Ecological Restoration and Rural Livelihoods in Central India

Pooja Mukesh Choksi

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Abstract

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Ecological restoration has the potential to provide a multitude of benefits, such as conserving biodiversity and supporting natural-resources dependent livelihoods. Tropical dry forests (TDFs) occur in densely populated human- modified landscapes in the tropics and are susceptible to degradation, making them an important biome to restore when degraded. TDFs are also socio-ecological systems, where local people rely on the forest for subsistence and livelihoods and effectively manage them for desire outcomes. People's reliance on TDFs necessitates restoration projects to take into account more than biophysical and abiotic considerations when they are designed. In this decade of restoration, while there is the much-needed impetus to restore degraded land, to achieve enduring and just outcomes at large spatial scales, restoration projects need to more intentionally address local considerations, such as traditional land tenure systems and livelihood strategies, and goals such as socio-economic development. At the same time, to guide restoration efforts and realistically forecast the consequences of these efforts in the future, there is a need for rapid and accurate assessment tools to quantify the impact of restoration on biodiversity and people at several time steps. In **Chapter 1**, I use India, a country with high biophysical potential for restoration, as a case study to demonstrate a people-centric approach for identifying restoration opportunities. I find that there is a large overlap between areas of high biophysical restoration potential and high poverty, indicating potential and need to pursue restoration in a manner that addresses both ecological and social goals. In **Chapter 2,** I study a commonly adopted livelihood strategy, seasonal migration,

in forest-dependent communities in India. I find that households in more agricultural and prosperous districts experience lower rates of migration but are more sensitive to climatic variability than households in poorer districts. In **Chapter 3**, I examine the impact of ecological restoration of a tropical dry forest in central India (CI). I find no significant difference in the cumulative number of bird species detected, but a significant difference in bird communities across the sites. In the lower frequencies dominated by birds and insects, I find that restored sites were positively associated with acoustic space occupancy in comparison to unrestored and low Lantana density (LLD) sites. In **Chapter 4**, I study the combined socio-ecological outcomes of restoration in the same sites in CI. I find that in the absence of alternative, people rely on *Lantana camara*, an invasive shrub, for subsistence and livelihoods, in the form of firewood and farm boundaries. I do not find any significant effect of restoration or LLD on people's perception of ease of forest use, except for the distances covered for grazing, an important indicator of restoration success in this landscape. Finally, I also find that restoration is not associated with any significant changes in soundscapes in the higher frequency ranges dominated by insects and bats. Taken together, my chapters contribute to a greater understanding of the potential for restoration to meet social and ecological goals, the vulnerability of the livelihoods of people living on forest-fringes of TDFs to climate variability and expected and unexpected socio-ecological outcomes of restoration.

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Through countless discussions, my advisor, Prof. Ruth DeFries, taught me how to think about and approach a research question. She taught me how to write my first scientific paper and create robust sampling designs to test hypotheses. Most importantly, she reminded me to always ask, '*so what?'*. These are skills that I will carry with me wherever I go. My committee members, Prof. Meghna Agarwala, Prof. Arun Agrawal, Prof. Duncan Menge and Prof. Eleanor Sterling provided the most thoughtful comments on my work and helped plug every hole in my research idea. Through data collection during the several waves of covid-19, Prof. Meghna Agarwala remained available on the phone to help make several last-minute changes to my sampling design in order to get the minimum amount of data necessary to complete this dissertation, and for that I am extremely grateful.

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Dedication

To *didi*,

I wouldn’t be here if I wasn’t trying to be just like you

Introduction

Ecological restoration has the potential to provide a multitude of benefits, such as conserving biodiversity (Brancalion *et al* 2019, Crouzeilles *et al* 2016), especially specialist species with specific habitat needs (Hariharan and Raman 2021), supporting natural-resources dependent livelihoods (Erbaugh *et al* 2020) and to a limited extent, mitigating climate change (Griscom *et al* 2017, Cook-Patton *et al* 2021). Tropical dry forests (TDFs) are some of the most historically exploited forests and occur in densely populated human-modified landscapes in the tropics (Gillespie et al. 2012; Janzen 1988; Portillo-Quintero and Smith 2018), making them an important biome to restore when degraded (Powers 2022). TDFs often represent socio-ecological systems, where local people rely on the forest for subsistence and livelihoods and manage them for desired outcomes such as the availability of firewood, non-timber forest products (NTFPs) among other resources (Powers 2022). This reliance necessitates restoration projects to take into account more than biophysical and abiotic considerations when they are designed. In this decade of restoration, global agreements and sustainable development commitments such as the Bonn Challenge and the United Nations Sustainable Development Goals provide the much needed impetus to restore degraded forests and lands around the world (CBD 2010, UN 2010). However, to achieve enduring and just outcomes at large spatial scales, restoration projects need to more intentionally address local considerations, such as traditional land tenure systems and livelihood strategies, and goals such as socio-economic development. At the same time, given the magnitude of ongoing and planned restoration efforts around the world, to guide restoration efforts and realistically forecast the consequences of these efforts in the future, there is a need for rapid and accurate assessment tools to quantify the impact of restoration on biodiversity and people at several time steps.

In my dissertation, I assess (a) non-biophysical considerations to design restoration programs, (b) the socio-ecological impacts of ecological restoration and (c) livelihood strategies of people dependent on socio-ecological systems such as TDFs. Given the high biophysical restoration potential in India, the country's large restoration targets for the Decade of Restoration and the reliance of a large rural population on ecosystems like TDFs for subsistence and livelihoods, India makes an ideal study site to answer my research questions. At the spatial scale of the country, I first demonstrate a people-centric approach to help policymakers translate biophysical-centric global restoration prioritization studies for application to a country-specific context to balance the environmental and development agenda. I then zoom into the Central Indian landscape (CIL), spanning the states of Madhya Pradesh, Maharashtra and Chhattisgarh to understand a predominant livelihood strategy for TDF-dependent people. Understanding existing livelihood strategies can allow public and private entities to design effective economic and environmental interventions, which could indirectly help restore these forests (*e.g.*, DeFries et al. 2021). In order to upscale small restoration projects to a landscape scale, understanding outcomes of ecological restoration at a fine-scale is critical (Chazdon *et al* 2017). Therefore, finally, I further zoom into the TDFs in Mandla district in Madhya Pradesh to quantify the socio-ecological impacts of restoration. The applied research in my dissertation provides outputs and insights that restoration program managers, policy-makers and local NGOs and the forest department (FD) leading small-scale restoration efforts can implement.

In **Chapter 1,** I used India as a case study to demonstrate a people-centric approach to identifying restoration opportunities. India has a high biophysical restoration potential (Brancalion *et al* 2019, Griscom *et al* 2017, Strassburg *et al* 2020) and one of the largest Bonn Challenge land restoration targets of 26 million hectares by 2030. India also has a large proportion (64%) of a rural population, which relies on local ecosystems for livelihoods through small-scale agriculture and common pool resources, making a people-centric lens to restoration design and implementation necessary. In this analysis, I combine the biophysical restoration potential (as quantified in Strassburg et al 2020) to the living standards component of the multidimensional poverty index (Oxford Poverty & Human Development Initiative 2018) to identify people-centric restoration opportunities for 579 districts with complete datasets. Furthermore, I classify de jure land tenure regimes by aggregating village-level census data to identify prevalent land tenures. Land tenure is important for understanding who may have the authority to change land use. I found that there was a large overlap between areas of high restoration potential and high poverty (above 50th percentile for biophysical potential and poverty of 579 districts), indicating potential and need to pursue restoration in a manner that addresses both ecological and social goals. Similarly, a large proportion (168 of 579 districts) have low restoration potential in districts of low poverty levels (below 50th percentile for biophysical potential and poverty of 579 districts). By analyzing biophysical, socio-economic and land tenure data together, policy makers can devise restoration programs more holistically.

In **Chapter 2**, I study a commonly adopted livelihood strategy, seasonal migration, in forest-dependent communities in India. I quantified the relative sensitivity of a decision to migrate for the first time to climate and socio-economic variables and how the sensitivities vary for different segments of the population. To do so, I used existing data from a survey of 5000 households in 500 forest-fringe villages in the CIL to identify patterns of migration from 2013 to 2017. I then predicted the probability of first-time migration of a household member based on climate variables and household- and district-level characteristics. I found that households in more agricultural and prosperous districts experience lower rates of migration but are more sensitive to climatic variability than households in poorer districts. The probability of first-time migration from a household in the most prosperous district increases by approximately 40% with one standard deviation in mean maximum temperature or rainfall from the 1981–2017 mean. However, the probability of migration did not vary as a function of climatic variability for households in the poorest district. I attributed the difference in sensitivities to the greater dependence on agriculture and irrigation in more prosperous districts and poverty-driven dependence on migration regardless of the climate in poorer districts. Households investing remittances from migration in agricultural intensification could become increasingly sensitive to climate variability, particularly with water shortages and projected increases in climate variability in the region. Moreover, these finding are also important in the context of ecological restoration potential in this landscape, because the promotion of non-agricultural livelihood options and climate-resilient agriculture could the reduce sensitivity of migration to climate variability in the study region.

In **Chapter 3**, I zoomed into the TDFs in the buffer region of the Kanha National Park in Mandla district, Madhya Pradesh to examine the impact of ecological restoration of a tropical dry forest in central India. Here, the state forest department and a non-governmental organization work with local communities to remove an invasive shrub, *Lantana camara* (hereafter Lantana), in the forest, to assist natural regeneration, primarily for the purpose of improving access to forest resources for forest-dependent people. I used acoustic technology to examine the bird community composition and the acoustic space used (ASU) in the frequency range dominated by birds and insects (2-8k Hz) across statistically comparable restored, unrestored (with Lantana) and naturally low Lantana density (LLD) sites. I found no significant difference in the cumulative number of bird species detected, but a significant difference in bird communities across the sites. Furthermore, I found that restored sites were positively associated with ASU in comparison to unrestored and LLD sites, which could represent a temporary increase in ASU as animal communities are reorganized following the complete removal of Lantana. My results suggest that small-scale restoration efforts that aim to help meet livelihood needs have the potential to contribute to ecological goals in this landscape. However, given the short time since the first restoration effort in 2017, and the lack of ground truthing of acoustic data, it is necessary to monitor the trajectory of regeneration in restored sites and the possible changes in ASU in the next few years.

In **Chapter 4,** I study the combined socio-ecological outcomes of restoration in the same sites as those used for Chapter 3. I quantified the impact of Lantana invasion and subsequent restoration through Lantana removal on people's livelihoods and perceptions and vocalizing fauna. To do so, I carried out household surveys across the study sites and used acoustics in restored, unrestored, and reference, LLD forest sites. I found that a significantly higher proportion of respondents in villages near unrestored sites use Lantana as firewood and farm boundaries than the proportion of respondents in villages near restored and LLD sites. However, contrary to my expectations, I did not find any significant effect of restoration on variables representing increased ease of forest use such as shorter distances covered for grazing in the forest and lesser time spent collecting firewood, which we postulate is because of small spatial scales of restoration and slow regeneration in TDFs. Furthermore, I found that lower acoustic space occupancy (ASO), which represents the number of acoustic niches (frequency bins) which were occupied in a given period of time, in higher frequencies (9-24k Hz) is significantly associated with LLD sites, which may indicate the presence of a larger predatory community in these sites. However, this result could be due to increased signal scattering in dense vegetation in unrestored sites and not necessarily large differences in vocalizing fauna across sites. In sum, I found that in the absence of better alternatives, people rely on invasive species for their subsistence and livelihoods and that changes in the understory due to restoration do not have significant effects on ASO over a short period of time.

Considering the sum of all the parts of this dissertation, my findings shed light on (a) the potential for restoration to meet social and ecological goals, (b) the vulnerability of the livelihoods of people living on forest-fringes of TDFs to climate variability and (c) a few unexpected socio-ecological outcomes of restoration. My results indicate that some of the more resource dependent populations live in some of parts of India with high value for restoration. Further, my findings also suggest that people rely on inferior resources in their immediate surroundings in the absence of viable alternatives. I also demonstrate the complexities of novel ecosystems, where naturalized invasive species are generally negatively perceived but also become primary resources in the absence of alternatives (Hobbs et al 2009). In this context, restoration is complex, and would require restoration programs to provide alternatives to meet local people's resource needs in order to avoid negatively impacting local subsistence and livelihoods as forests regenerate due to restoration. The surprising results of the small differences in the soundscapes across the restored, unrestored and reference sites make a contribution to the small but growing body of research on the Acoustic Niche Hypothesis as acoustic technology becomes the preferred tool for rapid assessments for vocalizing fauna. The outputs of my chapters could help inform policy-makers to design restoration programs that balance several objectives including biodiversity conservation, forest regeneration and the welfare of local people.

Chapter 1: Combining socioeconomic and biophysical data to identify people-centric restoration opportunities

Pooja Choksi, Arun Agrawal, Ivan Bialy, Rohini Chaturvedi, Kyle Frankel Davis, Shalini Dhyani, Forrest Fleischman, Jonas Lechner, Harini Nagendra, Veena Srinivasan, Ruth DeFries

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Ecological restoration is a crucial nature-based solution for carbon sequestration and biodiversity conservation (Chazdon *et al* 2016). To fulfill targets of the Nationally Determined Contributions, the Bonn Challenge (The Bonn Challenge 2022) and land degradation neutrality (UNCCD 2022), research has identified areas of high value to restoration across the world based on biophysical characteristics (Bastin *et al* 2019, Brancalion *et al* 2019, Strassburg *et al* 2020). While global restoration studies and prospecting tools enable private and public entities to decide where to focus restoration efforts for maximum biodiversity and carbon sequestration value, they leave people off the map. Designing and siting successful restoration projects requires consideration and integration of socio-economic needs and cultural characteristics of local stakeholders. Although there is an increasing recognition that local people need to be engaged and their interests need recognition in the design and implementation of restoration projects (Erbaugh *et al* 2020, Fleischman *et al* 2022), there are few examples of systematic consideration of people's livelihoods and interests in restoration at large spatial scales (Chaturvedi *et al* 2022). Coarse socio-economic datasets cannot replace local consultations and needs assessments to ensure restoration projects provide benefits to local people. However, these data can be used as preliminary filters for different restoration methods. Here, we propose an explicit consideration of people's socio-economic needs through the combination of biophysical and socio-economic factors to identify people-centric restoration opportunities. We also assess the de jure land tenure system to identify which types of land could be targeted for more tenure-responsive, long-lasting and socially just outcomes (McLain *et al* 2021).

We use India as a case study as it has a high biophysical restoration potential (Erbaugh *et al* 2020, Strassburg *et al* 2020) and one of the largest restoration targets of 26 million hectares by 2030 (Binod *et al* 2018). A large proportion (64%) of India's population is rural and relies on local ecosystems for livelihoods through small-scale agriculture and common pool resources, making a people-centric lens to restoration design and implementation necessary. India's focus on socio-economic development through programs such as the Aspirational Districts Programme (Government of India 2018), emphasizes the need for the environmental agenda to align with the development agenda. For this analysis, we thus consider the living standards component of the multidimensional poverty as our socio-economic metric at the district level (N = 579 districts) to reflect dependence on natural resources. We choose this metric because people more dependent on natural resources for their subsistence and livelihoods are more likely to (a) be vulnerable to decisions made regarding land uses and (b) benefit from improved availability of natural resources in the short term. We compare this metric with the biophysical restoration potential (as quantified in Strassburg et al. 2020) to identify different socio-environmental conditions restoration programs must consider in order to balance environmental and social goals. Furthermore, we classify de jure land tenure regimes by aggregating village-level census data (Government of India 2011b) to identify prevalent land tenures. Land tenure is important for understanding who may have the authority to change land use. Although the biophysical restoration potential considered in this study refers to restoration without human disturbance (Strassburg *et al* 2020), we argue that such restoration is challenging and socially unjust in a country with high human population densities. Therefore, we define restoration as any activity which restores ecological functionality to degraded landscapes (The Bonn Challenge 2022), ranging from alternative agricultural and pastoral practices to natural ecosystem restoration.

We find that approximately 29% of districts (N = 166) with high biophysical potential are also above average poverty levels in India (above 50th percentile for biophysical potential and poverty of 579 districts; Fig 1.1, Fig 1.2 quadrant 1). Similarly, 30% (N = 168) of districts have both below average biophysical potential and below average poverty (below 50th percentile for biophysical potential and poverty; Fig 1.2, quadrant 3). This overlap indicates the potential and need to pursue restoration in a manner that addresses both ecological and social goals.

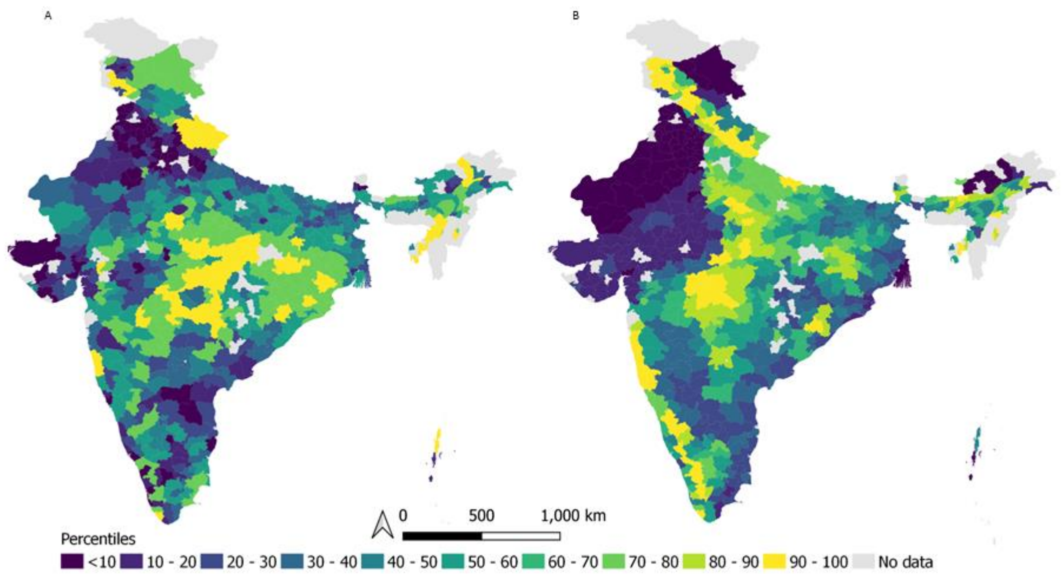

Figure 1. 1: Map of India displaying districts mapped according to variables considered in this study. (A)Living standards component of the Multidimensional Poverty Index and (B) Biophysical restoration potential (quantified by Strassburg et al. 2020). The colors represent the percentile range to which the districts belong.

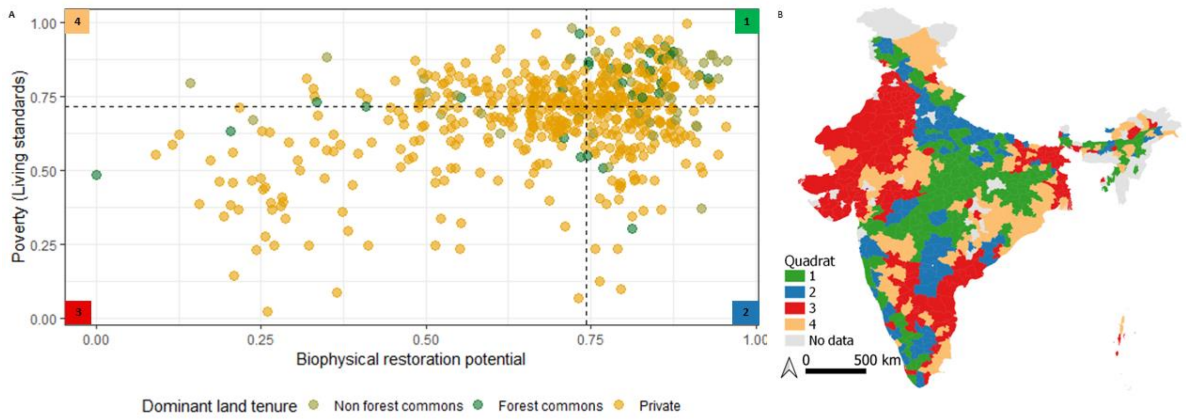

Figure 1. 2: A comparison of each district's biophysical potential and poverty level. (A) Districts plotted in reference to biophysical restoration potential and poverty measured by the living standards component of multidimensional poverty. Each district is presented as a circle. Colors represent the dominant land tenure in the district. Vertical and horizontal dashed lines represent the 50th percentile according to biophysical restoration potential and poverty. The numbers in the corner of each quadrant correspond to districts of the same color in (B)

In the majority of the 579 districts considered in this study, private land is the predominant land tenure, followed by non-forest commons, then forest commons (Fig. 1.3). Although recent restoration efforts have overwhelmingly focused on afforestation (Borah *et al* 2018, DeFries *et al* 2022), recent evidence indicates a larger climate change mitigation potential in alternative agricultural systems, such as agroforestry and trees outside forests (ToF), than in areas which are likely to be managed as closed-canopy forests (Gopalakrishna *et al* 2022). Furthermore, the disproportionate focus on carbon-centric forest-based projects has led to underrepresentation of projects aimed at reducing emissions of other greenhouse gases (GHGs) such as methane with enormous mitigation potential (DeFries *et al* 2022). Traditional agroforestry practices and ToF (*e.g.*, live fences, silvi-pastures, horti-pastoral systems) are common in India (Dhyani *et al* 2021) and could lower other GHG emissions. While it may be simpler to facilitate agroforestry among individual land holders with clear land titles; restoring degraded common lands may facilitate broader benefits, particularly among the poorest people who often don't own land or have a strong culture of common ownership (*e.g.*, pastoralist communities in Gujarat and Rajasthan). However, restoration of the commons can be complex when the source of degradation (*e.g.*, an invasive species), becomes a source of livelihood for a section of the local community (Nerlekar *et al* 2022).

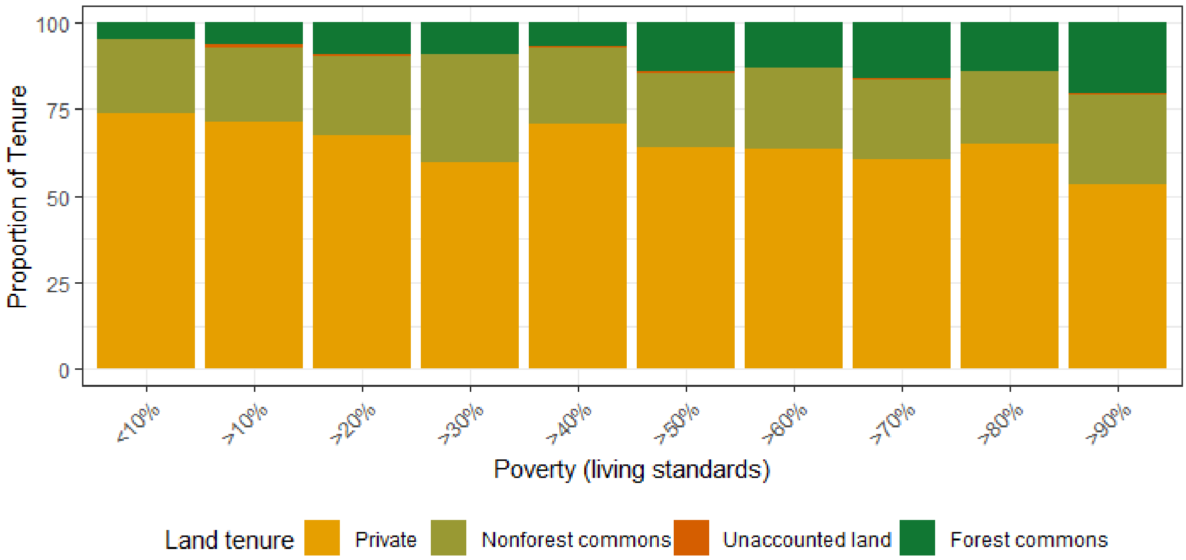

Figure 1. 3: The proportion of each land tenure in the 579 districts belonging to the ten percentiles in ascending order. Districts above 90th percentile are poorer than districts under the 10th percentile.

By analyzing biophysical, socio-economic and land tenure data together, policy makers can devise restoration programs more holistically. For example, ten of the fourteen poorest districts that have very high biophysical restoration potential (above 90th percentile in both restoration potential and poverty), have a predominance (> 50%) of non-forest (N = 8) and forest commons (N = 2). In districts above the 80th percentile in terms of both restoration potential and poverty, approximately 40% had a predominant land tenure of forest (N = 9) and non-forest commons (N = 9, total = 45 districts). It may be tempting to situate reforestation and afforestation projects, which are based mainly on plantation models (Borah *et al* 2018), in poorer districts with high value for restoration. However, emerging evidence shows that afforestation projects do not always increase forest cover (Coleman *et al* 2021), sometimes reduce pastoralist access to grazing lands (Ramprasad *et al* 2020), and do not contribute much to the local communities' needs for firewood and fodder (Coleman *et al* 2021). We argue that in districts with high biophysical restoration potential and high poverty, it could be more effective to (a) encourage traditional agroforestry practices, (b) leverage economic policies and schemes designed to raise living standards (DeFries *et al* 2021), (c) use alternative restoration practices, such as invasive species management in districts with a high proportion of common land and (d) allow for greater community rights to manage the commons (Lele *et al* 2020). For example, approximately 30% of the districts above the 80% percentile of both restoration potential and poverty are in Madhya Pradesh. Managing an invasive species, Lantana camara in forest and non-forest commons in that state increased the local communities' access to firewood and fodder (Borah *et al* 2018). Moreover, recent evidence from some of these districts shows that switching to alternative energy sources for cooking and use of durable housing materials raised living standards, as well as provided a safer cooking fuel option and contributed to forest regeneration near villages (DeFries *et al* 2021).

Similar evidence of forest regeneration with the adoption of biogas digesters in a district with high poverty but low biophysical restoration potential, such as Chikkaballapur in Karnataka, emphasizes the potential of human well-being policies to have positive ecological outcomes (Agarwala *et al* 2017). In districts with high biophysical restoration potential and low poverty, including Malappuram and Thrissur in Kerala, agroforestry and cash crop plantations, along with other livelihood alternatives, have played a role in alleviating poverty and increasing food security (Menon and Schmidt-Vogt 2022). These traditional agroforestry systems and private home gardens could continue to be supported and incentivized. Furthermore, novel tools such as Diversity for Restoration (D4R) help people select appropriate species for planting based on the outcomes they are interested in, such as erosion control (Fremout *et al* 2022). In regions with low poverty and low biophysical potential (both factors below 50th percentile), such as districts in Rajasthan and Gujarat, the predominant land tenure is private. These districts could be targeted for irrigation management to increase drought resistance and agri-pastoral projects which could simultaneously contribute to reductions in methane emissions (DeFries *et al* 2022, Dhyani *et al* 2021). With a considerable area of non-forest commons (>33.33% land tenure), pasture and open natural ecosystems (ONEs) restoration could also be beneficial to the numerous indigenous pastoralist communities in these states (Hughes *et al* 2022, Madhusudan and Vanak 2021). Moreover, ONEs would not necessarily store more carbon if afforested (Vanak *et al* 2017). Thus, preserving these non-forest ecosystems will not only benefit pastoralists but also conserve unique non-forest ecosystem biodiversity (Madhusudan and Vanak 2021, Vanak *et al* 2017). The interventions suggested in the four different socio-environmental conditions were not designed in the context of the relationship between biophysical restoration potential and poverty. Therefore, it is critical to understand the applicability of these interventions in the context of these different conditions, and the cost-effectiveness of these interventions to successfully scale them.

Our analysis has some limitations. First, the district administrative unit is a convenient spatial scale to plan interventions and programs. But we recognize that households are not socio-economically uniform and thus, restoration programs will not have uniform effects in a district. As an example, agroforestry programs can have very different food security outcomes for people who own land and those who do not. Second, the analysis carries inherent uncertainties found in the data sources.

This study attempts to demonstrate a people-centric approach to translating global biophysical restoration potential studies for application to a country-specific context, rather than prescribing restoration priorities. Based on a country's development and environmental agenda, the variables used to determine the different socio-environmental conditions may be different. An analysis of this nature can help policy makers and an emerging diversity of actors in the field of ecological restoration broadly filter restoration methods best suited for different socio-environmental conditions.

1.1 Materials and Methods

Data sources and preparation:

Land uses and de jure land tenure regimes: We aggregated the most recent publicly available census data (2011)(Government of India 2011b) at the village level to the district level to quantify the de jure land tenure regimes that include individual land, common non-forest land and forest land. For this study, we consider 579 districts for which we had a complete dataset, including the data on poverty and biophysical restoration potential. From the census data, for every village, we extracted the data listed in Table 1.1 (column 2) as well as a column named 'Total area in hectares' that provides the total of all land use and land cover categories. We categorized the land use data available at the census village level into the following *de jure* land tenures:

Table 1. 1: ***De jure*** **land tenures for land cover and land use categories in the Census 2011 records.**

Land tenure regime	**Land use and land cover categories from Census 2011**
Private land	1. Net sown area 2. Current fallow land 3. Fallow lands other than current fallows
Common non-forest land	1. Culturable wastelands (grasslands) 2. Area under non-agricultural use 3. Barren or uncultivable land 4. Permanent pastures or grazing lands 5. Land under miscellaneous tree crops (orchards)
Common forest land	Forest

In order to only include inhabited census villages, we removed census villages with zero as total populations and those explicitly labelled ‘uninhabited’ in the village name. Further, we included only non-state owned land by filtering out the following categories of census villages:

Table 1. 2: Terms used to filter out state-owned land the Census 2011.

Type of state-owned land	**Terms used in the census village name**
Army owned land or firing range	*firing range*
Forest	*reserve, beat, block, forest, camp, range, gate, K.M.*

In order to report the total hectares of specific land uses and to calculate the proportion of *de jure* land tenures, we treated any inconsistencies in the original census land use data in the following manner:

Table 1. 3: Details of inconsistencies in Census 2011 data and treatment of the inconsistency.

Inconsistency in the land use records	**Description of the inconsistency**	**Potential reason for inconsistency**	**Treatment of inconsistency**
No land use/ land cover records	All land use and land cover columns show zero hectares but ‘Total area in hectares’ column has a positive value.	The census enumerators did not reach these villages	These villages were removed from the analysis.
Total areas in hectares reported not equal to total of all land uses/covers	‘Total area in hectares’ Column from Census 2011 records not equal to actual total hectares of all land uses and land covers. There are two possibilities:	Error in addition of land uses by census enumerator or land use is currently disputed.	1. We considered the total of all land uses and land covers to calculate the proportion of land tenure for a village. 2. We created a variable ‘*Unaccounted land*’

	a: Total area in hectares > Total of all land uses or b. Total area in hectares < Total of all land uses		= (Total area in hectares - Total of all land uses and land covers)
Total area in hectares is reported as zero but land use records exist	All land use and land cover columns have a positive value in hectares but ‘Total area in hectares’ column is zero	Error in addition of land uses by census enumerator.	We considered the total of all land uses and land covers to calculate the proportion of land tenure for a village.

Living standards component of the multidimensional poverty index: Our study used one dimension (living standards) of the three dimensions of the multidimensional poverty index (living standards, health and education) (Oxford Poverty & Human Development Initiative 2018). We chose to only look at the percent contribution of living standards to poverty in a district because education and health services are provided largely by the government and may not necessarily reflect poverty due to the lack of viable livelihood options. For 579 districts, the percent contribution of living standards to multidimensional poverty ranged from 18.2% to 56.7%. We scaled this percentage from 0 to 1 to ensure that we could make a fair comparison with the biophysical potential for restoration taken from Strassburg et al. 2020. We split the districts into 10 percentiles based on their value, with values closer to zero indicating higher living standards and 1 denoting lower living standards or higher levels of poverty (Fig. 1.1A).

Biophysical potential for restoration: We used the spatial data from Figure 1(e) from Strassburg et al. 2020, which considers the ecological restoration potential of countries around the world based on the biodiversity conservation and climate change mitigation potential that a location holds while considering the cost of land. In R computing software, using the packages *raster* and *rgdal,* we clipped the map of the restoration potential of the districts in India to compute the mean biophysical restoration potential of a district. The values of the original dataset ranged from 1 to 20, denoting 5% increments in restoration potential. We rescaled the values from 0 to 1 to make a fair comparison with the living standards component of the multidimensional poverty index. We split the 579 districts into 10 percentiles for presentation (Fig. 1.1B).

All maps in this study were created using QGIS version 3.16.8 (QGIS Development Team 2022)

Chapter 2: Sensitivity of seasonal migration to climatic variability in Central India

Pooja Choksi, Deepti Singh, Jitendra Singh, Pinki Mondal, Harini Nagendra, Johannes Urpelainen, Ruth DeFries

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2.1 Introduction

Many studies identify extreme climatic events and variability associated with climate change as 'push' factors for permanent migration, especially in low-income countries (Thiede *et al* 2016, De Longueville *et al* 2019, Missirian and Schlenker 2017, Islam and Hasan 2016). Climatic variability and extreme events affect patterns of migration in different ways. For example, various studies in different locations show that extreme precipitation events are associated with short-distance migration (Bohra-Mishra *et al* 2017, Warner *et al* 2012, Sedova and Kalkuhl 2020). A rainfall deficit is linked to higher internal and international migration out of regions dependent on rain-fed agriculture (Leyk *et al* 2017, Abel *et al* 2019, Gray and Mueller 2012, Nawrotzki *et al* 2017). Positive temperature anomalies and gradual temperature increases are significantly correlated with the increase in migration (Missirian and Schlenker 2017, Mueller *et al* 2014, Kaczan and Orgill-Meyer 2020, Mastrorillo *et al* 2016).

It is well established that agricultural dependency influences the climate- migration relationship, especially in rural landscapes (Hoffmann *et al* 2020, Sedova and Kalkuhl 2020, Viswanathan and Kumar 2015). While agricultural land is a physically immovable asset, lowering the likelihood of migration is some cases (Gray and Mueller 2012, Thiede and Gray 2017); higher dependence on agriculture may also increase the exposure of a household to climatic variability (Gray and Bilsborrow 2013). Climatic variability and adverse shocks are associated with reductions in agricultural yields and incomes (Asseng *et al* 2015, Burgess *et al* 2014). For example, an increase of one standard deviation (SD) in a warm spell duration increases the odds of migration by 15% of rural Mexicans, primarily dependent on subsistence farming or agricultural employment (Nawrotzki *et al* 2015). In Bangladesh, Carrico and Donato (2019) find there is a significant increase in the probability of internal migration for the first time from agricultural households when experiencing one SD increase in a dry spell duration (Carrico and Donato 2019). Non-agricultural households, in contrast, remain largely unaffected by dry spells (Carrico and Donato 2019). Similarly, Sedova and Kalkuhl (2020) note that negative precipitation anomalies only significantly impact rural agricultural households and not non-agricultural households in India, encouraging the urban-bound migration of a household member (Sedova and Kalkuhl 2020).

