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Techniques and Challenges of the Machine Learning Method for Land Use/Land Cover (LU/LC) Classification in Remote Sensing Using the Google Earth Engine

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Abstract— In order to accurately observe the globe, land use and land cover are crucial. Due to the proliferation of several global modifications associated with the existence of the planet, land use/land cover (LU/LC) classification is now regarded as a topic of highest significance in the natural environment and an important field to be researched by researchers. Google Earth provides satellite image dataset which contains high-resolution images; these images are used to analyze the land area. In order to address the dearth of review articles throughout the land use/land cover classification phase, we proposed a full evaluation, which might help researchers continue their work. Therefore, the purpose of this study is to investigate the methodical steps involved in classifying land use and land cover utilizing the Google Earth platform. The most widely used techniques researchers employ to achieve LU/LC classification using Google Earth Engine are examined in this work. The classification of land use and land cover for a specific region using time series was covered in this study, along with the many types of land use and land cover classes and the approach employed by Google Earth. The limits of the GEE tool and difficulties encountered during the process of classifying land use and cover have also been covered in this survey document. The importance of this review rests in inspiring future scholars to tackle the LU/LC analysis problem successfully, and this study offers researchers a road map for assessing land use/land cover classification.

Keywords-: Land use land cover classification; Remote sensing; Google earth engine; Landsat, machine learning; Classifiers.

I. INTRODUCTION

Particularly in metropolitan areas, the significance of accurate and timely information regarding the kind and extent of land holdings, as well as changes through time, is on the rise. Understanding how the Earth appears from orbit is crucial for determining how human activity affects natural resources over time. Maps of the earth's features and infrastructure now use more complex data from remote sensing satellites. The terms "land use" and "land cover" have different connotations when used in the context of remote sensing for science. Forests, marshes, grasslands, river lands, and urbanized and developed areas are examples of natural and biological ecosystems that can be detected from the earth's surface known as land cover. Land use categories define the activities that occur on the ground and reflect the present usage of lands such as developed institutions, supermarket run malls, greens grounds, and dams.[15] Rapid advancements in ML algorithms and prepared ease of use of big datasets put geographies on the threshold of impressive growth. In order to manage natural resources, it is necessary to classify remote sensing images in order to derive usable information from their spectral signatures of land cover type. [14] Earth-surface and ground-cover can understand the Earth's surface phenomena. The evaluation of sparse-temporal image classification in LULC can also be significant for studying and attracting human activities with the environment, environmental disaster risk estimation, development policies for environment, spatial forecast, and complex exchanges between carbon cycles. [3] To classify land cover types for a particular area we use multispectral and multitemporal images. These images easily provided by the remote sensing techniques. Remote sensing techniques are reliable way to define land cover classes because these techniques provide easily accessible large-scale data. AI machine learning (ML) and deep learning (DL) are innovative systems with remote sensing (RS) images for image processing. Land cover classification is the most fundamental sources of information when managing environmental and agricultural monitoring tasks. [4] For the planning and sustainable development of the agricultural system, knowledge of crop yield and yield is very important. Consistent information of the crop fields provides planners, and policy makers with valuable information to make decisions regarding procurement, storage, public supply, export-import and eventually food safety of the nation [6] The most popular use of images is the marking of pixels in captured images is referred to as classification with useful real-world data for im-proved performance and information extraction that is useful thematically cadastral records, vegetation, and other data are all stored on maps and the type of land cover could be calculated using the satellite picture description.[16] Several distant Approaches to image classification based on sensing have been used for the mapping of LU/LC. It includes the widely used supervised form, supervised and unsupervised processes can be used. ISODATA (Iterative Self-Organizing Data Analysis) clustering, the neural network, K-means and Fuzzy C-means clustering approach are the unsupervised approaches. The k-nearest neighbor (KNN), minimum distance classifier, maximum likelihood classifier (MLC), support vector machines (SVM) and Random Forest Classifiers (RFC) are some of the most widely used supervised methods [29]. The use of remotely sensed images to predict LU/LC classification has sparked a lot of interest among researchers.

