ASSESSING FOREST COVER CHANGE DURING THE COVID-19 PANDEMIC: A CASE STUDY IN CENTRAL INDIA

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ABSTRACT

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The COVID-19 pandemic brought about unprecedented disruptions to society and the environment. With climate change and deforestation already placing heavy stress on forest ecosystems, many wondered how the additional stress of the COVID-19 pandemic would affect forests. Early reports (based on remote sensing analysis) warned of increased deforestation in the first months of the pandemic; however, these were limited to certain regions and relied on broad, global remote sensing data. Our research examined a single study site in Madhya Pradesh, India asking the question: Did forest cover change significantly during the pandemic compared to previous years? Our goal is to provide a specific analysis of forest cover from 2000-2022 by using remote sensing tools like Google Earth Engine (GEE), which utilizes Landsat 8 and Sentinel-2 data at up to 30 m resolution. Within GEE, we used the Continuous Change Detection and Classification algorithm to create land cover maps for any given period of time. Our results indicate that dense forests and open forests remained relatively stable from 2000-2022. We detected no significant change in forest cover during the COVID-19 pandemic. With such stable results we suggest possible explanations, while demonstrating the important role of forests as safety nets for rural livelihoods. We conclude by stating limitations, the need for future research and management implications.

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I thank my parents Lisa and Patrick Nagle for their continued love and support. They always encouraged my education, and I thank them for their patience. Lastly, I thank my dog Macy, who has lived with me in Flagstaff the last four years.

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PREFACE

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THESIS INTRODUCTION

More than three years have passed since the World Health Organization (WHO) declared the novel coronavirus, COVID-19, a global pandemic on March 11, 2020 (World Health Organization, WHO Director). Around the world people, governments, companies, and NGOs, are not only processing the difficulties of the pandemic, but reflecting on the valuable insights learned in the event of future disasters. As of this writing, 6,915,287 global deaths have been attributed to the COVID-19 pandemic according to WHO (World Health Organization, COVID-19 Dashboard).

While much of the focus tends to be the negative anthropogenic aspects of the pandemic in terms of death-count and economic impact, there were positive benefits as well. For example, many individuals changed careers, strengthened their family relationships, and reprioritized life values. On the environmental front, many readers might recall all the positive news stories, from cleaner air in Los Angeles to dolphins swimming in the canals of Venice (Srikath, 2021; Plautz, 2020). The swift halt of human activity on a global scale, presented a unique opportunity to witness the immediate, and drastic impacts of our role on the world environment.

On the other hand, there was great concern about possible negative impacts of the COVID-19 pandemic on the environment. In particular, forests already faced unprecedented stressors due to climate change, and many wondered if the pandemic would exacerbate deforestation rates around the world. Research is needed to better understand the role of forests during times of crisis like the pandemic, and assessing forest cover change that took place during this period. This research will need to be conducted in various parts of the world to get a timely assessment.

The research presented in this thesis is part of a larger project that asks those questions for three locations in India. The study sites are in the states of Assam, Himachal Pradesh, and Madhya Pradesh. In-person household surveys, ground photos, and drawing on expert knowledge were primary methods of data collection. For quantitative data, remote sensing was used to measure forest cover change annually from 2000 to 2022. This thesis concerns only the study site in Madhya Pradesh and utilizes only remote sensing data. By analyzing the forest cover data from 2000 to 2022, we were able to determine that there was no significant change during the COVID-19 pandemic (2020-2022).

CHAPTER 1

ASSESSING FOREST COVER CHANGE DURING THE COVID-19 PANDEMIC: A CASE STUDY IN CENTRAL INDIA

Emerging research at the start of the pandemic indicated cleaner air quality in cities around the world, reduction in greenhouse gas emissions, less water pollution, and overall reduction in environmental pressures (Rume & Islam, 2020). While the global economic slowdown created these immediate results, great concern was expressed for the health of forests and increased deforestation around the world due to various factors. For example in Brazil, critical factors such as the lack of forest monitoring, protection, and enforcement due to the loss of personnel during the pandemic lead to these concerns (The Guardian, 2020).

An article published by de Andreazzi et al. (2020) summarizes the concerns of several Brazilian scientists at the start of the pandemic. They warned of increased rates of deforestation due to disregard for environmental laws, scientific evidence and recent attacks on environmental institutions and conservation organizations. Similarly, Golar et al. (2020) conducted interviews with several Forest Management Unit (FMUs) personnel in Indonesia, and had concurrent observations of illegal logging and increased deforestation during the start of the pandemic (2020).

In many developing countries such as India, reverse migration from densely populated cities to rural areas took place due to loss of jobs during the pandemic (Bhagat et al., 2020; Khanna, 2020). Some were concerned that this reverse migration placed additional stressors on forests and forest-dependent communities and was opposite of historical trends seen in developing countries, where many citizens are forced to move to cities or overseas in the name of economic viability. Fox et al. (2020), demonstrated that Nepal had experienced decades of outmigration with many young citizens sending money back home. With the support of these remittance payments and lack of available workers, many farmers let their land go uncultivated or farmed their land less intensively, resulting in a 20-year increase in forest cover in Nepal. Their research conducted 60 telephone interviews of farmers in two districts of Nepal, and in the Kavrepalanchok District noted that a majority of the farmers left 70% of their land uncultivated before the COVID-19 pandemic. However, those same farmers indicated that they have resumed farming or cleared trees on more than half of that uncultivated land since the start of the pandemic.

During times of stress and shock, it has been well documented that forests can act as safety nets for adjacent and forest-dependent communities (Delacote, 2007; Paumgarten, 2005; Rasmussen et al., 2017; Shackleton and Shackleton, 2005). The term safety nets here is used in the sense that the forest can produce both timber and non-timber products that greatly aid in community livelihoods. In times of economic hardship such as the COVID-19 pandemic, commonly used cooking fuels may become unavailable or too expensive due to supply chain disruptions. Forests can provide fuelwood to fill this gap. Forests act as safety nets by providing back-up necessities to communities especially those in poor regions. Non-forest timber products (NFTPs) such as food, medicine, and tools are just a few examples of forest products that promote livelihoods.

However, much of the above mentioned research relied on qualitative data in the form of online questionnaires and telephone interviews. This ground-level data raises concerns about deforestation; but remote sensing analyses might tell a different story. Results of research published using remote sensing varied at the start of the pandemic. A majority of this research published uses large-scale, remote sensing alerts like those from Global Land Analysis & Discovery (GLAD), which are not as precise or use high resolution satellite imagery found in other tools. For example, Brancalion et al. (2020), used a multi-temporal analysis of GLAD alerts and indicated increased deforestation in tropical regions with a total of 9,583km^2 of deforestation alerts across the global tropics during the first month following the implementation of government confinement measures. This is nearly double of that of 2019 (4,732 km^2). A similar study by Amador-Jimenez et al. (2020) used data from the Visible Infrared Imaging Radiometer Suite (VIIRS) and Moderate Resolution Imaging Spectroradiometer (MODIS) to detect forest fires in Columbia. Overall, they found an increase in forest fires correlated with illegal armed groups, which could have led to higher rates of deforestation.

