A Dynamic LUCIS Framework for Identifying Urban-Hazard Conflicts in the Kelani River Basin Using Near Real-Time Earth Observation Data

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***Abstract*— Rapid urbanisation in Sri Lanka frequently bypasses formal planning, resulting in concealed land-use conflicts where infrastructure encroaches on disaster-prone areas. Traditional Land-Use Conflict Identification Strategy (LUCIS) models are based on static, outdated survey data and fail to capture real-time risks. This temporal lag leads to undetected unauthorized settlements in hazard zones increasing disaster vulnerability. This study introduces a Dynamic LUCIS framework utilizing near real-time Earth Observation (EO) data from Google Earth Engine, specifically the Dynamic World and Open Buildings datasets. Focused on the Kelani River Basin, the model identifies critical risk conflicts between urban development and flood/landslide safety zones. Validation using high-resolution drone imagery yielded an overall accuracy of 82.84%, F1-score of 0.83 and a Kappa coefficient of 0.66. The results demonstrate that EO-driven models can identify unauthorized settlements in hazard-prone areas with high precision, providing a scalable tool for resilient urban governance.**

Keywords*— *LUCIS, Earth Observation, Kelani River Basin, Urban Resilience, Remote Sensing, Google Earth Engine.

I. Introduction

The Kelani River Basin serves as Sri Lanka's primary economic artery, yet it is increasingly characterized by a conflict of resilience [1]. The basin has experienced a dramatic 130% increase in urban land area over the past two decades [1]. As urban pressure expands from Colombo into the upper reaches of Gampaha and Kegalle development frequently overlaps with critical flood retention zones and steep landslide-prone slopes [3].

Traditional urban planning in the Global South has historically relied on the Land Use Conflict Identification Strategy (LUCIS) to identify spatial competition between agricultural, conservation, and urban interests [4]. However, the efficacy of traditional LUCIS is increasingly hampered by the temporal lag inherent in survey-based data collection [5]. The foundational framework relies on static Land Use/Land Cover (LULC) maps derived from decadal surveys or low-frequency updates, which fail to capture hidden risks in regions where unauthorized urban sprawl outpaces official mapping cycles [1], [6]. These risks include the construction of industrial warehouses in flood retention zones or residential clusters on slopes exceeding the 30° safety threshold mandated by the National Building Research Organization (NBRO) [7].

Despite these well-documented hazards, Sri Lankan authorities often utilize land-use maps for urban planning that are several years old, failing to account for rapid, unauthorized construction. This paper proposes a methodology to bridge this gap by adapting the LUCIS model into a dynamic framework. By integrating AI-detected building footprints and near real-time satellite imagery, we can identify hidden conflicts as they emerge, rather than years after the risk has been established [8].

II. Related Work

Urban expansion and land-use change in river basins like the Kelani River have intensified conflicts between development and environmental hazards. Urban sprawl has actively encroached into floodplains and high-risk zones, leading to more frequent minor floods exceeding 20 events in two decades, increased flood damage, loss of riparian vegetation, pollution from multiple runoff sources, and altered hydrological regimes [2], [9]. Spatial regression models further confirm strong correlations between this unchecked urban expansion and extreme hydrological events.

Recent advances in remote sensing, geospatial modeling, and machine learning have enabled more accurate flood mapping, vulnerability assessment, and the integration of socio-economic factors into hazard analysis to address these dynamic changes [1], [10], [11], [12], [13], [14]. While direct land-use change detection approaches such as Sentinel-2 optical monitoring or Synthetic Aperture Radar (SAR) based building detection excel at identifying physical land alterations [14], [15], [16] they often lack the policy-oriented contextualization required for urban governance [18]. Standard change detection algorithms can indicate the construction of a new structure, but they do not inherently evaluate whether that structure violates zoning laws or safety thresholds.

