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Assessment of Cropland Changes Due to New Canals in Vientiane Prefecture of Laos using Earth Observation Data

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ABSTRACT

The lower catchment area of a Mak Hiao river system is vulnerable to flash floods and water stress. So it is important to construct irrigation structures in this area to minimize floods during the rainy season and store water for the winter season. The Asian Development Bank (ADB) has been supporting the Government of Laos in constructing such small reservoirs like Donkhuay schemes 1 & 2, Mak Hiao, Nalong 3 and Sang Houabor projects in lower catchment areas. Our study evaluated the impacts of small irrigation schemes in terms of land-use/land-cover (LULC), crop intensity, and productivity changes, using high resolution satellite imagery, socioeconomic, and ground data. We analyzed the temporal cropping pattern in the Vientiane prefecture of Laos using Planet and Sentinel-2 data. On the other hand, crop intensity and cropland changes were mapped using Sentinel-2 data and spectral matching techniques (SMTs). The crop classification accuracy based on field-plot data was 88.6%. Our results show that irrigation projects in the lower catchment areas brought about significant on-site changes in terms of cropland expansion and increased crop intensity. Remarkable changes in LULC were observed especially in the command areas owing to an increase of about 300% in crop area with access to irrigation and increase of water bodies by 31%. Our study found that interventions at the level of the command area do improved on-site soil, water and environmental services. They study emphasized underline the role of land-use regulations in reducing pressure on natural land-use systems and thereby serving the major goal of up-scaling sustainable natural resource management. The study documented the vital role of small/medium irrigation projects in restoring ecosystem services such as cropping patterns and LULC conversion.

1. Introduction

The Lao People's Democratic Republic (PDR) is a landlocked country with 80% of its land falling within the mountainous topography of the uplands of the Mekong River Basin and 20% falling in the flood plains of many small rivers. The country has a monsoon climate with a combination of wet season and a dry season. The hydropower and irrigation systems located in the mountainous regions sustain agriculture in the plains. About 75% of the total population of Laos is dependent upon agriculture, which contributes nearly 50% of the country's Gross Domestic Product (GDP). [1,2]. The major staple crops are rice and maize [3]; the economically important crops include coffee, sugarcane, cassava, sweet potato and industrial tree crops such as rubber, eucalyptus and acacia.

The irrigation systems we covered for the present study are located in the plains of Vientiane prefecture. Traditionally, farmers in these plains used indigenous methods to irrigate crops. These systems, however, were not able to cater to the increasing demand for water from sectors like agriculture and domestic use (drinking water). This has forced them to switch over to modern irrigation systems (such as dams and reservoirs) which can enhance the water availability and thereby the demand during dry season [4,5].

Managing natural resources is important for sustainable agricultural development [6,7]. Small and minor irrigation projects are essential for enhancing the WUE as well as increasing the water productivity [8–10]. One of the major purposes of medium and minor irrigation projects is to control floods and preserve the water for off-season [11,12]. Given such a context, monitoring minor irrigation projects is important for

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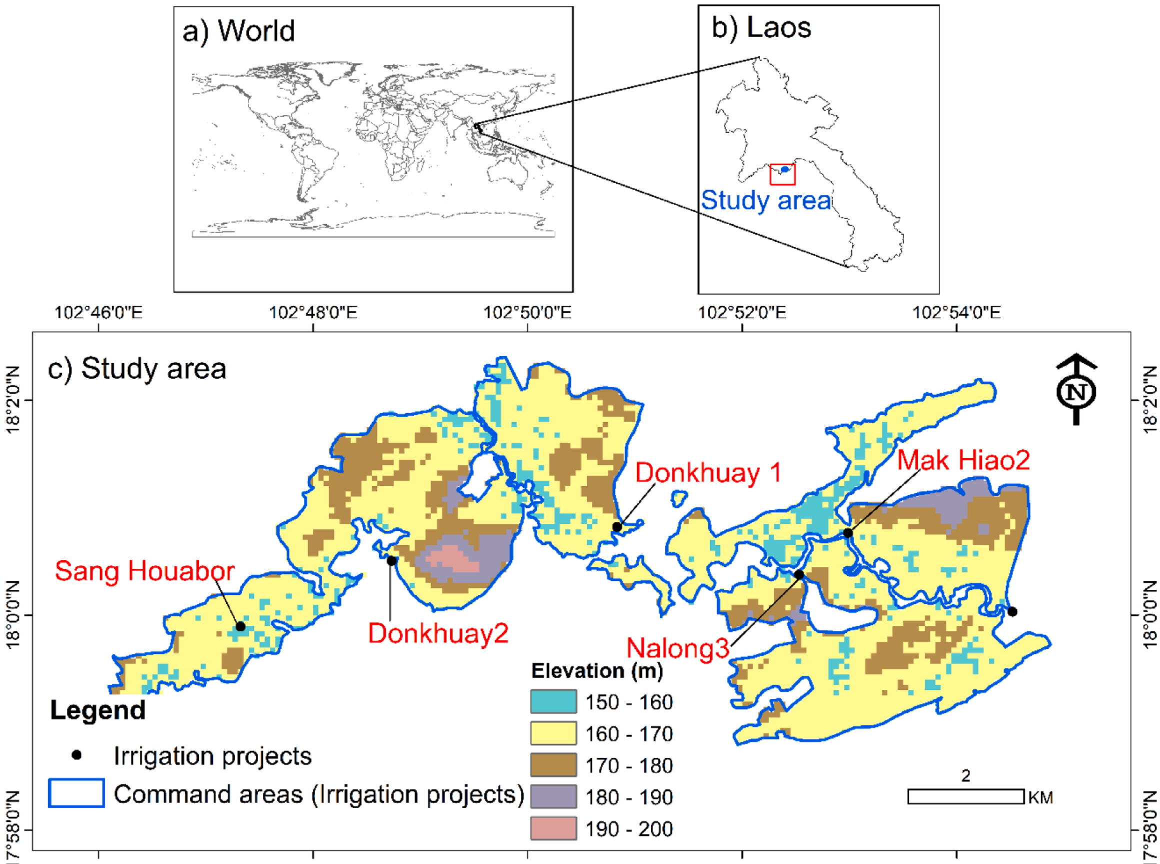

Fig. 1. A map of the study area in Vientiane prefecture of Laos showing canal irrigation schemes, digital elevation map (DEM) and the command area.

