Supplementary Material:

1. HHS

1.1 Data Collection

The household survey data was collected during the first quarter of 2020 in cooperation with Dr Vishal Gaikwad and his team from the Gokhale Institute of Politics and Economics (Pune, India). The survey was conducted in the form of anonymous door-to-door interviews based on a structured questionnaire, which was transformed into a digital version (available in both English and Mahathi) on the Survey Solutions app developed by the World Bank Group.

The variables treated in this paper were collected through the questions below:

Filled Before Interview (*by enumerator*)
Type of residential zone: 1- Standard Urban Area; 2- Slum Area; 3- Guarded Housing Society; 4- Township; 5- Rural Type of dwelling: 1- Independent house; 2- Apartment; 3- Slum/hut/camp; 4- Others
Household Identification
How many people live here in your household (people who share the same kitchen with you for the last 6 months)? ______ (Counts) How many years of education have the household head completed? (E.g. illiterate: 0 years, primary education completed: 8 years, secondary level: 10 years, higher secondary level: 12 years, etc.) ______ Years How many rooms (except bathrooms) are there in your house? ______ (Counts)
Water Sources, Use and Expenditure
Does your household use any water storage equipment? 1- Yes; 0- No *If yes:* How large is your storage capacity in total? (Aggregated) ______ Liter (*Note: in case the household doesn't know the volume of their water storage container(s), please kindly ask if they can show you the container(s) and estimate the volume(s).*) Does your household own a toilet in your house? 1- Yes; 0- No (*Note: please choose '0- No' if the household uses only public/community/neighbor's toilets*) *If yes:* How many toilets does your household have? ______ (Counts) What type of toilet does your household have? (multiple choices) 1- flush toilet; 2- semi-flush/septic tank latrine; 3- traditional pit latrine; 4- others
Energy sources, Use and Expenditure
Does your household / your building have any back-up aggregate (e.g. generator, battery, genset, etc.)? 1- Yes; 0- No *If yes:* How often do you use it? 1- Almost every day; 2- 1-2 times per week; 3- 1-2 times per month; 4- 1-2 times per year; 5- Never; 6- I don't know
Housing Conditions, Income and Food Expenditure
How much living space does your household have in total? ______ Square feet What type of cooling device does your household usually use in your house? (multiple choices) 1- Air conditioner; 2- Ventilator; 3- Air cooler; 4- Other cooling device During which month(s) does your household usually need to use the cooling devices? (open question) How much money does your household typically get every month (including all types of income, e.g. salary, pension, donation, etc., for all the members in the household)? ______ Rupees /month/household How much does your household spend for food per month (on average)? ______ Rupees /month

Migration

Note: the following questions concern individuals. Please ask the respondents about themselves and (if applicable) their partners.

Have you ever experienced flood at your current or formal place of residence? 1- Yes; 0- No

If yes:

Did the flood happen at this location? 1- Yes; 0- No

When was it? ______ (Month-Year)

How much was the damage caused by the flood? 1- Everything was lost; 2- Severe damage (around 75% property loss); 3- Minor damage (around 25% property loss); 4- Nothing was lost

Did you have to leave your home due to the flood? 1- Yes, permanently; 2- Yes, temporarily; 3- No

Have you or your partner moved/changed your usual place of residence to or within PMC/PCMC/your village? 1- Yes, ONLY I moved here; 2- Yes, ONLY my partner moved here; 3- Yes, both my partner and I moved here; 4- No, we were both born here

If yes:

When, and **from** where?

	You	Your partner
Year of arrival		
Rural/urban		
Country		
State/Union Terr.		
District		
Taluka/Tehsil		

If rural, was sugarcane a dominant crop in the area where you come from? 1- Yes; 0- No

If rural, were you also involved in sugarcane farming / business? 1- Yes; 0- No

If yes, please specify the sugarcane business that you were / your partner was involved in.

What were the reasons for migration? (*Please refer to the reason code from the table below.*)

	You	Your partner
Primary reason		
Secondary reason (if applicable)		
Tertiary reason (if applicable)		

Would you describe your migration as circular (e.g. staying every year during a certain season in the city and going home in between?

You	Your partner
1- Yes ǀ 0- No	1- Yes ǀ 0- No

Would you like to share any further experiences/thoughts on your migration? (*open question*)

Codes for reasons of migration:

1	**Environment** *Changing environmental conditions and disasters*	**2**	**Work** *(Employment/Business)*
1.1	Soil degradation	2.1	(Better) employment
1.2	Water scarcity	2.2	Transfer of Service/Contract
1.3	Water pollution	2.3	Starting new, or moving with existing business
1.4	Heatwave	2.4	Proximity to place of work
1.5	Drought	**4**	**Other Reasons**

1.6	Flood		
1.7	Tsunami	4.1	Education/studies
3	**<u>Housing and Living Standard</u>**	4.2	Marriage
		4.3	Moved with household
3.1	High cost of living (e.g. rent)	4.4	Post retirement
3.2	Difficulties finding suitable accommodation	4.5	Social / political problems e.g. riots, terrorism
3.3	Lack of adequate water supply		
3.4	Lack of adequate energy supply	4.6	Displaced by residential/commercial development (e.g. township)
		4.7	Displaced by Infrastructure project (e..g. dam, road, etc.)
3.5	Lack of other amenities	4.8	Displaced by large-scale agriculture (e.g. sugarcane farm)
3.6	Frequent health issues (e.g. waterborne or malnutrition related)	4.9	Other: (specify)
3.7	Search for more /better food		
3.8	Search for better healthcare		

