Accurate Cropland Delineation from Multi-Temporal Satellite Images using Spatio-Temporal Edge Detection

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I. Preface

In this study, a dual class cropland classification for the area of study is produced using pixel based machine learning methods on Sentinel-2 satellite multi-spectral temporal images using the red, green, blue, near infrared and shortwave infrared bands and derived indices - Normalized Difference Vegetation Index (NDVI), Normalized Difference Water Index (NDWI) and Norm. The classification output of the various algorithms implemented is validated using ground truth values provided by the Ministry of Forest and Agriculture of Slovenia [1]. Finally, the accuracy of three gradient boosting [2] machine learning models - LightGBM [3], Catboost [4] and XGBoost [5] for this classification problem are compared in order to conclude that the Catboost algorithm with it's default parameters is optimum for the problem of cropland delineation, resulting in a classification accuracy of 96%.

II. Acknowledgement

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III. Authors Declaration

We hereby declare that this project report titled 'Automation of Cropland Delineation using Spatio-temporal edge detection' submitted to the TREES program of SAC, ISRO, Ahmedabad is a record of original work done under the guidance of Dr. Anand S. Sahadevan. The information and data given in the report is authentic and to the best of our knowledge.

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IV. Introduction

The worlds population is expected to increase by 2 billion persons in the next 30 years, from 7.7 billion currently to 9.7 billion in 2050 [?]. This population growth impacts food supply systems worldwide [?]. Timely and accurate information on the global cropland extent is critical for applications in the fields of food security, agricultural monitoring, water management,land-use change modeling and Earth system modeling [6]. The availability of such methodologies represents a prerequisite for realising the United Nations (UN) Sustainable Development Goals (SDG), including no poverty and zero hunger [?].

It has been estimated that approximately 20% of the SDG indicators can be interpreted and measured either through direct use of geospatial data itself or through integration with statistical data [?]. Remotely sensed data can significantly lower costs, speed up work and improve reliability compared to ground visits [?].

There are various studies, using supervised or unsupervised algorithms, dedicated to cropland mapping from time series or single-date remote sensing images [?]. The cropland mapping methods applied to time series images have proven to perform better than single-date mapping methods [?] The traditional approach to cropland delineation uses a single strong predictive model like a decision tree. A more recent,more effective approach would be to build an ensemble of models. An ensemble consists of a set of individually trained classifiers whose predictions are combined when classifying novel instances. [?]. Gradient boosting decision tree (GBDT) [7] is the de-facto choice of ensemble method. GBDT achieves state-of-the-art performances in many machine learning tasks, such as multi-class classification [3]. It is backed by strong theoretical results that explain how strong predictors can be built by iteratively combining weaker models (base predictors) via a greedy procedure that corresponds to gradient descent in a function space [?].

The objective of this study was to assess the effect of edge detection on cropland classification. In this paper, we compare the effectiveness of 3 different gradient boosting algorithms - 1. Random Forest [3] 2. LightGBM [?] 3. CatBoost [5]

Edge detection improves the accuracy of pixel based classifiers as it reduces the number of pixels that are highly prone to being classified as either of the semantic classes present in the image. It allows us to discard pixels present at the boundaries of croplands from the training and test sets.
Boundary detection significantly improves semantic segmentation [?]. In this study, we propose to explicitly represent boundaries as a separate class and to exclude them in the classification process. By class boundaries, we mean the pixel boundaries between regions that belong to different semantic classes (cultivated & non-cultivated land).

V. Data & Study Area

The multi-spectral time series satellite data used for this project is free and open access data obtained using the eo-learn package [8] in python that downloads data from the European Space Agency's (ESA) website [9].

The area of interest for this study is a square box bounded region in Slovenia. Projected longitude and latitude values of the upper left and bottom right corners of this bounding box into meters are ([357,737.03, 632593.82], [5016135.99, 5204957.80]). Slovenia has a total area of $2.0273e+7m^2$, out of which a total area of approximately $9e+4m^2$ (1000x1000 pixels) is studied. Slovenia being a small, predominantly hilly and mountainous country located in the middle of Europe, finds its principal model of agriculture to be family farming. Thus, the cultivated lands in this area are fragmented.

The time span for which data was retrieved ranges over a period of a year, from 1^{st} January 2017 to 31^{st} December 2017.

