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Cover Page

ISO 9001:2015 Certification; A step towards achieving the center's vision of "Center of Excellence in the field of Surveying and Mapping"

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EDITORIAL

It gives me and my team immense pleasure to present you the fourth issue of 'Journal of Land Management and Geomatics Education'. For an academic institution like Land Management Training Center which is continuously focusing on imparting the knowledge of geoinformation in Nepal through various educational activities, this journal plays a significant role. It's a big part of our institution that, we believe, will help the readers to gain some perspectives about geomatics field and enhance their knowledge on the domain to a great extent. For this purpose, we have been very conscious about improving the content and quality of this academic piece. We have requested and included articles from wide range of theme such as environment, climate change, disaster management, land administration and diverse topics such as remote sensing, Global Positioning System, UAV, Surveying and Mapping, etc. In addition, special effort has been given by our team of guest editors for maintaining the standard of those articles.

The major highlights of this journal are the use of GIS, remote sensing and machine learning techniques for decision making, land use/land cover study and disaster management. Further, it also includes the history and current practices gravity survey in Nepal.

Getting the journal published was not an easy journey. Therefore, I would like to express my sincere gratitude to all those direct and indirect helping hands that made this attempt possible. On behalf of editorial committee, I would kindly like to thank the authors for their contribution on this issue. Similarly, I am very grateful to the advisory council for their valuable suggestions and the editorial team for their constant dedication and effort. I express my sincere gratitude to all the members of editorial committee for making their efforts in publishing this issue. Lastly, I express my warm regards to all our readers for being big source of motivation for us to publish this great piece of knowledge.

As center has been certified with ISO 9001:2015 recently, the responsibility of the editorial board as well as center has been recognized high and henceforth, I would like to thank the whole LMTC family for the certification. We will be back again with the next issue of this journal in the upcoming year!

A big congratulations to our institution in its 54th anniversary !

Ramesh Gyawali

Editor in Chief

July, 2022

Executive Director's Message!

It gives me immense pleasure to present the fourth issue of the "Journal of Land Management and Geomatic Education" on the auspicious occasion of the 54th Anniversary of the Land Management Training Center (LMTC). Let me take this opportunity to congratulate entire LMTC family, who are associated with this glorious institution in one way or the other, and extend heartiest thankfulness to those whose contribution played significant role in attaining the height that LMTC has today.

Personally, I feel proud to have the opportunity of presenting subsequent issues of the journal to the date from its inception. In the first issue, I highlighted the historical evolution of the center along with the significant achievements made so far and some newer initiatives taken that year to develop the center as the "Center of Excellence". In the second issue, I presented our outstanding achievements made through innovative works over the years. In the third issue, I mentioned about the spirit that we walked through to witness the achievements of even higher level, despite the impact of global pandemic of COVID-19. In the fourth issue, with a great pride, I am reiterating our continued devotion and commitment in uplifting the Center's strength in terms of capacity, quality and scope to bring the Center at the highest possible level that it can attain.

Despite the effect of COVID-19 pandemic in the first quarter of this fiscal year, we kept on coping with the situation with a strong determination and demonstrated that we do not compromise anything in attaining our goal. Ministry of Land Management, Cooperatives and Poverty Alleviation has issued a new directive entitled "Land Management Training Center (Operation and Management) Directives, 2022" for the Center in line to develop the Center as the Center of Excellence. We have established a Continuously Operating Reference Station (CORS) in the premises of the Center to receive real time data from the Global Navigation Satellite System (GNSS). Likewise, establishment of Sun Dail, installation of calibration laboratory, improvement of the museum and physical facilities for the training as well as other basic requirements, continued efforts for continuous professional development of the staff at the Center, and timely modification and amendments in the curriculum of the trainings, among others are some of the great achievements of this year.

Let me also reiterate the fact that the Center is determined to keep improving the quality of trainings. Our courses are delivered by passionate and dedicated faculties/trainers, who possess wealth of knowledge in national as well as international issues, and are highly qualified from renowned national and international universities. We are thrilled to see that young and energetic officers are highly motivated and attracted to join this institution. One of the strongest part of LMTC is that current workforce is strong enough to conduct any kind of training courses in the field of Geomatics and land administration and management. It is also proud moment to mention that we have been recognized to meet the quality requirements of international standard.

Our major aspiration is to make this journal the most sought after journal for the professionals and academicians of land management and geomatics domain. As in the past, the glory of this journal is that all the papers are peer reviewed by the leading Geomatics academicians and professionals from Nepal including Mr. Janak Raj Joshi, Dr. Jagannath Aryal, Dr. Dev Raj Paudyal, Dr. Arun Kumar Pratihast, Dr. Subash Ghimire, Dr. Reshma Shrestha and Mr. Uma Shankar Panday, as the Guest Editors of the Journal. Er. Sanjeevan Shrestha, Chief Survey Officer at Survey Department, was also kind to review one of the papers.

I would like to express my sincere appreciation to the fellow colleagues, the members of Advisory Committee, and the Editorial Committee for their invaluable contribution in bringing out this issue. More importantly, I extend my sincere gratitude to all the Guest Editors and reviewer Er. Shrestha for their invaluable efforts on reviewing the papers and guiding us to improve the quality of the Journal. I would like to thank all the authors for their resourceful professional contribution. I am confident that such a support and professional contribution will be continued in the upcoming issues too.

Finally, let me extend special thanks to Mr. Ramesh Gyawali for facilitating the overall process of this publication, and Er. Sharad Mainali and Er. Bhagirath Bhatt for their tireless efforts to bring out the Journal in stipulated time. I must say, we are still starving of quality papers. I, once again, encourage my fellow colleagues from the Centre as well as the professionals of Land Management and Geomatics to contribute to the journal by providing quality articles in the future.

We expect your critical feedback on our endeavor.

Happy Reading!!!

By the way, I proudly bring into your kind information that we are now ISO (9001:2015) Certified!

Ganesh Prasad Bhatta

Executive Director

Land Management Training Centre

July 14, 2022

Original Articles

COMPARISON OF RANDOM FOREST, SUPPORT VECTOR MACHINE AND ARTIFICIAL NEURAL NETWORK CLASSIFIERS FOR LAND COVER CLASSIFICATION USING SENTINEL-2 IMAGERY

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ABSTRACT

Land cover maps are important for making strategies for planning and management of land and land resources. In this study, we have implemented three advanced non parametric machine learning classifiers: Random Forest, Support Vector Machine, and Artificial Neural Network for land cover classification using Sentinel-2 imagery. Accuracy assessment was performed by using different evaluation metrics such as mean precision and recall. The accuracy of each land cover class was further assessed in terms of sensitivity and specificity. Further, the significance of the difference between the resulting classifications obtained by using three different classifiers was evaluated by a t-test. All classification results showed high precision and recall values. The mean precision values for artificial neural network, random forest and support vector machine were 0.84, 0.80 and 0.78 respectively. Similarly, the recall values for ANN, random forest and support vector machine were 0.78, 0.72 and 0.62 respectively. The assessment of the classification with different evaluation metrics showed artificial neural network as the most suitable machine learning classifier for land cover classification for Sentinel 2 imagery.

KEY WORDS

Land Cover Classification, Random Forest, Support Vector Machine, Artificial Neural Network, Training Sample Data, Test Sample Data, Tuning Parameters

1. INTRODUCTION

Land cover refers to the physical and biological cover at the surface of the earth, including water, vegetation, bare ground, man-made structures, etc (Zhou, L., & Yang, X. (2008)). Land cover maps can be prepared by using different approaches such as unsupervised classification, supervised classification, object-based image classification, and by using machine learning algorithms. The use of machine learning algorithms in land cover classification is increasing due to the availability of different machine learning algorithms with better computational capabilities than traditional approaches of classification. In this study, we have performed land cover classification of freely available Sentinel 2 imagery using three different classification algorithms: Artificial Neural Network (ANN), Random Forest (RF), and Support Vector Machine (SVM). The output obtained from different classifiers was compared with each other and with test data. Further, the accuracy and quality assessment of the classification was done and the most optimal model was determined.

Random Forest is one of the most widely used non parametric machine learning algorithms (Betts et al. 2017). Random forests are an ensemble learning method for classification, regression, and other tasks, that operate by constructing a multitude of decision trees at training time and producing the class that is the mode of the classes (classification) or mean prediction (regression) of the individual trees (Breiman, L. 2001). The popularity of this algorithm is due to the fact it can be used for both classification and regression purposes, and thus can be used with categorical and continuous variables (Woznicki et al. 2019). Because of this flexibility, RF has been used in a wide range of Earth Science applications including modelling forest cover (Betts et al. 2017), land-use (Araki et al. 2018), land-cover (Nitze et al. 2015), and object-oriented mapping (Kavzoglu 2017).

Support vector machine (SVM) is another important machine learning classifier used for land cover mapping (Mountrakis et al. 2011). The principle behind the SVM classifier is a hyperplane that separates the data for different classes. The main focus is the construction of a hyperplane by maximizing the distance from the hyperplane to the nearest data point of either class. These nearest data points are known as support vectors (Cortes, C., & Vapnik, V. (1995)).

SVM builds the optimal separating hyper planes based on a kernel function (K). All images, of which feature vector lies on one side of the hyper plane, belong to class -1 and the others belong to class +1. Support vector machines (SVM) has been shown to outperform other classifiers due to its overall high capacity to generalize complex features (Mountrakis et al. 2011). A land-cover classification study using Landsat-8 and involving six land-cover classes found that SVM was able to achieve a relatively high overall accuracy of 88% (Goodin et al. 2015). Recently, Mansaray et al. (2019) analyzed the impact of training sample size on the overall accuracies of SVM and RF for mapping paddy rice in China in 2015 and 2016. They found that for 2015, SVM and RF achieved overall accuracies of 90.8% and 89.2%, respectively, using 10 satellite observations from Landsat-8 and Sentinel-1A. However, in 2016 SVM and RF achieved overall accuracies of 93.4% and 95.2%, respectively, using 14 satellite observations from Landsat-8, Sentinel-1A and Sentinel-2A.

Artificial neural networks are models based on biological neural networks (Zhou, L., & Yang, X. (2008)). They consist of an interconnected group of neurons. Each neuron contains a single computation process. The multi-layer-perceptron (MLP) feed-forward backpropagation neural networks are the most popular in practice due to their easiness to understand and implement. A typical structure of a MLP neural network is comprised of neurons and their links in a layered structure. The input to a neuron in such a network is the weighted sum of the outputs of neurons at the previous layer. Each neuron at both hidden and output layers contains a single process which is to transform the input using a linear or non-linear function, namely, the activation function.

According to Bischof et al., 1992, MLP neural networks are more accurate for land cover classification than traditional statistical methods (Bischof et al., 1992). However, their applicability has been challenged by the complexity of neural network parameterization. A number of factors need to be considered when parameterizing neural networks, which include input data, training samples, output settings, network architecture, initial weights, and training parameters. Most of the previous studies targeted several external factors, such as input data and training samples. Several studies investigated some internal parameters, such as the number of hidden layers (Kanellopoulos and Wilkinson, 1997), activation function (Shupe and Marsh, 2004), and the combination of training rate and momentum (Kavzoglu and Mather, 2003). However, their findings are not consistent. Further research is needed to comprehensively investigate the possible impacts of these internal parameters on the performance of land cover classification.

1.1 Objectives

The major objective of the study was to perform land cover classification of the study area by the use of machine learning algorithms Random Forest, Support Vector Machine, and Artificial Neural Network. Further, the accuracy of each classification algorithm was assessed and the most optimal method of land cover classification with Sentinel-2 data was determined.

1.2 Study Area

The study area comprises a portion of Kaski district, Gandaki Province, Nepal. It mainly covers the city Pokhara and nearby areas with the coordinates of the bounding box as follows: Long. 83.900 E and Lat. 28.400 N at upper left and Long. 84.280E and Lat. 28.050 N at lower right. The area comprises heterogeneous land cover types including built-up regions, cultivated area, water bodies (rivers lakes, etc.), forests, and fallow land. The map of the study area is given in Figure 1.

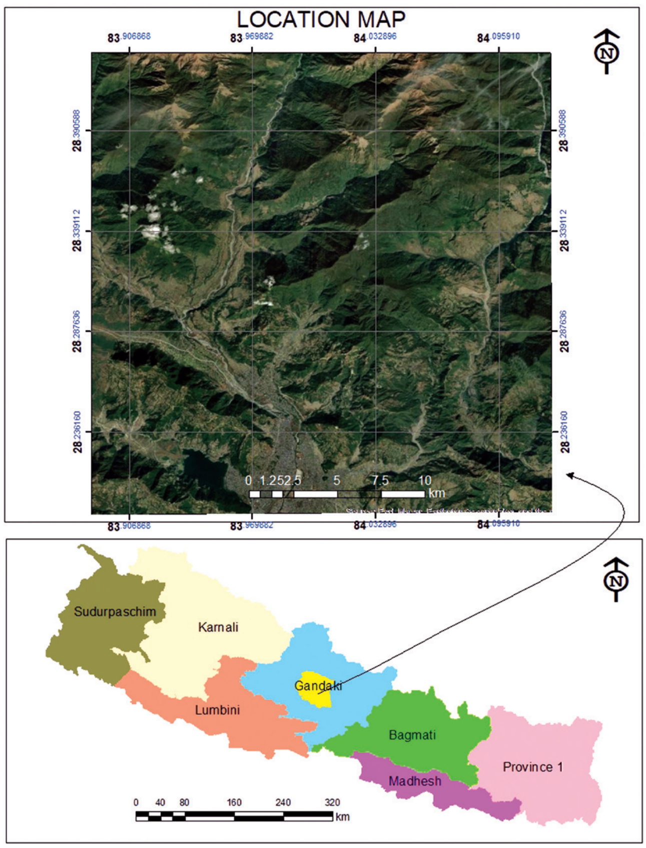

Figure 1. Location Map of the Study Area

2. DATASETS

Land cover classification of the study area was done by using Sentinel-2 imagery which was downloaded from Copernicus Open Access Hub(https://scihub.copernicus.eu/dhus). The Sentinel 2 imagery consists of 13 bands of which four bands are of 10m resolution (Band 2, Band 3, Band 4 and Band 8)) and six bands are of 20m resolution (Band 5, Band 6, Band 7, Band 8A, Band 11 and Band 12) were used for classification. We didn't use 60m resolution bands: Band 1, Band 9 and Band 10 for land cover classification, which carry information about atmospheric water content and are not suitable for land cover classification. The detail information of the bands of Sentinel -2 imagery is given in Table 1.

Table 1. Sentinel-2 Bands

Sentinel – 2 Bands	Sentinel – 2A		Spatial Resolution (m)
	Central Wavelength (nm)	Bandwidth (nm)	
Band 1-Coastal Aerosol	442.7	21	60
Band 1-Blue	492.4	66	10
Band 3-Green	559.8	36	10
Band 4-Red	664.6	31	10
Band 5-Veg. Red Edge	704.1	15	20
Band 6-Veg. Red Edge	740.5	15	20
Band 7-Veg. Red Edge	782.8	20	20
Band 8-NIR	832	106	10
Band-8A-Narrow NIR	864.7	21	20
Band 9-Water Vapour	945.1	20	60
Band 10-SWIR Cirrus	1373.5	31	60
Band 11-SWIR	1613.7	91	20
Band 12-SWIR	2202.4	175	20

3. METHODOLOGY

Land cover classification of the study area was performed by using three different machine learning algorithms: Random Forest, Support Vector Machine, and Artificial Neural Network. The coding of the entire classification process was carried out using R programming. The image downloaded from Copernicus Open Access Hub was pre-processed prior to classification. The pre-processing process included cropping of the image to the extent of the study area, resampling 20m bands to 10m, and normalization of band values. The pre-processed image was used for land cover classification. Optimal models were generated for each classification algorithm: RF, SVM, and ANN using the same training sample data. Different parameters were tested for each classification algorithm and the most optimal parameters were used for the generation of the model. The optimal models were used for the classification of the image. The accuracy assessment of the classified image was done by using the test sample data and the results obtained from different classifiers were compared with each other. The accuracy of the classification was assessed by using different evaluation metrics such as mean precision and recall. Further, the accuracy of each land cover classes was evaluated based on the sensitivity and specificity of land cover classes. The flowchart showing the study methods for land cover classification of Sentinel 2 image is shown in Figure 2.

3.1 Training and Test Data

Within the study area, six land cover classes were distinguished: builtup, cultivation, forest, grassland, waterbody, and others. Training data was generated for these six classes in QGIS using Bing Aerial Imagery. Google Earth Pro and Sentinel-2 Image were also used as references while digitizing training polygons. For each class, the proportion selected was arbitrary, but was guided by the desire for a minimum sample size of 50, where possible, while yet retaining a sufficient sample size for training purposes. The training data was split into training sample data and test sample data in the proportion of 70% and 30% respectively. The details of the training and testing sample sizes used in the study are given in Table 2.

Table 2. Training & Test Sample Data

S.N.	Land Cover Class	Training (Pixels)	Testing (Pixels)
1.	Builtup	274	117
2.	Cultivation	812	348
3.	Forest	16271	6972
4.	Grassland	163	69
4.	Waterbody	4715	2020
5.	Others	135	57
	Total	22370	9583

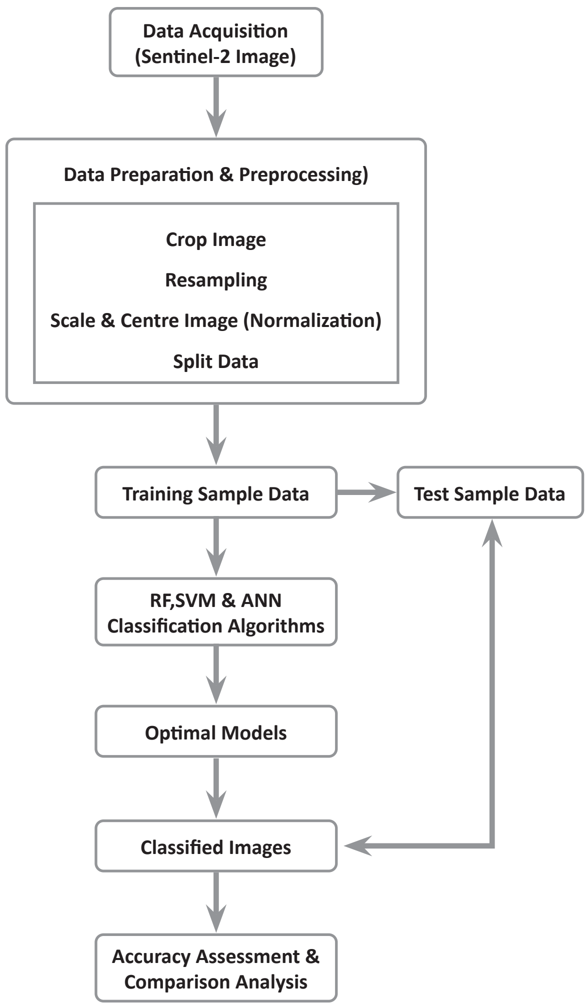

Figure 2. Flowchart of Study Methods

3.2 Classification Algorithm and Tuning Parameters

Tuning parameters play an important role in producing high accuracy results when using the machine learning classification algorithms SVM, RF, and ANN. Each classifier has different tuning steps and tuned parameters. For each classifier, we tested a series of values for the tuning process with the optimal parameters determined based on the highest overall classification accuracy. In this study, the classified results obtained from the most optimal parameters of each classifier were used to compare the performance of classifiers.

3.2.1 Random Forest (RF)

In order to implement the RF, two parameters need to be set up: the number of trees (ntree) and the number of features in each split (mtry) (Breiman, L. (2001)). mtry refers to the number of variables available for splitting at each tree node. ntree refers to the number of trees to grow. Larger number of trees produces more stable models and covariate importance estimates, but requires more memory and a longer run time. Several studies show that satisfactory results could be achieved with the default parameters.

3.2.2 Support Vector Machine (SVM)

The tuning parameters used in the SVM classifier are the Cost and Loss functions. The cost parameter decides how much an SVM should be allowed to "bend" with the data. For a low cost, we aim for a smooth decision surface, and we aim to classify more points correctly for a higher cost. It is also simply referred to as the cost of misclassification. The values of cost used for tuning are 0.2, 0.5, and 1. Loss functions L1 and L2 are used for minimizing the error. The values of the loss function i.e. L1 or L2 are chosen in such a way that the best-fitted model is obtained.

3.2.3 Artificial Neural Network (ANN)

The architecture of ANN used for classification is shown in Figure 3. For the ANN, we have used two parameters: size (number of hidden units) and decay (learning rate).

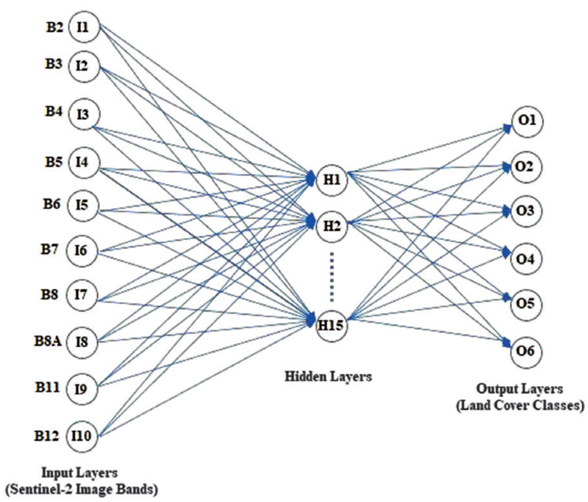

Figure 3. The architecture of the Artificial Neural Network

3.3 Accuracy Assessment and Comparisons

Based on the test sample data, the confusion matrices were first calculated and the classification accuracies of three classifiers were assessed by computing mean precision and recall. The accuracy of each land cover class was assessed by means of sensitivity and specificity. Further, the significance of the differences between classification results was evaluated by means of t-tests.

3.3.1 Sensitivity and Specificity

Sensitivity is referred to as the true positive rate while specificity is the true negative rate.

$$Sensitivity = \frac{TP}{P} \ldots\ldots\ldots\ldots\ldots\ldots(1)$$

$$Specificity = \frac{TN}{N} \ldots\ldots\ldots\ldots\ldots\ldots(2)$$

where, TP refers to positive tuples that were correctly labelled by the classifier.

TN refers to negative tuples that were correctly labelled by the classifier.

P and N refers to all positive and negative tuples respectively.

3.3.2 Precision

Precision refers to the measure of exactness. It is the ratio of correctly predicted positive observation to total predicted positive observation.

$$P = \frac{TP}{TP+FP} \ldots\ldots\ldots\ldots\ldots\ldots(3)$$

where FP refers to negative tuples that were incorrectly labelled as positive

3.3.3 Recall

Recall refers to the measure of completeness. It is calculated as the ratio of correctly predicted positive observations to the all observations in actual class.

$$R = \frac{TP}{TP+FN} \ldots\ldots\ldots\ldots\ldots\ldots(4)$$

where FN refers to positive tuples that were mislabeled as negative.

4. RESULTS AND DISCUSSION

4.1 Tuning Results

To find the optimal parameters for the RF classifier, several values of mtry (2, 3, 4, 5, 6, 7 & 8) were tested while the default value was used for ntree. The value of mtry should lie between the range of 1 and 10 as the number of input variables is 10(10 sentinel bands). The graph showing the optimized value of mtry is given in Figure 4. The tuning results of random forest show that the most appropriate value of mtry is 2.

For the SVM method, we used L2 regularized SVM with Linear Kernel. Cost and loss functions were used as tuning parameters. The results of the tuning process are shown in Figure 5. From the tuning process, it was found that the most optimal parameters for the SVM classifier are 1 for the cost function and L2 for the loss function.

For ANN, the tuning parameters size (number of hidden units) and decay (learning rate) were used. and the most optimal parameters were determined. The number of hidden units tested are 5, 10, and 15 while that of learning rate are 0.001, 0.01, and 0.1 The results of the tuning process are shown in Figure 6. The best results were obtained with a learning rate of 0.01 and the number of hidden units at 15.