Despite the sensitivity of agricultural yield to climatic variability, agriculture is generally considered a common pathway out of poverty. Mainstream developmental policies and welfare schemes promote agriculture and agricultural intensification as a way to alleviate poverty especially amongst rural, and often forest-dependent populations (Bezemer and Headey 2008, World Bank 2008, Miller and Hajjar 2020, OECD/ICRIER 2018). Interestingly, several studies find that migrants invest in agricultural land and agricultural transformation practices when they accumulate wealth from migration over years (Chiodi *et al* 2012, Damon 2010, Redehegn *et al* 2019). For example, in rural Mexico, the proportion of agricultural land, both irrigated and non-irrigated, significantly increases with a migrant in a household over a decade (Chiodi *et al* 2012). In rural Ethiopia, a percentage increase in remittances from migrants is associated with a 0.11-hectare increase in landholding and a significant increase in agricultural income back home (Redehegn *et al* 2019). While agriculture has had a positive impact on poverty reduction for the poorest and most vulnerable societies in the recent past (Ligon and Sadoulet 2018, Christiaensen and Martin 2018, Diao *et al* 2010), with expected future increases in climate variability, it is crucial to evaluate rural livelihood strategies in the context of climatic variability.

A primarily agrarian nation, India is at the forefront of risks from climate change (OECD/ICRIER 2018). In recent decades there is a trend of higher maximum temperatures in comparison to the past (Joshi *et al* 2020). While parts of India have seen a mean decline of 10% in precipitation in the last 65 years, there has also been a 75% increase in the frequency of extreme precipitation events (Roxy *et al* 2017). Projections indicate increasing heat stress and a weakening summer monsoon, which is crucial for water security in parts of the country (Joshi *et al* 2020, Roxy *et al* 2015). Additionally, the sub-seasonal and inter-annual precipitation variability of the monsoon is also projected to increase (Mishra *et al* 2021, Katzenberger *et al* 2020, Singh *et al* 2019). India's increasing climatic variability leaves a vast population, especially those engaged in agriculture, highly vulnerable to livelihood losses (OECD/ICRIER 2018).

Due to spatial and social disparities in economic development, livelihood options in rural Indian landscapes are often limited (Mosse *et al* 2002, Deshingkar *et al* 2008, Sah and Shah 2005). Seasonal migration (defined as the absence from one's place of residence for up to six months a year; Keshri and Bhagat 2013) is a common livelihood strategy amongst socially vulnerable groups in India (Sanyal and Maity 2018, Srivastava 2019, Dodd *et al* 2016, Sah and

Shah 2005, Keshri and Bhagat 2013). Approximately 83% of seasonal migrants recorded in the National Sample Surveys (2005, 2010, 2012) belonged to socio-economically disadvantaged communities officially recognized in India (Srivastava 2019). While seasonal migration is common in India, people often migrate in distress rather than aspirational reasons, such as skills development or wealth accumulation (Warner *et al* 2012, Baquié *et al* 2021, Sah and Shah 2005, Deshingkar *et al* 2008, Dodd *et al* 2016). Rapid economic development in the country in the recent past has created a large demand for seasonal migrants, especially in the construction sector in urban and peri-urban areas (Srivastava and Sutradhar 2016, Srivastava 2019). However, migrants work in harsh conditions and live in unsafe makeshift accommodations (Srivastava and Sutradhar 2016, Adhikari *et al* 2020). Further, migrants are often part of informal labor markets, which do not provide adequate financial compensation and other employment benefits (Srivastava and Sutradhar 2016, Sanyal and Maity 2018).

The covid-19 pandemic has brought to light the dire living and working conditions of seasonal migrants in India (Srivastava 2019, Adhikari *et al* 2020). The financial slow-down due to lockdowns in Indian cities has compelled panicking migrants to return to their homes from urban areas in the first and second waves of covid-19 (Jazeera 2020, WSJ 2021, Irudaya Rajan *et al* 2020). As a result, we can expect that rural households will re-evaluate their livelihood strategies. As evidence emerges from other countries, we can also expect an increase in dependence on agriculture, and agricultural transformation and intensification practices amongst households that once had migrants (Fox *et al* 2020). In the recent past, agricultural technologies, such as irrigation, have indeed allowed households in India to increase agricultural yields and reduce dependence on migration remittances (Zaveri *et al* 2020). However, the agricultural pathway out of poverty is complex due to its links to a changing climate. In this light, the effectiveness of rural development policies and welfare schemes relies on understanding evolving livelihood strategies and the sensitivity of sections of a population to climatic variability.

Using central India as a study system, this analysis addresses a rural household's decision to adopt migration as a livelihood strategy in relation to climatic variability, household-level socio-economic characteristics, and surrounding livelihood options reflected in district-level poverty indices. We focus on the Central Indian Landscape (CIL) because it experiences a high amount of inter-annual variability in the summer monsoon (Singh *et al* 2019), has a large proportion of households with members who migrate seasonally (Baquié *et al* 2021), and is one of the poorest regions of the country.

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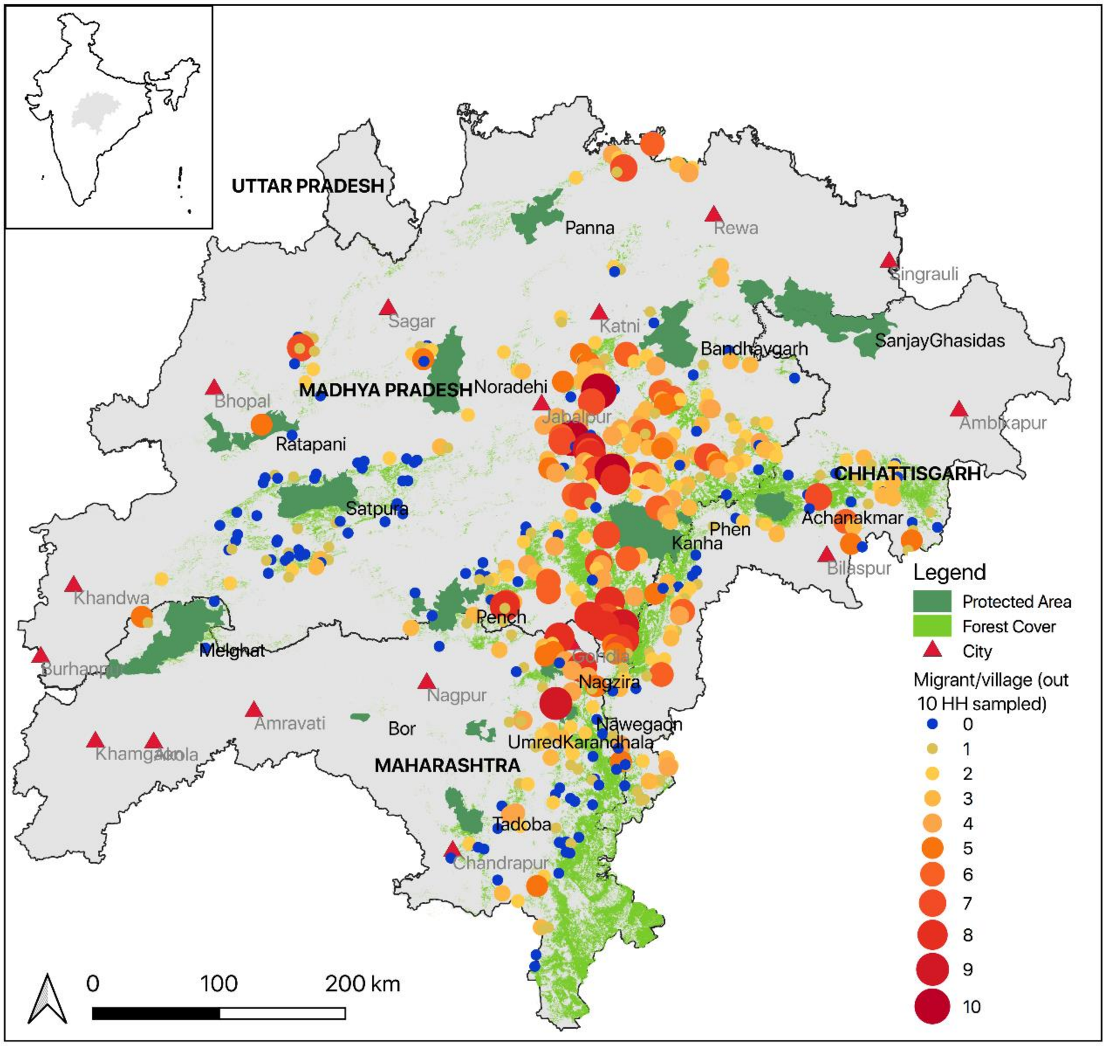

Figure 2. 1: Map of the Central India Landscape. The colour and the size of the circles represent the proportion of households (out of a maximum of 10 households) with at least one seasonal migrant.

Focusing on the CIL (Fig. 2.1), for the time period between 2013 and 2017, we ask the following questions: (1) what is the relative sensitivity of a household's decision to send a member to migrate for the first time to climate anomalies and household and district characteristics?; and (2) how does this sensitivity vary for different segments of the population?

2.2 Methods and Materials

Study Area

We define the CIL as 32 administrative districts spread across the states of Madhya Pradesh (MP), Maharashtra, and Chhattisgarh (Fig. 2.1). The CIL is home to one of India’s largest tribal populations, predominantly the Gond and Baiga tribes. Approximately 22% of the population belongs to an officially recognized Scheduled Tribe (Government of India 2011a). The region is predominantly rural, and approximately 37% of the villages in the region are forest fringe villages (defined in this study as villages within 8 kilometres of a patch of forest >500 hectares). Many tribal populations are either landless or hold small plots of agricultural land (Velho *et al* 2018, Neelakantan *et al* 2020).

Livelihoods in the CIL

While livestock rearing, fishing, and collection of non-timber forest products were primary livelihoods in the latter half of the last century, forest-fringe village economies in several central Indian districts have shifted to more intensive agriculture (Deshingkar *et al* 2008). Due to the lack of livelihood options in less prosperous districts, migration is an important source of income particularly for scheduled castes and tribes (Deshingkar *et al* 2008, Deshingkar and Akter 2009, Baquié *et al* 2021, Sah and Shah 2005). In households with migrants, up to half of a household’s total income may be derived from migration for mainly non-farm sector work (Deshingkar *et al* 2008). Depending on when a household member migrated for the first time, migration may allow poorer households to ‘catch up’ with richer ones by clearing debts and through wealth and asset accumulation (Deshingkar *et al* 2008, Deshingkar and Akter 2009, Baquié *et al* 2021).

Climatic variability in the CIL

The CIL is mainly dependent on rain-fed agriculture (Davis *et al* 2019). Moreover, agricultural technologies, such as canal and groundwater irrigation, are also dependent on the summer monsoon and thus impacted by variability in precipitation and temperature (Zaveri and B. Lobell 2019, Jain *et al* 2021). In the recent past, the CIL has experienced large climatic variability (Figure 2). There has been a weakening of the summer monsoon (Roxy *et al* 2015, Singh *et al* 2019) and an increase in the frequency and duration of heatwaves in the CIL from 1901 to 2012 (Roxy *et al* 2015).

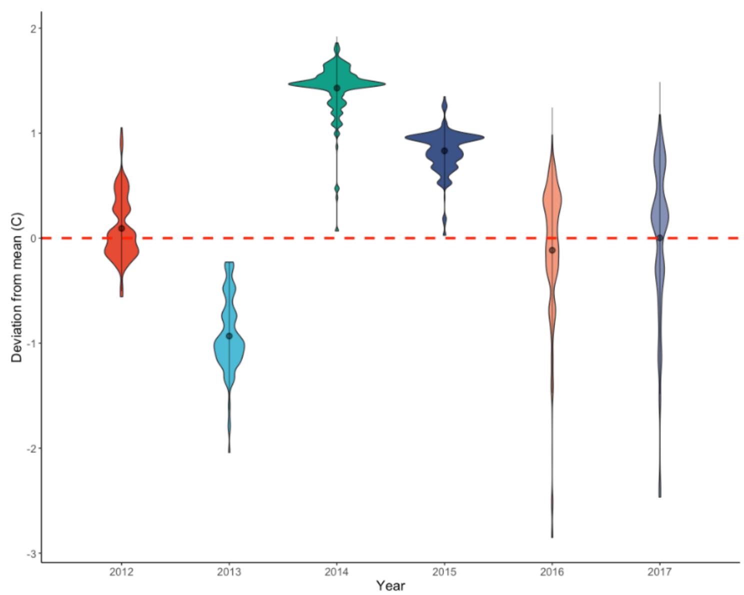

Figure 2. 2: Violin plots representing the deviation from the long-term (1981 to 2017) mean maximum temperature in the summer monsoon. The monsoon months are June, July August and September. The plots represent data from 2012 to 2017 across 476 surveyed villages of this study. The mean maximum temperature of 476 villages for every year is represented by the black dot on each of the violin plots. The density and distribution of the deviations from the mean are depicted by the breadth and length of each violin plot. Temperature data was derived from Climate Prediction Center (https://www.cpc.ncep.noaa.gov/).

In the next four decades, the CIL is projected to experience an increase of 1.92 degrees Celsius relative to 1976- 2005 in annual mean surface temperature (Scenario: Representative Concentration Pathway 4.5) (Krishnan *et al* 2020). Projections indicate uncertainty in the seasonal mean precipitation but an increase in inter-annual variation in precipitation during the monsoon season (Krishnan *et al* 2020, Singh *et al* 2019, Katzenberger *et al* 2020).

Household Survey Data

This study examines seasonal migration in rural populations in forest-fringe villages. From January to April 2018, we surveyed ten households each across 500 villages in the CIL, irrespective of the total population of the village. Each survey lasted approximately 45 minutes and included questions about household members who have migrated for work, the duration and destination of their migration, and a household's socio-economic characteristics. We selected the years 2013 to 2017 for this study because the survey questions about the first year of migration relied on the respondent's ability to recall past events, which are less reliable over longer time periods. Baquie et al (2020) provide details of the sampling strategy and survey.

Of the 5000 households surveyed, approximately 18% of the surveyed households (889 households) had at least one migrant. For this study, we examined 4323 surveyed households (SI Table 1), of which 418 households had first-time migrants between 2013- 2017 (Figure 3). Migration, as per our survey, is predominantly seasonal (SI Fig.1). 92% of migrants across 418 households migrate for 3 months or less. Approximately 66% of all the migrants in this survey engage in unskilled labor, such as daily wage labor, brick making, and industry jobs (SI Fig. 2).

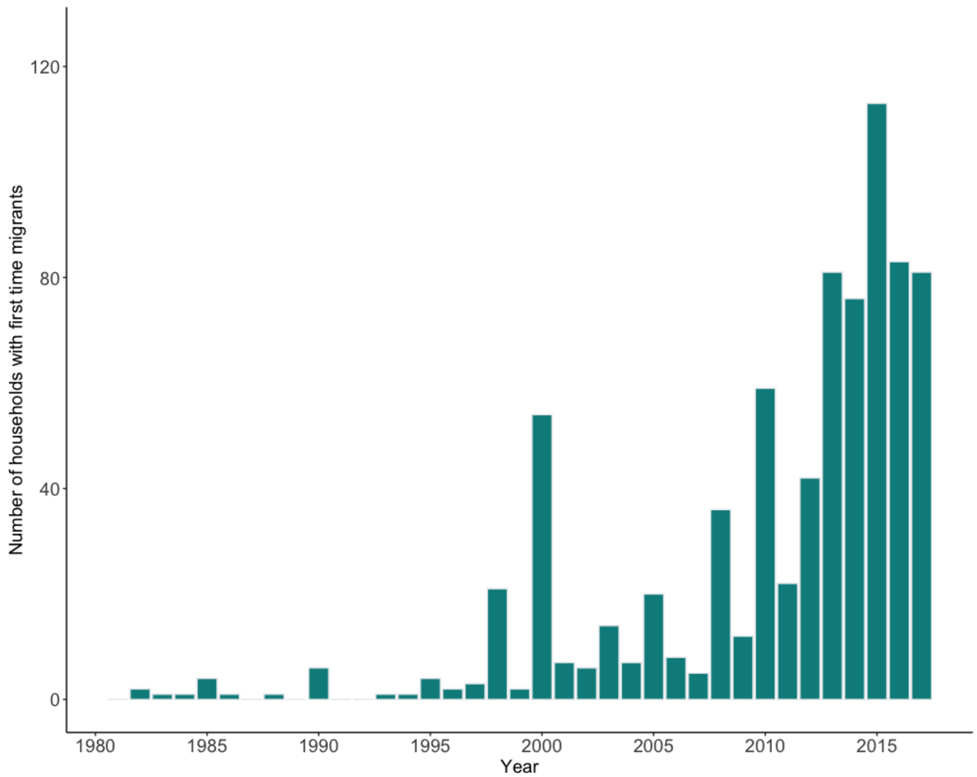

Figure 2. 3: Number of first time migrants from 4323 households across 476 villages in every year since 1981. Due to reliability of recall, we only consider first-time migrants from 2013 to 2017 in this study. Data derived from household survey.

The survey displays the fairly homogenous group of people living in forest-fringe villages in the CIL. For example, 78% of the respondents surveyed were not educated beyond secondary school, and approximately 96% of households identified as scheduled caste or tribe or another backward caste (official government designations). Approximately 62% of the households considered agriculture their primary occupation, which is likely combined subsistence and market-oriented agriculture given small landholding sizes (mean = 2.64 acres ± 4.37 acres). An additional 26% engaged in agriculture as their secondary occupation during the summer monsoon. Only 28% of the households had access to irrigated land in 2013 and 2018.

Outcome and Predictor Variables

Based on previous studies, we included socio-economic variables at the household, village, and district levels as predictor variables (Deshingkar *et al* 2008, Keshri and Bhagat 2013) (Table 2.1). The response variable is binary – whether the household had a first- time seasonal migrant in a particular year considered in this study (2013- 2017) or not. We control for household size, debt and education.

At the district level, the multi-dimensional poverty index (MPI) is an indicator of the overall poverty and access to education and health facilities in the household's location (Oxford Poverty and Human Development Initiative 2020) (SI Fig. 3 and SI Table 2). The MPI considers ten indicators of poverty across the three dimensions – health, nutrition, and living standards: child mortality, nutrition, years of schooling, school attendance, cooking fuel used in a household, sanitation, availability of drinking water, availability of electricity, state of a house (mud or cement house) and assets a household owns (Oxford Poverty and Human Development Initiative 2020).

At the village level, we accounted for spatially uneven economic development by including the distance to a Class I city (population>500,000) in the model (Asher *et al* 2019), as over 85% of the migrants seasonally migrate to Class I cities. Given the significance of agriculture in the region, we considered climatic variables for the summer monsoon period only (June to September; SI Table 3). Based on previous literature, we selected commonly used climatic indices descriptive of trends in temperature and precipitation (Mondal *et al* 2015). We used the Climate Hazards Group InfraRed Precipitation and Station Data (CHIRPS) for precipitation indices (Funk *et al* 2015). Temperature data was derived from the Climate Prediction Center (CPC; https://psl.noaa.gov/). We calculated the standard deviation (SD) for each climatic variable for the years 2013 to 2017 relative to the long-term mean (1981-2017). Due to the high co-linearity of climatic variables (SI Fig. 4a), we tested individual climatic variables in pairs to capture a lag effect (the climatic variables for the current and previous year) in the mixed-effects logistic regression model and chose the model using the climatic variables with the lowest AIC value (SI Table 4). Continuous variables were scaled and centred to create the z score to be used to estimate the statistical model (R Development Core Team 2019). All analyses were carried out in R software (version 3.6) (R Development Core Team 2019).

Table 2. 1: Summary statistics of independent variables considered in the model for this study.

Covariate	Abbreviation	Unit	Mean	SD	Mean	SD	Source
			Migrants (N=418)		**Non-migrants (N = 3905)**		
Education (Attended high school)	ED	1| 0	2.2%	NA	19.48 %	NA	Household questionnaire
Debt	DT	1| 0	1.64%	NA	12.21 %	NA	Household questionnaire
Irrigated land owned in 2013	IL	Acres	0.49	1.37	0.96	2.95	Household questionnaire
Household Size	HS	Number of individuals	5.48	2.16	5.34	2.30	Household questionnaire
Multi-dimensional Poverty Index	MPI	-	0.19	0.06	0.17	0.06	(Oxford Poverty and Human Development Initiative 2020)
Distance to Class 1 city	DC	Kilometre	108.73	39.55	112.96	36.9	(Asher *et al* 2019)
Mean maximum daily temperature variation in	MT	Standard Deviation	0.29	0.91	0.26	0.89	CPC

previous monsoon							
Mean maximum daily temperature variation in current monsoon	MT- PY	Standard Deviation	0.28	0.97	0.23	0.95	CPC
Total rainfall in current monsoon	TR	Standard Deviation	0.16	0.20	0.24	0.23	CHIRPS
Total rainfall in previous monsoon	TR- PY	Standard Deviation	0.42	0.16	0.49	0.19	CHIRPS

First- Time Migration Model and Expectations

With the variables listed in Table 1 we estimated a mixed-effects logistic regression model using the R package *lme4* (Bates *et al* 2015), for every year from 2013 to 2017 and for a panel-like dataset of the years combined (2013-2017). First-time migration of an individual *i* in a household was modelled for the combined years (Eq 1and 2) and for each individual year (Eq 3 and 4) as:

$$\text{Logit}(Y_i) = b_0 + b_1ED_i + b_2DT_i + b_3DC_i + b_4MPI_i + b_5HS_i + b_5IL_i + b_6MT\text{-}PY_i + b_7MT_i + b_8MT\text{-}PY_i{*}IL_i + b_9MT\text{-}PY_i{*}MPI_i + (1|v) + (1|t) \quad \text{(Eq. 1)}$$

$$\text{Logit}(Y_i) = b_0 + b_1ED_i + b_2DT_i + b_3DC_i + b_4MPI_i + b_5HS_i + b_5IL_i + b_6TR\text{-}PY_i + b_7TR_i + b_8TR\text{-}PY_i{*}IL_i + b_9TR\text{-}PY_i{*}MPI_i + (1|v) + (1|t) \quad \text{(Eq. 2)}$$

$$\text{Logit}(Y_i) = b_0 + b_1ED_i + b_2DT_i + b_3DC_i + b_4MPI_i + b_5HS_i + b_5IL_i + b_6MT\text{-}PY_i + b_7MT_{i+} b_8MT\text{-}PY_i{*}IL_i + b_9MT\text{-}PY_i{*}MPI_i + (1|v) \quad \text{(Eq. 3)}$$

$$\text{Logit}(Y_i) = b_0 + b_1ED_i + b_2DT_i + b_3DC_i + b_4MPI_i + b_5HS_i + b_5IL_i + b_6TR\text{-}PY_i + b_7TR_{i+} b_8TR\text{-}PY_i{*}IL_i + b_9TR\text{-}PY_i{*}MPI_i + (1|v) \quad \text{(Eq. 4)}$$

Where $Y_i = 1$ when a household has a first-time migrant in a specific year and $Y_i = 0$ when a household does not have a first-time migrant in a specific year. Terms b_1 to b_9 are model coefficients. ED, DT, DC, MPI, HS and IL are abbreviations for predictor variables. MT, MT-PY, TR and TR-PY refer to climatic variables, mean maximum temperature and total rainfall considered in the current and previous year respectively (Table 2.1). Because mean maximum temperature and total rainfall are co-linear (SI Fig. 4b), we run two separate sets of models with each climate variable. One set of models incorporates the mean maximum temperature in the current and previous year and the other set of models considers total rainfall in the current and previous year (Table 2.3 and SI Table 5). Terms $(1|t)$ and $(1|v)$ represent the random effects for the year, 2013 to 2017, and village, v respectively (Eq.1). We used the Wald-Z statistic, assuming a normal distribution, to compute the p-values for coefficient estimates and the confidence intervals around these estimates. Additionally, we estimated a model with an interaction term with the climatic variable in the current year instead of the previous year (SI Table 4).

The interaction between the variability in the mean maximum temperature (or variability in the total rainfall in the second set of models) in the previous year and the district's MPI explains the sensitivity of a household's local socio-economic conditions and access to education facilities to climatic variability. The second interaction, between the variability in the mean maximum temperature (or the variability in the total rainfall) in the previous year and the ownership of irrigated land, controls for the household level differences in their ability to cope with climatic variability (Skoufias *et al* 2017).

To quantify the sensitivity of different segments of the population to climatic variability, we computed predictions based on the interaction term of the variability in the mean maximum daily temperature (or total rainfall in the second set of models) and the district's MPI value using the R package *ggeffects* (Lüdecke 2018). We considered mean values for the predictor variables, distance to the city, household size and irrigated land to make the predictions. We assigned the value of zero to the binary variables, education and debt, to represent the majority of the population.

2.3 Results

Table 2.2 presents the results for the mixed-effects logistic regression models (individual year models in SI Table 5).

Table 2. 2: Mixed effects logistic regression model. These models use the variability in mean maximum temperature (Model 1) and variability in total rainfall (Model 2) for the combined data (2013-2017) with first-time seasonal migration as the response variable. Values represent the odds ratio for every predictor. 95% Confidence intervals calculated using fixed effects of the models given in parenthesis below estimates. Model results for single year models from 2013 to 2017 available in SI Table 5. Significance of a predictor: *** p< 0.001 ** p< 0.01 * p<0.05 +p<0.1

Odds Ration and 95% Confidence Intervals in parenthesis		
	Model 1	**Model 2**
Predictor Variable	**2013-2017**	**2013-2017**
Total rainfall in summer monsoon	NA	0.87** (0.79-0.96)

Total rainfall in summer monsoon in previous year	NA	0.84** (0.76-0.94)
Mean maximum temperature in summer monsoon	1.07 (0.97-1.19)	NA
Mean maximum temperature in summer monsoon in previous year	1.18** (1.05-1.31)	NA
Distance to city	0.85** (0.76-0.95)	0.86** (0.77-0.96)
Irrigated land owned	0.64*** (0.51-0.81)	0.67*** (0.54-0.83)
Household size	1.13* (1.02-1.24)	1.12* (1.02-1.24)
district MPI	1.45*** (1.28-1.63)	1.44*** (1.27-1.62)
Education	1.31* (1.03-1.67)	1.30* (1.02-1.66)
Debt	1.38* (1.05-1.81)	1.38* (1.05-1.81)
Mean maximum temperature in previous year*MPI	0.91^{+} (0.82-1.02)	NA
Mean maximum temperature in previous year*MPI	0.79* (0.66-0.95)	NA
Total rainfall in previous year*Irrigated land owned	NA	1.10^{+} (0.99-1.23)
Total rainfall in previous year*Irrigated land owned	NA	1.17^{+} (0.99-1.38)
N	20790	20790
Villages (groups)	476	476
Years (groups)	5	5
AIC	4000.5	4000.0

Consistent with previous studies (Warner *et al* 2012, Sanyal and Maity 2018), household characteristics such as its size, the respondent's education, and assets are significant predictors of first-time seasonal migration in our study. For example, a household in debt is 38% more likely to have a first-time migrant when compared to a household that is not in debt.

Overall, households in poorer districts (MPI ≥ 0.174) rely on seasonal migration more than households in richer districts (MPI<0.174). On average, 12.15% (range across districts=

2.96 – 20.00%) of the households surveyed in poorer districts (MPI $\geq$ 0.174) had first-time migrants in comparison to 6.41% (range across districts= 1.54 - 20.69%) of the households surveyed in richer districts (MPI <0.174; SI Table 7). This result is consistent with the historically high rate of seasonal migration in ST (Scheduled Tribe) populations, which continues in present times (Srivastava and Sutradhar 2016, Sanyal and Maity 2018, Keshri and Bhagat 2013). In our study, poorer districts, on average, have a 55% higher proportion of ST households in their population compared to richer districts (Government of India 2011a) (SI Table 6).

The key finding of our study is that households in richer (lower MPI) rather than poorer (higher MPI) districts are more sensitive to annual variability in the mean maximum temperatures (Model 1) or total rainfall during the summer monsoon (Model 2) (Figure 4)[1]. The probability of migration for a household in the richest districts (MPI = 0.031) increases by approximately 40% when it experiences 1 SD change in temperature (At mean: p = 0.005, 95% CI = 0.004–0.008, increase by 1 SD: p = 0.007, 95% CI = 0.005–0.011) or total rainfall (At mean: p = 0.007, 95% CI = 0.005–0.010; decrease of 1 SD: p = 0.010, 95% CI = 0.006–0.017). For households at mean MPI (0.174), the probability of sending a first-time migrant increases by 15% and 13% respectively when experiencing an 1 SD change in temperature (At mean: p = 0.013, 95% CI = 0.011-0.016; increase by 1 SD: p = 0.015, 95% CI=0.013-0.018) or rainfall (At mean: p = 0.015, 95% CI = 0.013–0.018, decrease by 1 SD: p = 0.017, 95% CI = 0.014–0.021). In contrast, the probability of first-time migration from a household in the poorest district (MPI = 0.278) remains unchanged when experiencing a change of 1 SD in temperature (At mean: p =

[1] We categorized the MPI of a district based on the minimum (MPI = 0.031), maximum (MPI = 0.278), mean (MPI = 0.174) and first (MPI = 0. 117) and the third (MPI = 0.214) quantile values.

0.025, 95% CI = 0.020–0.032; 1 SD increase: p = 0.026, 95% CI = 0.020– 0.033; 2 SD increase: p = 0.026, 95% CI = 0.018–0.036) or total rainfall (At mean: p = 0.026, 95% CI = 0.020–0.032; 1 SD decrease: p = 0.026, 95% CI = 0.019–0.034). Mean maximum temperature and total rainfall are highly co-linear variables (SI Fig 2.4). Thus, the results and predictions of Model 1 and 2 show similar results at 1 SD (Fig 2.4). However, at more extreme climatic variability, rainfall deficits have a marginally larger impact on the probability of migration from richer districts than temperature increases (SI Table 6).

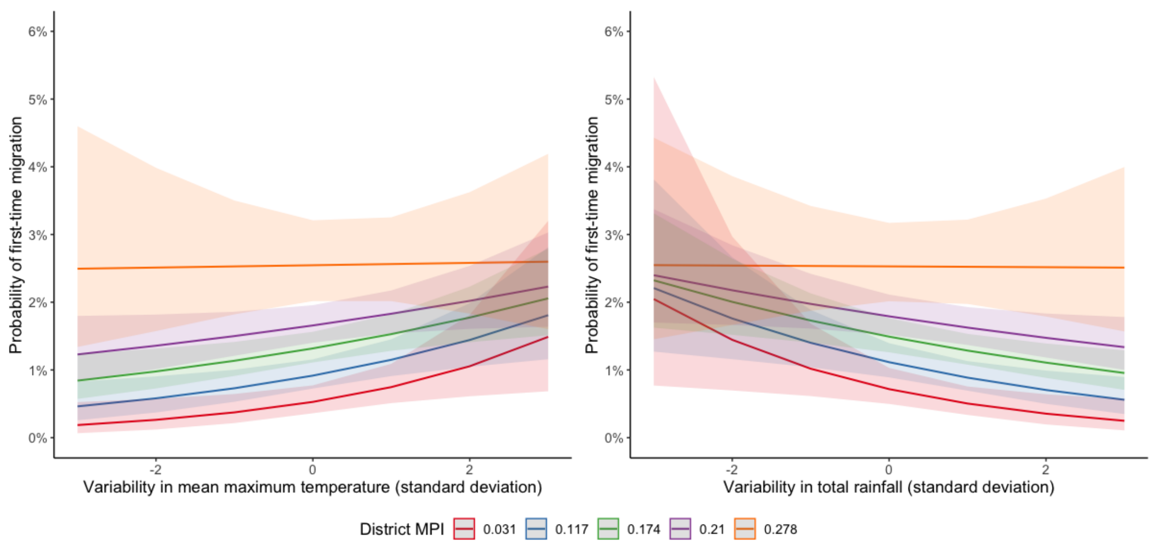

Figure 2. 4: Predicted probability of seasonal migration based on variability in climate. (A) Probability of first- time seasonal migration as a function of the interaction of variability in the mean maximum temperature in the previous year and the district's MPI based on combined data (2013- 2017). (B) Probability of first- time seasonal migration as a function of the interaction of variability in the total rainfall in the previous year and the district's MPI based on combined data (2013- 2017). Refer to SI Table 5 for the discussion of predictions of Figure 4(b). The confidence intervals are based on fixed effects only and are calculated assuming a normal distribution (for random effects of both the models, refer to SI Figure 5 (a, b). District MPI values represent the minimum, first quantile, mean third quantile and the maximum (in ascending order). Higher MPI values indicate higher multidimensional poverty in a district.

2.4 Discussion

We examine this sensitivity of households in richer districts by examining the differences in the households and districts. In our study, households in richer districts (MPI<0.174), with lower rates of seasonal migration, owned, on average, 20% more agricultural land (2.93 ± 4.81 acres) and 80% more irrigated land (1.18 ± 3.53 acres) than households in poorer districts (MPI≥ 0.174; total land: 2.42 ± 4.31 acres; irrigated land: (0.66 ± 1.93 acres), indicating a larger occupational focus on agriculture. Irrigation is mainly used for a market-oriented second crop in winter, predominantly wheat (Zaveri and B. Lobell 2019). Previous studies in India demonstrate that households with agricultural assets and technologies, including irrigation, are more likely to have agriculturally focused occupations and thus, less likely to engage in occupational diversification, such as migration, for income-smoothing (Skoufias *et al* 2017, Zaveri *et al* 2020). This may be because households with larger land ownership have higher labor requirements and thus, are less likely to undertake seasonal migration for work (Kaczan and Orgill-Meyer 2020). We find evidence of this relationship between agriculture and migration amongst this socio-economically vulnerable population as on average, richer districts have half the proportion of households with first-time migrants compared to poorer districts.

We interpret our results to suggest that the sensitivity of forest-fringe households to climate is mediated by their agricultural focus, much like households in non forest-fringe rural areas in India (Sedova and Kalkuhl 2020) and other countries such as Mexico (Nawrotzki *et al* 2015) or Bangladesh (Carrico and Donato 2019). Our results align with that of Sedova and Kahkuhl (2020) who demonstrate that in India negative precipitation anomalies only significantly impact agricultural households inducing migration to urban centres, and not non-agricultural households with already higher rates of migration. Such similarity in the sensitivity of agricultural households in forest-fringe and non forest-fringe villages to climatic variability suggests that a forest- fringe household's focus on agriculture can reduce its dependence on forest products drastically (Illukpitiya and Yanagida 2010). In such a case, the proximity of a household to the forest becomes irrelevant. Our study, thus, illustrates the differential sensitivity of households to climatic variability, based on their occupational focus, in this socio-economically vulnerable population in our study region.