1.2 Reasons for Migration

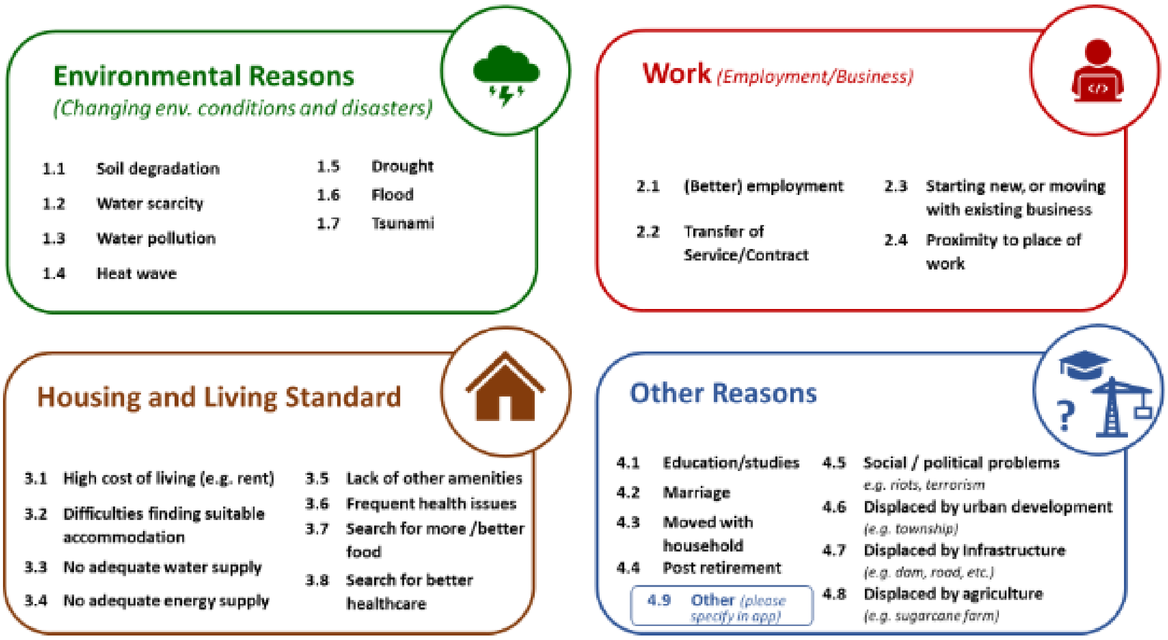
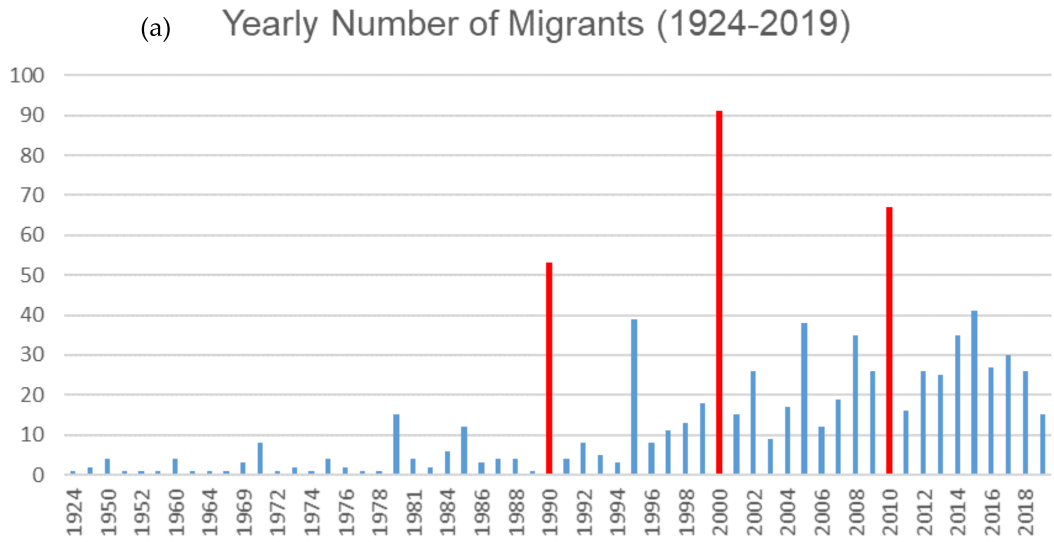


Figure S1: Reasons for migration categories used in HHS.

1.3 Descriptive Statistics



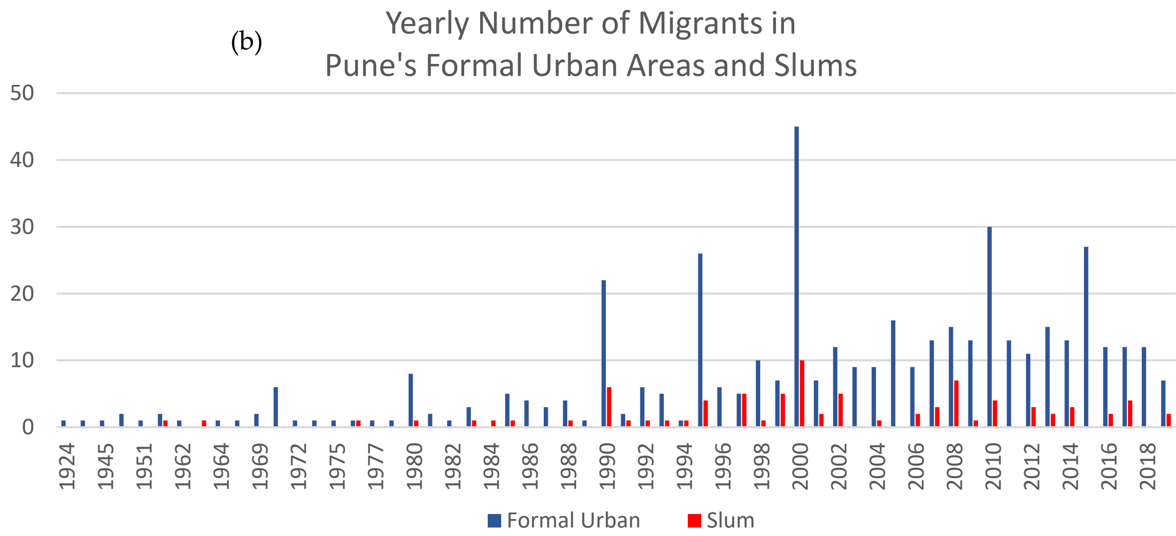


Figure S2: (a) Yearly number of migrants in Pune and (b) yearly number of migrants in Pune’s formal urban areas and slums (1924-2019) based on HHS.

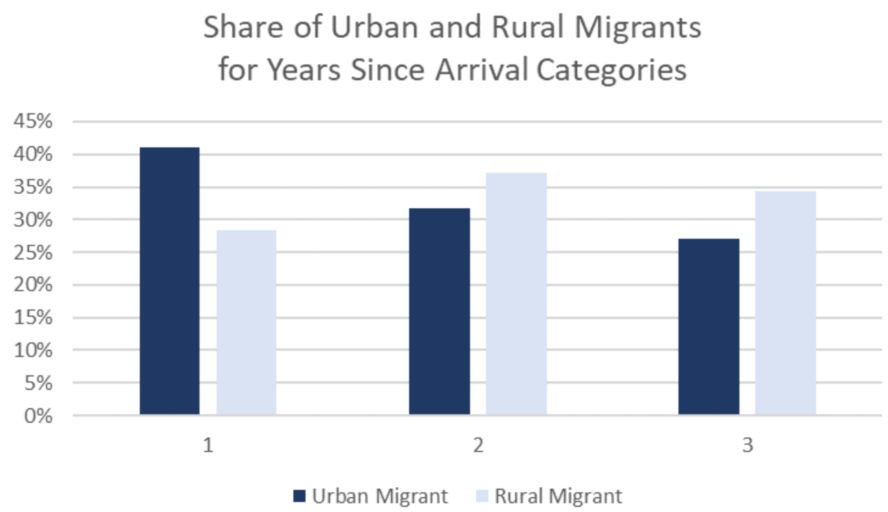


Figure S3: Share of Urban and Rural Migrants for years since arrival categories.