The reference data used to validate the classification outputs from the various algorithms is provided by the Slovenian Ministry of Agriculture, Forestry and Food on it's website [1]. The ground truth values provided classify the land cover into 11 different classes (No data, Cultivated land, Forest, Grassland, Shrub land, Water, Wetlands, Tundra, Artificial surface, Bare land, Snow and ice). For the purpose of cropland delineation, as only 2 classes are required, all pixels corresponding to land cover types other than cultivated land are classified into an umbrella class - non-cultivated land.

VI. Methodology

After applying a mask produced by an edge detection algorithm to negate edge pixels, dual class classification is implemented on the remaining pixels. n edge detection methods have been analysed along with 3 gradient boosting models - LightGBM [3], CatBoost [?] & Random Forest [5]. Figure 1 is a flowchart of the approach followed.

Fig. 1. True Color Image of AOI

A. Preparation of Data

Once the sentinel-2 NIR & Red band data for the area of interest has been downloaded, the NDVI (Normalized Difference Vegetation Index) is calculated for each images in the time-series, thus producing a new dataset of grayscale images with pixel values ranging from 0 to 1. This image data is then vectorized and split into training and test sets.

To calculate pixel classification accuracy, the reference data that is available in vector format is converted to raster form. The data has labels that differentiate between 11 different kinds of land cover - (no data, cultivated land, forest, grassland, shrubland, water, wetland, tundra, artificial surface, bareland & snow and ice). For the purpose of cropland detection, as classes other than cultivated land are not relevant, all classes of the reference data that are not labeled as cultivated land are grouped under a single label - uncultivated land.

