Agricultural shocks and drivers of livelihood precariousness across Indian rural communities

Agricultural shocks and drivers of livelihood precariousness across Indian rural communities

Tristan Berchoux (corresponding author)
t.berchoux@soton.ac.uk
Geography & Environment, University of Southampton, United Kingdom 44/2035, University Road, Southampton SO17 1BJ

Gary R. Watmough
gary.watmough@ed.ac.uk
School of GeoSciences, University of Edinburgh, United Kingdom Surgeon's Square, Drummond Street, Edinburgh EH8 9XP

Craig W. Hutton
cwh@geodata.soton.ac.uk
GeoData Institute, University of Southampton, United Kingdom 44/2091, University Road, Southampton SO17 1BJ

Peter M. Atkinson
pma@lancaster.ac.uk
Lancaster Environment Centre, Lancaster University, United Kingdom Lancaster University, Lancaster LA1 4YQ

Abstract

Spatial factors, such as environmental conditions, distance to natural resources and access to services can influence the impacts of climate change on rural household livelihood activities. But neither the determinants of precarious livelihoods nor their spatial context has been well understood. This paper investigates the drivers of livelihood precariousness using a place-based approach. We identify five community types in rural regions of the Mahanadi Delta, India; exurban, agro-industrial, rainfed agriculture, irrigated agriculture and resource periphery by clustering three types of community capitals (natural, social and physical). Based on this typology, we characterise the associations between precarious livelihood activities (unemployment or engagement in agricultural labour) with agricultural shocks and household capitals. Results demonstrate that, the type of community influences the impact of agricultural shocks on livelihoods as four of the five community types had increased likelihoods of precarious livelihoods being pursued when agricultural shocks increased. Our research demonstrates that the bundle of locally available community capitals influences households' coping strategies and livelihood opportunities. For example, higher levels of physical capital were associated with a lower likelihood of precarious livelihoods in agro-industrial communities but had no significant impact in the other four. Results also indicate that agricultural shocks drive livelihood precariousness (odds ratios between 1.03 and 1.07) for all but the best-connected communities, while access to household capitals tends to reduce it. Our results suggest that poverty alleviation programmes should include community typologies in their approach to provide place-specific interventions that would strengthen context-specific household capitals, thus reducing livelihood precariousness.

Keywords: livelihoods, community typologies, rural development, agricultural shocks, chronic poverty, India

1 Introduction

Investigating the impacts of climate change on rural livelihoods and rural poverty is a continuing concern within environmental sciences and development studies. Repeated exposure to climatic stresses can undermine current and future coping capacity, which can lead to shifts from transient to chronic poverty (Ahmed, Diffenbaugh, & Hertel, 2009). However, the impacts of climate shocks on rural households depend on coping strategies and livelihood opportunities and cannot be explained by income-based approaches alone (Scoones, 2015). Livelihood approaches reveal that inequalities in access to livelihood capitals and in livelihood opportunities are spatially dependent and that they perpetuate poverty and undermine households' ability to cope with external shocks (de Sherbinin et al., 2008). Understanding the links between multiple stressors and livelihoods is central to achieving sustainable development pathways. However, insufficient work assesses the spatial distribution of livelihoods as a consequence of weather shocks. This paper aimed to bridge this gap by conducting a place-based analysis of the associations between livelihood strategies, agricultural shocks and livelihood capitals. The objective of this paper was to demonstrate how the type of rural community in which households are situated modifies the relationships between livelihood strategies, agricultural shocks and access to livelihood capitals.

Our research demonstrates that the bundle of locally available community capitals influences households' coping strategies and livelihood opportunities, thus influencing the drivers of rural poverty. We also argue that agricultural shocks drive livelihood precariousness, while access to capitals tends to reduce it. Our results suggest that poverty alleviation programmes should include community typologies in their approach to provide place-specific interventions that would strengthen context-specific household capitals, thus reducing livelihood precariousness.

1.1 Access to Community Capitals and Household Livelihood Activities

A major theoretical issue that has dominated the field of livelihood studies for many years concerns the use of quantitative methods to characterise rural livelihoods and their dynamics (Jiao, Pouliot, & Walelign, 2017). However, most of these studies have considered that the effect of capitals on livelihood strategies is constant across space, without considering community-level effects (Berchoux & Hutton, 2019; Bhandari, 2013). For example, access to a common agricultural area in the village can have a positive effect on livelihoods as it can create synergies between farmers to invest into agricultural equipment or irrigation infrastructure and it can increase their bargaining power (Agarwal, 2018). Community-level studies that paid particular attention to the spatial component of livelihoods led to descriptive results, such as the creation of indices (e.g. Singh and Hiremath, 2010). Although such indices are a useful mapping tool for policy makers, they fail to break down the different livelihood components and thus characterise the place-based dimensions of rural poverty.

Overall, despite the recommendations from previous poverty studies (e.g. Palmer-Jones and Sen, 2006) and from livelihood studies (e.g. Angelsen et al., 2014) that have shown the importance of place-based approaches to rural poverty, there have been very few studies that have characterised the place-based sensitivity of livelihood strategies to livelihood capitals and external shocks. To the authors' best knowledge, the only study that looked at the associations between livelihood capitals and livelihood strategies using a place-based approach relied on an arbitrary categorisation of community types based on a total of six settlements (Fang, Fan, Shen, & Song, 2014). In their study, Fang et al. (2014) demonstrated that different settlement types affect how access to capitals influences households' livelihood strategies. However, the interpretation of the results was micro-localised and difficult to reproduce across a larger spatial extent. Our approach helps meet this challenge by identifying how the effects of key determinants of precarious livelihood strategies vary across a broad geographic extent.

Community capitals can be defined as public goods through which people are able to widen their access to resources and to economic opportunities (Lindenberg 2002; Gutierrez-Montes et al. 2009). They can include factors such as environmental conditions (e.g. elevation, rainfall, soil quality), distance to natural resources (e.g. forest, wetlands) and access to services (e.g. markets, hospitals, schools). These community capitals vary spatially and can shape differential vulnerabilities and influence the impacts of climate change on rural households (Berchoux, Watmough, Johnson, Hutton, & Atkinson, 2019). These spatial factors form a group of interacting services that co-occur in time and space, creating bundles of community capitals (Turner, Odgaard, Bøcher, Dalgaard, & Svenning, 2014; Yang et al., 2015).

1.2 Characterising community capitals using typologies

Typologies are useful tools for policy-makers, planners and other practitioners to improve place-specific understandings of rural heterogeneity and rural change. The heterogeneity of rural areas can be categorised into community typologies that reflect similar combinations of natural resources (i.e., water, cropland, forest), social services (including education, health, governance), and productive infrastructures (Alessa, Kliskey, & Altaweel, 2009; Van Eetvelde & Antrop, 2009). These different combinations of assets reflect different underlying types of communities (van der Zanden, Levers, Verburg, & Kuemmerle, 2016), which influence the drivers of livelihood strategies and rural poverty, and therefore lead to different responses to multiple stressors. In this paper, we investigate the drivers of livelihood precariousness using a place-based approach. We create a typology of rural communities (defined here as villages derived from national population and housing censuses) by clustering characteristic variables of community capitals, focused on natural resources, social services and productive infrastructures. Based on this typology, we characterise the associations between precarious livelihoods, agricultural shocks and household capitals for each community type. This approach helps to elucidate how the type of community can determine the impact that agricultural shocks can have on household livelihood activities and in particular on the likelihood that households pursue precarious activities.

1.3 Weather shocks and impacts on livelihood activities

Despite the Government of India's efforts to enhance livelihood security in rural areas, only 53.2% of the working age rural population is able to get work throughout the year (Indian Ministry of Labour and Employment, 2015). While the majority of the employed population depends on agriculture, forestry and the fishing sector for their livelihoods, around 78% of households do not earn any wages. Weather shocks affect agricultural production through frequent floods, droughts, and storm surges with subsequent impacts on rural livelihoods (Birthal, Roy, & Negi, 2015). Households put in place coping strategies to adjust to the loss of wages following a crop failure.

Coping strategies are defined as temporary adjustments made by households in their livelihood systems in response to shocks, which can be external (natural hazards, movements in markets, changes in policy environment) or internal (health problems, changes in household composition, social rituals) (Scoones, 2015). Three different types of coping mechanisms can be highlighted based on their reversibility: (i) reversible mechanisms (temporary activity shift, disposal of protective assets); (ii) erosive mechanisms (disposal of productive assets such as land); and (iii) destitution (unemployment, distress migration). Reversible mechanisms can be observed when some members take wage labour or migrate to find paid work (temporary activity shift) or when using self-insurance mechanisms, such as selling protective assets. Protective assets include any asset held as a store of value and that can be sold if the household faces an external shock, including cash, jewellery or livestock (Chena et al., 2013). Erosive mechanisms are usually implemented in response to heavy shocks or persisting stresses and undermine households' productive capacity. In the case of disposal of agricultural land, this leads to a long-term livelihood change, as households shift from cultivation to other activities, for example, agricultural labour. The last category of coping mechanisms comes as a last resort for the household and indicates its destitution, with household members becoming unemployed or choosing permanent out-migration.

In India, although the percentage of farmers with land access rights declined from 72 to 45% between 1951 and 2011, the percentage of landless agricultural labourers increased from 28 to 55% (Indian Ministry of Labour and Employment, 2015). This considerable rise in landless agricultural labourers is an indication that many households have put in place erosive mechanisms to cope with the impacts of agricultural shocks (Williams et al., 2016). However, the effects of such shocks vary widely across a broad geographic extent, with livelihood opportunities (and, thus, the ability to put in place reversible coping mechanisms) being conditioned by access to community capitals (Berchoux et al., 2019).

2 Conceptual framework

The approach taken in this paper (Figure 1) is based on the household livelihood strategy framework (Nielsen, Rayamajhi, Uberhuaga, Meilby, & Smith-Hall, 2013) and shows the different components used to understand how access to community capitals can influence the associations between precarious livelihoods, agricultural shocks and livelihood capitals.

A livelihood system combines the capabilities, assets and activities of one household to achieve its means of living (Scoones, 2015). Assets are resources that people have access to, which can be private goods (household capitals) or public goods (community capitals). Household assets are grouped into a set of five livelihood capitals: natural (private natural resource stocks), physical (productive assets), financial (liquidities and protective assets), human (capabilities and capacities of the households) and social (networks and kinships). Regarding community capitals, three categories can be differentiated (Flora, Flora, & Gasteyer, 2015): common-pool natural resources, social services (access to social amenities) and productive infrastructures (road networks, markets and industries). Based on their access to community and household assets, households put in place a range of livelihood activities to achieve their basic needs. Livelihood opportunities depend on the household and community capitals that households have access to. The combination of capitals and activities leads to livelihood outcomes if the household does not face any shocks, which are reinvested in the system. In the case of a shock (internal or external), households can implement three types of coping strategies depending on their assets, as well as public assets from the community they live in: reversible mechanisms (activity shift, sell of protective assets), disposal of productive assets (sell land) and destitution (unemployment, distress migration).

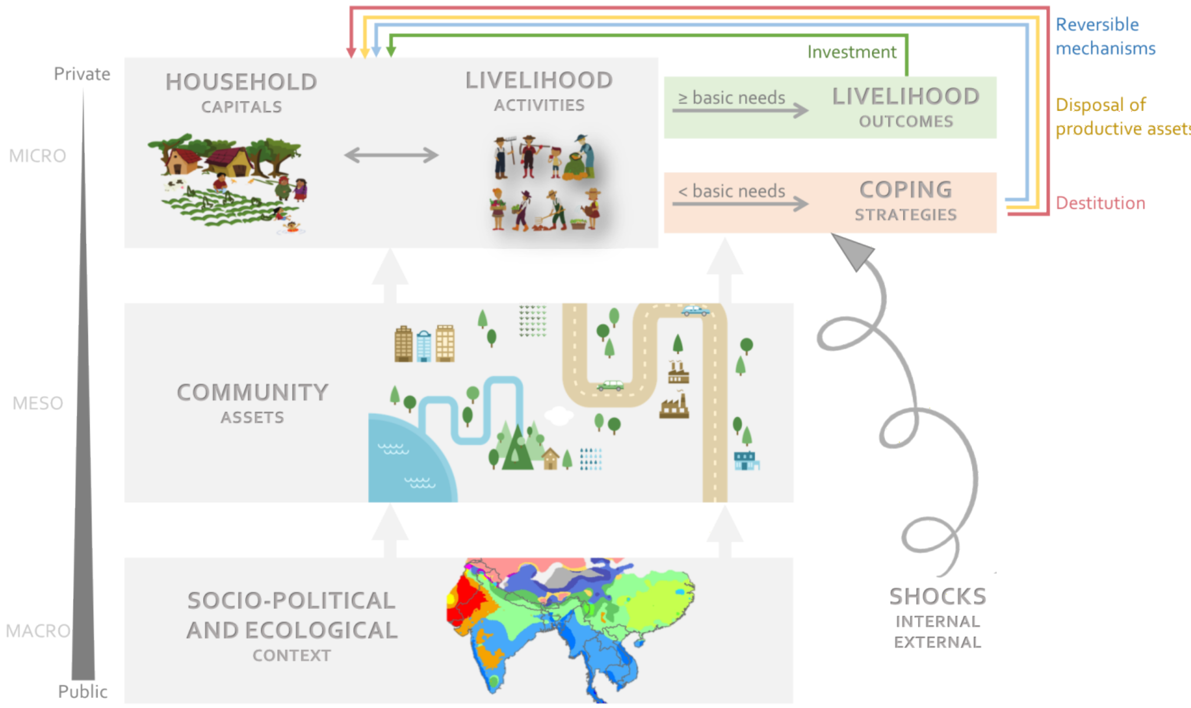


Figure 1: Dynamic multilevel livelihood framework.

165

3 Methods

Most of the people who live in deltas rely on agriculture to ensure their food security and to generate economic incomes. However, deltas are exposed to multiple stressors arising from both terrestrial (such as run-off from rivers) and marine processes (such as storms, waves or sea-level from oceans), which are a threat for rural populations relying on agriculture for their livelihoods. Moreover, deltas are one of the most exposed ecosystems to climate change (Ericson, Vorosmarty, Dingman, Ward, & Meybeck, 2006). As a consequence, rural households located in deltas that rely on agriculture are amongst the most vulnerable to climate change, as their main livelihood is highly vulnerable to the projected increase in the frequency of floods and droughts. Despite the ecological services they perform, the economic value they generate and that they are home to around 500 million people (Ericson et al., 2006), little attention has been paid to deltas as a socio-ecological unit. Therefore, we selected the Mahanadi Delta located within the state of Odisha in East India as study site.

3.1 Study site

The Mahanadi Delta in Odisha, India, is a populous delta where livelihood opportunities are affected negatively by environmental stressors, such as floods, droughts cyclones, erosion and storm surges. The combination of environmental stresses has resulted in a loss of income for rural households who are dependent on agriculture for their livelihoods (68% of the delta's population), due to major crop failures (Duncan, Tompkins, Dash, & Tripathy, 2017). As a consequence of their inability to cope with the impacts of environmental shocks, many households have to sell off their agricultural land. Their members often become unemployed with limited livelihood opportunities to move out of poverty, either to migrate or become agricultural labourers (Sahu & Dash, 2011).

This research focused on an area covering the five districts of the Mahanadi Delta in Odisha, eastern India: Bhadrak, Jagatsinghpur, Kendrapara, Khorda and Puri (**Error! Reference source not found.**). Given that communities are statutory units in India with a definite boundary and separate land records, we used the administrative boundaries provided by the Registrar General and Census Commissioner (2011) for our analysis. In total, 9,829 rural communities were considered.

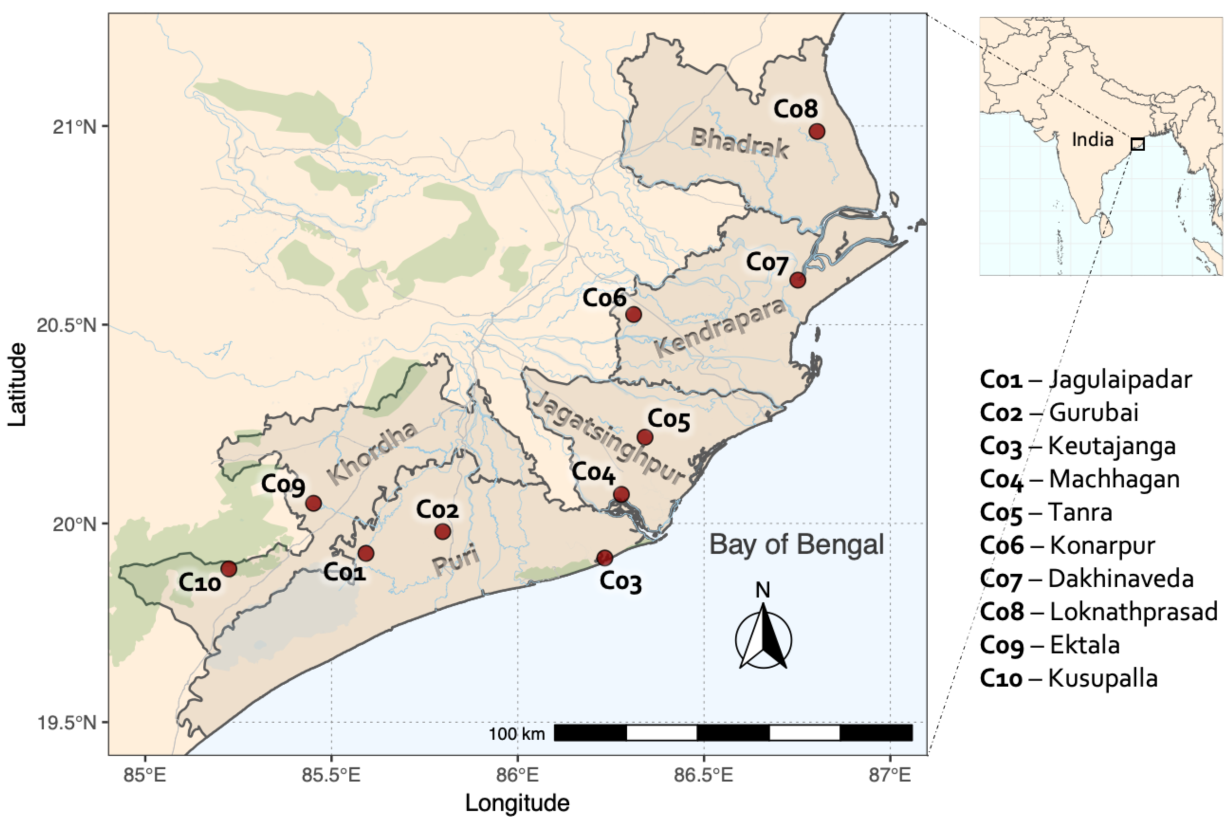


Figure 2: Location of the study area. *The study area covers all five districts (Bhadrak, Jagatsinghpur, Kendrapara, Khorda and Puri) located within the Mahanadi Delta. Rapid Rural Appraisals were conducted in ten communities (C01-C10).*

3.2 Local perceptions of the drivers of livelihood strategies

Fieldwork was conducted between February and May 2016 to identify indicators that stakeholders, experts and local residents perceive as representative and robust to examine the effects of community and household capitals on their livelihoods. A Rapid Rural Appraisal (RRA) was used for data collection to highlight the perceptions and opinions of rural dwellers (Supplementary Material S1). This method enables local people to share their knowledge and discuss their situation using their own terms (Mukherjee, 2005). In total, ten communities were selected by using stratified random sampling based on their access to community capitals and on the main livelihood activities conducted by households (Fig. 2).