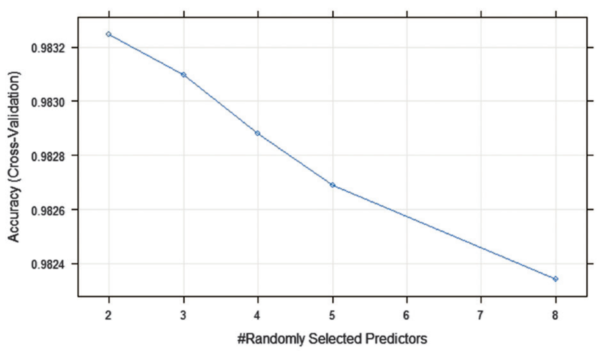

Figure 4. Tuning Results of the mtry parameter of the Random Forest Classifier

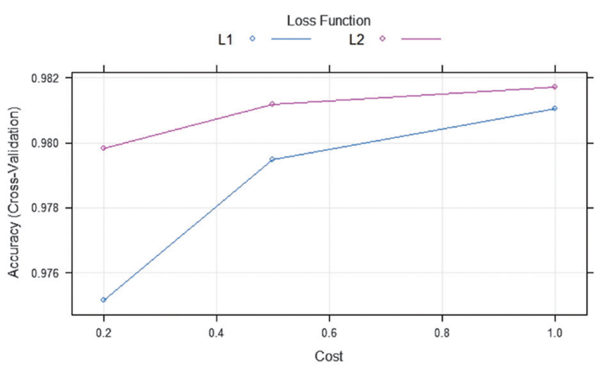

Figure 5. Tuning Results of the Support Vector Machine Classifier

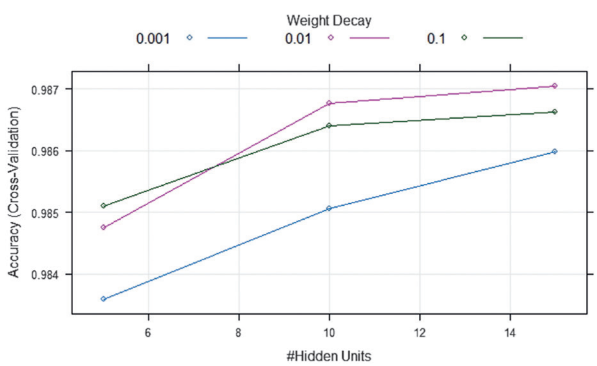

Figure 6. Tuning Results of the Artificial Neural Network Classification

4.2 Land Cover Classification Outputs

Three different land cover maps were obtained from the land cover classification using three classification algorithms: RF, SVM, and ANN. The land cover maps from the RF, SVM, and ANN classifiers are shown in Figure 9, Figure 10, and Figure 11 respectively. The land cover maps depict six land cover classes: Builtup, Cultivation, Forest, Grassland, Waterbody, and Others . The land cover class Others include open spaces and areas not included in the rest of the classes. We can see from the maps that there is not much difference between the maps in terms of visual appearance. The major features like lakes in Pokhara, other water bodies, forest areas, and cultivated areas are clearly depicted in all three maps. However, builtup areas are well represented by ANN and RF classifiers in comparison with the SVM classifier. Similarly, if we look in terms of individual features there are some differences in the representation of features in maps obtained from three different classification algorithms. For example, river which is a linear feature is clearly represented by SVM and ANN classifiers while it is not cleary depicted by random forest classifier as shown in the figures 7, 8 and 9.

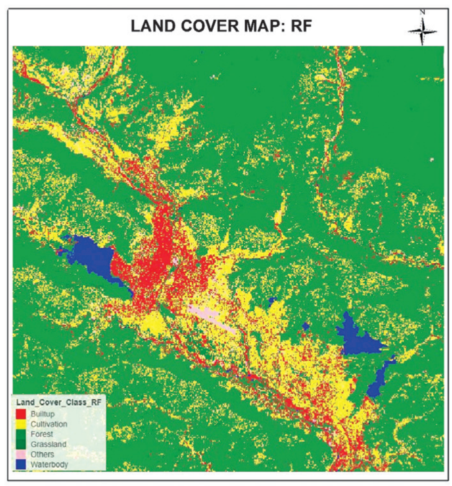

Figure 7. Land Cover Map from the Random Forest Classifier

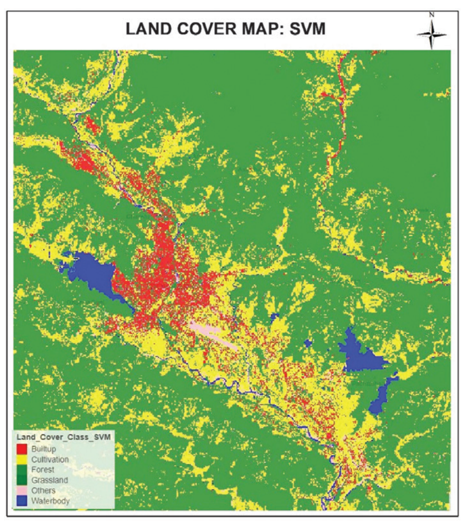

Figure 8. Land Cover Map from the Support Vector Machine Classifier

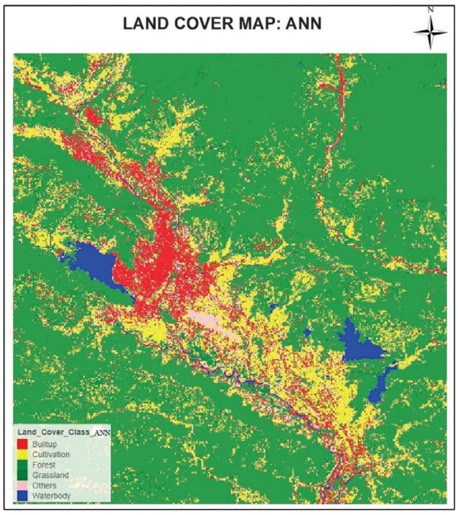

Figure 9. Land Cover Map the Artificial Neural Network Classifier

4.3 Predictor Importance

The importance values indicate the loss in performance when the effect of the predictor is negated. Higher values mean the variables are more important. Figure 10 shows the importance of different predictor variables in the classification of each land cover class. In the figure, we can observe that bands: B11 and B05 have a higher importance in the prediction of the class 'Cultivation' compared to other bands. Similarly, band B11 is more important in predicting the class Grassland and bands B2 and B12 are more important for predicting the class Builtup.

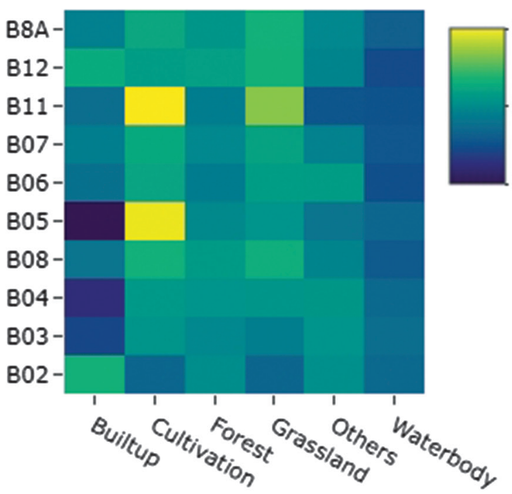

Figure 10. Predictor Importance (Land Cover Class vs Sentinel-2 Bands)

4.4 Comparison of Models

Of all compared classification results, the mean precision for ANN classifier was highest(0.84) followed by random forest(0.80) and support vector machine(0.78). Similarly, the values of recall for artificial neural network, random forest and support vector machine were 0.78, 0.72 and 0.62 respectively. The accuracy of each land cover class for each classifier is determined in terms of sensitivity and specificity. Table 3 shows the sensitivity and specificity of each land cover clas.

Table 3. Sensitivity & Specificity of Land Cover Classes

Classifier	Class	Evaluation Metrics	
		Sensitivity	Specificity
RF	Builtup	0.7863	0.9986
	Cultivation	0.9712	0.9944
	Forest	1.00	0.9958
	Grassland	0.7101	0.9995
	Others	0.5087	0.9992
	Waterbody	0.9985	1.00
SVM	Builtup	0.7948	0.9982
	Cultivation	0.9684	0.9889
	Forest	0.9997	0.9885
	Grassland	0.00	1.00
	Others	0.1929	0.9996
	Waterbody	0.9985	0.9996
ANN	Builtup	0.86325	0.99915
	Cultivation	0.97701	0.99632
	Forest	0.9999	0.9977
	Grassland	0.6522	0.9993
	Others	0.7368	0.9990
	Waterbody	0.9995	0.9999

The boxplot showing the different evaluation metrics: Mean Recall, Mean Sensitivity, Mean Specificity, Mean F1, Mean Precision, Accuracy, Kappa coefficient, Mean Balanced Accuracy, Mean Detection Rate, Positive Prediction value and Negative Prediction Value for each classifier is shown in Figure 11.

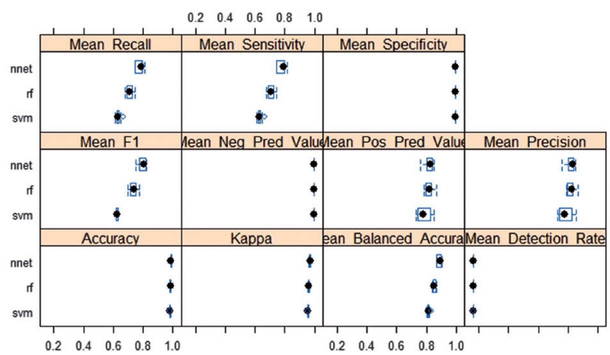

Figure 11. Boxplot of Different Evaluation Metrics

4.4.1 t-test:

The paired t-tests with Bonferroni multi-test corrections on p-values show that there are significant differences between the ANN model and the other two, while there are no significant differences between the RF and SVM models. In this case we can choose the ANN model as the "best" model. However, the differences in accuracies were significantly small between. The ANN model had a marginally better accuracy than the RF model only by 0.38% and the SVM by 0.53% only.

Table 4. Results of t-test

	RF	SVM	ANN
RF		0.001540	-0.003795
SVM	0.06784		-0.005335
ANN	2.655e-06	1.975e-05	

5. CONCLUSION

In this study, we have implemented, evaluated, and compared the performance of three non-parametric classifiers: Random Forest, Support Vector Machine, and Artificial Neural Network using the Sentinel-2 image dataset. The mean precision and recall of each classifier were calculated to evaluate the performance of each classifier. A t-test was performed to further determine the most suitable classifier. All classification produced good results with high mean precision and recall values ranging from 0.78 to 0.84 and 0.62 to 0.78 respectively. This study concludes that RF, SVM, and ANN are powerful classifiers for Land Cover classification. However, among all classifiers, the ANN proved to be more stable and reliable classifier with the highest precision and recall.

6. REFERENCES

Araki, S., Shima, M., & Yamamoto, K. (2018). Spatiotemporal land use random forest model for estimating metropolitan NO2 exposure in Japan. Science of The Total Environment, 634, 1269-1277.

Betts, M. G., Wolf, C., Ripple, W. J., Phalan, B., Millers, K. A., Duarte, A., ... & Levi, T. (2017). Global forest loss disproportionately erodes biodiversity in intact landscapes. Nature, 547(7664), 441-444.

Bischof, H., & Pinz, A. J. (1992, June). Neural networks in image pyramids. In [Proceedings 1992] IJCNN International Joint Conference on Neural Networks (Vol. 4, pp. 374-379). IEEE.

Breiman, L. (2001). Random forests. Machine learning, 45(1), 5-32.

Chen, Y. Q., Yin, T., & Babri, H. A. (1997, September). A stochastic backpropagation algorithm for training neural networks. In Proceedings of ICICS, 1997 International Conference on Information, Communications and Signal Processing. Theme: Trends in Information Systems Engineering and Wireless Multimedia Communications (Cat. (Vol. 2, pp. 703-707). IEEE.

Chen, Y. Y., Lin, Y. H., Kung, C. C., Chung, M. H., & Yen, I. H. (2019). Design and Implementation of Cloud Analytics-Assisted Smart Power Meters Considering Advanced Artificial Intelligence as Edge Analytics in Demand-Side Management for Smart Homes. Sensors (Basel, Switzerland), 19(9), 2047. https://doi.org/10.3390/s19092047

Cortes, C., & Vapnik, V. (1995). Support-vector networks. Machine learning, 20(3), 273-297.

Ghimire, B., Rogan, J., Galiano, V. R., Panday, P., & Neeti, N. (2012). An evaluation of bagging, boosting, and random forests for land-cover classification in Cape Cod, Massachusetts, USA. GIScience & Remote Sensing, 49(5), 623-643.

Goodin, D. G., Anibas, K. L., & Bezymennyi, M. (2015). Mapping land cover and land use from object-based classification: an example from a complex agricultural landscape. International Journal of Remote Sensing, 36(18), 4702-4723.

Kavzoglu, T. (2017). Object-oriented random forest for high resolution land cover mapping using quickbird-2 imagery. In Handbook of neural computation (pp. 607-619). Academic Press.

Knorn, J., Rabe, A., Radeloff, V. C., Kuemmerle, T., Kozak, J., & Hostert, P. (2009). Land cover mapping of large areas using chain classification of neighboring Landsat satellite images. Remote Sensing of Environment, 113(5), 957-964.

Lu, D., & Weng, Q. (2007). A survey of image classification methods and techniques for improving classification performance. International journal of Remote sensing, 28(5), 823-870.

Mansaray, L. R., Wang, F., Huang, J., Yang, L., & Kanu, A. S. (2020). Accuracies of support vector machine and random forest in rice mapping with Sentinel-1A, Landsat-8 and Sentinel-2A datasets. Geocarto International, 35(10), 1088-1108.

Mountrakis, G., Im, J., & Ogole, C. (2011). Support vector machines in remote sensing: A review. ISPRS Journal of Photogrammetry and Remote Sensing, 66(3), 247-259.

Melgani, F., & Bruzzone, L. (2004). Classification of hyperspectral remote sensing images with support vector machines. IEEE Transactions on geoscience and remote sensing, 42(8), 1778-1790.

Nitze, I., Barrett, B., & Cawkwell, F. (2015). Temporal optimisation of image acquisition for land cover classification with Random Forest and MODIS time-series. International Journal of Applied Earth Observation and Geoinformation, 34, 136-146.

Qian, Y., Zhou, W., Yan, J., Li, W., & Han, L. (2015). Comparing machine learning classifiers for object-based land cover classification using very high-resolution imagery. Remote Sensing, 7(1), 153-168.

Roli, F., Serpico, S. B., Bruzzone, L., & Vernazza, G. (1996, September). Classification of multispectral remote-sensing images by neural networks. In 1996 8th European Signal Processing Conference (EUSIPCO 1996) (pp. 1-4). IEEE.

Tutorial, E. N. V. I. (2013). Exelis visual information solutions. Boulder, Colorado.

Woznicki, S. A., Baynes, J., Panlasigui, S., Mehaffey, M., & Neale, A. (2019). Development of a spatially complete floodplain map of the conterminous United States using random forest. Science of the total environment, 647, 942-953.

Zhou, L., & Yang, X. (2008). Use of neural networks for land cover classification from remotely sensed imagery. The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences, 37, 575-578.

SUITABILITY ANALYSIS TO IDENTIFY THE SUITABLE DUMPING SITE ON KANCHACNPUR USING MCDA (MULTI CRITERIA DECISION ANALYSIS)

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ABSTRACT

Lack of suitable land for solid waste dumping is a major issue in urban and developing areas. Suitability analysis performed is useful in determining suitable location for the dump site in the particular area. The aim of this study was to identify possible places for appropriate dumping sites in Kanchanpur. Geographic Information System (GIS) environment was used to imply the MCDA approach to determine the suitable dumping site. The Analytical Hierarchy Process (AHP) was used to assign weightage based on different criteria such as Land Use, Road, River, Settlement, and Slope were all elements considered when selecting ideal sites.

These Data were acquired from various secondary sources and the data required for this research were prepared using various tool of GIS such as Clip, Dissolve, Extract by Mask. Under data visualization, Euclidean distance, slope, resample, reclassify was performed. And then finally weighted overlay was performed.

The criteria defined were classified accordingly, with classes divided into five suitability levels: Restricted, Less Suitable, Moderately Suitable, Suitable, and Most Suitable. Each map layer was created using GIS, and the final suitability map was created using weighted overlay analysis and leveled as the restricted, less suited, and suitable area. The weights assigned For Land Use, 12%; for Road, 13%; for River, 21%; for Settlement, 49%; and for slope, 5% was provide. The result from Weighted overlay showed that, 47.7% of the study area was restricted, 47.6% less suitable and 4.7% suitable. The ideal locations for dumping site in Kanchanpur were found in Raikar Bichawa, Krishnapur, Jhalari, and Suda.

KEY WORDS

Waste, GIS, MCDA, Analytical Hierarchy process, Suitability Analysis

1. INTRODUCTION

Waste is defined as materials that are not prime products (that is, products produced for the market) and for which the generator has no further use in terms of production, transformation, or consumption and wishes to dispose (OECD Glossary of Statistical Terms - Waste Definition, n.d.). As a result, unique disposal strategies are frequently required to minimize or decrease the risks they cause (Ng'ang'a et al., 2014). Source reduction, recycling, and waste transformation are common approaches for managing solid waste; yet, even after the recovery process for disposal, there is always residual residue. Landfilling is the process of disposing of these waste outputs in a cost-effective manner (Alanbari, Al-Ansari, Jasim, et al., 2014). The proper selection of a landfill site is a critical step in proper waste disposal and environmental, public health, and quality of life preservation. Many subsequent processes in the disposal process are determined by it, and if properly implemented, should prevent nuisances and negative long-term impacts. (Ng'ang'a et al., 2014). According to (Shafqat et al., 2014), In developing countries, municipal solid waste disposal is in a precarious state due to a lack of resources, poor planning, and a growing population. In certain regions, it is proportionality to develop the environment and health.

To find the best possible disposal location for a landfill, an intensive spatial analysis is required. The site selection process should make the most of the information provided (Sumathi et al., 2008). As a result, a wide range of spatial data is required to select the best dump site.

Geographic Information System (GIS) has become increasingly important in decision-making in recent years. The GIS-based approach to site selection has the benefit of saving time and money. It also offers a digital data inventory for the site's long-term monitoring (Mussa & Suryabhagavan, 2021). GIS has evolved into a sophisticated tool for integrating different types of spatial data and performing various spatial analyses. Significant advancements in computer technology, as well as the availability and quantity of data, had fueled the evolution (Alanbari, Al-Ansari, & Jasim, 2014). GIS and Multi criteria Decision Analysis (MCDA) integration is a strong tool for solving the landfill site selection problem. MCDA provides consistent ranking of the potential landfill area based on a variety of criteria by dividing the decision problems into more small understandable parts, analysing each part separately, and then integrating the parts in a logical manner, while GIS provides efficient data manipulation and presentation (Yesilnacar et al., 2012). In this study, for the suitability analysis a well-defined and widely used method MCDA method was applied.

Previous studies had also applied this approach. This approach was used to locate a dump site in Kathmandu Valley(Basnet, 2015). But it has not been applied particularly for Kanchanpur.

The objective of the study was to identify the most suitable locations for the dumpsite in Kanchanpur District using spatial techniques.

2. STUDY AREA

Kanchanpur District is chosen as the study area for this study. The region is located between 28°38' north latitude and 29°28' north latitude, and between 80°03' east longitude and 80°33' east longitude. It is located on the southwest part of the country. Although it is located on the terai, the northern half of the district has some higher elevations. The district's highest point is 1504 meters, while its lowest point is 159 meters. Figure 1. Shows the study area.

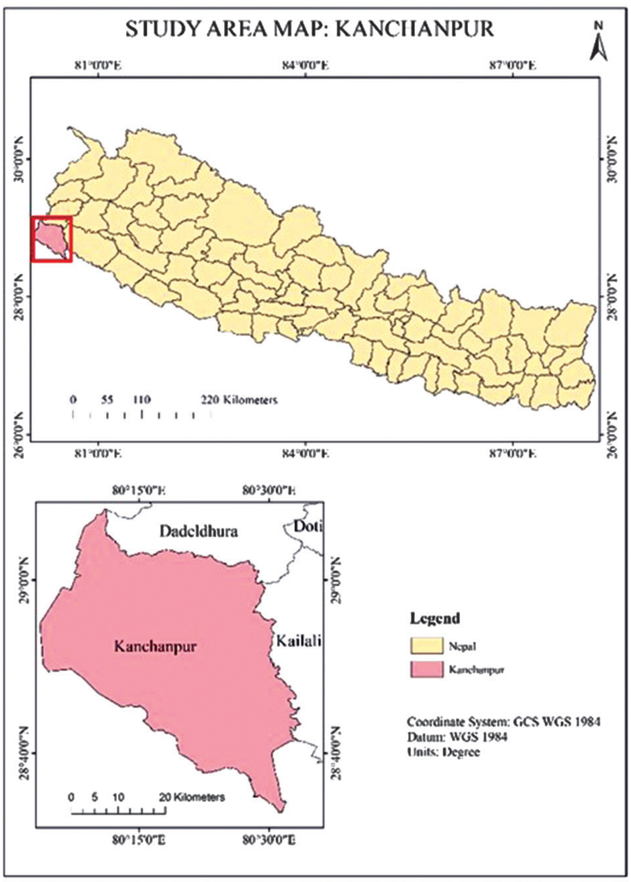

Figure 1. Map of Study Area

In Kanchanpur, there is yet to establish a dumping site for the disposal of regularly generated waste (Bhimdatta Municipal Government Has No Place to Manage Town's Waste, n.d.).

This study identified the suitable locations for a dumping site.

3. METHODOLOGY

Figure 2. Shows the overall methodological framework of the research project. It consist of following steps:

- Planning
- Data Acquisition
- Data Preparation
- Data Visualization

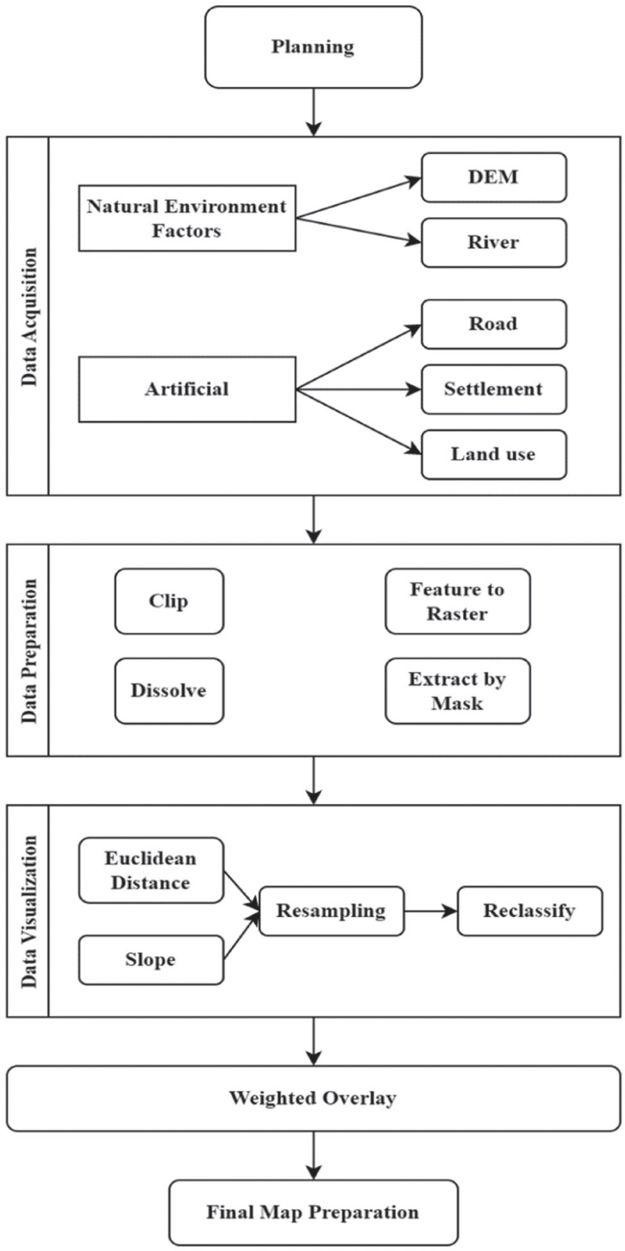

Figure 2. Methodological framework of the study

- Weighted Overlay
- Final Map Preparation

3.1.1 Planning and Data Acquisition

The possible factors influencing the location of dump site was identified in planning phase. It was decided to use AHP priority calculator for determination of weightage for each factor and MCDA technique for suitability analysis.

