Dirección y Organización*, Vol. 68 No. July, pp. 33–40.
- Ranjbari, M., Shams Esfandabadi, Z., Scagnelli, S.D., Siebers, P.-O. and Quatraro, F. (2021), “Recovery agenda for sustainable development post COVID-19 at the country level: developing a fuzzy action priority surface”, *Environment, Development and Sustainability*, No. 0123456789, available at:<https://doi.org/10.1007/s10668-021-01372-6>.
- Ranjbari, M., Shams Esfandabadi, Z., Zanetti, M.C., Scagnelli, S.D., Siebers, P.-O., Aghbashlo, M., Peng, W., *et al.* (2021), “Three pillars of sustainability in the wake of COVID-19: A systematic review and future research agenda for sustainable development”, *Journal of Cleaner Production*, Vol. 297,

p. 126660.

- Regmi, P.P. and Weber, K.E. (2000), “Problems to agricultural sustainability in developing countries and a potential solution: diversity”, *International Journal of Social Economics*, Vol. 27 No. 7/8/9/10, pp. 788–801.
- Rehber, E. (2012), “Food for thought: ‘four Ss with one F’”, *British Food Journal*, Vol. 114 No. 3, pp. 353–371.
- Rezaei, M., Soheilifard, F. and Keshvari, A. (2021), “Impact of agrochemical emission models on the environmental assessment of paddy rice production using life cycle assessment approach”, *Energy Sources, Part A: Recovery, Utilization, and Environmental Effects*, Vol. 00 No. 00, pp. 1–16.
- Rezaei, S. (2013), “Food security is a main priority of the government”, *Livestock and Agro-Industry*, Vol. 174, pp. 32–34.
- Roy, D.P., Kovalskyy, V., Zhang, H.K., Vermote, E.F., Yan, L., Kumar, S.S. and Egorov, A. (2016), “Characterization of Landsat-7 to Landsat-8 reflective wavelength and normalized difference vegetation index continuity”, *Remote Sensing of Environment*, Vol. 185, pp. 57–70.
- S, M., SH, K., Zarkesh M, K., F, D., Safaval P, A., Mirzapour, S., Karimi, S., *et al.* (2018), “Mapping the Spatial Distribution of Rice Fields in Southern Coast of Caspian Sea Using Landsat 8 Time-series Images”, *Journal of Geography & Natural Disasters*, Vol. 08 No. 01, available at:<https://doi.org/10.4172/2167-0587.1000215>.
- Sabouri, A., Afshari, R., Raiesi, T., Babaei Raouf, H., Nasiri, E., Esfahani, M., Kafi Ghasemi, A., *et al.* (2018), “Superior adaptation of aerobic rice under drought stress in Iran and validation test of linked SSR markers to major QTLs by MLM analysis across two years”, *Molecular Biology Reports*, Vol. 45 No. 5, pp. 1037–1053.
- Sabouri, A., Alinezhad, F. and Mousanejad, S. (2020), “Association analysis using SSR markers and identification of resistant aerobic and Iranian rice cultivars to blast disease”, *European Journal of Plant Pathology*, European Journal of Plant Pathology, Vol. 158 No. 2, pp. 561–570.
- Seyed Raoufi, R., Soufizadeh, S., Amiri Larijani, B., AghaAlikhani, M. and Kambouzia, J. (2018), “Simulation of growth and yield of various irrigated rice (*Oryza sativa* L.) genotypes by AquaCrop under different seedling ages”, *Natural Resource Modeling*, Vol. 31 No. 2, p. e12162.
- Silwal, S., Bhattarai, S.P. and Midmore, D.J. (2020), “Aerobic Rice with or without Strategic Irrigation in the Subtropics”, *Agronomy*, Vol. 10 No. 11, p. 1831.
- SRTM. (2018), “CGIAR-CSI SRTM – SRTM 90m DEM Digital Elevation Database”.

