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Multi-level socioecological drivers of agrarian change: Longitudinal evidence from mixed rice-livestock-aquaculture farming systems of Bangladesh

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A B S T R A C T

Coastal systems are facing natural and human-driven change coupled with a rising population. With increasing shifts in socioecological conditions during the past several decades, it is important to understand how socio-ecological drivers at different hierarchical levels: -micro, -meso, and -macro affect coastal farming systems, which play a crucial role in the livelihoods of coastal dwellers. Mixed rice-livestock-aquaculture farming in Southern Bangladesh exemplifies the rapid change occurring in many of the world's coastal farming systems in response to these drivers. We used panel data observations from the above study area and modeled trajectories of farm typologies, and the impact of multi-level socioecological drivers by a novel approach. Our approach integrates: (1) a well-articulated conceptual frame of change observed using (2) a temporal view of the potential drivers, change process and farm type outcomes, with the twenty years panel data of 502 households that is analyzed by means of (3) multivariate statistics in conjunction with panel data models that operationalize the conceptual frame. Our approach allows (a) estimating dynamic effects over time that typically cannot be estimated in a cross-sectional data set, (b) distinguishing between time-invariant fixed and time dependent random effects of multi-level socioecological drivers, and (c) controlling for omitted variables to a certain extent. Considering farming systems both within and outside of polder embankment systems intended to protect against oceanic water intrusion, we found a gradual shift from heterogeneous, rice-livestock farm types to more homogenous farms with less livestock and more off-farm activities. Micro-level factors including farm plot fragmentation, farmers' experience in cropping, machinery, salinity and soil fertility were influencing changes in farming systems. Meso-level factors including markets, road infrastructure, labor availability, access to extension and land tenure also affect the trajectory of farming systems change. Among macro-level drivers, increasing population density positively and significantly influenced cropping intensity among farms outside polder systems. Within polders, a positive but non-significant trend was observed for the influence of population density on cropping intensity. Our data also indicate negative and significant influence of cyclonic storms on cropping intensity over time in both areas. Our results underscore the importance of accounting for multiple levels of socioecological drivers of change when developing appropriate policy options for sustainable development in South Asia's coastal farming systems.

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1. Introduction

Alongside a range of ecosystem services and economic benefits (Martinez et al., 2007), coastal systems provide multiple opportunities for diverse farm enterprises that integrate crops, livestock and aquaculture. Rural farmers in tropical coastal deltas are however highly vulnerable to global environmental change (Krupnik et al., 2015; Ishtiaque et al., 2017). More than 400 million people in South Asia who live in coastal areas are experiencing significant changes in rural economies, population density, agricultural practices, and climate that affect their livelihoods (UNISDR-UNDP, 2012). Farmers in coastal zones are disproportionately vulnerable to flooding, coastal erosion, soil and water salinity, and have high sensitivity to climate change and environmental shocks (Ali and El-Magd, 2016; Krupnik et al., 2015). Poised at the interface of multiple socioecological drivers, including biophysical and socioeconomic factors of both natural and anthropogenic origin, the coastal farming systems are undergoing rapid change. With increasing shifts in agroecological conditions during the past several decades, it is important to understand how socioecological drivers at different hierarchical levels: -micro (e.g., household), -meso (e.g., institutions), -macro (e.g., population) affect coastal farming systems, which play a crucial role in the livelihoods of coastal dwellers.

Coastal farming systems comprise of population of individual farms organized by their crop, livestock and aquacultural components, and that have similar resource bases and livelihood patterns for which similar development interventions may be appropriate (Dixon et al., 2001). Understanding past and present agricultural diversity, dynamics, and trajectories of change is crucial to inform policies aimed at meeting Sustainable Development Goals (Valbuena et al., 2015; Domingues et al., 2018). Only a limited number of studies have explored how coastal farming systems have responded and adapted to socioecological drivers.

Farm typologies and characterization of farming systems have been widely used to understand systems complexity and agricultural development trajectories by simplifying and organizing farms into separate but relatively homogenous groups internally (Iraizoz et al., 2007; Tittonell et al., 2010; Alvarez et al., 2018). Trajectories of farming systems can be studied in different ways, for example through inductive (Pelling et al., 2008) or deductive approaches (Valbuena et al., 2008; Tittonell et al., 2010). The former are defined by the actors (for e.g. farmers or extension agents) themselves while the latter are drawn from theory or conceptual frameworks developed by researchers (Overmars and Verburg, 2007; Sierra et al., 2017). Deductive approaches have been used to study pathways and trajectories of change in socio-ecological systems (Valbuena et al., 2015; Groot et al., 2016), though most recent (Sierra et al., 2017; Alvarez et al., 2018; Lopez-Ridaura et al., 2018; Jelsma et al., 2019) and widely cited (cf. Valbuena et al., 2008; Righi et al., 2011; Tittonell et al., 2010; Daloğlu et al., 2014; Cortez-Arriola et al., 2015; Kuivanen et al., 2016) studies use single year cross- sectional data or aggregate country/regional data. While cross-sectional data cannot control for personal fixed effects (e.g. level of education), aggregate data can underestimate the influence of individual farm-level change. This reduces the accuracy and applicability of insights derived from trajectory studies. Typological analysis of cross-sectional data collected from different farms is only plausible when farm type change and dynamics are independent realizations of the same evolutionary process across the farming system. However, constructed cross-sectional typologies represent only a possible occurrence order of a small set of properties or traits at a particular point of time when the data was collected. They cannot reveal the dynamic process of farming system change. Useful insights can conversely be gained using long-term panel data.

Hierarchical clustering on Principal components (from principal component analysis (PCA)) is the most common statistical method used to analyze development trajectories of farm types (Valbuena et al., 2008; Tittonell et al., 2010; Cortez-Arriola et al., 2015; Kuivanen et al., 2016). But linking farming systems' development trajectories to a handful of principal component (PC) axes may be misleading—what appears like the signal of an interesting biophysical or socioeconomic property may simply be an artifact stemming from how PCA is computed. Falconnier et al. (2015) and Valbuena et al. (2015) built longitudinal farm typologies for analysis of PC axes and generated clusters for different time periods. But they did not attempt any statistical extension using panel data models. By focusing analyses exclusively on the PC axes, as is commonly done in trajectory studies, researchers are, in effect, taking a biased sample of a multivariate distribution (Mitteroecker et al., 2004), while also ignoring stochasticity that can cause some dimensions to diverge more rapidly, while others exhibit less divergence across time periods (Uyeda et al., 2015).

Unlike cross-sectional analyses, most panel data tends to be analyzed using parametric models involving Generalized Linear Mixed Models or using marginal methods including Generalized Estimating Equations. When considering trajectory studies, these classical approaches could however also be biased because variables in panel data are typically sparse and highly dimensional (Di et al., 2014). Integrating multivariate statistics with panel regression may therefore help to reduce the high dimensionality of longitudinal data (Yao et al., 2005).

Apart from statistical issues, knowledge gaps regarding the historical influences determining changes in farming systems have also led to inefficiencies in agricultural policy development (Adamson et al., 2018). The idea that multiple levels of contextual influence affect complex systems through interdependent interactions is an ecological view that has a long tradition since Bronfenbrenner's socioecological systems theory published in 1989. A set of factors function at multiple hierarchical levels: -micro (e.g., household), -meso (e.g., institutions), −macro (e.g., population) has been emphasized in systems analysis (Berkes and Folke, 1998; Hettig et al., 2016), though quantification of the effects of these factors on trajectories is rare. For instance, despite researchers recognizing the role of meso- level factors that condition changes in infrastructure and market and institutional systems (Hazell and Wood, 2008; Anderies et al., 2016), longitudinal evidence on farming systems change remains largely lacking in South Asia, as are studies that consider and integrate meso- and micro-level factors. These factors, which for example may include farmers' level of agricultural experience, changes in crops, irrigation and farm machinery, tenure and land fragmentation (Piotrowski et al., 2013; Paul and wa Gĩthĩnji, 2018), could shed new insight on how and why farming systems change, with important implications for development policies and environmental adaptation priorities (Adamson et al., 2018).

This paper introduces a new systems analysis approach to model trajectories of farm typologies, systems dynamics and socioecological drivers using the south-central coast of Bangladesh as a study area. This new approach is characterized by integrating a well-articulated theoretical frame of change observed using a temporal view of change processes and outcomes. We used twenty years panel data from 502 households and analyzed those utilizing multivariate statistics in conjunction with panel data models that operationalize our theoretical framework. Our approach estimates the dynamic change effects over time that cannot typically be estimated utilizing cross-sectional data set. The approach also distinguishes between time-invariant fixed and time-independent random effects of multi- level socioecological drivers, while also controlling for omitted variables.

Bangladesh is the world's most densely populated deltaic country with low per-capita farmland and rural development challenges (Turner and Ali, 1996; World Bank, 2015). About 40 million people in Bangladesh remain severely food insecure. Another 11 million suffer from acute hunger (WFP, 2016), the majority of whom inhabit coastal areas. More than 40% of productive land is projected to be lost in the southern region of Bangladesh for a 0.65 meter sea-level rise (World Bank, 2013). In Bangladesh's south-central coastal zone, tidal water flooding during the monsoon "*Kharif*" season (June–August) is common, though transplanted *'aman'* rice (*Oryza sativa*) is widely grown during this period. Without large-scale irrigation development, farmers however experience water scarcity during the cool, dry winter "*Rabi*" season (November to April). Soil and water salinity as well as cyclonic storms pose further challenges in the *Kharif* –*Rabi* seasons. Farmers tend to fallow their land or grow low risk, low-input 'opportunity' crops including broadcast, unfertilized legumes predominantly mungbean (*Vigna radiata*) and lathyrus (*Lathyrus sativus*) during the *Rabi* season. Development approaches that increase farm productivity by conserving natural resources, increasing resource use efficiency and ecosystem services while improving social equity, i.e. sustainable intensification (SI) (Godfray et al., 2010), have been proposed to guide policy in Bangladesh's coastal farming systems (MOA-FAO, 2013; Krupnik et al., 2017). A component of SI involves increasing cropping intensity, i.e. the number of crops grown per year on the same land, thereby raising yield per year per unit of farmland, while also minimizing land expansion and consequent biodiversity loss.

A system of embankments known as polders, consisting of dykes and sluicegate controls were constructed by the Bangladeshi government in 1960s to control oceanic water intrusion, protect against cyclones and support coastal agriculture. Poor maintenance and competition for resources has however resulted in many poorly functioning polders and sluice gates. Poor drainage, land subsidence, and soil salinity pose mounting problems, although their effect is spatially heterogeneous (Krupnik et al., 2017). The diversity of these linked socioecological issues calls into question the usefulness of standard and 'blanket' development approaches (Goswami et al., 2014). This research responds to these theoretical and methodological challenges and employs panel data models to the study of farming systems change both within and outside polders in Bangladesh's central coast. Our objective is to improve understanding of farm trajectories of change by untangling multilevel drivers that influence farming systems dynamics, and to use this information to inform relevant policy aimed at sustainable development in coastal South Asia.

