Mobility, Information, and Climate Resilience: Evidence from India's Rural Poor

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Abstract

Agricultural communities in India are substantially vulnerable to weather shocks. Information on how to mitigate their effects, however, can be difficult to access, as it spreads slowly through potentially sparse and distant social networks. Using novel cellphone mobility and farmer help-line call data, we characterize farmer mobility throughout the planting season, identify geographic areas that appear isolated and characterize how mobility interacts with information seeking from the government in the face of adverse weather events.

The majority of India's poverty is concentrated in rural areas, where agriculture is the dominant economic activity and therefore particularly vulnerable to climate change (WorldBank, 2012; Kala, 2023). An important mediator in how well and how quickly farmers learn climate-adaptive practices is how information spreads within their communities. However, information sharing in societies can be hampered by frictions such social stigmas and preferences for homophily (Chandrasekhar, Golub, and Yang, 2019; Goffman, 1963; Golub and Jackson, 2009). A burgeoning literature has illuminated that *who* receives information may be instrumental for its widespread dissemination (Banerjee et al., 2019; Beaman et al., 2021). Still, social learning may depend on how such a society *seeks* information and relief in times of distress within its socioeconomic network.

In this project, we use NetMob's origin-destination and population density data to create several measures that capture important facets of mobility and insularity. We combine this with daily call log data from India's Kisan Call Center (KCC), one of the world's largest agricultural extension programs, as well as daily precipitation data from the Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS) and daily air temperature data from the ERA5 product of the European Centre for Medium-Range Weather Forecasts (ECMWF). We utilize this data to: **(1)** Document temporal and spatial patterns in mobility across India, and their relationship to other aspects of development; **(2)** Illuminate how climate hazards – such as consecutive hot or dry days[1], which can be harmful for agricultural

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[1]We define a "dry day" as a day with fewer than 2mm of precipitation, and a "hot day" as a day with a maximum temperature above a certain threshold, which we set flexibly at 30C, 35C, and 40C. Hogan and Schlenker (2024) documents that temperatures generally above 30C are harmful to several crop types; Zivin and Shrader (2016) documents that high temperatures, generally above 29C dramatically increases mortality.

production, interact with farmers' demand for information from KCC; and **(3)** Examine how mobility mediates the demand for and diffusion of information surrounding climate hazards.

1 Characterizing Mobility

First, we characterize the mobility pattern of India's agricultural population. In Table 1, we explore differences in subdistrict characteristics and mobility between the full sample of Mission Antyodaya administrative data, made available through the Socioeconomic High-resolution Rural-Urban Geographic Platform for India (SHRUG) (Asher et al., 2021), and rural subdistricts which sought information in a farmer helpline. These summary statistics illuminate the stark mobility deficit the rural poor face, not only in terms of total trips but in the length, duration, and speed of those trips, which may be attributable to their relative lack of access to transport and infrastructure (see: Table 3).

1.1 Patterns of Mobility

We first exploit India's rapidly expanding cellular network coverage and cell phone penetration in the past decade to characterize the mobility patterns of rural agricultural communities. Although there are obvious data limitations in the coverage of rural populations, for those selected into our sample, there are some first order descriptive statistics which have been understudied using real time data. The closest analogue are time use surveys, but these can only determine average mobility patterns over a time period. Using the Spectus Origin-Destination (OD) data, we first attempt to characterize the mobility pattern of an on and off-season work week for an average farmer in rural India, and how their mobility might change throughout the season.

We begin by examining how people India move and to where. Figure 1 plots the distribution of the number of daily outbound trips from a geohash, defined as a trip for which the start geohash is different than the end geohash. We observe that there is a large spread in the distribution – some places have well over 30 outbound trips per day. However, the majority of geohashes are the origin of relatively few (fewer than five) outbound trips per day. Zooming out, we illustrate in Figure 2 that over 75% of geohashes only contain trips within itself.

Having documented that mobility is overall quite low in India, we proceed to explore how trips and the length of those trips interact. In Figure 3, we plot the relationship between total trip count and the mean length of those trips for each geohash. The plot extends into the first quadrant, which communicates that, when the trip count is high, so, too, is the length of those trips. The bulk of the first quadrant mass implies that a large number of trips span several kilometers, implying that these are likely not intra-community trips but rather trips across villages or even towns. In other words, highly mobile places are characterized not just by the sheer number of trips but also by the relatively long distances those trips span.

1.1.1 Measures of Mobility

1. **Total Mobility Index:** calculated as the origin-destination population-weighted number of trips within and outside a geohash; the probability of a geohash only containing trips within itself; the distribution-ranked, population-weighted trips into a geohash (Inbound Popularity Rank) and out of a geohash (Outbound Popularity Rank); and an indicator for whether individuals in a geohash only move within their own geohash.

2. **Mobility Transition Matrix:** A row-stochastic transition matrix that normalizes trips by the row-sum of total outbound trips, to determine the probability that in the observation window a trip from unit i will end in unit j.

3. **Isolated Indicator:** Value equal to one if the geographic unit only has trips to itself during the entire observation period.

4. **Social Connectedness Mobility Index**: Based on Bailey et al. (2018), total number of trips between two locations i and j, divided by the product of their total trips.

5. **Within-farm trips:** We assume a log-normal distribution for trip length and gamma distribution for trip duration, in order to fully characterize the distribution given the mean and variance for each geographic unit. Errors are estimated based on implied parametric median and reported median. We assume a "within-farm" trip is of length and duration less than or equal to the 75th percentile of the distribution for fully agricultural geographic units, for that time period in the year.

1.2 Correlates of Mobility

One aspect of mobility that is of particular interest is its role in information diffusion and access to resources. We hypothesize that off-farm travel will naturally expose a farmer to different sources of information, whether they are directly seeking information or not. A natural example is a farmer visiting a local market as they source inputs for the upcoming season, a government office in order to apply to a subsidy or receive any form of aid, or simply visiting friends, who given well-documented social homophily in India, exposes them to varied and sometimes novel pieces of information. In other words, we cannot determine the purpose of any given trip, but we argue that their trips will inevitably result in information diffusion which can facilitate resource gathering.

We formally test for what aspects of infrastructure are most highly correlated with mobility in Table 2. Using data on village facilities from Mission Antyodaya, as accessed through the SHRUG, run regressions of mobility on facilities, giving us correlational estimates. The results confirm that access to roads and public transport indeed corresponds with people moving more on a daily basis. In the columns (2) and (3), we explore how infrastructure correlates with other descriptors of mobility, such as our Total Mobility Index, calculated as the origin and destination normalized number of trips take to, from, and within a geohash, and the probability of self-transition, which expresses the likelihood that a given trip in a given geohash will end in the same geohash. We use the probability of self transition as a proxy for insularity. Between the two, our aim is to explore whether these aspects of infrastructure correlate with outside or insular movement. While many of the estimates are statistically indistinguishable from zero due to large standard errors, we observe that public transport and all weather roads are correlated with a lower probability of self transition. In other words, it appears people with access to these facilities are more likely to travel significant distances from their own communities. Furthermore, geohashes with weekly haats (bazaars) have higher TMI, implying more overall travel to, within, and from those places, as intuition would predict given its central role in the sale and purchase of agricultural products.

In Table 3, we allow for these facilities to be regressed in their own separate regressions, adding in district fixed effects to account for and absorb differences that are simply due to subdistricts being in different districts. Our outcome is therefore simplified to the log of total trips. We find strong positive coefficients on nearly the full swath of regressors: public transport, existence of all weather roads, existence of internal pucca roads, railway stations, and the existence of regular markets.

2 Farmer Helpline: Kisan Call Center (KCC)

To complement our agricultural mobility estimates with agricultural demand for information, we merge call logs of a nationwide, all-purpose farmer helpline. These Kisan Call Centers (KCC, literally farmer call center) aim to provide a centralized, unique phone number that can answer farmer queries ranging from weather forecasts and access to government schemes, to crop and pest management. Each call is geo-located at the sub-district level, which we use as a key to merge onto the mobility data. For the relevant time period (2019-2020) this results in over 1.5 million individual calls, while the complete dataset spans from 2006-2024 and includes over 40 million calls.

Each call log provides rich details, including a rough transcript of the question raised by the farmer, the answer provided by the operator, as well as broad topic classification including the crop the farmer was inquiring about. What is particular about this government service is that it is an exclusively "information seeking" mechanism. In other words, the data explicitly show the agricultural population's demand for information.

Our first observation is that the demand for information about crop management is strikingly seasonal and aligns exactly with the times of planting and harvest of each crop (see Figure 4). The result is non-obvious since one could expect that a farmer concerned about the upcoming season would be inquiring about input sourcing, expected issues, soil management, pest threats, etc. However, it appears that this is not the case and the demand for KCC crop management information is highest during the growing season of each particular crop.

This is non-obvious given that most farmers focus on a single crop and demand for information could be reasonably homogeneous throughout the year, as farmers time the beginning of monsoon, prepare their soil, anticipate possible pests etc. which will likely affect them in the upcoming season. Nonetheless, this gives us a meaningful high frequency benchmark for the relative crop-specific level of concern at the sub-district level.

3 Climate Hazards, Movement, and Demand for Information

In this section we document how mobility and calls to KCC respond to climate shocks, and how those responses move in tandem. Recent work has explored how mobility can be a climate-adaptive action, as people can migrate to less shock-exposed areas (Lee et al., 2022). However, we have documented in previous sections that mobility is quite low among India's agricultural communities. In this case, relatively immobile rural households may respond to climate hazards not through movement but through information provision, calling KCC to understand what they can do to recover.

