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CONTACT US

info@lmtc.gov.np

Land Management Training Center

Ministry of Land Management, Co-operatives, Federal Affairs and General Administration

Dhulikhel, Kavre, Nepal

G.P.O. Box number. 12695, Kathmandu, Nepal

Phone number. 00977 11 415055/51

Fax. 00977 11 415078

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Cover Page

The cover page was developed using a combination of technical data visualizations and generative AI to illustrate the scope of current geomatics research.

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It is my immense pleasure to present the Eighth Edition of the *Journal of Land Management and Geomatics Education*. As the fields of geoinformatics, land management, and geospatial sciences continue to evolve rapidly, research and innovation have become indispensable for addressing contemporary challenges related to land administration, sustainable development, climate resilience, and spatial decision-making.



This edition features articles addressing contemporary environmental, technological, and land governance issues. The studies basically cover air pollution estimation in Kathmandu Valley using remote sensing and machine learning, global trends in land abandonment, flood susceptibility assessment using geospatial data, women's property rights and judicial influence, DEM generation using InSAR, illegal building detection through LiDAR, AI-driven land tenure mapping, and the accuracy assessment of UAV-derived geospatial products. Together, these contributions demonstrate the growing role of geospatial technologies, artificial intelligence, and innovative research approaches in supporting sustainable land management and informed decision-making. In addition, this edition features technical, legal, policy, and land management – oriented studies that advance knowledge and professional practice across these interdisciplinary domains, while serving as a valuable platform for researchers, academicians, students, and professionals to share innovative ideas, research findings, and practical experiences.

The Land Management Training Centre remains committed to promoting research, academic excellence, and professional development in the fields of land management and geomatics. Through this journal, we aim to encourage geoscience based insightful discourse and facilitate the dissemination of quality research that contributes to national and global geospatial communities.

Lastly, I would like to express my sincere gratitude to all authors and researchers for their valuable contributions and to the reviewers for their dedicated efforts in maintaining the scientific quality of the journal through a rigorous peer-review process. My earnest appreciation also goes to the editorial board members especially to Er. Grishma Pradhan for his tireless efforts, advisory committee, and all individuals whose continuous support and commitment made the publication of this edition possible.

Finally, I invite our readers to engage with the diverse articles presented in this edition and hope that the knowledge shared herein will inspire further research, innovation, and collaboration in the fields of land management and geomatics.

Thank you and enjoy reading!

Message from Dean



It gives me immense pleasure to know that the Land Management Training Centre (LMTC) is preparing to release its eighth edition of the Journal of Land Management and Geomatics Education. Since 2007, Kathmandu University, School of Engineering, has been running the undergraduate program Bachelor in Geomatics Engineering in collaboration with the Land Management Training Center (LMTC), Ministry of Land Management, Co-operatives and Poverty Alleviation. Since then, we have together uplifted and strengthened our collaboration in running graduate (Masters in Land Administration and ME/MS in Geoinformatics) and postgraduate programs (PhD in Land Administration and Geomatics Engineering), thereby producing skilled human resources in the field of land management and geospatial science.

I would like to express my sincere appreciation to the editorial team of the journal and the whole institution for their efforts and the steps they have taken to create such a platform, which is truly inspiring and also essential for the dissemination of knowledge and research within the geospatial and surveyor's community. I would also like to extend my best wishes to the editorial team and LMTC and look forward to collaborating much more in the near future to make more meaningful strides in the surveying and land management sector.

Prof. Manish Pokharel, PhD
Dean, School of Engineering
Kathmandu University

Executive Director's Message

It gives me great pleasure to present this annual issue of the Journal of Land Management and Geomatics Education, published by the Land Management Training Centre. This journal reflects our continued commitment to advancing knowledge, fostering academic dialogue, and strengthening professional practice in the fields of land management, surveying, geomatics, land administration and related disciplines.

Academic journals play a vital role in connecting research, education, policy, and practice. They provide a credible platform for scholars, practitioners, educators, and students to share new ideas, research findings, innovations, and experiences that contribute to the improvement of institutions and the broader land sector. For academic institutions, such publications are not only repositories of knowledge but also instruments for encouraging critical thinking, evidence-based decision-making, and a culture of continuous learning.

I would like to express my sincere appreciation to all authors and contributors whose valuable articles, research papers, technical notes, and insights have enriched this edition. Their dedication to generating and sharing knowledge is essential for the advancement of our profession and for addressing emerging challenges in land governance, spatial data management, climate-responsive land administration, and sustainable development.

My special thanks go to the Editorial Board and esteemed reviewer for their tireless efforts in managing the review process, maintaining academic quality, and ensuring the timely publication of this journal. The commitment of editors, reviewers, and supporting staff has been instrumental in upholding the credibility and scholarly standards of this publication.

I also extend heartfelt gratitude to our readers, academics, researchers, professionals, students, policymakers, and institutional partners whose engagement gives meaning and relevance to this endeavor. Your continued interest and constructive feedback encourage us to further strengthen this journal as a respected platform for knowledge exchange.

As the land sector continues to evolve with rapid technological advancement and increasing societal demands, the importance of research-informed education and professional dialogue becomes ever greater. I hope this journal will inspire further inquiry, collaboration, and innovation, and will contribute meaningfully to the development of competent human resources and effective land governance systems.

On behalf of the Land Management Training Centre, I congratulate everyone involved in the publication of this issue and wish the Journal of Land Management and Geomatics Education continued success in the years ahead.



Janak Raj Joshi

Executive Director

Land Management Training Center

July, 2026

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IDENTIFICATION OF ILLEGAL BUILDINGS USING LIDAR DATA

Shib Raj Bhatt¹, Asst. Prof. Bhoj Raj Ghimire, PhD²

^{1,2}Open University, Lalitpur, Nepal

¹ bhatta32@yahoo.com, ² bghimire@nou.edu.np

Keywords: building height extraction, LiDAR data, DTM, DSM, nDSM, Informal Housing

ABSTRACT:

In developing countries, urbanization is rapidly growing. To manage such urbanization, identifying and tracking building construction to keep it up to date in all dimensions is the essential and challenging job of the government. The objective of this research work is to find the individual building height and identify the illegal buildings in the selected area located in the Godavari municipality of Kailali district, Nepal. For this research work, the latest airborne LiDAR and cadastral datasets were acquired from the Survey Department. It reduces the manual field survey effort, gives accurate results, and minimizes interference from the external environment. One of the most important dimensions of LiDAR data is the z-axis value, which gives the accurate height of the object. A normalized digital surface model is calculated with the help of DTM and DSM. By utilizing the normalized Digital Surface Model (nDSM), precise building heights were extracted, which facilitated the estimation of the total number of floors per structure. This derived floor count data was then cross-referenced with municipal records to identify discrepancies. By adopting this process, the municipality can systematically verify building heights and automate floor-area and floor height calculations to ensure alignment with local building codes, and perform more accurate property tax assessments.

Introduction

Urbanization is a global phenomenon where a large portion of the population is migrating from rural areas to developed towns and cities [1][2] in search of higher living standards [3]. It is also extensively growing in Nepal [1]. A certain level of development in cities and towns is necessary for the overall development of the nation [4]. The exponential pace of building construction is presenting unforeseen urban management challenges, including the disruption of public services, unregulated urban density, and environmental degradation. Addressing these problems requires the implementation of robust, sustainable urban planning and management strategies [5]. These urban centers are disproportionately vulnerable to catastrophic natural disasters, including floods, landslides, and other systemic risks [6].

The government has to track, manage, and control such types of construction activities [7] and has to develop sustainable infrastructure. The government has to develop infrastructure and make plans for these cities. Moreover, the expansion of informal settlements into agricultural areas will strain critical services, especially water, sanitation, and transport networks [8]. Urban citizens may be significantly influenced by the structural density of buildings and the extent of surrounding vegetation. So, it is important to identify buildings, vegetation [9], and to have control over the building construction process. For this, building identification and tracking are imperative and a preliminary responsibility [10] of the government. Untracked and unmanaged building construction may lead to unhealthy urban living conditions, increase vulnerability to natural disasters, and pose a significant threat to public safety [11]. Illegal or informal

buildings may hinder the people's access to essential public services [12]. To control this, the government of Nepal has formulated and implemented rules and regulations. The National Urban Policy [13], the Building Acts [14], the National Building Code, the National Urban Development Strategy [15], and associated directives provide the legal basis for the building construction process.

Informal settlements are residential areas where housing is developed without a land ownership certificate [16]; residents have no legal claim to the building or the land [12][17], often termed sukumbashibasti. Additionally, structures that have violated local building code, bylaws, or National Building Code (NBC) 2015 are called illegal buildings, even if the land itself is legally owned [18]. The property owner can construct or modify the structure of buildings only after having permission and approval from the relevant government authorities [19]. The Government invests significant time and financial resources to track such works and update databases for building footprints, heights, and floor counts [20].

Light Detection and Ranging (LiDAR) is the latest technology that is becoming popular and attractive for area and height extraction with less interference from fog, rain, storms, and other external environmental factors [21][22].

Compared to conventional technologies, it is faster, cost-effective [23], and requires less effort and resources [22], while maintaining high accuracy [21]. With the help of LiDAR data, developing countries are solving land zoning issues, designing

and developing urban plans[23] and infrastructure- such as roads, canals, sewerage, water supply, transportation networks[24] - creating a digital world and a digital twin [22]. LiDAR data can generate a large-scale 3D model of modern cities and towns and provides an actual picture of the ground using less time, less effort, and low cost –[25]. So, it has gained the highest position among the other geospatial technologies[26]. LiDAR is a modern optical remote sensing technology that is a powerful tool and the fastest method to capture and store accurate geographical data [27] and detailed attributes of the points[28].

1. Objective:

The main objective of this research is to identify illegal buildings using LiDAR Data. To achieve this, the following specific objectives have been established:

- To extract the building footprints of selected study areas.
- To estimate the building height and determine the corresponding number of stories
- To identify discrepancies between the LiDAR-derived building height and official municipal records to detect illegal buildings.
- To quantify the resulting revenue loss and annual tax deficiency caused by these unregistered or non-compliant structures.

2. Related Work

Currently, LiDAR data is becoming a reliable, accurate, easy-to-use, and primary source of information[29]. For processing LiDAR data, numerous automated procedures - such as open-source libraries, applications, and scanning tools - make the workflow fast, easy, and user-friendly[30].

M. Liu et al.[31] used a deep learning approach, specifically the Mask R-CNN, to extract the building footprints; the DELaMa model was used to process the Digital Surface Model (DSM) to derive building heights in the rural area of Pingquan, Hebei Province, China. Faten Hamed Nahhas et al. [32] discuss a deep learning approach for building height detection using LiDAR data and orthophotos. R. Wang et al.[33] derived a normalized height model by subtracting the DTM from LiDAR data to extract building height. Buildings were separated from vegetation. Shapes were reconstructed as rectangles using the Hough transformation or as regular polygons using SLT and EHT.

Arzu Erener et al.[34] studied Istanbul, Turkey, and estimated the heights of buildings using the nDSM from point clouds; the accuracy was about 79%. Y.He et al.[35] classified LiDAR data

into ground, vegetation, and buildings using an energy-based method, with VDP optimizing vertex selection. A hybrid approach combined explicit modeling for regular edges and implicit modeling to fill gaps. The method is robust to noise, achieves a low RMSE, and produces accurate building polygons independently.

Mohammad Awrangjeb et al.[36] have identified an automatic building detection technique using LiDAR and multispectral imagery. This work uses primary and secondary building masks from LiDAR data, extracts line segments, and applies NDVI to remove vegetation. In another study, Mohammad Awrangjeb et al.[37] used a LiDAR dataset and a region-growing technique to find the roof type for data classification. Data were classified according to the clustering of points. Building detection correctness was 89%. Ala'a Al-Habashna[38] developed an open-source system designed for the automatic extraction of building height from street-view images. This system uses deep learning (DL), advanced image processing techniques, and geospatial data to enhance the accuracy of building height estimations. Xiangyun Hu et al. [39] differentiate flat roofs from rough vegetation rapidly and extract buildings from dense LiDAR data. It uses scan line analysis and the Douglas-Peucker algorithm for segmentation. It was processed by applying simple geometric rules and a region-growing algorithm. Z. Zhou et al. [40] introduce a deep learning-based method to automatically detect residential buildings from airborne LiDAR data. This method does not require any pre-defined geometric or texture features. Building height is calculated using a normalized Digital Surface Model (nDSM).

Different researchers have used normalized digital surface models to estimate the heights of buildings. They have used the Digital Terrain Model and the Digital Surface Model to calculate the Normalized Digital Surface Model. In the case of a sloped roof, the height difference is calculated. Buildings are artificial objects consisting of piecewise and continuous surface segments that can be described as polyhedral forms. Alternatively, building boundaries are defined by planar surfaces and lines[33].

Materials and Methods:

This research work focuses on a selected area within Attariya, located in Godawari Municipality-2 of the Kailali district, Nepal. The building stock in this region primarily consists of commercial complexes, residential structures, institutional facilities, and industrial or warehousing units. The area maintains a population density of approximately 320 per km². Attariya is a major transportation artery and economic gateway of the Far-Western region of Nepal[41]. Situated approximately 483 kilometers west of Kathmandu by air[19], but about 650 kilometers by road. Reinforced Concrete (RCC) frame structures are the most

common modern buildings. Load-bearing brick masonry is common in the residential wards surrounding the main market. The area is characterized by the flat topography of the Terai plains, which facilitates accurate DTM extraction. The altitude lies between 170 and 200 meters above sea level. The settlement pattern features buildings clustered linearly along the highway and transitions into scattered rural clusters. Traditional Terai dwellings (Kucha/Semi-Pukka) can be found as you move away from the highway toward the more rural parts of Municipality. Public and institutional buildings differ from standard residential blocks. This region's cultural mosaic is composed of a blend of the indigenous population and migrants from the neighbouring hilly

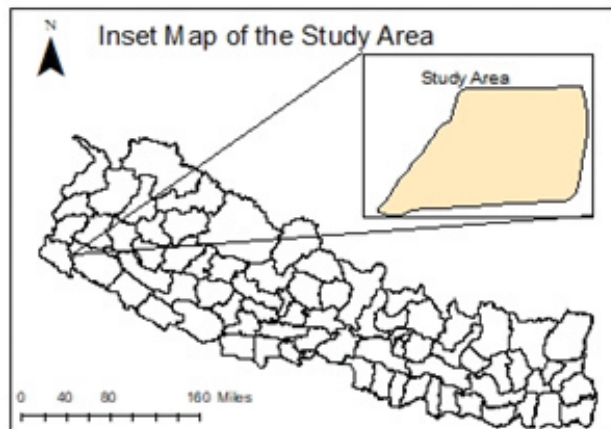


Figure 1: Inset Map of the Study Area

For this study, an airborne LiDAR dataset was acquired from the Survey Department of Nepal. The dataset consists of 2,117,418 points covering an area of 273,984 m². The average point density is 18.04 samples/m², with a point spacing of 0.24 m. The elevation within the study area ranges from a minimum of 194.11 m to a maximum of 220.79 m. The aerial view of this extent is presented in Figure 2.



Figure 2: Aerial view of the selected area

Data acquisition: Building construction permit records were obtained from Municipality Office, which serves as the regulatory authority, and is responsible for issuing permits and maintaining building records within its municipal area.

Computational Framework: In this study, the Global Mapper and the Python Programming Language were used to extract building height and calculate the number of stories. The research employs a Python-based pipeline for the processing and analysis of LiDAR datasets. The Laspy library serves as the core interface for reading, writing, and modifying LiDAR data in the LAS and LAZ file formats, ensuring the integrity of point format versions and header metadata. Vector operations, including height thresholding, distance computations, and spatial transformations, are performed using NumPy and SciPy. For the extraction of structural features, scikit-learn is employed to implement the DBSCAN clustering algorithm and to group discrete points into distinct building clusters. The geometric boundaries or "footprints" of these classified clusters are then generated using Alphashape and Shapely. Additionally, Whitebox Tools is integrated via its Python wrapper to leverage advanced pre-built functions, such as the Simple Morphological Filter, for efficient ground classification.

Methodology and Data Processing: To ensure the spatial integrity of the airborne LiDAR and cadastral datasets, the WGS 84 / UTM Zone 45N coordinate reference system was adopted. The LiDAR dataset is classified into categories including ground, buildings, vegetation, power lines, poles, and noise points. This classification process involves assigning classes to LiDAR data points based on their height and other characteristics.

Main LiDAR Data Process Methodology

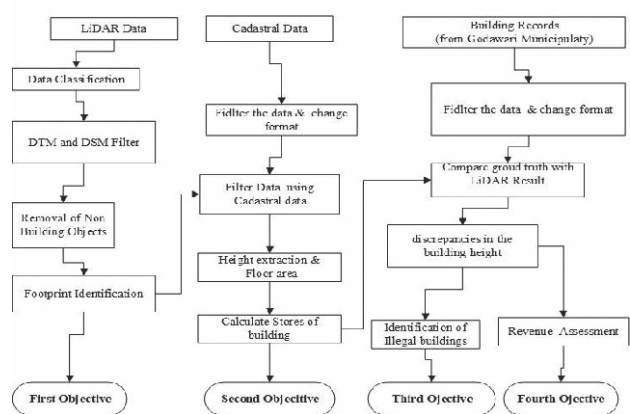


Figure 3: Main LiDAR Data Process Methodology

There are several methods to classify data. In the point cloud classification process, the following methodology was used. The

classification workflow distinguishes between ground and non-ground points [43]. Without classifying the ground points, other classes cannot be identified because they are related to ground height [44]. For this process, the Global Mapper software was utilized. It uses two types of algorithms for ground data classification. The Maximum Likelihood algorithm is a geospatial algorithm designed to classify LiDAR data into ground and non-ground points [45]. It filters non-ground points by calculating local surface curvature, typically in smaller grid cells, making it ideal for a lower-density dataset. Vegetation, buildings, electric lines, towers, etc., belong to the non-ground class.

Following the ground extraction, non-ground points were further classified into Medium Vegetation, Building, Wire Conductor (Phase), and Transmission Tower classes based on their height above the ground surface [46]. After classification of LiDAR data, buildings are illustrated in Figure 3. The result from the classification process is checked manually using visualization tools. Noise points were removed, and misclassified data were corrected. Any LiDAR data cluster that was incorrectly categorized as a separate class was merged back into the suitable class [47]. After classifying ground and non-ground points, the final classification output is ready. The building category (Class 6) is clearly defined. In geospatial analysis, accurate Digital Terrain Model (DTM) and Digital Surface Model (DSM) generation are the fundamental steps to determine building heights, as they provide the “zero-elevation” baseline for the ground [60]. A normalized digital surface model (nDSM) was generated to isolate above-ground features. This nDSM was calculated by subtracting the DTM from the DSM [48]. By removing the DTM surface from the DSM, the remaining data belongs to objects on the surface of the earth. From that, we identified the building points. Building points are distinguishable from other objects like vegetation, shrubs, roads, and vehicles. Consequently, features can be differentiated by shape, size, height, and texture by visual interpretation in point cloud data [49]. LiDAR data has high-precision building elevation information. We can exactly differentiate between building and tree using LiDAR data [50].

During the building extraction process, the classified building features were filtered and output as polygonal geometries. Building footprint extraction involves the identification and delineation of building 2D ground-level perimeters.

To refine the dataset and remove non-building objects—such as vegetation, vehicles, and temporary structures—a combination of geometric and shape-based filtering techniques was applied.

These methods identify buildings based on structural characteristics, such as planar surfaces and well-defined edges, while excluding smaller objects (e.g., cars or small sheds) that fall below a minimum area threshold of 10 m².

Planarity checks and eigenvalue analysis were used to distinguish smooth, consistent building surfaces from the irregular, high-variance structure of tree canopies. Additionally, a Normalized Digital Surface Model (nDSM) enables height-based filtering. Algorithms like the Cloth Simulation Filter (CSF) were employed to separate the ground from non-ground points, allowing objects below a specific threshold of 3 m to be reclassified as low vegetation or vehicles.

Further refinement was achieved through morphological operations—including regularization, erosion, and dilation—to sharpen building boundaries and separate overlapping features like overhanging tree limbs.

To distinguish true structures from dense canopies, RANSAC (Random Sample Consensus) is used to detect planar roof surfaces, while eigenvalue/covariance Analysis identifies the shaggy or scattered spatial signature of trees versus the smooth, planar surface of buildings.

Clustering techniques, such as DBSCAN implemented in Python libraries like laspy, help identify and remove outliers based on point density.

The height of each building was determined by subtracting the Digital Terrain Model (DTM) from the Digital Surface Model (DSM) [51][52].

$nDSM = DSM - DTM$

Floor and story calculation: in the Terai region of Nepal, average floor height and basement elevations are 1 m and 3.3 m respectively determined by the building construction regulation of Nepal [53].

$$n = \frac{h - z_y}{k_y}$$

Where n is the number of stories; h is the calculated height of the building from the LiDAR-derived nDSM; z_y is the plinth height (standardized at 1 m for the Terai region); and k_y is the average floor height (standardized at 3.3 m per the Building Construction Regulation of Nepal [53]).

Illegal buildings are identified by intersecting the building vector layer derived from LiDAR data with the cadastral parcels [54]. A structure is classified as illegal if it exceeds the maximum height or floor count permitted for its specific land-use zone.

Finally, manual quality control—using 3D profile visualization and targeted class corrections—ensures high-precision results by allowing analysts to verify and resolve any remaining misclassifications.

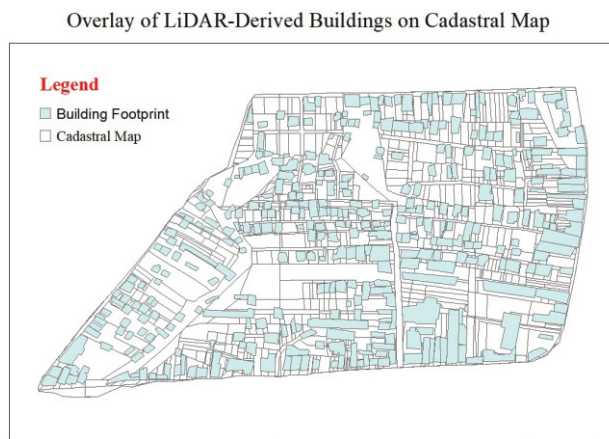


Figure 4: Overlay of LiDAR-Derived Building on Cadastral Map

1. Result and Discussion

Processing the airborne LiDAR cloud point dataset following outputs are generated, which accurately represent the physical condition of the study area.

Point cloud classification Result:

LiDAR point cloud is classified into the following classes.

Table 1: Point classification

S. No.	Class-code	Class	Point Count
1	2	Ground	967698
2	4	Medium Vegetation	330063
3	6	Building	410819
4	14	Wire conductor(phase)	60580

Classification of Buildings: The resulting building classification from the LiDAR dataset is shown in the figure 4.

Table 2: Point Cloud Count Graph

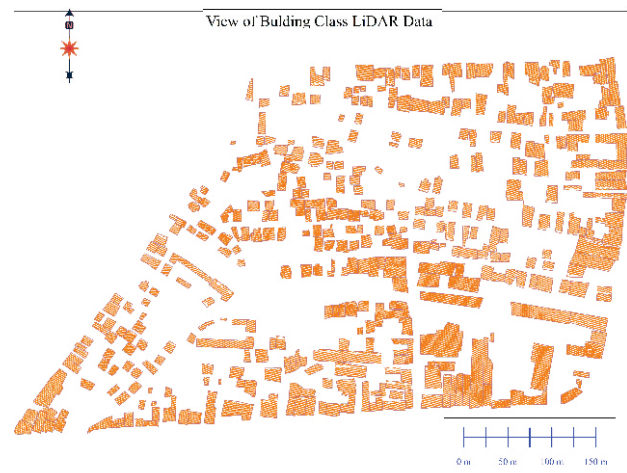
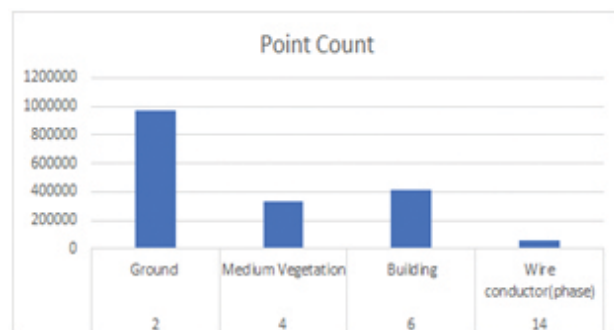


Figure 5 : LiDAR data After classification of buildings

Calculation of building height:

For calculating nDSM, there is need to calculate the DTM and DSM is as the following.

Digital Terrain Model: To generate the Digital Terrain Model (DTM), the entire point cloud dataset is selected, and the DTM is produced as shown below.

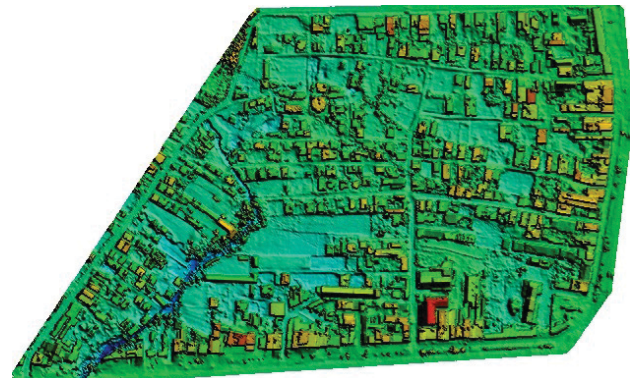


Figure 6: Digital Terrain Model of the study area

Digital Surface Model: After generation of the Digital Terrian Model, point cloud data were used to compute the Digital Surface Model (DSM). The output of DSM is illustrated in the Fig 6.

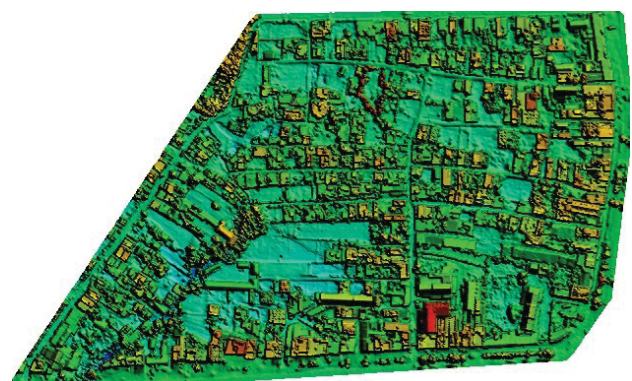


Figure 7: Digital Surface Model of Attariya

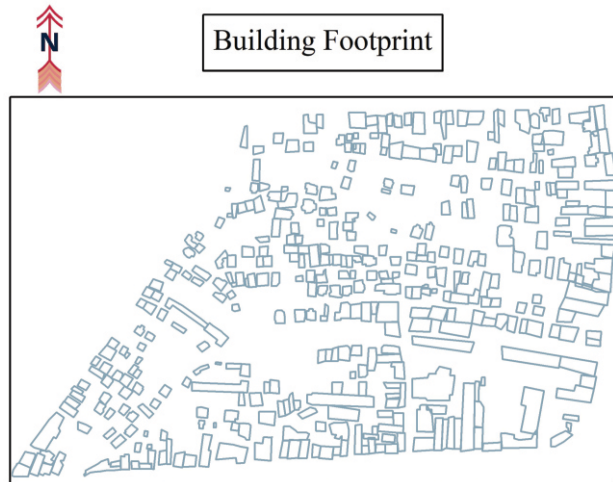
Building Footprint:

Figure 8: LiDAR-extracted Building footprints of the study area

Building Height Extraction: Following the generation of the Digital Terrain Model (DTM) and the Digital Surface Model (DSM), the normalized Digital Surface Model (nDSM) was derived to isolate building heights. The resulting values are detailed in Table 2, with a representative sample of these calculations provided below.

Table 3: Comparative Analysis of Building Stories and Area (LiDAR vs. Municipal Records)

A1	B1	LiDAR Data				Municipal Record		Difference	Difference	Remark
		C1	D1	E1	F1	G1	H1			
1	523	13	4	904	3608	3	2731	101	877	
2	447	10.2	3	872	2616	2	1943	949	623	

Note

1. A1: S.No, B1: Parcel No, C1: Height of Building(in meters), D1: Calculated Storey of Building, E1: Unit Area of Floor, F1: Total Area of all Floor, G1: Stories of Buildings, H1: Total Area of Buildings, I1: Stories of Building, J1: Area of Building, K1: Total Difference of Area.
2. In the same way, all the data is compared, and the difference is calculated.

Table 3: Summary of Comparative analysis of LiDAR-Derived data vs.Municipality data (Number and Area)

Number of stories	Municipality data		LiDAR Derived Data	
	Storey of buildings	Area of Building (feet)	Storey of buildings	Area of Building(feet)
1	58	54575.54	73	85093.23
2	66	132261.8	79	183419.4
3	45	143327.2	59	209462.3
4	12	83247	17	101261.4
5	0	0	9	66020.3
Total	180	413411.5	237	645256.6

$$\begin{aligned}\text{Total Area Difference} &= \text{LiDAR Derived Area} - \text{Municipal Recorded Area} \\ &= 645256.6 - 413411.5 \\ &= 231845.1\end{aligned}$$

Table 4: Accuracy Assessment and Error Metrics for LiDAR-Derived Heights

S.No.	Performance Metric	Calculated Value	Units
1	Correlation (r)	0.936	
2	Mean Absolute Error (MAE)	1286.34	Foot
3	Root Mean Square Error (RMSE)	1297.11	Foot

Table 5: Accuracy Assessment and Error Analysis of LiDAR Data

S. No.	Statistical Parameters	LiDAR Derived Data	Municipal Records
1	Count	237	181
2	Average	2722.60	2284.041547
3	Median	2204	1920
4	Mode	2440	1850
5	Standard Deviation	2049.13247	1760.656931
6	Variance	4198943.89	3099912.83
7	Minimum	645	0
8	Maximum	16125	13765
9	Sum	645256.6	413411.52

Revenue Loss Estimation: Two distinct categories of revenue loss were identified and evaluated: the estimated Direct Permit Revenue Gap (DPRG) from building permits and the Estimated Annual Property Tax Deficiency (EAPTD).

Direct Permit Revenue Gap: From the above table, the discrepancy between LiDAR-derived measurements and municipal records is 231,845.1 square feet. And the rate for construction permission is Rs. 5 per square foot. The total DirectPermit Revenue Gap(DPRG) for this selected area is as follows.

$$\begin{aligned}\text{DPRG} &= \text{Difference in Area} \times \text{Rate per Square Foot} \\ &= \text{Rs. } 231,845.1 \times 5 \\ &= \text{Rs. } 1,159,225\end{aligned}$$

Note: In the Municipality, the building permit certificate rates vary between 5 and 8 (Financial Act, 2082); however, the minimum rate of Rs. 5 per square foot has been applied for these calculations.

Estimated Annual Property Tax Deficiency: In the same way, there is an Estimated Annual Property Tax Deficiency (EAPTD). Annual tax rate is Re. 1 per square foot. The total

$$\begin{aligned}
 \text{EAPTD} &= \text{Difference of area X rate} \\
 \text{per square foot} &= \text{Rs. } 231,845.1 * 1 \\
 &= \text{Rs. } 231,845.1
 \end{aligned}$$

In accordance with the law, the precise calculation of the tax rate is multifaceted. The municipality applies different rates based on floor level and building location. For simplicity, an estimated lowest flat rate of Rs. 1 per square foot has been utilized for this purpose

Penalties and interest charges have not been included in this calculation. In the actual field, there are many temporary tin shades or shade-like structures found above the buildings. LiDAR data cannot differentiate the temporary tin shade other building like structures from the actual storey.

Challenges in Extracting Building Heights

Roof Objects: In the building there may be non-structural things like transparent roof for heat and light, Building water storage vessel, water Tank shed, climate control machinery, heat exchange equipment, Active air exhaust systems, Emergency power supply, Solar Panels, Electricity generator, thermal panels for water, glass panels for natural light, insulation layers, outdoor lounging area, High-end aquatic facilities, haystack, corn-stack stock, big umbrella, chairs, tables and other enumerable obstacles are found in top of the room complicates the calculating height of building.

Object that effects on classification of data: Overhead drying rack/wire looks like wire, and data is classified into the wire category. Haystacks look like extra room. Rooftop room for views, Stair or elevator access enclosure, Area for basking is also considered in calculating the height of the building. Garden in the roof also classifies data into the vegetation area.

Shades and temporary structures: There are older houses, which were built before the rule and regulation started, or the municipality's establishment; are also without permissions. Temporary shelters look like buildings so it needs to identify manually these shelters whether they are permanent or temporary.

Problem of cadastral Number: Data is collected from the

municipality office is based on the parcel number. Whereas LiDAR data have no parcel number, so without any proper key it is impossible to compare building data with data derived from LiDAR data. To solve this type of problem and identify every LiDAR data by parcel number, the LiDAR data must contain the parcel number. To solve this problem cadastral map of selected area is collected from survey Department.

the process of overlaying building footprints with cadastral data begins with Coordinate Alignment, where datasets are re-projected to meet specific projection standards for high precision. Once aligned, the LiDAR-derived footprints are overlaid onto the official cadastral map. By linking this information together through a spatial join, a cadastral number can be automatically assigned to each identified building. Finally, both visual inspections and statistical analyses are conducted to verify the accuracy of the overlay.

After the overlay of cadastral data and point clouds, we can analyse and find the parcel number for each point cloud and make it easy to compare individually every building data with the LiDAR data.

For this purpose, it is necessary to add a new attribute, parcel number, in LiDAR data according to the overlay of the cadastral parcel.

Land ownership certificate: There are many land owners who do not have a legal land ownership certificate. Without a land ownership certificate, the municipality does not give permission to construct a building.

Implementing any model within the government sector is a formidable task. One must navigate numerous obstacles, including rigid regulations and multi-layered decision-making processes

5. Conclusion and Recommendations

The main aim of this study is to identify the informal buildings of selected area by calculating building height and the number of stories of building. For this, it has used LiDAR data and cadastral data are obtained from Survey Department. The calculated result is compared to municipal BPRs. Based on this comparison, buildings without the permissions or different from the legal permissions are identified. Based on this result loss of revenue and annual tax loss is calculated. This study is helpful for local bodies to find out about informal buildings.

These results empower governments to refine urban planning and resolve zoning disputes while addressing critical housing needs. Furthermore, they facilitate the design and development of resilient infrastructure, ranging from utilities like water and electricity to transportation networks, while enhancing disaster management and environmental risk assessments.

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AUTHOR INFORMATION



Name : Shiva Raj Bhatta

Academic Qualification : MCA, MPhil in ICT

Organization : Survey Department

Current Designation : Information Technology Director

Work Experience : 29 years of experience in the field of Information Technology

Published Articles : 2

ESTIMATION AND PREDICTION OF PM_{2.5} AND PM₁₀ CONCENTRATION IN KATHMANDU VALLEY USING REMOTE SENSING AND MACHINE LEARNING

Indra Paudel¹, Ashim Poudel², Aashish Baral³, Aayush Chand⁴, Gaurav Baral⁵
¹²³⁴⁵ Department of Geomatics Engineering, Pashchimanchal Campus, IOE, Tribhuvan University, Nepal
¹pas077bge022@wrc.edu.np, ²pas077bge005@wrc.edu.np, ³pas077bge002@wrc.edu.np, ⁴pas077bge003@wrc.edu.np,
⁵pas077bge021@wrc.edu.np

KEYWORDS: PM_{2.5}, PM₁₀, Remote Sensing, Air Quality, Machine Learning

ABSTRACT:

In recent years, public health and the environment have been seriously threatened by air pollution, especially in low and middle income nations like Nepal, where the challenge is compounded by sparse ground-level monitoring stations that provide limited spatial coverage. To address this data gap, this study uses machine learning algorithms and satellite data to meet the pressing demand for precise PM_{2.5} and PM₁₀ prediction. Ground station data from the monitoring stations of the Department of Environment covering the period from January 2022 to December 2023 were combined with satellite-derived parameters including Aerosol Optical Depth (AOD), Land Surface Temperature (LST), Normalized Difference Vegetation Index (NDVI) and soil moisture to train the models. The Gradient Boosting algorithm performed consistently well, with average R² scores of 0.82 and 0.84 for PM_{2.5} and PM₁₀ respectively, proving efficient in capturing non-linear relationships in air quality data. Likewise, Random Forest also showed reliable accuracy with R² values of 0.80 and 0.82 for PM_{2.5} and PM₁₀ respectively. Spatial maps created from model predictions highlight pollution hotspots, providing actionable insights for targeted interventions. The study demonstrates the potential of integrating satellite data with machine learning for air quality monitoring in data-scarce regions, supporting evidence-based environmental policy in Nepal and similar contexts. Future research to incorporate high-resolution datasets and additional metrological variables to enhance model reliability and scalability.

1. INTRODUCTION

Air pollution constitutes the presence of toxic substances in the atmosphere, leading to adverse effects on human health and millions of premature deaths each year. Air pollution became the second leading risk factor for death worldwide, with 8.1 million deaths recorded in 2021, including children under five years of age (UNICEF, 2024). Approximately 91% of the burden falls on low and middle income nations in Southeast Asia and the Western Pacific. Major pollutants include sulphur dioxide (SO₂), particulate matter (PM), nitrogen dioxide (NO₂), carbon monoxide (CO) and ozone (O₃).

Particulate matter (PM) with aerodynamic diameters smaller than 2.5 µm (PM_{2.5}) and 10 µm (PM₁₀) has received significant attention due to its impact on human health and ecosystems (Bodor et al., 2022; Ghasemi et al., 2019; Yunesian et al., 2019; Zoran et al., 2020). Elevated PM₁₀ levels are linked to higher hospital admissions for lung and heart diseases, while PM_{2.5} poses a greater health risk as it penetrates deeper into the respiratory system (Mamić et al., 2023).

A report by Nepal's Ministry of Health and Population (2020) attributed 42,100 annual deaths to air pollution, reducing average life expectancy by 4.1 years. More recent global estimates (UNICEF, 2024) record 8.1 million air pollution-related deaths worldwide in 2021, underscoring that the burden remains acute and growing. The same report found that more than 90% of these deaths (7.8 million) were linked to exposure to fine particulate matter (PM_{2.5}) from outdoor and household pollution sources. Air quality monitoring in Nepal faces significant challenges due

to the sparse network of ground-based sensors, leaving many areas unmonitored (Timilsina et al., 2023). The Air Quality Index (AQI) is widely used to estimate pollution severity, but its ground-based calculation is limited to monitored locations (Lo Re et al., 2014; Bechle et al., 2013).

Satellite remote sensing data, particularly aerosol optical depth (AOD), offers broad spatial coverage and has been widely used to derive PM_{2.5} and PM₁₀ concentrations (Martin, 2008; Xue et al., 2019). Geostatistical methods such as Kriging (Jerrett et al., 2005; Mercer et al., 2011) and regression (Eeftens et al., 2012) have been used, though station coverage remains sparse in sub-urban and rural areas. Advanced machine learning approaches integrating satellite data are enhancing exposure assessments in alignment with WHO air quality guidelines.

This study aims to predict PM_{2.5} and PM₁₀ concentrations in the Kathmandu Valley by integrating satellite-derived data with ground-based measurements using two ensemble learning models: Random Forest (RF) and Gradient Boosting (GB). Prior to implementing these models, a Linear Regression approach was also evaluated. However, due to the non-linear nature of the relationship between the predictor variables and particulate matter concentrations, the model produced unsatisfactory results. Hence, these two algorithms were selected for their proven ability to handle non-linear relationships, robustness to outliers, and strong performance in prior PM prediction studies (Mamić et al., 2023; Sakti et al., 2023). The findings provide insights for developing targeted intervention strategies and aid air quality monitoring in regions lacking dense ground based station networks.

2. STUDY AREA

The selected study area is the Kathmandu Valley, spanning an area of 933.73 km². The geographical boundaries are defined by latitudes 27.403° N to 27.818° N and longitudes 85.189° E to 85.566° E. Located in the lesser Himalayas of Central Nepal, the valley is bowl-shaped with a central elevation of 1,425 m, surrounded by four mountain ranges: Shivapuri (2,732 m), Phulchowki (2,695 m), Nagarjun (2,095 m), and Chandragiri (2,551 m), with the Bagmati River flowing through it.

The valley comprises three districts ie Kathmandu, Bhaktapur, and Lalitpur, with population densities of 5,169, 3,631, and 1,433 persons per km² respectively. Its subtropical, semi-humid climate has a mean temperature of 18.3°C and mean annual rainfall of 1,439.7 mm. Pollution originates from vehicular emissions, open fires, construction dust and post-earthquake damage, compounded by the valley's topography which limits wind dispersal.

Kathmandu Valley was selected due to its highest concentration of air quality monitoring stations in Nepal: 7 governmental stations operated by the Department of Environment and 44 Purple Air sensors, providing a substantial dataset for model development. Model performance was evaluated using an 80/20 train-test split, with the held-out 20% test subset serving as the basis for accuracy assessment. Once the model performs reliably well, it is intended for extension to the rest of Nepal incorporating high resolution datasets and additional metrological variables.

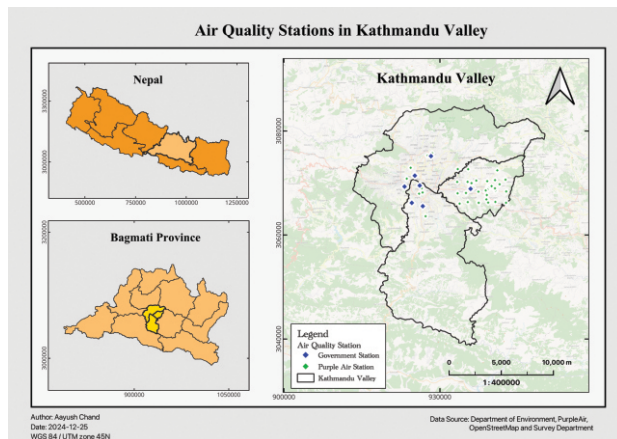


Figure 1. Study Area - Kathmandu Valley

3. MATERIALS AND METHODS

3.1 Description of Datasets

Data from both remote sensing and ground-based observations were utilised, spanning two years from January 1, 2022, to December 31, 2023. Ground level PM_{2.5} and PM₁₀ data were sourced from seven monitoring stations of the Department of Environment, Government of Nepal. The two-year period was sufficient to capture seasonal variations, long-term trends and short-term pollution spikes.

