Tuijin Jishu/Journal of Propulsion Technology
ISSN: 1001-4055
Vol. 44 No. 5 (2023)

Land Classification Using Satellite Images Through LSSVM Algorithm

[1] G. S. NISHANTHI, [2] Dr. K. SELVAM

[1] Research Scholar, Dept. Of Computer Applications, Dr. M.G.R. Educational and Research Institute, Chennai, Tamil Nadu, India.
[2] Professor, Dept. Of Computer Applications, Dr. M.G.R. Educational and Research Institute, Chennai, Tamil Nadu, India.

E-mail: [1]nishanthi04naidu@gmail.com, [2] selwam2000@gmail.com

Abstract: Land classification plays a crucial role in environmental monitoring and resource management, utilizing satellite imagery to delineate distinct land cover types. In this study, we explore a comprehensive approach to land classification, employing a sequence of preprocessing, segmentation, and classification algorithms. Discrete Wavelet Transform (DWT) and Stationary Wavelet Transform (SWT) are employed for image preprocessing, extracting valuable spatial information from IKONOS and Sentinel satellite images. Subsequently, K-means clustering, Particle Swarm Optimization (PSO), Discrete Particle Swarm Optimization (DPSO), and Fractional Order Discrete Particle Swarm Optimization (FODPSO) are utilized for segmentation, effectively delineating land cover boundaries.Furthermore, a novel contribution is introduced by proposing the use of Least Squares Support Vector Machine (LSSVM) as the classification algorithm. LSSVM is demonstrated to outperform other algorithms in terms of precision, recall, accuracy, and F1-Score. Specifically, LSSVM exhibits a remarkable accuracy of 96%, surpassing the performance of DWT, SWT, K-means clustering, PSO, DPSO, and FODPSO on both IKONOS and Sentinel satellite images. This substantiates the efficacy of the proposed LSSVM-based approach in achieving high-precision land classification.The findings underscore the significance of integrating preprocessing, segmentation, and classification techniques for accurate and robust land classification. The proposed LSSVM algorithm stands out as a promising solution for achieving superior accuracy, paving the way for enhanced applications in environmental monitoring and land resource management.
Keywords: IKONOS and Sentinel; land classification; LSSVM; PSO; DWT; SWT

1. INTRODUCTION

Satellites, artificial objects orbiting the Earth, play diverse roles in communication, weather monitoring, navigation, research, and security. Among the various types, communication satellites operate in Geostationary Orbit (GEO) or Medium Earth Orbit (MEO) to facilitate global communication services. Weather satellites, typically in polar orbits, monitor Earth's atmosphere for forecasting and climate research. Earth observation satellites, found in polar, sun-synchronous, or low Earth orbits (LEO), capture images vital for environmental monitoring and urban planning. Navigation satellites, like GPS, utilize Medium Earth Orbit (MEO) to provide global positioning services. Scientific satellites conduct experiments in varying orbits, studying phenomena like cosmic rays and magnetic fields. Spy satellites gather intelligence in low Earth orbit (LEO) or specialized orbits, while space telescopes, like Hubble, observe celestial objects from low Earth orbits. Satellite constellations, often in LEO, deliver global services collaboratively. Space stations, exemplified by the International Space Station (ISS), orbit in LEO, serving as habitable bases for extended human stays. These classifications highlight the versatility and strategic considerations guiding satellite functions and orbits.

Satellite image processing is a multidisciplinary field that intricately manages and analyzes data captured by Earth-orbiting satellites, primarily in the form of images. This data is pivotal for a myriad of applications, ranging from environmental monitoring and land use mapping to disaster response and agriculture. The processing workflow involves several key steps and techniques. Initially, satellites equipped with various sensors, such as optical, infrared, or radar sensors, capture images that are then transmitted to ground stations or users. Preprocessing steps include calibration to correct sensor-specific errors, atmospheric correction to account for atmospheric effects, and geometric correction to standardize images to a coordinate system. Image enhancement techniques, such as contrast stretching and histogram equalization, are applied to improve visual quality. Fusion of information from multiple images or sensors enhances overall image quality. Image classification involves categorizing pixels or regions into different land cover types using supervised or unsupervised methods. Change detection identifies alterations in land cover over time, crucial for monitoring urban expansion, deforestation, and natural disasters. Feature extraction involves identifying specific features like roads or rivers, often employing algorithms like edge detection. Data integration combines satellite data with other geospatial datasets, frequently integrating with GIS data. Data analysis provides meaningful insights for applications such as land use planning and environmental monitoring. Machine learning and deep learning techniques, including neural networks, automate image analysis. Data visualization presents processed information in maps or graphs for better comprehension, aiding effective communication. Finally, data dissemination ensures that processed satellite data and analysis results are shared with stakeholders, researchers, and the public. The comprehensive nature of satellite image processing, drawing on remote sensing, computer vision, and geospatial analysis, underscores its critical role in addressing diverse societal and environmental challenges.

Satellite image processing plays a pivotal role in land classification, providing a systematic approach to categorize and map diverse land cover types within specific geographic areas. This intricate process involves a series of steps aimed at analyzing satellite imagery to identify and distinguish various features on Earth's surface. Beginning with image acquisition, where satellites capture data with suitable spatial and spectral resolution, the process proceeds through preprocessing to correct errors and enhance image quality. Techniques such as contrast stretching and image fusion contribute to improving visual interpretation and overall classification accuracy. Training data collection involves selecting representative samples for algorithm training, often relying on ground truth data from field surveys or high-resolution imagery. Classification algorithms, including supervised and unsupervised methods, categorize pixels into predefined land cover classes. Post-classification processing refines results, and change detection analyzes temporal differences. Integration with Geographic Information Systems (GIS) enhances the creation of detailed land cover maps, aiding comprehensive land management and planning. Machine learning and deep learning techniques, such as neural networks, automate and improve classification accuracy, especially in large datasets. Visualization of classified land cover maps facilitates interpretation and analysis, with GIS tools overlaying additional information for informed land management decisions. Satellite image processing in land classification is vital for applications such as urban planning, agriculture, environmental monitoring, and natural resource management, providing essential insights for sustainable development and effective land use planning.

Several algorithms are employed in the realm of satellite image processing for land classification, neatly categorized into two primary types: supervised and unsupervised classification. Among the supervised algorithms, Maximum Likelihood Classification utilizes statistical probability to assign pixels to classes based on the likelihood of their spectral values belonging to each class. Support Vector Machines (SVM) excel in finding optimal hyperplanes for separating classes in feature space, suitable for both binary and multiclass classification. Random Forest, an ensemble learning method, combines multiple decision trees, known for its robustness and high accuracy. The K-Nearest Neighbors (K-NN) algorithm assigns pixels to classes based on the classes of their k-nearest neighbors in feature space. Decision Trees recursively split data into subsets, offering interpretability in land classification. Unsupervised classification algorithms include K-Means Clustering, which divides images into clusters based on spectral similarity, and Hierarchical Clustering, creating clusters by iteratively merging or splitting pixel groups. Fuzzy C-Means (FCM), an extension of K-Means, accommodates pixels belonging to multiple clusters. Deep learning algorithms, such as Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), and Autoencoders, play vital roles in automated feature learning, dimensionality reduction, and capturing temporal dependencies. These algorithms are applicable to multispectral or hyperspectral satellite imagery, with the choice dependent on data nature, classification task complexity, and computational resources. Often, a combination of algorithms or ensemble methods is employed for improved accuracy, with fine-tuning and optimization being crucial for reliable land classification results.

