Effects of Social Learning on Rural Farmers’ Adaptive Capacity: Empirical Insights from the Vietnamese Mekong Delta

Thong Anh Tran, Helen James & Dang Kieu Nhan

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ABSTRACT
Environmental challenges in the Vietnamese Mekong Delta characterized by adverse impacts of climate change, upstream hydropower development and localized dyke expansion present imperatives for rural farmers to “learn to adapt.” However, little is known about how learning contributes to improving their capacity in adapting to these “wicked” problems. This study investigates potential effects of farmers’ learning on their adaptive capacity, utilizing nine focus group discussions, 33 interviews, and a structured survey of 300 farmers. The exploratory factor analysis produced two factors for social learning: (1) learning through social interactions and (2) self-reflection, and one factor for adaptive capacity. The regression results show that the social learning factors have significantly positive effects on adaptive capacity. Farmers with a higher level of social learning are likely to demonstrate higher adaptive capacity. The findings call for policy considerations to promote learning in a broader context of the delta to enhance local capacity.

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KEYWORDS
Adaptive capacity; farming households; floods; rural livelihoods; social learning; Vietnamese Mekong Delta

Introduction
The Vietnamese Mekong Delta (VMD) is exposed to adverse impacts of climate change, upstream hydropower development, and localized dyke expansion (Dang et al. 2016). Together with the state policy on hydraulic development to support agricultural intensification (Chu et al. 2014), these “wicked” problems have triggered unpredictability and complexity of hydrological regimes (Delgado, Merz, and Apel 2012; Nguyen et al. 2012). To address such complexities, local governments have continuously reframed water management policies (van Staveren, van Tatenhove, and Warner 2017; Tran, Pittock, and Tuan 2019). At the household level, adaptation is evidenced by farmers’
transformation of traditional livelihood practices in adapting to environmental change (Tran and James 2017).

The VMD provides an important lifeblood for the majority of rural inhabitants. It occupies an area of nearly 4 million hectares (ha), of which 2.56 million ha are devoted to agricultural production (GSO 2017). The delta includes two fertile and resource-rich floodplains: the Long Xuyen Quadrangle and the Plain of Reeds. Local floods occur from July to December each year. At high flood occurrences, about half of the delta area (1.9 million ha) becomes inundated (Kuenzer et al. 2013).

Social learning plays a key role in addressing problems in the natural resource management (Schusler, Decker, and Pfeffer 2003; Nykvist 2014). In the European contexts, social learning is used as a policy instrument to tackle water management complexities (Blackmore, Ison, and Jiggins 2007; Ison, Röling, and Watson 2007). Under the Water Framework Directive, river basin management adopted social learning to avoid competing interests among stakeholders (Borowski 2010) and promote “learning together to manage together” (Kranz et al. 2005). In the VMD, the role of social learning, however, is not fully recognized in policy development.

Evolving literature on climate change addressed linkages between social learning and adaptive capacity (Pelling and High 2005; Albert et al. 2012; Ensor and Harvey 2015). Drawing on case studies in the Alps of Europe and the Mekong, Lebel, Grothmann, and Siebenhüner (2010) note that social learning is important for building adaptive capacity. Pelling’s (2011) study on the Welsh dairy farmers cooperative (Grasshoppers) suggested that, individual farmers, when promoted by openness and the sharing of information, were able to learn and proactively adapt to climate change.

While the relationship between social learning and adaptive capacity is well established in the global context of climate change, its relational understanding has been poorly understood in the VMD. Recent literature has discussed the concepts from the institutional perspective (Clemens et al. 2015; Phuong et al. 2018); yet, there are no studies that conceptualize and operationalize the concepts and examine their causal relationships in quantitative terms. This study aims to measure how social learning influences rural farmers’ capacity to adapt to the “wicked” problems. We contend that the sufficient empirical knowledge of this association would help local governments make better informed decisions on local adaptation conundrums.

Adapting to the “wicked” problems illuminates the ways rural societies involved in various forms of learning, whereby they developed innovative livelihood practices (i.e., new farming models). Explored in the “rural communities of practice”, these narratives exhibit how various forms of social relationships shape the ways farmers get together for learning and shift their livelihood strategies (Tran, James, and Pittock 2018). Extending from this analysis, drawing on Reed et al. (2010) and Glasser’s (2009) social learning definitions in relation to the adaptive capacity concept, we attempt to quantify farmers’ everyday “learning to adapt” practices, and the ways they deal with change.

A mixed-methods approach was deployed to gather data in three flood-prone areas in the VMD (i.e., An Giang, Dong Thap, and Can Tho). Building on the study findings, we argue that social learning plays an essential role in leveraging farmers’ capacity in adapting to local flooding environments. This analysis provides critical insights into how the concepts are defined, how it complements the conventional understanding
of learning, and how it is linked to adaptation in the social, cultural, and political context of the VMD (Clemens et al. 2015). More importantly, it advances the state of knowledge of how farmers’ learning outcomes contribute to “fixing” conventional views on the significance of farmer-led adaptation.