Satellite-based AOD data were sourced from the MCD19A2.061 MODIS Terra and Aqua MAIAC product via the Google Earth Engine Catalog, providing daily coverage at 1 km spatial resolution. Additional variables included NDVI from MODIS (1 km, monthly); LST from MODIS MOD11A1 V6.1 (1 km, daily); precipitation from CHIRPS (5.56 km, daily); and soil moisture

from SMAP SPL4SMGP/007 (9 km, resampled to 1 km, 3-hour intervals). Precipitation was excluded from model training due to near zero variance (>75% zero values).

Table 1. Description of Datasets (* resampled to 1 km)

Datasets	Source	Type	Spatial Res.	Temporal Res.
Shapefile	Survey Dept.	Vector	-	-
Ground PM _{2.5} /PM ₁₀	Dept. of Env.	CSV	-	1 Day
AOD	MODIS	Raster	1 KM	1 Day
LST	MODIS	Raster	1 KM	1 Day
NDVI	MODIS	Raster	1 KM	1 Month
Soil Moisture	SMAP	Raster	9 KM*	3 Hour

3.2 Methodology

The study aimed to establish machine learning models to estimate and predict ground-level PM_{2.5} and PM₁₀ concentrations in the Kathmandu Valley using heterogeneous satellite and meteorological data.

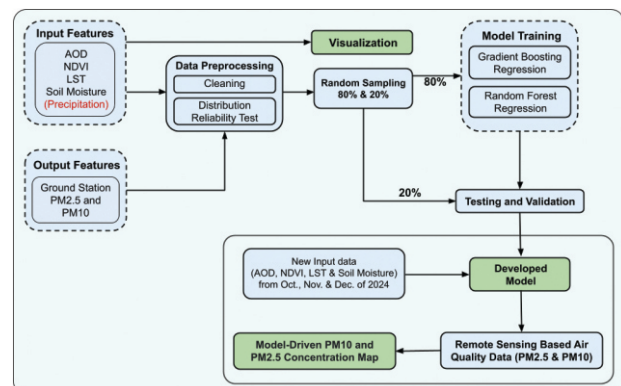


Figure 2. Methodological Flowchart

3.2.1 Data Extraction, Cleaning and Analysis: Ground-based PM_{2.5} and PM₁₀ data were collected as daily averages. AOD and LST data shared daily temporal resolution; NDVI values (monthly) were interpolated by assigning the first-day value to all days within ±15 days. Soil moisture values were matched to the closest 3-hour timestamp coinciding with MODIS AOD acquisition. Point values for each remote sensing dataset were extracted for the pixel containing each ground station. Missing values, duplicates and outliers beyond three standard deviations were removed using Python's Pandas library, yielding 987 clean records.

3.2.2 Model Development: Two ensemble algorithms were employed: Random Forest Regression (RFR) and Gradient Boosting Regression (GBR). Random Forest combines the predictions of multiple decision trees, producing a robust model capable of handling complex, non-linear relationships. Gradient Boosting builds models sequentially, with each successive tree correcting the residual errors of the previous one. Hyperparameters for each model were tuned iteratively to avoid underfitting and overfitting. This dataset was split into training and testing subsets. An 80/20 train-test split was applied, a widely adopted ratio in environmental machine learning studies (Mamić et al., 2023; Wu et al., 2024) that balances the need for sufficient training samples against an adequate hold-out set for unbiased

performance evaluation. Accordingly, 80% of the records were used for training, while the remaining 20% was reserved for testing purposes, allowing us to validate the models' predictive capabilities with random sampling to ensure representative subsets.

3.2.3 Accuracy Assessment: Model accuracy was assessed using Root Mean Square Error (RMSE), Mean Square Error (MSE), R-squared (R^2), Adjusted R^2 , and Mean Absolute Error (MAE). The key metrics are defined as follows:

$$RMSE = \sqrt{\sum(y - \hat{y})^2 / n} \quad (1)$$

$$MSE = \sum(y - \hat{y})^2 / n \quad (2)$$

$$R^2 = 1 - \sum(y_i - \hat{y}_i)^2 / \sum(y_i - \bar{y})^2 \quad (3)$$

$$\text{Adjusted } R^2 = 1 - (1 - R^2)(n - 1) / (n - k - 1) \quad (4)$$

$$MAE = \sum|y - \hat{y}| / n \quad (5)$$

Where,

y = predicted value

$\hat{y}$ = observed value

$\bar{y}$ = mean of observed values

n = number of observations

k = number of predictors

R^2 = Adjusted coefficient of determination

3.2.4 Statistical Distribution of Variables: Prior to model training, the statistical distribution of all predictor and target variables was examined to characterise their behaviour and inter-relationships. Kernel Density Estimation (KDE) plots were produced to visualise the probability distributions of each variable, and boxplots were generated to display central tendency, dispersion, and outliers. Pearson correlation analysis was then applied to quantify linear associations between predictor and target variables, and to assess multicollinearity among predictors. These analyses guided feature selection and informed interpretation of model results.

3.2.5 Visualization of Prediction Results: Trained models were applied to predict $PM_{2.5}$ and PM_{10} concentrations at 935 evenly spaced points (1 km apart) across the valley, using input data collected at 10-day intervals for October, November, and December 2024. The final $PM_{2.5}$ and PM_{10} values were obtained by averaging the outputs from both approaches. The predicted values were then mapped using a color scale ranging from white to red, where white represented lower concentrations and red indicated higher concentrations, effectively capturing spatial pollution variations as shown in figure 14. These visualizations help to highlight pollution hotspots and temporal trends, offering valuable insights into air quality distribution. This approach demonstrates the capability of the model in identifying high risk zones, aiding policymakers in designing targeted air quality management strategies.

4. RESULTS

4.1 Data Visualization

To represent the spatial and temporal variations of air quality and associated environmental parameters, we developed comprehensive maps for each parameter: Aerosol Optical Depth (AOD), Land Surface Temperature (LST), Normalized Difference Vegetation Index (NDVI), and Soil Moisture. These maps were created for four distinct four-month intervals spanning

the years 2022 and 2023, providing a seasonal perspective of air quality dynamics in the Kathmandu Valley.

4.1.1 Aerosol Optical Depth (AOD)

The average AOD was extracted from the MCD19A2.061 MODIS Terra and Aqua MAIAC satellite data using the Google Earth Engine Catalog. These datasets, with a 1km spatial resolution, were averaged over the specified intervals to visualize the concentration of aerosols across the study area.

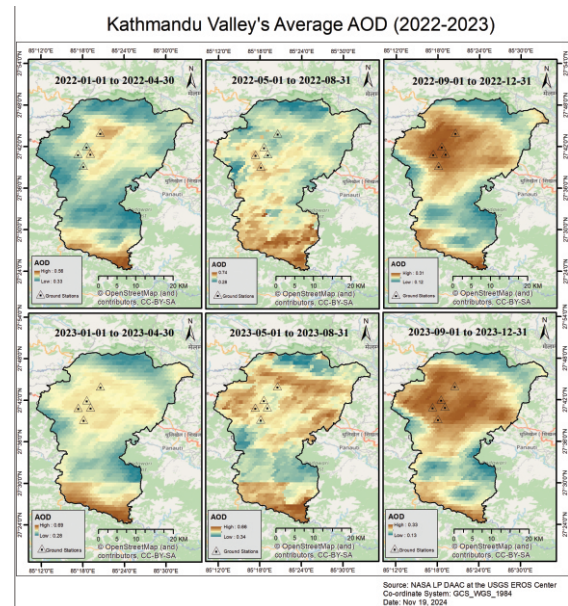


Figure 3. Kathmandu Valley's Average AOD (2022-2023)

4.1.2 Land Surface Temperature (LST)

LST data were derived from the MODIS MOD11A1 V6.1 dataset, which provides daily temperature and emissivity values with a 1km spatial resolution. The data were aggregated to represent average LST for each four-month interval. These maps help correlate temperature variations with aerosol distributions, emphasizing seasonal effects on air quality.

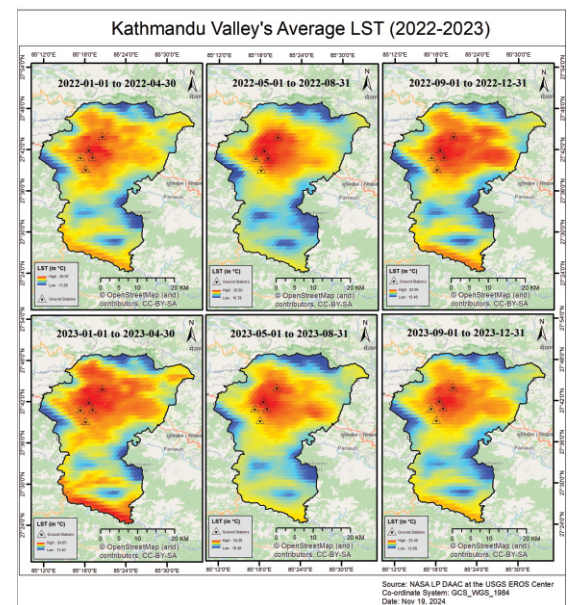


Figure 4. Kathmandu Valley's Average LST (2022-2023)

4.1.3 Normalized Difference Vegetation Index (NDVI)

NDVI data were sourced from MODIS satellite data at a 1km spatial resolution and a monthly temporal resolution. The interval-averaged NDVI maps provide insights into vegetation coverage and health, factors that influence air quality by regulating particulate deposition and secondary aerosol formation.

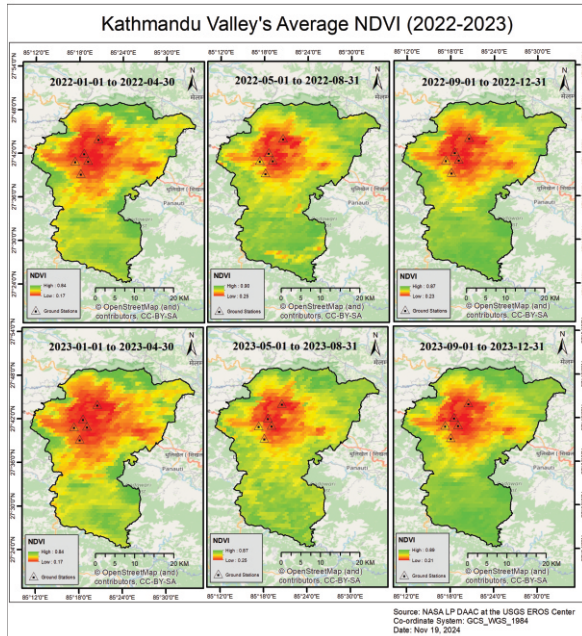


Figure 5. Kathmandu Valley's Average NDVI (2022-2023)

4.1.4 Soil Moisture

Soil moisture data were obtained from the SMAP dataset ("NASA/SMAP/SPL4SMGP/007"), originally available at an 9 km resolution. These data were resampled to a 1km spatial resolution and aggregated for four-month intervals. The resulting maps highlight the influence of soil moisture on surface-level air quality by affecting aerosol resuspension and deposition dynamics.

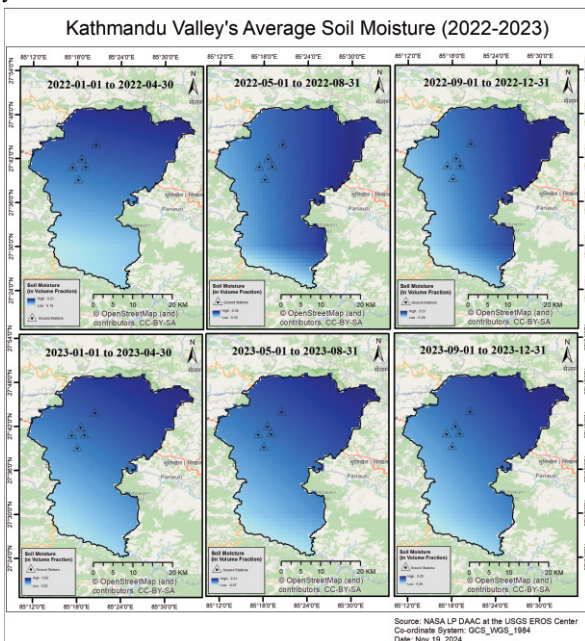


Figure 6. Kathmandu Valley's Average Soil Moisture (2022-2023)

4.2 Statistical Evaluation

As described in Section 3.2.4, statistical evaluation of all predictor and target variables was performed prior to model training. Kernel Density Estimation (KDE) plots revealed that AOD values are positively skewed (0.2–0.7 range), LST follows a near-normal distribution peaking around 27°C, soil moisture also follows a near-normal distribution with most values concentrated between 0.2 and 0.4, and NDVI is moderately skewed (0.2–0.6). PM_{2.5} values are near-normally distributed (50–150 $\mu\text{g}/\text{m}^3$), while PM₁₀ is right-skewed (50–100 $\mu\text{g}/\text{m}^3$).

The boxplots illustrate the distribution of environmental variables, highlighting their central tendencies, variability, and outliers. AOD has a median around 0.3 with variability between 0.2 and 0.5, along with several high-value outliers. LST shows a median of approximately 25°C and ranges from 20°C to 30°C, with a few extreme values above 40°C. NDVI values indicate sparse vegetation, with a median near 0.3 and limited higher outliers above 0.6. Precipitation is mostly low, with a median of 0, though occasional heavy rainfall appears as outliers. Soil moisture remains relatively stable around 0.3, with minor variations and some drier outliers. PM₁₀ levels show moderate pollution (median $\sim 75 \mu\text{g}/\text{m}^3$) with occasional severe spikes, while PM_{2.5} indicates high pollution (median $\sim 100 \mu\text{g}/\text{m}^3$) with some lower-value outliers.

Pearson's correlation analysis showed that AOD has the strongest positive correlation with PM₁₀ ($r = 0.53$) and PM_{2.5} ($r = 0.49$). Soil moisture exhibited a notable negative correlation with both PM₁₀ ($r = -0.43$) and PM_{2.5} ($r = -0.43$). NDVI showed a weak negative correlation with PM_{2.5} ($r = -0.22$). PM_{2.5} and PM₁₀ were strongly positively correlated ($r = 0.77$). The weak inter-predictor correlations indicated that multicollinearity was not a concern.

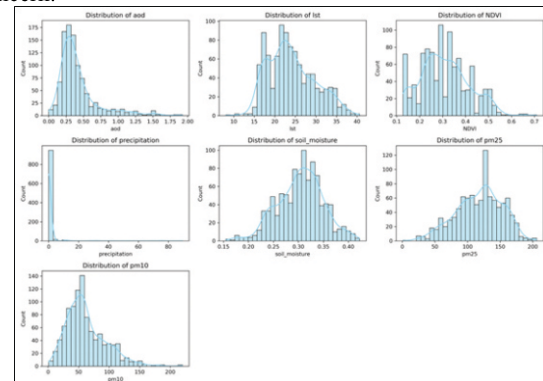


Figure 7. Data Distribution (KDE Plots) of Predictor and Target Variables

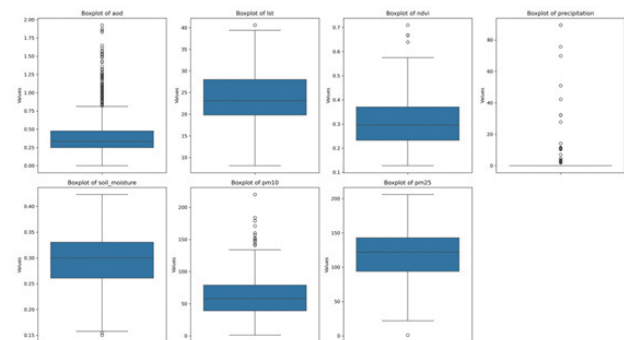


Figure 8. Boxplots of predictor and target variables

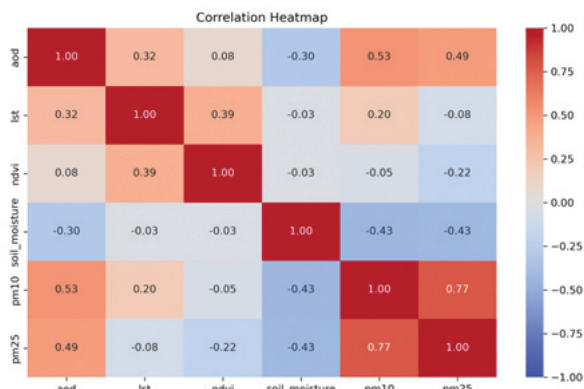


Figure 9. Correlation Heatmap of Predictor and Target Variables

4.3 Random Forest Model Performance Evaluation

The Random Forest model explained 80% of the variance in PM_{2.5} ($R^2 = 0.80$) with an MAE of 10.98 and RMSE of 15.17. For PM₁₀, the model achieved $R^2 = 0.82$, MAE = 9.32, and RMSE = 15.05. Cross-validation metrics remained stable across all folds, confirming the model's generalization capability.

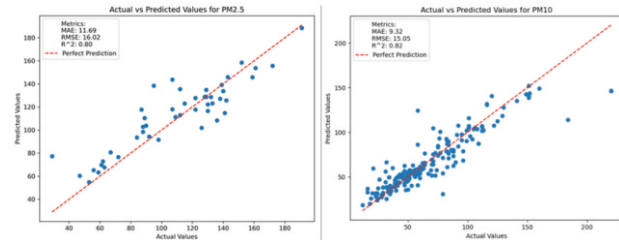


Figure 10. Actual vs. Predicted Values - Random Forest

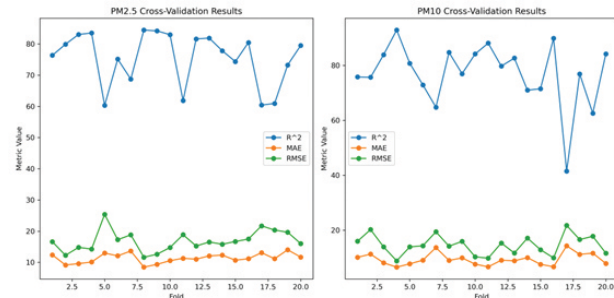


Figure 11. Cross-Validation Results - Random Forest

4.4 Gradient Boosting Model Performance Evaluation

Gradient Boosting achieved $R^2 = 0.82$ (MAE = 10.42, RMSE = 14.13) for PM_{2.5} and $R^2 = 0.84$ (MAE = 8.16, RMSE = 14.09) for PM₁₀, outperforming Random Forest on all metrics. Cross-validation across 20 folds showed consistently high R^2 values and stable MAE and RMSE, confirming the absence of overfitting. A summary of all accuracy metrics is provided in Table 2.

Table 2. Model Accuracy Metrics (RF = Random Forest; GB = Gradient Boosting)

Metric	RF PM _{2.5}	RF PM ₁₀	GB PM _{2.5}	GB PM ₁₀
MAE	10.99	9.32	10.42	8.16
MSE	229.97	226.64	199.55	198.40
RMSE	15.17	15.05	14.13	14.09
R^2 Score	0.80	0.82	0.82	0.84
Adj. R^2	0.79	0.82	0.82	0.84

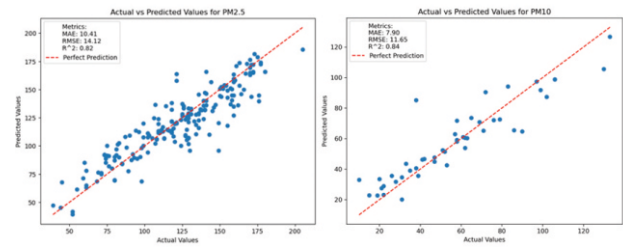


Figure 12. Actual vs. Predicted Values - Gradient Boosting

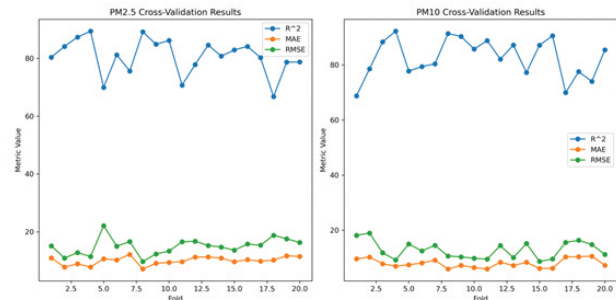


Figure 13. Cross-Validation Results - Gradient Boosting

4.5 PM_{2.5} and PM₁₀ Concentration Maps

Spatial prediction maps for October to December 2024, at 10 day intervals, reveal PM_{2.5} concentrations (119.1–158.2 $\mu\text{g}/\text{m}^3$) and PM₁₀ concentrations (64.2–108.5 $\mu\text{g}/\text{m}^3$) with highest concentration in the central, densely urbanised areas of the valley. These hotspots, concentrated primarily over the Kathmandu metropolitan core (Ratnapark–Sundhara area), Patan in Lalitpur, and the Bhaktapur urban area, are consistent with high vehicular emissions, industrial activity, and urban heating in those districts. Peripheral, less-developed zones (the northern slopes of Shivapuri and the southern foothills near Chandragiri) exhibit markedly lower concentrations.

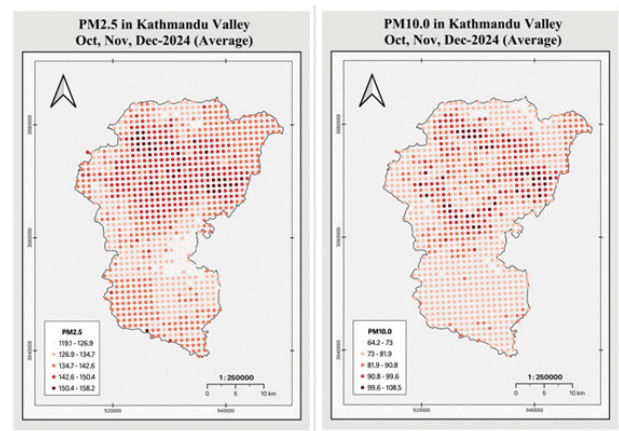


Figure 14. Predicted PM_{2.5} (left) and PM₁₀ (right) Concentration Maps, Kathmandu Valley

5. DISCUSSION

This study demonstrates that machine learning models integrating satellite-derived parameters and ground-based monitoring stations data can effectively estimate $PM_{2.5}$ and PM_{10} concentrations in a data-scarce urban environment, with both Random Forest and Gradient Boosting models achieving R^2 values above 0.80. These results are consistent with comparable studies in other regions too. Mamić et al. (2023) reported R^2 values of 0.77–0.88 for PM prediction in Europe using similar ensemble methods, while Wu et al. (2024) achieved R^2 of 0.85 for $PM_{2.5}$ estimation in Beijing using satellite data, lending confidence to the methodological approach adopted here.

Gradient Boosting consistently outperformed Random Forest across all metrics for both $PM_{2.5}$ and PM_{10} , consistent with its sequential residual-correction mechanism that allows it to progressively reduce prediction error. This advantage has been noted in other environmental ML studies where the target variable exhibits non-linear, skewed distributions (Sakti et al., 2023). The strong influence of AOD and soil moisture as predictors, compared to LST and NDVI, suggests that aerosol loading and surface moisture conditions are the dominant controls on near-surface PM concentrations in this valley environment. The role of soil moisture as a negative predictor ($r = -0.43$ with both PM species) likely reflects the suppression of road dust resuspension during and after rainfall periods, a mechanism particularly relevant in the Kathmandu Valley where unpaved roads and construction sites are widespread sources of coarse particulate matter. The relatively weaker signal from LST and NDVI may reflect the coarse monthly resolution of NDVI data and the indirect relationship between surface temperature and aerosol formation at the scale of this study.

Several limitations should be acknowledged. First, the coarse spatial resolution of SMAP soil moisture (9 km, resampled to 1 km) and the monthly temporal resolution of NDVI may introduce interpolation uncertainty at the point-scale used for model training. Second, the 2-year training period (2022–2023), while sufficient to capture seasonal cycles, may not fully represent inter-annual variability driven by exceptional events such as major dust storms or forests fires. Third, key meteorological covariates like wind speed, relative humidity, etc were excluded due to data availability constraints; their inclusion in future iterations could substantially improve performance, particularly for cold-seasons when temperature inversions trap pollutants within the valley.

Finally, $PM_{2.5}$ and PM_{10} concentrations at a given location are influenced not only by local emission sources but also by spatial dependence and pollutant transport from surrounding areas. Therefore, restricting the prediction domain strictly to the Kathmandu Valley boundary may introduce boundary effects and underestimate concentrations near the edges of the study area, as neighboring interactions and aerosol transport from outside the valley cannot be fully captured within a hard administrative boundary. Addressing these limitations through higher-resolution inputs, extended training datasets and a spatially buffered prediction domain or spatially continuous prediction grids to better account for cross-boundary aerosol transport represents the primary direction for future work.

6. CONCLUSIONS

This study demonstrates the viability of combining remote sensing data with machine learning for predicting $PM_{2.5}$ and PM_{10} concentrations in the Kathmandu Valley, where ground-based monitoring is sparse. Both Random Forest ($R^2 \geq 0.80$) and Gradient Boosting ($R^2 \geq 0.82$) models performed reliably, with Gradient Boosting achieving superior accuracy. Aerosol Optical Depth and soil moisture emerged as the strongest predictors.

The spatial prediction maps identify persistent pollution hotspots in the central valley, providing actionable information for targeted air quality interventions and urban environmental policy. The approach is scalable to the broader national context once additional ground-truth data are available. Future work should incorporate higher-resolution datasets, additional meteorological variables, and longer training periods to improve model reliability and seasonal coverage.

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AUTHOR INFORMATION



Name : **Indra Poudel**

Academic Qualification : BE Geomatics Engineering

Organization : Kent State University

Current Designation : Graduate Teaching Assistant
Kent State University

Work Experience : Geomatics Engineer Intern 2024-2025 May
(Ghar Engineering Consultancy)

MACHINE LEARNING BASED FLOOD SUSCEPTIBILITY ASSESSMENT IN THE WEST RAPTI RIVER BASIN USING MULTI SOURCED GEOSPATIAL DATA

Dibikshya Shrestha¹, Rabi Shrestha²

¹Kathmandu Metropolitan City, jbdibikshyashrestha@gmail.com

²NEA Engineering Company Ltd, rabi.shrestha@neaec.com.np

KEY WORDS: Flood Susceptibility Mapping (FSM), Random Forest (RF), Extreme Gradient Boosting (XGBoost), Artificial Neural Network (ANN)

ABSTRACT:

Floods are one of the most destructive natural hazards, causing significant human loss. Identification of flood-prone areas is a substantial need for effective planning and risk management. This study aims to generate flood susceptibility maps for the West Rapti River Basin incorporating three machine learning models: Random Forest (RF), Extreme Gradient Boosting (XGBoost), and Artificial Neural Network (ANN). Among the models, XGBoost achieved the highest predictive performance with an accuracy of 0.9706, followed by RF (0.9510) and ANN (0.9412). Variable importance analysis showed that distance from the river is the most influential factor. The resulting flood susceptibility maps indicate that approximately 30% of the basin is highly susceptible to flooding, primarily in low lying areas near river channels. The findings demonstrate the effectiveness of machine learning approaches in flood susceptibility assessment. This study provides valuable insights for disaster risk reduction and early warning systems in the West Rapti River Basin.

1. INTRODUCTION

1.1 Background

Floods are considered as one of the most catastrophic natural disasters that has affected a large population worldwide, causing significant damage to the environment as well as socio-economic systems (Bhattraï & Ghimere, 2023). It ranks among the most devastating natural disaster that severely affect human safety and infrastructure (Nusit et al., 2025). Their increasing occurrence depends on both climatic factors such as heavy rainfall, snowmelt, and extreme weather conditions and human activities, including deforestation, rapid urban growth, and improper land use practices (Asrade et al., 2026) which has resulted in billions of dollar in damages along with disrupting livelihoods especially in vulnerable region of the world (Rahman et al., 2025).

The assessment of extreme events such as floods is important for mitigating risk and adapting sustainable strategies —(Hussain et al., 2023). In order to access their associated risk, damage and spatial extend, many researchers have focused on estimating and explaining flood hazards for which reliable and accurate Flood Susceptibility Mapping (FSM) is essential (Seydi et al., 2023). FSM quantifies the risk of flooding in a specific region in accordance to its relationship with its causes (Seydi et al., 2023). It reveals flood-prone areas under specific conditions of topography, hydrology, land cover, rainfall, and artificial constructions (Nguyen et al., 2023). Traditionally, FSM has applied quantitative, semi-quantitative and qualitative methodologies which often face uncertainties (Abdo et al., 2025).

In recent years, Machine learning techniques have arisen as powerful alternative to model flood susceptibility due to their ability to capture relationship efficiently (Nusit et al., 2025). High level Machine learning models such as: Artificial Neural Network (ANN), decision trees can predict floods in low computational costs without in-depth knowledge of physical and hydrological processes involved (Kaur et al., 2025; Nusit et al., 2025). For instance, (Nguyen et al., 2023) achieved accuracy of (AUC>0.9), training ML models: XGBoost, RF, CART and LightGBM using a set of 11 topological and hydrological variables. Despite these studies, the issue of which model performs better in a particular geographical location is still a prevailing issue.

Nepal is extremely vulnerable to flood events due to its complex geology, topography and climatic events due to which flood events occur frequently (Bhattraï & Ghimere, 2023). West Rapti River Basin (WRRB), located in the mid-western part of Nepal, is one of the flood prone river basins that is inundated each year due to heavy rainfall (Bhattraï & Ghimere, 2023). Literature shows that despite being extremely vulnerable to flood events, most previous studies have adapted traditional approach to map flood susceptibility in this river basin. Given this context, this study aims to map flood susceptibility in West Rapti River basin and evaluate the performance of three different machine learning models: Random Forest (RF), Xtreme Gradient Descent (XGBoost) and Artificial Neural Network (ANN) along with 10 different multi-sourced flood inducing variables. The findings of this study can assist in early warning systems, risk management measures and proper infrastructure planning

2. OBJECTIVES

The main objective of this research includes:

1. Generate Flood Susceptibility Maps (FSMs) for Random Forest (RF), Xtreme Gradient Descent (XGBoost) and Artificial Neural Network (ANN) models,
2. Evaluate and validate the models using statistical measures,
3. Identify flood vulnerability in terms of land use type and affected settlements.

3. MATERIALS AND METHODS

3.1 STUDY AREA

- a) The study area for this research is West Rapti River Basin (WRR), located in the mid-western part of Nepal with an area of 6971 km². It is one of the tributaries of Kamali River (known as Ghagra River in India). The boundary of the basin extends from 27°40'35" N to 28°34'21" N latitude and 81°39'23" N to 83°09'39" E longitude. This river basin stands at a maximum elevation of 3665m and minimum elevation of 125m. (river atlas of nepal) The Rapti River in this basin originates in the central highlands of Nepal and flows southward. The basin includes several tributaries such as: Arun Khola, Jhimruk Khola, Dundhuwa River, Mari Khola and Lungri khola. The river flows downstream from the junction of the Jhimruk and Madi Khola. With an average slope of 16.8%, the runoff is mainly caused by monsoon rainfall and groundwater (Bhattraï & Ghimire, 2023).

b)

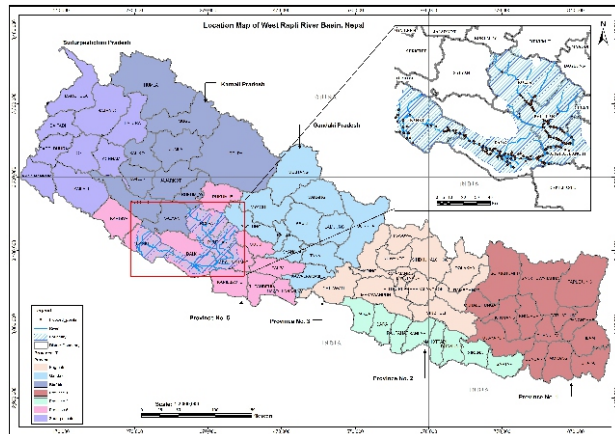


Figure 1: Location Map of West Rapti River Basin

c) The upper portion of the basin (>2000 meter from mean sea level) experiences a temperate climate with dry winters and warm summer and hot summers below 2000 meters. In contrast, the lower portion of the basin has tropical climate. During summer, temperatures in the lower WRRB can exceed 45 degrees Celsius, while in the upper WRRB temperature drop below 2 degrees Celsius in winter, which shows a wide variation of climate across the basin. WRRB experiences four main seasons: Pre monsoon (March–May), Monsoon (June–September), Post-monsoon (October–November), and Winter (December–February) (Talchabhadel et al., 2021). The average annual rainfall of this river basin is 1587mm (Secretariat, 2024). The study area receives summer monsoon rainfall from June to September which accounts for about 80% of the total annual rainfall. The relative humidity ranges from around 60% in May to more than 90% in January (Bhattraï & Ghimire, 2023).

3.2 Data Sources

The different types of datasets used in this study, along with their sources are presented in Table 1. These datasets are analysed using GIS and ESA SNAP Software to evaluate various flood conditioning factors and to identify areas with high flood risk in the WRRB.

Table 1: Datasets used and their sources

S.N	Datasets	Source
1.	SRTM DEM (30m)	USGS
2.	Soil/Soil Moisture (9 km)	FAO/UNESCO, SMAP
3.	Land Use (10m)	Esri/Sentinel 2
4.	Rainfall (5 km)	Chirps
5.	NDVI (30 m)	Landsat 8
6.	Historic Flood Points(10m)	Copernicus/Sentinel 1
7.	Nepal Boundary/ River Network	National Geoportal of Nepal
8.	River basin boundary	HydroSHEDS

3.3 Research Methodology

a) This study employed a remote sensing and machine learning based approach to develop flood susceptibility maps for the West Rapti River Basin (WRRB). The overall methodology integrates satellite image processing, spatial analysis, and machine learning techniques to identify areas vulnerable to

flooding in the study area.

- b) The pre-flood and post-flood Sentinel-1 Synthetic Aperture Radar (SAR) images from the Copernicus Open Access Data Platform was collected. Three major historical flood events that occurred in 2017, 2019, and 2024 were selected for the analysis. Sentinel-1 imagery was chosen because of its ability to acquire data under all weather conditions, including cloudy environments during flood events.
- c) The collected Sentinel-1 images were preprocessed using the European Space Agency's Sentinel Application Platform (SNAP). The preprocessing procedure included the application of orbit files, subsetting of the study area, thermal noise removal, radiometric calibration, speckle filtering, terrain correction, and band mathematics for the identification of water surfaces. These preprocessing steps improved the quality and reliability of the satellite data for flood mapping.

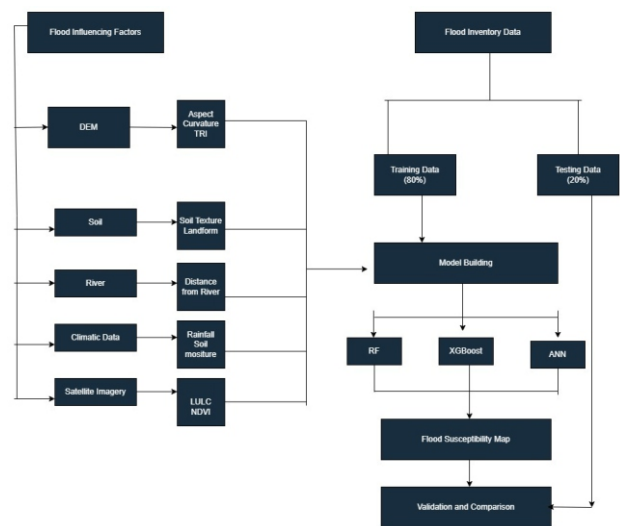


Figure 2: Methodological Flowchart

- d) Following preprocessing, flooded areas were identified using thresholding techniques, change detection methods, and manual digitization in QGIS and Google Earth Pro. Flooded points were then extracted from the identified inundated areas for each flood event year (2017, 2019, and 2024). A total of 280 flooded points were collected and labeled as “1” to represent flood occurrence.
- e) To prepare the flood-conditioning dataset, the values of all influencing factors were extracted at the flooded point locations using Google Earth Engine and QGIS. The selected flood-conditioning factors included aspect, curvature, Terrain Ruggedness Index (TRI), rainfall, soil moisture, distance from river, Normalized Difference Vegetation Index (NDVI), soil texture, land use/land cover (LULC), and landform. These factors were selected based on their relevance to flood occurrence and previous flood susceptibility studies.
- f) Similarly, 280 non-flooded points were generated through manual digitization using post-flood satellite imagery. These points were spatially distributed across the study area to ensure balanced representation of non-flooded locations. To minimize spatial autocorrelation and improve model performance, a buffer distance of 2500 meters was maintained between flooded and non-flooded points. The non-flooded points were labeled as “0”.

- g) The final dataset consisted of 560 points, including both flooded and non-flooded samples. Prior to model development, the dataset was cleaned by removing null values and applying Interquartile Range (IQR) capping to reduce the influence of outliers. In addition, collinearity analysis was performed among the input variables to examine multicollinearity. The correlation values for all variables were found to be below ± 0.5 , indicating the absence of significant multicollinearity among the predictors.
- h) The prepared dataset was then divided into training and testing datasets using an 80:20 ratio, where 80% of the data were used for model training and 20% were used for model testing and validation. Finally, three machine learning models Random Forest (RF), Extreme Gradient Boosting (XGBoost), and Artificial Neural Network (ANN) were applied to generate flood susceptibility maps for the West Rapti River Basin. The overall methodological framework adopted in this study is illustrated in Figure 2.

3.3 Flood Influencing Factors

Studies have identified four main categories of factors that influence flood occurrence: geomorphological, geological, hydrological and anthropogenic factors (Asrade et al., 2026). Based on these studies, availability of relevant data and avoiding multicollinearity among the input variables, in the study area, nine flood conditioning factors were selected for analysis. These factors include Aspect (direction that a slope faces), Curvature (shape of the terrain surface), Terrain Ruggedness Index (TRI) (quantifies how uneven or rugged the surface is by calculating the average variation in elevation), Rainfall (amount, intensity and duration of rain), Soil Moisture (amount of water present in the soil), Distance from River, Normalized Difference Vegetation Index (NDVI) (remote sensing indices used to measure the density and health of a vegetation), Soil Texture (relative proportion of mineral particles in soil) and Land Use Land Cover (LULC).

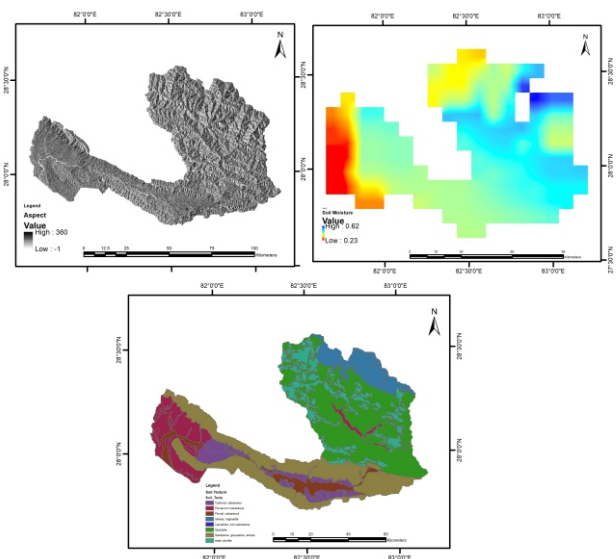
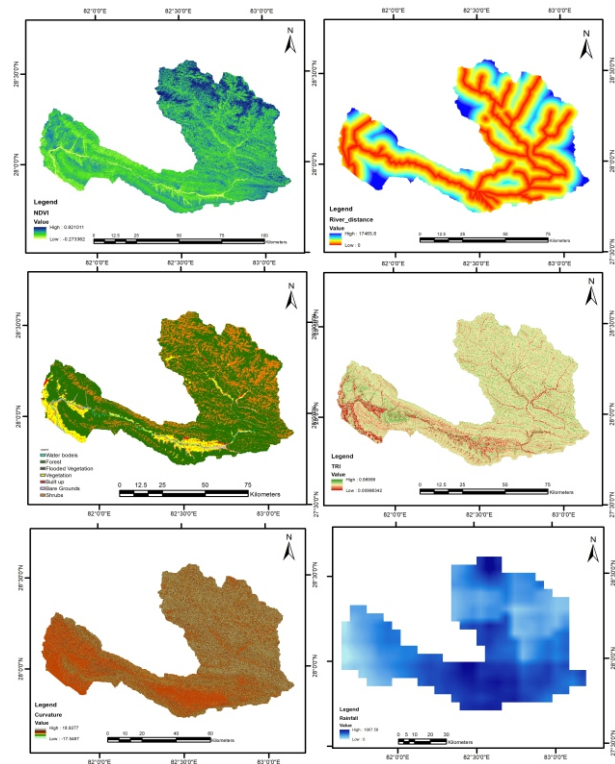


Figure 3: Major factors that influence flood occurrence as represented in maps

3.4 Multicollinearity analysis

Multicollinearity analysis refers to the process of identifying the degree of correlation between independent variables in a machine learning model. It is an important step in flood susceptibility assessment as highly correlated variables can distort model performance. In this study, two commonly used multicollinearity test methods Variance Inflation Factor (VIF) and Pearson Correlation Coefficient (PCC) are employed to evaluate multicollinearity. VIF measures the increment in the variance of predicted regression coefficient due to collinearity with other predictors. Similarly, Pearson Correlation Coefficient (PCC) measures the linear relationship between two independent variables. VIF Equation (1) and PCC Equation (2) is formulated as shown:

$$VIF = \frac{1}{1 - R^2} \quad (1)$$

$$PCC = \frac{\sum_{i=1}^n (X_i - \bar{X})(Y_i - \bar{Y})}{\sqrt{\sum_{i=1}^n (X_i - \bar{X})^2} \sqrt{\sum_{i=1}^n (Y_i - \bar{Y})^2}} \quad (2)$$

Where, R^2 represents the unadjusted coefficient of determination, X_i and Y_i represents the individual input variables and $\bar{X}$ and $\bar{Y}$ are the mean of X and Y respectively.