- Statistical Center of Iran. (2020), “Statistical Center of Iran”, available at:
<https://www.amar.org.ir/english>.
- Suwannaporn, P., Linnemann, A. and Chaveesuk, R. (2008), “Consumer preference mapping for rice product concepts”, *British Food Journal*, Vol. 110 No. 6, pp. 595–606.
- Taherparvar, M. and Pirmoradian, N. (2018), “Estimation of Rice Evapotranspiration Using Reflective Images of Landsat Satellite in Sefidrood Irrigation and Drainage Network”, *Rice Science*, Vol. 25 No. 2, pp. 111–116.
- Tanksale, A. and Jha, J.K. (2015), “Implementing national food security act in India: Issues and challenges”, *British Food Journal*, Vol. 117 No. 4, pp. 1315–1335.
- Tey, Y.S., Ibragimov, A., Brindal, M., Sidique, S.F., Abduraupov, R. and Makhmudov, M. (2020), “Moving smallholders up rice value chain: a system dynamics approach”, *British Food Journal*, Vol. 122 No. 3, pp. 852–869.
- Tiraieyari, N., Hamzah, A. and Abu Samah, B. (2014), “Organic Farming and Sustainable Agriculture in Malaysia: Organic Farmers’ Challenges towards Adoption”, *Asian Social Science*, Vol. 10 No. 4, pp. 1–7.
- UN. (2015), *Transforming Our World: The 2030 Agenda for Sustainable Development*, General Assembly, available at:<https://doi.org/10.1163/157180910X12665776638740>.
- Valiollahi Bisheh, A., Veisi, H., Liaghati, H., Mahdavi Damghani, A.M. and Kambouzia, J. (2017), “Embedding gender factor in energy input–output analysis of paddy production systems in Mazandaran Province, Iran”, *Energy, Ecology and Environment*, Vol. 2 No. 3, pp. 214–224.
- Wu, W., Wang, W., Meadows, M.E., Yao, X. and Peng, W. (2019), “Cloud-based typhoon-derived paddy rice flooding and lodging detection using multi-temporal Sentinel-1&2”, *Frontiers of Earth Science*, Vol. 13 No. 4, pp. 682–694.
- Xiao, X., Boles, S., Frohling, S., Li, C., Babu, J.Y., Salas, W. and Moore, B. (2006), “Mapping paddy rice agriculture in South and Southeast Asia using multi-temporal MODIS images”, *Remote Sensing of Environment*, Vol. 100 No. 1, pp. 95–113.
- Zolin, M.B., Cavapozzi, D. and Mazzarolo, M. (2021), “Food security and trade policies: evidence from the milk sector case study”, *British Food Journal*, Vol. 123 No. 13, pp. 59–72.