3.1 Response of Movements and Calls to Climate Hazards

First, we explore how mobility and demand for information (calls) respond to climate shocks independently through OLS regressions of total trips and total calls on rain and temperature shocks. We test responses to multiple definitions of these shocks, though we are consistent in how we define them temporally: heatwaves are always defined as three or more days for which the maximium daily temperature is above a certain threshold, and droughts are always defined as 15 or more days with fewer than 2mm of precipitation, taken as the average of the CHIRPS pixel values of daily precipitation across an administrative unit. We test different values of the temperature threshold for heatwaves – 30C, 35C, and 40C – as high temperatures may be harmful for different reasons. For example, 30C may be harmful for crops (Hogan and Schlenker, 2024) but not as much for people laboring outside. At 35C, the damage may scale up for crops and also for human health, and even further at 40C, where the ambient temperatures may be so extreme that even mild exposure could be dangerous for human health. We additionally test coefficients on consecutive days above (below) heat (rain) thresholds, as longer exposure may be more harmful and beget stronger adaptive actions.

In Table 5, we report our results on this exercise. The mobility response to heat shocks is always positive. While, at a geohash-5 level, we must remain agnostic as to what these movements mean, it is clear that trips increase by 21-23% in response to heatwaves, with the marginal additional day above a temperature threshold inducing additional trips at a rate of 0.2-1.3%, depending on the threshold. The mobility coefficients on droughts and consecutive dry days are negative, implying fewer trips in response to droughts. While we cannot disaggregate what specific actions are reflected in these fewer trips, it is possible that the adaptive actions that farmers take in response to droughts are different than those taken in response to heatwaves.

In columns (2) through (5), we examine how demand for information from KCC responds to these same climate shocks. Across the board, all significant coefficients are negative, particularly in response to shocks where the mobility response is quite high. This is suggestive that farmers that are more mobile are less likely to demand information over the course of a day. While this is suggestive that the two may be substitutes, we formally test for this in the following section.

3.2 Interaction of Information Provision and Mobility

Next, we explore whether information provision is a substitute or a complement to mobility. Preliminary regression results on the relationship between mobility and information provision are presented in Table 4. Every coefficient is negative, suggesting that calls increase when mobility is low. This pattern is evident as well in daily trip counts, as shown in Figure 6: individuals in places that have called to KCC are much less mobile than those in places that do not, suggesting that those who utilize KCC may not otherwise have the capacity to access other support networks.

Furthermore, mobility may be an important means of adapting to climate shocks. Individuals in places with high mobility maybe have better access to external support networks or may benefit from more intra-community social cohesion. In this case, KCC may prove critical for those unable to access network resources. In Table 5, we document that total trips unambiguously increase in response to high temperatures and heatwaves, though they decrease in response to droughts. The coefficients on calls to KCC are negative when statistically significant, thus calls drop when movement increases, and vice versa.

We explore this relationship more formally in Table 6, where we examine how our Total Mobility Index (TMI), which captures the population-weighted sum of total trips into and out of a place, interacts with the call response to climate shocks. Again, where statistically significant, the interaction coefficients are negative, suggesting KCC may provide a substitute for mobility as a response to climate shocks when mobility is low. These results are supported by results in Table 7, where we interact instead with the proportion of geohashes that only contain trips within itself – a measure of insularity. Additional results interacting with the probability of only taking trips within one's own geohash (Table 8) and the distribution-ranked, population-weighted measures of inbound and outbound trips, bolster the narrative suggested in our aforementioned results.

Finally, we explore whether mobility mediates information diffusion. Information gained through KCC may spread more quickly in places that have high mobility, as people interact more and have more opportunities to share information. If this is the case, the rate of calling in response to climate shocks should revert to their normal levels more slowly in low mobility places as more individuals need to call in order for information to saturate. We therefore plot event studies of the call response to climate shocks in Figures 10 and 11, and we plot the event studies of the mobility-shock interactions in Figures 12, 13, 14, and 15. A consistent patttern does not emerge, suggesting potential non-linearities in how mobility mediates the demand for information.

4 Discussion and Future Work

4.1 Conclusion

Together, results may indicate that publicly provided information can substitute for social cohesion, interaction, or network access, particularly at times when India's agricultural poor are most at risk. Thus, from a policy perspective, the value of remote extension services such as KCC is particularly high for socially insular communities, which can be detected using novel mobility data. This is important in context: several historical and cultural factors contribute to social frictions among India's agricultural poor, which may hinder information diffusion, productivity growth, and resilience in the face of worsening climate risk.

4.2 Future Work

We are excited to continue working the current data and we hope to utilize the other datasets – including the 3-hourly data and the H3 resolution 7 OD data – as we expand this work. With additional data, we believe we could explore two main important extensions of our current work:

1. With more spatially granular OD and PD data, we may be able to understand whether movements are agricultural or not. This may be important in the big picture of climate adaptation, as one main adaptation may be to move away from farming and towards work that is less affected by climate risk. We could do this by first characterizing what agricultural movements look like, noting that the majority of India's farms are smallholder farms under 2 hectares, and then examining deviations from them across the agricultural cycle, across the year, and in response to shocks. The accuracy of farm specification could be greatly improved by combining these with novel machine learning techniques for remote sensed outlines of individual farms. On a larger time scale, if we examine population and trip outflow from rural areas to less rural areas in response to shocks, this could be evidence of such occupational switching, which may open the door towards structural development.

2. With further years of OD and PD data, we can examine whether the patterns we examine above and propose in the preceding point have material consequences for farmers, particularly in terms of agricultural yield and therefore income. In other projects, we have already gathered the MODIS EVI/NDVI data, which we can use to proxy for agricultural growth. This would add a level of richness as we would be able to explore not only how farmers adapt to climate risks but also how much those adaptations materially matter.

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Tables

Table 1: Mission Antyodaya Summary Statistics Comparison

	Full Sample (5480 subdistricts)		KCC Sample (3895 subdistricts)	
Variable	Mean	SD	Mean	SD
Has Public Transport	0.853	0.154	0.820	0.165
Connected to All-weather Road	0.850	0.140	0.810	0.147
Has Internal Pucca Road	0.527	0.237	0.515	0.219
Has Railway Station	0.068	0.091	0.052	0.075
Has Mandi	0.042	0.087	0.039	0.082
Has Regular Market	0.157	0.202	0.139	0.179
Has Weekly Haat	0.194	0.191	0.207	0.189
Total Population	296357.452	271548.473	258028.291	211690.667
Total Households	60635.351	46410.117	51929.920	36780.057
Has Bank	0.377	0.239	0.297	0.188
Has Broadband	0.579	0.264	0.490	0.253
Log(1 + Trips)	3.611	1.118	0.871	1.901
Log(1 + Trip Length)	8.397	1.352	1.914	3.759
Log(1 + Trip Duration)	4.887	0.930	1.140	2.315
Trip Speed	55.323	123.869	12.169	60.570

Table 2: Regressions: Mission Antyodaya Facilities, Total Trips, TMI, Prob. Self-Transition, and Total Calls

	(1) Log(1+Total Trips)	(2) Total Mobility Index	(3) Prob. Self-Transition	(4) Log(1+Total Calls)
Log(1+Total Pop.)	0.715*** (0.165)	-0.02136*** (0.00431)	-0.00847*** (0.00190)	0.213*** (0.0507)
Log(1+Total Farmers)	-0.564*** (0.116)	0.01126*** (0.00253)	0.00791*** (0.00144)	0.0694. (0.0346)
Public Transport	0.403 (0.310)	-0.02226 (0.01519)	-0.00581** (0.00191)	-0.166 (0.151)
All Weather Road	0.597** (0.215)	-0.02799. (0.01432)	-0.00947* (0.00389)	0.0775 (0.0940)
Internal Pucca Road	-0.148 (0.122)	-0.00340 (0.00641)	0.00237 (0.00204)	-0.127** (0.0449)
Railway Station	0.484 (0.344)	-0.07350*** (0.01147)	-0.00828 (0.00494)	-0.0969 (0.0947)
Mandi	0.995 (0.532)	0.00902 (0.03065)	-0.00444 (0.00974)	0.00934 (0.131)
Regular Market	0.361 (0.374)	0.01589 (0.01467)	-0.00632. (0.00334)	-0.0263 (0.0530)
Weekly Haat	-0.302 (0.210)	0.03296** (0.01107)	0.00332 (0.00284)	-0.0674 (0.0736)
Log(1 + No. of Self Help Groups)	-0.077 (0.075)	0.00536* (0.00220)	0.00095 (0.00077)	0.00306 (0.0212)
Observations	516,567	1,431,612	1,431,612	230,299
R^2	0.391	0.279	0.032	0.511
Within R^2	0.078	0.031	0.015	0.026

Table 3: Regressions: Mission Antyodaya Facilities and Total Trips

Dep. Var.: Log(1+Total Trips)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Log(1 + Total Pop.)	0.5683***								
	(0.0829)								
Log(1 + Total Farmers)		0.1837*							
		(0.0777)							
Public Transport			0.7756**						
			(0.2645)						
All Weather Road				0.8145***					
				(0.2227)					
Internal Pucca Road					0.0703				
					(0.1824)				
Railway Station						1.912***			
						(0.3924)			
Mandi							0.4980		
							(0.4258)		
Regular Market								0.8656**	
								(0.3186)	
Weekly Haat									-0.5037.
									(0.2642)
Fixed-Effects:									
District FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	790,011	790,011	790,011	790,011	790,011	790,011	790,011	790,011	790,011
R^2	0.29588	0.28112	0.28037	0.28137	0.27849	0.28521	0.27883	0.28162	0.27984
Within R^2	0.02417	0.00371	0.00267	0.00405	0.000059	0.00938	0.00054	0.00440	0.00193

Table 4: Regression: Correlations Between Mobility and Calls to KCC

	Regression Models			
Dep. Variable: Total Calls				
	(1)	**(2)**	**(3)**	**(4)**
Log(1 + Total Trips)	-0.2552***			
	(0.0332)			
Log(1 + Total Length)		-0.1211***		
		(0.0090)		
Log(1 + Total Duration)			-0.2030***	
			(0.0175)	
Log(1 + Speed)				-0.2417***
				(0.0162)
Fixed-Effects:				
Subdistrict FE	Yes	Yes	Yes	Yes
Observations	807,677	807,677	807,677	807,677
R^2	0.54261	0.54278	0.54274	0.54275
Within R^2	0.00063	0.00101	0.00092	0.00094

