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Scenario-Driven Land-Use Changes Anomaly Assessment for Decision Support in Border-Adjacent Regions

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Abstract - This study develops a scenario driven decision-support framework that is driven by scenarios for the assessment of anomalous land-use change patterns with the help of remote sensing-inspired indicators. Rather than being an automated monitoring or surveillance system, the proposed method is designed to assist human analysts openly by pointing out the areas that warrant prioritized exami0nation. The method overcomes the limitation of inaccessible defense- or security-sensitive satellite datasets through the use of synthetically generated feature representations to mimic realistic land-change scenarios and to allow controlled testing of model performance under data-limited conditions. The framework brings together different kinds of abstract numerical indicators, which are among the spectral change metrics, the temporal behavior attributes, the historical stability measures, the spatial context descriptors, and the regulatory or policy-based constraints. These indicators are formulated to represent land- use changes in a more holistic and contextual manner than by relying only on pixel-level change detection, thereby emphasizing contextual interpretation. Unlike the traditional methods, which predominantly depend on a limited selection of spectral indices such as NDVI, NDWI, and NDBI, the approach in question encompasses a greater spatio-temporal context as a means to lessen the occurrences of false alarms and increase the interpretability. By separating normal civilian expansion from potentially anomalous land-use behavior, the framework supports environmental monitoring, local planning, and decision-making for land-use assessment in border-near areas, while still keeping the analytical emphasis on human intervention.

Keywords: Decision-support system, Land-use change analysis, Remote sensing indicators, Scenario-driven assessment, Synthetic data modeling, spatio-temporal context

1. INTRODUCTION

In many places, the issue of cross-border infiltration has long been recognized and is receiving increasing attention to manage the borders and monitor the land use. The unauthorized movement across the borders not only raises concerns related to governance and jurisdiction but also creates several other problems such as unregulated settlement areas, informal infrastructure, and the depletion of the national resources. Internal conflicts like smuggling, human trafficking, and others have historically been associated with infiltration corridors and they have been affecting the stability and governance of the region [12]. These types of activities very rarely happen all of a sudden; rather they come up gradually through the establishment of temporary camps, access roads, and the building of supporting infrastructure. These activities tend to cause changes that can be recognized in land-use and land-cover, such as change in the vegetation, disturbance of the water bodies, and expansion of the built-up area. The changes are usually indicated by remote sensing through NDVI, NDWI, and NDBI, which are the main indicators that scientists use for detecting these changes. As a result, remote sensing and GIS-based land-change detection approaches have been extensively used. Nevertheless, a lot of the techniques depend on few spectral indicators and are unable to adequately separate everyday civilian development from land-use change that may indicate potentially anomalous activity that leads to high false-alarm rates in diverse and rapidly changing landscapes [2,4]. The limitation of direct data- driven analysis is that access to satellite imagery for areas concerning defense or security is still restricted. To overcome these issues, this research creates a scenario-based land-use change risk assessment framework that is viewed as a decision-support tool rather than an operational surveillance system. The framework is not based on pixel-wise or event-based detection methods but rather on revealing the underlying land-change trends with the help of domain-specific numerical indicators that are drawn from vegetation dynamics, urban growth, temporal persistence, and geographic context. Due to the lack of available comprehensive datasets related to defense, synthetically generated feature representations are used to simulate realistic land-change scenarios and to conduct controlled methodological evaluation. The framework mainly concentrates on risk interpretation and regional prioritization so as to assist human decision-making that is well-informed even with data-constrained conditions. This methodological emphasis also enhances transparency, aids replicability, and shows this method can be applied in diverse border-adjacent areas without claiming operational deployment or real-time surveillance capability under globally data- constrained environments.

