Impact of farm size on the function of landscape-level payments for ecosystem services: An agent-based model study

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This paper is a non-peer reviewed preprint submitted to EarthArXiv. This manuscript has been submitted for peer-reviewed publication in Environmental Research Communications.

ABSTRACT

Reducing pesticide use and restoring biodiversity are among the most pressing environmental challenges. Enhancing natural pest control ecosystem services through the integration of non-crop habitats (NCH) offers promising potential, creating a positive feedback loop by harnessing insect biodiversity to reduce pesticide reliance. Policy support is needed at the landscape level to encourage adoption of this currently underutilized approach, which depends on spatial coordination and collective behavioral change. Farm size, which critically influences farmers' agrochemical inputs, agroecological practices, and interactions with neighboring farms, varies across agricultural landscapes. It is unclear what role farm size plays in landscape-scale agri-environmental incentive programs, which have recently seen growing attention in scientific research and policy implementation. We employ framed field games and agent-based modeling as complementary research tools, exploring how farm size impacts the function of landscape-scale NCH subsidies aimed at encouraging coordinated provision and sharing of natural pest control services to reduce pesticide use. Our model simulation shows that, in landscapes of larger average farm size or lower farm size heterogeneity, NCH subsidies are significantly more effective at reducing pesticide use and increasing NCH efficiency in providing joint production benefits. Our results imply that landscape-scale payments for natural pest control ecosystem services face fewer obstacles as incentive-based mechanisms in landscapes of larger, more homogeneous farms, supporting the implementation of landscape-scale initiatives in such areas to effectively enhance ecosystem services. Our findings contribute to the growing discussion around landscape-level financial incentive programs that depend on spatial coordination, highlighting the importance of farmers' land holding size.

Keywords: payments for ecosystem services, landscape-scale, pest control, non-crop habitat, farm size, coordination game, agent-based model

INTRODUCTION

Synthetic pesticides have become a hallmark feature of agriculture worldwide, serving as the primary method for pest management (1). However, their widespread use drains farmers' budgets (2), imperils human health (3, 4), causes long-lasting damage to soil and water (5, 6), and reduces biodiversity and the associated ecosystem services (7, 8). The latter further deepens pesticide reliance due to the loss of beneficial insects, companion plants, and soil biota essential to natural pest control (9). Furthermore, weakened ecological safeguards have imminent bearings on food security and poverty vulnerability, as biodiversity-poor, pesticide-intensive systems are less resilient and more susceptible to climate warming-triggered pesticide resistance, pest damage, and yield loss (10-13).

The persistent increase in pesticide use and decrease in habitat functionality are the main drivers of the loss of biodiversity and natural pest control ecosystem services in agricultural production systems (14, 15). Finding opportunities to replace pesticide use with natural ecosystem services through the integration of non-crop habitats (NCH) presents promising potential, as NCH provides essential shelters, resources, and breeding grounds for natural enemies, which can keep pest densities below economic thresholds and thereby avoid pesticide applications that temporarily eliminate local pest populations (16, 17). This approach has gained attention and proven effective in agricultural production systems globally (18-21). By harnessing insect biodiversity to reduce pesticide reliance, it establishes a positive feedback loop and has the potential to become a core feature of ecological intensification (22, 23).

However, natural enemy-based biocontrol through NCH management brings risks and challenges that limit its adoption (24). It requires landscape-level restructuring and coordination for two types of spillover effects: first, most natural enemies are mobile, providing crop production benefits to nearby cropland (25, 26); second, pesticide drift from neighboring farms can kill natural enemies, negating NCH benefits (27). These factors, combined with the cost of adoption, technical complexities, and economic uncertainties, create significant barriers for farmers. Financial incentives at the landscape level can help overcome these obstacles and encourage adoption until the system becomes self-sustaining (28).

