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Research Article

Machine Learning in Water Resources Management: Paddy Rice Irrigation Case Study

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Abstract

Paddy rice irrigation takes an important role in water consumption. Therefore, the savings to be made in paddy rice irrigation will have significant impacts. In the sustainable use of water resources, both the irrigation methods and the methods to be used in the planning of water resources are critical. Hence, the use of drip irrigation should be expanded. On the other hand, the use of modern satellite technologies and machine learning models should be used while planning irrigation. In this study, Google Earth Engine (GEE), which is a cloud-based image processing platform was employed in the calculation of paddy rice cultivation areas. Random Forest (RF) and Support Vector Machines (SVM) machine learning algorithms were applied. The results showed that RF algorithm can calculate the paddy cultivation areas with an accuracy of 97%. A difference of 27.69 km^2 was found between the officially declared cultivation areas and the calculated area. This can yield a miscalculation of water requirement with an error of 33.8, 38.1 and 155 million m^3, in subsurface drip irrigation, drip irrigation and basin irrigation methods, respectively. Results showed that accurate calculation of paddy rice cultivation areas and drip irrigation will both minimize this error and allow 4 times more area to be irrigated.
Keywords: Remote sensing, Machine learning, Random forest, Support vector machine, Drip irrigation, Paddy rice

Su Kaynakları Yönetiminde Makine Öğrenmesi: Çeltik Sulaması Uygulama Örneği

Öz

Su tüketiminde çeltik sulama önemli bir yer tutmaktadır. Dolayısıyla çeltik sulamasında yapılacak tasarruf önemli etkiler meydana getirecektir. Su kaynaklarının sürdürülebilir kullanımında hem sulama yöntemleri hem de su kaynaklarının planlanmasında kullanılacak yöntemler kritik öneme sahiptir. Bu nedenle damla sulama kullanımı yaygınlaştırılmalıdır. Öte yandan, sulama planlaması yapılırken modern uydu teknolojilerinden ve makine öğrenme modellerinden yararlanılmalıdır. Bu çalışmada çeltik ekim alanlarının hesaplanmasında bulut tabanlı bir görüntü işleme platformu olan Google Earth Engine (GEE) kullanılmıştır. Rassal Orman (RO) ve Destek Vektör Makineleri (DVM) makine öğrenimi algoritmaları kullanılarak hesaplamalar yapılmıştır. Sonuçlar, RO algoritmasının çeltik ekim alanlarını %97 doğrulukla hesaplayabildiğini göstermiştir. Resmi olarak beyan edilen ekim alanları ile hesaplanan alan arasında 27,69 km^2 fark olduğu belirlenmiştir. Bu durumun, yüzeyaltı damla sulama, damla sulama ve göllendirme ile sulama yöntemlerinde sırasıyla 33,8, 38,1 ve 155 milyon m^3'lük bir hata ile su ihtiyacının yanlış hesaplanmasına neden olduğu tespit edilmiştir. Sonuçlar, çeltik ekim alanlarının doğru hesaplanması ve damla sulama uygulamalarının hem bu hatayı en aza indireceğini hem de 4 kat daha fazla alanın sulanabilmesini sağlayacağını göstermiştir.
Anahtar Kelimeler: Uzaktan algılama, Makine öğrenmesi, Rassal orman, Destek vektör makineleri, Damla sulama, Çeltik

Introduction

Although paddy rice is grown all over Türkiye, Marmara and Black Sea Regions are the major producers (Tuna, 2012). In order Türkiye to become self-sufficient in paddy rice production, cultivation areas should be expanded. The only way of achieving this goal is to increase irrigated areas (Gençtan, Çölgeçen and Başer, 1995). However, there are constraints such as the paddy rice plant's relatively high-water consumption compared to other plants and the decrease in water resources due to climate change.

