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Sensitivity of seasonal migration to climatic variability in central India

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Title: Sensitivity of Seasonal Migration to Climatic Variability in Central India

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Abstract:

Extreme climatic events and variability are on the rise around the world, with varying implications for populations across socio-economic conditions. Effective strategies for climate adaptation and development depend on understanding these differential sensitivities to climatic variability. This study focuses on a vulnerable population living in forest-fringe villages of central India, where seasonal migration is a common livelihood strategy for poor households to supplement their incomes with remittances. We quantify 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. We surveyed 5000 households in 500 forest-fringe villages to identify patterns of migration from 2013-17. Using a mixed-effects logistic regression model, we predicted the probability of first-time migration of a household member based on climate variables and household- and district-level characteristics. We 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. 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 does not vary as a function of climatic variability for households in the poorest district. We attribute this 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. Promotion of non-agricultural livelihood options and climate-resilient agriculture could the reduce sensitivity of migration to climate variability in the study region.

Keywords: seasonal migration, central India, rural livelihoods, COVID, climate change

INTRODUCTION

Many studies identify extreme climatic events and variability associated with climate change as 'push' factors for migration, especially in low-income countries (1–4). 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 (5–7). A rainfall deficit is linked to higher internal and international migration out of regions dependent on rain-fed agriculture (8–11). Positive temperature anomalies and gradual temperature increases are significantly correlated with the increase in migration (3,12–14).

It is well established that agricultural dependency influences the climate- migration relationship, especially in rural landscapes (7,15,16). Agricultural land is a physically immovable asset, lowering the likelihood of migration in some cases (10,17). However, higher dependence on agriculture may also increase the exposure of a household to climatic variability (18). Climatic variability is associated with reductions in agricultural yields and incomes (19,20), which may compel household members to migrate to cope financially. 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 (21). 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 (22). Non-agricultural households, in contrast, remain largely unaffected by dry spells (22). 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 (7).

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 (23–26). Interestingly, several studies find that migrants invest in agricultural land and agricultural transformation practices when they accumulate wealth from migration over years (27–29). 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 (27). 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 (29). While agriculture has had a positive impact on poverty reduction for the poorest and most vulnerable societies in the recent past (30–32), 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 (26). In recent decades there is a trend of higher maximum temperatures in comparison to the past (33). 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

(34). Projections indicate increasing heat stress and a weakening summer monsoon, which is crucial for water security in parts of the country (33,35). Additionally, the sub-seasonal and inter-annual precipitation variability of the monsoon is also projected to increase (36–38). India's increasing climatic variability leaves a vast population, especially those engaged in agriculture, highly vulnerable to livelihood losses (26).

Due to spatial and social disparities in economic development, livelihood options in rural Indian landscapes are often limited (39–42). Seasonal migration (defined as the absence from one's place of residence for up to six months a year (43)) is a common livelihood strategy amongst socially vulnerable groups in India (42–48). Approximately 83% of seasonal migrants recorded in the National Sample Surveys (2005, 2010, 2012) belonged to socio-economically disadvantaged communities officially recognized in India (46). While seasonal migration is common in India, people often migrate in distress rather than aspirational reasons, such as skills development or wealth accumulation (6,41,42,47,49). 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 (46,50). However, migrants work in harsh conditions and live in unsafe makeshift accommodations (50,51). Further, migrants are often part of informal labor markets, which do not provide adequate financial compensation and other employment benefits (44,50).

Rural households continually re-evaluate their livelihood strategies. For example, 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 (52–54). As evidence emerges from other countries through the pandemic, we can expect an increase in dependence on agriculture, and agricultural transformation and intensification practices amongst households that once had migrants (55). 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 (56). 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 (38), has a large proportion of households with members who migrate seasonally (49), and is one of the poorest regions of the country.