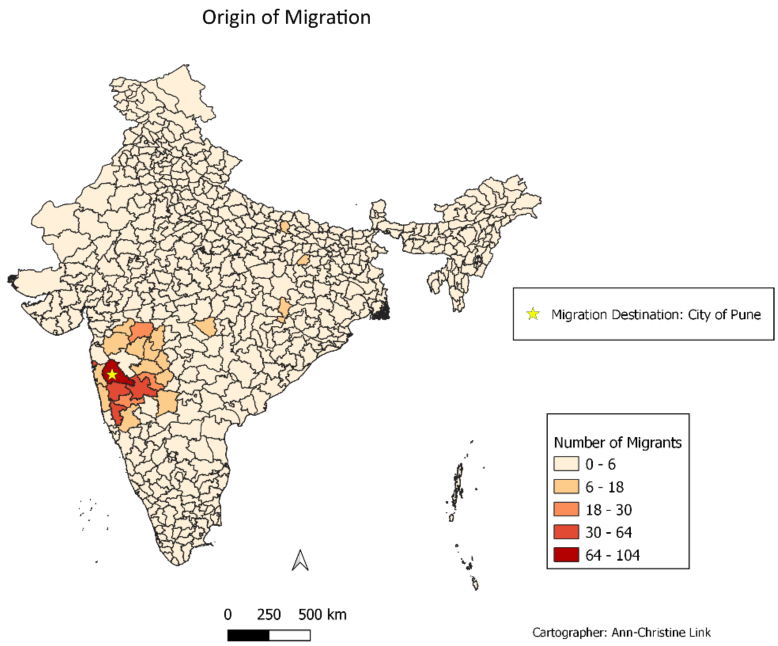


Figure **S4:** Origin of migration of Pune migrants based on HHS.

2. Model

2.1 Data Processing

The pre-processing of HHS variables for the PCA and SEM analysis included turning variables that are directly linked to the size of the household to per capita variables (income, space, rooms). This was done by dividing the respective value by the household size. The income variable was a special case since it was divided by the number of working household members (teenagers and adults) since children and the elderly are typically not part of the working force. The food-income ratio is the result of the division of food expenditures by income.

A PCA was applied to condense the data and produce weights for each variable, depending on the variation and covariation of the data matrix. The weighting method is objective, easy to compute and compatible with many data types [1]. A PCA leads to the generation of a relatively small number of new variables which include the essentials of the original information while noise is removed. The new variables, known as principal components, are linear combinations of the original variables. These linear combinations represent the maximum possible fraction of the variability included in the original data set. The first principal component is that linear combination of original variables that encompasses the highest variance [2]. The factor loadings describe the relationship between principal components and original variables. The signs of the factor loadings also matter. When the sign of the factor loading is negative, a high negative value contributes to a decreased object score whereas a high positive value contributes to an increased object score. The object score matrix combines the transposed loading matrix and the matrix from the standardized original matrix. Object scores are the numerical values that indicate the household's standing on the latent factor.

The RCI results are displayed using kernel density estimations (kde) and a grid-cell map. Only for the sub-groups with a sample size larger than 3 the resilience was calculated and displayed in the matrices. Additionally, if the sample size is still relatively small (n <10) this is indicated in the matrix table with a star (*).

To test whether the groups of interest display significant differences, an unpaired t-test was used when the sample size was above 30. If the sample size was smaller than 30, a Shapiro test was applied to assess whether the data is normally distributed. If the variance of the two compared groups was different, implying heteroscedasticity, a Welch t-statistic was run. When the sample size was smaller than 30 and the data was not normally distributed, a Wilcox-Test was used to determine the significance of the difference between the two focus groups.

2.2 Structure

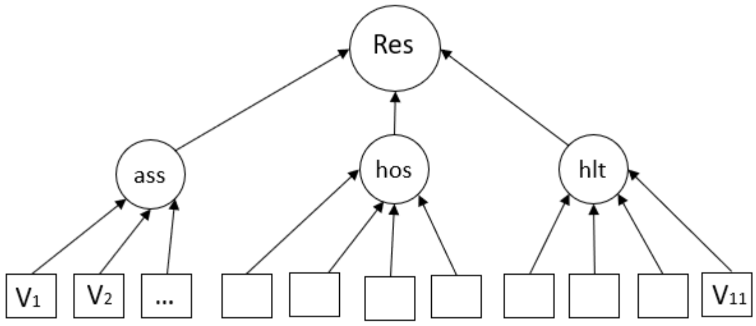


Figure S5: Path diagram of hierarchical Resilience Model based on assets (ass), housing (hos), health (hlt) where circles represent latent variables, rectangles observable variables.

Table S1: Categories and Indicators of the Resilience Model.

Category	Indicators
Assets	• **Monthly Income**: monthly per capita income (rupees) o 1= < 5000 o 2= >5000 and < 9000 o 3= >9000 and <15000 o 4= > 15000 and <23333 o 5= > 23333 • **Education**: Years of education of the household head o 0= 0 (illiterate) o 1= 1-7 o 2= 8 (primary education) o 3= 9 o 4= 10 (secondary education) o 5= 11 o 6= (higher education) o 7= > 12 • **Food-Income Ratio:** monthly food expenditure/ monthly income (%) o 1= >38 o 2= >25 and <38 o 3= >18.7 and <25 o 4=>13 and <18.7 o 5= <13
Housing	• **Zone:** type of residential zone o 0= slum o 1= peri-urban o 2= formal urban o 3= township • **Dwelling:** o 0= slum o 1= no slum • **Space:** living space per capita (square feet) o 1= <75 o 2= > 75 and <113 o 3= >113 and <67 o 4= >67 and <250 o 5= >250 • **Room:** rooms per capita

