

Article

Identification of Shift in Sowing and Harvesting Dates of Rice Crop (*L. Oryza sativa*) through Remote Sensing Techniques: A Case Study of Larkana District

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Abstract: The present study aimed to determine the impact of climate variability on rice crops in terms of sowing and harvesting dates and crop period. The identification of sowing and harvesting dates were spotted by mask identification, variations in land surface temperature (LST) on a temporal scale in the respective months, and a field-level social inquiry. The study was conducted during a time period (1994–2017), in which geo-referenced crop samples, farmer's perception survey data, Landsat satellite images, and climate data of district Larkana were used. The analysis of satellite imageries revealed that on 20 June 1994, the rice was transplanted on 14.7% of the area of the region while it was only 7.1% of the area in 2017. Similarly, the area under rice crop in the first week of July 1994 was 18.3% compared to 8.15% during the same period in 2017. However, in the first week of October 2017, the rice crop was standing on 46.8% of the area while it was on 34.6% of the area during the year 1994 on the same date. This LST variation depicts a delay in the sowing and harvesting of the rice crop. This changing pattern is further confirmed through mean LST. Mean LST (°C) has been increasing in the sowing period of rice crop from 31.9 °C in June 1994 to 35.8 °C in June 2017, and from 32.8 °C in July 1994 to 36.8 °C in July 2017. Furthermore, the LST decreased during the harvesting period of rice crop from 31 °C in October 1994 to 28.6 °C in October 2017. The present study quantifies a delay of 15–30 days in sowing and harvesting dates of the rice crop in the district due to climate variability.

Keywords: GIS and remote sensing; climate variability; rice sowing and harvesting dates; supervised classification; land surface temperature

1. Introduction

Pakistan is located in a sub-tropical region and has arid and temperate climate. The country enjoys two seasons for agriculture, summer (April–September) and winter (October–December)—both of which are suitable for growing a variety of crops with optimal production. About 26% of the area of

Pakistan is estimated to be cultivable [1]. Agriculture is the primary source of income for about 53% of the population of Pakistan [1]. Agriculture, specifically, rice production is one of the sectors, which plays a crucial role in Pakistan's economic development. During the 1950s, Pakistan's agricultural sector contributed about 53% of the gross domestic product (GDP). While between 2012–2014, it was reported that 21.4% dramatically dropped due to certain problems such as climate variability (changes in regional climate patterns, i.e., temperature and precipitation) impacts on agricultural production, deteriorating investment in the agricultural sector, urban migration, and a growing services sector in developing countries [2]. The fiscal year of 2012 to 2013 proved to be the third consecutive year in which the worst impacts of climate variability damaged crops [2]. Climate variability is severely affecting both agricultural and socioeconomic activities in many countries [3]. It has impact on crop yield in most developing countries, where climate is an essential element of agricultural production [4]. Past studies have also shown that climatic variability affected agricultural production and food security [5].

Climatic variability is one of the world's leading problems and Pakistan is also amongst the most vulnerable on the list of countries facing climate extremes [6]. Zhu [7] calculated that rising temperatures usually reduce yields by accelerating plant growth, causing early crop maturation and a decrease in high-yield production periods. Rice is more climate-sensitive than wheat, and other crops, especially those that are unable to adapt to these changes in climatic conditions, suffer the worst. Such climate variability has a direct influence on farmers incomes and thus on Pakistan's economy. Climate variability can influence the sowing and harvesting dates of crops as well as their growing period. In this study, we quantify the change in sowing and harvesting dates (crop calendar) of rice crops in the Larkana district region. The triangulation approach is used to investigate the change in the rice sowing and harvesting calendar from 1994 to 2017. The area of rice yields was estimated through the Landsat images and later this land use and land cover changes were verified through changes in land surface temperature (LST) from the area of study. Then, a social investigation was carried out using a farmer's perception survey to further validate the hypothesis.

LST was used to identify the changes in vegetation [8], urban heat island due to rapid urbanization [9,10], drought and soil moisture monitoring [11], and high-temperature risk assessments of crops at the regional scale [12]. Stoyanova et al. [11] studied the spatial-temporal variability of land surface dry anomalies in the climate aspect, and identified drought-prone areas through LST maps. The results derived from satellite LST data were used to identify the drought occurrence and its severity. They reported that the Soil Moisture Availability Index (SMAI) has a meaningful statistical relationship with LST [11]. The LST is a key factor controlling most physical, chemical, and biological processes on earth. Knowledge of the LST is necessary for many agricultural, environmental, and management activities related to surface resources. LST results from an energy exchange at the surface. Satellite-based monitoring is regarded as an essential prerequisite of regional and global observations of surface water, energy, and radiation budget. Different studies investigated that land use and land cover changes influenced the land surface energy balance significantly [13–17]. Irrigated agriculture (e.g., type of crop, planting pattern, water conditions, and crop canopy) has influenced this energy balance of the earth's surface environment [18] substantially. For example, irrigated agriculture impacted the range of diurnal air temperature [19]. Guoming et al. [20] studied the relationship between LST and paddy rice expansion. They found that LST decreases with the increased fraction of the rice paddy area more rapidly when the rice paddy is aggregated and accounted for by more than 80% of each study grid. On the other hand, land surface temperature was substituted for air temperature, and Kimura [21] examined the rice quality using LST satellite data from the Moderate Resolution Imaging Spectroradiometer (MODIS) during the ripening stage (August) in the Tottori prefecture.