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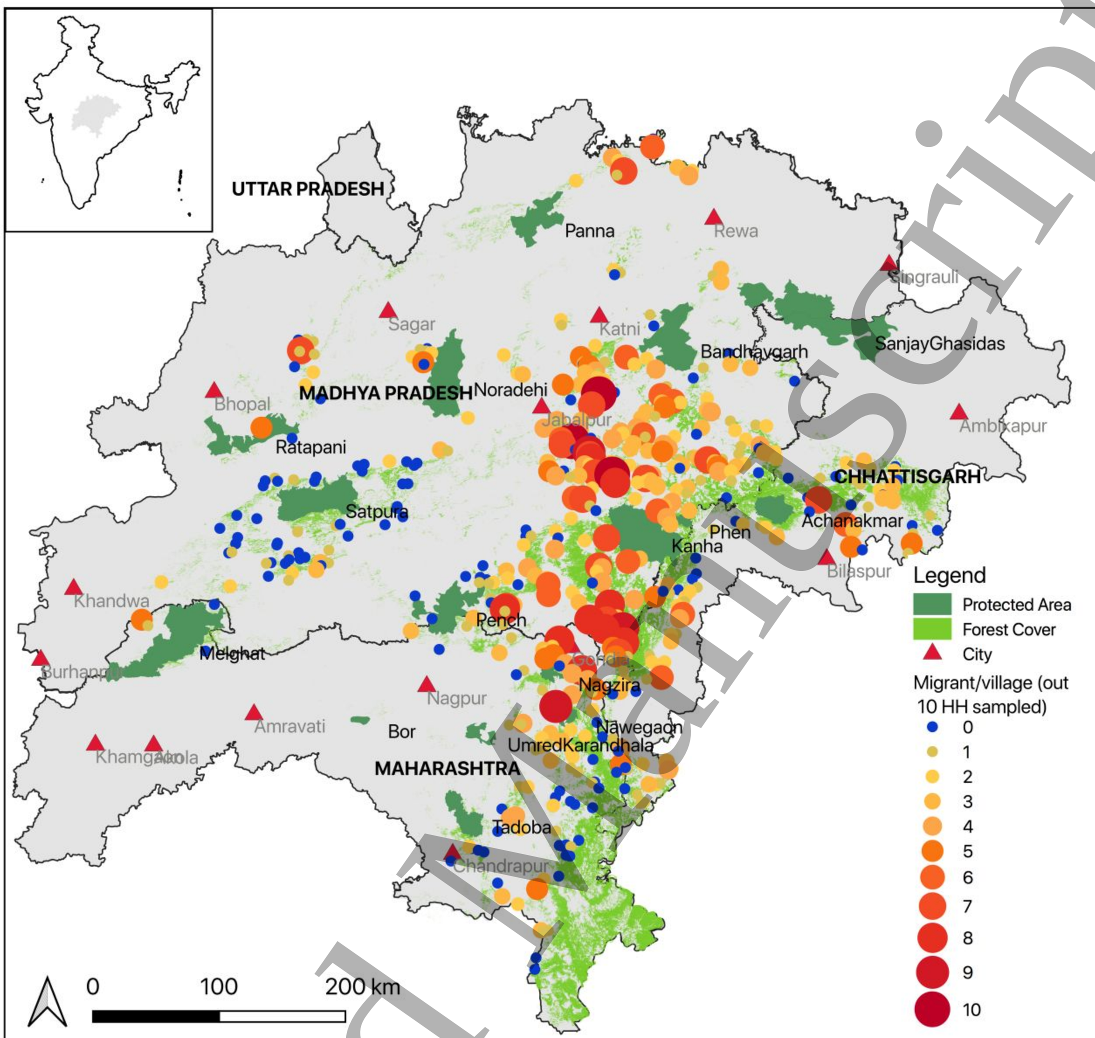

Figure 1: *Map of the Central India Landscape. Circles represent 500 survey villages included in this survey. The colour and the size of the circles represent the proportion of households (out of a maximum of 10 households) with at least one seasonal migrant.*

Focussing on the CIL (Figure 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?

DATA AND METHODS

Study Area

We define the CIL as 32 administrative districts spread across the states of Madhya Pradesh (MP), Maharashtra, and Chhattisgarh (Figure 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 (57). 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 (58,59).

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 (41). Due to the lack of livelihood options in less prosperous districts, migration is an important source of income particularly for scheduled castes and tribes (41,42,60,61). In households with migrants, up to half of a household's total income may be derived from migration for mainly non-farm sector work (41). 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 (41,60,61).