Table 1
Ground sample points collected for classification

S.No	Class	No. of Points
1	Rice	84
2	Other Crop	18
3	Barren land/Fallow	13
4	Built up	12
5	Forest	23
6	Other LULC	4
7	Plantation	5
8	Water Bodies	9
Total		**168**

evaluating land and water productivity [13–16].

Floods during the wet season and drought during the dry season are a regular phenomenon in the Vientiane prefecture. The Greater Mekong Sub-region Flood and Drought Risk Management and Mitigation Project, funded by the Asian Development Bank and executed by the Department of Irrigation under the Ministry of Agriculture and Forestry, is aimed at improving preparedness for flood and drought risk mitigation [17]. Improved groundwater (GW) due to deep percolation during the dry season and higher GW levels in the wet season help farmers by enabling the use of groundwater for irrigation in the dry season [18]. Increasing population and food demand make it imperative to promote minor irrigation projects at appropriate locations. At the same time, there is a need for real-time monitoring of land-use changes using advanced technologies like remote sensing in association with machine learning algorithms.

Remote sensing is a low-cost but effective tool for identifying the spatial distribution of land-use/land-cover (LULC) changes and assessing their impact at various scales. Several studies have monitored land-use changes in the context of improving water resources and have proven the usefulness of geospatial technologies [19–22]. Several studies have also documented LULC changes using remote sensing technology and machine learning algorithms supported by ground data and secondary information [23,24]. However, methods of monitoring LULC changes vary from the small to large scale [25,26]. Monitoring of croplands and changes in land use at various scales [27,28,47], from the watershed level to the global scale [29,30], relies on the application and type of satellite imagery sourced from platforms like MODIS, Landsat and Sentinel [31,32]. Mapping of soil moisture and floods during the rainy season uses Sentinel-1 data [33–35]. Several studies have assessed flood damage, crop stress and even LULC changes in mountain regions [36,37], etc.

Monitoring of LULC changes is important for multi-disciplinary teams such as economists, breeders, hydrologists and planning departments working on improvement of agriculture and water productivity [38–40], and also for research. Cloud-based image-processing platforms such as Google Earth Engine (GEE), which also hosts catalogues of imagery from different satellite platforms such as Sentinel-1, can provide quick and nearly accurate information of ground conditions using preloaded algorithms such as machine learning algorithms including Random Forest (RF), Support Vector Machines (SVM), and many regression techniques.

Our study highlighted the application of remote sensing technology for monitoring and evaluation of irrigation projects in relation to LULC

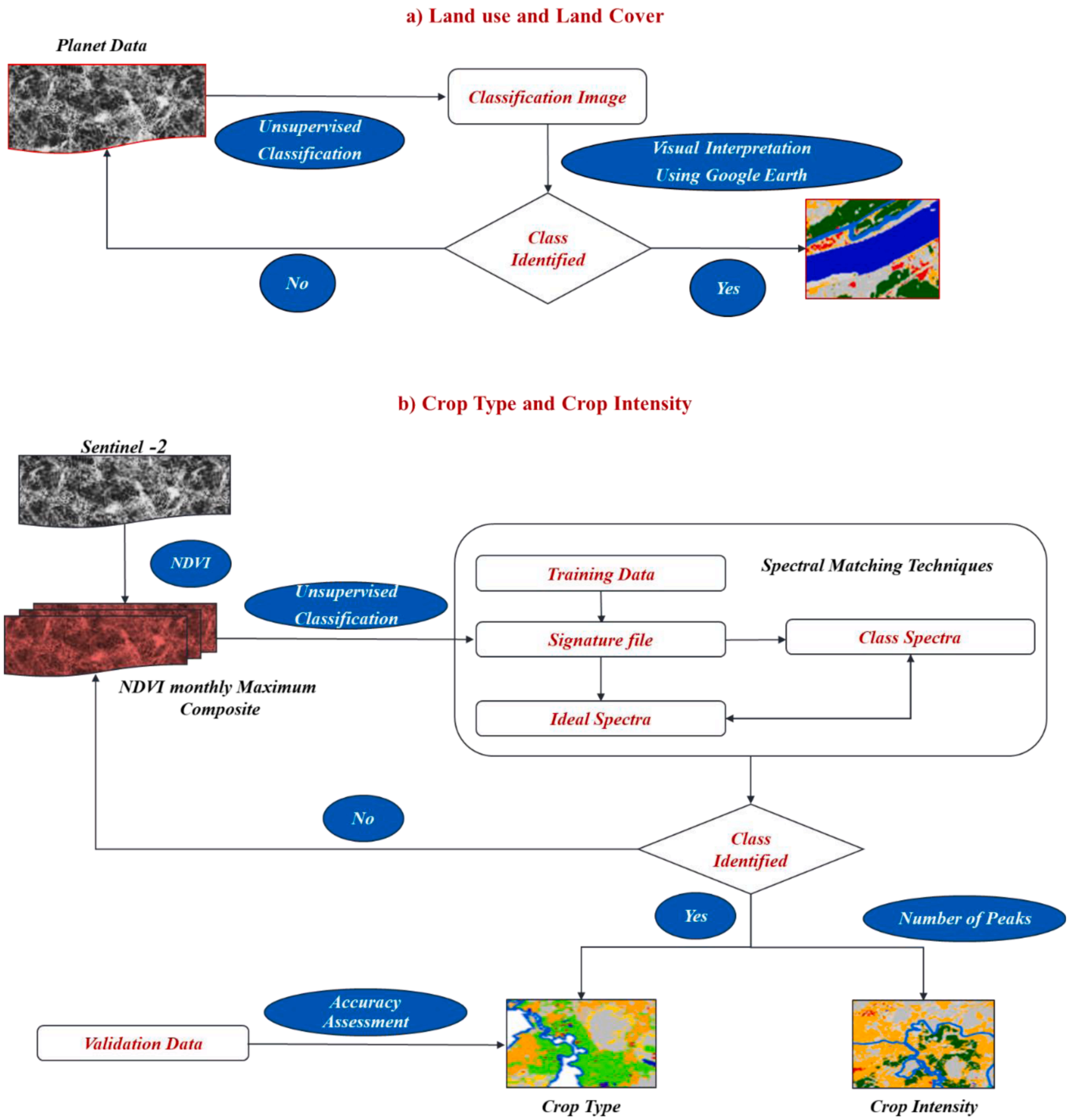

Fig. 2. Classification of (a) land-use/land-cover classes and (b) crop type and crop intensity.

changes over time. This paper generated quantitative estimates of cropped area with a season-wise break-up that could help in the prioritization of activities and investments in a project area.