LST datasets were applied in the lower Indus delta area to identify the land use and land cover changes. Different studies found that changes in the vegetative cover significantly impacted the LST in the Indus delta [22,23]. Rehman et al. [22] found that LST in the Keti Bandar area of the Indus delta is increasing due to the decrease in the vegetation of the area. They also reported that due to the mangrove's plantation drive of the Sindh government, LST was significantly decreasing in 2014

as compared to 2010. Siyal et al. [23] studied the Indus delta region and found a negative statistical correlation coefficient of determination R^2 0.65 between LST and the Normalized Difference Vegetation Index (NDVI).

The Crop Reporting Services (CRS) department collected the crop data annually through a randomized farmers survey. The discrepancies present in the field survey and data reporting creates a severe doubt to use such data for research purposes. Siyal et al. [24] studied Larkana district rice crop acreage and found that the Crop Reporting Sensing (CRS) overestimated (19–24%) the rice crop in Larkana district from 2006–2010. Thus, the annual crop reporting data is not reliable to use in finding the sowing and harvesting dates for rice crops. To prevail over these deficiencies in secondary data, we estimate the rice crop area using rice Crop Mask over Landsat imageries available in 1994, 2000, 2010, and 2017.

2. Materials and Methods

2.1. The Study Area

Larkana District was selected for this study because it is the leading rice-producing district in Pakistan's Sindh Province (Figure 1). Larkana is situated in northwestern Sindh Province between longitude 67°56' E to 68°27' E and latitude 27°4' N to 27°56' N. Larkana District is comprised of four talukas (Taluka Ratodero, Taluka Larkana, Taluka Bakrani and Taluka Dokri) and 47 UCs (union councils). The main crops grown in Larkana District are rice, wheat, sugarcane, barley, gram, pulses, and jawar. The rotation of rice and wheat crops is common in this district. Rice transplanting starts in June and harvesting stretches from mid-September to end-November. The geographical area of the district is about 7234 km². According to the 2017 population census, the population of Larkana District is about 15.24 million [25].

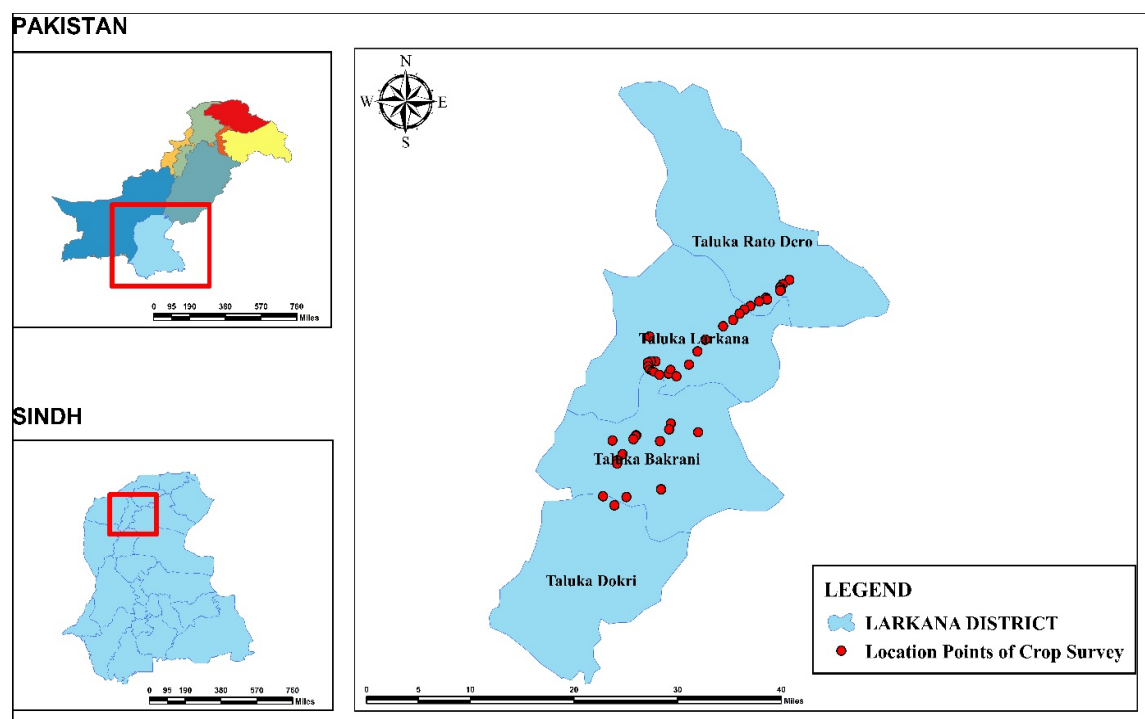


Figure 1. Map of the study area and spatial distribution of farmer survey sampling location in Larkana District.

During the summer season (April to September), the average maximum temperature of the district is 42 °C, and the average minimum temperature is 31 °C, while during the winter season (October to March) the average maximum temperature is 21 °C and the average minimum temperature is 11 °C.

Larkana has the third-highest temperature ever recorded in Pakistan (53 °C), which occurred on 26 May 2010. The annual precipitation of Larkana is about 130 mm; which is not enough to meet the daily rice crop evapotranspiration demand (4.5 mm to 4.6 mm) taken from the On-Farm Water Management Field Manual Volume V1 & V2. The agricultural activities of Larkana District mainly depend on irrigation water from the Rice Canal, Dadu Canal, Warah Canal, and Khirthar Canal. The Rice Canal and Daddu Canal pass through the Larkana District for approximately 76 km and 80 km, respectively [26,27]. The reference crop evapotranspiration for the study is 1026 mm annually, and the potential crop water requirement for rice crops is 1303 mm. The cropping intensity reported was 88% annually and 50% during the summer season. The canal water allocation is 1860 L per second for a 1000 ha area [28].