2. Conceptual framework: farm typologies and drivers of change

The socioecological views explaining agricultural growth, unlike population-pressure theories by Mathusian (neo-Malthusian) and Boserupian (Boserup, 1965), emphasize human-environment relationships and their influence on agriculture (Ali, 1995). These relationships, however, are driven by numerous socioecological factors, particularly the multiple levels of constraints imposed by the population pressure, biophysical environment, and the socio-technological and economic abilities of farm households to reduce and modify those constraints (Ali, 1995; Aravindakshan et al., 2018). These constraints can be harnessed to sustainably intensify farming systems rather than leading to uncontrollable natural resource depletion. To do so, the forms (types) and pathways of farming systems responses should be understood and modeled by socioecological drivers across spatio-temporal scales.

We outline a conceptual framework for the study of farm trajectories of change at different scales in consideration of the dynamics of systems change (Fig. 1). The process of change is represented over time (t), t_1 to t_2. In t_1, a farming system may consist of 'n' number of farm types, which are likely to follow 'm' number of pathways with a probability 'p'. This results in $n + q$ farm types at time t_2, with $q < 0$ if farming systems tend towards homogeneity (less diverse) in structures and functions over time, and $q > 0$ if diversity increases. 'q' can take any value including 0, but not < '$-n$'.

The factors driving these dynamics include complex and interacting biophysical, socioeconomic, behavioral, or social influences that operate at multiple scales (Hettig et al., 2016). Macro- and meso-level factors are exogenous and beyond the control of individual farmers; micro-level factors are conversely endogenous and subject to farmers' agency. A farm belonging to a particular type undergoes change over time, forming a trajectory of change in terms of selected farm features. Although we only show two pathways of change in Fig. 1, a farm has multiple 'm' options based on the direction and magnitude of influence of different factors. This conceptualization is intended as a general model of farm trajectories and factors of change, although it is likely to differ from system to system according to prevailing drivers.

At the macro-level, three major factors are widely considered to influence agrarian change over time. Firstly, population density is considered as a major driver of agricultural intensification as it can increase both the demand for food and supply and demand for farm labor, in addition to land fragmentation (Boserup, 1965). Declining population density on the other hand may lead to farmland consolidation, land fallowing, and/or land sales and sharecropping. Secondly, economic growth may change diets and consumption patterns, thereby increasing demand for food products even without population growth. Third, variability in climate and extreme weather events – for example tropical storms and cyclones in the Bay of Bengal (Knutson et al., 2010; Huq et al., 2015) – may affect agricultural change (Hazell and Wood, 2008).

The diversity of farming systems can be represented by typologies that segregate farm households into different farm types which may be defined by the structural (e.g. landholding, crops, livestock size) and/or functional variables (e.g. cropping intensity, technology adoption) that may result from interactions between micro- and meso-level factors, and macro-level drivers (Fig. 1). A range of micro-level factors, including past experience of cropping, household level adoption of improved crop varieties, irrigation, and machinery, tenure and land fragmentation could influence household livelihood strategies (Piotrowski et al., 2013; Paul and wa Gĩthĩnji, 2018). Farmers' decisions could also be conditioned and mediated by meso-level factors, including access to finance, extension services and civil infrastructure that in turn can influence relative farm input-output prices and access to new technologies and markets (Shiferaw and Bantilan, 2004; Amjath-Babu et al., 2016). Many studies of agrarian change focus on macro-level drivers without considering lower level drivers or the diversity of farming systems types (cf. Boserup, 1965; Turner and Ali, 1996; Pingali, 2012). Furthermore, assumptions of the homogenous impact of multi-level factors across farm types may be overly simplistic. For example, in case of farm types experiencing land scarcity, population growth can lead to fragmentation of landholdings and competition for natural resources. An additional challenge in the study of agrarian change is the difficulty in measuring the dynamics of farming systems change in and of itself. Our approach, detailed below, is to first illustrate the farm types present at a given time 't_1' and proportion of farms changed from one type to another in a time 't_2', then subsequently identifying the dominant variables influencing these changes. These variables are then related to potential micro-, meso- and macro-level driving forces.

3. Methods and materials

3.1. Study area

The study area in the south-central part of Bangladesh has been identified as potentially suitable for cropping systems intensification using surface water irrigation to forgo *Rabi* season land fallowing (Krupnik et al., 2017). The region is characterized by a dense network of interconnected rivers and natural canals that flow into the Bay of Bengal. Annual rainfall ranges from 1955 to 2100 mm (BBS, 2013), with a humid sub-tropical climate. Most soils are medium to high textured silty clay loams (SRDI, 2010). The southern-most part of the central coast (Patuakhali, Barguna and Pirojpur districts) is protected by polders constructed since 1960s. So far 123 polders covering an area of about 13 million ha have been constructed across coastal Bangladesh that include 6000 km of channels, 2500 water control structures, and 5000 km of embankments (World Bank, 1990).

Across Barisal, Patuakhali, Barguna and Pirojpur, approximately 70% of the households within polders are engaged in farming, while farming households are 59% outside the polders (BBS, 2016). The

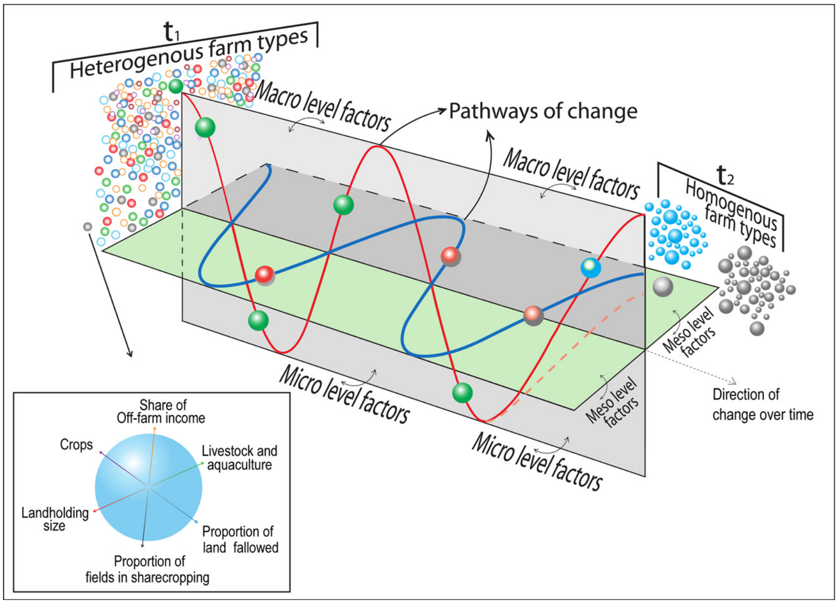

Fig. 1. Theoretical framework for farm trajectories of change and select potential influencing factors. Blue and red solid lines indicate hypothetical trajectories (pathways) followed by a farm type. Blue and red dots indicate alternative trajectories possible. The large blue sphere on the bottom left represents a farm type which captures, for example, households' landholding, fallow land, sharecropped land, cropping, livestock and aquaculture assets, and off-farm activities. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.).

farming systems both within and outside polders are traditionally mixed, in which rice, livestock and pond aquaculture are integrated on the same farm. The majority of agrarian households (HHs) both within and outside polders are engaged in rainfed cropping in the *Kharif* (mid-March to mid-November) and *Rabi* (mid-November to mid-March) seasons. *Kharif* sowing coincides with the onset of monsoon, and is further divided into pre-monsoon *Kharif-1* (mid-March to mid-July) during which local '*aus*' rice varieties are grown, and monsoon *Kharif-2* (mid-July to mid-November) when *aman* rice is grown. The *Rabi* season falls during the dry winter period, when farmers within polders grow primarily pulses, while farmers in non-polder areas cultivate pulses, mustard and vegetables. Irrigated *Rabi* season rice production known as *'boro'* occurs in select areas proximal to water sources.

3.2. Data and sample

We developed a balanced panel dataset at farm household level of 502 HHs in coastal Bangladesh in Barisal division, spanning 20 years from 1995 to 2015 as part of the multi-year Cereal Systems Initiative for South Asia (CSISA) project. This dataset is compiled from a farm household level primary survey, NGO records pertaining to household characteristics, farmer focus groups and secondary data sources. Sample were selected from a list of farm HHs provided by the NGO (Bangladesh Development Society) that keeps village level records of selected coastal districts in Southern Bangladesh. Two districts within polders (Patuakhali and Barguna) and a single district outside polders (Barisal district) were selected for the study (Table 1; Fig. 2). We selected these three districts of the total 27 districts in southern Bangladesh due to specific interest considering the potential for crop intensification and surface water irrigation in coastal Bangladesh (see Krupnik et al., 2017). In addition, data from districts other than the above for the time period 1995–2010 was not available from our partner NGOs or other sources for the study.

A non-probability purposive sampling procedure was subsequently used to select HHs from the list whose information on select variables (Refer Table 2 for variable description) were available in the NGO records. Out of the 311 and 336 households outside and within polder areas in the list, 107 and 38 households were excluded due to data gaps, respectively. A final sample of 204 HHs outside polders and 298 HHs within polder areas were selected such that at least 5% of all HHs in each of the selected villages were sampled as advised by Turner (2003). HH level information on several variables for these selected HHs, spanning for a period of 1995–2010 were then compiled. These same HHs were surveyed in 2015 by the authors in order to develop a twenty year panel data set by combining the compiled information with the authors HH survey. Above panel data set used in this paper is made openly available by CIMMYT DataVerse for interested users here: http://hdl.handle.net/11529/10898.

The variables in the panel data set developed included farm structural and functional characteristics, household resource endowment, agricultural management information, and data on off- and on-farm income, in addition to biophysical and socio-economic attributes. Village-level population and demographic data for twenty years period used in this study was obtained from Bangladesh Bureau of Statistics. In addition to the above, gaps from missing data were filled by collecting and validating information through a combination of 9 farmer focus group discussions and presentation of raw data to household members and through secondary sources including household income and expenditure survey (HIES) by Bangladesh government. Graphical overviews of selected variables for years 1995 and 2015 are given in Figs. 3

Table 1
Details on study locations.

Environment	District	Village names	*Predominant crops by season*			*n*
			Kharif-1	*Kharif-2*	*Rabi*	
Non-polder	Barisal	Dehergati, Barpasha, Tabirkathi	*aus* rice	*aman* rice	*boro* rice, vegetables, mustard, pulses	204
Polder	Patuakhali and Barguna	Dakshin Bazargona, Auliapur Paschim Chakamaiya, East Amirabad, Angulkata, Bazarkhali	*aus* rice	*aman* rice	Pulses, groundnut	298

Note: In Bangladesh and several parts of South Asia including eastern India, rice is cultivated three times in a year differentiated by names "*aus, aman or boro"*. The *aman* (broadcast and transplanted) rice is generally cultivated in mid-July to mid-November, sown with the onset of South-west monsoon rains, *boro* (irrigated rice) in Feb-May, and *aus* rice in mid-March to mid-July cropping seasons utilizing summer rains.