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2. LITERATURE SURVEY

Land use and Land cover (LULC) change detection using remote sensing and machine learning has been widely studied. Many approaches focus on classifier evaluation, spectral index extraction, and multi-temporal satellite imagery; however, several limitations persist regarding data availability, feature diversity, and contextual interpretation of changes. Study [2] evaluated multiple machine learning models using multi spectral data. Although effective for classification, the study was limited by small sample size and insufficient temporal variation, reducing its ability to capture long- term land changes. In [4], sentinel-2 imagery and indices such as NDVI, EVI, NDBI and MNDWI were employed. The authors reported confusion between spectral similar materials (e.g., barren land and river sand) along with mixed pixel effects and data availability issues, highlighting the limitation of purely spectral features. Multi-temporal analysis was explored in [6] using Landsat and AVHRR data. Despite capturing large-scale trends, the approach faced cloud cover, limited data availability, and difficulty in distinguishing similar terrains, affecting detailed change interpretation. To address data scarcity [17, 18, 19] introduced a large synthetic dataset. However, the method showed a 20% error rate between real and generated images, was limited to 16 land cover classes, indicating that synthetic data alone does not fully resolve generalization issues. Overall, existing literature demonstrates that both real-data-based and synthetic-image-based approaches face limitations in feature diversity, contextual reasoning, and generalization. Most studies focus on detecting visual changes rather than interpreting the significance or risk associated with those changes. These limitations motivate the need for a scenario driven, synthetic-feature-based decision-support framework, which integrates spectral, temporal, spatial, historical, and contextual indicators to assess land change behavior under data restricted conditions.

3. METHODOLOGY

3.1 System Overview

This study investigates scenario-driven patterns of anomalous land use change through a structured dataset of environmental indicators, with the objective of supporting interpretive decision making. The analysis is performed on the given dataset, consisting of 5,000 samples, with each sample symbolically representing an ROI. Rather than functioning as an automated surveillance process, the framework explores how combinations of spectral, temporal, spatial, historical, and regulatory factors relate to varying levels of land use change risk with regard to land change. The outputs are used to highlight potentially relevant scenarios and are not intended to replace human assessment.

3.2 Dataset Description and Observed Structure Feature

The constructed dataset contains 5,000 samples, where each belongs to a different hypothetical ROI that is described by twelve numeric features and comes along with a risk label. The dataset is of a tabular structure that allows one to directly assess feature distributions, class balance, and relationships between features. The samples in this dataset are stratified on predefined risk classes so that comparisons regarding model performance in varying scenarios of land change can be made. In the given set of data, every row in the set of data represents an entire observation, thus allowing the model to be developed in the presence of all the variables at the same time. All observations contain complete information, so no missing value treatment was required during model training. The class distribution was deliberately structured to enable comparison across different land change scenarios rather than to predict individual events.

3.3 Feature Design and Value Representation

The set of features captures complementary phenomena of land change dynamics exhibited in the data. The change rate of continuous features like NDVI, NDBI, temporal persistence, and spatial isolation are represented as scaled numbers ranging from 0 to 1, to ensure scale independent representation. The binary features hold information about policies like the presence of a buffer zone or if an activity is allowed. Spectral indicators correspond to the signals of change at the level of the surface, while temporal indicators point to the stability and irregularity of the signal with respect to time, and spatial indicators cover the accessibility and contextual exposure, and the stability data is provided by the historical indicators. A review of the feature distributions indicates that the classification results are influenced by the combined effect of multiple indicators, rather than being driven by any single feature.

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Table 1 - Scenario-based feature groups and their conceptual roles

Feature Group	Dataset Features	Value Type	Conceptual Role in Land-use Change assessment
Spectral Change Indicato rs	Ndvi_change_rat e Ndbi_change_rat e	Continuous (0-1)	Surface level and land change
Hydrolog ical Stability Indicator	Ndwi_stability	Continuous (0-1)	Water disturbance persistence
Temporal Behavior Indicators	Activity_persiste ncettemporal_irre gularitysesonal_c onsistency	Continuous (Scaled)	Duration and stability of change
Spatial- Context Indictaors	Spatial_isolation, near_settlement, near_road	Continous/Binary	Accessibility and exposure context
Regulator y/Policy Constrain ts	In_buffer_zone Permitted_activit y_zone	Binary(0/1)	Represent legal or regulatory land use restrictions
Scenario Risk Label	Risk_label	l(Low/Medi um/High)	Defines scenario- based-land-change risk level for supervised analysis

3.4 Label Assignment Logic

The risk labels of the dataset do not rely on actual real-world labels but rather follow definite scenario-based rules defined and applied throughout the dataset creation phase. High risk labels refer to a combination of factors like high vegetation reduction, high temporal persistence, isolation, and an overstep of the regulatory limit. The low risk labels refer to a combination of gradual or stable changes close to the settlement and road network within the prescribed areas. This labelling approach is used to examine how different indicators interact under controlled conditions and is not meant to claim real-world surveillance or operational accuracy. Accordingly, the labelling strategy is intended to evaluate relative risk behavior across scenarios rather than to assert real-world ground truth.