A variety of additional activities were used to cross-check the data acquired from the RRA. First, a focus group was held to identify general information about the village and the evolution of its infrastructure. The focus group also investigated differences in livelihood assets and strategies within the community which were combined into a series of categories by the participants. The proportion of households falling into each livelihood category were subsequently quantified by the participants. The last activity was a participatory photography workshop using the photovoice methodology (Wang & Burris, 1997) on the theme of “Key assets to achieve your livelihoods”; a theme broad enough to let the participants themselves highlight the different roles that community and household capitals play in their decision to pursue an economic activity.

3.3 Developing Community Typologies

Every community has common-pool resources (i.e. road, market, forest, lake) that can provide services for rural dwellers' livelihoods. For example, a road can provide farmers with alternative outlets for their agricultural production, while a forest can give the opportunity for households to collect and sell non-timber forest products. Such common-pool resources appear together repeatedly in the landscape, creating bundles of community capitals (Bański & Mazur, 2016). We used cluster analysis on 18 variables derived from open source data to generate community typologies. Indicators were selected based on participatory rural appraisals conducted in ten communities located across the Mahanadi delta. Participants argued that remoteness plays an important role in their access to community capitals, and thus in their choice of livelihood strategy. As a consequence, we used travel time to key amenities rather than amenity availability to reflect community remoteness in the cluster analysis. Euclidean distances are inappropriate for this purpose as the Mahanadi delta has several water bodies, which act as boundaries to travel. We thus estimated accessibility to key amenities by creating a least accumulative cost surface to estimate time (in hours) to travel from each community to the nearest amenity of interest, using the R package “gdistance” (van Etten, 2017).

3.3.1 Estimating accessibility

We downloaded road data from OpenStreetMap, using the R package “osmdata” (Padgham, Rudis, Lovelace, & Salmon, 2017). Roads were converted to a raster with 30 m spatial resolution and merged with 30 m spatial resolution land cover data from 2010 GlobeLand30 (Chen et al., 2014). Based on a previous study in India (Watmough, Atkinson, Saikia, & Hutton, 2016), average speeds were assigned to each land cover class (Table 1) and were based on travel by foot across land covers and footpaths and travel by motorised vehicles on other forms of road and track.

Table 1: Estimated travel speeds for different land cover types (based on Watmough et al. 2016). *Pedestrian movement was assumed where no roads exist, travel by motor vehicles was assumed where roads are available and travel by boat was assumed on waterways. Speeds were then used to generate travel cost to nearest amenities.*

Class	**Estimated speed** ($\mathrm{min.km}^{-1}$)
ROAD TYPE	
Trunk	0.6
Primary	0.8
Secondary	1.2
Tertiary	2.0
Footpath	20.0
LAND COVER	
Water	20.0
Evergreen needleleaf trees	36.0
Evergreen broadleaf trees	60.0
Deciduous needleleaf trees	48.0
Deciduous broadleaf trees	36.0
Shrub	36.0
Grass	24.0
Cereal crops	36.0
Broadleaf crops	36.0
Urban and built-up	2.0
Barren or sparse vegetation	24.0

3.3.2 Variables for community typologies

In total, 18 variables were chosen to be included in the cluster analysis (Table 2). These were selected to represent the diversity of drivers that were highlighted by participants during the participatory rural appraisals. They can be grouped into three categories, natural resources, social services and productive infrastructure. Locations of the main amenities were extracted from the Village Amenities tables of the 2011 Indian National Population and Household Census and from OpenStreetMap data. We used 2010 MODIS data at 250 m spatial resolution to obtain a land cover dataset detailing the different types of cropping systems found in the delta (Gumma et al., 2014). Travel costs to the nearest amenity of interest were computed from the least accumulative cost surface dataset mentioned earlier. In situations where multiple indicators for the same service were found (type of education or health facility), we favoured the indicator that exhibited the greatest variation among communities. Based on the results from RRA (S1), travel times to six types of amenities were chosen to reflect access to social services: public services and polling stations, secondary schools, banks and credit cooperatives, hospitals, worship temples and recreational areas, such as sports centres and playgrounds. Three amenities were used to reflect access to productive infrastructures: travel time to communication services, agricultural outlets and industrial areas. Availability of public transport was also chosen to represent productive infrastructures, as they can be used by smallholders to access agricultural markets. Eight variables were chosen to reflect the natural resources from which most households derived their incomes, seven of which were derived from satellite sensor data and one from OpenStreetMap data (Table 2). The variables to reflect the natural resources included: the area of forest, the area of cropland available per household, the type of agricultural system (based on the proportion of each cropping pattern within the community) and the travel time from each community to the nearest aquaculture ponds. These variables were chosen since the number of growing seasons and the availability of irrigation systems can be a determinant for livelihood outcomes.

Table 2: Variables used for community typologies. *Indicators for social services are based on travel times to the closest service found by using a least accumulative cost surface dataset, computed from road networks and land cover data. Natural services are derived from agricultural-relevant metrics from land cover data.*

Variables	Description	Source
NATURAL RESOURCES		
Forest	Total area of forest	MODIS
Cropland	Total area of cropland	MODIS
Single rainfed	Proportion of cropland cultivated as single rice rainfed	MODIS
Single mixed	Proportion of cropland cultivated as single mixed crops rainfed	MODIS
Single irrigated	Proportion of cropland cultivated as single rice irrigated	MODIS
Double irrigated	Proportion of cropland cultivated as double rice irrigated	MODIS
Triple irrigated	Proportion of cropland cultivated as triple rice irrigated	MODIS
Aquaculture	Travel time to aquaculture farms	OSM
SOCIAL SERVICES		
Official	Travel time to public services and polling station	Census
Education	Travel time to secondary school	Census
Banks	Travel time to closest financial service amenity	Census
Health	Travel time to nearest hospital	Census
Worship	Travel time to closest worship area	OSM
Recreation	Travel time to closest recreation area	OSM
PRODUCTIVE INFRASTRUCTURES		
Transport	Availability of public transport	Census
Communication	Travel time to closest communication services (public phone, post)	Census
Market	Travel time to closest market or agricultural outlet	Census
Industry	Travel time to industrial area	OSM

3.3.3 Clustering method

We used a model-based clustering method to avoid the limitations of deterministic procedures, such as hierarchical and *k*-means clustering algorithms. As demonstrated by (Raykov, Boukouvalas, Baig, & Little, 2016), these two popular clustering methods rely on restrictive assumptions that lead to severe limitations in accuracy and interpretability. In particular, these algorithms cluster data points based on geometric closeness to the cluster centroid, without taking cluster densities into account. Therefore, they implicitly assume that each cluster must contain the same number of data points, which is a biased assumption for building community typologies. On the contrary, model-based clustering considers that the data comes from a distribution that is a mixture of two or more clusters, and assigns to each data point a probability of belonging to each cluster (C Fraley & Raftery, 2002). Each cluster is modelled by the

Gaussian distribution and is characterised by its mean vector, covariance matrix and the probability of each point belonging to this cluster. These parameters are estimated using the Expectation-Maximisation algorithm, which is initialised by hierarchical model-based clustering. The covariance matrix determines the geometric shape of each cluster, the latter being centred at the mean, around which there is an increased density of points. The model with the greatest integrated likelihood, or Bayesian Information Criterion (BIC), is considered as the best fitting model. We used the R package "mclust" (Chris Fraley, Raftery, Murphy, & Scrucca, 2012) to implement the model-based clustering algorithm, which estimated the best finite mixture model according to different covariance structures and different numbers of clusters.

3.4 Quantifying livelihood capitals

The quantification of livelihood capitals was based on register data at the village level from a subset of the 2011 Indian National Population and Household Census. The variables selected to quantify livelihood capitals are proxies for the participants' views, regarding the capitals that they perceived as determinant for their livelihood opportunities (Supplementary Material S2). Given the high correlation amongst the selected variables, a principal component analysis was used to circumvent the problem of multicollinearity and to derive a single factor score for each capital. Multiple factors were not combined as this would have distorted what the component represents and would have made interpretation difficult (McKenzie, 2005). After ensuring that the factor loadings corresponded with the conceptualisation of each capital based on the RRA activity, the first factor score was selected to represent each capital. Low loading factors ($|\lambda| \leq 0.2$) were kept as excluding them would have distorted the views from RRA participants. Moreover, McKenzie (2005) showed that low loading factors should be included when measuring inequality, especially when the variable is a known (or perceived) determinant of poverty.

Table 3: List of variables used for the quantification of household livelihood capitals. *The associated factor loading retrieved from the PCA represents the weight for each variable in the construction of their associated livelihood capital. The justification for the inclusion of each variable is based on participants' views from participatory rural appraisals.*

Category	Variables	Source	Weight	Justification from Rapid Rural Appraisal
NATURAL CAPITAL				
Cropland	Average area sown per cultivator	Census	0.382	Influences households' incomes and food security.
Tree plantation	Average area of tree crops per cultivator	Census	0.398	Enables households to generate extra incomes.
Pasture	Average area of pasture per cultivator	Census	0.440	Enables households to develop livestock rearing.
PHYSICAL CAPITAL				
Electricity	No access to electricity (%)	Census	−0.083	Lack of electricity prevents households to conduct their livelihood activity (to operate agricultural pumps and machinery).
Means of transportation	Access to bicycle (%)	Census	0.445	Enables households to look for new outlets for their production and increase their access to nearby social services through the reduction of travel times.
	Access to motorcycle (%)	Census	0.530	
	Access to car (%)	Census	0.400	
HUMAN CAPITAL				
Dependency ratio	Number of inactive per active person	Census	−0.687	High dependency limits the range of activities that the household can put in place and reduces investment.
Illiteracy	Illiterate individuals (%)	Census	−0.687	Educated members were a strength for one household because they "did not suffer from unemployment".
FINANCIAL CAPITAL				
Financial services	Access to financial services (%)	Census	0.682	Enables households to invest in their other capitals and develop their livelihood opportunities.
Housing conditions	"Dilapidated" houses (%)	Census	−0.682	Value and condition of housing represents the financial condition of households.
SOCIAL CAPITAL				
Marital status	No married couples (%)	Census	−0.395	Marriage is one of the most important kinship encountered at the household level in rural settings.
Mobile phone	Ownership of mobile phone (%)	Census	0.569	Mobile phones enable households to communicate with migrants and strengthen networks.

3.5 Quantifying precarious livelihoods

The census indicators comprise population enumeration including cultivators, agricultural labourers, entrepreneurs and unemployed. Detailed examinations of poverty structures in rural India show that households engaged in agricultural labour or the unemployed are the poorest of the rural poor (Ravi and Engler, 2015). We, thus, defined precarious livelihoods as the proportion of working-age people (15-59) who are engaged in agricultural labour or unemployed, as defined in the Census of India. The census defines a person as an agricultural labourer if they work on another person's land for wages in money or kind or share, with no right of lease or contract on the land on which they work, while a person is defined as a non-worker if they do not engage in any economically productive activity for more than 6 months per year.

3.6 Proxying climate shocks

Extreme events, such as heat waves, droughts, floods and cyclones are becoming more frequent and both their frequency and intensity are likely to increase in the future (Baker et al., 2018). Extreme weather events can result in agricultural losses, which can lead to shifts from transient to chronic poverty (Krishnan & Dercon, 2000). Decreases in agricultural production can be identified by remotely sensed satellite sensor data in the form of abrupt changes in vegetation greening (Liu, Liu, & Yin, 2013). This section presents the materials and methods used to detect decreases in agricultural production, which are used as proxies of weather shocks (see Supplementary Material S3 and S4 for R codes).

3.6.1 Choosing a vegetation index to capture crop production

We used the Wide Dynamic Range Vegetation Index (WDRVI) as it preserves a linear relationship with LAI/vegetation fraction and captures well crop growth dynamics. It was also found to be more accurate than other vegetation indices at estimating crop yield over the Mahanadi Delta (Duncan, Dash, & Atkinson, 2015). The index is calculated following the equation:

$$WDRVI = \frac{\alpha * \rho_{NIR} - \alpha * \rho_{red}}{\alpha * \rho_{NIR} + \alpha * \rho_{red}}$$

Where ρ_{NIR} is the near-infrared reflectance, ρ_{red} the red reflectance and α a weighting parameter selected by the user. A weighting of α = 0.20 was used, as it has been found to be the optimum value to monitor phenological processes when using computer-intensive algorithms (Testa, Soudani, Boschetti, & Borgogno Mondino, 2018). We used band 1 (ρ_{red}, 620-670 nm) and band 2 (ρ_{NIR}, 841-876 nm) from MODIS surface reflectance products to compute the WDRVI at a spatial resolution of 250 m and a temporal resolution of every 8-days for the time period 2000 to 2011 (506 composite images from 26/02/2000 until 26/02/2011.

3.6.2 Detecting breaks in crop production

The Breaks For Additive Season and Trend (BFAST) technique was used to detect changes in time-series of WDRVI to identify crop failures. This method was used to determine the number, type, and timing of trend and seasonal changes within historical time-series (Verbesselt, Hyndman, Newnham, & Culvenor, 2010). It estimates the dates, the magnitude and direction of change without setting a threshold or defining a reference period, and thus can be used to characterise changes occurring in seasonal and trend components. The general decomposition model fits a piecewise linear trend T_t and a seasonal model S_t, and is of the form: $Y_t = T_t + S_t + e_t$, with $t = 1,\ldots, n$. The ordinary least squares (OLS) residuals-based MOving SUM (MOSUM) test is used to detect whether one or more breakpoints are occurring. If breaks are occurring, the number and position of breaks are determined by minimising the residual sum of squares and by minimising an information criterion, such as the Bayesian Information Criterion (BIC). The intercept and slope of consecutive linear models are used to characterise the magnitude and direction of abrupt changes in the trend.

Figure 3 presents the outputs from the break detection in the WDRVI time-series, where only negative breaks were considered. The algorithm was run on pixels that were used for agricultural production throughout 2000-2011. Pixels that changed land use during that period (i.e. specifically if they were converted to urban) were not included to prevent the detection of falsebreaks due to land use changes. Thanks to the linear correlation that exists between WDRVI and crop yield over the Mahanadi Delta (Duncan et al., 2015), breaks in WDRVI time-series represent abrupt changes in crop production, and negative breaks are thus considered to represent crop failures. Moreover, Watts and Laffan (2014) showed that breaks in vegetation indices detected by BFAST corresponded with the timing of known floods in the study region for between 68% and 79% of breaks detected across the sample pixels. Taken together, these studies indicate that the BFAST method is able to detect abrupt changes in vegetation greening caused by climatic hazards. We thus consider negative breaks in the WDRVI time-series as proxies of weather shocks that had a negative impact on crop production.