The geospatial software Google Earth Engine (GEE) was released in 2001. The GEE platform had forty-year multitemporal data available, which aided researchers in their study of analysis the Earth's surface. Researchers, particularly those in the RS group, can benefit from the many tools that GEE provides for studying geographical data. The main benefit of GEE is that it does not require users to download or manage data on a local computer and is a free cloud-based service [13]. It is built on Google's cloud computing infrastructure, and Google does calculations for it automatically. All operations are performed in bulk and in parallel on Google's CPUs and GPUs [3]. The intricacies of parallel computing are disguised by this system automation [9].

In addition to the different datasets already included in GEE, researchers can easily add and distribute their own datasets, scripts, and templates via URLs [5]. Other maps and items are made-to-order. whenever a user requests it. Furthermore, since almost all of the necessary resources are already available on GEE [16], Installing third-party software packages like ENVI and ERDAS is not necessary.

A robust web-based programming interface is used in combination with GEE. Users will concentrate on the logic of data collecting and programmable workflow. You only need to log in in order to access all GEE control. Additionally, there is an online code editor where you can create scripts, debug them, and view the outcomes immediately after compilation.

The GEE library contains a wide number of functions and algorithms for evaluating different datasets. All the algorithms are parallel in nature and can automatically manage data through several servers. To help users put their ideas into practice, the GEE platform combines machine learning, image processing, vector processing, geometric analysis, various visualization, and several complex algorithms. The GEE functions are typically sufficient to meet the requirements of a standard scientific project. Users may also use GEE to implement their own algorithms and then post-process the data.

During the land use land cover classification process Google Earth images were used as datasets. Some researchers explained their results revealed the Random Forest, k-nearest neighbor, and the support vector machine were in order of overall accuracy. According to survey the LU/LC classification process, using RF classifier provides good accuracy.

II. MOTIVATION

According to the findings of the report, there is currently no complete discussion of the land use/land cover classification method utilizing Google Earth Engine in any of the literature reviews on LU/LC. As a result, we feel compelled to write a scientific review paper that covers all phases of the LU/LC classification process using the Google Earth Engine tool for the knowledge of future researchers around the world.

III. OBJECTIVE

The following is a list of this review's primary goals:

- The primary aim of this assessment article is to discuss the significance/applications of LULC classification, summaries LULC classes and basics of image processing required for categorization of land use and land cover to forecast possible land cover.
- The second objective is to discuss the flow of methodology and summarize various stages of the land use/land classification process using Google Earth Engine and techniques /methods involved in those stages.
- The end purpose is to outline the GEE tool's limits as well as the numerous difficulties faced in LU/LC categorization in order to make it easier for future academics to tackle the issue.

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IV. SECTONS OF THE PAPER

The remainder of the paper is divided into parts and arranged as follows: The "Methodology of LULC Classification" describe the step-by-step process of LULC classification. Then Sub-sections describing all steps of classification in detail. "Dataset collection" sub-section describes the datasets and their origins that are eligible for LULC classification in GEE. The sub-section "Image pre-processing techniques" discusses the techniques for pre-processing satellite images. The land cover classes (categories) are defined in the "Define Land Cover Land Use Classes" sub-section. Then comes sample collection for training. The "LU/LC classification methods" sub-section includes a few examples of LU/LC classification techniques. The "Result analysis and accuracy assessment" sub-section described methods to validate results and commonly used metrics. Finally, we have discussed the challenges and limitation of GEE tool in section named "Challenges" and the "Conclusions" section illuminate the study's findings.

V. METHODOLOGY OF LULC CLASSIFICATION

The procedure of LU/LC classification was prompted by natural causes and major changes on the earth's surface over a lengthy period of time. In a remote sensing situation, many photos from several satellites, plus a GIS environment have been chosen as the most important facts a place where several types of land cover shift such as deforestation, agricultural land expansion, and population growth over time, there has been an increase in urbanization and a loss of wetlands at variety of time intervals are predictable [27]. Stages used in the process of LU/LC classification select region of interest, chose dataset, image pre-processing, Training sample collection, classification, Result analysis and accuracy assessment.