Finally, Cespedes et al. (2022) provides one of the best examples of research on the effects of COVID-19 on global deforestation. Using a multistep approach, they looked at overall continental deforestation as well as five key tropical countries: Brazil, Indonesia, the Democratic Republic of Congo, Peru and Columbia. Their study differed in its use of historical data, and concluded that during the first year of the COVID-19 pandemic, deforestation rates in the Americas and Asia did not exceed projected trends for 2020, while in Africa they only marginally exceeded projected trends. These results are similar to those published by Saavedra (2020), who showed that the increase in deforestation alerts at the start of the pandemic were already in line with historical trends, and should not be attributed solely to the COVID-19 pandemic.

Much of the broad, continental size research shows no change in deforestation during the pandemic when compared to historical data (Cespedes et al., 2020). However on a country-by-country basis, or even on an individual forest stand level, the results vary drastically. As previously mentioned, some of the research like Amador-Jimenez et al. (2020) suggested that the start of the pandemic brought about an increase in deforestation in countries like Colombia, while research done by Cespedes et al. (2022) showed no change in deforestation trends during the pandemic in Brazil and Indonesia. What remains unanswered is how and if the COVID-19 pandemic affected certain countries' rates of deforestation compared to previous years? Research is needed not only on a country level, but also in various regions.

We use Google Earth Engine (GEE) using Landsat 8 and Sentinel-2 data to better understand the impact of the COVID-19 pandemic on forest cover. In addition to utilizing higher-resolution satellite data (e.g. 10-m): household surveys, field analysis, local knowledge, and LiDar (Light Detection and Ranging), can greatly improve our analysis, but remain costly. In forest management, LiDar remains significantly more costly than common remote sensing methods, especially with larger areas (Wunder et al., 2008), although the Global Ecosystem Dynamics Investigation (GEDI) has greatly increased LiDar data availability (Dubayah et al. 2020). Household surveys, field analysis, ground pictures, and obtaining local knowledge, all require paid personnel on-site, which is often difficult to fund.

Research is needed to better understand the effects of the COVID-19 pandemic on forest cover, structure, and overall sustainability. By utilizing free remote sensing tools such as GEE and high-resolution imagery from Norway's International Climate and Forest Initiative (NICFI), improvements can be made towards assessing forest cover over a given period of time. Our goal is to utilize these remote sensing tools to ask our primary research question: **Did the COVID-19 pandemic lead to increased rates of deforestation when compared to the years since 2000?**

To answer our research question, we examined a single study site in Madhya Pradesh, India. India is a highly diverse country with a population expected to outpace China this year (Frayer, 2023) and a heavily forest dependent population in some regions. Our hypothesis is that deforestation in terms of forest cover will be higher during the COVID-19 pandemic than when compared to historical trends (i.e. years before the pandemic). We attribute this to reverse migration and economic stresses that happened at the start of the pandemic as described in the paper by Saxena et al. (2021). In answering this question, our goal is to provide a very specific analysis of forest cover from 2000-2022, at site in central India mostly within the Ratapani Wildlife Sanctuary, and in doing so provide a remote sensing method that is accurate, free, and easy to implement. This will enable the ability to do similar, much needed research across other parts of the world.

Methods:

Study Site:

In India's central state of Madhya Pradesh, about 36 km southeast of Bhopal, the state capital, lies the study area we selected to conduct our remote sensing analysis (Figure 1). The area is roughly the shape of a rectangle measuring in at a total of 50,140 hectares (Figure 2). It can be described as a dry deciduous mixed forest with Teak (*Tectona grandis*) as the main tree species (Saxena, 2015). It is surrounded by many rural, small villages, with populations in the hundreds. A majority of our study area is within the boundaries of the Ratapani Wildlife Sanctuary (RWS), which was designated a National Park in the late 2000's for the protection of biodiversity, notably tigers (Saxena, 2015). This Madhya Pradesh (MP) study site is just one of three, with the other two located in the northern state of Himachal Pradesh (HP) and the northeastern state of Assam. The combination of all three sites make up a bigger research project, where sites were chosen based on long-term knowledge and collaborations of researchers. To reiterate for clarity, this thesis only concerns the MP site.

The area around the Ratapani National Park has a significant population that is dependent on the forest for fuelwood extraction, where it is estimated that fuelwood is close to about 20% of the total income that a household makes per year and non-timber forest products (NTFP) is between 5-13% of total income per year (Saxena, 2015). Saxena (2015) argues that the established national park and its boundaries will have significant impacts on the livelihood of local communities, while increased forest personnel and monitoring will have positive impacts on forest cover. Finally, this site was selected because it has a low-income, forest-dependent community that is adjacent to a protected wildlife sanctuary, so it will test whether people's relationship with the forest changed during the COVID-19 pandemic (i.e. increase in illegal clear cutting & forest extraction).

Figure 1. Study site location in Madhya Pradesh, central India.