A commonly proposed pathway out of poverty and a means to tackle climatic variability is agricultural intensification and transformation. In India, earlier policies based on the Green Revolution, have allowed central Indian states like Madhya Pradesh and Maharashtra to increase agricultural yields by 29% and 21% respectively in recent decades (Zaveri and B. Lobell 2019). However, the rate of gains from agricultural intensification has slowed in recent years, and may pose a challenge for agricultural households in a future of uncertain climate (Zaveri and B. Lobell 2019, Zaveri *et al* 2020). Prior evidence from the CIL suggests that commonly grown crops, such as rice and wheat, are highly sensitive to temperature increases (Mondal *et al* 2015). Climate projections for the CIL indicate variation in rainfall patterns (Singh *et al* 2019), but a statistically significant increase in annual temperatures (Mondal *et al* 2014). Policies in the last decade, such as *Kisan Credit Card* and the *Pradhan Mantri Krishi Sinchayee Yojna* have improved farmers' access to fertilisers, seeds, credit and improved irrigation (OECD/ICRIER 2018, Jain *et al* 2019). However, given the recent increased dependence on irrigation, parts of central India have depleted their groundwater (Zaveri and B. Lobell 2019, Jain *et al* 2021) and could face severe water shortages and reductions in crop production as early as 2025 (Jain *et al*

2021). Thus, investments in agricultural intensification may not serve as a reliable pathway out of poverty in the future as it has in the past.

Research from other parts of the world provides much evidence of higher reliance on agriculture once migrants begin to accumulate wealth from several years of migration (Chiodi *et al* 2012, Redehegn *et al* 2019). Give our findings, we postulate that in the near future if households in poorer districts follow the agricultural path to poverty reduction as some richer districts have done (Zaveri and B. Lobell 2019), it may reduce their seasonal migration but make households in poorer districts more vulnerable to climatic variability in the long run.

2.5 Conclusion

This study enhances our understanding of livelihood strategies amongst a socio-economically vulnerable population in central India, one that other analyses based on large datasets of India's diverse population do not explicitly consider. Households in poorer districts, with a higher prevalence of seasonal migration overall, are less sensitive to climatic variability in comparison to households in richer districts. We attribute the sensitivity of households in richer districts to climatic variability to an occupation focus on agriculture, specifically adoption of common agricultural intensification practices, which promote irrigation, without accounting for long-term climate resilience. We conclude that households in this population on the forest-fringes, following the mainstream agricultural pathway out of poverty as in other communities in India, may be able to increase incomes due to agricultural intensification and, thus become less dependent on migration overall (Zaveri *et al* 2020) but may be more vulnerable to climatic variability. Our findings contribute to a growing body of evidence about the complex relationship between temperature and precipitation anomalies and urban-bound migration from rural landscapes (Carrico and Donato 2019, Sedova and Kalkuhl 2020, Mueller *et al* 2014, Bohra-Mishra *et al* 2017, Nawrotzki *et al* 2015, Call *et al* 2017).

Quantifying the sensitivity of households to climatic variability assists NGOs, managers and policymakers in targeting policies to alleviate poverty and reduce dependence on migration amongst this historically socio-economically vulnerable population. Given our findings, alternative livelihood options (*e.g.*, Mahatma Gandhi National Rural Employment Guarantee Act or non-extractive forest-based livelihoods such as eco-tourism) other than intensified agriculture, may be more appropriate for alleviating poverty for building climate resilience amongst forest-fringe populations in poorer districts. Additionally, policies promoting climate-resilient agriculture in poorer districts may ensure those households increasing their agricultural activities and investments are adequately capacitated to face climatic variability. Similarly, policies promoting climate-resilient agriculture in agricultural households in richer districts could reduce dependence on migration in times of extreme climatic variability.

This study has several limitations. Our statistical model is not a true panel model. We acknowledge that the structure of our data restricts our ability to make more accurate predictions of the sensitivity of households to climatic variability. Further, unlike a panel dataset, we are unable to quantify the changes in socio-economic characteristics associated with migration over a period of time. Given the high correlation between temperature and precipitation indices, our statistical methods are unable to disentangle the individual impact of each of them on migration in the CIL. This study is a snapshot of five years. Thus, tracking the relationship of climatic variability and local socio-economic conditions with seasonal migration over a longer period of time will provide a more accurate picture of this livelihood diversification strategy for socio-economically vulnerable populations. Lastly, unlike some studies on forest-dependent populations (Noack *et al* 2019), without a quantification of forest dependence at different time steps, we cannot deduce whether forest-based livelihoods, such as non-timber forest product extraction, provided a 'cushion' in years of higher climatic variability. Moreover, our survey design limits our ability to understand the differences climatic variability has on forest- fringe and non forest-fringe populations. A comparison of the two populations may provide more insight into how different populations in India, based on their immediate environment, are coping with climatic variability.

Chapter 3: Listening for Change: Quantifying the Impact of Ecological Restoration on Soundscapes in a Tropical Dry Forest

Pooja Choksi, Mayuri Kotian, Siddharth Biniwale, Pravar Mourya, Devendra Korche, Meghna Agarwala, Sarika Khanwilkar, Vijay Ramesh, Ruth DeFries

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3.1 Introduction

Tropical forests support over half of the world's biological diversity and are significant reserves of carbon (Pimm *et al* 1995, Sullivan *et al* 2017). Increased tropical forest fragmentation (Taubert *et al* 2018) and loss in the recent decades have underscored the need to protect (Cook-Patton *et al* 2021) as well as ecologically restore forests in the human-dominated landscapes of the tropics (Grantham *et al* 2020, Cook-Patton *et al* 2021). Ecological restoration has the potential to provide a multitude of benefits, such as conserving biodiversity (Brancalion *et al* 2019, Crouzeilles *et al* 2016), especially specialist species with specific habitat needs (Hariharan and Raman 2021), supporting natural-resources dependent livelihoods (Erbaugh *et al* 2020) and to a limited extent, mitigating climate change (Griscom *et al* 2017, Cook-Patton *et al* 2021).

In this United Nations' decade of restoration, global agreements and sustainable development commitments such as the Bonn Challenge and the United Nations Sustainable Development Goals provide the much needed impetus to restore degraded forests and lands around the world and subsequently contribute to biodiversity conservation and human development goals (CBD 2010, UN 2010). Given the magnitude of ongoing and planned restoration efforts around the world, there is a need for rapid and accurate assessment tools to quantify the impact of restoration on biodiversity at several time steps to guide restoration efforts and realistically forecast the consequences of these efforts in the future. Compared to traditional biodiversity surveys, acoustic surveys are less time- and resource- intensive and, to an extent, eliminate human biases as one can listen to the data as many times as required (Burivalova *et al* 2019, Deichmann *et al* 2018, Shaw *et al* 2021), making them ideal for long-term monitoring of ecological restoration sites.

Based on the premise of the Acoustic Niche Hypothesis (ANH) of ecoacoustics, it is generally inferred that degraded habitats would have fewer acoustic niches occupied in comparison to more intact habitats (Rappaport *et al* 2022, Campos-Cerqueira *et al* 2020). However, empirical evidence, largely from humid tropical forests, suggests that this implied linear relationship between acoustic space use and habitat intactness may not always hold (Rappaport *et al* 2020, Eldridge *et al* 2018, Vega-Hidalgo *et al* 2021a). In the context of using acoustics to monitor ecological restoration, such uncertainties in previous findings present the need for more evidence on ecoacoustic from diverse geographies to better understand changes in landscapes that continue to be restored around the world.

A large proportion of the research on quantification of restoration efforts is from humid tropical forests (Crouzeilles *et al* 2016, Osuri *et al* 2019) as tropical dry forests remain comparatively understudied and undervalued (Dirzo *et al* 2011). While limited in their capacity to sequester carbon and support biodiversity in comparison to humid tropical forests, tropical dry forests are extensive (covering approximately 42% of the tropics) (Miles *et al* 2006, Morales-Barquero *et al* 2014) and are often socio-ecological systems (forests managed by people for subsistence and livelihood needs) supporting over a billion people around the world (Schröder *et al* 2021). Dry forests remaining today mainly occur in densely populated human-modified landscapes of the world, making them further vulnerable to degradation and thus, are an important biome to restore (Gillespie *et al* 2012) .

This study examines passive ecological restoration of a tropical dry forest through the removal of the shrub Lantana camara (Linnaeus). The British introduced L. camara (Verbenaceae), an invasive woody shrub native to central and southern America, to India in the 1800s (Mungi *et al* 2020). L. camara dominates the understory of forests due to its allelopathic properties and ecological tolerance (Negi *et al* 2019). Prior evidence suggests that higher densities of L. camara are associated with lowered densities of sapling and seedlings of native vegetation, often species which may be necessary for wildlife (Wilson *et al* 2014) or of livelihood interest (timber and non-timber forest products) to local communities (Aravind *et al* 2010). Furthermore, L. camara can grow in tall dense thickets or can function as a liana (Hiremath 2018), thus becoming a barrier for people to access spaces where L. camara is overgrown.

Previous studies in India have largely focused on the impact of *L. camara* on vegetation regeneration over the impact of *L. camara* on fauna (Wilson *et al* 2014, Ramaswami *et al* 2017, Aravind *et al* 2010). This study aims to contribute to closing this gap in our knowledge on the impact of restoration of forests previously invaded by *L. camara* on fauna and, more generally, the soundscape. Furthermore, our work refines our understanding of the outcomes of restoration efforts, primarily carried out for the convenience of local communities and to increase visibility in a forest, of an often undervalued biome (Gillespie *et al* 2012).

The objective of this study is to quantify the impact of ecological restoration on soundscapes. We use sites in dry tropical forests of the Central Indian Highlands to ask the following questions.

1. How does the cumulative number of bird species detected aurally differ between comparable restored, unrestored, and low *Lantana* density sites?

2. How does the bird community vary in comparable restored, unrestored, and low *Lantana* density sites according to the habitat preferences of the individual bird species?

3. How does the acoustic space use in the frequency range 2 – 8 kHz in comparable restored, unrestored, and low *Lantana* density sites differ?

3.2 Methods and Materials

Study region

This study was carried out in Bichhiya, a subdistrict of Mandla district, Madhya Pradesh, which is part of the Central Indian Highlands (CIH), a significant tiger conservation landscape (Jhala *et al* 2019). The average elevation in the district is 539 metres above sea level. Tropical deciduous vegetation dominates this region (Agarwala *et al* 2019), and one of the largest populations of constitutionally recognized socio-economically disadvantaged Scheduled Castes and Tribes in India is dependent on timber and non-timber forest products (NTFP) for livelihoods in this region (DeFries *et al* 2021, Choksi *et al* 2021). These forests represent classic socio-ecological systems, which have been managed by local communities for their livelihood and subsistence needs for generations (Agarwala *et al* 2019). While intensive agricultural expansion is taking place in parts of this region, locals largely engage in subsistence and small-scale market-oriented agriculture, which is primarily rain-fed (Choksi *et al* 2021). The region has been experiencing a weakening of the monsoon as well as an increase in the frequency and intensity of heatwaves in recent decades (Choksi *et al* 2021).

Restoration method

In our study area, the state forest department and the local communities, with the support of a local non-governmental organization, Foundation for Ecological Security (FES), carried out ecological restoration. The restoration used a common strategy of rigorously removing *L. camara* for three consecutive years in the months before the flowering season in October (the plants can have a flowering season in the monsoon months as well) (Negi *et al* 2019) and then allowing a site to naturally regenerate. This method of *L. camara* removal involves uprooting the entire rootstock and weeding following the initial removal of *L. camara* is commonly practiced across India for more effective invasive species eradication (Love *et al* 2009, Prasad *et al* 2018). In these sites, 2017 was the first of the three years of *L. camara* removal (Figure 3.1).

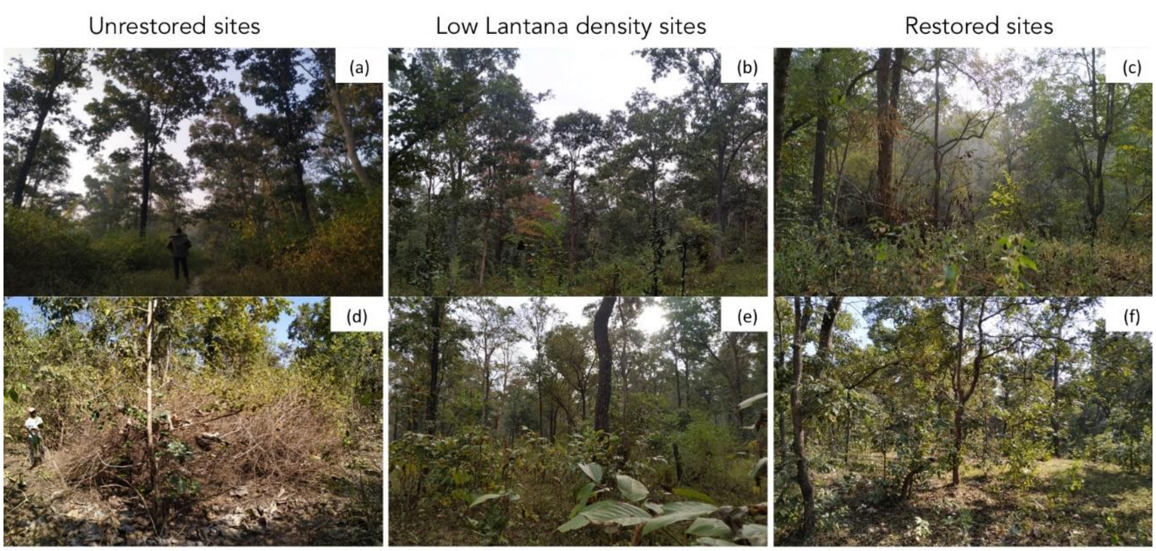

Figure 3. 1: Pictures from unrestored, low Lantana density, and restored sites.

Site selection

We selected the study sites through a two-step matching process using propensity score matching, an alternative for true randomization (Luellen *et al* 2005) since restoration had already taken place in these sites. We used the package *matchIt* (Ho *et al* 2011) to carry out the propensity score match in the R programming environment (R Development Core Team 2019). Communities in villages generally request the state forest department for permission to restore a section of the forests within their village boundaries. Therefore, we started this study by identifying eight 'treatment' (restored) villages in the officially designated buffer of Kanha National Park (KNP) in the Bichhiya subdistrict where FES, the state forest department, and local communities had carried out restoration. They restored a demarcated area of a forest (a minimum of 20 hectares) within a village's boundary, which local communities use for their subsistence and livelihoods (hereafter referred to as sampling site). We selected 'control' villages by matching villages (unrestored N = 8; references N = 4; categories explained below) from the KNP buffer villages in the same subdistrict to the treatment (restored) villages using a propensity score based on socio-economic (Government of India 2011a) and remotely-sensed geographic variables (Table S1). We classified 'control' villages as (a) unrestored (with a high density of *L. camara*) and (b) reference sites representing a low *L. camara* density through site visits. Reference sites, which we refer to as low *Lantana* density (LLD) sites, represent the possible trajectory of restored sites in the event that there is little to no *L. camara* reinvasion in the future. We consulted members of the local community and local forest guards, where possible, about the natural lack of *L. camara* in the last five years in forests in LLD villages. We chose LLD sites outside the core area of KNP as the forest department restricts human use inside the park and because KNP has a large focus on plantation forests reflecting its colonial past (Agarwala *et al* 2019).

After we matched villages, we identified sampling sites in forests within and adjacent to village boundaries by consulting local community members and the local forest guards. These are areas of the forest where the majority of the local community members extracted firewood and non-timber resources. After this consultation, we drew 20 polygons representing exact sampling sites (restored N = 8, unrestored N = 8, low *Lantana* density N = 4; mean area of polygons: 58.32 ± 30.93 Hectares) within the forests of villages classified as restored, unrestored and LLD. To ensure there is no data contamination from sounds and vocalizations outside the sampling sites, we first buffered in the polygon of the treatment or control site by 70 metres, to represent the core of the site in which we collected data. To determine exact sampling locations (recorder locations) for vegetation and acoustic data collection, we then used a random point generator in QGIS 3.6.1 (QGIS Development Team 2022) to establish two or more locations (depending on the size of the polygon) between 380 to 500 meters apart to set up acoustic recorders within the core of a site. In each sampling site, we had 3 (±1) sampling locations.

Vegetation data collection

Between January and early April 2021, at every sampling location (recorder location), we established a circular 314.2 m^2 plot (10- meter radius plot) to sample the vegetation. Within the 1-metre radius, we (authors PC and DK) noted the diversity of identifiable grasses. In the 3-metre radius, we identified and counted all seedlings and saplings, the number of *L. camara* saplings (single stems below 1 meter in height) and mature *L. camara* plants (>1 meter in height). In the 10-metre radius, we measured the diameter at breast height (DBH) and visually estimated the height of all trees above the height of 2 meters (refer to Table S2 and S3 for more details on the vegetation in sites). At four sampling locations in two restored sampling sites, due to COVID-19 related travel restrictions, we were abruptly unable to return to the site collect data and have used vegetation metrics from the closest sampling locations (approximately 400 meters away) within the sampling site.

After vegetation sampling, we performed a secondary match (an optimal full match using the *matchIt* R package) for all the sampling locations (N = 55; Figure 2) for all the restored, unrestored and LLD sampling locations to ensure a balanced sample based on vegetation composition and structure (of the overstory), socio-economic and geographic variables that previous studies have found to be important for quantifying people's forest-resource use (DeFries *et al* 2021) (Table 3.1).

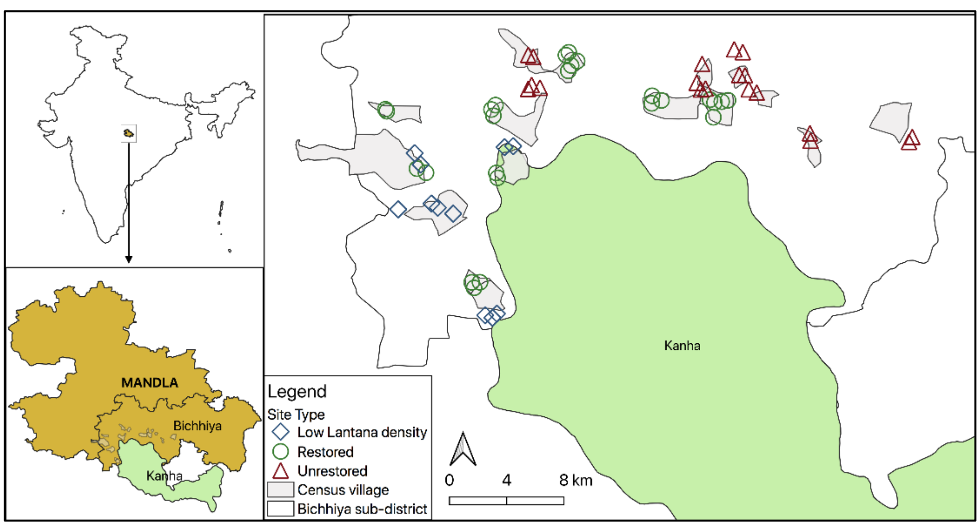

Figure 3. 2: Map of restored, unrestored and low Lantana density sites in Mandla district. Acoustic recorder locations in restored, unrestored and low Lantana density forest sites are represented by the circle, triangles and diamond symbols respectively around the census villages (in gray) that use the particular forests for subsistence.

Table 3. 1: Summary of the mean and standard deviations of matching and predictor variables. The standard deviations for variables are provided in parenthesis.

Treatment type		**Restored**	**Unrestored**	**Low Lantana density**
Definition of treatment		*Sites where restoration by way of L. camara removal has taken place in the last 5 years*	*Sites with high density of L. camara where no restoration has taken place in the last 5 years*	*Sites which naturally have very few L. camara plants or no L. camara plants in the last 5 years*
Variable for matching	**Definitions of variable and source of data**	**Mean of variables in treatment (restored) sites**	**Means of variables in control (unrestored) sites**	**Means of variables in control (low Lantana density) sites**
Tree density	Number of small, medium and large trees in a 10-metre radius plot Source: Vegetation survey	29.56 (25.82)	26.98 (11.60)	22.32 (10.50)
Large trees density	Number of large trees (>10 cm Diameter at Breast Height) density in 10 meter radius plot Source: Vegetation survey	16.20 (7.45)	17.93 (6.85)	12.96 (5.85)
Plot Simpson diversity index	Simpson diversity index of all tree in 10 meter radius plot Source: Vegetation survey	0.69 (0.19)	0.62 (0.28)	0.76 (0.11)

% Forest cover in 3 km buffer	Source: (Khanwilkar *et al* 2021)	46 (23.00)	44 (13.11)	65 (6.09)
% Farm land in 3 km buffer	Source: Khanwilkar et al. 2021	9 (6.95)	15 (6.12)	7.3 (5.87)
Total population (Census 2011) in 3km buffer	Source: (Government of India 2011a)	5251 (2145)	6628 (5505)	4018 (2123)
Total sampling sites (recorder locations) matched		**25**	**19**	**11**

Acoustic data collection and analysis

At each sampling location (N=55), we tied acoustic recorders at approximately 2 metres above ground on tree trunks. We used Audiomoth 1.0.0 (sampling rate = 48 kHz, gain = medium) (Hill *et al* 2018) and sampled every 1 minute in 5 minutes for 24 hours in a day for a period of 7 to 10 days (Bradfer-Lawrence *et al* 2019) during the winter seasons (December – early March) in 2020 and 2021. We were unable to record over spring and summer due to increased COVID-19 infections through the peaks of different waves. In total, we recorded 30.44 ± 8.27 hours in 2020 and 42.24 ±12.05 hours in 2021 across all sampling locations. At four instances (at three sampling locations in a single year), we experienced recorder malfunctions, and had to remove those recordings from the analysis. For example, for 55 sampling locations over two years, for any outcome variable, instead of a total of 110 observations, we have only 106 observations.

(a) Bioacoustics: Bird community

We randomly selected 45 minutes in the morning hours (5:30- 9:30 AM) per year (Table S4) from each sampling location (N = 55) to be manually annotated for all avian species detected (Table S5 provides a list of all species heard in the manually annotated data). Our choice of morning hours was based on two factors: (1) although the sunrise hours are when the birds are most vocal, we chose a larger range of hours to annotate data because these forests are actively used by local communities in the mornings, and this human activity could affect temporal trends in bird vocalizations and (2) it is often difficult to hear all the species calling and distinguish between them correctly with a lot of background vocalizations during the dawn chorus. In some cases (mainly unrestored sites), we annotated additional minutes over two years to compensate for recorder malfunctions, bad weather, and fewer sampling locations (Table S4). Authors (SB and PV) annotating this data are also eBird (Sullivan *et al* 2014) reviewers for central India and possess knowledge of the natural history and the wide repertoire of vocalizations of birds in this region. To make annotation easier, the audio data, which were minute-long, were split into 10-second clips and used a presence/absence matrix to note whether a particular avian species was heard in a 10-second clip or not. We used Raven Pro (version 1.5) (Cornell Lab of Ornithology 2021) to visualize each 10-second file and then note the presence or absence of a species in a matrix. In the event there was uncertainty about the identity of an avian species, the specific 10-second clip, and the larger minute-long clip it belonged to was sent to other bird call experts, mainly other eBird reviewers for Central India. We then finalized the identity of the species based on the majority consensus amongst the experts. We classified all the bird species identified through manual analysis as generalist or forest- and woodland- affiliated species based on the classifications by State Of India's Birds (SoIB) (The SoIB partnership 2020). We only considered these two categories of habitat preferences as our study sites are tropical deciduous forests and all the other categories of habitat preferences as per the SoIB (grassland, scrub, and wetland) accounted for only 2 to 5% of the species across all our sites. In the rare event (3 species; Table S5) that a species fell into two habitat categories in the SoIB, we classified the predominant habitat specialization based on the experiences of authors.

(b) Ecoacoustics: Acoustic space use quantification

We followed the method of calculating acoustic space use (ASU) from Campos-Cerqueira et al. (2020). The proportion of acoustic space could represent the abundance or diversity of species at a point of time. First, we created a mean spectrum for each 1-minute recording by computing a short-time Fourier transform (f = 48000, wl = 512, wn = "hanning", norm = FALSE) using the *meanspec* function from the *seewave* package in the R programming environment (R Development Core Team 2019). This resulted in a two-column matrix of frequency and amplitude values for 256 frequency bins, with the minimum absolute amplitude over all files at 0.073 dB and the maximum at 12104.95 dB. We then used the *fpeaks* function in the same R package to detect the peaks of the frequency spectrums. We scaled these amplitude values in the *fpeaks* output from -1 to 1. To separate biophony from background noise, we applied a scaled amplitude threshold of 0.003 and selected only the frequency peaks above the threshold (frequency distance threshold set to zero). This selection resulted in a two-column matrix of frequency and scaled amplitude values above the threshold. Thus, effectively, if there was a peak in a particular frequency/ time bin, it was considered as an acoustic niche that is ‘occupied’. We then aggregated the selected frequency peaks between 0 – 24 kHz for each audio recording into 3072 bins (128 frequency bins of 187.5 Hz x 24 time bins). For our analysis, we filtered the frequency bins of interest, between 2000 and 8000 Hz (a total 768 frequency/time bins), to focus largely on biophony in the frequency range audible to humans (Kasten *et al* 2012). We calculated the proportion of acoustic space used in a frequency/time bin by aggregating the number of recordings when the scaled amplitude threshold of 0.003 (Campos-Cerqueira *et al* 2020) was crossed in each bin and dividing it by the total number of recordings in each hour (we recorded one minute for every 5 minutes, giving us a maximum of 12 recordings in an hour).

Predictor variables

We included the variables that were used to match the sites for a pairwise comparison as predictor variables in our statistical models (correlation plot of matching variables in Figure S1). Table 3.1 shows the summary statistics of the predictor variables across all the sites. All continuous variables were scaled and centered to create the z-score to estimate the statistical model described below.

Statistical tests and models

We tested the significance of associations between restoration efforts and the bio- and eco-acoustics using parametric and non-parametric approaches. We performed a permutational multivariate analysis of variance (PERMANOVA) using the *adonis* function in the R *vegan* package (Oksanen *et al* 2019) to determine whether there was a significant difference in the bird community across the sites based on their type (restored, unrestored and Low *Lantana* density) (N permutations = 999). We also fit Generalized Linear Mixed Models (GLMM) for the following outcome variables at the level of the sampling location: (1) cumulative number of bird species, (2) cumulative number of forest- and woodland- affiliated species, and (3) cumulative number of generalist species detected aurally. For the GLMMs, we used a *poisson* distribution and included predictor variables listed in Table 3.1 as fixed effects, and the sampling sites (N =20) as a categorical random effect to account for the variation in space. We added the year of data collection (2020 and 2021) as a categorical fixed effect in our model. Additionally, for these three outcome variables mentioned above, we also performed a Wilcoxon test of significance to determine whether the medians of site types are significantly different from each other across the years and in each year.

For the ecoacoustics analysis, we similarly performed a PERMANOVA analysis to test the differences in ASU between the three types of sites (N permutations = 999). For the PERMANOVA analyses, we used the predictor variables listed in Table 1. For these tests we used the matrix of the proportion of acoustic space use in each frequency/ time bin in the range 2000-8000 Hz (768 frequency/time bins in total) for each day of recording at each sampling location. To estimate a GLMM (using a binomial distribution), we aggregated the frequency bins between 2000-8000 Hz to compute the acoustic space used across the frequency range at a given time in 24 hours as the outcome variable. Thus, we have a single value representing the total proportion of acoustic space used (count of all recordings when the amplitude threshold was crossed divided by the total number of recordings in an hour) at every hour in 24 hours. The predictor variables listed in Table 1 and the year (2020 and 2021) were fixed effects in this model. We accounted for variation in space by including the sampling site (N =20) as a categorical random variable. To account for the variation in time, we used the Julian date of recording (N =100), the time in 24 hours (N =24) as random effects. Additionally, to determine whether the day time (06:00 to 18:00) ASU is significantly different from the night time (18:00 to 06:00), we performed a Wilcoxon test.

We estimated all the GLMMs using the R package *lme4* (Bates *et al* 2015). Further, for all our models, using an inflation threshold of 5, we ran a variance inflation factor test, using the R package *car* (Fox and Weisberg 2019), to ensure there is no collinearity in the predictor variables. None of the models displayed variance inflation, and we have thus presented the full models controlling for all the propensity score matching variables with alternative models for reference. Alternative models do not include correlated predictor variables in the same model. We then validated the model results using the residuals of the GLMMs (Zuur and Ieno 2016).

Expectations

We expect significant differences in the cumulative number of species detected across the sites as well as in the bird community composition based on prior research (Jayapal *et al* 2009). Furthermore, we expect restored sites to have lower ASU (or fewer 'occupied' acoustic niches) compared to LLD and unrestored sites, where no such sudden structural changes have occurred (Burivalova *et al* 2021). Further, based on the premise of the ANH, we expect LLD sites, which are the least 'disturbed' sites (as no sudden structural changes have taken place and they are not dominated by *L. camara*), to display highest ASU.

3.4 Results

Bioacoustics: Bird community composition

There are no significant differences in the cumulative number of aurally identified species (median number of species at restored and LLD sites = 38, unrestored sites = 41) between the sites (Table S6, S7). Furthermore, we did not find significant differences in the cumulative number of forest and woodland- affiliated and generalist species in the three types of sites (Figure 3.3, Table S6, S7). However, there is a significantly lower number of generalist species in restored sites compared to unrestored sites (median restored = 20, unrestored = 23; Table S6). Also, we found that in 2021 compared to the year 2021, in the case of unrestored and LLD sites there was a decrease in the cumulative number of birds and subsequently the cumulative number of generalist and specialist species detected (Table S7). In the case of restored sites, we found an increase in the cumulative number of birds and generalists detected between 2020 and 2021 (Table S7).

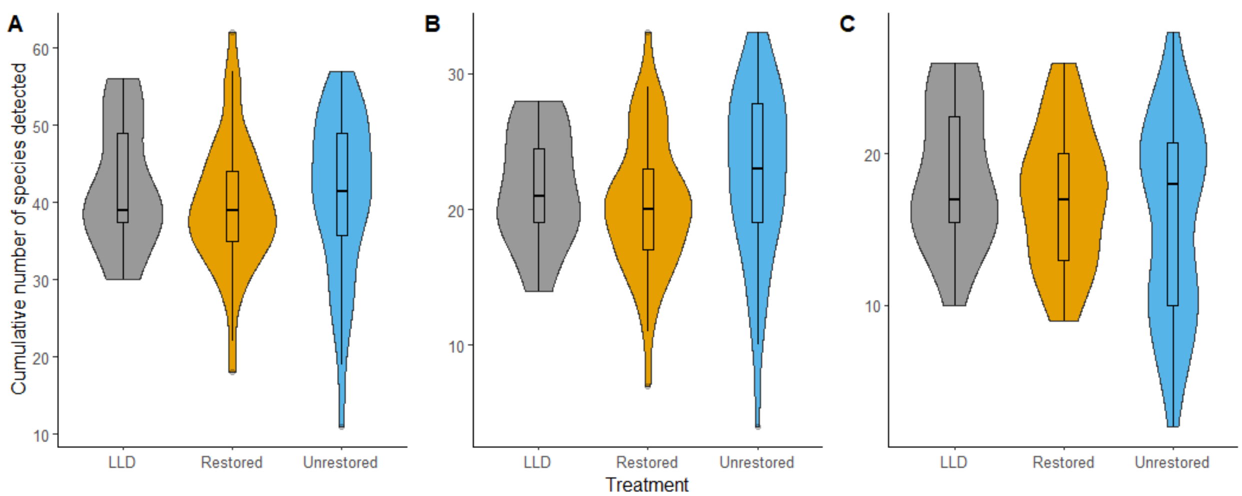

Figure 3. 3: Violin plots displaying the cumulative number of species detected for different categories of birds. (A) the cumulative number of bird species detected, (B) the cumulative number of generalist species detected, and (C) cumulative number of forest- and woodland-affiliated species detected across the sites. Refer to Tables S6 and S7 for the Wilcoxon test of significance results.

We found that there is a significant difference in the species community across the sites (PERMANOVA $R^2 = 0.049$, $p = <0.001$). The sites have 100 species in common, with a majority of generalist birds across all sites (Table S5). Thirteen species were unique to restored sites, of which only two were forest- affiliated species such as the Scarlet minivet (*Pericrocotus speciosus)* that tends to prefer the canopy over the understory. Eleven species, predominantly forest-affiliated, were unique to unrestored sites, and only three species were unique to LLD sites. Restoration is negatively associated with the cumulative number of species (GLMM coefficient = -0.126, std. error = 0.074, p = 0.089) and significantly negatively associated with the number of generalists detected aurally per year (GLMM coefficient = -0.092, std. error = 0.105, p = 0.036; Table S9a; alternative models in Tables S10, S11, S12). Restoration also has the largest negative effect, albeit with large variation, on the number of species detected aurally amongst all the predictor variables (Table S9a).

Ecoacoustics: Acoustic space use

We found a difference (approaching significance) in the ASU between sites (PERMANOVA $R^2 = 0.023$, $p = 0.052$) (Table S13). Figure 3.4 shows the outcome variable for the GLMM, the aggregated proportion of ASU for every 1-hour bin over 24 hours. The results indicate that restored sites have significantly higher ASU than LLD and unrestored sites, but ASU in restored and LLD sites is more similar to each other in comparison to unrestored sites (Table S14). With the exception of day time hours (06:00 – 18:00), when restored sites have a marginally higher ASU than LLD sites (median ASU in restored = 0.148, LLD = 0.139) (Table S14). Overall, across sites, ASU is higher in the night hours (18:00 to 06:00) compared to the day time hours (06:00 to 18:00), and thus, we conclude that ASU across all sites is largely driven by night- time acoustic activity, often dominated by insects. The first and third quantiles of ASU reported for each type of site in Table S14 indicate that there is considerable variation between sampling locations. Restoration is positively, but not significantly, associated with ASU (GLMM coefficient = 0.056, std. error = 0.045, p = 0.180) (Table S15; alternative models in Table S16). When we examine the effect size, it has a relatively smaller association with ASU with large variation compared to predictors such as tree density (GLMM coefficient = 0.082, std. error = 0.006, p < 0.001; Table S15) and large tree density (GLMM coefficient = -0.109, std. error = 0.006, p < 0.001, Table S15). While LLD sites have significantly higher ASU than unrestored sites (Table S14), there is no significant association between LLD sites and the outcome variable, ASU (GLMM coefficient= -0.001, std. error = 0.056, p = 0.986; Table S15) indicating that we could attribute the ASU to other highly significant predictors, such as the vegetation structure and composition.