3.5 Model Training and Experimental Design

The land change assessment is formulated as a supervised classification task to examine how different models respond to structure risk scenarios-based on the observed pairs of features and labels from the available data. The data was split into training and testing data with 80% and 20% proportions, respectively, for the assessment of generalization properties on new examples. A fixed random seed was used for reproducibility of the results. Several classical models in the realm of machine learning, like Logistic Regression, KNN, SVM, XGBoost, and Random Forest, have also been considered because they handle structured numerical data effectively. The model's performance has been calculated based on accuracy, precision, recall, F1, and ROC AUC, given the capability to differentiate between various classes instead of focusing on the highest class. The dataset was divided into 4000 training samples and 1000 testing samples. The reported performance metrics reflect the model’s ability to differentiate among relative risk categories, rather than how well they detect any single class.

3.6 Design Assumptions and Potential Bias

This is evident in that the dataset is based on design assumptions that are rooted in remote sensing and land-use reasoning. The design assumptions relate to the emphasis on change patterns that are permanent, isolated, and violating land-use policies, which may introduce structural emphasis toward certain anomaly patterns within the dataset. This implies that the results should be considered indicative of model characteristics in controlled conditions rather than measures of land-use distribution in reality.

4 . RESULTS

Table 2 presents a comparative evaluation of five classical machine learning models applied to the scenario-driven land-use change dataset. All models were trained on 4,000 samples each and their performance was evaluated on a separate test set of 1,000

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samples, in accordance with the experimental setup explained in the methodology. The evaluation metrics represent the capability of the models to differentiate between the various land-change risk scenarios as they are reflected in the data.

Table 2 - Model Performance Comparison (%)

Model	Accuracy	Precision	Recall	ROC- AUC	F1-Score
KNN	0.801	0.849	0.774	0.932	0.790
SVM	0.933	0.933	0.934	0.993	0.934
XG-boost	0.875	0.895	0.850	0.969	0.867
Logistic Regression	0.828	0.845	0.826	0.955	0.835
Random Forest	0.875	0.899	0.853	0.973	0.871

From the assessed methods, the Support Vector Machine (SVM) has the highest performance value, where the accuracy is 0.933 and the metrics of precision (0.933), recall (0.934), F1-score (0.934), and ROC–AUC (0.993) are constantly high. These results indicate that the SVM effectively differentiates between the risk classes that have been formed by the combined impact of spectral change, temporal persistence, spatial isolation, and regulatory constraints. Its learning mechanism, which is based on margins, seems to be a good fit for the normalized and multi-dimensional structure of the scenario-based feature space. XGBoost and Random Forest show very similar predictive behavior , the accuracy of both models is 0.875. The Random Forest method has a little bit better F1-score (0.871), recall (0.853), and precision (0.899) than XGBoost, but both of them have quite strong ROC-AUC rates (0.973 for Random Forest and 0.969 for XGBoost). This points to the fact that the ensemble methods possess the ability to recognize the non-linear dependencies among the features and they are even robust enough over the entire range of simulated land-change scenarios. Random Forest provides the main advantages for decision- making support, though SVM has been the model with better accuracy in this evaluation. The tree-like structure of Random Forest allows spotting of the importance of features used and also the paths taken in reaching the final classification, thus, giving clearer insights on the risk classification made based on various indicators. On the other hand, SVM classifiers are less clear in terms of the decision boundaries learned, thus, the trade-off between performance in predictions and interpretability is shown. Logistic Regression shows moderate performance with an accuracy of 0.828 and a fairly balanced precision and recall. This is a clear indication of the shortcomings of linear models in dealing with scenario-driven data where the risk patterns are the result of complex, non-linear interactions among several factors. The K-Nearest Neighbors (KNN) model gets the lowest accuracy (0.801) which means that it is more influenced by the local feature distributions and lacks consistency in representing the broader scenario- level patterns. To sum up, the results indicate that models capable of learning non-linear and multi-factor relationship learning are more appropriate for the extraction of land-change risk scenarios in the controlled experimental setting. SVM gives the best predictive performance while Random Forest provides a good mix of accuracy and interpretability, which is in line with the framework's goal of facilitating informed human assessment rather than automating the decision-making process entirely.