	○ 1= <0.5 ○ 2= >0.5 and <0.67 ○ 3= > 0.67 and <0.8 ○ 4= >0.8 and <1 ○ 5= > 1
Health	• **Flush Toilet:** ○ 0= no ○ 1= yes • **Electricity Backup:** ○ 0= no ○ 1= yes • **Total Water storage:** rooftop + basement (litres) ○ 1= <166.67 ○ 2= > 166.67 and <400 ○ 3= >400 and <1010 ○ 4= >1010 and <5010 ○ 5= >5010 • **Number of cooling devices**

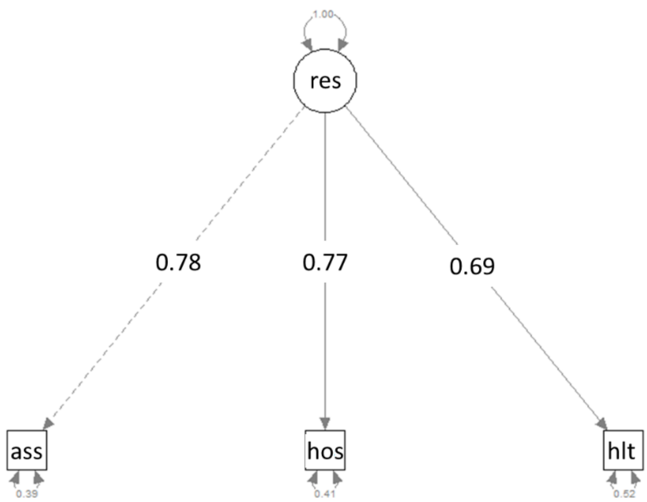


Figure S6: Path diagram of Structural Equation Model displaying how each pillar relates to resilience.

2.3 Testing Resilience Interventions with Model

Moreover, adding objective predictor variables to the HHS such as flood damage or health issues associated with heatwaves and floods would allow for dynamic resilience approaches by employing partial least squares analyses or MIMIC. A dynamic resilience approach allows establishing the main determinants of resilience and the most effective adaptation approaches. Also, to increase the applicability of our RM there is a need to test the effect of resilience interventions on household resilience. This can be done by changing the original data according to the resilience intervention (e.g., compensation payments for flood-affected households, education investments by guaranteeing primary education, or sanitary investments by guaranteeing flush toilets) and predicting the new resilience scores, using the same matrix of the three pillars. Nevertheless, currently, the predict function of the PRINCALS package has not been implemented (plan to be implemented in 2022) and therefore the predict function would have to be coded from scratch.

2.4 Pillars

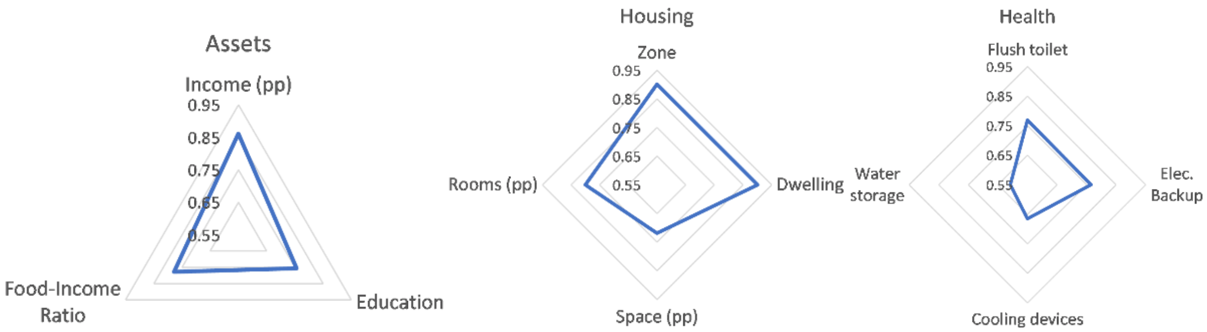
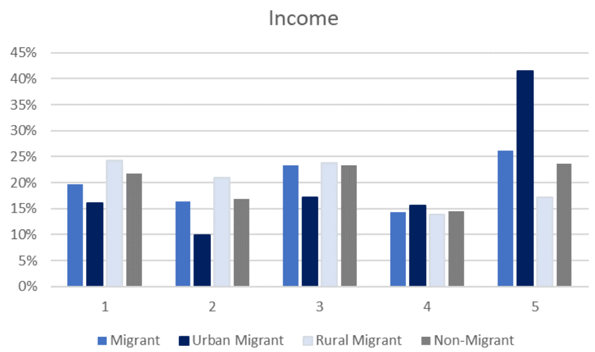


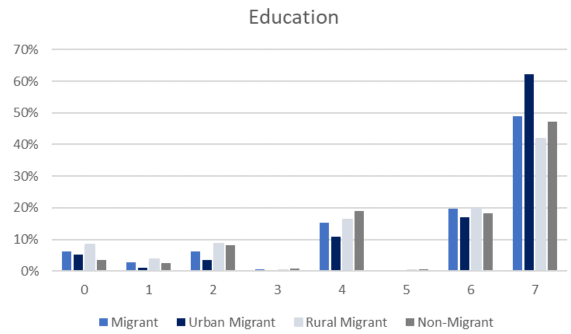
Figure S7: Resilience Structure Matrix of three pillars assets, housing, and health.

2.4.1 Assets

One of the most direct and prevalent measures of the standard of living is income [3]. In our work, income refers to all types of income such as salary, pensions, donations etc. Income can be viewed as comprising claims on goods and services by individuals and households that permit them to obtain goods and services [4]. Consequently, income is a deciding factor when households are exposed to stressors. This is the case because income is viewed as the starting point in the coping process to stressors, considering that a higher income can lead to higher savings, which can then be beneficial during the post-stressor recovery phase. The food-income ratio serves as a proxy for a household's standard of living based on Engel's law [5]. He states that the proportion of food expenditure to income, is the most suitable measure of the material living standard of a population since the poorer a household is, the greater is the proportion of food expenditure.

Additionally, education impacts resilience. The capacity to adapt is directly associated with an individual's ability to learn from technological progress [6]. Typically, the higher the literacy rate or years of educational attainment, the higher the adaptive capacity [3]. The higher the years of education, the higher the chances that individuals know how to prepare for and react to stressors. Apart from that, the years of education do not only determine the human capital of an individual but also the financial capital since it influences job attainment. The assets pillar has a superior status since it strongly influences all other pillars. High financial (income) and human capital (education) tend to increase a household's resilience since it positively influences a household's access to water, health care, sanitation and housing while reducing its vulnerability to external stressors. Hence, the number of years of education is often utilized as a proxy indicator of knowledge and skills, for example, by the United Nations Human Development Index [7].