Table 5: Climatic Events, Trips, and Calls

	(1) Total Trips	(2) Total Calls	(3) Weather Calls	(4) Crop Mgmt. Calls	(5) Finance Calls
Any Shock	0.0592** (0.0174)	-0.0623 (0.0620)	-0.1232* (0.0496)	0.0337 (0.0894)	-0.0104 (0.0269)
Heatwave (30C)	0.2329*** (0.0161)	-0.0200 (0.0467)	-0.0211 (0.0243)	0.0177 (0.0769)	-0.0129 (0.0215)
Heatwave (35C)	0.2326*** (0.0121)	-0.1618*** (0.0438)	-0.1041* (0.0422)	-0.1384* (0.0604)	-0.0607* (0.0281)
Heatwave (40C)	0.2130*** (0.0121)	-0.2517*** (0.0474)	-0.2509*** (0.0462)	-0.1653* (0.0660)	-0.0566. (0.0297)
Consecutive Days Above 30C	0.0028*** (0.0002)	-0.0001 (0.0006)	0.0011* (0.0004)	-0.0008 (0.0009)	-0.0005. (0.0003)
Consecutive Days Above 35C	0.0046*** (0.0005)	-0.0041*** (0.0007)	-0.0019* (0.0007)	-0.0046*** (0.0011)	-0.0013. (0.0007)
Consecutive Days Above 40C	0.0132*** (0.0023)	-0.0146*** (0.0028)	-0.0110** (0.0032)	-0.0141*** (0.0019)	-0.0026 (0.0021)
Drought	-0.1054*** (0.0175)	-0.2182*** (0.0458)	-0.2213 (0.0681)	-0.1072** (0.0350)	0.0082 (0.0182)
Consecutive Days Precip. < 2mm	0.0003 (0.0005)	-0.0047*** (0.0007)	-0.0060*** (0.0011)	-0.0033*** (0.0005)	0.0005 (0.0004)

Note: All regressions include subdistrict fixed effects, and standard errors are clustered at the subdistrict level. All dependent variables are expressed as their $\log(1 + x)$ transformation. Heatwaves are defined as 3 or more consecutive days with a maximum daily air temperature above a certain threshold, which test at different levels (30C, 35C, 40C). Droughts are defined as 15 or more consecutive days with less than 2mm of precipitation.

Table 6: Call Response to Climate Events Interacted with Total Mobility Index (TMI)

	(1) Total Calls	(2) Weather Calls	(3) Crop Mgmt. Calls	(4) Finance Calls
Any Shock	-0.0462 (0.0609)	-0.1136* (0.0540)	0.0500 (0.0863)	-0.0191 (0.0257)
Any Shock*TMI	-0.2489 (0.3213)	-0.1480 (0.2769)	-0.2518 (0.3596)	0.1338 (0.1541)
Heatwave (30C)	-0.0320 (0.0420)	-0.0362 (0.0217)	0.0139 (0.0725)	-0.0248 (0.0195)
Heatwave (30C)*TMI	0.1807 (0.2325)	0.2279 (0.2059)	0.0563 (0.2923)	0.1789 (0.1127)
Heatwave (35C)	-0.1509** (0.0422)	-0.0873. (0.0451)	-0.1237* (0.0561)	-0.0584. (0.0314)
Heatwave (35C)*TMI	-0.1549 (0.2477)	-0.2404 (0.2813)	-0.2096 (0.2426)	-0.0325 (0.1369)
Heatwave (40C)	-0.2442*** (0.0556)	-0.2525*** (0.0601)	-0.1321. (0.0712)	-0.0614 (0.0365)
Heatwave (40C)*TMI	-0.1003 (0.2238)	0.0218 (0.2626)	-0.4474 (0.3310)	0.0650 (0.1504)
Consec. Days > 30C	-0.0005 (0.0005)	0.0006 (0.0004)	-0.0008 (0.0008)	-0.0004* (0.0002)
Consec Days > 30C * TMI	0.0052 (0.0043)	0.0075. (0.0044)	0.0005 (0.0030)	-0.0003 (0.0013)
Consec. Days > 35C	-0.0038*** (0.0010)	-0.0018. (0.0010)	-0.0040** (0.0013)	-0.0009 (0.0006)
Consec. Days > 35C * TMI	-0.0036 (0.0068)	-0.0007 (0.0066)	-0.0073 (0.0053)	-0.0049 (0.0032)
Consec. Days > 40C	-0.0157*** (0.0028)	-0.0125** (0.0035)	-0.0133*** (0.0017)	-0.0029 (0.0024)
Consec. Days > 40C * TMI	0.0140 (0.0115)	0.0197 (0.0124)	-0.0105 (0.0187)	0.0036 (0.0060)
Drought	-0.1480** (0.0498)	-0.2356** (0.0740)	-0.0685. (0.0387)	0.0080 (0.0202)
Drought*TMI	-1.0425*** (0.1693)	-1.2284*** (0.2271)	-0.5736*** (0.1347)	0.0025 (0.0607)
Consec. Days Precip. < 2mm	-0.0039*** (0.0007)	-0.0051*** (0.0012)	-0.0030*** (0.0006)	0.0007 (0.0004)
Consec. Days Precip. < 2mm*TMI	-0.0112*** (0.0027)	-0.0133*** (0.0035)	-0.0041. (0.0022)	-0.0017. (0.0010)

Note: All regressions include subdistrict fixed effects, and standard errors are clustered at the subdistrict level. All dependent variables are expressed as their $\log(1 + x)$ transformation. Heatwaves are defined as 3 or more consecutive days with a maximum daily air temperature above a certain threshold, which test at different levels (30C, 35C, 40C). Droughts are defined as 15 or more consecutive days with less than 2mm of precipitation.

Table 7: Call Response to Climate Events Interacted with Proportion of Geohashes in Subdistrict Traveling Only Within Own Geohash

	(1) Total Calls	(2) Weather Calls	(3) Crop Mgmt. Calls	(4) Finance Calls
Any Shock	-0.0999	-0.1412.	-0.0245	-0.0203
	(0.0624)	(0.0697)	(0.0867)	(0.0377)
Any Shock*Prop. Within	0.0447	0.0214	0.0690	0.0117
	(0.0424)	(0.0496)	(0.0523)	(0.0254)
Heatwave (30C)	-0.0531	-0.0175	-0.0459	-0.0218
	(0.0412)	(0.0290)	(0.0704)	(0.0303)
Heatwave (30C)*Prop. Within	0.0396	-0.0044	0.0761.	0.0106
	(0.0293)	(0.0292)	(0.0374)	(0.0241)
Heatwave (35C)	-0.1839***	-0.0754.	-0.1901*	-0.0689.
	(0.0436)	(0.0409)	(0.0705)	(0.0378)
Heatwave (35C)*Prop. Within	0.0263	-0.0340	0.0613.	0.0098
	(0.0240)	(0.0288)	(0.0355)	(0.0185)
Heatwave (40C)	-0.2137***	-0.1603**	-0.1757.	-0.0714.
	(0.0523)	(0.0525)	(0.1023)	(0.0414)
Heatwave (40C)*Prop. Within	-0.0447	-0.1065**	0.0123	0.0174
	(0.0334)	(0.0360)	(0.0684)	(0.0239)
Consec. Days > 30C	-0.0007	0.0006.	-0.0017*	-0.0001
	(0.0004)	(0.0003)	(0.0007)	(0.0002)
Consec Days > 30C * Prop. Within	0.0006	0.0006	0.0010*	-0.0004
	(0.0005)	(0.0006)	(0.0005)	(0.0003)
Consec. Days > 35C	-0.0039***	-0.0008	-0.0053***	-0.0011
	(0.0010)	(0.0008)	(0.0013)	(0.0007)
Consec. Days > 35C * Prop. Within	-0.0002	-0.0012.	0.0009	-0.0002
	(0.0007)	(0.0007)	(0.0009)	(0.0005)
Consec. Days > 40C	-0.0120***	-0.0060*	-0.0155***	-0.0017
	(0.0031)	(0.0028)	(0.0036)	(0.0033)
Consec. Days > 40C * Prop. Within	-0.0031	-0.0059*	0.0016	-0.0011
	(0.0024)	(0.0028)	(0.0042)	(0.0017)
Drought	-0.1445*	-0.2428**	-0.0641	0.0104
	(0.0601)	(0.0843)	(0.0514)	(0.0261)
Drought*Prop. Within	-0.0882.	-0.0903	-0.0515	-0.0026
	(0.0482)	(0.0552)	(0.0401)	(0.0137)
Consec. Days Precip. < 2mm	-0.0040***	-0.0055***	-0.0035**	0.0010*
	(0.0008)	(0.0011)	(0.0011)	(0.0004)
Consec. Days Precip. < 2mm*Prop. Within	-0.0008	-0.0006	0.0002	-0.0005*
	(0.0010)	(0.0008)	(0.0009)	(0.0002)

Note: All regressions include subdistrict fixed effects, and standard errors are clustered at the subdistrict level. All dependent variables are expressed as their $\log(1 + x)$ transformation. Heatwaves are defined as 3 or more consecutive days with a maximum daily air temperature above a certain threshold, which test at different levels (30C, 35C, 40C). Droughts are defined as 15 or more consecutive days with less than 2mm of precipitation.