In Türkiye, paddy rice is grown on an area of approximately 50,000 hectares in the Thrace Region, where paddy farming is most intense. The irrigation is generally in the form of flooded ponds up to 10-20 cm continuously. This means 1.4×10^9 m^3 water is required every year in Thrace region. Considering that the flow rate of Meric river, main water source in İpsala, decreases to 0.9×10^9 m^3 during the irrigation season, the importance of water restriction in paddy rice especially in the Thrace region, becomes evident (Delibaş et al., 2010).

In Türkiye and especially in the Marmara Region, studies on the application of subsurface and drip irrigation (DI) methods have been started in paddy rice cultivation in recent years. Nar et al., (2018) determined the performance of DI with water retention barriers in same region. They reported that water applied in conventional, drip irrigation and drip irrigation + water retention barrier applications were 5,580, 1,375 and 930 mm, respectively. They observed a decrease in yield while significant water was saved with alternative methods. Demirel et al., (2020) investigated the performance of the subsurface drip irrigation method and again the water retention barrier. It has been stated that up to 50% water can be saved with the subsurface drip irrigation method, and up to 69% water can be saved if this method is used together with the water retention barrier.

Ponding irrigation can be applied in flat lands while the drip irrigation is applicable in almost all lands as far as the slope is concern. Therefore, even though there is a decrease in yield with drip irrigation method, the increase in irrigable area may tolerate this disadvantage (Beşer and Sürek, 2009).

Sustainable use of soil and water resources has become essential to maintain food security which is an important issue. Therefore, modern decision support tools are needed to determine the optimum water requirement. One of these tools is Remote Sensing (RS) technique (Köksal, 2007). The RS is the method of obtaining information about the Earth's surface without being in contact with it (Jensen, 2007). Remote sensing data is usually spatial in nature and typically in the form of images. The processing of remotely sensed data requires multidisciplinary knowledge including engineering, computer science, mathematics and statistics (Blake and Warner, 2014). In recent years, satellite images have become the most important data source used in fields such as land use/land cover mapping (Shelestov et al., 2017).

Today, satellites that regularly send high-resolution images are a very important source of data. In addition, newly sent satellites such as Sentinel-1, Sentinel-2, Proba-V and Landsat-8 increase the data capacity to be measured in petabytes (Roy et al., 2014). It is very difficult to work with such large data with expensive and complex software installed on desktop computers. Therefore, user-friendly cloud-based systems make it possible to access and analyze massive data through a web browser with efficient coding languages. The GEE is one of those tools has been used in RS studies (Gorelick et al., 2017). The GEE is a cloud-basedimage processing software that does not have to be installed on a computer. It provides free access to satellite images, the use of algorithms of machine learning models, and different operations on images. The first step was to determine the satellite image to be processed and the desired period and visualize it on the GEE platform. Satellite images are taken at certain time intervals and are in clusters called collections.

Automated classification methods applied to RS data to determine what the land is covered with or for what purpose they are used are based on the calculation of the spectral signatures of the selected land cover classes using training data and pixel-based decomposition between different land cover types (Pfeifer et al., 2012). Different types of surfaces reflect radiation differently in various channels. The reflected radiation in the form of wavelength is called the spectral signature (ESA, 2022). Therefore, GEE can also be defined as a platform for automatic classification of differences in wavelengths of energy reflected by surfaces covered with different materials.

The Machine Learning (ML) algorithms are defined as the self-training of the computer with the experience and information it learns from the data without any human intervention and its ability to classify (Mohri et al., 2018). The most recommended machine learning algorithms in the discipline of remote sensing are RF and SVM (Tassi and Vizzari, 2020). In this study, it was aimed to determine paddy rice cultivation areas by using satellite images, RF and SVM machine learning algorithms in

Edirne province, İpsala district. İpsala was chosen since approximately 16% of the Türkiye's paddy rice production is done there. Therefore, it was concluded that the results to be obtained would be meaningful for the region.

The water used in irrigation with traditional methods and the amount of water to be used in case of drip irrigation as an alternative were calculated.

Material and Method

Study Area and Used Data

The study was conducted using satellite data and other terrestrial data of Edirne province, İpsala district located at latitude 40.8865 and longitude 26.3712 (Figure 1).