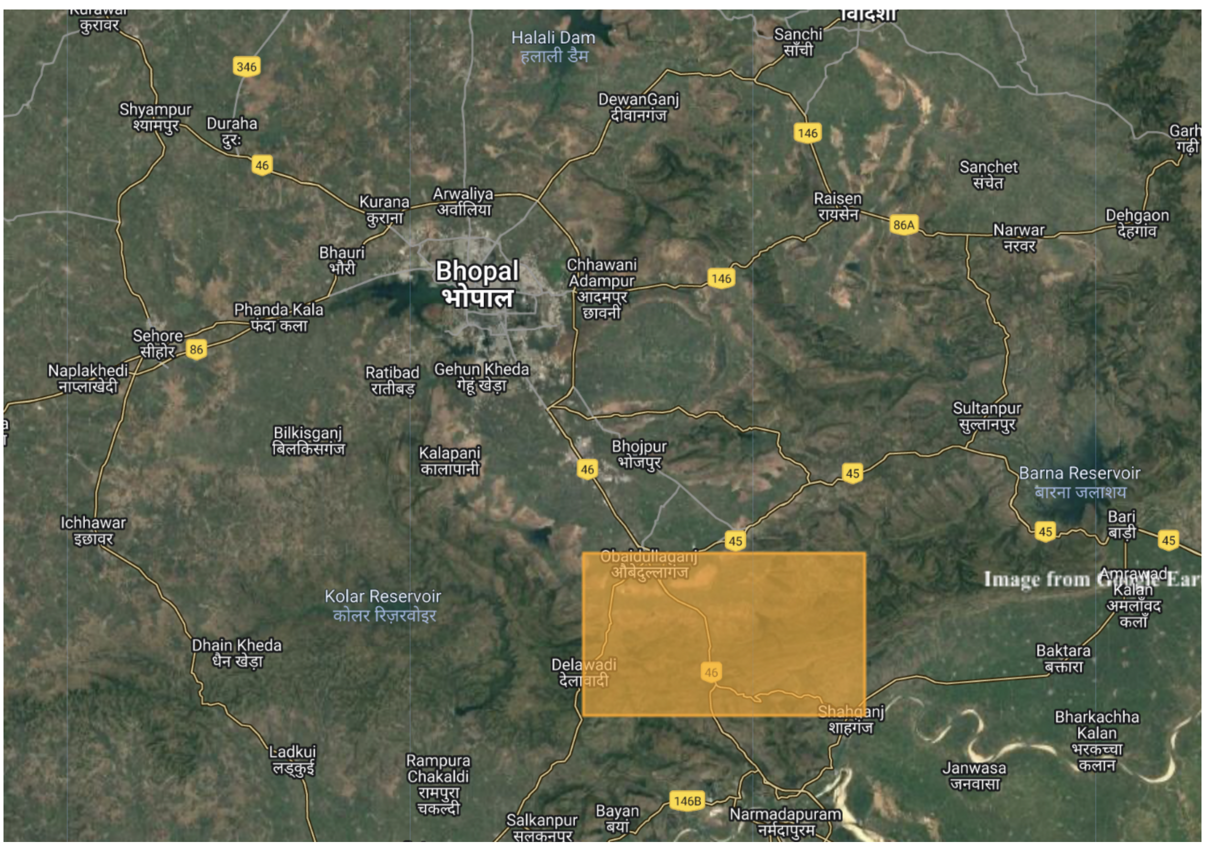

Figure 2. Study site location (about) 36 km SE of Bhopal, the state capital.

Remote Sensing:

By utilizing the Google Earth Engine (GEE) platform, we had access to several different remote sensing bands at various resolutions. The Moderate Resolution Imaging Spectrometer (MODIS) provided by the National Aeronautics and Space Administration (NASA), uses two vegetation indices to measure the vegetation canopy greeness, chlorophyll, and overall canopy structure (NASA, MODIS, 2023). By using the reflectance of red, near-infrared, and blue wavebands, the two vegetation indices are the normalized difference vegetation index (NDVI) and enhanced vegetation index (EVI), which are atmospherically corrected to remove cloud cover, water, fog, pollution, etc. Through GEE, we utilized the latest global Terra/MODIS NDVI version (MOD13Q1v061) which obtains data at a 250 m spatial resolution, every 16 days. This resolution is double that of previous products (MOD13A1) which were at 500 m resolution (NASA, MODIS, 2023).

High spatial resolution satellite imagery at a fine scale of 30 m, was used from Landsat 8 and Sentinel-2 to measure any change to forest cover. The Sentinel-2 data is provided by the European Space Agency and Landsat 8 is a collaboration between NASA and the United States Geological Survey (USGS). We chose to use these data sources as they are available for free through GEE, which enables researchers across the globe the ability to access this dataset. GEE allowed us to compare yearly data from 2000 to present. We chose to start collecting data in 2000 because Landsat data earlier is sparse and low quality. Additionally, the 20 years before the start of the COVID-19 lockdown, provides enough data to establish historical trends on deforestation rates for our study area.

Land classifications:

In GEE, we created a total of five land classifications: dense forest, open forest, agriculture, water and other. Note that other included everything else that did not fit the other classifications and included residential homes, mines, bare ground and roads. We defined open forest as areas where an individual square pixel contains less than 50% forest cover and is visabilly thinned (Figure 3). Since our study is primarily concerned with forests and changes in forest cover, these classifications were created to support this objective while also keeping classifications simple. We expanded upon P. Mondal et al. (2019), which only created three classes: intact forests, non-intact forests (showing signs of degradation such as thinned canopy), and non-forest by adding the classes of agriculture and water. This allowed us to identify any correlation between temporal and spatial trends in the classes. For instance, there could be a correlation in deforestation of dense forest and increase in agriculture. We identified a total of 706 points in our study site (dense forest: 200, open forest: 145, agriculture: 133, water: 104, other: 124). These classification points were used to train our model to identify land areas in one of these five categories. For each of the 706 classification points, we manually identified an individual square pixel plot at the 30 m scale, based on the freely available, high resolution imagery from Google and NICFI. These points were not generated randomly within our study site, but rather were selected areas that we deemed as good examples of each land classification. The plots were not clustered in particular areas, but scattered throughout the study site. The number of plots per land class was based roughly on the proportion it represents in our study site.

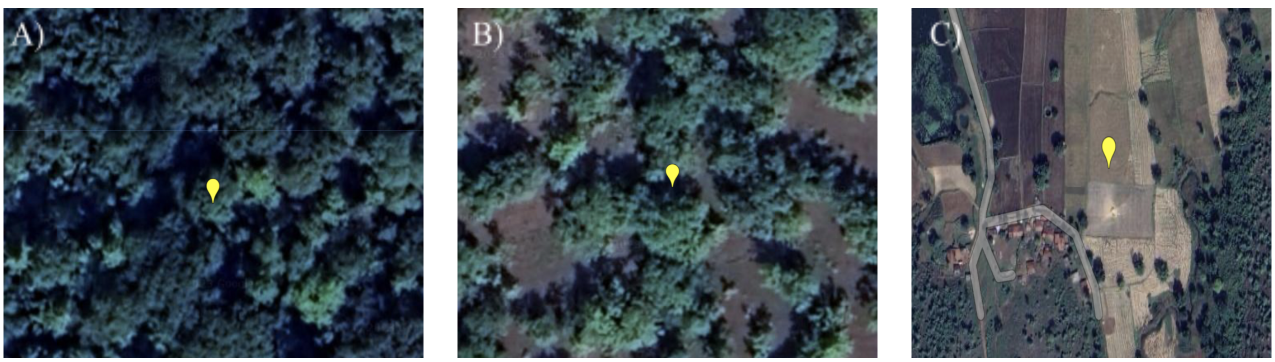

Figure 3. Sample regions showing classification locations for (a) dense forest (b) open forest and (c) non-forest, agriculture.

Continuous Change Detection and Classification (CCDC):

After manually identifying our land classification points, we used the Continuous Change Detection and Classification (CCDC) algorithm to help determine land classifications. The CCDC algorithm uses all seven bands of available Landsat data to monitor and detect land changes over a given period of time. The term "continuous" refers to the algorithm's ability to continuously detect change detection every time a new image is collected (Zhu & Woodcock, 2014). With Landsat sensors overlapping the same geographical region as often as every 16 days, the CCDC algorithm has the ability to detect land changes in almost real time (Zhu & Woodcock, 2014). However, this temporal scale varies depending on region and quality of images. For instance, cloud cover can often mask regions reducing the amount of data available for model fitting. The CCDC algorithm identifies a land change when the difference between the observed and predicted image exceeds a threshold three consecutive times. When this threshold is exceeded, an individual pixel is identified as changed. Research published in 2014 by Zhu & Woodcock indicated that the CCDC algorithm had an overall accuracy of 90% when producing land cover maps with 16 categories. These are a few of the reasons we chose to use the CCDC algorithm in our study.