The major objectives of this paper includes

- Mapping LULC using high-resolution multispectral Planet© data at 3m spatial resolution
- Quantifying land-use changes in terms of crop type and crop intensity using high spatio-temporal resolution Sentinel-2 satellite imagery and assessed the impact due to new irrigation projects.
- Economic impact due to construction of minor irrigation projects

2. Data

2.1. Study area

The area selected for the present study includes the gross command areas (GCAs) of four irrigation canals of the Mak Hiao River: the Donkhuay schemes 1 & 2, Mak Hiao, Nalong 3 and Sang Houabor projects located in Vientiane Prefecture in south-central Laos (Fig. 1) with the Mekong River forming the southern boundary. The climatic conditions in this region are quite varied compared to the other parts of Laos. Temperatures in winter are slightly higher and milder in the range of 16-28°C; in summer, they vary from 24°C to 34°C. Rains are abundant from July to October, making up an annual average of nearly 1,700 mm. The major soils in this region are alluvial with some parts having laterite soils. The dominant crop in this region is paddy, apart from corn, cassava, vegetables and fruits.

2.2. Satellite Data

As stated earlier, we used Planet multispectral and 3-m spatial resolution static data for land use/land cover characterization; for crop classification and assessment of crop intensity during the period 2016-2020, we have used Sentinel-2 10-m data. With the help of GEE, using a cloud-free algorithm for Sentinel-2 which uses Quality Assurance (QA)

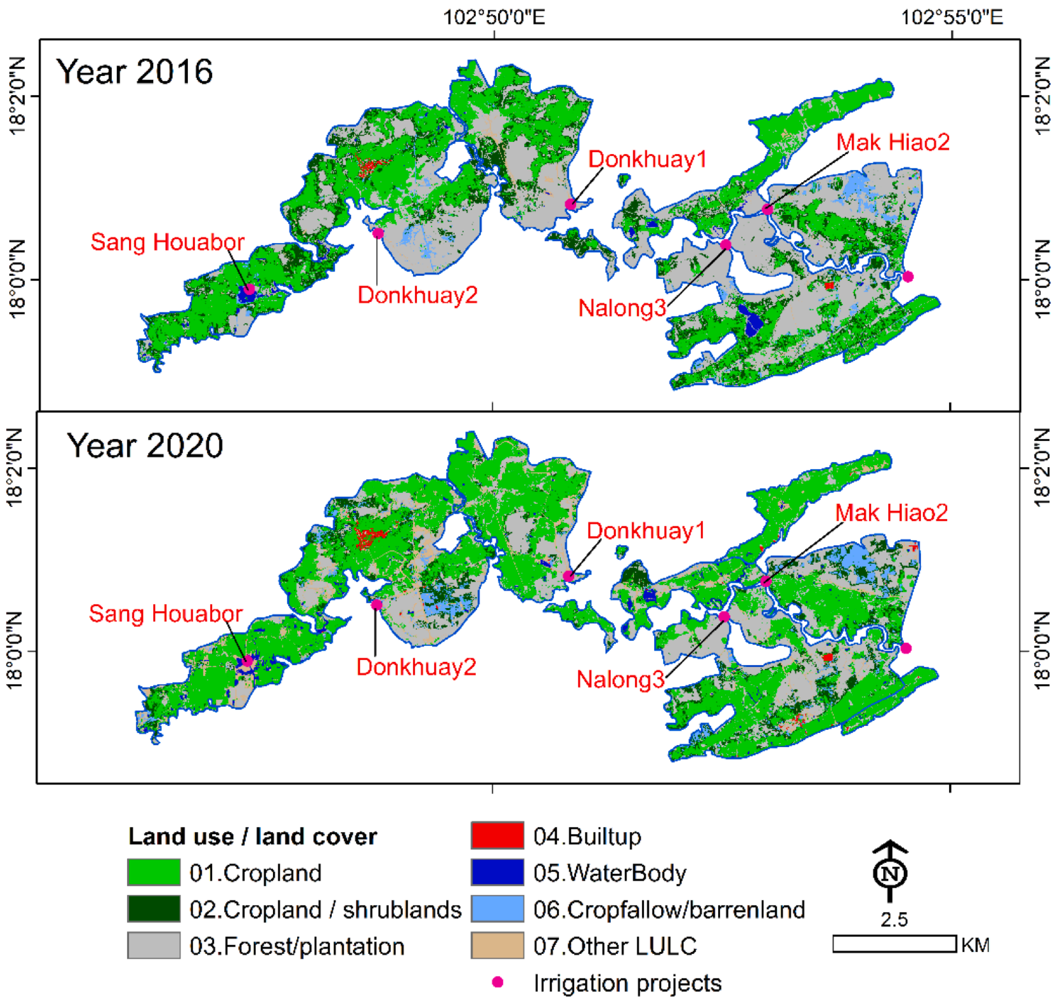

Fig. 3. Spatial distribution of LULC classes for the years 2016 and 2020 on the basis of Planet 3 m data.

Table 2
LULC classes for the years 2016 and 2020.

Land-use/land-cover	Area (ha) 2016	2020	Percent Change
1. Cropland	1,351	1,843	36%
2. Cropland/shrub land	573	337	-41%
3. Forest/plantation	1,589	1,016	-36%
4. Built-up area	9	22	144%
5. Water bodies	53	73	38%
6. Crop fallow/barren land	107	148	38%
7. Other LULC	61	305	400%
	3,743	3,743	

band that considers the probability of presence of cloud and shadow in satellite imagery, pixels with cloud in the Sentinel-2 imagery were removed; this was followed by making estimates of the maximum Normalized Difference Vegetation Index (NDVI) for every 15 days and stacking them as a single composite. The NDVI index was calculated on the basis of the normalized difference between Band 8 (near-infrared) and Band 4 (red) (Thenkabail et al.), which is ideal for differentiating vegetation from other land-use classes and also for detecting variations within the vegetation levels.