The generic flow of the LU/LC classification using GEE tool is clearly presented in this paper, the conceptual view shown in Figure 1. This figure is showing step by steps process of LULC classification using GEE tool. We have given the detail of all available datasets in GEE in table 1 with its purpose and source of each dataset. Selection of dataset is very important step in LULC classification process. Because dataset is the input to next step of the process. Next, we have discussed Image preprocessing techniques available in GEE. Preprocessing methods depends on datasets, which dataset we have chosen for our study because GEE provide some already corrected datasets which take less processing time as we have already discussed in this section above. Because it is the first step after dataset selection, pre-processing of satellite images should be done properly. Then we need to define the classes before training sample selection. Any number of classes we can define according to the purpose of our research. Next, we have discussed many methods of training sample selection. stratified random sampling, stratified systematic, stratified sampling and simple random sampling methods are used by researchers Then next step is run ML classifier, we have discussed all classification methods provided by GEE in subsection. Next step is drawing the result of the classification and accuracy assessment. We have discussed in detail about kappa coefficient and confusion matrix. So, this is basic flow of the classification methodology used in GEE for LULC classification. The detailed description of techniques/ methods used in all steps are presenting in following sub sections.

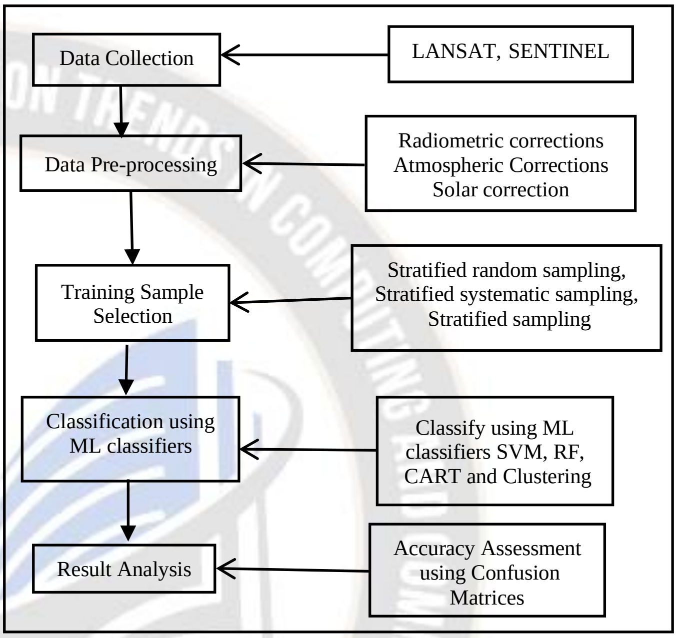

Figure 1. Flow chart of the methodology

A. Data Set Collection

The most important step in the LU/LC classification is choosing an appropriate dataset. The image data was taken from https://earthexplorer.usgs.gov/. Datasets from various time periods must be carefully collected before being processed in a remote sensing environment. We discovered that several datasets were used by scholars and scientist in the study of the LU/LC classification in different studies. Table 1 represents a couple of them. The Table 1 is available on Github (https://github.com/amita1101/LULC-Process-Tables/blob/main/GEE-Dataset.docx?raw=true)

B. Image Data Prepossessing

The consistency and clarity of satellite images are enhanced using image pre-processing techniques. A few of the image pre-processing methods offered by GEE are shown in Table 2. In Google Earth Engine Landsat-8 SR, Landsat-8 TOI and Landsat-8 OLI data sets are Geometrically, atmospherically, and radiometrically corrected. Only clouds masking is done by researcher by using 'pixel_qa' band, it is used to remove clouds

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from the image. But we have Landsat-8 Raw dataset also, if we use this in our research then we can use tool to remove these errors but we have already corrected data so use that pre corrected data as it took less processing time. In Sentinal 1 has thermal noise removal, Radiometric calibration, Terrain correction. These corrections already done by GEE using sentinal1-toolkit. Sentinal 2 has cloud removal band (QA60) for cloud masking. In Google Earth Engine, the image pre-processing tool enables users to create cloud-free, topographically corrected image compo-sites for a user-defined extent and time (GEE). Within seconds, the tool visualizes the image composite, allowing the user to perform a crosscheck and, if necessary, change the strategy. After that, the image composite can be saved to the user's Google Drive for later use.