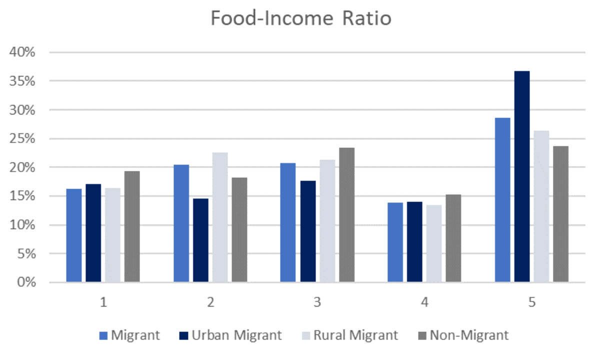


Figure S8: Figures of descriptive statistics of *assets* pillar (income, education, and food-income ratio) for migrant, urban migrant, rural migrant, and non-migrant.

Table S2: Tables of descriptive statistics of *assets* pillar (income, education, and food-income ratio) for migrant, urban migrant, rural migrant, and non-migrant (* low sample size).

Income	Migrant	*n*	Urban Migrant	*n*	Rural Migrant	*n*	Non-Migrant	*n*
1	19.71%	*109*	16.06%	*31*	24.27%	*58*	21.76%	*287*
2	16.46%	*91*	9.84%	*19*	20.92%	*50*	16.83%	*222*
3	23.33%	*129*	17.10%	*33*	23.85%	*57*	23.35%	*308*
4	14.29%	*79*	15.54%	*30*	13.81%	*33*	14.48%	*191*
5	26.22%	*145*	41.45%	*80*	17.15%	*41*	23.58%	*311*

Education	Migrant	*n*	Urban Migrant	*n*	Rural Migrant	*n*	Non-Migrant	*n*
0	6.33%	*35*	5.18%	*10*	0.083682008	*20*	0.035633055	*47*
1	2.89%	*16*	1.04%	*2**	0.037656904	*9**	0.025018954	*33*
2	6.15%	*34*	3.63%	*7**	0.087866109	*21*	0.081122062	*107*
3	0.54%	*3**	0.00%	*0**	0.0041841	*1**	0.009097801	*12*
4	15.19%	*84*	10.88%	*21*	0.163179916	*39*	0.188779378	*249*
5	0.18%	*1**	0.00%	*0**	0.0041841	*1**	0.004548901	*6**
6	19.71%	*109*	17.10%	*33*	0.20083682	*48*	0.183472328	*242*
7	49.01%	*271*	62.18%	*120*	0.418410042	*100*	0.472327521	*623*

Food/Income	Migrant	*n*	Urban Migrant	*n*	Rural Migrant	*n*	Non-Migrant	*n*
1	16.27%	*90*	17.10%	*33*	16.32%	*39*	19.33%	*255*
2	20.43%	*113*	14.51%	*28*	22.59%	*54*	18.27%	*241*
3	20.80%	*115*	17.62%	*34*	21.34%	*51*	23.43%	*309*

4	13.92%	*77*	13.99%	*27*	13.39%	*32*	15.31%	*202*
5	28.57%	*158*	36.79%	*71*	26.36%	*63*	23.65%	*312*

2.4.2 Housing

Satisfactory housing conditions also determine the livelihood status of households since the type of residential zone and dwelling reflects their financial capital. Households living in slums tend to experience the lowest standard of living compared to those living in formal urban areas and independent houses or apartments. Additionally, housing space and rooms can also be used as proxies of the standard of living. Moreover, housing influences a household's access to important services such as schools, health centres, water, electricity and markets.

Conditions in slums vary greatly ranging from temporal shelters in squatter settlements to relatively well-constructed settlements. In India, slums are categorized by their building type, described as pucca or kutcha. A Pucca tends to be made of more permanent building materials such as asbestos cement, bricks, metal, stones whereas a kutcha is made of non-permanent building materials, for example, bamboo, carton, clay, leaves or wood [8]. Not only the low structural quality of slum houses but also their improper location on fragile lands such as floodplains, wetlands or hillslopes increase the vulnerability of households living in slums [9]. On top of higher exposure to extreme events and higher vulnerability of slum households, unrecognized slum households do not receive any governmental support, for example, after being exposed to severe stressors such as floods or fires [10]. According to Vaid and Evans [11], Indian slum households perform worse compared to public households in the majority of the examined categories (cleanness and clutter, basic services, structural quality, crowding, and housing quality).