Five major factors which can influence the dump site selection were selected for the suitability Analysis.

There were two types of factors influencing the location of dump site. They were Natural Environment Factors and Artificial factors.

Natural Environment Factors include Digital Elevation Model and river data whereas artificial factors include Road, Settlement and Land Use for suitability analysis. Sources of each datasets are shown in table 1.

Table 1: Data Used and its Source

S.N.	Data	Source
1	DEM	Humanitarian Data Exchange (Nepal Digital Model Elevation (DEM) - Humanitarian Data Exchange, n.d.)
2	Land Use	ICIMOD (ICIMOD | RDS, n.d.)
3	Settlement	Humanitarian Data Exchange
4	Road	ICIMOD
5	River	ICIMOD

3.1.2 Data Preparation and Visualization

The data's covering the extent of whole country was clipped using the administrative boundary of Kanchanpur district. The retrieved data covers the entire country.

For vector data, the clip tool was used to extract the data that was within the Kanchanpur District Boundary, and the Dissolve operation was used to aggregate multiple features within a layer into one, based on a common attribute value. The obtained data was then rasterized.

For raster data i.e. DEM, DEM within the Kanchanpur District Boundary was extracted using the extract by mask tool.

For the visualization of all the datasets Euclidean Distance, Slope, Resample, Reclassify tools were used. The model was created to aid with data visualization and analysis.

For settlement, road, river and land use, Euclidean distance tool was employed. Output obtained was the raster map of Euclidean Distance of each data. Similarly, raster map of slope was obtained by using the DEM as an input for the slope tool.

Resampling of these raster were performed in order to make the same spatial properties. The cell size of slope was used for all other raster datasets.

The next step in Data Visualization was to reclassify the data. So, for the reclassification suitability criteria was defined for all the raster data. The information for the suitability criteria was

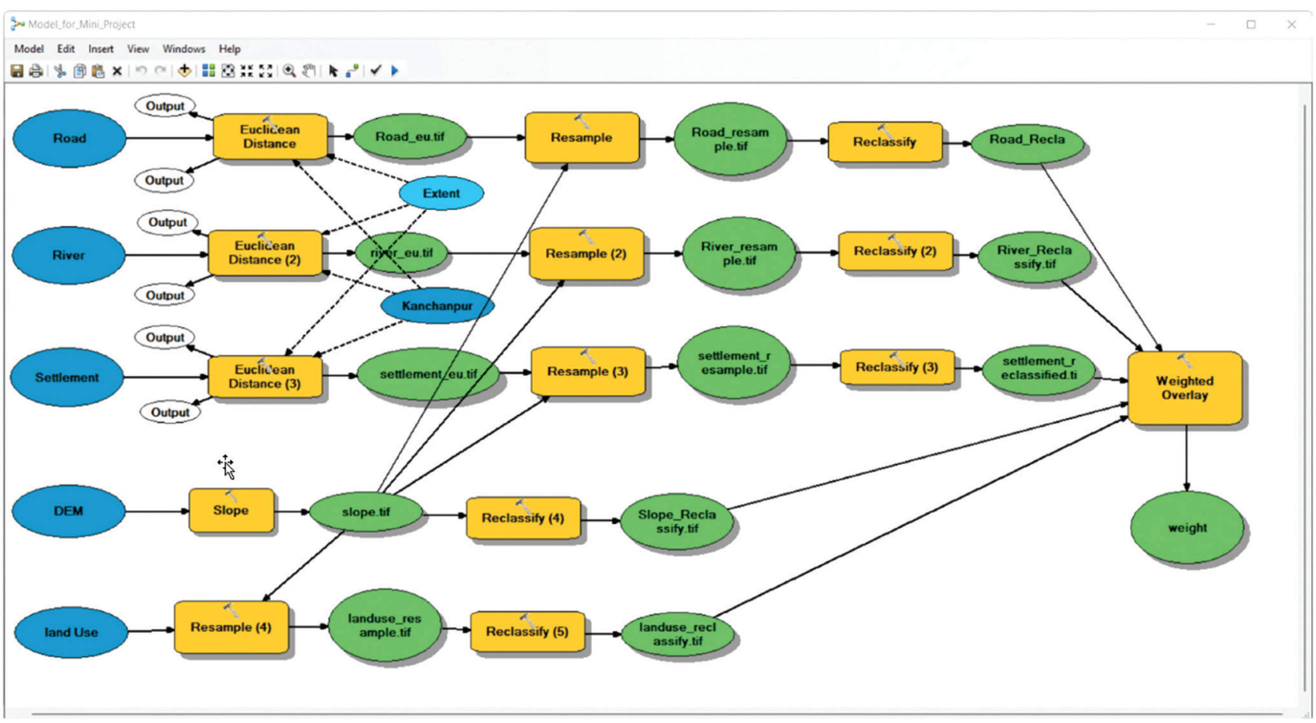

Figure 3. Model for Suitability Analysis

defined after reviewing research papers of (Mussa & Suryabhagavan, 2021) (Ng'ang'a et al., 2014). For the suitability criteria, rank was provided to the buffer distances of each raster. There were total 5 classes for all the datasets. Table 2 specifies the suitability level and rank for the different factors.

Table 2: Suitability Level

Suitability	Ranking
Restricted	1
Less Suitable	2
Moderately Suitable	3
Suitable	4
Most Suitable	5

The classified maps were created using a variety of suitability criteria (multi criteria), as tabulated in table 3. Mentioned ranking has been selected based on the study conducted by (Thapalia et al., 2021). Classified maps are attached in result section.

Table 3: Criteria for dump site selection suitability and their rank

Factors	Parameter (m)	Suitability Class	Rank
Road	0-500	Restricted	1
	500-1000	Less Suitable	2
	1000-1500	Moderately Suitable	3
	1500-2000	Suitable	4
	>2000	Most Suitable	5
River	0-500	Restricted	1
	500-1000	Less Suitable	2
	1000-1500	Moderately Suitable	3
	1500-2000	Suitable	4
	>2000	Most Suitable	5
Settlement	0-1000	Restricted	1
	1000-2000	Less Suitable	2
	2000-3000	Moderately Suitable	3
	3000-4000	Suitable	4
	>4000	Most Suitable	5
Land Use	Water body	Restricted	1
	Built-Up Area	Less Suitable	2
	Forest	Suitable	4
	Bare-Land	Most Suitable	5
Slope	over 20 %	Restricted	1
	15%-20%	Less Suitable	2
	10%-15%	Suitable	4
	Less than 10%	Most Suitable	5

3.1.3 Weighted Overlay

The datasets derived had different degree of influence of dumping site selection. MCDA method was used and The Analytic Hierarchy Process (AHP) developed by (Saaty, 1980) had been employed to derive the relative importance weighting of each criterion. A comparison matrix was created between the criterions, which was then used to construct an eigenvector, which finally indicated the criteria ranking. Pairwise comparisons were conducted among the criteria to determine the relative importance of each criterion among others (Sumathi et al., 2008). Taking into consideration (Ng'ang'a et al., 2014), (Alanbari, Al-Ansari, Jasim, et al., 2014), (Mussa & Suryabhagavan, 2021) comparison matrix for this study was developed among the criteria and it is shown below in table 4. The five most important criteria were used and the consistency ratio (CR) obtained was 6.10% which was below 10%, which indicated a reasonable level of consistency in the pairwise comparison.

Table 4. Pair wise Comparison Matrix

Criteria	Land Use	Road	River	Settlement	Slope
Land Use	1	1/2	1	1/8	3
Road	2	1	1/3	1/8	3
River	1/2	3	1	1/3	3
Settlement	4	4	3	1	8
Slope	1/3	1/3	1/3	1/8	1

Based on the above pairwise comparisons, weightage of each of the factors were calculated and it is shown below in table 5.

Table 5. Weightage of factors for weighted overlay

Factor	Priority	Rank
Settlement	49%	1
River	21%	2
Road	13%	3
Land Use	12%	4
Slope	5%	5

The higher the weight, the more influence a particular factor will have in the dumping site selection. As stated in the table 4, Weights were assigned to each criteria. In a weighted overlay analysis, all of the reclassified factor layers were employed. The output obtained from weighted overlay analysis is shown in result section.

3.1.4 Final Map Preparation

Using the weighted overlay analysis, raster map was obtained. Layout of the suitability map was performed. The obtained suitability map for suitable dumpsite location for the Kanchanpur district is attached in result section 4.

4. RESULT AND DISCUSSION

This study investigates the best suitable location for a dump site in a typical urbanizing district. The optimal dumping site in Kanchanpur was found using a multi-criteria approach that included giving weights to the factors affecting the location derived using the AHP calculator and GIS-Based overlay analysis. Weighted overlay analysis had classified the district area into 3 classes i.e. Restricted, Less Suitable and Suitable areas. The area coverage of each class is tabulated below in table 6.

Table 6: Area coverage of each class

Class	Area (in Km2)	Area Percentage (%)
Restricted	708.437	47.7
less Suitable	707.863	47.6
Suitable	70.70	4.7

Result of this study revealed that the 708.437 km2 (47.7%) of the study area was restricted for waste dump site. This restricted area included areas near river, road and settlement, areas with a steep slope (>20%). After eliminating the restricted land, 707.863 km2 (47.6%) was found to be less suitable area. Waste dump site is less preferable in these sites. The suitable areas included areas near road and settlement. Only 70.70 km2 (4.7%) of the research area was determined to be appropriate for disposal sites. Waste dump sites in these areas are preferred because they have the fewest negative effects on the environment and the general public.

The major outcomes of this research included, classified maps, Suitability map, restriction map and Suitable area map of the study area. The major outcomes are presented from figure no. 4 to figure no. 10.

Land Use Classified Map

Figure 4 represents the land use classification map of Kanchanpur. Using the specified suitability class as per table 4, the map is reclassified in four classes. It includes, Water, Flooded vegetation, Crops, Built up Area, Bare Ground, Shrubs, Forest and Grass.

Road, River, Settlement Classified Map

Figure 5 represents the classification of road, Figure 6 represents the classification of River, Figure 7 represents the classification of settlement area based on suitability class as per table 4, map is reclassified in five classes. It includes, Restricted, Less Suitable, Moderately Suitable, Suitable and Most Suitable.

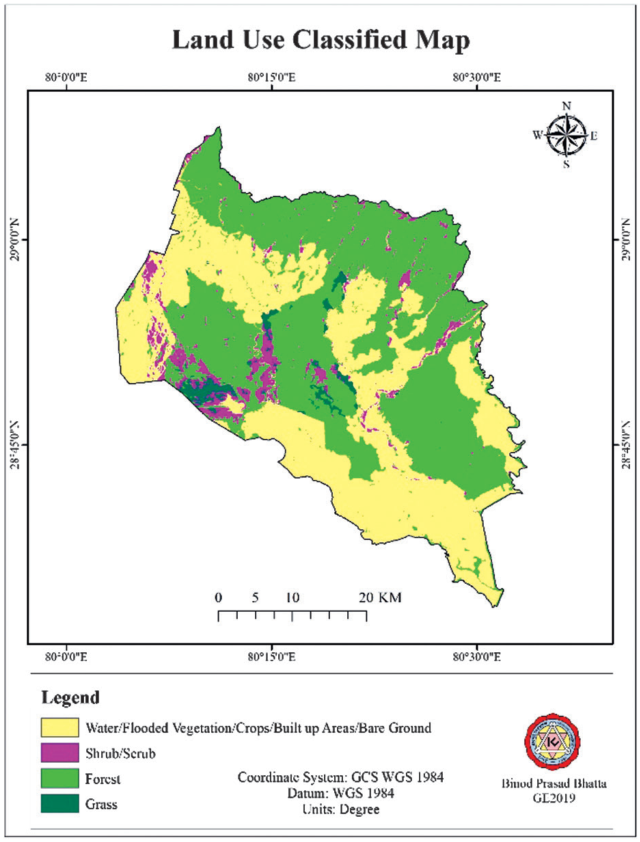

Figure 4. Land Use Classification

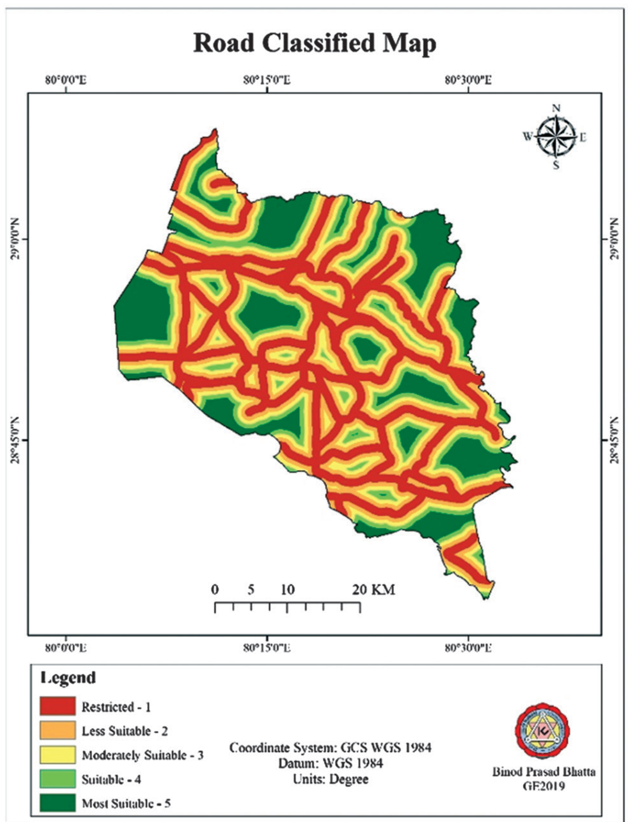

Figure 5.Classes of road

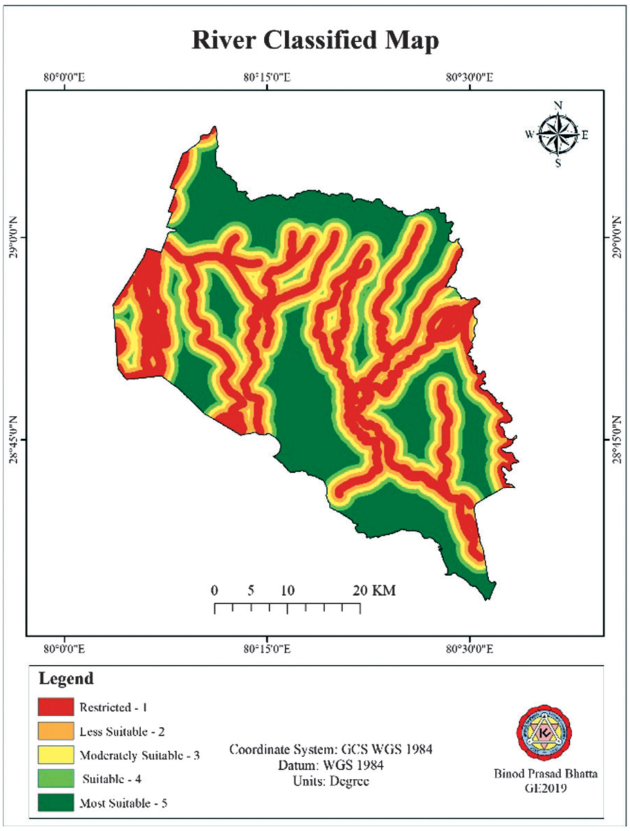

Figure 6. Classes of River

Slope Classified Map

Figure 8 represents the classification of slopes based on suitability classes, as shown in Table 4. The map has been classed into four categories. It includes, Restricted, Less Suitable, Suitable and Most Suitable.

Suitability Map

Figure 9 represent the output obtained as a Suitability Map. This map was obtained as a result of Weighted Overlay. It includes three class viz. Restricted, Less Suitable and Suitable Area.

Result showed that, 47.7% of the study area was restricted area. Most of the restricted area for the dumping site has been covered by the large part of the Shuklaphanta National Park, Similarly, 47.6 % of the study area was identified as a less suitable area and only 4.7% of the study area was identified as a suitable area for dumpsite location. Suitable region mostly lies in north most part of the study area.

Suitable area for Dumping Site

Figure 10. Represents the most suitable area for Dumping Site in Kanchanpur District. Most suitable dump sites were situated in Raikar Bichawa, Krishnapur, Jhalari, and Suda. Only 4.7% of the study area was suitable for the Dumping site.

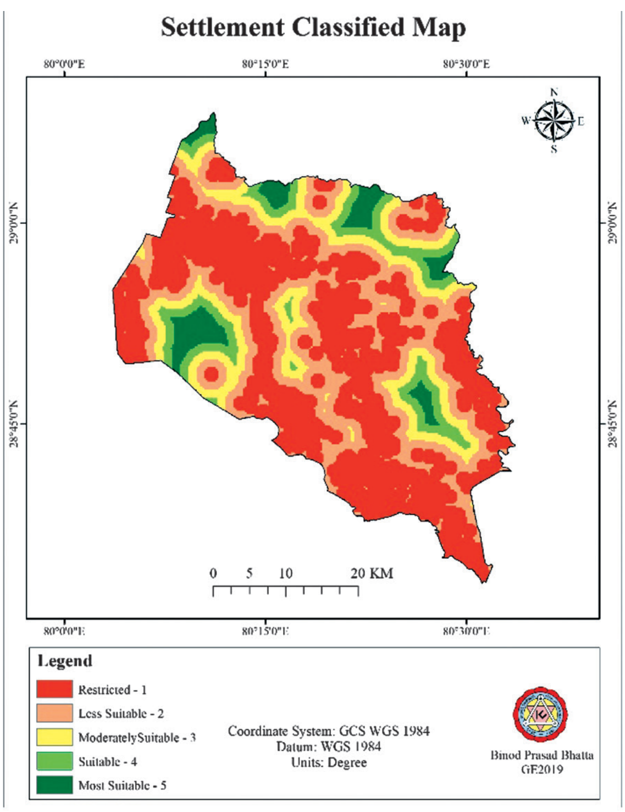

Figure 7. Settlement Area of Kanchanpur

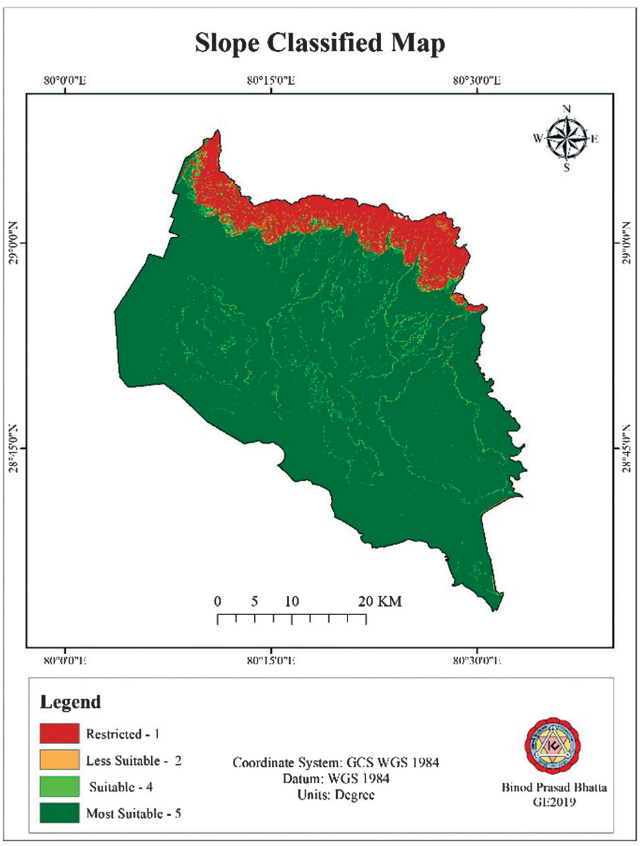

Figure 8. Slope Categories

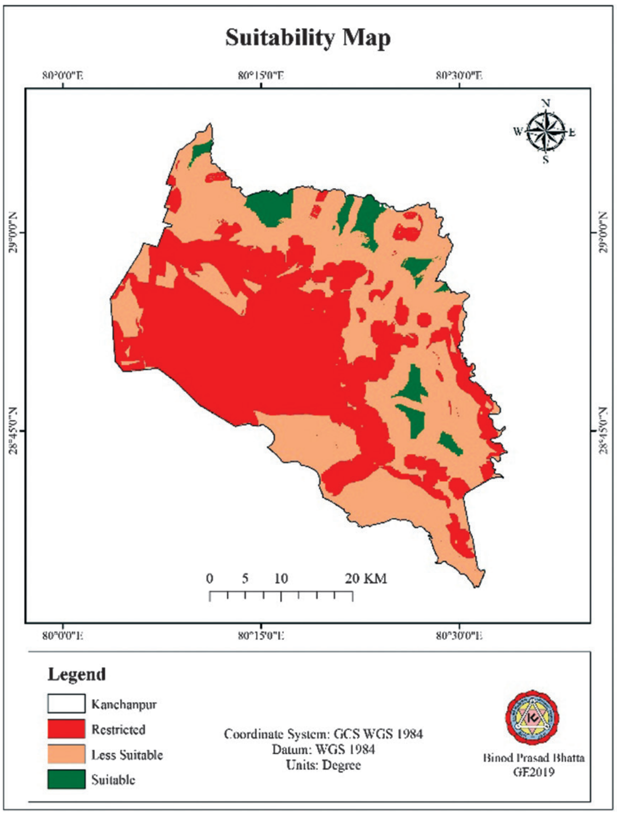

Figure 9. Suitability Area for Dumpsite Location at Kanchanpur

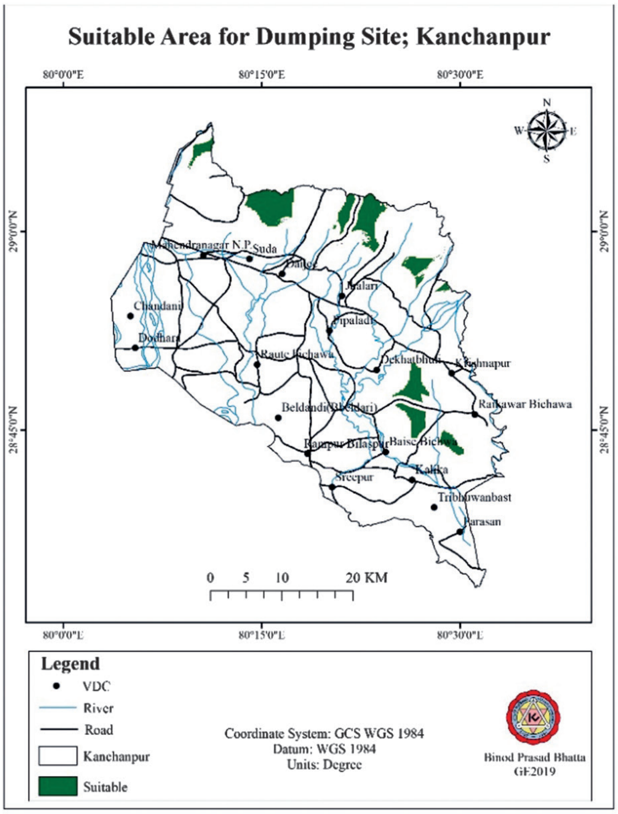

Figure 10. Suitable Area for Dumping Site

5. CONCLUSION

The study's main goal was to locate a suitable dumpsite in Kanchanpur District. This study followed a process of selecting dumpsite involving more criteria by using GIS technology where MCDA was used. AHP was used to measure the relative importance of criterions. With the use of GIS, each map layer was created. Several factors (Land Use, Road, River, Settlement, and Slope) were considered for the suitability analysis. These factors were reclassified into Restricted, Less Suitable, Moderately Suitable, Suitable and Most Suitable region.

Weighted overlay classified area into Restricted, Less Suitable, and Suitable region. Only 4.7% of the research area was suitable for the Dumping site. The best suitable location for dumping site identified were Raikar Bichawa, Krishnapur, Jhalari, and Suda. Waste dump sites in these areas are preferred because they have the fewest negative environmental and public health consequences.