2.3. Ground Data

On the basis of preliminary crop classification based on previous knowledge, ground data targeting major LULC changes were collected throughout the study area during August 2020. Samples were collected over large homogenous areas (minimum of 90 m x 90 m plots) for each LULC class for ease of classification. Areas with a bit of ambiguity were cross-checked during data collection. We recorded location coordinates, LULC category, crop type and cropping pattern, method of irrigation and the farmer's interview (wherever possible).

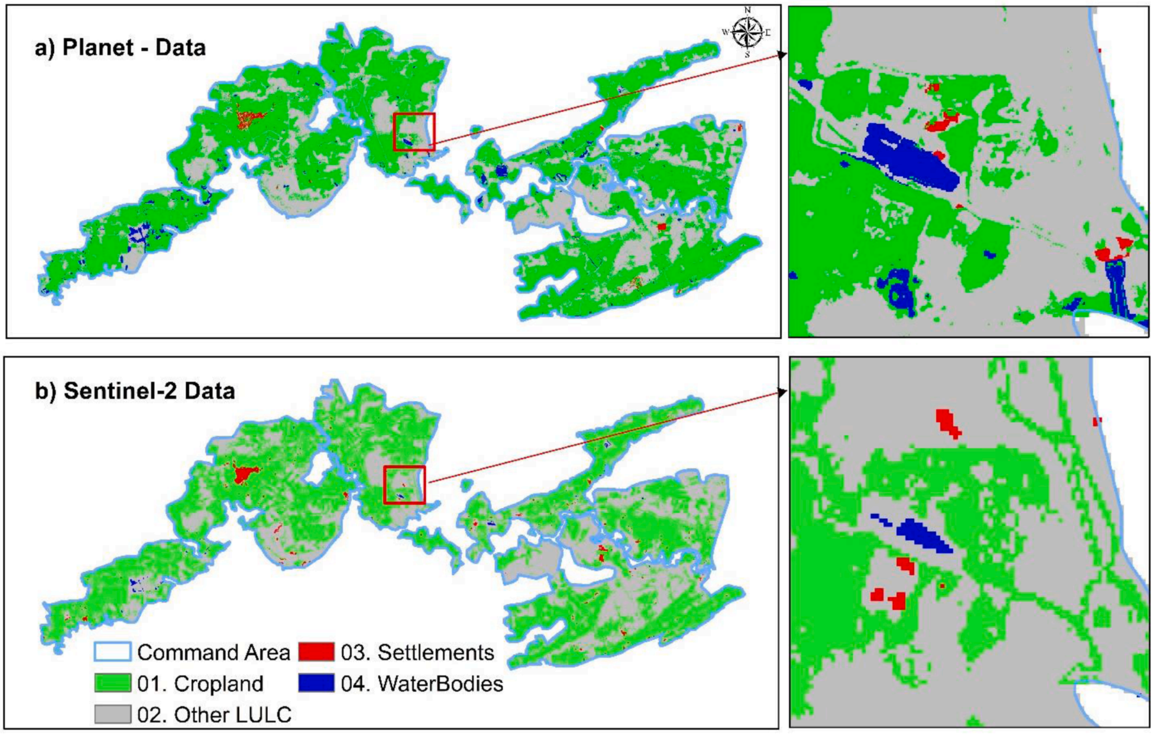

Fig. 4. Comparison of LULC classification derived from Planet and Sentinel-2 data

Later, during classification, the collected data were divided into two independent datasets for training (64) and validation (104) (Table 1).

We have used our own mobile application "iCrops" to collect ground data (http://maps.icrisat.org/rs/Downloads/Data/iCrops_v3.zip), iCrops, an android-based application developed by RS-GIS Team, ICRISAT for ground data collection. The mobile application is quite simple in its operation. This application mainly captures Geographic location; Location class like Cropland, Forest, and Grassland; and Land cover information like Water source, Crop intensity, Primary crop, Secondary crop, and Livestock.

3. Methods

3.1. Mapping land-use/land-cover and rice areas

The process started with the preparation of two data composites, i.e., one with Planet data and the other with Sentinel-2 data. The LULC classes were mapped using Planet data whereas cropping pattern and crop intensity were mapped using Sentinel-2 data with the help of spectral matching techniques and field survey data for the year 2021 (Fig. 2). Accuracy assessment was performed with independent validation data. Spatial products were generated with higher resolution satellite imagery and changes were calculated using spatial analysis.

We used Planet data for the initial land use and land cover classification for the cropping years 2016 and 2020, the main idea being to delineate fragmented LULC areas (Fig. 2a). The satellite imagery was classified using ISOCLASS cluster K-means unsupervised classification with 30 classes. These classes were labelled using visual interpretation with the aid of Google Earth high-resolution imagery (GEHRI). If a gap arose in any class, that class was reclassified and the process repeated.

For classification of the cropping pattern and cropping intensity, we used Sentinel-2 time-series data because of their high quality of spatial and temporal resolution (Fig. 2b). The NDVI maximum monthly composite was classified using unsupervised ISOCLASS cluster K-means classification with a convergence value of 0.99 and 40 iterations, yielding 40 classes followed by successive generalization. We used unsupervised classification rather than supervised classification to capture the variability in phenology across the study area. Identification and labeling of the various classes were based on NDVI time-series plots, ideal spectra, ground-truth data and very high-resolution images (Google Earth). Ideal spectra were generated using time-series imagery with precise field plot data of the same type of land use at spatially distributed locations. The standard procedure included grouping of class spectra based on class similarities by comparing them with ideal spectra generated from training data along with GEHRI for class identification and labeling. Most of the classes were identified except some mixed classes [41, 42]; such classes were reclassified by masking them out and repeating the process. Further processes included resolving mixed classes with the help of the slope [43]. The classes generated from unsupervised classification were aggregated into a minimum number of classes and labeled on the basis of spectral similarity. Cropping intensity was classified by identifying the number of NDVI spectral peaks throughout the study season.

About Spectral matching techniques:

The unsupervised class temporal profiles (NDVI curves) are matched with ideal temporal profiles (quantitatively based on temporal profile similarity values) in order to (a) group and identify classes for a specific crop class Ideal temporal profile (b) some of the class temporal profile signatures that are similar profile (based on correlation values), (c) ideal temporal profile signature matched with class temporal profiles, and (d) the ideal temporal profile matches with class temporal profiles.