Table 8: Call Response to Climate Events Interacted with Probability of Self Transition

	(1) Total Calls	(2) Weather Calls	(3) Crop Mgmt. Calls	(4) Finance Calls
Any Shock	-0.0582	-0.1191*	0.0409	-0.0103
	(0.0652)	(0.0510)	(0.0925)	(0.0261)
Any Shock*Pr(Self Transition)	0.3605	0.3544	0.6271	0.0088
	(0.4307)	(0.4792)	(0.4133)	(0.2307)
Heatwave (30C)	-0.0153	-0.0186	0.0261	-0.0130
	(0.0497)	(0.0265)	(0.0800)	(0.0207)
Heatwave (30C)*Pr(Self Transition)	0.4122	0.2248	0.7359.	-0.0064
	(0.3225)	(0.2979)	(0.4097)	(0.1767)
Heatwave (35C)	-0.1617**	-0.1053*	-0.1323*	-0.0662*
	(0.0459)	(0.0439)	(0.0625)	(0.0273)
Heatwave (35C)*Pr(Self Transition)	0.0071	-0.1152	0.5771	-0.5215.
	(0.3502)	(0.3009)	(0.3932)	(0.2556)
Heatwave (40C)	-0.2582***	-0.2587***	-0.1627*	-0.0634*
	(0.0488)	(0.0457)	(0.0663)	(0.0274)
Heatwave (40C)*Pr(Self Transition)	-0.6912.	-0.8259	0.2662	-0.7199.
	(0.3842)	(0.5775)	(0.5179)	(0.4139)
Consec. Days > 30C	-0.0001	0.0012*	-0.0007	-0.0005.
	(0.0007)	(0.0005)	(0.0009)	(0.0003)
Consec Days > 30C * Pr(Self Transition)	0.0065	0.0087.	0.0078	-0.0047.
	(0.0048)	(0.0051)	(0.0050)	(0.0026)
Consec. Days > 35C	-0.0041***	-0.0020*	-0.0045***	-0.0014*
	(0.0007)	(0.0008)	(0.0012)	(0.0006)
Consec. Days > 35C * Pr(Self Transition)	-0.0072	-0.0072	0.0042	-0.0154*
	(0.0062)	(0.0053)	(0.0097)	(0.0056)
Consec. Days > 40C	-0.0155***	-0.0119**	-0.0143***	-0.0033
	(0.0029)	(0.0035)	(0.0021)	(0.0020)
Consec. Days > 40C * Pr(Self Transition)	-0.0806**	-0.0726	-0.0120	-0.0628***
	(0.0281)	(0.0497)	(0.0267)	(0.0138)
Drought	-0.2302***	-0.3310***	-0.1146**	0.0077
	(0.0481)	(0.0668)	(0.0361)	(0.0180)
Drought*Pr(Self Transition)	-1.0402*	-1.0954*	-0.6470*	-0.0395
	(0.4071)	(0.4172)	(0.2947)	(0.1337)
Consec. Days Precip. < 2mm	-0.0049***	-0.0062***	-0.0034***	0.0005
	(0.0007)	(0.0012)	(0.0005)	(0.0004)
Consec. Days Precip. < 2mm*Pr(Self Transition)	-0.0202*	-0.0195**	-0.0070	-0.0064*
	(0.0091)	(0.0067)	(0.0049)	(0.0031)

Note: All regressions include subdistrict fixed effects, and standard errors are clustered at the subdistrict level. All dependent variables are expressed as their $\log(1 + x)$ transformation. Heatwaves are defined as 3 or more consecutive days with a maximum daily air temperature above a certain threshold, which is tested at different levels (30C, 35C, 40C). Droughts are defined as 15 or more consecutive days with less than 2mm of precipitation.

Table 9: Call Response to Climate Events Interacted with Inbound Popularity Rank

	(1) Total Calls	(2) Weather Calls	(3) Crop Mgmt. Calls	(4) Finance Calls
Any Shock	-0.211***	-0.186*	-0.233*	-0.006
	(0.071)	(0.074)	(0.106)	(0.047)
Any Shock*PopRankIn	0.000025*	0.000011	0.000045*	-0.000001
	(0.000012)	(0.000007)	(0.000018)	(0.000005)
Heatwave (30C)	-0.101*	-0.025	-0.181*	-0.009
	(0.051)	(0.036)	(0.088)	(0.029)
Heatwave (30C)*PopRankIn	0.000014	0.000001	0.000034*	-0.000001
	(0.000009)	(0.000004)	(0.000015)	(0.000003)
Heatwave (35C)	-0.283***	-0.163	-0.301**	-0.063
	(0.068)	(0.086)	(0.097)	(0.059)
Heatwave (35C)*PopRankIn	0.000021*	0.000010	0.000028*	0.0000005
	(0.000009)	(0.000010)	(0.000012)	(0.000006)
Heatwave (40C)	-0.422***	-0.370***	-0.381***	-0.048
	(0.077)	(0.095)	(0.102)	(0.058)
Heatwave (40C)*PopRankIn	0.000030*	0.000021	0.000038**	-0.000001
	(0.000011)	(0.000013)	(0.000012)	(0.000006)
Consec. Days > 30C	-0.001	0.001	-0.003*	-0.001
	(0.0009)	(0.0006)	(0.0014)	(0.0004)
Consec Days > 30C * PopRankIn	0.0000002	0.0000001	0.0000004	0.00000002
	(0.0000002)	(0.0000001)	(0.0000002)	(0.00000004)
Consec. Days > 35C	-0.005***	-0.002**	-0.007***	-0.001
	(0.0008)	(0.0006)	(0.0014)	(0.001)
Consec. Days > 35C * PopRankIn	0.0000002	0.0000001	0.0000005*	-0.00000006
	(0.0000001)	(0.0000001)	(0.0000002)	(0.0000001)
Consec. Days > 40C	-0.015***	-0.011**	-0.019***	-0.001
	(0.004)	(0.003)	(0.002)	(0.003)
Consec. Days > 40C * PopRankIn	0.0000001	-0.0000001	0.000001	-0.0000004
	(0.0000004)	(0.0000005)	(0.0000005)	(0.0000002)
Drought	-0.325**	-0.423**	-0.194*	0.037
	(0.094)	(0.133)	(0.074)	(0.039)
Drought*PopRankIn	0.000018	0.000018	0.000015	-0.000005
	(0.00001)	(0.000013)	(0.000009)	(0.000004)
Consec. Days Precip. < 2mm	-0.006***	-0.007***	-0.004***	0.001*
	(0.001)	(0.001)	(0.001)	(0.0004)
Consec. Days Precip. < 2mm*PopRankIn	0.0000002	0.0000002	0.0000001	-0.00000008
	(0.0000001)	(0.0000001)	(0.0000001)	(0.00000005)

Note: All regressions include subdistrict fixed effects, and standard errors are clustered at the subdistrict level. All dependent variables are expressed as their $\log(1 + x)$ transformation. Heatwaves are defined as 3 or more consecutive days with a maximum daily air temperature above a certain threshold, which is tested at different levels (30C, 35C, 40C). Droughts are defined as 15 or more consecutive days with less than 2mm of precipitation.

Table 10: Call Response to Climate Events Interacted with Outbound Popularity Rank

	(1) Total Calls	(2) Weather Calls	(3) Crop Mgmt. Calls	(4) Finance Calls
Any Shock	-0.210***	-0.185*	-0.231*	-0.007
	(0.070)	(0.073)	(0.104)	(0.046)
Any Shock*PopRankOut	0.000025*	0.000010	0.000044*	-0.000001
	(0.000012)	(0.000007)	(0.000018)	(0.000005)
Heatwave (30C)	-0.100*	-0.025	-0.179	-0.009
	(0.050)	(0.036)	(0.087)	(0.029)
Heatwave (30C)*PopRankOut	0.000014	0.000001	0.000034*	-0.000001
	(0.000009)	(0.000004)	(0.000015)	(0.000003)
Heatwave (35C)	-0.282***	-0.163	-0.301**	-0.063
	(0.068)	(0.086)	(0.096)	(0.059)
Heatwave (35C)*PopRankOut	0.000021*	0.000010	0.000028*	0.000001
	(0.000009)	(0.000010)	(0.000012)	(0.000006)
Heatwave (40C)	-0.422***	-0.370***	-0.381***	-0.049
	(0.077)	(0.095)	(0.101)	(0.058)
Heatwave (40C)*PopRankOut	0.000030*	0.000021	0.000038**	-0.000001
	(0.000011)	(0.000013)	(0.000012)	(0.000006)
Consec. Days > 30C	-0.001	0.001	-0.003*	-0.001
	(0.0009)	(0.001)	(0.001)	(0.0004)
Consec Days > 30C * PopRankOut	0.0000002	0.0000001	0.0000004	0.00000002
	(0.0000002)	(0.0000001)	(0.0000002)	(0.00000004)
Consec. Days > 35C	-0.005***	-0.002***	-0.007***	-0.001
	(0.0008)	(0.001)	(0.001)	(0.001)
Consec. Days > 35C * PopRankOut	0.0000002	0.0000001	0.0000005*	-0.00000006
	(0.0000001)	(0.0000001)	(0.0000002)	(0.0000001)
Consec. Days > 40C	-0.015***	-0.011**	-0.019***	-0.001
	(0.004)	(0.003)	(0.002)	(0.003)
Consec. Days > 40C * PopRankOut	0.0000001	-0.0000001	0.000001	-0.0000004
	(0.0000004)	(0.000001)	(0.000001)	(0.0000002)
Drought	-0.324**	-0.422**	-0.194*	0.036
	(0.093)	(0.132)	(0.073)	(0.038)
Drought*PopRankOut	0.000018	0.000018	0.000015	-0.000005
	(0.00001)	(0.000013)	(0.000008)	(0.000004)
Consec. Days Precip. < 2mm	-0.006***	-0.007***	-0.004***	0.001*
	(0.001)	(0.001)	(0.001)	(0.0004)
Consec. Days Precip. < 2mm*PopRankOut	0.0000002	0.0000002	0.0000001	-0.00000008
	(0.0000001)	(0.0000001)	(0.0000001)	(0.00000005)

Note: All regressions include subdistrict fixed effects, and standard errors are clustered at the subdistrict level. All dependent variables are expressed as their $\log(1 + x)$ transformation. Heatwaves are defined as 3 or more consecutive days with a maximum daily air temperature above a certain threshold, which is tested at different levels (30C, 35C, 40C). Droughts are defined as 15 or more consecutive days with less than 2mm of precipitation.