Under any approach to encouragement, the challenge of enhancing natural pest control ecosystem services in rural spaces changes with farm size, as spatial coordination is essential. Landscapes of larger, more homogeneous farms tend to support less biodiversity (29). The homogeneous farm sector is, however, easier to manage and govern, with shifts toward greater farm size heterogeneity presenting policy challenges (30). Landholders of different scales have varying motivations for risk management, agrochemical inputs (31-34), and agroecological practices (35). Inter-farmer cooperation (36-37) and competition (38-39) is also influenced by farm size. Variation in farm size thus forges a nexus of biodiversity, policy feasibility, and farmer decision-making that is of critical importance in planning for farm landscapes of the future. Driven by the growing recognition that effective restoration of biodiversity and ecosystem services requires spatial coordination and landscape-level action (40-43), landscape-scale agri-environmental financial incentive programs have recently gained momentum in both scientific research and policy implementation (44-47). However, the role of farm size in these landscape-scale incentive programs remains unclear.

We employed framed field games and agent-based modeling (ABM) as complementary research tools to examine how varying farm size and farm size heterogeneity influence the effectiveness of payments aimed at encouraging the coordination and sharing of NCH-based natural pest control services. Framed field game experiments allow stakeholders to interact and coordinate farming decisions within framed environments representing relevant aspects of real-world challenges and group dynamics (48-52), while ABMs enable the extension of behaviors observed in field game experiments, simulating numerous "farmer agents" at much larger scales across multiple contexts over time (53-55). We developed an ABM based on established behavioral theories (56, 57) and patterns extracted from NonCropShare game datasets (49), which investigated decision-making around sharing NCH benefits to reduce pesticide use, and applied the model to simulated heterogeneous farm landscapes. This novel field-to-laboratory approach provides a first exploration, making use of available behavioral data, of how incentives and the coordination problem change across landscapes of varying farm scales, specifically informing the question: "how robustly do NCH subsidies encourage natural enemy ecosystems services and discourage pesticides at the landscape level across varied farm size distributions?"