3.5 Machine learning Algorithms

3.5.1 Random Forest (RF)

Random Forest (RF), is an ensemble learning algorithm used for both classification and regression tasks. It performs by combining multiple decision trees, which increases stability and reduces variance. RF is based on bootstrap aggregating (bagging), where the final prediction is obtained by averaging the outputs of several trees, as shown in Equation (3):

$$\hat{Y} = \frac{1}{M} \sum_{m=1}^M hm(x) \quad (3)$$

where, $\hat{Y}$ represents the predicted output, M is the total number of decision trees, and $hm(x)$ is the prediction from the mth decision tree for input variables x. In flood susceptibility studies, RF is advantageous because it can handle complex and diverse datasets (Abdo et al., 2025; Rahman et al., 2025).

3.5.2 Extreme Gradient Boost (XGBoost)

Extreme Gradient Boost (XGBoost) is a type of tree-based ensemble machine learning technique that works based on the gradient boosting approach, where decision trees are built one after another. Each new tree is created by correcting the errors made by the previous trees, and this process continues until the overall loss function is minimized.

XGBoost develops and ensemble of decision trees, using the following formulation Equation (4):

$$\hat{y}_i = \sum_{k=1}^K f_k(x_i), f_k \in F \quad (4)$$

where, $\hat{y}_i$ is the predicted output at location i , K is the number of trees, and $f_k(x_i)$ is the prediction from k th decision tree for the i th location based on input variables. F is the space of all decision trees.

XGBoost is widely used in flood susceptibility mapping because it can effectively analyse complex data such as topography, climate, soil, and vegetation, and identify the most important factors influencing flood risk. It manages overfitting by adding regularization terms (Abdo et al., 2025; Rahman et al., 2025).

3.5.3 Artificial Neural Network (ANN)

ANN is a machine learning model inspired by the human brain organized into input, hidden and output layers. ANN has the ability of identifying patterns and modelling complex and non-linear relationships. The relationship between input and output in ANN can be expressed as Equation (5):

$$Z = f(\sum_{i=1}^n w_i x_i + b) \quad (5)$$

where, z is the predicted output by ANN, x_i is the input independent variable, w_i represents the connecting weights, b stands for bias and f is the activation function. In flood susceptibility mapping, ANN possesses a high significance due to its ability to model non-linear relationships, handle large and complex datasets (Abdo et al., 2025; Rahman et al., 2025).

3.6 Accuracy Assessment

After the final cleaning of the dataset, 80% of the data was used for Machine Learning training purposes and the rest 20% of the dataset was used for testing and validation. To ensure unbiased and representative split of the data, random sampling was employed. The accuracy and the performance of the predictive models were assessed using: Accuracy, Recall, F1-score and Area Under the Curve- Receiver Operating Characteristics (AUC-ROC) Curve.

3.6.1 Accuracy

It measures the overall correctly classified flood prone and non-flood prone areas. Accuracy is calculated by Equation (6):

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \quad (6)$$

where, TP, TN, FP and FN stand for True Positive, True Negative, False Positive and False Negative respectively (Abdo et al., 2025).

3.6.2 Recall

Recall measures the ratio of accurately identified flood prone areas to the total number of actual flood prone areas. Recall is calculated by Equation (7):

$$\text{Recall} = \frac{TP}{TP+FN} \quad (7)$$

where, TP (True Positive) is the correctly predicted flood area and FN (False Negative) is the actual flood area that the model missed (Halder et al., 2024).

3.6.3 F1-Score

F1-Score measures the balance between Recall and Precision particularly beneficial when the data is imbalanced. F1-Score is calculated by Equation (8):

$$\text{F1-Score} = \frac{2 \times TP}{2 \times TP + FP + FN} \quad (8)$$

Where, TP is True Positive, FP is False Positive and FN is False Negative (Halder et al., 2024).

3.6.4 Area Under the Curve - Receiver Operating Characteristics (AUC-ROC)

AUC measures how accurately the model distinguishes between flooded and non-flooded areas whereas ROC is the graphical representation of AUC value. AUC is calculated by Equation (9):

$$\text{AUC} = \sum TP + \sum TN / (K + S) \quad (9)$$

where, K represents the total number of flooded events and S represents the total number of non-flooded events (Abdo et al., 2025).

4. RESULTS AND DISCUSSION

4.1 Multicollinearity analysis

Multicollinearity among the nine input variables was evaluated using the Pearson Correlation Coefficient (PCC) and Variance Inflation Factor (VIF). The result indicates that all variables are free from multicollinearity, as all PCC values are below 0.6 and all VIF values are less than 5. The highest PCC value was observed between Soil Texture and NDVI (0.39), while the lowest was between Curvature and NDVI (-0.01). Similarly, the highest VIF value was for NDVI (1.58), and the lowest was for Aspect (1.01). These results suggest that there is no significant correlation among the variables, and each variable can be considered independent. The value of PCC and VIF for each variable is shown in Table (2):

Table 3: Value of PCC and VIF for each variable

Variables	PCC	VIF
NDVI	0.151	1.582
TRI	0.116	1.130
Rainfall	0.041	1.180
LULC	0.111	1.201
Curvature	0.077	1.031
Aspect	0.032	1.014
River distance	0.300	1.243
Soil Texture	0.110	1.336
Soil Moisture	0.056	1.327

4.2 Importance of Variables

The importance of the nine input variables was evaluated using feature importance graph in order to understand their contribution to the model. The results indicate that river distance is the most significant variable across all the three models, with an importance score of 0.30, indicating its strong effect on the outcome. In contrast, Aspect has the lowest contribution, with an importance score of 0.03, indicating a weak effect in the model's outcomes.

4.3 Model Performance and Validation

Three Machine Learning models: Random Forest (RF), Extreme gradient Boosting (XGBoost) and Artificial Neural Network (ANN) were employed for flood susceptibility mapping. These models were particularly selected due to their ability to handle complex and non-linear relationships. The optimal parameters of Machine learning algorithms or the hyperparameter tuning parameters was identified using GridSearch CV method which is a technique used in Machine Learning to find the optimal combination of parameters for a model. The final optimal parameter for each model is presented in Table (3):

Table 3: Final optimal parameters for each model

Model Name	Optimal Parameters
RF	n_estimators = 128, max_depth = 16, max_features = 'sqrt', min_sample_split = 2, bootstrap = 'True'
XGBoost	N_estimators = 150, max_depth = 4, learning rate = 0.08, gamma = 0.1, sub_sample = 0.85
ANN	hidden_layer_sizes = (128,), activation = 'relu', batch_size = 64, learning_rate = 0.005, solver = 'adam'

The final susceptibility map was prepared from the predicted probabilities of the best model which was further classified into 5 categories: very low, low, moderate, high and very high susceptibility using the jensky classification method that minimize variance within classes while maximizing differences between them. The final values of the model suggest that 27.64%, 30.87% and 33.01% of the total area of the basin is highly susceptible to the flood. Overall, almost 30% of the basin is highly susceptible to flood which is mainly confined to the western part of the basin. The final flood susceptibility map from three different models is shown in Error! Reference source not found.

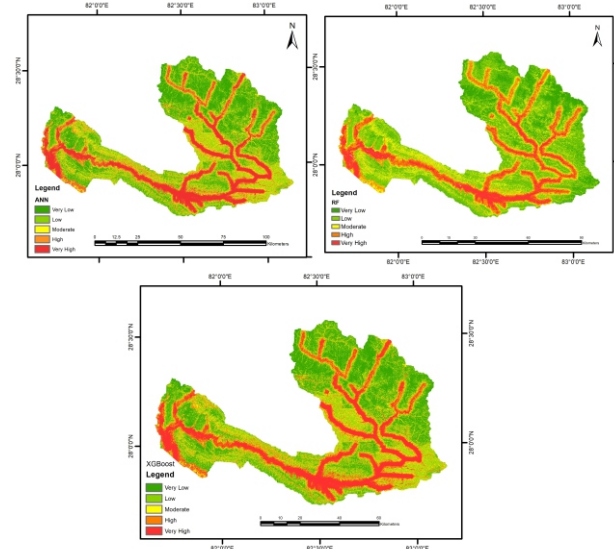


Figure 5: Final Susceptibility Maps as per different models classified under jensky classification method

4.3.1 Model Validation

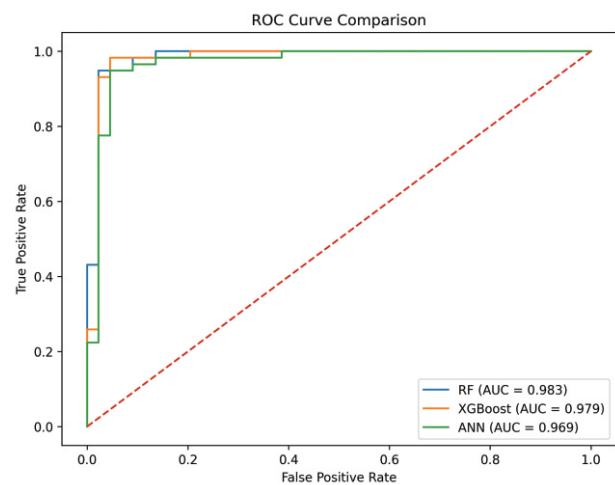
The performance of each model was evaluated using four different statistical measures which include accuracy, recall, f1-score and AUC-ROC Curve. In this study, each model has been trained using a 10-fold cross validation method in order to avoid

overfitting of the model. All the performance evaluation metrics are shown in Table (4):

Table 4: Performance evaluation metrics

ML Model	Accuracy	AUC	F1-Score	Recall
RF	0.9510	0.9828	0.9565	0.9483
XGBoost	0.9706	0.9788	0.9744	0.9828
ANN	0.9412	0.9690	0.9474	0.9310

XGBoost model attained the highest accuracy of 0.9706 followed by RF (0.9510) and ANN (0.9412). Regarding, the values of F1-Score and Recall for models they have achieved as follows : XGBoost (F1-Score is 0.9744, Recall is 0.9828), for RF (F1-Score is 0.9565, Recall is 0.9483) and for ANN (F1-Score is 0.9474, Recall is 0.9310). Regarding AUC, RF, XGBoost and ANN has acquired accuracy of 0.9788, 0.9828 and 0.9690 respectively as shown in Figure 6.



1. DISCUSSION

- The West Rapti River Basin (WRRB) is highly susceptible to recurrent flood events, which significantly affect human life, infrastructure, agriculture, and the regional economy each year. In recent decades, rapid anthropogenic activities and the increasing impacts of climate change have intensified the frequency and severity of flooding events, highlighting the urgent need for accurate flood susceptibility assessment and management strategies (Rahman et al., 2025). In this context, the present study employed data driven machine learning approaches to develop flood susceptibility maps for the WRRB, differing from previous studies that primarily relied on multi-criteria decision making techniques and conventional statistical approaches.
- A total of nine flood conditioning factors were integrated with flooded and non-flooded sample points to evaluate flood susceptibility across the basin. Previous research has demonstrated the effectiveness of machine learning techniques in flood susceptibility mapping due to their ability to model complex nonlinear relationships among environmental variables (Abdo et al., 2025; Rahman et al., 2025). The flood susceptibility maps generated by all three machine learning models consistently indicated that areas located in close proximity to river channels and water bodies are highly vulnerable to flooding. This finding is consistent with the geomorphological characteristics of the WRRB, which is predominantly composed of low-lying and relatively flat Terai plains that facilitate flood inundation during intense rainfall events.

- c) Although precipitation is considered the primary triggering factor for flood occurrence, several additional environmental and topographic variables also play significant roles in influencing flood susceptibility. In the present study, variables such as distance to river, land use/land cover (LULC), soil moisture, and topographic characteristics contributed considerably to model performance. Among these factors, distance to river emerged as the most influential predictor across all models, whereas aspect demonstrated the least influence on flood occurrence. The dominance of river proximity as a controlling factor can be attributed to the hydrological behavior of the basin, where river overflow and lateral expansion during monsoon periods are the major causes of inundation.
- d) The performance evaluation of the models demonstrated excellent predictive capability, with overall accuracy values ranging from 0.94 to 0.97. The strong performance of the models can largely be attributed to their ability to capture nonlinear relationships and interactions among flood conditioning variables. Among the evaluated models, XGBoost achieved the highest predictive performance. The superior performance of XGBoost may be associated with its regularization capability, which effectively minimizes overfitting while enhancing model generalization and predictive accuracy. Similar findings were reported by Li et al. (2026), who identified XGBoost as the best-performing model among several machine learning algorithms for flood susceptibility assessment. In contrast, the Artificial Neural Network (ANN) model demonstrated comparatively lower performance, which may be associated with limitations related to training data volume, computational constraints, and model optimization requirements.
- e) Despite the satisfactory predictive performance obtained in this study, several limitations remain that should be addressed in future research. One of the primary concerns is the potential risk of overfitting, particularly in tree based ensemble models such as Random Forest (RF) and XGBoost. Although the present study implemented 10 fold cross-validation and hyperparameter tuning to improve model robustness, overfitting remains a persistent challenge in machine learning applications. Future studies may further reduce this issue through the incorporation of higher-resolution field based datasets and more representative hydrological observations, which could improve the spatial accuracy of susceptibility predictions. Additionally, the present study incorporated only three historical flood events due to data limitations. The inclusion of a larger number of historical flood records and long term hydrometeorological datasets could further enhance model reliability.
- f) Overall, the findings of this study demonstrate the significant potential of machine learning approaches, particularly XGBoost, for flood susceptibility mapping in data scarce regions such as the West Rapti River Basin. The generated flood susceptibility maps can support policymakers, disaster management authorities, and urban planners in implementing effective flood mitigation, land use planning, and disaster preparedness strategies for reducing future flood risk in the region.

2. CONCLUSION

- a) Flooding is one of the most destructive natural hazards affecting the West Rapti River Basin (WRRB), causing significant impacts on human life, infrastructure, agriculture, and regional socio-economic activities. Therefore, flood

susceptibility mapping is essential for effective flood risk assessment, disaster preparedness, and the development of early warning systems. The present study aimed to classify the WRRB into different flood susceptibility zones and to evaluate the performance of various machine learning (ML) models for flood susceptibility prediction. For this purpose, a total of 560 flooded and non-flooded sample points were collected from three major historical flood events that occurred in 2017, 2019, and 2024. In addition, nine flood conditioning factors were incorporated to analyze their influence on flood occurrence. These datasets were used to train and evaluate three machine learning models, namely Extreme Gradient Boosting (XGBoost), Random Forest (RF), and Artificial Neural Network (ANN).

- b) The results revealed that distance to river was the most influential factor controlling flood susceptibility within the basin, emphasizing the strong hydrological influence of river proximity on flood occurrence in the predominantly flat Terai region. Among the evaluated models, XGBoost demonstrated the highest predictive performance, outperforming RF and ANN in terms of overall accuracy and model reliability. The generated flood susceptibility maps indicated that approximately 30% of the total basin area falls within highly susceptible flood zones, whereas nearly 58% of the basin is categorized under low flood susceptibility. The highly susceptible areas are primarily concentrated near river channels and water bodies.
- c) The findings of this study provide valuable insights into the spatial distribution of flood prone areas within the WRRB and can support policymakers, planners, and disaster management authorities in implementing effective flood mitigation and risk management strategies. Furthermore, the proposed machine learning based methodology demonstrates strong potential for application in other flood prone regions for hazard assessment and susceptibility mapping.

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AUTHOR INFORMATION



Name : **Dibikshya Shrestha**
Academic Qualification : Geomatics Engineer
Organization : Kathmandu Metropolitan City
Current Designation : GIS Engineer
Work Experience : 2 years
Published Article : 2

AI-DRIVEN LAND TENURE MAPPING FOR SUSTAINABLE LAND GOVERNANCE: A REVIEW WITH REFERENCE TO NEPAL

Siwangi Pokharel^{1*}, Subash Ghimire², Dipesh Prajapati³
^{1,2,3} Department of Geomatics Engineering, Kathmandu University
 siwangi37@gmail.com, subash_ghimire@ku.edu.np, dipeshpraja70@gmail.com

KEYWORDS: Artificial Intelligence, Land Tenure Mapping, Sustainable Land Governance, GIS, Nepal, Cadastral Mapping

ABSTRACT

Land tenure insecurity is a major challenge in Nepal, affecting millions of households across its diverse socio-economic and geographic landscape. A large portion of Nepal's land system is composed of informal, customary, and communal tenure arrangements, which are challenging to fully capture using traditional cadastral mapping techniques and are also often slow and expensive. To improve the land tenure system and sustainable land governance in Nepal, this paper examines the use of AI-driven methods integrating Machine Learning (ML), Deep Learning (DL), Geographic Information Systems (GIS), and participatory mapping. The study analyses how Artificial Intelligence (AI) can automate parcel boundary detection, land-use classification, change detection, and the integration of informal tenure into formal land administration systems, drawing on secondary data from government and international sources, evidence from comparative international practices, and Nepal's national land reform context. Secondary data indicate that approximately 35% of Nepal's land remains unregistered in the cadastral system; informality rates are particularly high in mountainous and hilly regions. The study suggests that AI-driven mapping can enhance evidence-based policymaking, reduce costs, and increase mapping efficiency. However, issues such as algorithmic bias, gaps in digital infrastructure, limited institutional capacity, and unclear legal frameworks for AI-generated outputs must be addressed immediately. The study concludes that AI-based land tenure mapping offers a viable route to just and sustainable land governance in Nepal when incorporated into inclusive governance frameworks and backed by legislative reforms.

1. INTRODUCTION

Land is among the fundamental resources in any society, which supports economic growth, food security, livelihoods, and environmental sustainability. Due to the country's varied topography, a history of feudal land concentration, numerous overlapping legal frameworks, and long-standing informality in land occupancy and transactions, Nepal has a particularly complex land tenure system. Despite multiple government land reform efforts since the 1960s, the country still faces issues such as unequal land distribution, unregistered land rights, inadequate cadastral coverage, and poor institutional coordination (Adhikari, 2011). Only about 65% of Nepal's total land area is covered by the Department of Land Management and Archives' (DoLMA) national cadastral database; the remaining 5.1 million hectares are not officially registered (MoLMCPA, 2019). This number is disproportionately concentrated in isolated, hilly, and mountainous regions, where marginalised groups like women, Dalits, and indigenous peoples face the highest rates of tenure insecurity. (MoLMCPA, 2019). According to Enemark et al. (2014), traditional cadastral mapping methods that depend on manual digitisation, plane table methods, and ground surveys are costly, time-consuming, and often unavailable to these communities. This hinders agricultural investment and fuels ongoing land conflicts. According to a 2020 World Bank assessment, over 1.2 million parcels in the Terai region alone remain disputed or informally occupied, discouraging agricultural investment and contributing to ongoing land conflicts. The rapid advancement of AI, GIS, and Remote Sensing (RS) technologies is creating revolutionary new opportunities for global land administration (Mishra et al., 2025; Ndiema, 2024). At scales and speeds previously unattainable with manual methods, machine learning algorithms applied to high-resolution satellite imagery and UAV data can automate parcel boundary detection, land use classification, and change monitoring (Cigna & Tapete, 2021). According to Mishra et al. (2025) and Zhu et al. (2017), deep learning architectures such as Convolutional Neural Networks (CNNs) have achieved land cover classification accuracies exceeding 90% across heterogeneous landscapes, including those typical of Nepal's mixed terrain environments. International frameworks such as the Fit-for-Purpose (FFP) Land Administration approach (Enemark et al., 2014) and the FAO Voluntary Guidelines on the Responsible Governance of Tenure

(VGGT) (FAO, 2012) guide accessible, inclusive, and technology-enabled land documentation (Ansari & Ghimire, 2024).

This study examines the potential benefits of AI-driven land tenure mapping for Nepal's sustainable land governance. It analyses the current state of land tenure. It also evaluates the institutional and technical aspects of AI integration. Additionally, it draws comparisons with international practices in countries that have made notable advancements in digital land administration, using secondary data from Nepal's government records, reports from international organisations, and published academic research.

The objectives of this study are: 1) to find out how much land tenure mapping processes can be automated and enhanced by using Deep Learning (DL), Machine Learning (ML), Artificial Intelligence (AI), and GIS; and 2) to assess how much participatory methods can help advance tenure security, sustainable land governance, and the inclusion of informal tenure arrangements in the Nepalese context when combined with AI-driven mapping technologies.

2. METHODOLOGY

This study's qualitative, desk-based research design is predicated on a comprehensive analysis and compilation of secondary data. Given the complexity of land tenure governance, the variety of AI applications, and the requirement to interpret contextual evidence from Nepal's institutional and geographic setting, a qualitative approach is appropriate. Instead of relying on primary field surveys, the study includes information from government policy documents, published academic literature, documented national programs, technical reports from international organisations, and case studies of AI-driven land administration from similar developing country contexts.

The study adopts a three-stage analytical approach: (i) secondary data synthesis from national and international sources to establish the baseline context of Nepal's land tenure situation; (ii) a conceptual analysis of AI and GIS methodologies and their technical applicability to land tenure mapping challenges; (iii) a structured comparative analysis of international case studies from Rwanda, India and Kenya to identify transferable lessons and adaptations. The three-stage approach allows for the systematic

triangulation of evidence across technical, institutional and governance dimensions.

2.1. Secondary Data Sources

Secondary data was systematically gathered from multiple authoritative sources to ensure reliability and comprehensiveness. A literature search was conducted across databases. National-level data on land administration, cadastral coverage, and tenure insecurity were collected from the Ministry of Land Reform and Management, the National Land Policy (Government of Nepal, 2019), the Central Bureau of Statistics (CBS) and the Department of Land Management and Archives (DoLMA) annual reports. Data on land conflict, compensation, and governance practices were drawn from the Nepal Land Governance Assessment Framework (World Bank, 2020) and the Land Alliance Nepal reports (2021). Population and demographic data were obtained from the National Population and Housing Census (CBS, 2021). International comparative data were obtained from FAO technical reports, UN-Habitat publications, World Bank assessments, and peer-reviewed academic journals, including Remote Sensing, Land Use Policy, and the Journal of Computer Science and Technology.

2.2. AI, GIS, and Participatory Mapping Techniques

The conceptual analysis of AI-driven land tenure mapping draws on three interconnected technological methodologies, consistent with the integrated framework described by Mishra et al. (2025) for smart land use planning.

2.3. Machine Learning and Deep Learning for Parcel Mapping

Machine learning (ML) algorithms like Random Forest (RF), Support Vector Machines (SVM), and Gradient Boosting are used to categorise land use and land cover (LULC) categories essential for tenure mapping, such as agricultural land, forest, settlement, and water bodies. (Landsat-8, Sentinel-2)(Mishra et al., 2025; Belgiu and Dragut, 2016). Standard deep learning algorithms, particularly Convolutional Neural Networks (CNNs) and semantic segmentation models such as U-Net, enable pixel-level boundary delineation and object detection from very high-resolution imagery obtained from UAVs and commercial satellites (Zhu et al., 2017). Long Short-Term Memory (LSTM) networks are applied to multi-temporal datasets to detect land use change and model tenure transition dynamics (Reichstein et al., 2019).

2.4. Comparative Analysis Framework

To situate Nepal's experience within broader global trends, a structured comparative analysis was conducted examining AI and digital land administration practices in Rwanda, India, and Kenya--three developing countries that have made notable progress in deploying technology-enabled land governance systems. Four dimensions were used to structure the comparison: (i) the use of AI and GIS tools; (ii) institutional and legal frameworks; (iii) mechanisms for community participation; and (iv) results for tenure security and transparency in governance. In order to determine applicable lessons and necessary context-specific adjustments, Nepal's context was evaluated in relation to these dimensions.

3. RESULTS AND FINDINGS

This section presents the results and findings of the study.

3.1. Current Status of Land Tenure in Nepal

Nepal's land tenure system is characterised by significant complexity, inequality, and informality. According to the Ministry of Land Management, Cooperatives and Poverty Alleviation (MoLMCPA, 2019), approximately 5.1 million hectares, representing about 35% of the total land area, remain

outside formal cadastral registration. Of the registered land, a 2021 assessment by Land Alliance Nepal found that women hold formal ownership rights in only 20.4% of land parcels (Raj Joshi et al., 2021), despite comprising approximately 51% of the population (CBS, 2021). Among Nepal's landless population, Dalits are severely overrepresented, with 41.4% of Madhesi Dalits and 36.7% of Hill Dalits having no land, reflecting systematic exclusion of marginalised groups from formal land rights (IDSN, 2015).

The cadastral system suffers from significant spatial inaccuracies and outdated records. According to a study conducted by the Department of Land Management and Archives (DoLMA) in 2020, a technical investigation, about 40% of cadastral sheets in hilly districts were last updated between 1970 and 1990, making them insufficient for the demands of modern land administration. In the Kathmandu Valley, rapid urbanisation has produced an estimated 350,000 informal or unregistered structures, creating acute tenure insecurity for urban migrants and low-income communities. The Terai region similarly shows approximately 1.2 million disputed or informally occupied parcels, frequently generating land conflicts that burden the judicial system (Land Conflicts in Nepal, 2017). The 2015 Gorkha earthquake destroyed over 600,000 homes, leaving a massive backlog of unresolved property rights claims that manual systems have been unable to adequately handle (National Reconstruction Authority, 2020).

Ansari & Ghimire (2024) empirically documented the institutional fragmentation, lack of transparency, and inefficiency that continue to threaten land governance processes in their study of land acquisition and compensation for the Kathmandu–Terai Madhesh Fast Track Road Project (KTFTRP). Their results showed that 64% of impacted landowners thought compensation procedures were very opaque, 90% thought the process was very complicated and time-consuming, and 64% of participants thought compensation rates were less than 25% of market replacement cost (Ansari & Ghimire, 2024). These results highlight systemic shortcomings in participation, transparency, rule of law, efficiency, and effectiveness, the fundamentals of good land governance.

3.2. AI and GIS Applications for Land Tenure Mapping in Nepal

The results of the secondary data synthesis demonstrate that AI and GIS technologies hold significant and largely untapped potential for addressing Nepal's land tenure mapping challenges. The results are presented in the following subsections.

3.2.1 Machine Learning for Boundary Detection and Land Classification

Mishra et al. (2025) show that the application of ML algorithms to Sentinel-2 and Landsat-8 imagery across Nepal's diverse terrain demonstrates that automated LULC classification can achieve overall accuracies of 85–92%, with Random Forest models consistently outperforming traditional maximum likelihood classification, particularly in mixed-use terrain. Similarly, Li et al. (2021) report comparable performance in diverse landscape settings. CNN-based semantic segmentation models applied to very high-resolution imagery (sub-meter UAV data) have demonstrated strong performance in parcel boundary delineation in peri-urban contexts, significantly reducing manual digitisation effort and associated costs (Zhu et al., 2017).

In the context of Nepal's specific terrain, ML-based classification of Sentinel-2 imagery at 10m resolution has been validated for mapping agricultural land parcels, forest cover, and water bodies in the Gandaki and Koshi river basins. However, the complex topography of Nepal's high mountain zones, combined with persistent cloud cover limiting optical satellite imagery availability to approximately 40–60% of the year in affected

regions, presents significant challenges for consistent ML-based mapping (Robinson et al., 2019)

3.2.2. GIS-Based MCDA as a Complementary Decision Support Tool

While GIS-based Multi-Criteria Decision Analysis (MCDA) is not completely an AI method, it functions as a critical spatial decision-support tool that complements AI-driven mapping by informing where tenure formalisation interventions should be prioritised. In practice, AI outputs such as land-use classifications and parcel boundary maps are most actionable when integrated with a structured prioritisation framework, which MCDA provides. Applying GIS-based MCDA to Nepal's cadastral and socioeconomic data layers enables the systematic identification of areas in greatest need of immediate tenure formalisation, taking into account factors such as infrastructure accessibility, conflict frequency, degree of informality, and ecological sensitivity (Malczewski, 2006). In this way, MCDA bridges the gap between AI-generated spatial data and evidence-based policy decisions. Three priority zones have been identified through such analysis. First, the Terai plains (including Bara, Parsa, and Rautahat districts), where informal occupation is most concentrated. Second, the mid-hill belt (including Sindhupalchok, Kavrepalanchok, and Ramechhap districts), where earthquake-damaged properties remain officially unresolved following the 2015 Gorkha earthquake. Third, the urban fringe zones surrounding Kathmandu, Pokhara, and Biratnagar, where unregistered settlements have increased as a result of rapid immigration (UN-Habitat, 2018; World Bank, 2020).

3.3 Barriers to AI Implementation for Land Tenure Mapping in Nepal

The barriers that currently constrain the systematic adoption of AI-driven land tenure mapping in Nepal are:

1. Digital infrastructure and data availability: Broadband connectivity in rural areas is still limited, and only about 43% of Nepal's population has internet access (NTA, 2021). Most of Nepal's 753 local governments lack reliable connectivity, which is necessary for cloud-based AI processing platforms. In order to enable contemporary AI applications, current national spatial datasets, such as the 1:25,000 topographic series maintained by the Survey Department, must be significantly updated. High-resolution satellite and UAV imagery, although critical for accurate land-tenure mapping, are also expensive and therefore limit the scalability of AI-driven approaches in Nepal.
2. Institutional fragmentation: The various organisations in Nepal that perform activities related to land administration include the Department of Land Management and Archives (DoLMA), the Survey Department, the Department of Urban Development and Building Construction (DUDBC), and provincial and local governments. The development of integrated AI-GIS platforms is hampered by coordination problems and data interoperability barriers (Ansari & Ghimire, 2024).
3. Existing legal framework: The existing legal framework, including Nepal's Civil Code (2017) and Land Act (2021), does not recognise AI-generated cadastral data as legally permissible inputs for land registration or dispute resolution. Consequently, the absence of legal recognition for AI-generated cadastral outputs creates significant uncertainty around the validity of AI-assisted tenure documentation and discourages institutional adoption of these approaches.
4. Algorithmic Bias and Inequitable Data Representation: AI models learn patterns from the data on which they are trained. When training datasets are composed predominantly of imagery and records from well-documented, formally registered land areas—typically lowland urban zones or accessible rural areas—the model develops a systematic bias towards recognising those landscape types and tenure arrangements.

Inequitable data representation refers to this condition: the underrepresentation of informal settlements, indigenous communal territories, and remote mountainous regions in training datasets relative to their actual prevalence on the ground. In Nepal's context, where the areas of greatest tenure insecurity are precisely those that are most remote and least formally documented, this means AI models are likely to perform worst in the communities that need accurate mapping the most. Consequently, uncritical deployment of such models risks producing outputs that reinforce and deepen existing disparities in land administration rather than correcting them (Ndiema, 2024).

5. Capacity Constraints: Nepal lacks qualified GIS and data science experts, especially outside of Kathmandu. While the Survey Department has been exploring geospatial technologies, national and land administration organisations still lack AI-specific expertise, limiting their ability to develop, deploy and maintain AI-driven land mapping systems.

4. DISCUSSION

The findings of the study are discussed in this section.

4.1 Nepal's AI Land Governance in the International Context

The results from Nepal's case can be effectively compared with those from Rwanda, India, and Kenya, three nations that have made significant progress in implementing AI and digital technologies for land governance, to find both attainable benchmarks and lessons that apply to Nepal's situation.

Rwanda exemplifies a prominent, rapid, technologically enabled land formalisation, through a systematic demarcation process that involved community involvement, aerial photography, and analysis of recent satellite imagery. Rwanda registered about 10.4 million land parcels between 2009 and 2013 (Ali et al., 2014). This resulted in nearly universal coverage at a cost of about USD 6–8 per parcel, compared to the global average of USD 20–50 per parcel for conventional methods (World Bank, 2020; UN-Habitat, 2018). AI-generated suitability maps, GIS-based zoning tools, and public dashboards available to both citizens and planners are now features of Rwanda's National Land Use Planning Portal (Ali et al., 2014).

India's experience offers important lessons for a federal and institutionally complex context closer to Nepal. India's Digital India Land Records Modernisation Programme (DILRMP), which aims to digitise all land ownership records and integrate them with GIS platforms, has advanced significantly in states like Karnataka, Andhra Pradesh, and Telangana (Mishra et al., 2025). Even in complex settlement environments, rapid, accurate parcel mapping is achievable, as demonstrated by the SVAMITVA program's use of UAV-based drone surveying, which has mapped over 50,000 villages with sub-decimeter accuracy (Government of India, 2022).

In Nepal's struggle for community and indigenous land rights, Kenya's experience is especially helpful. More than 120 community land parcels totalling 2.3 million hectares in Laikipia County, Kenya (Ali et al., 2014), that had not previously been recorded in official cadastral records were formally registered through a three stage workflow: (i) UAV aerial surveys were conducted to capture high resolution imagery of community land boundaries; (ii) community members participated in ground-truthing and validation of boundary demarcation to ensure local tenure arrangements were accurately reflected; (iii) validated boundaries were digitised and integrated into GIS-based cadastral database for formal registration.

A similar dual legal-technical approach that combines legislative recognition of community tenure with participatory AI-GIS mapping would be beneficial for Nepal's diverse customary tenure landscape, which includes Limbu Kipat, Newari Guthi, and Adivasi Janajati communal territories (Nepal & Marasini, 2018).

4.2. Opportunities for Nepal

Several specific opportunities for Nepal to use AI-driven land tenure mapping within a stronger governance framework are revealed by the comparative analysis. First, with 753 local governments granted authority by the 2015 Constitution, Nepal's federal structure offers a decentralised platform that facilitates the testing and expansion of community-anchored participatory mapping processes that are integrated with the country's AI-GIS infrastructure.

Second, the Survey Department's national topographic database and the ongoing modernisation of DoLMA's Land Information System provide a fundamental spatial data infrastructure that can be enhanced to support AI-driven cadastral applications at relatively low incremental cost (MoLMCPA, 2019). Third, international organisations like UN-Habitat, the World Bank, FAO, and the International Land Coalition are actively supporting land governance reform in Nepal and have demonstrated a willingness to invest in technology-enabled approaches through ongoing projects like the Land Pooling in Urban Areas Project and the Participatory Land Use Management initiative. Fourth, Nepal's growing network of engineering and geomatics graduates trained at Kathmandu University, Tribhuvan University, and Pokhara University offers an emerging human capital base for developing domestic AI-GIS expertise if appropriate training and institutional development investments are made.

4.3. Policy Implications

Based on the analysis, six priority policy actions are recommended for Nepal.

First, legal framework reform is needed. The Land Act (2021) and related regulations should be amended to specifically acknowledge AI-assisted cadastral mapping outputs as legally acceptable inputs for land registration, subject to established community validation and quality assurance standards.

Second, the National AI-GIS land platform should be created. A single, cloud-based National Land Information System under the Survey Department-Nepal's legally designated national mapping agency and primary custodian of spatial data, should incorporate socioeconomic, satellite, cadastral, and participatory data layers and be made available to all 753 local governments.

Third, systematic tenure formalisation using the Fit for Purpose Land Administration (FFPLA) approach (Enemark et al., 2014) represents another alternative. The FFPLA approach should be adopted for the systematic registration of customary and informal tenure, combining community-validated boundary demarcation with AI-assisted imagery interpretation to lower costs and improve coverage.

Fourth, inclusive design and community ownership. All AI-driven mapping programs should require gender-disaggregated data collection, joint titling by default, and indigenous community participation, with clear protocols for capturing women's secondary rights and communal tenure (FAO, 2012).

Fifth, an independent National Geospatial Governance Board should be established with an extensive role to monitor equity outcomes of digital land administration programs, enforce data privacy standards, audit AI systems for algorithmic bias, and guarantee that communities maintain meaningful access to mapping outputs. This ethical governance framework is essential for ensuring that AI-driven approaches serve the public interest.

Sixth, targeted capacity-building programs at national and subnational levels should be established to train GIS and AI professionals, particularly in underserved areas, to enable sustainable implementations of AI-driven land tenure mapping systems.

5. CONCLUSION

This study has examined the potential of AI-driven land tenure mapping and GIS-based Multi Criteria Decision Analysis

(MCDA) – as a complementary spatial decision support tool for prioritising tenure formalisation interventions - to strengthen sustainable land governance in Nepal, using secondary data from Nepal's national land administration, international comparative evidence, and the body of research on AI applications in land management.

The analysis shows that AI approaches- specifically, machine learning and deep learning for parcel boundary detection and LULC classification supported by complementary GIS-based tools, for informal tenure documentation, provide technically feasible and economical solutions for Nepal's land tenure challenges. Drawing on international evidence, technology-enabled land formalisation is achievable at scale in developing country contexts as long as community involvement, legal recognition, and institutional capacity are suitably developed alongside technical systems. These comparisons also show how Nepal's federal structure, expanding geospatial human capital, and active international development partnerships offer significant enabling foundations for a national AI land mapping program that can be progressively expanded across the country's diverse terrain and tenure landscape.

However, the study also makes it clear that technology alone cannot solve Nepal's land governance issues. Algorithmic bias, gaps in digital infrastructure, the lack of coordination among multiple land administration institutions, the absence of legal recognition for AI-generated cadastral outputs, and the potential for poorly designed digital systems to replicate existing inequalities all require immediate policy attention.

Realising equitable tenure security outcomes requires integrating AI-driven mapping within an inclusive governance framework grounded in principles of participation, transparency, accountability, and the rule of law. Primary data collection through field-based AI-assisted mapping pilots in particular Nepalese districts, detailed evaluation of algorithmic performance across different terrain and tenure types, and co-design procedures with marginalised communities should be the top priorities for future research. When used responsibly and inclusively, AI-driven land tenure mapping is a truly promising path toward sustainable, equitable, and transparent land governance in Nepal.

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AUTHOR INFORMATION



Name : Siwangi Pokharel

Academic Qualification : Bachelor of Geomatics Engineering

Organization : Kathmandu University

Current Designation : Geomatics Engineering Student

SPATIO-TEMPORAL ASSESSMENT OF URBAN HEAT ISLANDS AND FUTURE PREDICTION: A CASE STUDY OF KATHMANDU VALLEY USING OPTICAL REMOTE SENSING

Sandeep Gautam¹, Bibek Karki¹, Namrata Thapa¹, Subekshya Subedi¹

¹Department of Geomatics Engineering, Pashchimanchal Campus, IOE, Tribhuvan University, Pokhara, Nepal
pas077bge040@wrc.edu.np, pas077bge010@wrc.edu.np, pas077bge025@wrc.edu.np, pas077bge046@wrc.edu.np

KEY WORDS: Kathmandu Valley, LST, LULC, NDBI, NDVI, Urban Heat Island, Remote Sensing

ABSTRACT:

Kathmandu Valley has experienced among the most rapid and concentrated urban expansion in South Asia over the past two decades, with direct but incompletely characterised consequences for surface thermal conditions. This study assesses the spatio-temporal evolution of Urban Heat Islands (UHI) across the valley from 2008 to 2023 using multi-temporal Landsat imagery processed in Google Earth Engine (GEE), and projects land surface conditions to 2028. Land Use Land Cover (LULC) was mapped using a Random Forest (RF) classifier at five-year intervals; Land Surface Temperature (LST) was retrieved from thermal bands via an emissivity-corrected inversion. The Normalised Difference Vegetation Index (NDVI) and Normalised Difference Built-up Index (NDBI) were used to quantify vegetation cover and impervious surface intensity and their relationship with LST. A CA-Markov model was used for LULC projection to 2028, followed by RF Regression to forecast LST under projected land-cover conditions. Pearson's correlation analysis yielded $r = +0.751$ for LST–NDBI and $r = -0.759$ for LST–NDVI, both statistically significant. Built-up area expanded from 8,720 ha (9.32%) in 2008 to 18,525 ha (19.82%) by 2023, with mean LST peaking at 27.34°C in 2018. UHI intensity was highest in the central built-up core (class mean 1.00–1.19) and negative over forested hillsides (−0.91 to −0.83). By 2028 built-up cover is projected to reach 25.47% of the valley, with mean LST rising to approximately 26.88°C and the central thermal hotspot expanding further. These findings demonstrate that vegetation management and targeted greening in high-density wards can partially counteract UHI intensification, providing quantitative evidence to support climate-resilient land-use planning in the Kathmandu Valley.

1. INTRODUCTION

Global urban populations now exceed 4.2 billion and are projected to reach 6 billion by 2041 (Kuddus et al., 2020). As cities expand, natural land surfaces are progressively replaced by impervious materials such as concrete, brick, and asphalt, which alter the surface energy balance by reducing evapotranspiration and increasing sensible heat flux. This process gives rise to the Urban Heat Island (UHI) effect, a well-documented phenomenon in which urban cores are measurably warmer than surrounding rural zones (de Almeida et al., 2021; Kim and Brown, 2021).