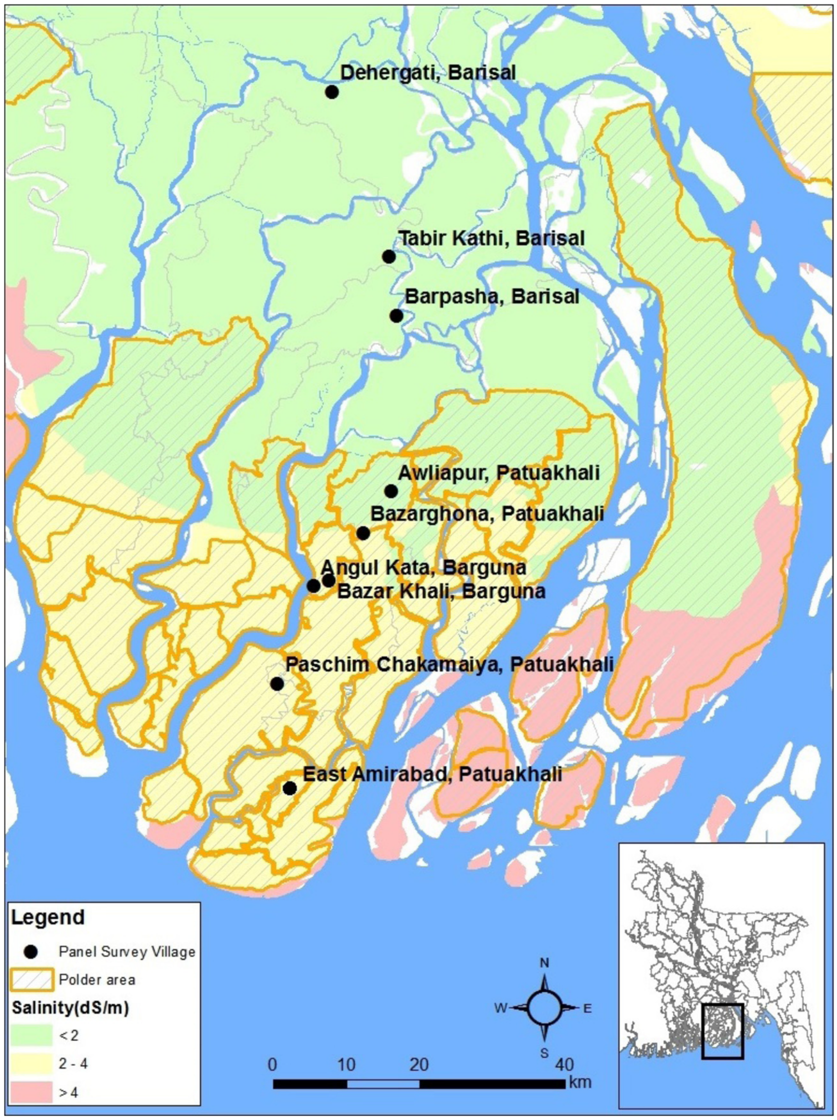

Fig. 2. Map of the study area showing study districts. Black spots indicate the study villages. Salinity data refers to soil and water salinity and was taken from SRDI (2010). White colored areas denote lack of salinity data.

and 4 for sample outside and within polders, respectively. Detailed summary statistics are provided in Table 2.

3.3. Analytical process

Our analysis for farm HHs outside polders (OP) and within polders (WP) proceeded in three steps. First, we developed farm typologies for farm households outside and within polders separately. Distinct farm types were identified for 1995 and 2015. In the second step, we identified the most important variables contributing farm type changes across panel years. In the last step, we identified the multi-level factors driving farm type dynamics using panel data regression models. A historical review of literature was also carried out to complement our findings.

3.3.1. Analyzing farm type dynamics

In the first analytical stage, transition from one farm type to another is captured by farm trajectories of change over time. Towards this, both Principal Component analysis (PCA) and Cluster Analysis were employed (Alvarez et al., 2018) to categorize farm HHs based on the basis of their structural (resource endowment) and functional (production and land use objectives/livelihood strategies) characteristics (Kuivanen et al., 2016). Following the PCA on the data, Agglomerative Hierarchical Clustering employing Ward's minimum-variance method, was done on the PCA (PCs' scores) to identify clusters. The Ward's method minimizes within-cluster variation by comparing two clusters using the sum of squares between the two clusters, summed over all variables (Alvarez et al., 2018). The number of clusters (i.e. farm types) was defined using the dendrogram shape, in particular the decrease of the dissimilarity index ("Height") according to the increase of the number of clusters (Alvarez et al., 2018). We named these clusters based on four criteria: own landholding area, crop-livestock-aquaculture activities, off-farm income and sharecropping. We used Bangladesh's National Agricultural Extension Policy criteria to categorize farms based on the first criteria, i.e. landholding area, such that marginal farmers are those with landholdings of 0.2 to 0.6 ha; small farmers between 0.61 and 1.00 ha; medium between 1.01 and 3.03 ha; and large 3.03 ha or more (MOA, 2012, pp. 2; para 3).

In the second stage, we explored the principal components for changes in typology variables' contribution across panel years from 1995 to 2015 to farming systems change. Variables highly correlated with a principal component (PC) contribute most to its scores (Husson et al., 2017). The percentile contributions of each variable to the principal components can be assessed to determine if any variables

Table 2
Descriptive statistics for key structural and functional farm variables used in the analyses, disaggregated for polder and non-polder environments.

Variables	Unit	Farms outside polders (n = 204)				Farms within polders (n = 298)			
		1995		2015		1995		2015	
		Mean	*SD*	*Mean*	*SD*	*Mean*	*SD*	*Mean*	*SD*
I. Candidate typology variables									
A. *Structural variables*									
Age of the household head	Years	37.79	10.93	50.08	12.66	36.43	10.34	47.14	12.55
Education of the household head	Years	4.24	3.27	5.44	3.60	3.94	3.08	4.94	3.29
Household size of the household	Numbers	10.74	2.05	5.89	2.07	10.92	2.09	5.65	2.19
Total land owned by the household	ha	0.70	0.52	0.41	0.38	0.97	0.87	0.54	0.46
Tropical livestock unit[c]	TLU farm^{-1}	4.50	1.22	0.38	0.56	4.62	1.32	1.05	1.41
Pond area under aquaculture	ha	0.05	0.17	0.04	0.24	0.05	0.08	0.08	0.22
Sharecropping intensity[d]	%	0.19	0.23	0.31	0.30	0.17	0.27	0.29	0.28
Total family labor used on farm	psd year $^{-1}$	262.78	82.84	163.41	106.68	254.51	76.55	181.79	105.26
Total hired labor used on farm	psd year^{-1}	83.13	54.46	75.83	47.48	84.86	67.32	74.22	56.22
Annual income of the household (000)	BDT	18.22	16.57	125.48	136.17	15.54	13.63	159.01	186.62
Annual net savings of the household (000)	BDT	10.81	14.71	20.30	26.85	5.74	5.42	27.60	35.95
B. *Functional variables*									
Area under cash crops	ha	0.35	0.19	0.37	0.33	0.48	0.22	0.43	0.30
Area under food crops	ha	1.25	1.04	0.74	0.50	1.08	1.15	0.69	0.59
Gross cropped area	ha	1.61	1.07	1.10	0.67	1.56	1.22	1.12	0.80
Cropping intensity[e]	%	145.64	28.67	168.57	18.25	145.30	33.14	151.95	28.12
Area under irrigation	ha	0.01	0.08	0.03	0.08	0.00	0.00	0.05	0.10
Amount of *Aman* season fallow	ha	0.03	0.10	0.04	0.12	0.27	0.38	0.25	0.45
Amount of *Rabi* season fallow	ha	0.91	1.00	0.39	0.33	0.87	1.11	0.44	0.30
Share of total crops sold	%	70.61	7.93	80.34	14.54	70.99	9.97	85.31	8.80
Months of food self-sufficiency	Number of months	9.80	1.57	10.30	2.18	9.24	1.64	10.08	2.34
Share of expenditure for food	%	56.34	16.38	62.48	18.00	61.82	13.30	58.88	17.96
Off-farm income	%	41.98	31.31	56.60	27.35	41.28	33.84	49.42	30.46
Remittances received per annum (000)	BDT	0.03	0.29	10.66	19.76	0.01	0.20	14.37	23.40
II. Factors driving farm trajectories of change									
*Micro-level household variables*A.									
Household's experience in cropping	Years	20.81	11.00	33.37	12.70	19.35	10.12	30.66	12.62
Household head's involvement in farming	Ordered categorical (1 = no involvement, 2 = partial and 3 = full involvement)	1.48	0.77	1.37	0.74	2.43	0.82	2.84	0.51
Share of land under machine tillage	%	1.71	5.70	98.75	5.37	0.00	0.00	95.40	13.58
Degree of fragmentation of farmland[b]	Scale of 1 = low to 5 = high level	3.35	1.22	2.25	0.72	2.39	2.22	2.16	1.67
Inundation class	Lowland = 1, medium land = 2 and 3 = highland	2.08	0.48	2.00	0.40	2.35	0.60	2.45	0.51
Perceived soil fertility of the farm	Low = 1, medium =2 and 3 = high	2.36	0.88	2.00	0.78	2.20	0.91	2.21	0.80
Perceived soil and water salinity of the farm	Low = 1, medium =2 and 3 = high	NA	NA	NA	NA	2.08	0.53	1.99	0.99
*Meso-level conditioning variables*B.									
Distance to input-output markets	km	3.88	1.72	2.64	0.98	8.30	3.42	5.68	3.12
Distance to the irrigation canal	km	0.38	0.24	0.14	0.13	0.19	0.17	0.14	0.15
Distance to the main road	km	1.66	0.96	1.10	0.52	1.78	1.17	1.65	1.05
Access to extension	Dummy (1 = has access, 0 otherwise)	0.46	0.50	0.67	0.47	0.40	0.49	0.47	0.50
Access to credit	Dummy (1 = has access, and 0 otherwise)	0.41	0.49	0.75	0.44	0.27	0.45	0.08	0.27
Tenure rights	Dummy (1 = has access, and 0 otherwise)	0.27	0.44	0.16	0.37	0.72	0.45	0.93	0.26
Availability of hired farm labor	Dummy (1 = has access, and 0 otherwise)	0.51	0.50	0.50	0.50	0.21	0.41	0.16	0.37
*Macro-level driver variables*C.									
Village population	Numbers	1908.47	817.69	2053.67	861.27	4018.43	3116.31	4674.00	3645.76
Cyclone severity index[a]	–	3.72	2.52	1.45	0.94	3.82	2.61	2.74	2.44

Notes:- psd = person-day, which is 8 h of work.
[a] Index developed by summing up the product of cyclone events and farmer's perception on an individual cyclone's severity on a scale of 0–3 in the respective years observed.
[b] Categories on a scale of 1–5; 1 = low level and 5 = high level of fragmentation. 1USD was ~40 BDT in 1995 while it was ~78 BDT in 2015.
[c] Tropical livestock unit (TLU) was calculated according to method given by Harvest Choice 2015 (https://harvestchoice.org/data/an05_tlu).
[d] Sharecropping intensity is ratio of sharecropped land to total land available for cultivation in %.
[e] Cropping intensity averaged across fields is calculated as $\frac{Gross\ harvested\ area\ (ha)\ farm^{-1}\ year^{-1}}{Total\ land\ area\ (ha)\ farm^{-1}\ year^{-1}} \times 100$ and will exceed 100% where double or triple croppingis practiced.
All monetary values are nominal.