The Process:

Within GEE we created three scripts which essentially represented our three main steps at land classification. In the first script, we created five land class categories (dense forest, open forest, agriculture, water, and other) and manually identified these points in our study area. In script two, a CCDC image was created based on our training data and this image was used in the final script to produce land classification maps for January 15 of every year from 2000-2022. The final product produced by GEE were exported GeoTIFF files which were then imported into ArcGIS Pro for analysis (Figure 4). Twenty three GeoTIFF files were created for the years 2000-2022. Through ArcGIS Pro we were able to view pixel counts for each land classification and see how those pixel counts changed from year-to-year. Finally, with each pixel equaling 825 square meters, we converted our pixel count to total square meters and then divided that by 10,000 to get the total number of hectares per year.

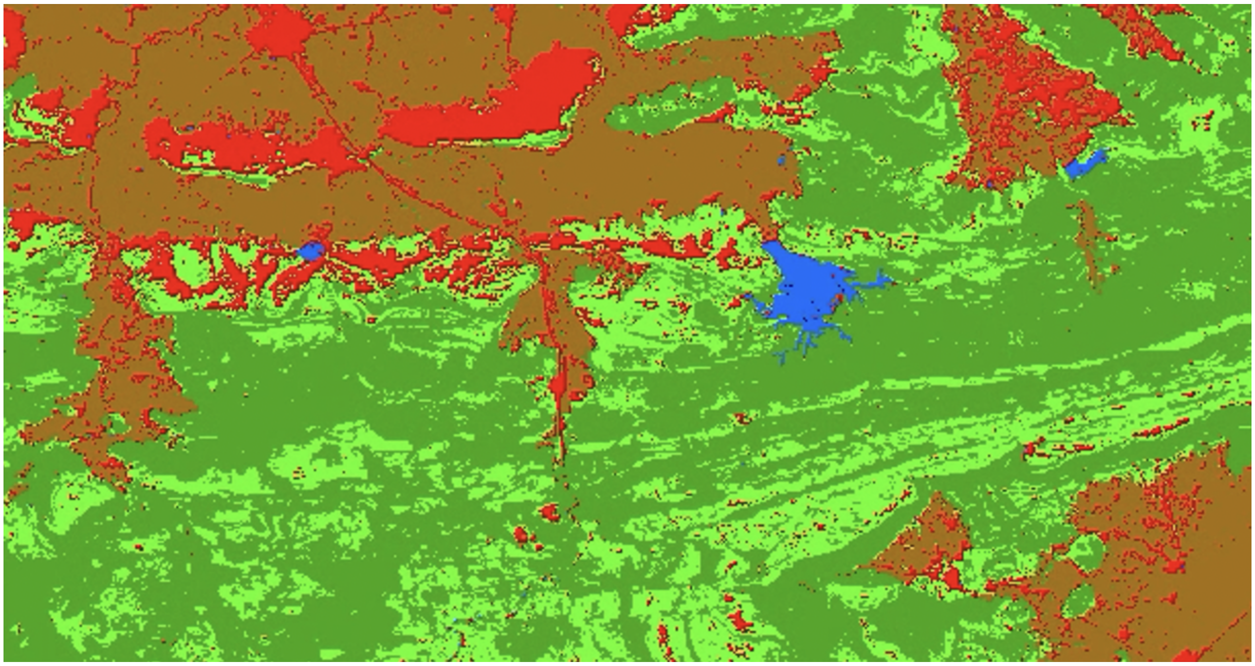

Figure 4. Image of land classifications from 2013. Dense forest = dark green, open forests = light green, agriculture = brown, water = blue, and other = red.

Validation:

Within ArcPro we used the “create accuracy assessment points” tool to create 250 random points in our study area (ArcGIS Pro, Create Accuracy Assessments Points). This tool shows each points land classification based on the CCDC algorithm. We then downloaded high resolution images from Planet through our membership to the Norway’s International Climate and Forests Initiative and Satellite Data Program (NICFI). We downloaded images from the same day that we ran the CCDC algorithm in GEE. We then did a visual “ground truth” assessment of all 250 points and documented these land classifications vs. what the algorithm projected. Finally, we used the “compute confusion matrix” tool in ArcPro to create a confusion matrix based on the output from the create accuracy assessment points tool (ArcGIS Pro, Compute Confusion Matrix). The confusion matrix calculates the user’s accuracy and producer's accuracy for each land classification as well as an overall kappa index of agreement. User accuracy shows false positives in which pixels are incorrectly identified as a certain class when they should have been labeled something else. Producer’s accuracy is a false negative, when pixels of a known class are identified as some other class. The kappa index of agreement gives an overall assessment of the accuracy of the classification (ArcGIS Pro, Compute Confusion

Matrix). The user accuracy for classifications is as follows (rounded): dense forest 94%, open forest 88%, agriculture 98%, water 100%, and other 71%. The kappa index of agreement was 89% accuracy (Table 1).

Table 1. Confusion matrix shows user accuracy, producer's accuracy and kappa index of agreement. C1 dense forest, C2 open forest, C3 agriculture, C4 water, C5 other.

ClassValue	C_1	C_2	C_3	C_4	C_5	Total	U_Accuracy	Kappa
C_1	105	6	0	0	1	112	0.9375	
C_2	1	45	0	0	5	51	0.8824	
C_3	0	0	61	0	1	62	0.9839	
C_4	0	0	0	10	0	10	1	
C_5	0	1	5	0	15	21	0.7143	
Total	106	52	66	10	22	256	0	
P_Accuracy	.099	0.8653	0.9242	1	0.6818	0	0.9218	
Kappa								0.88955

Results:

From 2000-2022, we found overall stable forest cover in both classifications of open forest and dense forest (Figure 5 and 6). Both forest types experienced stable forest ecosystems with only a few outlier years of deforestation or afforestation. Agriculture (Figure 7) had stable growth, increasing 26% since 2000. Water (Figure 8) remained stable while other (Figure 9) experienced a steady decline since 2000.