In Nepal, where the national urban growth rate is approximately 3% per year, Kathmandu Valley represents the sharpest point of urban pressure. The valley accommodates close to a quarter of the country's urban population and has seen its built-up footprint expand more than fourfold between 1989 and 2016 (Ishtiaque et al., 2017). Prior research has established the broad outlines of this thermal problem, but with significant gaps. Sarif et al. (2020) documented LULC changes and their UHI consequences in the valley between 1988 and 2018 but did not produce quantitative LST–index correlations. Mishra et al. (2019) evaluated the NDVI–LST relationship from 2000 to 2018, confirming negative correlation but offering no future projections. Maharjan et al. (2021) placed Kathmandu among the most thermally intense cities in South Asia using multi-city comparisons, yet did not model future LULC or LST change. Most recently, Khatri et al. (2025) used GEE and CA-Markov to project UHI conditions to 2030, but did not couple those LULC projections to a machine-learning-based LST forecast. Collectively, these studies leave two gaps unaddressed: (i) the absence of a machine-learning-derived LST prediction conditioned on projected LULC, and (ii) a quantitative analysis of the NDVI–NDBI–LST relationships across multiple epochs within the valley.

The present study was designed to address both gaps. Using multi-temporal Landsat imagery processed in GEE alongside analysis conducted in QGIS and Python, a connected workflow spanning 2008 to 2028 was constructed. The specific objectives of this study are: (i) to produce LULC, NDVI, NDBI, and LST maps for four epochs - 2008, 2013, 2018, and 2023; (ii) to analyse spatio-temporal changes in each parameter and quantify their mutual relationships; (iii) to project LULC and LST conditions for 2028 using CA-Markov and RF Regression respectively; and (iv) to draw practical implications for UHI management in the valley. By integrating classification, spectral index analysis, spatial modelling, and machine-learning prediction into a unified framework, the study aims to provide a reproducible and evidence-based contribution to the growing body of remote sensing literature on Himalayan urban thermal environments.

2. STUDY AREA

Kathmandu Valley (85°11'–85°33'E; 27°24'–27°49'N) covers ~570 km² across three districts: Kathmandu, Lalitpur, and Bhaktapur. The bowl-shaped valley floor lies at ~1,400 m above sea level, enclosed by hills rising upto ~2,800 m that traps heat and pollutants, amplifying UHI intensity. The climate is subtropical highland (monsoon-influenced), with ~1,400 mm annual rainfall (June–September). Population surpasses 2.5 million, growing at ~6.5% per year, making it one of South Asia's fastest growing urban city, creating urgency for predictive UHI modeling (Timsina, 2020). The Bagmati River and tributaries surround the floor but face intense encroachment pressure.

Kathmandu Valley was selected as the study area for four reasons: (1) it holds nearly one-quarter of Nepal's urban population, making UHI effects particularly consequential for human health and energy demand; (2) its bowl-shaped topography (1400 m floor, surrounded by ~2800 m hills) traps heat and pollutants,

amplifying UHI intensity; (3) urban growth rate (~6.5% annually) ranks among the fastest in South Asia, creating urgency for predictive UHI modeling; and (4) previous studies documented

7–9°C center-rural temperature differentials, establishing a baseline for comparison.

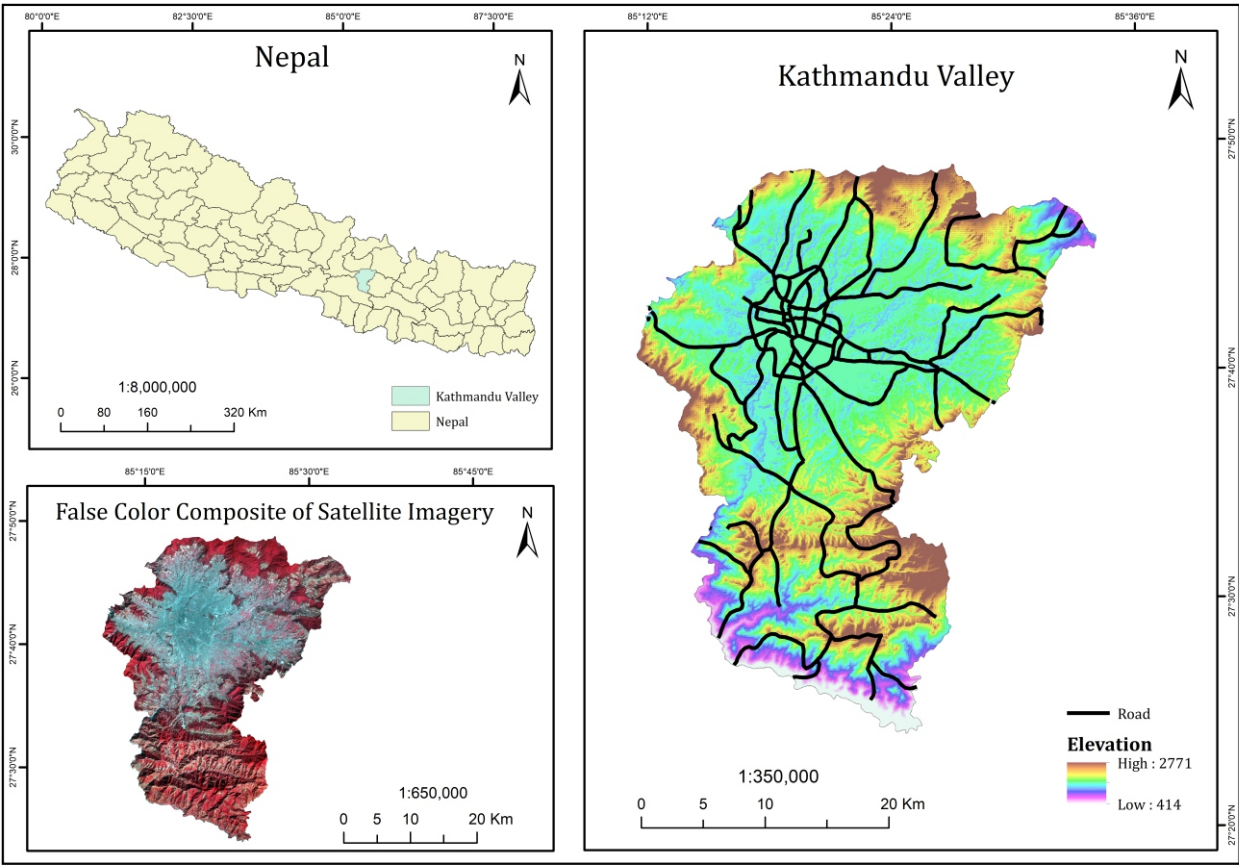


Figure 1. Kathmandu Valley study area: administrative boundary, elevation (SRTM), and road network

3. DATASETS AND METHODS

3.1 Data Sources

Landsat 8 OLI/TIRS (30/100 m) was used for 2013, 2018, and 2023 and Landsat 5 TM (30/120 m) for 2008, all sourced from the GEE catalog with minimal cloud cover. MODIS MOD11A1.061 (1 km daily LST) provided independent validation data. Ancillary data comprised the valley administrative boundary (Survey Department), road network (ICIMOD), and SRTM DEM (30 m).

Table 1. Datasets used in the study

Dataset	Source	Resolution	Epoch
Landsat 8 OLI/TIRS	GEE Catalog	30/100 m	2013, 2018, 2023
Landsat 5 TM	GEE Catalog	30/120 m	2008
MODIS MOD11A1.06	GEE Catalog	1 km	2013 (validation)
Valley Boundary	Survey Dept.	1:1,000,000	—
Road Network	ICIMOD	1:250,000	—
DEM (SRTM)	NASA	30 m	—

3.2 Workflow Overview

The end-to-end methodological workflow is illustrated in Figure 2. Spectral processing, classification, and index computation were carried out in GEE. LULC change analysis and CA-Markov simulation were conducted in QGIS using the MOLUSCE plugin. Pearson's correlation analysis, RF Regression modelling, and raster sampling were performed in Python (Jupyter Notebook) using Scikit-learn and Rasterio.

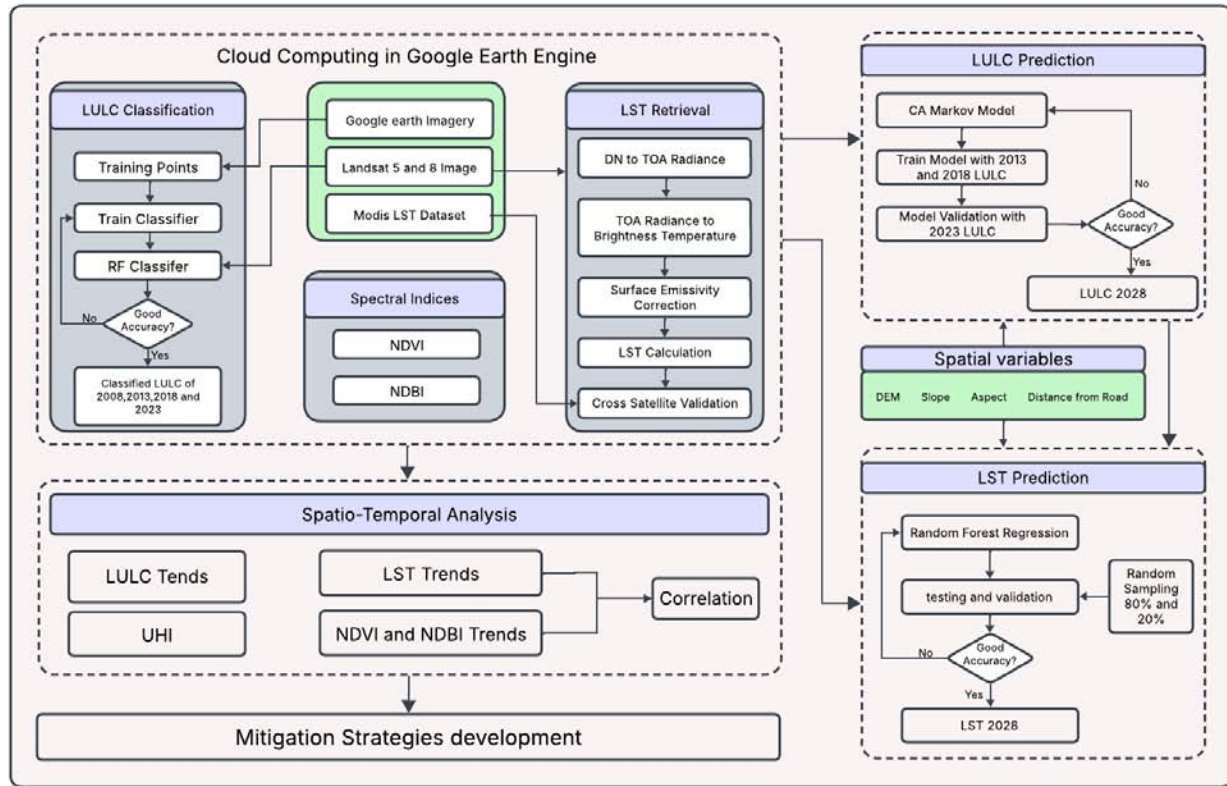


Figure 2. Methodological workflow from data acquisition to UHI prediction for 2028

3.3 LULC Classification

To minimise the influence of seasonal vegetation phenology and residual cloud cover, median annual composites were constructed for each study epoch within GEE. Reference points for five land-cover classes: Forest, Built-up, Water, Agriculture, and Barren were collected by visual interpretation of the Landsat composites alongside Google Earth Pro high-resolution imagery. Training samples per epoch were collected and divided 80:20 into training and validation subsets, ensuring spatial independence between the two sets. A Random Forest (RF) classifier with an ensemble of 100 decision trees was applied; final class assignment for each pixel was determined by majority vote across the trees (Tikuye et al., 2023). Map accuracy was assessed using overall accuracy (OA) and the Kappa coefficient (κ), computed as follows:

$$\text{Overall Accuracy (\%)} = \frac{\text{Correctly Classified Pixels}}{\text{Total Reference Pixels}} * 100 \quad (1)$$

$$\kappa = \frac{\text{Samples} * \text{Corrected Samples} - \sum(\text{column total} * \text{row total})}{(\text{Total Sample})^2 - \sum(\text{column total} * \text{row total})} * 100 \quad (2)$$

3.4 LST Retrieval

LST was derived from the thermal band of each Landsat acquisition: Band 10 for Landsat 8 (central wavelength 10.8 μm) and Band 6 for Landsat 5 (central wavelength 11.5 μm) following a standard four-stage radiometric inversion procedure. First, digital numbers were converted to top-of-atmosphere (TOA) spectral radiance using the gain and offset coefficients provided in the image metadata. Second, brightness temperature was

calculated from the TOA radiance using the Planck function. Third, land surface emissivity (ϵ) was estimated from the NDVI-derived fractional vegetation cover (P_v), following the approach of Sobrino et al. (2004), as expressed in Equations (3) and (4). Fourth, LST was retrieved by solving the radiative transfer equation, given in Equation (5):

$$\epsilon = 0.004 * P_v + 0.986 \quad (3)$$

$$P_v = \left(\frac{NDVI - NDVI_{min}}{NDVI_{max} - NDVI_{min}} \right)^2 \quad (4)$$

$$LST = \frac{T}{1 + \left(\frac{\lambda}{\rho} \right) \ln(\epsilon)} \quad (5)$$

where T is the at-satellite brightness temperature (K), λ is the band-centre wavelength (10.8 μm for Landsat 8; 11.5 μm for Landsat 5), and $\rho = hc/\sigma = 1.438 \times 10^{-2} \text{ m} \cdot \text{K}$ (h = Planck's constant, c = speed of light, σ = Boltzmann constant). The resulting LST raster was upsampled from 100 m to 30 m by bilinear resampling to maintain spatial consistency with the optical bands.

3.5 Spectral Indices

3.5.1 NDVI.

$$NDVI = \frac{NIR - RED}{NIR + RED} \quad (6)$$

The Normalised Difference Vegetation Index was originally proposed by Tucker (1979) as a measure of green vegetation

density and photosynthetic activity. It was used in this study to quantify the temporal change in surface vegetation cover across the valley and to examine its inverse relationship with LST. For Landsat 8 the NIR and RED inputs corresponded to Bands 5 and 4; for Landsat 5, Bands 4 and 3 were used. NDVI values above 0.60 indicate dense, healthy canopy; 0.20–0.60 represents moderate or sparse vegetation; values between 0.0 and 0.20 are typical of bare soil or impervious surfaces; and negative values are diagnostic of open water.

3.5.2 NDBI.

$$NDBI = \frac{SWIR - NIR}{SWIR + NIR} \quad (7)$$

The Normalised Difference Built-up Index was introduced by Zha et al. (2003) to delineate impervious urban surfaces from satellite imagery. It was selected for this study because it serves as a direct spectral indicator of built-up intensity linked to the formation of Urban Heat Islands (UHI). For Landsat 8, SWIR and NIR corresponded to Bands 6 and 5; for Landsat 5, Bands 5 and 4 were used. Positive NDBI values indicate built-up or barren surfaces; negative values correspond to vegetated or water-covered areas.

3.6 UHI Intensity

Rather than relying on absolute LST thresholds which vary year to year with atmospheric conditions, UHI intensity was expressed as a standardised thermal anomaly relative to the valley-wide mean for each epoch:

$$UHI = \frac{T_s - T_m}{SD} \quad (8)$$

where T_s is the LST at a given pixel ($^{\circ}\text{C}$), T_m is the valley-wide image mean LST, and SD is the image standard deviation of LST. Positive values identify pixels that are anomalously warm relative to the spatial mean; negative values indicate cooler surfaces. This standardised metric allows meaningful UHI comparison across epochs with differing absolute temperature levels.

3.7 Predictive Modelling

3.7.1 CA-Markov LULC Projection.

Future LULC for 2028 was projected using a Cellular Automaton–Markov (CA-Markov) model, implemented in the MOLUSCE plugin for QGIS, an approach demonstrated by Muhammad et al. (2022) for spatio-temporal LULC forecasting. The model comprises two coupled components. The Markov Chain component computes a transition probability matrix from two historical LULC maps, quantifying the likelihood of each land-cover class transitioning to every other class over a defined time interval. The Cellular Automaton component uses these probabilities alongside spatial contiguity rules and driver layers to simulate the geographic pattern of change. In this study, transition potentials were trained on the 2013 and 2018 LULC maps using an Artificial Neural Network (ANN) multilayer perceptron. Spatial driver variables incorporated into the transition potential model were: DEM, slope, aspect, and Euclidean distance from the road network. The calibrated model was subsequently run five years forward from the 2023 classification to generate the 2028

LULC projection. Model performance was assessed by comparing the simulated 2023 LULC against the independently produced 2023 classified map, using percentage correctness and the Kappa coefficient.

3.7.2 RF Regression for LST Forecasting.

LST for 2028 was forecasted using a Random Forest Regression model, following the framework applied by Waleed et al. (2023) for urban thermal field prediction. Training data consisted of all historical epoch observations (2008, 2013, 2018, 2023) for which both measured LST values and spatial predictor layers were available. Predictor variables were: LULC class (encoded as integer), DEM, slope, aspect, and Euclidean distance from the road network, all resampled to a common 30 m grid. The training and test subsets were divided 80:20 using a random split to ensure that test pixels were independent of training pixels. Model performance was evaluated on the held-out test set using four metrics: the coefficient of determination (R^2) which explains the proportion of variance in LST accounted for by the model (0 to 1 scale), Root Mean Square Error (RMSE, $^{\circ}\text{C}$) which measures the average deviation (in $^{\circ}\text{C}$) between predicted and actual LST values with lower RMSE indicating better model precision, Mean Square Error (MSE, $^{\circ}\text{C}^2$) quantifies the squared errors, penalizing larger deviations more heavily than smaller ones, and Mean Absolute Error (MAE, $^{\circ}\text{C}$) which represents the absolute average error. Once validated, the model was applied to the projected 2028 LULC raster alongside the static driver layers (DEM, slope, aspect, road distance) to generate a spatially continuous LST forecast surface for 2028. UHI intensities for 2028 were subsequently derived from that surface using Equation (8).

3.8 Validation

Two independent validation strategies were employed to assess the reliability of the LST retrieval. First, cross-sensor validation was conducted for the 2013 epoch by comparing the Landsat 8-derived LST surface against the contemporaneous MODIS MOD11A1.061 daily LST product. The Landsat LST raster was spatially aggregated to match the 1 km MODIS grid using a mean resampling kernel, and Pearson's correlation coefficient was computed between the two surfaces across all valley pixels for which valid MODIS retrievals existed. This provided an objective, sensor-independent check on the thermal inversion procedure. Second, spatial validation was performed by extracting mean LST values over two purposively selected study sites with contrasting urban density: Baneshwor, a dense commercial ward in central Kathmandu and Dholahity, a comparatively low-density residential area on the southwestern valley margin..

4. RESULTS AND DISCUSSIONS

4.1 LULC Change Analysis

Built-up area grew from 8,720 ha (9.32%) in 2008 to 18,525 ha (19.82%) in 2023 (net +9,805 ha). With this rate (around 654 ha/year) surpassing earlier estimates for 1989–2016 (Ishtiaque et al., 2017), it suggests that urbanization is picking up speed. Agriculture declined from 40,283 ha to 33,342 ha. Forest cover showed a modest net gain of ~3,310 ha on hillsides (Table 2, Figure 2). All four classified maps exceeded 80% OA and $\kappa > 0.75$, confirming RF classification reliability. The built-up estimate for 2023 (19.82%) matches the findings of (Sarif et al., 2020; 18.9% for 2018) and (Khatri et al., 2025; 20.1% for 2023).

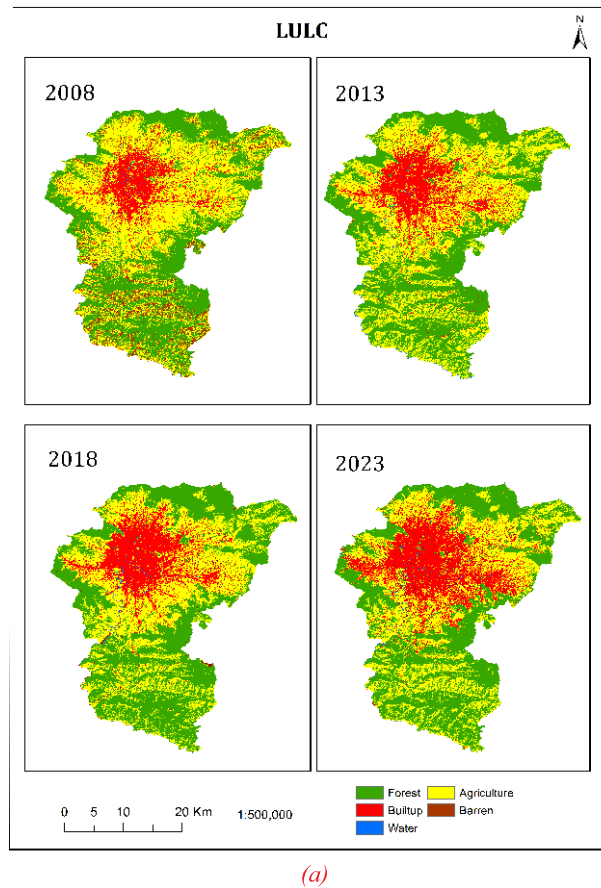


Table 2. LULC classification accuracy and built-up area summary

Year	OA	κ	Built-up (ha)
2008	0.84	0.78	8,720
2013	0.85	0.80	12,529
2018	0.92	0.90	13,859
2023	0.86	0.80	18,525

The transition probability matrix (Table 3) provides additional granularity on the sources of built-up expansion. Approximately 24% of all agricultural pixels present in 2008 had been converted to Built-up by 2023. The pattern indicates that urban expansion mainly takes place on agricultural land in the valley floor, rather than through deforestation on hillsides. This finding has policy implications: efforts to mitigate UHI should prioritize the preservation of remaining agricultural buffer zones over reforestation. Around 34% of water-body pixels experienced encroachment over the same interval, reflecting ongoing pressure on the Bagmati floodplain and its tributaries. By contrast, only 1.7% of Forest pixels transitioned to Built-up, indicating hill area conservation.

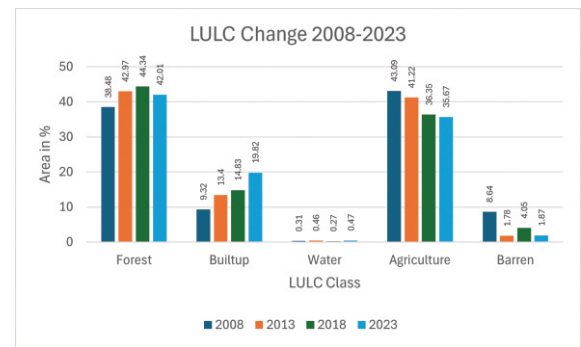


Figure 3. a) LULC classification maps for 2008, 2013, 2018, and 2023. b) Area change bar chart by class across epochs.

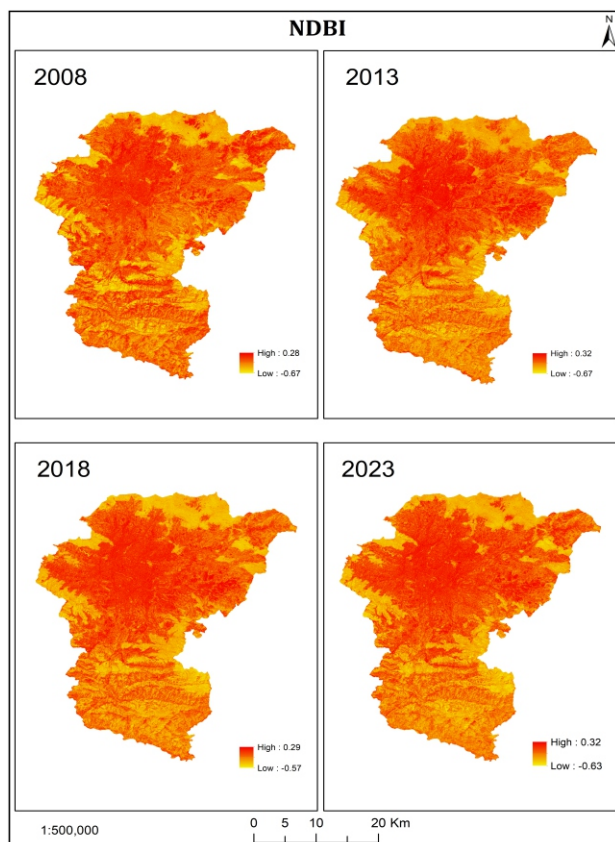
Table 3. Transition probability matrix 2008–2023

From \ To	Forest	Built-up	Water	Agri.	Barren
Forest	0.905	0.017	0.003	0.074	0.001
Built-up	0.010	0.841	0.013	0.112	0.025
Water	0.170	0.339	0.342	0.130	0.019
Agriculture	0.151	0.240	0.003	0.576	0.030
Barren	0.064	0.104	0.000	0.801	0.031

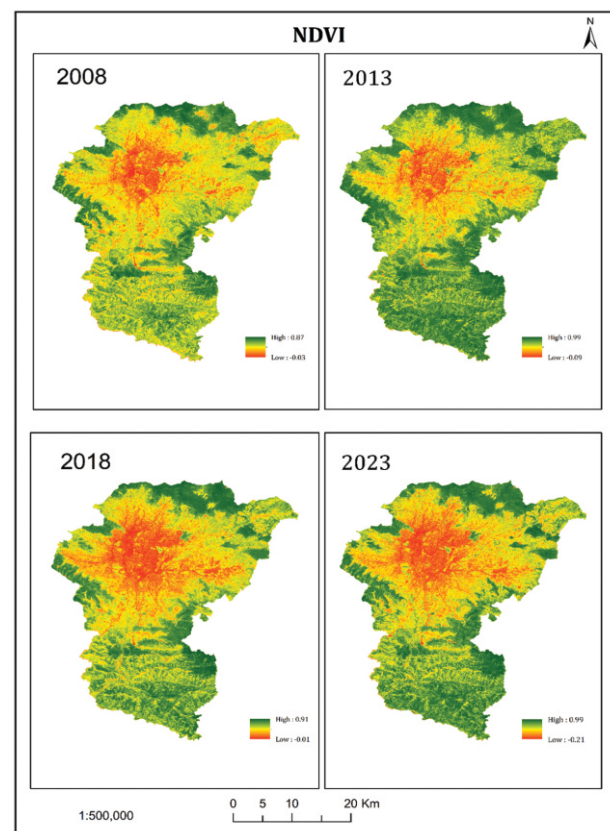
4.2 NDBI and NDVI Temporal Trends

Valley-wide mean NDBI shifted from -0.09 in 2008 to -0.19 in 2013 before recovering to -0.12 in 2018 and stabilising near -0.13 in 2023. The 2013 trough coinciding with relatively limited impervious surface growth in that interval is consistent with a period of slightly slower built-up densification and higher vegetation cover. At the class level, Built-up pixels consistently returned the highest NDBI values (near zero) across all epochs, while Forest pixels remained substantially negative (approximately -0.32), confirming the index's discriminative capacity for impervious surfaces.

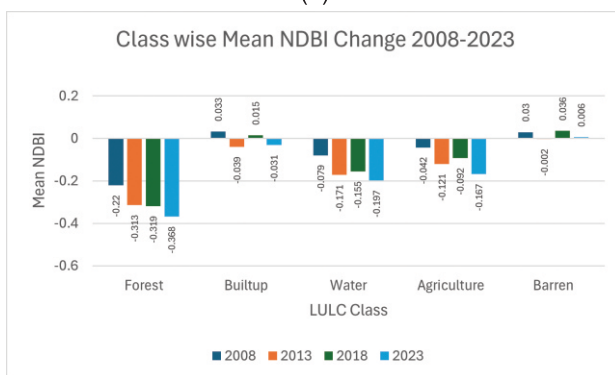
Mean NDVI exhibited a complementary temporal pattern, peaking at 0.63 in 2013, the highest value across the entire study period before declining to 0.53 in 2018 and recovering marginally to 0.54 in 2023. The Built-up class recorded the lowest NDVI of any class in all four epochs (0.25 – 0.35), consistent with the sparse and fragmented nature of urban greenery. Forest class NDVI ranged between 0.62 and 0.80 , confirming the integrity of hillside vegetation across the study period. The NDVI trend in central urban areas is declining, which indicates a gradual loss of vegetation. This suggests that urban growth is intruding on green spaces and diminishing the natural cooling effect of the valley. The growing NDBI trend, especially the growth of red zones in NDBI maps from 2008 to 2023, indicates a swift and ongoing densification of built-up areas, implying that urban sprawl is increasingly converting pervious surfaces into impervious ones.



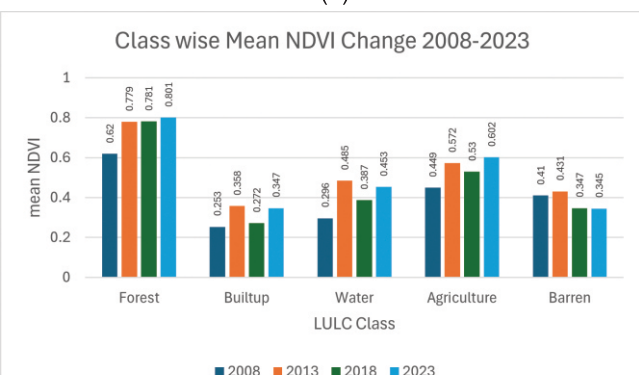
(a)



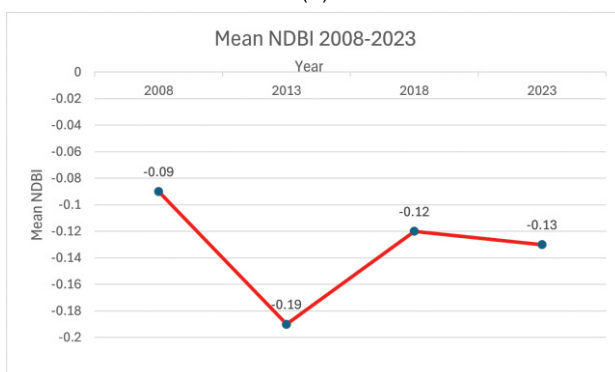
(a)



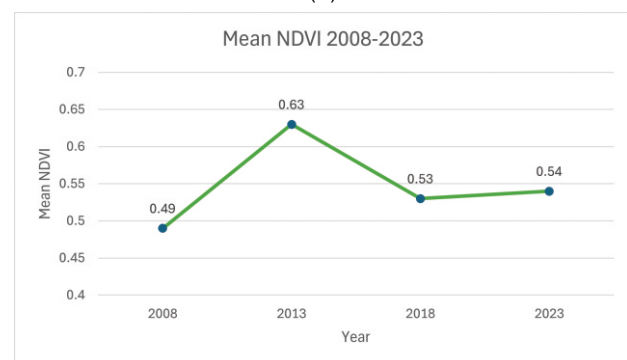
(b)



(b)



(c)



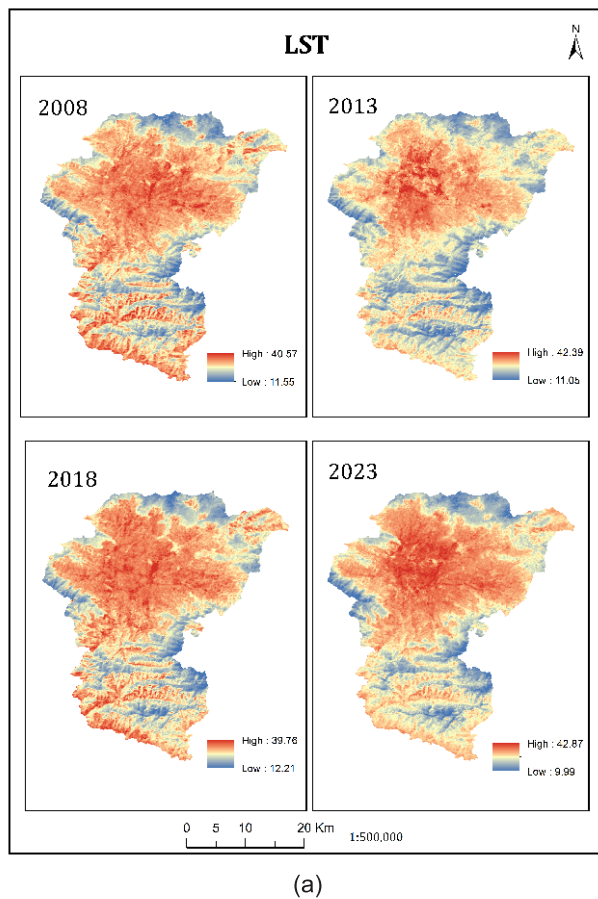
(c)

Figure 4. a) Temporal NDBI maps (2008–2023).
b) Mean NDBI trend. c) Class-wise mean NDBI.

Figure 5. a) Temporal NDVI maps (2008–2023).
b) Mean NDVI trend. c) Class-wise mean NDVI.

4.3 Land Surface Temperature

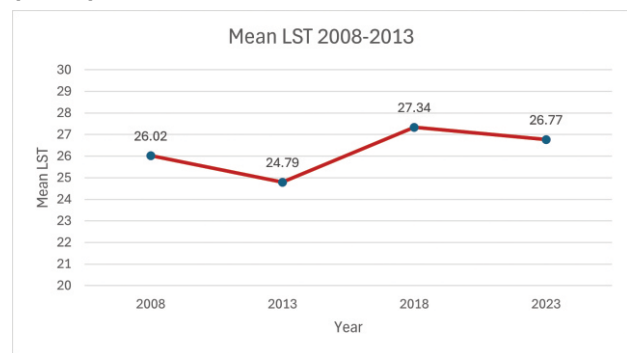
Mean valley-wide LST peaked in 2018 at 27.34°C and declined to 26.77°C by 2023, while pixel-level extremes revealed a 32.88°C range between dense built-up surfaces (42.87°C) and forested ridges (9.99°C), confirming that land cover type drives thermal contrast. The 2013 anomaly where mean LST fell by 1.23°C despite a 3,800 ha increase in built-up area is explained by the concurrent NDVI peak (0.63), providing direct empirical evidence that vegetation enhancement can offset urbanization-induced warming. Class-mean LST was consistently highest for Built-up (30.2–31.9°C) and lowest for Forest (22.3–24.3°C), with a persistent 7–9°C differential across all epochs, implying that any conversion of vegetated land to impervious surfaces will raise local LST by this magnitude. These findings align with Mishra et al. (2019), Sarif et al. (2020), and Khatri et al. (2025), and carry a clear policy implication: preserving forest cover and strategically expanding urban green spaces can meaningfully attenuate UHI even during active urban expansion.



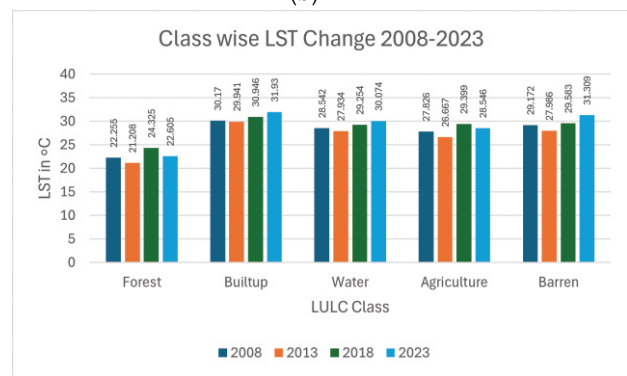
(a)

4.4 UHI Intensity

Built-up areas consistently exhibited the highest class-mean UHI intensity (1.00–1.19) while forested hillsides showed negative values (−0.91 to −0.83), confirming that the central urban core functions as a persistent thermal hotspot and vegetated peripheries as cooling zones, consistent with Maharjan et al. (2021) and Sarif et al. (2020). The spatial gradient from dense inner-city districts like Baneshwor and Thamel outward to the peri-urban fringe implies that UHI intensity scales continuously with built-up density, suggesting that strategic greening of rapidly urbanizing fringe areas identified by Ishtiaque et al. (2017) as agricultural zones undergoing conversion could prevent them from becoming future hotspots. The maximum pixel UHI intensity peaked at 4.06 in 2013 despite that year having the lowest mean absolute LST, reflecting widened thermal contrast driven by the exceptionally high NDVI (0.63) which cooled vegetated surfaces sufficiently to amplify the relative warmth of the built-up core in the standardized metric. This finding carries a key policy implication: standardised UHI is a more sensitive indicator of thermal inequity than absolute LST alone, and policymakers should monitor both metrics simultaneously as recommended by Khatri et al. (2025) to avoid misinterpretation of greening intervention outcomes.



(b)



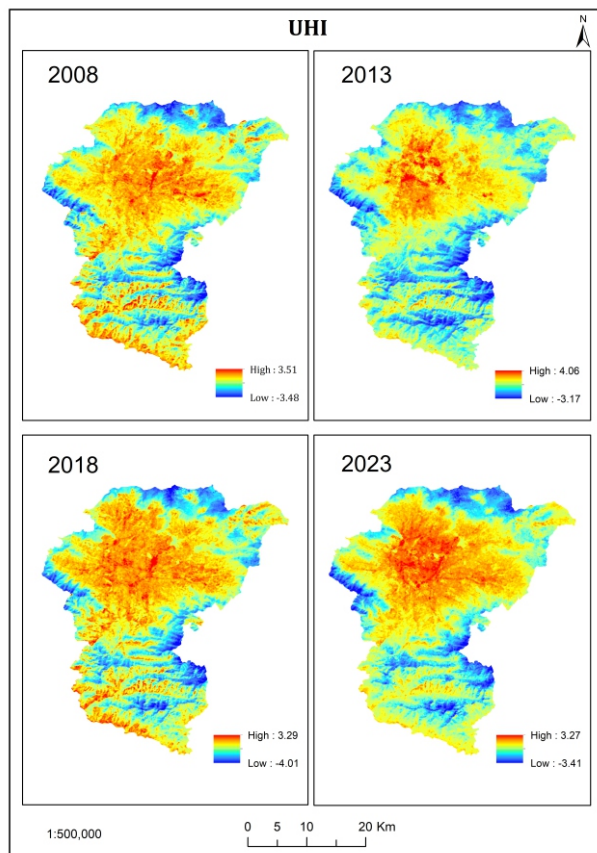
(c)

Figure 6. a) LST maps (2008–2023). b) Mean LST trend. c) Class-wise mean LST

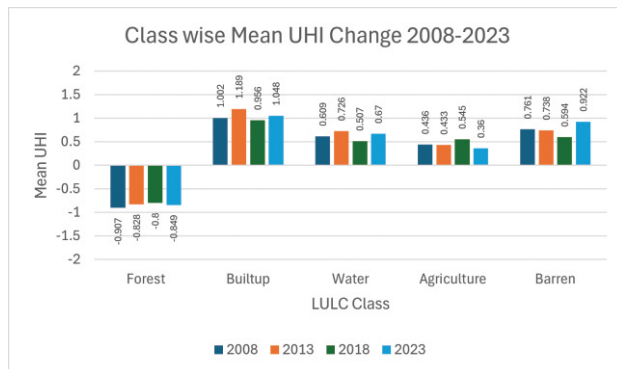
4.5 Correlation Analysis

Pearson's correlation coefficients were computed from pixel-level co-registered composite rasters spanning all four study epochs. The investigation uncovers a robust positive correlation ($r = 0.751$) between land surface temperature (LST) and normalized difference built-up index (NDBI), signifying that built-up density is the primary thermal driver. In contrast, the negative correlation ($r = -0.759$) with the normalized difference vegetation index

(NDVI) indicates that vegetation is the main cooling mechanism. These results correspond with comparable research conducted in Bangladesh and China, underscoring the near-symmetry of these relationships. Scatter plots (Figure 8) show linear relationships with no strong evidence of non-linearity that would compromise the Pearson's metric. The magnitude and symmetry of these two coefficients—one positive, one negative, both of similar absolute value—underscore the compensatory thermal role of vegetation relative to built-up cover



(a)



(b)

7. a) UHI intensity maps (2008–2023).
b) Class-wise mean UHI values

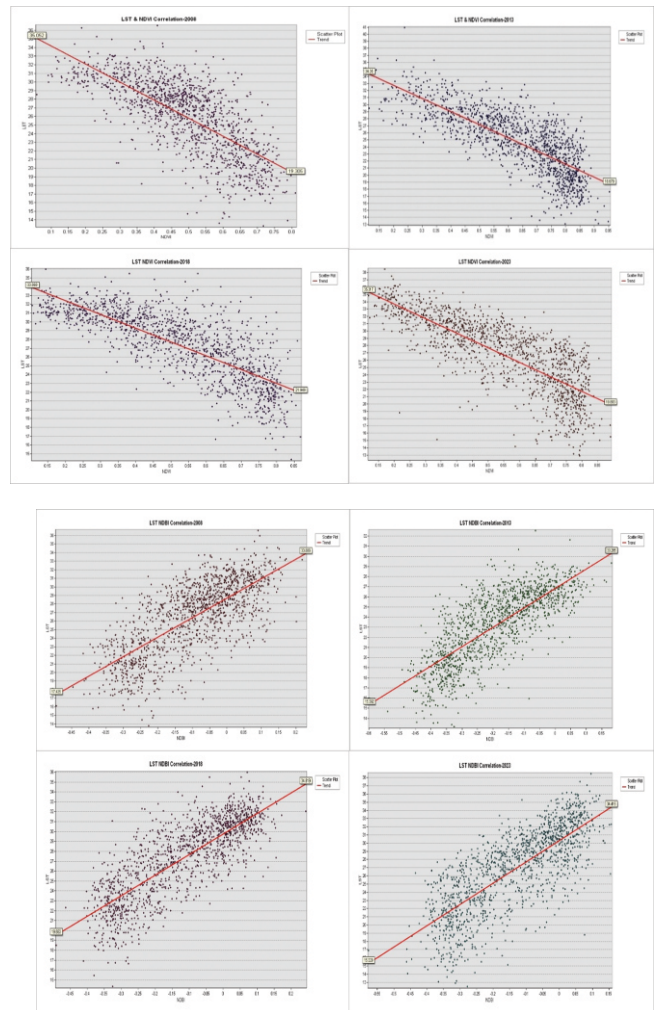


Figure 8. Pixel-level scatter plots: LST vs NDVI (top) and LST vs NDBI (bottom), all four epochs

4.6 Validation

Cross-sensor validation for 2013 was performed by aggregating the Landsat 8-derived LST raster to the 1 km MODIS grid using a mean resampling kernel, then computing Pearson's r between the two surfaces across all valid pixels within the valley boundary. The result was $r = 0.95$ (Figure 9), indicating strong agreement between the Landsat thermal inversion and the independent MODIS LST product. This provides objective evidence that the emissivity-corrected retrieval procedure is reliable for this study area and sensor configuration.