5. DISCUSSION

It is a challenging task to monitor land use changes in the areas which are of high security concern and also have restricted access to data since such changes usually take place slowly, are spread over a large area, and are not easy to identify. The traditional methods that mainly make use of individual spectral indices like NDVI or NDWI have a problem of separating normal civilian development from what is possibly unusual activity, particularly in heterogeneous landscapes where seasonal and other mixed land covers are common. The results of this study suggest that examining spectral indicators together with temporal persistence, spatial isolation, historical stability, and regulatory context leads to a more informative understanding of land-use behavior. The models evaluated showed that substantial scenario-based indicator usage allows us to distinguish the land-change patterns of lower risk and higher risk meaningfully without relying only on the detection of changes at pixel level. The changes that take place close to existing facilities like roads or settlements are usually linked with lower risk outcomes, while changes that are long-term, isolated and located within restricted or regulated areas are likely to be classified as higher risk. These patterns are consistent with the land-use dynamics represented within the controlled scenarios, where anomalous activities mainly develop slowly and continue to be disconnected from the regular civilian infrastructure. Among the methods tested, the classical machine-learning models like Support Vector Machines and Random Forests process these multi-dimensional numerical features efficiently while

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still providing a degree of interpretability that is important for analyst-driven assessment.

5.1 Uncertainty in Model Output

The results indicate that the models demonstrate strong classification capability; however, the outputs should be interpreted as indicative risk signals rather than definitive conclusions. The whole system is based on scenario-driven assumptions and employs synthetic feature representations to resemble realistic land-change conditions. Different ways to define the scenarios or how features interact can result in a difference in the risk scores obtained. Therefore, these scores reveal the different levels of concern in the simulated scenarios and are aimed at prioritization and further analysis support, not at providing certainty. The presence of uncertainty is consistent with the framework's purpose of supporting human judgment instead of replacing it.

5.2 Sensitivity to Feature Assumptions

The findings also indicate that the framework is impacted by the presumptions that are part of the feature design and scenario formulation. The risk levels that have been assigned can be altered according to the emphasis placed on the indicators such as time persistence, area isolation, or legal restrictions. This sensitivity reflects the correlation of land-use processes where no single factor can solely characterize abnormality. As a result, the framework's outcomes are highly influenced by the manner in which scenarios are created and the representation of the relationships among features. In the future, it might become possible to investigate this sensitivity in a more methodical manner by altering feature weights and scenario parameters to develop a more profound comprehension of the approach's robustness. The performance metrics show strong classification behavior within the defined experimental setting, although different scenario assumptions or feature weightings may lead to different outcomes. Therefore, the metrics should not be seen as absolute measures of the real- world operating performance but as demonstrating the behavior of the model under controlled conditions. Overall, the discussion highlights that a context sensitive, scenario based approach is effective for interpreting land use behavior in regions where direct monitoring and reliable labeled data are limited.

6. LIMITATION AND FUTURE WORK

The limitations of the proposed framework are multiple, and they must always be kept in mind while interpreting the results. The first limitation is that the analysis does not work with raw satellite images but with abstracted numerical indicators that are based on remote sensing principles. This makes it possible to carry out a controlled evaluation under data-restricted conditions, but at the same time, it prevents capturing the effects specific to sensors and fine-scale spatial variability which are present in real images. Second, the dataset consists of synthetically constructed features that aim to depict scenario-driven land-use behavior. Consequently, the learned patterns are influenced by the assumptions made in the scenario design instead of being based on the empirical distribution of land-use. Thus, the reported metrics should be viewed as indicative rather than operational performance measures. Third, the framework has not yet been used in a continuous operational monitoring setting, and it is meant to be a support tool in decision-making rather than an automated surveillance system. One possibility for the future is to validate the scenario-driven indicators through the use of actual multi-temporal satellite data, where access allows, to refine the scenario definitions with inputs from experts and to conduct controlled pilot deployments aimed at evaluating the usability and interpretability of analyst-driven workflows. Such extensions would contribute to closing the divide between controlled experimental analysis and real-world land-use monitoring applications.

7. CONCLUSION

The study presents a scenario-driven assessment framework for identifying potentially unusual land-use change patterns by moving beyond visual change detection toward context-aware, scenario-driven risk assessment. The framework is intended to support analyst decision-making in border monitoring and regional planning by providing indicative risk signals, rather than replacing human judgment [6,16].

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