METHODS

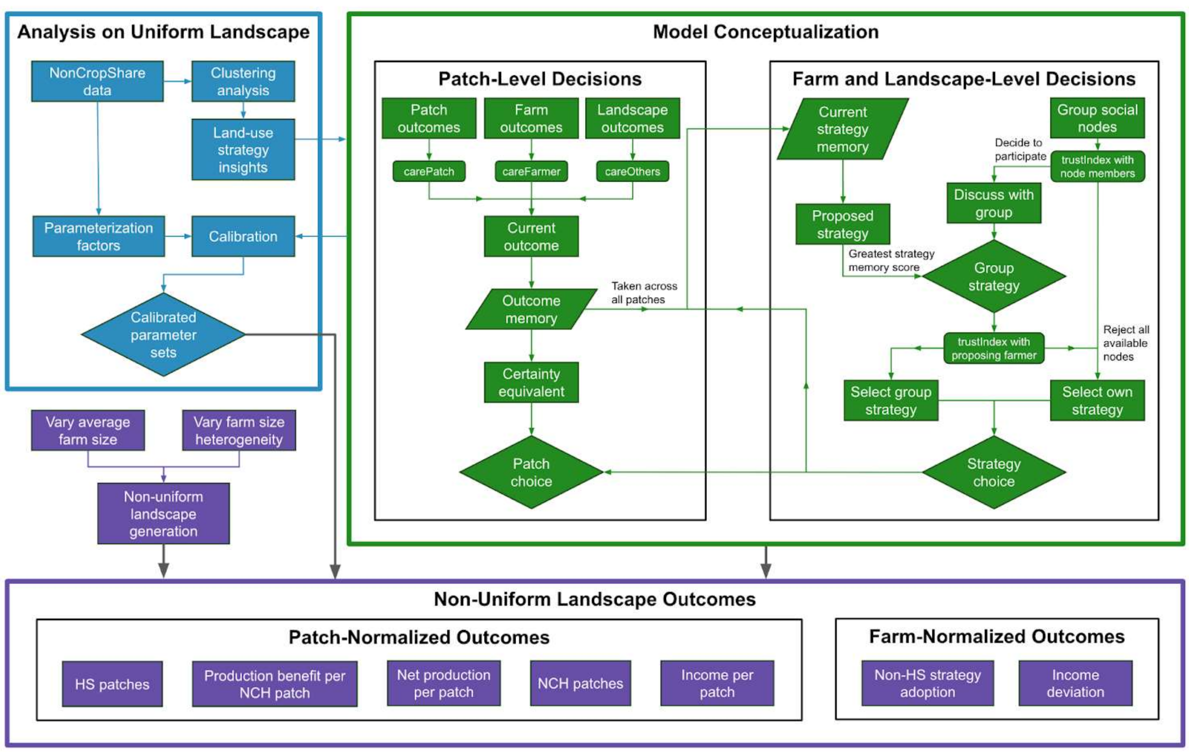

Figure 1. Outline of methodological approach to conceptualize and operate model utilizing field game data.

Our methodological approach to conceptualize and design the model using field game data is illustrated in figure 1.

2.1. Field game

NonCropShare is a symmetrical coordination game stylizing the challenge of sharing natural enemy ecosystem services (49). Each player manages a 3x3 grid-cell (patch) farm within a 6x6 grid-cell landscape. Farmers make decisions for each patch by selecting from four land-use choices with different cost, yield, and spatial spillover effects (table 1). Subsidies are awarded to NCH patches. Costs and yields are calibrated to establish two high production poles: a Nash equilibrium where all players rely solely on heavy spraying (HS), and a cooperative equilibrium where players efficiently share NCH-based ecosystem services while using judicious pesticide spraying, either no spraying (NS) or light spraying (LS). Landscapes with land-use strategies between these two poles have lower production. NCH subsidies aim to encourage a shift from the Nash equilibrium to the cooperative equilibrium, promoting collective environmental benefits. Each site had 512 participants, representing 32 farms from each of 16 villages. The villages were selected to have equal distribution of low, medium, and high landscape complexity based on visual classification, along a transect leading away from a city (Siem Reap city in Cambodia and Ha Noi in Vietnam) of approximately 4 hours in driving time. Each group of four farmers played four games of 8-10 rounds each. Game treatments 1 and 2 included no subsidy. Game treatments 3 and 4 included a randomly drawn subsidy value of 1 to 10 points. Free communication was allowed during the game. Companion survey data was collected after the game (table S2).

The Vietnam and Cambodia datasets include 147,456 and 134,784 land-use decisions, respectively. Both countries displayed the same k-means clustering patterns and are integrated into one analysis. Clustering into two groups, which showed best fit by the Davies-Bouldin Index (figure S3), revealed two distinct primary land-use strategies: the HS strategy, dominated by HS patches, and the non-HS strategy, characterized by a mix of NS, LS, and NCH patches (table 2). This informed the conceptualization of two geometrically generalizable farm-level land-use strategies in the model. We found that farmers who switch to the non-HS cluster eventually defect back to their original strategy 62% of the time, and farmers who switch to the HS cluster defect 50% of the time. Most of those defections occur on the turn immediately following their original strategy switch, and the proportion of defections continues to decrease as more rounds pass from the original switch (figure 2A). This suggests that new strategies are not sticky and farmers are not biased towards the new strategy they adopt after switching. From this, we structured farmer agents to not favor continued adoption of their current strategy when making future decisions. We then found that if multiple farmers in a landscape make the same strategy switch, they do so on the same round most frequently, with these same-turn collective switches accounting for just under half of all same-strategy switches (figure 2B). The high proportion of same-turn strategy switches supports the assumption that farmers actively coordinate strategy switching in addition to operating independently. This informed the conceptualization of social group interactions where farmers potentially adopt group strategies based on trust with other farmers.