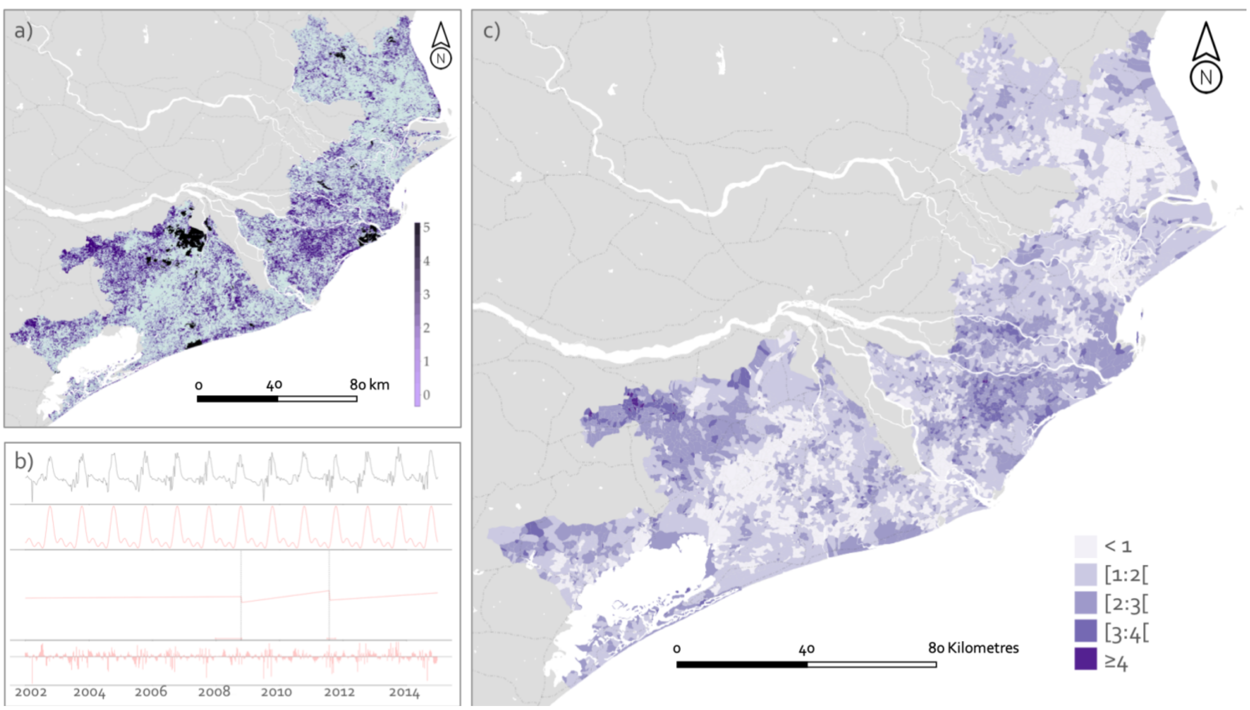


Figure 3: Breaks in WDRVI time series detected using BFAST. *For each pixel, the time series is decomposed into its seasonal and trend components to identify breakpoints using the Breaks For Additive Season and Trend (BFAST) technique. Figure b shows an example of the decomposition of the WDRVI time series for one random pixel, highlighting two breaks. These breaks represent shocks in the agricultural production. The maps show the count of negative breaks in croplands: per pixel at a resolution of 250 m (map a); and averaged at the village level for modelling purposes (map c).*

3.7 Statistical modelling

Multilevel regression techniques were used to control for contextual factors, by allowing the model to vary at the Tehsil level. To characterise how community typologies affect the associations between livelihood capitals, crop failures and precarious livelihood activities, we fitted separate models for each one of the village types identified through model-based clustering. Access to livelihood capitals is mediated by overarching systems of power, the demographic pressure and the local political context, which have been shown to be one of the main causal determinants of poverty in India (Lerche, 2009). To avoid inferring any definite causal relationship, we controlled for these mediating factors by using the respective proxy variables: proportion of scheduled castes and tribes, population density and District. For each community type, a two-level random intercept model was fitted using the R package "R2MLwiN" (Charlton, Rasbash, Browne, Healy, & Cameron, 2017):

$$\text{logit}_{\text{Cluster}}(\pi_{ij}) = \log\left(\frac{\pi_{ij}}{1-\pi_{ij}}\right) = \beta_{0j} + \beta_1 \text{District}_{ij} + \beta_2 \text{PopDensity}_{ij} + \beta_3 \text{SCST}_{ij} + \beta_4 \text{Breaks}_{ij}^{\text{WDRVI}} + \beta_5 \text{Natural}_{ij} + \beta_6 \text{Physical}_{ij} + \beta_7 \text{Human}_{ij} + \beta_8 \text{Financial}_{ij} + \beta_9 \text{Social}_{ij},$$

where π_{ij} refers to: the probability of being engaged in precarious livelihoods (unemployment and agricultural labour) for the village *i* in the Tehsil *j*. Each level 1 unit (village) had an associated denominator n_i, which was the total number of people of working age (every person aged 15-59. Two sets of explanatory variables were considered: livelihood capitals and the number of breaks in the WDRVI time-series, as a proxy of the number of crop failures. As the response variable is binomial, we used a linearisation method in the model to transform the discrete response model (binomial) to a continuous response model (Goldstein, 2003), with a Maximum Likelihood modelling approximation method to estimate the unknown parameters of interest in the model.

4 Results

4.1 Typology of rural communities

The clustering of 18 variables in three domains (natural resources, social services and productive infrastructures) resulted in five distinct clusters being identified. These formed the basis for five community typologies that could be used to investigate how the place-based relationships between livelihood precariousness, agricultural shocks and household capitals. The five community types were spatially clustered in the landscape (Figure 4) and each was named based on the type of services available to the community and on the dominant land cover class.

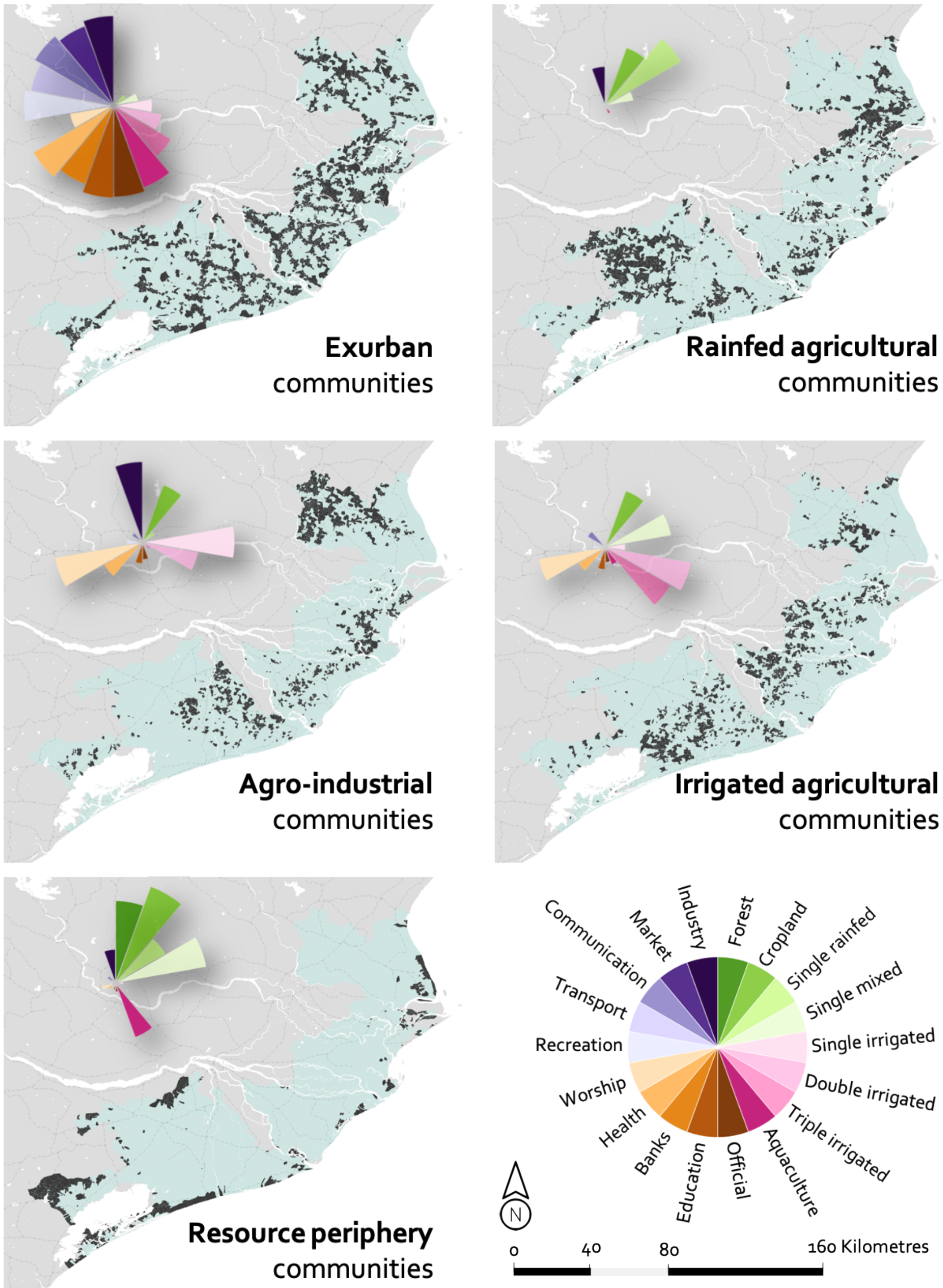


Figure 4: Community typologies as identified by model-based clustering*. Types of communities were identified based on their access to natural resources, social services and productive infrastructures. Five clusters were identified: communities with great access to productive infrastructures and social services (exurbs), production communities with low agricultural infrastructures (rainfed agricultural) and with irrigation infrastructures (irrigated agricultural), production communities with industries (agro-industrial) and remote communities with high natural resources (resource periphery).*

4.1.1 Exurban communities

This cluster reveals a clear geographic profile, with a total of 2,245 communities (total population of 1,928,232) located in the near vicinity of main roads. It reveals characteristics that are ascribed to communities well connected to urban and peri-urban areas, defined as exurbs. This cluster is characterised by a high availability of public transport and close proximity to markets (19 minutes average travel time) and industries (1h 29 minutes average travel time). Communities also have high levels of access to social services such as education (10 minutes average travel time) and health facilities (45 minutes average travel time) and are located near local official institutions (average travel time of 8 minutes). The main agricultural systems are a combination of freshwater aquaculture, irrigated rice crop grown once (22.8% of cropland area on average), twice (19.0% of cropland area on average) and thrice (22.1% of cropland area on average) per year. However, although the total area of land devoted to agriculture is lower than for other clusters (average of 91 ha), the average farm size is 1.07 ha per cultivator.

4.1.2 Rainfed agricultural communities

This cluster represents a total of 2,563 agricultural communities (total population of 2,511,527) mainly located in the south western and north-eastern parts of the delta. These communities are characterised by low access to social services (average travel times to secondary schools, hospitals and public offices are 56, 2h14 and 32 minutes respectively) and productive infrastructures, such as markets (average travel time of 1h 21 minutes) and industries (average travel time of 3h03 minutes). The main agricultural system is single rice crop (38.3% of cropland area on average) or single mixed crops (14.6% of cropland area on average) grown in rainfed conditions. The total cultivated area in each community is 101 ha on average, with an average farm size of 1.00 ha per cultivator.

4.1.3 Agro-industrial communities

The 2,174 communities (total population of 2,122,436) of this cluster are located in the northern part of the delta and in the south of the axis Bhubaneswar-Cuttack. They have a high access to worship amenities, a relatively high access to other social services (average travel times to secondary schools, hospitals and public offices are 51, 2h05 and 30 minutes respectively) combined with a greater proximity to industrial areas (1h 51 minutes average travel time) and markets (1h 14 minutes average travel time) compared to the other agricultural communities. The main agricultural system is irrigated rice crop grown once (36.5% of cropland area on average) or twice (20.0% of cropland area on average) per year. The communities within this cluster have an average cultivated area of 97 ha for an average of 0.96 ha per cultivator.

4.1.4 Irrigated agricultural communities

The 2,438 agricultural communities (total population of 2,422,307) of this cluster are located in the central part of the delta and near the Chilika lake. They share similar characteristics with agro-industrial communities in terms of their access to social services (average travel times to secondary schools, hospitals and public offices are 53, 2h04 and 30 minutes respectively) but with lower access to productive infrastructures (average travel times to markets and industries are respectively 1h17 and 2h57). However, unlike rainfed communities, the irrigated agricultural communities are characterised by a high share of irrigated rice crop grown twice (24.1% of cropland on average) and thrice (23.5% of cropland area on average) per year. The area of cropland is on average 98 ha in total and 0.99 ha per cultivator in the cluster.

4.1.5 Resource periphery communities

The 409 resource periphery communities (total population of 362,797) are located in remote areas, far from market towns and urban centres. These communities are characterised by a very low access to social services (average travel times to secondary schools, hospitals and public offices are 1h06, 3h18 and 41 minutes respectively) and to productive infrastructures (average travel time to industries: 4h10; and to markets: 1h40). Due to the lack of irrigation infrastructures, the main agricultural systems are single mixed crops (34.7% of cropland area on average) and single rice crop grown in rainfed conditions (26.5% of cropland area on average). The communities within this cluster are characterised by the dominance of natural resources, such as forests (area of 0.92 ha on average), proximity to aquaculture ponds and a large cropland area with an average of 1.11 ha per cultivator for a total cultivated area of 112 ha on average.

4.2 Statistical modelling

Odds ratios were used to quantify the relationships between the response variable (proportion of people engaged in precarious livelihood activities) and the explanatory variables (livelihood capitals and number of agricultural shocks), controlling for district and population density effects, but also for the effects of class and caste (Table 4). An odds ratio above one indicates that, as the explanatory variable increases, the odds of being engaged in precarious livelihood activities also increase. When explanatory variables are categorical (e.g. “District”), odds are interpreted by comparing the variable level to a reference (district “Bhadrak”). For example, in rainfed agricultural communities, an odds ratio of 0.74 for Jagatsinghpur can be interpreted as: the likelihood of being engaged in precarious livelihood activities for communities located in Jagatsinghpur is 26% lower compared to communities located in Bhadrak.

Table 4: Results of the logistic models for each community. *The dependent variable represents the odds of engaging in precarious activities (agricultural labourers and unemployed) for people who are within the legal working age. The explanatory variables represent the capitals that households have access to and the number of agricultural shocks that the community faced between 2000 and 2011.*

	EXURBAN OR [95% CI]	RAINFED AGRI. OR [95% CI]	AGRO-INDUSTRIAL OR [95% CI]	IRRIGATED AGRI. OR [95% CI]	RESOURCE PERIPH. OR [95% CI]
CONFOUNDERS					
District					
Bhadrak	1.00	1.00	1.00	1.00	1.00
Jagatsinghpur	0.97 [0.89, 1.05]	0.74 [0.69, 0.80] ***	0.77 [0.72, 0.84] ***	0.81 [0.75, 0.88] ***	0.97 [0.77, 1.22]
Kendrapara	0.97 [0.89, 1.04]	0.88 [0.82, 0.95] ***	0.86 [0.80, 0.93] ***	0.89 [0.83, 0.96] **	1.04 [0.85, 1.26]
Khordha	0.90 [0.83, 0.98] *	0.79 [0.73, 0.85] ***	0.83 [0.77, 0.89] ***	0.78 [0.72, 0.85] ***	0.90 [0.74, 1.10]
Puri	0.84 [0.77, 0.90] ***	0.78 [0.72, 0.83] ***	0.74 [0.69, 0.79] ***	0.76 [0.71, 0.82] ***	0.78 [0.65, 0.94] **
Population Density	0.94 [0.90, 0.97] ***	1.02 [0.90, 1.15]	1.05 [0.93, 1.18]	0.94 [0.85, 1.04]	1.05 [0.86, 1.27]
Castes and Tribes	1.13 [1.04, 1.22] **	0.94 [0.88, 1.01]	1.14 [1.06, 1.22] ***	1.05 [0.98, 1.13]	0.95 [0.80, 1.13]
HOUSEHOLD CAPITALS					
Natural	1.11 [1.02, 1.20] *	0.80 [0.64, 0.99] *	0.77 [0.61, 0.95] *	1.03 [0.85, 1.26]	0.81 [0.52, 1.27]
Physical	0.99 [0.96, 1.02]	0.98 [0.96, 1.01]	0.96 [0.94, 0.99] **	1.01 [0.99, 1.04]	1.00 [0.93, 1.07]
Human	0.83 [0.81, 0.85] ***	0.90 [0.88, 0.92] ***	0.93 [0.91, 0.95] ***	0.87 [0.85, 0.89] ***	0.87 [0.82, 0.93] ***
Financial	0.89 [0.87, 0.91] ***	0.93 [0.91, 0.95] ***	0.90 [0.87, 0.92] ***	0.89 [0.86, 0.91] ***	0.92 [0.86, 0.99] *
Social	0.87 [0.85, 0.89] ***	0.92 [0.91, 0.94] ***	1.03 [1.01, 1.05] **	0.99 [0.97, 1.00]	0.94 [0.89, 0.98] **
SHOCKS					
Agri. shocks	0.99 [0.97, 1.01]	1.07 [1.05, 1.09] ***	1.02 [1.00, 1.05]	1.07 [1.05, 1.09] ***	1.08 [1.03, 1.13] **
RANDOM EFFECTS					
Gram Panchayat	1.31 [1.29, 1.34] ***	1.30 [1.28, 1.32] ***	1.30 [1.27, 1.32] ***	1.29 [1.27, 1.31] ***	1.30 [1.24, 1.36] ***

**Indicates a significance level of 0.01 *Indicates a significance level of 0.05

Amongst the five household capitals, human and financial capital show consistent associations across all clusters: a greater access to these decreases the odds of being engaged in precarious livelihood activities (Table 4). The effect of human capital is the strongest in exurban communities (OR = 0.83, 95% CI = 0.81, 0.85) and the weakest in agro-industrial communities (OR = 0.93, 95% CI = 0.91, 0.95), while the effect of financial capital is the weakest in remote communities, such as rainfed agricultural (OR = 0.93, 95% CI = 0.91, 0.95) and resource periphery (OR = 0.92, 95% CI = 0.86, 0.99). The model shows that access to transportation and to electricity (physical capital) is associated with lower odds of engaging in precarious livelihood activities only for households located in agro-industrial communities (OR = 0.96, 95% CI = 0.94, 0.99). The odds of having a precarious livelihood decrease with greater access to natural capital in rainfed agricultural (OR = 0.80, 95% CI = 0.64, 0.99) and agro-industrial (OR = 0.77, 95% CI = 0.61, 0.95) communities, whereas it is the contrary in exurban communities (OR = 1.11, 95% CI = 1.02, 1.20). Social capital was found to be negatively associated with the odds of having a precarious livelihood in exurban (OR = 0.87, 95% CI = 0.85, 0.89), rainfed agricultural (OR = 0.92, 95% CI = 0.91, 0.94) and resource periphery (OR = 0.94, 95% CI = 0.89, 0.98) communities, but positively associated in agro-industrial communities (OR = 1.03, 95% CI = 1.01, 1.05).

The models show that it is more likely that households will engage in precarious livelihood activities when the number of agricultural shocks increases, except for exurban communities (OR = 0.99, 95% CI = 0.97, 1.01) and agro-industrial communities (OR = 1.02, 95% CI = 1.00, 1.05) where associations between shocks and livelihoods are not significant. Figure 5 shows the predicted probability of being engaged in precarious livelihood activities depending on the number of agricultural shocks faced by the community during the ten previous years. From these data, we can see that the probability of precarious livelihoods strongly increases with the number of agricultural shocks in agricultural-based communities with low access to productive infrastructures, such as rainfed agricultural, irrigated agricultural and resource periphery. However, we found that the number of agricultural shocks does not have a significant effect on precarious livelihoods in exurban and agro-industrial communities.