2.2. Rice Crop Acreage Estimation

Landsat 5, 7, and 8 satellite imageries of path 152 and row 41 for June, July, September, and October corresponding to the years 1994, 2000, 2010, and 2017, were downloaded from the USGS GloVis (Global Visualization Viewer) website (<http://glovis.usgs.gov/>). The Landsat satellite imagery for 22 July 2000 was available, but the imagery has cloud coverage of more than 10%. Since cloud coverage interferes with image classification for estimating the vegetation area, the nearest Landsat imagery from 15 August 2000, was used to represent this year (see Table 1).

Table 1. Landsat images used in the study and their radiometric coefficients, DOY (day of the year), d (earth–sun distance in astronomical units) and θ_s (sun elevation) taken from the metadata files of the selected images.

S. No	Landsat Scene ID	Image Acquisition Date	DOY	D	θ_s
1	LT51520411994171ISP00	20 June 1994	171	1.01618473	59.74174722
2	LT51520411994187ISP00	6 July 1994	187	1.01670828	58.74459703
3	LT51520411994267ISP01	24 September 1994	267	1.00318368	48.82472026
4	LT51520411994283ISP00	10 October 1994	283	0.99860956	45.01339828
5	LT51520412000156AAA02	04 June 2000	156	1.01453940	64.00056348
6	LE71520412000228SGS00	15 August 2000	228	1.01273390	62.272953
7	LT51520412000268XXX02	24 September 2000	268	1.00305870	52.40828426
8	LT51520412000284XXX02	10 October 2000	284	0.99848295	48.2356436
9	LE71520412010175SGS00	24 June 2010	175	1.01641456	66.94012887
10	LE71520412010191SGS00	10 July 2010	191	1.01664552	65.95491245
11	LE71520412010271ASN00	28 September 2010	271	1.00209418	53.58059737
12	LE71520412010287SGS00	14 October 2010	287	0.99751050	49.02271953
13	LC81520412017170LGN00	19 June 2017	170	1.01611869	68.84977931
14	LC81520412017186LGN00	5 July 2017	186	1.01667161	67.96541446
15	LC81520412017266LGN00	23 September 2017	266	1.00343920	56.00378398
16	LC81520412017282LGN00	25 October 2017	282	0.99882774	51.36404378

Based on Landsat satellite imagery, rice crop masks for June, July, September, and October corresponding to the years 1994, 2000, 2010, and 2017 prepared to determine spatial and temporal variations in the rice crop area in Larkana District. The images were classified into rice and non-rice crop areas using visual interpretation of the multi-temporal Landsat imagery in combination with high-resolution imagery from Google Earth, and employing local expert knowledge, with the maximum likelihood classification algorithm in Arc GIS 10.3.1. The Landsat data must be preprocessed before analyzing for any change detection between rice and non-rice areas [29]. Therefore, the Landsat data were preprocessed in ERDAS Imagine 2016 and ENVI 5.1 to gap-fill the scan lines of missing data in the Landsat 7 imageries. An extract the area of interest (AOI), and the GIS extract-by-mask tool were used. After preprocessing the data, the Landsat imageries were classified using the ArcGIS 10.3.1. The supervised classification method was used to train the satellite data in this study due to the non-availability of field data.

Initially, the Landsat data was classified into six different classes: water, rice, mango, guava, barren land, and vegetation. These divisions were determined using supervised classification with a maximum likelihood algorithm using field data samples; for every image, signature files were created. The six classes were then aggregated into two categories: rice and non-rice. The classified images were converted into a vector format from a raster to simplify area calculations. From the attribute table of the vector datasets, the rice crop area was determined based on the area covered by each class. The procedure was repeated for all selected Landsat imageries. After converting the classified Landsat images into vector format, the area under each class was calculated using a query builder tool. The accuracy level of image classification methods is reported in Table 2. The accuracy of the image classification depends on the classification technique and the number of training samples of each class.

Table 2. Comparison between the two image classification methods.

No.	Classification Types	Accuracy Level (%)	Statistical Kappa Coefficient (k)
1	Maximum Likelihood	89	0.82
2	Algorithm-Supervised Classification Support Vector Machine	94	0.91

The classification method based on support vector machine accuracy is 6% better than the maximum likelihood method, but in this study maximum likelihood algorithm (MLA)–supervised classification method was adopted. The results obtained through this method may vary up to 6% and can be improved by adopting a better classification approach [30]. The area under rice crop in June 1994 was compared with the area under rice in June of 2000, 2010, and 2017 to quantify any shift in rice sowing dates. Similarly, the area under rice crop in October for the years 2000, 2010, and 2017 was compared with an area under rice crop in October 1994 to determine any shift in harvesting dates.

2.3. Land Surface Temperature

The mean LST of Larkana District was calculated from thermal bands of Landsat satellite imagery for the years 1994, 2000, 2010, and 2017. The mean LST was calculated by averaging minimum and maximum LST of the study area [23]. Landsat 5, 7, and 8 images were used in this study due to the long temporal time series. The significant difference between these products is the resolution of the products. The LST is retrieved based on the number of algorithm and emissivity model. There are different algorithms such as the Mono Window Algorithm (MWA) [31], the Radiative Transfer Equation (RTE) [32] method, the Single Channel Algorithm (SCA), and the Split Window Algorithm (SWA) [33,34]. The surface emissivity models used were categorized as: classification-based emissivity method, NDVI-based emissivity method, multichannel emissivity methods, and physically based emissivity methods. In this study, we used a Land Surface Emissivity (LSE) model proposed by Sobrino et al., [35] for LST retrieval and for a comparative purpose in Landsat 5, 7, and 8 images. Thus, accuracy difference based on different Landsat product is not to be of importance as for as LST is concerned. LSE proposed by Sobrino et al., [35] is considered the best model for all Landsat missions.