3.2. Accuracy assessment

Accuracy assessment of the maps was performed on the basis of validation data provided by 104 ground survey samples [44]. For this we

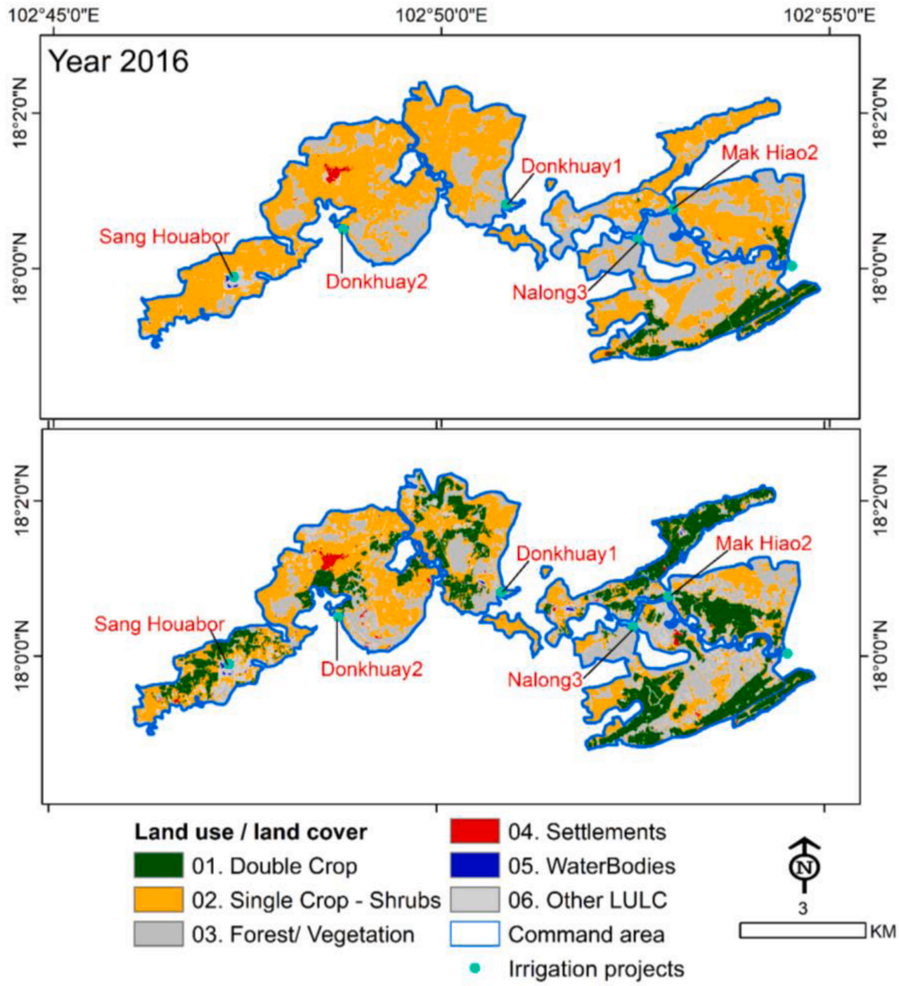

Fig. 5. Spatial distribution of cropping intensity in the study area.

Table 3
Change in cropping intensity, 2016-2020.

LULC change	Area (ha)	% Change
1. Rainfed-SC to irrigated-DC	585	16%
2. Other LULC to irrigated-DC	296	8%
3. Other LULC to rainfed-SC	276	8%
4. No change	2,593	69%

SC: Single Crop; DC: Double Crop

generated a confusion matrix in which the columns represented field-plot data points and the rows represented the results of classified rice maps [45]. The confusion matrix contains corresponding class changes in a multidimensional table. This statistical approach to accuracy assessment shows multivariate statistical analyses such as Kappa [46] to relate results from different classifications and regions; it provides a degree of agreement between the user and reference ground data with a score of homogeneity, or consensus.

4. Results and Discussion

4.1. Spatial distribution of land use/land cover using Planet 3 m data

Using Planet data at 3 m resolution, we prepared LULC maps for the years 2016 and 2020 (Fig. 3) delineating the classes cropland, cropland with shrubland, forest, built-up area, water bodies, crop fallow mixed with barren land, and other land uses. The major classes such as cropland, forests, built-up area and water bodies were classified with greater accuracy than mixed classes due to homogenous contiguity because of the dominance of shrubs in cropland, which is a tradeoff while classifying very high-resolution imagery.

We observed significant changes in LULC in the study area from 2016 to 2020 (Table 2): cropland increased from 1,351 ha to 1,843 ha, built-up area from 9 ha to 22 ha, and water bodies from 53 ha to 73 ha.

The major advantage of using Planet data compared to Sentinel-2 data was the extraction of small homogenous patches of LULC. In below Fig. 4, we can observe the classification of water bodies and croplands.

There is the difficulty of extracting mixed classes in Sentinel-2 data, especially in relation to built-up area and water bodies because of their larger fraction in a single pixel, which may yield a higher area estimation of those two classes in Sentinel-2 derived products.

Very high-resolution Planet imagery not only increased the accuracy of our LULC maps but also the precision of LULC estimates over a small area. However, we did not attempt crop-type mapping with Planet imagery due to the nonavailability of ground information during the date of acquisition and the lack of temporal acquisition.

4.2. Spatial distribution of crop type and cropping intensity using Sentinel-2 10 m data

From the spatial distribution of crop type and cropping intensity which was mapped using Sentinel-2 10m data for the years 2016 and 2020 with help of spectral matching techniques, we found that areas