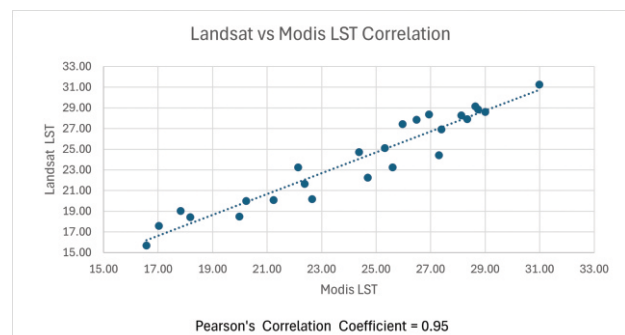


Figure 9. Cross Satellite Validation

Spatial validation using the two contrasting study sites returned mean LST values of 34.57°C at Baneshwor (high-density commercial) and 31.90°C at Dholahity (low-density residential), a differential of 2.67°C. Visual examination of contemporaneous Google Earth Pro imagery confirmed that Baneshwor is characterised by dense, contiguous impervious cover with minimal vegetation, while Dholahity retains a higher proportion of gardens, open land, and tree cover. The direction and magnitude of the temperature differential are therefore physically consistent with the NDBI–LST and NDVI–LST correlations established in Section 4.5, and support the interpretation that the LST maps accurately capture the spatial thermal gradient attributable to varying urbanisation intensity (Figure 10).

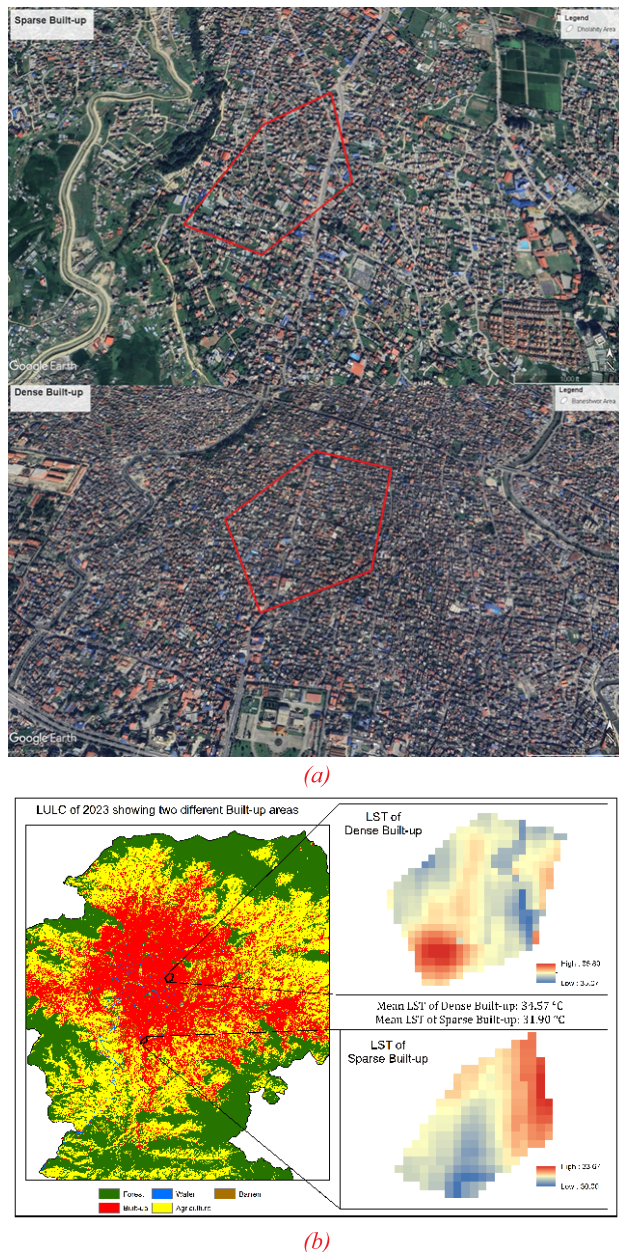


Figure 10. a) Google Earth Images of Baneshwor and Dholahity Area (2023).
b) Validation Map

4.7 LULC and LST Prediction for 2028

4.7.1 LULC Projection.

The validation metrics of the CA-Markov model (overall correctness = 81.79%, $\kappa = 0.714$, κ -location = 0.82) surpass those reported by Muhammad et al. (2022) for Linyi, China ($\kappa \approx 0.68$), indicating a reliable reproduction of spatial land-cover patterns. The 2028 projection indicates that the built-up area will reach 25.47% of the valley (+5.65 percentage points from 2023), mainly derived from Agriculture (−2.26 pp) and Forest (−1.53 pp) this aligns with Ishtiaque et al. (2017), who noted a fourfold increase in built-up area between 1989 and 2016. The anticipated reduction of water bodies to 0.23% mirrors the ongoing encroachment of rivers (34% converted to built-up areas by 2023), suggesting that without intervention, the valley's remaining surface waters are at risk of near-total loss, affecting local climate regulation as highlighted by Sarif et al. (2020).

Table 4. Projected LULC area changes from 2023 to 2028

Class	2023 (%)	2028 (%)	Change (%)
Forest	42.01	40.48	−1.53
Built-up	19.82	25.47	+5.65
Water	0.47	0.23	−0.24
Agriculture	35.67	33.41	−2.26
Barren	1.87	0.41	−1.46

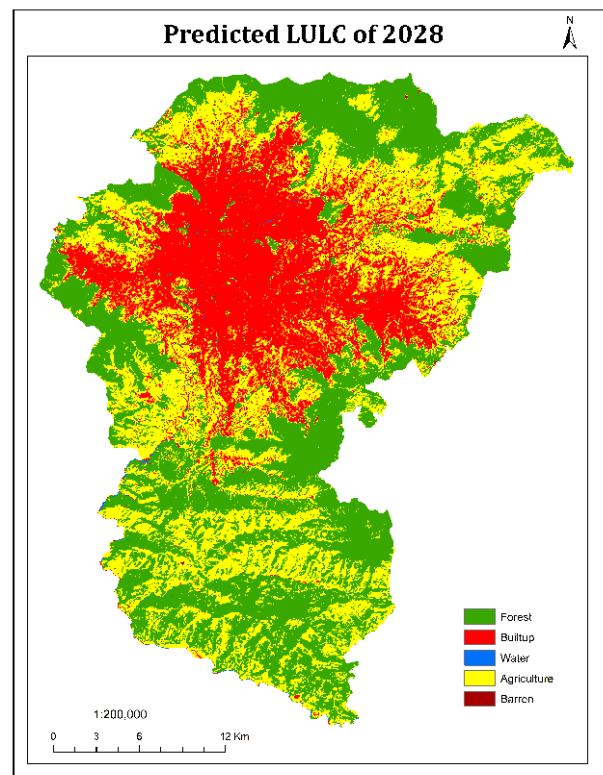


Figure 11. Predicted LULC map for 2028

4.7.2 LST and UHI Prediction.

The RF Regression model showed good performance ($R^2 = 0.817$, RMSE = 1.87°C), similar to Waleed et al. (2023), and predicts a mean LST of 26.88°C in 2028, with a maximum of 39.08°C in densely built-up regions. This extends the warming trend noted from 2008 to 2023 and corresponds with the projections of Khatri et al. (2025), who anticipated an intensification of UHI in the Kathmandu Valley by 2030. The UHI map generated indicates

that the central hotspot is expanding toward the northwestern and eastern edges of the valley, suggesting that anticipated built-up growth will spread thermal inequity beyond the traditional urban core, in line with the findings of Sarif et al. (2020), who recorded outward UHI expansion due to peri-urban development.

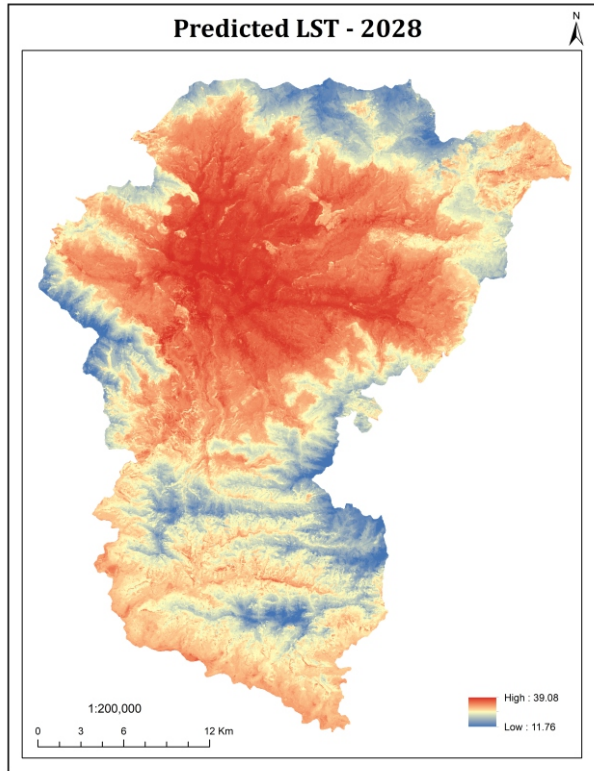


Figure 12. Predicted LST map for 2028

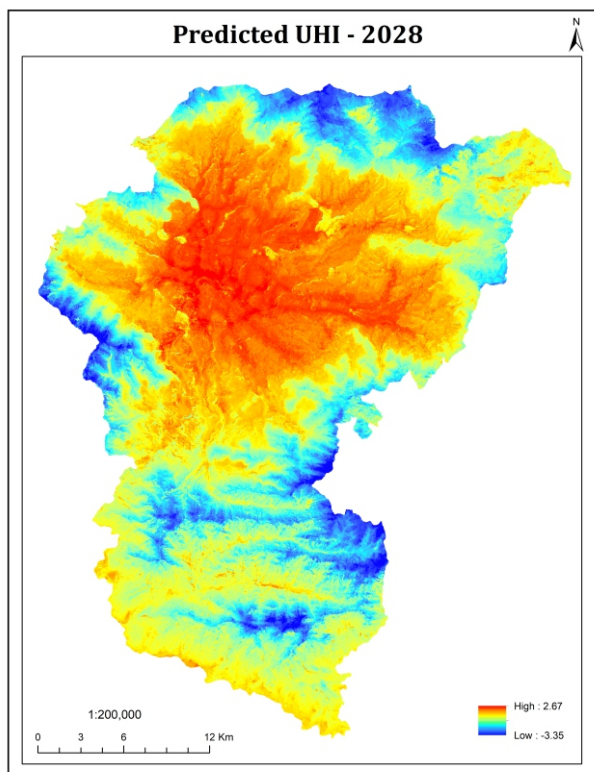


Figure 13. Predicted UHI intensity map for 2028

6. CONCLUSIONS

This study has produced a comprehensive spatio-temporal account of UHI dynamics in Kathmandu Valley spanning fifteen years (2008–2023), integrated with data-driven projections to 2028. Built-up land expanded by approximately 9,805 ha over the study period predominantly from agricultural land and water bodies while Forest cover recorded a modest net gain on the encircling hillsides. Mean LST ranged from 24.79°C (2013) to 27.34°C (2018), with the built-up class consistently recording class-mean values between 30.2 and 31.9°C across all epochs. LST was strongly and consistently correlated with both NDBI ($r = +0.751$) and NDVI ($r = -0.759$), confirming that impervious surfaces drive surface warming while vegetation suppresses it. The 2013 epoch provides the study's most important practical insight: the anomalously high NDVI (0.63) in that year was sufficient to depress mean LST by 1.23°C despite concurrent built-up growth of ~3,800 ha. This is not merely a statistical artefact; it demonstrates that the thermal balance of the valley is genuinely sensitive to vegetation cover and that deliberate greening programmes can produce measurable thermal relief even within an actively urbanising context.

The 2028 projections' built-up cover reaching 25.47%, mean LST of 26.88°C, maximum pixel LST of 39.08°C represent a plausible baseline scenario in the absence of policy intervention. The RF Regression model ($R^2 = 0.817$, RMSE = 1.87°C) provides a statistically defensible basis for this forecast, and the CA-Markov hindcast (correctness 81.79%, $\kappa = 0.714$) validates the LULC projection on which it rests. Together, these results establish a quantitative, reproducible evidence base for climate-resilient land-use planning in Kathmandu Valley. The integrated workflow - GEE-based spectral processing, RF LULC classification, CA-Markov simulation, and RF Regression forecasting is transferable to comparable mid-sized Himalayan and South Asian cities where Landsat coverage is available, offering a low-cost analytical pathway for cities with limited monitoring infrastructure.

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AUTHOR INFORMATION



Name	:	Sandeep Gautam
Academic Qualification	:	BE in Geomatics Engineering
Organization	:	Geo3D Modelling
Current Designation	:	Geomatics Engineer
Work Experience	:	1 year
Published Article	:	2

DEM GENERATION USING INTERFEROMETRIC SAR

Sachin Rayamajhi¹, Rubi Chaulagain¹

¹ [Department of Geomatics Engineering, Pashchimanchal Campus, Pokhara, pas077bge036@wrc.edu.np](mailto:pas077bge036@wrc.edu.np)

¹ [Department of Geomatics Engineering, Pashchimanchal Campus, Pokhara, pas077bge034@wrc.edu.np](mailto:pas077bge034@wrc.edu.np)

KEY WORDS: Digital Elevation Model (DEM), Interferometric Synthetic Aperture Radar (InSAR), Sentinel-1 SAR, Phase Unwrapping, Terrain Analysis

ABSTRACT:

Digital Elevation Models (DEMs) are critical for terrain analysis, hydrological modeling, disaster risk assessment, and land-use planning, especially in mountainous regions like Nepal. Conventional DEM generation methods such as field surveying, photogrammetry, and LiDAR are often costly and impractical in remote areas. Interferometric Synthetic Aperture Radar (InSAR) has emerged as a viable and cost-effective alternative, capable of generating high-resolution DEMs with vertical accuracies of 1–3 m RMSE. This study presents a comprehensive InSAR-based DEM generation workflow for a region covering Muglin and the surrounding central Himalayan terrain of Nepal using Sentinel-1 Single Look Complex (SLC) images acquired on May 10 and May 22, 2024, with a 12-day temporal baseline. The study area was defined by the available Sentinel-1 scene footprint, extending approximately from 84.04°E to 85.22°E longitude and 27.53°N to 29.21°N latitude, encompassing diverse topographic conditions ranging from the mid-hills around Muglin to higher Himalayan regions. The methodology involves coregistration, interferogram formation, Goldstein phase filtering, SNAPHU-based phase unwrapping, and phase-to-height conversion, producing a 10 m resolution DEM. The generated DEM was validated against ASTER DEM reference data at nine ground control points. The resulting Root Mean Square Error (RMSE) of approximately 52 m highlights the challenges posed by steep and complex Himalayan terrain, including geometric distortions such as layover, foreshortening, and shadow effects. Despite these limitations, the study establishes a reproducible InSAR processing framework applicable to geospatial and hazard-related applications in Nepal and similar mountainous environments.

1 INTRODUCTION

Digital Elevation Models (DEMs) are fundamental datasets used for terrain analysis, hydrological modeling, disaster risk assessment and land-use planning. Accurate elevation information is particularly important in mountainous countries like Nepal, where steep terrain and frequent hazards such as landslides and floods require reliable topographic information (Gaire et al., 2015; Scott Watson et al., 2019). Conventional DEM generation methods include field surveying, photogrammetry, and LiDAR; however, these approaches are often expensive and difficult to implement in remote mountainous regions. Remote sensing techniques have therefore become widely used for large-scale elevation mapping. Among these techniques, Interferometric Synthetic Aperture Radar (InSAR) has emerged as a powerful method for DEM generation—(Lu et al., 2007). InSAR derives terrain elevation by measuring the phase difference between two Synthetic Aperture Radar (SAR) images acquired from slightly different viewing geometries. One of the early comprehensive explanations of DEM generation using satellite SAR interferometry was presented by paper (Zhong et al., 2013) who described the interferometric processing chain and discussed factors affecting DEM accuracy such as baseline errors, atmospheric effects, and phase unwrapping uncertainties. Several studies have attempted to improve DEM extraction algorithms from interferometric data. For example, (Gao et al., 2017) proposed a multi-look iterative algorithm that first generates a coarse DEM and then refines it through successive iterations to improve spatial resolution while reducing phase noise. Their results demonstrated improved elevation accuracy compared with conventional multilooking approaches. Other researchers have investigated interferometric DEM generation using different SAR sensors. For example, (Li et al., 2018) developed an interferometric processing method for Gaofen-3 SAR data that balances phase noise reduction and spatial detail preservation. Their results demonstrated that

optimized multilooking and interferometric processing could improve phase quality while minimizing resolution loss, leading to DEMs with enhanced vertical accuracy and terrain representation.

The repeat-pass interferometry experiments using SAR data reported that DEMs generated from interferometric processing can achieve vertical accuracies of several meters in flat regions, although the accuracy decreases in mountainous terrain due to geometric distortions and decorrelation effects (T. Zhang et al., 2017). Similarly, the joint use of multi-orbit high-resolution SAR data for DEM generation found that combining interferometric observations from different orbital geometries can significantly reduce atmospheric phase errors and improve vertical accuracy (L. Zhang et al., 2014).

Recent research has also focused on improving interferogram quality to enhance DEM generation. A non-local filtering technique for interferometric data obtained from the TanDEM-X Mission, resulted that advanced filtering methods can effectively reduce noise while preserving terrain details (Baier et al., 2018).

Despite significant progress in DEM generation using Interferometric Synthetic Aperture Radar, most existing studies focus on algorithm development or applications in well-studied regions.

Applications of InSAR-based DEM generation in the Himalayan region, particularly in Nepal, remain limited due to complex terrain and challenging environmental conditions. Therefore, it is important to evaluate the applicability of InSAR techniques for DEM generation in this region. The objective of this study is to develop and demonstrate a practical methodology for generating a DEM using SAR interferometry for a Nepal scene. The study utilizes SAR data from Sentinel-1 SLC images and applies interferometric processing techniques including interferogram generation, filtering, phase unwrapping, and phase-to-height conversion. The proposed workflow aims to provide a clear and reproducible framework for DEM generation using InSAR data, which can support future terrain analysis and geospatial applications in Nepal.

2 DATA AND METHODOLOGY

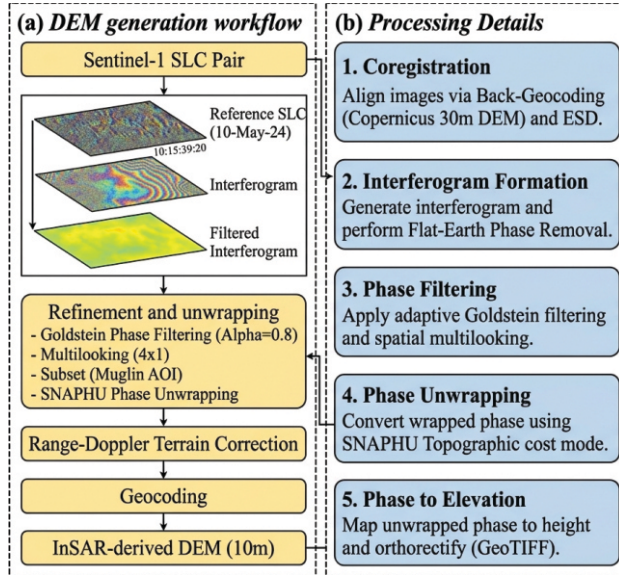


Figure 1. Methodological Chart

2.1. Data

For the DEM generation workflow, we used Sentinel-1 SAR data acquired over the study area in Muglin, Nepal. The area of interest (AOI) was defined by a polygon shapefile in WGS84 coordinates.

Type	Remarks
Sentinel 1 SLC Pair	Reference (Master): 5/10/2024
	Secondary (Slave): 5/22/2024
ASTER DEM	30 m for Validation

Table 1. Dataset Used

Category	Parameter	Value
SAR Pair	Temporal Baseline	12 days
	Orbit Direction	Descending
	Subswath	IW2
	Polarization	VV
Processing Parameters	Coherence Window	20 (range) $\times$ 5 (azimuth)
	Goldstein Filter	Alpha = 0.8
	Multilook	4 (range) $\times$ 1 (azimuth)
	SNAPHU Phase Unwrapping	4 $\times$ 4 tiles, 4 parallel workers, mask < 0.10 coherence

Table 2. Parameters

2.2 Principles of InSAR DEM Generation

Digital Elevation Models (DEMs) can be generated from the interferometric phase of two SAR acquisitions. The measured interferometric phase is composed of several components:

$$\phi_{Int} = \phi_{Topography} + \phi_{Change} + \phi_{Movement} + \phi_{Atmosphere} \quad \#(1)$$

For DEM generation, it is assumed that no surface displacement occurs between acquisitions, so the interferometric phase is dominated by topography:

$$\phi_{Int} \approx \phi_{Topography} + \phi_{Noise} \quad \#(2)$$

Where,

$$\phi_{Noise} = \phi_{Change} + \phi_{Atmosphere} \quad \#(3)$$

The unwrapped interferometric phase $\phi_{Topography}$ is then converted into absolute height values relative to the WGS84 ellipsoid:

$$DEM(height) = f(\phi_{Topography}, B, \theta) \quad \#(4)$$

Here:

B= interferometric baseline

θ = radar look angle

f = geometric conversion from phase to height

This assumption ensures that the derived DEM represents the terrain elevation without influence from surface motion or atmospheric effects.

2.3 Workflow

2.2.1. Coregistration: The methodology begins with the alignment of the reference and secondary Sentinel-1 Single Look Complex (SLC) images. Precise orbit vectors are applied to update the state vectors. Alignment is achieved via **Back-Geocoding**, which uses the Copernicus 30m Global DEM to account for topographic effects. For the Terrain Observation by Progressive Scans (TOPS) acquisition mode, Enhanced Spectral Diversity (ESD) is implemented to ensure azimuth shift correction with an accuracy exceeding 0.001 pixels, preventing phase jumps between bursts.

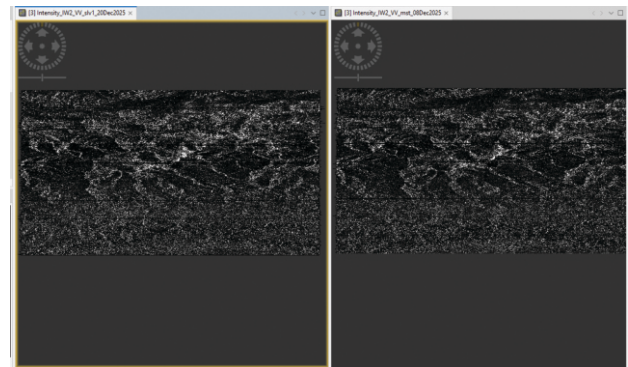


Figure 2. Applied Coregistration in Reference and Secondary SLC product

2.2.2. Interferogram Formation:

An interferogram is generated by multiplying the reference image by the complex conjugate of the secondary image. This step includes Flat-Earth Phase Removal, which eliminates the phase contribution related to the Earth's curvature based on a reference ellipsoid. This ensures that the remaining phase relates primarily to the topography and potential atmospheric delays.

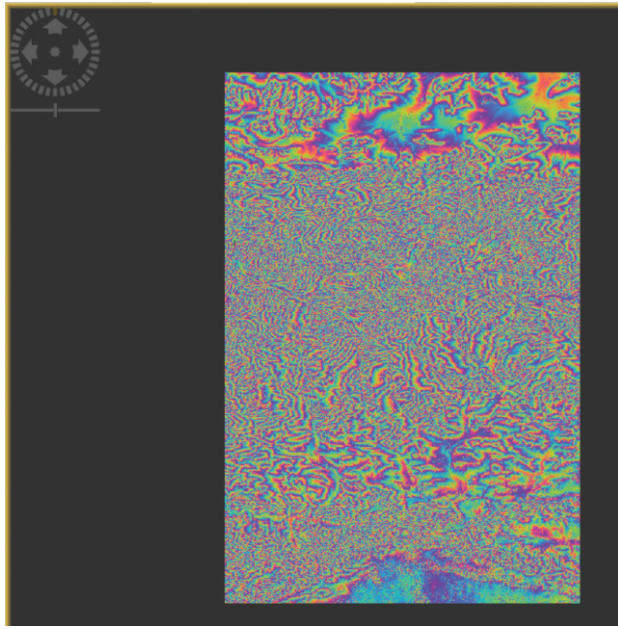


Figure 3. Phase Interferogram before Terrain Correction

2.2.3. Phase Filtering: To enhance the signal-to-noise ratio, Goldstein Phase Filtering is applied to the interferogram. This adaptive filtering technique reduces decorrelation noise caused by temporal or spatial baseline effects. Subsequently, Multilooking is performed (e.g., a 4:1 range-to-azimuth ratio) to reduce speckle noise and produce approximately square pixels, followed by a spatial Subset to the specific study area coordinates.

2.2.4. Phase Unwrapping: The filtered phase remains "wrapped" within the $[-\pi, +\pi]$ interval. To recover the continuous phase, the data is exported to the SNAPHU (Statistical-cost, Network-flow Algorithm for Phase Unwrapping). The algorithm uses a Topographic cost mode to resolve the integer 2π ambiguities, converting the fringe patterns into a continuous phase ramp representing the terrain.

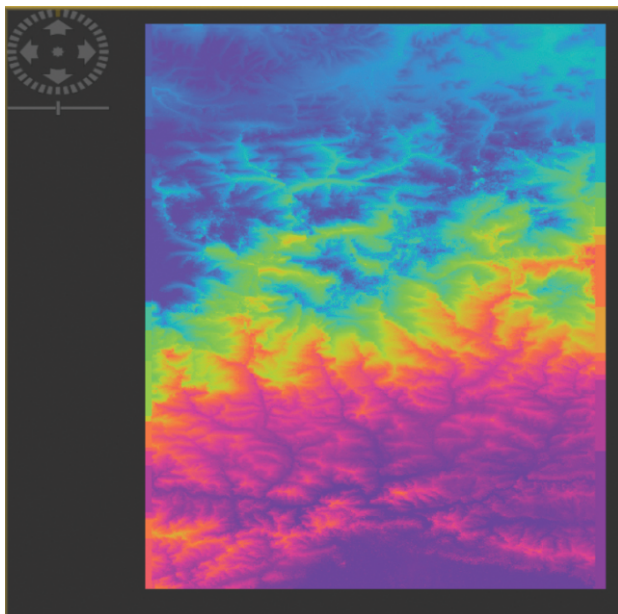


Figure 4. Phase Unwrapping using SNAPHU before Terrain Correction

2.2.5. Phase to Elevation (DEM Generation): The unwrapped phase is converted into absolute height values relative to the WGS84 ellipsoid. This transformation utilizes the interferometric geometry (baseline and look angle) to map phase values to elevation. Finally, Range-Doppler Terrain Correction is applied to orthorectify the data, transforming it from the radar's slant-range geometry into a geocoded GeoTIFF in a geographic coordinate system.

2.2.6. Validation: The InSAR-derived DEM was validated using the ASTER DEM as a reference dataset to evaluate its elevation accuracy. Elevation values from both DEMs were compared at selected sample points, and the differences were calculated to assess consistency between the two datasets.

3 RESULT AND ANALYSIS

The DEM generated using InSAR, with a spatial resolution of 10 m, is presented below.

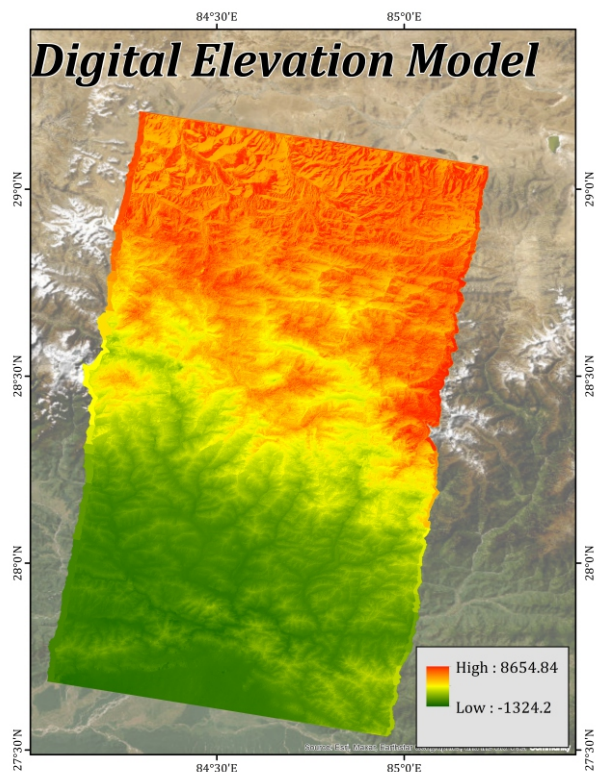


Figure 5. Digital Elevation Model

3.1 Validation

Ten points were selected to analyze the InSAR-derived DEM by comparing it with the ASTER DEM, as shown below.

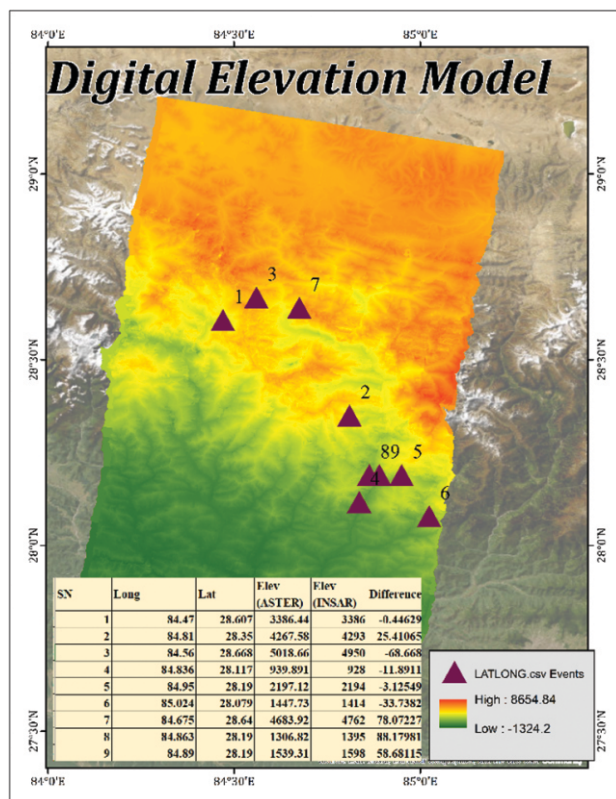


Figure 6. Cross Validation between Generated DEM and ASTER DEM

RMSE=

$$\sqrt{662.9185} \approx 51.61\text{m}\#(5)$$

An RMSE of ~52 m is relatively high for 10 m InSAR DEM resolution. These may correspond to steep slopes or layover areas. This is the strong limitation of the project.

4 LIMITATION AND RECOMMENDATION

The accuracy of the generated DEM is influenced by several inherent limitations of InSAR processing. Phase unwrapping errors may introduce unrealistic or negative elevation values, particularly in areas with low coherence or steep topography. DEM quality is also strongly dependent on the selection of SAR image pairs, as temporal decorrelation and unfavorable perpendicular baselines can reduce interferometric coherence and degrade elevation accuracy. In mountainous regions such as Nepal, geometric distortions including layover, foreshortening, and radar shadow are common and can significantly affect the reliability of the derived elevations. Furthermore, atmospheric phase delays introduce additional uncertainties that may propagate into the phase-to-height conversion process, resulting in elevation errors, especially over large spatial extents.

Future studies may improve DEM accuracy through several approaches that have been successfully demonstrated in previous research. Multi-temporal InSAR techniques such as Persistent Scatterer InSAR (PS-InSAR) and Small Baseline Subset (SBAS) methods have been shown to reduce noise and decorrelation effects by exploiting multiple SAR acquisitions (Berardino et al., 2002; Ferretti et al., 2001). Advanced interferogram filtering methods, including non-local filtering, have been reported to

improve phase quality while preserving terrain details, leading to more accurate DEM generation (Baier et al., 2018). The use of ascending and descending orbit combinations can help mitigate geometric distortions and improve terrain representation in mountainous environments (L. Zhang et al., 2014). Additionally, higher-resolution SAR sensors such as TerraSAR-X and COSMO-SkyMed have demonstrated improved DEM accuracy compared with medium-resolution systems due to their finer spatial resolution (Rizzoli et al., 2017). Atmospheric correction techniques based on GNSS observations or numerical weather models have also been shown to reduce phase-delay-related errors (Hanssen, 2001). Finally, increasing the number of ground validation points and integrating InSAR-derived DEMs with existing elevation products such as SRTM or ALOS DEM may further enhance accuracy and reliability for applications including landslide susceptibility assessment, flood modeling, and terrain analysis.

5 CONCLUSION

This study successfully demonstrates an InSAR-based DEM generation workflow for Muglin, Nepal, using Sentinel-1 SAR data. The methodology, encompassing coregistration, interferogram generation, phase filtering, SNAPHU unwrapping, and terrain correction, produced a 10 m resolution DEM. Validation against ASTER DEM yielded an RMSE of approximately 52 m, reflecting the inherent challenges of complex Himalayan terrain, including layover and atmospheric effects. Future improvements should include multi-temporal InSAR approaches, advanced filtering techniques, higher-resolution SAR sensors, and increased ground control points to enhance elevation accuracy and broaden the applicability of InSAR-derived DEMs for hazard monitoring and land-use planning in Nepal.

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AUTHOR INFORMATION



Name	: Sachin Rayamajhi
Academic Qualification	: Bachelor in Geomatics Engineering
Organization	: Glodal Inc., Japan
Current Designation	: Junior Research Associate
Work Experience	: 1 year
Published Article	: 1

GENDER, LAND, AND JUSTICE: ROLE OF SUPREME COURT IN ADVANCING WOMEN'S PROPERTY RIGHTS

Kapina Manandhar¹

¹Kathmandu University, manandharkapina305@gmail.com

KEY WORDS: Gender equality, Women's property right, Supreme Court of Nepal, Socio-economic security

ABSTRACT:

Women's property right is significant in promoting gender equality which makes women socially and economically secured. However, the existing socio-legal constraints have deprived women from the benefits of property right. The prevalent customary practices in our society have contributed gender disparity which has constrained women to be self reliant in financial matters. The Supreme Court of Nepal has played a significant role in shaping the rights of Nepali women through its landmark decisions on gender equality, particularly in inheritance and ownership rights. This study examines the role of Supreme Court in advancing women's property rights and assesses how this helps women to achieve social and economic security. This study is based on the qualitative desk study. It has reviewed the Constitution of Nepal, published and unpublished articles related to women's property right in Nepal. The landmark cases were reviewed thoroughly which has created milestone decisions in regard of equal coparcenary and inheritance right to parental and ancestral property by women regardless of their marital status. The Supreme Court has dismantled various discriminatory practices related to land, inheritance and tenancy right which have resulted in significant amendments in constitution 2015 and civil code 2017 of Nepal. This has established binding precedents that recognized women as equal right holders to land and property. Therefore, the Supreme Court has laid strong foundation on gender equality through its landmark decisions which established binding precedents formalizing women's property right. The court has dismantled deeply rooted customary norms of the communities which were barrier to the women in establishing socio-economic security. This study focuses on the role of Supreme Court to strengthen women's land right which is very much crucial in developing their social and economic security of women.

1. Background

Women experience less access to and control over economical resources like land in comparison to male (Kangas et al., 2014). Land ownership has played important role in promoting economic independence ensuring proper access to shelter and develop participatory confidence in decision making within household and communities (Print et al., 2025). But women experience significant barriers on control over property due to social and cultural restrictions prevailed in Nepal (Rijal, 2017). Women's property right is significant in promoting gender equality which makes women economically autonomous. According to legal reforms in the Constitution of Nepal, 2015 and Civil Code of Nepal, 2017, women are ensured equal right to own and inherit property. However, various socio-legal contexts restricted its enforcement. The prevalent customary practices in our society have contributed gender disparity which has constrained women to be self reliant in financial matters. It further limited their ability to own or control land. Therefore, education, leadership opportunities and societal changes is important ensuring women equality (Print et al., 2025). The women's status and their influence within households and communities is possible only if they have access and control over the fixed assets like house or land as wealth (Rijal, 2017).

Nepal's Supreme Court has played a pivotal role in shaping the rights of Nepali women through its landmark decisions on gender equality, particularly in inheritance and ownership rights (Malagodi, 2018). This strengthens women's access to property, which is very much essential for socio-economic security. The Supreme court is very important as it has power to interpret and adjudicate constitutional matters particularly in federal disputes (The et al., 2015). So it can play a key role in correcting discriminatory practices by reinterpreting laws in strengthening gender justice in favour of equality. The Supreme court plays a significant role in making legal precedents as a future guideline for cases of a similar nature, ensuring certainty and consistency in the legal system making the law uniform and clear to all (Supreme Court Booklet, 2080). According to the Constitution of Nepal, 2015 (Article 128(4)), "The interpretation of law made by

the Supreme Court shall be binding on all courts". According to Rajesh Kafle, Senior Advocate, Supreme Court of Nepal, The Supreme Court stands as a symbol of justice, which is more than a judicial institution. It interprets the constitution, protects fundamental rights, resolves disputes, and promotes judicial independence. It is the backbone of democracy, which needs to adapt the possible new challenges for providing justice and equality.

The interaction between judicial interpretation and women's property rights represent an important dimension of gender justice in Nepal. The analysis of landmark decisions made by Supreme Court provides valuable insights on how the judicial decisions have promoted legal reforms, protected women's property rights and contributed to their social and economic security.

2. Objective

The main objective of this research is to:

- Analyze the role of Supreme Court in shaping women's property right.
- To assess how supreme court's decisions have contributed women in achieving social and economic

3. Methodology

This study is based on qualitative desk study approach which included published and unpublished literatures such as academic journals, books, policy documents, government reports, landmark court decisions and online databases. The collected materials were used to enable critical examination of legal frameworks, landmark decisions made by court which ensures the women's right to equality.

4. Women's Property Right in Nepal

Property right is a legal claim to own and inherit property either by men or women. Although women equally contributes to society, the patriarchal culture of Nepal and the binding customary practices has denied women's right to land and property in the history of Nepal. This issue got attention only after 1975 which was strengthened later by the constitution of Nepal in 1990 that

states no discrimination by sex (Campus, 2021). Nepal started celebrating international Women's day on 8th of March following UN declaration of 1975. In the same year the Civil Code (*Muluki Ain*) was amended with the inclusion of women's right to inherit property who remains unmarried until the age of 35. This clause has its limitation of returning the property back to their brothers after deducting marriage cost. Nepal later started global commitments to Women's Rights including Beijing Platform for Action on International agreement on women's rights and gender equality. The government ratified the UN Convention on the Elimination of all forms of Discrimination against Women (CEDAW-1979) in 1991.

11th Amendment in Civil Code-2020 (1963) has brought significant achievement in equality of women. This reform has broadened the women's right including equal inheritance from birth, equal right to husband's property upon marriage, strengthened right of widow, access to divorce and property after divorce, strict punishment against polygamy, legalized abortion under specific conditions and harsh penalty for rape case.

5. Despite constitutional guarantees to equality, Women's land ownership has increased only to 23.8% (Census, 2021). Still there remains limitation, although land is legally in the name of women, decisions regarding the use, management and control is done by male member of the family. (Nepal & Marasini, 2018). This sort of things still makes women face challenges in having real control to their land. This shows that legal reforms alone may not empower women without shifting household dynamics. Here are some land mark decision made by the Supreme Court that created real milestone in terms of gender equality.

6. Land mark Precedents of Supreme Court in Women's property right

The supreme court plays instrumental role in social transformation enhancing equality of women's property right (Aggarwal, 2021; Campus, 2021). A decision made by Supreme Court of Nepal is considered as precedent, and it is binding unless the Parliament nullifies its effect by enacting new Act or the Supreme Court overrules its previous judgment. (Update et al., n.d.). The land mark decisions made by Supreme Court of Nepal in regard of women's property right has created milestone in gender equality. Some of the landmark decisions are reviewed here in this section.

6.1 Meera Kumari Dhungana v. Government of Nepal in 1995

7. *Government of Nepal in 1995 which challenged muluki Ain 1963 clause number 16 on partition of property which states that unmarried daughter over 35 years can inherit the parental property equal to son and if she got married after receiving share, she had to return back to her brothers deducting marriage expenses. The petitioner further argued that this provision discriminated the women based on the marital status. And violates the article 11,15 and 17 of constitution 1990 that advocates on equal right to property of all citizens which was against Nepal's commitments under CEDAW.* The government denied to amend this provision as removing this gives women double benefit from both paternal and marital property violating equality principles. Senior advocate Bal Krishna Neupane argued that different treatment is justified as sons and daughters are naturally unequal. Amicus Curiae Ganesh Raj Sharma further argued as equality doesn't mean identical treatment but is justified by social roles and conditions. The Supreme Court acknowledged clause 16 as discriminatory by ensuring that sons and daughter should have equal rights to parental property. Supreme court didn't immediately invalidate the provision as it could be seen arbitrary if radical changes to social practice is made without public acceptance. So it directed government to consult women's organizations, sociologists and lawyers and study international

practices before proposing amendments. Finally this led to the 11th amendments of Muluki Ain 2002 which granted daughters with equal inheritance rights as sons but married daughters still need to return their share. Later, with the amendment made in 2015 under section 1(a) of Muluki Ain, this discriminatory provision was abolished without distinguishing married and unmarried daughters and guarantees equal rights to parental property for all daughters. This has been a significant step towards gender justice in Nepal which has highlighted the importance of inclusive discussion to make significant change in social practices and norms. This decision was made by the supreme court on 2052/04/18 B.S and the decision number was 6013.