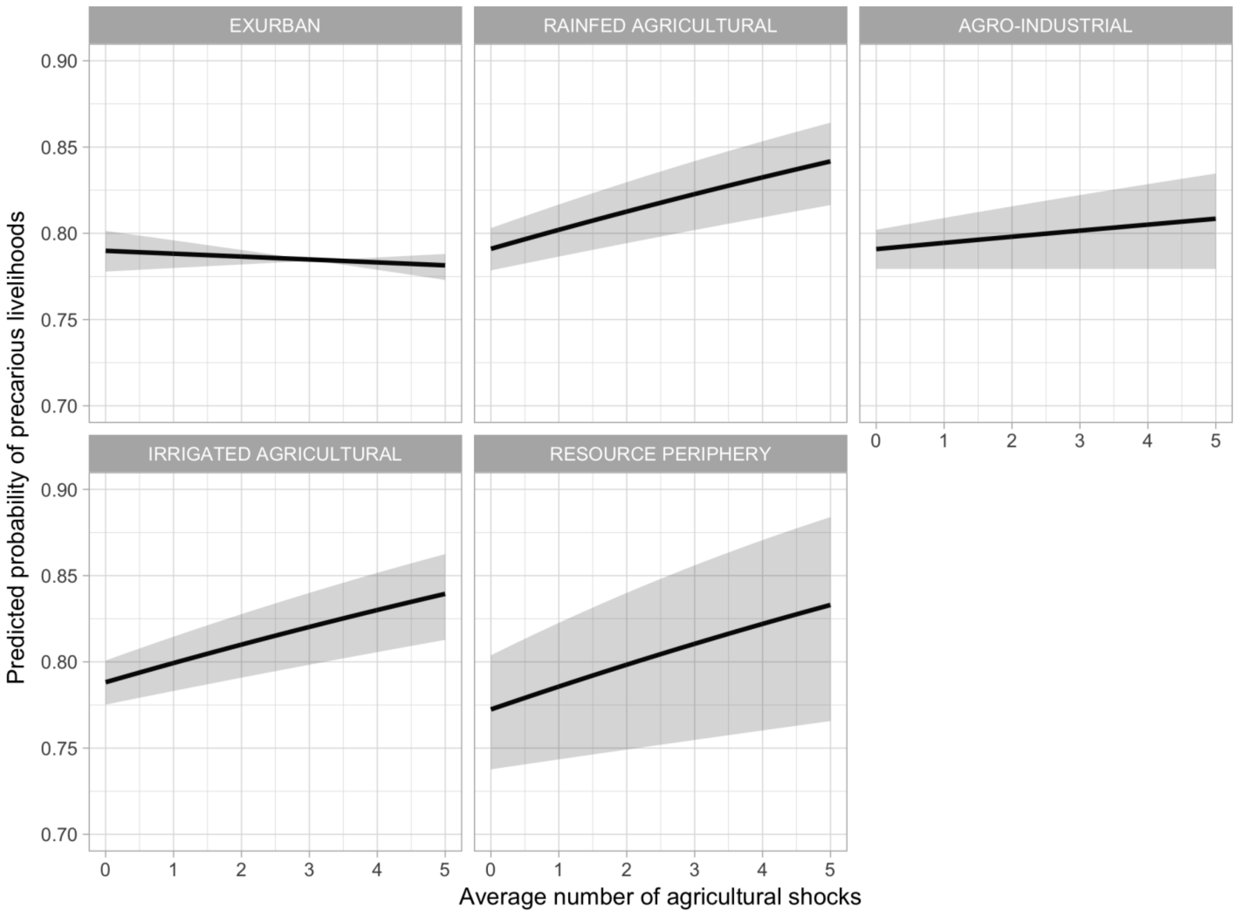


Figure 5: Predicted probability of precarious livelihoods conditioned on the average number of agricultural shocks for each community typologies. *Based on multiple logistic models (Table 4). The range of values in the x-axes are constrained to number of shocks that are likely to be observed in the area over 10 years. The envelope includes the mean plus or minus one standard error.*

Results for the control variables indicated that there was a significant and negative effect of population density on the odds of being engaged in precarious livelihoods only in exurb communities: an increase in population density is associated with a decrease in the odds of being an agricultural labourer or unemployed (OR = 0.94, 95% CI = 0.90, 0.97). It is also apparent that belonging to disadvantaged groups (scheduled castes and tribes) increases the odds of being engaged in precarious livelihoods only in exurban (OR = 1.13, 95% CI = 1.04, 1.22) and agro-industrial communities (OR = 1.14, 95% CI = 1.06, 1.22). Households located in Puri and

Jagatsinghpur have lower odds of engaging in precarious activities, compared to those located in Bhadrak, especially in rainfed agricultural communities (OR_{Puri} = 0.78, 95% CI = 0.72, 0.83; ($OR_{Jagatsinghpur}$ = 0.74, 95% CI = 0.69, 0.80).

5 Discussion

This paper presents a geographical perspective of livelihood systems and of the impact of agricultural shocks on livelihood activities. The results suggest that multiple agricultural shocks increase the probability for households engaging in precarious livelihood activities in most rural communities, except for those located near main roads and higher levels of productive infrastructures. Another important finding is that access to human capital and to financial capital are associated with more stable livelihoods, such as cultivation, self-employment and salaried employment. Self-employment, defined as household industry work in the census of India, is considered here as a more desirable livelihood compared to agricultural labour and joblessness as it is associated with greater returns to capital and skills (Falco & Haywood, 2016). Our findings also indicate that access to physical capital significantly reduces the likelihood of being engaged in agricultural labour or being unemployed only in agricultural communities with irrigation infrastructures and located near industrial areas (agro-industrial landscapes). We found that an increase in natural capital is associated with a decrease in the likelihood of having a precarious livelihood in rainfed agricultural and agro-industrial landscapes. Importantly, our findings show that this trend is reversed in exurban communities.

5.1 Climate change impacts on livelihoods and poverty

Our findings showed no significant associations between agricultural shocks and the likelihood of engaging in precarious livelihood activities in exurban communities and only weak associations in agro-industrial communities, when compared to more remote clusters. These results suggest that investments in infrastructure, such as connections to market centres and social services, provide households with a greater flexibility and agency to cope with climate shocks. Overall, the impact of an increase in the variance of climate will probably lead to a greater variability in agricultural productivity and to a greater number of crop failures (Challinor et al., 2014). The findings from this study support the idea that such changes are likely to drive households into precarious livelihood strategies, thus exacerbating rural poverty especially in remote rural agricultural communities. Although the probability to be an agricultural labourer or unemployed in resource periphery communities is lower than in other clusters in the absence of shocks, we found that it is the cluster where households' livelihoods are the most likely to be negatively impacted by crop failure. Arguably, the most important result from this research is that rural typologies should be included in the design of climate change assessments to take into account the differential vulnerability of communities to crop failure.

5.2 Spatial dimensions of livelihoods

Rural poverty is spatially distributed, with factors such as institutional linkages, access to and control over resources affecting livelihood opportunities. Previous studies showed that the sensitivity of on-farm and off-farm livelihood strategies to livelihood capitals exhibit different patterns depending on the type of settlement considered (Fang et al., 2014). Our findings demonstrate that the probability of engaging in precarious livelihoods depends on households' access to capitals, and that the type of community in which households live modifies this association. For example, financial capital has a weaker effect on livelihoods in remote communities than in exurban communities, natural capital is associated with more precariousness in exurban communities but reduces the likelihood of precarity in single rice crop agricultural systems and physical capital is a determinant only in agro-industrial communities.

In remote communities that did not benefit from the technological packages of the green revolution, such as rainfed agricultural and agro-industrial communities, farmers have kept traditional single rice cropping systems (Gumma et al., 2014). We found that in these communities, access to natural capital has a positive effect on stable livelihood strategies, notably because of the increased probability to engage in cultivation. This finding was also reported by van den Berg (2010) who showed that lack of access to natural resources in rural areas can drive households into more precarious on-farm activities such as daily-wage labour. However, access to natural capital is associated with precarious livelihoods in exurban communities. A similar finding is likely to be related to the connection of such communities to urban centres: proximity to market increases the pressure on farm holdings, encourages smallholders' land dispossession and thus leads to the cornering of natural resources by a few large-scale farmers (Manjunatha, Anik, Speelman, & Nuppenau, 2013). Previous research has demonstrated that a larger average of cropland per household was associated with fewer large-scale farms owning the natural resources (Levien, 2013). This hypothesis is further supported by the descriptive statistics presented earlier, showing that the area of cropland per cultivator in exurban communities is amongst the largest of all clusters, despite having the lowest average of cropland area. It shows that smallholders in exurban communities are more likely to be driven out of agriculture than in the other types of rural communities.

The findings show that access to human and financial capitals has a positive effect on the probability of engaging in stable livelihood strategies. Access to financial services and workforce availability enable households to decrease the barrier to engage in more remunerative on-farm activities, but also to engage in off-farm livelihood strategies (Jansen, Pender, Damon, Wielemaker, & Schipper, 2006). Our typology of rural communities shows that the effect of financial capitals is weaker in remote communities with rainfed agricultural systems (rainfed agricultural, resource periphery). These differences can be explained in part by the physical lack of access to job opportunities in remote communities: although access to financial services helps households to decrease the barrier to engage in stable activities, the lack of livelihood opportunities reduces the positive impact of access to financial capital (Zenteno, Zuidema, de Jong, & Boot, 2013). We found that access to physical capital reduces the probability of engaging in precarious activities, but only in agro-industrial communities. This result highlights the link between physical capital and off-farm strategies: private means of transportation enables households to reach more livelihood opportunities.

The overarching influence of social and cultural norms on lowest castes' access to decent employment depends on the proximity to productive infrastructures and markets. People who belong to disadvantaged groups are more likely to be engaged in precarious labour in exurban and agro-industrial communities, confirming that people with higher caste status have better endowments required for absorption in the non- farm market (Chandrasekhar & Mitra, 2018). On the contrary, it appears that the effect of caste is not the most significant driver to explain the causes of precarious livelihoods in more remote communities. This surprising result can be explained by the prevalence of culturally homogeneous communities in Odisha's remote areas, thus reducing its influence on access to land ownership and assets (Lakerveld, Lele, Crane, Fortuin, & Springate-Baginski, 2015).

5.3 Policy relevance

The above findings suggest several courses of action for public policies in India to reduce rural outmigration and reduce rural poverty. The National Rural Livelihood Mission (NRLM) aims to enable the poorest households to access self-employment and skilled wage employment opportunities seems to be well targeted to help reduce livelihood precarity. This research supports the scheme's main focus of strengthening human (skill building), financial (access to credit) and physical (access to markets) capitals for the poorest households, through their participation in strong and sustainable grassroots institutions (Self-Help Groups). However, important changes would need to be made to ensure that it plays a role in long-term poverty alleviation. We would argue that the NRLM should include community typologies in its approach to provide an opportunity for place-specific activities to strengthen livelihoods of the rural poor. In exurban communities, such activities could focus on human capital (skills) to ensure that households are able to adapt their livelihoods to off-farm strategies. In agro-industrial communities, schemes focusing on strengthening household physical capital, especially through the ownership of private means of transportation, would enable households to diversify their livelihood opportunities. In remote agricultural communities, in addition to activities strengthening human and financial capitals, the NRLM should work hand in hand with the Mahatma Gandhi National Rural Employment Guarantee Act (MGNREGA) to ensure work stability throughout the year, especially during the lean season. Finally, agricultural tenancy laws should be implemented and enforced to regulate rents and offer security of tenure to tenants. Interventions in property rights would prevent land grabbing by agro-industries and increase smallholders' bargaining power and secure their productive assets, thus reducing livelihood precarity.

Overall, the findings demonstrate that conducting place-based analyses of the determinants of livelihood strategies is necessary to design effective policies for poverty alleviation and rural development. Community typologies based on selected key indicators are an effective way to implement such analyses in order to highlight the different drivers of precarity within the landscape.

6 Conclusion

This research makes several contributions to the current literature. First, it defined a set of indicators that adequately capture the multi-dimensional and multi-attribute nature of rural communities and household capitals. Two different methods were used to obtain the final results: a deductive binning of indicators into different categories based on participatory rural appraisals, followed by an inductive indicator method constructed via model-based clustering for community typologies and via principal components analysis for household capitals.

Second, the community typologies show a distinct spatial pattern, highlighting a profile of rural communities with similar bundles of capitals. It was demonstrated that the type of rural community in which households live modifies the associations between livelihood capitals and precarious livelihoods. Access to physical capital reduces the likelihood of being engaged in precarious activities only in communities located near industrial areas, where people can find alternative livelihood opportunities. In rural communities, access to natural capital has a positive effect on stable livelihood strategies, notably because of the increased probability to engage in cultivation, while it has a negative effect in exurban communities, showing that smallholders in these places are more likely to be driven out of agriculture than in the other agricultural communities. Our results also demonstrate that lack of access to financial services and workforce unavailability prevent households to profit by local job opportunities that would enable them to engage in more sustainable livelihoods. Finally, people who belong to disadvantaged groups are more likely to be engaged in precarious labour in exurban and agro-industrial communities, confirming that people with higher caste status have better endowments required for absorption in the off-farm market and for land-ownership where agricultural land is scarce.

Third, the paper demonstrated quantitatively that the type of rural community in which households live modifies households' opportunities for coping strategies. The findings show that recurrent weather shocks are a driver of precarious livelihoods, except in exurban communities where the number of crop failures faced by the community does not influence livelihood opportunities. This result is explained by the availability of off-farm livelihood opportunities in well-connected communities: households can engage in off-farm daily wage activities as a coping strategy, preventing them to sell their productive assets and thus to become agricultural labourers or unemployed.

A final caveat is that this paper did not address the persistent difficulty in quantifying livelihood dynamics in the long-term, including questions of asset trade-off and migration. Nevertheless, such a quantitative analysis has a wider application for rural development policies seeking to make livelihoods more resilient to climate hazards and to reduce poverty. Identifying typologies of rural communities is useful for assessing needs and targeting intervention or mitigation programs. It provides an approach for policy makers to take into account the contextual factors that drive livelihood precarity and thus to target more strategically anti-poverty programmes to maximise their effect rather than equally distributing them across all places. Interventions should focus on strengthening human and physical capitals in well-connected communities to ensure that households are able to diversify their livelihoods to off-farm strategies, while they should be targeted on providing financial capital and complementary livelihood opportunities during lean season in remote areas.

Bibliography

Agarwal, B. (2018). Can group farms outperform individual family farms? Empirical insights from India. *World Development*, *108*, 57–73. http://doi.org/10.1016/j.worlddev.2018.03.010

Ahmed, S. A., Diffenbaugh, N. S., & Hertel, T. W. (2009). Climate volatility deepens poverty vulnerability in developing countries. *Environmental Research Letters*, *4*. http://doi.org/10.1088/1748-9326/4/3/034004

Alessa, L., Kliskey, A., & Altaweel, M. (2009). Toward a typology for social-ecological systems. *Sustainability: Science, Practice, & Policy*, *5*(1), 31–41. http://doi.org/10.1080/15487733.2009.11908026

Angelsen, A., Jagger, P., Babigumira, R., Belcher, B., Hogarth, N. J., Bauch, S., … Wunder, S. (2014). Environmental Income and Rural Livelihoods: A Global-Comparative Analysis. *World Development*, *64*(S1), S12–S28. http://doi.org/10.1016/j.worlddev.2014.03.006

Baker, H. S., Millar, R. J., Karoly, D. J., Beyerle, U., Guillod, B. P., Mitchell, D., … Allen, M. R. (2018). Higher CO2 concentrations increase extreme event risk in a 1.5 °c world. *Nature Climate Change*, *8*(7), 604–608. http://doi.org/10.1038/s41558-018-0190-1

Bański, J., & Mazur, M. (2016). Classification of rural areas in Poland as an instrument of territorial policy. *Land Use Policy*, *54*, 1–17. http://doi.org/10.1016/j.landusepol.2016.02.005

Berchoux, T., & Hutton, C. W. (2019). Spatial associations between household and community livelihood capitals in rural territories: An example from the Mahanadi Delta, India. *Applied Geography*, *103*(February), 98–111. http://doi.org/10.1016/j.apgeog.2019.01.002

Berchoux, T., Watmough, G. R., Johnson, F. A., Hutton, C. W., & Atkinson, P. M. (2019). Collective influence of household and community capitals on agricultural employment as a measure of rural poverty in the Mahanadi Delta, India. *Ambio*. http://doi.org/10.1007/s13280-019-01150-9

Bhandari, P. B. (2013). Rural livelihood change? Household capital, community resources and livelihood transition. *Journal of Rural Studies*, *32*, 126–136. http://doi.org/10.1016/j.jrurstud.2013.05.001

Birthal, P. S., Roy, D., & Negi, D. S. (2015). Assessing the impact of crop diversification on farm poverty in India. *World Development*, *72*(i), 70–92. http://doi.org/10.1016/j.worlddev.2015.02.015

Challinor, A. J., Watson, J., Lobell, D. B., Howden, S. M., Smith, D. R., & Chhetri, N. (2014). A meta-analysis of crop yield under climate change and adaptation. *Nature Climate Change*, *4*(March), 287–291. http://doi.org/10.1038/NCLIMATE2153

Chandrasekhar, S., & Mitra, A. (2018). Migration, caste and livelihood: evidence from Indian city-slums. *Urban Research and Practice*, *00*(00), 1–17. http://doi.org/10.1080/17535069.2018.1426781

Charlton, C., Rasbash, J., Browne, W. J., Healy, M., & Cameron, B. (2017). MLwiN. Centre for Multilevel Modelling, University of Bristol.