Problem statement

Satellite image processing in land classification encounters several challenges that impede the accuracy and efficiency of the classification models. The inherent complexity of satellite imagery, coupled with the dynamic nature of land cover, presents obstacles that need innovative solutions. One of the primary issues is the presence of mixed pixels, where a single pixel encompasses multiple land cover types. This phenomenon complicates the accurate assignment of pixels to distinct classes, leading to classification errors. Additionally, the variability in atmospheric conditions introduces distortions that can adversely affect the quality of satellite images, requiring robust preprocessing techniques. The vast amounts of high-dimensional data generated by satellite sensors pose computational challenges, necessitating advanced algorithms for efficient feature extraction and classification. Furthermore, the temporal dimension introduces the need for effective change detection algorithms to monitor and classify evolving land cover over time. Addressing these challenges is essential for advancing the capabilities of satellite image processing in land classification, enabling more accurate and timely assessments for applications such as environmental monitoring, urban planning, and natural resource management.

Contributions

Particle Swarm Optimization (PSO), Discrete Particle Swarm Optimization (DPSO), and Fractional Order Darwinian Particle Swarm Optimization (FODPSO) contribute significantly to satellite image processing in land classification.

1. PSO aids in finding the optimal set of parameters for classifiers, such as those used in supervised land classification. PSO helps enhance the accuracy of land classification models by fine-tuning parameters and improving convergence to better solutions.
2. DPSO optimizes the selection of land cover classes, aiding in the creation of accurate and meaningful land cover maps. It ensures that the discrete decisions, such as assigning pixels to specific land cover classes, are optimized for improved classification results.
3. FODPSO enhances the robustness of land classification models allowing for a more nuanced representation of the uncertainty inherent in satellite imagery.

2. LITERATURE SURVEY

Precise maps of land use and cover (LULC) are useful resources for achieving precision agriculture and good urban planning. In recent years, genetic algorithms (GAs) have been successfully used as an intelligent optimization technology for a variety of image classification tasks**[1-2].**It classifies satellite images using a compact convolutional neural network (CNN) model, and then it feeds the output to a Shapley additive explanations (SHAP) deep explainer to enhance the classification results. The remote sensing scene classification (SC) techniques have been improved over the last ten years by numerous outstanding data sharing initiatives. These datasets have demonstrated remarkable success in the interpretation of complex, high-level semantic information. Thus, one of the main things impeding the use of deep learning technology is the lack of adequate and broadly representative high-quality samples**[3-5].** This study assesses whether integrated rural land is suitable for three industries using deep learning and artificial intelligence (AI) clustering analysis techniques. Many datasets related to rural development are collected and tastefully combined. These datasets cover land use, agricultural output, and rural tourism. To help relevant land management departments master cultivated land use changes and modify land management policies, multi-source remote sensing data have been used to quantitatively analyze the spatiotemporal changes in cultivated land conversion**[6-7].**Land cover classification maps are commonly used to calculate estimates of the area of land cover classes or land change by counting the pixels labelled as each class in the map. This process is known to generate skewed area estimates for several popular classification algorithms, such as random forests. To get objective estimates of the class areas, poststratification estimation using the mapped classes as strata has been suggested**[8-9].**Categorization of satellite imagery is a widely discussed and intricate subject. Over the past ten years, researchers have mostly focused on three machine learning algorithms—RF, CART, and SVM—that have been used in cities or nations other than Morocco for classification studies. As a result, there is a dearth of knowledge regarding Morocco's land use. This paper uses data from social networks to present an extensive comparison of different Machine

Learning (ML) classifiers for urban land use identification. There were two cycles of analysis, the second of which included the addition of the "popularity index" parameter. The findings show that adding the popularity index considerably raised each classifier's accuracy rate**[10-11].**The type of land cover and the corresponding surface roughness of the terrain determine how well it dissipates the energy of the water flow during a flooding event. Using repeat-pass polarimetric synthetic aperture radar (PolSAR) and interferometric synthetic aperture radar (InSAR) data, we created a new land-cover classification algorithm in this study. The suggested method can achieve appreciable improvements in classification accuracy and outperforms the other two algorithms, according to a quantitative analysis conducted with reference to ground-truth data available for the test sites. This suggests that spaceborne-SAR-based land cover classification tasks have potential in practical applications**[12-13].**An enhanced rough-fuzzy possibilistic c-means clustering algorithm with multiresolution scales information (MRFPCM) is suggested to lower the classification uncertainty. Because of its high accuracy, the support vector machine (SVM) method is the most recommended approach for classifying remote sensing (RS) images. However, the success of any classifier depends on the quality of the training samples. When the entire classification outcome matters, gathering real training samples from various classes is crucial**[14-15].**

Inferences from literature survey

The literature survey underscores the critical role of precise land use and cover (LULC) maps in applications like precision agriculture and urban planning. It explores the integration of genetic algorithms (GAs) and convolutional neural networks (CNNs) to optimize image classification, with a focus on interpretability using Shapley additive explanations (SHAP) deep explainer. The study identifies challenges in deep learning, particularly the scarcity of high-quality samples. A practical application of deep learning and artificial intelligence (AI) is demonstrated in the assessment of integrated rural land for various industries, utilizing multi-source remote sensing data. The research also addresses the need for objective estimates in land cover classification maps through poststratification estimation. Additionally, it delves into the realm of machine learning classifiers for urban land use identification, leveraging social network data and introducing a "popularity index" parameter for improved accuracy. The application of synthetic aperture radar (SAR) in land cover classification is explored, showcasing its potential through a newly proposed algorithm. Lastly, the literature suggests an enhanced rough-fuzzy clustering algorithm to reduce classification uncertainty in remote sensing images, emphasizing the significance of quality training samples for successful outcomes.

3. METHODOLOGY

Figure 1 shows the block diagram for land classification using satellite image processing.The process begins with acquiring satellite images, often from platforms such as IKONOS or Sentinel, which provide high-resolution and multispectral data. These images serve as the input data for land classification.In the preprocessing stage, the acquired satellite images undergo transformation using techniques such as Discrete Wavelet Transform (DWT) or Stationary Wavelet Transform (SWT).