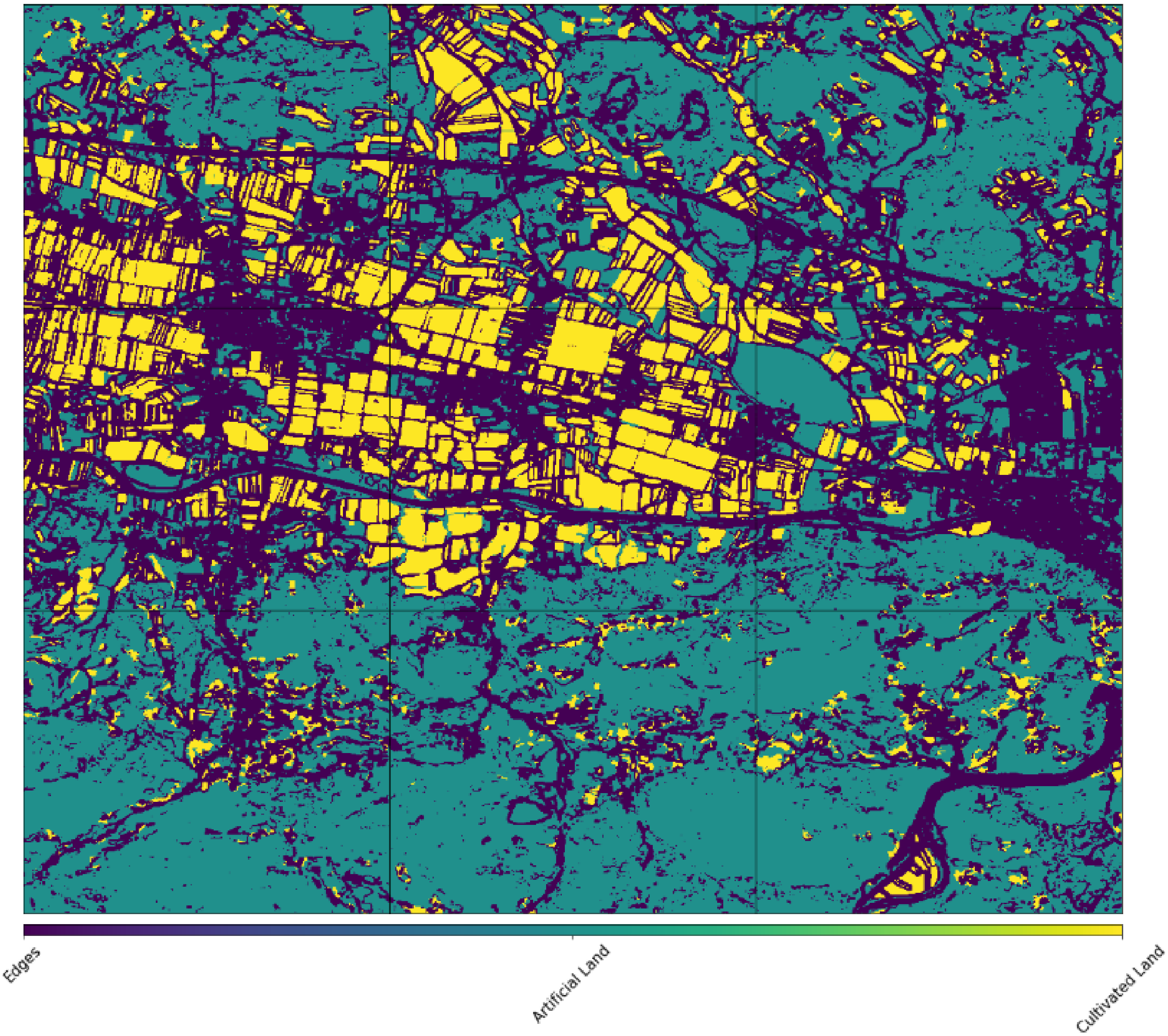

Fig. 2. Ground truth Image indicating 2 classes along with edges

B. Conceptual description of classification methods

When designing a model in domain-specific areas, one strategy is to build a model from theory and adjust its parameters based on the observed data. [7] The lack of such models for cropland delineation can be circumvented if one applies non-parametric machine learning techniques like neural networks, support vector machines, or any other algorithm at ones own discretion, to build a model directly from the data. [7]. These are supervised learning methods that required labelled data.

The most prominent examples of such machine learning ensemble techniques are random forests (Breiman, 2001) and neural network ensembles (Hansen and Salamon, 1990), which have found many successful applications in different domains (Fanelli et al., 2012; Qi, 2012).

Previous research has shown that an ensemble is often more accurate than any of the single classifiers in the ensemble (Opitz et. al.,1999c). Bagging (Breiman, 1996c) and Boosting (Freund Shapire, 1996; Shapire, 1990) are two relatively new but popular methods for producing ensembles.

Boosting methods are based on a different strategy involving ensemble formation where new models are added to the ensemble sequentially, training a new weak base-learner model in every iteration with respect to the error of the whole ensemble learnt so far.(Natekin et.al., 2013) In Gradient boosting machines (GBM's) the learning procedure consecutively fits new models to provide a more accurate estimate of the response variable (Natekin et.al., 2013).

1) Random Forest: Random forests or random decision forests are an ensemble learning method for classification, regression and other tasks that operates by constructing a multitude of decision trees at training time and outputting the class that is the mode of the classes (classification) or mean prediction (regression) of the individual trees [**?**]

2) LightGBM: Gradient-based One-Side Sampling (GOSS) and Exclusive Feature Bundling (EFB) are two novel features implemented in LightGBM in order to tackle the problem of unsatisfactory efficiency and scalability in prior implementations, where the feature dimension is high and data size is large [3]

3) Catboost: CatBoost is a variant of of GBM's with the implementation of ordered boosting, a permutation driven alternative to the classic algorithm. This was implemented to fight a prediction shift caused by a special kind of target leakage present in all currently existing implementations of gradient boosting algorithms [**?**].

C. Accuracy measures

- Precision - Precision and recall are well-suited to evaluating problems where the goal is to find a set of items from a larger set of items. Precision describes the proportion of entities e.g. mentions of people, events, or any given target phenomenon which a system returns that are correct. [**?**].
  $precision = \frac{tp}{tp+fp}$ [**?**]

- Recall - Recall describes the proportion of all entities that potentially should be found, that a given system actually returns $recall = sensitivity = \frac{tp}{tp+fn}$ [**?**]

- F1 - F score is derived from two summary measures: precision and recall. [**?**]

  $F - measure = \frac{(\beta^2+1)*precision*recall}{(\beta^2*precision*recall)}$ [**?**].

When one system achieves higher recall or precision than another, it does not imply that the better-scoring system accurately reproduces the results of the other and then exceeds them; rather, just the overall selection of entities is more precise, or more comprehensive, in some way.

All three measures distinguish the correct classification of labels within different classes. Recall is a function of its correctly classified examples (true positives) and its misclassified examples (false negatives). Precision is a function of true positives and examples misclassified as positives (false positives). The F-score is evenly balanced when $\beta = 1$. It favours precision when$\beta 1$, and recall otherwise [**?**].