Chen, J., Chen, J., Liao, A., Cao, X., Chen, L., Chen, X., … Mills, J. (2014). Global land cover mapping at 30 m resolution: A POK-based operational approach. *ISPRS Journal of Photogrammetry and Remote Sensing*, *103*, 7–27. http://doi.org/10.1016/j.isprsjprs.2014.09.002

Chena, H., Zhu, T., Krotta, M., Calvo, J. F., Ganesh, S. P., & Makot, I. (2013). Measurement and evaluation of livelihood assets in sustainable forest commons governance. *Land Use Policy*, *30*(1), 908–914. http://doi.org/10.1016/j.landusepol.2012.06.009

de Sherbinin, A., VanWey, L. K., McSweeney, K., Aggarwal, R., Barbieri, A., Henry, S., … Walker, R. (2008). Rural household demographics, livelihoods and the environment. *Global Environmental Change*, *18*, 38–53. http://doi.org/10.1016/j.gloenvcha.2007.05.005

Duncan, J. M., Dash, J., & Atkinson, P. M. (2015). The potential of satellite-observed crop phenology to enhance yield gap assessments in smallholder landscapes. *Frontiers in Environmental Science*, *3*(August), 1–16. http://doi.org/10.3389/fenvs.2015.00056

Duncan, J. M., Tompkins, E. L., Dash, J., & Tripathy, B. (2017). Resilience to hazards: rice farmers in the Mahanadi Delta, India. *Ecology and Society*, *22*(4). http://doi.org/10.5751/ES-09559-220403

Ericson, J., Vorosmarty, C., Dingman, S., Ward, L., & Meybeck, M. (2006). Effective sea-level rise and deltas: Causes of change and human dimension implications. *Global and Planetary Change*, *50*(1–2), 63–82. http://doi.org/10.1016/j.gloplacha.2005.07.004

Falco, P., & Haywood, L. (2016). Entrepreneurship versus joblessness: Explaining the rise in self-employment. *Journal of Development Economics*, *118*, 245–265. http://doi.org/10.1016/j.jdeveco.2015.07.010

Fang, Y., Fan, J., Shen, M., & Song, M. (2014). Sensitivity of livelihood strategy to livelihood capital in mountain areas: Empirical analysis based on different settlements in the upper reaches of the Minjiang River, China. *Ecological Indicators*, *38*, 225–235. http://doi.org/10.1016/j.ecolind.2013.11.007

Flora, C. B., Flora, J. L., & Gasteyer, S. P. (2015). *Rural communities: Legacy+ change*.

Fraley, C., & Raftery, A. (2002). Model-based clustering, discriminant analysis, and density estimation. *Journal of the American Statistical Association*, *97*(458), 611–631. http://doi.org/10.1198/016214502760047131

Fraley, C., Raftery, A. E., Murphy, T. B., & Scrucca, L. (2012). mclust Version 4 for R: Normal Mixture Modeling for Model-Based Clustering, Classification, and Density Estimation. *Technical Report 597, University of Washington*, 1–50.

Goldstein, H. (2003). *Multi-level statistical models* (3rd editio). London: Arnold. http://doi.org/10.1902/jop.1992.63.8.690

Gumma, M. K., Mohanty, S., Nelson, A., Arnel, R., Mohammed, I. a., & Das, S. R. (2014). Remote sensing based change analysis of rice environments in Odisha, India. *Journal of Environmental Management*, *148*, 31–41. http://doi.org/10.1016/j.jenvman.2013.11.039

Hall, R., Edelman, M., Borras, S. M., Scoones, I., White, B., & Wolford, W. (2015). Resistance, acquiescence or incorporation? An introduction to land grabbing and political reactions 'from below.' *Journal of Peasant Studies*, *42*(3–4), 467–488. http://doi.org/10.1080/03066150.2015.1036746

Indian Ministry of Labour and Employment. (2015). *India Labour year book 2011 and 2012*. Retrieved from http://labourbureau.nic.in/ILYB_2011_2012.pdf

Jansen, H. G. P., Pender, J., Damon, A., Wielemaker, W., & Schipper, R. (2006). Policies for sustainable development in the hillside areas of Honduras: a quantitative livelihoods approach. *Agricultural Economics*, *34*(2), 141–153. http://doi.org/10.1111/j.1574-0864.2006.00114.x

Jiao, X. I., Pouliot, M., & Walelign, S. Z. (2017). Livelihood Strategies and Dynamics in Rural. *World Development*, (May). http://doi.org/10.1016/j.worlddev.2017.04.019

Krishnan, P., & Dercon, S. (2000). Vulnerability, Seasonality and Poverty in Ethiopia. *Journal of Development Studies*, *36*(6), 25–51.

Lakerveld, R. P., Lele, S., Crane, T. A., Fortuin, K. P. J., & Springate-Baginski, O. (2015). The social distribution of provisioning forest ecosystem services: Evidence and insights from Odisha, India. *Ecosystem Services*, *14*, 56–66. http://doi.org/10.1016/j.ecoser.2015.04.001

Lerche, J. (2009). From ‘rural labour’to ‘classes of labour’: class fragmentation, caste and class struggle at the bottom of the Indian labour hierarchy. In *The Comparative Political Economy of Development* (pp. 90–111). Routledge.

Levien, M. J. (2013). Regimes of Dispossession: Special Economic Zones and the Political Economy of Land in India. *The Journal of Peasant Studies*, *39*(October), 933–969.

Liu, G., Liu, H., & Yin, Y. (2013). Global patterns of NDVI-indicated vegetation extremes and their sensitivity to climate extremes. *Environmental Research Letters*, *8*(2), 025009. http://doi.org/10.1088/1748-9326/8/2/025009

Manjunatha, A. V., Anik, A. R., Speelman, S., & Nuppenau, E. A. (2013). Impact of land fragmentation, farm size, land ownership and crop diversity on profit and efficiency of irrigated farms in India. *Land Use Policy*, *31*, 397–405. http://doi.org/10.1016/j.landusepol.2012.08.005

McKenzie, D. J. (2005). Measuring inequality with asset indicators. *Journal of Population Economics*, *18*(2), 229–260. http://doi.org/10.1007/s00148-005-0224-7

Nielsen, Ø. J., Rayamajhi, S., Uberhuaga, P., Meilby, H., & Smith-Hall, C. (2013). Quantifying rural livelihood strategies in developing countries using an activity choice approach. *Agricultural Economics*, *44*(1), 57–71. http://doi.org/10.1111/j.1574-0862.2012.00632.x

Padgham, M., Rudis, B., Lovelace, R., & Salmon, M. (2017). R Package “‘osmdata.’”

Palmer-Jones, R., & Sen, K. (2006). It is where you are that matters: The spatial determinants of rural poverty in India. *Agricultural Economics*, *34*(3), 229–242. http://doi.org/10.1111/j.1574-0864.2006.00121.x

Raykov, Y. P., Boukouvalas, A., Baig, F., & Little, M. A. (2016). What to do when K-means clustering fails: A simple yet principled alternative algorithm. *PLoS ONE*, *11*(9), 1–28. http://doi.org/10.1371/journal.pone.0162259

Registrar General and Census Commissioner. (2011). *Census Data 2011*. New Delhi, India.

Sahu, S. K., & Dash, M. (2011). Expropriation of Land and Cultures: The Odisha Story and Beyond. *Social Change*, *41*(2), 251–270. http://doi.org/10.1177/004908571104100204

Scoones, I. (2015). *Sustainable livelihoods and rural development*. Practical Action Publishing.

Singh, P. K., & Hiremath, B. N. (2010). Sustainable livelihood security index in a developing country: A tool for development planning. *Ecological Indicators*, *10*(2), 442–451. http://doi.org/10.1016/j.ecolind.2009.07.015

Testa, S., Soudani, K., Boschetti, L., & Borgogno Mondino, E. (2018). MODIS-derived EVI, NDVI and WDRVI time series to estimate phenological metrics in French deciduous forests. *International Journal of Applied Earth Observation and Geoinformation*, *64*(August 2017), 132–144. http://doi.org/10.1016/j.jag.2017.08.006

Turner, K. G., Odgaard, M. V., Bøcher, P. K., Dalgaard, T., & Svenning, J. C. (2014). Bundling ecosystem services in Denmark: Trade-offs and synergies in a cultural landscape. *Landscape and Urban Planning*, *125*, 89–104. http://doi.org/10.1016/j.landurbplan.2014.02.007

van den Berg, M. (2010). Household income strategies and natural disasters: Dynamic livelihoods in rural Nicaragua. *Ecological Economics*, *69*(3), 592–602. http://doi.org/10.1016/j.ecolecon.2009.09.006

van der Zanden, E. H., Levers, C., Verburg, P. H., & Kuemmerle, T. (2016). Representing composition, spatial structure and management intensity of European agricultural landscapes: A new typology. *Landscape and Urban Planning*, *150*, 36–49. http://doi.org/10.1016/j.landurbplan.2016.02.005

Van Eetvelde, V., & Antrop, M. (2009). A stepwise multi-scaled landscape typology and characterisation for trans-regional integration, applied on the federal state of Belgium. *Landscape and Urban Planning*, *91*(3), 160–170. http://doi.org/10.1016/j.landurbplan.2008.12.008

van Etten, J. (2017). R Package gdistance : Distances and Routes on Geographical Grids . *Journal of Statistical Software*, *76*(13). http://doi.org/10.18637/jss.v076.i13

Verbesselt, J., Hyndman, R., Newnham, G., & Culvenor, D. (2010). Detecting trend and seasonal changes in satellite image time series. *Remote Sensing of Environment*, *114*(1), 106–115. http://doi.org/10.1016/j.rse.2009.08.014

Wang, C., & Burris, M. A. (1997). Photovoice: Concept, Methodology, and Use for participatory Needs Assessment. *Health Education & Behavior*, *24*(3), 369–387.

Watmough, G. R., Atkinson, P. M., Saikia, A., & Hutton, C. W. (2016). Understanding the Evidence Base for Poverty–Environment Relationships using Remotely Sensed Satellite Data: An Example from Assam, India. *World Development*, *78*, 188–203. http://doi.org/10.1016/j.worlddev.2015.10.031

Watts, L. M., & Laffan, S. W. (2014). Effectiveness of the BFAST algorithm for detecting vegetation response patterns in a semi-arid region. *Remote Sensing of Environment*, *154*(1), 234–245. http://doi.org/10.1016/j.rse.2014.08.023

Williams, L. J., Afroz, S., Brown, P. R., Chialue, L., Grünbühel, C. M., Jakimow, T., … Roth, C. H. (2016). Household types as a tool to understand adaptive capacity: case studies from Cambodia, Lao PDR, Bangladesh and India. *Climate and Development*, *8*(5), 423–434.

http://doi.org/10.1080/17565529.2015.1085362

Yang, G., Ge, Y., Xue, H., Yang, W., Shi, Y., Peng, C., … Chang, J. (2015). Using ecosystem service bundles to detect trade-offs and synergies across urban-rural complexes. *Landscape and Urban Planning*, *136*, 110–121. http://doi.org/10.1016/j.landurbplan.2014.12.006

Zenteno, M., Zuidema, P. A., de Jong, W., & Boot, R. G. A. (2013). Livelihood strategies and forest dependence: New insights from Bolivian forest communities. *Forest Policy and Economics*, *26*, 12–21. http://doi.org/10.1016/j.forpol.2012.09.011

Acknowledgement

This work was carried out under the Deltas, vulnerability and Climate Change: Migration and Adaptation (DECCMA) project under the Collaborative Adaptation Research Initiative in Africa and Asia (CARIAA) programme, with financial support from the UK Government's Department for International Development (DFID), the International Development Research Centre (IDRC) (Canada) [grant number 107642] and the UK Economic and Social Research Council [grant number 1501613]. The views expressed in this work are those of the creators and do not necessarily represent those of DFID, IDRC, ESRC or its Boards of Governors. Prior to commencing the study, ethical clearance was obtained from the University of Southampton [ERGO number 15234]. Data used in this research come from the Census of India provided by the Office of the Registrar General & Census Commissioner of India. The authors acknowledge the use of the IRIDIS High Performance Computing Facility, and associated support services at the University of Southampton, in the completion of this work. The authors wish to thank all participants for providing their time and knowledge. Additional gratitude goes to Shubashree Samal and Pratap Malla who both helped in the organisation, planning and interpretation of field visits.

S1 - Results from Rapid Rural Appraisal

Local residents and stakeholders identified key factors which impact their livelihood opportunities. The following sections provide a reminder of the main capitals highlighted and their associations with livelihood activities.

S1.1. Community capitals

Public and common-pool assets were classified as community capitals and were further categorised into natural resources, social services and productive infrastructures based upon the views of the stakeholders and local residents.

Natural resources. The most important natural capital raised by the participants was land, used for agricultural purposes. Different characteristics fell under common-pool natural resources: (i) the size of cropland, pasture and fallow available in the community; and (ii) the topography and agro-meteorology of the land.

The total area of agricultural land (including cropland, pasture and fallow) was perceived as a positive community asset, especially in remote communities. According to participants, a greater area of cultivated area in the village enabled the creation of a supply force that would attract traders to come. For example, in the community C10, it was the fact that many households decided to breed goats that led traders to come and buy them. Interestingly, households who were engaged in non-agricultural activities also confirmed that a greater total surface of agricultural land in the village catalyses economic activities and livelihood opportunities. For agricultural households, the topography of the village was perceived as a key resource or as a key problem depending on the community visited (Table 1): communities who only had access to high lands for agriculture could cultivate their crops during one season only (*kharif*) and had to leave the land barren during *rabi*, while the one with access to low land could cultivate two crops per year (with an associated increase of flood risk).

Table 1: Main types of land in the Mahanadi Delta based on topography. As defined by Odisha's department of agriculture and farmers' empowerment (source: authors' interviews).

Land *(type)*	**Cultivated area** *(10^5 hectares)*	**Paddy** *(%)*	**Characteristics**
High	29.14	36	Drought-prone, no irrigation, low yield, usually one season
Medium	17.55	91	Flood-prone (flash floods), lower yield than low land
Low	14.82	98	Flood-prone (water logging), irrigated, high paddy yield

Beside land, participants raised the importance of access to open-water resources and to forest resources. Proximity to a lake, a river or the sea gave households the opportunity to diversify their livelihood activities and food security through fishing, shrimp farming or kitchen gardening (manual irrigation from local ponds). Concerning forest resources, different products were traded, such as timber (wood, charcoal) and non-timber forest products (bamboo, *sal* seeds, *kendu* leaves and *mahuwa* flowers).

The availability of irrigation canals and tanks in the community, mainly associated with the green revolution, plays a major role into mitigating the effects of weather shocks on agricultural production (through droughts or floods) and was mentioned as a key community capital.

Such irrigation facilities are considered as common-pool resources because they were publicly funded by the State Surface Flow Irrigation Schemes and most households are able to benefit from them regardless of their class or castes. For example, participants from non-agricultural households mentioned that they were able to collect water from the canals to irrigate their house gardens for their supply of vegetables.

Social services. According to participants, education and sanitation facilities were perceived as the most important social services to take into account as community capitals.

One of the main issues raised by the women was their lack of access to community amenities, such as schools, sanitation facilities (latrines, drinking water) and to health facilities (health centre, hospital). According to them, a better access to health facilities and to safe water infrastructures would diminish the risk of health problems, while access to schools would enable their children to spend their day there, giving them time for other activities and increasing their future livelihood opportunities. Overall, they argued that proximity to these community amenities would enhance their labour capacity.

Proximity to a bank was also raised as critical when it comes to state schemes and pensions: for example households needed a bank account in order to get paid for work they conducted under the Mahatma Gandhi National Rural Employment Guarantee Act (MGNREGA). Female participants emphasised the importance of Self-Help Groups as alternatives to traditional financial services as they argued that they could get access to loans through them.

It also emerged from the discussion that availability of recreation facilities, such as *chaupal* (public community space or building) or sport fields was an important community capital that enabled to build strong kinships and that also prevented younger males to migrate out of the village for work.

Productive infrastructures. Road connectivity and proximity to marketing outlets appeared to be the most important assets. Having access to all-weather transportation infrastructures (roads) was perceived as a factor that improves working opportunities through access to marketing outlets (traders are able to come to buy goods directly in the community).

Although households benefit differently from such assets depending on their wealth and social networks, proximity to a marketing outlet or industrial area was mentioned as a key determinant to develop income-generating activities. A marketing outlet could be of different types, from general (such as a market) to more specific (such as a cooperative or society). Proximity to an outlet or to a specific industry acts as a catalyst for activity diversification, such as milk or raw-fish production.

> "After the creation of the milk society 7 years ago, we started to breed Jersey cows because they give more milk. Now we sell our milk there everyday, and it is it located at a walking-distance." - *Male participant, community C4* -

S1.2. Household capitals

Private assets were classified as household livelihood capitals and were further categorised into natural, physical, human, financial and social capitals based upon the views of the stakeholders and local residents.

Natural capital. The most important household natural capital raised by the participants was land, used for agricultural purposes. Different characteristics fell under this natural capital component: (i) the size of cropland, tree plantation and pasture available to one household; and (ii) the ownership status of this land, which is shaped by social relations of class and caste

The number of acres available per household was, according to the participants, the capital with the greatest influence on households' choice of a livelihood strategy. Indeed, households who had access to a greater number of acres (two acres and above) produced enough to be food secure during the whole year. The rest of the production could be sold or the extra land could be used for commercial crops such as cashew-nuts cultivation, *betel* (leaf used in *paan* for chewing) or coconut plantation. On the contrary, households with little access to agricultural land (less than one acre) could not produce enough food to be food secure, hence they had to go for extra income-generating activities to reach food security. Land ownership was also raised as a determining capital for livelihood strategies: share-croppers had to give a part of their production to the land owner (around 50% of the harvest), who are usually from higher castes. As a consequence, a share-cropper with access to one acre of land had, in fact, a production of only half acre of land (despite working on one acre of land).

> "A sharecropper with 1 acre of land has to give half of the harvest to the owner, who is from outside the village most of the time." - *Male participant, community C8* -

Physical capital. Access to productive assets (for agriculture, fisheries, or handicraft) and to means of transportation were the most important assets raised by participants.