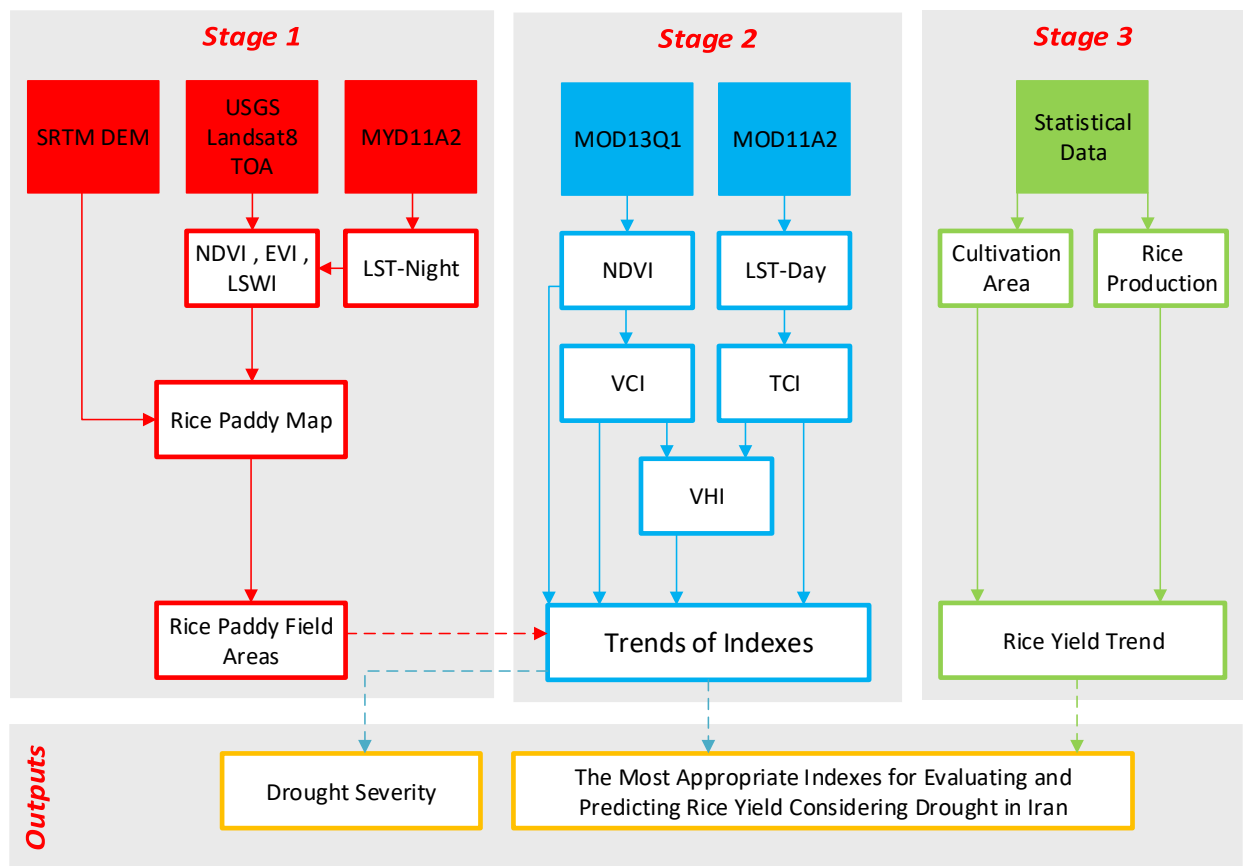


Figure 1. Methodology framework in the present study

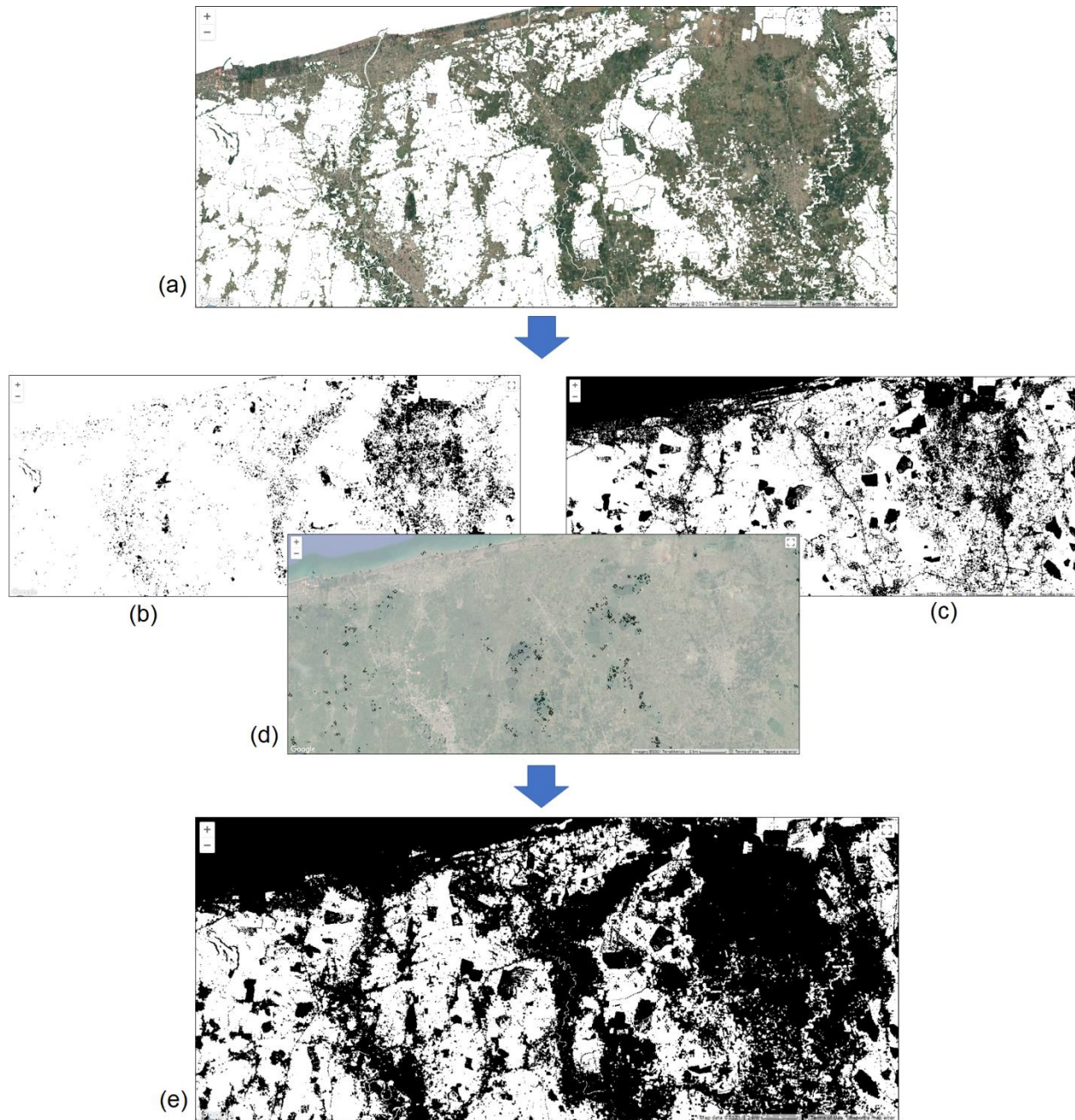


Figure 2. The Preliminary map (a), sparse vegetation mask (b), natural vegetation mask (c), sloping land mask (d), and the final map of paddy rice fields(e) in the study area in 2019