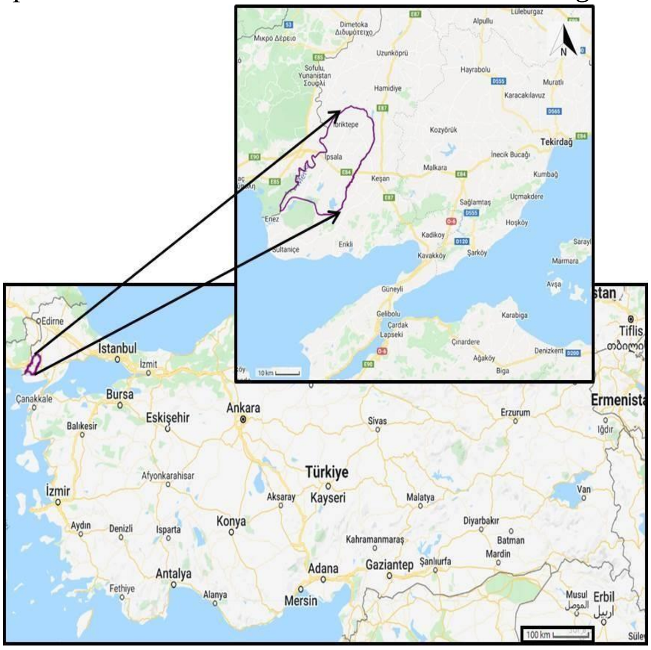


Figure 1. Study area

In this study, Sentinel-2 multispectral (MSI) Level-1C satellite image, which is provided free of charge by the European Space Agency (ESA) and has spatial resolution in the range of 10-60 m according to the bands it includes, was used. The main reason for launching this satellite is to collect data for studies on land cover and use (Dereli, 2019). These satellite images contain 13 bands of different wavelengths (Chung et al., 2019).

Another data used in the study is the coordinates of the paddy rice parcels in 2021. In order for the model to learn which of the reflectance values of the satellite image corresponds to the paddy areas, the samples of the cultivation areas were marked on the satellite image, and they were defined as paddy rice in the models. For this purpose, the coordinates of the paddy rice parcels in 2021 were obtained from the İpsala District Directorate of Agriculture and Forestry (IDDAF). Out of the data set containing all paddy parcels, 100 coordinates data were used in the model for model development (training phase), and another 100 coordinateswere used in the cross-validation phase to determine whether the model classifies the paddy rice parcels correctly.

Apart from the paddy rice cultivation areas, water surfaces (river, lake, dam, etc.), other vegetations and settlement areas were also determined. Settlement class included all areas except water, vegetation, and paddy rice. Training and verification data related to water, other vegetation and settlement areas were determined visually via satellite imagery. Since the aim of the study was only to determine the paddy rice parcels, ground verification of the other 3 classes, especially other vegetation, and other areas, was not required. After creating the classification map, vector data of Ipsala district in shape (shp) format was used to clip the main project area within the borders of Ipsala district.

Machine Learning Models

The most recommended machine learning models in land use studies are RF and SVM. The RF is an ensemble learning approach based on the decision trees (DT) algorithm. In other words, it is an algorithm that consists of more than one decision tree and therefore is defined as a random forest. In the RF algorithm, the training data set is divided into many subclasses and thus many decision trees are formed, and the performance of the model is determined according to the classification made by the class with the most votes. Trees are generated by establishing a subset of training examples by substitution. This means the chance of same samples to be selected more than a time always exists, while others samples may have selections chance of nothing. For example, about 2/3 of samples are used in training step, the remaining samples are used in cross-validation to predict the model performance. Each decision tree is generated independently without any pruning, and each node is split using a randomly selected, user-defined number of features. The forest is grown by the model up to a pre-defined number of trees, creating members with high variance and low bias (Breiman, 2001). The final classification decision is determined by averaging the class assignment probabilities calculated by all trees produced. Thus, a new unlabeled data entry is evaluated against all decision trees created in the community, and each tree votes for a class membership. The membership class that gets the most votes becomes the finally elected member (Breiman, 2001).