To bridge this contextual gap, the LUCIS framework, when enhanced with near real-time Earth Observation (EO) data, offers a promising approach to dynamically map and manage these urban-hazard conflicts. Integrating EO data with dynamic spatial models helps identify conflict hotspots and informs sustainable urban planning and disaster risk reduction strategies [13], [19]. This study builds upon current research on dynamic LUCIS-type frameworks and EO-based

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hazard mapping to apply a highly contextualized model to the Kelani River Basin.

III. METHODOLOGY

The core of this research is the Dynamic LUCIS framework, which adapts the classic Land-Use Conflict Identification Strategy to utilize high-velocity Earth Observation data as shown in Fig. 1. Unlike traditional models that rely on decadal survey maps, this approach integrates AI-detected building footprints and satellite-derived land-cover probabilities to identify active encroachments on hazard-prone land. The workflow involves three primary stages defining land-use goals for Sri Lanka:

- Urban Preference: Describes the development areas using AI-detected buildings & lights
- Conservation/Safety Preference: Identifies the lands to be preserved to prevent disasters proxied by steep slopes & flood retention zones
- Agriculture Preference: Identifies active agricultural land via crop-probability layers

This identifies spatial overlaps between these goals and validates the resulting critical risk conflicts using high-resolution drone imagery. This dynamic adaptation allows for the detection of unauthorized settlements that often bypass formal planning cycles in Sri Lanka.

A. *Study Area and Data Sources*

The study focuses on the Kelani River Basin. This region captures a vital cross-section of Sri Lankan hazards, ranging from urban flooding in the lower basin to landslide risks in the upper reaches of Gampaha and Kegalle [3]. All datasets were processed within Google Earth Engine (GEE). For land-use classification, the GOOGLE/DYNAMICWORLD/V1 dataset was utilized specifically filtered to generate a median probability composite for the period from January 2024 to January 2025 to provide near real-time accuracy. Building density was modeled using GOOGLE/Research/open-buildings/v3, which provides AI-detected footprints. Terrain analysis and slope calculations were derived from the COPERNICUS/DEM/GLO30, offering a 30m Global Digital Elevation Model (DEM) that exceeds the accuracy of traditional SRTM data. The 10m *Dynamic World* dataset and the building influence heatmaps were resampled to a uniform 30m spatial resolution using nearest-neighbor interpolation to match the DEM prior to executing the combinatorial conflict logic.

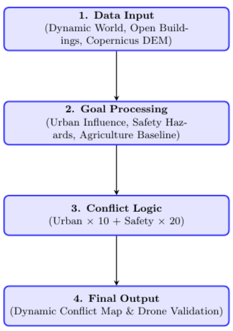

Fig. 1. Methodology Workflow of the Dynamic LUCIS

B. *The Dynamic LUCIS Framework*

The framework defines competing goals within the study area to identify where development pressure exceeds environmental safety limits. The Safety/Conservation Goal is established by identifying zones critical for disaster mitigation. Following NBRO standards, slopes exceeding 30° are categorized as high-risk landslide zones. Additionally, Dynamic World classes for water and flooded vegetation are isolated to represent essential flood retention zones. The Urban Development Goal identifies areas under intense construction pressure using a focal maximum reducer utilizing a 3- pixel circular kernel on building footprints to create a heatmap of urban influence. A binary threshold was applied where any pixel falling within this region and assigned a value of 1, officially classifying it as an active urban zone.

While the Agriculture Goal was initially modeled using crop-probability layers to define the basin's baseline land-use, the final conflict logic prioritizes the Urban-Safety intersection as agricultural conflicts are negligible in the context of acute disaster risk within the basin. This prioritization focuses specifically on immediate life-safety hazards where building footprints actively collide with disaster-prone terrain as these represent the most critical hidden unauthorized settlements in Sri Lanka.