Access to productive assets, such as draft animals, equipment (seeds, fertilisers), machinery (tractor with plow, water-pump, fishing boats) and means of transportation (bicycle, motorcycle, car), was also a raised by participants as determinants for their livelihoods. Means of transportation (either private or public) allowed households to look for new marketing outlets for their production and also to reduce travel times to nearby services. For participants, investing in productive assets would enable them to increase their agricultural or fishing productivity, thus increase incomes (for the same workforce and time spent). For example, some households were able to cultivate during *rabi* thanks to irrigation equipment they had invested in, such as water pumps.

> "We can't cultivate during *rabi*, there is water scarcity [...] I am the only one in the community who cultivates during *rabi* season, thanks to the water-pump I bought. I have 3 acres and I produce pulses, ginger, cucumber, sunflower and watermelon." - *Female participant, community C9* -

Human capital. According to participants, workforce and education were perceived as the most important assets to take into account in the human capital.

Due to the gendered division of labour, male participants described male workforce availability as the most important component of human capital for livelihood opportunities. Men were found to be in charge of cultivation and of earning incomes (through migration or daily-wage employment). For example, a household with only one man tended to engage in agriculture and would not be able to migrate as he had to look after the farm. As a consequence the household would look for daily-wage labour to diversify their incomes. On the contrary, if the household had more than 2 men, at least 1 man stayed to look after the farm and the rest were going for migration for 6 months (off-*kharif* season). The overall number of active members in the household also had a great influence on the range of livelihood activities the household could put in place. A great number of members allowed the household to cope faster in the case of an external shock, as all members could look for income-generating activities (mainly daily-wage labour). However, it was perceived that "large households" was a negative asset, as it was creating extra expenses for the households and increased the risk of food insecurity (decreased cropland area per person and thus problems of food security). It is interesting to note that women did not mention male workforce as a capital but they raised it as a social constraint that prevented the household to diversify their activities.

> "We didn't inherit from any land, we do share-cropping. We have three daughters, so my husband is the only man in the household. He cannot go for migration, he has to stay to take care of the household and of our agricultural land. So he is doing daily wage labour and we also rely on cow milk production." - *Female participant, community C4* -

At the household level, the presence of educated and skilled members was perceived as driving households towards a diversification of their activities. Actually, educated members were more likely to get a permanent employment in the public sector, such as teacher or administrator (at the *panchayat* or block level), or in the private sector (hairdresser, driver, etc.). They also were more likely to set up their own business such as service provider or trader. In some cases, there were also some specific skills that enabled members to go for "skilled" migration. The most famous example raised during the rapid rural appraisals were the plumbers from Pattamundai in Kendrapara, commonly called the "Plumbing Capital of India", who were going on long-term migration in other States of India and abroad and who were sending remittances back to their household in the community.

Financial capital. According to participants, the main financial resources of one household are invested in protective assets such as electronics (TVs, radios, phones), furniture, clothing and jewellery. For household who were not involved in livestock rearing, ownership of cattle and goat was also considered as a protective asset, used as a saving and insurance instrument. Protective assets were to be sold if the household faced an external shock (crop failure, death, disease, wedding). Having access to financial services was mentioned by the participants as providing two different services, savings and loans, although only better-off households were able to have savings in a bank account. Access to loans allowed households to invest in their means of production (agriculture or other income-generating activities) or to cope with external shocks and reduced the likelihood of distress migration.

Participants primarily mentioned the importance of having access to banks in order to obtain formal financial services. However, due to the privatisation of these institutions after the liberalisation, tenant cultivators are denied access to formal credits. The inability for smallholder farmers to access formal credit forces them to rely on "informal sources", such as the traders who provide agricultural inputs or local moneylenders with usurious interest rates. Such dynamics push farmers into a long-term indebtedness, which undermine their future financial capital and livelihoods.

Social capital. Participants felt that family connections were a key asset to find job opportunities and to be integrated into migration networks, arguing that household size helps to expand networks. While discussing with widows, it emerged that unmarried or widowed households were to suffer from social exclusion, especially from community groups and unions.

S1.3. Local perceptions of the effects of livelihood capitals on activities

The findings from rapid rural appraisals show that participants perceive that there is a link between households' access to livelihood capitals and their choice of a livelihood activity.

Household-level drivers. On-farm activities as main livelihood are driven by a great access to natural and physical capitals. Large farms provide higher incomes to farmers and therefore, increase farm survival. Quality and quantity of agricultural land have a positive effect on engaging into cultivation, while having access to productive capital is likely to lead to a specialisation into commercial agriculture. The caste system also plays a role in the choice of conducting an activity, for example fishing: fishermen is perceived as a job for the low castes. As a consequence, dwellers from higher castes do not go fishing, even if they have access to water resources and even under the circumstance of an external shock.

> "We can't go fishing because we are not from the fisherman caste, we are from the general caste." - *Male participant, community C3* -

The drivers of off-farm activities mainly fall under human, financial and social capitals. Permanent employment and self-employment are both positively influenced by the level of education of the household's members and by their ownership of protective assets. Starting a business or migrating requires a financial input, either to buy equipment to start the business, or to pay for transport and accommodation for migrants. Moreover, being able to migrate also depends on the strength of social networks (or migration networks) and on the communication facilities one household has access to. Households take the decision to have one of their members migrating only if there is a man that can stay to take care of the farm. Availability of male workforce is a key driver of migration and more specifically of seasonal migration.

Community-level drivers. According to the findings, livelihoods were found to be shaped by their geography and access to common goods, managed at the community level. The literature points out that access to common-pool resources is shaped by social relations of castes, lowest castes being prevented to access water or forest resources. However, the rapid rural appraisals conducted within this study showed that access to norms of self-identity, with middle-castes preventing themselves to use some common-pool resources, as it might be seen as an activity for lower castes, confirming previous studies. Similarly, regarding irrigation facilities, although clandestine encroachment and tampering with the water course can be found among wealthy farmers of dominant castes, who rely upon their status to assuage dissent and on political connections to suppress official complaints, inequalities in water access depend more on the ability to monopolise groundwater supplies by digging expensive and uncertain bore-wells than on monopolisation of tank water.

The total agricultural area of the community was perceived as a stimulating factor for cultivation, as it motivates traders to come directly to the community in order to buy the goods. Evidence suggests that an increase in the access to operational land reduces the tendency to close down farms, thus reducing the likelihood of farm exit and of households engaging in precarious livelihoods. The total agricultural area in the village has a positive effect over the possibilities of other capitals: it can create synergies between farmers to buy agricultural equipment (physical capital), invest into irrigation infrastructures (physical capital) or in can increase their bargaining power. The success of most agricultural activities depends on the capacity of households to sell their products and so is also dependent of a good road connection with an outlet nearby. Access to water resources is a *sine qua non* condition to conduct fishing activities, but making a living out of it also requires an access to outlets to sell the products and to private fishing equipment. Concerning forest resources, activities are independent of the existence of an outlet nearby, they rely on good road connections and on the area of forest available, which provides households with high value-added products (*sal* seeds, *kendu* leaves, *mahuwa* flower). Selling these products to traders that come directly to the communities to buy the goods enable households to earn extra income and to cope better with external shocks. Access to communal lay land, defined as customary communal tenure that can be used for animal grazing, is an incentive to put in place livestock rearing activities.

The main difference between the two communities relies upon the proportion of dwellers involved in "others" activities, which can be attributed to their road connectivity, *Keutajanga* benefiting from the proximity to a trading-centre (Puri), while *Kusupalla* is more remote. Proximity to trading-centres with community amenities was perceived as driving off-farm activities. This can be explained by the very good connectivity and the proximity of a market for both communities. It is interesting to note that *Dakhinaveda* and *Loknathprasad* have a very different structure of livelihood activities even though they are located nearby, thus should benefit from a similar access to natural and physical capitals. A possible explanation for this might be that both communities suffer from land erosion, Loknathprasad being much more affected due to its exposure to three rivers whereas Dakhinaveda is exposed to one. As a conclusion, participants perceived that their access to community capitals have an influence on the type of livelihood activities they put in place. Natural resources and productive infrastructures are perceived as drivers of on-farm activities, while the combination of social services seem to induce off-farm activities.

Overarching drivers. Interestingly, no participants mentioned the issues of scheduled castes and tribes until a conflict emerged during one of the activity. Separate discussions were then held with the participants involved in the incident and the theme of social balance emerged. Participants from a caste in minority in the community reported that the unbalanced ratio between general castes and scheduled castes, tribes and other backward castes had led to one caste taking over the other and to the exclusion of some of them from the community social groups such as SHG. As a consequence, participants felt that their community networks were impoverished.

> "In our hamlet, scheduled caste is the main population; we general caste are a minority now. SC are the majority and they have a strong voice so they have the power. As general caste, we do not benefit from governmental schemes and subsidy loans for SHG, whatever is left, we get that. So the SC women asked us to leave SHG groups, there are no more mixed SHG groups now. We keep silence to keep no tension, but if we want to raise tension, then there will be tension." - *Female participant, community C1* -

S2 - Measuring household capitals using Principal Component Analysis

Natural capital. A common view amongst participants was that the amount of agricultural land (rainfed and irrigated cropland, tree plantation) available to one household influences their potential income and food, and they considered them as determining factors for their choice of a livelihood activity. Participants in inland communities (C2, C5 and C6) argued that the area of pasture available per household was also a key determinant of employment, as it enabled them to develop livestock rearing as a diversification strategy. The four highest loadings of the eigenvector from the Principal Component Analysis represent these capitals highlighted by participants as determinants for the choice of their livelihood strategy: cropland area per cultivator ($\lambda_{\text{cropland}} = 0.38$), area of pasture per household ($\lambda_{\text{pasture}} = 0.44$) and area of tree plantation per cultivator ($\lambda_{\text{tree plantation}} = 0.40$).

Physical capital. A number of factors falling under household physical capital were identified by participants as determinant in their choice of a livelihood strategy. First, private access to electricity enables households to conduct their livelihood activity by operating agricultural pumps and machinery ($\lambda_{\text{no\_electricity}} = -0.08$). Means of transportation ($\lambda_{\text{bicycle}} = 0.45$, $\lambda_{\text{motorcycle}} = 0.53$, $\lambda_{\text{car}} = 0.40$) also came up during the rapid rural appraisals, since they allow households to look for new outlets for their production or for livelihood opportunities and increase their access to nearby services (hospitals, banks, schools) through the reduction of travel times.

Human capital. A recurrent household human capital that was identified by participants as influencing their choice of a livelihood strategy was the number of active members in the household ($\lambda_{\text{dependencyratio}} = -0.69$). A high dependency ratio limits the range of activities that one household can put in place. Finally, level of education and individual skillsets surfaced in most focus groups. Participants argued that educated members were a strength for one household because they "did not suffer from unemployment". Based on existing literature about poverty, levels of female illiteracy were used as a negative proxy for this asset ($\lambda_{\text{illiteracy}} = -0.69$).

Financial capital. One of the proxies used to quantify household financial capital are households' access to financial services for savings and credits ($\lambda_{\text{financial\_services}} = 0.68$). This indicator only captures financial inclusion as defined in the census: only households with access to banking services provided by nationalised banks, private banks, foreign banks and co-operative banks are considered to have access to financial services. However, many smallholder farmers –particularly households from lower castes and the poor– lack access to formal credit and are forced to rely on semi-formal (credit and thrift societies, self-help groups, primary agricultural credit societies) or informal (moneylenders and shopkeepers) sources. Moreover, access to such financial services can become a negative asset when the debt-to-capital ratio is greater than one. Participants also identified housing as a measure of the financial capital available to one household, as it is associated with access to financial services. Based on census variables, housing condition was used as a proxy to represent such an asset ($\lambda_{\text{dilapidated}} = -0.68$).

Social capital. Household social capital is about the value of social networks, including bonding with norms of reciprocity. Although not identified clearly as a capital, it emerged from the focus groups that marriage is one of the most important kinship encountered at the household level in rural settings, and so one of the pillar of social capital. Households' marital status was used to represent such kinships ($\lambda_{\text{married\_0}} = -0.40$). Finally, participants mentioned that households who owned a mobile phone had stronger social networks, especially outside the village, enabling them to have access to alternative livelihood opportunities ($\lambda_{\text{telephone}} = 0.57$).

S3 - Extracting phenology metrics (R script)

S3.1. Compute WDRVI with quality checks

```r
##############################################################
# Calculate WDRVI's and apply Quality Assessment masks
##############################################################

##### load library #####
library(raster)
library (tools)
library(tcltk)
library(compositions)

#-----------------------------#
# band   centered   band_name
#-----------------------------#
#   1     648 nm      Red
#   2     858 nm      NIR
#----------------------------#

#### indices formulas ####
# WDRVI  = ((a * b2 - b1) / (a * b2 + b1))
rm(list=ls())
a  <- 0.2

# set working directory
setwd()

# list files
lst <- list.files(pattern='.sur_refl_b01')
image.lst <- sapply(strsplit(lst, split='.', fixed=TRUE), function(x) (x[1]))
image.list <- sapply(strsplit(image.lst, split='_', fixed=TRUE), function(x) (x[2]))
rm(lst, image.lst)

#### band names ###
band <- c(".sur_refl_b01.tif", ".sur_refl_b02.tif")

### Quality band ###
quality <- ".sur_refl_qc_250m.tif"

### values to build mask ###
### values derived from quality assessment ###
qa.binary <- c('000000000000000','100000000000000','010000000000000','110000000000000',
'001000000000000','101000000000000','011000000000000','111000000000000','000000000001100',
'100000000001100','010000000001100','110000000001100','001000000001100','101000000001100',
'011000000001100','111000000001100','000000000000010','100000000000010','010000000000010',
'110000000000010','001000000000010','101000000000010','011000000000010','111000000000010',
'000000000001110','100000000001110','010000000001110','110000000001110','001000000001110',
'101000000001110','011000000001110','111000000001110')

qa.va <- c()
for(i in 1:length(qa.binary)){qa.va <- c(qa.va,unbinary(qa.binary[i]))}

pb <- tkProgressBar(title = "wdrvi quality", min = 0,max = length(image.list), width = 300)
```

```
for (i in 1:length(image.list)){
  ### set working directory for loop ###
  setwd("/Volumes/berchport/soton/mod09q1/coastal/")

  ############# bands as variables ###################
  b1 <- raster(paste('coastalMOD09Q1_', image.list[i], band[1], sep = ""))
  b2 <- raster(paste('coastalMOD09Q1_', image.list[i], band[2], sep = ""))

  #### compute indices #####
  WDRVI   <- ((a * b2 - b1) / (a * b2 + b1))

  #### build the mask ######
  qc <- raster(paste('coastalMOD09Q1_', image.list[i], quality, sep = ""))

  for(j in 1:length(qa.va)) {
    qc[qc == qa.va[j]] <- 1
  }
  qc[qc != 1     ] <- 0

  #### apply mask #######
  ### apply mask WDRVI ###
  WDRVImasked  <- qc * WDRVI

  #### save results ###
  #### save WDRVI ######
  setwd("/Volumes/data/wdrvi/coastal/")
  writeRaster(WDRVImasked, paste(image.list[i],"_WDRVI","_MOD09Q1", sep = ""),
    datatype="FLT4S", format = "GTiff",overwrite=TRUE)

  #### remove files from workspace ####
  ### remove bands ###
  rm(b1, b2)
  ### remove indices ###
  rm(WDRVI)
  ### remove quality band ###
  rm(qc)
  ### remove masked indices ###
  rm(WDRVImasked)

  Sys.sleep(0.1)
  setTkProgressBar(pb, i,
    label=paste("Loop",i,"(",round(i/length(image.list)*100, 0),"% done)"))
}

close(pb)
```

S3.2. Remove WDRVI noise and outliers using spline smoothing filters

```
library(greenbrown)
library(parallel)
library(plyr)

setwd()
load("df_wdrvi_coastal_cleaned.RData")
df2 <- df[,3:length(df[1,])]

# spline
smooth <- function(x) {
  vi.smooth <- TSGFspline(ts(as.numeric(x), start = c(2000,8),
    end = c(2014,46), freq = 46))
  wdrvi <- list(vi.smooth)
  return(wdrvi)
}

# pre-processing
cl <- makeCluster(detectCores())
clusterEvalQ(cl,c(library(greenbrown)))
clusterEvalQ(cl, smooth <- function(x) {
  vi.smooth <- TSGFspline(ts(as.numeric(x), start = c(2000,8),
    end = c(2014,46), freq = 46))
  wdrvi <- list(vi.smooth)
  return(wdrvi)
})
clusterExport(cl,'df2')

# parallel processing
system.time(wdrvi.smoothed <- parRapply(cl,df2,smooth))

# clean workspace
stopCluster(cl)
gc()

# structure
n <- length(wdrvi.smoothed)
wdrvi.df <- structure(wdrvi.smoothed,row.names = c(NA,-n),class='data.frame')
wdrvi <- data.frame(matrix(unlist(wdrvi.df), nrow=n, byrow=T))
colnames(wdrvi) <- colnames(df2[1,])
wdrvi <- cbind(df[,2:3],wdrvi)

rm(cl,n,wdrvi.smoothed,df,df2,wdrvi.df)
rm(smooth)

save.image('df_wdrvi_coastal_smoothed_spline.RData')
```

S4 - Detection of crop failure using BFAST (R script)

```
library(rts)
library(rgdal)
library(bfast)
library(tcltk)
path <- system.file("external", package="rts")

setwd()
df <- read.csv("df_wdrvi_mod09q1.csv",header=TRUE)
df2 <- df[,4:601]

total <- length(as.numeric(df2[,1])) ; anomalies <- c()
pb <- tkProgressBar(title = "bfast", min = 0, max = total, width = 300)

for (i in 1:total) {
  fit <- bfast(ts(as.numeric(df2[i, ]), start = 2002, freq = 46),
               h = (46*2/length(as.numeric(df2[1, ]))), season = "harmonic", max.iter = 2)
  ifelse(fit$output[[1]]$Vt.bp==0,
         anomalies <- c(anomalies,0),
         anomalies <- c(anomalies,length(fit$output[[1]]$bp.Vt$breakpoints))
  )
  Sys.sleep(0.1)
  setTkProgressBar(pb, i, label=paste("Loop",i,"/486734 (",round(i/total*100, 0)," %)")
      )
}
close(pb)

anomalies <- function(x) {
  fit <- bfast(ts(as.numeric(x), start = 2002, freq = 46),
               h = (46*2/598), season = "harmonic", max.iter = 2)
  ifelse(fit$output[[1]]$Vt.bp==0,
         anomaly <- 0,
         anomaly <- c(length(fit$output[[1]]$bp.Vt$breakpoints))
  )
  return(anomaly)
}

 bfast.anoms <- pbapply(df3,1,anomalies)
```

S5 - Geographies of livelihoods (R script)

Socio-Ecological System Profiling of Rural Communities - Data

Tristan Berchoux

November 2017

1 Loading data

The data required for the analysis here are in several different formats: text files (`.csv`), shapefiles (`.shp`) and raster (`.tif`), as well as data downloaded using R packages. The standard data needed for the analysis are population data (text files), administrative boundaries (shapefiles), amenities (text files and/or shapefiles) and land cover (raster).