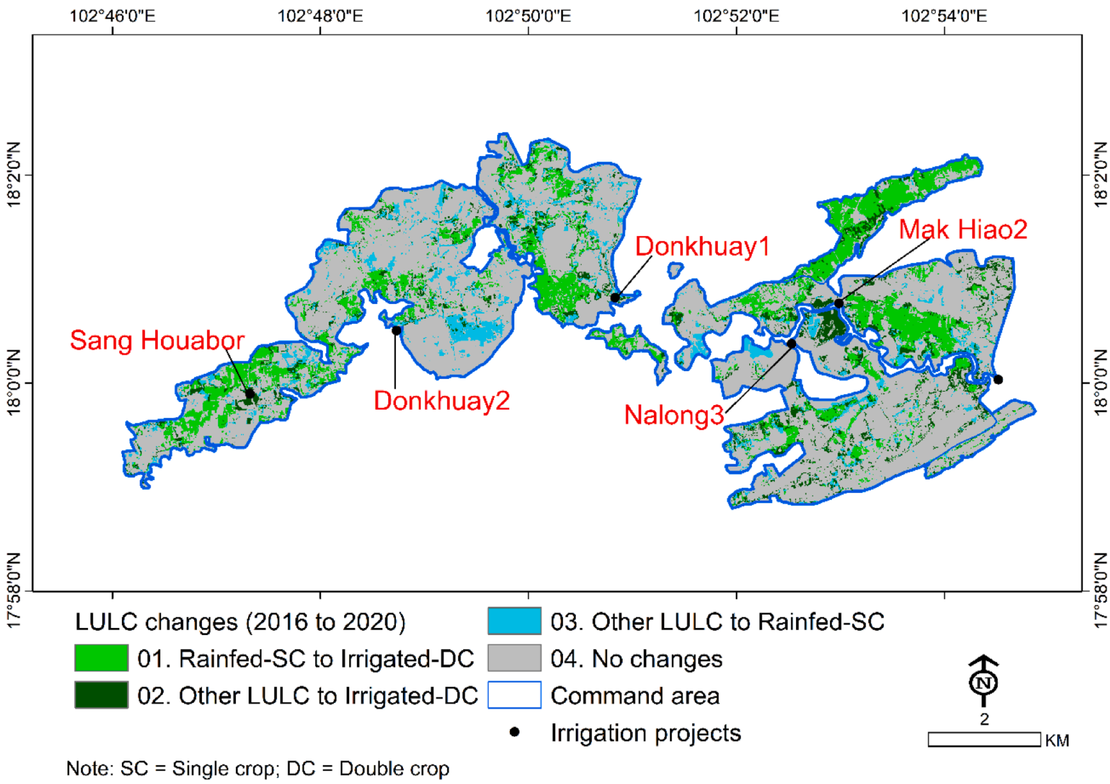

Fig. 6. Spatial distribution of LULC changes in terms of crop intensity.

that were single-cropped in 2016 (Fig. 5) had changed to double-cropping in 2020.

This was due to the availability of water from four irrigation schemes. Given enhanced access to irrigation, there was a definite increase in cropping intensity in their command areas (Table 3).

The spatial distribution of LULC changes is shown in Fig. 6. The extent of change from rainfed single cropping to irrigated double cropping was nearly 585 ha while the change from 'other LULC' class to irrigated double cropping was almost 296 ha. Conversion from 'other LULC' class to single cropping was about 276 ha. Cumulatively, 2,593 ha of land was impacted by the establishment of those four irrigation schemes.

The spatial distribution of crop type indicates the change in cropping pattern in the command areas during 2016-20. The major crop in the region is rice in addition to other mixed crops such as vegetables, plantations, etc. (Fig. 7).

There was a significant change in the rice-growing area, i.e., from single-cropping (rice) in 2016 to double-cropping (rice followed by pulses such as mung bean and soybean). Remarkable changes in LULC were observed especially in the command areas owing to an increase of about 300% in area with access to irrigation (rice-rice) with a corresponding reduction in the area under rainfed crops (Table 4). The geographic coverage of water bodies increased by 31% during the study period. The above two changes are due to construction of new projects and providing irrigation facilities. The area under other types of land use decreased while a slight increase was noticed in the forest/vegetation area. The other land use decreased because of conversion of other LULC to croplands.

The major objective of this paper was to demonstrate the usefulness of very high-resolution imagery in assessing the impact of small irrigation schemes in terms of increasing cropping intensity while improving the livelihoods and incomes of smallholders. However, we used Sentinel-2 time-series data for mapping crop type and cropping intensity. The crop identification and labeling process was carried out using NDVI 15-day composites as well as monthly Maximum Value Composite's (MVCs). The major advantage of using monthly maximum composites is to get cloud-free or near-cloud-free images for classification. Additionally, the ideal spectral signatures generated from the training data using composite imagery enable easy identification of cropping systems across seasons (e.g., wet and dry seasons) and ecosystems (irrigated, rainfed, upland, etc.). These spectral matching techniques aided by high-resolution images were particularly successful in differentiating cropping patterns such as rice-rice, rice-fallow and continuous crops, etc.

Freely available high-resolution satellite imagery from Sentinel-2 has been widely used for monitoring changes in agriculture. Satellite-derived crop area data have been used for village-level crop assessment and in estimating crop statistics even in inaccessible areas for micro-level crop management and advisory. As Sentinel-2 satellite data are optical data, which are vulnerable to cloud cover, availability of data is hampered on cloudy days especially during the rainy season. In such cases, use of microwave (SAR) imagery from Sentinel-1 helps to a large extent. Sentinel-2 10-m data can be used to identify homogenous patches with a minimum of 90 m x 90 m plots in order to perform analysis of smallholdings at field scale. On the other hand, Planet data, available at 3 m resolution, are commercial and optical data. The problem of mixed classes experienced with Sentinel-2 crop classification can be overcome by using Planet data.

4.3. Accuracy assessment

Accuracy assessment of our crop-type classification showed an overall accuracy of 88.5% (Table 5) out of 104 validation points considered for the study. Crop-type classes such as irrigated (rice-rice)