Figures

Figure 1: Distribution of Outbound Trips

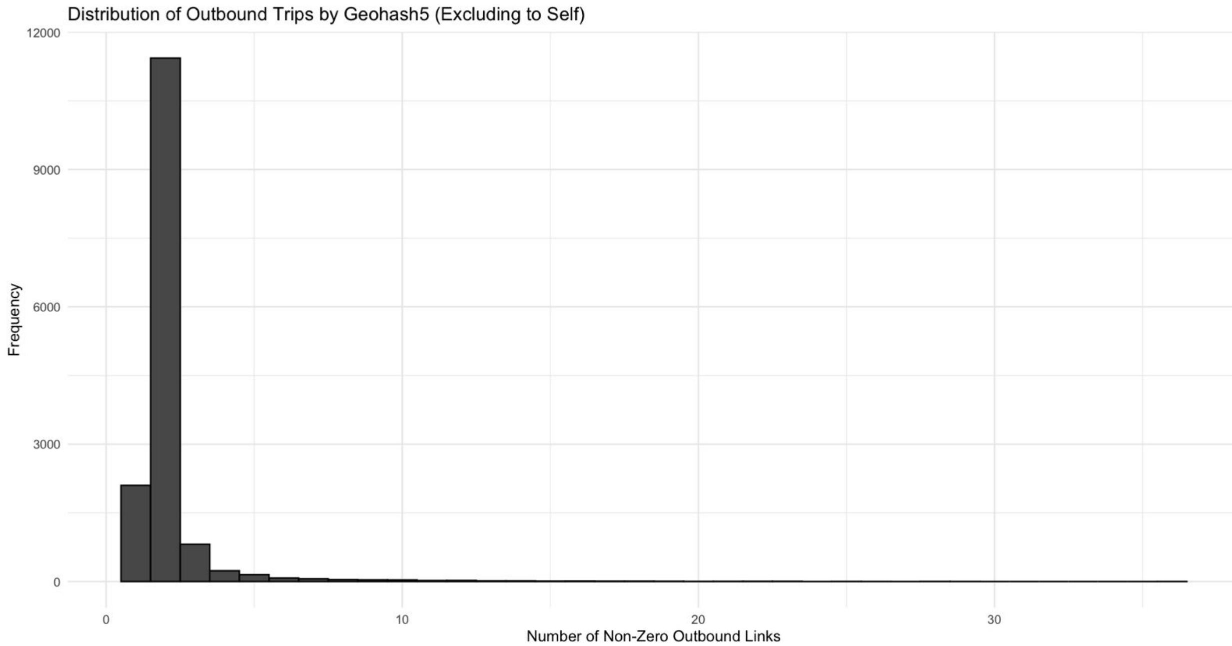


Figure 2: Insularity of Geohash Travel

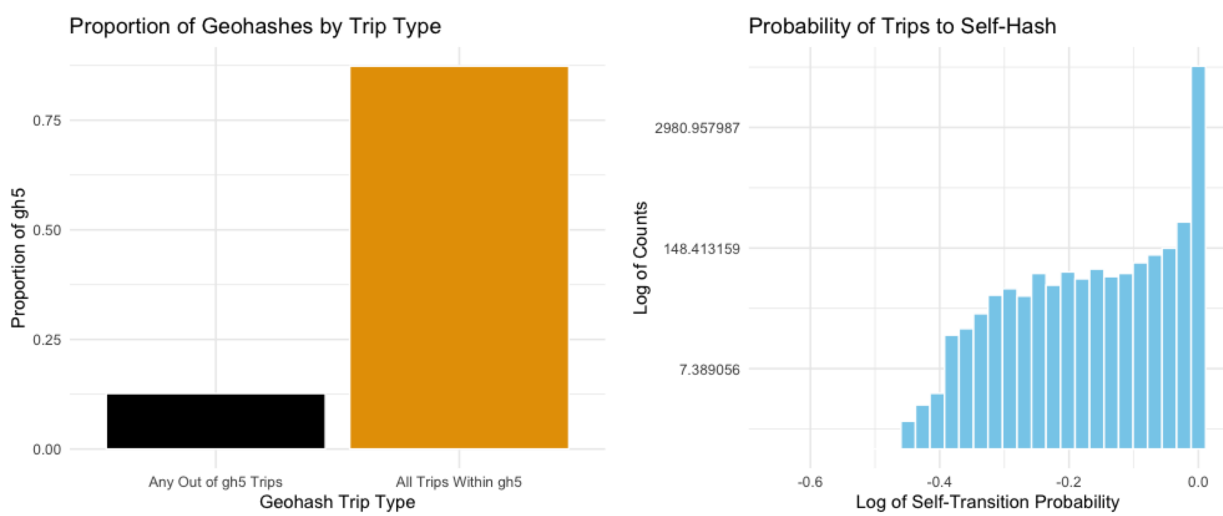


Figure 3: Relationship Between Number of Trips and Mean Trip Distance (m)