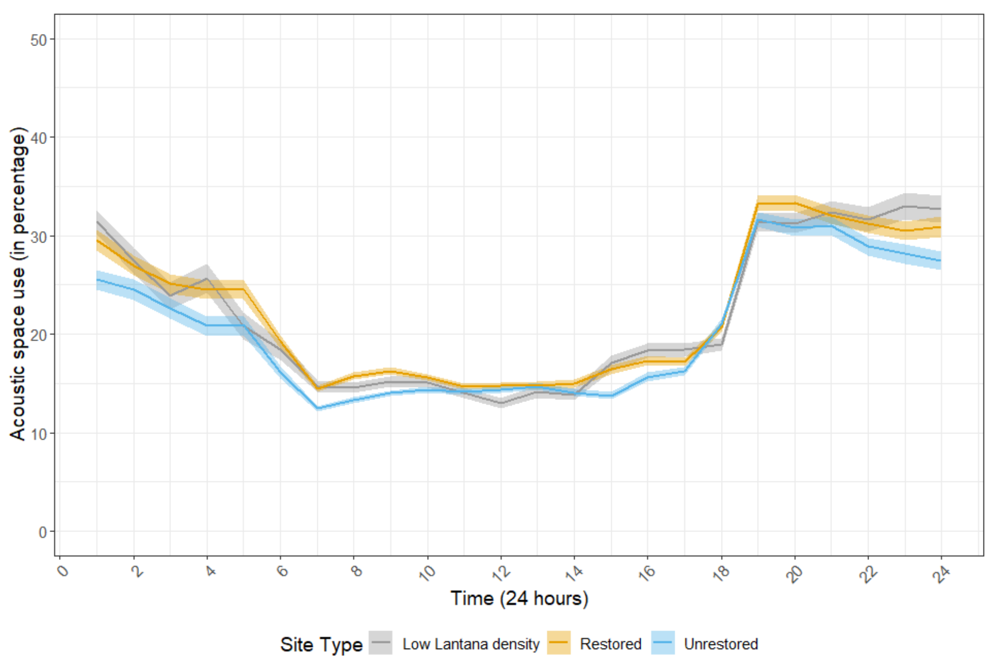

Figure 3. 4: Acoustic space used in lower frequencies over time in 24 hours. The lines represent the average across all days of data collection across all sampling locations. The

transparent bands represent the standard deviations of the means represented by the solid line.

3.4 Discussion

Large-scale ecological restoration projects require quick and frequent biodiversity appraisals. In this study, we provide an example of how bio- and eco- acoustics may be combined to gain insights on the impact of restoration on fauna and soundscapes. While we found no significant difference in the cumulative number of species at a site, it is noteworthy that there is a significant difference in community composition across the sites. Our results align to a limited degree with other evidence on ecological restoration, for example, from southern India, where restoration interventions are associated with a significant turnover in species richness and composition after two decades (Hariharan and Raman 2021). However, we did not find a significant difference in the total number of species detected. Further, while the difference in the site types was small and insignificant, unrestored sites had a marginally higher number of species, which may be indicative of the availability of more food sources (*L. camara* berries) in a *L. camara* dominated understory (Ramaswami *et al* 2017, Aravind *et al* 2010). However, we expect that as restored sites naturally regenerate in the coming years, there will be species turnover associated with the forest age (Owen *et al* 2020). Moreover, we also hypothesize that a change in the understory may change the abundances of different birds, which we did not quantify in this study. Last, there are differences in the number of species detected aurally from one year to the next. The only change over the two years of data collection was a temporary lockdown due to COVID-19 and we are unable to attribute these small changes between 2020 and 2021 to any concrete reason.

Although we matched the sites on several factors, small differences in predictor variables impact the bird community composition and ASU. For example, having a higher proportion of forest cover in a 3 km buffer, which is often a significant predictor of bird diversity (Shoffner *et al* 2018), did not significantly increase ASU and the total number of species detected, but is significantly associated with a greater number of forest- and woodland- affiliated species. Furthermore, human-modified land covers, such as the percent farm cover in a 3 km buffer, positively impact the total number of species detected at sites, but negatively impact ASU. We speculate that this could be because a majority of the bird species in this study are generalists and may benefit from farms as potential food sources. ASU is most likely driven by insects at our sites as previous studies have found and not birds (Campos-Cerqueira *et al* 2020, Aide *et al* 2017).

Overall, restored and LLD sites displayed marginally higher (statistically significant) ASU than unrestored sites. However, the lack of significant association of ASU with the site types indicates that the small differences in the geographic and vegetation composition and structure are driving the results in that the overstory matters more than the understory for ASU in the central Indian landscape. We postulate that this result is also in part because (1) tropical dry forests are slow-growing (Murphy 1986) and it may take some time to see significant differences due to restoration, if any or (2) changes in the understory may impact other facets of species' behavior and not the vocalizations. Restored sites had marginally higher ASU than LLD sites. This result is supported by another study on ecological restoration in Costa Rica (Vega-Hidalgo *et al* 2021a), which finds a lower acoustic energy of broadband insects in reference sites compared to restored sites, possibly due to a robust or more diverse predator community of bats (Vega-Hidalgo *et al* 2021a). We speculate that our results too may be an indication of a potentially larger presence of a predatory insectivorous bird abundance (which we did not quantify) in LLD sites in comparison to restored and unrestored sites, for which there is some prior evidence from this landscape (Aravind *et al* 2010). Another reason for the marginally lower ASU in the LLD sites may be that species, for example, birds, may rely less on vocal communication and instead have more visual communication when using these particular sites in the forest.

When evaluating our results using the lens of the ANH, we find that across restored, unrestored and LLD sites, all acoustic niches in our frequency range of interest (768 frequency/time bins) were 'occupied' as such. Contrary to our expectations, the removal of *L. camara,* which we expected would decrease forest structural diversity, thereby possibly decreasing structural niches (Jayapal *et al* 2009, Holmes *et al* 1979), did not display empty acoustic niches or a reduction in ASU. Therefore, following the ANH, we interpret the association of restoration and ASU as a positive indication of the ecological health of the restored sites. Further, we speculate that we see no reduction in ASU in restored sites due to three reasons: (1) species largely dependent on this shrub may easily and quickly adapt to a new vegetation structure following the complete removal of *L. camara* and thus, acoustic niches never become empty; (2) structural niches may not have a linear relationship with acoustic niches in this landscape, or (3) a, possibly temporary, influx of species contributing to different acoustic niches as a response to a change in the forest structure. We find that the second and third reason may be the most reasonable assumptions for our study. In the Brazilian Amazon, a study found similar non-linearity in structural complexity (represented by biomass) and acoustic niches, where patterns in ASU in logged and previously burned and reference forests were similar (Rappaport *et al* 2022). As the ANH is tested in more places around the world, a better understanding of the relationship between ecological health and acoustic niche occupancy will emerge.

This study has a few limitations. We focused on vocalizing diversity in this study. However, non-vocalizing invertebrates are critical to restoration because of soil health and ecosystem functions and are equally important to measure (Schowalter *et al* 2018). Also, we used a space-for-time approach for site selection; we accounted for various vegetation, geographic and human resource use differences across sites, there is always a possibility that we have not captured some underlying unknown variation in the sites, which may impact vocalizing biodiversity.

In sum, our results indicate that people-centric restoration, carried out to improve access and visibility for local communities and not intended to increase faunal diversity, has a marginal biodiversity co-benefit over short timescales. Monitoring these sites over the long term to understand ASU and faunal responses to changes in vegetation can further guide restoration efforts. For such future monitoring efforts, our data and study act as a ‘time capsule’, providing a baseline for acoustic studies. We also note that these positive associations between ASU and restoration exist at small spatial scales and it is necessary to carry out such a study at a larger scale for a better understanding of the relationship between ASU and restoration.

Chapter 4: Social and Ecological Outcomes of Tropical Dry Forest Restoration

4.1 Introduction

Tropical dry forests (TDFs) are some of the most exploited forests worldwide and occur in densely populated human-modified landscapes (Gillespie *et al* 2012, Janzen 1988, Portillo-Quintero and Smith 2018). Although reduced in extent due to historic clearing, TDFs provide critical ecosystem functions, such as erosion control and water regulation (Nelson *et al* 2020), and support endemic biodiversity (Gillespie *et al* 2012). TDFs are also estimated to support the livelihood and subsistence needs of millions of people around the world (Schröder *et al* 2021).

Rather than complete deforestation, a predominant threat to TDFs is degradation, which results in an alteration of forest structure and diversity (Choksi 2020, Morales-Barquero *et al* 2014). Sources of degradation are numerous: unsustainable logging, overexploitation of nontimber forest products (NTFPs), overgrazing, and spread of invasive species, among others (Choksi 2020, Dimson and Gillespie 2020). TDFs are considered highly susceptible to invasion (Mungi *et al.* 2021), and the spread of exotic invasive species, in particular the shrub, *Lantana camara* (hereafter Lantana), is a major concern to TDFs.

Lantana's allelopathic properties and ecological resilience allow it to colonize a wide range of climate and precipitation niches, making it one of the top ten invasive plants in the world (Bhagwat *et al* 2012, Mungi *et al* 2020). Despite efforts using fire, mechanical, and manual labour-intensive methods to eradicate or manage Lantana and restore forests, the shrub has continued to spread aggressively in the 20th century, especially in India and Australia

(Bhagwat *et al* 2012). The long-term ecological impact of Lantana invasion ranges from disrupting forest succession and regeneration to increased occurrences of forest fires (Prasad 2010). Lantana invasion can also have social impacts; for example, reduction in the availability of non-timber forest products due to overcrowding of native plants of livelihood interest (Kannan *et al* 2016).

The British introduced Lantana as an ornamental shrub in India in the 1800s and the shrub has recently become a major concern as the country works towards its forest restoration targets (Borah *et al* 2018) in this United Nations' Decade of Restoration (2020-2030). In TDFs in India, research has predominantly focused on the ecological impact of Lantana invasion and subsequent restoration through Lantana removal and succession (Prasad 2012; Sharma and Raghubanshi 2007, Sundaram and Hiremath 2012). For example, studies of experimental restoration (via Lantana removal) in a southern Indian TDF showed an increase in herb and shrub species richness associated with restoration (Prasad 2010). Studies quantifying the impact of Lantana invasion on fauna have largely focused on birds (Aravind *et al* 2010, Ramaswami *et al* 2017). As an example, Aravind et al. (2010) found that with an increasing density of Lantana, there was a decline in bird species diversity and an increase in species evenness, indicating that some species are able to use the Lantana-dominated habitat widely (Aravind *et al* 2010).

As ecological restoration has taken centre stage in the last few years, researchers and practitioners have called for (a) holistic design of restoration projects, taking into consideration people living on and using the land to be restored (Erbaugh and Oldekop 2018, Erbaugh *et al* 2020, Fleischman *et al* 2022) and (b) an evaluation of the impact of restoration, which considers both social and ecological outcomes equally (Pritchard 2021, Coleman *et al* 2021). While ecological indicators of success of restoration are easier to define and are more widely accepted, social indicators are more context dependent (Le *et al* 2012). For example, positive ecological outcomes could include increased tree species richness or diversity. Positive social indicators could include increased livelihood opportunities, income, or availability of food and fibre (Le *et al* 2012).

In the context of Lantana invasion and TDF restoration, social outcomes of invasion and restoration are little known. One study in India found that Lantana poses a hindrance to people's forest-based livelihoods. People's perception of a change in the composition of the overstory and the reduced abundance of NTFP species due to Lantana invasion was supported by ecological evidence of such changes (Sundaram *et al* 2012). At the same time, Lantana is sometimes used as supplementary fuelwood for cooking and heating in north India (Negi *et al* 2019), despite being a lower quality fuel compared to other species. There are also important gaps in the research on ecological impacts. Few studies quantify impacts of Lantana invasion and restoration beyond bird diversity, such as changes in hydrology, soil erosion, or the richness and diversity of less studied fauna, such as insects. Understanding a variety of outcomes, intended and unintended, is crucial to inform restoration programs, so that they can achieve the multifaceted objectives of biodiversity conservation, forest regeneration, and the welfare of local people.

In this study, we use central India as a case study to quantify ecological and social outcomes of Lantana invasion and subsequent TDF restoration. We choose two outcomes, which address current research gaps on the impact of invasion and TDF restoration: (a) people's livelihoods and perceptions and (b) less studied fauna. We use acoustic technology, and focus on the higher frequencies which are occupied by lesser studied taxa such as insects and bats. Although acoustically derived biodiversity measures are agnostic to the species producing the vocalisations, they can rapidly provide a preliminary estimate of acoustic energy in the soundscape (Sueur *et al* 2008, Rappaport *et al* 2022) and act as a proxy for species richness and diversity (Aide *et al* 2017, Dröge *et al* 2021). Specifically, we ask the following questions:

(1) For local people, what are the perceived benefits and drawbacks of the presence of Lantana in forests and the subsequent restoration through the removal of Lantana?
(2) Is there a significant difference in perceptions of ease of forest use and impacts of Lantana invasion between households living in villages that have and have not undertaken restoration?
(3) Is there a significant difference in the soundscapes of restored, unrestored and control (Low Lantana density) sites?
(4) Is there a synergy between the social and ecological outcomes of TDF restoration?

4.2 Materials and Methods

Study region

We carried out our research in the buffer region of Kanha National Park (KNP) in the Bicchiya subdistrict, in Mandla district of Madhya Pradesh. The region is dominated by tropical deciduous forests, which act as an important habitat for charismatic species such as the Bengal tiger. The region is also home to one of the largest populations of constitutionally recognized socio-economically disadvantaged groups including some Scheduled Tribes, such as the *Gonds* and *Baigas*. These communities are dependent on the surrounding forest for livelihood and subsistence to varying degrees and also rely on small-scale farming (DeFries *et al* 2021, Choksi *et al* 2021).

Restoration method

We studied the impact of restoration through Lantana removal by local communities in partnership with the state forest department and a local non-governmental organization, Foundation for Ecological Security (FES). Local communities use a widely implemented method of Lantana removal, in which the entire rootstock of the plant is uprooted in the first year, followed by weeding over the next few years (Prasad *et al* 2018). 2017 was the first year of Lantana removal for all the restored sites.

Site Selection

Using a propensity score based on socio-economic (e.g., total number of households in the village, composition of village members) and geographic factors (e.g., % forest cover in 3 kms buffer; % farm land in 3 kms buffer Table S1), we first matched 'treatment' villages that had restored TDF sites (N = 8 villages) within their village boundaries or their surrounding forest with 'control' villages where no such restoration took place (unrestored N = 7 villages). Additionally, we included villages with little to no Lantana naturally occurring in their surrounding forests over the last five years (Low Lantana Density, or LLD sites, N = 4 villages). We hypothesize that restored sites will eventually regenerate to resemble LLD sites. In three out of eight villages where restoration took place, we established unrestored and LLD sites for comparison within the surrounding forests of the same village. These three villages had two distinct 'tolas' or neigbourhoods, which were at least a kilometre apart. Thus, we have a total of 16 matched villages with restored, unrestored and LLD sites within their surrounding forests.

For the restored sites, the NGO FES, the Forest Department and local community members mapped the restoration sites within the forests in 2017, when restoration was carried out. Thus, the polygons of where restored was carried out (N=8; hereafter sampling sites) were readily available to us. We consulted village members about their forest use to spatially determine the other sampling sites within the unrestored (N=8 sampling sites) and LLD (N = 4 sampling sites) forests mentioned above. We created one sampling polygon per sampling site in the surrounding forests of the matched villages where local people mentioned they frequented the forest for timber and non-timber forest product collection (unrestored, restored and LLD sampling sites N = 20; area = 58.32 ± 30.93 ha).

Within these sampling sites, to establish the exact locations to deploy acoustic recorders (hereafter sampling locations), we first created an inner buffer (70 m) within each sampling site polygon, in order to only sample within the core of the polygon and avoid any acoustic data contamination from outside of the sites. Next, we used a random point generator in QGIS ver. 3.14 (QGIS Development Team 2022) to create points at least 380 m distant from of each other within the core of the polygon (N random points generated = 55). Each of the 55 sampling locations were once again matched using a propensity score based on vegetation data (Section 2.6) collected at these locations, geographic and socio-economic factors (Table S2), to ensure that the sites were statistically comparable to each other and differed only in terms of their Lantana status. Choksi et al. (2023) provide more details on the matching of sites.

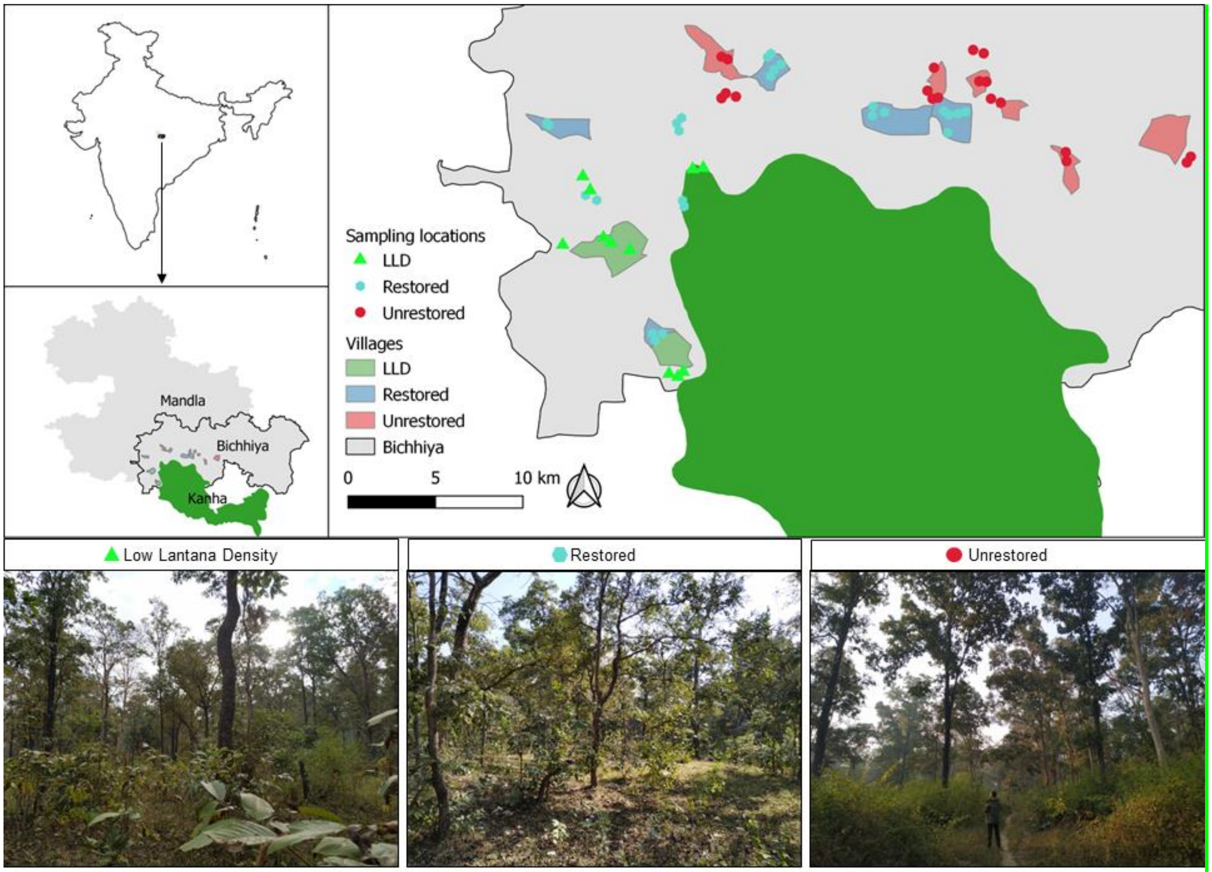

Figure 4. 1: Map of sampling locations and villages surveyed in the buffer region of Kanha National Park. Bottom: Photos of restored, unrestored, and reference sites (low Lantana density).

Acoustic data collection

At each sampling location (Fig. 4.1), we collected acoustic data for 7 to 10 days continuously at a sampling rate of 48 kHz at a medium gain (30.6 dB) using *Audiomoth* recorders (Hill et al., 2019). We first put the recorders in small Ziploc bags, to protected them from any potential water damage and then tied recorders to the trunks of trees at approximately 2 metres above the ground. The microphone was facing the ground and thus, we can assume that the recorders captured sounds closer to the ground than in the canopy of the forest. We set our recorders to record one minute for every five minutes and used a staggered sampling design to sample during the winter season. We faced some delays in collecting all our data between the alpha and delta waves of covid-19 and thus do not have a exact overlap in terms of months of data collection in 2020 and 2021. We collected data from January to March in 2020 and December to February in 2021. Thus, for every hour we collected 12 minutes of acoustic data. We were only able to collect data over the winter season due to covid-19 related complete lockdown and travel restrictions. all sampling locations, on average, we recorded 30.44 ± 8.27 hours in 2020 and 42.24 ±12.05 hours in 2021.

Household survey data collection

In January 2022, we surveyed 50 households in 13 of the 16 villages (5 restored, 6 unrestored, and 2 LLD) with a total of 656 surveys (Complete survey instrument in Appendix C). We did not survey all 16 villages, because three out of eight villages with restored sites also had unrestored or LLD sites in their surrounding forests (refer to section 'Site Selection' for more details). In each village, we sampled every other house on both sides of any lanes/ pathways within the village. Each survey lasted approximately 20 minutes and included questions about the socio-economic characteristics of a household, their livelihood and their perceptions of Lantana and restoration activities.

Vegetation data collection

At each sampling location, we collected vegetation data between January and April 2021. We established circular 314.2 m^2 plots (10 m radius plot). Using a 1-metre radius, we noted the diversity of identifiable grasses. Within a 3-meter radius, we collected the data on all seedlings and saplings and the number of Lantana saplings (single stems below 1 meter in height) and mature Lantana plants (>1 meter in height). While we could not identify all the shrubs below the height of 1 meter, we simply noted their presence within the 3-metre radius plot. Within the 10-meter radius, we collected data on the diameter at 1.35m up from the highest point of ground at the tree's base and the height (by visual estimation) of all trees (> 2 meters height). Due to the constantly changing covid-19 restrictions on travel, we were unable to collect data at four sampling locations (across two restored sampling sites). Therefore, we relied on vegetation metrics collected from the closest sampling locations (approximately 400 meters away) for these four missing sites.

Statistical analyses

Acoustic space occupancy quantification

For our response variable, we computed the acoustic space occupancy (ASO) by modifying the methods noted in (Campos-Cerqueira *et al* 2020). First, we first obtained a mean spectrum for each 1-min recording by computing a short-time Fourier transform (f = 48000, wl = 512, wn = "hanning", norm = FALSE) using the *meanspec* function (*seewave* package) in R programming environment. From this, we obtained a two-column matrix, with frequency in the first column and absolute amplitude values in the second column for 256 frequency bins. Here, the minimum absolute amplitude over all files was 0.073 and the maximum was 12104.95. We then used the *fpeaks* function in the same R package to detect the frequency peaks in the spectrums. We scaled the amplitude values resulting from the *fpeaks* to values between -1 and 1.

To distinguish biophony from background noise, we used a threshold for scaled amplitude of 0.003 (Campos-Cerqueira *et al* 2020) and selected only frequency peaks above the threshold (frequency distance threshold set to zero). This selection resulted in a two-column matrix of frequency and scaled amplitude values above the scaled amplitude threshold. Thus, effectively, if there was a peak in a particular frequency/ time bin, it was considered as an acoustic niche that was ‘occupied’. For our analysis, we only considered the peaks in the higher frequency range between 9 and 24 kHz. We then aggregated the peaks into 3888 bins (81 frequency x 48 time bins) with bin sizes for frequency and time set as 0.1875 kHz and 30 minutes respectively (i.e. each bin would consist of the 6 minutes recorded for every 30 minutes). We then calculated the ASO as the proportion of frequency bins where the scaled amplitude threshold of 0.003 was crossed for each 30-minute time bin and the total number of frequency bins (81 bins). We assumed the acoustic space occupied to represent abundance or diversity of species vocalizing in the specified higher frequency range (Burivalova *et al* 2019, Gottesman *et al* 2021, Zwerts *et al* 2022).

Statistical tests and models

(a) Socio-economic benefits and perceptions analysis:

For the household survey data analyses, we first provide descriptive statistics of perceptions related to Lantana invasion and restoration (question *i* to *iv* below).

(i) What is your perception of the Lantana density in your surrounding forest?

(ii) What use or benefit do you derive from Lantana in your surrounding forest?

(iii) What are the difficulties you face due to the presence of Lantana in your surrounding forest?

(iv) What do you perceive as the benefit of ecological restoration by way of removal of Lantana in your surrounding forest?

We used a two-tailed Z-test to determine if the differences in the proportions of responses from surveyed households with restored, unrestored, and LLD plots in their forest are significant. We then used generalised linear mixed models (GLMM; R package: *lme4*) to quantify the associations between the treatment and the dependent variables representing perceived ease of use of forest and impacts of Lantana in Table 1 (Fig S1 shows correlation between all independent variables considered). To account for spatial variation, we included a random effect for the village in our model (N=13). The four dependent variables are commonly accepted indicators of success of restoration (Le et al., 2012) and are relevant to this landscape (a-d in Table 4.1). Due to high collinearity (cutoff: R = 0.5; Figure S1) between the variables, % farm in 3 kms, % forest in 3 kms, size of the restoration site and distance to Kanha National Park, we only selected one variable for the model: % forest in 3 kms (Table S3 for summary statistics of all variables considered in this model). We selected the% forest in 3km as it is most relevant to our research questions given the high dependence on forest products in this landscape (Agarwala *et al* 2016, DeFries *et al* 2021). Furthermore, to test whether the total population in the village had an impact on the perception of benefits from restoration, we also fit all GLMMs with an interaction term of total households and treatment (restored, unrestored, low Lantana density). The predictor variables and controls are described in Table 4.1 (summary statistics in Table S3). We present the models with the lower AIC (of models with interaction term and without interaction term) in this paper and the models with higher AIC in the Supplementary Information.

Table 4. 1: Outcome, treatment and predictor variables used in the models with their data sources. Refer to Tables S2 and S3 for summary statistics of each variable for the treatment and control groups.

Variables	Unit	Data source
Outcome variables		
(a) Distance covered to take cattle grazing	Kilometres covered in a day	Household survey
(b) Time for firewood collection	Hours in a day	Household survey
(c) Incidence of cattle lost to depredation in last 5 years	1 = Yes 0 = No	Household survey
(d) Perception of percentage of crop loss due to crop raid	1 = high crop raid 0 = low crop raid instances	Household survey
(e) Acoustic space occupancy (ASO)	% Of frequency bins used of all frequency bins within 9 to 24k Hz	Acoustic data
Treatment variable	0 = No restoration 1 = Restoration carried out 2 = Low Lantana density	
Predictor, control, and random variables ease of forest use and perceptions models in Table 2:		
Land owned	Acres of land owned by household	Household survey

Cows owned	Number of cows owned by household	Household survey
Buffaloes owned	Number of buffaloes owned by household	Household survey
Agriculture as primary occupation	1 = Yes 0 = No	Household survey
Firewood collection	Number of days a member of the household collects firewood in a week	Household survey
Lantana as firewood	1 = Lantana as firewood used in the household 0 = Lantana not used as firewood in household	Household survey
Interval between refills of liquified petroleum gas (LPG) cylinder	Number of months between refills of LPG cylinder.	Household survey
Predictor, control and random variables ASO model in Table 3:		
Tree density	Number of small, medium and large trees in a 10-metre radius plot	Vegetation survey

Large tree density	Number of large trees (>10 cm diameter at breast height) density in 10-meter radius plot	Vegetation survey
Simpson index of plot	Simpson diversity index of all small, medium and large trees in 10-meter radius plot	Vegetation survey
% Forest cover in 3km radius	% Forest cover in 3 km radius of sampling location	Khanwilkar *et al* (2021)
Total population in 3km radius	Number of people in 3 km radius of sampling location	Govt of India census 2011
Year of data collection	2020 or 2021	Acoustic data
Date of data collection	101 days of data collection as a factor variable	Acoustic data
Sampling site	Factor variable representing 20 polygons within which sampling locations for acoustic and data collection were established	

(b) Acoustic space occupancy analysis:

We used a GLMM (R package: *lme4*) to quantify the effect of restoration on ASO in the frequency range 9- 24k Hz. We used the predictor, treatment, and outcome variables listed in Table 4.1 (summary statistics for these variables provided in Table S2). We scaled and centred all the continuous variables for this model. We incorporated random effects for temporal and spatial factors which could influence our results – the sampling site (N = 20) and the date of recording (N = 101 days).

Expectations

We hypothesize that people in restored and low Lantana density (LLD) sites will report having lower Lantana densities in their surrounding forests. We expect that Lantana is a significant obstacle to people's subsistence and livelihoods, mainly firewood collection and grazing. After controlling for several socio-economic and geographic factors, we expect villages with restored and LLD sites to be associated with positive outcomes including shorter distances covered for grazing, fewer hours spent collecting firewood, fewer incidences of livestock depredation and perceived crop loss due to crop raids. Prior evidence from these study sites finds no significant association of soundscape measures and restoration in the lower frequencies (2- 8k Hz) dominated by birds and insects (Choksi *et al* 2023). However, we expect restored and LLD sites to be significantly associated with higher ASO in comparison to unrestored sites, signifying that higher number of acoustic niches are occupied.

4.3. Results

Socio-economic benefits and perceptions analysis

(a) *For local people, what are the perceived benefits and drawbacks of the presence of Lantana in forests and the subsequent restoration through removal of Lantana?*

Figure 4.2 presents the results to questions listed in the section above. We found two key significant differences in the three groups with respect to their perceptions of Lantana density and its uses and disadvantages. First, we found that perceptions of Lantana density accurately reflected the conditions of sites, when Lantana invasion is high. A significantly lower proportion of respondents (61%) in villages near LLD sites reported ‘high’ Lantana densities in their surrounding forest, compared to 93% and 86% (restored – LLD: z = 5.287, p-value = 0.000; unrestored - LLD: z = 7.800, p-value = 0.000) in villages near unrestored and restored sites, respectively (Fig. 2, Fig S2, Table S4a). There was also a significant difference between restored and unrestored groups (z = 2.500, p-value = 0.014). The proportion of respondents reporting medium and low Lantana densities in villages with LLD sites was significantly higher than in the villages with restored and unrestored sites (Table S4a). Second, we found that a significantly higher proportion of respondents in villages near unrestored sites used Lantana as firewood and farm boundaries than the proportion of respondents in villages. However, we acknowledge that our acoustic data was not ground truthed due to covid-19 related challenges and thus, we are limited in the recommendations we can provide for restoration policy makers near restored and LLD sites (restored – unrestored: z = 9.286, p-value = 0.000, unrestored – LLD: z = 4.536, p-value = 0.000; Table S4b).

Except for a few responses, the three treatment groups were similar in their responses to the questions about the disadvantages of Lantana in their surrounding forest and the benefits of ecological restoration through Lantana removal (Table S4c and S4d). For example, all three groups perceived Lantana to be a reason for high livestock depredation (proportion of respondents in restored = 48%, unrestored = 49%, LLD = 49%; Table S4c). However, a significantly higher proportion of people in unrestored and restored listed crop raids as a difficulty due to the presence of Lantana, (restored – LLD: $z = 2.730$, p-value = 0.006; unrestored – LLD: $z = 2.893$, p-value = 0.004). Additionally, compared to villages with unrestored and LLD sites, villages with restored sites had a significantly lower proportion of people who listed '*difficulty in walking through Lantana*' as a drawback of having Lantana in their surrounding forest (restored – LLD: $z = 2.374$, p-value = 0.018; restored – unrestored: $z = 3.330$, p-value = 0.001). The objective of restoration was to increase the local community's access to timber and non-timber forest products. However, our results show that labour payment to assist in the removal of Lantana was the most commonly reported benefit of restoring their surrounding forest (proportion of respondents in villages with restored sites = 51%, unrestored sites = 53%, LLD sites = 62%; Fig. 4.2 and Table S4d).

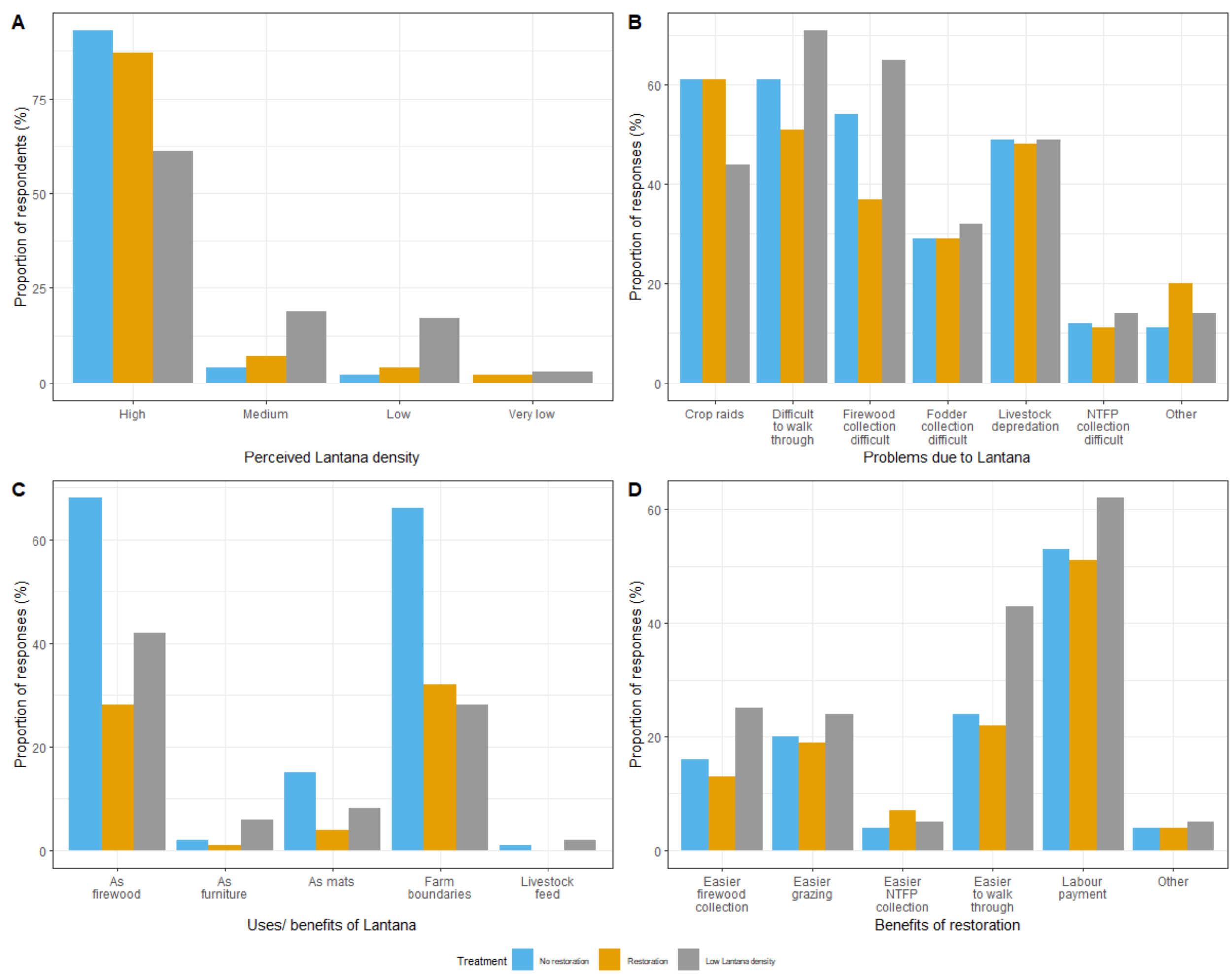

Figure 4. 2: Treatment group-wise responses to survey questions. Colors refer to the treatment group to which respondents belong. (A) Perceived densities of Lantana camara in the surrounding forests; (B) Uses and perceived benefits of having Lantana camara in the surrounding forests; (C) Perceived difficulties due to the presence of Lantana camara in the surrounding forests; (D) Perceived benefits of ecological restoration in the surrounding forests. Refer to Fig S2 for the results for all the surveyed households without the treatment groups and Table S5 for results on differences in the group.