For further work, It is recommended to include additional factors because only five primary parameters were taken into account to determine the potential dumping location in the study area and Since this study is based upon the spatial analysis, it is important to integrate the social issues as well because, the (Not in My Backyard) NIMBY is a global concept that is needed to be addressed while locating the dumping sites. Hence, it is also recommended for the further study that to explore either the result of this spatial analysis is able to address the NIMBY in Kanchanpur District.

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6. REFERENCES

Alanbari, M. A., Al-Ansari, N., Jasim, H. K., & Knutsson, S. (2014). Modeling Landfill Suitability Based on GIS and Multicriteria Decision Analysis: Case Study in Al-Mahaweelqadaa. *Natural Science*, *06*(11), 828–851. https://doi.org/10.4236/ns.2014.611081

Basnet, D. (2015). Identification of Landfill Site by Using Geospatial Technology and Multi Criteria Method- A Case Study of Kathmandu, Bhaktapur and Lalitpur District of Nepal. *International Journal of Environment, 4*(1), 121–129. https://doi.org/10.3126/ije.v4i1.12183

Bhimdatta municipal government has no place to manage town's waste. (n.d.). Retrieved May 12, 2022, from https://kathmandupost.com/sudurpaschim-province/2021/04/18/bhimdatta-municipal-government-has-no-place-to-manage-town-s-waste

ICIMOD | RDS. (n.d.). Retrieved May 21, 2022, from https://rds.icimod.org/

Mussa, A., & Suryabhagavan, K. V. (2021). Solid waste dumping site selection using GIS-based multi-criteria spatial modeling: a case study in Logia town, Afar region, Ethiopia. In *Geology, Ecology, and Landscapes* (Vol. 5, Issue 3, pp. 186–198). https://doi.org/10.1080/24749508.2019.1703311

Nepal Digital Model Elevation (DEM) - Humanitarian Data Exchange. (n.d.). Retrieved May 21, 2022, from https://data.humdata.org/dataset/nepal-digital-model-elevation-dem

Ng'ang'a, T. M., Muturi, W. P., Wangai, K. J., Joash, W., & Matheri, N. (2014). Solid Waste Dumping Site Selection Using GIS and Remote Sensing for Kajiado County, Kenya. J*ournal of Earth Science and Engineering, 10(*4), 597–604. https://doi.org/10.17265/2159-581X/2014

OECD Glossary of Statistical Terms - Waste Definition. (n.d.). Retrieved May 27, 2022, from https://stats.oecd.org/glossary/detail.asp?ID=2896

Saaty, T. (1980). The Analtic Hierarchy Process. In *McGraw-Hill, New York, USA*.

Shafqat, A., Noor, S., & Fatima, M. (2014). Practices and challenges of municipal solid waste management in Bahawalpur city, Pakistan. *Journal of Sustainability Science and Management, 9*(1), 90–98.

Sumathi, V. R., Natesan, U., & Sarkar, C. (2008). GIS-based approach for optimized siting of municipal solid waste landfill. *Waste Management, 28*(11), 2146–2160. https://doi.org/10.1016/j.wasman.2007.09.032

Thapalia, P., A. Dhakal, R.Gautam, & Shrestha, R. (2021). Quantum Gis Based Suitability Analysis for Effective Planning of. *Foss4G - Asia 2021 October*, 1–15.

Yesilnacar, M. I., Süzen, M. L., Kaya, B. Ş., & Doyuran, V. (2012). Municipal solid waste landfill site selection for the city of Şanliurfa-Turkey: An example using MCDA integrated with GIS. *International Journal of Digital Earth, 5*(2), 147–164. https://doi.org/10.1080/17538947.2011.583993

SMOKE SCENE DETECTION FROM SATELLITE IMAGERY USING DEEP LEARNING

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ABSTRACT

The use of satellite remote sensing has expanded a variety of environmental analysis applications. Forest fires are a serious threat to humans and other living things, but because of advances in satellite technology, forest fires can now be constantly monitored. Forest wildfires are indicated by the presence of smoke in the atmosphere. Fire detection plays an important role in avoiding damages and other fire disasters. To avoid large scale fires, fire detection from visual scenes of smoke is important but the existing systems in smoke detection have lot of shortcomings as these methods mainly focus on smoke detection from a few specific classes. To improve the accuracy of smoke detection model from the satellite imagery, different deep learning approaches of convolution neural network (CNN) and CNN based ResNet-50, VGG-16 based on transfer learning are designed and trained on USTC_SmokeRS dataset consisting of 6225 satellite images from six classes (i.e., cloud, dust, haze, land, seaside, and smoke). The experimental result of three models reveals that ResNet-50 model achieves good accuracy of 85% and Kappa coefficient of 0.81 with RMSE error 1.230.

KEY WORDS

Smoke Detection, Forest Fire, CNN, ResNet-50, VGG-16

1. INTRODUCTION

Wild fires are an essential threat to forest resources, animals, human life and property around the world (Priya & Vani, 2019). The smoke emitted by biomass burning affects the atmospheric radiation balance, air quality and ecological energy budget. Fire smoke on the other hand can be a significant signal of biomass burning that plays a crucial role for wildfire detection (Taylor et al., 2010). In recent years, machine learning algorithms have made significant advances in computer vision and image processing, giving a new momentum in the field of remote sensing as well. Identification of smoke from satellite imagery from landcover datasets is still challenging (Ba et al., 2019).

On the basis of differences between smokes and similar factors like clouds, haze and dust, a number of smoke detection techniques have been implemented. Some of the satellites like ERS-1 (European Remote-sensing Satellite-1), GOES (Geostationary Operational Environment Satellite), DMSP (Defence Meteorological Satellite Program), MODIS (Moderate Resolution Imaging Spectroradiometer) have been used for wildfire detection (Taylor et al., 2010). Visual interpretation is the common method of detecting smoke from satellite imagery. Three spectral bands of satellite sensor as the three channels of red, green and blue (RGB) are used to generate true color and false color composition. In MODIS, channel 1, 4 and 3 are used to generate true color RGB image. Xie et al.(Xie et al., 2005) has used thresholds to discriminate smoke pixels and modified them using the MODIS data.

A large amount of satellite data provides a unique opportunity to use the deep learning method for smoke detection. There are several methods found in literatures for machine learning approaches for smoke detection from satellite imagery. The datasets are mainly collected from surveillance cameras and categorized into smoke images and non-smoke images (Zhang et al., 2016). Machine learning methods, in particular deep learning (DL), have been successfully applied in solving challenging tasks such as regression and classification problems, object detection and semantic segmentation. Recently, different deep learning methods like convolutional neural network (CNN) and varieties of state-of-art CNN based model such as ResNet, VGGNet, AlexNet, GoogleNet of image classification on benchmark dataset like CIFAR-100, ImageNet are also being used.

Several researchers have used machine learning and deep learning methods for smoke classification. Priya & Vani, used CNN based Inception-v3 model for forest fire classification. They used binary classification for classifying image into two fire or non-fire) and achieved accuracy of 98%. The limitation of their research is, ground based images were analysed while training the model with only two classes.

Similarly, (Rostami et al., 2022) have used deep multiple kernel learning for active fire detection from Landsat -8 imagery. The MultiScale-Net was successfully tested in data incorporating clouds and solitary fire pixels separated from main fire zones. The output was satisfactory but they did not consider other smoke similar factors like dust, haze, land etc. Seydi et al.(Seydi et al., 2022) developed deep learning framework called FireNet. They used Landsat-8 imagery for the detection of active forest fire detection. They have fused optical band with thermal modality Thies from the image for more accuracy. They were able to achieve 97.35% accuracy.

This paper presents deep learning approach for smoke detection from satellite imageries. CNN, ResNet50 and VGG16 classifiers are used on USTC_SmokeRS dataset and performance of each model are compared. ResNet50 classifier outperformed CNN and VGG16 classifier.

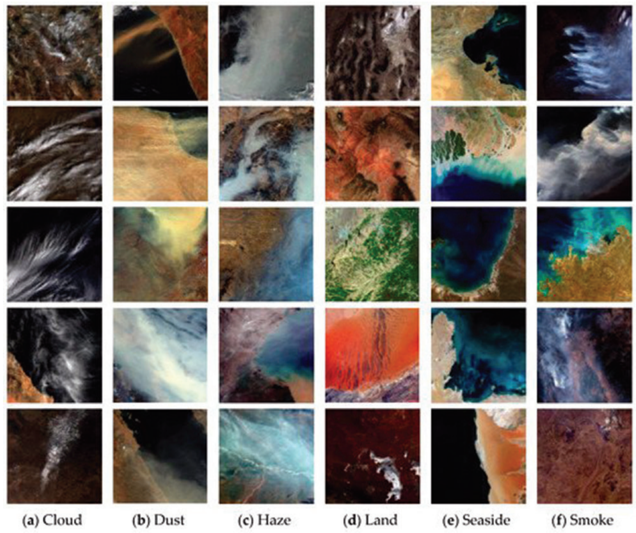


Figure 2. Example images of the six classes in the USTC_SokeRS dataset

2. MATERIALS AND METHODS

2.1 Dataset

The study was conducted using USTC_SmokeRS dataset. (source: https://pan.baidu.com/share/init?surl=GBOE6xRVzEBV92TrRMtfWg) MODIS data of wildfires are used to create the dataset as MODIS sensor mounted on Terra and Aqua satellites are widely used for wildfire detection. The dataset consists of six different classes (Cloud, Dust, Haze, Land, Seaside and Smoke) and 6225 images where 4481 images were reserved for training the model, 1121 images were used for validation and 623 images were considered for testing purpose which was 70 :20: 10 splits. The dimension of a single image was 256 × 256 × 3 corresponding to its width, height and RGB values and the spatial resolution of 1km. The distribution of the images is presented in Figure 1. Figure 2 shows some examples of six different classes of dataset and Table 1 consist of number of images for each class.

2.2 Methods

A framework of proposed work for smoke scene detection is shown in Figure 3. The major stages of our implementation are: data exploration, data pre-processing, use of CNN and state of art CNN based architecture VGG-16 and ResNet-50 classifier, visualize the classification area, and explain the output using CNN explainer. First the datasets are split into train, test and validation sets. Then the training set data are pre-processed and passed through different deep learning classifier model. Since the output of CNN model cannot be interpreted easily by mathematics, GRAD Cam visualization technique and SHAP explainer are used. The scene classification models are evaluated using confusion matrix and other evaluation metrics like Kappa coefficient, precision, recall, MAE, MSE and RMSE.

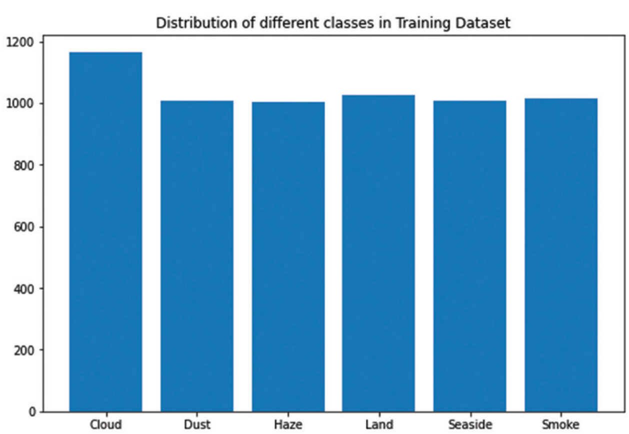


Figure 1. Distribution of six classes of images

2.2.1 Data Preprocessing

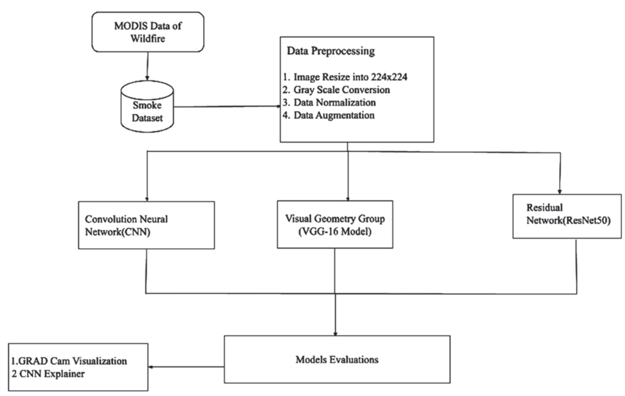


Figure 3. Framework of proposed work

Grayscale Images

The first step of data processing was converting RGB images into grayscale images. Grayscale images produce higher classification accuracy in testing dataset than RGB images. Furthermore, it reduces the number of features by two thirds reducing the computation cost for machine for training large dataset (Zeng et al., 2015).

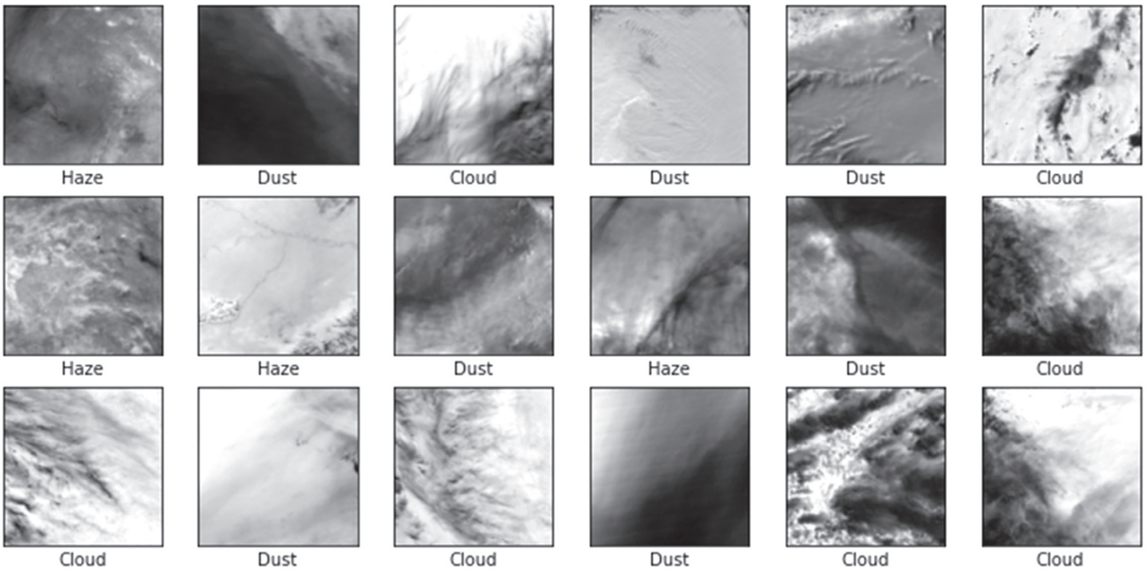


Figure 4. Grayscale images of dataset

Z Score Data Normalization

Z score normalization is the technique that replaces a raw feature value with a floating-point value representing the number of standard deviations from that feature's mean (Patro & Sahu, 2015). The feature distribution of the dataset does not contain extreme outliers, so this normalization technique is implemented in the research.

Data Augmentation

When training a machine learning model, it is necessary to tune its parameter such that it can map image to a particular label. To achieve better results, our machine learning model is supposed to be trained with the tuned parameter and giving low model loss. In order to make machine learning model, data augmentation can help to increase the amount of relevant data in the dataset (Shorten & Khoshgoftaar, 2019).Data regularization is a method that generates more training data from the original data. It is performed by applying random geometric transforms such that the class labels are not changed (Phung & Rhee, 2019).

2.2.2 Classification

Artificial neural network is a popular approach in image classification. A neural network is a mathematical model based on connections of each nodes of artificial neurons. Convolutional neural networks (CNNs) have been used for scene classification due to its effectiveness, scalable and end-to-end learning structures (Ba et al., 2019). Along with base CNN model, state of art model VGG and ResNet model are often used for scene classification. These models can optimize the model and improve the accuracy of deep networks (He et al., 2016).

Convolutional Neural Network (CNN)

A Convolutional Neural Network (CNN) is a Deep Learning model that can take an input image, assign weights and biases to various aspects/objects in the image, and distinguish one image from other. It requires few preprocessing for making input ready to feed the model as compared to other classifiers

Traditional architecture of CNN structure is shown in Figure 5. Generally, it consists of feature extraction layer

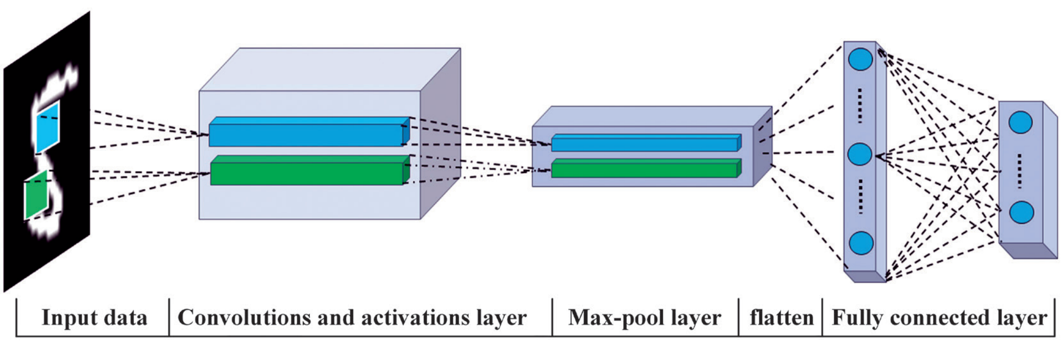


Figure 5. Typical architecture of CNN

and feature mapping layer. The feature extraction layer consists a convolutional layer and a pooling layer. There are several convolutional units which are optimized by back propagation. The number of convolutional kernels is same as the number of channels as the feature map. When convolution is used, convolutional kernels are slid onto a feature map with a fixed stride, and the sum of the inner product at the corresponding positions is transferred to the new feature map's corresponding positions. Each pixel in the feature map is only linked to the previous feature map's portion. This is referred to as weight sharing. The amount of computation in convolution will be dramatically reduced as the stride of convolution grows. The geographic relationship between the local feature and other features is also identified once it has been extracted. The pooling layer often reduces the size of the feature map output of the convolution layer by down-sampling. It can improve the over fitting problem of the model while reducing the subsequent computation without changing the feature structure of the image. Table 2. illustrates detailed architecture of the CNN model. A 3× 3 kernel size was applied for all Conv layers and 2× 2 window max pooling layers were used. We used 32 filters for the first convolutional layer, 64 for second, 128 and 256 for respective layers.

VGG-16

VGG16 is regarded as one of the best vision model architectures ever created. The most distinctive feature of VGG16 is that, rather than having a huge number of hyper-parameters, the model is focused on having 3x3 convolution layers with a stride 1 and always use the same padding and max pool layer of 2x2 filter with stride 2.

Throughout the architecture, the convolution and max pool layers are arranged in the same way. It has two FC (completely connected layers) in the end, followed by a SoftMax for output. The 16 in VGG16 alludes to the fact that it contains 16 layers with different weights (Theckedath & Sedamkar, 2020).

Table 1. Detailed parameter of purposed model

No.	Layer	Output Size	Filter Size
1	Input	224 x224x3	
2	Convolution 1	222x222x16	3x3
3	Relu	222x222x16	
4	Maxpooling	111x111x16	
5	Convolution 2	109x109x32	3x3
6	Relu	109x109x32	
7	Maxpooling	54x54x32	
8	Convolution 3	52x52x64	3x3
9	Relu	52x52x64	
10	Convolution 4	50x50x64	3x3
11	Relu	50x50x64	
12	Maxpooling	25x25x64	
13	Convolution 3	23x23x128	3x3
14	Relu	23x23x128	
15	Convolution 4	21x21x128	3x3
16	Relu	21x21x128	
17	Maxpooling	10x10x128	
18	Convolution 3	8x8x256	3x3
19	Relu	8x8x256	
20	Convolution 4	6x6x256	3x3
21	Relu	6x6x256	
22	Convolution 4	4x4x256	3x3
23	Relu	4x4x256	
24	Maxpooling	2x2x256	
25	Flatten	1024	
26	Dense1	512	
27	Dense2	512	
28	Dense 3	6	

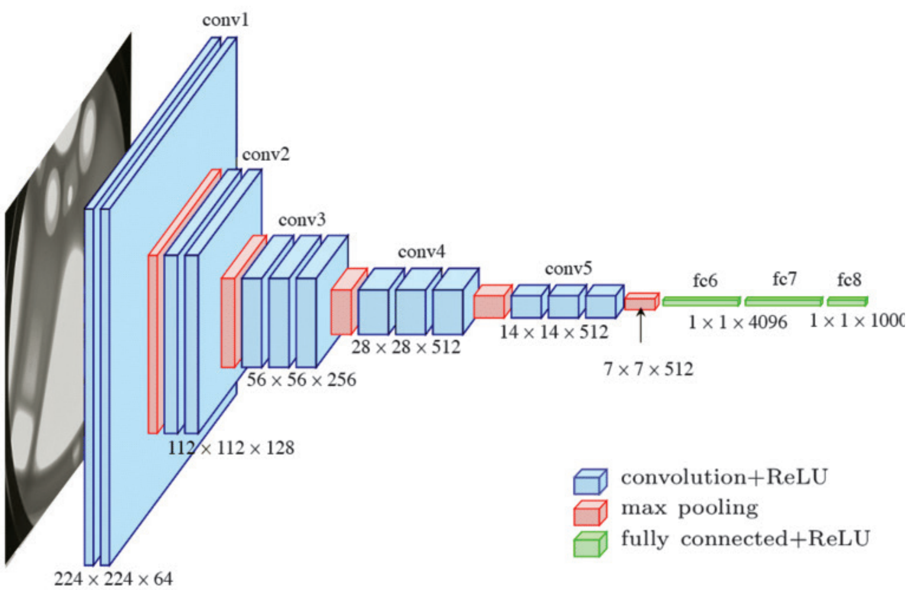


Figure 6. Architecture of VGG-16

ResNet-50

The problem of training very deep networks has been relieved with the introduction of these Residual blocks.

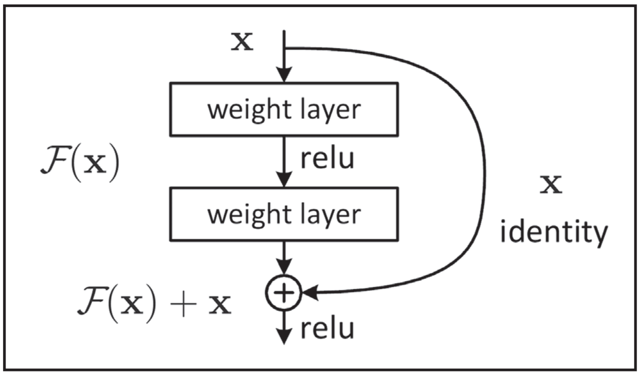


Figure 7. Deep Residual Learning for Image Recognition (He et al., 2016)

In the Figure 7, there is a direct connection that skips some layers of the model. This connection is called 'skip connection.

The skip connection skips training from a few layers and connects directly to the output. The approach behind this network is instead of layers learn the underlying mapping, we allow network fit the residual mapping. The benefit of including this type of skip connection is that any layer that degrades architecture performance will be bypassed by regularization. As a result, very deep neural networks can be trained without the issues caused by vanishing/ exploding gradients.

This network uses a 34-layer plain network architecture inspired by VGG-19 in which the shortcut connection is added. These shortcut connections then convert the architecture into residual network.

Evaluation methods

Confusion matrix and other different evaluation metrics like testing accuracy, Kappa coefficient (K), mean absolute error (MAE), mean square error (MSE) and root mean square error (RMSE) have been used to quantitatively assess the model performance. To explain model prediction, gradient-weighted class activation mapping (Grad -CAM) and CNN explainer are also used.

Accuracy and Kappa Coefficient (K)

Testing accuracy is computed by dividing the correctly classified testing images by the total number of testing images.