2.4. Farmers Perception Survey

A field survey of the rice crop was conducted in Larkana District during Kharif season 2017, aided by a map and Garmin 64 s GPS device. The field survey was conducted between September and October 2017. Before the field visit, a proforma for collecting the required geo-referenced data was prepared. The tabular proforma contained longitude, latitude, date, union council names, Taluka names, and district and crop name. The proforma was completed during the field visit using a Garmin 64 s GPS device for taking coordinates of the survey respondent locations. The perception survey of farmers was conducted to validate the sowing and harvesting shift in the rice crop plantation and the

total rice crop grown in the district. The sample size (100) was calculated through a Cochran's formula because it is best when the population size is large and not known.

$$no = Z^2 \times \frac{pq}{e^2} \quad (1)$$

where: e is the desired level of precision (i.e., the margin of error), p is the (estimated) proportion of the population which has the attribute in question, q is $(1 - p)$ [36].

We selected small, medium, and large farmers from all union councils of Larkana District for the farmer's perception survey. Thus, we can say it is a multistage random sampling. During the field survey, nearly all the union councils (UCs) of the district where rice crop production occurs were covered. The spatial distribution of the field data sampling points in Larkana District are shown in Figure 1.

2.5. Meteorological Data

Meteorological data from 1994–2017 in Larkana District was collected from the Pakistan Meteorological Department (PMD) in Karachi. The data consists of the mean monthly and annual minimum and maximum temperature in degrees centigrade ($^{\circ}\text{C}$), as well as the mean monthly and annual sum of precipitation in millimeters (mm). The crop season (June–October) maximum and minimum temperature and rainfall series were analyzed for trend analysis and changes in the trend slope. For trend detection, the Mann Kendall non-parametric test was used and the trend slope estimated through Sen's estimator. It is widely used to detect trends in time series data. It is a distribution-free test and does not require normally distributed data [37–40]. The N values time series are ranked from smallest to largest and computed by the Sen's estimator. Sen's estimator of the slope is the median of these N values.

3. Results

3.1. Temperature and Rainfall

The annual temperature and annual rainfall data of Larkana District from 1994 to 2017 were analyzed on an annual basis as well as for the crop season months (June–October) to identify temporal changes in temperature and rainfall patterns. The crop season maximum and minimum temperature and the rainfall are graphically represented in the following Figure 2.

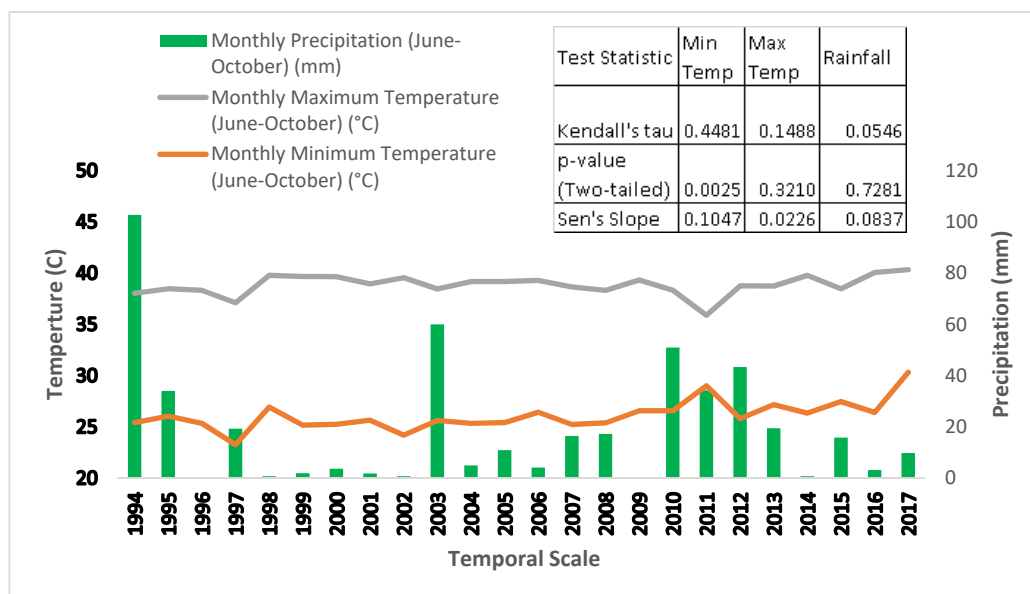


Figure 2. Monthly maximum and minimum temperature and monthly rainfall of Larkana District.

Trend analyses for monthly mean maximum and minimum temperature series reveal that minimum temperature series during the crop season shows an increasing trend ($0.105\text{ }^{\circ}\text{C}/\text{Year}$). In contrast, the maximum temperature series do not have a significant trend, but the Sen's slope is $0.022\text{ }^{\circ}\text{C}/\text{Year}$. The mean precipitation trend for the crop months also does not have a significant trend in the series, while the Sen's slope shows a $0.087\text{ mm}/\text{year}$ increase annually during the crop season months. Salma et al. studied the different climatic zones of Pakistan and found that the southwest zone of Pakistan does not have a significant trend in temperature and rainfall patterns [41]. The tendency of air temperature to rise also influences the LST, as [42] suggests that air temperature alone explained 81–98% variance in LST under clear sky and cloudy conditions.