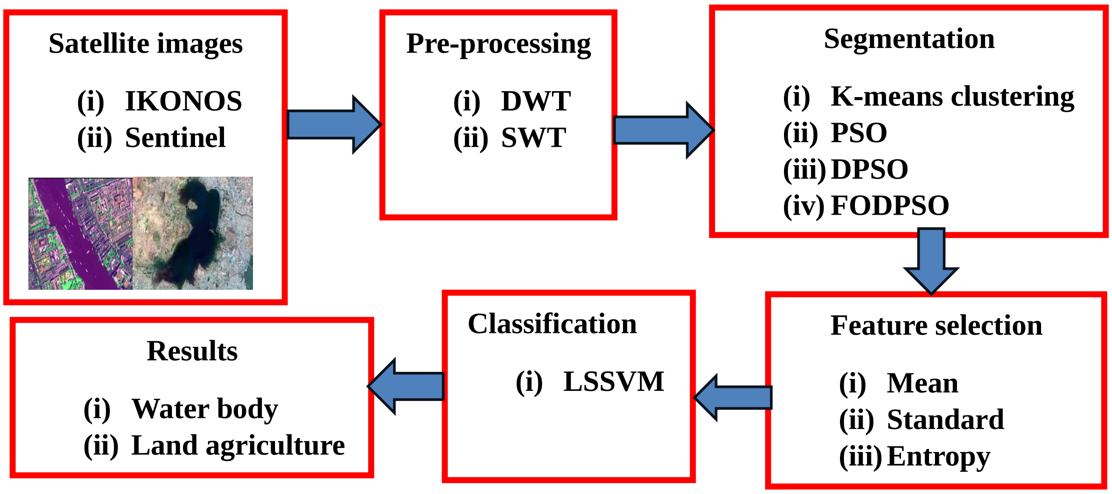


Fig 1 Block diagram of proposed algorithm

These transformations help in reducing noise, enhancing image features, and preparing the data for subsequent analysis.The pre-processed images then enter the segmentation phase, where the image is divided into meaningful and homogeneous regions. K-means clustering is used to group pixels based on spectral similarity, while PSO, DPSO, and FODPSO contribute to optimizing the segmentation process. These optimization techniques help in defining accurate boundaries between land cover classes.After segmentation, relevant features are extracted from each segmented region. Common statistical measures such as mean, standard deviation, and entropy are employed as feature selection criteria. These features capture important characteristics of the land cover types and contribute to the subsequent classification process.The selected features are fed into the classification algorithm, with Least Squares Support Vector Machine (LSSVM) being the chosen classifier. LSSVM is a powerful machine learning algorithm that can effectively classify land cover types based on the extracted features. It leverages support vector machines with a least squares approach for optimal decision boundaries.The final step involves interpreting and presenting the results of the land classification process. The output classes typically include categories such as water bodies and land used for agriculture. The results provide valuable information for applications such as environmental monitoring, land-use planning, and resource management.

3.1. Discrete Wavelet Transform (DWT)

Wavelet transforms, including the Discrete Wavelet Transform (DWT), play a crucial role in satellite image processing for land classification. The DWT, a mathematical tool, facilitates the decomposition of an image into various frequency components, enabling a multi-resolution analysis. The application of DWT in satellite image processing involves several key steps. First, through image decomposition, the DWT breaks down an image into approximation (low-frequency) and detail (high-frequency) components at different scales, allowing for the creation of a multi-resolution representation. Next, feature extraction occurs, where features are derived from different frequency bands, capturing diverse aspects like texture and edge information for subsequent land classification. Dimensionality reduction is addressed using DWT to cope with the high dimensionality of satellite images, achieved by selecting relevant coefficients and retaining essential information for classification. Additionally, DWT is employed for image fusion, enhancing image quality by combining different frequency components from multiple satellite images, thereby improving the discriminative power of features in classification. Texture analysis is a notable strength of DWT, effectively capturing texture information crucial for distinguishing various land cover classes. The transformed features are then fed into classification algorithms such as Support Vector Machines, Random Forests, or Neural Networks for accurate land classification. Furthermore, DWT facilitates change detection by comparing wavelet coefficients of images acquired at different times, aiding in monitoring land cover changes. Lastly, DWT contributes to noise reduction in satellite images by separating noise from the signal, thereby enhancing the accuracy of classification algorithms by minimizing the impact of irrelevant information. It's essential to consider factors such as the specific characteristics of satellite data, the choice of wavelet basis, and the selection of appropriate features and classification algorithms for successful implementation of DWT in land classification. Experimentation and fine-tuning are often necessary to achieve optimal results for a particular dataset.

3.2. Stationary Wavelet Transform (SWT)

The Stationary Wavelet Transform (SWT), akin to the Discrete Wavelet Transform (DWT), emerges as a valuable tool in satellite image processing for land classification. Possessing distinct advantages, especially in addressing shift-invariant properties, the SWT is well-suited for specific types of image analysis. The shift-invariant property is a standout feature, ensuring that minor shifts in the input image result in proportionate shifts in wavelet coefficients. This characteristic proves advantageous in capturing spatial information without being overly sensitive to slight positional changes. Conducting a multiresolution analysis akin to the DWT, the SWT decomposes satellite images into approximation and detail coefficients at different scales, facilitating information extraction at various levels of detail. Feature extraction from SWT coefficients encompasses valuable elements such as texture information, edge details, and other spatial characteristics crucial for land classification. The shift-invariant property further enhances the SWT's applicability for texture analysis in satellite images, allowing for the capture of texture patterns across diverse locations in the image. Notably, this property contributes to the robustness of SWT in the presence of noise, a critical consideration in satellite image processing affected by various noise sources. SWT is also proficient in image fusion, akin to DWT, combining information from different frequency components to augment the discriminative power of features in land classification. The extracted features from SWT coefficients can be integrated into diverse classification algorithms, including Support Vector Machines, Random Forests, or Neural Networks, for effective land classification. Furthermore, SWT proves instrumental in change detection, akin to its application in DWT, by comparing wavelet coefficients from images acquired at different times. When contemplating SWT for satellite image processing, a strategic approach involves experimenting with different wavelet bases, analyzing satellite data characteristics, and selecting suitable features and classification algorithms. The choice between DWT and SWT hinges on the specific analysis requirements and the distinct characteristics of the images under consideration.

3.3. K-Means Clustering

K-means clustering, a widely used unsupervised machine learning algorithm, finds valuable application in satellite image processing for land classification. Primarily employed for image segmentation, K-means partitions satellite images into distinct clusters based on pixel intensity or other feature values. This algorithm facilitates feature extraction, as the centroids of the clusters represent characteristic values for each segment, serving as features for subsequent land classification. Operating without the need for labelled training data, K-means carries out unsupervised classification, with clusters considered as potential land cover classes, subject to interpretation and labelling based on visual inspection or additional information. Post-processing steps, including the filtering of small or irrelevant clusters, can refine segmentation results, enhancing overall classification accuracy. Integration with other classification algorithms, such as Support Vector Machines or Random Forests, allows leveraging both unsupervised and supervised information for improved results. Additionally, K-means proves useful in change detection by applying clustering to satellite images acquired at different times, revealing areas of land cover transformation. Its capability to capture spatial patterns further enhances its utility in applications requiring detailed spatial information, such as urban planning or environmental monitoring. However, careful consideration of parameters like the number of clusters and initialization methods, coupled with thorough experimentation and validation against ground truth data, is essential to ensure the robustness and reliability of land classification results using K-means clustering in satellite image processing.