C. Define Land Cover/ Land Use Classes

Land cover is defined as resulted features on land surface area of earth, and its relationship with economic function, it becomes land use [11]. Table 3 summarized maximum number of LULC classes defined by researchers. Fourteen LULC classes are mapped by level III classification in GEE map. Mostly researchers mapped only 6 basic level I classes: water, forest, urban, bare land, crop, desert and develop land [28]. For classify subcategory of any of the basic class we need to sub classify that class. Like this we can find out the maximum number of possible classes in our study area by increases the level of classification.

D. Training Sample Selection

The amount and distribution of samples have an impact on the outcome of land-cover classification. Missing or imbalance training samples have a detrimental impact on the classifier's parameter. The stratified random sampling is best to extract the same number of samples for each class, avoiding over-fitting and under-fitting problems. To obtain a preliminary spectral-related land use map, unsupervised classification using k-mean clustering is used in most of the studies.

Some other types like simple random sampling, stratified sampling and stratified systematic sampling are also used by researchers. Figure 2. shows stratified random sampling method used by many researchers in GEE. We can draw samples manually or by importing an existing vector shape via Google .CSV file. Earlier researchers were importing training data samples using Fusion table. But from December 2019 Google has turned off Fusion table service. So, the approach used by researcher earlier is failed today. This information is very useful for the future research her of the area. GEE uses region sampling to turn each picture pixel (at a specified scale) that intersects one or more areas into a Feature and returns it as a FeatureCollection. In addition to any characteristics copied from the input feature, each output feature will include one attribute for each band of the input image. In GEE we have many datasets each dataset has different number of bands and each band defines one feature of that dataset.

TABLE II. LAND USE/ LAND COVER CLASSES

	Tier1 classes		Tier 2 classes
1	Marshland [2,8]	1.1	Non tidal marshes
		1.2	Tidal marshes
2	Herbaceous planted land [2,8]	2.1	Hay
		2.2	Fallow
		2.3	Raw crops
		2.4	Urban
		2.5	Small grain
3	Semi natural vegetation [2,4][8]	3.1	Grassland
4	Shrubland [2,8]	4.1	Shurbland
5	Non natural woody land [2,8]	5.1	Vineyard, Orchard
6	Barren land [2,4,8]	6.1	Bare sand,clay,rock
		6.2	Transitional
		6.3	Strip mines
7	Forested upland land [2,4,8]	7.1	Evergreen forest
		7.2	Mixed forest
		7.3	Deciduous forest
8	Water land [2,4,8][10]	8.1	Partial water Ice, snow
		8.2	Open water
9	Developed land [2,8]	9.1	Commercial, Industrial, Transportation
		9.2	Low Intensity Residential
		9.3	High Intensity Residential

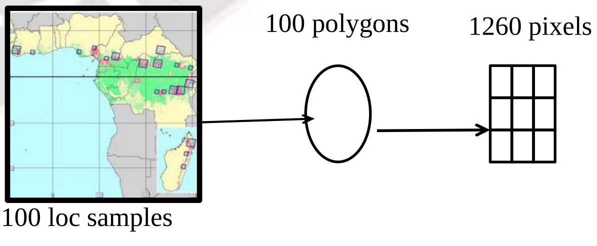

Figure 2. Training sample selection

E. Lu/Lc Classification Methods

Both supervised and unsupervised machine learning methods are accessible through the GEE library. Maximum Entropy classifier, Decision tree, Decision Tree ensemble, support vector machine classifier, minimum distance classifier, CART classifier, Gradient Tree Boost classifier, Naive Bayes classifier, and Random Forest classifier are a few of the supervised classification algorithms available in GEE. As mentioned above, GEE offers both sampling and training functions for supervised classification methods, which require labelled examples to train the classifiers. Several clustering techniques are also included in GEE, including the Learning Vector Quantization algorithm, Cobweb clustering algorithm, Cascade simple k-means algorithm, and X-Means, a K-Means algorithm with an effective cluster count estimation. In common mostly researchers used CART, SVM, and RF. According to the researchers RF classifiers is best for LULC classification, which provides the best performance and accuracy. Mostly used classifiers methods by researchers in previous studies shown in table 4. But as we have found that there are more classifiers available in GEE for land cover supervised classification like Maximum Entropy classifier, minimum distance classifier and Gradient Tree Boost classifiers are not frequently used by researchers. One study says that Gradient Tree Boost classifier provides more accurate classification than RF [23]. Two Studies [24,47], says that Maximum Entropy classifier gives less accurate results than CART and RF.