3.2. Quantification of the Change in Sowing and Harvesting Dates

Images for the months June, July, September, and October for the years 1994, 2000, 2010, and 2017 were classified to determine temporal variation in the area under rice crop in Larkana District and are graphically represented in Figure 3. For accuracy assessment of the crop mask for rice and non-rice areas, the results were compared with the previous study in the same district. Siyal et al. [24] estimate the area under rice cultivation through classified imagery between 2006 and 2013. Siyal et al. (2015) estimate the rice acreage for 2010 is 70,819 ha [24], whereas we estimate the rice acreage 69,873 ha. Hence, the crop mask prepared for this study was used reasonably to estimate the rice acreage quantification.

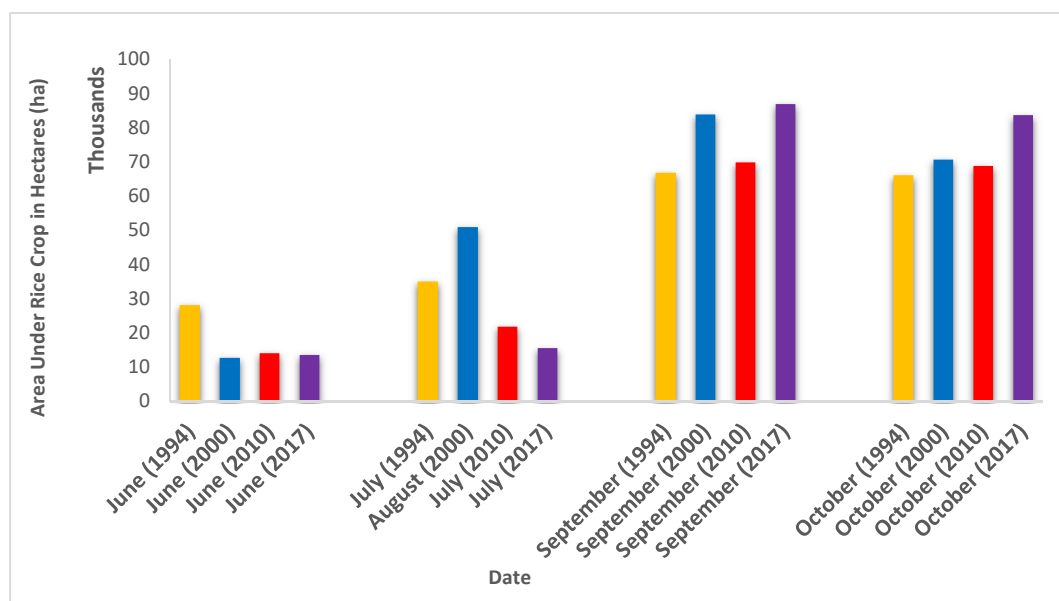


Figure 3. Temporal variation in the area under rice crop in the study area through Landsat satellite images.

The comparison of areas under rice crop of 20 June 1994, with the area under rice of 19 June 2017 are graphically represented in Figure 3. The graph shows that the area under rice crop in June from 1994 to 2017 decreased due to the shift in sowing dates. The results reveal that there is a 106% decrease in the rice crop area in June from 1994 to 2017, this gap narrowed down to 14% in July. We analyzed the satellite imageries for these sowing months (June and July) with only one-day difference. On 20 June 1994, rice grown on a 42% area in the district as compared to 19 June 2017, image, only 16% completed the sowing. The scenario for July was the same when 52% completed the sowing process in 1994 as compared to only 35% in 2017. These stats clearly depict the shift of rice sowing pattern towards first and second quarter of July. Harvesting months September and October showed that harvesting started from the first quarter of October in 1994 as compared to 2017, in which harvesting started in the third quarter. This indicates that the area under rice crop starts reducing as compared to September in the

first and third quarter of October in 1994 and 2017, respectively. The rice crop masks of Larkana District for the months, June, July, August 2000, September, and October of the years 1994, 2000, 2010, and 2017 are shown in Figure 4.