strongly influence a particular PC (David and Jacobs, 2014). The contribution (C_k) of a variable 'k' to a given PC is calculated as:

$$C_k = \frac{((\cos_k)^2 * 100)}{\sum_{k=1}^{K} (\cos_k)^2} \tag{1}$$

where $(cos_k)^2$ in Eq. (1) is the squared cosine of a variable 'k' that represents the quality of the representation of that variable quantified as

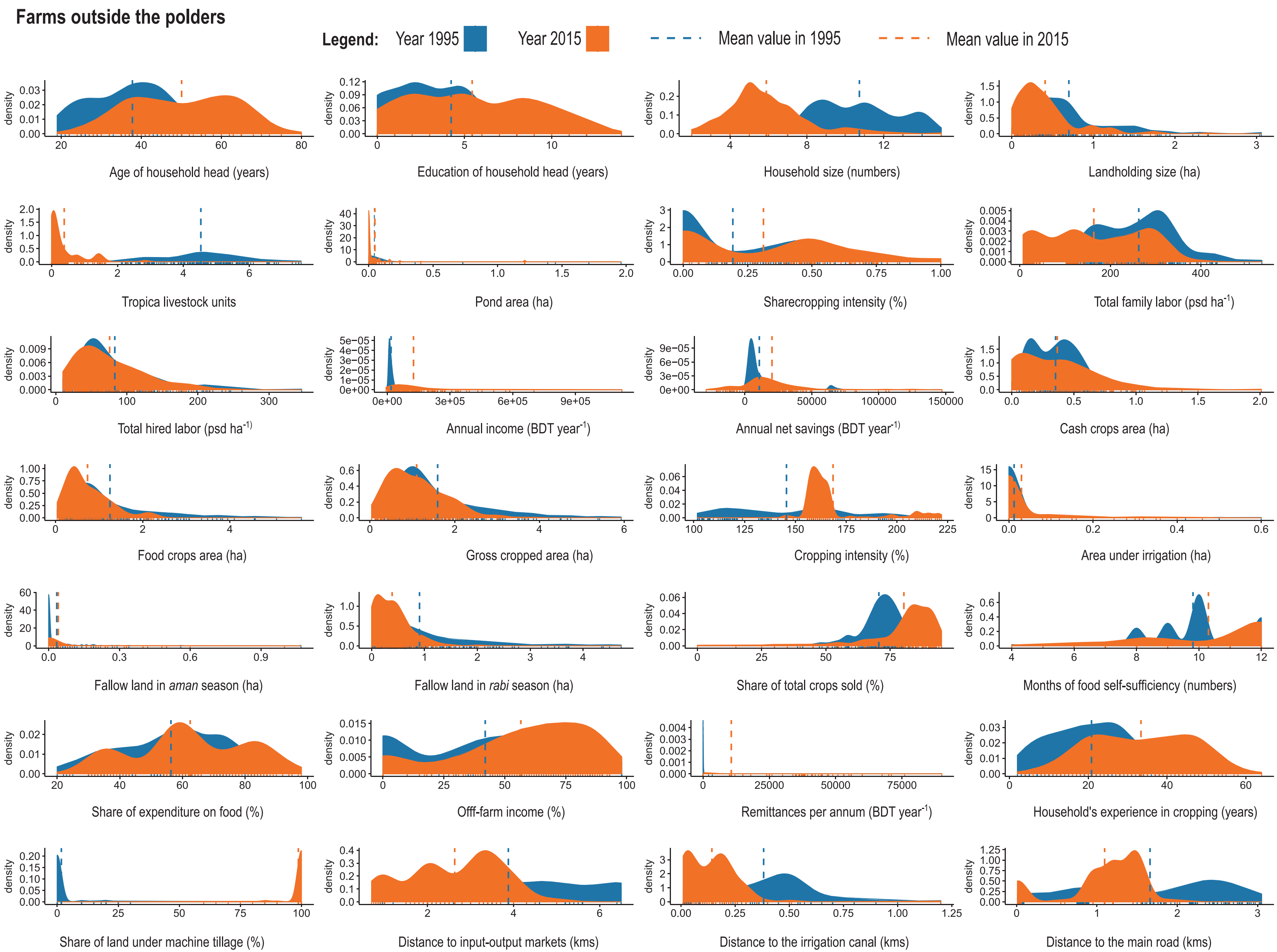

Fig. 3. Graphical overview of selected variables in the data from sample outside the polders. Y-axis in the plots indicates the density of farms.

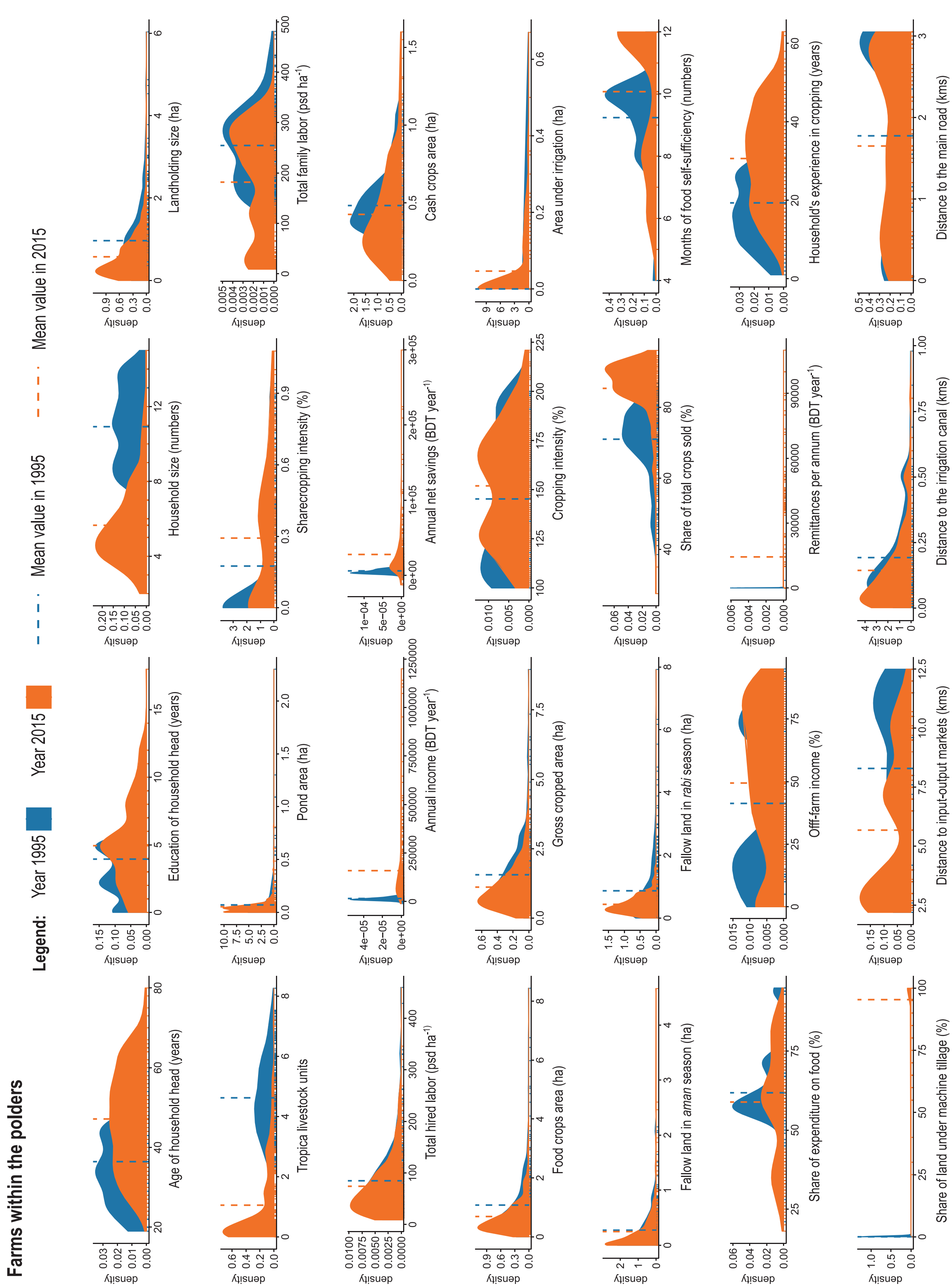

Fig. 4. Graphical overview of selected variables in the data from sample within the polders. Y-axis in the plots indicates the density of farms.

the squared loadings for that variable in the principal component. Squared cosines ($\cos^2$) thus help locate the variables important for a given PC based on their relative contribution (Abdi and Williams, 2010). Cumulative contributions of all variables in the selected PCs (with eigenvalues ≥ 1.0) for each panel year (1995 to 2015) were assessed to identify the variables showing strongest contribution to variance. Those with the greatest contribution across years are assumed to have robust linkages to change trajectories among sampled farms. These are the '*farm dynamicity inducing variables*' that were analyzed using panel regression models in the second stage as described below.

3.3.2. Modelling multi-level factors and drivers influencing farm change trajectories

In the third analytical stage, we analyzed the effects of multi-level factors/drivers of change on dominant variables contributing to farm type dynamics in panel years (T) by employing panel data modelling (Hsiao et al., 2000; Baltagi, 2008). Let the panel dataset contain observations of the multi-level factors and drivers of change (independent variables), $X_1, X_2, \ldots, X_k$ and the dominant variables contributing to farm type dynamics, whose identification is explained in Section 3.3.1 be treated as (dependent variables):$Y_1, Y_2, \ldots, Y_m$, with farm/farmer specific effects: $Z_i^{'}\alpha$. The model thus takes the form in Eq. (2):

$$Y_{\mathrm{it}} = X_{\mathrm{it}}'\beta + Z_i'\alpha + \varepsilon_{\mathrm{it}} \tag{2}$$

where $i = 1, \ldots, n$ and $t = 1, \ldots, T$, where the first subscript, i, refers to the farm being observed, and the second term t, refers to the observational year ($T = 5$ in our case). In Eq. (2), ε_{it} is the error term and $Z_i^{'}$ is a set of farm household-specific micro-level factors (Table 2). Since $Z_i^{'}$ in the data has both observed and farmers' perceived variables, the ordinary linear model fitted by least squares would suffer from bias (Baltagi, 2008). We therefore estimated a generalized fixed effects (FE) model (Eq. (3)) when $Z_i^{'}$ is unobserved, but correlated with X_{it}, and when $Z_i^{'}$ is observed, then we estimated a generalized random effects (RE) model by introducing a household specific random element μ_i as in Eq. (4).

$$Y_{\mathrm{it}} = X_{\mathrm{it}}'\beta + \alpha_i + \varepsilon_{\mathrm{it}} \tag{3}$$

$$Y_{\mathrm{it}} = X_{\mathrm{it}}'\beta + \alpha_i + \mu_i + \varepsilon_{\mathrm{it}} \tag{4}$$

We ran both FE and RE estimators for all dependent variables $Y_1, Y_2, \ldots, Y_m$obtained from stage 1 and compared results using the Hausman test, the results of which are reported in Section 4.3. The effect of multi-level factors/drivers were assessed from the coefficient estimates, i.e. 'β_s' and 'α_s'. All statistical analyses are conducted using packages *plm* (Croissant and Millo, 2008) and *FactoMineR* (Husson et al., 2017) in R (version 3.3.2).