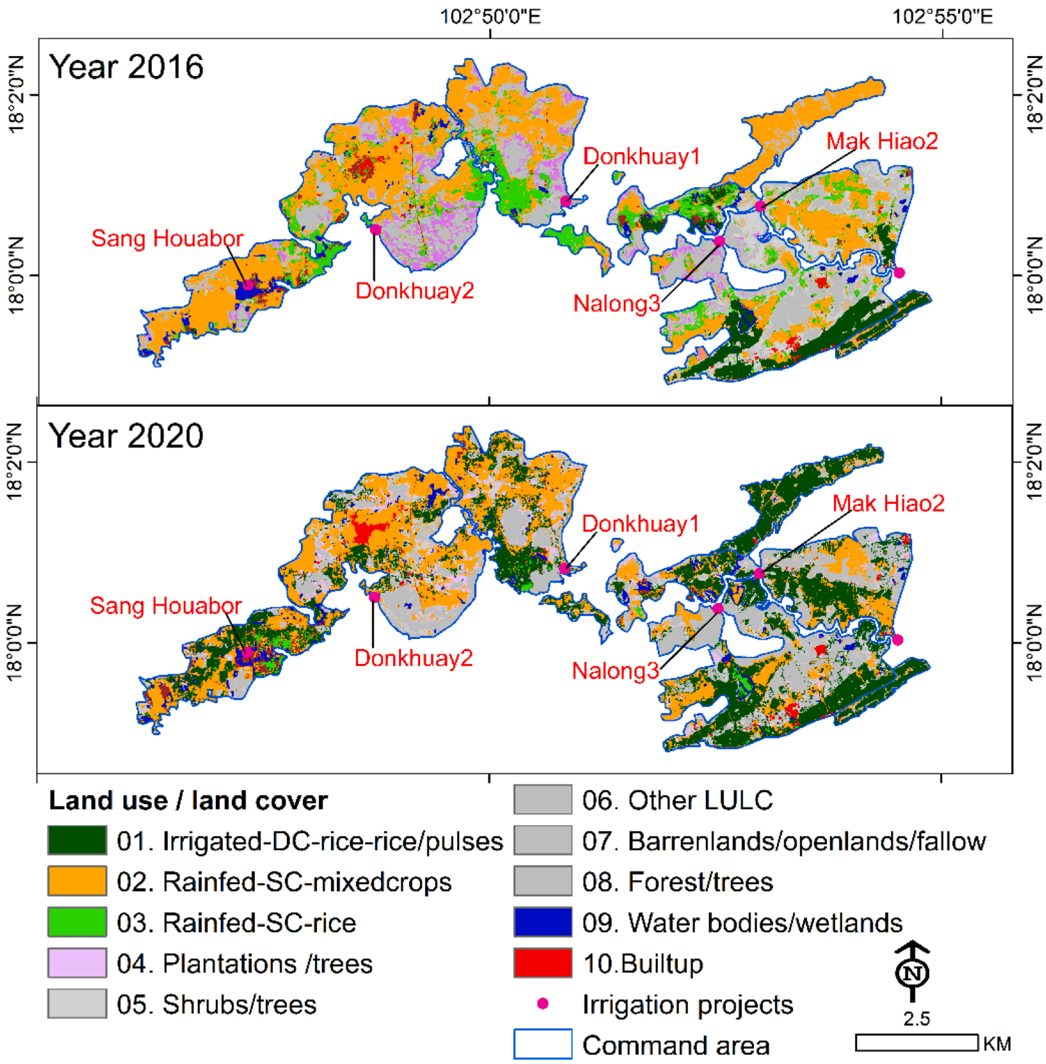

Fig. 7. Spatial distribution of crop type in the command area.

Table 4
Change in Land use / land cover (LULC) and major crop types.

Land use/land cover	Area (ha) 2016	2020	Land-use change (%)
1. Irrigated-DC-rice-pulses/rice	268	1071	300%
2. Rainfed-SC-mixed crops	1239	1080	-13%
3. Rainfed-SC-rice	437	32	-93%
4. Plantation/trees	188	136	-28%
5. Shrubs/trees	322	298	-7%
6. Other LULC	305	25	-92%
7. Barren land/open lands/fallow	66	58	-12%
8. Forest/trees	797	884	11%
9. Water bodies/wetlands	85	111	31%
10.Builtup	36	48	33%
Total area	3,743	3,743	

and rainfed (SC-rice) achieved good producer's accuracy. There was relatively less accuracy with mixed rainfed crops. The other LULC classes achieved a good level of accuracy except shrubs due to a mix of crops.

Table 6 shows the accuracy assessment of major LULC classes carried out using Planet data. The classification map achieved good accuracy but accuracy of mixed and other classes tended to be low. Major LULC classes like cropland, built-up area, water bodies, crop fallow showed good accuracy >90%, but cropland mixed with shrubs showed less user accuracy of about 67%. The less accuracy recorded because of misclassification of areas where shrubs are dominated in cropland areas in small holding farms and classification with sentinel-2 data Table 5. Accuracy assessment of crop-type classification, 2020 based on Sentinel-2 data.

4.4. Validating study with household surveys

A survey of 545 rural households conducted in 17 villages in 2021 elicited information on wet seasons from 2018 to 2020 and found that the number of rice producers increased from 123 to 249 during that period (Fig. 8). This may be due to the fact that irrigation systems can bring water to farmlands from a long distance through canals. Thus, irrigation projects helped more farmers engage in rice production in the wet season.

Source: Authors' calculation based on a 2021 household survey.

For the dry season, the number of rice producers in these irrigation schemes increased from 8 in 2018 to 278 in 2020. Thus, dry-season rice production went from being almost non-existent to a larger number of farmers taking it up than even the wet season. These findings are consistent with earlier findings from spatial information analysis.

Outside of the irrigation command areas too the number of rice farmers increased in both wet and dry seasons, although the increases were relatively smaller compared with the changes in the project area. Also, construction of an embankment along the Mekong River might have encouraged farmers to take up rice production because of the

Table 5
Accuracy assessment of crop-type classification, 2020 based on Sentinel-2 data.

Class	1. Irrigated-DC-rice-rice/pulses	2. Rainfed-SC-mixed crops	3. Rainfed-SC-rice	4. Plantations/trees	5. Shrubs/tree	6. Other LULC	7. Barren land	8. Forest/tree	9. Waterbodies	10.Builtup area	Row total	**Users accuracy**
1. Irrigated-DC-rice-rice/pulses	46	5	0	0	0	0	0	0	0	0	51	0.902
2. Rainfed-SC-mixed crops	1	13	0	0	1	0	0	1	0	0	16	0.81
3. Rainfed-SC-rice	0	0	1	0	0	0	0	0	0	0	1	1
4. Plantation/trees	0	0	0	1	0	0	0	0	0	0	1	1
5. Shrubs/tree	1	0	0	0	2	0	0	0	0	0	3	0.66
6. Other LULC	0	0	0	0	0	3	0	0	0	0	3	1
7. Barren land	0	0	0	0	0	0	3	0	0	0	3	1
8. Forest/tree	2	1	0	0	0	0	0	13	0	0	16	0.81
9. Waterbodies	0	0	0	0	0	0	0	0	5	0	5	1
10. Built up area	0	0	0	0	0	0	0	0	0	5	5	1
Column total	50	19	1	1	3	3	3	14	5	5	**104**	
Producer's Accuracy	0.92	0.68	1	1	0.66	1	1	0.92	1	1	**Overall Accuracy**	**88.46%**

reduced risk of floods.