**Conceptual Framework and Hypothesis**

**Conceptualization of Social Learning**

Social learning has appeared in a variety of disciplines (Rodela 2013). Yet, the concept has raised critical debates in terms of its meaning (Muro and Jeffrey 2008). Reed et al. (2010) interpret social learning as not solely learning by an act of imitation (Bandura 1977), but rather a change in individual understanding in groups through the process of social interactions. Glasser (2009, 49), however, contends that any learning that “involves some forms of input drawn from others, regardless of individuals or collectives, is characterized as social learning.” According to Keen and Mahanty (2006), three core elements of learning theories (systems orientation, negotiation and reflection) are essential to improve the management of human and environmental interactions. These learning patterns reflect the iterative feedback between individual learners and their environment, with the learners changing the environment and the environmental changes affecting the learners (Tábara and Pahl-Wostl 2007). Individuals, in this sense, are seen as both “products and producers of their own environments and of their social systems” (Muro and Jeffrey 2008, 328).

Reed et al. (2010) identified three key problems associated with the application of social learning. First, social learning can represent both a process (people learning from one another) and an outcome (the learning occurring as a result of social interactions). Second, the distinction between individual and wider social learning is not clearly made (Davidson-Hunt and Berkes 2003). In this sense, social learning can occur in an individual, which is indicated by a change in his understanding of the outside world. Third, social learning is often confusingly used with stakeholder participation through which individuals or groups take proactive actions. According to Tippett et al. (2005), the participatory process does not necessarily stimulate social learning to occur. Bouwen and Taillieu (2004) assume that social learning does not simply imply “community participation,” but rather has to do with the understanding of the limitations of existing institutions and mechanisms of governance.

Social learning is linked to public participation and institutional conditions (Tippett et al. 2005; Muro and Jeffrey 2008; Nykvist 2014). Existing literature regards social learning as a reflexive process of multiple-loop learning, including single loop, double loop, and triple loop learning (Pahl-Wostl et al. 2011; Medema et al. 2015). At the lowest level, single-loop learning suggests a refinement of actions to leverage performance. This level of learning, directed by the “how” question, involves the incremental improvement of established routines and experiment-based practices (Pahl-Wostl 2009; Medema et al. 2015). Double-loop learning concerns the learning of underlying assumptions that drive actions taken. To this end, it involves the transformation, innovation, and creation of new forms of institutional norms of interactions (Sol, Beers, and Wals
At the highest level, triple-loop learning refers to enquiry into values, beliefs, or norms that underpin operating assumptions and actions (Keen, Brown, and Dyball 2005; Medema et al. 2015). Overall, the operation of multiple loop learning is essential to stimulate innovations, improve adaptive capacity, and change governance regimes (Täbara and Pahl-Wostl 2007). In the VMD, the multi-loop learning pattern is of much relevance to the ways rural farmers ingeniously adapt their livelihoods to environmental change. It characterizes how farmers’ innovative farming practices, which are built on informal learning practices (e.g., chats), facilitate changes in farmers’ behaviors and adaptive actions. This study elaborates on how these practices are quantitatively measured to indicate levels of farmers’ capacity in dealing with local environmental conditions.

**Adaptive Capacity and its Relationship to Social Learning**

Adaptive capacity can be conceptualized in different ways. On the one hand, it is linked to adaptation (Adger, Arnell, and Tompkins 2005; Pelling 2011). According to the IPCC (2007, 869), adaptive capacity is “the ability of a system to adjust to climate change to moderate potential damages, to take advantage of opportunities, or to cope with the consequences.” On the other hand, it represents the capacity of a system to use resources (natural, financial, institutional or human) and access ecosystems, information, expertise and social networks (Brooks and Adger 2004). From Adger and Vincent’s (2005) perspective, adaptive capacity involves the capacity to modify the exposure to risks, to absorb and recover from impact losses, and to exploit new opportunities arising from adaptation processes. Folke, Colding, and Berkes (2003) relate adaptive capacity to resilience building based on four factors: (1) learning to live with change and uncertainty; (2) nurturing diversity for resilience; (3) combining different types of knowledge for learning; and (4) creating opportunity for self-organization to foster socio-ecological sustainability.

Adaptive capacity is closely linked to social learning. From the organizational perspective, Pelling (2011) sees that social learning is central to adaptive capacity. Lebel, Grothmann, and Siebenhüner (2010) confirm that social learning helps empower stakeholders to take adaptive actions, which corresponds to stakeholder interests and level of shared understanding. From the perspective of adaptive capacity, Armitage (2005, 703) sees learning as an “ability to experiment and foster innovative solutions in complex social-ecological circumstances.” Drawing on these theoretical underpinnings, this study seeks to conceptualize the respective dimensions of social learning and adaptive capacity and quantitatively examine their causal relationships. The examination of these two concepts is indicated in the following hypothesis.