Table 1. NonCropShare cost and yield of each land-use choice

	Land-use choice	Cost	Yield	Neighborhood effect
	Non-crop habitat (NCH)	0	0+subsidy	Provide +2 to the yield of patches in a Moore neighborhood of 2 patches
	Planting crop, no pesticide spray (NS)	0	5+NCH benefits	None
	Planting crop, light spray (LS)	1	5 + 2+NCH benefits	None
	Planting crop, heavy spray (HS)	2	5 + 7	Cancel out any benefits from NCH in a Moore neighborhood of 1 patch

Table 2. Cluster centers for k-means clusters of NonCropShare field game datasets

	Non-HS Cluster	HS Cluster
NCH Patches (%)	15.83%	2.21%
NS and LS Patches (%)	76.72%	8.70%
HS Patches (%)	7.45%	89.09%

NCH: non-crop habitat; NS: noSpray; LS: lightSpray; HS: heavySpray.

Figure 2A

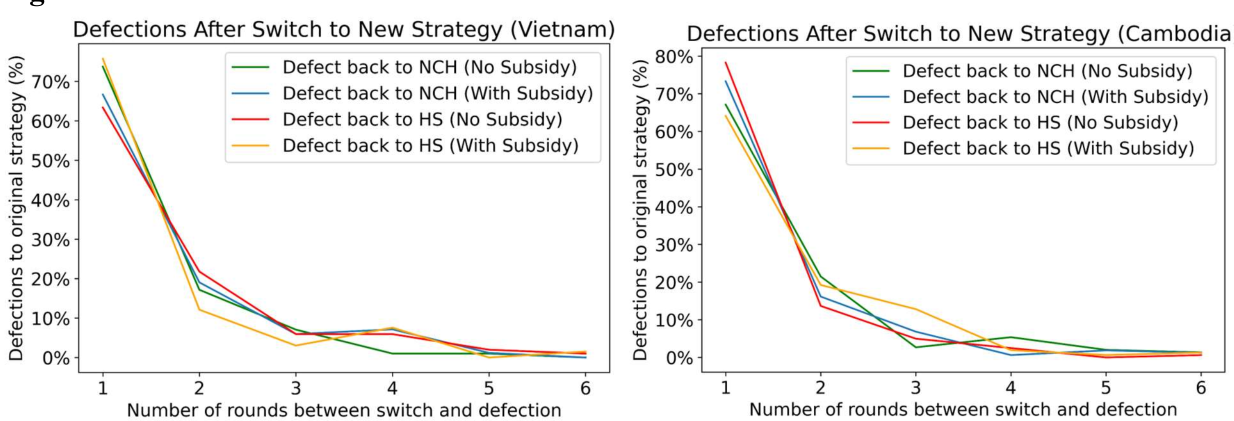

Figure 2B

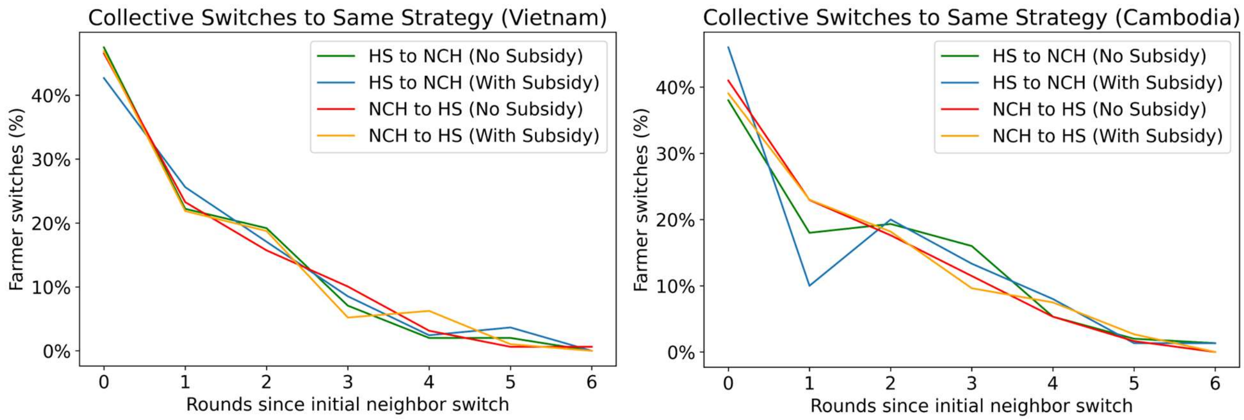

Figure 2 (A) Distribution of the number of rounds for farmers to defect to their original strategy after they switched to a new strategy for Vietnam (left panel) and Cambodia (right panel). (B) Distribution of the number of rounds between farmers making the same strategy switch for Vietnam (left panel) and Cambodia (right panel).