VII. Results & Discussion

A. *CatBooster*

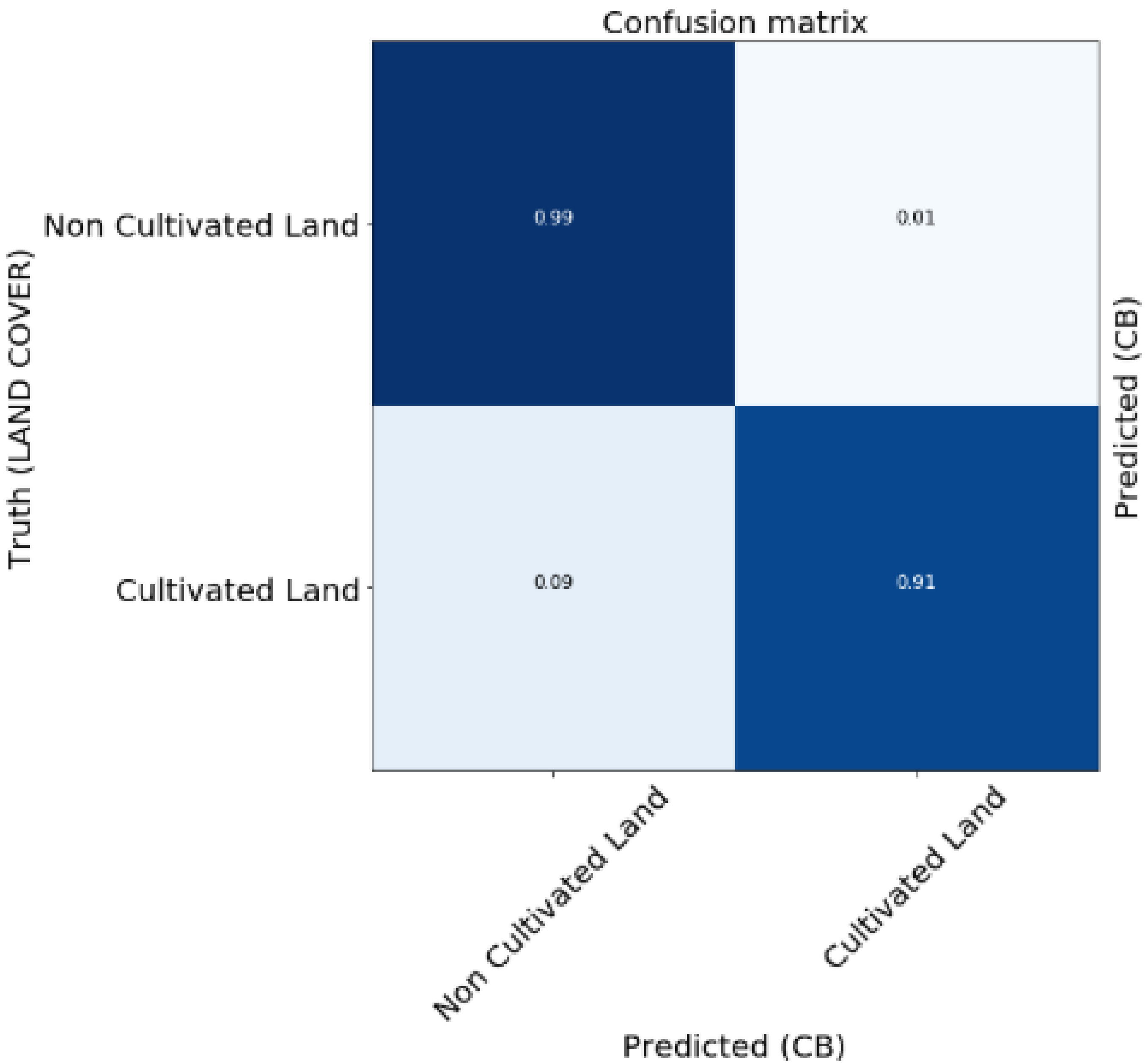

Fig. 3. Confusion Matrix of Catbooster Classifier

Class	F1	Recall	Precision
Non Cultivated Land	97	98.8	95.2
Cultivated Land	94	90.7	97.6