(b) Is there a significant difference in perceptions of ease of forest use and impacts of Lantana invasion between households living in villages that have and have not undertaken restoration?

Table 4.2 presents the results of the GLMMs for the dependent variables listed in Table 4.1. We found that restoration had no significant association with the outcomes. LLD sites are associated with significantly lower distances people needed to travel for grazing. However, beyond statistical significance, the effect sizes of the coefficients are important to note. All our models have large standard errors, which indicate that there was large variation between households within and across villages in each treatment type. First, restoration has a large negative effect on the distance travelled for grazing (coefficient: -0.272, SD: 0.197, p-value: 0.169). Restoration is associated with higher livestock depredation (coefficient: 0.518, SD: 0.401, p-value: 0.196) compared to unrestored sites.

Our hypothesis that restoration would be experienced differently based on the total number of households in the village did not hold (Table S5 a-c), except in the model of perception of crop loss due to crop raids (Table 4.2d). Perceptions of larger crop losses due to crop raids were negatively associated with the number of households in a village (coefficient: -0.075, SD: 0.162, p-value: 0.618). However, the perception of crop losses significantly changed depending on the whether the village had a restored forest site. (interaction term restoration x total households in village- Table 2d; coefficient: -1.116, SD: 0.389, p-value: 0.004).

Table 4. 2: Estimates and standard errors (in parentheses) for models of the four socio-economic outcome variables (a-d) considered in this study (details in Table 4.1). In this table, we present the models with the lower AIC of the two types of models we fit, the first not including an interaction term and the second including an interaction term. Refer to Table S5 for the estimates and standard errors of models with the higher AIC. 'NA' for any predictor variable signifies that that particular variable was not included in the model.

Variables	(a) Distance for grazing	(b) Time for firewood collection	(c) Cattle lost to depredation	(d) Perception of crop loss
Treatment: Restoration	-0.272 (0.197)	0.046 (0.134)	0.518 (0.401)	-0.196 (0.429)
Control: Low Lantana Density	-0.460 (0.246)#	0.098 (0.167)	0.340 (0.481)	-0.353 (0.5545)
Land owned	0.062 (0.038)	-0.012 (0.021)	0.105 (0.087)	-0.075 (0.085)
Cows owned	0.062 (0.039)	NA	0.101 (0.096)	NA
Buffalos owned	0.160 (0.040)***	NA	0.118 (0.097)	NA
Household size	0.053 (0.039)	-0.029 (0.021)	0.229 (0.098)*	-0.002 (0.089)
Number of days firewood collection/ week	NA	0.140 (0.020)***	NA	NA
Use of Lantana as firewood	NA	0.111 (0.051)*	NA	NA
Interval between filling LPG	NA	0.028 (0.022)	NA	NA
Agriculture primary occupation	0.003 (0.087)	0.012 (0.047)	0.141 (0.217)	0.369 (0.197)#

% Forest in 3 km buffer	0.053 (0.100)	-0.073 (0.067)	0.269 (0.204)	0.055 (0.216)
Total households in village	-0.018 (0.064)	0.115 (0.042)**	-0.504 (0.172)	-0.075 (0.162)
Restoration x Total households	NA	NA	NA	-1.116 (0.389)**
Low Lantana density x Total households	NA	NA	NA	-0.173 (0.507)
Random variable: Sampling site (N= 13 villages)	0.032 (0.179)	0.017 (0.130)	0.088 (0.297)	0.127 (0.357)
N observations	652	656	637	605
AIC	2551	2660	707	783
Distribution used	Negative Binomial	Negative Binomial	Binomial	Binomial

Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '#' 0.1 ' ' 1

Acoustic Space Occupancy (ASO) analysis

(c) Is there a significant difference in the soundscapes of restored, unrestored and control (Low Lantana density) sites?

Figure 4.3 shows the change in the outcome variable, ASO, over a 24-hour time period. Table 3 shows the parameters of the GLMM for the outcome variable ASO. We found that unrestored sites are associated with higher ASO (in the case of LLD, significantly higher) than restored and LLD sites. Furthermore, there is higher ASO during the day time hours (06:00 to 18:00) and not at night (18:00 to 06:00; Table 4.3).

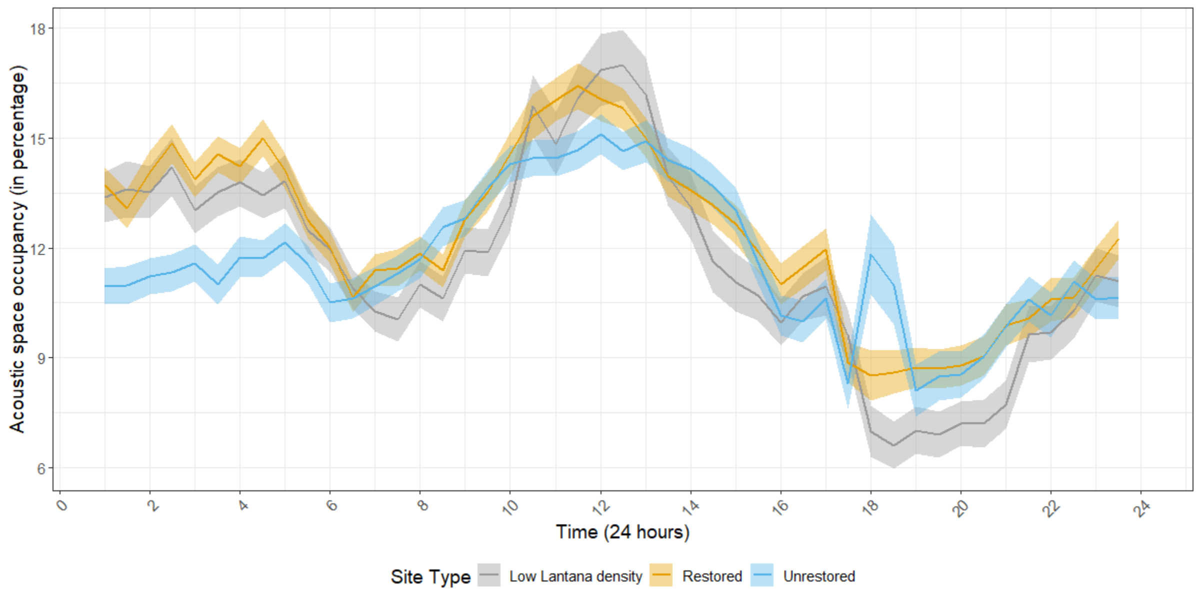

Figure 4. 3: Response variable, acoustic space occupancy of soundscapes between 9 to 24k Hz over a 24-hour period. Colours represent different site types and the shaded bands represent standard deviation around the mean represented by the solid line.

Table 4. 3: GLMM results for the model with outcome variable, ASO.

Variables	**Estimates and standard error**
Treatment: Restoration	-0.100 (0.116)
Control: Low Lantana Density	-0.438 (0.143) **
Year (2020/ 2021)	-0.066 (0.046)
% Forest in 3 km buffer	0.129 (0.017) ***

Total population in 3 km buffer	0.060 (0.015) ***
Tree density	0.027 (0.005) ***
Large tree density	0.043 (0.006) ***
Simpson Index for all trees	0.049 (0.005) ***
Time of day: Night	-0.344 (0.049) ***
Random variable: Sampling sites (N= 20)	0.051 (0.227)
Random variable: Date of recording (N = 101 days)	0.049 (0.222)
Random variable: Time (N = 48 time bins)	0.021 (0.144)
N observations	23861
Distribution used	Binomial

Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '#' 0.1 ' ' 1

4.4 Discussion

Our results demonstrate the complexity of novel ecosystems, whereby the naturalised invasive species are generally negatively perceived but also become primary resources in the absence of alternatives (Hobbs *et al* 2009). We found that people perceived Lantana as an impediment to forest access (Fig. 4.2). Lantana is considered poor fuel for fire (Negi *et al* 2019), yet we found that people in villages with unrestored sites relied significantly more on Lantana for firewood (Fig. 4.2, Table S5). People in villages with unrestored sites using Lantana to make farm boundaries is most likely an indication of the lack of bamboo, which is the preferred material for farm boundaries in this landscape. Our results resemble evidence on the use of invasive plants from other parts of India. For example, in the Banni grasslands of Gujarat, woody encroachment by the invasive *Prosipos juliflora* resulted in a novel ecosystem in which the tree has significantly degraded the ecosystem important for local pastoralists, but also provides local people supplementary income through charcoal production (Nerlekar *et al* 2022). Thus, if restoration is to take place at large spatial scales, it would be necessary to provide sustainable fuel and firewood alternatives to meet local people's resource needs in order to avoid negatively impacting local subsistence and livelihoods.

In all three treatment groups, people perceived the greatest benefit of restoration to be the payment for the removal of Lantana (Fig. 2, Fig. S2, Table S2a). The intended goal of restoration, such as the ease of collecting firewood and NTFPs, were not the most frequently reported benefits of restoration in our study. This could be due to two reasons: (a) the spatial scale at which restoration took place is too small for respondents to perceive such benefits, and (b) TDFs are slow-growing, and regeneration takes place over longer temporal scales in comparison to faster-growing humid forests (Murphy, 1986). Restoration was carried out in 2017, and we carried out data collection in 2020 and 2021.

Our results did not show that people perceive restoration to be connected to ease of forest use. However, the result that people from villages with restored and LLD sites reported higher durations for firewood collection (Table 4.2b) could be a reflection of the higher reliance on firewood and not necessarily a difficulty in collecting firewood. Further, we find higher instances of livestock depredation in restored and LLD sites, which could be due to differences in the carnivore populations in the vicinity of the villages for which we do not have data. We used %

forest in 3km to account for the presence of herbivores and carnivores. However, the finer differences in populations are likely to influence the model results significantly. At the same time, respondents did perceive restoration to be connected to several positive outcomes. For example, first, the distance travelled for grazing was perceived to be lower, even though not significantly so, at restored sites and significantly lower at LLD sites (Table 4.2). Second, there was a lower perceived crop loss at restored and LLD sites (Table 4.2). Prior research from a TDF in southern India found that local people's perception of higher instances of crop raids around high Lantana density forests is supported by vegetation data. This could be because Lantana invasions are connected to a reduction in forage availability, which can in turn lead to an increase in crop raids by herbivores (Sundaram *et al* 2012). Even though we interpret the association of villages with restored and LLD sites having a lower perceived crop loss due to raid as a positive outcome of restoration and lack of Lantana in the surrounding forests, we recognize that it is difficult to assign causality.

Given the premise of Acoustic Niche hypothesis, and our hypothesis of higher species diversity in restored and LLD sites, we expected more acoustic niches to be occupied in LLD and restored sites than unrestored sites. Contrary to our expectations, we found lower Acoustic Space Occupancy in the higher frequencies in LLD and restored sites in comparison to unrestored sites. Prior studies from the same area show that there were no significant differences in the acoustic space use in the lower frequencies (2-8kHz), which are dominated by birds and insects (Choksi *et al* 2023). A study from Costa Rica found that primary forest sites have lower acoustic energy in the higher frequency range, compared to recently restored forests. The authors attributed his lack of acoustic energy at primary sites due to (a) a strong insectivorous predator community or (b) the lack of preferred vegetation for certain insects (Vega-Hidalgo *et al.* 2021).

In our study, given the relatively small differences in ASO across all three types of sites (Fig. 4.3), we speculate that the differences in ASO are driven by vegetation structure and do not reflect differences in vocalising fauna such as insects and bats. Restored and LLD sites have a mostly clear understory with the absence of Lantana, and thus provide a different environment for signal attenuation than the dense understory of unrestored sites. Sounds in the higher frequency ranges are relatively more prone to scattering in forested habitats (Romer and Lewald 1992, Bullen and Fricke 1982), and thus we speculate that higher ASO could be due to reduced attenuation in forests with clearer understories. Given the slow regeneration times of TDFs, it is necessary to repeat these acoustic measurements at several time steps in the future to understand whether ASO is positively affected by restoration.

We find a limited synergy between the social and ecological outcomes of restoration. Prior evidence from these sites shows no significant difference in soundscapes (lower frequencies) and avian richness due to restoration. With no significant differences in the ASO in the higher frequencies either, if policy-makers and practitioners were to only consider the ecological outcomes based on the soundscapes, restoration would appear to have no significant biodiversity ‘benefit’. Thus, policy-makers could argue, for example, to not invest further in such efforts. However, when we consider social outcomes alongside the ecological, we find that respondents in villages reflect a few benefits of restoration, such as the lower dependence on Lantana for firewood or farm boundaries or the shorter distances covered for grazing and the lack of Lantana in their surrounding forests. Although national and state-led development programs advocate for a move away from dependence on forest resources (*e.g.*, providing of LPG or financing durable materials for the construction of houses; DeFries et al., 2021), in the short term, without affordable alternatives, such restoration efforts could alleviate a few inconveniences local people face from forest degradation due to Lantana invasion. Our study also finds that local people's perceptions of the condition of their surrounding forest are accurate, reaffirming the need to include people who will be affected by well-meaning restoration efforts in the decision-making process and not rely solely on top-down and technocratic approaches (Crowley *et al* 2017).

This study has some limitations. First, propensity score matching is an alternative in the absence of the opportunity to carry out a true randomization (Luellen *et al* 2005), but there could be inherent differences between the villages driving the results. We also acknowledge that it is more effective to sample the same village over time to better quantify the socio-ecological outcomes instead of matching treatment and control groups. However, this was not possible as restoration had already been undertaken in some villages and not others. Second, there could be biases in our data due to the method of data collection – surveys. For example, restoration was carried out by villagers in collaboration with the local NGO and the Forest Department. The respondents' answers can be determined by what the respondent thinks a surveyor wants to hear about a restoration program and may not provide an honest response. Alternatively, the respondent may have perverse incentives to answer dishonestly if they believe that their responses may influence future restoration programs. Acoustic data captures only vocalizing species. Several non-vocalizing species, that are not captured in acoustic data, may be critical to the success of restoration. Thus, acoustic data does not provide a complete picture of faunal diversity. Furthermore, we acknowledge that our acoustic data was not ground truthed due to covid-19 related challenges. Thus, we are cautious in the recommendations we can provide for restoration policy makers.

4.5 Conclusions

Land and forest degradation due to the proliferation of invasive species is a concern in several landscapes across different countries. As countries work toward their restoration goals, especially in TDFs, it is important to assess the varied and multidimensional impacts of the source of degradation and restoration efforts. Doing so can ensure that restoration is beneficial to people and biodiversity and is long-lasting in these unique socio-ecological systems. Our study provides a multidimensional view of the impacts of ecological restoration by assessing biodiversity outcomes in conjunction with socio-economic ones to assist policy makers with future direction of TDF restoration efforts at larger scales. The evidence we provide is applicable to numerous socio-ecological systems, which grapple with balancing biodiversity conservation and local resource needs.

Conclusion

The chapters in this dissertation make a contribution to the field of restoration ecology, soundscape ecology and migration studies. Further, given the applied nature of my dissertation, there are a few chapter outputs (*e.g.*, Fig 1.2 in Chapter 1) that can be immediately used for policy-making as well as findings that can guide governmental and non-governmental efforts in the central Indian landscape as well as other similar socio-ecological landscapes around the world.

First, in terms of understanding the potential for and the outcomes of restoration, my dissertation shows that there is (a) potential to carry out restoration in a way that meets social and ecological goals due to the large spatial overlap in the areas of high biophysical restoration potential and poverty in India and (b) small scale restoration efforts can have significant social impact in the short term. Biodiversity outcomes based on acoustic data require ground truthing before the results from the application of this tool can be taken into consideration for future restoration policy-making. Understanding the synergy between the social and ecological outcomes can help restoration managers and policy makers design projects that address the different needs of one project. The analysis of biophysical restoration potential and poverty in India can assist policy-makers to design projects that better address these social and ecological concerns. Further, the local non-governmental organization, Foundation for Ecological Security (FES), can use the results from quantification of social and ecological outcomes of restoration to design future restoration projects. For example, one of the most important findings from Chapter 4 is that people rely on the invasive shrub, *Lantana camara*, for livelihoods. Removing the shrub abruptly and completely at large spatial scales could impact people's daily lives. While restoration is needed for the regeneration of forests and has multiple benefits, as Chapter 4 shows, restoration projects need to consider people's reliance on this shrub when they make decisions at larger spatial scales.

Second, the application of acoustic technology in this dissertation provided very useful evidence for the acoustic niche hypothesis (ANH) not only from a generally underrepresented biome but also from an unprotected area. In the novel field of soundscape ecology, the first step is to collect evidence from different parts of the world to test simple hypotheses such as the ANH. On the premise of the ANH, we expected the least 'disturbed' sites to have the greatest number of occupied acoustic niches. However, our results, along with emerging evidence from other parts of the world show that this is not always the case. While this is critical empirical evidence, which will help guide this field of study towards refining current theories, I acknowledge the limitations of this tool and the need to ground truth the data before any policy decisions can be made based on these results. The next step in this study is to ground truth this acoustic data and to understand the drivers of differences in the ANH by comparing acoustic data and fine-scale biodiversity surveys that focus on lesser-studied vocalizing fauna such as insects and bats.

My chapter on rural livelihoods, mainly season migration, shows the impact of climatic variability on a common livelihood strategy. While several studies have shown that the poorest in the world are most climate vulnerable, my chapter zooms in on a small population to find that households in richer districts are more vulnerable to climate variability than those in poorer districts. This is an important finding for policy-makers addressing agriculture and migration in India and could help shape policy for alternative livelihoods and climate-resilient agricultural initiatives. A better understanding of this livelihood strategy and how it may be impacted in the future can also inform the design of restoration projects in a landscape such as central India.

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Appendix A: Supplementary Information for Chapter 2

Figure 1: Seasons of the year migrant households have at least one migrant away for seasonal work.

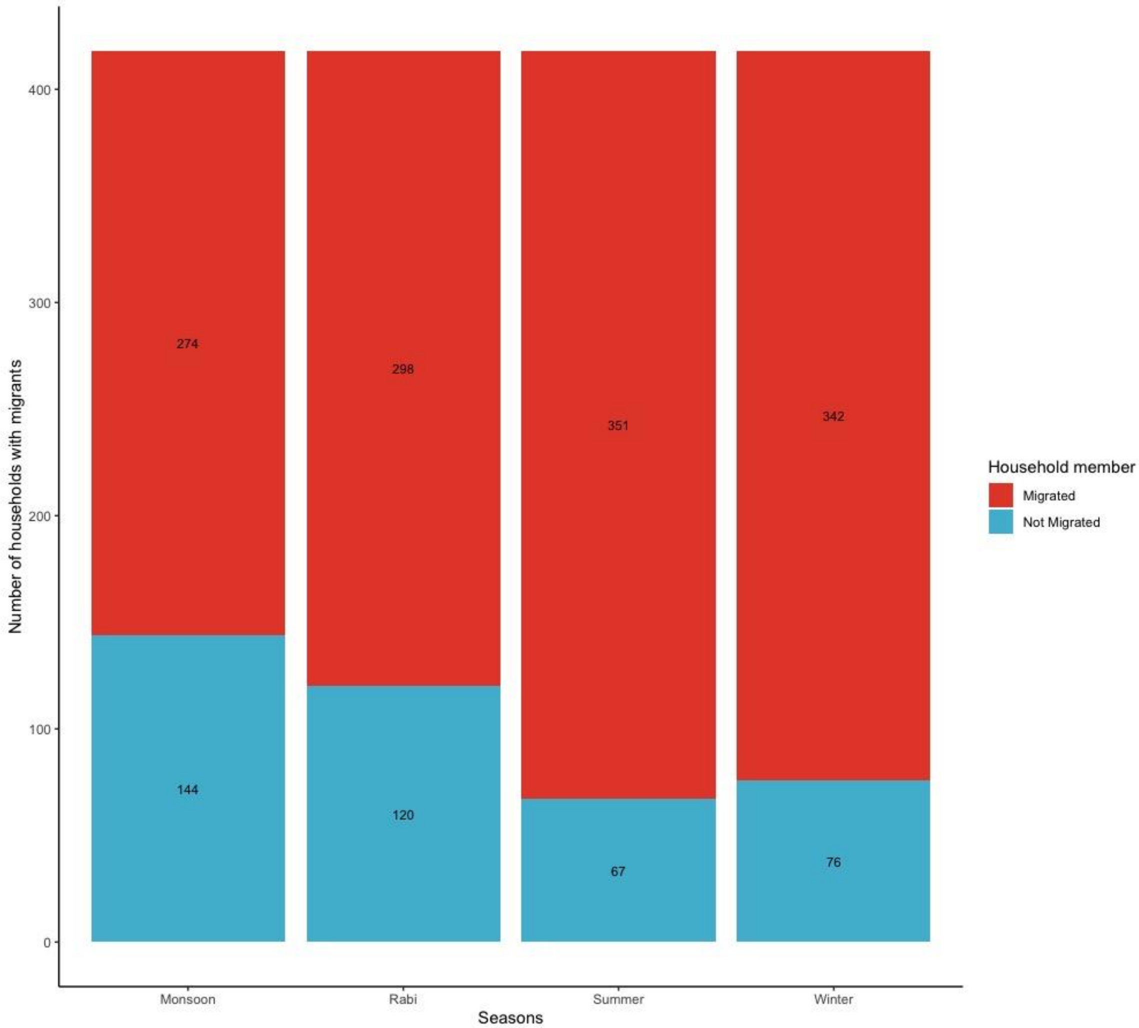


Figure 2: Jobs undertaken by migrants.

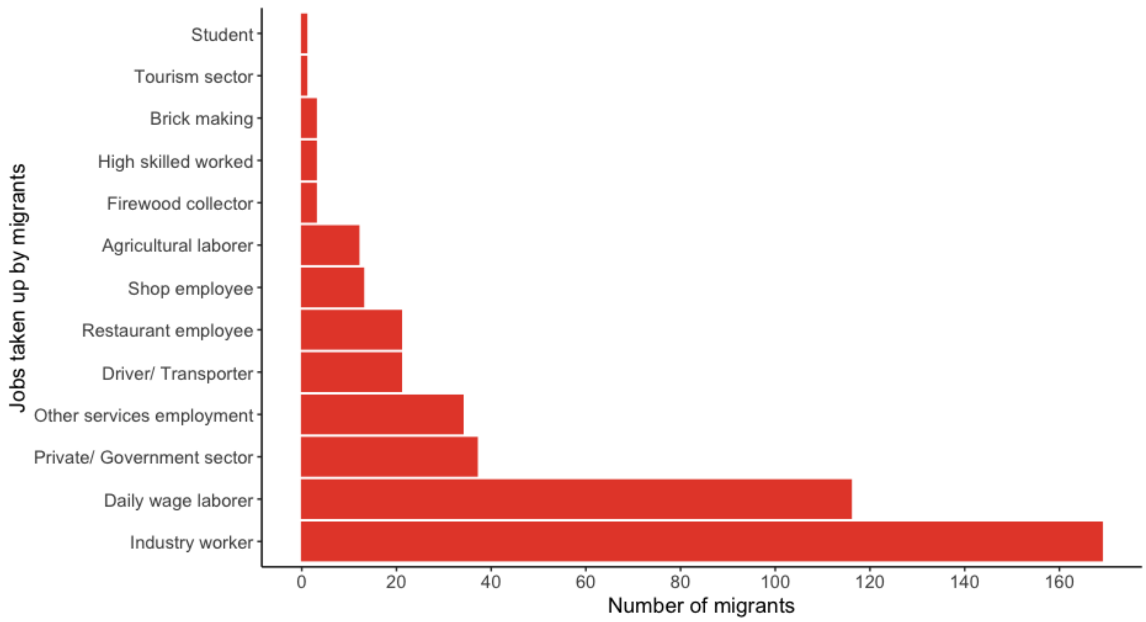


Figure 3: Multidimensional Poverty Index (Oxford Poverty and Human Development Initiative 2020) of surveyed districts in the CIL.

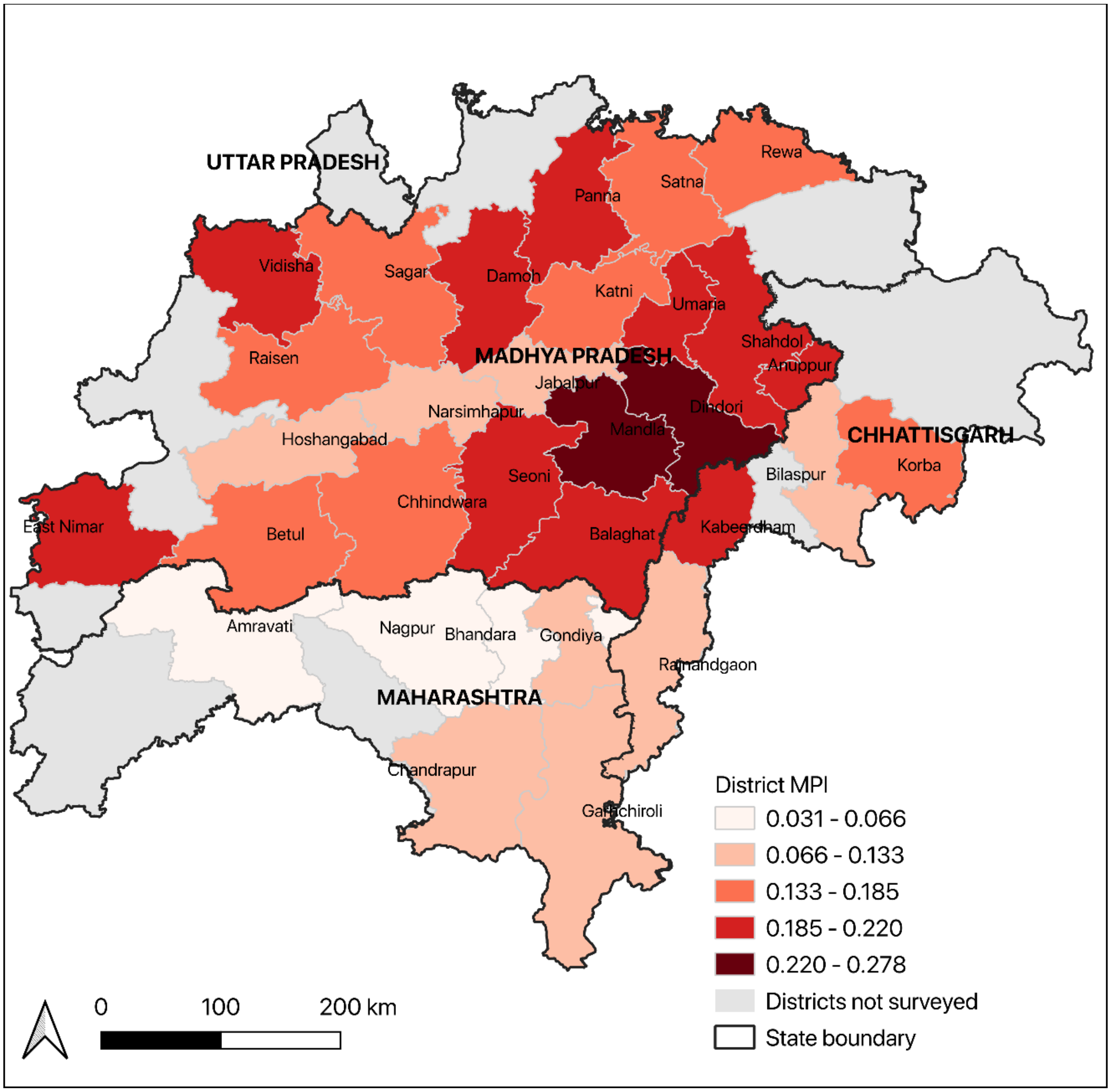
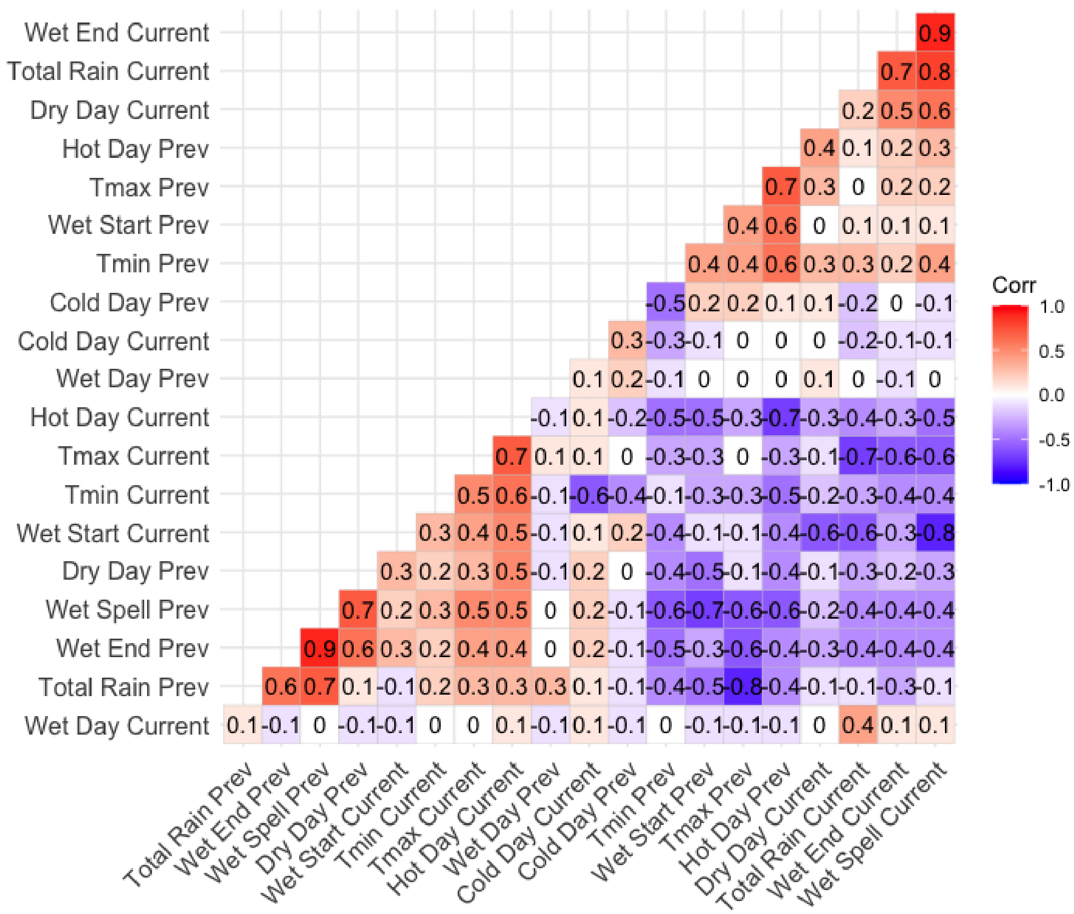


Figure 4: (a) Correlation Plot of all climatic variables considered in this study. The variables refer to the standard deviation in the climatic variable in the years 2013 to 2017 in comparison to the long term mean (1981-2017). *Current* refers to the current year and *Prev* refers to the previous year.



(b) Correlation plot of all the variables used in the final sets of models in Table 3 in the paper. *Current* refers to the current year and *Prev* refers to the previous year.

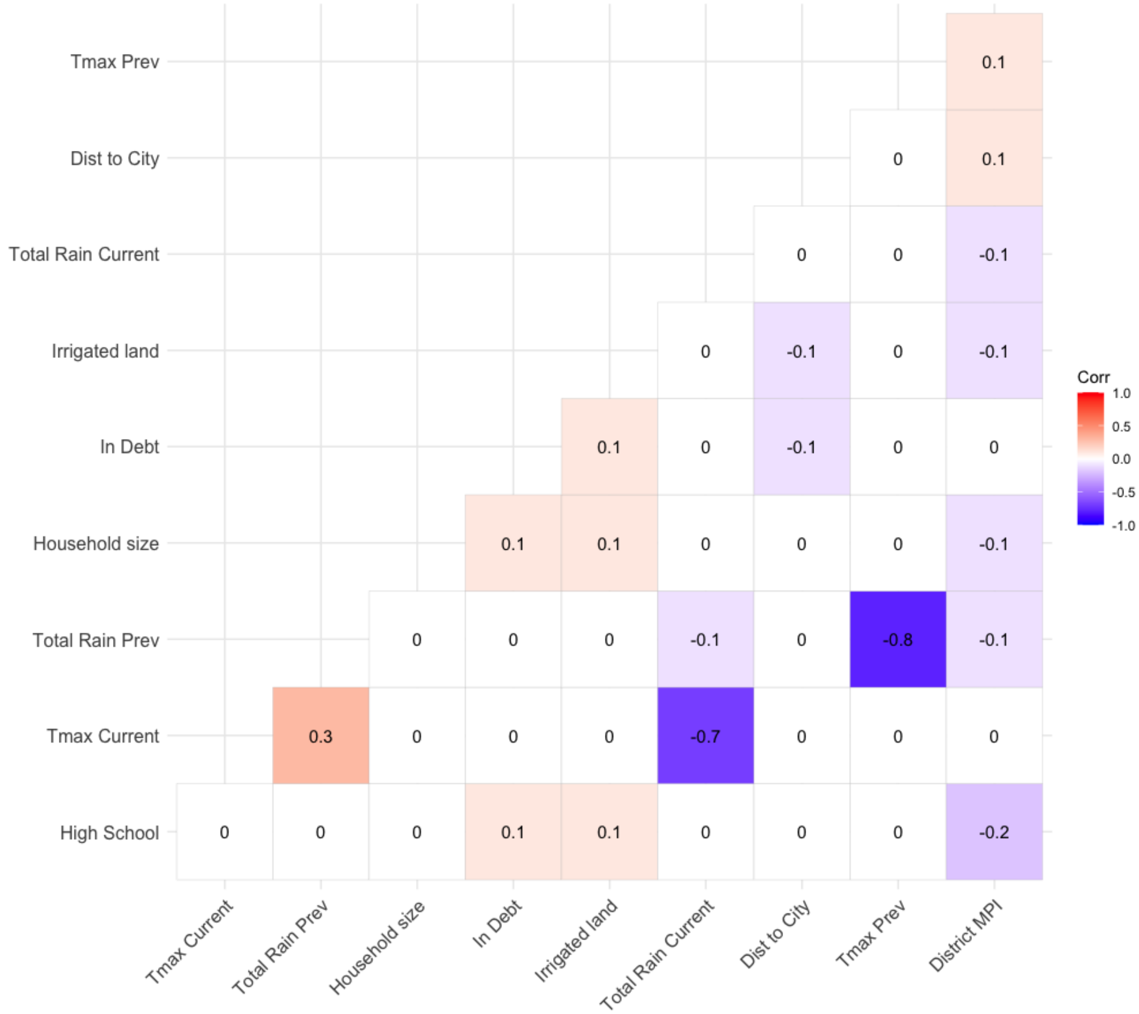


Figure 5: (a) Probability of first- time seasonal migration as a function of the interaction of variability in the mean maximum temperature in the previous year and the district's MPI based on combined data (2013- 2017). The predictions consider the random effects of the model. The confidence intervals are calculated assuming a normal distribution. District MPI values represent the minimum, first quantile, mean third quantile and the maximum (in ascending order). Higher MPI values indicate higher multidimensional poverty in a district.