C. *Conflict Identification*

Conflict identification is executed through a combinatorial logic where the Urban Goal is multiplied by 10 and the Safety Goal is multiplied by 20. Because agricultural overlaps were determined to be negligible regarding immediate life-safety, baseline agricultural and undeveloped pixels evaluated to 0. When these layers are overlaid, the resulting pixel values code the specific land-use status according to the truth table outlined in TABLE I. A value of 10 indicates Safe Urbanization, 20 indicates Safe Conservation, and 30 identifies a Critical Risk Conflict as shown in Fig. 2. These red zones signify pixels where active urban development directly overlaps with high-risk hazard zones. This mathematical approach ensures that unauthorized settlements on steep slopes or flood plains are mathematically isolated for analysis.

To validate the model's accuracy in identifying hazardous encroachments against high-resolution of 0.05 m drone imagery, the three-class Dynamic LUCIS output collapsed into a binary classification scheme. The Safe Urbanization and Safe Conservation zones were merged to form a single Safe (0) class representing areas free from hazard conflict. The Critical Risk Conflict zone was retained as the Risk (1) class.

Ground-truth validation was conducted using a stratified random sampling methodology. It is important to acknowledge that due to the lack of availability of high-resolution drone mapping, the surveyed extent covers a localized, targeted subset rather than the entire basin-wide area. The 'Critical Risk Conflict' area represents a small spatial proportion of the total basin so a purely random sample would heavily bias towards the majority 'Safe' classes. Stratified random sampling ensured that the minority risk class was adequately represented in the accuracy assessment. To balance this extreme class imbalance, the 303 validation points were explicitly allocated between the strata with 148 points within the Critical Risk Conflict stratum and 155 points within the Safe stratum distributed across the drone-surveyed extent as shown in Fig. 3 and Fig.4. These points were distributed to capture both the core areas of homogenous land cover and the complex boundaries at urban-water and urban-forest interfaces.

TABLE I. Combinatorial Logic Truth Table for Conflict Identification

Urban goal(U)	Safety goal (S)	Pixel Value(P)	Classification
0	0	0	Baseline / Agriculture / Safe Non-Urban
1	0	10	Safe Urbanization
0	1	20	Safe Conservation
1	1	30	Critical Risk Conflict

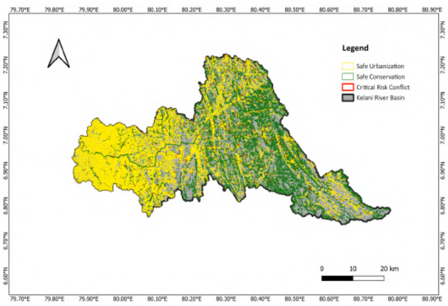

Fig. 2. Critical Risk Identification Map

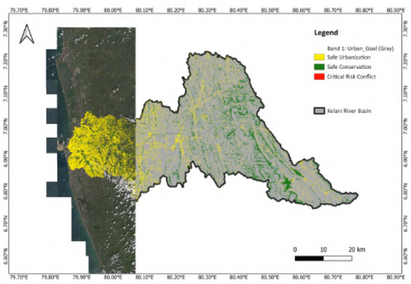

Fig. 3. Drone – Truth Validation Map

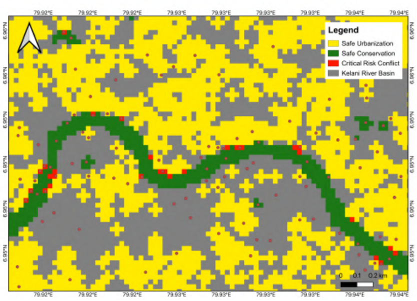

Fig. 4. Map of Validation Points

IV. Results

The Dynamic LUCIS model identified 188.78 ha of land-use conflicts within the Kelani River Basin, as detailed in TABLE II. These are red zones where high-density urban development encroaches upon high-risk hazard zones. While this represents a small spatial proportion of the total study area, these red zones represent 30-meter resolution pixels with a critical significance as they isolate specific unauthorized structures encroaching upon high-risk flood plains and landslide-prone slopes. The conflicts are concentrated in the lower basin's flood retention wetlands and the upper basin's slopes exceeding 30°. By utilizing near real-time (NRT) and EO data from the 2024–2025 period, the model captured recent physical structures that do not appear in previous static planning baselines. Validation against 303 high-resolution drone-surveyed points yielded an Overall Accuracy of 82.84%. As illustrated in the confusion matrix in Fig. 5, the model produced 129 True Positives and 122 True Negatives. The performance is characterized by a Recall of 87.16% and a Precision of 79.63%, supported by a Kappa Coefficient of 0.6573.