4. Results

4.1. Farm type dynamics

Farm typology analysis of data yielded a multivariate classification of distinct farm typologies segregated by those located within and or outside polders. Farm types observed in five-year increments from 1995 to 2015 are provided in the Supplementary Materials (Table SM 1 and SM 2). Performing typology analysis on 204 farms outside polders revealed seven distinct farm types for the baseline year 1995 (Fig. 5A). The same farms were re-classified into three types in 2015 (Fig. 5B). The dendrograms and cut-off points based on dissimilarity for all the years (1995–2015) for farms located within or outside polders are shown in the Supplementary Materials (Figure SM 1 (A) and (B)). Farm types identified outside polders are labelled as $t_1 1$ to $t_1 7$, and $t_2 1$ to $t_2 3$ respectively, where t_1 and t_2 correspond to time periods 1995 and 2015. Numbers conversely correspond to typology clusters. A detailed account of the farm types with the names defining structural and functional characteristics are provided in the Supplementary Materials (Text SM 1 to SM 4). For farms located within polders, the trend with respect to farming systems was similar to those outside polders: consolidation into fewer farm types was observed over time in both locational categories. The typology analysis for farms within polders for1995 and 2015 identified six and three farm types, respectively (Fig. 5C and D).

Fig. 6 shows shifts between farm types from the baseline in 1995 to the final year of analysis in 2015. Among farms outside polders, the proportion of marginal farms increased from 52% in 1995 to over 70% by 2015. The share of small farms also increased by 8% during the same period, while medium-sized farms whose proportion was 26% in 1995 disappeared entirely by 2015. Out of the medium-sized farms with rice-livestock-sharecropping systems ($t_1 7$), 92% became small farms with rice-pulse and aquaculture–sharecropping systems ($t_2 3$) in 2015, while the remaining 8% became marginal farms with rice-aquaculture systems and off-farm activities ($t_2 1$). Among farms within polders, 84% of small farm types transitioned into marginal farms by 2015. The remaining farms changed to two small farm types ($t_2 B$ and $t_2 C$) by 2015. There was only one marginal farm type in 2015 that can be described as rice-pulse-aquaculture systems with off- farm income ($t_2 A$). These constituted 67% of observed farms in 2015. In 1995, two medium-sized farm types were observed that comprised 20% of all farms surveyed. Roughly 22% of medium-sized sharecropping farms with rice-livestock-pulse-aquaculture systems ($t_1 E$) farms transitioned into marginal farms with rice-pulse-aquaculture supplemented by off-farm income ($t_2 A$) by 2015. The remaining 78% shifted into small rice-pulse-aquaculture and a significant proportion of sharecropping activities ($t_2 B$). Ninety-one percent of medium- sized sharecropping farms with rice-livestock-pulse-aquaculture systems ($t_1 E$) transitioned into type $t_2 B$ (Small farms with rice-pulse systems and off-farm income) by 2015, while 9% shifted into marginally sized farms with rice- aquaculture systems and off-farm income ($t_2 C$).

Within the polders, the real income from edible crops showed negative growth (−1.6%) for marginally sized farms between 1995 and 2015, there was however a remarkably higher growth rate from aquaculture (> 950%) and remittance (> 500%) (Table SM 6). Income from edible crops for small sized farms also exhibited a positive growth rate, but at just 6% during this twenty year period. Both income from aquaculture and remittance showed increase in growth rate of 180% and 131% respectively for small farms outside polders. A trend towards non-farm income generation also appears to be growing among marginally sized farms outside polders. This shift towards off-farm income outside polders is however less prominent among smaller farms, despite a slight 2% growth rate (Table SM 5). Among farms in polders, trends during this twenty years are only notable for small farms, as marginally sized were not existent in 1995, and medium sized farms had disappeared by 2015 (Fig. 8B). Growth in non-farm income (6%) was however observed with increasing remittances and off-farm income generation, in addition to income from cash crops (Fig. 8B and Table SM 6). The contribution of livestock to household income within polders has also conversely declined over time (Fig. 8B).

4.2. Relative farmland use changes and drivers

Five distinct cropping patterns practiced by farmers located outside polders were distinguished during the *Kharif-1* (spring), *Kharif-2* (summer), and *Rabi* (winter) seasons. Their corresponding drivers of change are found in Fig. 7A. Cropping patterns within polders were equally diverse, but their abundance differed when compared to those found outside polders (Fig. 7B). Four cropping patterns were practiced by most farms within polders during the *Kharif- 1* (spring), *Kharif-2* (summer), and *Rabi* (winter) seasons (Fig. 7B). During the 1995–2007 period, 'fallow-*aman* rice- lathyrus' rotations were practiced by > 60% farmers with land outside polders.

Both within and outside polder areas, cyclones *Sidr* and *Aila* appear to have had adverse impacts on irrigated rice production during 2007 and 2009. Farmers turned to less intensive cropping patterns including

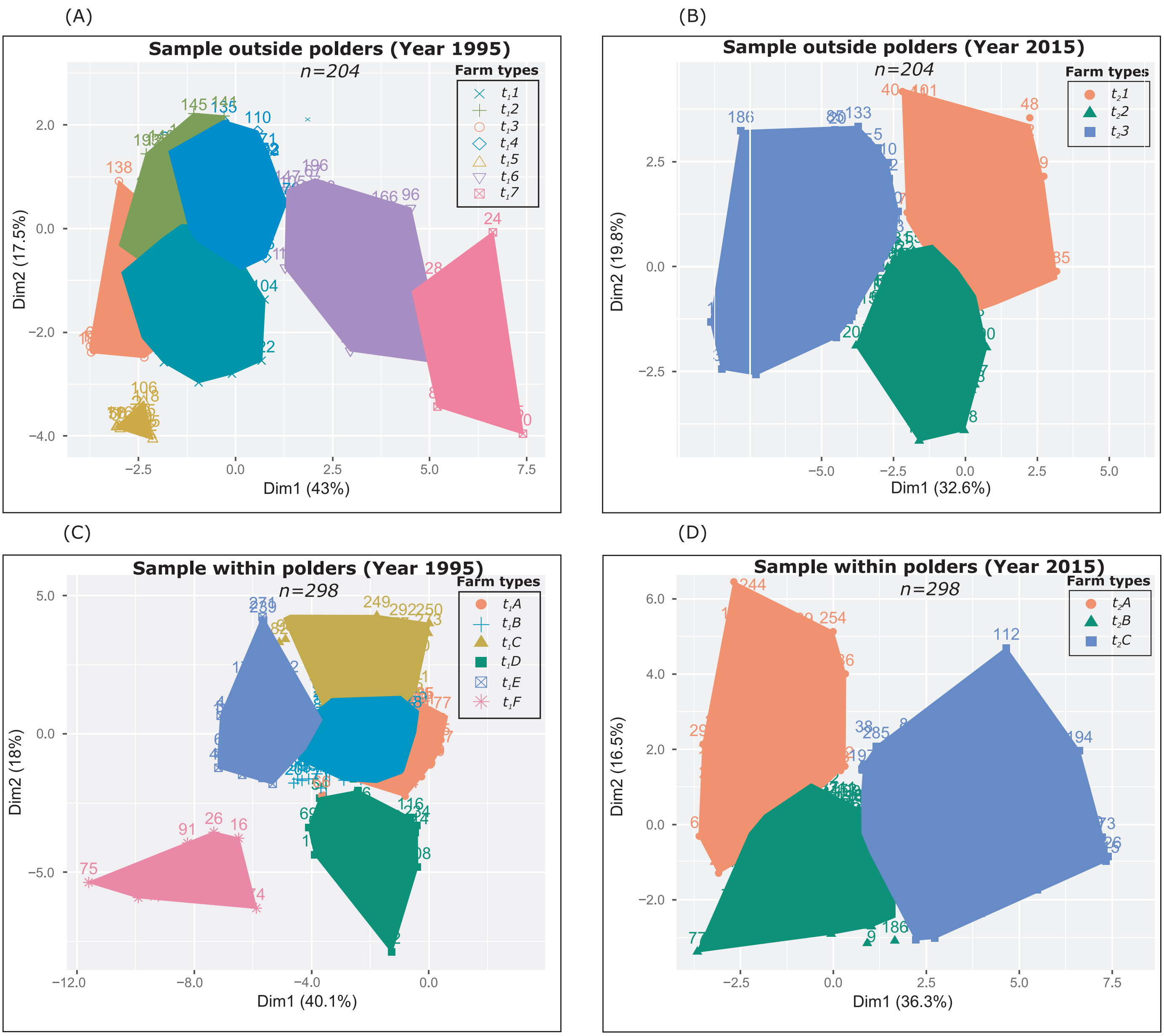

Fig. 5. Results of the typology analysis for farms within (A, B) and outside polders (C, D) in the year 1995 (A, C) and 2015 (B, D) along the first two principal components. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.).

pulses (which were slowly becoming more profitable) and land fallowing in the wake of both events. Towards the late 1990s, 'fallow-*aman* rice- mungbean' cropping sequences emerged as an important rotation outside of polders. By 2015 this pattern dominated — > 70% farms surveyed outside of polders followed this pattern, with mungbean as a widely favored pulse.

By the year 2000 each village sampled within polders on average had 4–5 low-lift irrigation pumps. This helped expansion of irrigated *boro* rice cultivation by drawing water from rivers and canals, though cyclones *Sidr* and *Aila* caused later damage to sluice gates that regulate water inflow and outflow from the canals. Sluice gates, which were initially installed through governmental programs, have yet to be repaired in a number of the surveyed villages. As an alternative to irrigated cultivation, farmers have slowly shifted to minor pulses including black gram, cowpea and field pea, grown prior to with spring rice (*aus*). Major pulses such as mungbean and lathyrus were also popular. The 'fallow-rice-various pulses' cropping pattern remained prominent until 2010 when mungbean began to replace other pulses. The other predominant cropping pattern, 'fallow-*aman* rice-fallow', declined from 10% to 4% between 1995 and 2015.