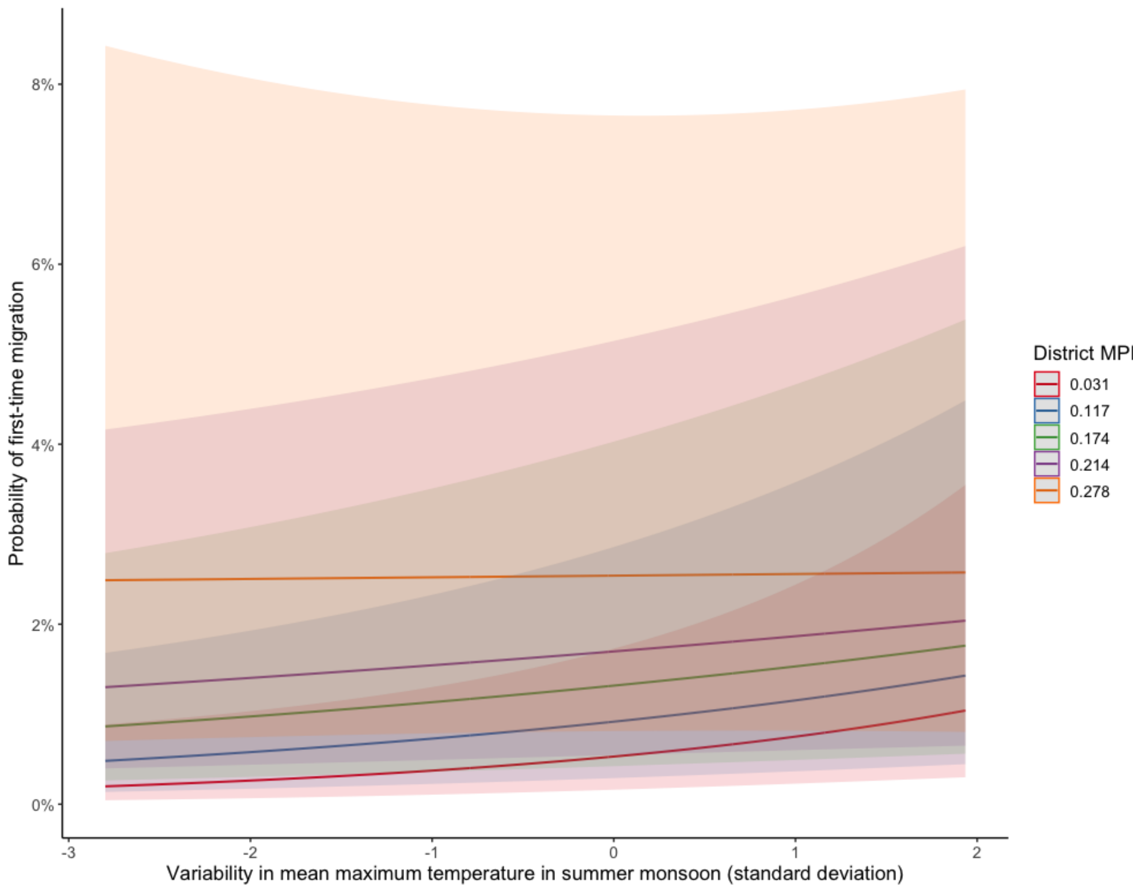


Figure 5: (b) Probability of first- time seasonal migration as a function of the interaction of variability in the total rainfall in the previous year and the district's MPI based on combined data (2013- 2017). The predictions consider the random effects of the model. The confidence intervals are calculated assuming a normal distribution. District MPI values represent the minimum, first quantile, mean third quantile and the maximum (in ascending order). Higher MPI values indicate higher multidimensional poverty in a district.

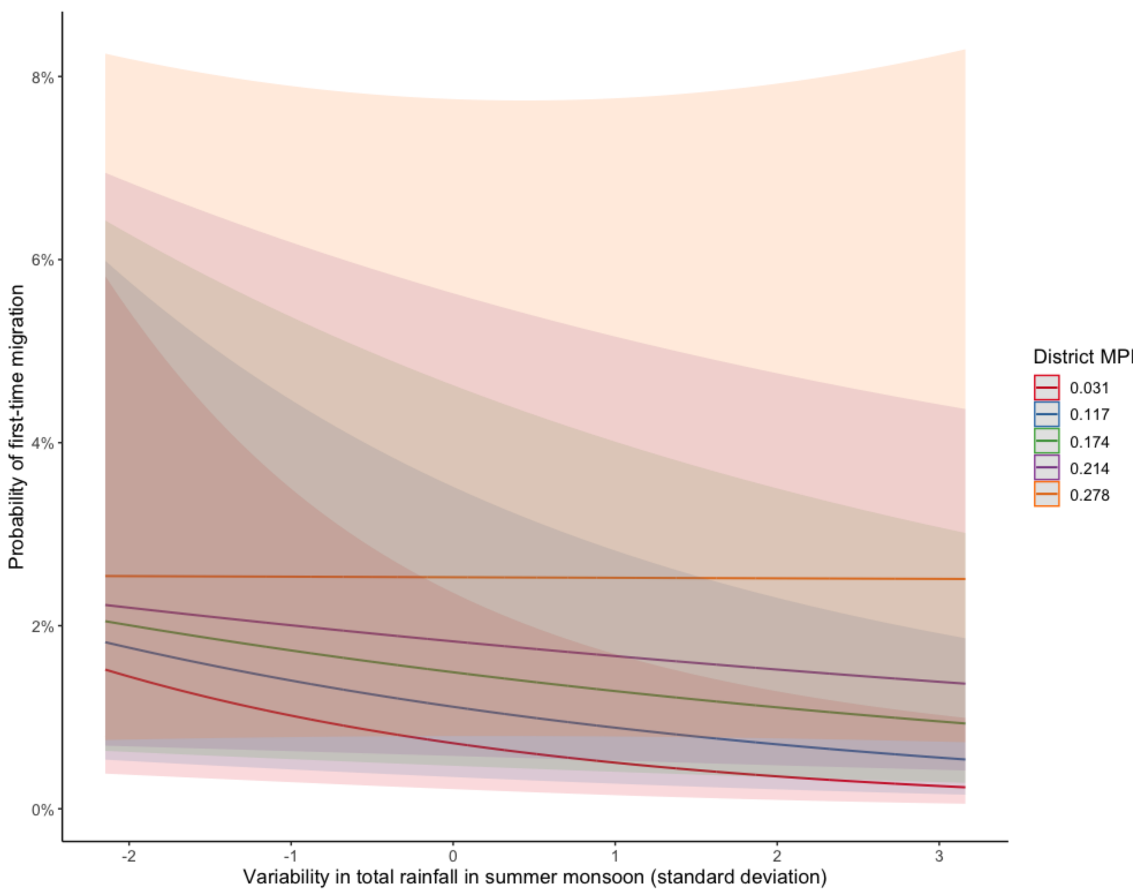


Table 1: This table presents the reason and the number of surveys, which were removed from the total of 5000 surveys. The 4323 surveys comprise 2828 surveys from MP, 794 surveys from Maharashtra and 701 surveys from Chhattisgarh.

Total number of surveys	**5000**
Surveys removed for because households reported first- time migrants before 2013	345
Surveys removed because the respondent was not aware if there was a migrant in the household	100
Surveys removed because households reported first-time migrants in 2018	10
Surveys removed because respondent was unaware of their caste	1
Surveys removed due to missingness of Economic Census 2013 survey data in SHRUG (Asher *et al* 2019)	221
Total number of surveys considered in this study	**4323**

Table 2: Details of districts surveyed for this study. The table presents the percentage contribution of deprivations of each dimension of the Multidimensional Poverty Index (MPI) – health, education, and living standard - to the overall MPI. Proportion of scheduled tribe population derived from the Government of India 2011 census. Proportion of villages in forest fringes is defined as a village within 8 km of a forest patch greater than 500 ha. In the CIL, irrigation is mainly used for a market-oriented second crop in winter, predominantly wheat

(Zaveri and B. Lobell 2019). Data for area of production for two key cereals in the central Indian landscape, rice and wheat, derived from International Crops Research Institute for the Semi-Arid Tropics (http://data.icrisat.org/dld/src/crops.html).

No.	District Name	State Name	District MPI	MPI-Health Component (%)	MPI – Education Component (%)	MPI – Living Standard Component (%)	Proportion Scheduled Tribe Population	Proportion of villages in forest fringe	Wheat cultivation (hectares) per 1000 hectares (as of 2013)
1	Amravati	Maharashtra	0.066	31.6	11.8	56.7	0.14	0.11	4.7
2	Anuppur	Madhya Pradesh	0.205	31.1	13.6	55.3	0.48	0.50	NA
3	Balaghat	Madhya Pradesh	0.201	37.3	10.9	51.9	0.23	0.79	17.52
4	Betul	Madhya Pradesh	0.173	31.8	17.9	50.3	0.42	0.47	122.8
5	Bhandara	Maharashtra	0.046	36.6	12.5	50.8	0.07	0.44	396.1
6	Bilaspur	Chhattisgarh	0.12	35.2	19	45.7	0.19	0.37	726.15
7	Chandrapur	Maharashtra	0.092	33.8	12.4	53.8	0.18	0.33	319.4
8	Chhindwara	Madhya Pradesh	0.148	31.9	16.4	51.8	0.37	0.32	146.14
9	Damoh	Madhya Pradesh	0.219	29.7	17.7	52.6	0.13	0.14	88.62
10	Dindori	Madhya Pradesh	0.278	29.8	14.6	55.6	0.65	0.91	NA
11	Gadchiroli	Maharashtra	0.117	31.6	16.7	51.6	0.39	0.75	NA
12	Gondiya	Maharashtra	0.102	40.5	7.4	52.1	0.16	0.55	NA
13	Hoshangabad	Madhya Pradesh	0.112	34.3	17.9	47.9	0.16	0.44	408.58
14	Jabalpur	Madhya Pradesh	0.104	32.9	20.5	46.5	0.15	0.30	218.66

15	Janjgir-Champa	Chhattisgarh	0.114	32.8	19.6	47.6	0.12	-	NA
16	Kabeerdham	Chhattisgarh	0.2	31.8	22.8	45.4	0.20	0.45	NA
17	Katni	Madhya Pradesh	0.185	33.7	14.1	52.2	0.29	0.47	NA
18	Khandwa (East Nimar)	Madhya Pradesh	0.21	30.7	24.4	44.9	0.35	0.08	128.37
19	Korba	Chhattisgarh	0.166	35.6	16	48.4	0.41	0.65	NA
20	Mandla	Madhya Pradesh	0.247	29.7	15.8	54.4	0.58	0.88	74.83
21	Nagpur	Maharashtra	0.031	42.4	14.3	43.3	0.09	0.16	77.8
22	Narsimhapur	Madhya Pradesh	0.133	32.6	17.3	50.1	0.13	0.3	93.17
23	Panna	Madhya Pradesh	0.211	28.2	21.4	50.5	0.17	0.23	85.23
24	Raisen	Madhya Pradesh	0.167	33.3	18.5	48.2	0.15	0.18	241.87
25	Rajnandgaon	Chhattisgarh	0.101	42.3	10.7	47	0.26	0.43	NA
26	Rewa	Madhya Pradesh	0.174	33.7	16.6	49.7	0.13	-	154.21
27	Sagar	Madhya Pradesh	0.174	30.1	16.8	53.1	0.09	0.13	228.79
28	Satna	Madhya Pradesh	0.159	31.9	17.9	50.2	0.14	0.13	146.54
29	Seoni	Madhya Pradesh	0.214	31.9	13.5	54.6	0.38	0.45	153.28
30	Shahdol	Madhya Pradesh	0.22	29.2	16.5	54.2	0.45	0.34	91.66
31	Umaria	Madhya Pradesh	0.22	30.2	17.1	52.7	0.47	0.86	NA
32	Vidisha	Madhya Pradesh	0.213	29.8	22.8	47.4	0.05	0.09	261.28

Table 3: Definition of climatic indices used in this study as per Mondal et al. (2014).

Climatic index	Definition
Precipitation indices (CHIRPS at 0.05 resolution) – Funk et al. 2015	
Wet season start date	First wet day (>1 mm) of first 5-day wet spell (wet spell amount ≥ _20-years (1981-2000) wet season mean *5) which is NOT immediately followed by 10-day dry spell with <10 mm (to exclude false start)
Wet season end date	Last wet day (>1 mm) of last 5-day wet spell which is NOT immediately preceded by 10-day dry spell with <10 mm (to exclude post-monsoon short spell)
Wet Season length	Wet season end date – Wet season start date
Heavy rainy days	Number of days with rain > 64.4 mm during wet season (as per Indian Meteorological Department definition)
Dry days	Number of days with rain < 1 mm during wet season (as per Indian Meteorological Department definition)
Total rainfall	Total rainfall during wet season
Temperature indices (CPC at 0.50 resolution)	
Hot Days	Number of days with maximum temperature > maximum temperature reference (90th percentile of daily June, July, August, September (JJAS) maximum temperature during 1981-2000)
Cold Days	Number of days with minimum temperature > minimum temperature reference (10th percentile of daily June, July, August, September (JJAS) minimum temperature during 1981-2000)
Mean Tmax	Average daily daytime maximum temperature during JJAS
Mean Tmin	Average daily daytime minimum temperature during JJAS

Table 4 (a and b): (a) Results of alternative mixed effects logistic regression models estimated with the combined data (2013- 2017) before choosing the model presented in the paper. The model uses year of migration and village as random effects, consistent with the model in the paper. Standard errors noted in parenthesis. The model estimated using the variability in total rainfall has the same AIC value as the model presented in the paper based on the mean maximum daily temperature. We ran a variance inflation factor test using the R package *car* (Fox and Weisberg 2019) to ensure there was no multi-collinearity in our models.

	Coefficients (Standard errors in parenthesis)							
Climatic variables (standard deviations for all variables used)	**Dry days**	**Heavy rainfall days**	**Wet season length**	**Wet season start date**	**Wet season end date**	**Minimum temperature**	**Hot days**	**Cold days**
	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**	**Model 7**	**Model 8**
Predictor variables								
Variability in climatic variable in current year (SD)	-0.02 (0.06)	0.01 (0.06)	-0.14 (0.06)	0.13 (0.05)	-0.06 (0.06)	-0.04 (0.06)	0.14 (0.08)	-0.03 (0.06)
Variability in climatic variable in previous year (SD)	0.06 (0.06)	-0.01 (0.06)	-0.12 (0.06)	0.08 (0.05)	-0.04 (0.06)	0.03 (0.06)	0.19 (0.78)	0.08 (0.06)
District MPI	0.37 (0.06)	0.37 (0.06)	0.39 (0.06)	0.39 (0.06)	0.37 (0.06)	0.37 (0.06)	0.40 (0.06)	0.36 (0.06)
Household size	0.12 (0.05)	0.12 (0.05)	0.11 (0.05)	0.12 (0.05)	0.12 (0.05)	0.12 (0.05)	0.12 (0.05)	0.12 (0.05)
Irrigated land owned in 2013	-0.44 (0.12)	-0.42 (0.12)	-0.42 (0.12)	-0.42 (0.12)	-0.41 (0.11)	-0.39 (0.11)	-0.44 (0.12)	-0.42 (0.12)
Debt	0.32 (0.14)	0.32 (0.14)	0.33 (0.14)	0.32 (0.14)	0.32 (0.14)	0.32 (0.14)	0.33 (0.14)	0.32 (0.14)
Distance to city	-0.15 (0.06)	-0.15 (0.06)	-0.15 (0.06)	-0.17 (0.06)	-0.15 (0.06)	-0.15 (0.06)	-0.18 (0.06)	-0.17 (0.06)
Education (Attended high school)	0.26 (0.13)	0.26 (0.13)	0.26 (0.12)	0.26 (0.12)	0.26 (0.12)	0.25 (0.12)	0.26 (0.13)	0.26 (0.13)
Variability in climatic variable in previous year (SD) * District MPI	-0.05 (0.06)	0.02 (0.06)	0.04 (0.06)	-0.11 (0.05)	-0.03 (0.05)	-0.04 (0.06)	-0.06 (0.05)	0.02 (0.06)

Variability in climatic variable in previous year (SD)* Irrigated land owned in 2013	0.19 (0.10)	0.12 (0.09)	0.17 (0.09)	-0.18 (0.12)	0.15 (0.11)	-0.14 (0.10)	-0.25 (0.10)	-0.08 (0.12)
N	20790	20790	20790	20790	20790	20790	20790	20790
Village (group)	476	476	476	476	476	476	476	476
Year (group)	5	5	5	5	5	5	5	5
AIC	4015	4018	4009	4005	4016	4017	4005	4017

Table 4(b): Alternative model with interactions using the standard deviation in mean maximum temperature in the current year instead of the previous year.

Predictor variables	**Coefficients**
Variability in climatic variable in current year (SD)	0.09 (0.06)
Variability in climatic variable in previous year (SD)	0.16 (0.05)
District MPI	0.36 (0.06)
Household size	0.12 (0.05)
Irrigated land owned in 2013	-0.4 (0.11)
Debt	0.31 (0.14)
Distance to city	-0.16 (0.06)
Education (Attended high school)	0.26 (0.13)
Variability in climatic variable in current year (SD) * District MPI	-0.06 (0.06)
Variability in climatic variable in current year (SD)* Irrigated land owned in 2013	-0.07 (0.11)
N	20790

Village (group)	476
Year (group)	5
AIC	**4007**

Table 5: Mixed effects logistic regression model using (a) variability in mean maximum temperature and (b) variability in total rainfall results for single year models of years 2013 to 2017 with first-time seasonal migration as the response variable. 95% Confidence intervals calculated using fixed effects of the models in parenthesis below estimates. Values represent the odds ratio for every predictor. Significance of a predictor:

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, + $p < 0.1$

Table 5 (a): Odds Ratio and 95% CI in Parenthesis					
Predictor variable	**Model 1**	**Model 2**	**Model 3**	**Model 4**	**Model 5**
	2013	**2014**	**2015**	**2016**	**2017**
Mean maximum temperature in current monsoon	1.96 (0.67-5.73)	0.88 (0.55-1.42)	1.3 (0.89-1.92)	0.87 (0.62-1.21)	2.04** (1.27-3.28)
Mean maximum temperature in	0.7 (0.26-1.88)	1.47 (0.91-2.37)	0.65^{+} (0.41-1.02)	1.7^{+} (0.97-2.97)	0.57* (0.35-0.92)

previous monsoon					
Distance to city	0.79 (0.57-1.09)	0.84 (0.6-1.17)	0.97 (0.78-1.2)	0.81 (0.58-1.12)	0.86 (0.69-1.07)
Irrigated land owned	0.66 (0.38-1.14)	0.84 (0.55-1.27)	0.44* (0.23-0.83)	0.57 (0.28-1.13)	0.67 (0.41-1.112)
Household size	1.05 (0.82-1.33)	1.17 (0.94-1.45)	1.09 (0.9-1.32)	1.04 (0.82-1.33)	1.21^{+} (0.98-1.48)
district MPI	1.54* (1.1-2.18)	1.51* (1.06-2.17)	1.3* (1.01-1.67)	1.06 (0.67-1.66)	0.96 (0.71-1.29)
Education	2.2** (1.27-3.83)	2* (1.15-3.47)	0.93 (0.54-1.59)	0.86 (0.44-1.67)	1.39 (0.82-2.37)
Debt	2.28** (1.29-4.02)	1.59 (0.85-2.95)	1.13 (0.63-2.01)	0.79 (0.37-1.71)	1.27 (0.69-2.35)
Mean maximum	0.78	1 (0.64-1.56)	0.61** (0.42-0.88)	0.99 (0.59-1.63)	0.92 (0.69-1.22)

temperature in previous year*district MPI	(0.51-1.19)				
Mean maximum temperature in previous year * Irrigated land owned	0.77 (0.33-1.77)	0.94 (0.48-1.86)	0.85 (0.35-2.11)	2.56* (1.05-6.25)	0.84 (0.61-1.15)
N	4323	4246	4172	4064	3985
Villages (group)	476	476	476	476	476

Table 5(b): Odds Ratio and 95% CI in Parenthesis					
Predictor variable	**Model 1**	**Model 2**	**Model 3**	**Model 4**	**Model 5**
	2013	2014	2015	2016	2017
Total rainfall in summer monsoon	0.87 (0.56-1.35)	0.98 (0.72-1.32)	0.68 (0.53-0.87)	0.79 (0.55-1.15)	0.92 (0.68-1.24)
Total rainfall in previous summer monsoon	1.02 (0.62-1.67)	0.74 (0.51-1.07)	0.98 (0.76-1.27)	0.58 (0.37-0.90)	0.92 (0.72-1.17)
Distance to city	0.74 (0.5-1.08)	0.81 (0.57-1.16)	0.90 (0.74-1.09)	0.89 (0.65-1.23)	0.84 (0.66-1.08)

Irrigated land owned	0.73 (0.42-1.27)	0.89 (0.6-1.33)	0.42 (0.21-0.81)	0.56 (0.27-1.16)	0.63 (0.38-1.05)
Household size	1.05 (0.83-1.34)	1.21 (0.98-1.50)	1.11 (0.92-1.34)	1.04 (0.81-1.32)	1.18 (0.96-1.44)
district MPI	1.74 (1.27-2.38)	1.68 (1.22-2.32)	1.09 (0.85-1.39)	1.05 (0.70-1.57)	1.16 (0.88-1.53)
Education	2.04 (1.17-3.54)	1.81 (1.05-3.13)	0.91 (0.53-1.55)	0.88 (0.45-1.71)	1.38 (0.82-2.34)
Debt	2.31 (1.30-4.09)	1.65 (0.89-3.06)	1.11 (0.62-1.97)	0.79 (0.36-1.70)	1.28 (0.70-2.37)
Total rainfall in previous year*district MPI	1.15 (0.8-1.66)	0.89 (0.62-1.28)	1.04 (0.81-1.34)	1.21 (0.83-1.79)	1.00 (0.75-1.34)
Total rainfall in previous year* Irrigated land owned	1.03 (0.6-1.78)	1.03 (0.74-1.43)	0.80 (0.44-1.48)	0.57 (0.31-1.04)	1.15 (0.78-1.68)
N	4323	4264	4172	4064	3985
Villages (group)	476	476	476	476	476

Table 6: Predicted probability of migration for richest (MPI = 0.031), poorest (MPI = 0.278) and mean MPI (0.174) districts.

District MPI	SD Change in climatic variable	Predicted Probability of migration	Lower Confidence Interval	Upper Confidence Interval
Increase in mean maximum temperature				
0.031	0	0.005	0.004	0.008
0.031	1	0.007	0.005	0.011

0.031	2	0.011	0.006	0.018
0.031	3	0.015	0.007	0.032
0.174	0	0.013	0.011	0.016
0.174	1	0.015	0.013	0.018
0.174	2	0.018	0.014	0.022
0.174	3	0.021	0.015	0.028
0.278	0	0.025	0.020	0.032
0.278	1	0.026	0.020	0.033
0.278	2	0.026	0.018	0.036
0.278	3	0.026	0.016	0.042
Decrease in total rainfall				
0.031	0	0.007	0.005	0.010
0.031	-1	0.010	0.006	0.017
0.031	-2	0.014	0.007	0.030
0.031	-3	0.020	0.008	0.053
0.174	0	0.015	0.013	0.018
0.174	-1	0.017	0.014	0.021
0.174	-2	0.020	0.015	0.026
0.174	-3	0.023	0.016	0.033
0.278	0	0.025	0.020	0.032
0.278	-1	0.025	0.019	0.034

0.278	-2	0.025	0.017	0.039
0.278	-3	0.025	0.015	0.044

Table 7: District multidimensional poverty index (MPI) wise quantification of assets and migration.

District MPI	Irrigated land owned (mean)	Irrigated land owned (SD	Land owned (mean)	Land owned (SD)	Number of seasonal migrants	Number of households surveyed	Proportion of migrants (%)
0.031	1.57	2.85	2.79	3.27	2	36	5.56
0.046	0.92	1.71	1.79	1.98	6	88	6.82
0.066	1.13	1.41	2.90	2.37	1	30	3.33
0.092	1.15	1.87	2.05	2.33	2	103	1.94
0.101	1.26	3.39	3.69	4.67	10	235	4.26
0.102	1.18	2.14	2.19	2.63	30	221	13.57
0.104	0.83	2.15	2.48	4.49	20	128	15.63
0.112	2.11	3.19	2.89	5.36	2	130	1.54
0.114	2.15	2.57	3.05	3.32	1	20	5.00
0.117	0.34	1.39	3.47	4.48	8	316	2.53
0.12	0.45	1.09	2.31	3.24	7	99	7.07
0.133	1.06	2.01	2.14	3.10	3	66	4.55
0.148	1.86	4.41	3.92	4.92	2	120	1.67
0.159	0.62	0.93	1.19	1.13	6	29	20.69
0.166	0.15	0.65	2.20	2.37	17	212	8.02

0.167	6.01	13.84	7.95	15.44	3	67	4.48
0.173	1.52	2.43	2.71	4.30	5	212	2.36
0.174	1.46	2.53	1.84	3.22	5	73	6.85
0.185	1.31	2.11	2.01	2.78	19	155	12.26
0.2	0.60	1.58	3.10	8.79	4	135	2.96
0.201	1.10	3.14	2.54	4.70	55	296	18.58
0.205	0.21	0.93	4.00	6.68	24	140	17.14
0.21	1.06	2.52	3.28	4.18	2	16	12.50
0.211	0.75	1.07	1.83	2.45	7	55	12.73
0.213	1.81	3.53	2.95	3.85	3	65	4.62
0.214	1.14	2.22	2.52	3.92	16	233	6.87
0.219	1.40	2.22	1.65	2.43	2	10	20.00
0.22	0.20	0.76	1.73	2.02	26	192	13.54
0.247	0.31	1.17	2.39	3.77	92	463	19.87
0.278	0.22	0.96	2.09	2.72	38	378	10.05

Appendix B: Supplementary Information for Chapter 3

TABLES:

Table S1: Summary of the mean and standard deviations of variables used for preliminary match of villages within which restored, unrestored and low Lantana density sites were used for this study. The standard deviation for variables is provided in parenthesis. Buffer distances for the geographic variables were based on previous studies on people's forest-resource use in this region (DeFries *et al* 2021) and an avian species habitat use (Atikah *et al* 2021, Zurita and Bellocq 2010). In three out of eight villages where restoration took place we found unrestored and low Lantana density sites for comparison within the census boundaries of the same village.

Variable for matching	**Mean of variables in villages with treatment (restored) sites**	**Means of variables in villages with control (unrestored) sites**	**Means of variables in villages with control (low Lantana density) sites**
Total population of village	467 (229)	412 (221)	489 (169)
Total households in village	107 (53)	94 (48)	114 (46)
Percent Literate in village	47.26 (6.40)	46.92 (6.34)	49.11 (4.87)
Percent Scheduled Tribe in village	93.67 (7.73)	90.85 (10.75)	96.00 (7.18)

Percent Scheduled Caste in village	1.16 (3.03)	1.37 (3.02)	8.64 (2.28)
Distance of village to Kanha National Park (kilometers)	4.44 (2.44)	5.04 (2.39)	3.10 (2.74)
Percent agricultural land in 3 km buffer of village census boundary	28.04 (12.27)	29.28 (10.92)	21.11 (9.39)
Percent forest cover in 3 km buffer of village census boundary	63.56 (15.32)	60.48 (14.53)	73.03 (11.49)
Total villages matched	**8**	**8**	**4**

Table S2: L. camara density categories within 3-meter radius plot. We classified a mature L. camara plant as one above one meter in height. See Figure S2 for photographs of each category of L. camara density.

L. camara density category	Lower limit	Upper limit	Unit of measurement	Numeric category of density assigned
No L. camara	0	0	Single stem saplings or mature plants	1
Very Low	1	25	Single stem saplings	2
Low	1	2	Mature plants	3
Medium	3	5	Mature plants	4
High	6	8	Mature plants	5
Very high	9	20	Mature plants	6

Table S3: Wilcoxon test results for vegetation composition and structure variables across restored, unrestored and low Lantana density sites. The numbers represent the median values for the variables and the 1st and 3rd quantiles in parenthesis. The Z statistic, W statistic and 95% confidence intervals for the Wilcoxon test are provided in the parenthesis under the median and range values.

Variable	**(a) Restored – Unrestored**	**(b) Restored – Low Lantana density**	**(c) Low Lantana density – Unrestored**
Sapling density	11 (6 - 17) - 6 (1 - 13) (Z = -1.27, W = 291.50, 95% CI = -2.00, 7.00)	11 (6 - 17) - (9 - 27) (Z = -1.36, W = 177.50, 95% CI = -3.00, 16.00)	21 (9 - 27) - 6 (1 - 13) (Z = -2.18, W = 155.50, 95% CI = 1.00, 19.00)
Small tree density	0 (0 - 1) - 0 (0 - 0) (Z = -0.45, W = 252.50, 95% CI = -0.00, 0.00)	0 (0 - 1) - 0 (0 - 1) (Z = -0.57, W = 151.50, 95% CI = -0.00, 0.00)	0 (0 - 1) - 0 (0 - 0) (Z = -0.95, W = 122, 95% CI = -0.00, 1.00)
Medium tree density	7 (4 - 16) - 8 (3 - 13) (Z = -1.23, W = 289.50, 95% CI = -2.00, 6.00)	7 (4 - 16) - 6 (4 - 12) (Z = -0.57, W = 120.50, 95% CI = -6.00, 3.00)	6 (4 - 12) - 8 (3 - 13) (Z = -0.35, W = 113.00, 95% CI = -0.35)
L. camara density (categorical variable explained in Table S2)	2 (1 - 2) - 5 (4 - 5)*** (Z = -4.88, W = 35.50, 95% CI = -4.00, -2.00)	2 (1 - 2) - 1 (1 - 1)** (Z = -2.59, W = 70.5, 95% CI = -1.00, -0.00)	1 (1 - 1)** - 5 (4 - 5)*** (Z = -4.37, W = 6.50, 95% CI = -4.00, -3.00)

p values are *** <0.001, ** <0.01, * <0.05, and # <0.10.

Table S4: Summary of the number of minutes manually analyzed for each sampling site and sampling location.

Site Name	**Number of seasons analyzed**	**Site codes for recorder locations**	**Site Type**	**Total number of 10-second clips analyzed**	**Number of minutes analyzed**
Amjhar	Winter_2020, Winter_2021	AM_1, AM_2	Unrestored	1212	202
Aroli_Benchmark	Winter_2021	AO_1, AO_2	Low Lantana density	552	92

Aroli_FD_Removed	Winter_2020, Winter_2021	AO_FD_1, AO_FD_2	Restored	1080	180
Barkheda	Winter_2020, Winter_2021	BR_2, BR_1	Unrestored	1867	311
Batwar_Benchmark	Winter_2020, Winter_2021	BT_2, BT_1	Low Lantana density	1182	197
Batwar_FD_Removed	Winter_2020, Winter_2021	BT_FD_2, BT_FD_1	Restored	1128	188
Bhagpur_FD_Removed	Winter_2020, Winter_2021	BH_FD_2, BH_FD_1, BH_FD_3	Restored	2100	350
Bhanpur_Kheda	Winter_2021, Winter_2020	BK_2, BK_1	Unrestored	1811	302
Chhichari	Winter_2021, Winter_2020	CH_2, CH_1	Restored	1062	177
Dilwara	Winter_2020, Winter_2021	DW_2, DW_4, DW_1, DW_3	Unrestored	2453	409
Jogi_Sondha	Winter_2021, Winter_2020	JS_2, JS_1	Unrestored	1080	180
Kutwahi	Winter_2021, Winter_2020	KW_4, KW_1, KW_3, KW_2	Low Lantana density	2340	390
Magdha	Winter_2020, Winter_2021	MAG_3, MAG_4, MAG_5,	Restored	2434	406

		MAG_2, MAG_1			
Manegaon_FV	Winter_2021, Winter_2020	MG_FD_2, MG_FD_3, MG_FD_1	Restored	1680	280
Mohgaon	Winter_2021, Winter_2020	MH_2, MH_3, MH_1	Restored	1677	280
Patpara	Winter_2020, Winter_2021	PT_3, PT_2, PT_1	Low Lantana density	1742	290
Simaiya_Bhagpur	Winter_2020, Winter_2021	SB_1, SB_3, SB_2	Unrestored	2080	347
Taktauwa	Winter_2020, Winter_2021	TW_4, TW_1, TW_2, TW_3, TW_5	Restored	2911	485
Urdali_Lantana	Winter_2021, Winter_2020	UR_1, UR_2	Unrestored	1090	182
Urdali_Mal	Winter_2020, Winter_2021	URM_1, URM_2	Unrestored	1183	197

Table S5: List of avian species detected aurally across two years of data collection. Habitat specialization details were taken from the State of India's Birds (The SoIB partnership 2020). Details about predominant feeding guild based on State of India's birds and provided by authors based on their knowledge of the species.