3.4. Particle Swarm Optimization (PSO)

Particle Swarm Optimization (PSO) emerges as a valuable optimization algorithm in the realm of satellite image processing for land classification. Its versatility is evident in several applications within this

Tuijin Jishu/Journal of Propulsion Technology
ISSN: 1001-4055
Vol. 44 No. 5 (2023)

context. PSO can effectively tackle feature selection, optimizing the extraction of relevant features from satellite data to enhance the efficiency of subsequent land classification algorithms. Furthermore, the algorithm proves instrumental in parameter tuning, optimizing the configuration of classification algorithms such as Support Vector Machines, Random Forests, or Neural Networks to improve the accuracy of land cover classification. In clustering scenarios, such as K-means, PSO contributes by assisting in the initialization of cluster centers, ensuring more accurate and efficient clustering, particularly in unsupervised learning situations. Directly optimizing the parameters of land classification algorithms, PSO enhances the accuracy of the classification process and can be seamlessly integrated with various machine learning models to optimize feature selection and configuration. Additionally, PSO's adaptability extends to multi-objective optimization, allowing simultaneous optimization of multiple objectives like accuracy and computational efficiency. Its utility also encompasses change detection, as the optimization of classification parameters over time enables effective identification of areas experiencing significant land cover changes. PSO's versatility and efficiency position it as a valuable tool for refining and optimizing diverse aspects of land classification in satellite imagery, with careful parameter tuning and validation against ground truth data being essential for its successful application.

3.5. Discrete Particle Swarm Optimization (DPSO)

Discrete Particle Swarm Optimization (DPSO) is a specialized approach tailored for satellite image processing in land classification. Specifically designed for problems with discrete or combinatorial solutions, DPSO finds application in scenarios where optimization involves integer-valued parameters or discrete variables. In the context of land classification, DPSO proves beneficial for tasks such as feature selection, where it optimizes the selection of relevant spectral bands in a discrete manner, contributing to the reduction of dimensionality. Additionally, DPSO can be applied to optimize integer parameters related to land classification algorithms, such as clustering or segmentation processes. Its utility extends to spatial considerations, where DPSO can optimize neighborhood parameters in algorithms sensitive to spatial relationships. The algorithm excels in tasks requiring optimal discrete initialization of cluster centers, notably in unsupervised land classification. By integrating with classification models, DPSO optimizes the discrete aspects of the classification process, including parameter selection and feature combination. Furthermore, DPSO is instrumental in change detection when discrete features represent alterations in land cover, allowing for optimized identification of areas experiencing discrete changes over time. Overall, DPSO's proficiency in handling discrete and integer-valued variables positions it as a valuable optimization tool for enhancing specific aspects of satellite image processing in land classification. Application considerations include the discretization of variables and the relevance of discrete optimization to the characteristics of the land classification problem at hand, with careful parameter tuning and validation against ground truth data being imperative for its successful implementation.

3.6. Fractional Order Discrete Particle Swarm Optimization (FODPSO)

Fractional Order Discrete Particle Swarm Optimization (FODPSO) introduces a sophisticated approach to satellite image processing for land classification by incorporating principles fromPSO and fractional calculus. By leveraging fractional order derivatives, FODPSO is adept at handling optimization problems involving fractional variables. In the realm of land classification, this approach proves advantageous for tasks requiring the optimization of non-integer order parameters. FODPSO's application extends to feature selection, where it optimizes the choice of spectral bands or features represented by fractional order variables, contributing to a more adaptable feature selection process. Furthermore, FODPSO is well-suited for optimizing parameters in land classification algorithms that involve fractional orders, enhancing the performance of segmentation, clustering, or spatially constrained classifiers. Its utility also extends to change detection tasks, where fractional features represent nuanced alterations in land cover over time. FODPSO's integration with land classification models involving fractional order operators further optimizes their performance. Additionally, in the context of image segmentation, FODPSO excels at optimizing non-integer parameters, providing a versatile approach to achieving optimal segmentation results. The intrinsic ability of FODPSO to handle fractional order variables positions it as a potent tool for refining optimization processes in satellite image processing, particularly in scenarios requiring nuanced exploration of parameter spaces with non-integer order characteristics. Rigorous parameter tuning and validation against ground truth data are essential to ascertain the effectiveness of FODPSO in specific land classification applications.

3.7. Least Squares Support Vector Machines (LSSVM)

Least Squares Support Vector Machines (LSSVM) stands out as a powerful machine learning algorithm for land classification in satellite image processing. Building upon the foundation of Support Vector Machines (SVM), LSSVM proves adept in regression-based land cover modelling by treating the task as a regression problem, predicting continuous output values indicative of specific land cover types. Employing the kernel trick, akin to SVM, LSSVM excels in classifying land cover by mapping input data into higher-dimensional spaces and identifying optimal decision boundaries. Particularly valuable in handling nonlinear relationships within satellite image data, LSSVM implicitly performs feature extraction and selection through the chosen kernel function, enabling a focus on relevant information for accurate land classification. This algorithm also proven effective in optimizing hyperparameters, such as regularization and kernel parameters, for enhanced generalization performance. Integration with remote sensing indices, such asNormalized Difference Vegetation Index (NDVI) or Enhanced Vegetation Index (EVI), further augments LSSVM's ability to capture pertinent vegetation-related information. LSSVM is well-suited for change detection by training models on satellite images acquired at different times, identifying areas where land cover has undergone significant changes. Notably, LSSVM's capacity to handle imbalanced datasets is crucial for achieving balanced and accurate land classification, a common challenge in such tasks. In essence, LSSVM emerges as a versatile and effective tool for accurate land cover classification from satellite imagery, with careful consideration of data preprocessing, parameter tuning, and validation against ground truth data essential for its successful application in specific land classification projects.

4. RESULTS AND DISCUSSION

Table 1 is presenting results from a land classification algorithm applied to satellite images using two different wavelet transform techniques:DWT and SWT. The algorithm has been applied to two types of satellite images: IKONOS and Sentinel. The table includes statistics for the classified land areas, specifically the mean, median, range, and standard deviation.