The SVM is a supervised machine learning model like RF. In such algorithms, when an unknown sample is presented to the model according to a training data set divided into different categories, the class of the new sample can be determined (Pradhan, 2012). The target of the SVM algorithm is to determine the location of the hyperplane that separates two different classes. When traversing the hyperplane, the data closest to each other (support vectors) in both classes are considered. The maximum margin hyperplane is passed to maximize the distance between these two support vectors, and the class of the new data, whose class is unknown, falls on which side of this margin, is determined (Kim et al., 2003).

Calculation of Paddy Rice Water Requirement for Ponding and Drip Irrigation Based on Regional Conditions

The water used in paddy rice irrigation varies based on the local conditions (climate and soil) of the region and even the tendency of the farmers. Considering the local conditions and the farmers preference, the amount of water used by the ponding method has been revealed as a priority. Nar et al., (2018), stated that the water used in ponding method in paddy rice production in one irrigation season is approximately 5,580 mm for the Enez, a neighbouring district with similar climatic and soil conditions. The same value was considered in the calculation of the water used in the ponding.

The same researchers calculated the required irrigation water employing Equation 1 in case of using drip irrigation method in a sample plot.

$$I = WHC \times P \times P_W \times A \tag{1}$$

In Equation 1; I is water used in liters, WHC is water holding capacity at a depth of 25 cm in mm, P is the consumed amount WHC (10-20%), P_W is the percentage of wetted area in the field, and A is the field surface area in m^2.

In this study, using the methods and data detailed above, required calculations, and suggestions were made based on the flowchart given in Figure 2.