4.3. Factors driving farm trajectories of change among polder and non-polder sample

We identified variables that contributed strongly to each principal component by computing the percentage contribution (*Ctr*) of each typology variable within a given principal component (Abdi and Williams, 2010; Husson et al., 2017) using Eq. (1) and present them in Fig. 8. Principal components with eigenvalues ≥1 selected for computing contribution explained > 70% of the variability in farm typology data both within and outside polders. Within polders, the first four PCs obtained for the years 1995, 2000, 2005 and 2015 explained cumulative variability of 77%, 73%, 73% and 72% respectively. In 2010, however, only the first three principal components had eigenvalues ≥1, explaining roughly 70% variability for samples outside the polder area in 2010. Within polders, the first three principal

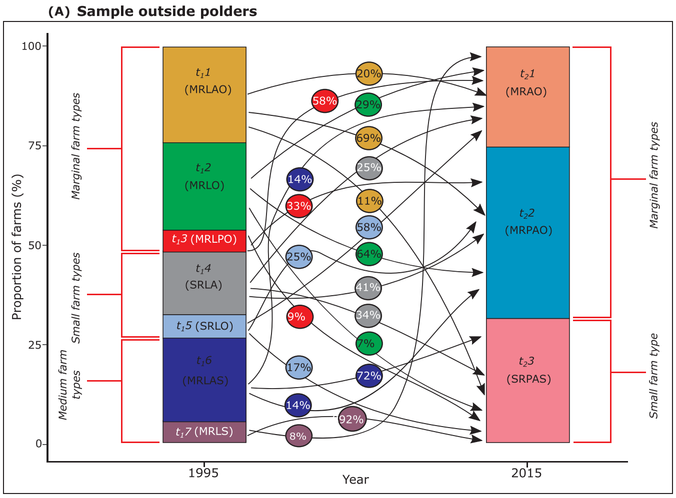

Fig. 6. Farm type dynamics in areas outside (panel A) and within polders (panel B) between 1995 and 2015 in south-central Bangladesh. Arrows represent the trajectory of change from one farm type in 1995 to another in 2015. Values within circles show the percentage of farms transitioning. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.).

components obtained for years 1995, 2000 and 2015 had eigenvalues ≥1, which explained cumulative variability of 77%, 70% and 73% respectively. While for years 2005 and 2010, first five principal components had eigenvalues ≥1. They explained 73% and 76% of cumulative variability for samples within polders for 2005 and 2010. Estimates of cumulative contributions of each typology variable for Fig. 8 are provided in the Supplementary Materials (Tables SM 3 and SM 4). Fig. 8 indicates that farm type dynamics are strongly linked to cropping intensity, off-farm income and landholding outside polders, while inside polders, the dynamics is linked to cropping intensity, off-farm income and livestock.

Tables 3 and 4 provide panel data model estimates of factors influencing farm change trajectories for samples within and outside polders. The Hausman test for the goodness of fit of the fixed effects versus random effects for all models informs whether the random effects estimator is consistent and the model is valid. The test was

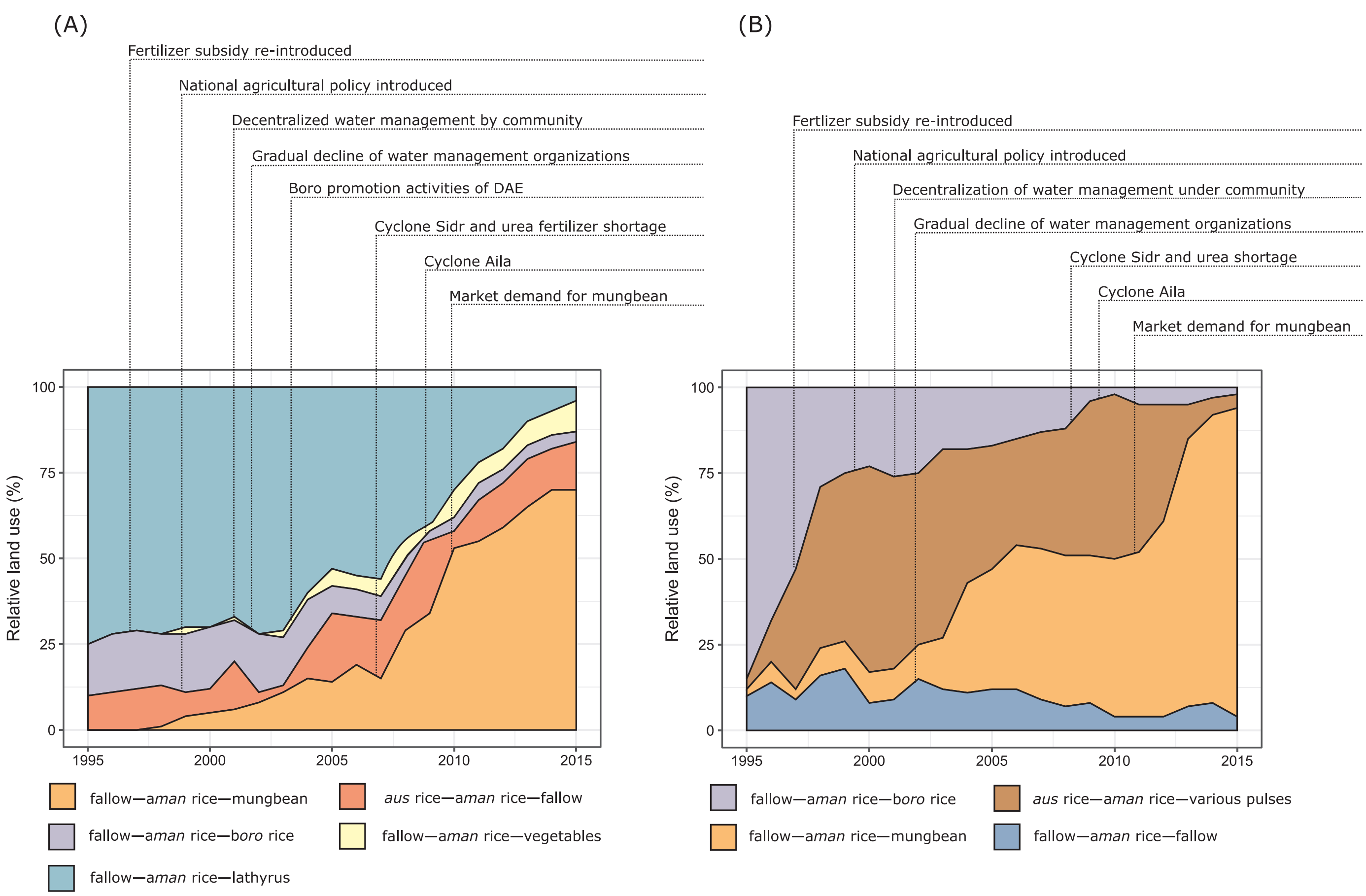

Fig. 7. Relative farmland use change in terms of cropping patterns for *Kharif* and *Rabi* seasons that represents proportion of HHs in non-polder (A) and polder (B) areas. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.).

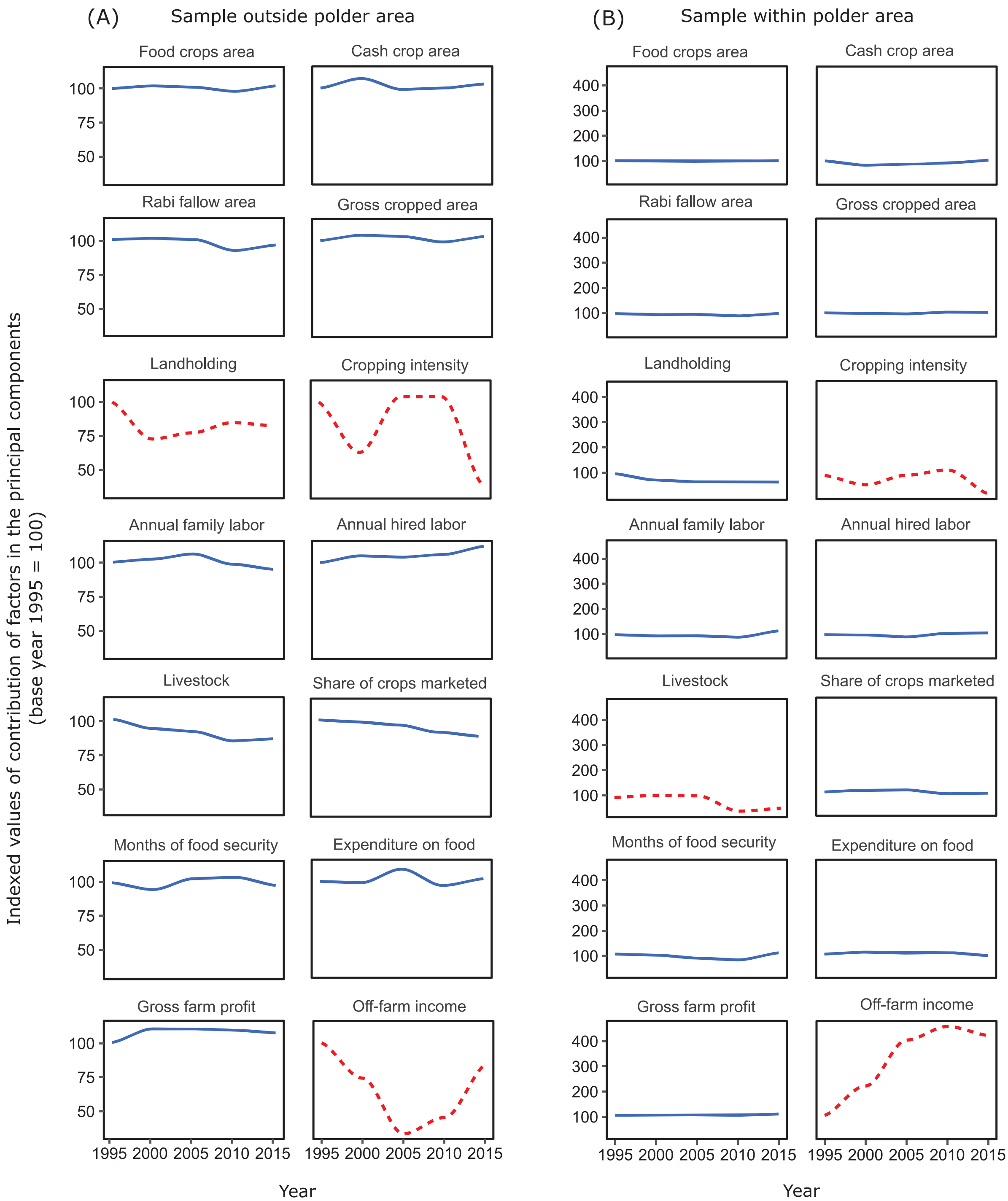

Fig. 8. Variable contribution to principal components across panel years. Index values of cumulative contributions in PCs with eigenvalues ≥1.0 are plotted, taking 1995 as base year = 100. Dynamicity inducing variables, i.e. the variables influencing farm type dynamics and variability significantly are represented by dotted red line. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.).

significant ($P > 0.05$), rejecting the null hypothesis of a consistent fixed effects estimator for all models.