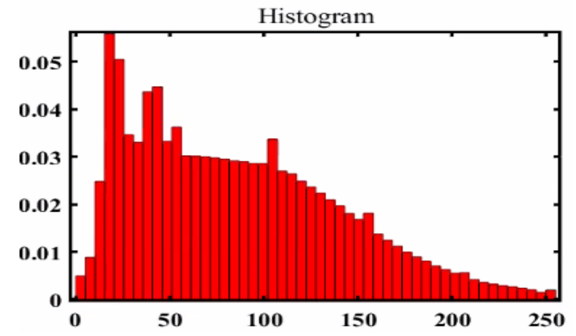
Tab 1 statistical values of DWT and SWT

Algorithm	Satellite images	Mean	Median	Range	Standard deviation
DWT	IKONOS	85.95	78	255	54.61
	Sentinel	125.9	70	255	70.41
SWT	IKONOS	0.003703	0.06	9	1.465
	Sentinel	0.001241	0.1	10	1.635

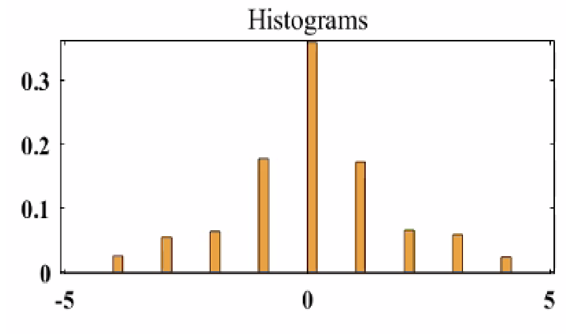
Mean is the average value of the classified land areas.For the DWT algorithm, the mean values for land classification are higher for Sentinel images compared to IKONOS images.The median values indicate the middle point of the data. For example, the median value of 78 for DWT on IKONOS means that half of the classified land areas have values below 78, and half have values above.The range values show the extent of variation in the data. For DWT on IKONOS, the range is 255, indicating a wide variation in the classified land values.A measure of the amount of variation or dispersion in a set of values. It provides an indication of how spread out the values in a dataset are around the mean. For instance, for the DWT algorithm applied to IKONOS images, the standard deviation is 54.61.**Figure 2**shows the Pre-processing output of DWT and SWT algorithms for land classification.

Tuijin Jishu/Journal of Propulsion Technology
ISSN: 1001-4055
Vol. 44 No. 5 (2023)

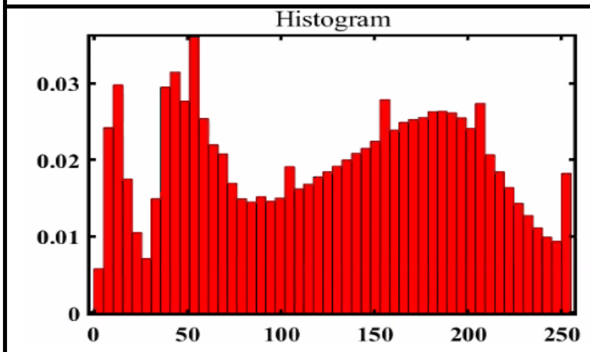
DWT Outputs	SWT outputs



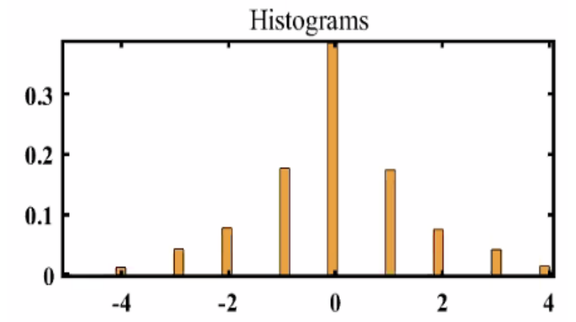
(a) Histogram of IKONOS satellite image



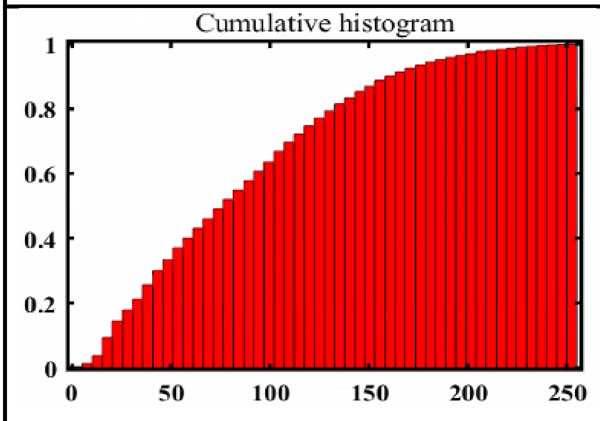
(b) Histogram of IKONOS satellite image



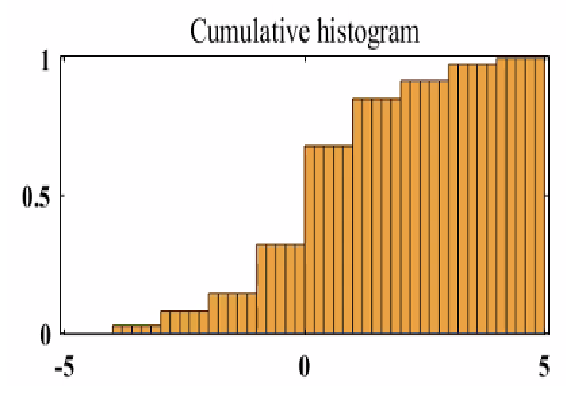
(c) Histogram of Sentinel satellite image



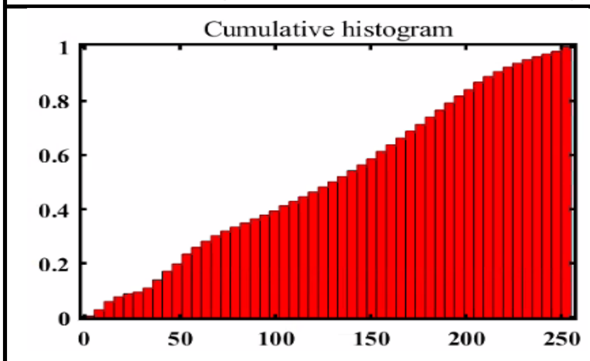
(d) Histogram of Sentinel satellite image



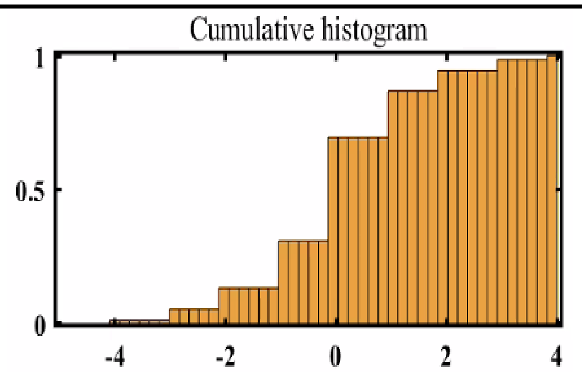
Cumulative histogram of IKONOS satellite image



