Satellite Imagery Analysis - impact measurement of trail bridges in Nepal

Hack4Good Project, Fall 2022

Hack4Good
Apply your data science skills to create real-world impact

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Abstract

Helvetas – a Non-governmental organization – offers, among other things, expertise and services in rural access such as supporting the construction and maintenance of rural roads and trail bridges which enable access to markets, schools, and health centers. In northern Nepal, the geography dictates its agrarian population to live in scattered settlements. There are many rural settlements in the mid- and upper hills and in the high mountains. Over the past decades, with the contribution of Helvetas, many trail bridges have been built, facilitating communication and movement of goods, services, and people. This project measures the impact of trail bridges in Nepal with a focus on the change of settlement and explores the potential of satellite imagery in large-scale countrywide impact measurement.

1 Introduction

Helvetas has been involved in improving rural access and building trail bridges in Nepal for several decades. The results and impact of these infrastructures have been widely considered very positive. Through the Hack4Good initiative, the goal is to numerically validate these positive results and understand if through satellite imagery these positive impacts can also be ascertained. The construction of these bridges might impact various development factors, including changes in settlement structures, the development of service centers, and the alignment of the roads. In this project, we focus on analyzing the change of settlement on a countrywide scale with the support of satellite imagery. Our objectives include:

- formulate the impact measurement problem and define metrics to identify positive changes;
- explore the potential of satellite imagery in impact measurement;
- design and implement an efficient, scalable, and cost-effective way to extract information from satellite data;
- analyze changes with respect to topology factors, as Nepal is a country of high mountains like the Himalayas;

2 Approach

In general, we use satellite data as predictor data, the location of the bridges in Nepal as points of interest, and use databases generated by deep learning techniques tools. Due to data availability reasons, we narrow down the scope of the project and focus on bridges built in 2019 and perform a temporal analysis for seven years (three years before and three years after the construction year).

Bridge data collection: A database containing several information about bridges built in Nepal, from which we will extract the geographic coordinates and the construction year of the bridges.

Predictor data: We use publicly available and free optical satellite imagery: Sentinel-2, a satellite mission from the European Space Agency (European Space Agency, 2022). It provides high resolution ($10 \times 10\ m$) with a frequent revisit time of 3-5 days and near-global coverage, so it is suitable for large-scale temporal analysis. Instead of directly applying the Sentinel-2 products in our project, we choose Dynamic World (DW), a land use classification map derived from Sentinel-2 products based on deep learning (Brown et al., 2022). An example of DW land use classification is shown in Figure 1. As DW provides classification results (nine land cover classes including tree, grass, built area, and crops) in the same high spatial and temporal resolution of Sentinel-2, we can keep all the advantages of Sentinel-2 and at the same time avoid the high computational requirements of deep learning.

Data processing: We choose Google Earth Engine (GEE) (Gorelick et al., 2017) to handle computationally expensive data querying and processing.

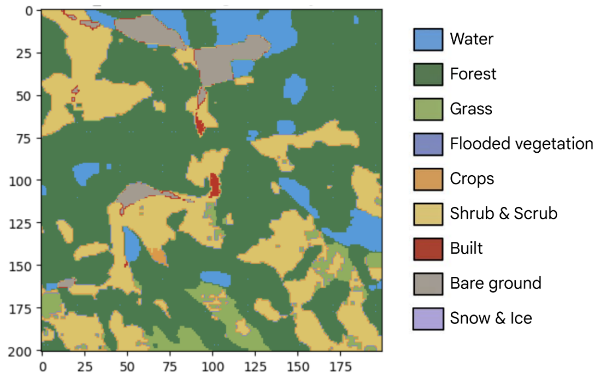

Figure 1: An example of Dynamic World land use classification map

Firstly, we inquire the DW land use classification maps covering the defined buffer (radius is 1 km) around the bridge location and compute the annual average map for each year on GEE. Then we calculate the relative amount of pixels for each class and year. For example, if there are $100 \times 100 = 10'000$ pixels in the annual maps and 1000 pixels are classified as the "built area" (marked red in Figure 1), the fraction of the built area equates to $\frac{1000}{10000} = 0.1$. Following this procedure, we obtain the annual fraction values for all nine land cover classes for all seven years.

Metric calculation: In this project, we define a metric to quantify the positive change brought by these bridges. Simply using the growth rate of the built-up area, is intuitively a biased metric. The construction of new buildings almost always outnumbers the destruction of old buildings (even without the impact of humanitarian projects), and hence, very likely leads to positive growth rates. A better methodology is to calculate the growth rate before and contrast it to the growth rate after the construction of the bridge. This enables us to compare the behavior of the community before the bridge was built versus after the bridge was built.

The growth rate of a given class reflects the change in its land cover fraction over time. The growth rate of each class is calculated per year as

$$r_t = \frac{\#\text{pixels}_t - \#\text{pixels}_{t-1}}{\Delta t}$$

which gives three growth rates before the bridge, and three growth rates after the bridge was built. Then, for both states, we perform a linear regression to yield the speed (or slope) of the growth rate for the time frame before building the bridge, s_b, and after s_a. These speeds describe how fast the land coverage of the given class changes over time. For example, in the case of all bridges built in 2019, the evaluated time frames range from 2016-2019 and 2019-2022, reflecting the expansion of a given class before and after the bridge was built. By comparing the speed of growth rate (slope) before and after construction, we can measure the impact of bridges on the given classes, such as the built area. Therefore, we define a metric called slope ratio,

$$\rho = \frac{s_\mathrm{a}}{s_\mathrm{b}}$$

to help further analysis.