Kappa coefficient (K) is frequently used in remote sensing for the assessment of accuracy and agreement degree. In brief, the higher the accuracy and K the better the classification results. The confusion matrix example of t classes and the formulas of these evaluation metrics are shown below.

$$Accuracy = \frac{\sum_1^t N_{ii}}{1}$$

$$Kappa\ Coefficient\ (K) = \frac{N\sum_1^t N_{ii} - \sum_1^t (N_{i+}\ N_{+i})}{N^2 - \sum_1^t (N_{i+}\ N_{+i})}$$

where,

i denotes a certain class

t denotes a certain number of class

N represents the total number of images

N_{ii} refers to the number of correctly classified images in the diagonal

N_{i+} and N_{+i} are the sum of images in the i th row and i th column respectively

MAE (Mean Absolute Error)

MAE measures the average magnitude of the errors in a set of predictions, without considering their direction. It's the average over the test sample of the absolute differences between prediction and actual observation where all individual differences have equal weight

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|P_{m,i} - P_{o,i}\right|$$

where $P_{m,i}$ Modeled value at point i

$P_{o,i}$ Observed value at point i

n Number of observations

RMSE (Root Mean Square Error)

It is the square root of mean square error (RMSE). RMSE is calculated by squaring the average difference between original and predicted values over data set.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(P_{m,i} - P_{o,i}\right)^2}$$

where $P_{m,i}$ Modeled value at point i

$P_{o,i}$ Observed value at point i

n Number of observations

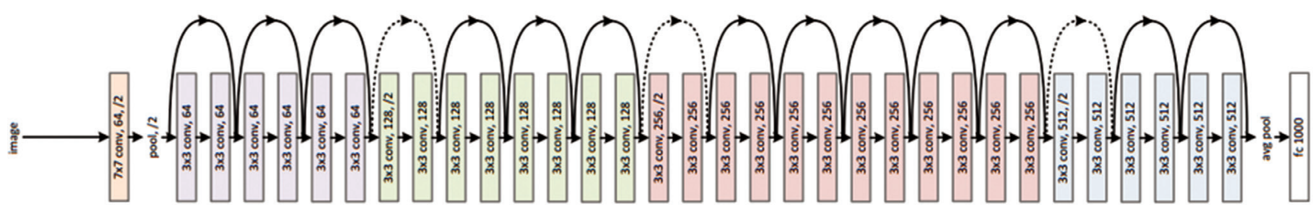


Figure 8. Architecture of ResNet 50(He et al., 2016)

Precision (P)

The fraction of correctly predicted positive observations among the total predicted positive observations.

$$\frac{TP}{TP + FP}$$

where TP is the true positive and FP: false positive.

Recall (R)

The fraction of correctly predicted positive observations among all the observations in the class.

$$\frac{TP}{TP + FN}$$

where TP is the true positive and FN: false negative

F-measure

The Precision and Recall criteria can be interpreted together rather than individually. To accomplish this, we consider the F-Measure values generated by the harmonic mean of the Precision and Recall columns, as the harmonic mean provides the average of two separate factors produced per unit. 1erefore, F provides both the level of accuracy of the classification and how robust (less data loss) it is:

$$F\text{ - Measure} = \frac{2 \times P \times R}{P + R}$$

where P is the precision and R is the recall

3. RESULTS

Accuracy Assessment

On the basis of different proportions of images from USTC_ SmokeRS dataset, CNN model, VGG-16 and ResNet-50 were evaluated. The evaluation metrics of these models are illustrated in the Table 3.

Table 2. Comparative evaluation of models

Models	Accuracy (%)	Kappa(K)	MSE	MAE	RMSE
CNN	74%	0.67	2.525	0.721	1.589
VGG-16	79%	0.73	1.831	0.563	1.353
ResNet-50	85%	0.81	1.514	0.429	1.230

It can be observed that, ResNet-50 outperformed CNN and VGG-16 model with accuracy of 85%, K of 0.81, MSE of 1.514, MAE of 0.429 and RMSE of 1.230. The model improves the accuracy and K by at least 7% and 10.95% over CNN and VGG-16 model. Furthermore, MSE, MAE and RMSE errors are also minimized by 17.31%, 23.8% and 9% respectively than that of the other two models.

Table 4 shows the confusion matrix on testing set of the ResNet-50 model trained with 70% training images. Table 4 shows the confusion matrix and model evaluation metrics like precision, recall and F1 score. The results reveal that smoke scene seems to be confused with land and haze. This is because the feature of haze and land during the day time like brightness, shape, reflectance are similar to that of smoke(Ba et al., 2019).

Also, it is difficult to detect the fire emitted area and classify it as a smoke scene among the highly reflective surfaces, lakes or mountains that also trigger misclassification. Furthermore, the texture of cloud, dust and haze are similar that can be misclassified as well. Looking at the precision, the model predict seaside precisely with 0.97 whereas the precision of smoke class is only 0.67. The recall of smoke class is satisfactory with 0.87 and F1 score with 0.76.

Visualization Analysis

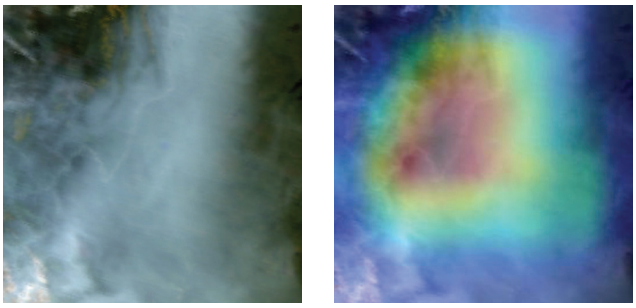
Grad cam visualization is used for evaluating the model on input image via visualization technique. A smoke image is passed through the ResNet-50 model and is visualized by plotting the heat map as shown in Figure 9.

Heat map of the input smoke image shows that the model is taking into account only the colour area. Thus, for feature extraction from the image, the texture from the coloured area is only being considered for scene classification.

Direct interpretation of the CNN model with mathematical model is difficult. In such cases, SHAP can be used for interpretation of input features on the model output. For each predicted output, SHAP gives the Shapley values for each feature for different categories of scene classification. Red pixels show positive SHAP values that increase the likelihood of the class. Negative SHAP values, on the other hand, are represented by blue pixels and that lowers the

Table 3. Confusion matrix and evaluation metrics of ResNet-50

Class	Cloud	Dust	Haze	Land	Seaside	Smoke	Precision	Recall	F1-Score
Cloud	103 (84.4%)	3	0	2	0	14	0.9	0.84	0.87
Dust	1	83 (86.5%)	4	1	1	6	0.87	0.86	0.87
Haze	0	5	82 (77.4%)	5	0	14	0.86	0.77	0.82
Land	5	2	3	75 (76.5%)	1	12	0.89	0.77	0.82
Seaside	0	0	0	0	88 (98.9%)	1	0.97	0.99	0.98
Smoke	5	2	6	1	1	97 (86.6%)	0.67	0.87	0.76
Accuracy	85%								
K	0.81								



(a) Input image smoke (b) Heat map of input image

Figure 9. GradCam Visualization

probability of the class (Gaur et al., 2022). Figure 10 shows visualization of smoke scene classification based on the SHAP values. For image f, there are large numbers of red pixels for category smoke. Pixels with red value suggests the features to be likely smoke. Similarly, for image d, looking at the SHAP values, it is likely to be either dust or smoke. If we consider image a, it is more likely to be dust.

4. DISCUSSION AND CONCLUSION

The classification results and visualization indicate that ResNet-50 can achieve better accuracy among traditional CNN and VGG-16 layers for scene classification on USTC_SmokeRS dataset. Previous researches on forest fire detection are performed using the data mainly collected from surveillance cameras with a smaller number of training samples. For the detection of wild fires from the satellite imagery more precisely, a good amount of dataset is required. The texture, reflectance and features of smoke can resemble with the features of cloud, haze dust etc. Furthermore, different other factors like illuminations, winds, the resolution of satellite also do affect the range of smoke and the land cover features in an image when these satellite images are processed in RGB images.

In this paper, traditional CNN model, VGG-16 layers and ResNet-50 models were implemented for scene classification from satellite imageries. Six different classes were considered as their spatial features are quite similar. To validate the performance of the models, confusion matrix and the evaluation metrics were used. The experimental results depict that ResNet-50 model can achieve better accuracy of 85% with Kappa coefficient 0.81 on 70% training images.

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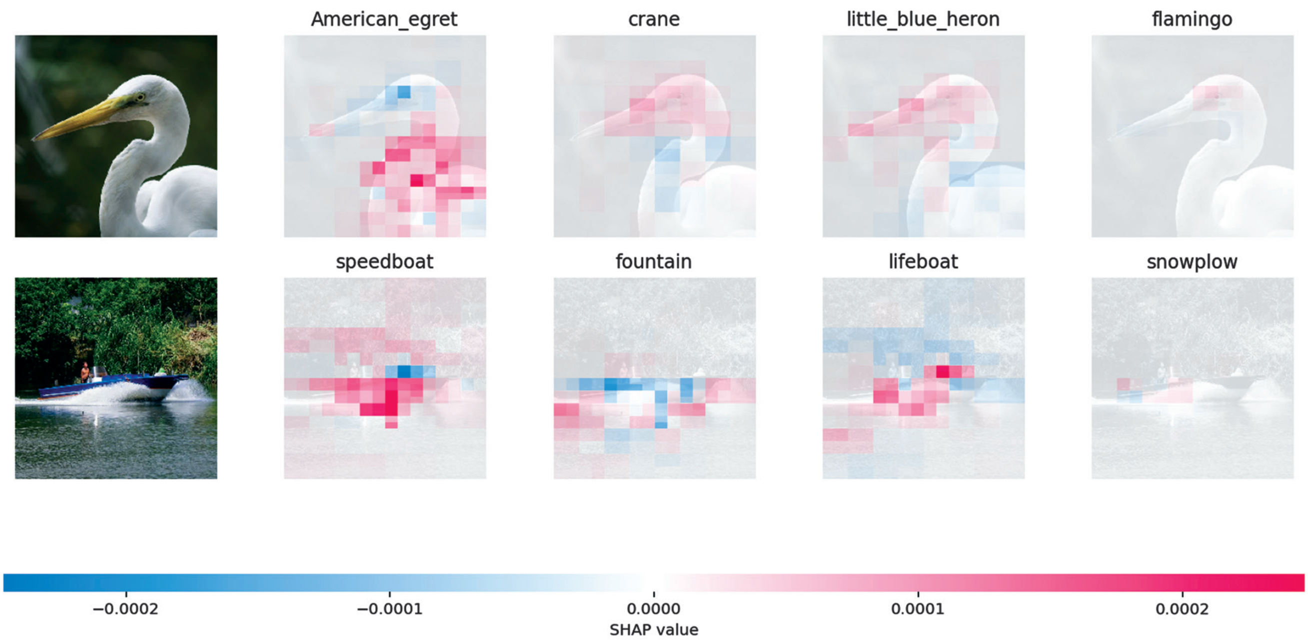

Figure 10. SHAP visualization on ResNet-50

6. REFERENCES

Ba, R., Chen, C., Yuan, J., Song, W., & Lo, S. (2019). SmokeNet: Satellite smoke scene detection using convolutional neural network with spatial and channel-wise attention. *Remote Sensing*, 11(14). https://doi.org/10.3390/rs11141702

Gaur, L., Bhandari, M., Razdan, T., Mallik, S., & Zhao, Z. (2022). Explanation-Driven Deep Learning Model for Prediction of Brain Tumour Status Using MRI Image Data. *Frontiers in Genetics*, 13. https://doi.org/10.3389/fgene.2022.822666

He, K., Zhang, X., Ren, S., & Sun, J. (2016). Deep residual learning for image recognition. Proceedings of the *IEEE Conference on Computer Vision and Pattern Recognition*, 770–778.

Patro, S., & Sahu, K. K. (2015). Normalization: A preprocessing stage. ArXiv Preprint *ArXiv:1503.06462*.

Phung, & Rhee. (2019). A High-Accuracy Model Average Ensemble of Convolutional Neural Networks for Classification of Cloud Image Patches on Small Datasets. *Applied Sciences, 9*, 4500. https://doi.org/10.3390/app9214500

Priya, R. S., & Vani, K. (2019). Deep learning based forest fire classification and detection in satellite images. *Proceedings of the 11th International Conference on Advanced Computing, ICoAC 2019*, 61–65. https://doi.org/10.1109/ICoAC48765.2019.246817

Rostami, A., Shah-Hosseini, R., Asgari, S., Zarei, A., Aghdami-Nia, M., & Homayouni, S. (2022). Active Fire Detection from Landsat-8 Imagery Using Deep Multiple Kernel Learning. In *Remote Sensing* (Vol. 14, Issue 4). https://doi.org/10.3390/rs14040992

Seydi, S. T., Saeidi, V., Kalantar, B., Ueda, N., & Halin, A. A. (2022). Fire-Net: A Deep Learning Framework for Active Forest Fire Detection. *Journal of Sensors, 2022*, 8044390. https://doi.org/10.1155/2022/8044390

Shorten, C., & Khoshgoftaar, T. M. (2019). A survey on image data augmentation for deep learning. *Journal of Big Data*, 6(1), 1–48.

Taylor, P., Rauste, Y., Herland, E., Frelander, H., & Soini, K. (2010). International Journal of Remote Satellite-based forest fire detection for fire control in boreal forests. *Int. J. Remote Sensing*, 18 (May 2013), 37–41.

Theckedath, D., & Sedamkar, R. R. (2020). Detecting affect states using VGG16, ResNet50 and SE-ResNet50 networks. *SN Computer Science*, 1(2), 1–7.

Xie, Y., Qu, J., Hao, X., Xiong, J., & Che, N. (2005). Smoke plume detecting using MODIS measurements in eastern United States. *EastFIRE Conference Proceedings*, 11–13.

Zeng, Y., Xu, X., Fang, Y., & Zhao, K. (2015). Traffic sign recognition using deep convolutional networks and extreme learning machine. *International Conference on Intelligent Science and Big Data Engineering*, 272–280.

Zhang, Q., Xu, J., Xu, L., & Guo, H. (2016). Deep convolutional neural networks for forest fire detection. *Proceedings of the 2016 International Forum on Management, Education and Information Technology Application. Atlantis Press*.

LANDSLIDE SUSCEPTIBILITY MAPPING ALONG POKHARA-BENI HIGHWAY USING FREQUENCY RATIO TECHNIQUES

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ABSTRACT

Nepal is among the most vulnerable country in the world when it comes to landslide-related risks. Pokhara-Beni highway is one of the important and primary roadways that connect districts like Baglung, Parbat, Myagdi, and Mustang with the rest of the country. Every year, there are reports of highway blockade by landslides, particularly during the monsoon season that spans from June until late September, making this area inaccessible by road. Despite the known landslide frequency, there have been no systematic landslide inventories conducted along this highway to date. In this study, landslides were mapped 3 km buffer zone along a highway using the various causative factors related to landslides such as elevation, slope, aspect, proximity to stream network, proximity to roads, proximity to faults, profile curvature, plan curvature, and land use. Frequency ratio techniques were used and the output susceptibility maps were reclassified into four classes ranging from very low to high susceptibility where 5.61% of the area is highly susceptible to landslide while 17.79% area is moderately susceptible, whereas 45.25% is low susceptible, and the remaining 31.35% is a very low susceptible area. A total of 191 landslides were identified and mapped within the study area of which 154 (80%) were used as training data and the remaining 37 (20%) were used as test datasets. The validity and the accuracy were tested by calculating areas under receiver operating characteristic curves (ROCs), and the areas under the curve (AUC). The landslide susceptibility maps can be used for hazard mitigation purpose and land use planning.

KEY WORDS

Susceptibility, Landslide, Receiver Operating Characteristic Curve, Area Under Curve, Frequency Ratio

1. INTRODUCTION

1.1 General Instructions

Landslide is one of the most occurring hazards caused by different triggering factors such as rainfall and earthquakes. Landslides are a major natural hazard and can be defined as phenomena in which a rock and soil body on a slope slides down a certain interface under the action of gravity, rainfall, and groundwater (Reference?). Landslides are among the most damaging natural hazards in the mountainous terrains of Nepal (Reference?). Nepal lies at the center of the 2,400-km-long Himalayan mountain range, which is one of the tectonically most active zones on the earth (Reference?). Among the various land degradation process prevalent in the Himalayas, landslides are one of the most significant phenomena as this region is tectonically very unstable with rugged topography, unstable geological structures, soft and fragile rocks, and common earthquakes, along with heavy and prolonged rainfalls during monsoon periods (Deoja et al. 1991). The study of landslides has drawn worldwide attention mainly due to increasing awareness of its socio-economic impact as well as the increasing pressure of urbanization on the mountain environment (Aleotti and Chowdhury 1999). In Nepal, a significant number of landslides occur each year. The impact of haphazard infrastructure construction and human interventions on mountain slopes followed by the expansion of agricultural land leads to an increase in landslides around the different parts of the country.

Landslide susceptibility measures the probability of landslides occurring in a certain area under basic inducing conditions such as topography, geological environment, and land cover (Guzzetti et al. 2005). Through the evaluation and mapping of landslide susceptibility, the probability of a landslide occurring is calculated, and the targeted implementation of relevant measures can effectively reduce losses caused by landslides; such reduction is of great significance to disaster prevention and mitigation planning in geo-hazardous areas (Mathew, Jha, and Rawat 2009). The ratio of the presence and absence of hazards (landslide, flood) can be used for landslide susceptibility assessment (Youssef and Hegab 2005). The frequency ratio model is a bivariate statistical analysis that analyses the landslide events and landslide-associated factors for landslide susceptibility analysis (Saro Lee and Pradhan 2006). The frequency ratio model is based on the connection between the distribution of landslides and each of the landslide-related factors(Mandal, Chakrabarty, and Maity 2018). The frequency ratio value comes from the ratio between the percentage of landslide pixel and the percentage of the entire area pixel in every factor's class.

1.2 Study Area

The study area for this research is Pokhara-Beni highway which is located in Gandaki Province of Nepal. It is only a proper roadway to connect hilly districts with the province capital Pokhara. It is 84 km in length and extends from latitude 28.209o N to 28.376o N and longitude from 83.564o E to 83.985o E. For this study, we are using a 3 km buffer from the centreline of the road on both sides which covers an area of 280.23 sq. km. The study area covers three districts of the country mainly Kaski, Parbat and Myagdi, and also the gateway to the main tourist destination of the country mustang district which is also known as the district beyond the mountain. Muktinath one of the main Hindu and Buddhist pilgrimage sites is also located in this district. This highway is not only the gateway to the religious sites but also a route for many farmers and traders to trade and connect with other parts of the country. One of the main trade points to China Korola is also connected via this route. That is the reason we have selected this as our study area so we can study the route in detail and find out the risk zone along the highway due to landslide-related hazard which not only helps local people and traders but also to many tourists to plan their journey.

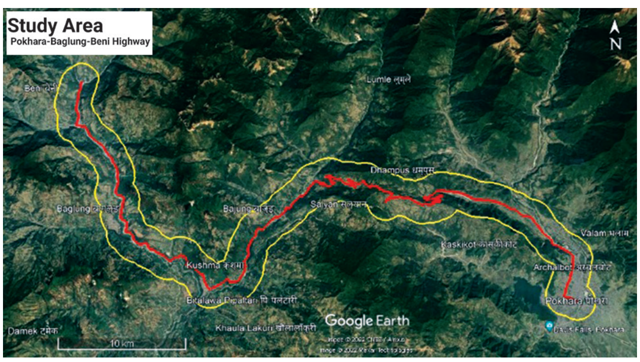

Figure 1. Study Area

2. MATERIALS AND METHODS

2.1 Data Used

The study incorporates both primary and secondary sources of data. Primary data was collected from the field survey and secondary data were collected from published and unpublished documents from both government and private organizations. Since the study needs nine types of data for analysis of the result among which landslide inventory was obtained from two sources historical landslides data and landslide map which was digitized from satellite and google earth imagery. Like-wise, drainage network, slope, plan curvature, profile curvature, and aspect were extracted from the digital elevation model in ArcGIS. Land Use Land cover map was created using a sentinel image in the Google Earth Engine platform using a random forest classifier. The other data required for this study includes topographical data (administrative boundary, road, and river) produced by the Survey Department of Nepal. Elevation data was obtained from the freely available ASTER DEM at 30m resolution which was used to extract slope and aspect. Fault line data were digitized using the geological map of Nepal.

2.2 Methodology

For landslide susceptibility mapping, it is important to assume that the spatial distribution of landslides is influenced by the landslide causative factors, and that future landslides will occur under the same conditions as the past landslides (S Lee and Talib 2005). The frequency ratio technique was used in this study for landslide susceptibility mapping using causative factors like elevation, slope, aspect, plan curvature, profile curvature, land use, proximity to a fault line, proximity to a stream, and proximity to a road. Landslide inventory was used as a training and testing dataset. A total of 191 landslides were identified and mapped within the study area of which 154 (80%) were used as training data and the remaining 37 (20%) were used as test dataset. The detailed methodology is shown in the figure 2:

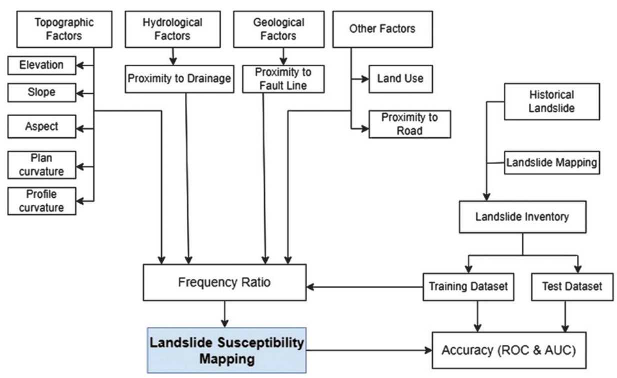

Figure 2. Methodology

The frequency ratio has been calculated using Eqn 1

$$FR = \frac{(NLS/\Sigma NLS_i)*100}{(NC/\Sigma NC_i)*100} \quad (1)$$

where FR = frequency ratio value, NLS = number of landslide pixels in a class of a factor, ΣNLS_i = sum of all landslide pixels in the entire area, NC = number of pixels in a class of a factor and ΣNC_i = sum of all pixel class in the entire area.

First of all, factor maps were prepared. Frequency ratio values have been acquired by the frequency ratio method, and then the factor map is regenerated by assigning the weight of the frequency ratio value of each class. The frequency ratios of each factor's type or class were summed to calculate the landslide susceptibility index

$$LSI = \Sigma FR_i \quad (2)$$

where LSI is the landslide susceptibility index and is the FR of each factor range or class.

3. RESULTS AND DISCUSSION

We have used the frequency ratio method to identify the determinant factor for landslide occurrences and the spatial distribution of landslides. It represents the relationship between landslide occurrences and factors explicitly. We have applied the frequency ratio method for landslide susceptibility mapping in this study. The receiver operating characteristics (ROC) curve was used for validating this method. The final landslide susceptibility map obtained by the FR model is shown in the Figure 3.

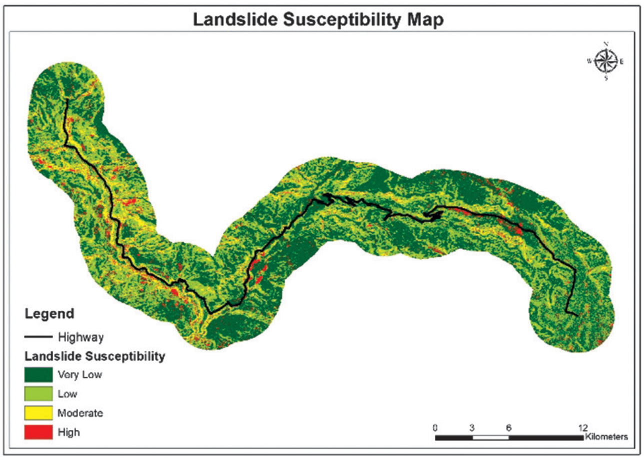

Figure 3. Suitability Map

We use the Frequency Ratio model to estimate the probability of each pixel for the entire area containing a landslide. We treat this probability as a quantitative estimate for landslide susceptibility, and once the entire set of probabilities has been rescaled from 0 to 1, these values are plotted as pixels within a new raster of susceptibility. Then, this landslide susceptibility map was divided into four classes (very low, low, moderate, and high) using the natural breaks classification method. About 5.61% of the area was highly susceptible to landslides while 17.79% area was moderately susceptible, whereas 45.25% was low susceptible, and the remaining 31.35% was a very low susceptible area. Among eight causative factors Land use and slope have a greater impact on landslide distribution especially on barren land and with slope gradient greater than 30 degrees.

The validity and the accuracy were tested by calculating areas under receiver operating characteristic curves (ROCs), and the areas under the curve (AUC). Fig.4 shows compatibility of the susceptibility models using the training dataset whereas Fig.5 shows prediction probability using the validating dataset. AUC for the success rate curve was 74.9% whereas 72.6% for the prediction rate curve.