F. Result Analysis and Accuracy Assessment

GEE tool Classifiers are usually evaluated based on key metrics such as accuracy. The review of these papers mainly evaluated the results in terms of the accuracy of classification of LULC classes and the percentage area of each land cover type While several papers within our sample provide values for matrices in these experiments, a direct comparison of studies based on these results is difficult.

Any classification project must include an essential component called accuracy assessment. It contrasts the classified image with a different information source that is regarded as accurate or ground truth information. The ground truth can be gathered on the spot, but the process is tedious and expensive. Interpreting existing classified imagery, high-resolution photography, or GIS data layers can also yield ground truth data. Even though it might be a two-step process, you still need to compare the results of different classification tactics or preparation sites because otherwise you risk not having the real facts and relying solely on the spec that was used to produce the classification. The most well-known method for evaluating the accuracy of a reviewed outline is to construct portions of irregular focuses from actual data and contrast them with the actual data in a confusion matrix. Accuracy evaluation is a significant and conclusive metric in the classification of remotely sensed images for identifying the LU/LC classification. The confusion matrix is used to equate the reference images to the classified images. The accuracy assessment determines how confident the classified photos are. The calculation of overall accuracy is the basic need, according to various studies, and the kappa coefficient is used to measure the correctness of the classification process. User accuracy and Producer accuracy should also consider because some-times if we only focus on overall accuracy, we may get an erroneous sense of accuracy. Overall accuracy can be 98% by chance then kappa coefficient value plays a major role to confirm the reliability of data and level of agreement. The range of possible kappa values is -1 to 1, while it is most commonly found between 0 and 1. The value of unity denotes 100% agreement, showing that the raters agree on how to classify each case. As if the raters had merely "guessed" every rating, zero indicates agreement no better than that expected by chance. For strong agreement, the kappa coefficient value should be between 0.80-0.90, and above 0.90-1.0 for complete agreement. So, in GEE frame-work uses Confusion matrix for accuracy assessment.

VI. CHALLENGES

This paper discusses challenges faced during the classification process and limitation of GEE tool that faced by re-searchers in LULC classification process.

We found that during the acquisition of an image, extracting the study area's region of interest via datum coordinates obtained from a compatible satellite system. For researchers, this is a difficult challenge.

The spatial resolution of currently accessible LULC data sets has to be improved. With the existing LULC data sets, which have a maximum spatial resolution of 30 meters, identifying grassland along roadside, streams, damaged portions of forest, and vegetative corridors across urban areas is difficult [20].

Geo-referencing (changing the location of the pixel) During satellite image pre-processing, a challenge is still the unknown coordinates of the ground truth image with the referenced satellite image for a particular region. (Sentinel data set.)24]

We discovered that supplying accurate training datasets via a ground survey is still a problem for the LU/LC categorization process.

It is still challenging to check the classified image for classification mistakes after classification.[20]

Although the limitations of GEE are small, it is important to be aware of them. The following sections go through some of GEE's major drawbacks.

While the data in the user's account is kept confidential, it is still stored on a private company's database, which many federal agencies and private companies find unacceptable.

We found that due to large map sizes and internet speed constraints, faced while attempting to retrieve processed data. It took very large time when internet speed is slow.

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VII. CONCLUSION

The future of RS is changing due to the growth of massive geodata as well as current innovations in cloud computing and big data analysis services. GEE fundamentally provides a real method for academics, developers, and GIS scientists to extract relevant information quickly and efficiently from large RS datasets without the burdens of traditional data analysis methodologies. To resolve LCLU categorization over large areas and landscape monitoring over many years, researchers may use GEE's enormous collections of RS datasets, such as archived Landsat and Sentinel photos.

It is found the stratified random sampling is best to extract the same number of samples for each class, avoiding over-fitting and under-fitting problems.