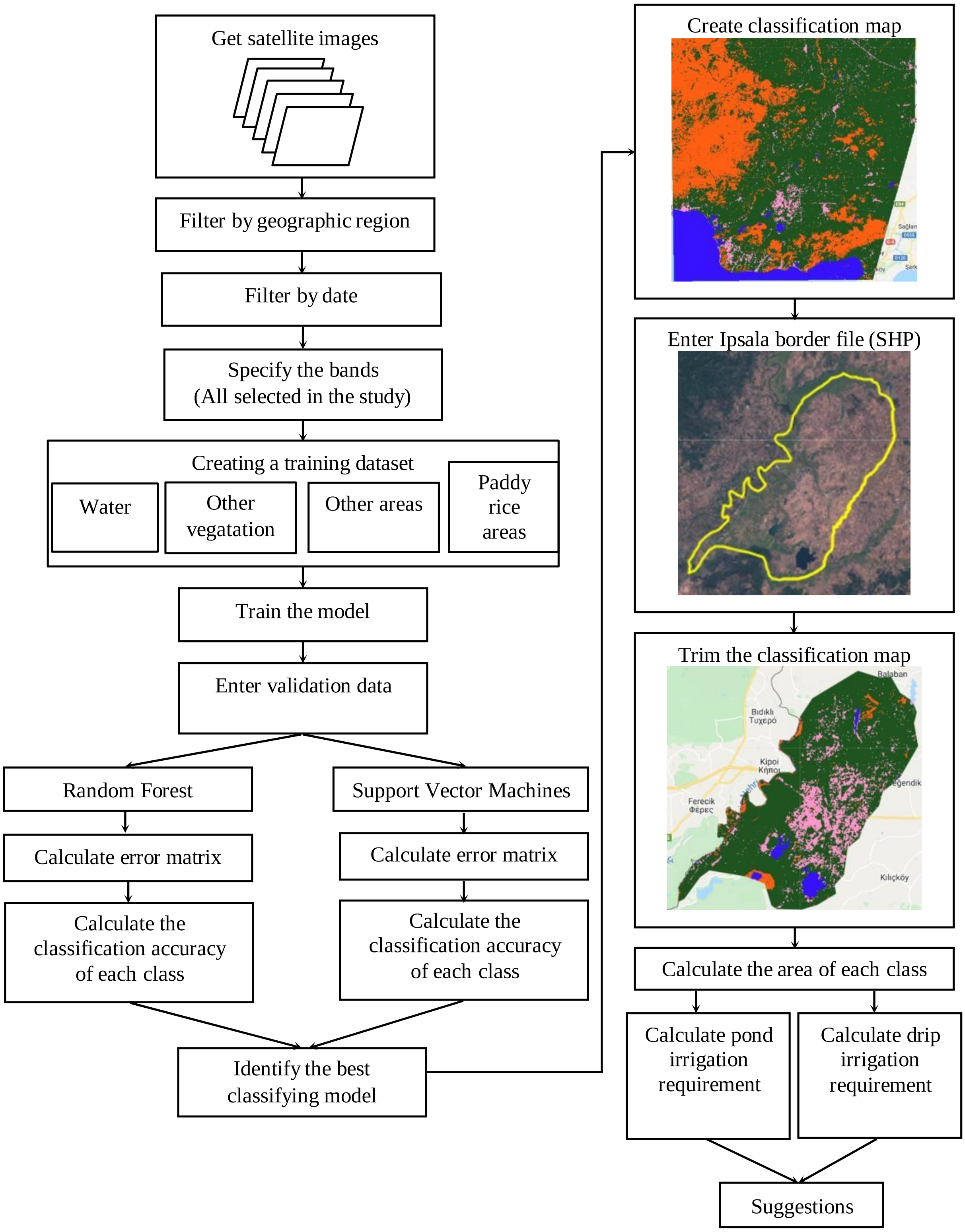


Figure 2. Flowchart of the study

Statistical Analysis of Model Results

One of the methods used to determine the classification performance of each algorithm is the creation of error matrices. The error matrix gives information about how often an observation belonging to a certain class is correctly detected and how often it is determined as another class

(Ruuska et al., 2018). Also, some statistical parameters such as general accuracy (GA), producer accuracy (PA), user accuracy (UA) and kappa coefficient (KC) are used to determine the classification performance of the model. GA is a concept that describes what percentage of validation data is classified as correct. PA refers to the percentage of correct classification in each row of the matrix. UA refers to the ratio of the number of correctly classified data in each class to the total amount of data in the rows in that class in the matrix. KC, on the other hand, is a coefficient used in calculating the fit between data belonging to more than one class (Yiğit and Uysal, 2021). In the study, classification performance of 4 classes of data was tested using these 4 parameters.

Results and Discussion

Training Dataset

The GEE is a cloud-basedimage processing software that does not have to be installed on a computer. It provides free access to satellite images, the use of algorithms of machine learning models, and different operations on images. The first step was to determine the satellite image to be processed and the desired period and visualize it on the GEE platform. Satellite images are taken at certain time intervals and are in clusters called collections. Initially, a wider area covering the study area, was loaded with satellite images. The most suitable image was determined from the collection containing 913 satellite images. The point to be noted here is that the paddy rice areas are covered with water. If a satellite image of a time when the paddy rice plant was very small is, machine learning algorithms assign these areas to the water class. If the post-harvest image of the time when the water is removed from the areas was used, the paddy rice area can be confused with other vegetation areas. Therefore, a date should be determined just before harvest and when the plant is most prominent in the field. Therefore, Sentinel-2 Multispectral (MSI) Level-1C satellite image of a cloudless day (17.09.2021) with these features was used.

Samples from paddy rice parcels, water-covered areas, settlements, and other vegetation areas should be presented to the model as training data on the satellite image. For this purpose, 100 paddy rice parcels, whose coordinate information was obtained from the IDDAF were located on the image.

The training data set was prepared after the paddy rice areas coordinates were marked with coding and the data in the other class were manually marked on the image (Figure 3). In the training dataset, 67 points covered with water, 67 points from settlements and 44 points from other vegetation areas were determined.