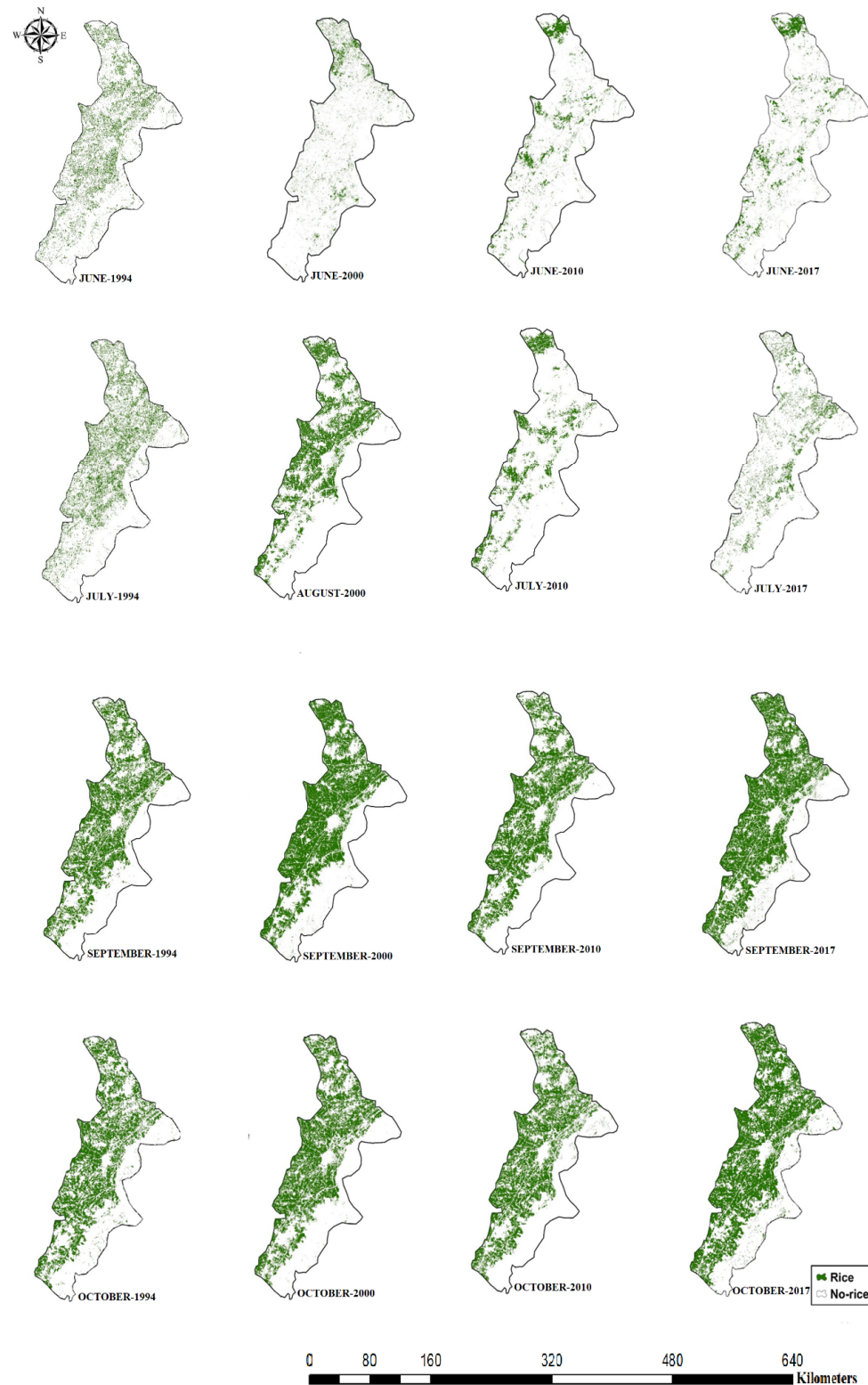


Figure 4. Rice crop masks of the study area from Landsat satellite imageries for crop sowing and harvesting period.

3.3. Sowing and Harvesting Dates Identified through Land Surface Temperature

To further validate the sowing and harvesting shift of the rice crop pattern, LST was analyzed for the selected satellite imageries. The results of the mean LST for the selected months for 1994, 2000, 2010, and 2017 was calculated from the satellite images shown in Table 3.

The LST has a strong correlation with vegetative growth on the field. The area under rice crop in different months and LST has a significant negative correlation, as shown in Table 3. Furthermore, the functional relationship between rice crop area and LST was established using a regression analysis method. The linear and nonlinear regression models between two variables were performed and the function of the relationship is shown in Figure 5. The logarithmic functional relationship between these two variables has the highest correlation coefficient ($R^2 = 0.7318$), as compared to the linear relationship ($R^2 = 0.7119$). Different studies also had similar findings [20,22,23]. It shows that the more vegetative growth on the land, the lower will the LST be, and vice versa. The impact of the shift in sowing and harvesting dates on the temporal scale influenced the LST of Larkana District for June and July (sowing period) and September and October (harvesting period) for the years 1994, 2000, 2010, and 2017. The results reveal that the mean LST of Larkana District has increased during June and July from the years 1994 to 2017. Furthermore, the mean LST has decreased during the harvesting period from 1994 to 2017. The LST of the study area for the targeted months and years are graphically shown in Figure 6. Mean LST ($^{\circ}\text{C}$) has been increasing in the sowing period of rice crop from 31.9°C in June 1994 to 35.8°C in June 2017, and from 32.8°C in July 1994 to 36.8°C in July 2017. Furthermore, the LST decreased during the harvesting period of rice crop from 31°C in October 1994 to 28.6°C in October 2017. This study found that LST is 11% more on 19 June 2017, as compared to 20 June 1994. This difference in temperature is due to a difference in the area under rice cover. The difference between the areas under rice crop also confirms from the difference in LST between 1994 to 2017, as shown in Figure 6, and the same trend is revealed in July. This temporal variation of LST also proves the shift of sowing of rice crop. The delay of rice crop harvesting also depicts from LST variation between October 1994 to 2017. As we have shown that there is more area under rice crop in October 2017 as compared to 1994, this will impact the LST to be 8% (28.6°C) less in 2017 as compared to 1994. For the last 24 years, mean LST in June and July has increased 3.9°C and 4°C respectively, whereas in October the temperature decreased to 2.4°C due to more area under crop as compared to 1994.