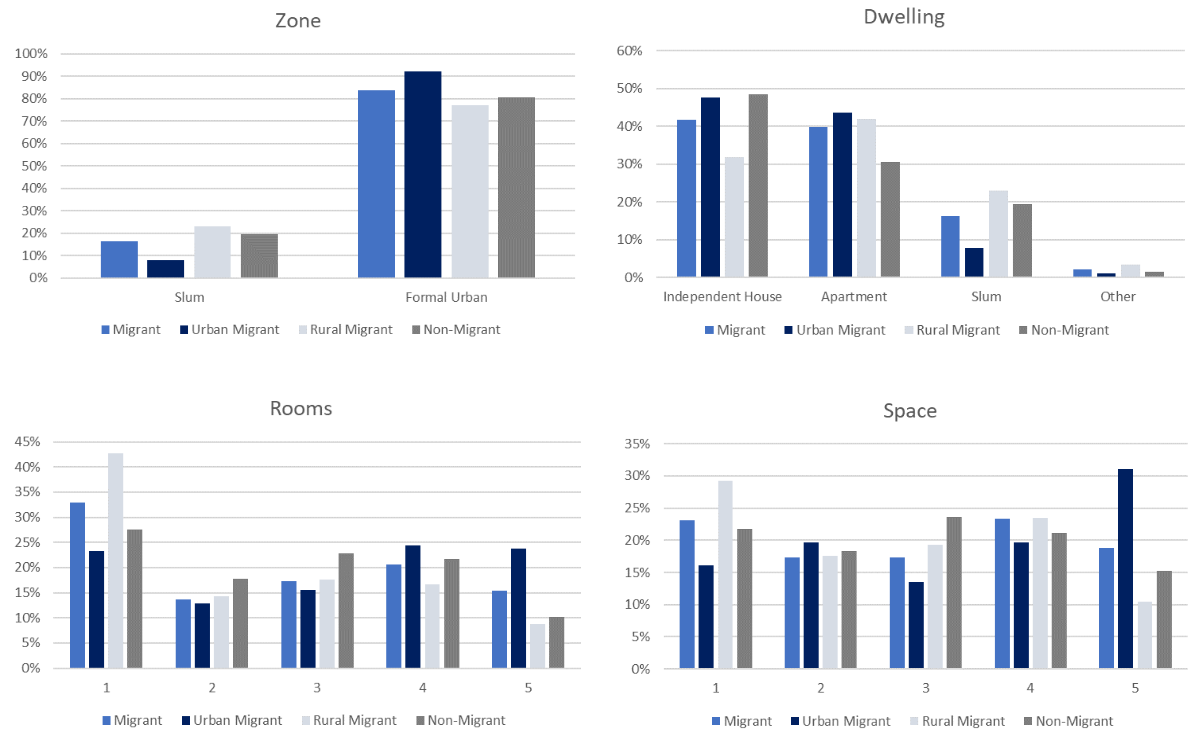


Figure S9: Figures of descriptive statistics of *housing* pillar (zone, dwelling, rooms, and space) for migrant, urban migrant, rural migrant, and non-migrant.

Table S3: Tables of descriptive statistics of housing pillar (zone, dwelling, rooms, and space) for migrant, urban migrant, rural migrant, and non-migrant (* low sample size).

Zone	Migrant	*n*	Urban Migrant	*n*	Rural Migrant	*n*	Non-Migrant	*n*
Slum	16.27%	*90*	7.77%	*15*	23.01%	*55*	19.33%	*255*
Formal Urban	83.73%	*463*	92.23%	*178*	76.99%	*184*	80.67%	*1064*

Dwelling	Migrant	*n*	Urban Migrant	*n*	Rural Migrant	*n*	Non-Migrant	*n*
Independent House	41.77%	*231*	47.67%	*92*	31.80%	*76*	48.52%	*640*
Apartment	39.78%	*220*	43.52%	*84*	41.84%	*100*	30.63%	*404*
Slum	16.27%	*90*	7.77%	*15*	23.01%	*55*	19.33%	*255*
Other	2.17%	*12*	1.04%	*2**	3.35%	*8*	1.52%	*20*

Rooms	Migrant	*n*	Urban Migrant	*n*	Rural Migrant	*n*	Non-Migrant	*n*
1	32.91%	*182*	23.32%	*45*	42.68%	*102*	27.60%	*364*
2	13.74%	*76*	12.95%	*25*	14.23%	*34*	17.74%	*234*
3	17.36%	*96*	15.54%	*30*	17.57%	*42*	22.74%	*300*
4	20.61%	*114*	24.35%	*47*	16.74%	*40*	21.76%	*287*
5	15.37%	*85*	23.83%	*46*	8.79%	*21*	10.16%	*134*

Space	Migrant	*n*	Urban Migrant	*n*	Rural Migrant	*n*	Non-Migrant	*n*
1	23.15%	*128*	16.06%	*31*	29.29%	*70*	21.76%	*287*
2	17.36%	*96*	19.69%	*38*	17.57%	*42*	18.27%	*241*
3	17.36%	*96*	13.47%	*26*	19.25%	*46*	23.58%	*311*
4	23.33%	*129*	19.69%	*38*	23.43%	*56*	21.15%	*279*
5	18.81%	*104*	31.09%	*60*	10.46%	*25*	15.24%	*201*

2.4.3 Health

The health pillar aims to capture the health and sanitation status of Pune's households by including information on flush toilets, water storage, electricity backup and cooling devices. The availability of flush toilets was included since open defecation is still a prevalent problem in India, practiced by almost half of the population [12]. An additional issue is that only 6% of India's cities have partial sewage systems, fewer than 20% have stormwater drains [13] and only 14% of the wastewater is getting treated [14]. Women and especially girls are affected the most by poor sanitation [15]. Bapat and Agarwal [16] provide evidence from Pune and Mumbai that women and girls face the risk of attacks and violence when they must walk long distances to toilets especially during the night. Moreover, the most researched health risks associated with open defecation are human excrement linked with infectious diseases [17]. Inappropriate waste disposal elevates the risk of pathogen exposure such as transferable infectious diseases, diarrhea, cholera, typhoid and viral infections [18]. Due to the poor waste and sewage disposal as well as poor sanitation infrastructures, India has the highest number of both child cases and deaths from diarrhea [19].

On top, dense and overcrowded slums represent breeding grounds for transmittable diseases, decreasing the health of slum households. Especially slum households have less reliable water supplies, influenced by supply gaps, low piped frequencies, low piped periods, higher wait times for tap water and seasonal supply distinctions [20]. Additionally, slum households tend to often experience inadequate electricity supplies and sanitation issues due to improper waste disposal [21]. A more reliable water supply and access to water can be achieved by installing water storage tanks. This can lead to higher productivity of households since they now have more reliable water supplies to perform necessary household activities while also spending less time waiting for and worrying about water.

Moreover, cooling devices are critical to reducing heat stress of particularly vulnerable groups such as children and the elderly since summer temperatures in Pune can reach values higher than 35°C [22]. Cooling devices can reduce the risks of suffering heat strokes by ensuring cooler temperatures at home which are crucial during the night [23]. The number of cooling devices is used as a proxy for the capacity of households to reduce heat stress. Additionally, the presence of an electricity aggregate is included in the health pillar since it allows households to perform all necessary household activities when the official supply is intermittent. Ultimately, all variables are important aspects of health and sanitation, determining the productivity and resilience of households [24].