3 Results

As the goal is to explore the impact of the bridge construction on the dynamics of the built area around that bridge, we calculate the slope ratio of built areas for bridges built in 2019 and conduct the analysis related to geographical and topological factors.

3.1 General trend of slope ratio

Based on the slope ratio, we classify bridges into two categories: construction of bridges that lead to an increase in the growth rate of built areas and those that lead to a decrease. As shown in Figure 2, there is no obvious pattern observable. However, we noticed that at high altitudes green dots seem to predominate, which may indicate a relationship between elevation and the impact of the bridges, which will be further examined in the subsequent subsection.

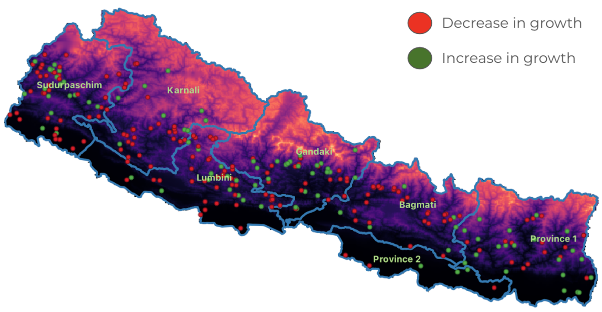

Figure 2: Visualization of the growth rate of built areas near bridges constructed in 2019. Here the green dots represent the increasing growth rates while the red dots represent decreasing ones. Provinces of Nepal are outlined in blue color and the background purple color indicates the elevation (brighter means higher altitude).

3.2 Correlation between the impact of bridges & topology

To determine whether the impact of built bridges is related to elevation, we perform a correlation analysis between the slope ratio and the elevation based on eight geographically based clusters. The clusters are generated by K-Means clustering based on geographical coordinates. In Figure 3, we notice that these correlation coefficients vary greatly between different clusters. The correlation coefficient amounts to about 0.5 for the brown cluster, where several high mountains are located.

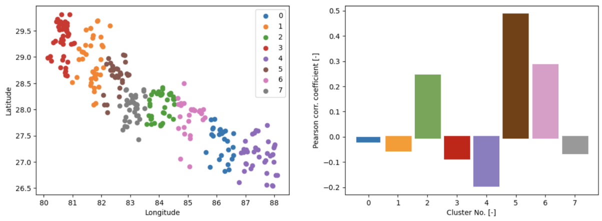

Figure 3: Pearson correlation coefficient between the slope ratio and altitude in different geographically-based clusters. (left: definition of eight clusters; right: Pearson correlation coefficient for different clusters.)

We also perform a detailed analysis of the transition between land use classes to investigate the effect of elevation on bridge impact. As demonstrated in Figure 4, in high-altitude areas, a general pattern after the construction of a bridge is the following: trees are turning into shrubs and shrubs are turning into built areas. However, crops play an important role in low-altitude areas. As shown in Figure 5, crops are transited into shrub and built areas. Although both patterns reflect an expansion of human activities, their difference proves the effect of elevation. Thus, elevation should be considered for future plan of construction.

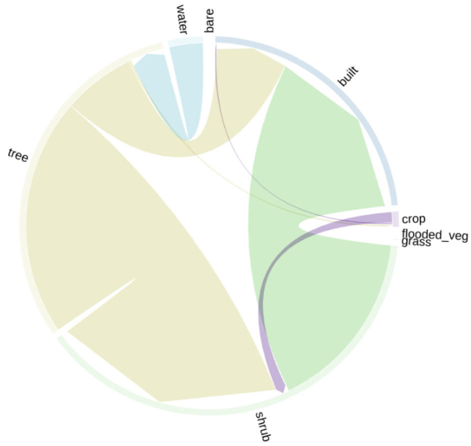

Figure 4: Chord diagram to show the transition between land use classes in *high altitude area*. Each color represents a land use class. The arrow shows the transition: for example, the light green arrow from shrub to built class indicates land areas are transited from shrub into built area after the bridge is built. The width of arrow shows the volume of areas changed.

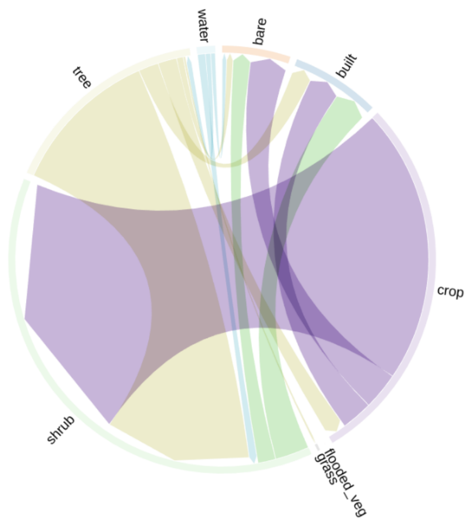

Figure 5: Chord diagram to show the transition between land use classes in *low altitude area*. Each color represents a land use class. The arrow shows the transition: for example, the light purple arrow from crop to shrub indicates land areas are transited from crop into shrub after the bridge is built. The width of arrow shows the volume of areas changed.

4 Limitations & Outlook

Based on current limitations, we recommend possible future directions to the Helvetas:

- From satellite products, we obtain fraction values for all classes but we focus on analyzing the change of built areas only. As crop seems to be an important factor for impact measurement, a future direction is to perform more analysis based on crops.
- The construction year recorded in the given bridge data can be confusing. We recommend the Helvetas team to double-check the construction year to perform an analysis on more bridges.
- As the GEE platform can provide land use classification products efficiently based on inquiries (e.g. location and date), it is possible to create an online dashboard or web application to demonstrate the land use change, which

may help spot the impact of bridges. Also, it would be nice to include this functionality in the current web application in Helvetas.

References

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