**Hypothesized Model**

A hypothesized model was developed to examine the relationship between social learning and adaptive capacity. We assumed that social learning would have effects on rural
farmers’ capacities in adapting to “flood-dyke” complexities in the VMD. This assumption led to the following hypothesis:

Social learning influences the level of capacity available to farmers to adapt to environmental change in the VMD.

Research Methods

Data Collection and Sample

Following Creswell and Clark (2011) mixed-methods approach, the data collection was conducted in two main phases. In the first phase, we conducted nine focus group discussions (FGDs) with three farming household groups (poor, medium, and better-off) and thirty-three interviews with government officials, environmental scientists, and knowledgeable farmers (Table 1). Semi-structured questions were used to explore farmers’ everyday adaptation practices, including: (1) local flood conditions; (2) farmers’ “living-with-floods” practices; and (3) farmers’ learning activities in adapting to environmental change. The qualitative analysis informs the design of structured surveys to be administered to target households in the second phase. The data collection lasted for 7 months, extending from October 2013 to April 2014.

The survey was distributed to farmers residing in three selected communes (Phu Thanh B, Phu Xuan, and Thoi Hung) (Figure 1). The stratified sampling approach was applied to recruit participants (Neuman 2011). In this study, households served as a unit of analysis as they are directly exposed to flood impacts and proactively engaged in learning activities in efforts to adapt to environmental change. Household heads (males) were targeted for survey administration. As claimed by Bookwalter, Fuller, and Dalenberg (2006), household heads are the main respondents because they can speak for the entire household. Information shared by the household heads therefore can act as a valid proxy for the entire household.

Table 1. Summary of research methods.

<table>
<thead>
<tr>
<th>Methods</th>
<th>Participants</th>
<th>Approaches for data collection and analysis</th>
<th>Data collected</th>
</tr>
</thead>
<tbody>
<tr>
<td>Focus group discussion (Phase 1)</td>
<td>9 FGDs with 3 farmer groups (poor, medium, better-off) in three communes</td>
<td>Selection of participants based on the participatory approach (King and Horrocks 2010; Neuman 2011) Thematic analysis (Neuman 2011)</td>
<td>Impacts of dykes on rural livelihoods, households’ learning activities and mechanisms for knowledge sharing</td>
</tr>
<tr>
<td>In-depth interviews (Phase 1)</td>
<td>33 interviews with government officials, environmental scientists, and farmers</td>
<td>Purposive sampling and snowball sampling (Liamputtong 2013) Thematic analysis (Neuman 2011)</td>
<td>Local flood conditions, households’ ‘living with floods’ practices, farmers’ learning activities in adapting to environmental change</td>
</tr>
<tr>
<td>Structured household surveys (Phase 2)</td>
<td>300 respondents selected in three communes</td>
<td>Stratified sampling (de Vaus 2002) Exploratory factor analysis Bivariate analysis (r-test, ANOVA) Multiple regression models</td>
<td>Attitudinal measurements of social learning and adaptive capacity dimensions</td>
</tr>
</tbody>
</table>
The recruitment of household groups was based on classification criteria (i.e., wealth ranking) (Narayanasamy 2009). Land ownership, level of income, source of income, and housing conditions are the key indicators to determine household groups in developing countries (Ellis and Freeman 2004; Tefera, Perret, and Kirsten 2004), which are adopted in this study. Various criteria are used in the delta (Ha et al. 2013). According to Nguyen (2011), a poor household is defined as being landless or owning little land (<0.5 ha) with wages as their main source of income. Medium households often own a larger size of agricultural land (about 1–2 ha), with income from on-farm and off-farm work. Better-off households often own the land-holding of more than 2 ha, and mostly engaged in farming.

Guided by the stratified approach, rural households were classified according to their socio-economic characteristics (poor, medium, and better-off), whereby a sampling frame was constructed (Neuman 2011). Those who engaged in on-farm and off-farm activities were categorized into these sub-populations (strata). Drawing on each of these strata, a random sample was drawn. The classification achieved the recruitment of 100 farmers in each commune with a total of 300 respondents participating in the survey.

Figure 1. Flood levels in the VMD and the study areas. Source: A base map adapted from Vo and Matsui (1998).
Measures

Defining appropriate dimensions for social learning and adaptive capacity concepts to validate their measurements is essential. Literature indicates that these constructs have not yet been defined in the VMD. There is neither an instrument available to operationalize and quantitatively measure their relationships. In this study, we adopted Myers and Oetzel (2003) approach, integrating the literature and qualitative analysis (FGDs and interviews) into selecting concept dimensions, whereby scales are constructed and measured (Table 2). This approach has been widely used in studies of environmental psychology (Gosling and Williams 2010; Brehm, Eisenhauer, and Stedman 2013).