Climatic variability in the CIL

The CIL is mainly dependent on rain-fed agriculture (62). 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 (63,64). In the recent past, the CIL has experienced large climatic variability (Figure 2). There has been a weakening of the summer monsoon (35,38) and an increase in the frequency and duration of heatwaves in the CIL from 1901 to 2012 (35).

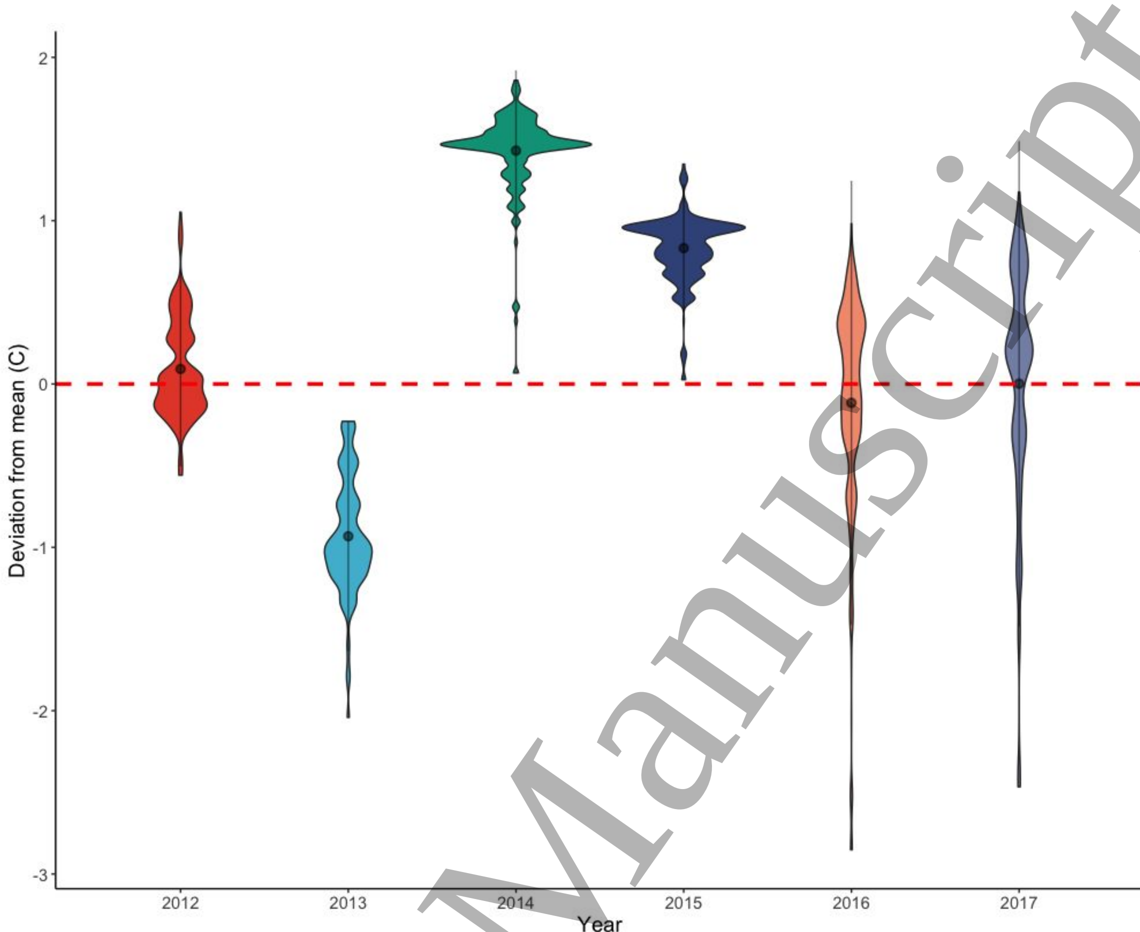

Figure 2: *Violin plots representing the deviation from the long-term (1981 to 2017) mean maximum temperature in the summer monsoon (June, July August and September) from 2012 to 2017 across 476 surveyed villages of this study. The mean maximum temperature of 476 villages for every year is represented 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) (65). Projections indicate uncertainty in the seasonal mean precipitation but an increase in inter-annual variation in precipitation during the monsoon season (37,38,65).

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 Figure 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 Figure 2).