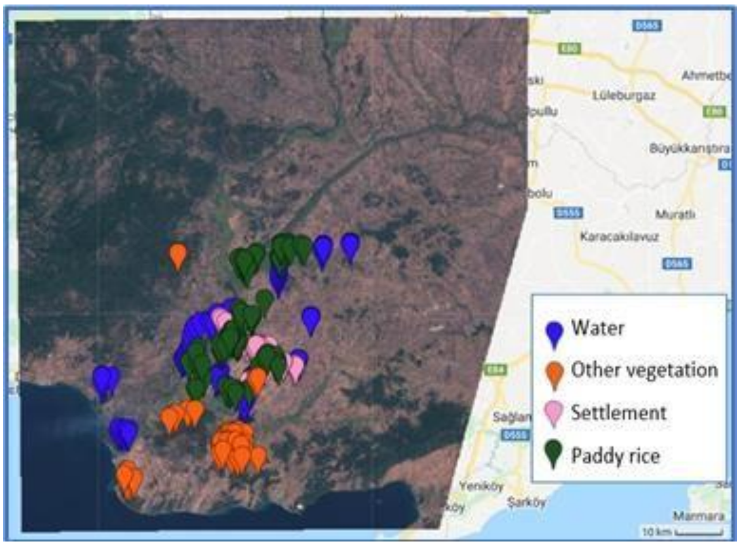
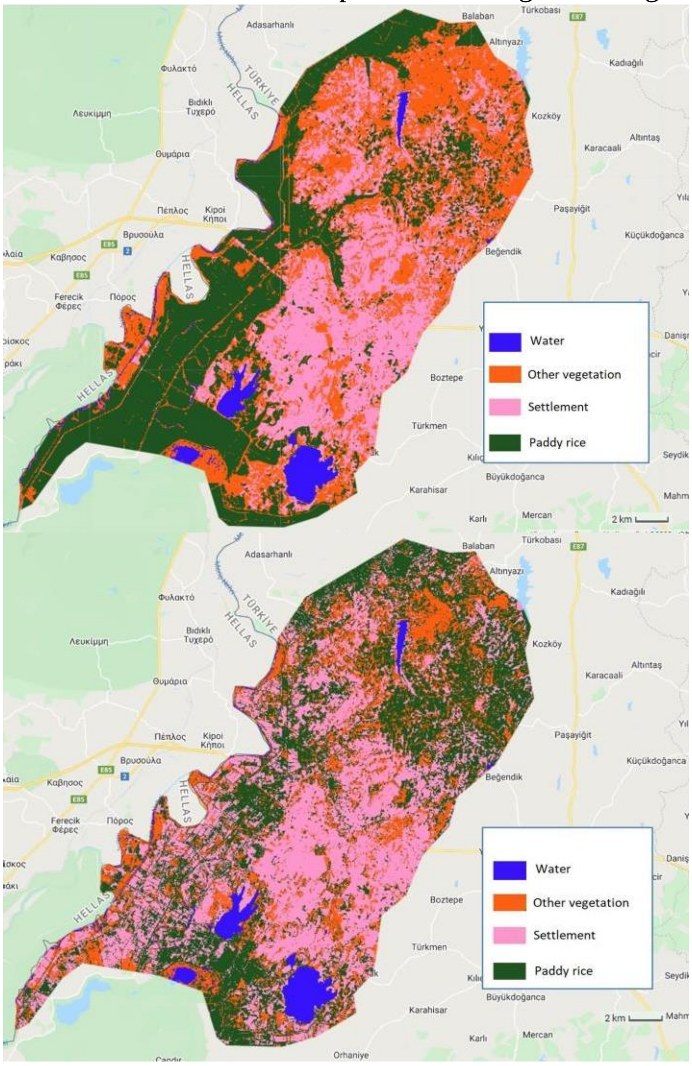


Figure 3. Training dataset

With a similar method, 100 different paddy rice areas coordinates and 50 data points belonging to other classes were prepared as a validation data set, and classification maps were created using machine learning algorithms.