The concept operationalization proceeded in two steps. The first step involved the exploration of their respective dimensions. Both literature review and qualitative analysis obtained an exhaustive list of dimensions. Selected dimensions should fit the social-cultural context of the VMD. Those that failed to suit this requirement were excluded from the list (Gosling and Williams 2010). Consequently, we yielded three dimensions for social learning: (1) communication, (2) interaction, and (3) reflection, and three for adaptive capacity: (1) access to resources, (2) institutional effectiveness, and (3) information dissemination.

An itemized instrument was developed in the second step to measure each dimension. According to de Vaus (2002), items should capture the particular content of each dimension. This was assisted by a pretest survey that was conducted to revise necessary items. Finally, the scales obtained 15 items for social learning and 18 items for adaptive capacity. Participants responded on a five-point Likert scale (1 = “strongly disagree”, 2 = “disagree”, 3 = “undecided”, 4 = “agree”, 5 = “strongly agree”).

Analytical Approaches

We applied the NVivo software to assist the qualitative analysis (Bazeley and Jackson 2013). Neuman’s (2011) approach was deployed to guide the analysis, following the analytical processes of open coding, axial coding and selective coding.

To measure the causal relationship between social learning and adaptive capacity, we employed exploratory factor analysis to deconstruct the concepts followed by the regression modeling. This analytical procedure has been widely adopted by several social researchers (Brown and Raymond 2007; Below et al. 2012) in identifying latent factors of the concepts, making them available for further analysis.

The principal axis factoring with Varimax rotation was used to examine the concept items. The analysis produced three principal factors with eigenvalue ≥1, including (1) external learning performance (ELP), (2) internal learning performance (ILP) (Appendix A), and (3) adaptive capacity (AC) (Appendix B). By definition, ELP items indicated farmers’ learning through social interactions, while ILP items indicated learning through “reflection-in-action.” Seven items were found to be attributable to the ELP, accounting for 29.87% of the common variance with an Eigenvalue of 4.34. The reliability assessment of the ELP items showed a high Cronbach’s alpha (α = 0.85). The ILP comprised four items, explaining 14.72% of the variance and an Eigenvalue of 1.66. Compared to the ELP, the ILP items produced the lower internal consistency level (α = 0.67). The AC obtained an Eigenvalue of 5.04, with a high level of reliability (α = 0.88).
<table>
<thead>
<tr>
<th>Concepts</th>
<th>Dimensions</th>
<th>Implications</th>
<th>Supporting literature</th>
<th>Key themes emerged from FGDs and in-depth interviews</th>
</tr>
</thead>
<tbody>
<tr>
<td>Social learning</td>
<td>Communication</td>
<td>A key element for transmitting knowledge and fostering social learning</td>
<td>Dlouhy et al. (2013), Harvey et al. (2012), and Newig et al. (2008)</td>
<td>Interactions occur among local stakeholders at local seminars or workshops where they can discuss and learn from one another.</td>
</tr>
<tr>
<td></td>
<td>Conditions for shared understanding and behavioral change for successful adaptation</td>
<td></td>
<td></td>
<td>Local farmers engage in informal communication with friends, neighbors on related production activities.</td>
</tr>
<tr>
<td></td>
<td>Interaction</td>
<td>Learning through deliberate interactions</td>
<td>Adger (2009), Reed et al. (2010), and Tippett et al. (2005)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Reflection</td>
<td>A reflective learning process when sharing knowledge, experiences, or ideas with others leading to a change in behaviors and actions</td>
<td>Dlouhy et al. (2013) and Kenin, Brown, and Dyball (2005)</td>
<td></td>
</tr>
<tr>
<td>Adaptive capacity</td>
<td>Access to resources</td>
<td>Ability to gain access to available resources</td>
<td>Della Bella and Ragasa (2014), Gupta et al. (2010), and Nelson et al. (2010)</td>
<td></td>
</tr>
<tr>
<td>Institutional effectiveness</td>
<td>Institutional support and decision making authority</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Information dissemination</td>
<td>Spatial sharing of information and knowledge</td>
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</tbody>
</table>
We employed the weighted factor-based scale to generate the summated scores of the three latent factors (de Vaus 2002). As such, the item scores were weighted by their loadings (all selected variables were multiplied by their corresponding loadings and then added up all together). The calculation produced final scores for the three factors, which were treated as continuous variables.

Before performing regression analyses, we compared the mean values of social learning and adaptive capacity factors in association with socio-demographic variables using \( t \)-test and the one-way analysis of variance (ANOVA) techniques. A set of explanatory variables (i.e., gender, age group, education, household group, and surveyed area) was analyzed respectively. The mean comparison between the categories in the explanatory variables was examined using the Tukey post-hoc test.