Fig. 4. F1, Recall and Precision scores of Catbooster Classifier

B. LightGBM

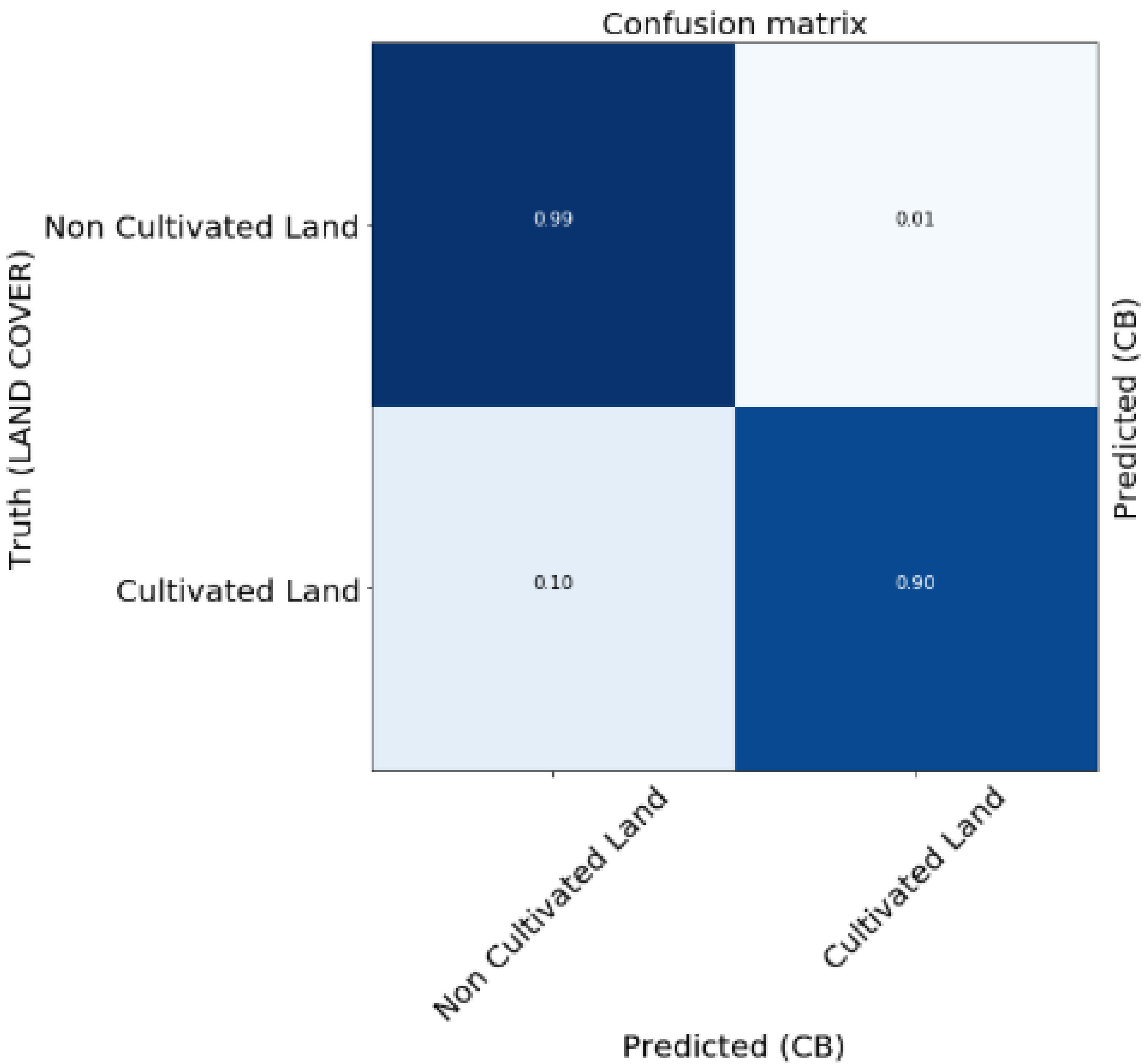

Fig. 5. Confusion Matrix of LightGBM Classifier

Class	F1	Recall	Precision
Non Cultivated Land	96.8	98.6	95
Cultivated Land	93.5	90.1	97.2