First we will need to set the working directory.

```
setwd("/Users/tb2g14/Dropbox/soton/projects/p2_ambio/")
```

Now let's load all the required packages. Make sure they're loaded in this order.

```
library(raster)
library(sf)
library(tidyverse)
library(cowplot)
library(spocc)
library(rgdal)
library(fpc)
library(maptools)
library(mapview)
library(osmar)
library(osmdata)
```

1.1 Loading .csv files

We have some population data stored as a `.csv` file. These data are the tables from the Census of India 2011 at the Community level. These data were downloaded from Office of the Registrar General & Census Commissioner. Below we use the `read_csv` function from the `readr` package (included in the `tidyverse` bundle) to load this file and the `summary` function to inspect the contents.

```
census.df <- read_csv("data/tbl_census/village_amenities_mahanadi_2011.csv")
census.df <- data.frame(census.df)
```

The summary function allows us to inspect the contents of the dataframe, however the dataset is quite large so we're just gonna check the names of variables.

```
names(census.df)
```

```
##   [1] "ST_CODE"                     "ST_NAME"
##   [3] "DIST_CODE"                   "DIST_NAME"
##   [5] "SDIST_CODE"                  "SDIST_NAME"
##   [7] "VILL_CODE"                   "VILL_NAME"
##   [9] "BLOCK_CODE"                  "BLOCK_NAME"
##  [11] "GRAM_CODE"                   "GRAM_NAME"
##  [13] "REF_YR"                      "SDISTHQ_NAME"
```

```
## [387] "AREA_SOWN"                 "AREA_UNIRRIGATED"
## [389] "AREA_IRRIGATED_TOTAL"      "AREA_IRRIGATED_CANAL"
## [391] "AREA_IRRIGATED_WELL"       "AREA_IRRIGATED_LAKE"
## [393] "AREA_IRRIGATED_WATERFALL"  "AREA_IRRIGATED_OTHER"
## [395] "TOWN_NEAREST"              "TOWN_DISTANCE"
```

1.2 Loading shapefiles

We are going to use the 2011 community boundaries for India. Downloaded from Bhuvan GeoServer We will be using both `sf` and `sp` packages for working with shapefiles. First, we will load the data using `st_read` and then convert it to an `sp` object:

```
village.sf <- st_read("data/fcl_admin/mahanadi/mahanadi_villages.shp")
```

```
## Reading layer `mahanadi_villages' from data source `/Users/tb2g14/Dropbox/soton/projects/p2_ambio/data/fcl_adm
in/mahanadi/mahanadi_villages.shp' using driver `ESRI Shapefile'
## Simple feature collection with 7456 features and 12 fields
## geometry type:  POLYGON
## dimension:      XY
## bbox:           xmin: 84.97032 ymin: 19.46461 xmax: 86.99878 ymax: 21.23928
## epsg (SRID):    4326
## proj4string:    +proj=longlat +datum=WGS84 +no_defs
```

```
village.sp <- as(village.sf, 'Spatial')
```

Note that the function we use to read in the data provides us with information about the contents of the shapefile. This includes the kind of geometry (point, polygon); the bounding box (i.e. the maximum and minimum coordinated) and the projection of the data (more about this later). We can also use the `summary()` function to inspect the contents of the shapefiles.

```
summary(village.sf)
```

```
##     ogc_fid        objectid        mdds_vt      st        d
##  Min.   :   1   Min.   :     0   395807 :   3   21:7456   09:1323
##  1st Qu.:1870   1st Qu.:423257   408738 :   3             10:1554

##  Median :3736   Median :430984   394630 :   2             11:1297
##  Mean   :3735   Mean   :428824   395160 :   2             12:   1
##  3rd Qu.:5601   3rd Qu.:435500   395771 :   2             17:1562
##  Max.   :7468   Max.   :443358   395808 :   2             18:1719
##                                  (Other):7442
##        sd             vt01              vt_name      mdds_st    mdds_d
##  0007    :1057   01644800:   4   Gopalpur    :  24   21:7456   378:1323
##  0004    :1025   01656600:   4   Nuagan      :  24             379:1554
##  0003    : 890   01713600:   3   Haripur     :  18             380:1298
##  0005    : 828   02898200:   3   Gopinathpur :  15             386:1562
##  0002    : 740   01507500:   2   Gobindapur  :  14             387:1719
##  0001    : 583   01509700:   2   Raghunathpur:  14
##  (Other):2333   (Other) :7438   (Other)     :7347
##     mdds_sd             vt_11                 geometry
##  02939   : 313   Gopalpur    :  24   POLYGON      :7456
##  02923   : 301   Nuagan      :  24   epsg:4326    :   0
##  02940   : 243   Haripur     :  18   +proj=long...:   0
##  03058   : 240   Gopinathpur :  15
##  02943   : 235   Gobindapur  :  14
##  03054   : 222   Raghunathpur:  14
##  (Other):5902   (Other)     :7347
```

1.3 Loading raster files

We will also be using some raster data in our analysis:

- Rice Cover Map 2010 500m derived from MODIS data. These data were downloaded from IRRI
- Land Cover Map 2010 500m derived from MCD12Q1 product of MODIS data. These data were downloaded in R using the `ModisDownload()` function of the `rts` package.

We will use the `raster()` function from the `raster` package to load these data, then outputting the contents will give us information about these data.

```
irri.img <- raster("data/img_lulc/irri_2010.tif")
values(irri.img)[values(irri.img) > 8] <- 0 ; values(irri.img)[values(irri.img) == 0] <- NA
irri.img
```

```
## class       : RasterLayer
## dimensions  : 2262, 2898, 6555276  (nrow, ncol, ncell)
## resolution  : 0.002105, 0.002105  (x, y)
## extent      : 81.38147, 87.48176, 17.80449, 22.566  (xmin, xmax, ymin, ymax)
## coord. ref. : +proj=longlat +datum=WGS84 +no_defs +ellps=WGS84 +towgs84=0,0,0
## data source : in memory
## names       : irri_2010
## values      : 1, 8  (min, max)
```

We are going to use the MODIS land cover to also create a forest layer `forest.img` where every forested pixel is set at a value of `1`, the rest is `NA`.

```
modis.img <- raster("data/img_lulc/modis_2010.tif")
forest.img <- (modis.img == 2 | modis.img == 3 | modis.img == 4 | modis.img == 5) ; values(forest.img)[values(for
est.img) == 1] <- 9 ; values(forest.img)[values(forest.img) == 0] <- NA
urban.img <- (modis.img == 9) ; values(urban.img)[values(urban.img) == 1] <- 10 ; values(urban.img)[values(urban.
img) == 0] <- NA
```

Now we can merge both the rice cover map with the forest layer. First we need to resample the forest raster to match resolution.

```
irri.img <- round(resample(irri.img, modis.img)) ; values(irri.img)[values(irri.img) == 0] <- NA
lulc.img <- merge(irri.img, forest.img)
lulc.img <- merge(urban.img, lulc.img)
lulc.img[is.na(lulc.img)] <- 0
```

1.4 Downloading data from online sources

We are going to use the `osmdata` package to download physical features data from the OpenStreetMap project.

First, we will need a bounding box to limit the records to those within our study area. Let's use our case study extent found in the administrative boundaries shapefile `odisha_village.shp`.

```
extent.box <- as_osmar_bbox(village.sp) %>% opq ()
```

We can then use the `osmdata_sf()` function from the `osmdata` package to download records for features of interest. OpenStreetMap represents physical features on the ground using tags attached to its basic data structures. Tags describe specific features of map elements and consist of two items, [a key and a value] (http://wiki.openstreetmap.org/wiki/Map_Features). For example, `amenity==marketplace` is a tag with a key of `amenity` and a value of `marketplace` which should be used on a way to indicate a place where trade is regulated, for example a square. The `osmdata` package also provides a function to convert the retrieved data to a list of `sf` object, one for each type of data feature (i.e. polygons, lines, points).

```
worship.sf <- osmdata_sf(add_osm_feature(extent.box, key = "amenity", value = "place_of_worship"))
industrial.sf <- osmdata_sf(add_osm_feature(extent.box, key = "landuse", value = 'industrial'))
aquaculture.sf <- osmdata_sf(add_osm_feature(extent.box, key = "landuse", value = 'aquaculture'))
```

Now let's download road networks.

```
trunk.sf <- osmdata_sf(add_osm_feature(extent.box, key = "highway", value = "trunk"))
primary.sf <- osmdata_sf(add_osm_feature(extent.box, key = "highway", value = "primary"))
secondary.sf <- osmdata_sf(add_osm_feature(extent.box, key = "highway", value = "secondary"))
tertiary.sf <- osmdata_sf(add_osm_feature(extent.box, key = "highway", value = "tertiary"))
```

Let's create the `sp` equivalent of each point of interest

```
worship.sp <- as(worship.sf$osm_points, 'Spatial')
industrial.sp <- as(industrial.sf$osm_points, 'Spatial')
aquaculture.sp <- as(aquaculture.sf$osm_points, 'Spatial')
```

1.5 Merging data

We are gonna merge the census dataframe `census.df` with our administrative boundaries `village.sp` by using the individual code of each village (respectively `ADMIN_VILL_CODE` and `mdds_vt`). Let's first make sure both are of the same class.

```
names(village.sp)[3] <- 'VILL_CODE'
village.sp$VILL_CODE <- as.numeric(levels(village.sp$VILL_CODE))[village.sp$VILL_CODE]
village.sp@data <- inner_join(village.sp@data, census.df)
village.sp <- village.sp[!is.na(village.sp$MRKT_AGRIMARKETSOC_AV),]
```

1.6 Extracting data

We are going to use the census data to extract the locations of different amenities and then create a new layer with their centroids by using the `gCentroid()` function, included in the `rgeos` package.

```
library(rgeos)
market.sp <- gCentroid(village.sp[village.sp$MRKT_AGRIMARKETSOC_AV == 1, ], byid=TRUE)
health.sp <- gCentroid(village.sp[village.sp$MED_HOSP_ALT_NB >= 1, ], byid=TRUE)
education.sp <- gCentroid(village.sp[village.sp$EDU_GVT_S_SCH_AV == 1, ], byid=TRUE)
transport.sp <- gCentroid(village.sp[village.sp$TRA_BUS_PUB_AV == 1, ], byid=TRUE)
communication.sp <- gCentroid(village.sp[village.sp$COM_POSTOFFICE_AV == 1, ], byid=TRUE)
water.sp <- gCentroid(village.sp[village.sp$WAT_TAP_UNTREATED_AV == 1, ], byid=TRUE)
bank.sp <- gCentroid(village.sp[village.sp$BANK_AGRISOC_AV == 1, ], byid=TRUE)
public.sp <- gCentroid(village.sp[village.sp$SOC_POLLSTATION_AV == 1, ], byid=TRUE)
recreation.sp <- gCentroid(village.sp[village.sp$SOC_COMCENTRE_AV == 1, ], byid=TRUE)
```

1.7 Plotting data

We can then plot the desired data using the package `mapview`.

```
mapview(irri.img) +  mapview(modis.img) + mapview(health.sp, col.regions = 'blue') + mapview(bank.sp, col.regions
 = 'green') + mapview(market.sp, col.regions = 'red') + mapview(trunk.sf$osm_lines, col.regions = 'black') + mapv
iew(primary.sf$osm_lines, col.regions = 'red')
```

2 Spatial analysis

2.1 Creating a friction-surface dataset

First we need to rasterize the different road layers we just downloaded. Let's create an empty raster that will be used as a base canvas for the rasterization process.

```
null.img <- raster(extent(modis.img), res =  0.01, crs=proj4string(modis.img))
```

We now have to coerce our simple features objects to Spatial* objects so we can use the `rasterize()` function from the `raster` package. Trunk roads in India have an average travel speed of 90km/h (0.67 min/km).

```
trunk.sp <- as(trunk.sf$osm_lines, 'Spatial')
trunk.img <- rasterize(trunk.sp, null.img)
values(trunk.img)[values(trunk.img) > 0] <- 0.67
```

Primary roads in India have an average travel speed of 70km/h (0.8min/km), secondary roads of 50km/h (1.2min/km) and tertiary roads of 30km/h (2min/km).

```
primary.sp <- as(primary.sf$osm_lines, 'Spatial')
primary.img <- rasterize(primary.sp, null.img)
values(primary.img)[values(primary.img) > 0] <- 0.85

secondary.sp <- as(secondary.sf$osm_lines, 'Spatial')
secondary.img <- rasterize(secondary.sp, null.img)
values(secondary.img)[values(secondary.img) > 0] <- 1.2

tertiary.sp <- as(tertiary.sf$osm_lines, 'Spatial')
tertiary.img <- rasterize(tertiary.sp, null.img)
values(tertiary.img)[values(tertiary.img) > 0] <- 2
```

Let's now merge the rasters of the different types of roads together. We are using the `merge()` function, which gives priority to the first input raster.

```
roads.img <- merge(trunk.img,primary.img)
roads.img <- merge(roads.img,secondary.img)
roads.img <- merge(roads.img,tertiary.img)
```

After getting the road network, we now have to assign travel time values to the different land covers. We are using the raster `modis.img` to which we assign new values stored in the first and third columns of the table `modis_legend.csv`, by reclassigying the raster data.

```
legend_modis.df <- read_csv('data/img_lulc/modis_legend.csv')
rcl <- legend_modis.df[,c(1,3)]
lulc_tt.img <- reclassify(modis.img, rcl)
rm(rlc)
```

```
## Warning in rm(rlc): object 'rlc' not found
```

Now we can merge the road network with the land cover travel time. But we first need to resample our roads raster to a similar resolution than the land cover. This is done by using the `resample()` function.

```
roads.img <- resample(roads.img, lulc_tt.img, 'bilinear')
friction.img <- merge(roads.img, lulc_tt.img)
```

2.2 Distance to main amenities

We are going to use the gdistance package to compute distances to main amenities. We first create a transition layer (permeability instead of friction) using the `transition()` function.

```
library(gdistance)
transition.img <- transition(friction.img, function(x) 1/mean(x), directions = 4)
transition.img <- geoCorrection(transition.img)
```

Now that we have a transition layer, we can compute the accumulated cost of travelling to different types of amenities and services by using the `accCost()` function.

```
market.img <- accCost(transition.img, market.sp) ; values(market.img)[values(market.img) == Inf] <- NA
health.img <- accCost(transition.img, health.sp) ; values(health.img)[values(health.img) == Inf] <- NA
education.img <- accCost(transition.img, education.sp) ; values(education.img)[values(education.img) == Inf] <- N
A
transport.img <- accCost(transition.img, transport.sp) ; values(transport.img)[values(transport.img) == Inf] <- N
A
communication.img <- accCost(transition.img, communication.sp) ; values(communication.img)[values(communication.i
mg) == Inf] <- NA
water.img <- accCost(transition.img, water.sp) ; values(water.img)[values(water.img) == Inf] <- NA
bank.img <- accCost(transition.img, bank.sp) ; values(bank.img)[values(bank.img) == Inf] <- NA
public.img <- accCost(transition.img, public.sp) ; values(public.img)[values(public.img) == Inf] <- NA
recreation.img <- accCost(transition.img, recreation.sp) ; values(recreation.img)[values(recreation.img) == Inf]
<- NA

worship.img <- accCost(transition.img, worship.sp) ; values(worship.img)[values(worship.img) == Inf] <- NA
industrial.img <- accCost(transition.img, industrial.sp) ; values(industrial.img)[values(industrial.img) == Inf]
<- NA
aquaculture.img <- accCost(transition.img, aquaculture.sp) ; values(aquaculture.img)[values(aquaculture.img) == I
nf] <- NA
```

In order to profile our communities, it is important to have an effort value at the village-level. This is done by extracting an average value at the community level thanks to the function `extract()` of the `raster` package.

```
village.sp$market <- as.numeric(raster::extract(market.img, village.sp, method = 'bilinear', fun = mean, na.rm=TR
UE))
village.sp$health <- as.numeric(raster::extract(health.img, village.sp, method = 'bilinear', fun = mean, na.rm=TR
UE))
village.sp$education <- as.numeric(raster::extract(education.img, village.sp, method = 'bilinear', fun = mean, n
a.rm=TRUE))
village.sp$transport <- as.numeric(raster::extract(transport.img, village.sp, method = 'bilinear', fun = mean, n
a.rm=TRUE))
village.sp$communication <- as.numeric(raster::extract(communication.img, village.sp, method = 'bilinear', fun =
mean, na.rm=TRUE))
village.sp$water <- as.numeric(raster::extract(water.img, village.sp, method = 'bilinear', fun = mean, na.rm=TRUE
))
village.sp$bank <- as.numeric(raster::extract(bank.img, village.sp, method = 'bilinear', fun = mean, na.rm=TRUE))
village.sp$public <- as.numeric(raster::extract(public.img, village.sp, method = 'bilinear', fun = mean, na.rm=TR
UE))
village.sp$recreation <- as.numeric(raster::extract(recreation.img, village.sp, method = 'bilinear', fun = mean,
na.rm=TRUE))

village.sp$worship <- as.numeric(raster::extract(worship.img, village.sp, method = 'bilinear', fun = mean, na.rm=
TRUE))
village.sp$industrial <- as.numeric(raster::extract(industrial.img, village.sp, method = 'bilinear', fun = mean,
na.rm=TRUE))
village.sp$aquaculture <- as.numeric(raster::extract(aquaculture.img, village.sp, method = 'bilinear', fun = mean
, na.rm=TRUE))
```