Species code	Common Name	Scientific Name	Predominant Feeding guild	Habitat specialization	# of Restored sites where species was detected	# of Unrestored sites where species was detected	# of Low Lantana density sites where species was detected
ALPA	Alexandrine Parakeet	*Psittacula eupatria*	Frugivorous	Woodland	8	8	4
APST	Asian Pied Starling	*Gracupica contra*	Omnivorous	Generalist	1	1	1
ASDR	Ashy Drongo	*Dicrurus leucophaeus*	Insectivorous	Woodland	6	7	2
ASKO	Asian Koel	*Eudynamys scolopaceus*	Frugivorous	Generalist	6	5	3
ASPR	Ashy Prinia	*Prinia socialis*	Insectivorous	Generalist	6	8	3
BABU	Barred Buttonquail	*Turnix suscitator*	Granivorous	Generalist	2	0	0
BBCU	Banded Bay Cuckoo	*Cacomantis sonneratii*	Insectivorous	Woodland	1	0	0

BCFU	Brown-cheeked Fulvetta	*Alcippe poioicephala*	Insectivorous	Woodland, Tropical Forest	7	5	2
BCPW	Brown-capped Pygmy Woodpecker	*Yungipicus nanus*	Insectivorous	Woodland	4	4	2
BHBA	Brown-headed Barbet	*Psilopogon zeylanicus*	Frugivorous	Generalist	8	7	4
BHOR	Black-hooded Oriole	*Oriolus xanthornus*	Frugivorous	Woodland	8	8	4
BHOW	Brown Hawk-Owl	*Ninox scutulata*	Insectivorous	Woodland	4	3	1
BLDR	Black Drongo	*Dicrurus macrocercus*	Insectivorous	Generalist	8	8	4
BNMO	Black-naped Monarch	*Hypothymis azurea*	Insectivorous	Woodland	6	3	4
BOWA	Booted Warbler	*Iduna caligata*	Insectivorous	Generalist	1	0	0
BRFL	Black-rumped Flameback	*Dinopium benghalense*	Insectivorous	Generalist	8	6	3

BRWA	Blyth's Reed Warbler	*Acrocephalus dumetorum*	Insectivorous	Generalist	7	7	3
CAEG	Cattle Egret	*Bubulcus ibis*	Insectivorous	Wetland	1	0	0
CBAB	Common Babbler	*Turdoides caudata*	Omnivorous	Generalist	1	3	2
CHCU	Common Hawk-Cuckoo	*Hierococcyx varius*	Insectivorous	Woodland	7	7	3
CHEA	Changeable Hawk-Eagle	*Nisaetus cirrhatus*	Carnivorous	Woodland	3	2	3
CITI	Cinereous Tit	*Parus cinereus*	Insectivorous	Generalist	6	5	3
COBA	Coppersmith Barbet	*Psilopogon haemacephalus*	Frugivorous	Woodland	8	7	4
COCU	Common Cuckoo	*Cuculus canorus*	Insectivorous	Generalist	2	1	1
COIO	Common Iora	*Aegithina tiphia*	Insectivorous	Woodland	7	7	4
COMY	Common Myna	*Acridotheres tristis*	Omnivorous	Generalist	8	8	4
COTA	Common Tailorbird	*Orthotomus sutorius*	Insectivorous	Generalist	8	8	4
COWO	Common Woodshrike	*Tephrodornis*	Insectivorous	Woodland	0	2	0

		pondicerianus					
CRWA	Clamorous Reed Warbler	*Acrocephalus stentoreus*	Insectivorous	Wetland	1	5	0
CSEA	Crested Serpent-Eagle	*Spilornis cheela*	Carnivorous	Woodland	5	4	3
CSPE	Yellow-throated Sparrow	*Gymnoris xanthocollis*		Woodland	8	8	4
EUHO	Eurasian Hoopoe	*Upupa epops*	Insectivorous	Grassland, Scrub	3	0	0
FTDC	Fork-tailed Drongo-Cuckoo	*Surniculus dicruroides*	Insectivorous	Woodland	0	2	0
GBCU	Grey-bellied Cuckoo	*Cacomantis passerinus*	Insectivorous	Woodland	3	4	1
GBEA	Green Bee-eater	*Merops orientalis*	Insectivorous	Generalist	7	7	2
GBPR	Grey-breasted Prinia	*Prinia hodgsonii*	Insectivorous	Generalist	4	6	2
GESA	Green Sandpiper	*Tringa ochropus*	Insectivorous	Wetland	1	0	0

GFLE	Golden-fronted Leafbird	*Chloropsis aurifrons*	Omnivorous	Woodland	8	6	3
GHCF	Grey-headed Canary-Flycatcher	*Culicicapa ceylonensis*	Insectivorous	Woodland	7	5	3
GRBU	Grey Bushchat	*Saxicola ferreus*	Insectivorous	Generalist	0	1	0
GRCO	Greater Coucal	*Centropus sinensis*	Omnivorous	Generalist	8	8	4
GREW	Grey Wagtail	*Motacilla cinerea*	Insectivorous	Generalist	2	0	0
GRFR	Grey Francolin	*Francolinus pondicerianus*	Omnivorous	Grassland	8	8	4
GRNW	Green Warbler	*Phylloscopus nitidus*	Insectivorous	Woodland	3	2	1
GRTD	Greater Racket-tailed Drongo	*Dicrurus paradiseus*	Insectivorous	Woodland, Tropical Forest	7	8	4
GRWA	Greenish Warbler	*Phylloscopus trochiloides*	Insectivorous	Woodland	8	8	4

HOCR	House Crow	*Corvus splendens*	Omnivorous	Generalist	8	8	4
HOSP	House Sparrow	*Passer domesticus*	Granivorous	Generalist	4	8	1
HUWA	Hume's Warbler	*Phylloscopus humei*	Insectivorous	Woodland	8	8	4
IEOW	Rock Eagle-Owl	*Bubo bengalensis*	Carnivorous	Generalist	2	2	0
IGHO	Indian Grey Hornbill	*Ocyceros birostris*	Frugivorous	Generalist	7	7	4
IGOR	Indian Golden Oriole	*Oriolus kundoo*	Frugivorous	Generalist	2	6	3
INBL	Indian Blackbird	*Turdus simillimus*	Omnivorous	Generalist	1	2	0
INCU	Indian Cuckoo	*Cuculus micropterus*	Insectivorous	Woodland	3	1	1
INNI	Indian Nightjar	*Caprimulgus asiaticus*	Insectivorous	Generalist	3	1	1
INNU	Indian Nuthatch	*Sitta castanea*	Insectivorous	Woodland	7	5	4
INPE	Indian Peafowl	*Pavo cristatus*	Omnivorous	Generalist	5	8	3
INPI	Indian Pitta	*Pitta brachyura*	Insectivorous	Woodland	0	1	0

INRO	Indian Roller	*Coracias benghalensis*	Carnivorous	Generalist	7	5	2
IPFL	Indian Paradise-Flycatcher	*Terpsiphone paradisi*	Insectivorous	Woodland	0	1	0
IPHE	Indian Pond-Heron	*Ardeola grayii*	Carnivorous	Generalist	2	0	0
IROB	Indian Robin	*Copsychus fulicatus*	Insectivorous	Generalist	6	8	1
ISBA	Indian Scimitar-Babbler	*Pomatorhinus horsfieldii*	Insectivorous	Woodland, Tropical Forest	6	6	4
ISBD	Indian Spot-billed Duck	*Anas poecilorhyncha*	Omnivorous	Wetland	0	1	0
ISOW	Indian Scops-Owl	*Otus bakkamoena*	Insectivorous	Woodland	6	4	3
ITKN	Indian Thick-knee	*Burhinus indicus*	Insectivorous	Generalist	8	6	4
IWEY	Indian White-eye	*Zosterops palpebrosus*	Omnivorous	Generalist	8	8	4
IYTI	Indian Yellow Tit	*Machlolophus aplonotus*	Insectivorous	Woodland	0	1	0

JBQU	Jungle Bush-Quail	*Perdicula asiatica*	Granivorous	Generalist	1	3	2
JELE	Jerdon's Leafbird	*Chloropsis jerdoni*	Omnivorous	Woodland	0	0	2
JUBA	Jungle Babbler	*Turdoides striata*	Insectivorous	Generalist	8	8	4
JUMY	Jungle Myna	*Acridotheres fuscus*	Omnivorous	Generalist	2	1	2
JUNI	Jungle Nightjar	*Caprimulgus indicus*	Insectivorous	Woodland	5	5	2
JUOW	Jungle Owlet	*Glaucidium radiatum*	Insectivorous	Woodland	8	8	4
JUPR	Jungle Prinia	*Prinia sylvatica*	Insectivorous, Nectivorous	Generalist	2	3	0
LACU	Large Cuckooshrike	*Coracina macei*	Insectivorous	Woodland	8	7	4
LADO	Laughing Dove	*Streptopelia senegalensis*	Granivorous	Generalist	4	6	2
LBCR	Large-billed Crow	*Corvus macrorhynchos*	Omnivorous	Generalist	6	8	3
LEWH	Lesser Whitethroat	*Sylvia curruca*	Insectivorous	Scrub	4	1	0

LGBA	Large Grey Babbler	*Turdoides malcolmi*	Omnivorous	Generalist	2	4	1
LICO	Little Cormorant	*Microcarbo niger*	Piscivorous	Wetland	0	0	0
LTSH	Long-tailed Shrike	*Lanius schach*	Insectivorous	Generalist	2	7	0
MPHO	Malabar Pied-Hornbill	*Anthracoceros coronatus*	Frugivorous	Woodland	2	3	2
MWOW	Mottled Wood-Owl	*Strix ocellata*	Carnivorous	Woodland	2	0	1
MWTH	Malabar Whistling-Thrush	*Myophonus horsfieldii*	Insectivorous	Tropical Forest	3	2	0
OBPI	Olive-backed Pipit	*Anthus hodgsoni*	Insectivorous	Generalist	4	5	1
OHBU	Oriental Honey-buzzard	*Pernis ptilorhynchus*	Carnivorous, Granivorous	Woodland	0	1	0
OHTH	Orange-headed Thrush	*Geokichla citrina*	Insectivorous	Generalist	5	1	2
OMRO	Oriental Magpie-Robin	*Copsychus saularis*	Insectivorous, Granivorous	Generalist	8	8	4
OSOW	Oriental Scops-Owl	*Otus sunia*	Insectivorous	Woodland	0	0	0

OTDO	Oriental Turtle-Dove	*Streptopelia orientalis*	Granivorous	Generalist	5	3	1
PAFR	Painted Francolin	*Francolinus pictus*	Omnivorous	Grassland	1	2	1
PASP	Painted Spurfowl	*Galloperdix lunulata*	Omnivorous	Woodland, Scrub	0	0	1
PBFL	Pale-billed Flowerpecker	*Dicaeum erythrorhynchos*	Omnivorous	Generalist	8	8	4
PHPA	Plum-headed Parakeet	*Psittacula cyanocephala*	Frugivorous	Woodland	8	8	4
PIBU	Pied Bushchat	*Saxicola caprata*	Insectivorous	Generalist	1	0	0
PICU	Pied Cuckoo	*Clamator jacobinus*	Insectivorous	Generalist	1	0	0
PLPR	Plain Prinia	*Prinia inornata*	Insectivorous	Generalist	5	6	2
PRSU	Purple-rumped Sunbird	*Leptocoma zeylonica*	Nectivorous	Generalist	6	8	2
PTBA	Puff-throated Babbler	*Pellorneum ruficeps*	Insectivorous	Woodland	4	3	1
PUSU	Purple Sunbird	*Cinnyris asiaticus*	Nectivorous	Generalist	8	8	4

RAQU	Rain Quail	*Coturnix coromandelica*	Granivorous	Grassland	0	1	0
RBFL	Red-breasted Flycatcher	*Ficedula parva*	Insectivorous	Woodland	8	7	4
REJU	Red Junglefowl	*Gallus gallus*	Omnivorous	Woodland	8	8	4
RESP	Red Spurfowl	*Galloperdix spadicea*	Omnivorous	Woodland	0	0	1
RNIB	Red-naped Ibis	*Pseudibis papillosa*	Carnivorous	Generalist	1	0	1
RRPA	Rose-ringed Parakeet	*Psittacula krameri*	Frugivorous	Generalist	8	8	4
RRSW	Red-rumped Swallow	*Cecropis daurica*	Insectivorous	Generalist	0	0	0
RUTR	Rufous Treepie	*Dendrocitta vagabunda*	Omnivorous	Generalist	8	8	4
RVBU	Red-vented Bulbul	*Pycnonotus cafer*	Omnivorous	Generalist	8	8	4
RWBU	Red-whiskered Bulbul	*Pycnonotus jocosus*	Omnivorous	Generalist	5	6	1
RWLA	Red-wattled Lapwing	*Vanellus indicus*	Insectivorous	Generalist	7	7	3

SANI	Savanna Nightjar	*Caprimulgus affinis*	Insectivorous	Grassland	3	3	1
SBFA	Spot-breasted Fantail	*Rhipidura albogularis*	Insectivorous	Woodland	3	3	2
SBKI	Stork-billed Kingfisher	*Pelargopsis capensis*	Piscivorous	Wetland	1	1	2
SBMU	Scaly-breasted Munia	*Lonchura punctulata*	Granivorous	Generalist	0	0	0
SBWA	Sulphur-bellied Warbler	*Phylloscopus griseolus*	Insectivorous	Generalist	1	0	0
SCMI	Scarlet Minivet	*Pericrocotus speciosus*	Insectivorous	Woodland	1	0	0
SHIK	Shikra	*Accipiter badius*	Carnivorous	Generalist	6	5	3
SIMA	Sirkeer Malkoha	*Taccocua leschenaultii*	Insectivorous	Scrub	0	0	0
SIRU	Siberian Rubythroat	*Calliope calliope*	Insectivorous	Wetland	0	0	0
SIST	Siberian Stonechat	*Saxicola maurus*	Insectivorous	Generalist	0	0	0
SMMI	Small Minivet	*Pericrocotus*	Insectivorous	Woodland	7	6	3

		cinnamomeus					
SPDO	Spotted Dove	*Streptopelia chinensis*	Granivorous	Generalist	8	8	4
SPOW	Spotted Owlet	*Athene brama*	Carnivorous	Generalist	2	0	0
TAFL	Taiga Flycatcher	*Ficedula albicilla*	Insectivorous	Woodland	7	4	2
TBBA	Tawny-bellied Babbler	*Dumetia hyperythra*	Insectivorous	Generalist	4	3	3
TBFL	Tickell's Blue Flycatcher	*Cyornis tickelliae*	Insectivorous	Woodland	8	7	4
TBFP	Thick-billed Flowerpecker	*Dicaeum agile*	Omnivorous	Generalist	7	4	2
TLWA	Tickell's Leaf Warbler	*Phylloscopus affinis*	Insectivorous	Generalist	3	1	0
TRPI	Tree Pipit	*Anthus trivialis*	Insectivorous	Generalist	7	5	2
ULFL	Ultramarine Flycatcher	*Ficedula superciliaris*	Insectivorous	Woodland	3	2	2
VEFL	Verditer Flycatcher	*Eumyias thalassinus*	Insectivorous	Woodland	0	3	2

VFNU	Velvet-fronted Nuthatch	*Sitta frontalis*	Insectivorous	Woodland	6	2	2
WBBU	White-browed Bulbul	*Pycnonotus luteolus*	Frugivorous	Woodland	7	3	1
WBDR	White-bellied Drongo	*Dicrurus caerulescens*	Insectivorous	Woodland	7	5	3
WBFA	White-browed Fantail	*Rhipidura aureola*	Insectivorous	Woodland	5	5	3
WBRW	White-browed Wagtail	*Motacilla maderaspatensis*	Insectivorous	Generalist	0	1	0
WEBU	White-eyed Buzzard	*Butastur teesa*	Carnivorous	Generalist	2	1	1
WNWO	White-naped Woodpecker	*Chrysocolaptes festivus*	Insectivorous	Woodland, Scrub	4	3	2
WRSH	White-rumped Shama	*Copsychus malabaricus*	Insectivorous	Woodland	0	2	2
WTKI	White-throated Kingfisher	*Halcyon smyrnensis*	Carnivorous	Generalist	8	6	3

YCWO	Yellow-crowned Woodpecker	*Leiopicus mahrattensis*	Insectivorous	Woodland	1	4	1
YEBA	Yellow-eyed Babbler	*Chrysomma sinense*	Insectivorous	Generalist	2	5	2
YFGP	Yellow-footed Green-Pigeon	*Treron phoenicopterus*	Frugivorous	Generalist	8	6	4
YWLA	Yellow-wattled Lapwing	*Vanellus malabaricus*	Insectivorous	Grassland	0	1	0

Table S6: Wilcoxon test results for bird species composition variables, including total number of birds aurally detected, total number of forest-affiliated and generalist birds aurally identified in two seasons (years) across restored, unrestored and low Lantana density sites. The numbers represent the median values for the variables and the 1st and 3rd quantiles in parenthesis. The Z statistic, W statistic and 95% confidence intervals for the Wilcoxon test are provided in the parenthesis under the median and range values. Refer to Tables S7 for information on seasonal variation in these variables.

Variable	**Restored –Unrestored**	**Restored- low Lantana density**	**Low Lantana density – Unrestored**
(a) Cumulative bird species	38 (34 – 43) – 41 (35 – 48)	38 (34 – 43) – 38 (37 – 48)	38 (37 – 48) – 41 (35 – 48)

aurally identified	(Z = -1.22; W = 788.50; 95% CI = -6.00, 2.00)	(Z= -0.15; W = 532; 95% CI = -2.00, 7.00)	(Z = -0.12; W = 353; 95% CI= -5.00, 5.00)
(b) Cumulative number of forest- and woodland-affiliated birds aurally identified	17 (13– 20) – 18 (10–21) (Z = -0.91; W= 1038; 95% CI = -1.00, 3.99)	17 (13 –20) – 17 (16–23) (Z =-1.03; W = 541. 50; 95% CI = -1.00, 4.00)	17 (16–23) – 18 (10–21) (Z = -1.46; W = 447.50; 95% CI = -1.00, 6.00)
(c) Cumulative number of generalists aurally identified	20 (17 – 23) – 23 (19 – 28)* (Z =-2.06; W = 690.5; 95% CI =-5.00, -0.00)	20 (17 – 23) – 21 (19 – 25) (Z= -0.80; W = 524.50; 5%CI = -1.00, 4.00)	21 (19 – 25) – 23 (19 – 28) (Z = -1.04; W = 299.50; 95% CI =-5.00, 1.00)

p values are *** <0.001, ** <0.01, * <0.05, and # <0.10.

Table S7:

(a) Wilcoxon test results of the total number of bird species detected aurally across all sampling locations presented according to the treatment types– restored (treatment), Low Lantana density (control) and unrestored (control). The numbers represent the median values for the variables and the 1st and 3rd quantiles in parenthesis. The Z statistic, W statistic and 95% confidence intervals for the Wilcoxon test are provided in the parenthesis under the median and range values.

Year	Restored -Unrestored	Restored- Low Lantana density	Unrestored – Low Lantana density
2020 (Year 1)	37 (34 – 42) – 46 (42 – 51) *** (Z= -3.65; W = 78.50; 95% CI = -13.00, -5.00)	37 (34 – 42) – 45 (38 – 53)* (Z= -2.47; W = 153; 95% CI = 1.00, 15.00)	46 (42 – 51) – 45 (38 – 53) (Z= -0.11; W = 73.50; 95% CI = -8.00, 7.00)
2021 (Year 2)	40 (34 – 43) – 37 (29 – 41) (Z = -0.15; W = 100.50 95% CI =-3.00, 3.00)	40 (34 – 43) – 37 (34 – 40) (Z= -0.95; W = 109.50; 95% CI = -9.00, 4.00)	37 (29 – 41) – 37 (34 – 40) (Z= -0.67; W = 120.50; 95% CI =-4.00, 10.00)

p values are *** <0.001, ** <0.01, * <0.05, and # <0.10.

(b) Wilcoxon test results of the total number of forest- and woodland- affiliated birds aurally across all sampling locations presented according to the treatment types – restored (treatment), Low Lantana density (control) and unrestored (control). The numbers represent the median values for the variables and the 1st and 3rd quantiles in parenthesis. The Z statistic, W statistic and 95% confidence intervals for the Wilcoxon test are provided in the parenthesis under the median and range values.

Year	Restored -Unrestored	Restored- Low Lantana density	Unrestored – Low Lantana density

2020 (Year 1)	15 (13–18) – 19 (11– 22) (Z = -1.04; W =185; 95% CI = -5.00, 3.00)	15 (13– 17) – 19 (15 – 25)# (Z = -1.86; W= 139; 95% CI = -0.00, 9.00)	19 (11– 22) – 19 (15 – 25) (Z = -1.06; W = 96.50; 95% CI = -4.00, 8.00)
2021 (Year 2)	19 (17– 23) – 13 (10 – 19)* (Z = -2.04; W = 324; 95% CI = 0, 8.00)	19 (17 – 23) - 17 (16 – 22) (Z= -0.74; W = 115.50; 95% CI = -4.00, 2.00)	13 (10 – 19) – 17 (16 – 22) (Z = -1.08; W = 130; 95% CI = -2.00, 8.00)

p values are *** <0.001, ** <0.01, * <0.05, and # <0.10.

(c) Wilcoxon test results of the total number of generalist birds aurally across all sampling locations presented according to the treatment types – restored (treatment), Low Lantana density (control) and unrestored (control). The numbers represent the median values for the variables and the 1st and 3rd quantiles in parenthesis. The Z statistic, W statistic and 95% confidence intervals for the Wilcoxon test are provided in the parenthesis under the median and range values.

Year	**Restored -Unrestored**	**Restored- Low Lantana density**	**Unrestored – Low Lantana density**
2020 (Year 1)	21(19– 24) – 28 (26 – 29)*** (Z= -6.00; W = 72; 95% CI = -9.00, -4.00)	21 (19 – 23) – 26 (24 – 27)* (Z= -2.42; W= 152; 95% CI = 1.00, 7.00)	28 (26 – 29) – 26 (24 – 27)# (Z =-1.66; W = 44.50; 95% CI = -5.00, 0.00)

2021 (Year 2)	19 (16 – 22) – 19 (17 – 22) (Z = -0.42; W= 255.50; 95% CI = -3.00, 4.00)	19 (16 – 22) – 19 (18 – 20) (Z = -0.36; W = 126.50; 95% CI = -4.00, 3.00)	19 (17 – 22) – 19 (18 – 20) (Z = -0.15; W = 100.50; 95% CI = -3.00, 3.00)

p values are *** <0.001, ** <0.01, * <0.05, and # <0.10

Table S8: PERMANOVA analysis of bird community composition (N permutations = 999).

Covariate	**Bird community composition**				
	Df	**Sum of Squares**	**Mean Squares**	**F**	**R^2**
Type of site (restored, unrestored, low Lantana density)	2	0.515	0.258	4.058	0.049***
Tree density	1	0.091	0.091	1.432	0.009
Large tree density	1	0.044	0.044	0.693	0.004
Total population in 3 km buffer	1	0.070	0.070	1.101	0.007
% Farms in 3 km buffer	1	0.038	0.038	0.605	0.004
% Forest in 3 km buffer	1	0.077	0.077	1.214	0.007

Simpson Index of plot	1	0.093	0.093	1.460	0.009
Year: (2020, 2021)	1	1.417	1.417	22.325	0.136***
Sampling site (N=20)	17	3.097	0.182	2.871	0.296***
Residuals	79	5.014	0.063		0.480
Total	*105*	*10.456*			*1.000*

p values are *** <0.001, ** <0.01, * <0.05, and # <0.10.

Table S9: Coefficients and standard errors for predictor variables and the treatment (restoration) or control (Lantana-free sites) of Generalized linear mixed models with the outcomes, total number of species, total number of forest and woodland- affiliated species and total number of generalist species detected aurally. For the treatment and control variable, the coefficients quantify the difference of these sites from the unrestored sites. A positive coefficient for the treatment and control variable indicates a higher number of species detected in these respective types of sites in comparison to unrestored sites. All models were checked for variance inflation (threshold = 5), and none of the models displayed variance inflation.

Covariate	**(a) Total number of species detected aurally**	**(b) Total number of forest- and woodland-affiliated species detected aurally**	**(c) Total number of generalist species detected aurally**

Control: Low Lantana density	-0.081 (0.092)	-0.106 (0.130)	-0.048 (0.077)
Treatment: Restoration	-0.126 (0.074)#	-0.092 (0.105)	-0.125 (0.060)*
Tree density	0.034 (0.030)	0.007 (0.044)	0.085 (0.030)**
Large tree density	-0.011 (0.035)	0.025 (0.051)	-0.060 (0.040)
Total population in 3 km buffer	-0.032 (0.044)	-0.034 (0.059)	-0.035 (0.036)
% Farms in 3 km buffer	0.026 (0.032)	0.056 (0.047)	0.004 (0.029)
% Forest in 3 km buffer	0.039 (0.033)	0.113 (0.048)*	0.009 (0.030)
Simpson Index of plot	0.041 (0.023)#	0.125 (0.037)***	-0.021 (0.026)
Year	-0.098 (0.031)***	0.062 (0.048)	-0.216 (0.042)***
N (each sampling location sampled for 2 years)	106	106	106
Variance and Standard Deviation of random variable			
Sampling sites (N =20)	0.012, 0.111	0.015, 0.121	0.000, 0.000

p values are *** <0.001, ** <0.01, * <0.05, and # <0.10.

Table S10: Alternative models without collinear variables for the total number of species detected aurally over each year of acoustic data collection. Values represent the coefficients and standard errors (in parenthesis) for predictor variables and the treatment (restoration) or control (low Lantana density sites) of the Generalized linear mixed models estimated. For the treatment and control variable, the coefficients quantify the difference of these sites from the unrestored sites. A positive coefficient for the treatment and control variable indicates a higher number of species detected in these respective types of sites in comparison to unrestored sites. We present the full model in the paper in Table S9. All models were checked for variance inflation (threshold = 5), and none of the models displayed variance inflation.

Covariate	**(a) Model 1**	**(b) Model 2**	**(c) Model 3**	**(d) Model 4**
Control: Low Lantana density	-0.051 (0.091)	-0.067 (0.091)	-0.071 (0.093)	-0.060 (0.098)
Treatment: Restoration	-0.115 (0.074)	-0.132 (0.076)$^{\#}$	-0.141 (0.076)	-0.130 (0.082)
Tree density	0.025 (0.031)	0.029 (0.020)	0.027 (0.032)	Not included
Large tree density	0.009 (0.036)	Not included	0.000 (0.038)	0.026 (0.025)
Total population in 3 km buffer	Not included	-0.035 (0.040)	-0.016 (0.036)	-0.032 (0.044)
% Farms in 3 km buffer	0.016 (0.029)	0.031 (0.034)	Not included	0.031 (0.036)
% Forest in 3 km buffer	0.053 (0.033)	0.042 (0.035)	0.050 (0.035)	0.039 (0.037)

Simpson Index of plot	0.039 (0.024)#	0.040 (0.024)#	0.038 (0.024)	0.040 (0.024)
Year	-0.010 (0.031)**	-0.100 (0.031)**	-0.101 (0.031)	-0.100 (0.031)**
N (each sampling location sampled for 2 years)	106	106	106	106
Variance and Standard Deviation of random variable				
Sampling site (N =20)	0.010, 0.102	0.010, 0.100	0.010, 0.101	0.012, 0.111

p values are *** <0.001, ** <0.01, * <0.05, and # <0.10.

Table S11: Alternative models without collinear variables for the total number of forest- and woodland-affiliated species detected aurally over each year of acoustic data collection. Values represent the coefficients and standard errors (in parenthesis) for predictor variables and the treatment (restoration) or control (low Lantana density sites) of the Generalized linear mixed models estimated. For the treatment and control variable, the coefficients quantify the difference of these sites from the unrestored sites. A positive coefficient for the treatment and control variable indicates a higher number of species detected in these respective types of sites in comparison to unrestored sites. We present the full model in the paper in Table S9. All models were checked for variance inflation (threshold = 5), and none of the models displayed variance inflation.

Covariate	**(a) Model 1**	**(b) Model 2**	**(c) Model 3**	**(d) Model 4**
Control: Low Lantana density	-0.089 (0.128)	-0.111 (0.127)	-0.107 (0.137)	-0.104 (0.131)
Treatment: Restoration	-0.074 (0.101)	-0.090 (0.103)	-0.102 (0.110)	-0.090 (0.105)
Tree density	0.003 (0.043)	0.022 (0.030)	0.002 (0.044)	Not included
Large tree density	0.034 (0.049)	Not included	0.028 (0.051)	0.030 (0.036)
Total population in 3 km buffer	Not included	-0.042 (0.056)	0.004 (0.052)	-0.033 (0.059)
% Farms in 3 km buffer	0.041 (0.040)	0.057 (0.046)	Not included	0.056 (0.047)
% Forest in 3 km buffer	0.122 (0.046)**	0.114 (0.047)*	0.126 (0.049)*	0.112 (0.048)*

Simpson Index of plot	0.124 (0.037)***	0.127 (0.036)***	0.120 (0.037)***	0.125 (0.037)***
Year	0.062 (0.048)	0.062 (0.0477)	0.060 (0.048)	0.062 (0.048)
N (each sampling location sampled for 2 years)	106	106	106	106
Variance and Standard Deviation of random variable				
Sampling site (N =20)	0.015, 0.123	0.014, 0.117	0.017, 0.132	0.015, 0.123

p values are *** <0.001, ** <0.01, * <0.05, and # <0.10.

Table S12: Alternative models without collinear variables for the total number of generalist species detected aurally over each year of acoustic data collection. Values represent the coefficients and standard errors (in parenthesis) for predictor variables and the treatment (restoration) or control (low Lantana density sites) of the Generalized linear mixed models estimated. For the treatment and control variable, the coefficients quantify the difference of these sites from the unrestored sites. A positive coefficient for the treatment and control variable indicates a higher number of species detected in these respective types of sites in comparison to unrestored sites. We present the full model in the paper in Table S9. All models were checked for variance inflation (threshold = 5), and none of the models displayed variance inflation.

Covariate	**(a) Model 1**	**(b) Model 2**	**(c) Model 3**	**(d) Model 4**
Control: Low Lantana density	-0.036 (0.076)	-0.045 (0.086)	-0.048 (0.077)	-0.036 (0.102)
Treatment: Restoration	-0.113 (0.059)#	-0.138 (0.067)#	-0.126 (0.060)*	-0.124 (0.081)
Tree density	0.079 (0.029)**	0.048 (0.025)#	0.085 (0.030)**	Not included
Large tree density	-0.046 (0.036)	Not included	-0.060 (0.039)	0.016 (0.031)
Total population in 3 km buffer	Not included	-0.019 (0.038)	-0.032 (0.030)	-0.025 (0.045)
% Farms in 3 km buffer	-0.011 (0.024)	0.005 (0.033)	Not included	0.006 (0.038)
% Forest in 3 km buffer	0.018 (0.029)	0.004 (0.034)	0.010 (0.030)	-0.010 (0.038)
Simpson Index of plot	-0.023 (0.026)	-0.024 (0.029)	-0.022(0.026)	-0.011 (0.029)

Year	-0.216 (0.042)***	-0.215 (0.042)***	-0.216 (0.042)***	-0.216 (0.042)
N (each sampling location sampled for 2 years)	106	106	106	106
Variance and Standard Deviation of random variable				
Sampling site (N=20)	0.000, 0.000	0.002, 0.047	0.000, 0.000	0.007, 0.081

p values are *** <0.001, ** <0.01, * <0.05, and # <0.10

Table S13: PERMANOVA analysis of the acoustic space use.

Covariate	**Acoustic space use**				
	Df	**Sum of Squares**	**Mean Squares**	**F**	**R^2**
Type of site (restored, unrestored, low Lantana density)	2	0.428	0.214	1.353	0.023[#]
Tree density	1	0.156	0.156	0.988	0.008
Large tree density	1	0.168	0.168	1.065	0.009
Total population in 3 km buffer	1	0.119	0.119	0.751	0.006

% Farms in 3 km buffer	1	0.142	0.142	0.897	0.008
% Forest in 3 km buffer	1	0.084	0.084	0.532	0.005
Simpson Index of plot	1	0.169	0.169	1.070	0.009
Year: (2020, 2021)	1	0.133	0.133	0.840	0.007
Sampling site (N=20)	18	4.353	0.242	1.531	0.233***
Residuals	82	12.957	0.158		0.693
Total	*109*	*18.709*			*1.000*

p values are *** <0.001, ** <0.01, * <0.05, and # <0.10.

Table S14: Wilcoxon test results for acoustic space use in the frequency range 2000-8000 Hz aggregated over 1-hour time intervals across two years of data collection. The numbers represent the median values for the variables and the 1st and 3rd quantiles in parenthesis. The Z statistic, W statistic and 95% confidence intervals for the Wilcoxon test are provided in the parenthesis under the median and range values.

Variable	**Restored – Unrestored**	**Restored- Low Lantana density**	**Low Lantana density – Unrestored**
(a) Acoustic space use in 2000-8000 Hz range over 24 hours	0.189 (0.125- 0.333) – 0.167 (0.111- 0.292)*** (Z = -8.719; W = 21187796; 95% CI = -0.018, -0.010)	0.189 (0.125- 0.333) – 0.188 (0.119- 0.333)* (Z = -2.065; W = 11165878; 95% CI = 0.000, 0.007)	0.188 (0.119- 0.333) – 0.167 (0.111- 0.292)*** (Z = -4.710; W = 9717094; 95% CI= -0.014, -0.002)
(b) Acoustic space use in 2000-8000 Hz range in	0.148 (0.109 – 0.200) – 0.134 (0.100 – 0.174)*** (Z = -9.107;	0.148 (0.109 – 0.200) – 0.139 (0.104 – 0.191)***	0.139 (0.1.4 – 0.191) – 0.134 (0.100 – 0.174)* (Z = -2.571; W = 2815752;

day-time hours (06:00 – 18:00)	W = 5889786; 95% CI = -0.014, -0.008)	(Z = -4.401; W = 3318431; 95% CI = 0.000, 0.010)	95% CI = -0.005, -0.000)
(c) Acoustic space use in 2000-8000 Hz range in night-time hours (18:00-06:00)	0.333 (0.185 – 0.500) – 0.292 (0.167 – 0.467)*** (Z =-5.560; W = 4547209; 95% CI = -0.035, -0.014)	0.333 (0.185 – 0.500) – 0.329 (0.208 – 0.472) (Z= -1.168; W = 2429298; 95%CI = -0.000, 0.017)	0.329 (0.208 – 0.472) – 0.292 (0.167 – 0.467)*** (Z = -3.558; W = 2094838; 95% CI = -0.030, -0.002)

p values are *** <0.001, ** <0.01, * <0.05, and # <0.10.

Table S15: Coefficients and standard errors for predictor variables and the treatment (restoration) or control (Lantana-free sites) of Generalized linear mixed models with the outcome, acoustic activity measured by the proportion of acoustic space used (%) over time (in hours) in the 2000-8000 Hz frequency range. For the treatment and control variable, the coefficients quantify the difference of these sites from the unrestored sites. A positive coefficient for the treatment and control variable indicates a higher amount of acoustic activity in these respective sites in comparison to unrestored sites. Alternative models without collinear variables presented in Table S16.

Covariate	Outcome variable: Acoustic space used (%) in the 2000- 8000 Hz frequency range
Control: Low Lantana density	-0.001 (0.056)
Treatment: Restoration	0.060 (0.045)
Tree density	0.082 (0.006)***
Large tree density	-0.109 (0.006)***
Total population in 3 km buffer	-0.030 (0.015)#
% Farms in 3 km buffer	-0.043 (0.010)***
% Forest in 3 km buffer	0.022 (0.015)
Simpson Index of plot	0.020 (0.004)***
Year: 2021	-0.081 (0.035)*
N of 1 hour time bins across 24 hours of all the days of recording at every sampling location (recorder location)	16738
Variance and Standard Deviation of random variables	
Sampling site (N = 20)	0.006, 0.072

Time in 24 hours (N = 24)	0.178, 0.422
Dates of recording (N = 100)	0.027, 0.165

p values are *** <0.001, ** <0.01, * <0.05, and # <0.10

Table S16: Alternative models without collinear variables for proportion of acoustic space used (%) over time (in hours) in the 2000-8000 Hz frequency range. Values represent the coefficients and standard errors (in parenthesis) for predictor variables and the treatment (restoration) or control (low Lantana density sites) of the Generalized linear mixed models estimated. For the treatment and control variable, the coefficients quantify the difference of these sites from the unrestored sites. A positive coefficient for the treatment and control variable indicates a higher amount of acoustic activity in these respective sites in comparison to unrestored sites. All models were checked for variance inflation (threshold = 5), and none of the models displayed variance inflation.