Multiple ordinary least squares (OLS) regression models were applied to examine the relationship between social learning and adaptive capacity. In these models, social learning was the explanatory variable represented by the two latent factors (ELP and ILP). Adaptive capacity (AC) was the response variable represented by its single factor. The models also included other explanatory socio-demographic variables represented by respective dummy variables. The equation for the linear regression models is shown below:

\[
Y = b_0 + b_1X_1 + b_2X_2 + \ldots + b_nX_n + \varepsilon
\]

In this equation, \( Y \) is a response variable representing AC. \( b_0 \) is the intercept term. \( b_1, b_2, \ldots b_n \) are the coefficients which correspond to their explanatory variables \( X_1, X_2, \ldots X_n \). ELP, ILP (continuous) and the socio-demographic (dummy) variables are the explanatory variables. Finally, \( \varepsilon \) is an error term.

Three regression models were constructed for farmers’ adaptive capacity, formed by the multiplication of the ELP and ILP by each dummy variable (i.e., interaction terms) in the models (Table 3). This study focused on how the effects of the ELP and ILP on the AC varied across three surveyed areas (Thoi Hung, Phu Thanh B, and Phu Xuan) and household groups (poor, medium, and better-off). To meet assumptions for linear regression, we transformed the dependent variable (AC) and the two independent variables (ELP, ILP) using the logarithmic transformation method (Chatterjee, Hadi, and Price 2000). These variables are standardized before being included in the regression models. The analysis was performed using Stata 13.

**Results and Discussion**

**Characteristics of Sampled Respondents**

This section presents socio-demographic characteristics of respondents. The proportion of males and females in the sample is not equally distributed. About three quarters (74%) were males. Most of the respondents were married (94%). Their age was distributed across four categories. Those within the range of 30–49 years of age account for the highest proportion (47.3%), followed by those aged 50–69 years (41.7%). The number of respondents aged under 30 years had the lowest proportion (4.3%).

More than half of the sample completed elementary school (51%), followed by those completing secondary school (25.3%). The illiteracy rate of respondents was relatively
high (12.3%). Those who completed high school and above had the smallest proportion (11.3%).

**Comparison of Social Learning and Adaptive Capacity Across Farmers’ Demographics**

Table 4 presents mean values of the ELP and ILP and the AC with five socio-demographic variables. The *t*-test results suggested a statistically significant difference in the mean of the ELP and the AC by gender. Males reported having significantly higher levels of the ELP than females (*p* < 0.001). This result suggests the key role males play in households, which offers them better opportunities to interact with people (Huynh 2015). Customary household divisions of Labor in Vietnam imply that women should stay at home (Bonnin and Turner 2014). That is the case in the VMD, where women are mainly responsible for cooking, cleaning and their domestic chores. Engaging women in learning therefore requires that they need to devote more time to social activities. Local governments should engage women in job creating workshops, whereby they can extend their social networks and obtain knowledge. Males also showed a significantly higher level of AC than females (*p* < 0.001).

The results suggested that farmers’ ELP level differed significantly among the four age groups (*p* < 0.01). Those within the 50–69 age range obtained the highest level of ELP. They also had the highest mean value of AC. Consistent with Habtemariam et al. (2016) study in Ethiopia, this study suggests that people in this age group were likely to obtain more experiences in farming activities and interacting with local environments. Those beyond 70 years of age had limited time in social activities.

Illiterate respondents had the lowest ELP level. We observed that they seldom engaged in learning. Two main constraints were realized. First, most illiterate farmers
were not informed of local training events due to their limited language ability. Second, most of illiterate farmers were poor, thus making a living is their priority. This kept them busy all the time. A female farmer indicated her concerns as follows:

I do not have free time to get involved in knitting activities since I have got to earn money to support my family. (FGD, Thoi Hung)

Respondents’ adaptive capacity differs significantly among the education level \((p < 0.01)\). Those with higher educational attainment were likely to have higher adaptive capacity. FGD results suggest that illiteracy restricted poor farmers’ engagement in learning, which undermines their capacity in learning and seizing possible opportunities to enhance their knowledge. These findings corroborate Deressa et al. (2009) study of farmer’s choice of adaptation methods in response to climate change in the Nile Basin of Ethiopia. They found that farmer’s education was positively associated with their adaptive capacity.

The difference in mean value of the ELP was statistically different across surveyed areas. Thoi Hung commune had the highest mean value of the ELP compared to its counterparts. The mean value of AC was also statistically different. The Tukey post-hoc test suggested significant difference in the mean value of Thoi Hung from those of Phu Xuan \((p < 0.05)\) and Phu Thanh B \((p < 0.001)\).