6.2 Sapana Pradhan Malla & Prakash Mani Sharma v. HMG

8. Advocates Sapana Pradhan Malla and Prakash Mani Sharma challenged section 26(1) of Land Act, 1964 (2013BS) filing the writ against His Majesty Government regarding the discrimination of women in inheritance and tenancy rights. Section 26(1) after the death of tenant, the tenancy rights transferred either to the wife or to the sons excluding daughters either married or unmarried and widowed daughter in law from succeeding such rights. The petitioner argued that this violated the Article 11 which focuses on right to equality of citizen before the law and addresses that citizens should not be discriminated despite of their religion, race, sex, caste, tribe or ideological conviction or any of these. Similarly it violates Article 17 right to property to all citizens. The government defended this provision was just to ensure the continuation of cultivation and integrity of tenancy land within the tenant family. As daughter moves to her husband's house after marriage, her entitlement was not recognized under the law. The supreme court didn't declare invalid accepting the government's reasoning. However, the court recognized gender inequality inherent in this provision. Therefore, court appealed government to draft a new law to fix the unfair rules in the Land Act. This decision of court has been regarded as one of the milestone in aligning gender equality in land and tenancy laws into constitution. This led to the amendment addressing gender equality in land right which was later incorporated in Muluki Ain.(Update et al., n.d.).

6.3 Advocate Tej Bahadur Katuwal v. the Office of the President, Sheetal Niwas

6 The petitioner challenged the provisions of Muluki Civil code 2074 which has created the confusion regarding coparcenary rights of the daughters if the married women have equal right to inherit parental or ancestral property as the sons. The petitioner further argued that denying equal coparcenary rights violated Article 38 (6) of the Constitution of Nepal, 2015 which ensures equality to women. The discrimination is based on sex and marital status. The court has decided that marriage changes social and family status but not coparcenary rights. Daughters either married or unmarried have equal right in parental property. This has supported equal coparcenary rights for daughters despite of their marital status. This has enhanced the right to equality. This judgment has been considered as the remarkable decision in Nepalese legal history that ensured equal property right and served as a guiding legal precedent to similar disputes.(Advisors, 2020).

6.4 Annapurna Rana v. Gorakh Shamsher J.B.R. (1998)

This is a land mark decision made by Supreme Court of Nepal that significantly advocated on the protection for privacy, dignity, bodily autonomy and gender equality. It is decision no. NLR 1998, Issue 8, Decision No. 6588 and writ no. 2187 of 1996 and **Order Date:** June 8, 1998 (2055 B.S). Annapurna Rana has filed case against Gorakh Samsher J.B.R. The Writ Petition challenged orders from Kathmandu District Court and later Patan Appellate Court. These orders requested her to undergo a gynaecological

“virginity test” and other body examinations to prove whether she had been married or had children. These tests were meant to prove if she had been married or has children as her relatives had claimed she was married, arguing that she should not get certain property or financial support. Compelling the women to undergo a virginity test or similar examination violates the fundamental right to privacy protected under Article 22 of Constitution of Nepal, 1990. Such types of test are degrading, discriminatory and undermine human dignity, affecting women disproportionately. The court has noted that these tests have no scientific basis and cannot prove whether someone is married or had children. Sexual activity or childbirth alone does not legally determine marital status, so the lower courts' assumptions were wrong. This decision is viewed as one of the major supreme court ruling in Nepal on the right to privacy which has set this as an important constitutional precedent. According to legal experts, this case has changed Nepal's approach to privacy and gender justice. It ended old patriarchal practices like using virginity tests as evidence and strengthened protections against gender discrimination in court (National Judicial Academy, Nepal, n.d.). The case is often cited in debates on privacy and evidence law in Nepal. This has protected the privacy, dignity and equality of women.

6.5 Inheritance Rights of Married Daughters in Nepal

According to online khabar, The petitioner, elder daughter of a family who has filed writ against her father and step mother regarding the denial of her inheritance citing her marital status and foreign citizenship. The issues were regarding the entitlement of married daughters if she could inherit paternal property. From the decision made by five full bench, the **majority opinion** of 3 judges: Manoj Kumar Sharma, Saranga Subedi and Abdul Ajj Musalman held that only daughters married after the 2072 BS Constitution and the 11th amendment of the Muluki Ain (Civil Codes) could claim inheritance. Daughters married before that would follow the old law. This meant the eldest daughter in the case, married in 2051 BS, was **not entitled** to her share, overturning lower court decisions. The **minority opinion drawn from 2 Judges Sapana Pradhan Malla and Mahesh Sharma Poudel** has advocated that married daughters **should receive inheritance**, pointing out that the 11th amendment in 2059 BS already gave daughters the right to inherit, which was later expanded after the 2072 BS Constitution. They argued the eldest daughter's right had already been created, so her marital status was irrelevant. They emphasized that denying her share would be discriminatory and contrary to constitutional guarantees. The case highlighted the debates on gender equality, inheritance rights, and constitutional interpretation and legal reform in Nepal.

6.6 Supreme Court, Land tenure, and its Socio-Economic Implications

Supreme Court with its Landmark Decisions has supported women's equal inheritance right to property which strengthen land tenure by ensuring land ownership, control and access to land. Land tenure secures economic independence and enhances bargaining power within households and communities. Land tenure is the relationship between land and people either individual or groups are legally or customarily defined. Land tenure determines who can use what resources for how long and under what condition. (Land & Studies, n.d.). It further states that land tenure can be enforced formally through court of law or through customary practice of the community or may be relatively poorly defined with ambiguities open to exploitation. The right of people on any object is considered as property. Different rights to a same parcel of land emerged the concept of bundle of right. (Land & Studies, n.d.)

7. Land has been considered as the important asset in operating social, political and economical activities that functions market institution. Human existence depends directly or

indirectly upon land as it is primary source of wealth and power of any nation. Land provides primary source of livelihood and provides investment opportunities. Access to land should be equitable and shouldn't be deprived based on sex, education or social status (Nuhu et al., 2020). The census 2021 Nepal shows that women's land ownership has increased to 23.8% but the ownership of land doesn't mean only having control over it. It is often the men in the family who makes decisions about how the land is used or sold (Nepal & Marasini, 2018).

8. Women's land right and tenure security plays very important role in promoting economic growth and development reducing poverty. Women's tenure security is not only the right that women holds but the extent to which this rights are secure (Doss & Meinzen-Dick, 2020).
9. Secure access to land plays a very important role in advancing the livelihoods, housing, food security and dignity of women which is fundamental for improving social and economic security. Discrimination in land ownership and inheritance can make women more vulnerable to poverty, eviction and displacement.
10. Women's land right strengthen their economic independence promoting their social status (Rights, 2022). Ownership to fixed assets like houses and lands are key indicator of wealth, social security and power in Nepal. These assets play significant role in defining women's status within households and communities. It influences on their economic dependence or independence and their ability to engage in productive economic activities (Rijal, 2017)
11. Therefore, land Tenure and ownership strengthen social status, dignity, and participation in decision-making. Collectively it secures their social and economic position. Supreme Court laid a strong foundation for gender equality in property rights. Land mark decision made by the Supreme court, dismantled discriminatory laws on land, inheritance, and tenancy These judicial interventions have directly influence legislative reforms leading amendments to Muluki Ain, promulgation of constitution of Nepal 2015 and civil code 2017. It has established binding precedents supporting gender equality. But the Social norms, customary laws, and weak enforcement have limited practical empowerment. Broader institutional accountability, public awareness, and social changes are essential for full impact. Legal reforms enable women's independent ownership and coparcenary rights.

12. Analysis and Discussion

The Supreme Court has played a crucial role in reshaping discriminatory laws against women by enhancing the land ownership and inheritance right of women in Nepal. In the initial phase, court was reluctant to amend the discriminatory property laws citing the possibility of arbitrary if radical changes are made without public acceptance. However, the directive orders made by court compelled to initiate legislative reforms which has triggered for the nationwide debate on strengthening women's right and movement.

13. A Land mark decision on women's equal right made by Supreme Court has led constitutional and statutory reform in constitution of Nepal 2015 and civil code 2017. It has recognized formal women's equal rights to property. The judicial interpretation and enforcement is seen pivotal as their judgments are final and binding on all courts and authorities.
14. Court has dismantled several historical entrenched discriminatory legal practices related to land ownership, inheritance and tenancy right to women. The landmark cases like *Meera Kumari Dhungana v. Government of Nepal*, *Sapana Pradhan Malla v. HMG*, and *Tej Bahadur Katuwal v. Office of the President* represent critical milestones in Nepal's legal history. This decision has given women either married or unmarried equal coparcenary and inheritance rights to parental

and ancestral property. These judicial interventions have directly influence legislative reforms leading amendments to Muluki Ain , promulgation of constitution of Nepal 2015 and Civil code 2017. These reforms have recognized women as independent right holders to land and property.

15. These land mark decisions helped women in establishing independent right to land which strengthened their secured land tenure which makes women socio-economically secured. Secured ownership and control over land enhances women's economic independence. Land tenure security strengthen the women's bargaining power within households and communities which increases their meaningful participation in decision making processes reinforcing their social status and dignity. Therefore, land functions not only as an economic asset but as a means of social recognition and stability.
16. This study also tried to highlight the gap between legal recognition and the effective enjoyment of land right. The deeply rooted entrenched customary practices in our patriarchal norms, unequal power division within the household continue to limit the women access and control over land even though the legal ownership exists. As a result the potential of land tenure to fully translate social and economic security remain constraint.

7. Conclusion

Therefore the Supreme Court has build strong foundation for gender equality in land and property right through its milestone decisions. This has helped women achieve substantive social and economic security but the deeply rooted social practices, customary laws of our patriarchal society has limited the potential of land tenure in achieving social and economical security. For the effective transformation of land tenure to meaningful empowerment, effective implementation of law, institutional accountability, public awareness and broader social change is very much essential. Strengthening the women's land right is considered as the crucial in advancing gender justice and social protection

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AUTHOR INFORMATION



Name	: Kapina Manandhar
Academic Qualification	: Master's in Land Administration PhD candidate in Geomatics Engineering
Organization	: Architectonic and Engineering Consult, Banepa
Current Designation	: Principal Architect
Work Experience	: 15 years

COMPARATIVE ACCURACY ASSESSMENT OF UAV-DERIVED ORTHOPHOTO, DSM, AND DTM GENERATED WITH AND WITHOUT GROUND CONTROL POINTS: A CASE STUDY OF THE LMTC PREMISES, NEPAL

Bhuwan Singh Bisht¹, Nabaraj Subedi¹, Ram Kumar Sapkota¹, Laxmi Devi Thapa¹

¹Land Management Training Center, Dhulikhel, Kavrepalanchok, Nepal

geo.bhuwan@gmail.com ; nabaraj.ge@gmail.com ; ramksap1@gmail.com; thapalaxmi8182@gmail.com

KEY WORDS: UAV photogrammetry, ground control points (GCPs), checkpoints (CPs), orthophoto, digital surface model (DSM), digital terrain model (DTM), accuracy assessment

ABSTRACT:

Unmanned Aerial Vehicle (UAV) photogrammetry is increasingly used for local-scale mapping because it enables rapid generation of high-resolution orthophotos and elevation products. However, the positional and vertical quality of these products depends strongly on the georeferencing strategy, particularly the use of Ground Control Points (GCPs). This study evaluates the effect of GCPs on the accuracy of UAV-derived orthophoto, Digital Surface Model (DSM), and Digital Terrain Model (DTM) at the premises of the Land Management Training Center (LMTC), Dhulikhel, Nepal. The same UAV image block of 334 images was processed under two workflows: one using only onboard image geolocation and another using five surveyed GCPs. Eight independent checkpoints were used for accuracy assessment. Orthophoto planimetric accuracy was evaluated using checkpoint coordinates, while vertical agreement of DSM and DTM was assessed using surveyed ground elevations. In addition, pairwise checkpoint-distance analysis and supplementary object-based comparison were used to examine relative geometric differences in the orthophotos. The with-GCP orthophoto achieved a horizontal RMSE_H of 0.063 m, whereas the without-GCP orthophoto showed an RMSE_H of 3.507 m. Similarly, the with-GCP DSM and DTM achieved RMSE_Z values of 0.131 m and 0.143 m, respectively, compared with 15.385 m and 15.347 m in the without-GCP workflow. The without-GCP orthophoto also exhibited systematic westward and northward displacement and minor scale-related geometric differences. The results demonstrate that GCP-based processing remains essential for reliable campus-scale UAV photogrammetry when the outputs are intended for measurement, terrain representation, planning, and other applications requiring dependable absolute accuracy.

1. INTRODUCTION

Unmanned Aerial Vehicle (UAV) photogrammetry has emerged as an efficient and accessible approach for generating high-resolution geospatial products for local-scale mapping and analysis. By acquiring multiple overlapping images from low-altitude aerial platforms and processing them through image matching, bundle adjustment, and three-dimensional reconstruction, UAV systems can produce orthophotos, Digital Surface Models (DSMs), and Digital Terrain Models (DTMs) suitable for surveying, engineering mapping, terrain analysis, infrastructure inspection, environmental monitoring, and land-management applications (Kovanič et al., 2023; Manfreda et al., 2018). Because UAV platforms are flexible, rapid, and comparatively low-cost, they are now widely used in site-scale geospatial workflows where timely and detailed spatial products are required.

The photogrammetric outputs derived from UAV imagery are fundamentally dependent on image geometry, flight configuration, and georeferencing quality. An orthophoto is a geometrically corrected aerial image in which relief and perspective distortions have been removed so that the image can be used for planimetric measurement. A DSM represents the elevation of the upper visible surface, including terrain, buildings, vegetation, and other above-ground objects, whereas a DTM represents the bare-earth terrain surface after excluding such features (Guth et al., 2021; Pix4D, n.d.-a). These products are valuable for mapping, planning, monitoring, and quantitative measurement, but their usefulness depends strongly on the positional and vertical reliability achieved during data acquisition and processing.

Previous studies have shown that the quality of UAV-derived products is influenced by several interacting factors, including

flight altitude, image overlap, ground sampling distance, terrain complexity, camera calibration, flight geometry, and the software used for photogrammetric reconstruction (Gerke & Przybilla, 2016; Kovanič et al., 2023; Szypuła, 2024). Among these factors, georeferencing strategy plays a particularly important role in determining absolute positional accuracy. In practical UAV photogrammetry, Ground Control Points (GCPs) provide external geometric control by linking the image block to accurately surveyed ground coordinates, whereas checkpoints are reserved for independent validation and should not be used during model adjustment (Pix4D, n.d.-b; Sanz-Ablanedo et al., 2018). The number, spatial distribution, and quality of GCPs can substantially influence the final positional and vertical accuracy of orthophotos and elevation models (Martínez-Carricondo et al., 2018; Sanz-Ablanedo et al., 2018; Szypuła, 2024).

The need to compare with-GCP and without-GCP workflows is both technically and practically important. In many campus-scale and institutional UAV surveys, especially those carried out with consumer-grade platforms, there is often a tendency to rely only on onboard image geolocation in order to reduce field effort, time, and equipment requirements. However, several studies have shown that products generated without GCPs may appear visually coherent while still exhibiting weak absolute positional reliability (Szypuła, 2024; Žabota et al., 2021). This distinction is important because a product that appears visually acceptable may still be unsuitable for precise mapping, engineering measurement, or land-management applications that require dependable absolute positioning.

This issue is directly relevant to the premises of the Land Management Training Center (LMTC), Dhulikhel, Kavrepalanchok, Nepal, where the study area includes open ground, buildings, internal roads, and mixed surface conditions that are suitable for evaluating both planimetric and elevation

products. In the present study, the same UAV image block was processed under two separate workflows: one using only onboard image geolocation and another using surveyed Ground Control Points. This design allows the effect of georeferencing strategy to be examined while keeping the study area, image dataset, and processing environment constant.

Accordingly, this study aims to assess the effect of Ground Control Points on the positional and elevation accuracy of UAV-derived orthophoto, DSM, and DTM products at the LMTC premises, Nepal. More specifically, the study compares with-GCP and without-GCP processing workflows, evaluates orthophoto planimetric accuracy using independent checkpoints, and assesses vertical agreement of the elevation products at surveyed ground checkpoint locations. In addition, the study examines whether the without-GCP orthophoto is affected only by systematic positional shift or also by relative geometric differences.

2. MATERIALS AND METHODS

2.1 Study area

The study was carried out within the premises of the Land Management Training Center (LMTC), located in Dhulikhel, Kavrepalanchok, Nepal, as shown in Figure 1. The study area covers 31,666.47 m² (approximately 3.17 ha).

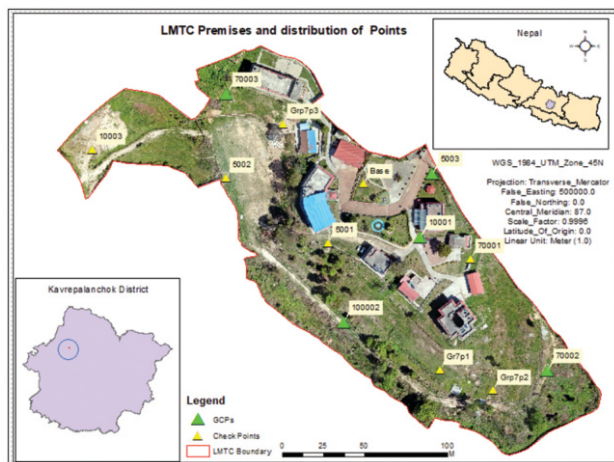


Figure 1. Location of the study area and distribution of Ground Control Points and checkpoints

2.2 Methodology

The overall methodology adopted in this study is illustrated in Figure 2. The workflow began with UAV data acquisition over the LMTC premises, followed by DGPS survey of pre-marked ground targets. The same UAV image block was then processed under two separate photogrammetric workflows: one using only onboard image geolocation and another using surveyed Ground Control Points (GCPs). In the with-GCP workflow, the surveyed GCPs were used for georeferencing, while the independent checkpoints were reserved only for validation. In the without-GCP workflow, no surveyed GCPs were introduced during processing, and georeferencing relied solely on onboard image geolocation.

After photogrammetric processing, the generated orthophoto, DSM, and DTM products from both workflows were clipped to the LMTC boundary in order to maintain a common analysis extent. Coordinates and elevation values were then extracted at the independent checkpoint locations for comparative evaluation. The resulting products were assessed through planimetric

analysis of the orthophoto and vertical agreement assessment of the elevation products at the checkpoint locations. In addition, supplementary relative-geometry analysis was carried out to examine whether the without-GCP orthophoto was affected only by positional shift or also by scale-related geometric differences. The complete methodological sequence is presented in Figure 2.

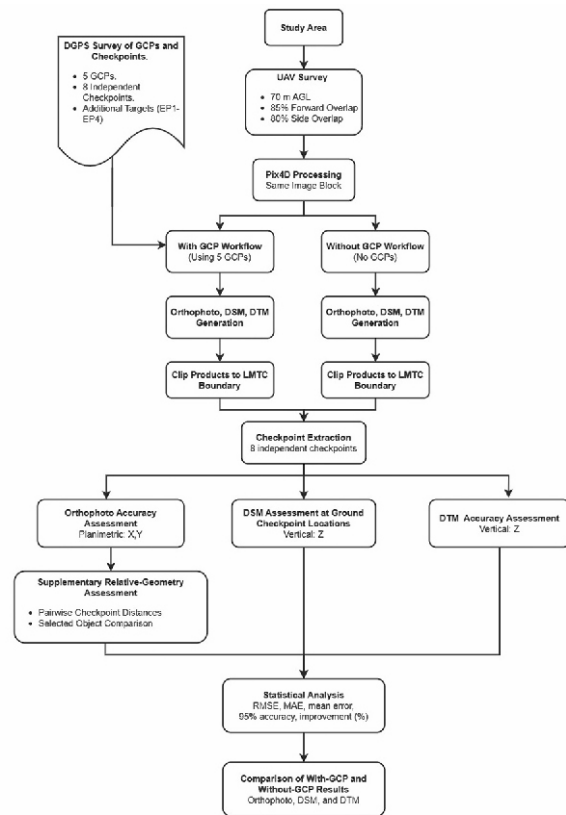


Figure 2. Methodological workflow of the study

2.3 UAV data acquisition

A UAV survey was conducted over the LMTC premises using a DJI Mavic 3 equipped with an RGB camera. Nadir images were acquired during the flight through the survey configuration. The flight was carried out at 70 m above ground level, maintaining 85% forward overlap and 80% side overlap. A total of 334 images were captured during the survey. These images were used to generate orthophoto, DSM, and DTM products under both processing scenarios.

2.4 Ground Control Points, Checkpoints, and Additional Targets

Pre-marked targets were established across the study area and surveyed on the ground using Trimble DGPS. Each station was observed for more than 2 hours, and the collected data were subsequently processed in Trimble Business Center software to obtain the final coordinates. The surveyed Ground Control Points (GCPs) and independent checkpoints listed in Table 1 are reported in the WGS 1984 UTM Zone 45N coordinate reference system (EPSG:32645). The projection is based on the Transverse Mercator system, with a central meridian of 87°, a scale factor of 0.9996, a false easting of 500000.0 m, and a false northing of 0.0 m. The horizontal coordinates are expressed in meters.

Because the study area was relatively small and campus-scale in extent, five GCPs were considered practically sufficient for

external control in the present comparison. However, a denser and more widely distributed GCP network would provide stronger redundancy and may further improve georeferencing robustness in future studies.

Five points, GCP1, GCP2, GCP3, GCP4, and GCP5, were used as Ground Control Points in the with-GCP workflow, as shown in Table 1. These points were introduced during photogrammetric adjustment to constrain the model in the output coordinate system. Eight points, CP1 to CP8, were used as independent checkpoints and were excluded from the adjustment. After product generation, the same checkpoints were used to assess the accuracy of the orthophoto, DSM, and DTM by comparing the extracted coordinates and elevations with the surveyed values.

Table 1. Surveyed GCPs and checkpoints used in the study

SN	Point Name	Easting(m)	Northing(m)	Elevation(m)	Remarks
1	CP1	356092.046	3055879.615	1486.559	CP
2	CP2	356178.297	3055869.848	1483.357	CP
3	CP3	356113.241	3055915.189	1490.748	CP
4	CP4	356159.554	3055802.329	1480.710	CP
5	CP5	356191.748	3055790.117	1479.035	CP
6	CP6	356064.682	3055951.382	1482.868	CP
7	CP7	355949.173	3055935.794	1478.221	CP
8	CP8	356030.024	3055918.795	1478.808	CP
9	GCP1	356154.897	3055921.294	1489.883	GCP
10	GCP2	356147.720	3055882.701	1488.432	GCP
11	GCP3	356224.548	3055801.769	1475.884	GCP
12	GCP4	356030.447	3055969.268	1482.351	GCP
13	GCP5	356101.087	3055830.983	1475.703	GCP

In addition, four extra pre-marked targets, EP1 to EP4, were visible in the UAV products but were not surveyed in the field. Because their ground coordinates were not available, these points were not included in the quantitative accuracy assessment. However, they were used for supplementary visual and relative comparison between the with-GCP and without-GCP orthophotos. The classification of points used in the study is presented in Table 2.

Table 2. Point categories used in the study

Point category	Point IDs	Count	Use in analysis
Ground Control Points	GCP1, GCP2, GCP3, GCP4, GCP5	5	Georeferencing only
Independent checkpoints	CP1, CP2, CP3, CP4, CP5, CP6, CP7, CP8	8	Absolute accuracy assessment
Supplementary visual targets	EP1, EP2, EP3, EP4	4	Relative orthophoto shift only

2.5 Processing scenarios

The same UAV image block was processed under two separate workflows to evaluate the effect of georeferencing strategy on the final products. In the first workflow, the imagery was processed using only the onboard image geolocation recorded in the image metadata, and no surveyed control points were introduced during adjustment. In the second workflow, the same imagery was processed again using the five surveyed Ground Control Points as GCPs, while the eight independent checkpoints were assigned only as checkpoints for validation. After GCP marking, checkpoint assignment, and bundle adjustment, orthophoto, DSM, and DTM products were generated. Because the same image block and acquisition conditions were used in both cases,

the comparison isolates the effect of GCP-based georeferencing on product accuracy.

The DTM used in this study was generated using the built-in terrain-model generation workflow in Pix4D Mapper. This clarification is important because DTM quality is dependent on the terrain-model generation and ground-classification procedure.

Pix4D Mapper was selected because it provides an integrated environment for image alignment, bundle adjustment, control-point management, orthophoto generation, DSM/DTM production, and processing-quality reporting within a single software workflow. Since the main objective of the study was to compare the effect of with-GCP and without-GCP georeferencing using the same UAV image block, the same processing software was intentionally retained for both workflows. A cross-software comparison could be valuable in future research, but it was beyond the scope of the present study.

1.2 Photogrammetric processing quality

The Pix4D quality reports indicate that both workflows calibrated all 334 images successfully. In the with-GCP workflow, the average GSD was 3.10 cm, the median number of keypoints per image was 11,242, the median number of matches per calibrated image was 6417.33, and the mean reprojection error was 0.146 pixel. Georeferencing was based on five 3D GCPs, with a mean RMS georeferencing error of 0.018 m. In the without-GCP workflow, the average GSD was 3.12 cm, the median number of keypoints per image was also 11,242, the median number of matches per calibrated image were 6422.72, and the mean reprojection error was 0.144 pixel. However, this workflow was processed without any 3D GCPs, and the camera optimization difference was noticeably larger, at 17.67%, than in the with-GCP workflow, where it was 3.65%. This indicates weaker geometric constraint in the no-control case. Selected processing-quality indicators derived from the Pix4D quality reports are summarised in Table 3.

Table 3. Selected processing-quality indicators from the Pix4D quality reports for the two workflows

Indicator	With GCP	Without GCP
Images calibrated	334/334	334/334
Average GSD	3.10 cm	3.12 cm
Median keypoints per image	11,242	11,242
Median matches per calibrated image	6417.330	6422.720
Mean reprojection error	0.146 pixel	0.144 pixel
Camera optimization difference	3.65%	17.67%
Georeferencing status	5 GCPs (5 3D), mean RMS 0.018 m	No 3D GCP

Further details from the Pix4D geolocation report of the with-GCP workflow showed that the GCP-based adjustment was well constrained. The GCP RMSE values were 0.022 m in X, 0.023 m in Y, and 0.010 m in Z, indicating a strong georeferencing fit. Independent checkpoint validation yielded RMSE values of 0.011 m in X, 0.031 m in Y, and 0.124 m in Z, demonstrating very good horizontal agreement and satisfactory vertical consistency. The absolute geolocation variance further indicated that the initial

onboard image geolocation contained systematic offsets, with mean values of -1.478 m in X, 3.254 m in Y, and -0.867 m in Z. The corresponding RMS values were 1.496 m, 4.035 m, and 0.994 m, respectively. These results suggest that although the onboard image geotags provided a usable initial position, the incorporation of surveyed GCPs was essential for achieving reliable absolute georeferencing. The georeferencing and checkpoint statistics derived from the Pix4D geolocation report are presented in Table 4.

Table 4. Georeferencing and checkpoint accuracy statistics from the Pix4D geolocation report for the with-GCP workflow

Statistic	X (m)	Y (m)	Z (m)
GCP RMSE	0.022	0.023	0.01
Checkpoint RMSE	0.011	0.031	0.124
Mean absolute geolocation variance	-1.478	3.254	-0.867
RMS absolute geolocation variance	1.496	4.035	0.994

The GCP RMSE values represent the fit of surveyed ground control points after bundle adjustment. The checkpoint RMSE values represent independent validation accuracy. The absolute geolocation variance describes the difference between the initial onboard image geolocation and the adjusted image geolocation.

2.7 Accuracy assessment and statistical analysis

Accuracy assessment was carried out separately for the orthophoto and the elevation products generated under the with-GCP and without-GCP workflows. For the orthophoto, the surveyed coordinates of the independent checkpoints were compared with the corresponding coordinates extracted from the orthophoto to evaluate planimetric accuracy. For the elevation products, the surveyed elevations of the checkpoints were compared with the raster-derived elevation values extracted from the respective products to evaluate vertical agreement.

Because all vertical validation checkpoints used in this study were located on ground surfaces, the checkpoint-based vertical assessment primarily represents elevation agreement at ground locations. In this context, the DTM evaluation directly represents bare-earth agreement, whereas the DSM evaluation reflects raster elevation agreement at the same ground checkpoint locations only and does not provide validation of elevated surface features such as rooftops, vegetation canopies, or other above-ground objects.

Residuals were computed as the differences between the model-derived values and the surveyed reference values. The residuals in the X and Y directions express planimetric displacement in easting and northing, respectively, while the residual in the Z direction expresses vertical deviation. For the orthophoto, these two horizontal residual components were combined into a single radial planimetric error term. For the elevation products, the vertical residual directly represents the difference between the extracted raster elevation and the surveyed elevation. The accuracy assessment in this study was based on eight independent checkpoints distributed across the LMTC premises. Although this number is lower than the larger checkpoint counts recommended for broader standards-based summary reporting, the checkpoints were retained because of the limited campus-scale extent of the study area and the availability of clearly identifiable surveyed targets. To improve transparency of the assessment, the revised analysis includes not only summary statistics but also checkpoint-wise residual reporting for the independent checkpoints.

To summarise the magnitude of error, Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) were computed. MAE represents the average magnitude of error without considering

sign, whereas RMSE gives greater weight to larger residuals and is therefore more sensitive to larger deviations. Mean error was used to identify systematic bias in the products. A positive mean error indicates overestimation, while a negative mean error indicates underestimation. Standard deviation (SD) was used to describe the spread or consistency of the residuals. The 95% horizontal and vertical accuracy metrics were calculated to provide a confidence-based summary of product accuracy following NSSDA-style reporting (FGDC, 1998). All positional and vertical accuracy statistics are reported to three decimal places in meters for consistency and practical interpretability.

In addition to absolute positional assessment, a relative-geometry analysis was carried out to examine whether the without-GCP orthophoto was affected only by systematic displacement or also by scale-related geometric differences. This was assessed through pairwise distance comparison among the independent checkpoints and supplemented by selected object-based comparisons of digitized footprints on the with-GCP and without-GCP orthophotos.

Finally, the improvement achieved through GCP-based processing was expressed as a percentage difference between the with-GCP and without-GCP error values. This metric was used to quantify the practical benefit of field control for orthophoto, DSM, and DTM generation. The residuals and statistical measures were computed using Equations (1) to (12).

$$e_X = X_{model} - X_{survey} \quad (1)$$

$$e_Y = Y_{model} - Y_{survey} \quad (2)$$

$$e_Z = Z_{model} - Z_{survey} \quad (3)$$

$$e_H = \sqrt{e_X^2 + e_Y^2} \quad (4)$$

$$RMSE_X = \sqrt{\sum \frac{e_X^2}{n}} \quad (5)$$

$$RMSE_Y = \sqrt{\sum \frac{e_Y^2}{n}} \quad (6)$$

$$RMSE_Z = \sqrt{\sum \frac{e_Z^2}{n}} \quad (7)$$

$$RMSE_H = \sqrt{RMSE_X^2 + RMSE_Y^2} \quad (8)$$

$$MAE = \frac{\sum |e_i|}{n} \quad (9)$$

$$Accuracy_{11,95} = 1.7308 \times RMSE_{11} \quad (10)$$

$$Accuracy_{Z,95} = 1.96 \times RMSE_Z \quad (11)$$

$$Improvement (\%) = \left(\frac{Error_{without} - Error_{with}}{Error_{without}} \right) * 100 \% \quad (12)$$

3.1 Orthophoto positional accuracy assessment

The orthophoto positional accuracy assessment based on eight independent checkpoints showed a clear improvement after the incorporation of Ground Control Points (GCPs). The checkpoint-wise residuals indicate that the with-GCP orthophoto produced only small planimetric residuals, whereas the without-GCP orthophoto showed substantially larger horizontal errors. These checkpoint-level results provide a clearer representation of the spatial distribution and consistency of positional error under both

workflows.

Table 5. Checkpoint-wise residuals for orthophoto positional accuracy assessment under the with-GCP and without-GCP workflows.

CP	eX with- GCP (m)	eY with- GCP (m)	eH with- GCP (m)	eX without- GCP (m)	eY without- GCP (m)	eH without- GCP (m)
CP1	0.022	-0.039	0.045	-1.670	2.976	3.413
CP2	-0.042	0.039	0.057	-1.194	2.856	3.096
CP3	0.034	-0.033	0.047	-1.519	3.211	3.552
CP4	-0.070	-0.053	0.088	-1.400	2.337	2.725
CP5	0.026	-0.025	0.036	-1.107	2.194	2.458
CP6	-0.012	0.035	0.037	-1.867	3.572	4.031
CP7	0.036	-0.020	0.042	-2.618	3.564	4.422
CP8	0.088	0.001	0.088	-2.02	3.367	3.926

A visual comparison of the orthophotos generated under the two workflows is presented in Figure 3. Although the without-GCP orthophoto appears visually coherent, it does not align reliably with the surveyed checkpoint positions.

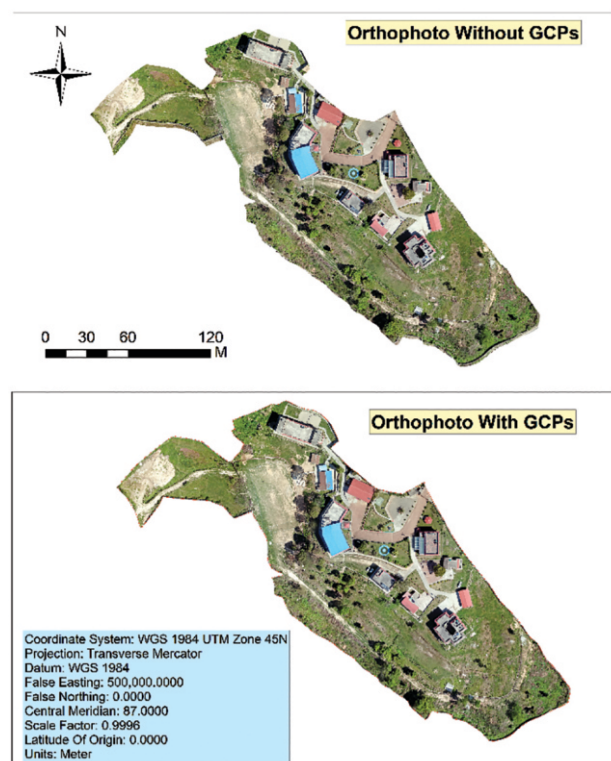


Figure 3. Orthophotos generated under the with-GCP and without-GCP workflows at the LMTC premises

The summary statistics further confirm the substantial improvement achieved through GCP-based processing. In the with-GCP workflow, the orthophoto produced RMSE values of 0.053 m in X and 0.034 m in Y, resulting in a combined horizontal RMSE_H of 0.063 m and a 95% horizontal accuracy of 0.108 m. In contrast, the without-GCP orthophoto produced RMSE values of 1.731 m in X and 3.050 m in Y, yielding a combined RMSE_H of 3.507 m and a 95% horizontal accuracy of 6.070 m. This corresponds to a horizontal RMSE improvement of 98.21% after the incorporation of GCPs.

Table 6. Summary statistics of orthophoto positional accuracy under the with-GCP and without-GCP workflows.

Statistic	With GCPs	Without GCPs
Mean Error X (m)	0.016	-1.669
Mean Error Y (m)	-0.012	3.010
MAE _X (m)	0.047	1.669
MAE _Y (m)	0.031	3.010
RMSE _X (m)	0.053	1.731
RMSE _Y (m)	0.034	3.050
RMSE _H (m)	0.063	3.507
95% horizontal accuracy (m)	0.108	6.070
Median horizontal error (m)	0.052	3.471
SD horizontal error (m)	0.022	0.672
Min horizontal error (m)	0.036	2.458
Max horizontal error (m)	0.088	4.422

The error statistics show that the without-GCP orthophoto was affected not only by larger absolute error but also by systematic positional displacement. In the without-GCP workflow, the mean errors in X and Y were -1.669 m and 3.010 m, respectively, indicating a consistent westward and northward shift. In contrast, the with-GCP orthophoto showed near-zero mean residuals in both directions, indicating that the GCP-based adjustment effectively constrained the image block in map space. The largest horizontal error in the without-GCP case was observed at CP7, which lies near the outer part of the study area, suggesting weaker positional reliability toward the periphery of the uncontrolled block.

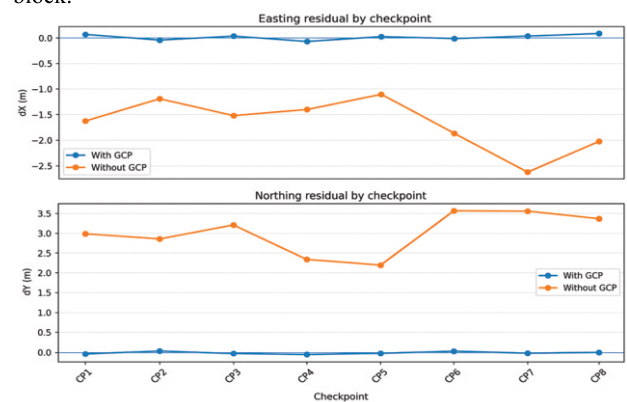


Figure 4. Easting and northing residuals of independent checkpoints under the with-GCP and without-GCP orthophoto workflows

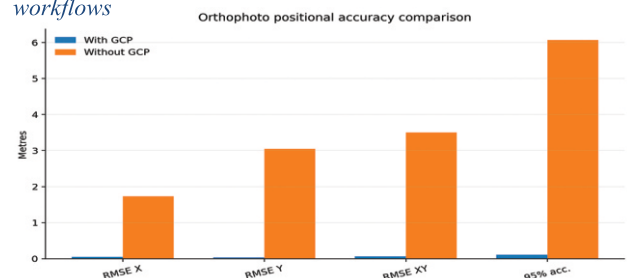


Figure 5. Comparison of key orthophoto positional-accuracy metrics under the with-GCP and without-GCP workflows

These results indicate that orthophotos generated without ground control may still possess weak absolute positional reliability. This finding is consistent with previous UAV photogrammetry studies reporting that products processed without sufficient external control can preserve general visual form while remaining unsuitable for precise planimetric measurement (Martínez-Carricondo et al., 2018; Sanz-Ablanedo et al., 2018; Szypuła, 2024).

3.2 Supplementary relative positional comparison of additional unsurveyed targets

In addition to the independent checkpoints, four extra pre-marked targets (EP1–EP4) visible in both orthophoto products were used for supplementary relative comparison. Because surveyed ground coordinates were not available for these targets, they were not included in the formal absolute accuracy assessment. However, they provide useful supporting evidence for evaluating relative positional differences between the with-GCP and without-GCP orthophotos.

The relative positional comparison of these additional targets is shown in Figure 6. The without-GCP orthophoto was displaced on average by -1.569 m in X and 3.254 m in Y relative to the with-GCP orthophoto, with a mean relative shift of 3.613 m. This displacement pattern is consistent with the westward and northward shift already identified from the independent checkpoint analysis. The relative positional differences for the four supplementary targets are summarised in Table 7, while the relative deviation pattern is further illustrated in Figure 7.

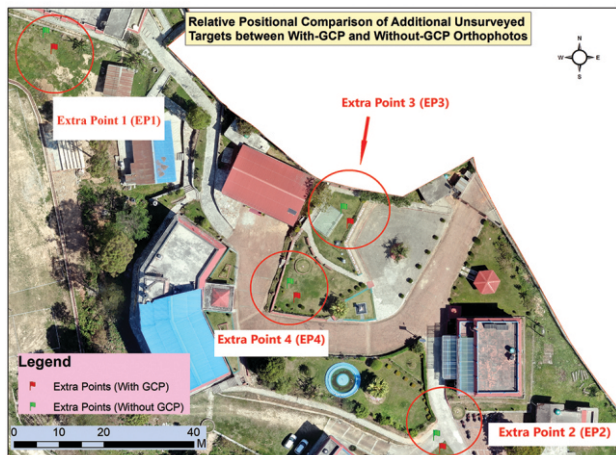


Figure 6. Relative positional comparison of additional points between the with-GCP and without-GCP orthophotos

Table 7. Relative positional differences of additional unsurveyed targets between the with-GCP and without-GCP orthophotos

Point ID	dX (m)	dY (m)	Relative shift (m)
EP1	-1.857	3.626	4.074
EP2	-1.397	2.929	3.245
EP3	-1.459	3.273	3.583
EP4	-1.562	3.190	3.552

Relative movement of additional unsurveyed targets from with-GCP to without-GCP positions

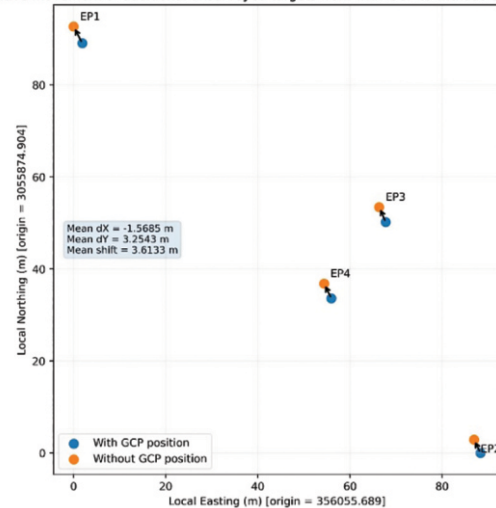


Figure 7. Relative deviation of additional points between the with-GCP and without-GCP orthophotos

The relative comparison based on these additional points supports the interpretation that the without-GCP orthophoto was systematically displaced in a broadly consistent manner across the study area. Although these targets cannot be used as independent absolute checkpoints, they provide useful supplementary evidence that the positional shift observed in the without-GCP orthophoto was not confined only to the formally surveyed checkpoints.