4.3.1. *Micro-level factors influencing farm trajectories*

Among micro-level factors, farm household heads' experience exerted a significant ($P \leq 0.05$) negative influence on cropping intensity within polders (Table 4). Outside polders, this effect though negative was nonetheless insignificant (Table 3). During focus groups, older farmers revealed their preference for growing rice over cash crops when monsoon rains are available, with land left fallow in the subsequent winter season. Rice being the main staple crop in Bangladesh, this preference according to them is to ensure household food security. Compared to households with no direct involvement in farming operations (i.e., those who tended to work as hired laborers), households fully involved in agricultural production had average cropping intensities that are 1.3 times greater, ceteris paribus. Household heads' direct involvement in farming activities however tend to negatively and significantly ($P \leq 0.001$) influence the households' share of off-farm income in polders.

Within polders, the proportion of land upon which farmers used

Table 3
Factors driving farm change trajectories in cropping intensity, landholding and off-farm income outside polders (random effects model; $n = 204$).

	Cropping intensity (%)	Land owned (ha)	Off-farm income (%)
Model intercept	192.580 (2.471)	0.0717 (0.189)	61.516*** (10.996)
A. Micro-level household determinants			
Experience in farming	−0.003 (0.016)	0.003* (0.001)	0.079 (0.074)
Household head's involvement in farming	1.291* (0.529)	−0.022 (0.040)	4.130 (2.358)
Share of land under machine tillage	0.013 (0.007)	−0.002** (0.001)	−0.157*** (0.034)
Degree of landholding fragmentation	−1.146*** (0.042)	−0.010 (0.032)	6.877*** (1.864)
Perceived soil fertility of the farm	1.406** (0.456)	0.037 (0.035)	1.574 (2.032)
Inundation class	0.640* (0.310)	0.084* (0.035)	−7.080*** (2.013)
B. Meso-level conditioning factors			
Distance to the input-output markets	−1.640*** (0.220)	0.014 (0.010)	−2.674** (0.974)
Distance to irrigation canal	−1.3924 (0.998)	0.157* (0.076)	−1.317 (4.43)
Distance to the main road	−1.2658*** (0.340)	0.077** (0.026)	−4.939*** (1.495)
Access to extension	3.744*** (0.690)	0.052 (0.410)	−0.197 (3.055)
Access to credit	−0.144 (0.918)	−0.071 (0.061)	2.103 (4.087)
Tenure rights	2.540** (0.923)	−0.091 (0.070)	−2.779 (4.108)
Labor availability	4.134*** (0.872)	0.058 (0.050)	−2.866 (3.884)
C. Macro-level drivers			
Village population density	0.001*** (0.000)	−0.001 (0.00)	0.002 (0.001)
Cyclone severity	−3.165*** (0.176)	−0.025* (0.010)	−1.986* (0.784)
Model goodness of fit measures			
Total Sum of Squares:	*809000*	*237.33*	*792130*
Residual Sum of Squares:	*36181*	*211.09*	*716480*
R-Squared:	*0.655*	*0.611*	*0.673*
Adj. R-Squared:	*0.641*	*0.609*	*0.662*
F-statistic:	*1429.680* on 15 and 1004 DF*	*8.320* on 15 and 1004 DF*	*7.067* on 15 and 1004*
Hausman Test (p-value)	*$Chi^2 = 22.762$, df = 15, P = 0.089*	*$Chi^2 = 15.529$, df = 15, P = 0.414*	*$Chi^2 = 13.793$, df = 15, P = 0.541*

Notes: *, **, and *** indicate significance at the 10%, 5%, and 1% levels. Coefficient estimates of linear probability models are shown with robust standard errors at household level in parentheses.

Table 4
Factors driving farm change trajectories in cropping intensity, tropical livestock units and off-farm income within polders (random effects model; $n = 298$).

	Cropping intensity (%)	Tropical livestock units	Off-farm income (%)
Model intercept	190.952*** (1.458)	3.573*** (0.385)	53.471*** (7.126)
A.Micro-level household determinants			
Experience in farming	−0.026* (0.013)	−0.005 (0.003)	−0.024 (0.063)
Household head's involvement in farming	0.189 (0.329)	0.004 (0.87)	−5.518*** (1.610)
Share of land under machine tillage	0.009* (0.005)	−0.015*** (0.001)	−0.039 (0.026)
Degree of landholding fragmentation	−0.409*** (0.087)	−0.006 (0.023)	4.728*** (0.423)
Perceived soil fertility of the farm	−0.260 (0.295)	−0.015 (0.078)	−1.09 (1.442)
Perceived soil salinity in the farm	−0.473* (0.210)	0.009 (0.056)	6.065*** (1.031)
Inundation class	0.253* (0.116)	−0.087 (0.077)	−2.253 (1.419)
B. Meso-level conditioning factors			
Distance to the input-output markets	−0.683*** (0.092)	0.051* (0.242)	−1.496*** (0.449)
Distance to irrigation canal	−1.759* (0.837)	0.259 (0.247)	1.233** (0.458)
Distance to the main road	−1.977*** (0.042)	0.092 (0.112)	0.504 (2.072)
Access to extension	2.375*** (0.451)	−0.006 (0.119)	−0.599 (2.204)
Access to credit	0.906 (0.600)	0.192 (0.158)	−3.507 (2.935)
Tenure rights	2.706*** (0.704)	−0.109 (0.186)	2.175 (3.442)
Labor availability	4.946*** (0.588)	0.067 (0.155)	−0.297 (2.872)
C. Macro-level drivers			
Village population density	0.001 (0.001)	0.001 (0.000)	−0.001 (0.000)
Cyclone severity	−1.686*** (0.148)	−0.093* (0.039)	−1.053 (0.722)
Model goodness of fit measures			
Total Sum of Squares	*1346100*	*3292.9*	*1230100*
Residual Sum	*43380*	*3019.5*	*1036600*
R-Squared:	*0.668*	*0. 630*	*0.457*
Adj. R-Squared	*0.657*	*0. 621*	*0.456*
F-statistic:	*2764.660* on 16 and 1473 DF*	*8.335* on 16 and 1473 DF*	*17.178* on 16 and 1473 DF*
Hausman Test (p-value)	*$Chi^2 = 11.872$, df = 16, P = 0.753*	*$Chi^2 = 12.147$, df = 16, P = 0.734*	*$Chi^2 = 11.39$, df = 16, P = 0.785*

Notes: *, **, and *** indicate significance at the 10%, 5%, and 1% levels. Coefficient estimates of linear probability models are shown with robust standard errors at household level in parentheses.

machinery for tillage was positively related to cropping intensity ($P \leq 0.05$) (Table 4). Mechanized tillage was inversely related ($P \leq 0.05$) to livestock holdings both within and outside of polders. Land fragmentation into separate parcels was observed to have a negative ($P \leq 0.001$) influence on cropping intensity in all study locations (Table 4). Farmers' perceptions of soil fertility showed a positive ($P \leq 0.1$) influence on cropping intensity outside polders, although within polders, no relationship could be discerned. Farmers located outside polders did not report problems of soil or water salinity, while those within polders reported low, moderate and high soil and water salinity. Perceived soil and water salinity within polders had a negative ($P \leq 0.1$) impact on cropping intensity.

Another qualitative variable farmers were surveyed on was 'Inundation class". This variable was based on classifications described by Brammer (2013) as the average perceived depth of flooding during the monsoon season, and is widely used by farmers to describe their land types. The level of inundation during the monsoon is important in determining the variety of rice that can be grown, and the speed at which floodwaters vacate following the summer monsoon to permit cropping in the early winter season (Krupnik et al., 2017). The official land inundation classification system is complex, with five classes. For simplification, we asked farmers to report if their fields on average belonged to "low" (> 180 cm average water depth) "medium" (30–180 cm water depth) or "high" (0–30 cm water depth) during the monsoon season. Our results indicated that lower inundation depths associated with progressively higher land on a micro-elevation basis positively and significantly ($P \leq 0.05$) influenced cropping intensity both within and outside polders (Table 4). Farms with a higher share of fields on 'highlands' are also more likely to be suitable for double-cropping. This result that could be influenced by drainage problems associated with land subsidence and poor polder engineering that prevents timely winter cropping, even on highlands, within polder systems in the central coast of Bangladesh (Krupnik et al., 2017). Model estimates showed positive ($P \leq 0.05$) relationship between landholding size outside polders and lower inundation depths (Table 3). These results indicate that farmers prefer in both locational classifications less flood-prone lands that can be more reliably cropped.

Turning to micro-level factors influencing off-farm income, land fragmentation positively and significantly ($P \leq 0.001$) influenced the share of farm household's off-farm income both within and outside polders. Outside polders, inundation class negatively ($P \leq 0.001$) influenced off-farm income (Table 3). In other words, farms with higher land less subjected to prolonged monsoon water stagnation were associated with a 7% reduction in share of off-farm income.

4.3.2. Meso-level factors influencing farm trajectories

Both increasing distance to the market and main road from the farm negatively and significantly ($P \leq 0.001$) influenced cropping intensities of all farms in the sample (Tables 3 and 4). A similar negative ($P \leq 0.001$) relationship was found between output market distance and share of off-farm income within and outside polders (Tables 3 and 4). Access to extension on the other hand had a positive and significant influence ($P \leq 0.001$) on cropping intensity within polders (Table 4). Access to credit was insignificant across locations, though approximately 5% of surveyed farmers in polders reported constraints in timely availability and access to agricultural finance. Farmers with secure land tenure were also found associated with increased cropping intensity compared to those heavily involved in share cropping. Tenure rights had a positive and highly significant influence ($P \leq 0.01$) on cropping intensities both within and outside of polders (Tables 3 and 4).

Irrigation canal proximally to farms had no significant influence on cropping intensity or off-farm income outside polders (Table 3). Irrigation canals situated near farmers' fields conversely had a marginally significant ($P \leq 0.1$) and positive influence on larger farm size (Table 3). Cropping intensity within polders decreased significantly ($P \leq 0.05$) with increasing distance to irrigation canals (Table 4). The influence of irrigation canal distance on off-farm income within polders was however positive and significant ($P \leq 0.01$), indicating that farmers may seek off-farm income opportunities when irrigation is distant and unreliable (Table 4). Our results also highlight the very significant ($P \leq 0.001$) and positive relationship between labor availability and cropping intensity both within and outside polders (Tables 3 and 4).

4.3.3. Macro-level drivers influencing farm trajectories

The relationship between village population size and cropping intensity was positive and significant ($P \leq 0.001$) outside polders (Table 3). Population density however had no effect on the amount of land owned or off-farm income (Table 3). Population growth also had no association with cropping intensity inside polders, despite a positive trend (Table 4). Importantly, past cyclone severity negatively and significantly affected cropping intensities of farms both within and outside polders ($P \leq 0.001$) (Tables 3 and 4). Past cyclones severity also negatively influenced the amount of land owned ($P \leq 0.05$) and off-farm income ($P \leq .05$) outside polders (Table 3), while within polders, cyclones severity was negatively associated with the number of livestock owned ($P \leq 0.05$) (Table 4). A single unit increase in cyclonic severity was associated with a two to three time reduction in cropping intensity within and outside polders, respectively. During focus groups, farmers who had experienced cyclones and extreme weather also indicated that they responded by reducing cropped area or by fallowing to hedge risks.