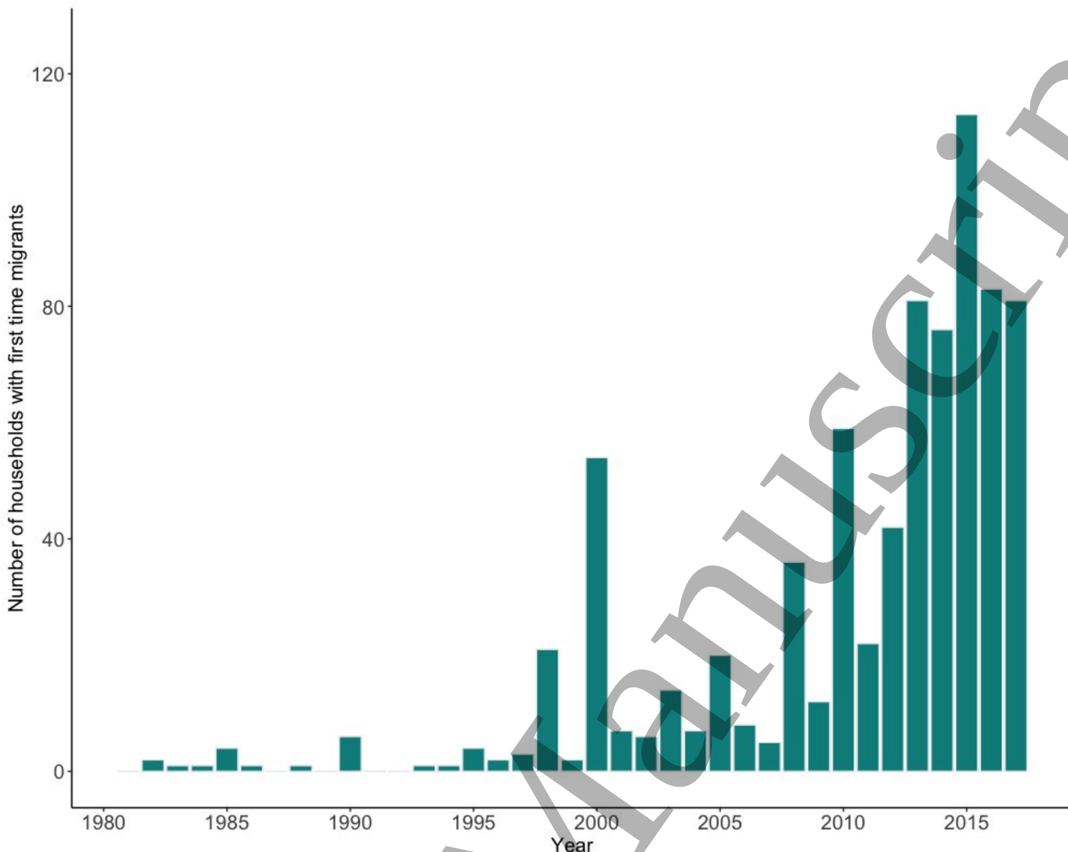

Figure 3: *Number of first time migrants from 4323 households across 476 villages in every year since 1981. Due to reliability of recall, we only consider first-time migrants from 2013 to 2017 in this study. Data derived from household survey.*

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 (41,43) (Table 2). 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 (66) (SI Figure 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 (66).

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 (67), 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 (68). We used the Climate Hazards Group InfraRed Precipitation and Station Data (CHIRPS) for precipitation indices (69). 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 Figure 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.

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 previous monsoon	MT	Standard Deviation	0.29	0.91	0.26	0.89	CPC
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

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

First- Time Migration Model and Expectations

With the variables listed in Table 2 we estimated a mixed-effects logistic regression model 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:

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

$$\text{Logit }(\text{Y}_i) = b_0 + b_1ED_i + b_2DT_i + b_3DC_i + b_4MPI_i + b_5HS_i + b_5IL_i + b_6TR\text{-}PY_i + b_7TR_{i+}\, b_8TR\text{-}PY_i{*}IL_i + b_9TR\text{-}PY_i{*}MPI_i + (1|v) + (1|t) \quad \text{(Eq. 2)}$$

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

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

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). Because mean maximum temperature and total rainfall are co-linear (SI Figure 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 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 indicates 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 (70).