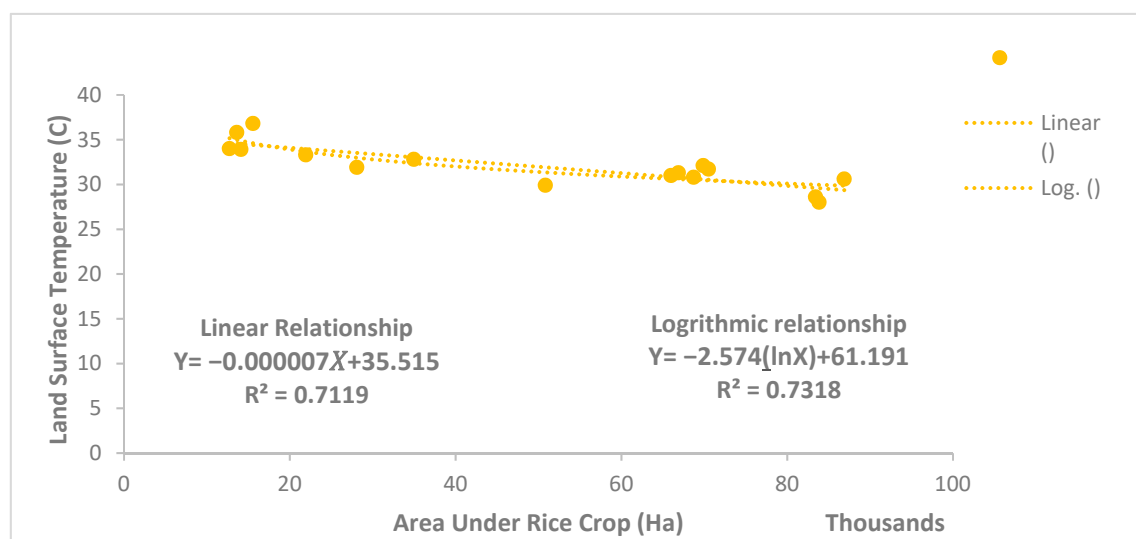


Figure 5. Linear and logarithmic relationship between land surface temperature (LST) and area under rice crop.

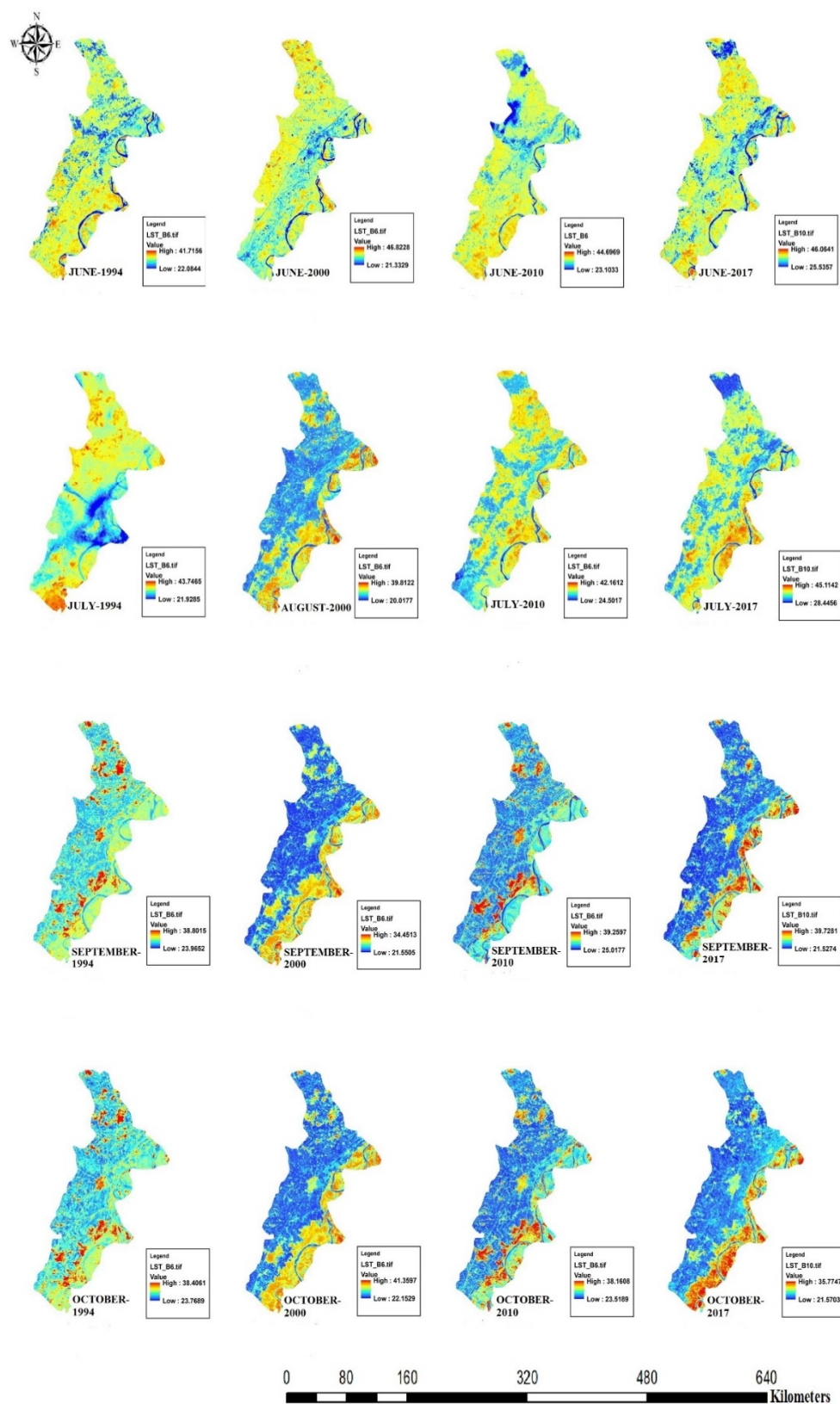


Figure 6. The land surface temperature of Larkana District for the selected months and years.