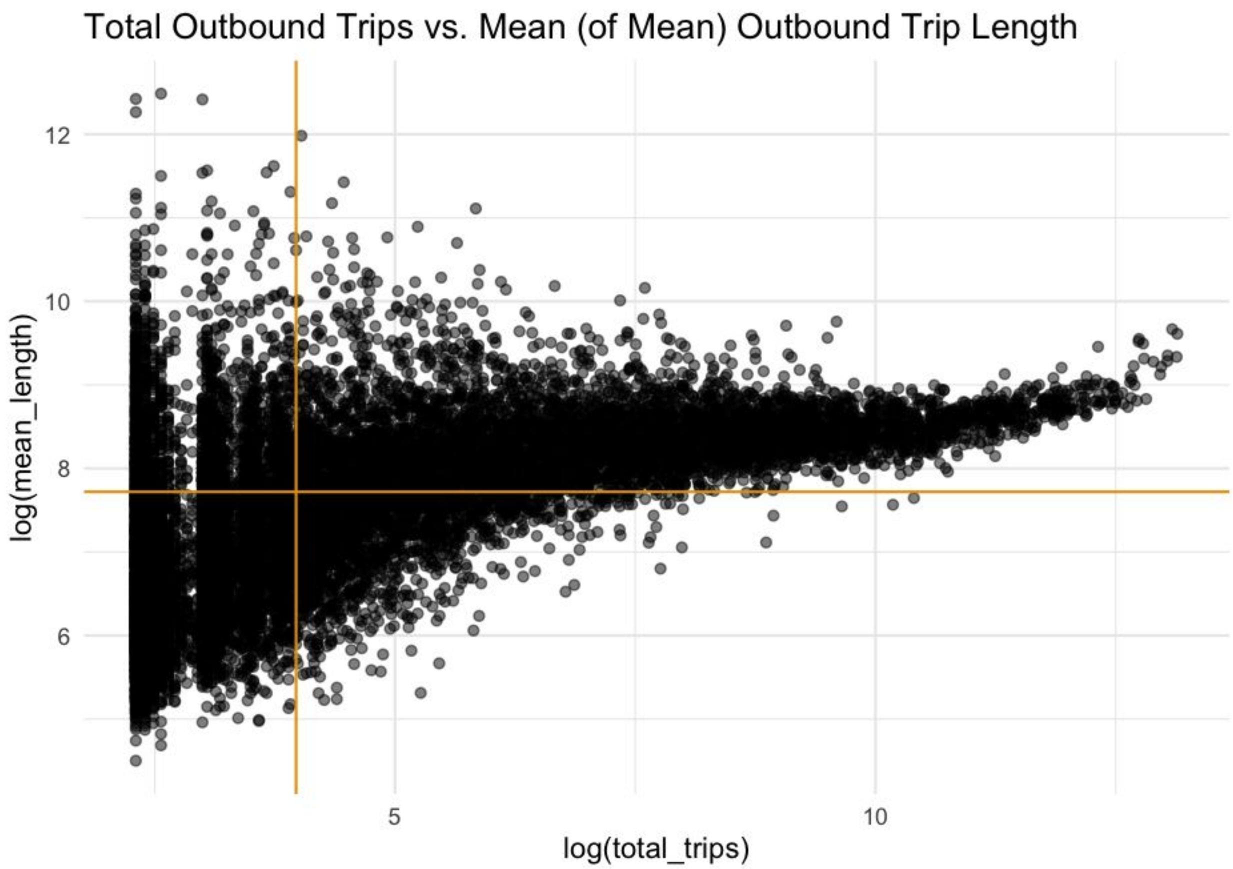


Figure 4: Seasonality of Calls for Top Crops Over Time

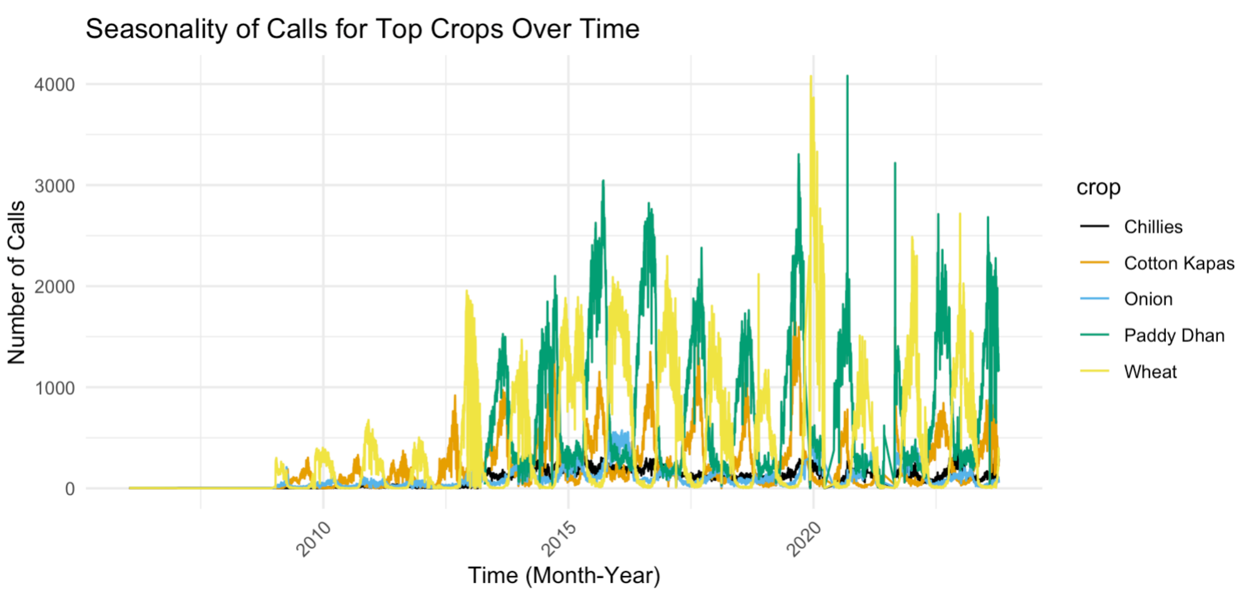


Figure 5: Evolution of Calls and Trips in Basmat in 2019

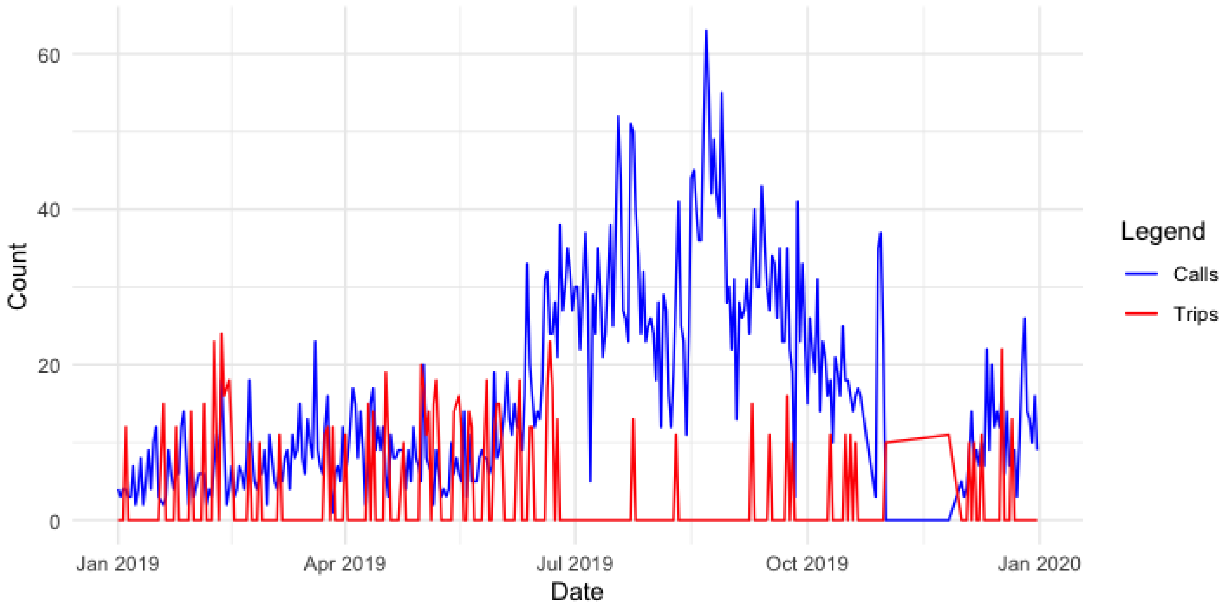
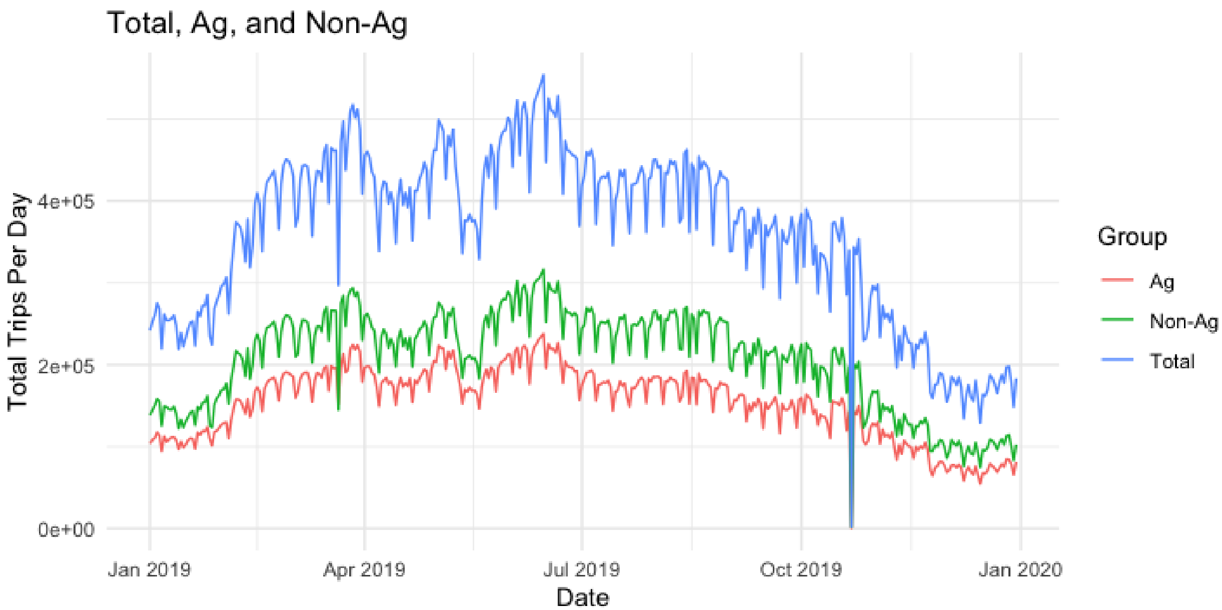