4. CONCLUSIONS

Landslide susceptibility mapping can be one of the

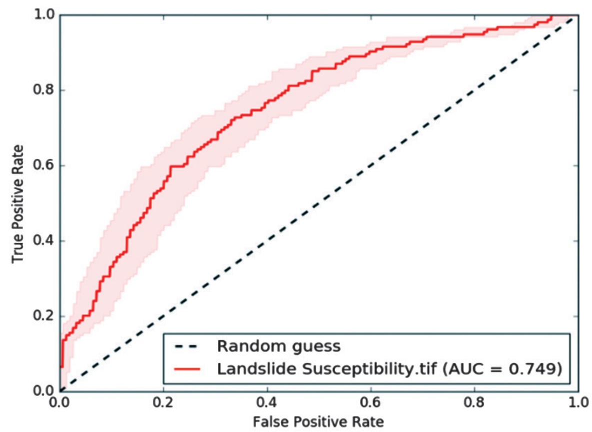

Figure 4. AUC of Success rate curve

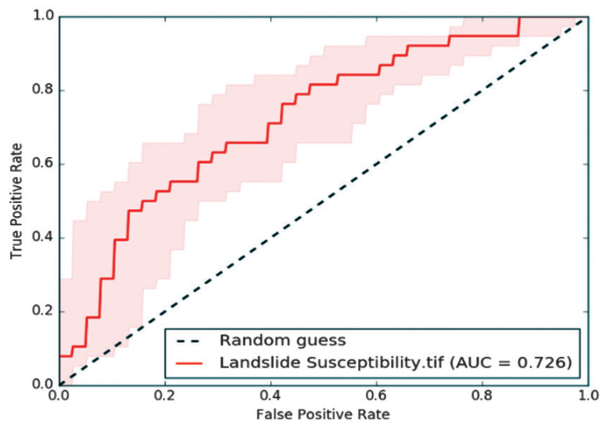

Figure 5. AUC of the prediction rate curve

preliminary steps toward understanding the possible causes of landslides and minimizing these damages. In this respect, landslide susceptibility mapping of the Pokhara-Beni road section and its surrounding region was performed based on a widely-accepted statistical model i.e. frequency ratio with the aid of GIS. Slope, aspect, profile curvature, elevation, plan curvature, proximity to faults, land use, proximity to a stream, and proximity to the road were used as the main conditioning factors for landslide susceptibility of the region. Out of 192 land-slides, 80% (154) were used as training datasets and 20% (38) were used as test datasets. Among eight triggering factors, land use and slope have a greater impact on landslide occurrence. The map has been validated by the success rate (74.9%) and prediction rate (72.6%) of the AUC curves.

5. ACKNOWLEDGEMENTS

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6. REFERENCES

A. Youssef and M. Hegab, “Using Geographic Information Systems And Statistics For,” *Fourth Int. Conf.*, vol.2, Jan. 2005.

Deoja B,. Dhital M. R, Thapa B, and Wagner A, “Mountain Risk Engineering Handbook: Vol II,” *Training Manuals*. 1991, [Online]. Available: http://lib.icimod.org/record/21344.

F. Guzzetti, P. Reichenbach, M. Cardinali, M. Galli, and F. Ardizzone, “Probabilistic landslide hazard assessment at the basin scale,” *Geomorphology*, vol. 72, no. 1, pp. 272–299, 2005, doi: https://doi.org/10.1016/j.geomorph.2005.06.002.

J. Mathew, V. K. Jha, and G. S. Rawat, “Landslide susceptibility zonation mapping and its validation in part of Garhwal Lesser Himalaya, India, using binary logistic regression analysis and receiver operating characteristic curve method,” *Landslides*, vol. 6, no. 1, pp. 17–26, 2009, doi: 10.1007/s10346-008-0138-z.

P. Aleotti and R. Chowdhury, “Landslide hazard assessment: summary review and new perspectives,” *Bull. Eng. Geol. Environ.*, vol. 58, no. 1, pp. 21–44, 1999, doi: 10.1007/s100640050066.

S. Lee and B. Pradhan, “Probabilistic landslide hazards and risk mapping on Penang Island, Malaysia,” *J. Earth Syst*. Sci., vol. 115, no. 6, pp. 661–672, 2006, doi: 10.1007/s12040-006-0004-0.

S. Lee and J. A. Talib, “Probabilistic landslide susceptibility and factor effect analysis,” *Environ. Geol.*, vol. 47, no. 7, pp. 982–990, 2005, doi: 10.1007/s00254-005-1228-z.

S. Mandal, A. Chakrabarty, and P. K. Maity, “Comparative evaluation of information value and frequency ratio in landslide susceptibility analysis along national highways of Sikkim Himalaya,” *Spat. Inf. Res.*, vol. 26, pp. 127–141, 2018.

GRAVIMETRY IN SURVEY DEPARTMENT: A BRIEF HISTORY AND CURRENT PRACTICES

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ABSTRACT

Gravimetry implies to the measurement of gravity, which may be relative or absolute. It aids in geotechnical, archeological, geophysical, geodetic etc. studies. Nepal initiated gravity survey in the 1970s when gravity transfer was made from Bangkok to Kathmandu and surveys were carried out for mineral exploration by the Department of Mines and Geology (DMG). Late on in the early 1980s the Ministry of Defence, United Kingdom (MoDUK) conducted a surface gravity survey. Since its inception, there have been several other endeavours aimed at achieving different goals like establishing multiple Absolute Gravity Bases, conducting absolute gravity measurements and detail gravity stations etc. Furthermore, geoid computation was done during the Eastern and Western Nepaplel Topographic Mapping Project (E/WNTMP) and later airborne gravimetry was conducted to prepare a geoid model for Nepal. Then for Everest Height Measurement Project (EHMP), a dense gravity survey was conducted in the Everest region extending to the Terai region towards the south. After this, a gravity survey was conducted by Survey Department (SD) itself for the Western Nepal LiDAR Mapping project and at precise levelling benchmarks for aiding gravimetric corrections and improving geoid. The methodology adopted to accomplish these tasks has been briefly described in this paper along with concise information on the historical events and current surveying practices for gravimetry in Geodetic Survey Division (GSD).

KEY WORDS

gravity, geodetic, precise levelling, gravimetry, geoid

1. HISTORICAL BACKGROUND

The gravity survey was started in Nepal during the 1980s. The first Fundamental gravity base station -KATHMANDU J was established at Tribhuvan International Airport by making a gravity transfer from an IGSN71 station in Bangkok and subsequently, DMG conducted a gravity survey for mineral exploration (Oli, 2007). During 1981-84, 45 other gravity base stations formed a base network and additional 345 detail gravity stations were established by the Ministry of Defence United Kingdom (MoDUK) (UK, 1985). Then in 1991, an absolute gravity survey was conducted at Nagarkot observatory and FAGS-1 was established by JILA absolute gravimeter and gravity transfer was made to Simara Airport (Winester et al., 1991). Since then, gravity surveys continued through projects like Eastern Nepal Topographic Mapping Project (ENTMP) (FINNMAP, 1993), and Western Nepal Topographic Mapping Project (Nepal and FINNMAP, 1997) in 1993 A.D and 1997 A.D respectively. Moreover, in 1996, 9 absolute gravity bases were established by National Oceanic and Atmospheric Administration (NOAA) and National Geodetic Survey (NGS) (NGS, 2012). A great leap was taken in 2010 when airborne gravity was conducted with the collaborative effort of SD with DTU Space (Denmark) and the National Geospatial-Intelligence Agency (NGA) for computing the geoid of Nepal (Olesen and Forsberg, no date). Another remarkable milestone was set during Everest Height Measurement Project (EHMP) when around 346 collocated Global Navigation Satellite System (GNSS) and gravity stations were established for geoid computation in the Sagarmatha region. Further details on Geodetic events including gravity survey can be found in a paper by KC and Acharya, 2022.

2. GRAVIMETRY AND ITS SIGNIFICANCE

The measurement of gravity i.e. gravimetry has an extensive application in geology, geodesy and geophysics. The gravity value at any location is proportional to the density of material beneath the surface, and the extent and depth of such material. This helps in determining the subsurface characteristics of the earth and the location of consolidated materials. Even the subsurface voids can be detected with gravity observations along with possible mines and minerals detection. By calculating the gravitational potential from observed gravity, the shape of the earth can also be defined. The observed gravity can also be used to correct the geometric height obtained from precise levelling. Gravimetry has applications in geotechinal, archeological, hydrological and tectonic studies too (Seigel, 1995). Among these applications, survey department has been conducting gravimetry especially for geodetic purposes i.e. gravimetric correction for precise levelling (planned to implement) and geoid computation. The survey conducted during E/

WNTMP and EHMP were all related to geoid computation for calculating orthometric heights. The transfer of gravity from IGSN71 station, establishment of gravity bases were all conducted for connecting Nepal to IGSN71 network and densifying the gravity network along with definition of datum for Nepal.

3. CURRENT SCENARIO

Currently, SD has been contributing to measuring and processing gravity data via annual programs and projects through GSD and Geographic Information Infrastructure Department (GIID). These programs include gravity observations for the LiDAR project conducted in 2020 for geoid computation in the western Terai region of Nepal. Gravity observations were carried out in 258 GNSS stations for this project. The observations were performed in a closed-loop by returning to the beginning station for every loop. The obtained gravity values were processed to calculate gravity anomalies and finally, a geoid for the respective region.

Gravity observations can also be integrated with precise levelling to provide corrections to the precise levelling data. According to (Märdla, 2014), the precise levelling results are affected by the earth's gravity field, especially in the areas with abrupt changes in the landscape. The geometric height difference obtained from precise levelling and the actual height difference between the observed point and reference point differ due to the non-parallelism of equipotential surfaces, as shown in Figure 1. The gravimetric corrections help to eliminate the effects of gravity field gradient in such areas. So, gravity observations should also be done along the levelling Benchmarks to provide relevant corrections (Märdla, 2014).

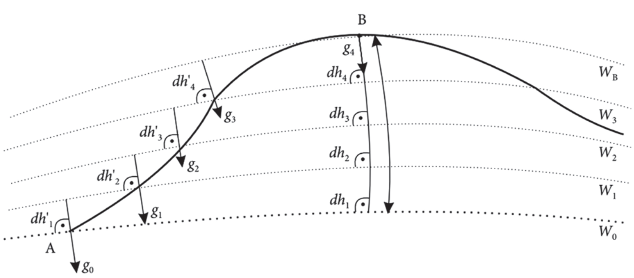


Figure 1: Equipotential Surfaces (W_0, W_1 ...), Levelled heights (dh'_1,dh'_2, ...) and orthometric heights(dh_1,dh_2, ...) (Märdla, 2014)

4. DATA ACQUISITION AND PRE-FIELD WORKS

The standard operating procedure and guidelines for gravity survey are being prepared at the GSD. To date, the methodology portrayed in Figure 3 has been adopted. A brief overview of the methodology has been discussed as follows:

3.1 Field Preparation

At first, all the official work required for the field is done. In this stage, human resources with all necessary instruments

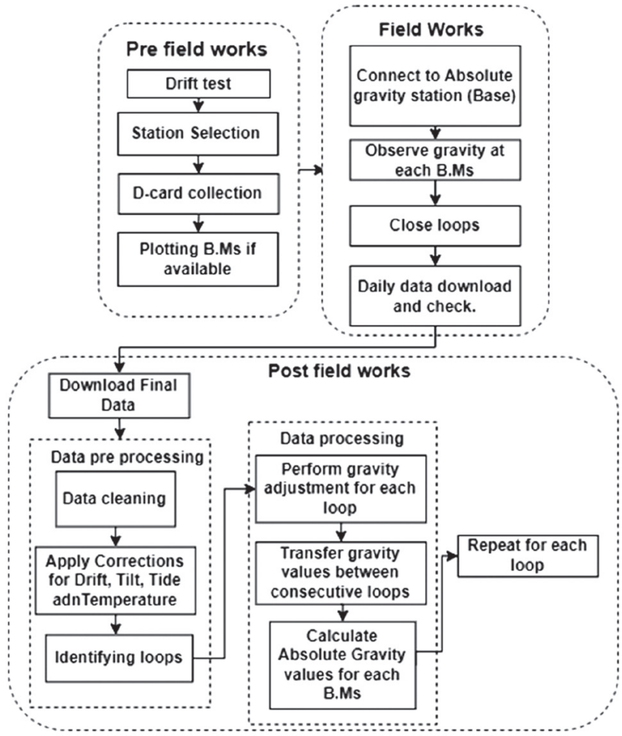


Figure 2: Gravity Survey workflow

and survey helpers required for gravity measurement are prepared. GSD uses a CG-6 AUTOGRAVTM gravimeter for the measurement of relative gravity at required stations. This instrument measures relative gravity values in the range of 8000 milliGals (mGals) with a reading resolution of 0.0001mGal at 10Hz of observation rate (Scintrex, 2018). The designed standard deviation for reading by CG-6 gravimeter is 0.005mGals (Scintrex, 2018).

Figure 3: CG-6 Gravimeter

3.2 Drift Calibration

All gravimeters are subjected to long-term drifts (due to elastic relaxation of spring tensions and the ageing of critical components, mechanical or electronic) and short–term drifts (due to shocks, vibration, temperature shocks etc.) (Seigel, 1995). So, drift tests should be done monthly for new instruments and periodically before any survey to calculate the contemporary drift rate of the instrument. Hence, the CG-6 gravimeter is calibrated with a drift test for at least 8 hours, before deploying it for a survey. It is found better to do drift calibration on the Ground floor at night to avoid the human traffic or any other external disturbances nearby the instrument.

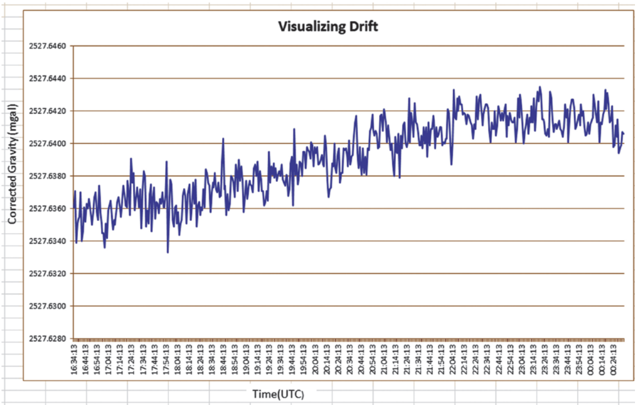


Figure 4: Gravimeter readings during drift calibration

A case of drift calibration performed for the Gravity Survey on Levelling Benchmarks by GSD has been illustrated in Figure 4. The CG-6 gravimeter was drift tested for 8 hours before deploying it for the survey. The calibration started on January 10 2022 16:34:13 (UTC) and ended on January 11 2022 00:33:13 (UTC) and was carried out in a room on the ground floor of GSD. A 60 seconds cycle was set and 480 readings were taken during 8 hours of the drift test period. A drift rate of 0.001389 milliGals (mGals)/day was observed after the test. Figure 4 portrays how the reading fluctuated during the eight hours of the drift test period. The readings taken at the same station during those 8 hours even after applying the aforementioned corrections show different values due to residual drift. The plot shows how the residual drift in corrected data with time.

3.3 Gravity Observation

Currently, GSD has adopted a loop sequence model for gravity measurement. This model was adopted during the Everest Height Measurement Project and Western Terai LiDAR project.

But, recently using the Ladder Sequence model was found to be more appropriate for high accuracy network densification as suggested by (Dewhursi, 1985). So, GSD has been adopting this observation model from this fiscal year 2078/79. So, here a detailed description of methods adopted for gravity measurement nowadays is described hereafter.

In the Ladder Sequence Technique, first of all, a station with a known absolute gravity value is selected as a base station. Then observations are taken in the required station and again at the base station, making a closed-loop. In the case of the stations that are at a distance, intermediate stations are observed to reach that particular point, which will also be closed similarly as discussed earlier. In the Ladder Sequence technique, the loop begins and ends at the same station while observing the survey points twice.

3.4 Data Processing and Post field works

Data pre-processing includes data cleaning, filtering, and then applying two minor corrections namely: tilt correction and temperature correction followed by two major corrections; tidal correction and drift correction respectively. Next observations are subjected to least-

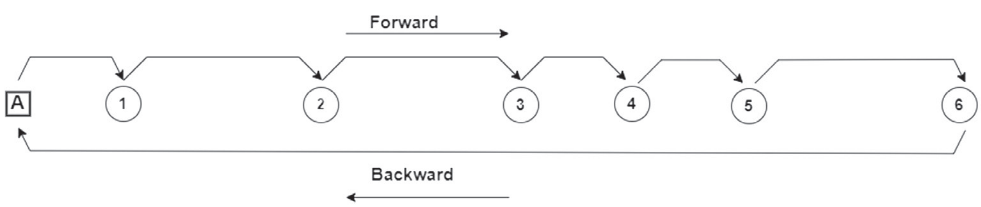
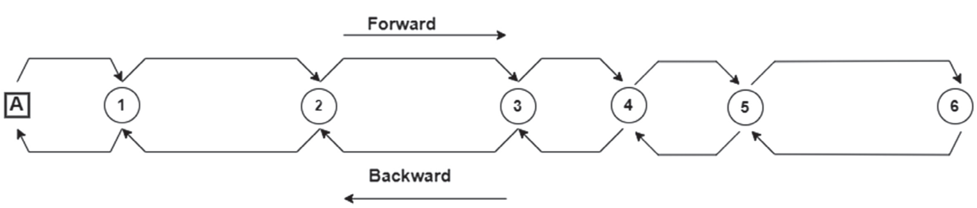


Figure 5: Loop Sequence Model of Gravity Network Observation



Observation in a Ladder Sequence

Figure 6: Ladder Sequence Model of Gravity Network Observation

square adjustment to get the final absolute gravity value with associated uncertainty in terms of standard error/ standard deviation. Each of these steps: data download, cleaning, filtering, tilt and temperature correction, tidal correction, drift correction and gravity adjustment are discussed below.

3.4.1 Data download and cleaning:

The observed data are stored in a text format in the internal storage of the gravimeter. These data are downloaded from the instrument and scrutinised for any faults. There can be several data with null and invalid values along with data exceeding the tolerance limit for discrepancies between consecutive readings. Generally, data at a station with a discrepancy within 0.010mGals are assumed to be consistent during field works. But still, inconsistent data also exists in the data, so these data should be identified and removed. After data cleaning, there are two modalities for further processing of gravity data using: 1) corrected gravity values and; 2) raw gravity values. If raw gravity values are used, then upcoming tilt, temperature, tidal and drift corrections need to be applied accordingly. Whereas, corrected values can directly be used for adjustment.

3.4.2 Applying corrections:

a. Tilt Correction:

Tilt error occurs whenever the instrument is not truly vertical i.e. the vertical axis of the instrument does not coincide with the plumb line. This causes measured gravity 'gm' to deviate from the true value ‘g’ with an angle of tilt 'θ', as (Seigel, 1995):

$$g_m = g(1 - \theta^2/2) \quad (1)$$

This implies, rfr a tilt of 10” of arc, the error will be 0.001mGal.

b. Tidal Reduction/Correction:

Due to the change in the gravitational attraction of the sun and moon, a significant variation in gravity measurement occurs, known as the tidal effect. The tidal gravity effects can contribute up to 0.3mGals difference to the measurements (Seigel, 1995). The tidal corrections can be a function of latitude, longitude and Universal Coordinated Time (UTC) of the survey point (Seigel, 1995). This correction can be applied manually or automatically by the instrument after acquiring the correct position and time.

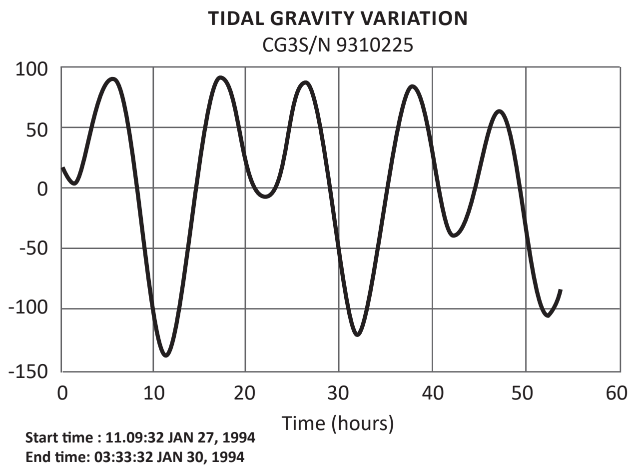


Figure 7: Tidal gravity variation (Seigel, 1995)

c. Drift Correction:

As mentioned in section 3.2, the instrument is subjected to a long-term drift. This drift is generally calculated for an instrument before conducting any survey with a drift test. The obtained drift rate after the test is then set as the current drift rate in the instrument and applied during the survey automatically or later manually. Although the drift correction calculated from drift test is applied based on current drift rate, additional drift is stil observed in the measurements during the survey period, termed as residual drift. This drift occurs due to temporal changes in the sensor or due to any tares before or during survey. This residual drift can be detected by taking multiple observations at the base station and linearly apportioned to all measurements for that day in accordance with the time of each measurement (Seigel, 1995).

3.4.3 Gravity Adjustment:

The gravity observations in the field are carried out in loops with the ladder sequence technique (Fig.6). So, first of all, loops are identified in the data and the corrected relative gravity values of each station are stored in a single file according to the loop it belongs to. Then adjustment is carried out in each loop. The software package used by GSD implements least-squares adjustment to calculate the adjusted gravity values. After calculating adjusted values for each station, the overlapping stations to the subsequent loop are taken as base and their values are fixed, based on which further adjustment is done in the loop and gravity measurements are calculated. Acquiring base station values from the previous loop, adjusting the observed values in the loop and calculating base station values for the next loop, is the procedure for calculating adjusted values for every station.

Thus, absolute gravity values are calculated for each station that can be used for precise levelling corrections. However, for calculating geoid, gravity anomalies are computed using appropriate algorithms with the absolute gravity values and elevation models.

4. CONCLUSION AND RECOMMENDATION

SD, through the GSD, has been conducting several gravity-related programs for different purposes like geoid computation, precise levelling corrections etc. The currently adopted methodology for gravity survey was briefly illustrated in this paper. Moreover, the overview of features of instruments and techniques implemented before, during, and after a gravity survey was demonstrated.

Gravity survey also plays a vital role in defining a vertical reference system, so gravity survey should be highly encouraged with extensive programs and projects.

Moreover, the applications of gravity survey are more than what SD has been implementing to date. So, other applications of gravity survey should also be addressed, like geology, hydrology, minerals and mines exploration etc. by collaborating with respective authorities or agencies. This would help SD in creating another milestone towards contribution to the overall scientific community here in Nepal and abroad.

5. ACKNOWLEDGEMENTS

We would like to acknowledge all the courageous souls who contributed through any means to the GSD. Their contribution has led to the development of geodesy in the SD and enabled the people of this generation to learn the history as well as envisage a path for future endeavours.

6. REFERENCES

Dewhursi, W.T. (1985) Input Formats and Specifications of the National Geodetic Survey Data Base. Rockville ,MD: U.S Department of Commerce, National Oceanic and Atmospheric Administration. Available at: https://books.google.com.np/books?id=M89PoYgiQdcC&lpg=SA11-PA1&ots=DmaBBG0Wgv&dq=adjusted gravity control grav adju data&pg=SA11-PA1#v=onepage&q=adjusted gravity control grav adju data&f=false (Accessed: 11 March 2022).

FINNMAP, F.-I. (1993) *Eastern Nepal Topographic Mapping Project, Report on GPS - Surveys*.

KC, S. and Acharya, T.D. (2022) 'Advancements of Geodetic Activities in Nepal: A Review on Pre- and Post-2015 Gorkha Earthquake Eras with Future Directions', *Remote Sensing*, 14(7), p. 1586.

Märdla, S. (2014) 'Precise levelling data processing near terraced landforms', *Geodesy and Cartography*, 40, pp. 51–57.

Nepal, H.M.G.S.D. of and FINNMAP, F.-I. (1997) *Western Nepal Topographic Mapping Project Phase I Final Report of Ground Control Surveys Vol I: Report*. Kathmandu.