---

### Table 4. Mean values of social learning and adaptive capacity by socio-demographic variables \((N = 300)\).  

<table>
<thead>
<tr>
<th></th>
<th>External learning performance (ELP)</th>
<th>Internal learning performance (ILP)</th>
<th>Adaptive capacity (AC)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Gender</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Males ((n = 222))</td>
<td>17.31 (2.91)</td>
<td>9.02 (1.23)</td>
<td>30.72 (3.78)</td>
</tr>
<tr>
<td>Females ((n = 78))</td>
<td>15.19 (3.01)</td>
<td>8.92 (1.32)</td>
<td>28.66 (4.13)</td>
</tr>
<tr>
<td>T-values ((df = 298))</td>
<td>5.49***</td>
<td>0.63ns</td>
<td>4.05***</td>
</tr>
<tr>
<td><strong>Age group</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>17–29 ((n = 13))</td>
<td>14.80* (2.41)</td>
<td>8.71 (0.84)</td>
<td>28.33* (2.91)</td>
</tr>
<tr>
<td>30–49 ((n = 142))</td>
<td>16.55 (3.14)</td>
<td>8.97 (1.25)</td>
<td>29.77 (4.18)</td>
</tr>
<tr>
<td>50–69 ((n = 125))</td>
<td>17.34* (2.96)</td>
<td>9.12 (1.25)</td>
<td>30.94* (3.64)</td>
</tr>
<tr>
<td>70 and over ((n = 20))</td>
<td>15.94 (3.04)</td>
<td>8.57 (1.51)</td>
<td>29.65 (4.39)</td>
</tr>
<tr>
<td>F-values ((df = 296))</td>
<td>4.05**</td>
<td>1.41ns</td>
<td>3.16*</td>
</tr>
<tr>
<td><strong>Education</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Illiterate ((n = 37))</td>
<td>14.71abc (3.15)</td>
<td>8.98 (1.30)</td>
<td>28.40ab (4.54)</td>
</tr>
<tr>
<td>Elementary school ((n = 153))</td>
<td>16.30ade (3.03)</td>
<td>8.97 (1.27)</td>
<td>29.91 (4.00)</td>
</tr>
<tr>
<td>Secondary school ((n = 76))</td>
<td>18.15bd (2.52)</td>
<td>9.17 (1.25)</td>
<td>31.15c (3.54)</td>
</tr>
<tr>
<td>High school and over ((n = 34))</td>
<td>17.94ce (2.59)</td>
<td>8.73 (1.16)</td>
<td>31.20c (3.34)</td>
</tr>
<tr>
<td>F-values ((df = 296))</td>
<td>15.36***</td>
<td>1.00ns</td>
<td>5.17**</td>
</tr>
<tr>
<td><strong>Survey area</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Phu Thanh B ((n = 100))</td>
<td>15.98a (2.83)</td>
<td>9.11 (1.14)</td>
<td>29.04a (3.77)</td>
</tr>
<tr>
<td>Phu Xuan ((n = 100))</td>
<td>16.08a (3.15)</td>
<td>8.99 (1.36)</td>
<td>29.98b (3.92)</td>
</tr>
<tr>
<td>Thoi Hung ((n = 100))</td>
<td>18.22ab (2.72)</td>
<td>8.88 (1.26)</td>
<td>31.53ab (3.86)</td>
</tr>
<tr>
<td>F-values ((df = 297))</td>
<td>18.97***</td>
<td>0.86ns</td>
<td>10.65***</td>
</tr>
<tr>
<td><strong>Household group</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Poor group ((n = 100))</td>
<td>15.08ab (3.14)</td>
<td>8.70a (1.28)</td>
<td>29.11a (4.59)</td>
</tr>
<tr>
<td>Medium group ((n = 100))</td>
<td>16.76bc (2.80)</td>
<td>8.99 (1.24)</td>
<td>30.02b (3.59)</td>
</tr>
<tr>
<td>Better-off group ((n = 100))</td>
<td>18.45bc (2.27)</td>
<td>9.29a (1.18)</td>
<td>31.43bc (3.30)</td>
</tr>
<tr>
<td>F-values ((df = 297))</td>
<td>37.35***</td>
<td>5.69**</td>
<td>9.11***</td>
</tr>
</tbody>
</table>

Notes: Mean values and standard deviation (in brackets) are shown. Mean values with similar lettered superscripts denote the statistically significant difference at \(p < 0.05\) level on the Tukey post-hoc comparison test. Significance of the results: \(^*p < 0.05\), \(^{*}* p < 0.01\), \(^{*}{*}* p < 0.001\) (2-tail significance); ns: not significant.
There was a statistically significant difference in the ELP level between the household groups, $F(2, 297) = 37.35, p < 0.001$. According to the Tukey post-hoc test, the ELP was significantly higher for the better-off group than the poor group ($p < 0.001$) and the medium group ($p < 0.001$). Compared with its counterparts, the better-off group obtained the best opportunities to interact and learn in a wider social network. Similarly, the results of the Tukey post-hoc test suggested that the better-off group had a higher ILP level compared to the poor group ($p < 0.01$). This finding implies that, besides interacting with others, better-off farmers also invest their time in the self-learning process.