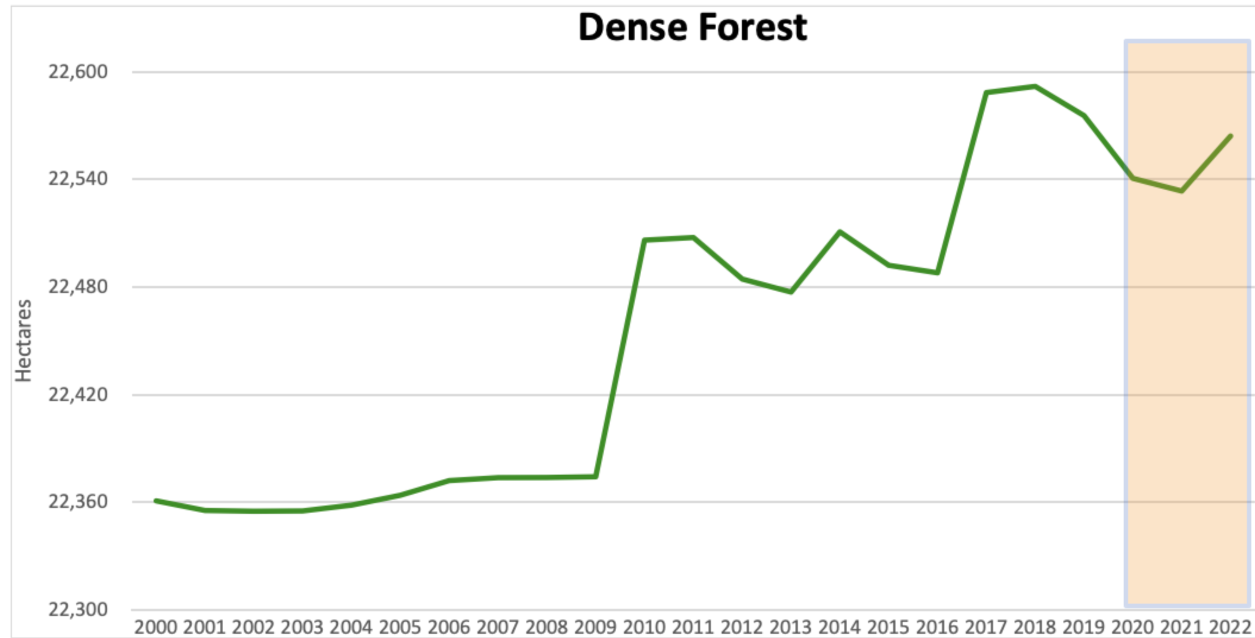

Figure 5. Dense forest canopy cover measured in hectares from 2000-2022. Dense forest increased 0.9% (203 ha) since 2000.

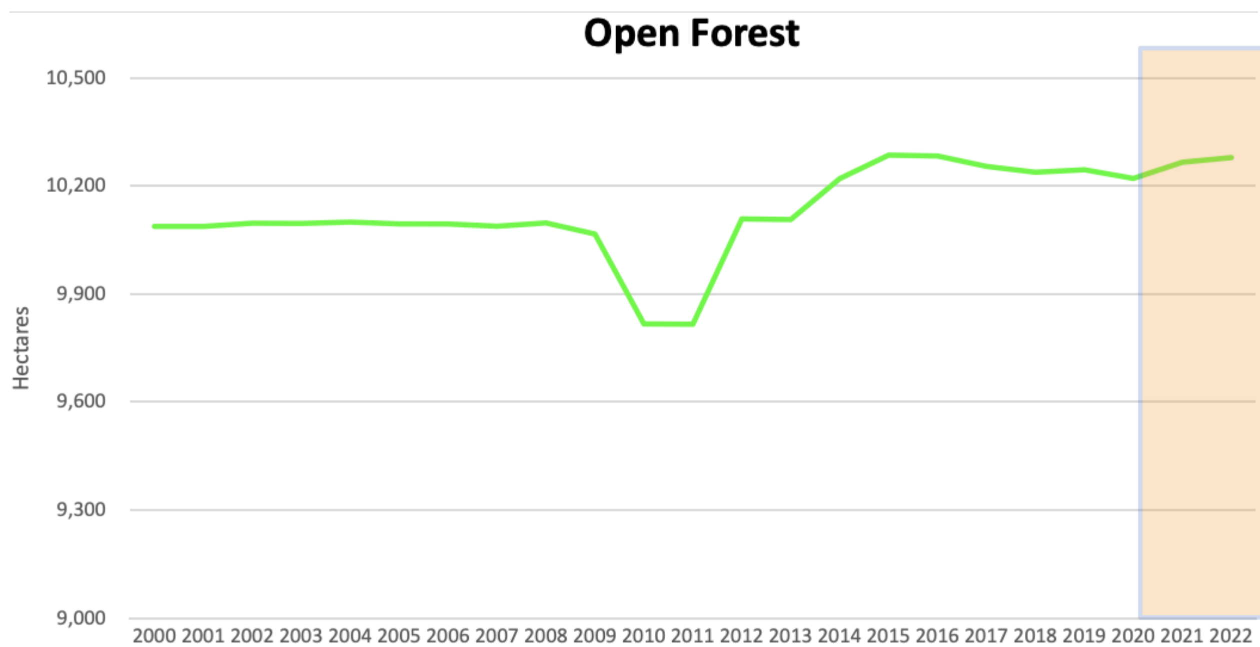

Figure 6. Open forest canopy cover measured in hectares from 2000-2022. Open forest increased 1.9% (191 hc) since 2000.

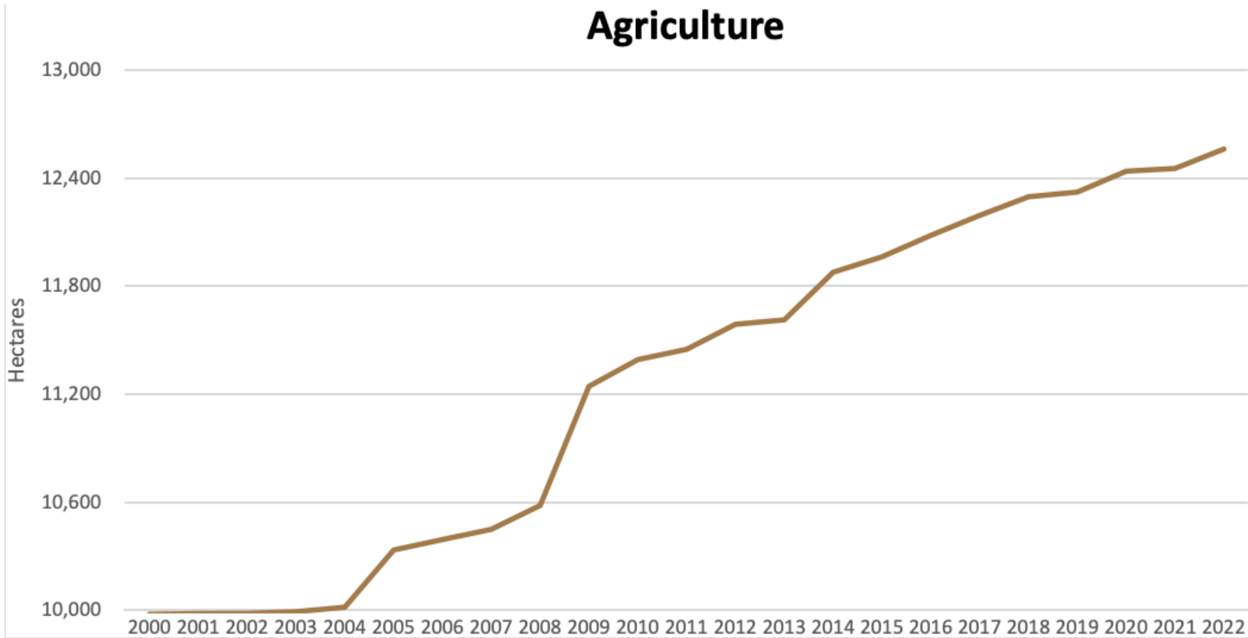

Figure 7. Agriculture experienced the largest growth in our land classifications from 2000-2022. Agriculture increased 26% (2,586 ha) since 2000.