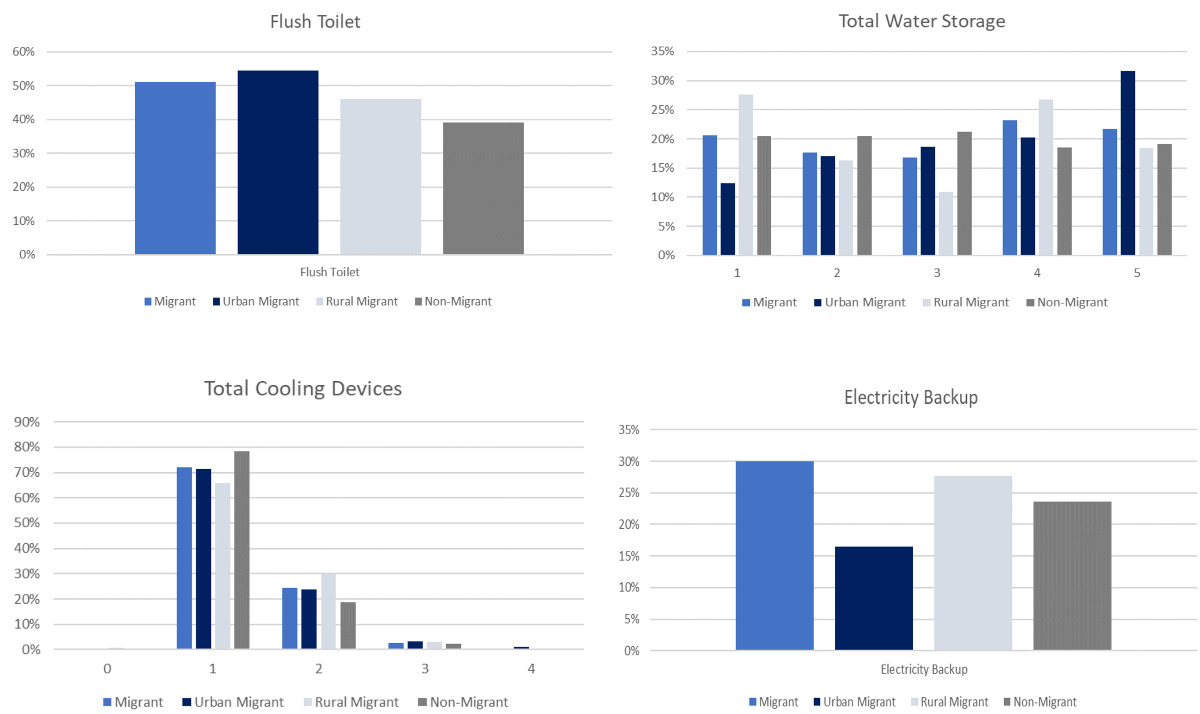


Figure S10: Figures of descriptive statistics of *health* pillar (flush toilet, total water storage, total cooling devices, and electricity backup) for migrant, urban migrant, rural migrant, and non-migrant.

Table S4: Figures of descriptive statistics of health pillar (flush toilet, total water storage, total cooling devices, and electricity backup) for migrant, urban migrant, rural migrant, and non-migrant (* low sample size).

Flush Toilet	Migrant	*n*	Urban Migrant	*n*	Rural Migrant	*n*	Non-Migrant	*n*
Flush Toilet	49.01%	*271*	54.40%	*105*	46.03%	*110*	39.12%	*516*
No	50.81%	*282*	45.60%	*88*	53.97%	*129*	60.88%	*803*

Tot. Water Storage	Migrant	*n*	Urban Migrant	*n*	Rural Migrant	*n*	Non-Migrant	*n*
1	20.61%	*114*	12.44%	*24*	27.62%	*66*	20.55%	*271*
2	17.72%	*98*	17.10%	*33*	16.32%	*39*	20.55%	*271*
3	16.82%	*93*	18.65%	*36*	10.88%	*26*	21.23%	*280*
4	23.15%	*128*	20.21%	*39*	26.78%	*64*	18.50%	*244*
5	21.70%	*120*	31.61%	*61*	18.41%	*44*	19.18%	*253*

Tot Cooling	Migrant	*n*	Urban Migrant	*n*	Rural Migrant	*n*	Non-Migrant	*n*
0	0.54%	*3**	0.52%	*1**	0.84%	*2**	0.53%	*7**
1	71.97%	*398*	71.50%	*138*	65.69%	*157*	78.47%	*1035*
2	24.41%	*135*	23.83%	*46*	30.13%	*72*	18.73%	*247*
3	2.53%	*14*	3.11%	*6**	2.93%	*7**	2.20%	*29*
4	0.54%	*3**	1.04%	*2**	0.42%	*1**	0.08%	*1**

Electricity Backup	Migrant	*n*	Urban Migrant	*n*	Rural Migrant	*n*	Non-Migrant	*n*
Yes	30.02%	*167*	16.53%	*80*	27.62%	*67*	23.58%	*312*
No	69.98%	*386*	83.47%	*113*	72.38%	*172*	76.42%	*1006*

3. Migration Characteristics

3.1 Flood Exposure

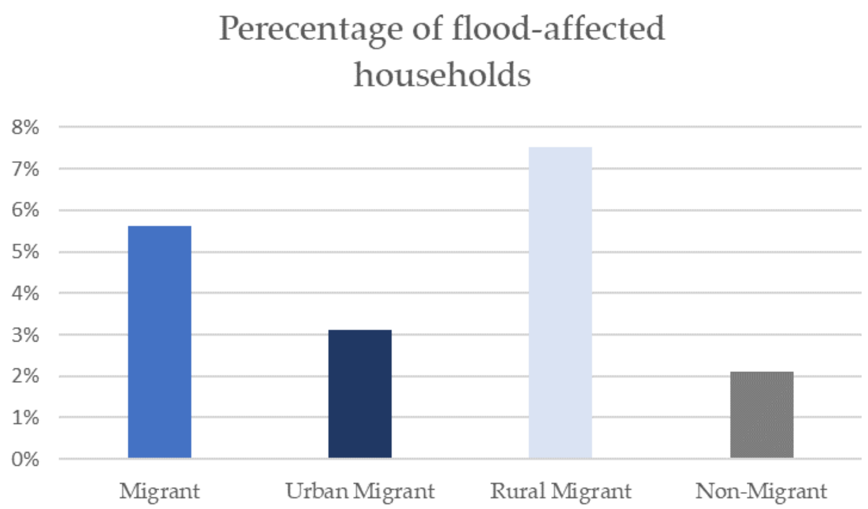


Figure S11: Percentage of flood-affected households (migrant, urban migrant, rural migrant, and non-migrant).

3.2 Heat Exposure

In the case of temperature exposure, remote sensing data was downloaded, processed, and analyzed accordingly. Moderated Resolution Imaging Spectroradiometer (MODIS) Terra 8-day average night surface temperature in Kelvin from January 2019 until April 2021 was downloaded from the National Aeronautics and Space Administration (NASA) Earth Data platform (Wan et al., 2015). The spatial resolution of MODIS Terra satellite images is 1km x 1km, allowing a detailed analysis. Next, the required canal *day surface temperature* was read into QGIS. To use the QGIS batch mode, the canal was exported in a tifs-file format and read back into QGIS. After that, the satellite images were projected in WGS 84 EPSG: 4326. Using the QGIS Python console, the values were transformed from Kelvin into degrees Celsius subtracting 273.15 and multiplying each raster value with the required scaling factor 0.02 of the MODIS Terra images. Next, the satellite images were clipped to an extent covering all the HHS households. Then, the raster values were added to the HHS coordinates, applying the point sampling and join attributes by location function. Satellite images that had cloud cover, masking the households, were deleted. The 90^{th} percentile of night temperatures of each year was calculated. Then, the exceedance of this 90th percentile for each household was counted and split into two categories, namely low (<7) and high heat exposure (>=7). The number of extreme heat exposures was interpolated to display spatial trends in Pune (Figure S).