A statistically significant difference was found in the strength of AC across the household group, $F(2, 297) = 9.11, p < 0.001$. The better-off had higher AC than their counterparts. Due to having stronger social connections, better-off farmers were in a more advantageous position to access various resources (e.g., financial capital) and technical knowledge from bonding and bridging networks. Meanwhile, the poor were more likely to seek support or knowledge within the bonds of spatial proximity and kinship. This corroborates with Vincent’s (2007) argument that farmers whose contacts and knowledge are reliant on the village will have less AC in facing climate constraints than those whose networks extend over a large geographical range, or over various institutions.

The AC constraints faced by poor farmers were likely characterized by their limited opportunities and access to available resources. A poor farmer in Phu Thanh B expressed that: “There are many poor people in this commune. Therefore, not all of them are provided with boats in the flood season. It is because the local government cannot afford it.” Others indicated that “We cannot borrow money from Women’s Association if we are beyond the working age.” These findings resonate with Dulal et al. (2010) study, suggesting that poor farmers in the Koshi Tappu area, Nepal lacked capital assets and government support in sustaining their livelihoods, which reduced their abilities to adapt to extreme flood events. Inadequate education was one of the key challenges that limit their capacity to contribute to local decision-making processes.

**Measuring the Relationship Between Social Learning and Adaptive Capacity**

Regression models were used to identify how the ELP and ILP and six socio-demographic variables best predicted the measures of AC (Table 5). To do that, we developed three models that were indicated in the following.

Model I suggested that the ELP and ILP had the strongest effects on AC ($p < 0.001$, $R^2 = 0.52$). The ILP had a less significant contribution to farmers’ AC. These findings suggested that the ELP played a more dominant role in household adaptation than the ILP. Phu Thanh B had significantly lower AC than Thoi Hung ($p < 0.05$). Other socio-demographic variables did not contribute significantly to the regression model.

The ELP and ILP had significant positive effects on AC in Model II ($p < 0.001$, $R^2 = 0.54$). Compared to the ILP, the ELP had greater effects on AC. The regression results showed the significance in the interaction term between the ELP and Phu Xuan ($p < 0.01$), indicating that the significant effects of the ELP on AC between Phu Xuan and Thoi Hung.
The ELP and ILP also had significant positive effects on AC as observed in Model III ($p < 0.001$, $R^2 = 0.56$). The ILP contributed more significantly to AC than the ELP. Of the surveyed areas, Phu Thanh B has a significantly lower AC than Thoi Hung. The significant interaction effects suggested the statistically significant difference in the effects of the ILP on AC of the better-off and medium groups, compared to the poor. Qualitative evidence confirmed that poor households did not have opportunities to interact with others (Tran, James, and Pittock 2018). As noted, struggles for survival kept them busy and frequently working far from home. Constraints on making a living limited their capacity to maintain bonding relationships in their original residence and build new relationships in new working areas.

## Conclusions

The study highlights the important role of social learning in enhancing farmers’ adaptive capacity. The exploratory factor analysis achieved two social learning patterns: (1) learning through social interactions (ELP) and (2) self-reflection (ILP), which corresponded to the social learning theories conceptualized by Reed et al. (2010) and Glasser (2009). While the ELP items represented the farmers’ proactive engagement in social
interactions to acquire knowledge, the ILP items demonstrated their learning through “reflection-in-action” practices. This study adds a significant component to the social learning scholarship in the context of climate change adaptation in the rural VMD. Importantly, it contributes to validating a research method that defines the social learning and adaptive capacity concepts and quantitatively measure their relationships. This study, however, revealed some limitations in the ways the concept dimensions were selected, and farming households sampled to produce findings for larger-scale transferability. Future studies should extend this approach to other contexts.

Our findings confirmed the hypothesis that social learning had significant effects on farmers’ adaptive capacity. Those with a higher level of social learning were likely to demonstrate higher adaptive capacity. The study presents disparity in the ways knowledge is acquired among farming groups. While the better-off and medium obtain greater opportunities to learn, the poor resort to self-learning as a means of sustaining their livelihoods. Given extensive social networks, the better-off farmers gained greater access to resources, while the poor depended largely on their bonding networks. From the policy perspective, this study calls for urgent needs to promote adaptive capacity at the local level. Formal learning platforms (e.g., job creation workshops), therefore, should be provided to marginalized groups, especially the poor and women. These activities help them build social networks and acquire new knowledge. However, creating their motivations to participate implies that possible incentives (e.g., remunerative policies) need to be considered to offset their daily lost earnings.