Classification Maps

After the datasets were prepared, classification maps created using RF and SVM algorithms. While determining the model parameters in coding, classification was started by using default parameters, then these parameters were changed by trial-and-error method until achieving the highest classification accuracy. After classification, cropping process was carried out using the shp file showing the district borders of Ipsala. The classification maps created by the RF and SVM algorithms based on the selected model parameters are given in Figure 4.



(a) RF classification (b) SVM classification

Figure 4. Machine learning classification maps

The error matrices of both algorithms were calculated. Accordingly, the error matrix for the SVM classification is given in Table 1.

Table 1. Error matrix for SVM classification
Çizelge 1. DVM için hata matrisi

	Water	Other vegetation	Settlement	Paddy Rice Area	User Accuracy
Water	46	2	2	0	0.92
Other vegetation	0	41	1	8	0.82
Settlement	0	2	45	3	0.90
Paddy Rice Area	0	25	36	39	0.39
User Accuracy	1.00	0.59	0.54	0.78	

As can be seen in Table 1, the model developed using the SVM algorithm correctly classified 39 out of 100 paddy rice areas used for validation. Of the remaining paddy rice areas, 25 were misclassified as other vegetation and 36 as settlements. When other statistics are examined, PA and UA were obtained in the water class. The lowest PA was obtained in the paddy rice area classification, and the lowest UA was obtained in the settlement class. The GA of the model was approximately 69%. In other words, only 69% of the 250 data used for validation belong to the correct class. The KC, which expresses the agreement between the classified data, was determined as 0.584 in the SVM algorithm. Landis and Koch (1977) suggested Table 2 in the evaluation of the kappa coefficient.

Table 2. Kappa coefficients interpretation
Çizelge 2. Kappa katsayılarının yorumu

Kappa coefficient	Status
<0	Very Bad
0.01 – 0.20	Insignificant
0.21 – 0.40	Poor
0.41 – 0.60	Average
0.61 – 0.80	Good
0.81 – 1.00	Very Good

Considering Table 2, it is seen that the agreement between the data is at a moderate level. All the evaluation parameters obtained; it is seen that the SVM algorithm is insufficient in classifying 4 different classes of land use in this study.

Similarly, the error matrix created for the RF algorithm is given in Table 3. In the classification made with the RF algorithm, it is seen that 97 out of 100 paddy areas are correctly classified. In addition, GA rate was 93%. Considering the KC, a very high fit value of 0.89 was obtained. Higher values of PA and UA were obtained based on the SVM algorithm. Both accuracy values of the paddy rice class are quite high.

Table 3. Error matrix for RF classification
Çizelge 3. RO için hata matrisi

	Water	Other vegetation	Settlement	Paddy Rice Area	User Accuracy
Water	48	2	0	0	0.96
Other vegetation	0	47	0	3	0.94
Settlement	0	10	39	1	0.78
Paddy Rice Area	0	2	1	97	0.97
User Accuracy	1.00	0.77	0.98	0.96	

The RF algorithm yielded more successful results based on all statistical parameters. Therefore, the area value obtained by this algorithm is used in the calculation of irrigation water requirement. The areas of each class calculated by the RF are given in Table 4.

Table 4. Calculated areas
Çizelge 4. Hesaplanan alanlar

	Area (km^2)			
Algorithm	**Water**	**Other Vegetation**	**Settlement**	**Paddy Rice Area**
RF	147.03	326.70	59.06	221.92

According to the data obtained from the IDDAF for 2021, the declared paddy rice cultivation area was 194,23 km^2. However, this data is based on the farmer's decleration as stated above. It is known that mostly declared statements do not represent real production areas (Sitokonstantinou et al., 2021; Xu et al., 2021). As can be seen here, 27.69 km^2 more paddy rice cultivation was calculated in Ipsala district in 2021 than declared. Comparative analysis of models for paddy rice mapping classification is given Table 5.