3.3 Relative geometry and scale-related differences in the orthophoto

To examine whether the without-GCP orthophoto was affected only by positional shift or also by relative geometric distortion, a pairwise distance analysis was carried out among the eight independent checkpoints. The results are presented in Table 8. The with-GCP orthophoto preserved checkpoint-pair distances very closely, whereas the without-GCP orthophoto showed consistently larger distances in nearly all checkpoint pairs. Scale factor was calculated as the ratio of orthophoto-derived checkpoint-pair distance to the corresponding surveyed checkpoint-pair distance, where values close to 1.000 indicate preservation of relative geometric scale.

Table 8. Pairwise distance comparison among the independent checkpoints under the survey, with-GCP, and without-GCP orthophoto datasets

Pair ID	Survey distance (m)	With-GCP distance (m)	Without-GCP distance (m)	Distance with-GCP (m)	Distance without-GCP (m)	Scale factor with-GCP	Scale factor without-GCP
CP1 - CP2	86.802	86.730	87.289	-0.072	0.487	0.999	1.006
CP1 - CP3	41.409	41.421	41.689	0.011	0.279	1.000	1.007
CP1 - CP4	102.618	102.568	103.277	-0.050	0.659	0.999	1.006
CP1 - CP5	133.979	133.973	134.921	-0.006	0.941	1.000	1.007
CP1 - CP6	76.807	76.888	77.434	0.081	0.627	1.001	1.008

CP1 - CP7	153.521	153.515	154.619	-0.006	1.098	1.000	1.007
CP1 - CP8	73.361	73.326	73.866	-0.034	0.505	0.999	1.007
CP2 - CP3	79.297	79.194	79.767	-0.104	0.470	0.999	1.006
CP2 - CP4	70.072	70.168	70.627	0.096	0.555	1.001	1.008
CP2 - CP5	80.858	80.932	81.525	0.074	0.667	1.001	1.008
CP2 - CP6	139.843	139.817	140.808	-0.027	0.964	1.000	1.007
CP2 - CP7	238.425	238.334	239.99	-0.091	1.564	1.000	1.007
CP2 - CP8	156.143	156.008	157.088	-0.135	0.945	0.999	1.006
CP3 - CP4	121.993	121.972	122.847	-0.021	0.854	1.000	1.007
CP3 - CP5	147.67	147.659	148.750	-0.011	1.081	1.000	1.007
CP3 - CP6	60.563	60.641	61.058	0.078	0.495	1.001	1.008
CP3 - CP7	165.357	165.356	166.491	0.000	1.135	1.000	1.007
CP3 - CP8	83.295	83.243	83.802	-0.052	0.507	0.999	1.006
CP4 - CP5	34.432	34.512	34.757	0.080	0.325	1.002	1.009
CP4 - CP6	176.685	176.728	177.978	0.043	1.293	1.000	1.007
CP4 - CP7	249.145	249.073	250.831	-0.072	1.686	1.000	1.007
CP4 - CP8	174.191	174.109	175.341	-0.081	1.150	0.999	1.007
CP5 - CP6	205.31	205.381	206.863	0.071	1.553	1.000	1.008
CP5 - CP7	282.957	282.951	284.958	-0.006	2.001	1.000	1.007
CP5 - CP8	206.67	206.638	208.116	-0.032	1.445	1.000	1.007
CP6 - CP7	116.556	116.516	117.301	-0.040	0.745	1.000	1.006
CP6 - CP8	47.572	47.522	47.824	-0.049	0.252	0.999	1.005
CP7 - CP8	82.619	82.665	83.244	0.047	0.626	1.001	1.008

The summary results of the pairwise distance analysis is presented in Table 9. The with-GCP orthophoto preserved checkpoint-pair distances very closely, with a mean absolute distance difference of 0.053 m, an RMSE of distance difference of 0.063 m, and a mean scale factor of 1.000. In contrast, the without-GCP orthophoto showed a mean absolute distance difference of 0.890 m, an RMSE of distance difference of 0.998 m, and a mean scale factor of 1.007. The minimum and maximum scale factors for the without-GCP orthophoto were 1.005 and 1.009, respectively. These results indicate that the no-control orthophoto was affected not only by systematic positional displacement but also by minor scale-related geometric differences.

Table 9. Summary of pairwise distance and scale-factor analysis among the independent checkpoints

Metric	With GCP	Without GCP
Mean absolute distance difference (m)	0.053	0.890
RMSE of distance difference (m)	0.063	0.998
Mean scale factor	1.000	1.007
Minimum scale factor	0.999	1.005
Maximum scale factor	1.002	1.009

A supplementary object-based comparison further supported this interpretation. Selected object footprints were digitized from the with-GCP and without-GCP orthophotos, and their areas and perimeters were compared (Table 10). For most selected objects, the without-GCP measurements were slightly larger than those derived from the with-GCP orthophoto. For example, the digitized area increased from 141.710 m² to 142.408 m² for the Administrative Building, from 341.586 m² to 343.101 m² for Boys Hostel, from 130.767 m² to 132.210 m² for the Canteen, and from 472.754 m² to 476.931 m² for the Executive Quarter. Similarly, perimeter values were generally greater in the without-GCP case. Although the Waiting Area showed a very small decrease in area, the overall pattern suggests that the without-GCP orthophoto was affected not only by systematic positional displacement but also by minor scale-related geometric differences.

Table 10. Supplementary object-based comparison of selected digitized features from the with-GCP and without-GCP orthophotos

Object name	Area with GCP (m ²)	Area without GCP (m ²)	Area difference (%)	Perimeter with GCP (m)	Perimeter without GCP (m)	Perimeter difference (%)
Administrative Building	141.710	142.408	0.49	49.487	49.663	0.360
Boys Hostel	341.586	343.101	0.440	100.523	100.860	0.330
Canteen	130.767	132.210	1.100	49.597	50.005	0.820
Control Point Buffer	10.405	10.607	1.940	11.478	11.600	1.060
Executive Quarter	472.754	476.931	0.880	87.746	87.983	0.270
Football Ground	1141.665	1156.786	1.320	139.885	140.836	0.680
Girls Hostel	268.249	270.610	0.880	73.884	74.123	0.320
Waiting Area	23.684	23.673	-0.040	17.952	18.063	0.620

The overlay of the selected digitized object footprints is shown in Figure 8, where the without-GCP outlines display both systematic displacement and slight enlargement relative to the with-GCP outlines.

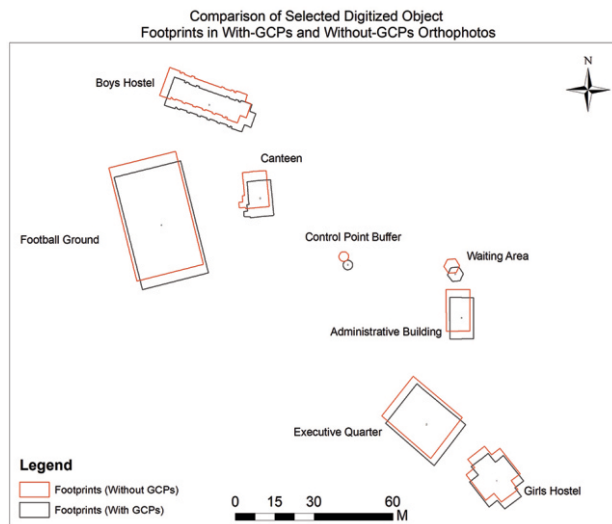


Figure 8. Overlay of selected object footprints digitized from the with-GCP and without-GCP orthophotos.

The without-GCP outlines show systematic positional displacement and slight geometric enlargement relative to the with-GCP outlines. Taken together, the pairwise distance analysis and the object-based comparison suggest that the without-GCP orthophoto was not affected only by translation-like shift. Rather, it also exhibited minor geometric expansion relative to the surveyed and with-GCP geometry. Because the object footprints were manually digitized and no independently surveyed rooftop dimensions were available, the object-based comparison is interpreted here as supplementary evidence of relative geometric consistency rather than as a formal absolute accuracy assessment. Nevertheless, both analyses consistently indicate that the no-control orthophoto retains reduced geometric fidelity even where the image appears visually coherent.

3.4 Vertical accuracy assessment at ground checkpoint locations

Because all vertical validation checkpoints used in this study were located on ground surfaces, the DSM and DTM assessments are presented here within a common vertical-accuracy framework. The DTM results directly represent ground-surface agreement, whereas the DSM results indicate elevation agreement at the same ground checkpoint locations only and do not constitute full validation of elevated surface features such as rooftops, vegetation canopies, or other above-ground objects.

3.4.1 DSM assessment at ground checkpoint locations

At the ground checkpoint locations, the DSM generated under the with-GCP workflow showed substantially better vertical agreement than the DSM generated without GCPs. As summarised in Table 11, the with-GCP DSM produced a mean vertical error of -0.053 m, a MAE of 0.110 m, and an RMSE_z of 0.131 m, corresponding to a 95% vertical accuracy of 0.256 m. In contrast, the without-GCP DSM showed a mean vertical error of 15.318 m, a MAE of 15.318 m, and an RMSE_z of 15.385 m, corresponding to a 95% vertical accuracy of 30.155 m. Thus, the incorporation of GCPs reduced DSM RMSE_z by 99.15%.

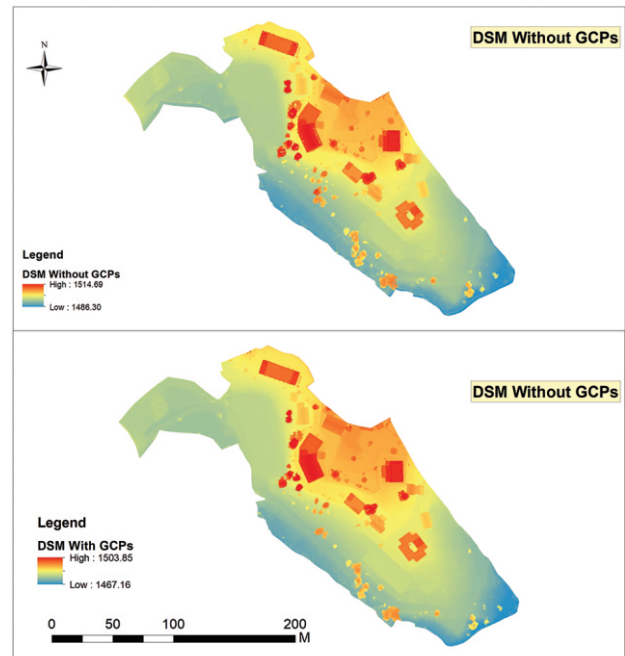


Figure 9. DSMs generated under the with-GCP and without-GCP workflows at the LMTC premises

Table 11. Summary statistics of DSM vertical agreement at ground checkpoint locations under the with-GCP and without-GCP workflows.

Statistic	With GCP	Without GCP
Mean Error _z (m)	-0.053	15.318
MAE _z (m)	0.110	15.318
RMSE _z (m)	0.131	15.385
95% vertical accuracy (m)	0.256	30.155
Median absolute error (m)	0.083	15.321
SD of error (m)	0.128	1.536
Min error (m)	-0.240	12.945
Max error (m)	0.083	17.686

The point-wise DSM height differences and the comparison of key DSM vertical-accuracy metrics are shown in Figures 10 and 11, respectively.

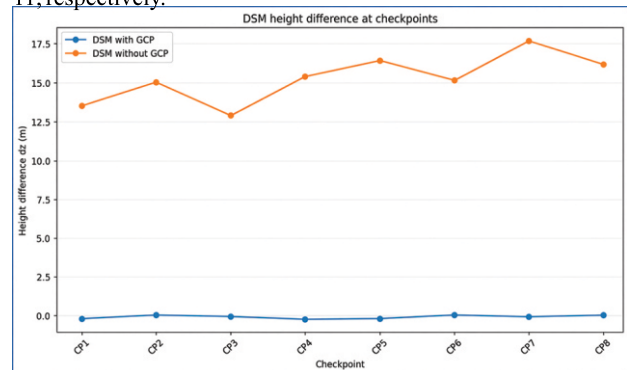


Figure 10. Point-wise DSM height differences between surveyed checkpoint elevations and DSM-derived elevations under the with-GCP and without-GCP workflows

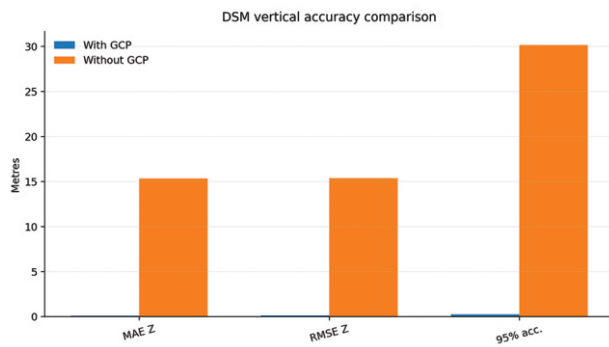


Figure 11. Comparison of key DSM vertical-accuracy metrics under the with-GCP and without-GCP workflows

3.4.2 DTM accuracy assessment

The DTM comparison showed a similarly strong effect of GCP incorporation. As shown in Table 12, the with-GCP DTM produced a mean vertical error of -0.070 m, a MAE of 0.121 m, and an RMSE_z of 0.143 m, corresponding to a 95% vertical accuracy of 0.280 m. In contrast, the without-GCP DTM produced a mean vertical error of 15.276 m, a MAE of 15.276 m, and an RMSE_z of 15.347 m, corresponding to a 95% vertical accuracy of 30.080 m. This represents a 99.07% improvement in RMSE_z after GCP incorporation.

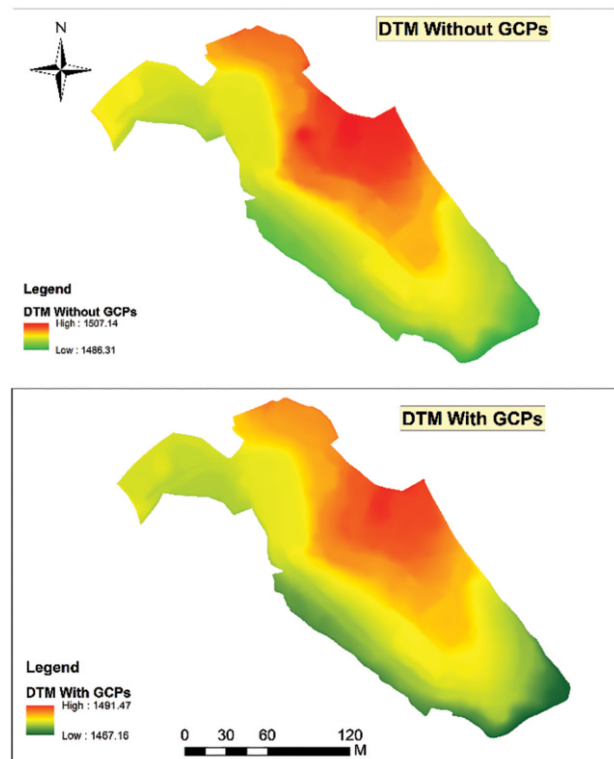


Figure 12. DTMs generated under the with-GCP and without-GCP workflows at the LMTC premises

Table 12. Summary statistics of DTM vertical agreement at ground checkpoint locations under the with-GCP and without-GCP workflows

Statistic	With GCP	Without GCP
Mean Error _z (m)	-0.070	15.276
MAE _z (m)	0.121	15.276
RMSE _z (m)	0.143	15.347
95% vertical accuracy (m)	0.280	30.080
Median absolute error (m)	0.078	15.316
SD of error (m)	0.133	1.575
Min error (m)	-0.252	12.947
Max error (m)	0.077	17.651

The point-wise DTM height differences and the comparison of key DTM vertical-accuracy metrics are presented in Figures 13 and 14, respectively.

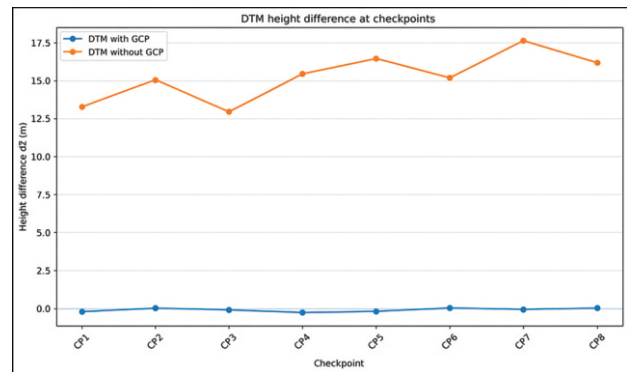


Figure 13. Point-wise DTM height differences between surveyed checkpoint elevations and DTM-derived elevations under the with-GCP and without-GCP workflows

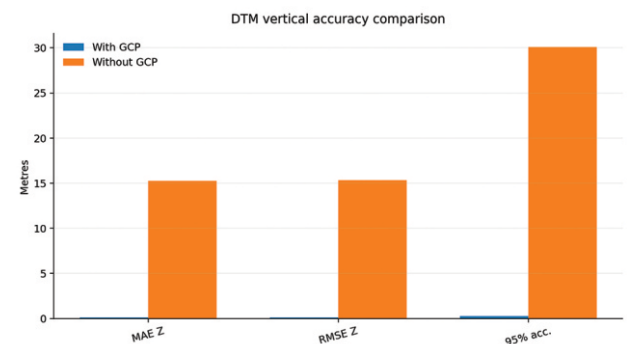


Figure 14. Comparison of key DTM vertical-accuracy metrics under the with-GCP and without-GCP workflows

An important feature of both elevation products is that the without-GCP case was affected mainly by a strong positive vertical offset. This is indicated by the large positive mean errors in both DSM and DTM, together with the comparatively smaller standard deviations of 1.536 m and 1.575 m, respectively. In other words, the no-control elevation products were not merely noisy; they were systematically displaced upward. This interpretation is also consistent with the visual comparison of the raster surfaces, in which the general surface pattern remains broadly similar while

the absolute elevation level is markedly offset. Therefore, the main limitation of the without-GCP elevation products lies in absolute vertical positioning rather than complete loss of relative surface form.

The similarity between the DSM and DTM statistics is largely related to the ground-based location of all validation checkpoints. Because the checkpoints were located on ground surfaces, the DTM assessment is directly representative of bare-earth vertical agreement, whereas the DSM assessment reflects agreement at ground-visible locations only. For this reason, the DTM results provide the more direct interpretation of ground-surface vertical accuracy in the present study, while the DSM results should be understood more cautiously as ground-location vertical agreement rather than full-feature surface validation.

5. DISCUSSION

The results of this study show a clear and consistent improvement in product quality after the incorporation of Ground Control Points (GCPs). The with-GCP workflow produced centimetre-level horizontal accuracy in the orthophoto and decimetre-level vertical agreement in both the DSM and DTM, whereas the without-GCP workflow exhibited metre-level horizontal displacement and a strong positive vertical offset. These findings indicate that visually coherent UAV products generated without ground control may still possess weak absolute positional reliability and therefore cannot be assumed to be suitable for accurate mapping or measurement.

The orthophoto results show that the without-GCP product was affected by both systematic positional shift and minor relative geometric distortion. The checkpoint residuals presented in Table 5 and the summary statistics in Table 6 indicate a consistent westward and northward displacement in the without-GCP orthophoto. This interpretation is further supported by the supplementary relative comparison of the additional unsurveyed targets (Figure 6 and Table 7), which showed a similar displacement pattern. In addition, the pairwise checkpoint-distance analysis (Table 8 and Table 9) and the object-based footprint comparison (Table 10 and Figure 8) suggest that the no-control orthophoto was not affected only by translation-like shift, but also by small scale-related geometric differences. Although some internal geometric relationships may remain broadly preserved, the without-GCP orthophoto cannot be considered equivalent to the with-GCP product for applications requiring dependable absolute planimetric accuracy.

The vertical results lead to a similar conclusion. Both the DSM and DTM generated without GCPs retained broadly similar surface form, yet they were affected by strong positive elevation bias. This is evident from the large positive mean errors and RMSEZ values reported in Tables 11 and 12. At the same time, the relatively smaller spread of errors indicates that the without-GCP elevation products were not merely noisy, but systematically displaced upward. The observed pattern suggests that the primary limitation of the no-control elevation products lies in absolute elevation positioning rather than complete loss of relative surface form.

A further important point is that all vertical validation checkpoints used in this study were located on ground surfaces. Consequently, the DTM assessment directly represents bare-earth vertical agreement, whereas the DSM assessment reflects elevation agreement at ground checkpoint locations only and should not be interpreted as full validation of elevated surface features such as rooftops, vegetation canopies, or other above-ground objects. For

this reason, the DTM results provide the more direct interpretation of ground-surface vertical accuracy in the present study, while the DSM results should be understood more cautiously.

The larger camera optimization difference observed in the without-GCP workflow also supports a more careful interpretation of the no-control results. The higher optimization difference indicates weaker geometric constraint in the uncontrolled image block, which suggests that the observed error should not be attributed to onboard image geolocation alone. Rather, the without-GCP results likely reflect the combined influence of weaker external control, onboard image geolocation uncertainty, image block geometry, and camera optimization instability. This is consistent with previous research showing that the number and spatial distribution of control points strongly influence the absolute positional and vertical quality of UAV-derived products (Martínez-Carricondo et al., 2018; Sanz-Abanado et al., 2018; Žabota et al., 2021; Szypuła, 2024).

Overall, the present study confirms that GCP-based processing remains essential for reliable campus-scale UAV mapping when the outputs are intended for measurement, planning, terrain representation, or other tasks requiring dependable absolute accuracy. Although the without-GCP workflow produced visually interpretable products, these outputs retained substantial positional and vertical bias and therefore are not suitable for applications where robust absolute accuracy is required.

5. CONCLUSION

This study evaluated the effect of Ground Control Points on the positional and vertical quality of UAV-derived orthophoto, DSM, and DTM products at the premises of the Land Management Training Center, Dhulikhel, Nepal, by processing the same UAV image block under with-GCP and without-GCP workflows. The results clearly demonstrate that GCP incorporation substantially improves both horizontal and vertical product reliability.

For the orthophoto, the with-GCP workflow achieved centimetre-level positional accuracy, while the without-GCP workflow showed metre-level horizontal displacement. The checkpoint residuals, the supplementary comparison of additional unsurveyed targets, the pairwise checkpoint-distance analysis, and the object-based footprint comparison consistently indicate that the no-control orthophoto was affected not only by systematic positional shift but also by minor scale-related geometric differences. Although the without-GCP orthophoto remained visually coherent, it did not provide dependable absolute positional accuracy for precise mapping and measurement.

For the elevation products, the with-GCP DSM and DTM showed much closer agreement with the surveyed checkpoint elevations, whereas the without-GCP products exhibited strong positive vertical bias. At the same time, the vertical error pattern suggests that the main weakness of the no-control products lies in absolute elevation positioning rather than complete loss of relative surface form. Because all validation checkpoints were located on ground surfaces, the DTM assessment provides the more direct interpretation of ground-surface vertical accuracy, while the DSM assessment should be understood as agreement at ground checkpoint locations only.

In summary, the findings demonstrate that GCP-based processing remains essential for reliable campus-scale UAV photogrammetry when the outputs are intended for measurement, engineering use, terrain representation, planning, or land-

management applications requiring robust absolute accuracy. The without-GCP workflow may still retain limited relative geometric usefulness in some visually oriented or low-tolerance applications, but it cannot substitute for GCP-based processing where dependable absolute positional and vertical reliability are required.

A limitation of the present study is that the vertical validation checkpoints were confined to ground surfaces and no independently surveyed elevated-feature checkpoints were available. In addition, the study was conducted within a relatively small campus-scale area using a single processing software environment. Future studies could extend this work by testing denser and more widely distributed GCP networks, incorporating independently surveyed checkpoints on elevated features, and comparing the effects of alternative photogrammetric processing software and direct georeferencing strategies.

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AUTHOR INFORMATION



Name	: Bhuwan Singh Bisht
Academic Qualification	: MSc in Geoinformatics
Organization	: Land Management Training Center
Current Designation	: Instructor
Work Experience	: 7 years
Published Article	: 7

CLIMATE RESPONSIVE LAND GOVERNANCE IN SOUTH ASIA: REFLECTIONS FROM THE SUMMER SCHOOL 2026

Ram Kumar Sapkota¹, Janak Raj Joshi²

¹ Land Management Training Center, ramksap1@gmail.com

² Land Management Training Center, janakrajjoshi@hotmail.com

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Abstract

Climate change has increasingly emerged as one of the most significant challenges affecting land governance systems across the globe. In South Asia, the impacts of floods, landslides, droughts, environmental degradation, and rapid urbanization are directly influencing land tenure security, disaster resilience, land-use systems, and the livelihoods of vulnerable communities. Recognizing the urgent need for integrated and climate-responsive approaches to land administration, the Land Management Training Center (LMTTC), Nepal, in collaboration with Landstack India and the International Land Coalition–Asia (ILC-Asia), organized the Summer School on Climate Responsive Land Governance from 21–26 April 2026 in Dhulikhel, Nepal. The programme brought together 23 participants and 25 distinguished resource persons from Nepal, India, Myanmar, and Australia representing government agencies, academic institutions, civil society organizations, and geospatial technology sectors. The six-day Summer School combined policy dialogue, academic learning, technological demonstrations, field-based observation, and collaborative action planning to strengthen regional understanding of the complex relationship between climate change, land governance, disaster management, and sustainable development. Major thematic areas included land tenure security, policy and institutional frameworks, GeoICT and digital land administration systems, gender-responsive governance, climate-induced displacement, and participatory land-use planning. This article presents the institutional background, structure, key thematic discussions, day-wise highlights, outcomes, lessons learned, and future implications of the Summer School. The article argues that climate-responsive land governance is essential for building resilient societies and that secure, inclusive, and technology-driven land administration systems are central to climate adaptation and sustainable development in South Asia.

1. Introduction

Climate change has fundamentally transformed the way governments, institutions, and communities understand land governance. Across the world, climate-induced disasters such as floods, droughts, landslides, glacial lake outburst floods, sea-level rise, and environmental degradation are affecting land-use systems, property rights, agricultural productivity, settlement patterns, and livelihoods. These impacts are particularly severe in developing countries where weak land administration systems, rapid urbanization, poverty, and social inequality already place significant pressure on land resources.

South Asia is among the regions most vulnerable to climate-related disasters. Countries such as Nepal, India, and Myanmar regularly experience floods, riverbank erosion, droughts, landslides, and extreme weather events that threaten communities and disrupt land tenure systems. Climate change has intensified vulnerabilities among smallholder farmers, indigenous groups, women, informal settlers, and marginalized populations who often lack secure access to land and resources.

In this context, climate-responsive land governance has emerged as a critical area of policy and practice. Climate-responsive land governance refers to the integration of climate adaptation, disaster risk reduction, environmental sustainability, social inclusion, and land tenure security into land administration systems and land-use planning processes. It emphasizes the need for resilient, inclusive, and adaptive governance mechanisms capable of addressing environmental risks while protecting the rights and livelihoods of vulnerable populations.

Recognizing these emerging challenges, the Land Management Training Center (LMTTC), Nepal, organized the Summer School on Climate Responsive Land Governance from 21 to 26 April 2026 at Dhulikhel, Kavrepalanchok. The programme was jointly organized in collaboration with Landstack India and the International Land Coalition–Asia (ILC-Asia), with support from Community Self Reliance Centre (CSRC) Nepal, UN-Habitat Nepal, Kathmandu University, Habitat for Humanity Nepal, the

University of Melbourne, Caritas Nepal, and the Ministry of Agriculture, Food and Rural Affairs (MAFRA) of the Republic of Korea.

The Summer School was designed as an intensive regional learning platform bringing together land professionals, policymakers, researchers, academics, civil society representatives, and technical experts to explore the intersections between land governance, climate change, disaster management, and sustainable development.

2. Objectives of the Summer School

The Summer School aimed to strengthen participants' understanding of climate-responsive land governance and equip them with multidisciplinary knowledge and practical skills to address emerging climate-related land challenges.

The specific objectives included:

- Enhancing understanding of the relationship between land governance, climate change, and disaster management.
- Examining global and regional policy frameworks related to climate-responsive land administration.
- Promoting regional knowledge exchange among land professionals and institutions.
- Demonstrating technological innovations and GeoICT applications in land governance.
- Encouraging gender-responsive and inclusive approaches to land administration.
- Supporting participants in developing action plans for their respective institutions and countries.
- Building a regional network of professionals committed to climate-responsive land governance.

3. Participants and Resource Persons

A total of 23 participants attended the programme, including 18 participants from Nepal and 5 international participants from

India and Myanmar. Participants represented government agencies, universities, civil society organizations, research institutions, and private geospatial sectors.

The Summer School also brought together 25 distinguished resource persons from Nepal, India, and Australia. The faculty included government officials, university professors, researchers, land policy experts, GIS specialists, climate experts, civil society leaders, and practitioners working in land rights and disaster resilience.

The multidisciplinary nature of the participants and resource persons created a highly interactive learning environment that encouraged dialogue between policy, technology, academia, and grassroots experiences.

4. Structure and Methodology

The Summer School adopted a multidimensional learning approach that combined theoretical discussions with practical application. The programme methodology included:

- Expert lectures and thematic presentations.
- Policy discussions and academic reflections.
- Participant case-sharing sessions.
- Hands-on GeoICT and GIS demonstrations.
- Group discussions and collaborative learning.
- Field-based observation and experiential learning.
- Action planning and regional networking.

The programme was structured around six thematic days, each focusing on specific dimensions of climate-responsive land governance.

5. Day-wise Highlights of the Summer School

Day 1: Climate Risks and Land Governance

The Summer School formally commenced on 21 April 2026 at the Land Management Training Center, Dhulikhel. The opening ceremony was chaired by the Executive Director of the Land Management Training Center, while the Secretary of the Ministry of Land Management, Cooperatives and Poverty Alleviation graced the occasion as the Chief Guest. The ceremony was attended by senior government officials, representatives of partner organizations, resource persons, and participants. The inaugural session introduced the overall objectives and expectations of the programme. An exhibition of traditional and modern surveying instruments was also organized at LMTC on the opening day, providing participants with insights into the evolution of surveying technologies. Serene Ho from University of Melbourne, Australia delivered keynote speech during opening ceremony.



Figure 1: Opening Ceremony of Summer School 2026

First session of the first day was delivered by Mr. Ganesh Prasad Bhatta focusing on land governance concepts and good governance principles in land administration. Participants discussed transparency, accountability, public participation, and institutional effectiveness in land management systems.

Warm-up sessions with introduction and mapping expectations from summer school was facilitated by Janal Raj Joshi, Pranab Choudhury and Dharma Raj Joshi showcasing the importance of climate-responsive land governance and enabled participants to share their expectations and learning objectives for the program.

One of the major highlights of the first day was the discussion on the “Land Use–Tenure–Climate Nexus,” led by Mr. Pranab Choudhury. The session emphasized that land is not only an economic resource but also a social and cultural relationship deeply connected with identity, livelihoods, and environmental sustainability. The discussion explored how climate change affects land tenure systems, especially among vulnerable communities. Case studies from Nagaland and shifting cultivation systems were presented to illustrate customary land governance practices and community stewardship.

Dr. Serene Ho delivered a session on systems thinking and climate change impacts. The discussion introduced participants to the interconnected relationships between environmental systems, social systems, and land governance structures.

Day 2: Policy and Institutional Frameworks

The second day focused on policy frameworks and institutional dimensions of land governance. Participants explored global frameworks such as the Sustainable Development Goals (SDGs), Fit-for-Purpose Land Administration (FFP), the Framework for Effective Land Administration (FELA), and the Land Governance Assessment Framework (LGAF). Mr. Janak Raj Joshi highlighted the importance of global policy frameworks in addressing land governance challenges, informality, and sustainable development.

A session by Mr. Brij Agrawal examined land administration systems in South Asia and discussed legal reforms, digital technologies, blockchain applications, and modernization approaches.

Participants also learned about Nepal's Land Issues Resolving Commission through a presentation by Mr. Susheel Dangol. The session discussed constitutional provisions, land distribution procedures, and challenges related to landless communities.

Another important session by Dr. Subash Ghimire focused on land markets and property valuation systems. Discussions highlighted the growing challenges of land valuation in rapidly urbanizing and climate-vulnerable regions.

The day also included participant case-sharing sessions where participants presented experiences related to informal settlements, women's land rights, land markets, and community land issues from their respective countries and institutions.

Day 3: Tools, Technologies, and GeoICT Applications

The third day concentrated on technological innovation and GeoICT applications in climate-responsive land governance. Mr. Raja Ram Chhatkuli presented a case study on sustainable land management practices in Dang district, emphasizing climate-smart land use, livelihood security, and sustainable resource management.

A major highlight of the day was the session on GeoICT in land governance delivered by Mr. Tanka Prasad Dahal. Participants

explored GIS, Land Information Systems (LIS), spatial decision support systems, and geospatial data management.

Mr. Shekhar Gaikwad presented several innovative land administration systems implemented in Maharashtra, India, including Mahabhulekh, MahaBhunaksha, e-Mojni, e-FerFar, e-Registration, and SVAMITVA.

The Roshi River Basin case study presented by Mr. Ram Kumar Sapkota, Mr. Bigyan Banjara, and Mr. Grishma Pradhan demonstrated how GIS and remote sensing technologies can be used to analyze flood impacts, restore distorted parcel boundaries, and support post-disaster land management.

Participants also engaged in discussions about digital cadastral systems, flood mapping, geospatial analysis, and technological approaches for disaster preparedness.

Day 4: Field Visit to Melamchi Valley

Melamchi Valley is a scenic mountain valley in Sindhupalchok District, Bagmati Province, located northeast of Kathmandu. The valley is traversed by the Melamchi River and is known for its rich natural environment, agricultural landscapes, and cultural heritage. It is also nationally significant as the location of the Melamchi Water Supply Project, which supplies drinking water to the Kathmandu Valley. In 2021, Melamchi Valley experienced a devastating debris-laden flood that caused widespread damage to settlements, infrastructure, and agricultural land, highlighting the increasing risks of climate-induced disasters and the need for resilient land governance and disaster risk management.

The field visit to Melamchi Valley on 24 April 2026 was one of the most impactful components of the Summer School. Melamchi Valley experienced catastrophic flooding in 2021 that caused extensive damage to settlements, infrastructure, agricultural land, and local livelihoods. The field visit provided participants with direct exposure to the realities of climate-induced disasters and their impacts on land governance systems.

Participants observed altered river courses, damaged land parcels, community displacement, and rehabilitation efforts. Interaction sessions with disaster-affected communities allowed participants to hear firsthand experiences regarding land loss, recovery challenges, and resilience. Melamchi Municipality conducted a presentation explaining the impacts of the disaster, lessons learned, and the implementation of early warning systems and precautionary measures.



Figure 2: Interaction with disaster-affected communities

Participants also visited the source area of the Melamchi Drinking Water Project and discussed the relationship between watershed management, climate change, and land-use planning. The field visit transformed theoretical concepts into practical understanding and reinforced the importance of adaptive and resilient land governance mechanisms.

Day 5: Social Dimensions of Land Governance

The fifth day focused on social inclusion, gender-responsive governance, participatory planning, and community stewardship.

Dr. Reshma Shrestha delivered a session on pro-poor and gender-responsive land governance, emphasizing the importance of integrating Gender Equality and Social Inclusion (GESI) principles into land administration systems. Participants discussed how women, indigenous peoples, informal settlers, and marginalized groups are disproportionately affected by climate change and insecure land tenure.

Mr. Amba Jamir presented community stewardship experiences from Nagaland, focusing on shifting cultivation systems and local community perspectives on climate resilience.

Professor Achut Wagle delivered a special session on the economic dimensions of land-use planning, discussing land use, land misuse, and land abuse.

Mr. Prakash Joshi facilitated discussions on participatory and risk-sensitive land-use planning approaches, including multi-hazard analysis and federal land-use systems.

The final session of the day by Mr. Pranab Choudhury examined the relationship between renewable energy, carbon markets, and land governance. Discussions highlighted concerns about land grabbing, displacement, and the protection of community rights in large-scale energy and carbon market projects.

Day 6: Action Planning and Way Forward

The final day of the Summer School focused on future strategies, regional cooperation, and action planning.

Mr. Deepak Sanan led discussions on land administration debates in South Asia, including challenges associated with presumptive and conclusive titling systems.

Another important session by Mr. Pranab Choudhury explored tenure due diligence and climate-responsive governance beyond traditional land records. The discussion highlighted the importance of understanding recorded realities, observed realities, and lived realities.

A high-level panel discussion on transboundary climate impacts brought together experts including Mr. Madhusudhan Adhikari, Dr. Sunil Babu Shrestha, Dr. Suresh Dhakal, and Mr. Deepak Sanan. The panel explored institutional gaps, displacement challenges, tenure security issues, and policy reform needs in South Asia.

Participants then presented group action plans focusing on climate-responsive land governance strategies for their respective countries and institutions.

The programme concluded with a formal closing ceremony and certificate distribution led by Mr. Janak Raj Joshi, Executive Director of LMTC. Participants shared reflections, learning experiences, and future commitments.

6. Major Outcomes of the Programme

The Summer School achieved several important outcomes:

- Enhanced understanding of climate-responsive land governance concepts among participants.

- Improved knowledge of GeoICT, GIS, remote sensing, and digital land administration systems.
- Strengthened regional collaboration and South–South knowledge exchange.
- Increased awareness regarding gender-responsive and inclusive land governance.
- Practical exposure to post-disaster land governance through the Melamchi field visit.
- Development of action plans for institutional and policy implementation.
- Creation of a regional network of professionals committed to climate-responsive land governance.

The programme also reinforced the understanding that climate resilience requires integrated approaches combining technology, policy reform, institutional coordination, and community participation.

7. Challenges and Future Directions

Despite significant progress, participants identified several continuing challenges in South Asia's land governance systems. These include institutional fragmentation, outdated land records, weak policy coordination, rapid urbanization, informal settlements, limited technical capacity, and increasing climate risks.

Participants emphasized the need for:

- Stronger integration between land governance and climate policies.
- Expansion of digital land information systems.
- Improved tenure security for marginalized populations.
- Strengthened disaster preparedness and recovery systems.
- Greater investment in geospatial technologies and climate-sensitive land-use planning.
- Continued regional cooperation and knowledge exchange.

Future programmes should focus on research collaboration, policy advocacy, advanced technical training, and community-centered climate adaptation strategies.

8. Conclusion

The Summer School on Climate Responsive Land Governance represented a timely and significant regional initiative for advancing dialogue, knowledge exchange, and institutional collaboration on climate-responsive land administration in South Asia. By bringing together professionals from government agencies, universities, civil society organizations, and technical sectors, the programme successfully created a multidisciplinary platform for understanding the complex relationship between land governance, climate change, disaster resilience, and sustainable development. The programme demonstrated that climate-responsive land governance is not solely a technical or administrative concern but a broader developmental challenge closely connected with social justice, environmental sustainability, and human resilience. Secure land tenure, inclusive governance systems, community participation, digital innovation, and regional cooperation emerged as central pillars for building climate resilience.

The field-based learning experiences in Melamchi Valley particularly highlighted the urgent need for adaptive land administration systems capable of responding effectively to climate-induced disasters and protecting vulnerable communities.



Figure 3: Group Photo after closing ceremony

Importantly, the Summer School strengthened regional networking and established the foundation for a growing community of practice dedicated to climate-responsive land governance in South Asia. As climate change continues to intensify environmental and social vulnerabilities across the region, institutions such as LMTC and its partner organizations have an increasingly important role in promoting policy innovation, technical capacity building, collaborative research, and inclusive land governance practices. The Summer School ultimately reaffirmed that resilient and equitable land governance systems are essential for achieving climate adaptation, disaster resilience, and sustainable development goals in South Asia and beyond.

9. Brief information of Organizers & Supporting Partners

Organizers

Land Management Training Center (LMTC)

The Land Management Training Center (LMTC) is Nepal's premier institution for education and capacity building in land management and geomatics under the then Ministry of Land Management, Cooperatives and Poverty Alleviation. Since its establishment in 1968, it has trained more than 13,000 land professionals through various training programs and academic collaborations. LMTC is certified with ISO 9001:2015 for Quality Management, reflecting its commitment to excellence in professional education.

Landstack, India

Landstack is an international organization dedicated to promoting sustainable, inclusive, and people-centered land governance. It connects experts and institutions to strengthen land tenure security through research, technology, policy support, and capacity building. Its work emphasizes gender equality, climate resilience, and the empowerment of Indigenous peoples, women, and youth.

International Land Coalition (ILC) Asia

ILC Asia is the regional platform of the International Land Coalition, a global alliance promoting people-centered land governance. It brings together 59 organizations across 14 Asian countries to advance secure and equitable land rights. The network supports collaboration, advocacy, and knowledge sharing to strengthen land governance across the region.

Supporting Partners

Community Self Reliance Centre (CSRC) is a prominent civil society organization in Nepal dedicated to promoting land rights, agrarian reform, and social justice for marginalized and vulnerable communities. The organization works extensively on issues related to land tenure security, community empowerment, policy advocacy, and sustainable livelihoods, particularly supporting landless farmers, indigenous peoples, and disadvantaged groups across the country.

Kathmandu University is one of Nepal’s leading academic and research institutions, recognized for its contributions in higher education, innovation, and interdisciplinary research. The university plays an important role in advancing studies in geomatics engineering, environmental science, climate change, land administration, and sustainable development, while also fostering collaboration between academia, government, and development partners.

UN-Habitat Nepal is the Nepal country programme of the United Nations Human Settlements Programme (UN-Habitat), which supports sustainable urbanization and inclusive human settlements. Its work in Nepal focuses on urban resilience, housing, land governance, climate adaptation, disaster recovery, and improving living conditions for vulnerable and low-income communities through policy support and technical assistance.