Fig. 6. F1, Recall and Precision scores of LightGBM Classifier

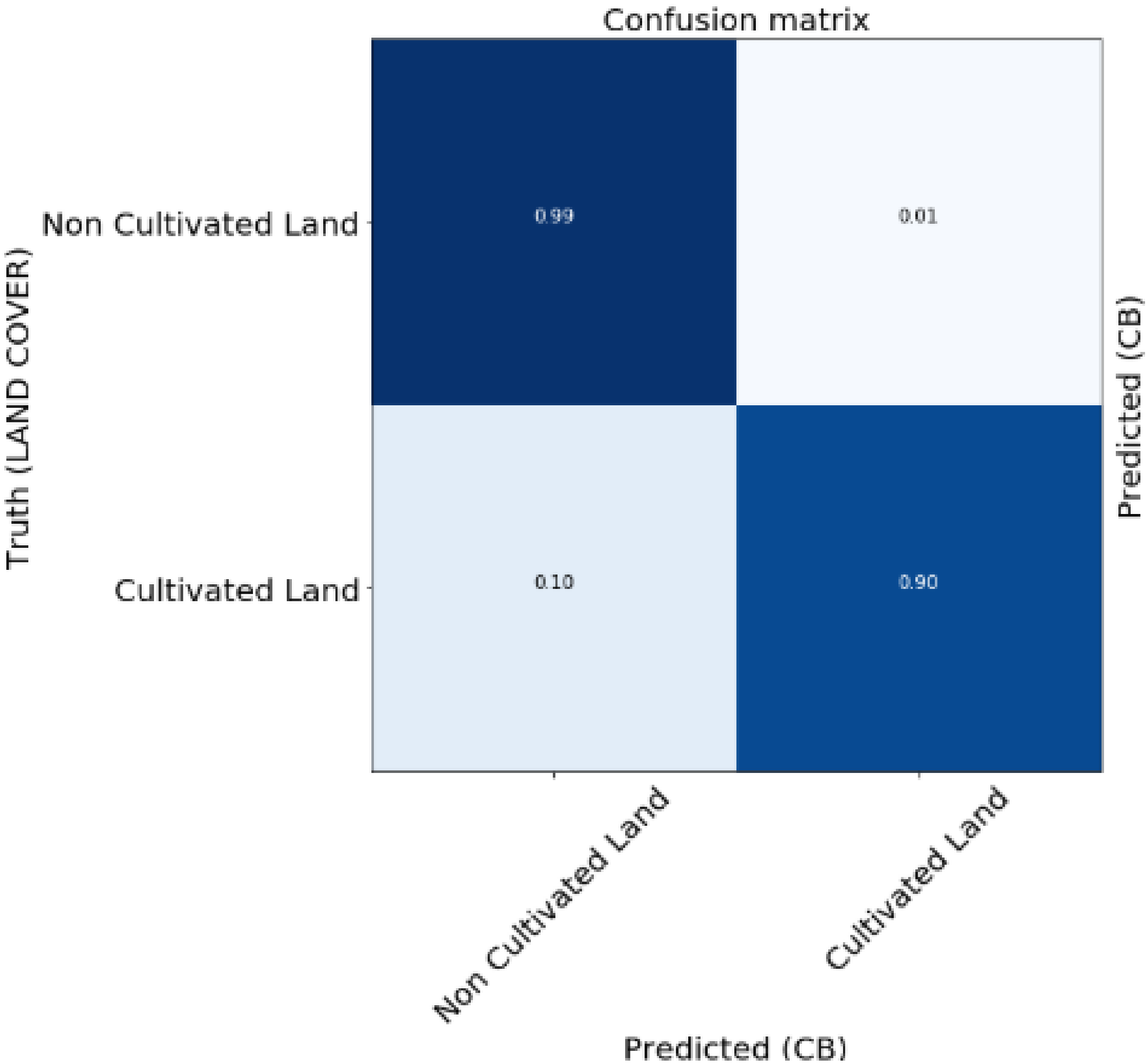

Fig. 7. Confusion Matrix of Random Forest Classifier

Class	F1	Recall	Precision
Non Cultivated Land	96.7	98.8	94.7
Cultivated Land	93.4	89.5	97.6