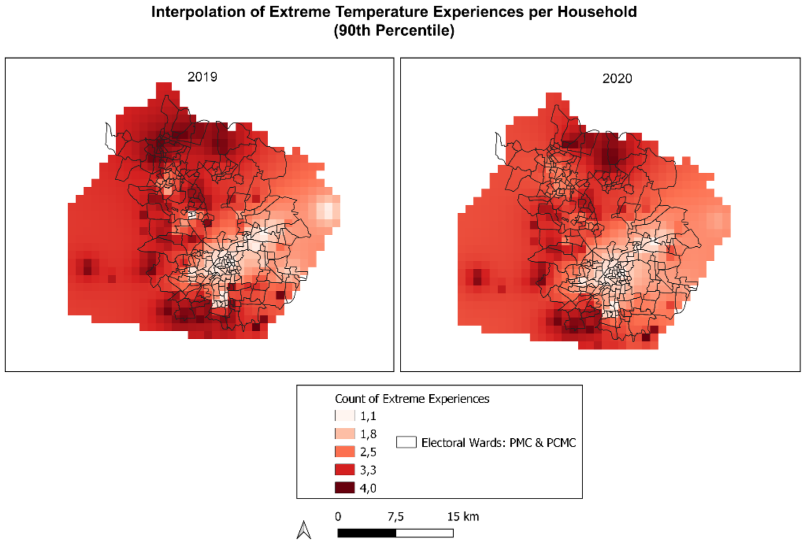


Figure S12: Interpolation of extreme temperature experiences per household (90th percentile).

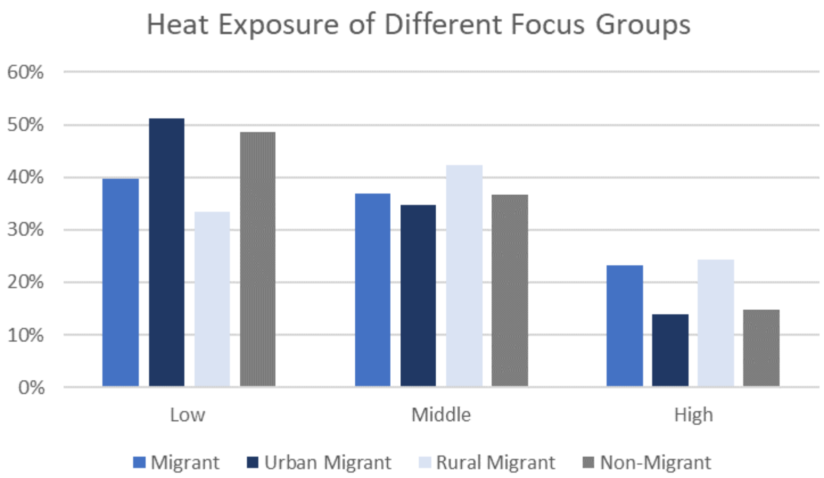


Figure S13: Heat exposure (low, middle, high) experienced by different focus groups (migrant, urban migrant, rural migrant, and non-migrant).

3.3 Experiments with environmental data

To increase the complexity of the RM we attempted to considers the following environmental stressors and factors: extreme temperature, extreme rainfall, Normalized Difference Vegetation Index (NDVI), distance to floods, and elevation.

In this case, remote sensing data can provide valuable insights into whether climate and vegetation factors influence resilience [25,26]. For the rainfall data, Famine Land Data Assimilation System (FLDAS) monthly rainfall flux and anomaly rainfall flux from January 2019 until March 2021 was downloaded from NASA'S Earth Data platform (NASA GSFC Hydrological Sciences Laboratory [HSL], 2018a, 2018b). The monthly rainfall data was generated from the monthly data, as a 35-year (1982-2016) monthly average. The monthly anomaly data was produced by using the difference between the monthly data and monthly rainfall data for each grid point. This difference represents how a particular month compares to the 35-year rainfall. The spatial resolution of the FLDAS is 0.1 x

0.1 degrees, which equals a resolution of 10 km x 10 km, which is coarser than the spatial resolution of MODIS satellite images. For more usable values the unit was transformed from kg/m^2s to g/m^2s by multiplying each raster by 1000. Then, the same procedure as previously described was applied to the FLDAS data. Subsequently, extreme rainfall data of each considered year (2019, 2020 and 2021) was read into the RM.

Variables that can reduce the consequences of extreme rainfall and temperature are vegetation, elevation and distance to rivers. These factors are simple approaches to addressing the complexity of factors determining resilience to environmental stressors. A digital elevation model was used to assess the elevation of HHS households. It is hypothesized that the higher the elevation of the households, the lower the exposure of floods and heatwaves since temperatures at higher elevations tend to be cooler (Botzen et al., 2013). Vegetation cover is a useful indicator of how well impacts of floods and heatwaves can be reduced. To assess vegetation cover, the NDVI is used as a proxy. A higher NDVI is associated with higher water uptake by the vegetation and soil, reducing the amount of surface water that can contribute to floods (Vargas-Luna et al., 2015). Also, the higher the NDVI, the higher the potential of vegetation to reduce the temperatures of the surrounding areas due to photosynthesis (Reis & Lopes, 2019). In QGIS, Landsat 8 rasters with no cloud cover from 2019 until April 2021 were downloaded. The monthly NDVI was calculated with the following equation:

$$\text{(Near Infrared-Red)/(Near Infrared+Red)} \qquad (1)$$

The NDVIs were averaged per season (winter, summer and post-monsoon) and year (2019, 2020, 2021). To link the NDVI to individual household coordinates a vector grid of the clip-to-extent raster was used. The closest distance of a household to a river was calculated by reading in a river shapefile of India, clipping it to the extent of PD and using the NNJoin Plugin to calculate the nearest distance of the HHS households to the river polygons.

Since PRINCALS revealed that NDVI, elevation, and distance to the river did not correlate with the other environmental variables (temperature, rainfall data), they were excluded from the RM. PRINCALS for the other pillars, namely assets, housing, health, extreme temperature and extreme rainfall revealed high factor loadings and high variances explained.

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