Acknowledgments

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References


**Appendix A.** Factor loadings for social learning items.

<table>
<thead>
<tr>
<th>Social learning items</th>
<th>Factor loadings</th>
<th>Uniqueness</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>External learning performance (learning through social interactions)</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>When necessary, I can call on extension officials for help.</td>
<td>0.76</td>
<td>0.42</td>
</tr>
<tr>
<td>When attending seminars, I usually take part in discussions with other participants.</td>
<td>0.75</td>
<td>0.41</td>
</tr>
<tr>
<td>I am assisted by extension officials enthusiastically.</td>
<td>0.73</td>
<td>0.47</td>
</tr>
<tr>
<td>The learning interactions between local farmers and extension officials take place during seminars.</td>
<td>0.72</td>
<td>0.37</td>
</tr>
<tr>
<td>I usually visit successful flood-based production models to learn and follow.</td>
<td>0.64</td>
<td>0.58</td>
</tr>
<tr>
<td>Shared learning and discussions on production activities in the flood season provide me with compelling initiatives.</td>
<td>0.59</td>
<td>0.56</td>
</tr>
<tr>
<td>I usually discuss flood-based production activities when having coffee or parties with friends.</td>
<td>0.48</td>
<td>0.74</td>
</tr>
<tr>
<td><strong>Internal learning performance (self-reflection)</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>I usually learn from my friends’ failures and draw lessons for myself.</td>
<td>0.70</td>
<td>0.48</td>
</tr>
<tr>
<td>Early failures give me quite a few lessons that are useful for successive efforts.</td>
<td>0.56</td>
<td>0.59</td>
</tr>
<tr>
<td>I do not strictly follow what I have learned but create my own ways.</td>
<td>0.54</td>
<td>0.70</td>
</tr>
<tr>
<td>I do not easily believe things until I experience them myself.</td>
<td>0.48</td>
<td>0.77</td>
</tr>
<tr>
<td>Number of items retained</td>
<td>7</td>
<td>4</td>
</tr>
<tr>
<td>Eigenvalue</td>
<td>4.34</td>
<td>1.66</td>
</tr>
<tr>
<td>Percentage of explained variance</td>
<td>29.87</td>
<td>14.72</td>
</tr>
<tr>
<td>Cronbach’s alpha (α)</td>
<td>0.85</td>
<td>0.67</td>
</tr>
</tbody>
</table>

Notes: The items are measured on a five-point Likert scale: (1) = strongly disagree; (2) = disagree; (3) = undecided; (4) = agree; (5) = strongly agree.

Eigenvalues greater than 1 selected.

Factors retained with loading values greater than 0.4.

Four items were dropped from the scale.
### Appendix B  Factor loadings for adaptive capacity items.

<table>
<thead>
<tr>
<th>Adaptive capacity items</th>
<th>Factor loadings</th>
<th>Uniqueness</th>
</tr>
</thead>
<tbody>
<tr>
<td>Farmers’ initiatives through flood production models are highly recognized by the local government</td>
<td>0.80</td>
<td>0.37</td>
</tr>
<tr>
<td>The local government encourages farmers’ shared experiences and initiatives through flood production activities</td>
<td>0.76</td>
<td>0.43</td>
</tr>
<tr>
<td>Technical assistance provided by agricultural experts helps farmers implement their flood production activities successfully</td>
<td>0.70</td>
<td>0.52</td>
</tr>
<tr>
<td>Learning experiences among farmers contribute a great deal to emerging, developing, and expanding flood production activities across the region</td>
<td>0.68</td>
<td>0.54</td>
</tr>
<tr>
<td>Shared learning in the community helps increase local household income from flood production activities</td>
<td>0.67</td>
<td>0.55</td>
</tr>
<tr>
<td>I believe that sharing information and knowledge is an effective approach to increase farmers’ knowledge on flood production activities</td>
<td>0.62</td>
<td>0.62</td>
</tr>
<tr>
<td>The local government often organizes seminars or training courses on flood production models for local farmers to participate in</td>
<td>0.62</td>
<td>0.62</td>
</tr>
<tr>
<td>I think that flood production models offer local people a great deal of employment in the flood season</td>
<td>0.61</td>
<td>0.63</td>
</tr>
<tr>
<td>The local government provides great support to farmers’ employment in the flood season</td>
<td>0.55</td>
<td>0.70</td>
</tr>
<tr>
<td>I share my farming experiences with those who not only reside locally but also elsewhere</td>
<td>0.54</td>
<td>0.71</td>
</tr>
<tr>
<td>I always receive support from the local government in the flood season</td>
<td>0.51</td>
<td>0.74</td>
</tr>
<tr>
<td>I believe I have sufficient knowledge and skills to implement flood production models of my own</td>
<td>0.49</td>
<td>0.76</td>
</tr>
<tr>
<td>I think everyone has a say in the decision-making process on local dyke matters</td>
<td>0.47</td>
<td>0.78</td>
</tr>
<tr>
<td>Number of items retained</td>
<td>13</td>
<td></td>
</tr>
<tr>
<td>Eigenvalue</td>
<td>5.04</td>
<td></td>
</tr>
<tr>
<td>Cronbach’s alpha (α)</td>
<td>0.88</td>
<td></td>
</tr>
</tbody>
</table>

Notes: The items are measured on a five-point Likert scale: (1) = strongly disagree; (2) = disagree; (3) = undecided; (4) = agree; (5) = strongly agree.
Eigenvalues greater than 1 selected.
Factors retained with loading values greater than 0.4.
Five items were dropped from the scale.