Figure 6: Daily Total Trips by Group



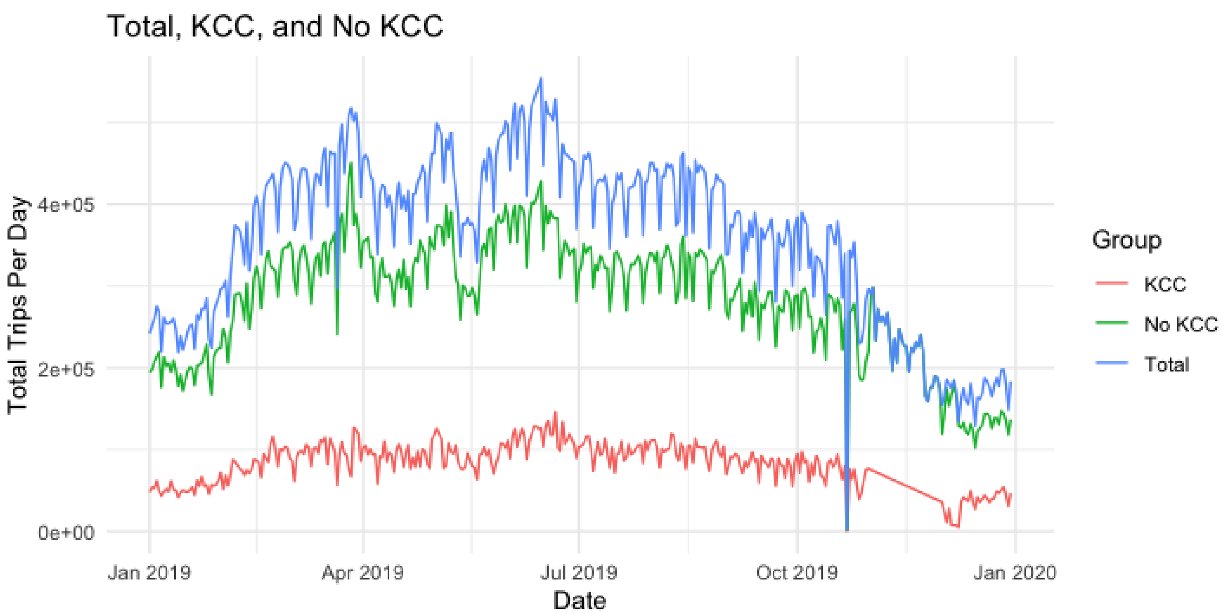


Figure 7: Daily Total Trips by Group in June

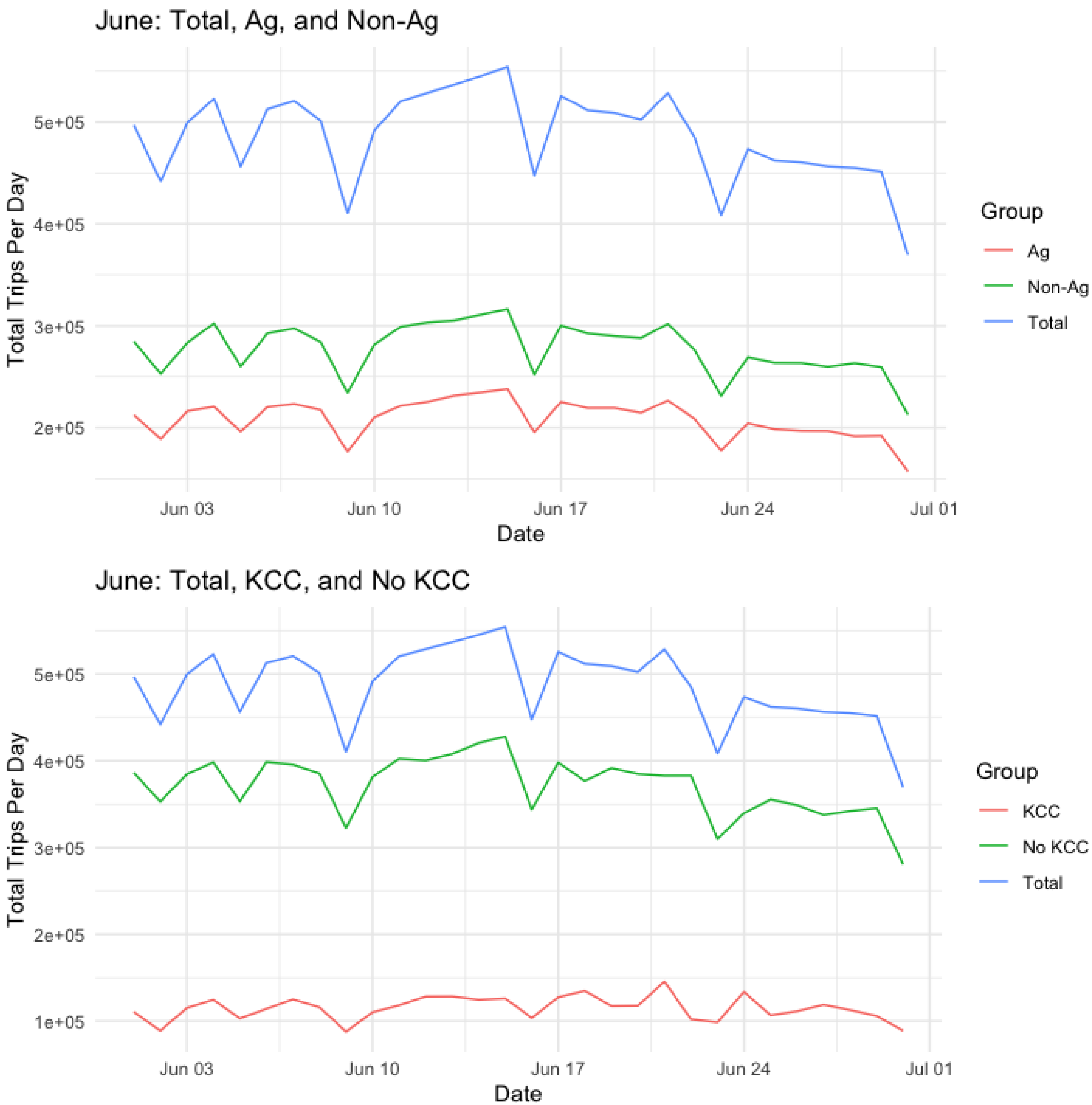


Figure 8: Spatial Distribution of Total Mobility Index and Calls to KCC

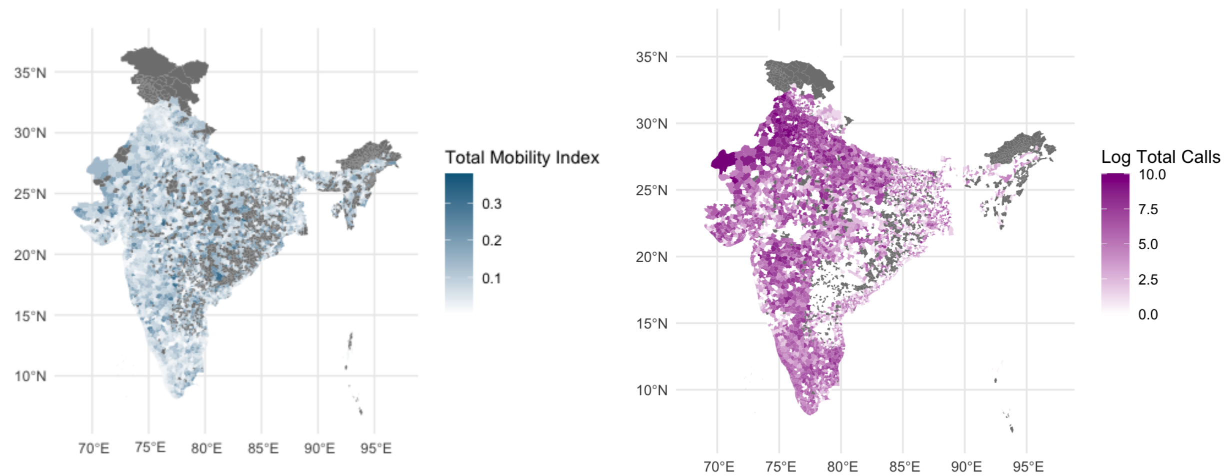


Figure 9: Spatial Distribution of Hot and Dry Days

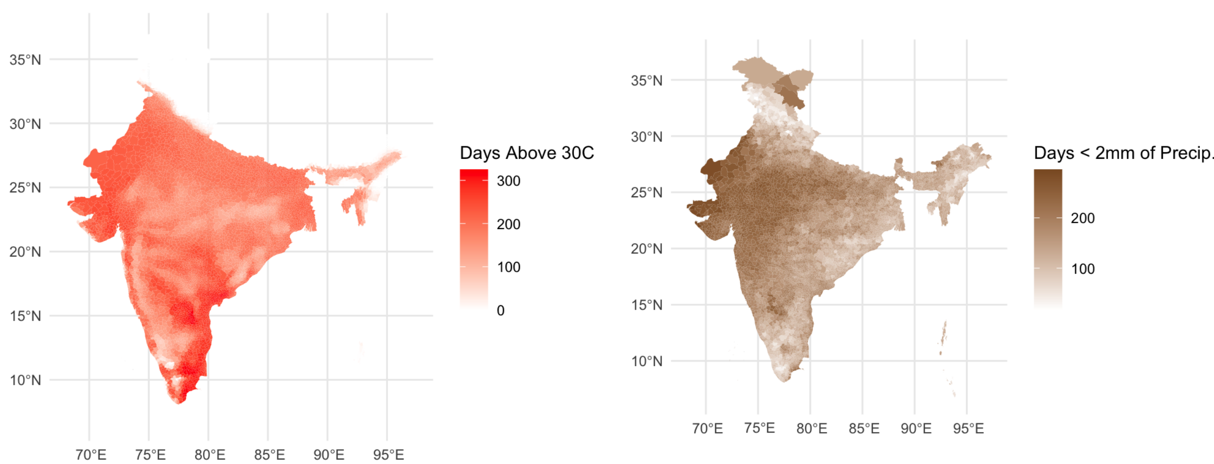


Figure 10: Call Volume Response to Consecutive Hot Days, by Threshold

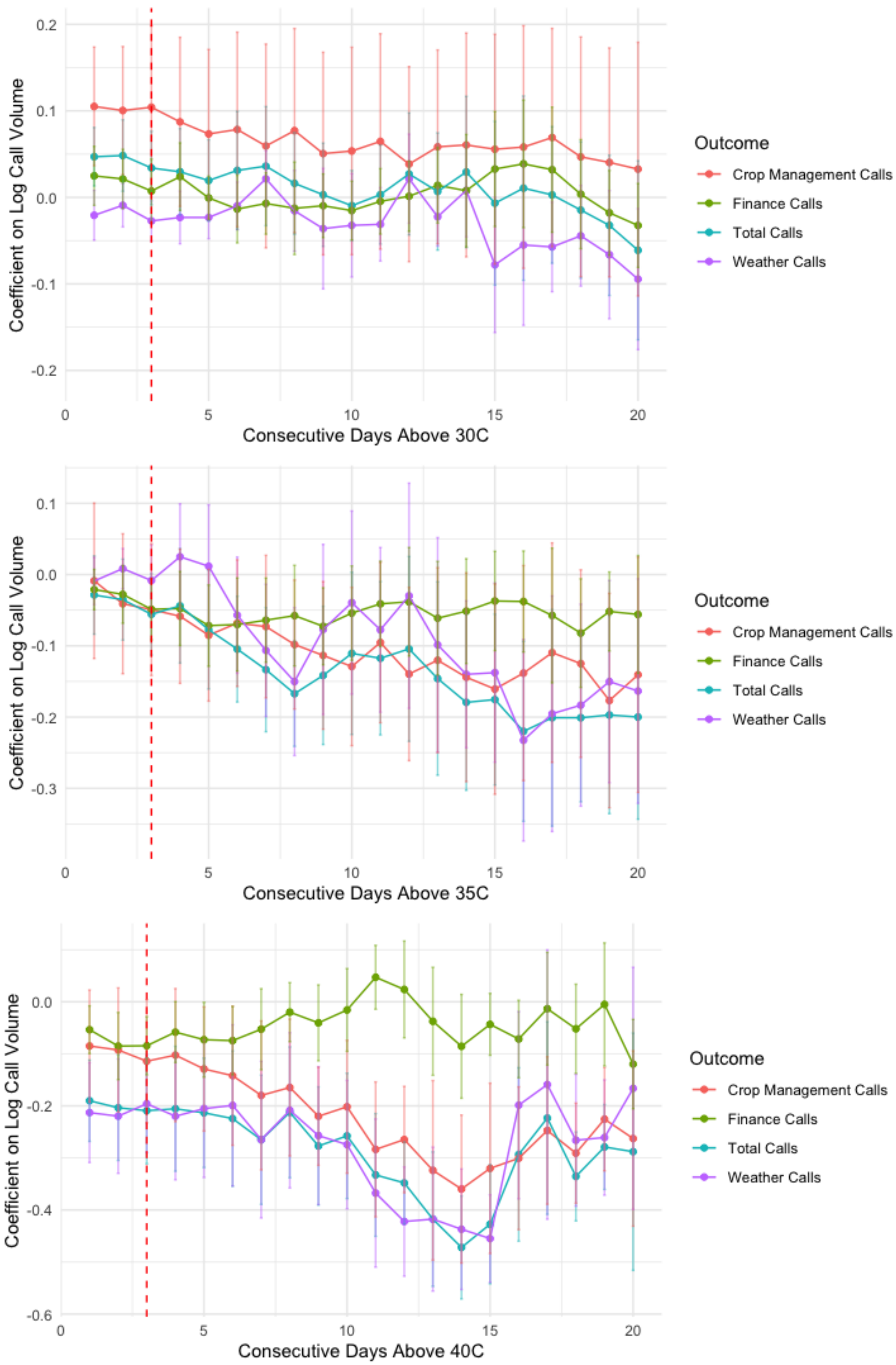


Figure 11: Call Volume Response to Consecutive Dry Days