Researchers employed various ML classification algorithms to classify the preprocessed satellite image into multiple classes. For the pre-processed satellite image mostly used classifiers are Clustering, CART, RF and SVM but we found that the RF classification methods provide good accuracy. Some classifiers like Maximum Entropy classifier, minimum distance classifier and Gradient Tree Boost classifiers are not commonly used by researchers. But we found that Gradient Tree Boost classifiers provide better accuracy the RF and Maximum Entropy classifier provide less accuracy than SVN, RF and CART. For drawing the result of the classification and accuracy assessment. We have deliberated in detail about kappa coefficient and confusion matrix.

Today's land resource management decisions benefit from applying prediction methodologies to determine the LU/LC classification.

Additionally, this information will aid government organizations like the Forest Service and urban planners in taking the necessary precautions to protect the LU/LC ecosystem.

TABLE III. LIST OF IMAGE PREPOSSESSING TECHNIQUES OF GEE FRAMEWORK

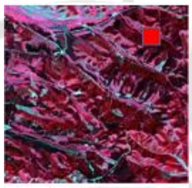
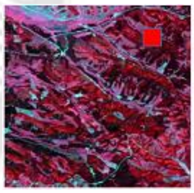
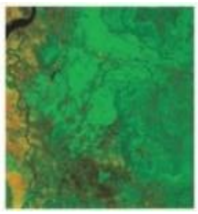
Pre- Prossessing Techniques	Explanation	Methods	Before Correction	After Correction
Radiometric Correction [17,39] [4,6]	This correction is used for improving the image qaulity by removing sensor error.	linear transformation [25]	 [20]	 [20]
Topographic Correction [19,40,44]	It's utilised to take into consideration illumination factors like slope, aspect, and elevation that might lead to variations in reflectance values for similar features in various topographical situations.	Digital elevation model (DEM) [25] Dymond-Shepherd Approach [25]	 [22]	 [22]
Atmospheric Correction [1,2,6],[4] [18,37, 40]	This method is used to improve the clarity of satellite image by removing the atmospheric effects. It provides Cloud free image.	Rudimentary cloud scoring algorithm [26]	 [4]	 [4]
Geometric Correction [4,43,44]	In order to account for the effects of relief and view direction, it is helpful to align images with its correct geographic location. It's crucial to check that an image is placed precisely.	Geo-referencing [25]	 [21]	 [21]

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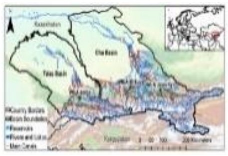
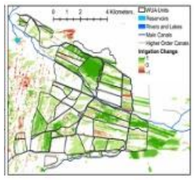
TABLE IV. MOSTLY USED CLASSIFICATION METHODS OF GEE

Classifier Method	**Description**	**Before Classification**	**After Classification**
Clustering (Unsupervised Classification) [17,38]	Patterns and structure in labelled and unlabeled data sets can be discovered with this effective method.	 [13]	 [13]
Random Forest Classifier (Supervised Classification) [6,34]	The random forest classifiers are used in the decision trees process. It is used to enhance the predictive accuracy of LU/LC classification and to avoid data overfitting.	 [12]	 [12]
SVM (Supervised Classification) [6,37,42]	Although there are less training data volumes, this method is memory-efficient and yields accurate categorization of LU/LC groups.	 [20]	 [20]
CART (Supervised Classification) [19,42]	This approach is used for both classification and regression calculation problems.	 [20]	 [20]

REFERENCES

[1] Christopher Potter, (2020). Changes in Growing Season Phenology Following Wildfires in Alaska. Remote Sensing in Earth Systems Sciences. https://doi.org/10.1007/s41976-020-00038

[2] Ibrahim-Bathis K, Syed Ashfaq Ahmed,(2019) Geospa-tial Approach for Evaluating LULC Pattern in the Dodda-halla Watershed, Chitradurga District, India", Remote Sensing in Earth Systems Sciences:108–119

[3] Yinghuai Huang, Xiaoping Liu, Xia Li, Yuchao Yan, and Jinpei Ou, (2018) Comparing the Effects of Temporal Features Derived from Synthetic Time-Series NDVI on Fine Land Cover Classification, IEEE journal of selected topics in applied earth observations and remote sensing.