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. 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. We carried out all analyses in R software (71), using packages *lme4* (72) for the statistical model and *ggeffects* (73) for the model predictions.

RESULTS

Table 3 presents the results for the mixed-effects logistic regression models (individual year models in SI Table 5).

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

Table 3: *Mixed effects logistic regression model results using 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

Consistent with previous studies (6,44), 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 ≥ 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 (43,44,50). In our study, poorer districts, on average, have a 55% higher proportion of ST households in their population compared to richer districts (57) (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 = 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 Figure 4). Thus, the results and predictions of Model 1 and 2 show similar results at 1 SD (Figure 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).

[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.

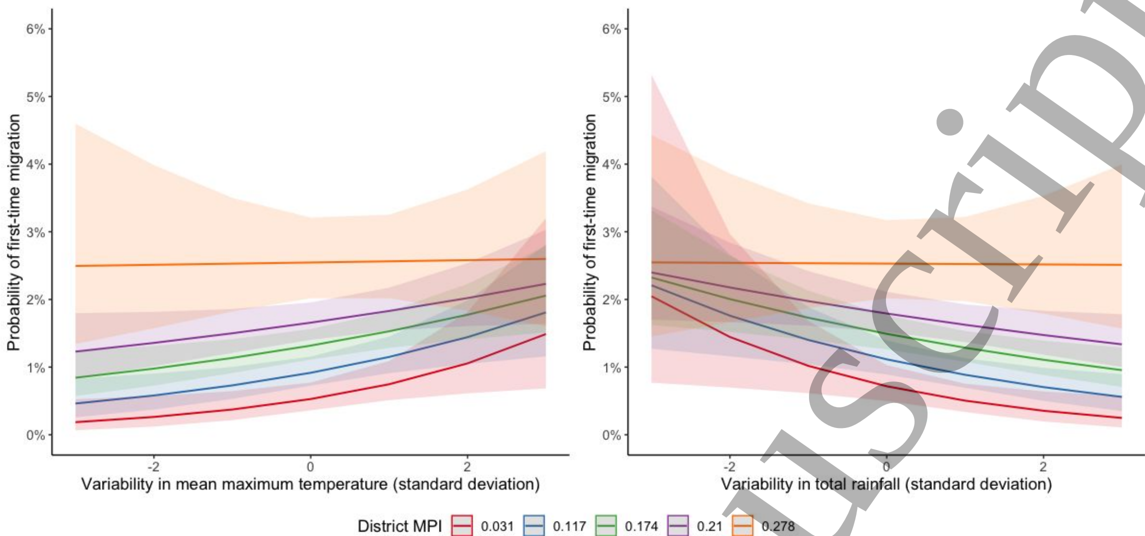

Figure 4: *(a) Probability of first- time seasonal migration as a function of the interaction of variability in the mean maximum temperature in the previous year and the district's MPI based on combined data (2013- 2017). (b) Probability of first- time seasonal migration as a function of the interaction 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.*

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 (63). 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 (56,70). This may be because households with larger land ownership have higher labor requirements and thus, are less likely to undertake seasonal migration for work (13). 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 (7) and other countries such as Mexico (21) or Bangladesh (22). 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 (74). In such a case, the proximity of a household to the forest becomes less relevant for their income (59,74). 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 (63). 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 (56,63). Prior evidence from the CIL suggests that commonly grown crops, such as rice and wheat, are highly sensitive to temperature increases (68). Climate projections for the CIL indicate variation in rainfall patterns (38), but a statistically significant increase in annual temperatures (75). 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 (26,76). However, given the recent increased dependence on irrigation, parts of central India have depleted their groundwater (63,64) and could face severe water shortages and reductions in crop production as early as 2025 (64). 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 (27,29). 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 (63), it may reduce their seasonal migration but make households in poorer districts more vulnerable to climatic variability in the long run.

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. Other non-forest fringe communities in India have expanded and intensified agriculture to increase incomes, reduce dependence on migration and move out of poverty (56). A similar pathway could occur for the forest-fringe population in our study region, which could reduce dependence on migration but make households 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 (5,7,12,21,22,77).

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. Given the large population in India, providing livelihood options at the origin, which compete financially with livelihoods in cities, may give household members more agency in their decision to migrate and also reduce the population pressure on cities. 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 (78), 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.

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