Fig. 8. F1, Recall and Precision scores of Random Forest Classifier

C. Random Forest

D. Comparison of models

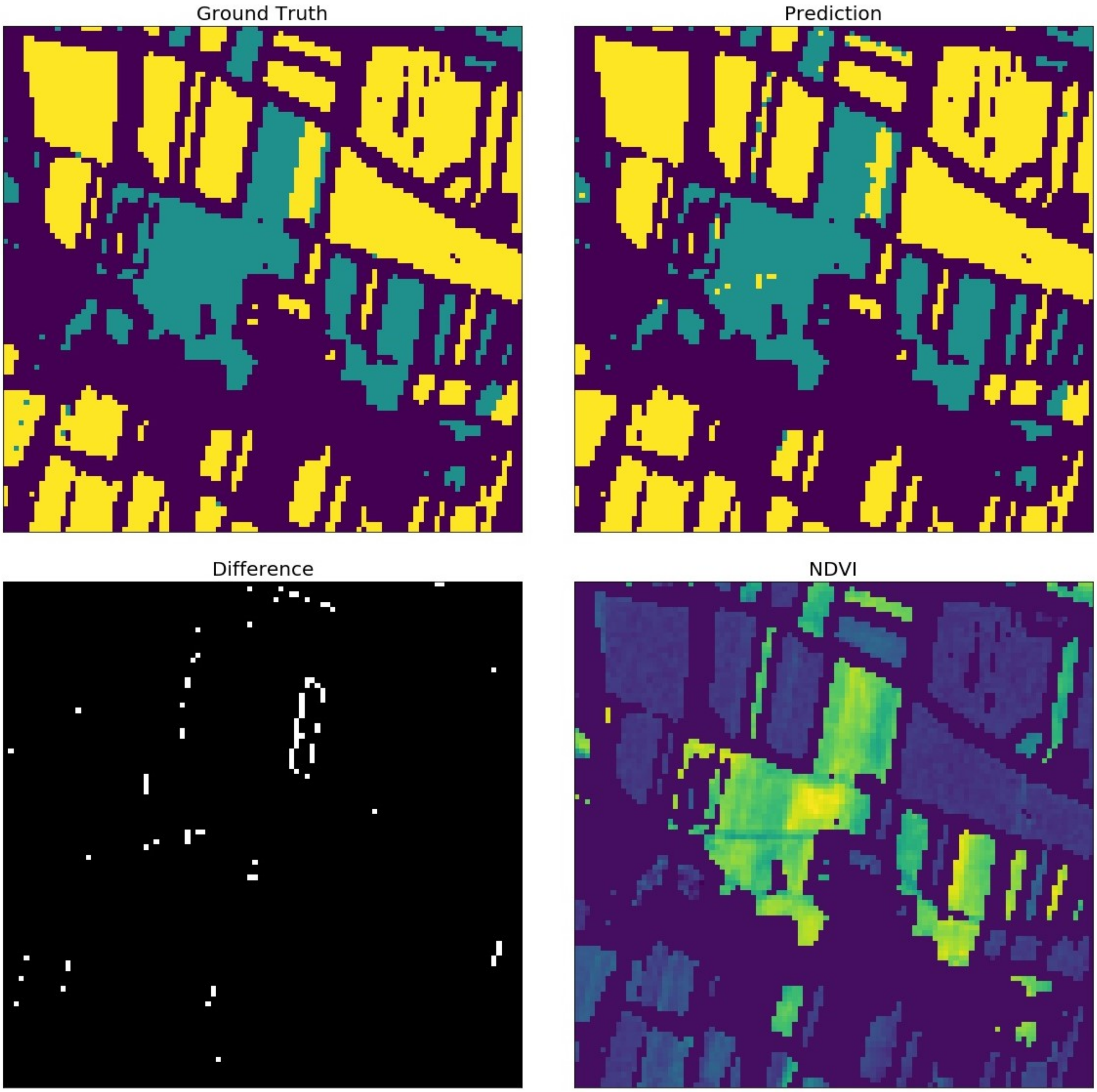

Fig. 9. Comparison of true and predicted images using Catbooster Classifier

From these observations we can see that all three classifiers gives almost same scores with Catboost giving slightly higher score. Along with scores, Catboost and LightGBM being Gradient Boosting Methods converges very fast than simple Random Forest.The false rate of all classifiers is very less which is a good sign for any model. Also using edges in classification have greatly improved the accuracy compared to classification done without edges which justifies our edge detection model.

	2 classes without edge	2 classes with edge
CatBooster	91.20%	96.00%
LightGBM	91.00%	95.70%
Random Forest	89.60%	95.60%

Fig. 10. Classification Accuracy of different models

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