[4] Nataliia Kussul, Mykola Lavreniuk, Sergii Skakun, and Andrii Shelestov, (2017). Deep Learning Classification of Land Cover and Crop Types Using Remote Sensing Data, IEEE geoscience and remote sensing letters.

[5] R. Torres et al. (2012) "GMES Sentinel-1 mission," Remote Sens. Environ. 9–24.

[6] Nagy A, Feher J, Tamas J (2018). Wheat and maize yield forecasting for the Tisza river catchment using MODIS NDVI time series and reported crop statistics. Compute Electron Agric. 41–49. https:// doi.org/10.1016/j.compag.2018.05.035.

[7] Bikash Ranjan Parida, Avinash Kumar Ranjan, (2019) Wheat Acreage Mapping and Yield Prediction Using Land-sat-8 OLI Satellite Data: A Case Study in Sahibganj Prov-ince, Jharkhand (India)", Remote Sensing in Earth Systems Sciences.96–107

[8] Potter C (2015) Vegetation cover change in Yellow-stone National Park detected using Landsat satellite image analysis. J Biodivers Manage Forestry.4:3

[9] Christopher Potter, (2019) Changes in Vegetation Cover of Yellowstone National Park Estimated from MODIS Greenness Trends, 2000 to 2018", Remote Sensing in Earth Systems Sciences.147–160

[10] NRSC (2006) Land use / land cover database on 1:50,000 scale, Natural Resources Census Project, LUCMD, LRUMG, RS & GIS AA, National Remote Sens-ing Centre, ISRO, Hyderabad.

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[11] Shivani Agarwal & Harini Nagendra (2020): Classifi-cation of Indian cities using Google Earth Engine, Journal of Land Use Science, DOI:0.1080/1747423X.2020.1720842

[12] Ragettli, Silvan; Herberz, Timo; Siegfried, (2018) "An Unsupervised Classification Algorithm for Multi-Temporal Irrigated Area Mapping in Central Asia" Remote Sens. 10, no. 11: 1823. https://doi.org/10.3390/rs10111823

[13] Himanshu Sharma, Vijay Kumar Joshi. (2023). An Efficient Load Balancing Approach For Resource Utilizations In Green Cloud Computing. International Journal of Intelligent Systems and Applications in Engineering, 11(2s), 395–404. Retrieved from https://ijisae.org/index.php/IJISAE/article/view/2735

[14] Shobita Shetty, Enschede, The Netherlands, March, (2019) Analysis of Machine Learning Classifiers for LULC Classification on Google Earth Engine (Ph.D. Thesis)

[15] Fonji SF, Taff GN (2014) Using satellite data to moni-tor land-use land cover change in North-eastern Latvia. Springer plus 3(1):61. https://doi.org/10.1186/2193-1801-3-61

[16] Usman B (2013) Satellite imagery land cover classifi-cation using K means clustering algorithm: computer vi-sion for environmental information extraction. Elixir Jour-nal of Computer Science and Eng: 18671–18675

[17] Sánchez-Ruiz, Sergio & Moreno, Alvaro & Piles, Maria & Maselli, Fabio & Carrara, Arnaud & Running, Steven & Gilabert, M.A.. (2016). Quantifying water stress effect on daily light use efficiency in Mediterranean ecosystems using satellite data. International Journal of Digital Earth. 10. 1-16. 10.1080/17538947.2016.1247301.

[18] Zhengyang Lin, Fang Chen, Zheng Niu, Bin Li, Bo Yu, Huicong Jia, Meimei Zhang,(2018) An active fire detection algorithm based on multi-temporal FengYun-3C VIRR data, Remote Sensing of Environment,Volume 211,Pages 376-387, ISSN 0034-4257, https://doi.org/10.1016/j.rse.2018.04.027.

[19] Lu, Shanlong & Jia, Li & Zhang, Lei & Wei, Yongping & Baig, Muhammad Hasan Ali & Zhai, Zhaokun & Meng, Ji-hua & Li, Xiaosong & Zhang, Guifang. (2017). Lake water surface mapping in the Tibetan Plateau using the MODIS MOD09Q1 product. Remote Sensing Letters. 8. 224-233. 10.1080/2150704X.2016.1260178.