NGS (2012) *National Geodetic Survey*. Available at: https://geodesy.noaa.gov/GRAV-D/ (Accessed: 22 February 2022).

Olesen, A.V. and Forsberg, R. (no date) *Nepal Airborne Gravity and Geoid Project: Data Acquisition and Gravity Processing Report*. Copenhagen.

Oli, P.P. (2007) 'Astronomy and Gravity Surveying in Nepal', *Nepalese Journal of Geoinformatics*, 6, pp. 16–24.

Scintrex (2018) CG-6 *Autograv Gravity Meter Operation Manual*. Concord, ON, Canada: SCINTREX LIMITED. Available at: https://scintrexltd.com/wp-content/uploads/2018/04/CG-6-Operations-Manual-RevB.pdf (Accessed: 11 March 2022).

Seigel, H. (1995) *A Guide to High Precision Land Gravimeter Survey*. Concord, Ontario, Canada.

UK, D. of M.S.M. of D. (1985) *Report and Results of Gravity Surveys in Nepal 1981-84*. Kathmandu, Nepal.

Winester, D. et al. (1991) *Absolute Gravity; Nagarkot Observatory, Observations, Corrections, Results; Gravity Ties to Kathmandu and Simara Airport*

USING GEOSPATIAL TECHNOLOGIES FOR DISASTER MANAGEMENT IN DEVELOPING COUNTRIES

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ABSTRACT

Due to a lack of resources, infrastructure, and knowledge, disaster management has proven challenging for least developed countries. As a consequence, geospatial technology can reduce the risk while also preparing an early warning system. It looks into the advantages, disadvantages, and future improvements to the deployment of various technologies. An integrated system includes maps, pie charts, and graphs. It uses mobile and computer platforms to perform geographic analysis of hotspots and low places using historical landslide records and community input. Every community does not have access to the smartphones and computers installed in the ward office. Instead, they will broadcast an alarm message across various media, including newspapers, radio, and television. Those with a smartphone will train to gather data and provide a set of sirens and basic search and rescue equipment such as life vests and ropes. For preparedness, reaction, recovery, and reduction, the alert will have four levels. The case study findings demonstrate that an effective early warning system helps communities become safer and more resilient. The community's engagement in risk assessment, communication and distribution, and urgent reaction actions is aid by integrated geospatial technology. The research emphasizes the necessity for a free and open-source early warning system for disaster management in developing countries like Nepal, leveraging geospatial technology like geographic information systems and remote sensing. Different nations have a great chance to work together in a collaborative framework with a coordinated approach. It will provide people with the tools they need to respond rapidly and effectively during and after a disaster, enabling effective management and informed decisions to reduce the risk to vulnerable groups and individuals.

KEY WORDS

Geospatial Technologies; Vulnerable; Disaster Management; Minimizing Risk

1. INTRODUCTION

Disasters have raised concern globally for natural disasters and the human factor. Many studies have shown that frequency and magnitude of catastrophe significantly increase, which has impacted a large population (Bello & Aina, 2014; Bouwer, 2011). Around 95 million people were affected by 396 natural disasters across the world in 2019 (Kankanamge et al., 2019; *Natural Disasters 2019 - World*, n.d.; Pourebrahim et al., 2019). Only in 2019, there were significantly more than in the previous decade (2009-2018) (*Natural Disasters 2019 - World*, n.d.). This phenomenon raises such an incident, the comprehensive study considers different dimensions such as environmental, life loss, and livelihood (Ellis, 2000; Tschakert et al., 2019; Warner et al., 2010). They were also beginning a global awareness campaign for reducing, mitigating this through disaster management. However, there are limited studies and programs are implemented in developing countries like Nepal.

Nepal's fragile terrain and its extreme change in relief in shorter distances make it one of the highest fatality rates globally from landslides and floods. Other is its climate change, low literacy rate, unplanned settlers, rapidly growing population, and geological structure boost to increase natural disasters every year (*AN OVERVIEW OF DISASTER MANAGEMENT IN NEPAL*, n.d.; Dodman et al., 2013; Peasants' Federation, 2011). Only 2020 had three times more casualties and incidents than the last year (*Nepal*, n.d.). Around 291 had already lost their lives, and 67 were still missing due to disaster from April to September (D. E. Alexander, 2010; Quarantelli, 2001; Sanyal & Routray, 2016). Such a vulnerable stage demands a proper early warning system using geospatial technologies. Thus, this study's early warning system prototype shows geospatial technology helps detect hazards and analyze risk factors through a vulnerable map. Such a system will provide response and recovery measures for pre, during, and post disasters to help implement a management program related to disaster for reducing and mitigating people and communities. As every aspect of a disaster is related to the location, geospatial technologies such as global positioning, geographic information system, and remote sensing seem natural fit and appropriate (Croner et al., 1996; Manfré et al., 2012; Thomas & Kemec, 2007; Westlund, 2012).

2. MATERIALS AND METHODS

2.1. Study Area

Nepal is ranked fourth, eleventh, and thirtieth for climate change, earthquake, and flood risks, respectively (Dangal, 2011; Koirala, 2014; Nepal et al., 2018; Rimal et al., 2015;

Shreevastav et al., 2019). Every year a significant number of people severely suffer from natural disasters. More than two every day, and around ten million were affected during half of the decades due to natural disasters (D. Alexander, 2018; Pawan Thapa & Dhulikhel, 2019; Van Aalst, 2006). In the last 30 years, it faced several floods and landslides, which rapidly threatened people's livelihood (Glade & Crozier, 2005; Kjekstad & Highland, 2009; Rimal et al., 2015). Moreover, it is fragile and susceptible to numerous natural hazards; For example, the 1934 Bihar-Nepal Earthquake (M8.3), the 1988 Udaypur Earthquake (M6.6), and the 2015 Gorkha Earthquake (M7.6) were the most devastating earthquakes in Nepal during the last 80 years (Chapagain et al., n.d.; Chaudhary et al., 2015; Shrestha, 2019). Jure landslide of 2014 and the 1993 floods in south-central Nepal resulted in a massive loss of lives and properties, including housing and other infrastructures (roads, hydropower, and electricity) (Espejo, 2014; Zhang et al., 2017).

2.2. Data Collection

The datasets acquired from the following sources are in Table 2.1.

Table 2.1. The datasets used for the study.

Datasets	Data Source
Natural Disaster	Nepal Disaster Risk Reduction Portal http://drrportal.gov.np/publication Nepal desinventar database https://www.desinventar.net/
Rainfall & Temperature	Department of Hydrology and Meteorology https://www.dhm.gov.np/

2.3. Methods

4R is one of the most straightforward methods: Readiness, Response, Recovery, and Reduction. During the readiness phase using the geographic information system, developing an early warning system. It determines the expected frequency and magnitude of hazards. A specific place can respond, recover, and reduce the impact with this detailed information and analysis. A proper early warning system will be appropriate for developing countries like Nepal for financial and technical terms. An early system includes a chain of activities: understanding and mapping flood vulnerability, monitoring rainfall and water levels, forecasting upcoming events, processing, and disseminating and communicating understandable warnings to decision-makers and the population so that they can take appropriate and timely actions in response (B. D. R. C. UNISDR, 2007; I. UNISDR, 2007). This system should build using free and open source to minimize its operational cost. Also, it needs to be timely and up-to-date information, such as the location of potential victims, the location of critical facilities (e.g., shelters, hospitals), available resources (e.g., food, water, blankets, medical

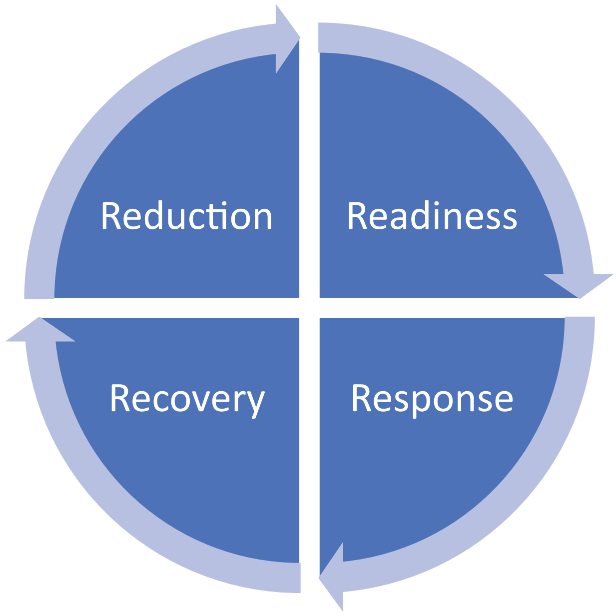

Figure 1: The methodological framework for Disaster Management

supplies, etc.), infrastructure conditions (e.g., damaged roads/bridges/utility lines, etc.), and evacuation or supply drop off points. Much of this information is spatial, analyzed in a GIS, then disseminated as maps (Kemp, 2008).

These four stages are interrelated; while an early system can support reliable information regarding the disaster, it will directly improve the three stages of disaster management. Notably, in Nepal, such critical conditions lack transmission and coordination of vital information that risks people's lives; however, this system will be accessible for everyone through smartphones and computers. Moreover, it will incorporate risk knowledge for readiness, response capabilities with evacuation center, search and rescue, and access such as roads. Similarly, reducing these disasters includes rainfall, river level, and warning systems.

3. RESULTS

The occurrence and impact of disasters increase the vulnerability of exposed populations and communities (Banholzer et al., 2014; Disaster-Related Displacement in a Changing Climate, 2016). The main objective of the early warning system is to protect lives and property. Early warning is thus one of the critical elements in any disaster reduction strategy. The early warning provides valuable and up-to-date information about hazards for reducing risk and effective response (Multi-Hazard Early Warning Systems: A Checklist, Outcome of the First Multi-Hazard Early Warning Conference, n.d.; Multi-Hazard Early Warning Systems (MHEWS), n.d.). It will incorporate the necessary information and strategies for managing disasters. Thus, effective early warning systems save lives and help protect livelihoods and national development gains (Cools et al., 2016; Xuan et al., 2007).

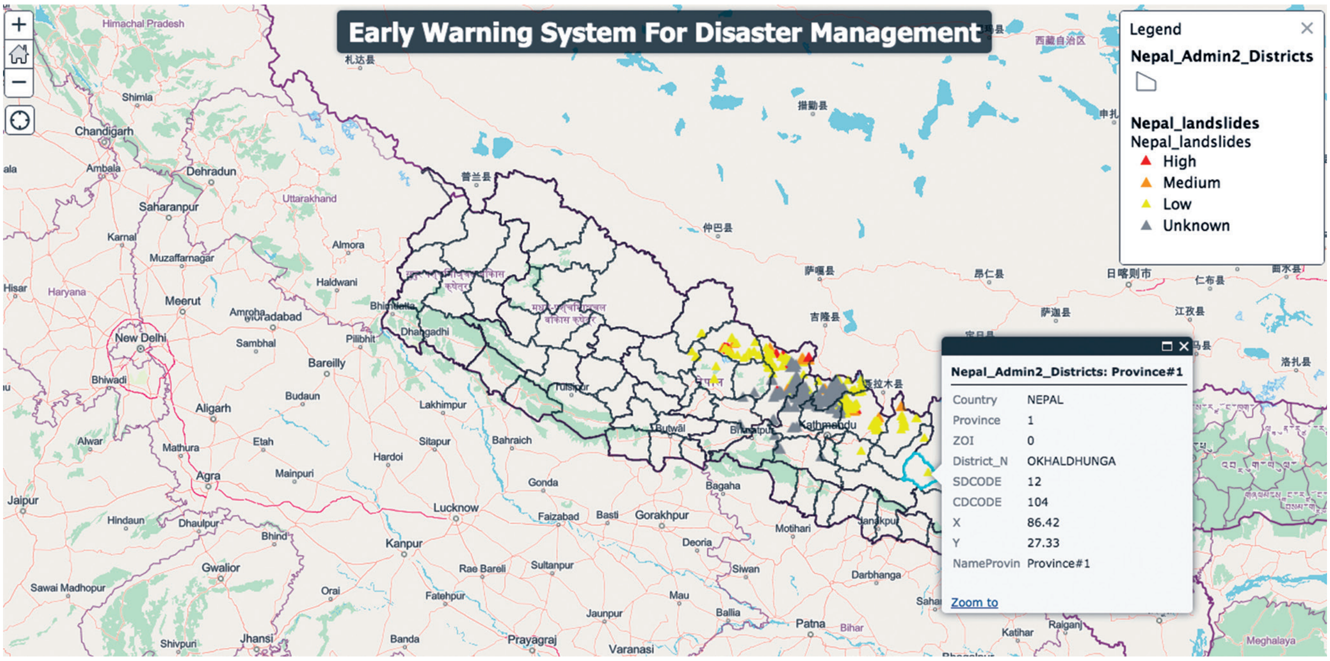

Figure 2: Early warning system developed using geospatial technology Landslides.

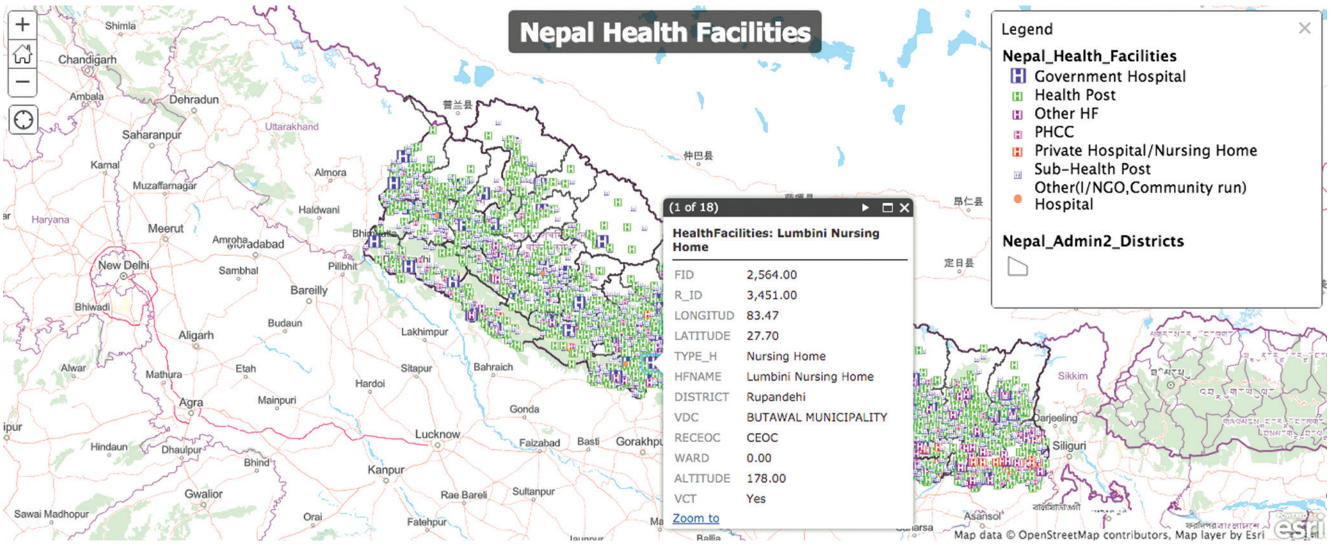

Figure 3: Early warning system developed using geospatial technology Health Facilities.

The readiness, response, recovery, and reduction of the natural disaster can be achieved by using an early warning system prototype prepared to support the accessibility of critical information to the people and community using different platforms such as radio, television, mobile, and the internet. Thus, there is a vast potential to help the government, risk area people, health workers, hospitals, and other stakeholders take intensive measures before a disaster to reduce its risk and after for response and recovery. However, as developing countries do not have technical and financial resources, proper early warning systems help respond, recover, and reduce the disaster. Therefore, they must focus on a suitable early system using a free and open-source platform for disaster management.

3.1 Case Studies on Community-Based Landslide Early Warning Systems

Landslide is a devastating and recurring disaster in the district; this repeating pattern shows high-risk communities—devastating landslides causing around thirty-five on the 6th August 2016 (CCRI-Nepal_Landslide-Case-Study-1-Bhirkot-_final_1808.Pdf, n.d.; P. Thapa, 2020). Large settlements are affecting combined where around 16 people died, and 100 houses are at high risk last two years (300 Quake-Victims under Huts in Dolakha - Nepal, n.d.; AN OVERVIEW OF DISASTER MANAGEMENT IN NEPAL, n.d.; Prüss-Üstün et al., 2016). Local governments and NGOs try to support victims. Still, it is non-effective due to lack of coordination, awareness, poverty incidence,

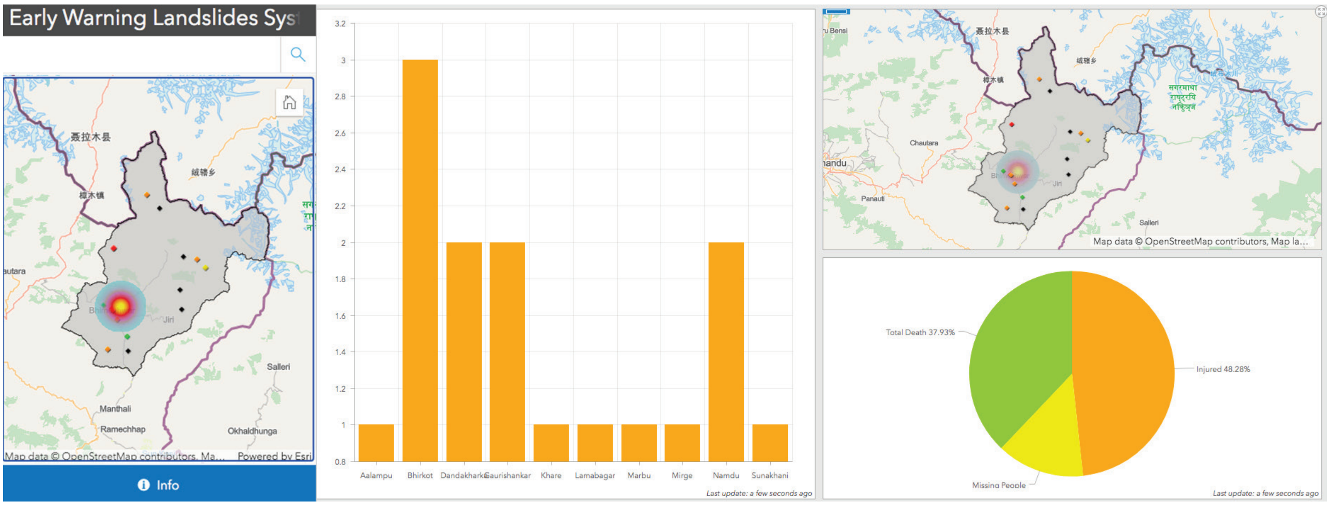

Figure 4:Early warning system using geospatial technology for Landslides of Dolakha district

unequal access to resources, physical vulnerability, and traditional beliefs are the fundamental underlying causes of the unsafe and more vulnerable conditions in the community. Also, reliable data sources, unavailability of a platform where landslide incidents can be forecasted, and share information with the district. here

The early warning system for landslides is an integrated system with central spatial and non-spatial data that includes injured, death, rainfall, and temperature from the Nepal Disaster Risk Reduction Portal, Nepal de inventor database, and the Department of Hydrology and Meteorology. These data are visualized as maps, pie charts, and graphs for easy understanding and information extraction from the district's residents. It uses mobile and computer platforms to conduct geographic analysis of hotspots and low places using historical landslide records and community feedback. Every neighborhood does not have access to the smartphones and computers installed in the ward office. Instead, they will broadcast an alarm message across various media, including newspapers, radio, and television. Those with a smartphone train to gather data and provide a set of sirens and basic search and rescue equipment such as life vests and ropes. The alert system will have four stages for readiness, reaction, recovery, and reduction. It will give individuals nearly an hour's warning, giving them enough time to flee and save their lives and possessions. All houses will inform about the early warning system, and user testing will improve the system. It will update on an annual basis or as needed to ensure that it fulfills its intended purpose. An effective early warning system helps communities become safer and more resilient. Nonetheless, equitable participation and support from the government, society, universities, international non-governmental organizations, and non-governmental organizations (NGOs) must meet unique needs and objectives. The community's engagement in risk assessment, communication and distribution, and urgent reaction actions is aid by integrated geospatial technology.

4. DISCUSSION

Over the last decade, the early warning system has reduced the number of people killed in catastrophes worldwide (Basha & Rus, 2007; Basher, 2006). It encourages the advancement and use of scientific knowledge, as well as the better transmission of information. Nepal requires an integrated early warning system with four preparedness, reaction, recovery, and reduction stages. To successfully distribute messages, warn effectively, and status for desired results, such systems require active public, private, and media participation (Communication-Framework.Pdf, n.d.; Government of Canada, 2016). Geospatial technologies are valuable platforms for disaster management (Croner et al., 1996; He et al., 2017). However, reliable computer networks, internet connections, cellphones, and electric power supplies are scarce in underdeveloped nations like Nepal. It could install 753 local office computers and cellphones (Durbar, 2015), broadcasting radio, newspapers, mobile alerts, and televisions. In some instances, the performance of outdated information and communication technology is obscure by its actual performance during a crisis. Primary GIS data layers, for example, were unavailable following the 2015 earthquake in Nepal. Lack of coordination for appropriate mapping and data, various government agencies, and unavailability of central database systems will result in the development of a central database, including disaster management techniques that are effective, efficient, and cost-effective. The FOSS approach is ideal for developing nations for various reasons, including affordability, freedom, accessibility, customizability, compatibility, and capacity building (Herold, 2009; Herold & Sawada, 2012; Yildirim & Ansal, 2011). The absence of licensing fees comprehends as a substantial benefit (Rajani et al., 2003).

5. CONCLUSIONS

A people-centered early warning system that uses geospatial technology can empower individuals and communities vulnerable to catastrophes. It can offer enough time and in the right way to limit and mitigate the loss of people, property, and the environment. The following parts make up a comprehensive, effective, efficient, and cost-effective system: readiness, response, recovery, and reduction. These four aspects should have higher inter-linkages that may be established utilizing geospatial technology to maximize their use. The role and responsibilities of the entities involved in disaster management are distinct under this system. To decrease natural catastrophes, well-trained technical human resources, modern technology, and appropriate means and resources are also required. In addition, to raise public awareness, disaster management teaching incorporation in the school and university curriculum. An efficient early warning system is necessary to build a scientific detection system to monitor physical environment changes. Vulnerability analysis and mapping are required because Nepal's sectors are yet undeveloped. Finally, political leaders and policymakers must have a strong willingness and commitment to developing a catastrophe early warning system effectively.

6. REFERENCES

300 quake-victims under huts in Dolakha—Nepal. (n.d.). ReliefWeb. Retrieved December 31, 2020, from https://reliefweb.int/report/nepal/300-quake-victims-under-huts-dolakha

Alexander, D. (2018). *Natural disasters*. Routledge.

Alexander, D. E. (2010). The L'Aquila earthquake of 6 April 2009 and Italian Government policy on disaster response. *Journal of Natural Resources Policy Research, 2*(4), 325–342.

AN OVERVIEW OF DISASTER MANAGEMENT IN NEPAL. (n.d.). Retrieved December 20, 2020, from https://www.adrc.asia/countryreport/NPL/NPLeng99/Nepal99.htm

Banholzer, S., Kossin, J., & Donner, S. (2014). The impact of climate change on natural disasters. In *Reducing disaster: Early warning systems for climate change* (pp. 21–49). Springer.

Basha, E., & Rus, D. (2007). Design of early warning flood detection systems for developing countries. *2007 International Conference on Information and Communication Technologies and Development*, 1–10.

Basher, R. (2006). Global early warning systems for natural hazards: Systematic and people-centred. *Philosophical Transactions of the Royal Society a: Mathematical, Physical and Engineering Sciences, 364*(1845), 2167–2182.

Bello, O. M., & Aina, Y. A. (2014). Satellite remote sensing as a tool in disaster management and sustainable development: Towards a synergistic approach. *Procedia-Social and Behavioral Sciences, 120*, 365–373.

Bouwer, L. M. (2011). Have disaster losses increased due to anthropogenic climate change? *Bulletin of the American Meteorological Society, 92*(1), 39–46.