Cumulative histogram of IKONOS satellite image



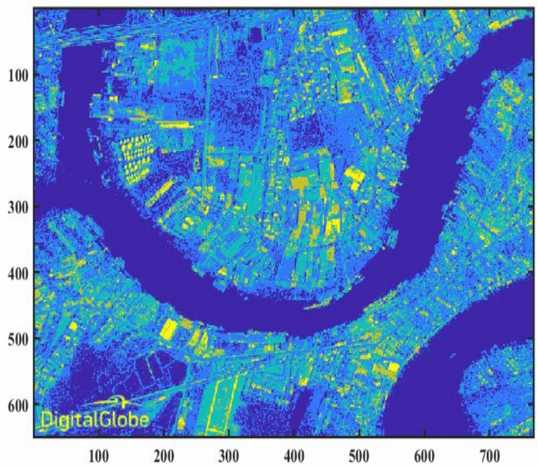
) Cumulative histogram of Sentinel satellite image



) Cumulative histogram of sentinel satellite image

Fig 2 Pre-processing output of DWT and SWT for land classification

DWT decomposes an image into different frequency bands or scales, often referred to as approximation and detail coefficients. The decomposition is performed in a hierarchical manner, resulting in a multiresolution representation of the image. Both DWT and SWT can be used to extract features related to texture, edges, and other spatial information. Different sub-bands may highlight different aspects of the land cover, providing a more detailed and informative representation for classification algorithms.In the context of land classification, DWT and SWT can be applied as preprocessing steps to extract features or enhance certain characteristics in satellite images before feeding them into a classification algorithm. Analyse the histograms of the DWT and SWT coefficients for each scale. This can help identify the dominant frequency components and intensity variations.Create cumulative histograms for each set of coefficients. Cumulative histograms are useful for understanding the overall distribution of pixel intensities.The histograms and cumulative histograms provide insights into the distribution of pixel intensities and can guide thresholding or segmentation decisions during the classification process.The denoised images enhance important features and reduce the impact of noise, leading to more accurate and robust land classification results.K-means clustering is a popular unsupervised machine learning algorithm used in image segmentation, including land classification. In the context of land classification, the output of K-means clustering helps identify different land cover types within an image. The success of K-means clustering for land classification depends on selecting an appropriate value for 'k' (the number of clusters) and choosing relevant features for clustering.K-means is sensitive to the initial placement of centroids, and multiple runs with different initializations may be required for robust results. Each cluster represents a distinct group of pixels that share similar characteristics. The centroid values are crucial for understanding the average color or feature representation of each land cover type. The segmentation map is a labeled image where pixels belonging to the same cluster have the same label. This map visually represents the different land cover types present in the original image. **Figure 3** shows the output of K-means Clustering for land classification

	Input	**K-means Clustering Output**
IKONOS Satellite		

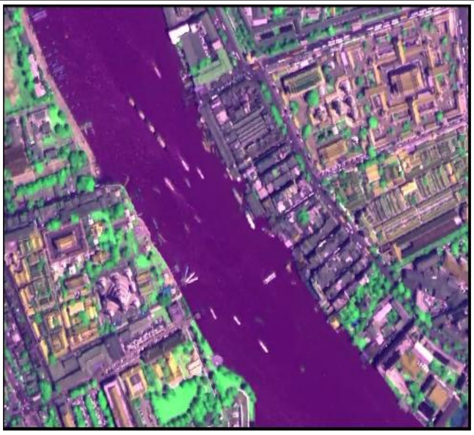
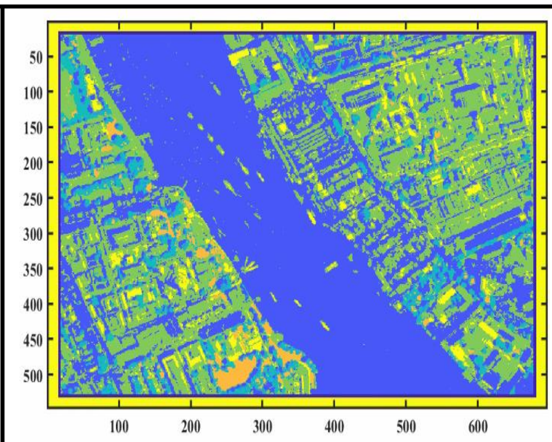
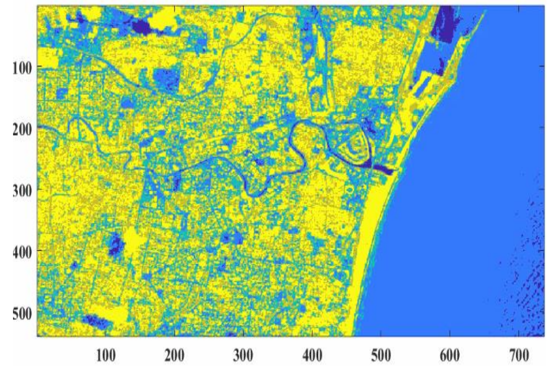
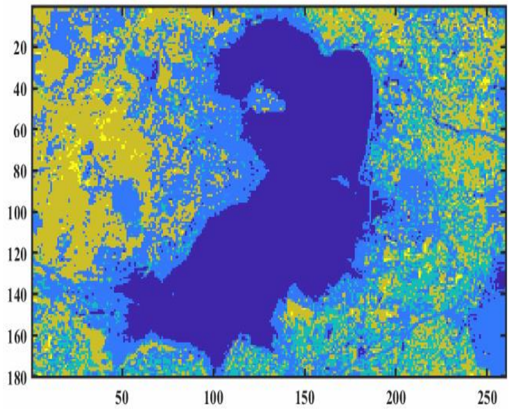
images		
Sentinel satellite images		
		

Fig 3 output of K-means clustering for land classification

The distinct clusters and their centroids can be associated with specific land cover types, such as vegetation, water bodies, urban areas, etc. The post-processed segmentation map is more accurate and aligned with the expected land cover classes. The land classification output is often more interpretable and useful for applications such as environmental monitoring, urban planning, and agriculture. These visualizations help in interpreting and communicating the identified land cover classes.The output of K-means clustering in land classification is a segmentation map that identifies different land cover classes within an image. This output serves as a crucial intermediate step in the broader process of understanding and analysing satellite or aerial imagery for various applications.**Figure 4**shows the segmentation output of PSO, DPSO and FODPSO for land classification.