Table 3. Correlations statistics for area under rice crop and LST.

Landsat Imagery	Rice Crop (ha)	LST (°C)	Correlation Factor	Overall Correlation Factor
June	28,089	31.9	−0.83	−0.84
	12,722	34		
	14,117	33.9		
	13,611	35.8		
July	34,966	32.8	−0.93	
	50,843	29.9		
	21,929	33.3		
	15,563	36.8		
September	66,897	31.3	−0.67	
	83,854	28		
	69,874	32.1		
	86,895	30.6		
October	65,992	31	−0.88	
	70,522	31.7		
	68,724	30.8		
	83,432	28.6		

3.4. Crop/Socioeconomic Survey of Larkana District

The responses and results obtained from the crop/socioeconomic survey of Larkana District (i.e., Taluka Ratodero, Taluka Larkana, Taluka Bakrani, and Taluka Dokri) are discussed and graphically represented as follows:

From all the responses in Table 4 during the rice crop sowing and harvesting survey of Larkana District, the study concluded that the sowing and harvesting dates of the rice crop in the district shifted 15–30 days during the last 25 years. Secondly, the responses regarding rainfall and temperature reveal that the amount of rainfall in the district has decreased, while the temperature has increased during the last three decades.

Table 4. Survey of sowing and harvesting of rice crop of Larkana District.

S. No.	Questions	Responses
1	When do you transplant the rice in the current scenario?	73% of the people responded that they transplant the rice in the first and second week of June, while 27% of the people responded for the first week of July.
2	In which month did transplantation take place 25 years ago?	81% of the people responded that 25 years ago they used to transplant the rice in the last week of May, while 19% of the people did not respond.
3	When do you harvest the rice crop in the current scenario?	68% of the people responded that they harvest the rice on November 1, while 32% of the people responded for October.
4	In which month was rice harvested 25 years ago?	88% of the people responded that 25 years ago they used to harvest the rice in the third week of September, while 12% of the people responded for the second week of August.
5	Has temperature increased/decreased in summer during the last 25 years?	61% of the people responded that the temperature has increased in summer since the last 25 years, while 39% of the people had responded with mixed ideas.
6	Has rainfall increased/decreased in summer during the last 25 years?	75% of the people responded that the rainfall has increased in summer since the last 25 years, while 25% of the people had no idea about that.

4. Discussion

LST and its contributing factors in an irrigated environment have practical and theoretical implications for managing the agricultural production system better. Changing patterns of LST—due to multiple reasons, has a more significant influence on crop growth. Different studies find a significant negative correlation between NDVI and LST. The correlation coefficient we have found in the different months was stronger as compared to the reported results of Siyal et al. [23] and relatively weaker as compared to Guoming et al. [19]. Guoming et al. [20] reported that the correlation coefficient between paddy rice and LST was stronger (greater than 95%)—except for August, as compared to our study (less than 90%). The reason for this difference in statistical correlation between Guoming’s findings and our study is probably due to study area features. Northern Sanjiang Plain area is a relatively cooler area as compared to Larkana. Different studies found that LST influencing factors are intricate and may depend upon the surface air temperature, wind speed, and land terrain, etc., [42–44]. It might be possible that the variation of this statistical correlation is due to the study area specific characteristics. The same is the case for study with Siyal et al. [23]; they found a lower value of correlation as compared to our study. The Indus delta has a different landscape, with a large area of tidal floodplain area and a relatively larger number of water bodies as compared to Larkana. These contributing factors of LST influence the relationship with NDVI.

5. Conclusions and Recommendations

The use of geospatial tools for the estimation of the shift in the sowing and harvesting dates of the crop is a new field in the Pakistani context. For this purpose, literature for the comparison purpose is a huge limitation we faced. This study is unique in the local context of Sindh and Pakistan. Based on the ground truth surveys, results obtained from Landsat satellite imageries, historical rice crop data, meteorological data, and crop/socioeconomic surveys, the following conclusions are drawn. On 20 June 1994, the rice was transplanted on 14.7% of the area of the district while it was only 7.1% of the area in 2017. Similarly, the area under rice crop in the first week of July 1994 was 18.3% compared to 8.15% during the same period in 2017. Thus, showing a delay/shift in the sowing of the rice crop. However, in the first week of October 2017, the rice crop was standing on 46.8% of the area while it was on 34.6% of the area in the year 1994 on the same date. This LST pattern depicts a delay in the harvest of the rice crop. Mean LST (°C) has been increasing in the sowing period of rice crop from 31.9 (°C) in June 1994 to 35.8 (°C) in June 2017, and from 32.8 (°C) in July 1994 to 36.8 (°C) in July 2017. Furthermore, the LST decreased during the harvesting period of rice crop from 31 (°C) in October 1994 to 28.6 (°C) in October 2017. One of the possible reasons for the delay in sowing and harvesting dates is soil moisture anomalies and their relationship with LST [10]. This hypothesis needs to be further examined in future studies in this area. The study of LST is important to understand the impact on rice crop growth, crop tiller, and consequently, on yield. In future research, these aspects of being considered as control variables so that future cropland planning may account for these changes.

Based on the results, we recommend the remote sensing technique for the estimation of actual crop grown area, and it is more viable and gives a reliable estimation as compared to the crop reporting services. Canal commands of Pakistan’s cultivated on the rotation basis; thus, late sowing of the one crop may influence the optimum sowing dates of the other crops. For the proper crop scheduling, there is a need to optimize the sowing dates of rice–wheat cropping pattern as an adaptation strategy of the future climate variability scenarios.

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