Ministry of Agriculture, Food and Rural Affairs is the government ministry responsible for formulating and implementing policies

related to agriculture, rural development, food security, and natural resource management in the Republic of Korea. The ministry also supports international cooperation initiatives aimed at sustainable agriculture, rural resilience, and climate-responsive development practices.

Habitat for Humanity Nepal is a non-profit organization working to ensure safe, adequate, and affordable housing for vulnerable communities in Nepal. In addition to housing support, the organization is actively engaged in disaster resilience, land and property rights, climate adaptation, and community development initiatives, particularly for low-income and disaster-affected populations.

University of Melbourne is a globally recognized research-intensive university known for its excellence in climate research, urban planning, sustainability studies, and land administration. The university contributes internationally through research, innovation, and policy engagement on issues related to climate resilience, environmental governance, and sustainable development.

Caritas Nepal is a national social service organization working in the areas of humanitarian assistance, disaster response, climate resilience, social inclusion, and community development. Through partnerships with local communities, government agencies, and international organizations, Caritas Nepal supports vulnerable populations by promoting sustainable livelihoods, resilience building, and social protection initiatives across Nepal.

AUTHOR INFORMATION



Name	: Ram Kumar Sapkota
Academic Qualification	: MSc in Geodesy and Geoinformation
Organization	: Land Management Training Center
Current Designation	: Director
Work Experience	: 18 Years
Published Article	: 9

GUIDELINES FOR AUTHORS PREPARING MANUSCRIPTS FOR PUBLICATION IN THE JOURNAL GOING TO BE PUBLISHED BY LMTC

Author Name¹, Author Name², Author Name³

¹Author Affiliation and Email Address

²Author Affiliation and Email Address

³Author Affiliation and Email Address

ABSTRACT:

These guidelines are provided for preparation of papers for publications in the journal going to be prepared by Land Management Training Centre. These guidelines are issued to ensure a uniform style throughout the journal. All papers that are accepted by the editorial board of this journal will be published provided they arrive by the due date and they correspond to these guidelines. Reproduction is made directly from author-prepared manuscripts, in electronic or hardcopy form, in A4 paper size 297mm x 210mm (11.69 x 8.27 inches). To assure timely and efficient production of the journal with a consistent and easy to read format, authors must submit their manuscripts in strict conformance with these guidelines. The editorial board may omit any paper that does not conform to the specified requirements.

KEY WORDS: Manuscripts, Journals, LMTC, Guidelines for Authors, StyleGuide

1. MANUSCRIPT

1.1 General Instructions

The maximum paper length is restricted to 7 pages. The paper should have the following structure:

1. Title of the paper
2. Authors and affiliation
3. Keywords (6-8 words)
4. Abstract (100–250 words)
5. Introduction
6. Main body
7. Conclusions
8. Acknowledgements (if applicable)
9. References
10. Appendix (if applicable)

1.2 Page Layout, Spacing and Margins

The paper must be compiled in one column for the Title and Abstract and in two columns for all subsequent text. All text should be single-spaced, unless otherwise stated. Left and right justified typing is preferred.

1.3 Length and Font

All manuscripts are limited to a size of no more than eight (8) single-spaced pages (A4 size), including abstracts, figures, tables and references. ISPRS Invited Papers are limited to 12 pages. The font type Times New Roman with a size of nine (9) points is to be used.

Table 1. Margin settings for A4 size paper

Setting	A4 size paper	
	mm	inches
Top	25	1.0
Bottom	25	1.0
Left	20	0.8
Right	20	0.8
Column Width	82	3.2
Column Spacing	6	0.25

2. TITLE AND ABSTRACT BLOCK

2.1 Title

The title should appear centered in bold capital letters, at the top of the first page of the paper with a size of twelve (12) points and single-spacing. After one blank line, type the author(s) name(s),

affiliation and mailing address (including e-mail) in upper and lower case letters, centred under the title. In the case of multi-authorship, group them by firm or organization as shown in the title of these Guidelines.

2.2 Key Words

Leave two lines blank, then type "**KEY WORDS:**" in bold capital letters, followed by 5-8 key words. Note that ISPRS does not provide a set list of key words any longer. Therefore, include those key words which you would use to find a paper with content you are preparing.

2.3 Abstract

Leave two blank lines under the key words. Type "**ABSTRACT:**" flush left in bold Capitals followed by one blank line. Start now with a concise Abstract (100 - 250 words) which presents briefly the content and very importantly, the news and results of the paper in words understandable also to non-specialists.

3. MAIN BODY OF TEXT

Type text single-spaced, **with** one blank line between paragraphs and following headings. Start paragraphs flush with left margin.

3.1 Headings

Major headings are to be centered, in bold capitals without underlining, after two blank lines and followed by a one blank line.

Type subheadings flush with the left margin in bold upper case and lowercase letters. Subheadings are on a separate line between two single blank lines.

Subsubheadings are to be typed in bold upper case and lower case letters after one blank line flush with the left margin of the page, with text following on the same line. Subsubheadings may be followed by a period or colon, they may also be the first word of the paragraph's sentence.

Use decimal numbering for headings and subheadings

3.2 Footnotes

Mark footnotes in the text with a number (1); use the same number for a second footnote of the paper and so on. Place footnotes at the

bottom of the page, separated from the text above it by a horizontal line.

3.3 Illustrations and Tables

3.3.1 Placement: Figures must be placed in the appropriate location in the document, as close as practicable to the reference of the figure in the text. While figures and tables are usually aligned horizontally on the page, large figures and tables some-times need to be turned on their sides. If you must turn a figure or table sideways, please be sure that the top is always on the left-hand side of the page.

3.3.2 Captions: All captions should be typed in upper and lower case letters, centered directly beneath the illustration. Use single spacing if they use more than one line. All captions are to be numbered consecutively, e.g. Figure 1, Table 2, Figure 3.

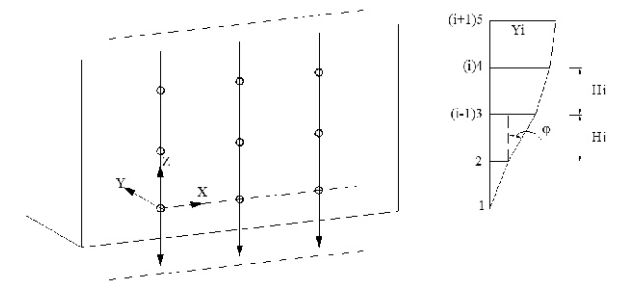


Figure 1. Figure placement and numbering

3.4 Equations, Symbols and Units

3.4.1 Equations:

Equations should be numbered consecutively throughout the paper. The equation number is enclosed in parentheses and placed flush right. Leave one blank lines before and after equations:

$$x = x_0 - c \frac{X - X_0}{Z - Z_0}; y = y_0 - c \frac{Y - Y_0}{Z - Z_0} \quad (1)$$

where c = focal length

x, y = image coordinates

X_0, Y_0, Z_0 = coordinates of projection center

X, Y, Z = object coordinates

3.4.2 Symbols and Units: Use the SI (Système Internationale) Units and Symbols. Unusual characters or symbols should be explained in a list of nomenclature.

3.5 References

References should be cited in the text, thus (Smith, 1987a), and listed in alphabetical order in the reference section. The following arrangements should be used:

3.5.1 References from Journals: Journals should be cited like (Smith, 1987a). Names of journals can be abbreviated according to the "International List of Periodical Title Word Abbreviations". In case of doubt, write names in full.

3.5.2 References from Books: Books should be cited like (Smith, 1989).

3.5.3 References from Other Literature: Other literature should be cited like (Smith, 1987b) and (Smith, 2000).

3.5.4 References from websites: References from the internet should be cited like (Maas et al. 2017). Use of persistent identifiers such as the Digital Object Identifier or (DOI) rather than a URLs is strongly advised. In this case last date of visiting the web site can be omitted, as the identifier will not change.

3.5.5 References from Research Data: References from internet resources should be cited like (Dubaya et al., 2017).

3.5.6 References from Software Projects: References to a software project as a high level container including multiple versions of the software should be cited like (GRASS Development Team, 2017).

3.5.7 References from Software Versions: References to a specific software version should be cited like (GRASS Development Team, 2015).

3.5.8 References from Software Project Add-ons: References to a specific software add-on to a software project should be cited like (Lennert and GRASS Development Team, 2017).

3.5.9 References from Software Repository: References from internet resources should be cited like (Gago-Silva, 2016).

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APPENDIX (OPTIONAL)

Any additional supporting data may be appended, provided the paper does not exceed the limits given above.

Note: The format for the journal is taken and modified from the format of ISPRS archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences

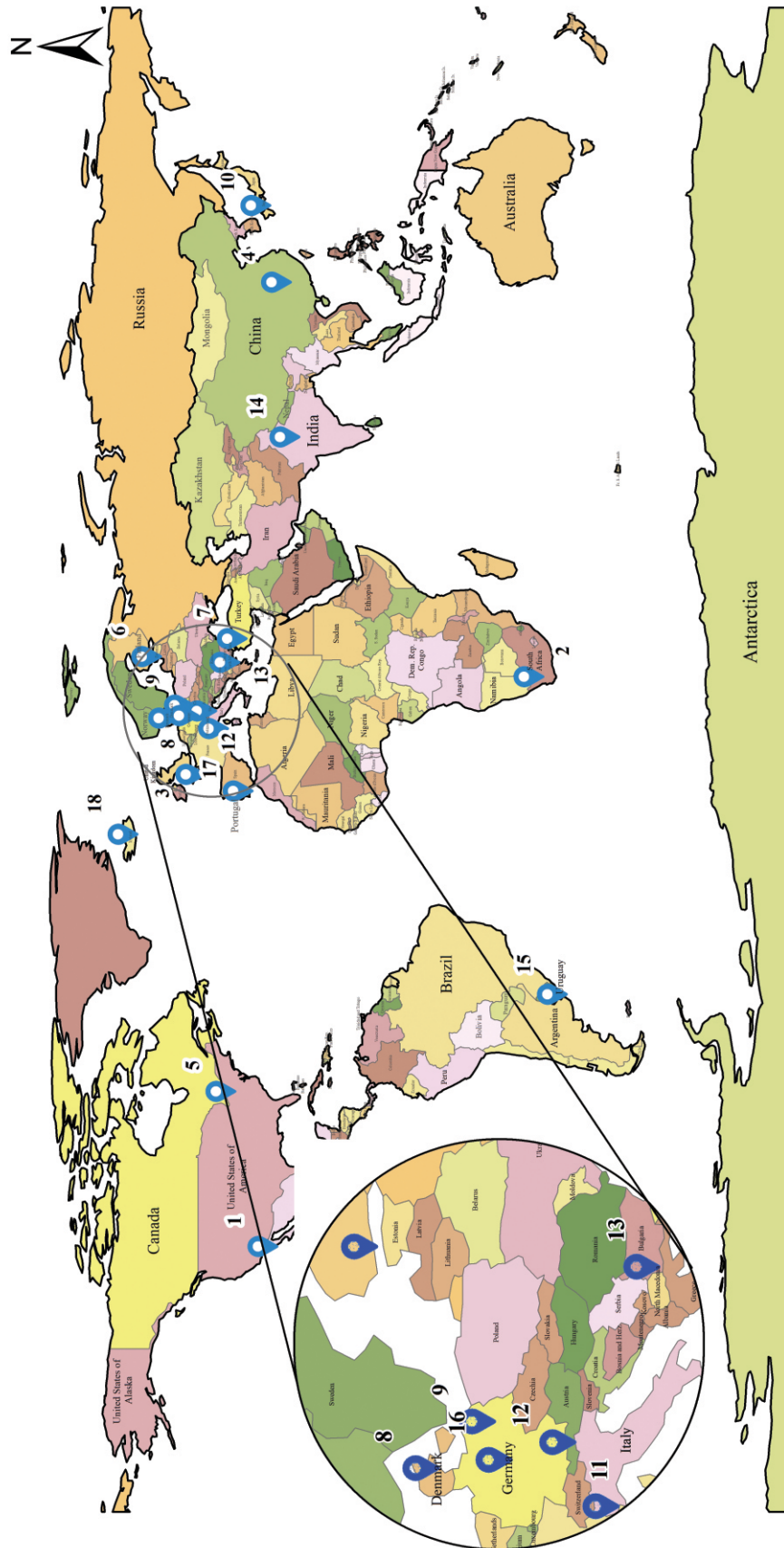
LIST OF INTERNATIONAL JOURNALS IN THE FIELD OF LAND
MANAGEMENT AND GEOMATICS EDUCATION

SN	Journal	Publisher	Scope
1	Land	MDPI	Land use, land change, WELF nexus, agriculture, sustainability
2	ISPRS International Journal of Geo-Information	MDPI	photogrammetry, remote sensing, spatial information systems, computer vision, and related fields
3	Geomatics	MDPI	Geomatics, geoinformatics
4	Journal of Geomatics	Indian Society of Geomatics	GIS, GPS, photogrammetry, cartography, remote sensing, surveying, spatial data infrastructure and technology including hardware, software, algorithms and modelling
5	International Journal of Geoinformatics	Association for Geoinformation Technology	Remote Sensing, Geographic Information Systems (GIS), Photogrammetry, and Global Positioning Systems (GPS)
6	International Journal of Disaster Studies and Climate Resilience	Resilience Press	disaster risk reduction, emergency management, and climate-change resilience
7	Journal of Integrative Agriculture	Elsevier	Agriculture, land use, food systems, sustainability
8	Iraqi Journal of Agricultural Sciences	Univ. of Baghdad	Agriculture, land use, food security
9	Land Management Journal	United Nations Convention to Combat Desertification	land tenure, sustainable land management, land use"
10	Land Use Policy	ScienceDirect	land use policies, geography, agriculture, forestry, irrigation, environmental conservation, housing, urban development and transport
11	African Journal of Empirical Research	AJER Publishing	empirical research, meta-analyses, and systematic reviews across social, pure, and applied sciences,

Calendar of Major International Geoinformatics Events

- 1 **Esri Developer & Technology Summit 2026**
Date: 10-13 March, 2026
Place: Palm Springs, California
Website: <https://www.esri.com/en-us/about/events/uc/>
- 2 **FIG CONGRESS 2026**
Date: 24-29 May, 2026
Place: Cape Town, South Africa
Website: <https://www.fig.net/fig2026/index.htm>
- 3 **Machine Learning for Earth Observation**
Date: 22-24 June, 2026
Place: University of Exeter, England
Website: <https://ml4eo.org/>
- 4 **International GeoInformatics Summer School (IGSS)**
Date: 22-29 June, 2026
Place: Wuhan, China
Website: <https://liesmars.whu.edu.cn/geosummerschool/s2026/index.htm>
- 5 **ISPRS Congress 2026**
Date: 4-11 July, 2026
Place: Toronto, Canada
Website: <https://www.isprs2026toronto.com/>
- 6 **ESA/JRC International Summer school on GNSS**
Date: 13-24 July, 2026
Place: Korpilampi, Finland
Website: <https://www.esa-jrc-summerschool.org/>
- 7 **Earth Observation Summer School 2026**
Date: 17-21 August, 2026
Place: Istanbul, Turkey
Website: <https://opengeohub.org/2026/01/29/earth-observation-summer-school-2026/>
- 8 **Summer School on Satellite-Based Hydrological Data Assimilation**
Date: 25-28 August, 2026
Place: Aalborg University, Denmark
Website: <https://www.en.plan.aau.dk/research/geodesy/summer-school-satellite-based-hydrological-data-assimilation-geodesyda#venue>
- 9 **Workshop on GNSS Ionosphere**
Date: 31 August - 3 September, 2026
Place: DLR, Neustrelitz, Germany
Website: <https://iwgi2026.welcome-manager.de/front/index.php>
- 10 **FOSS4G 2026 Academic Track**
Date: 30 August - 5 September, 2026
Place: Hiroshima, Japan
Website: <https://2026.foss4g.org/en/>
- 11 **International Remote Sensing Summer School 2026**
Date: 7-11 September, 2026
Place: Courmayeur - Italy
Website: <https://www.fondazionemontagnasicura.org/progetti-in-corso/international-remote-sensing-summer-school-2026>
- 12 **InterGEO Conference**
Date: 15-17 September, 2026
Place: Messe München, Germany
Website: <https://www.intergeo.de/en/>
- 13 **14th International FIG Workshop on the Land Administration Domain Model & 3D Land Administration**
Date: 1-2 October, 2026
Place: Sofia, Bulgaria
Website: <https://gdmc.nl/3DCadastres/workshop2026/>
- 14 **47th Asian Conference on Remote Sensing**
Date: 12 - 16 October, 2026
Place: New Delhi, India
Website: <https://acrs2026.in/>
- 15 **The SIRGAS 2026 Symposium**
Date: 3-6 November, 2026
Place: Montevideo, Uruguay
Website: <https://sirgas.ipgh.org/en/symposium-2026/>
- 16 **ISPRS WG II/3: 9th International ISPRS Workshop on LowCost 3D - Sensors, Algorithms, Applications**
Date: 18-20 November, 2026
Place: University of Braunschweig, Germany
Website: <https://lc3d.fbk.eu/>
- 17 **The Nineteenth International Conference on Advanced Geographic Information Systems, Applications, and Services
GEOProcessing 2027**
Date: 18-22 April, 2027
Place: Lisbon, Portugal
Website: <https://www.iaria.org/conferences2027/GEOProcessing27.html>
- 18 **2027 IEEE International Geoscience and Remote Sensing Symposium**
Date: 11-16 July 2027
Place: Reykjavík, Iceland
Website: <https://www.grss-ieee.org/event/2027-ieee-international-geoscience-and-remote-sensing-symposium/>

Major geoinformatics events across the world



Event number and their corresponding venue country

Major International Events

- | | | | |
|----------------------------------|--------------------------------|----------------------------|---|
| 1. Palm Springs, California | 6. Korpilampi, Finland | 11. Courmayeur - Italy | 16. University of Braunschweig, Germany |
| 2. Cape Town, South Africa | 7. Istanbul, Turkey | 12. Messe München, Germany | 17. Lisbon, Portugal |
| 3. University of Exeter, England | 8. Aalborg University, Denmark | 13. Sofia, Bulgaria | 18. Reykjavík, Iceland |
| 4. Wuhan, China | 9. DLR, Neustrelitz, Germany | 14. New Delhi, India | |
| 5. Toronto, Canada | 10. Hiroshima, Japan | 15. Montevideo, Uruguay | |

Articles Published in Previous Editions

Volume I (Published in 2076 B.S.)

- 1. Comparison of Machine Learning and Classical Algorithms based on Supervised Classification for Forest Types Discrimination using Rapid Eye Imagery**
Sanjeevan Shrestha, Stavros Sakellariou
- 2. Effects of Service-Specific On-the-Job Training-A Case Study of the Digital Cadastre and Office Management Training Programme**
Bhurwan Ranjit, Sudarshan Gautam
- 3. Assessing the Overall Accuracy of UAV Photogrammetry: A Methodology for Different Combination of Imagery Parameters and Terrain Type**
Basant Awasthi, Shashank Karki, Pratikshya Regmi, Deepak Singh Dhami, Shangharsha Thapa, Uma Shankar Panday
- 4. Management of Public Land for Urban Open Space: In Case of Disaster Risk Reduction**
Sanjaya Manandhar, Janak Raj Joshi
- 5. Outburst Flood Hazard Assessment of Tsho-Rolpa Glacial Lake**
Sanjeevan Shrestha, Karuna Shrestha, Yashoda Acharya
- 6. Vulnerability Assessment of Indigenous Communities to Climate Change in Nepal**
Pawan Thapa, Dr. Pradeep Sapkota Upadhyaya

Volume II (Published in 2077 B.S.)

- 1. A Collaborative Model and “Knowledge Transfer Vehicle” For Capacity Development: Geo-Information and Land Administration Education at Kathmandu University Jointly with Land Management Training Center**
Reshma Shrestha, Ganesh Prasad Bhatta
- 2. Assessment of Pre-Processing Methods of Digital Elevation Models for Stream Delineation**
Shangharsha Thapa, Lone Mokkenstorm, Julika Wolf, Birkan Çalişkan
- 3. German School of Thoughts on Geography and Its Implication in Nepal**
Sanjaya Manandhar
- 4. Comparison of Early Season Characteristics of Nepalese Forest Fires Retrieved by MODIS and VIIRS**
Him Lal Shrestha, Mahesh Poudel
- 5. Impact of Labour Migration on Land Use Change: A Case of Nepal**
Gobinda Ghimire
- 6. Ultra-High Resolution UAV Images for Land Pooling**
Aman Manandhar, Sagar Bayalkoti
- 7. Identifying Suitable Resettlement Areas for Squatters Using Multi Criteria Evaluation**
Atul Man Joshi, Bhurwan Ranjit

Volume III (Published in 2078 B.S.)

- 1. Encroachment of Forest Cover in Chitwan and Parsa Districts of Nepal: A Spatiotemporal Quantification Over 25 Years**
Pratikshya Regmi, Nimisha Wagle
- 2. Assessing the Status of Land Tenure System of Nepal Using Swot Matrix Method**
Sharad Chandra Mainali
- 3. Route Planning Using Least Cost Path Analysis (A Case Study of Janakpur – Birgunj Section)**
Sushmita Subedi, Bishal Kumar Jha, Shova Acharya, Nandeshwar Kushwaha
- 4. Land Slide Susceptibility Mapping of Budhigandaki River Sub-Basin Using Analytic Hierarchy Process and Machine Learning Methods**
Sudarshan Gautam, Binod Humagain, Sanjeevan Shrestha
- 5. Landslides In Nepal: A Case Study of Postearthquake Landslides in Upper Bhotekoshi**
Sharad Chandra Mainali, Sudarshan Gautam, Khem Raj Devkota
- 6. Quantification of Surface Velocity and Ice Thickness of Glacier: A Case Study of G9 Glacier, Hidden Valley Nepal**
Nabin Raj Bhatt, Sujana Sapkota, Dinesh Prasad Bhatt, Shangharsha Thapa, Dr. Rijan Bhakta Kayastha
- 7. Comparative Analysis of Different Methods of Spatial Interpolation: Interpolating Annual Precipitation On The Koshi Basin**
Sudarshan Gautam, Binod Humagain, Rebanta Aryal, Prakash Lakandri, Jagannath Aryal

Volume IV (Published in 2079 B.S.)

- 1. Comparison of Random Forest, Support Vector Machine and Artificial Neural Network Classifiers for Land Cover Classification Using Sentinel-2 Imagery**
Bhagirath Bhatt, Suraj KC, Sanjeevan Shrestha
- 2. Suitability Analysis to Identify the Suitable Dumping Site on Kanchanpur Using MCDA (Multi Criteria Decision Analysis)**
Binod Prasad Bhatta, Sudeep Kuikel, Reshma Shrestha
- 3. Landslide Susceptibility Mapping Along Pokhara-Beni Highway Using Frequency Ratio Techniques**
Sagar Karki, Bishal Thapa, Rajan Kumar Adhikari, Shreeram Bhandari
- 4. Smoke Scene Detection from Satellite Imagery Using Deep Learning**
R. Aryal, P. Thapa, M.Karki
- 5. Gravimetry in Survey Department: A Brief History and Current Practices**
Stallin Bhandari, Sandesh Upadhyaya, Shanker KC
- 6. Using Geospatial Technologies for Disaster Management in Developing Countries**
Pawan Thapa

Volume V (Published in 2080 B.S.)

1. **The Land-use Planning and Its Economic Implication**
Prof. Achyut Wagle
2. **Land Banking Initiative in Nepal for Sustainable Land Management: Unfinished Agenda of Decentralizing Land Use Planning and Land Reform**
Bhupendra Jung Keshari Chand
3. **A Brief History of Advances in Geodesy with National Cases**
Shanker K.C., Tri Dev Acharya
4. **Perceiving, Preserving and Promoting Indigenous Land Use Role Model with Drone Mapping in Nepal**
Sunil Bogati
5. **Reutilization Of Abandoned and Fallow Agricultural Land in Nepal: Lensing Through the Vedic Wisdom Perspective**
Basu Dev Kaphle
6. **Landcover Classification Using Decision Tree Algorithm**
Dhruba Poudel, Sanjeev Kumar Raut
7. **Identification of Land Market Impact Factors in The Context of The Introduction of The Land Use Regulation in Nepal: Stakeholders' Perspective**
Dr. Nab Raj Subedi, Professor Kevin McDougall, Dr Dev Raj Paudyal
8. **Summary Report on International Workshop on Land Use Planning and Land Administration: Integration and Decentralization**
Ganesh Prasad Bhatta, Rheechea Sharma, Sharad Chandra Maimali

Volume VI (Published in 2081 B.S.)

1. **Mapping Burn Severity of Wildfire and its Analysis with Topographical Factors: A Case Study of Chitwan District**
Aagya Dhungana, Anjali Singh, Anju Lage, Punam Koirala, Man Kumari Chaulagain, Sunil Thapa, Dr. Reshma Shrestha
2. **Spatio-Temporal Analysis of Air Pollutants Before, During and After Covid-19 Outbreak Over Kathmandu Valley**
Binod Prasad Bhatta, Mamta Kadel, Gorakh Nath Pandey, Sadiksha Adhikari, Manoj Kumar Bhat
3. **Practical Learning about Time using Sundial at Land Management Training Center**
Bhagirath Bhatt, Sushmita Timilsina, Shivaji K.C., Hareram Yadav
4. **Ecotourism and Ecovillage Mapping in Kavrepalanchowk District, Nepal**
Prakash Ghimire, Rheechea Sharma
5. **Concepts and Principles for Identification of Logical Errors in Cadastral (Parcel) Database Developed by Digitization of Analogue Cadastral (Parcel) Maps**
Er. Mahesh Thapa
6. **Modernizing Nepal's Height System: Leveraging GNSS and Gravity Observations for Global Compatibility**

Sushmita Timilsina

7. **Dependency of Orientation of Image Capture on Vegetation Indices**
Sanjeev Kumar Raut, Dhurba Poudel, Umang Raj Dotel, Shree Krishna Adhikari
8. **Land Management Training Center: The Center of Excellence in Land Management and Geomatics Education**
Tina Baidar, Ram Kumar Sapkota
9. **Effective Land Administration in Nepal: Navigating Governance, Legal and financial Pathways within the Climate Change- Land Nexus: Summary Report**
Umang Raj Dotel, Sushmita Timilsina
10. **Land Literacy Program: A Joint Effort of the Government and Non-Governmental Organizations Towards Land Issues Awareness on Communities**
Dharma Raj Joshi

Volume VII (Published in 2082 B.S.)

1. **Identification of Potential Agricultural Land Pooling Sites in Kaski District Using AHP and GIS**
Dhaka Ram Gaire, Shailendra Shahi, Oshi Humagain, Bir Bahadur Khatri, Umesh Bhurtyal, Milan KC
2. **Assessing the Spatial Variation of Aerosol Optical Depth and Its Relationship with Land Use/Land Cover in Kathmandu Valley, Nepal**
Dibikshya Shrestha, Aayush Chand, Prejika Thapa, Bibek Ojha
3. **Assessment of Landsat-8 And Sentinel-2 Imagery for Estimation of Aboveground Biomass and Carbon Stocks in Chure Forests of Nepal**
Er. Bhagirath Bhatt, Dr. Upama Ashish Koju, Dr. Reshma Shrestha
4. **Wings Over the Geoid: Employing Airborne Gravity Data in Geoid Determination**
Er. Shusmita Timilsina
5. **Ground Water Potential Zoning Using GIS And AHP: Case Study of Bagmati River Basin, Nepal**
Er. Kamal Shahi
6. **Flood Risk Assessment in Narainapur Rural Municipality Using Analytical Hierarchy Process**
Rekha Paudel, Rubi chaulagain, Bijaya Adhikari
7. **Comparative Analysis Between AHP & Fuzzy AHP: A Case Study on Flood Susceptibility of Koshi River Basin**
Dikshya Khadka, Aashish Kumar Karki, Bipul Chaudhary, Pratiksha Dahal, Rupa Bajgain, Dr. Reshma Shrestha, Er. Ajay Kumar Thapa
8. **Transforming Survey Offices: Technology, Management and Coordination**
Ram Kumar Sapkota
9. **Leveraging UAV Technology in Local Geoid Modelling**
Shusmita Timilsina, Bhagirath Bhatt
10. **Urban Heat Island Effect Analysis of Kathmandu Metropolitan City in Nepal**
Sudipta Poudel, Ishwor Pd. Dhital

MAJOR PROGRAMS CONDUCTED IN FISCAL YEAR 2082-83

SN	Major programs	Theme	Conducted (Month, Year)	Number of participants	Location
A	Training of Trainers	ToT			
1	Training of Trainers	Adoption of Modern Technology	Fagun 2082, 2083 Ashadh 2083, Ashadh 2083	62	LMTC
B	Academic Programs (Long Term (1 Year) Trainings)				
1	Junior Survey Training (Batch 61, Inservice Group)	Geoinformation, Land Administration	Ashadh 2083	24	LMTC
2	Junior Survey Training (Batch 62, Province and Local Level Group)	Geoinformation, Land Administration	Ashadh 2083	23	LMTC
3	Junior Survey Training (Batch 63, Fresh Group) *	Geoinformation, Land Administration	Kartik 2082- Kartik 2083	23	LMTC
4	Junior Survey Training (Batch 64, Inservice Group)*	Geoinformation, Land Administration	Ashadh 2083-Ashadh 2084	19	LMTC
C	Inservice, Induction Trainings				
1	Induction Trainings for Survey Officers (SOSET)	Induction Training	Kartik 2082	11	LMTC
2	Inservice Trainings for Survey Professionals (Amin, Surveyor)	In-Service Training	Bhadra 2082	42	LMTC
D	Short Term Specialization Trainings				
1	Training on LiDAR Data Use and Processing	Adoption of Modern Technology	Jeth 2083	17	LMTC
2	Training on Cadastral Mapping and Land Registration for professionals working in Survey Offices	Adoption of Modern Technology	Push 2082	28	Palpa
3	Training on Modern Surveying Equipments Handling and Data Processing	Adoption of Modern Technology	Magh 2082, Chaitra 2082	42	LMTC
4	Basic Remote Sensing Training	Adoption of Modern Technology	Push 2082	16	LMTC
5	Advanced Remote Sensing Training	Adoption of Modern Technology	Magh 2082	14	LMTC
6	Basic Geographic Information System Training	Adoption of Modern Technology	Magshir 2082	14	LMTC
7	Advanced Geographic Information System Training		Jesth 2083	17	LMTC
8	Training on use of GNSS and UAV for Cadastral Mapping	Adoption of Modern Technology	Chaitra 2082	18	LMTC
9	Trainig on NeLIS Operation	Adoption of Modern Technology	Baisakh 2083	20	LMTC
10	Training on Cadastral Mapping and Land Registration for professionals working on Informal Land Management	Land Administration	Push 2082	23	Dang
11	Land Administration and Management Training for Officers working at Land Administration Offices	Land Administration	Mangshir 2082	15	DLOMA
12	Land Administration and Management Training for Subordinates working at Land Administration Offices	Land Administration	Mangshir 2082	26	DLOMA
13	LRIMS and PAM Training for professionals working at Land Administration Offices	Land Administration	Jesth 2083	25	DLOMA
14	GIS Training For Local Level Staff	Land Use/Land Management	Chaitra 2082, Baisakh 2083, Baishakh 2083	60	Bhojpur, Bara, Jumla
15	Land Use/Land Management Trainings for professionals working at Local Level	Land Use/Land Management	Ashoj 2082	20	Chitawan
16	Annual Review and Planning	Organizational Development	Shrawan 2082	20	LMTC
17	Orientation Program for District Judges	Strengthening Judiciary	Mangsir 2082	20	LMTC
18	Mapping and Land Administration Trainings for Officers working in Judiciary	Strengthening Judiciary	Push 2082	20	LMTC
19	Mapping and Land Administration Trainings for Subordinates working in Judiciary	Strengthening Judiciary	Chaitra 2082	20	LMTC
E	Research and Innovation				
1	Research with Grant	Geoinformatics, Land Management	Need basis	2	LMTC
2	Shadowing with Real Work	Geoinformatics, Land Management	Need basis	1	Pokhara
3	Lecture of the Month Series	Land Governance	Need basis	6 Episodes	LMTC
4	Audio-Visual Lab for preparing Reading Materials	Land Literacy	Need basis		LMTC
5	E-learning Platform	Academic Development	Need basis		LMTC
F	Scholarship For Academic Programs (in collaboration with Kathamndu University)				
1	BE in Geomatics Engineering	Scholarship for Academic Program	Shrawan 2082- Ashadh 2083	24	Kathmandu University
2	ME/MS in Geoinformatics	Scholarship for Academic Program	Shrawan 2082- Ashadh 2084	6	Kathmandu University
3	MA in Land Administration	Scholarship for Academic Program	Shrawan 2082- Ashadh 2085	4	Kathmandu University
4	PhD in subjects related to Geomatics and Land Administration	Scholarship for Academic Program	Shrawan 2082- Ashadh 2086	1	Kathmandu University

* The training will be completed in the next Fiscal Year

MAJOR PROGRAMS FOR THE FISCAL YEAR 2083-84

SN	Major Programs	Theme
A	Training of Trainers	ToT
1	Training of Trainers	Adoption of Modern Technology
B	Academic Programs (Long Term (1 Year) Trainings)	
1	Junior Survey Training (Batch 64, Inservice Group)	Geoinformation, Land Administration
2	Junior Survey Training (Batch 65, Province and Local Level Group)	Geoinformation, Land Administration
3	Junior Survey Training (Batch 66, Fresh Group)	Geoinformation, Land Administration
C	Inservice, Induction Trainings	
1	Induction Trainings for Survey Officers (SOSET)	Induction Training
2	Inservice Trainings for Survey Professionals	In-Service Training
D	Short Term Specialization Trainings	
1	Training on LiDAR Data Use and Processing	Adoption of Modern Technology
2	Training on Cadastral Mapping and Land Registration for professionals working in Survey Offices	Adoption of Modern Technology
3	Training on Modern Surveying Equipments Handling and Data Processing	Adoption of Modern Technology
4	Remote Sensing Training	Adoption of Modern Technology
5	Geographic Information System Training	Adoption of Modern Technology
6	Training on use of GNSS and UAV for Cadastral Mapping	Adoption of Modern Technology
7	Training on NeLIS Operation	Adoption of Modern Technology
8	Training on Cadastral Mapping and Land Registration for professionals working on Informal Land Management	Land Administration
9	Land Administration and Management Training for Officers working at Land Administration Offices	Land Administration
10	Land Administration and Management Training for Subordinates working at Land Administration Offices	Land Administration
11	LRIMS and PAM Training for professionals working at Land Administration Offices	Land Administration
12	Orientation for Front Desk Officials	Land Governance
13	Land Literacy Programs	Land Governance
14	Land Use/Land Management Trainings for professionals working at Local Level	Land Use/Land Management
15	Annual Review and Planning	Organizational Development
16	Orientation Program for District Judges	Strengthening Judiciary
17	Mapping and Land Administration Trainings for Officers working in Judiciary	Strengthening Judiciary
18	Mapping and Land Administration Trainings for Subordinates working in Judiciary	Strengthening Judiciary
E	Research and Innovation	
1	Research with Grant	Geoinformatics, Land Management
2	Shadowing with Real Work	Geoinformatics, Land Management
3	Lecture of the Month Series	Land Governance
4	Audio-Visual Lab for preparing Reading Materials	Land Literacy
F	Scholarship For Academic Programs (in collaboration with Kathmandu)	
1	BE in Geomatics Engineering	Academic Program
2	ME/MS in Geoinformatics	Academic Program
3	MA in Land Administration	Academic Program
4	PhD in subjects related to Geomatics and Land Administration	Academic Program

LECTURE OF THE MONTH SERIES ORGANIZED AT LMTC

S.N.	Date	Subject	Speaker
1	2082/03/26	Importance of Geomatics Education	Former Director General Krishna Raj B.C. (Episode-13)
2	2082/04/30	Surveying in Australia: Surveying Profession, Cadastre and Gedodetic Infrastructure	Lecturer from University of Southern Queensland Dr. Dev Raj Poudel (Episode-14)
3	2082/05/17	Survey Profession and Professionalism	Joint Secretary at Government of Nepal Ganesh Prasad Bhatta (Episode-15)
4	2082/07/23	Winter Health Safety: How to stay warm, active, and healthy in outdoor work	Senior Cardiologist at Dhulikhel Hospital Dr.Rajendra Koju (Episode-16)
5	2082/10/15	Managing Stress through Positive attitude for excellence	Retd. Senior Director of Studies at NASC Dr. Kedar Rayamajhi (Episode-17)
6	2082/10/29	Health and Happiness	Former Secretary at Government of Nepal Dr. Ganesh Prasad Pandey (Episode -18)
7	2083/02/26	Positive thinking for a joyful life	Motivational Speaker Raman Adhikari Nepali (Episode- 19)



GOVERNMENT OF NEPAL
Ministry of Land Management, Cooperatives, Federal Affairs and General Administration
LAND MANAGEMENT TRAINING CENTER
Dhulikhel, Kavrepalanchok



INTRODUCTION

Land Management Training Center (LMTc), under the Ministry of Land Management, Cooperatives and Poverty Alleviation, Government of Nepal was established in 1968. LMTc is the oldest and the only governmental institution continually and significantly producing human resources and enhancing the capacity of government personnel in the field of Surveying Mapping, and Land Management since its establishment. The center has already produced more than 13,000 land professionals at different levels through various types of training courses.

LMTc is certified with ISO 9001:2015 for Quality Management on 29 June 2022 A.D. The center has been conducting a wide range of long and short-term training incorporating state-of-the-art modern technologies. Along with this, LMTc has collaborated to run academic courses with Kathmandu University (KU). Additionally, the Center contributes to the capacity building of Provincial and Local Governments.

VISION

To be the Center of Excellence in Land Management and Geomatics Education.

MISSION

Building and Enhancing Individual and Institutional Capacity in Land Management and Geomatics Sector.

GOAL

To produce qualified and skilled human resources in the field of Land Management and Geomatics.

OBJECTIVES

- To conduct various professional courses.
- To carry out Pre-service and In-service Training, Refresher courses, and Orientation programs.
- To collaborate with national and international academia and professional organizations.
- To promote Research and Development
- To support provincial and local governments in developing qualified human resources.

OUR FACULTIES/TRAINERS

Our courses are delivered by passionate and dedicated faculties/trainers who possess wealth of national and international experiences, and high qualification obtained from renowned national and international universities.

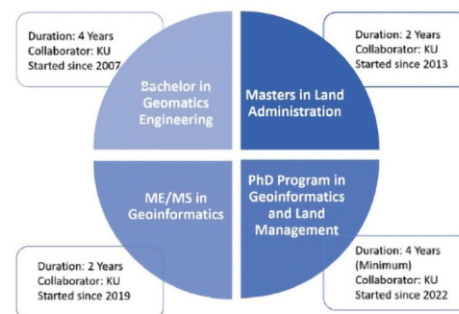
ANNUAL PUBLICATION

JOURNAL OF LAND MANAGEMENT AND GEOMATICS EDUCATION

OFFICIAL WEBSITE

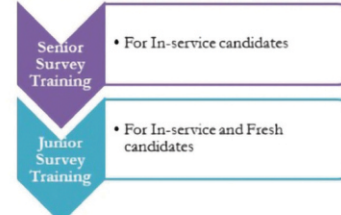
www.lmtc.gov.np

ACADEMIC COURSES (In Collaboration)



TRAINING COURSES

LONG TERM TRAININGS



SHORT TERM TRAININGS



FUTURE PLANS

- To contribute in Policy Research in the sector of Geomatics and Land Management
- To contribute to capacity Building of Local Governments in the sector of Geomatics and Land Management
- To extend collaboration with academia and regional training institutions



Government of Nepal
Ministry of Land Management, Cooperatives, Federal Affairs and General Administration

LAND MANAGEMENT TRAINING CENTER



ACHIEVEMENT OF FY 2082/83

NOVEL SUCCESSES & INNOVATIONS

Achievements of 2082/83

- Establishment of Audio-Visual Lab for preparing Reading Materials
- Deployment of a comprehensive E-learning Platform
- Successfully Conducted 6 episodes of Lecture of the Month Series
- Initiation of Research with Grant and Shadowing with Real Work programs
- Conducted Summer School on Climate Responsive Land Governance (with ILC Asia & Landstack)



TRAININGS LAUNCHED THIS FISCAL YEAR

GIS Training for Local Level Staff	60
Judiciary Mapping & Orientation	60
Training of Trainers (ToT)	62
Informal Land Management Mapping	23
Land Use & Land Management	20
LiDAR Data Use & Processing	17

ADDITIONAL CAPACITY BUILDING SHORT TRAININGS

NeLIS Operation (20)	Modern Survey Equipments (42)
GNSS & UAV Mapping (18)	Remote Sensing (Basic/Adv) (30)
Land Admin & Mgmt (Officers) (15)	Land Admin & Mgmt (Subordinates) (26)
Basic & Adv GIS Training (31)	LRIMS & PAM Training (25)
Annual Review and Planning (20)	Cadastral Mapping (Survey Offices) (28)



LONG TERM TRAININGS

Junior Survey Training Inservice (Batch 61) (24)	Junior Survey Training Inservice (Batch 64) (19)
Junior Survey Training Inservice/Local (Batch 62) (23)	Junior Survey Training Fresh (Batch 63) (23)



SCHOLARSHIPS & INSERVICE TRAININGS

Inservice Trainings for Survey Professionals	42
Induction Trainings for Survey Officers (SOSET)	11
BE in Geomatics / ME in Geoinformatics	30
MA Land Admin / PhD Programs	5

The figures in the parenthesis are the numbers of trainees



Opening Ceremony of Summer School on Climate Responsive Land Governance