Apart from the project impacts, external factors such as good weather and the increasing farm-gate prices of rice might have encouraged farmers to produce rice both inside and outside the irrigation schemes. It is difficult to isolate the influence of such external factors. However, if these external factors affect rice production evenly, the large increase in rice production in the irrigation schemes, especially during the dry season, can be characterized as project impacts.

4.5. Economic impact due to construction of minor irrigation projects

The major benefit from construction of minor irrigation projects is enhancement of rice production. Spatial information obtained from satellite imagery indicates an expansion of rice production in the dry season. Spatial analysis showed that the area under double cropping of rice has increased from 268 ha in 2016 to 1,071 ha in 2020. Based on the ground-level survey, the double-cropping area could have yielded 5.9 tons of rice per ha during 2016. This was estimated to have increased to 7.3 tons per ha in 2020. Therefore, total rice production due to double cropping of land is calculated to have increased from 1,581 tons to 7,818 tons per year. The increased rice yields in these irrigation schemes could be due to increased use of chemical fertilizer and other inputs under assured conditions. Under rainfed conditions, farmers normally face risks of drought or water shortages. Under such circumstances, farmers may hesitate to apply agricultural inputs and carry out recommended management practices. Construction of five minor-irrigation projects is likely to have encouraged rice growers by reducing water stress conditions in the command area. This facilitated stabilization of rice cultivation in the command area as well as protected the rice crop from moisture stress. The enhanced irrigation facilities not only expanded the area but also promoted rice cultivation in the project area. This has motivated the farmers to adopt necessary technologies for enhancing rice productivity. Cumulatively, small and marginal farmers in the project area have significantly benefited with enhanced productivity as well as higher household incomes.

5. Conclusion

We studied the impact of construction of minor irrigation projects in Vientiane prefecture of Laos by monitoring the situation before (2016) and after (2020) the intervention. In order to view these changes at high resolution, the study used both Planet (3 m) and Sentinel-2 (10 m) satellite imagery, and also used ground data to aid classification and validation. Major LULC classes were mapped using Planet data whereas crop type and cropping intensity were mapped using Sentinel-2 data using NDVI time-series and SMT approaches.

The study found major changes and shifts in cropping intensity, i.e., from single to double cropping (about 300 ha converted to double cropping) from other LULC classes. Along with croplands, there was an increase in water bodies as well as settlements. The change from single cropping (rice) to double cropping (rice/pulses) was a major evidential change in the project area.

The socio-economic survey also confirmed that there is significant cropped area allocation towards paddy cultivation during both wet and dry seasons in the project area. The absolute no. of farmers changed their cropping pattern are higher in dry season when compared to wet season. The survey also validated that the paddy productivity has been remarkably increased to 7.3 from 5.9 tons per ha under double cropping systems. This clearly visualizes that the construction of minor and small irrigation projects not only enhanced the water-use-efficiency (WUE) but also stabilized the paddy cultivation in the project area. There is reduced moisture stress as well as risk of paddy cultivation during dry season. These positive changes encouraged small & medium farmers to adopt better technologies and investments in paddy cultivation.

Table 6
Accuracy assessment of LULC mapping, 2020 based on Planet data.

	1. Cropland	2.Cropland/ shrubs	3. Forest/ plantation	4.Built-up area	5. Water bodies	6.Crop fallow	7.Other LULC	Total	**User's accuracy**
1.Cropland	60	0	0	1	0	0	0	61	0.98
2.Cropland/shrubs	1	6	0	1	0	1	0	9	0.67
3. Forest/ Plantation	2	0	17	0	0	0	0	19	0.89
4.Builtup	0	0	0	3	0	0	0	3	1.00
5. Water Bodies	0	0	0	0	5	0	0	5	1.00
6.Cropfallow	0	0	0	0	0	4	0	4	1.00
7.Other LULC	0	0	0	0	0	0	3	3	1.00
Total	63	6	17	5	5	5	3	104	
Producer's accuracy	0.95	1	1	0.6	1	0.8	1	**Overall accuracy**	**0.94**

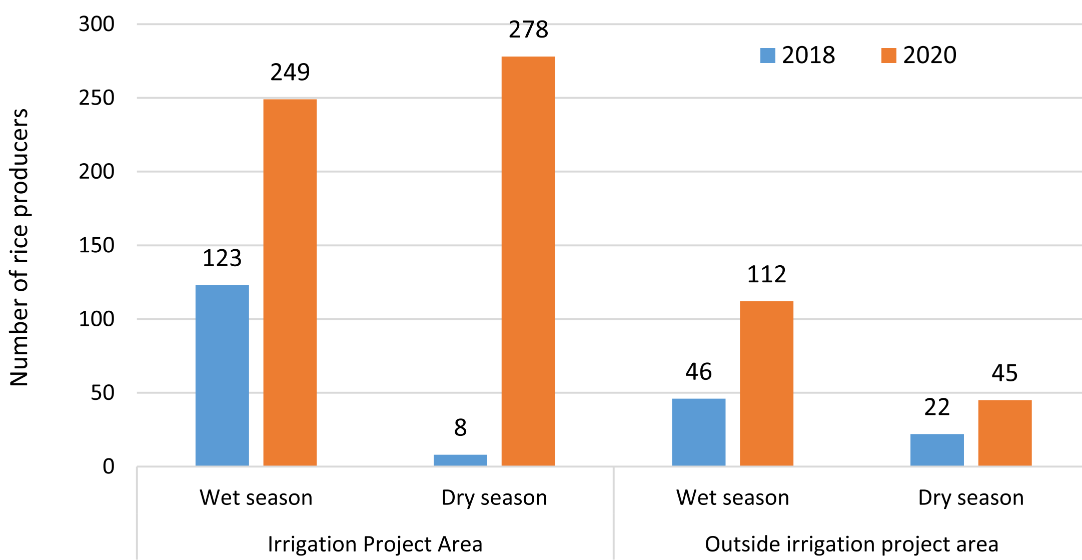

Fig. 8. Increase in the number of rice producers from 2018 to 2020.

Declaration of Competing Interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest

Data availability

Data will be made available on request.

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Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.atech.2022.100149.

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