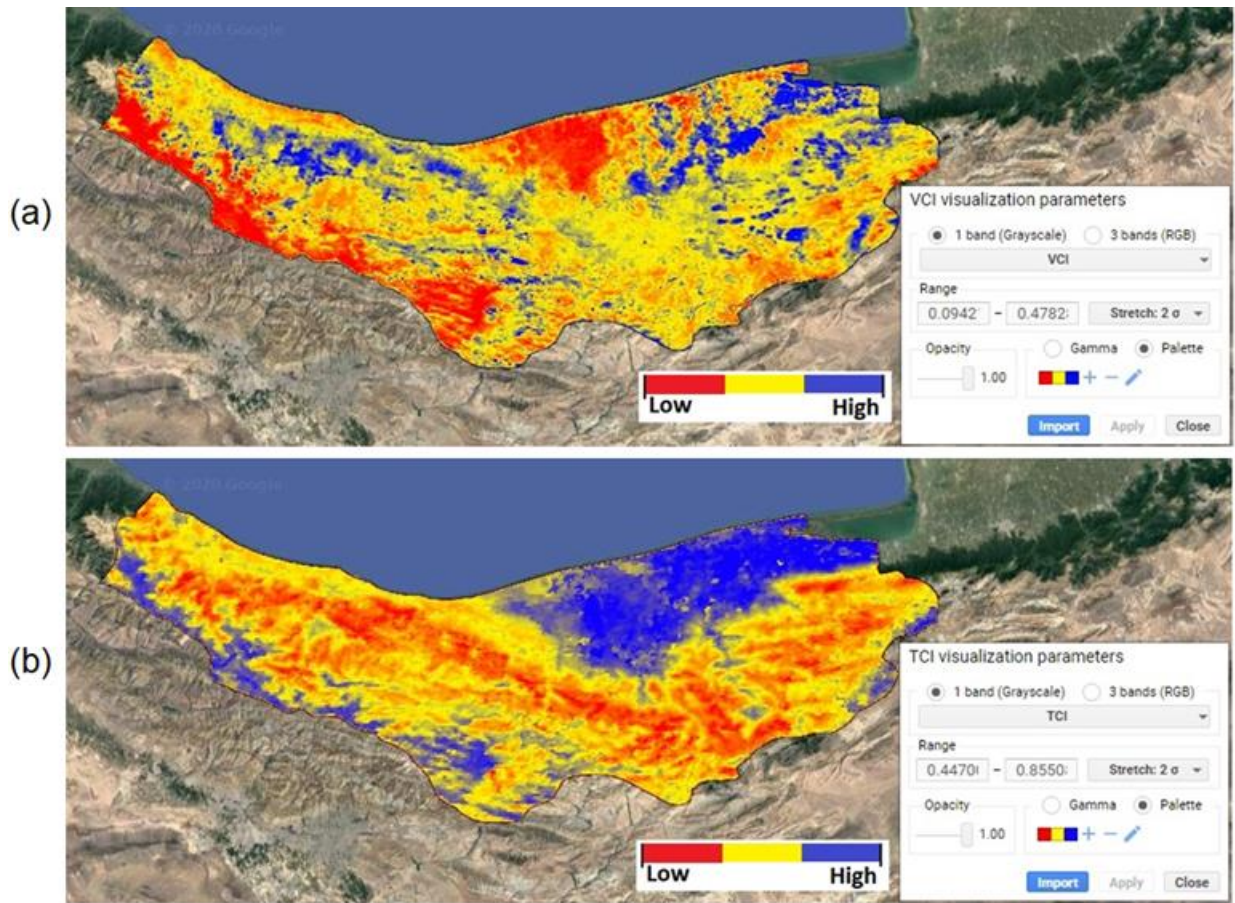
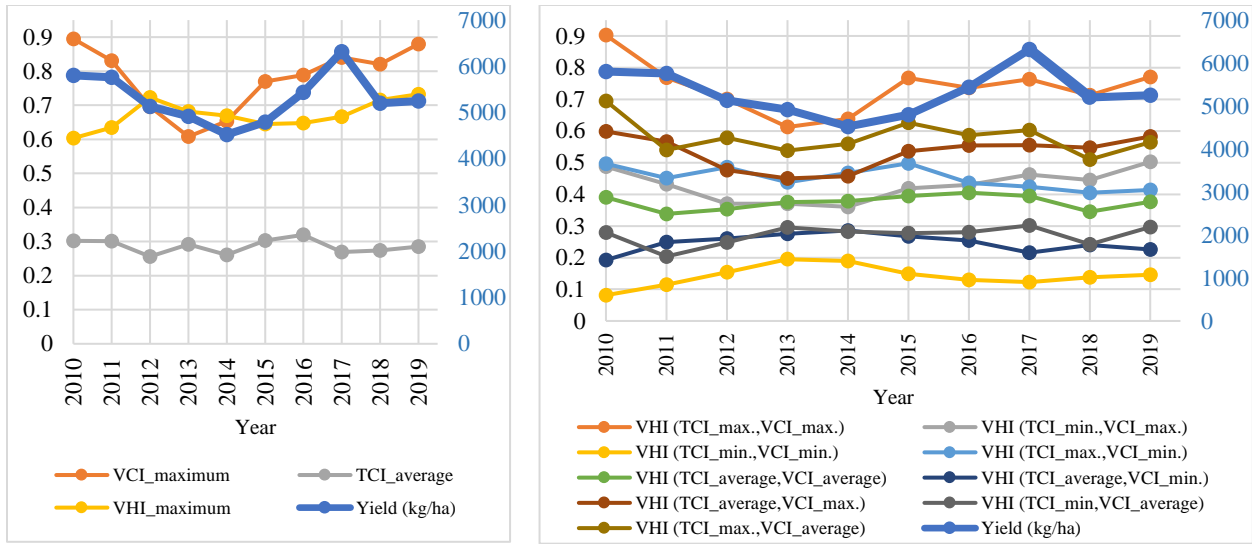


Figure 3. Visualization of VCI (a) and TCI (b) in the study area (2010-2019)



(a) (b)

Figure 4. Comparison between rice yield trend and TCI, VCI, VHI, and the proposed VHI-related indices trend (a), and the trends of VHI considering various combinations of TCI and VCI (b) in Mazandaran (March 5- September 17 in the period 2010-2019)

Table 1. R^2 of the regression line for each of the studied indices and the rice yield

Index	Condition	R^2
TCI	Average	<0.15
VCI	Maximum	0.470
VHI	Maximum	<0.15
	<i>TCI_{min}, VCI_{min}</i>	0.617
	<i>TCI_{min}, VCI_{max}</i>	0.400
	<i>TCI_{max}, VCI_{min}</i>	<0.15
	<i>TCI_{max}, VCI_{max}</i>	0.384
	<i>TCI_{min}, VCI_{average}</i>	<0.15
	<i>TCI_{max}, VCI_{average}</i>	<0.15
	<i>TCI_{average}, VCI_{average}</i>	<0.15
	<i>TCI_{average}, VCI_{min}</i>	0.625
	<i>TCI_{average}, VCI_{max}</i>	0.443