V. Discussion

A detailed evaluation of the model performance underscores the significance of the precision-recall trade-off in urban safety. While the precision of 79.63% reflects minor over-classification at urban-forest interfaces, the high recall of 87.16% is scientifically prioritized to ensure that unauthorized settlements in critical hazard zones are not overlooked. This ensures the framework serves as a conservative early-warning system for disaster mitigation.

The discrepancy between the model's recall of 87.16% and precision of 79.63% reflects a programmed sensitivity towards disaster risk mitigation. A high recall rate is scientifically preferable in hazard mapping as it minimizes false negatives thereby reducing the probability of failing to identify a building in a critical risk zone. The 33 false positives primarily occurred at the margins of urban-forest interfaces where the focal maximum reducer on building footprints over-extended the urban influence into adjacent vegetation classes. However, the F1-score of 0.83 confirms that the model maintains a robust balance between sensitivity and specificity. The dynamic aspect of this LUCIS adaptation overcomes the temporal limitations of traditional LULC maps by utilizing the Dynamic World V1 dataset which updates at a frequency that matches the rate of informal urban sprawl in Sri Lanka. This temporal snapshot identifies unauthorized construction that occurred between the last official survey and the current EO data acquisition. However, few limitations must be acknowledged. First, the model is subject to the Modifiable Areal Unit Problem (MAUP). At a 30m resolution (900 m²), a flagged pixel may contain only one small structure alongside vegetation. Consequently, for urban governance, this tool serves as a regional early-warning system for targeted inspections rather than a precise parcel-level survey. Second, near real-time operationally translates to a latency of days to weeks. Because the model relies on optical imagery, inevitable data gaps occur during Sri Lanka's monsoon seasons due to heavy cloud cover. Although a formal pixel-by-pixel change detection was not the primary objective the model effectively serves as a temporal proxy by isolating development that has bypassed traditional multi-year planning identifying hidden conflicts such as unauthorized settlements on NBRO-restricted slopes or floodplains that are typically absent from official 5-year survey cycles.

TABLE II. AREA STATISTICS BY LAND-USE

Category	Area (km^2)
Safe Urbanization	356.28
Safe Conservation	220.03
Critical Risk Conflict	1.89

Note: Model validation was conducted using a targeted drone survey covering 37.78 km^2 (6.53% of the total study area), verified against 303 stratified random points.

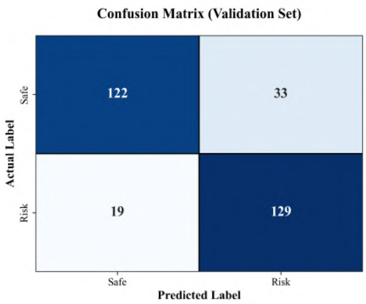

Fig. 5. Confusion Matrix

VI. CONCLUSION

This study demonstrates that a Dynamic LUCIS framework powered by near real-time Earth Observation data and AI building footprints provides a technically viable solution for urban-hazard conflict identification in Sri Lanka. The accuracy achieved of 82.84% indicates that open-source global EO datasets can be localized to meet national safety standards such as the NBRO slope thresholds. The model successfully isolates critical risk zones in the Kelani River Basin offering a scalable tool for proactive urban governance and disaster risk reduction. Future research should focus on incorporating temporal change detection, higher resolution building footprints and integrating municipal governance workflows into a dynamic predictive early-warning system for landslide and flood events.

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