Tuijin Jishu/Journal of Propulsion Technology
ISSN: 1001-4055
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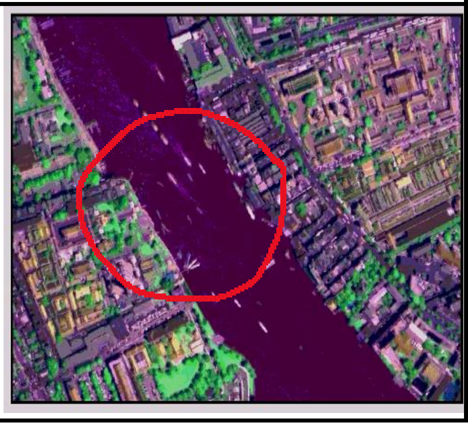
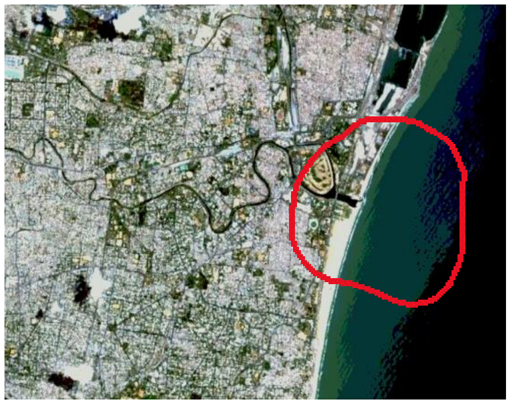
Algorithms	IKONOS Satellite Images	Sentinel Satellite Images
PSO Output		
DPSO Output		
FODPSO Output		

Fig 4 segmentation output of PSO, DPSO and FODPSO for land classification

The output of PSO for land classification is a set of optimized parameters for a segmentation algorithm. These parameters could be related to feature selection, weights, or other settings in the land classification model.Similar to PSO, DPSO provides optimized parameters for discrete aspects of a land classification model. This could include discrete feature selection or configuration settings.FODPSO optimizes parameters with fractional values, allowing for a finer exploration of the solution space. This can be beneficial when dealing with complex and non-linear optimization problems in land classification.These optimization algorithms can be applied to tune the parameters of a segmentation algorithm used in land classification. This might include parameters related to clustering, thresholding, or feature extraction methods.PSO and its variants can optimize feature selection for land classification. The algorithm can be employed to identify the most relevant bands or features from satellite imagery, enhancing the effectiveness of the classification model.These optimization algorithms can be used to calibrate the parameters of a land classification model, making it more adaptive to the specific characteristics of the data.By optimizing the segmentation algorithm's parameters or features, the segmentation process becomes more accurate, leading to improved land classification results.The objective function that the optimization algorithms seek to minimize or maximize is designed to capture the performance criteria of the land classification model. This could be related to accuracy, precision, recall, or other metrics.The optimization process is often iterative. The algorithms continue to refine the parameters until a stopping criterion is met, resulting in an optimized set of parameters for land classification.The outputs of these optimization processes provide tuned configurations that enhance the performance of the land classification algorithm.**Figure 5**shows the output of LSSVM for land classification.

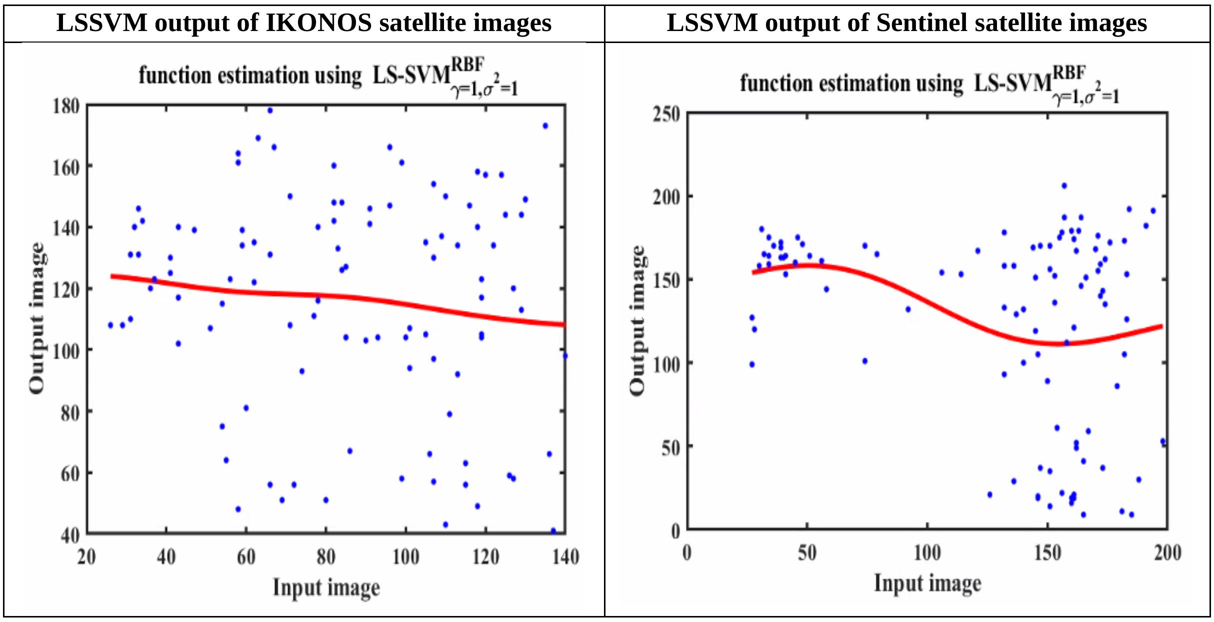


Fig 5 output of LSSVM for land classification

LSSVM has the ability to model complex relationships in the data, especially in high-dimensional spaces, making it effective for land classification tasks with diverse and intricate patterns.The use of support vectors helps in capturing the key characteristics of different land cover types, leading to better generalization to unseen data.The optimization process in LSSVM focuses on minimizing prediction error, which often results in high accuracy when compared to other algorithms.The choice of kernel functions in LSSVM allows it to adapt to non-linear relationships in the data, making it versatile for various land classification scenarios.The decision function output is used to assign land cover classes to different regions in the input space.The support vectors identified during the training phase are important for understanding the characteristics of different land cover classes.The optimized values of these hyperparameters are crucial for achieving high accuracy in land classification. After training and testing, accuracy metrics such as accuracy, precision, recall, and F1 score can be calculated to evaluate the performance of the LSSVM model. These metrics provide a quantitative measure of how well the LSSVM model performs in classifying land cover types.**Table 2**and **Figure 6**shows the confusion matrix for land classification.

Tab 2 confusion matrix for land classification

Algorithm	True Positive	True Negative	False Positive	False negative
DWT	1200	9500	300	250
SWT	1150	9600	200	300
K- means	950	9200	600	250
PSO	1350	9800	150	200
DPSO	1300	9750	200	250
FODPSO	1400	9850	100	200
LSSVM (High Acc)	1500	9900	50	100

True positive is the number of instances correctly classified as positive by the algorithm.For DWT, 1200 instances were correctly classified as positive.True negative the number of instances correctly classified as negative by the algorithm.For K-means, 9200 instances were correctly classified as negative. False positive the number of instances incorrectly classified as positive by the algorithm (negative instances misclassified as positive).