CCRI-Nepal_Landslide-Case-Study-1-Bhirkot-_final_1808.pdf. (n.d.). Retrieved January 2, 2021, from http://www.sias-southasia.org/wp-content/uploads/2015/12/CCRI-Nepal_Landslide-Case-Study-1-Bhirkot-_final_1808.pdf

Chapagain, P. S., Gnyawali, B., Neupane, B. K., Ghimire, P., & Sapkota, L. (n.d.). *THE GEOGRAPHIC BASE*.

Chaudhary, S., Jimee, G. K., & Basyal, G. K. (2015). Trend and geographical distribution of landslides in Nepal based on Nepal DesInventar data. *The 14th International Symposium on New Technologies for Urban Safety of Mega Cities in Asia. Retrieved from: Http://Www. Nset. Org. Np/Usmca2015/Session8/8_SN8-8_fullPaper_SureshChaudhary. Pdf.*

Communication-framework.pdf. (n.d.). Retrieved December 21, 2020, from https://www.who.int/mediacentre/communication-framework.pdf

Cools, J., Innocenti, D., & O'Brien, S. (2016). Lessons from flood early warning systems. *Environmental Science & Policy, 58*, 117–122.

Croner, C. M., Sperling, J., & Broome, F. R. (1996). Geographic information systems (GIS): New perspectives in understanding human health and environmental relationships. *Statistics in Medicine, 15*(18), 1961–1977.

Dangal, R. (2011). Country profile Nepal. *Disaster Risk Management: Policies and Practices in Nepal. Kobe: Asian Disaster Reduction Center.*

Disaster-related displacement in a changing climate. (2016, March 21). World Meteorological Organization. https://public.wmo.int/en/resources/bulletin/disaster-related-displacement-changing-climate

Dodman, D., Brown, D., Francis, K., Hardoy, J., Johnson, C., & Satterthwaite, D. (2013). *Understanding the nature and scale of urban risk in low-and middle-income countries and its implications for humanitarian preparedness, planning and response.* International Institute for Environment and Development London.

Durbar, S. (2015). *Constitution of Nepal 2015*. 161.

Ellis, F. (2000). *Rural livelihoods and diversity in developing countries*. Oxford university press.

Espejo, R. (2014). *Are Natural Disasters Increasing?* Greenhaven Publishing LLC.

Glade, T., & Crozier, M. J. (2005). Landslide hazard and risk: Concluding comment and perspectives. *Landslide Hazard and Risk. Wiley, Chichester*, 767–774.

Government of Canada, C. R. and T. C. (CRTC). (2016, September 22). *Emergency Alert Messages and the National Public Alerting System (NPAS)* [Consumer information]. https://crtc.gc.ca/eng/television/services/alert.htm

He, Y., Zhang, D., & Fang, Y. (2017). Development of a mobile post-disaster management system using free and open source technologies. *International Journal of Disaster Risk Reduction, 25,* 101–110.

Herold, S. (2009). *The potential of free and open source geospatial information technology to improve local level capacity for natural disaster management in developing countries* [PhD Thesis]. University of Ottawa (Canada).

Herold, S., & Sawada, M. C. (2012). A review of geospatial information technology for natural disaster management in developing countries. *International Journal of Applied Geospatial Research (IJAGR), 3*(2), 24–62.

Kankanamge, N., Yigitcanlar, T., Goonetilleke, A., & Kamruzzaman, M. (2019). Can volunteer crowdsourcing reduce disaster risk? A systematic review of the literature. *International Journal of Disaster Risk Reduction, 35*, 101097.

Kemp, K. (2008). *Encyclopedia of geographic information science.* Sage.

Kjekstad, O., & Highland, L. (2009). Economic and social impacts of landslides. In L*andslides–disaster risk reduction* (pp. 573–587). Springer.

Koirala, P. K. (2014). Country Profile: Nepal. *Disaster Management Instution and System in Nepal*.

Manfré, L. A., Hirata, E., Silva, J. B., Shinohara, E. J., Giannotti, M. A., Larocca, A. P. C., & Quintanilha, J. A. (2012). An analysis of geospatial technologies for risk and natural disaster management. *ISPRS International Journal of Geo-Information, 1*(2), 166–185.

Multi-hazard Early Warning Systems: A Checklist , Outcome of the first Multi-hazard Early Warning Conference. (n.d.). 20.

Multi-Hazard Early Warning Systems (MHEWS). (n.d.). Retrieved December 20, 2020, from https://www.wmo.int/pages/prog/drr/projects/Thematic/MHEWS/MHEWS_en.html

Natural Disasters 2019—World. (n.d.). ReliefWeb. Retrieved December 20, 2020, from https://reliefweb.int/report/world/natural-disasters-2019

Nepal, P., Khanal, N. R., & Sharma, B. P. P. (2018). Policies and institutions for disaster risk management in Nepal: A review. *Geographical Journal of Nepal, 11*, 1–24.

Nepal: Why more women die in natural disasters. (n.d.). Retrieved December 20, 2020, from https://www.preventionweb.net/go/73982

Peasants' Federation, A. N. (2011). *Documentation of Climate Change Impacts, Community Perceptions, and Adaptation Practices in a Rice Farming Community in Nepal.*

Pourebrahim, N., Sultana, S., Edwards, J., Gochanour, A., & Mohanty, S. (2019). Understanding communication dynamics on Twitter during natural disasters: A case study of Hurricane Sandy. *International Journal of Disaster Risk Reduction, 37*, 101176.

Prüss-Üstün, A., Wolf, J., Corvalán, C., Bos, R., & Neira, M. (2016). *Preventing disease through healthy environments: A global assessment of the burden of disease from environmental risks*. World Health Organization.

Quarantelli, E. L. (2001). Statistical and conceptual problems in the study of disasters. *Disaster Prevention and Management: An International Journal.*

Rajani, N., Rekola, J., & Mielonen, T. (2003). *Free as in education: Significance of the free/libre and open source software for developing countries.* Ministry for Foreign Affairs of Finland, Department for Development Policy.

Rimal, B., Baral, H., Stork, N. E., Paudyal, K., & Rijal, S. (2015). Growing city and rapid land use transition: Assessing multiple hazards and risks in the Pokhara Valley, Nepal. *Land*, 4(4), 957–978.

Sanyal, S., & Routray, J. K. (2016). Social capital for disaster risk reduction and management with empirical evidences from Sundarbans of India. *International Journal of Disaster Risk Reduction, 19*, 101–111.

Shreevastav, B. B., Tiwari, K. R., & Mandal, R. A. (2019). Flood Scenario and its Risk Management, Policy, Practices in Nepal. *Annals of Ecology and Environmental Science, 3*(2), 1–14.

Shrestha, B. R. (2019). An Assessment of Disaster Loss and Damage in Nepal. *The Geographic Base, 6*, 49–57.

Thapa, P. (2020). *Spatial Estimation of Soil Erosion Using RUSLE Modeling: A case study of Dolakha District*.

Thapa, Pawan, & Dhulikhel, N. (2019). Observed and Perceived Climate Change Analysis in the Terai Region, Nepal. *GSJ*, 7(12).

Thomas, D. S., & Kemec, S. (2007). The role of geographic information systems/remote sensing in disaster management. In *Handbook of disaster research* (pp. 83–96). Springer.

Tschakert, P., Ellis, N. R., Anderson, C., Kelly, A., & Obeng, J. (2019). One thousand ways to experience loss: A systematic analysis of climate-related intangible harm from around the world. *Global Environmental Change*, 55, 58–72.

UNISDR, B. D. R. C. (2007). Good Practices and Lessons Learned. *United Nations Development Program, Geneva*.

UNISDR, I. (2007). *Guidelines: National Platforms for Disaster Risk Reduction.* UN, UN/ISDR-03-2007-Geneva.

Van Aalst, M. K. (2006). The impacts of climate change on the risk of natural disasters. *Disasters, 30*(1), 5–18.

Warner, K., Hamza, M., Oliver-Smith, A., Renaud, F., & Julca, A. (2010). Climate change, environmental degradation and migration. *Natural Hazards, 55*(3), 689–715.

Westlund, S. (2012). The use of geospatial technology in disaster management. In *Geospatial Technologies and Advancing Geographic Decision Making: Issues and Trends* (pp. 21–34). IGI Global.

Xuan, W., Chen, X., & Zhao, G. (2007). Early warning monitoring and management of disasters. *2007 IEEE International Geoscience and Remote Sensing Symposium*, 2996–2999.

Yildirim, N., & Ansal, H. (2011). Foresighting FLOSS (free/libre/open source software) from a developing country perspective: The case of Turkey. *Technovation*, 31(12), 666–678.

Zhang, J., Regmi, A. D., Liu, R., Khanal, N. R., Schenato, L., Gurung, D. R., & Wahid, S. (2017). Landslides inventory and trans-boundary risk management in Koshi river basin, Himalaya. In *Land Cover Change and Its Eco-environmental Responses in Nepal* (pp. 409–426). Springer.

GUIDELINES FOR AUTHORS PREPARING MANUSCRIPTS FOR PUBLICATION IN THE JOURNAL OF LAND MANAGEMENT AND GEOMATICS EDUCATION

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ABSTRACT

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KEY WORDS

Manuscripts, Journals, LMTC, Guidelines for Authors, StyleGuide

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The maximum paper length is restricted to 8 pages. The paper should have the following structure:

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

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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

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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.

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:

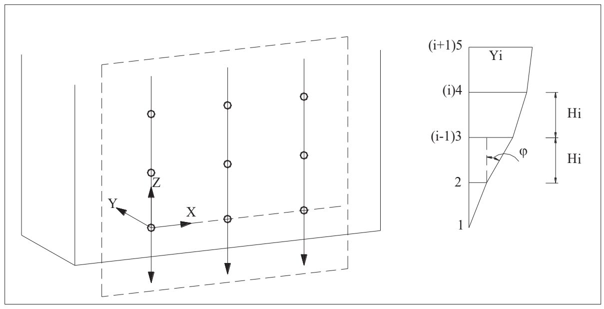


Figure 3. Figure placement and numbering

$$x=x_0 - c(X-X_0)/(Z-Z_0);\ y=y_0 - c(X-X_0)/(Z-Z_0) \qquad (1)$$

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).

4. ACKNOWLEDGEMENTS (OPTIONAL)

Acknowledgements of support for the project/paper/ author are welcome.

REFERENCES

Dubayah, R.O., Swatantran, A., Huang, W., Duncanson, L., Tang, H.,Johnson, K.,Dunne, J.O., and Hurtt, G.C., 2017. CMS: LiDAR-derived Biomass, Canopy Height and Cover, Sonoma County, California, 2013. ORNL DAAC, Oak Ridge, Tennessee, USA https://doi.org/10.3334/ORNLDAAC/1523.

Gago-Silva, A., 2016. GRASS GIS in Grid Environment. Figshare https://doi.org/10.6084/m9.figshare.3188950.

GRASS Development Team, 2017. Geographic Resources Analysis Support System (GRASS) Software, Open Source Geospatial Foundation http://grass.osgeo.org (20 September 2017).

GRASS Development Team, 2015. Geographic Resources Analysis Support System (GRASS) Software, Version 6.4. Open Source Geospatial Foundation http://grass.osgeo.org (1 June 2017).

Lennert, M. and GRASS Development Team, 2017. Addon i.segment.stats. Geographic Resources Analysis Support System (GRASS) Software, Version 7.2, Open Source Geospatial Foundation https://grass.osgeo.org/grass7/manuals/addons/i.segment.stats.html (1 June 2017).

Maas, A., Rottensteiner, F., Heipke, C., 2017. Classification under label noise using outdated maps. In: ISPRS Annals of the Photogrammetry, Remote Sensing and Spatial Information Sciences, Vol. IV-1/W1, pp. 215-222, doi.org/10.5194/isprs-annals-IV-1-W1-215-2017.

Smith, J., 1987a. Close range photogrammetry for analyzing distressed trees. Photogrammetria, 42(1), pp. 47-56.

Smith, J., 1987b. Economic printing of color orthophotos. Report KRL-01234, Kennedy Research Laboratories, Arlington, VA, USA.

Smith, J., 1989. Space Data from Earth Sciences. Elsevier, Amsterdam, pp. 321-332.

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

GOVERNMENT OF NEPAL

MINISTRY OF LAND MANAGEMENT, COOPERATIVES AND POVERTY ALLEVIATION

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 capacity of the government personnel in the field of Surveying and Mapping, and Land Management since its establishments. The center has already produced more than 8000 land professionals at different levels through various types of training courses.

LMTC has been conducting wide range of long and short term training incorporating state-of-art modern technologies. Moreover, LMTC has been collaborating to run academic courses with Kathmandu University (KU) and Council for Technical Education and Vocational Training (CTEVT).

VISION

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

MISSION

To conduct academic courses, professional trainings, refresher courses and research in Land Management and Geomatics sector for the production of qualified and skilled human resources.

OBJECTIVES

- To produce qualified and skilled human resources in the field of Surveying, Mapping, Geo-information and Land Management.
- To conduct and promote research and development activities in the field of Surveying and Mapping, Geo-information and Land Management.
- To establish collaborative relationship with national and international institutions for mutual benefit by knowledge sharing, professional trainings and technology transfer.

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.

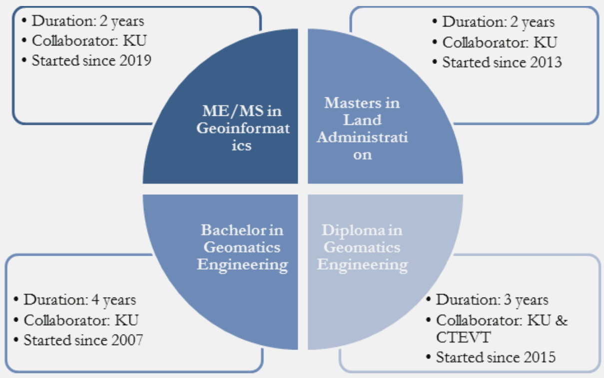
ANNUAL PUBLICATION

JOURNAL OF LAND MANAGEMENT AND GEOMATICS EDUCATION

OFFICIAL WEBSITE

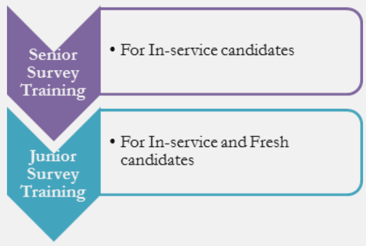
www.lmtc.gov.np

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 and Poverty Alleviation

LAND MANAGEMENT TRAINING CENTER

ACHIEVEMENT OF FY 2078/79

NOVEL SUCCESSES

- ISO 9001:2015 Certification
- Residential Training of Trainers (TOT) for capacity building of LMTC staff
- Refresher Course for High Level Officials in land related issues
- Begun conducting trainings for Land Issues Resolving Committee
- Conducted several trainings for Local Level

COPING WITH COVID-19

Adopted online method for teaching of Senior Survey Training and Junior Survey Training courses such that trainees graduate in scheduled dates.

Successful conduction of several trainings on GIS, Remote Sensing and web GIS adopting 100% online mode and open-source software.

TRAININGS LAUNCHED THIS FISCAL YEAR

GIS Training for Local Level	18
Training for District Judges	40
Instrument Handling & Orientation	65
Land Management for Local Level	62
GNSS+UAV	10
Informal Land Tenure Training	23

ADDITIONAL CAPACITY BUILDING SHORT TRAININGS

- Digital Cadastre (33)
- Orientation Training for New Officers (50)
- Remote Sensing (23)
- Land Administration & Management Gazetted Class III (45)
- Land Administration & Management Non-Gazetted (34)

LONG TERM TRAININGS

- Senior Survey Training Inservice (27)
- Junior Survey Training Fresh (43)
- Junior Survey Training Inservice (46)
- Diploma in Geomatics Engineering (3rd Year: 45)

INSERVICE TRAINING GRANTING 2 POINTS

Professional course on Geomatics & Land Administration (Gazetted Class III)	15
Digital Cadastre & Office Management Training (Non-Gazetted Class I)	15
Digital Cadastre & Office management Training (Non-Gazetted Class II)	15

SALIENT FEATURES

Extended MOU with Kathmandu University in 2019 and Launched ME/MS in Geoinformatics in-addition to previously running MS in Land Administration and Bachelors in Geomatics Engineering Courses

The figures in the parenthesis are the numbers of trainees

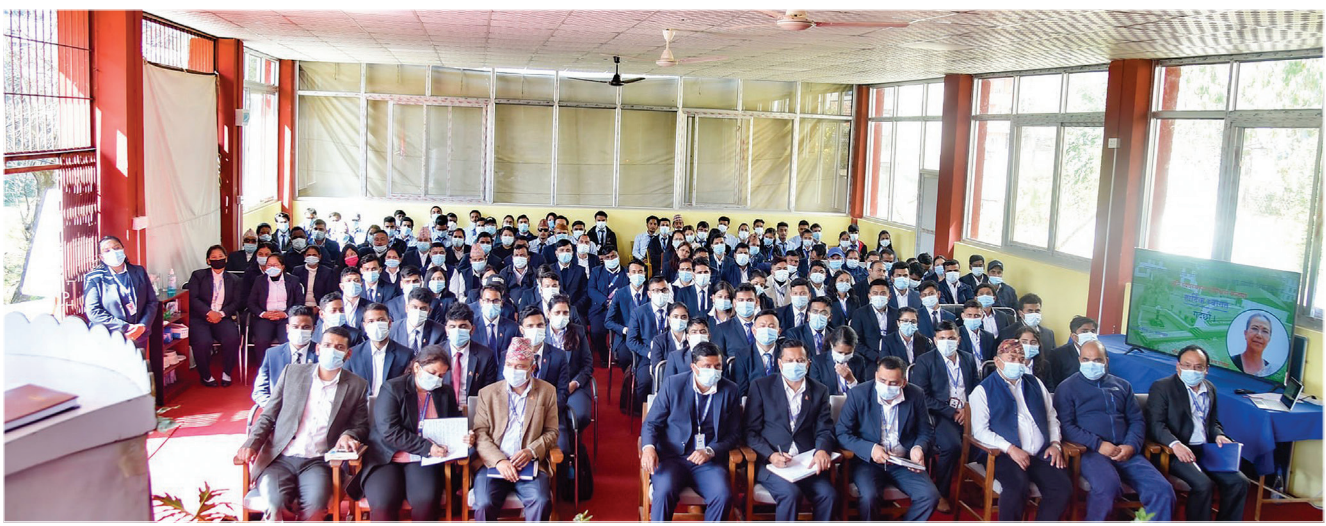
PHOTO GALLERY

Closing Ceremony of Land Management Training for Local Levels at Lumbini Province

Closing Cremony of Land Mangement and Administration Training for Newly Recruited Land Revenue Officers

LMTC Staff After Successful Completion of Awareness Training on ISO 9001: 2015 (Quality Management System)

Honourable District Judges at Orientation Training on Land Management



Participants at Closing Ceremony of Orientation Training for Newly Appointed Survey Officers

Field Camp of LMTC at Lele, Lalitpur 2078

Opening of Field Camp at Lele 2078

Opening of Field Camp at Lele by the Executive Director of Center

Closing Ceremony of Orientation Training for Newly Appointed Officers

Chess Competition at LMTC Sports Event

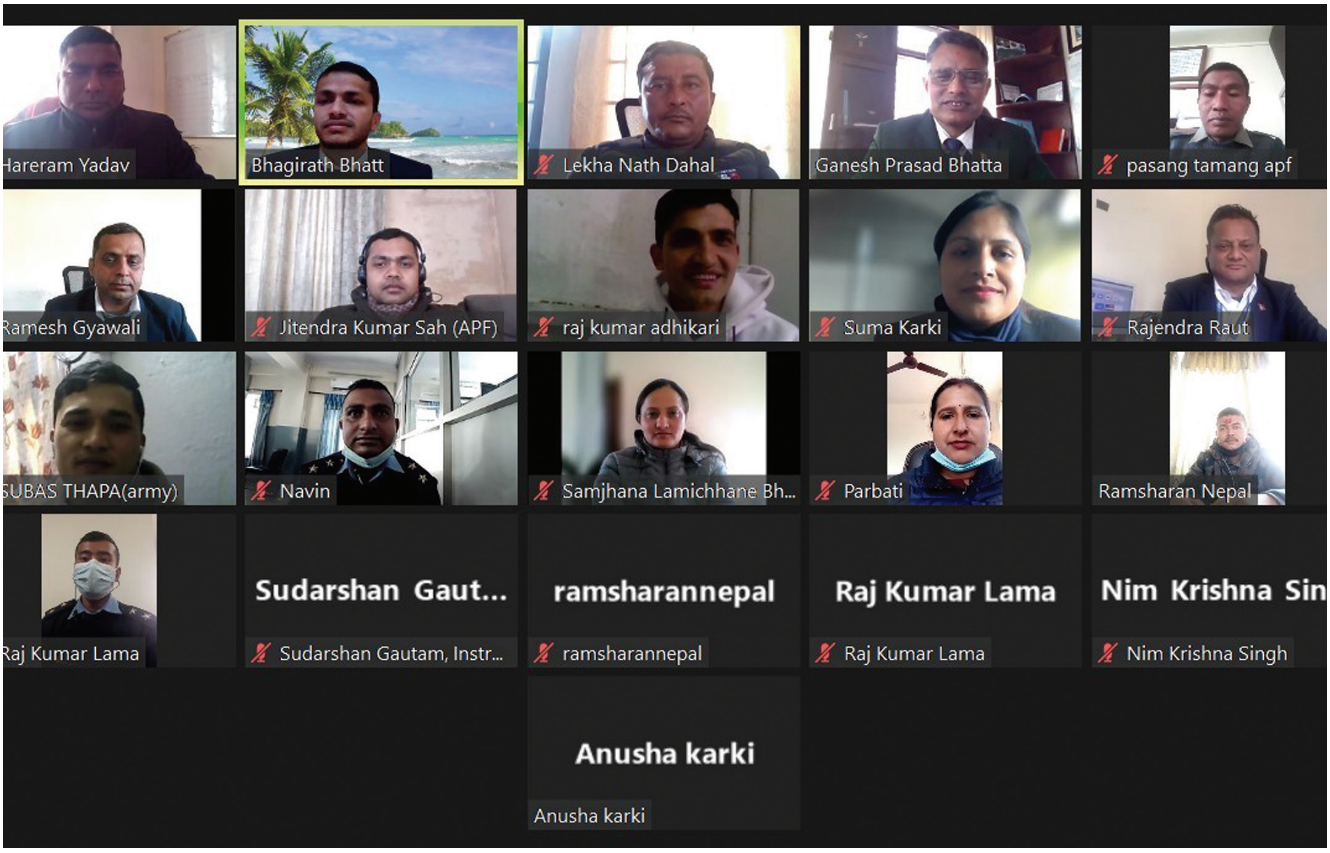
Volleyball Competition at LMTC Sports Event

Quiz Competition at LMTC Sports Event

Visit of Minister for Land Management, Cooperatives and Poverty Alleviation at the Center

Participants of Digital Cadastre Training

Participants of Orientation Training on Land Management for District Judges



Virtual Basic GIS Training for Employess from Different Government Institutions 2078

Participants of Advanced Remote Sensing and Web GIS Training 2079

Participants of the First Meeting of Thematic Committee Meeting on Land Management, Cooperatives and Poverty Alleviation Chaired by Honourable Minister Shashi Shrestha and Participated by the Honourable Ministers of all Provinces

Participants of Pre Service Training for Survey Officers 2078

Executive Director of LMTC Meeting Vice Chancellor of Nepal Open University for Potential Collaboration Between Two Institutions

Participants of Preservice Training for Survey Officers 2079

MEMBER OF

IQNET

Building trust together.

CERTIFICATE

Quality Austria

has issued an IQNET recognized certificate that the organization:

LAND MANAGEMENT TRAINING CENTER (Governed by Ministry of Land Management, Cooperatives and Poverty Alleviation, Government of Nepal)

Dhulikhel, Kavre, Nepal

for the following scope:

Providing academic & non-academic course and training in the field of surveying and mapping (Geomatics), Land Administration, and Land Management

EAC: 37

has implemented and maintains a

QUALITY MANAGEMENT SYSTEM

which fulfils the requirements of the following standard

ISO 9001:2015

Issued on:	**2022-06-29**
Validity Date:	**2025-06-28**
Quality Austria certified since:	**2022-06-29**

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President of IQNet

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