Table 5. Comparative analysis of models for paddy rice mapping
Çizelge 5. Çeltik haritalaması için modellerin karşılaştırmalı analizi

Author	Model	Image Property	Genaral accuracy
Onojeghuo et al., 2018	SVM and RF	Sentinel-1 and Landsat	0.82 – 0.97
Thorp and Drajat, 2021	Recurrent neural network (RNN)	Sentinel-1 and Sentinel-2	0.76 – 0.80
Sitokonstantinou et al., 2021	K-means and RF	Sentinel-1 and Sentinel-2	0.87 – 0.97
Torbick et al., 2017	RF	Sentinel-1, Landsat-8 OLI and PALSAR-2	0.78
Nguyen et al., 2016	Decision Tree (DT)	Sentinel-1	0.87

As can be seen in Table 5, The GA of the proposed study is promising when compared to previous studies. GA can be increased by using more images in the training set. This causes an overfitting problem in the model.

After the actual paddy rice cultivation area was determined using Sentinel 2 satellite image and RF algorithm, the paddy rice water requirement was calculated based on the climatic conditions of the region according to both the traditional ponding method and the drip irrigation method. As explained in the method section, it is stated that the application of the ponding method in regional conditions is 5,580 mm (Nar al., 2018). This figure reveals an irrigation application of more than 4,000-5,000 mm as reported in Özgenç and Erdoğan (1988). In fact, these amounts are almost double the water required by the paddy rice plant, even in ponding irrigation. Demirel et al., (2020) used 2,444 mm of water for paddy rice in their study in Edirne, where they applied the ponding method in a controlled study. Therefore, an excessive amount of water consumption is observed in paddy rice production. The same researchers stated that total irrigation water amount would decrease up to 1,220 mm in application of subsurface drip irrigation. Nar et al., (2018) also calculated the amount of water required for paddy rice irrigation with drip irrigation as 1,375 mm, which is compatible with other literature. The irrigation water requirements in the current situation in case of using drip irrigation application, which were calculated and summarized in Table 6.

Table 6. The amount of water used in 3 different irrigation systems
Çizelge 6. Üç farklı sulama sisteminde kullanılan su miktarları

		Subsurface Drip Irrigation (m^3)	Drip Irrigation (m^3)	Ponding Irrigation (m^3)
Official area (km^2)	194.23	0.237×10^9	0.267×10^9	1.080×10^9
Calculated area (km^2)	221.92	0.271×10^9	0.305×10^9	1.240×10^9

As summarized in Table 6, approximately 4,6 times more water is consumed comparing to subsurface drip irrigation, and 4.1 times more than drip irrigation, by ponding method in paddy rice cultivation areas in a production season.

It is normal to have yield losses with drip irrigation method. Nar et al., (2018) reported the yield losses encountered in drip irrigation in the study region. They stated that while the yield of 708 kg da^{-1} was obtained in the ponding irrigation method in which 5,580 mm of water was applied, this yield decreased to 576 kg da^{-1} with drip irrigation. However, it should be considered that the area that can be irrigated under current conditions increases more than 4 times with the drip irrigation method. Therefore, since the area to be planted may increase during the total production season, this 19% decrease in yield can be compensated. In addition, it is thought that the high amounts paid for irrigation labor will be minimized by the drip irrigation method. It is stated that with the decrease in field preparation practices, labor, diesel and time savings will be achieved. This, in turn, will reduce the cost of expenses, which are the most important for farmers.

Conclusions

There is a difference of 27.69 km^2 between the paddy rice cultivation areas calculated in this study and the offical data. There will be a large margin of error when planning irrigation. Such a difference is very important in the calculation of paddy rice cultivation areas, or more generally in agricultural production planning. In system planning, subsurface drip irrigation corresponds to an incorrect capacity calculation of 33.8, 38.1 and 155 million m^3 in drip irrigation and ponding methods, respectively. Therefore, it is seen that the capacity, area, and consumption values calculated by machine learning methods obtained with satellite images in real time will be very useful in regulations and studies related to drought that arises due to global climate change.

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Authors' Contributions

The authors declare that they have contributed equally to the article.

Conflicts of Interest Statement

The authors declare no competing interests.

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