5. Discussion

Using a novel systems analysis approach integrating multivariate statistics with panel data models that operationalize the theoretical framework described in Section 2, we studied how biophysical processes interact with complex human and management components that define coastal farming systems both within and outside polder areas using two decades of data. Farming systems studied exhibit spatial and temporal dynamics that highlight how farm types transition over time in response to multi-level drivers of change. Both within and outside polders, marginal and small farms dominated in 2015, as compared to larger farms twenty years earlier. The number of medium and large farms for example also sharply declined in north-western Bangladesh since 2005 (Misra, 2017). Similar observations have been made for population dense and intensively cultivated landscapes in parts of South East Asia and sub-Saharan Africa (Rigg et al., 2016; Jayne et al., 2016).

Our findings highlight a consistent trend throughout for farms observed outside polders. Once heterogeneous, rice-livestock farms have shifted to more homogenous farms with aquaculture and increasing off-farm income generating activities. Within polders, trends were only notable for smaller farm types. Growth in remittances and off-farm income generation was however observed, in addition to income from cash crops. The contribution of livestock to household income conversely declined. Considering marginally sized farms within polders, there was more than a nine and five-fold increase in income contribution from aquaculture and remittances, respectively. Income from edible crops for small sized farms also exhibited a positive trend, but at just 6%. For smaller farms outside polders, both income from aquaculture and remittances showed increased growth rates of 180% and 131%, respectively. Farmers also shifted from subsistence aquaculture to the production of commercial species including tilapia, pangasius, and catfish (Hernandez et al., 2018). Unlike the south-western Bangladesh where prawn production has competed with rice for land and water resources, aquacultural intensification in south-central Bangladesh appears to have had limited negative environmental and social impacts (Henriksson et al., 2018).

Irrespective of typology, farming systems in both the study locations continued to be *aman* rice-based. Until approximately 2005, *boro* rice production (during the winter *Rabi* season) also flourished both within and outside polders, but then declined. In polders outside our study area in south-western Bangladesh, concerns of elite capture of surface water resources by commercial prawn farmers diverting saline water into canal systems have been common (cf. Dewan et al., 2015). South-central Bangladesh however has more hydrologically active freshwater canal systems – in some cases even within polders (Krupnik et al., 2017).

Between 1996 and 1998, national agricultural policy in Bangladesh re-introduced fertilizer price subsidies. Changes included increased control on input market price volatility, making fertilizers affordable (Jaim and Akter, 2012). Farmers outside polders may have responded by transitioning to new cropping patterns including 'fallow- *aman* rice-vegetables', with the latter crop requiring increased fertilizer. This period also saw the expansion of 'fallow-*aman* rice-irrigated *boro* rice' corresponding to expanding availability of low-lift surface water pumps, in addition to fertilizer (Mottaleb et al., 2016). In the winter season, *boro* rice area continued to decrease within and outside polders from 2005 to 2010. This appeared to be a result of urea shortages that followed the introduction of a government subsidized fertilizer voucher system. Focus group interviews indicated that politically connected farmers captured more vouchers than less well-connected farmers, rending the system less efficient and negatively influencing aggregate *boro* production. Differences in cropping patterns outside and within polders were evident until 2010. Farmers outside polders favored 'fallow-*aman* rice-lathyrus' rotations compared to '*aus* rice-*aman* rice-mungbean' within the polders. Nonetheless, there is now a clear shift towards 'fallow-*aman* rice-mungbean' sequences in both areas, with a definite growth in mungbean cultivation.

The GoB's Master Plan for Development in the Southern region proposed by the MOA and FAO in 2013 suggests initiatives to increase *boro* rice production in place of fallows. This however conflicts with the growing popularity of mungbean in the winter season. Focus groups indicated that low paddy prices and relatively higher labor costs provide disincentive against *boro*, in addition to high irrigation costs. Although mungbean is favored as a low-input opportunity crop that fetches better prices, it fairs poorly in the face of storms and waterlogging common in the coastal region (Biswas et al., 2018). Further studies regarding its suitability *vis-a-vis* other options are still warranted.

Changes in farm types appeared to be linked to dynamicity inducing variables: (1) cropping intensity and (2) off-farm income, and (3) landholding and livestock, the former two are for both outside and within polders. Our analysis revealed the influence of multi-level socioecological drivers of trajectories of farming systems change. Ours results show that while cropping intensities both within and outside polders reduce with increased farm fragmentation; farmers responded to this and other environmental stresses through off-farm income generation. Bangladeshi inheritance laws stipulate the sub-division of land to multiple heirs after loss of parents (Rahman and Rahman, 2009). Amending these laws in order to prevent sub-division may be an important consideration in policy supportive of crop intensification.

Secure land tenure rights was positively associated with cropping intensity. In focus groups, sharecroppers reported aversion to investment in land management or irrigation in the absence of secure land rights. Tenure insecurity could also reduce farmers' interest in improving soil quality over time as farmers discount future investments (Tenaw et al., 2009). At current rates, the cost of securing tenure rights through land registration is roughly 10% of total land value (Islam and Lee, 2016). This is prohibitive to small and marginal farmers in the coastal region, which provides evidence on the need for land tenure policy reformation and improvements in informal land sharing arrangements.

Our data also indicated that most farmers in the central coast have tended to depend on inherent soil fertility with little application of inorganic or organic amendments. This observation aligns with concerns of declining soil fertility in Bangladesh (Barmon et al., 2008). Balanced nutrient 'budgets' have been reported to contribute to farmers' willingness to shifts from single cropping to double and even triple cropping in Bangladesh (Schulthess et al., 2019). Extension systems should therefore maintain a focus on appropriate nutrient management regimes.

The inundation classes to which a farm belongs had positive influence on cropping intensity: farmers with highlands and medium-highlands tend to grow more crops per year. On medium-lowlands and below, as well as within polders with land subsidence, social (e.g. water users' groups) and technical (e.g., drainage canals) may be necessary to help drain stagnant water after the monsoon. Drainage systems are however complex and will require careful coordination to permit land preparation so a diversity of subsequent winter season crops can be grown (Krupnik et al., 2017). Finally, the environmental risks posed by cyclones had a negative influence on both cropping intensity and off-farm income generation. There have been considerable crop losses associated with previous extreme weather events in coastal Bangladesh. Opportunities for climate services that increase farmers' ability to anticipate and cope with extreme climatic events may also be beneficial in reducing risk. Cyclones and extreme weather are widely cited as risk-bearing factors that can limit rural developments efforts in coastal South Asia (Mottaleb et al., 2016); options for farm insurance can also be explored to hedge risks.

The farming systems in the central coast of Bangladesh draw attention to the range of socioecological drivers that affect agricultural intensification pathways and rural livelihoods. Boserup (1965) and several others recently, including Jayne et al. (2014), Muyanga and Jayne (2014) and Ricker-Gilbert et al. (2014), have shown the significance of population pressure as the main driver of agrarian change. Surprisingly, our data showed inconsistent effects of population pressure, with positive significance outside polders, and a non-significant positive trend within them. Our research however underscores the significance of a host of additional and equally important factors, including those associated with climatic risks and tenure insecurity that negatively affect cropping intensity. Farm households observed in our data can be seen as either '*hanging in, stepping up, or out'* of farming as a primary livelihood strategy (cf. Dorward et al., 2009). Such dynamics have been measured in sub-Saharan Africa (Tittonell, 2014) but not previously in South Asia. Increasing importance of off-farm income (remittances and off-farm employment), particularly for small and marginally sized farms can be seen as '*stepping out*' of farming. Conversely, 12% and 22% of farms outside and within polders, respectively, tended to continuously fallow land during the winter between 2005 and 2015. This indicates a '*hanging in*' strategy for farms less reliant on off-farm income. Increasing income from intensified cropping is likely to require considerable changes and inclusion of high value crops supported by requisite irrigation infrastructure, market access, and supportive policies (Krupnik et al., 2017). Although sufficiently robust to detect the abovementioned trends, our approach may however be to some extent be sensitive to difficulties encountered when farmers attempt to recall information during surveys. These risks were however mitigated in our study through cross-validation with secondary sources and confirmation of observed trends through follow-up focus groups.

According to Singh (2002) farming systems in the coastal region of South Asia are solely represented by 'coastal artisanal fishing mixed farming systems' comprising of mixed systems of rice, pulses, livestock and aquaculture. We therefore consider that our data and sample exemplifies the agrarian change in mixed rice-livestock-aquaculture systems typical for much of the coastal areas in South Asia, including Eastern parts of India, Bangladesh and Sri Lanka (Dixon et al., 2001). As a result, the findings of this study are likely most applicable to the above locations than other parts of South Asia. This is due to the comparable agro-climate and similarities with regard to agricultural practices, demographics, and other socioecological factors.

6. Conclusions and implications

This study aimed to elucidate farm change trajectories and likely factors/drivers influencing changes in the farming systems of Bangladesh's central coast using a novel systems analysis approach. We presented a new framework for analyzing farm trajectories using long-term panel data. While we adopted both fixed and random effects models similar to Baltagi (2008), our approach was unique in that we employed data dimensionality reduction techniques, hierarchically clustered farm typology analysis, and examined how they changed over time. We also extracted the underlying latent factors that helped explain what drives change over time using panel data modelling. The conceptual model and the analysis provided here illustrate how it is meaningful to consider a wide range of socioecological system properties potentially influencing agricultural intensification, rather than singling out macro-drivers such as population pressure as the primary metric of agrarian change and intensification.

Our approach, which can be adapted to other farming systems and geographies, showed that coastal farming systems exhibit farm type dynamics that are spatially and temporally diverse. With several socioecological drivers as key influencers of change, farming systems in our study area have gradually moved from heterogeneous, rice-livestock based farm types into more homogenous farm types with less livestock and increased emphasis on income generated from pulses, aquaculture and off-farm employment. Evidence also suggests that farm typological diversity has decreased within and outside of polders. Marginal- and small-sized farms now dominate compared to a more diverse mix of marginal to large farm types twenty years before. We have shown the influence of both micro- and meso-level factors in addition to macro-level drivers (e.g. population and cyclone intensity) in driving changes in cropping intensity. The inundation class to which farmland belongs had a positive influence on cropping intensities of the studied areas, reinforcing the requirement for both post-monsoon field drainage and clearing existing drainage canals to facilitate winter season cropping. Finally, the environmental risk posed by cyclones had a negative influence on both cropping intensities and off-farm income activities in the area.

These topics, however, have not been adequately dealt with through policy, which has instead focused on promoting *boro* rice cultivation. Our data clearly indicate that this approach is less appealing for farmers. Rather than focusing on *boro* rice cultivation in the winter season, the development of stress tolerant mungbean varieties and extension support to improve nutrient management may be beneficial, alongside efforts to improve in-field drainage to facilitate early winter season land preparation. Setting these issues aside, pathways to catalyze intensification of these systems are also likely require efforts to ameliorate environmental risks posed by extreme weather, policy to improve sharecropping arrangements and land tenure security, alongside farming systems re-design that incorporates household's development aspirations and the attributes affecting their crop choices.

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Appendix A. Supplementary data

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