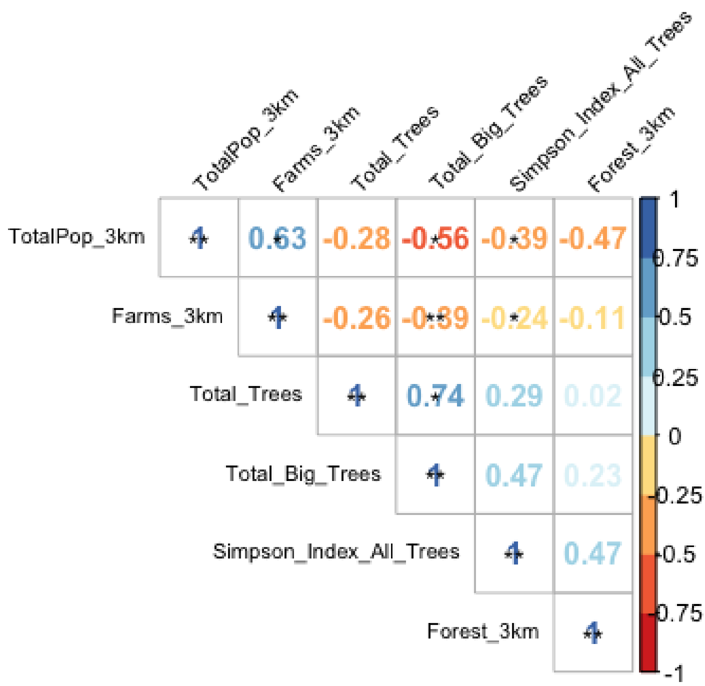
Covariate	**(a) Model 1**	**(b) Model 2**	**(c) Model 3**	**(d) Model 4**
Control: Low Lantana density	0.024 (0.058)	0.087 (0.065)	-0.013 (0.055)	-0.022 (0.051)
Treatment: Restoration	0.085 (0.045)#	0.114 (0.052)*	0.060 (0.044)	0.072 (0.041)#
Tree density	0.082 (0.006)***	0.010 (0.004)*	0.080 (0.006)***	Not included
Large tree density	-0.107 (0.006)***	Not included	-0.106 (0.006)***	-0.052 (0.004)***
Total population in 3 km buffer	Not included	0.013 (0.016)	-0.062 (0.013)***	-0.030 (0.015)*

% Farms in 3 km buffer	-0.052 (0.008)***	-0.025 (0.010)*	Not included	-0.033 (0.010)***
% Forest in 3 km buffer	0.029 (0.015)#	-0.010 (0.016)	0.018 (0.014)	0.033 (0.014)*
Simpson Index of plot	0.019 (0.004)***	0.019 (0.004)***	0.023 (0.004)***	0.018 (0.004)***
Year	-0.081 (0.035)*	-0.057 (0.035)	-0.078 (0.035)*	-0.073 (0.035)*
N (1 hour time-bins in 24 hours of all days of recording at sampling location	16738	16738	16738	16738
Variance and Standard Deviation of random variables				
Sampling site (N = 20)	0.007, 0.085	0.009, 0.094	0.006, 0.078	0.005, 0.071
Time in 24 hours (N = 24)	0.178, 0.422	0.179, 0.422	0.178, 0.422	0.178, 0.422
Dates of recording (N =100)	0.027, 0.165	0.027, 0.163	0.027, 0.165	0.027, 0.165

p values are *** <0.001, ** <0.01, * <0.05, and # <0.10.

FIGURES

Figure S1: Correlation plot of variables used for sampling site match**.**



Appendix C: Supplementary Information for Chapter 4

FIGURES:

Figure S1: Correlation plot of predictor and control variables considered in the GLMMs and causal forest analyses. We removed any variables with correlation coefficient higher than ±0.5.

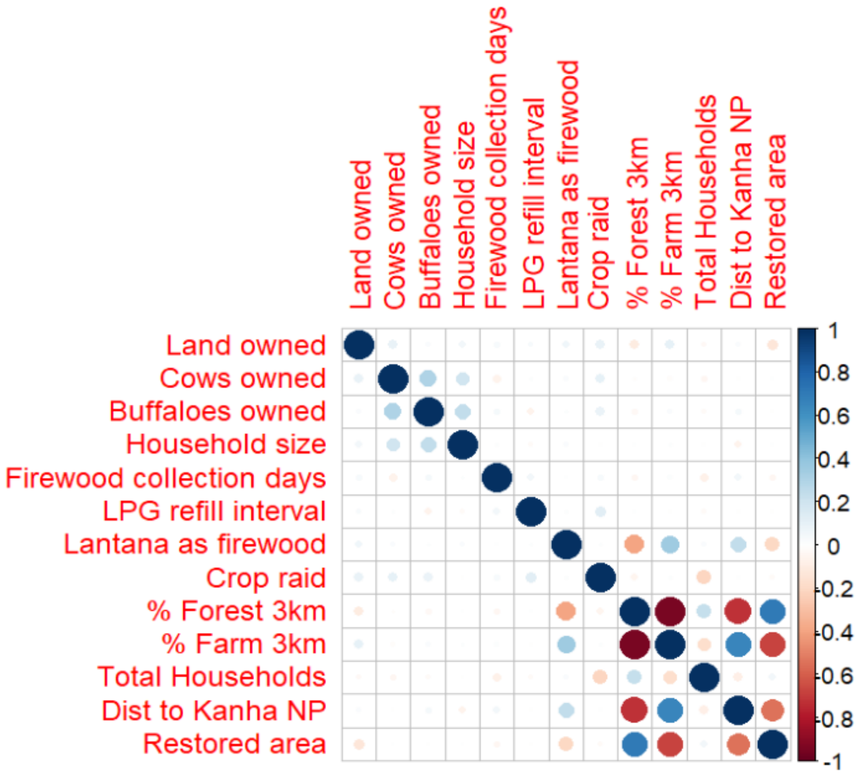
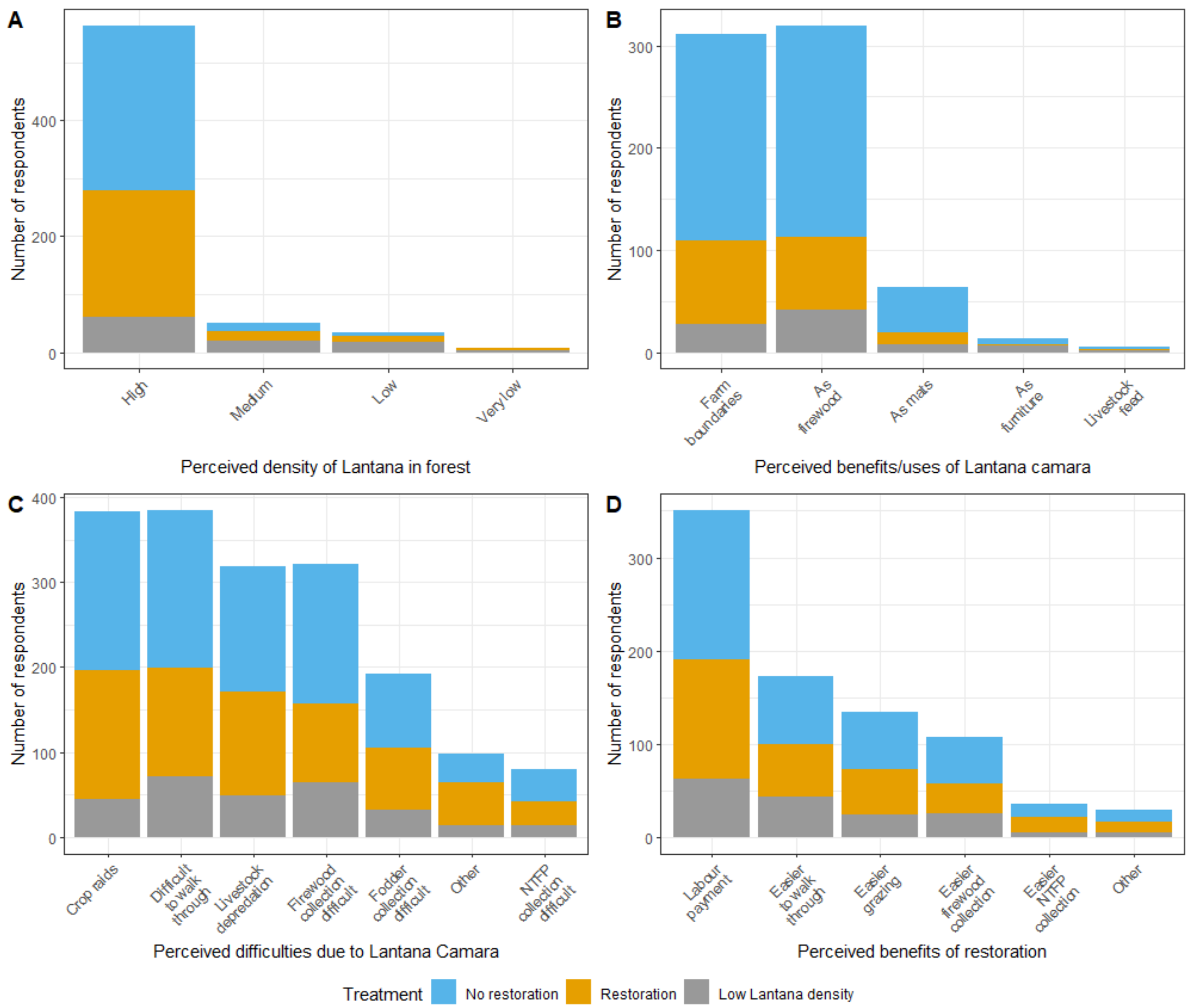


Figure S2: (A) Perceived densities of Lantana camara in the surrounding forests; (B) Uses and perceived benefits of having Lantana camara in the surrounding forests; (C) Perceived difficulties due to the presence of Lantana camara in the surrounding forests; (D) Perceived benefits of ecological restoration in the surrounding forests. Colors refer to the treatment group to which respondents belong. Refer to Table S5 for results on differences in the group.



TABLES:

Table S1: Mean and standard deviations (in parentheses) of variables used for preliminary match of villages within which restored, unrestored and low Lantana density sites were used for this study. Buffer distances for the geographic variables were based on previous studies on people's forest-resource use in this region (1,2). In three out of 8 villages where restoration took place, we established unrestored and low Lantana density sites for comparison within the census boundaries of the same village.

Variable for matching	**Villages not experiencing restoration ('unrestored')**	**Villages experiencing restoration (restored)**	**Villages with Low Lantana density forest**
Total population of village	412 (221)	467 (229)	489 (169)
Total households in village	94 (48)	107 (53)	114 (46)
Percent Literate in village	46.92 (6.34)	47.26 (6.40)	49.11 (4.87)
Percent Scheduled Tribe in village	90.85 (10.75)	93.67 (7.73)	96.00 (7.18)

Percent Scheduled Caste in village	1.37 (3.02)	1.16 (3.03)	8.64 (2.28)
Distance of village to Kanha National Park (kilometres)	5.04 (2.39)	4.44 (2.44)	3.10 (2.74)
Percent agricultural land in 3 km buffer of village census boundary	29.28 (10.92)	28.04 (12.27)	21.11 (9.39)
Percent forest cover in 3 km buffer of village census boundary	60.48 (14.53)	63.56 (15.32)	73.03 (11.49)
Total villages matched	8	8	4

Table S2: Means and standard deviations (in parentheses) for variables used to match exact sampling locations in restored, unrestored and low Lantana density (LLD) sites. These variables (excluding % farm cover in 3 km buffer) are also used as independent variables in the GLMM presented in Table 3:

Variable	**Unrestored sites**	**Restored sites**	**Low Lantana density sites**

Tree density	26.98 (11.60)	29.56 (25.82)	22.32 (10.50)
Large trees density	17.93 (6.85)	16.20 (7.45)	12.96 (5.85)
Plot Simpson diversity index	0.62 (0.28)	0.69 (0.19)	0.76 (0.11)
% Forest cover in 3 km buffer	44 (13.11)	46 (23.00)	65 (6.09)
% Farm land in 3 km buffer	15 (6.12)	9 (6.95)	7.3 (5.87)
Total population in 3km buffer	6628 (5505)	5251 (2145)	4018 (2123)

Table S3: Means and standard deviations (in parentheses) for predictor variables used in GLMMs in Table 2.

Variable	**Villages not experiencing restoration**	**Villages experiencing restoration**	**Villages with Low Lantana density forest**
Land owned (acres)	2.849 (2.769)	3.082 (4.853)	4.276 (12.699)

Cows owned	1 (2)	2 (2)	1 (3)
Buffaloes owned	2 (2)	2 (2)	2 (2)
Household size	5 (2)	5 (2)	5 (2)
Agriculture as primary occupation	39 (5)	36 (3)	27 (1)
Lantana as firewood	30 (12)	13 (8)	5 (2)
Interval between refills of liquified petroleum gas (LPG) cylinder	3 (2)	4 (3)	3 (2)
Firewood collection	3 (2)	3 (2)	3 (1)
Total households in village	100(60)	93(34)	74(34)
% Forest in 3km buffer	48 (10)	68 (8)	70 (1)

Table S4: Two tailed Z-test results for the differences between proportions of responses to questions (i-iv) listed in Section 2.6.2(a). The values represent the proportion of the response with 95% confidence intervals presented in parentheses.

(a) What is your perception of the Lantana density in your surrounding forest?

Responses	**Restored- Unrestored**	**Restored- Low Lantana density**	**Unrestored- Low Lantana density**

High	0.869 - 0.934 (0.011 - 0.119) Z = 2.500 p-value = 0.014	0.869 – 0.610 (0.147 – 0.370) Z = 5.287 p-value = 0.000	0.934 – 0.610 (0.218 – 0.430) Z = 7.800 p-value = 0.000
Medium	0.071 - 0.043 (-0.071 – 0.014) Z = 1.280 p-value = 0.200	0.071 – 0.190 (0.028 – 0.209) Z = 3.078 p-value = 0.002	0.043 – 0.190 (0.060 – 0.234) Z = 4.516 p-value = 0.000
Low	0.044 – 0.023 (-0.054 - 0.013) Z = 1.127 p-value = 0.260	0.044 – 0.170 (0.042 – 0.211) Z = 3.732 p-value = 0.000	0.023 – 0.170 (0.065 – 0.229) Z = 5.150 p-value = 0.000
Very low	NA	0.016 – 0.030 (-0.030 – 0.058) Z = 0.432 p-value = 0.665	NA

(b) What use or benefit do you derive from Lantana in your surrounding forest?

Responses	**Restored- Unrestored**	**Restored- Low Lantana density**	**Unrestored- Low Lantana density**
As firewood	0.282 – 0.681 (0.320 – 0.479)	0.282 – 0.420 (0.020 – 0.257)	0.681 – 0.420 (-0.377 - -0.144)

	Z = 9.286 p-value = 0.000	Z = 4.731 p-value = 0.017	Z = 4.536 p-value = 0.000
As mats	0.044 – 0.148 (0.0535 – 0.155) Z = 3.929 p-value = 0.000	0.044 – 0.080 (-0.029 – 0.102) Z = 1.010 p-value = 0.271	0.148 – 0.080 (-0.141 – 0.005) Z = 1.577 p-value = 0.115
As furniture	0.008 – 0.020 (-0.011 – 0.0345) Z = 0.805 p-value = 0.421	0.008 – 0.060 (-0.003 – 0.107) Z = 2.559 p-value = 0.011	0.020 – 0.060 (-0.015 – 0.096) Z = 1.718 p-value = 0.086
As livestock feed	0.004 – 0.007 (-0.0120 – 0.017) Z = 0.000 p-value = 1.000	0.004 – 0.020 (-0.019 – 0.052) Z = 0.833 p-value = 0.405	0.007 – 0.020 (-0.022 – 0.049) Z = 0.594 p-value = 0.553
As farm boundaries	0.321 – 0.664 (0.261 – 0.425) Z = 7.970 p-value = 0.000	0.321 – 0.280 (-0.15 – 0.071) Z = 0.630 p-value = 0.529	0.664 - 0.280 (-0.493 – -0.275) Z = 6.619 p-value = 0.000

(c) What are the difficulties you face due to the presence of Lantana in your surrounding forest?

Responses	**Restored- Unrestored**	**Restored- Low Lantana density**	**Unrestored- Low Lantana density**

Difficult to collect firewood	0.365 – 0.543 (0.092 – 0.263) Z = 4.098 p-value = 0.000	0.365 – 0.650 (0.167 – 0.403) Z = 4.731 p-value = 0.000	0.543 – 0.650 (-0.008 – 0.223) Z = 1.762 p-value = 0.078
Difficult to collect NTFPs	0.111 – 0.125 (-0.044 – 0.071) Z = 0.372 p-value = 0.710	0.111 – 0.140 (-0.056 – 0.114) Z = 0.572 p-value = 0.568	0.125 – 0.140 (-0.069 – 0.099) Z = 0.216 p-value = 0.829
Difficult to collect fodder/ graze	0.290 – 0.286 (-0.0826 – 0.076) Z = 0.000 p-value = 1.000	0.290 – 0.320 (-0.0834 – 0.145) Z = 0.432 p-value = 0.666	0.286 – 0.320 (-0.077 – 0.145) Z = 0.517 p-value = 0.605
Livestock depredation	0.484 – 0.487 (-0.083 – 0.089) Z = 0.000 p-value = 1.000	0.484 – 0.490 (-0.116 – 0.128) Z = 0.000 p-value = 1.000	0.487 – 0.490 (-0.113 – 0.119) Z = 0.000 p-value = 1.000
Crop raids	0.607 – 0.612 (-0.080 – 0.090) Z = 0.026 p-value = 1.000	0.607 – 0.440 (-0.289 – -0.046) Z = 2.730 p-value = 0.006	0.612 – 0.440 (-0.290 - -0.54) Z = 2.893 p-value = 0.004
Difficult to walk through	0.508 – 0.612 Z = 2.374	0.507 – 0.710 (0.087 – 0.317)	0.612 – 0.710 (-0.013 – 0.209)

	p-value = 0.018	Z = 3.330 p-value = 0.001	Z = 1.650 p-value = 0.989

(d) What do you perceive as the benefit of ecological restoration by way of removal of Lantana in your surrounding forest?

Responses	**Restored- Unrestored**	**Restored- Low Lantana density**	**Unrestored- Low Lantana density**
Labour payment	0.508 – 0.530 (-0.065 – 0.108) Z = 0.424 p-value = 0.672	0.508 – 0.620 (-0.008 – 0.232) Z = 1.784 p-value = 0.074	0.530 -0.620 (-0.027 – 0.208) Z = 1.461 p-value = 0.144
Easier NTFP collection	0.067 – 0.043 (-0.067 – 0.017) Z = 1.095 p-value = 0.274	0.067 – 0.050 (-0.077 – 0.042) Z = 0.366 p-value = 0.714	0.043 – 0.050 (0.050 – 0.048) Z = 0.025 p-value = 0.980
Easier firewood collection	0.131 – 0.161 (-0.032 – 0.092) Z = 0.881 p-value =0.379	0.131 – 0.250 (0.018 – 0.221) Z = 2.556 p-value = 0.011	0.161 – 0.250 (-0.012 – 0.190) Z = 1.842 p-value = 0.065
Easier to walk through	0.222 – 0.243 (-0.053 – 0.095)	0.222 – 0.430 (0.091 – 0.326)	0.243 – 0.430 (0.072 – 0.302)

	Z = 0.487 p-value = 0.626	Z = 3.779 p-value = 0.000	Z = 3.441 p-value = 0.001
Easier for grazing	0.194 – 0.201 (-0.063 – 0.076) Z = 0.0762 p-value = 0.939	0.194 – 0.240 (-0.058 – 0.149) Z = 0.805 p-value = 0.421	0.201 – 0.240 (-0.062 – 0.141) Z = 0.696 p-value = 0.487

Table S5: Alternative models with higher AIC values for models presented in Table 2.

Independent variables	**(a) Distance for grazing**	**(b) Time for firewood collection**	**(c) Cattle lost to depredation**	**(d) Perception of crop loss**
Intercept	0.934 (0.134)	1.172 (0.093)	-1.634 (0.323)	0.344 (0.364)
Treatment: Restoration	-0.294 (0.193)	0.040 (0.134)	0.715 (0.416)#	-0.059 (0.550)
Control: Low Lantana Density	-0.559 (0.259)*	0.113 (0.176)	0.708 (0.518)	-0.165 (0.669)
Land owned (acres)	0.059 (0.038)	-0.012 (0.021)	0.110 (0.087)	-0.075 (0.086)
Cows owned	0.062 (0.039)	NA	0.098 (0.096)	NA

Buffalos owned	0.161 (0.040)***	NA	0.116 (0.097)	NA
Household size	0.051 (0.040)	-0.029 (0.021)	0.232 (0.098)*	-0.002 (0.089)
Number of days grazed/ week	NA	0.139 (0.020)***	NA	NA
Use of Lantana as firewood	NA	0.113 (0.051)*	NA	NA
Interval between filling LPG	NA	0.028 (0.022)	NA	
Agriculture primary occupation	0.005 (0.087)	0.012 (0.047)	0.141 (0.217)	0.367 (0.197)#
% Forest in 3 km buffer	0.072 (0.099)	-0.068 (0.068)	0.192 (0.200)	-0.103 (0.272)
Total households in village	0.017 (0.074)	0.120 (0.50)*	-0.804 (0.321)*	-0.305 (0.177)#
Restoration x Total households	-0.091 (0.161)	-0.045 (0.111)	0.484 (0.422)	NA
Low Lantana density x Total households	-0.210 (0.240)	0.052 (0.162)	0.577 (0.519)	NA

Random variable: Sampling site (N= 13 villages)	0.029 (0.169)	0.016 (0.129)	0.065 (0.255)	0.280 (0.529)
N observations	653	656	637	605
AIC	2554	2663	709	785
Psuedo R^2	0.049	0.219	0.109	0.094
Distribution used	Negative Binomial	Negative binomial	Binomial	Binomial

Significance codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘#’ 0.1 ‘ ’ 1

Section 1 BACKGOUND INFORMATION		
Field	*Question*	*Answer*
q_100 (required)	100) ID of interviewer	
q_101 (required)	101) Name of Interviewer	
q_102 (required)	102) Name of supervisor	
q_103 (required)	103) Date of Interview (dd/mm/yyyy)	
q_104 (required)	104) Interview Start Time	

q_106 (required)	106) Language of the interview	
uniqe_id (required)	Unique Id	
q_state_name	State name is [state_cal]	
q_state_code	State census code (2011) is [state_code_cal]	
q_106	106) Village name is [vill_cal]	
q_107	107) Village________ (in 2011 census code) is [vil_code_cal]	
q_108	108) District name is [dist_name_cal]	
q_sub_dist	Sub District name is [sub_dist_name]	
q_109	109) District ______ (in 2011) census code is [dist_code_cal]	
Section_1 (required)		
q_110gmorsel_note	Introduction to Respondent (Household Head if possible) Good morning! I work with MORSEL, an organization based in Lucknow that conducts surveys in India. [Interviewer shows ID card to the respondent]. Your household has been	

	selected to participate in a short survey about your lifestyle. It will take no more than 20 minutes. You are allowed to refuse to answer any question and you may end participation in this study at any time during the interview.	
q_111 (required)	111). Would you like to participate?	1 Yes
	(ask for female HH head)	0No
q_111_reason (required)	why not, please give reason	
q_112 (required)	112) Name of the respondent (to be anonymized)	
Section 2: SOCIO- ECONOMIC INFORMATION		
q_200 (required)	200) Are you household head?	1 Yes
		0 No
q_200a_relation (required)	200a) Relation with household	
q_201_gender (required)	201) Gender [INTERVIEWER OBSERVES– MALE OR FEMALE]	1 Female
		0 Male
q_202_age (required)	202) What is your age	
q_203 (required)	203) What is your caste?	1 Forward Caste

		2 Other Backward Caste
		3 Scheduled Caste
		4 Gondi
		6 Baiga
		6 Scheduled Tribe
		7 Other
q_203_Other (required)	Other (specify):	
q_204_a (required)	204_a) What is your level of education?	1 No formal education
		2 Primary
		3 Secondary
		4 High School
		5 Intermediate
		6 Graduate/Post Graduate
		7 Other
q_204_b (required)	204_b) Who is the most educated member in your family?	1 No formal education
		2 Primary

		3 Secondary
		4 High School
		5 Intermediate
		6 Graduate/Post Graduate
		7 Other
q_204_c_Other (required)	Other (specify)	
q_205_a (required)	205_a) What is the household head's primary occupation? (Housewife can be coded as not working here)	1 Agriculture
		2 Labourer
		3 Government employee
		4 Business
		6 Not working
		7 Other
		8 Service
q_205_b (required)	205_b) What is the household head's secondary occupation? (Housewife can be coded as not working here)	1 Agriculture
		2 Labourer

		3 Government employee
		4 Business
		6 Not working
		7 Other
		8 Service
q_205_c_Other (required)	Other (specify)	
q_206 (required)	206) How many people live in this household? _______ people	
q_207 (required)	207) How many members in your family migrate seasonally to the city for work?	0
		1
		2
		3
		4
		6 or more
Section 3: ASSETS		
q_300 (required)	300) Is the house *pucca* (made of cement) or *kucha* (made of mud) [INTERVIEWER OBSERVES]	1 Pucca
		0 Kucha

		2 Mixed
q_301_a (required)	If the response to q_300 is *pucca*: Indicate actual year (e.g.: 2013, 2014) 301_a) when did you make your house *pucca*?	
q_301_b (required)	301_b) Generally, where do you get most of the wood to repair your house? (Multiple options may apply)	1 Depot
		2 Forest
		3 Market
		4 Own trees in backyard
		6 Other:
q_301_c_other (required)	Other (specify):	
q_302 (required)?	302) Do you own cattle (like cows, buffaloes and goats etc)?	1 Yes
		0 No
q_303_a	303_a) how many pigs?	
q_303_b	303_b). how many goats?	
q_303_c	303_c) how many chicken?	
q_303_d	303_d) how many cows?	

q_303_e	303_e) how many oxen?	
q_303_f	303_e) how many buffaloes?	
q_304	304) In the last five years, did a tiger or leopard kill your livestock?	1 Yes
		0 No
		2 I can't remember
q_304_a	304_a) If answer to 304 is yes: Where did the kill happen?	1 In the forest
		2 In the bushes
		3 In the village
		4 Other
q_304_a_other	304_a_other) Other:	
q_305	305) Do you own land?	1 Yes
		0 No
305_a) how much land does your family unit own? (Specify your immediate family, not extended family which includes relatives)		
q_305_a_now (required)	Time: Now	
q_305_a_unit	Unit	1 Acre
		2 Hectare
		3 Kood
		4 Ward
		5 Decimal

		6 Other (specify):
q_305_a_unit_other (required)	Other (specify):	
q_305_b_5yearsago (required)	**5 years ago – how much land?**	
q_305_b_5yearsago	Unit	1 Acre
		2 Hectare
		3 Kood
		4 Ward
		5 Decimal
		6 Other (specify):
q_305_b_5yearsago_ unit_other (required)	Other (specify):	
q_306	306) Do wild herbivores such as wild boards and barking dear often raid your crops?	1 Yes
		0 No
q_306_a	306_a) If the answer to 306 is yes: How much crop do you lose when this happens?	1 less than 25%
		2 25%
		3 50%
		4 Over 50%
		5 Other

q_306_a_other	306_a_other) Other:	
Section 4: CURRENT FOREST RESOURCE USE		
q_401 (required)	401) If answer to q_302 is yes: Do you take your cattle grazing?	1 Yes
		0 No
q_401_b (required)	401_b) If answer to q_302 is yes: Where do you take your cattle grazing? (Select all that apply)	1 Forest around the village
		2 Agricultural land
		3 Provide fodder at home
		4 Other
q_401_b_other)	401_b_other) Other:	
q_401_c (required)	401_c) If answer to q_401 is yes: In a month, how many days do you take your cattle grazing? Answer should be option of days (E.g.: 10 days. If everyday, 30 days)	
q_401_d (required)	401_d) If answer to q_401 is yes:	

	In a day, how many hours do you take your cattle grazing?	
q_401_e (required)	401_e) If answer to q_401 is yes: In a day, how far do you take your cattle grazing? (Indicate number of kilometres) ________ KILOMETER	
q_402_a (required)	402_a) If answer to q_401 is yes: If you provide fodder at home, where you acquire fodder from? (Select all that apply)	1 Purchase from another villager
		2 Collect it from the forest
		3 Use agricultural residue
		4 Use food waste
		6 From the eco-development committee
		6 From the restored site (where lantana has been removed)
		7 Other

q_402_a_other	402_a_other) Other:	
403) Firewood Collection		
q_403	403) Do you use firewood for cooking or heating purposes in your home?	1- Never
		2- Sometimes
		3- Always
		4- A lot
q_404	404) Do you buy firewood from a neighbour or in the market nearby?	1- Never
		2- Sometimes
		3- Always
		4- A lot
q_405	405) Do you or any family member go to the forest to collect firewood?	1- Never
		2- Sometimes
		3- Always
		4- A lot
FIREWOOD COLLECTION:		

q_406_a (required)	406_a) In a typical week, how many days did you or a person in the household to collect firewood?	
q_406_b (required)	406_b) On average, how many hours did you or a person in the household spend collecting firewood on ONE day?	
q_406_c (required)	406_c) On average, what distance did you or a person in the household travel for collecting firewood? Indicate in kilometres __________ Kilometres	
q_407	407) Do you use Lantana as firewood?	1- Never
		2- Sometimes
		3- Always
		4- A lot
408) NTFP extraction: In the last year, besides firewood, did you collect any other forest product, such as leaves, flowers or fruit?		
408)	408) Do you extract any NTFPS for personal consumption or sale?	1 Yes
		0 No

q_408_a	408_a) If answer to 408 is yes: What did you extract? (Select all that are applicable)	*Tendu patta* (*Diospyros melanoxin* leaves)
		Mahua (*Butea monosperma* flowers)
		Amla (*Phyllanthus emblica* fruit)
		Harra (*Terminalia chebula* fruit)
		Baheda (*Terminalia bellerica* fruit)
		Honey
		Other
q_409 (For every product listed in q_408, ask this question. Various units are locally used- to be converted to kgs if used in the analysis)	409_a) NTFP1: How many units (kg/ *gunnies*/ headloads/*sekad/boris /gatthis*) of the NTFP did you collect? _________ (unit)	
	409_b) NTFP2: How many units (kg/ *gunnies*/ headloads/*sekad/ boris /gatthis*) of the NTFP did you collect? _________ (unit)	

	409_c) NTFP3: How many units (kg/ *gunnies/* headloads/*sekad/ boris /gatthis*) of the NTFP did you collect? __________ (unit)	
q_410	410) Does your village make certain rules about collecting/ extracting firewood, grass and NTFPs or grazing in the nearby forests?	1 Yes
		0 No
		Other
q_410_other	410_other) Other:	
q_411 (required)	411) Does your household use liquified petroleum gas (LPG) for cooking?	1 Yes
		0 No
q_411_a (required)	411_a) When did you start using it?	1 Before 2013
		2 2013
		3 2014
		4 2015
		5 2016
		6 2017
		7 2018
		8 2019
		9 2020
		10 2021

q_411_b	411_b) How often do refill your LPG cylinder? Every ________ months	
SECTION 5: LANTANA IN FOREST		
q_500	500) How much *Lantana camara* is there in the forest that surrounds your village?	1 A lot
		2 Some
		3 Little
		4 Very little
q_501	501) What are the problems/difficulties you face due to having *Lantana camara* in the surrounding forest (Select all that apply)	1 Hard to collect firewood
		2 Hard to collect NTFPs
		3 Hard to collect grass
		4 Livestock depredation
		5 Crop raids

		6 Difficulty to walk through patches with a of *Lantana camara*
q_502	502) Do you get any benefit from/ do you have any use of *Lantana camara* in the jungle?	1 Yes
		0 No
q_502_a	502_a) What benefits/ uses do you get from *Lantana camara?*	1 Use *Lantana camara* to make farm boundary
		2 Use *Lantana camara* as firwood
		3 Use *Lantana camara as mats outside*
		4 Use *Lantana camara* to make furniture
		5 Use *Lantana camara* for fodder
q_503	503) Do you agree with the statement?	1 Strongly agree

	Leopards/ tigers can hide in the *Lantana camara* bushes and ambush cattle.	
		2 Agree
		3 No opinion
		4 Disagree
		5 Strongly disagree
q_504	504) Do you agree with the statement? Wild boards can hide in the *Lantana camara* bushes and easily come close to farms under the cover to raid the crops.	1 Strongly agree
		2 Agree
		3 No opinion
		4 Disagree
		5 Strongly disagree
Section 6: LANTANA REMOVAL		
q_600	600) Do you know of any restoration work that has taken place in the forest surrounding you?	1 Yes
		0 No
q_601)	ONLY if response to 600 is Yes:	1 Forest Department

	601) Who ordered for the restoration and who paid you for the lantana removal? (Select all that are applicable)	
		2 Eco- development committee
		3 Joint Forest Management Committee
		4 FES (NGO)
		5 Village Panchayat (council)
		6 Other
q_601_other	601_other) Other:	
q_602	Only if q_600 is yes: 602) In which year did the institution/people/NGO restore the forest around your village? (Indicate year. E.g.: 2013, 2014) ________________________________ OR 1	1 I don't know
q_603	603) Did you assist in the restoration effort?	1 Yes
		0 No
q_604	ONLY if response to 603_is Yes:	1 Yes

	604) Did you earn any money from helping to restore the forest?	
		0 No
q_605	605) What did you do with the plot where you removed *Lantana camara*?	1 Plant trees with the Forest Department
		2 Plant trees with the help of FES
		3 Leave the land as it is
		4 Plant grasses
		6 I don't know
		7 Other
q_606	Only if the response to q_605 is 1, 2: 606) What trees did the Forest Department or FES (NGO) plant? (Select ALL that are applicable)	1 Teak (*Tectona grandis*)
		2 Bamboo (*Bambusa vulgaris*)
		3 Khamair (*Acacia catechu*)

		4 Lendhia (*Laegerstroaema parviflora*)
		5 Other
Q_606_other	Specify other trees ______________________	
q_607	607) Why did you assist in the restoration efforts? (Select all that are applicable)	1 The panchayat (council) asked me to participate
		2 The eco-development committee asked me to participate
		3 The forest department told me to participate
		4 The whole village was participating, so I joined
		5 The NGO, FES, told me to participate

		6 I earned daily wages for helping with the restoration efforts
		7 Other
q_607_other	607_other) Other:	
q_608	608) Did you personally receive any benefit from restoring the forest around you?	1 Yes
		0 No
q_609	If 608 is yes: 609) What kind of benefit did you receive? (Select all applicable)	1 I received a daily wage
		2 Easier to collect grass
		3 Easier to collect NTFPS
		4 Easier to collect firewood
		5 Easier to walk through the forest
		6 The system makes the village people more equal

		7 Other
		8 Easier to take cattle grazing
q_609_other	609_Other) Other:	
610)	610) Do you agree with this statement? By removing *Lantana camara* in the surrounding forest, you experience fewer events of livestock depredation.	1 Strongly agree
		2 Agree
		3 No opinion
		4 Disagree
		5 Strongly disagree