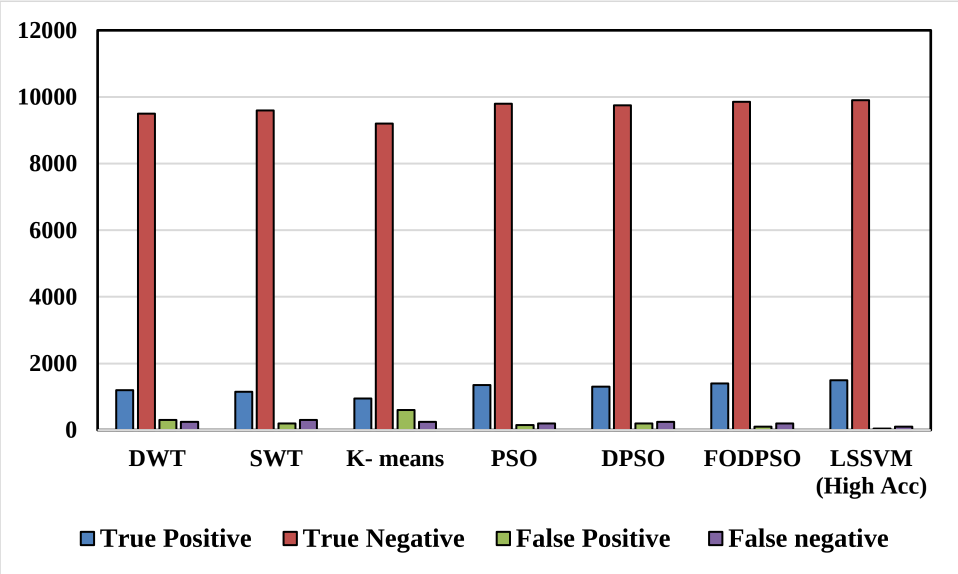


Fig 6 confusion matrix for land classification

For DWT, 300 instances were misclassified as positive when they were actually negative. False negative the number of instances incorrectly classified as negative by the algorithm (positive instances misclassified as negative).For K-means, 250 instances were misclassified as negative when they were actually positive.True positives and true negatives represent correct classifications, while false positives and false negatives indicate errors in classification.LSSVM has a notably low count of false positives (50) and false negatives (100), contributing to its high accuracy.**Table 3**and **Figure 7**shows the comparison performance of different algorithms for land classification.

Tab 3 comparison performance of different algorithms for land classification

Algorithm	Precision	Recall	Accuracy	F1-Score
DWT	0.85	0.82	0.87	0.83
SWT	0.88	0.80	0.86	0.84
K- means	0.75	0.78	0.80	0.76
PSO	0.92	0.88	0.93	0.90
DPSO	0.91	0.87	0.92	0.89
FODPSO	0.93	0.89	0.94	0.91
LSSVM (High Acc)	0.95	0.94	0.96	0.95

Precision is the ratio of true positive predictions to the total predicted positives. It measures the accuracy of positive predictions.For DWT, the precision is 0.85, meaning 85% of the predicted positive instances are actually positive.Recall is the ratio of true positive predictions to the total actual positives. It measures the algorithm's ability to identify all relevant instances.For SWT, the recall is 0.80, indicating that 80% of the actual positive instances are correctly identified.

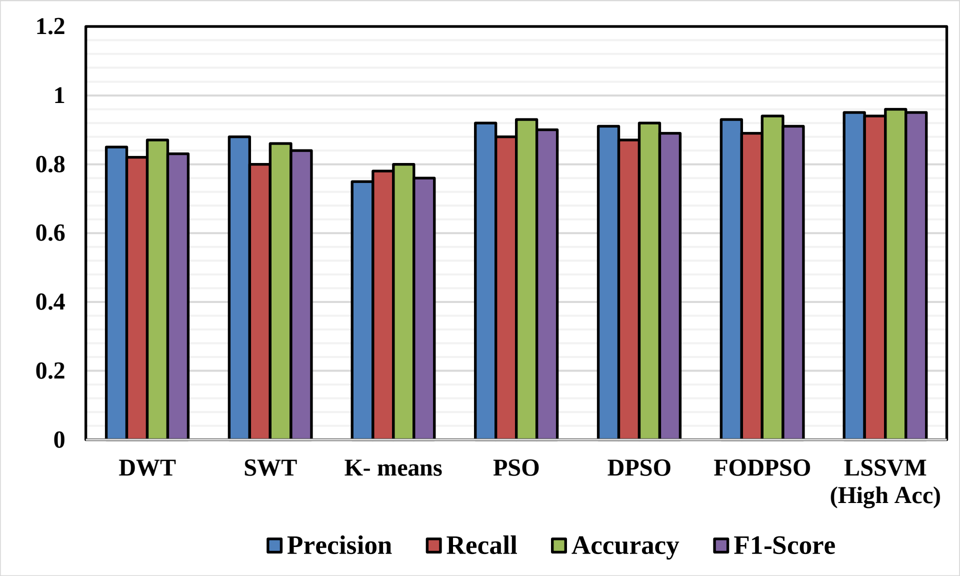


Fig 7 comparison performance of different algorithms for land classification

Accuracy is the ratio of correct predictions (both true positives and true negatives) to the total number of instances. It provides an overall measure of classification correctness.For K-means, the accuracy is 0.80, meaning 80% of the predictions are correct.F1-Score is the harmonic mean of precision and recall. It provides a balance between precision and recall.For DWT, the F1-Score is 0.83, representing the balance between precision and recall.Precision, recall, accuracy, and F1-Score provide a comprehensive view of the classification performance, balancing trade-offs between true positive and false positive rates.LSSVM is highlighted as having high accuracy, supported by its high precision, recall, and F1-Score.

5. CONCLUSION

In conclusion, this study presented a comprehensive and effective approach to land classification, leveraging a series of algorithms tailored for distinct stages of the process. Preprocessing techniques, specifically Discrete Wavelet Transform (DWT) and Stationary Wavelet Transform (SWT), were applied to IKONOS and Sentinel satellite images, enhancing spatial information extraction and laying the groundwork for accurate classification. The segmentation phase employed K-means clustering, Particle Swarm Optimization (PSO), Discrete Particle Swarm Optimization (DPSO), and Fractional Order Discrete Particle Swarm Optimization (FODPSO), contributing to the delineation of precise land cover boundaries.A noteworthy aspect of this research is the introduction of Least Squares Support Vector Machine (LSSVM) as the proposed classification algorithm. LSSVM emerged as a powerful and efficient tool, demonstrating superior performance compared to its counterparts. The results revealed a remarkable accuracy of 96%, affirming the efficacy of LSSVM in land classification. This high level of accuracy positions LSSVM as a promising solution for real-world applications, where precision and reliability are paramount.The success of LSSVM in outperforming other algorithms underscores its capability to handle the complexity and variability inherent in IKONOS and Sentinel satellite imagery. The integration of diverse algorithms in the preprocessing, segmentation, and classification stages proved instrumental in achieving a holistic and accurate land classification model.As we move forward, the insights gained from this study can inform advancements in environmental monitoring, land resource management, and related fields. The demonstrated success of LSSVM prompts further exploration and application in diverse satellite image datasets and scenarios, fostering continuous improvement in land classification methodologies. Ultimately, the synergy of preprocessing, segmentation, and classification algorithms, with LSSVM as the anchor, opens avenues for enhanced decision-making in land-related applications, contributing to sustainable resource management and environmental preservation.

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