[20] Christopher Davies, Matthew Martinez, Catalina Fernández, Ana Flores, Anders Pedersen. Predicting Dropout Risk in Higher Education Using Machine Learning. Kuwait Journal of Machine Learning, 2(1). Retrieved from http://kuwaitjournals.com/index.php/kjml/article/view/170

[21] N.A Wahap and Helmi Z.M. Shafri,(2020),Utilization of Google Earth Engine (GEE) for land cover monitoring over Klang Valley, Malaysia,IOP Conference Series: Earth and Environmental Science, https://doi.org/10.1088/1755-1315/540/1/012003

[22] Toutin T. (2003) Geometric Correction of Remotely Sensed Images. In: Wulder M.A., Franklin S.E. (eds) Remote Sensing of Forest Environments. Springer, Boston, MA. https://doi.org/10.1007/978-1-4615-0306-4_6

[23] Kshirsagar, D. P. R. ., Patil, D. N. N. ., & Makarand L., M. . (2022). User Profile Based on Spreading Activation Ontology Recommendation. Research Journal of Computer Systems and Engineering, 3(1), 73–77. Retrieved from https://technicaljournals.org/RJCSE/index.php/journal/article/view/45

[24] Xiao, Sa & Tian, Xinpeng & Liu, Qiang & Wen, Jianguang & Ma, Yushuang & Song, Zhenwei. (2018). A SEMI-EMPIRICAL TOPOGRAPHIC CORRECTION MODEL FOR MULTI-SOURCE SATELLITE IMAGES. ISPRS Annals of Photogrammetry, Remote Sensing and Spatial Information Sciences. IV-3. 225-232. 10.5194/isprs-annals-IV-3-225-2018.

[25] Wagle, N.; Acharya, T.D.; Kolluru, V.; Huang, H.; Lee, D.H. Multi-Temporal Land Cover Change Mapping Using Google Earth Engine and Ensemble Learning Methods. Appl. Sci. 2020, 10, 8083. https://doi.org/10.3390/app10228083

[26] Marie Delalay, Varun Tiwari, Alan D. Ziegler, Vik Gopal, and Paul Passy "Land-use and land-cover classification using Sentinel-2 data and machine-learning algorithms: operational method and its implementation for a mountainous area of Nepal," Journal of Applied Remote Sensing 13(1), 014530 (28 March 2019). https://doi.org/10.1117/1.JRS.13.014530

[27] Dr. Naveen Jain. (2020). Artificial Neural Network Models for Material Classification by Photon Scattering Analysis. International Journal of New Practices in Management and Engineering, 9(03), 01 - 04. https://doi.org/10.17762/ijnpme.v9i03.88

[28] Kaspar Hurni, Andreas Heinimann, and Lukas Würsch (2017) Google Earth Engine Image Pre-processing Tool: Background and Methods, Centre for Development and Environment (CDE) University of Bern.

[29] Yuhao Jin, Xiaoping Liu, Jing Yao, Xiaoxiang Zhang & Han Zhang (2020) Mapping the annual dynamics of cultivated land in typical area of the Middle-lower Yangtze plain using long time-series of Landsat images based on Google Earth Engine, International Journal of Remote Sensing, 41:4, 1625-1644, DOI: 10.1080/01431161.2019.1673917

[30] Yulia Sokolova, Deep Learning for Emotion Recognition in Human-Computer Interaction , Machine Learning Applications Conference Proceedings, Vol 3 2023.

[31] Kareem, R.S.A., Ramanjineyulu, A.G., Rajan, R. , MK Gupta, et al. (2021). Multilabel land cover aerial image classification using convolutional neural networks. Arab J Geosci 14, 1681 (2021). https://doi.org/10.1007/s12517-021-07791-z

[32] A Jangid, MK Gupta (2021) Investigating the Effect of Lockdown During COVID-19 on Land Surface Temperature Using Machine Learning Technique by Google Earth Engine: Analysis of Rajasthan, India. Communication and Intelligent Systems, 2021

[33] SR Dogiwal, PJ Desai, MK Gupta, V Goyal 2019, Plant Leaf Classification Using Supervised Classification Algorithm International Journal of Computer Systems vol 3 issue 12, 2019.