2.3 Access to natural resources

```
village.sp$SCrainfed1 <- as.numeric(raster::extract(area(lulc.img)*(lulc.img==1), village.sp, method = 'bilinear'
, fun = sum))
village.sp$SCrainfed2 <- as.numeric(raster::extract(area(lulc.img)*(lulc.img==2), village.sp, method = 'bilinear'
, fun = sum))
village.sp$SCrainfed3 <- as.numeric(raster::extract(area(lulc.img)*(lulc.img==3), village.sp, method = 'bilinear'
, fun = sum))
village.sp$SCirrigated <- as.numeric(raster::extract(area(lulc.img)*(lulc.img==4), village.sp, method = 'bilinea
r', fun = sum))
village.sp$DCirrigated <- as.numeric(raster::extract(area(lulc.img)*(lulc.img==5), village.sp, method = 'bilinea
r', fun = sum))
village.sp$TCirrigated <- as.numeric(raster::extract(area(lulc.img)*(lulc.img==6), village.sp, method = 'bilinea
r', fun = sum))
village.sp$SCmixed <- as.numeric(raster::extract(area(lulc.img)*(lulc.img==7), village.sp, method = 'bilinear', f
un = sum))
village.sp$shrubagri <- as.numeric(raster::extract(area(lulc.img)*(lulc.img==8), village.sp, method = 'bilinear',
 fun = sum))
village.sp$forest <- as.numeric(raster::extract(area(lulc.img)*(lulc.img==9), village.sp, method = 'bilinear', fu
n = sum))
village.sp$urban <- as.numeric(raster::extract(area(lulc.img)*(lulc.img==10), village.sp, method = 'bilinear', fu
n = sum))
```

3 Save results

Save the workspace image.

```
rm(list=setdiff(ls(), "village.sp"))
save.image(file='data/ambio.RData')
```

Socio-Ecological System Profiling of Rural Communities - Cluster Analysis

Tristan Berchoux

November 2017

1 Loading data

Let's load all the required packages. Make sure they're loaded in this order.

```
library(raster)
library(sf)
library(tidyverse)
library(cowplot)
library(spocc)
library(rgdal)
```

```
## Warning: package 'rgdal' was built under R version 3.4.3
```

```
library(fpc)
library(maptools)
library(mapview)
library(osmar)
library(osmdata)
```

We are now going to load the data that we already pre-processed and we will also set the working directory.

```
setwd("/Users/tb2g14/Dropbox/soton/projects/p2_ambio/")
village.sf <- st_read("outputs/villageOUT.shp")
```

```
## Reading layer `villageOUT' from data source `/Users/tb2g14/Dropbox/soton/projects/p2_ambio/outputs/villageOUT.
shp' using driver `ESRI Shapefile'
## Simple feature collection with 6859 features and 429 fields
## geometry type:  POLYGON
## dimension:      XY
## bbox:           xmin: 84.97032 ymin: 19.46461 xmax: 86.99057 ymax: 21.23928
## epsg (SRID):    4326
## proj4string:    +proj=longlat +datum=WGS84 +no_defs
```

```
village.sp <- as(village.sf, 'Spatial')
```

2 Preparing the variables

```
census.sp <- village.sp[!is.na(village.sp$markt),]
census.sp$area <- raster::area(census.sp)
mydata <- census.sp@data[,408:430]
```

Distance

```
mydata[, 1:12][mydata[, 1:12] == 0] <- 1
mydata[,1:12] <- 1/mydata[,1:12]
```

Area

```
mydata[,13:22] <- (mydata[,13:22]/census.sp@data[,36])
```

```
mydata <- data.frame(scale(mydata[,1:22]))
```

3 Cluster analysis

We are going to use four packages to compute different types of cluster analysis.

```
library(mclust)
```

```
## Warning: package 'mclust' was built under R version 3.4.3
```

```
#library(pvclust)
#library(dbscan)
```

```
fit <- Mclust(mydata) ; summary(fit)
```

```
## ----------------------------------------------------
## Gaussian finite mixture model fitted by EM algorithm
## ----------------------------------------------------
##
## Mclust VEV (ellipsoidal, equal shape) model with 4 components:
##
##  log.likelihood    n   df      BIC      ICL
##        326511.8 6853 1040 643837.9 643761.8
##
## Clustering table:
##    1    2    3    4
## 2571 3345  805  132
```

```
mydata$CLUSTER <- fit$classification

census.sp$CLUSTER <- fit$classification
save(census.sp,file='cluster.RData')
#amenities.df <- mydata[,1:12]
#lulc.df <- mydata[,13:22]
```

We are gonna set a new function called `multiplot()` that will enable us to plot different figures on a same plot when using `ggplot`.

```
multiplot <- function(..., plotlist=NULL, file, cols=1, layout=NULL) {
  library(grid)

  # Make a list from the ... arguments and plotlist
  plots <- c(list(...), plotlist)

  numPlots = length(plots)

  # If layout is NULL, then use 'cols' to determine layout
  if (is.null(layout)) {
    # Make the panel
    # ncol: Number of columns of plots
    # nrow: Number of rows needed, calculated from # of cols
    layout <- matrix(seq(1, cols * ceiling(numPlots/cols)),
                     ncol = cols, nrow = ceiling(numPlots/cols))
  }

  if (numPlots==1) {
    print(plots[[1]])

  } else {
    # Set up the page
    grid.newpage()
    pushViewport(viewport(layout = grid.layout(nrow(layout), ncol(layout))))

    # Make each plot, in the correct location
    for (i in 1:numPlots) {
      # Get the i,j matrix positions of the regions that contain this subplot
      matchidx <- as.data.frame(which(layout == i, arr.ind = TRUE))

      print(plots[[i]], vp = viewport(layout.pos.row = matchidx$row,
                                      layout.pos.col = matchidx$col))
    }
  }
}
```

After defining a color palette for each variable by using the `RColorBrewer` package, we are running a loop to plot the mean value of the different variables for each cluster.

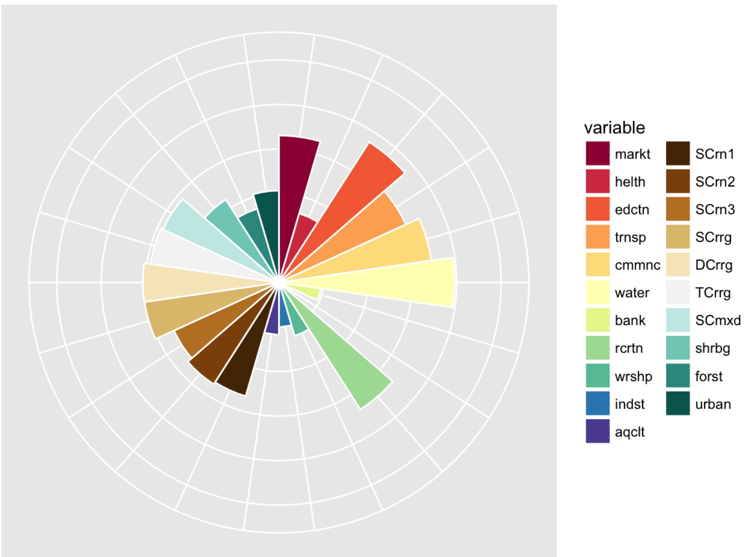
```
library(RColorBrewer)
cols <- c(brewer.pal(11, "Spectral"), brewer.pal(11, "BrBG"))


for (i in 1:fit$G){
  DF <- as.data.frame(colMeans(mydata[mydata$CLUSTER == i, 1:length(mydata[1,])-1]))
  DF <- data.frame(rownames(DF), DF[,1]) ; DF[,2] <- DF[,2] + 1 ; DF
  names(DF) <- c('variable','value')
  DF$variable <- factor(DF$variable, as.character(DF$variable))

  plot <- ggplot(DF, aes(variable, value, fill = variable)) +
    geom_bar(width = 1, stat = "identity", color = "white") +
    ylim(0,5) +
    #scale_y_discrete(breaks = 0:nlevels(DF$variable)) +
    scale_fill_manual(values=cols) +
    theme_gray() +
    theme(axis.ticks = element_blank(),
      axis.text = element_blank(),
      axis.title = element_blank(),
      axis.line = element_blank())

  nam <- paste('p',i, sep='')
  assign(nam, plot + coord_polar())
}

p1 ; p2 ; p3 ; p4
```



Socio-Ecological System Profiling of Rural Communities - Logistic Regression

Tristan Berchoux

December 2017

1 Loading data

```
setwd("/Users/tb2g14/Dropbox/soton/projects/p2_ambio/")
```

1.1 Loading packages

Let's load all the required packages. Make sure they're loaded in this order.

```
library(raster)
library(sf)
library(tidyverse)
library(cowplot)
```

```
library(spocc)
library(rgdal)
```

```
## Warning: package 'rgdal' was built under R version 3.4.3
```

```
library(fpc)
library(maptools)
library(mapview)
library(osmar)
library(osmdata)
```

1.2 Loading data

We are now going to load the data that we already pre-processed and we will also set the working directory.

```
census.sf <- st_read("outputs/cluster_V2.shp")
```

```
## Reading layer `cluster_V2' from data source `/Users/tb2g14/Dropbox/soton/projects/p2_ambio/outputs/cluster_V2.
shp' using driver `ESRI Shapefile'
## Simple feature collection with 6853 features and 431 fields
## geometry type:  POLYGON
## dimension:      XY
## bbox:           xmin: 84.97032 ymin: 19.46461 xmax: 86.97855 ymax: 21.23928
## epsg (SRID):    4326
## proj4string:    +proj=longlat +datum=WGS84 +no_defs
```

```
census.sp <- as(census.sf, 'Spatial')
census.df <- data.frame(read_csv('data/tbl_census/census.csv'))
```

```
names(census.sp)[3] <- 'ADMIN_VILL_CODE'
census.sp@data <- inner_join(census.sp@data, census.df,by = "ADMIN_VILL_CODE")
mydata <- census.sp@data
```

1.3 Preparing the data

```
mydata$NATURAL_HH_RANK5_V2 <- factor(mydata$NATURAL_HH_RANK5_V2)
mydata$PHYSICAL_HH_RANK5_V2 <- factor(mydata$PHYSICAL_HH_RANK5_V2)
mydata$HUMAN_HH_RANK5_V2 <- factor(mydata$HUMAN_HH_RANK5_V2)
mydata$FINANCIAL_HH_RANK5_V2 <- factor(mydata$FINANCIAL_HH_RANK5_V2)
mydata$SOCIAL_HH_RANK5_V2 <- factor(mydata$SOCIAL_HH_RANK5_V2)
```

2 Logistic regression

```
library(R2MLwiN)
options(MLwiN_path = '/Users/tb2g14/Documents/mlwin/mlnscript')
```

2.1 Cluster 1

```
(model1 <- runMLwiN(logit(LIV_UNEMPL, DENOM2) ~ 1 + SOC_POPDENSITY + ADMIN_DISTRICT_NAME + NATURAL_HH_RANK5_V2 +
 PHYSICAL_HH_RANK5_V2 + HUMAN_HH_RANK5_V2 + FINANCIAL_HH_RANK5_V2 + SOCIAL_HH_RANK5_V2 + (1 | ADMIN_GRAM_NAME), D
 = "Binomial", data = mydata[mydata$CLUSTER==1,]))
```

```
(model2 <- runMLwiN(logit(LIV_UNEMPL, DENOM2) ~ 1 + SOC_POPDENSITY + ADMIN_DISTRICT_NAME + NATURAL_HH_RANK5_V2 +
 PHYSICAL_HH_RANK5_V2 + HUMAN_HH_RANK5_V2 + FINANCIAL_HH_RANK5_V2 + SOCIAL_HH_RANK5_V2 + (1 | ADMIN_GRAM_NAME), D
 = "Binomial", estoptions = list(nonlinear = c(N = 1, M = 2), startval = list(FP.b = model1@FP, FP.v = model1@FP.
cov, RP.b = model1@RP, RP.v = model1@RP.cov)), data = mydata[mydata$CLUSTER==1,]))
```

```
##
## -*-*-*-*-*-*-*-*-*-*-*-*-*-*-*-*-*-*-*-*-*-*-*-*-*-*-*-*-*-*-*-*-*-*-*-*-*-*-*-*-*-*-*-*-*-*-*-*-*-
## MLwiN (version: 3.01)  multilevel model (Binomial)
##                  N min     mean max N_complete min_complete mean_complete
## ADMIN_GRAM_NAME 807   1 3.164808  15        807            1      3.164808
##                 max_complete
```

```
## ADMIN_GRAM_NAME           15
## Estimation algorithm:  IGLS PQL2        Elapsed time : 1.1s
## Number of obs:  2554 (from total 2554)        The model converged after 5 iterations.
## Log likelihood:      NA
## Deviance statistic:  NA
## ---------------------------------------------------------------------------------------------------
## The model formula:
## logit(LIV_UNEMPL, DENOM2) ~ 1 + SOC_POPDENSITY + ADMIN_DISTRICT_NAME +
##     NATURAL_HH_RANK5_V2 + PHYSICAL_HH_RANK5_V2 + HUMAN_HH_RANK5_V2 +
##     FINANCIAL_HH_RANK5_V2 + SOCIAL_HH_RANK5_V2 + (1 | ADMIN_GRAM_NAME)
## Level 2: ADMIN_GRAM_NAME     Level 1: l1id
## ---------------------------------------------------------------------------------------------------
## The fixed part estimates:
##                                       Coef.   Std. Err.        z     Pr(>|z|)         [95% Conf.   Interval]
## Intercept                           1.01461     0.02882    35.20   1.687e-271   ***      0.95812     1.07110
## SOC_POPDENSITY                     -0.02489     0.00643    -3.87    0.0001077   ***     -0.03748    -0.01229
## ADMIN_DISTRICT_NAMEJagatsinghapur  -0.01164     0.02704    -0.43       0.6669           -0.06464     0.04136
## ADMIN_DISTRICT_NAMEKendrapara      -0.00066     0.02451    -0.03       0.9787           -0.04870     0.04739
## ADMIN_DISTRICT_NAMEKhordha         -0.10126     0.02581    -3.92    8.729e-05   ***     -0.15185    -0.05068
## ADMIN_DISTRICT_NAMEPuri            -0.16642     0.02522    -6.60    4.135e-11   ***     -0.21585    -0.11700
## NATURAL_HH_RANK5_V22                0.00584     0.01838     0.32       0.7505           -0.03017     0.04186
## NATURAL_HH_RANK5_V23                0.02643     0.01771     1.49       0.1357           -0.00829     0.06114
## NATURAL_HH_RANK5_V24               -0.00305     0.01716    -0.18        0.859           -0.03669     0.03059
## NATURAL_HH_RANK5_V25               -0.05234     0.01866    -2.80     0.005037   **      -0.08891    -0.01576
## PHYSICAL_HH_RANK5_V22               0.20794     0.01771    11.74    7.766e-32   ***      0.17323     0.24265
## PHYSICAL_HH_RANK5_V23               0.22567     0.02154    10.48    1.097e-25   ***      0.18346     0.26789
## PHYSICAL_HH_RANK5_V24               0.23534     0.02250    10.46     1.32e-25   ***      0.19124     0.27943
## PHYSICAL_HH_RANK5_V25               0.26058     0.02602    10.02    1.307e-23   ***      0.20958     0.31157
## HUMAN_HH_RANK5_V22                 -0.20794     0.01734   -11.99    3.979e-33   ***     -0.24193    -0.17395
## HUMAN_HH_RANK5_V23                 -0.27984     0.01869   -14.97    1.178e-50   ***     -0.31648    -0.24320
## HUMAN_HH_RANK5_V24                 -0.43473     0.02059   -21.11    6.547e-99   ***     -0.47510    -0.39437
## HUMAN_HH_RANK5_V25                 -0.53887     0.02395   -22.50   4.325e-112   ***     -0.58581    -0.49192
## FINANCIAL_HH_RANK5_V22             -0.02993     0.01892    -1.58       0.1136           -0.06702     0.00715
## FINANCIAL_HH_RANK5_V23             -0.12534     0.01931    -6.49    8.504e-11   ***     -0.16319    -0.08750
## FINANCIAL_HH_RANK5_V24             -0.09779     0.02154    -4.54    5.614e-06   ***     -0.14000    -0.05558
## FINANCIAL_HH_RANK5_V25             -0.10848     0.02474    -4.39    1.159e-05   ***     -0.15697    -0.05999
## SOCIAL_HH_RANK5_V22                -0.07821     0.01688    -4.63    3.618e-06   ***     -0.11131    -0.04512
```

```
## SOCIAL_HH_RANK5_V23                -0.15347     0.01843    -8.33    8.402e-17   ***     -0.18960    -0.11734
## SOCIAL_HH_RANK5_V24                -0.13555     0.02074    -6.54    6.299e-11   ***     -0.17620    -0.09491
## SOCIAL_HH_RANK5_V25                -0.26956     0.02269   -11.88       1.5e-32   ***     -0.31404    -0.22509
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
## ---------------------------------------------------------------------------------------------------
## The random part estimates at the ADMIN_GRAM_NAME level:
##                  Coef.   Std. Err.
## var_Intercept   0.12623     0.00401
## ---------------------------------------------------------------------------------------------------
## The random part estimates at the l1id level:
##                Coef.   Std. Err.
## var_bcons_1   1.00000     0.00000
## -*-*-*-*-*-*-*-*-*-*-*-*-*-*-*-*-*-*-*-*-*-*-*-*-*-*-*-*-*-*-*-*-*-*-*-*-*-*-*-*-*-*-*-*-*-*-*-*-*-
```