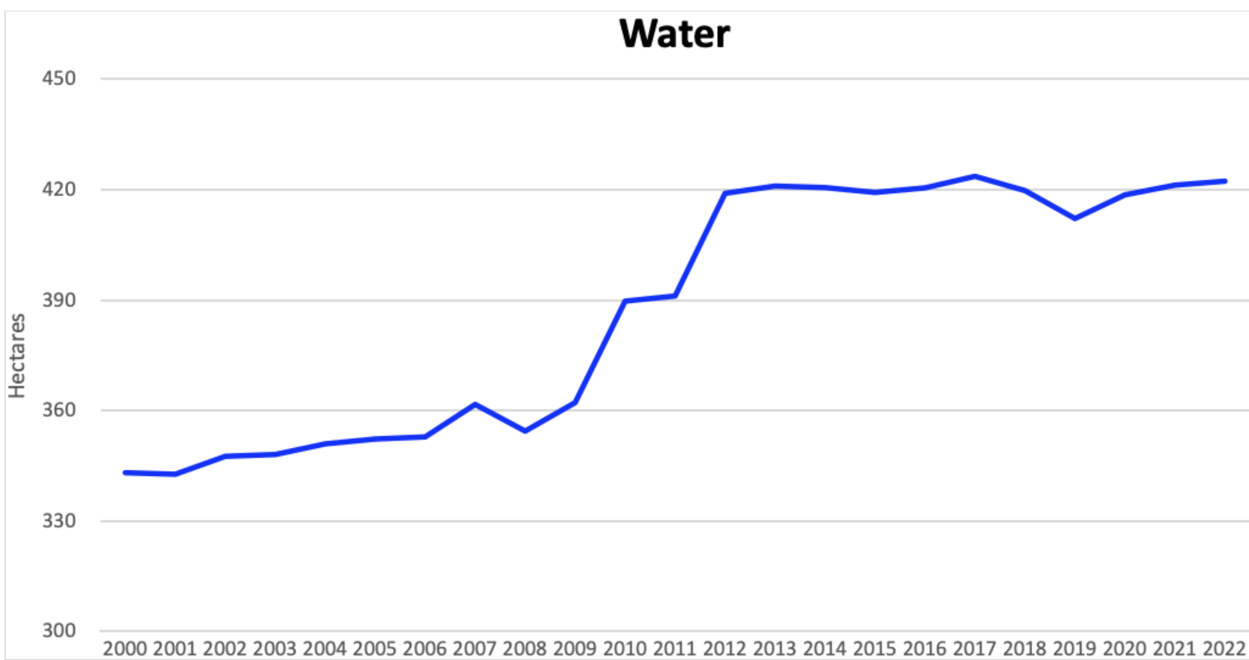

Figure 8. Water measured in hectares from 2000-2022. Water increased 23% (79 ha) since 2000.

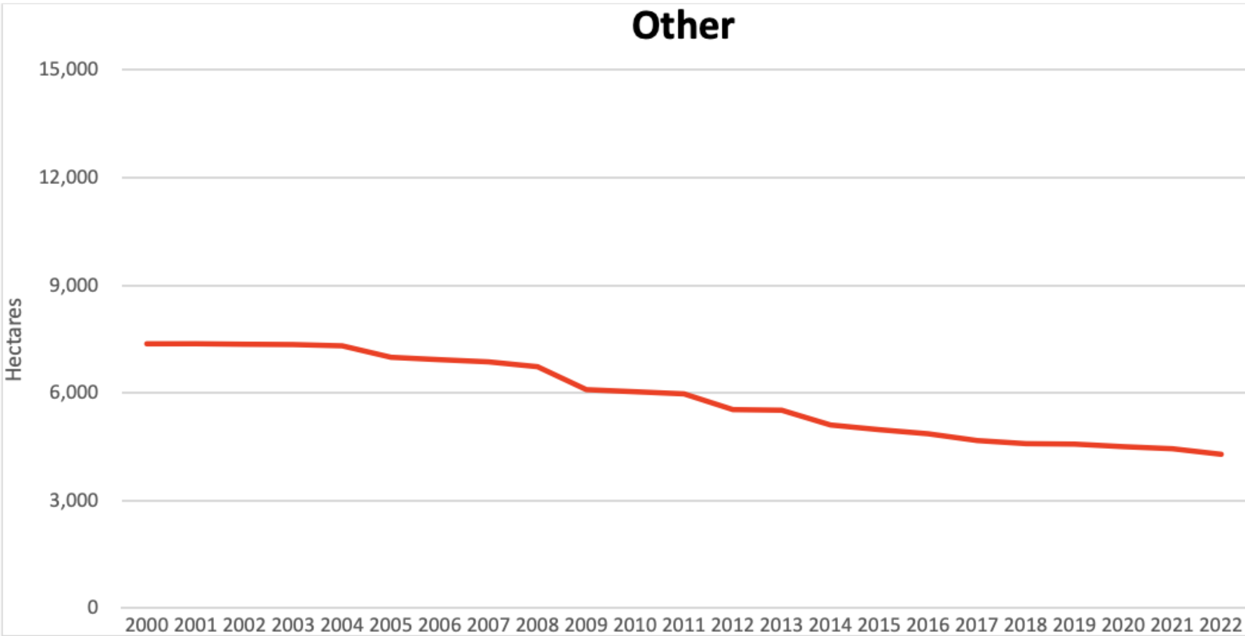

Figure 9. Other includes roads, buildings, mines, bare ground and everything else that didn't fit the other four land class categories. Other measured in hectares from 2000-2022. Other decreased 42% (3,080 ha) since 2000.