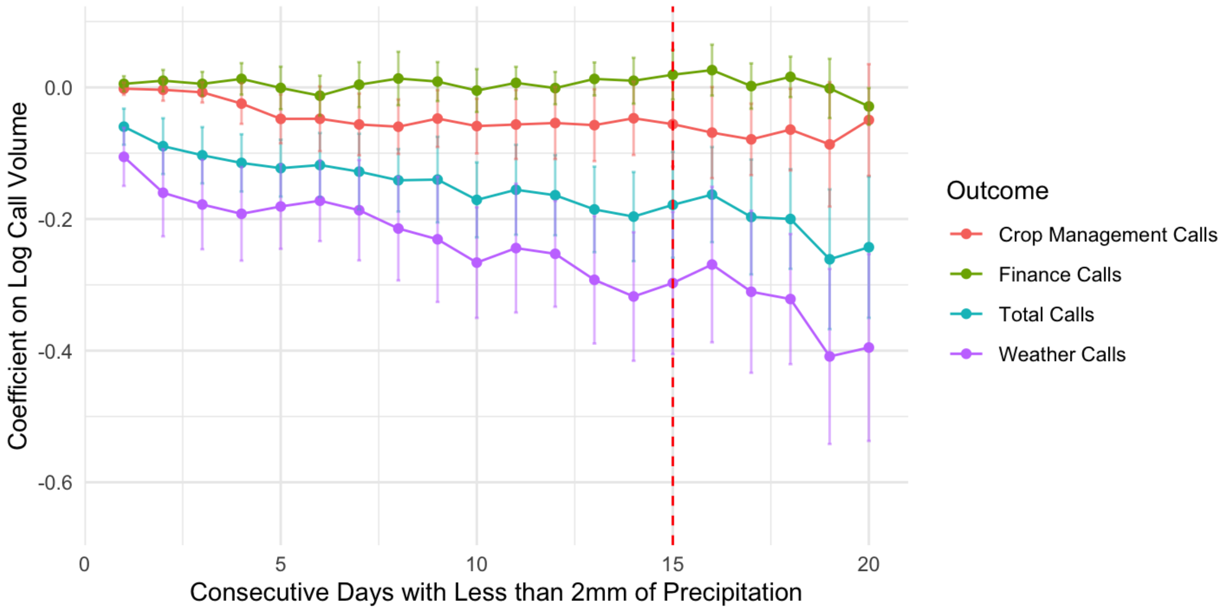


Figure 12: Call Volume Response to Consecutive Days Above 40C by TMI Quintile

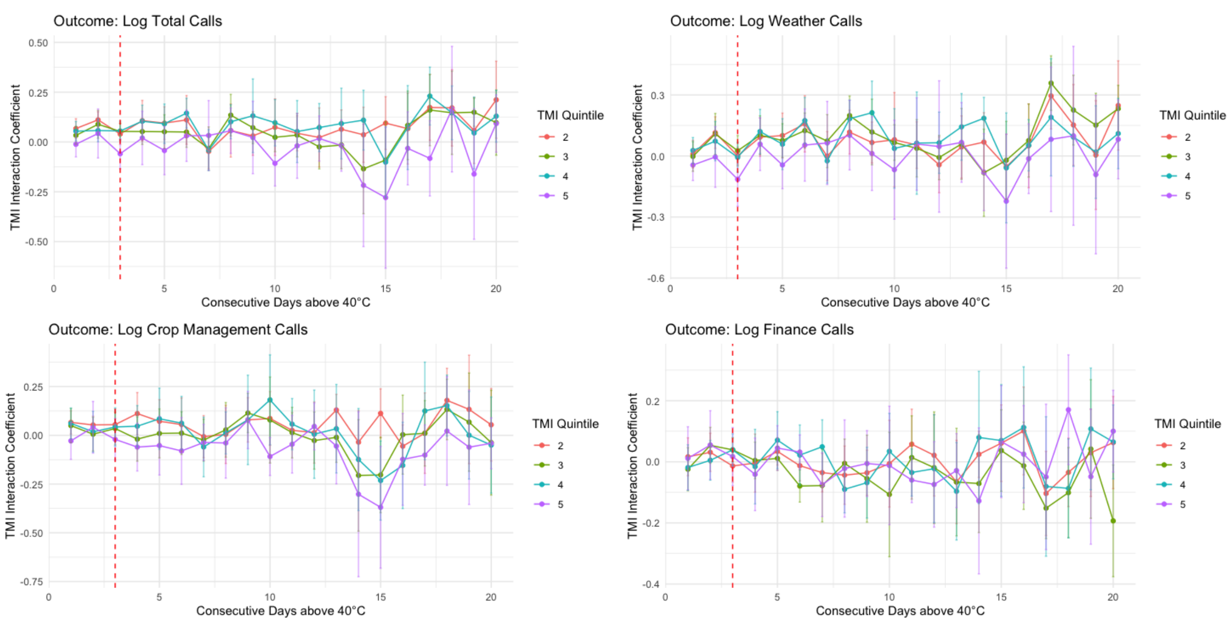


Figure 13: Call Volume Response to Consecutive Dry Days by TMI Quintile

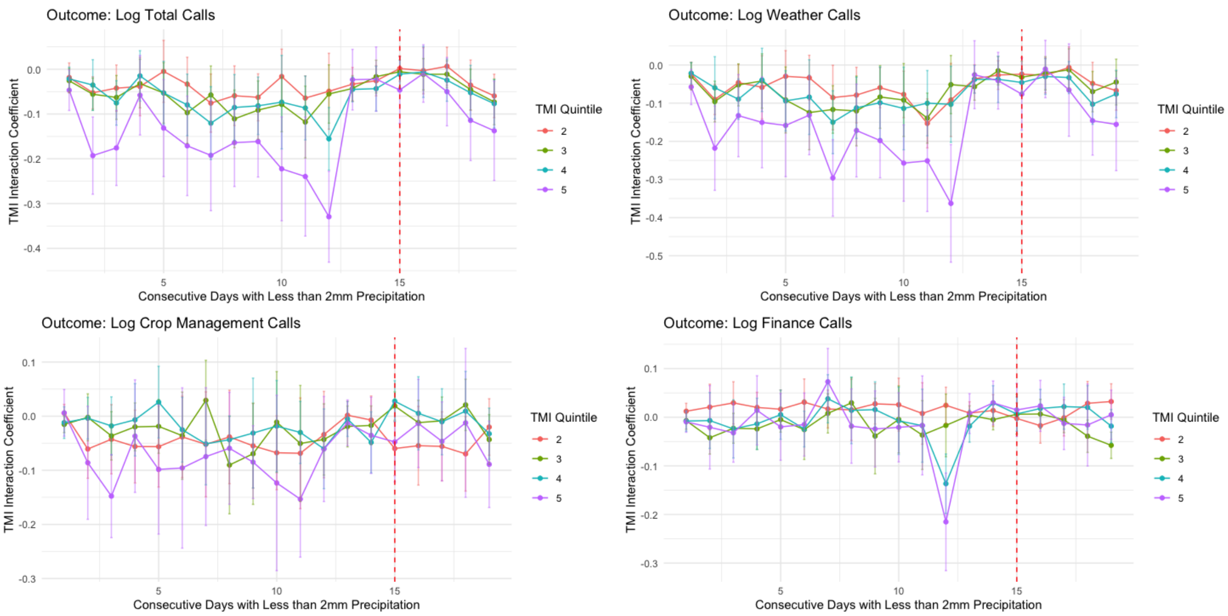


Figure 14: Call Volume Response to Consecutive Days Above 40C by Pr(Self Transition) Quintile

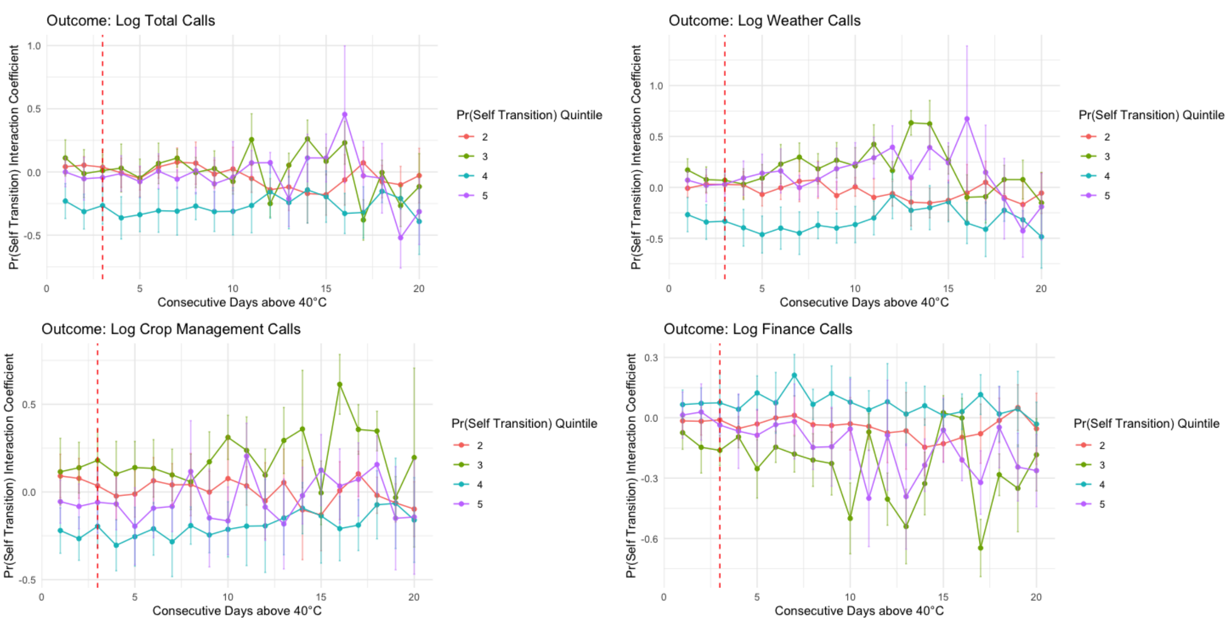


Figure 15: Call Volume Response to Consecutive Dry Days by Pr(Self Transition) Quintile