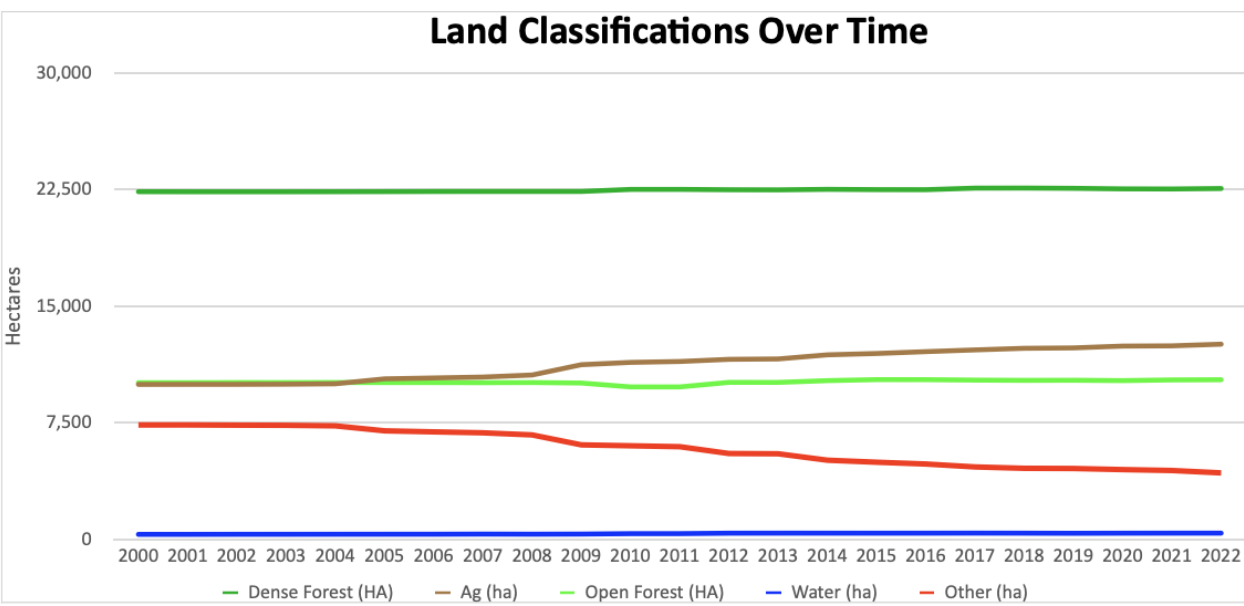

Figure 10. All land classifications in hectares from 2000-2022.

Table 2. Hectares per year for each of the five land classifications of our study site.

	Dense Forest (Ha)	Open Forest (Ha)	Agriculture (Ha)	Water (Ha)	Other (Ha)
2000	22,361	10,088	9,977	343	7,372
2001	22,355	10,087	9,981	343	7,373
2002	22,355	10,096	9,982	348	7,359
2003	22,355	10,096	9,991	348	7,350
2004	22,358	10,099	10,016	351	7,315
2005	22,364	10,094	10,334	352	6,995
2006	22,372	10,094	10,392	353	6,929
2007	22,374	10,088	10,449	362	6,868
2008	22,374	10,097	10,582	354	6,733
2009	22,374	10,066	11,244	362	6,094
2010	22,506	9,817	11,393	390	6,035
2011	22,508	9,816	11,450	391	5,976
2012	22,484	10,108	11,589	419	5,538
2012	22,477	10,106	11,614	421	5,520
2014	22,511	10,220	11,878	421	5,109
2015	22,492	10,285	11,964	419	4,978
2016	22,488	10,283	12,083	421	4,863
2017	22,589	10,254	12,194	424	4,676
2018	22,592	10,238	12,298	420	4,588
2019	22,576	10,245	12,324	412	4,575
2020	22,541	10,221	12,440	419	4,505
2021	22,534	10,266	12,455	421	4,446
2022	22,564	10,279	12,563	422	4,292

Dense Forests:

In 2022 dense forests made up exactly 45% of total land area for our study site. Overall dense forest cover went from 22,361 hectares in 2000, to 22,564 hectares in 2022 (Figure 5). Dense forests' largest positive change was from January 15, 2009 to January 15, 2010 where dense forest increased by 0.59% or 132 hectares. For the years before the pandemic (January 15, 2000 to January 15, 2020), the average percentage change per year was a positive 0.04%, which equals an average gain of 9 hectares per year. During the pandemic (January 16, 2020 – January 15, 2022) the average change per year was a positive 0.05%, which equals an average gain of 11.8 hectares per year. On January 15, 2021 there was a 7.1 hectare loss in dense forest when compared to the previous year, however on January 15, 2022 there was an increase of 30.7 hectares compared to the previous year. Overall dense forests experienced a slight loss of 7.1 hectares during the first year of the pandemic, however the second year experienced a gain of 30.7 hectares, creating a net positive of dense forest growth during the pandemic.

Open Forests:

In 2022 open forests made up 20.5% of the total land area of our study site. Overall open forest cover went from 10,088 hectares in 2000, to 10,279 hectares in 2022 (Figure 6). Similar to dense forests, the year from 2009 to 2010 saw the largest change per year with a loss of 250 hectares, which equals a decline of 2.54%. For the years before the pandemic (January 15, 2000 to January 15, 2020), the average percentage change per year was a positive 0.06%, which equals an average gain of 6.66 hectares per year. During the pandemic (January 16, 2020 – January 15, 2022) the average change per year was a positive 0.28%, which equals an average gain of 29 hectares per year. On January 15, 2021 there was 45 hectare gain in open forests when compared to the previous year and on January 15, 2022 there was an increase of 12.9 hectares compared to the previous year.

Agriculture:

Although our main concern is with forest classification, it's important to note changes to our other land categories, notably agriculture. Agriculture is the only land category that experienced significant fluctuations from year-to-year, averaging 117.6 hectares of agriculture gain per year from 2000-2022. It is also the only land category to continuously increase from year-to-year, never having a single year of decline. In 2022, agriculture made up 25.06% of total land area of our study site, which is up from 19.99% in 2000. Overall agriculture went from 9,977 hectares in 2000 to 12,563 hectares in 2022 (Figure 7).

Water:

In 2022 water made up 0.8% of the total land area of our study site. Overall water went from 343 hectares in 2000 to 422 hectares in 2022. The average gain per year from 2000 to 2022 was 3 hectares.

Other:

Our other category, which includes roads, buildings, bare ground, and everything else that doesn't fit into the previous classifications, steadily decreased from 2001 onwards. In 2022 other made up 8.6% of the total land area of our study site. Overall other went from 7,372 hectares in 2000 to 4,282 hectares in 2022. The average loss per year from 2000 to 2022 was 134 hectares.

Discussion & Conclusions:

The COVID-19 pandemic disrupted the lives and livelihoods of people around the world. Forests provide both timber and non-timber products that many people depend on for their livelihoods and survival (Saxena et al., 2021). Major disruptive events like forest fires, hurricanes, shifts in political parties, and clear cutting, can cause immediate impacts on forest ecosystems. A global pandemic like COVID-19 can greatly affect the supply chain of both timber and non-timber forest products. This makes the COVID-19 pandemic a great opportunity for research on how these disasters affect forests, forests' role as safety nets, and how these learnings could be applied in the event of future global disasters.

Our hypothesis was that there would be a significant shift in deforestation rates in our central India study site during the pandemic. This was based on emerging research at the start of the pandemic that indicated increased reverse migration, lack of forest monitoring, disruptions in supply chains, and the conversion of forest to agriculture. However as our data show, both dense and open forests remained relatively stable before and during the pandemic. Dense forests never deviated more than 0.59% change per year, open forests not more than 2.54% per year. The other classes like agriculture and other tell a different story. Agriculture steadily increased from 2001 onwards and by 2022 had increased 26%. Other declined steadily since 2001 as well and by 2022 had decreased 42%. As a reminder, other includes a variety of land classes including bare ground, developed areas such as houses and roads. It could be argued that there is a correlation between the gain in agriculture and the decline in other. Since dense forest and open forest numbers remain stable for the whole time duration, it is fair to say that agriculture didn't gain much from the removal of trees. We believe that bare ground was slowly converted to agriculture from 2001-2022.

Our specific region showed that forests can be resilient and protected in times of crisis. However the answer to our primary research question will likely vary depending on the region studied. As mentioned earlier, similar research done by Céspedes, et al (2022) showed that certain countries like Columbia and Peru had deforestation rates higher than historical trends, while countries like Brazil, Indonesia and the Democratic Republic of Congo did not deviate from projected.

Our goal was to (1) provide a simple, free and accurate method of remote sensing analysis that could be implemented for future research, and (2) to assess if deforestation rates changed during the COVID-19 pandemic in our central India study site. Additionally we leaned on existing research of forests' role as safety nets for rural, and often impoverished communities to see if forests acted as safety nets during the pandemic. So did forests act as a safety net in our MP study area? We are unable to fully answer that question based on remote sensing alone. However, if the forest-dependent communities around our study area did collect fuelwood in our site, it wasn't significant enough to detect with remote sensing. At the moment our results are limited to remote sensing alone and answering the single research question regarding forest cover change during pre vs post pandemic. As we have shown in the above results, there was no significant change in forest cover during the COVID-19 pandemic for our study area. For example with dense forest, the average percentage change per year increased only 0.01% during the pandemic when compared to the pre-pandemic years since 2000. For open forests, the average percentage change per year increased 0.22% during the pandemic when compared to the pre-pandemic years since 2000. Although open forests increased greater than dense forests, it is still under a quarter of one percent.

The results of this study will be coupled with the findings from survey and qualitative research about households' use of forests during the pandemic to better understand what was happening. For now we can only attempt to answer a part of that question through remote sensing analysis. Our research would be improved if we had more data capturing methods. For instance, additional household surveys at the other two sites, field pictures, LiDar, and additional local knowledge and gathering of rainfall data, could greatly improve this research, but some of these methods are costly.

There could be several reasons to explain why our forest remained largely unaffected by the pandemic. First, our study area surrounds and largely contains the Ratapani Tiger Reserve, which is a protected area of 318 square miles (Wikipedia, Ratapani Tiger Reserve). This area has been a protected wildlife sanctuary since 1976, which further supports why we see little forest change from 2000 to 2022.

The future of forests depends on our understanding of how global disasters, especially economic, can impact these critical ecosystems. The COVID-19 pandemic hopefully will be a once-in-a-lifetime experience, so the research was timely and ongoing. Creating resilient forests that act as safety nets is essential to our mutually beneficial relationship with nature. However this depends on the efforts of people, and we hope this case study highlights how that is possible.

CHAPTER 2

MANAGEMENT IMPLICATIONS OF RESEARCH

Management Implications of Research:

There are several management implications that arise from our research. First, by utilizing remote sensing, improvements can be made towards the United Nations Sustainable Development Goals (SDG) indicator 15.1.1, "*Forest area as a proportion of total land area*" and 15.2.1, "*Progress towards sustainable forest management*" (United Nations, Sustainable Development Goals, 2023). We outlined our methodology of using Google Earth Engine (GEE) in conjunction with high-resolution imagery from Norway's International Climate and Forest Initiative (NICFI) to create accurate land map assessments for any given day and year from 2000 to present. The NICFI images are available as an add-on tool within GEE and both programs are free, accurate, and easy to implement, which allows researchers across the globe to follow our methodology and make improvements. From our viewpoint, the Continuous Change Detection and Classification (CCDC) algorithm was highly accurate in predicting our five land class categories as described in the validation section of methods. Research published by Zhu & Woodcock (2014) which in comparison shows that the CCDC accuracy assessment results for detecting land change, have a "producer's accuracy of 98%, and user's accuracies of 86% in the spatial domain and temporal accuracy of 80%". Our results have various user's accuracies depending on the land class; however every class except other were above 88% user's accuracy. This accuracy along with simple methodology practices described, make it easy to implement for forest managers around the globe, however accuracy will vary based on location and application.

Second, we have previously discussed the forests' role as safety nets to support livelihoods of rural, forest-dependent communities. Although we can measure overall changes in forest cover on a temporal level and some signs of forest degradation (i.e. thinning of forest canopy), there are ground-level and below canopy vegetation that can't be measured by our remote sensing method alone. The remote sensing analysis needs to be supplemented with other ground level analysis that includes community preferences and activities. The larger research project that this thesis is a part of, is ongoing, and will contain more on the ground methods to better answer our primary research question. Additionally the larger research project has more research questions, objectives, and hypotheses then our single research question: **Did the COVID-19 pandemic lead to increased rates of deforestation when compared to the years since 2000?** Although we can talk about changes in forest cover for our study area over time and analyze pre-pandemic statistics vs pandemic statistics, we can't answer questions about forest use, if fuelwood and non-timber forest products collection habits were different during the pandemic, and other additional insights. These questions that demand quantitative data are being done by the bigger research project. We created household surveys, which as of this writing, have collected 429 in-person questionnaire responses from village residents around the Madhya Pradesh study site.

The surveys contain 80 questions. Additionally, local knowledge and developed relationships were fostered through thesis chair professor Alark Saxena, who grew up in the Madhya Pradesh (MP) state and also worked on forest personnel near the MP study site. Pictures and land observations were collected in the summer of 2022, in which some members of this thesis committee traveled and stayed near the MP study site. When all qualitative and quantitative data is collected and the full scope of the research is published for all three study sites in India, then we will better understand forests role as safety nets during the pandemic, if there were any significant changes in deforestation and forest degradation during the pandemic when compared to historical data. These findings can have future implications on forest management practices during times of crisis, forests' role at providing economic relief in these times of instability, best practices for maintaining healthy and resilient forest ecosystems, and finally the remote sensing methods to monitor forest loss or gain per year.

Our specific research study site in MP showed us that forests can be protected over long periods of time and even during an unprecedented global pandemic. A large part of our study region is in the Ratapani National Park, which has been a protected wildlife area since 1976, so it can partly be attributed to not only the efforts of forest personnel, but also the community that surrounds this forest area as a possible explanation for such stable forest cover for 22 years. Further research could be improved by interviewing forest personnel on management practices as well as obtaining budget data on the sale of fuelwood and non-timber forest products. Additionally the use of Light Detection and Ranging (LiDar) remote sensing method and use of drones could improve our research.

We hope that the methods and questions raised in this thesis promote further discussion and development of best practices for forest managers.

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