2.2. ABM

2.2.1. Model description

A detailed model description following the ODD protocol (54, 55) is described in Supplementary Information section S1. The purpose of this model is to explore how subsidies interact with varied farm size and farm size heterogeneity to influence farmers' decisions about sharing natural enemy service to reduce pesticide use in a spatially explicit environment. The model is informed by strategic and behavioral patterns in the NonCropShare game data and theories of bounded rationality (58-60) and case-based reasoning (61, 62).

The model represents an abstracted farming environment that exists at three geometric scales: patch (individual piece of land), farm (area of adjacent patches controlled by one farmer), and landscape (the entire collection of farms). Farmers are motivated by income and record in memory states the income generated at different geometric scales in previous agricultural seasons. This drives decision processes around farm-level strategy and patch-level land use. Farmers under the non-HS strategy do not use HS patches while farmers under the HS strategy use all four patch-level land-use choices. For each patch they own, farmers select the land use choice with the highest objective measure, calculated based on behavioral preferences and the income per patch generated at each geometric scale (see S1 *Design concepts: Objectives*). Based on initialized trust values with neighbors, farmers decide whether to coordinate with a social cluster in adopting a collective group farm-level strategy (see S1 *Submodels: Cluster interaction*). Farmers who decide not to coordinate simply choose the strategy with the highest average income in their memory.

2.2.2. Parameterization, sensitivity analysis, and simulation

We calibrated the model to these factors from game data: income, yield, NCH patches, HS patches, and strategy shifts. For each game dataset, we calculated parameterization factors as average per round values at each subsidy level. We used genetic algorithm optimization (63), running 10 iterations of 5000 generations each, to find parameter sets that maximized model fitness across 50 time steps to game parameterization factors, calculated using the following equation with all factors scaled to [0,1]:

$$\prod\left(1-\left(x_{model}-x_{game}\right)^2\right)$$

We chose the parameter sets with the greatest fitness, validated across 10 different seeds, for each context (table 3).

Across all experiments, subsidy is varied from 0 to 10. Average farm size (number of farms on the landscape) and farm size heterogeneity are varied to create heterogeneity in landscape structure. The number of farms range from 4 (the amount in the game study) to 50, generating landscapes with average farm sizes from 2% to 25% of the total landscape area. Varied farm size heterogeneity is achieved by initializing the landscape with heterogeneityIndex from 0 to 2 (see S1 *Initialization*). Farm size heterogeneity is measured as the Gini coefficient of all farm sizes according to the following equation, where there are N total farm and P total patches:

$$\frac{\sum_{i=1}^{N}\sum_{j=1}^{N}\left|size_i-size_j\right|}{2NP}$$

When calibrating to NonCropShare game data, the modeled landscape is a 6x6 uniform distribution. In simulation and sensitivity analysis, the modeled landscape is a 15x15 heterogeneous distribution (figure S2).

Table 3. Model parameters calibrated from Vietnam and Cambodia field game experiment data

Parameter	Description	Range	Vietnam	Cambodia	Difference (% of range)
nonHSPercent	Proportion of farmers initialized to non-HS strategy	[0, 1]	0.56	0.22	34%
carePatchMean	Weight farmers place on individual patch income	[0, 1]	0.76	0.86	10%
careFarmMean	Weight farmers place on collective farm income	[0, 1]	0.52	0.07	45%

careLandscapeMean	Weight farmers place on income of other farmers	[0, 1]	0.09	0.27	18%
trustindexMean	Modulates chance for cooperation	[0, 1]	0.58	0.56	2%
memory	Number of previous harvests farmers remember	[5, 30]	13	30	68%
initialExperience	Initial expected value of each land-use choice	[5, 10]	8.2	8.8	12%

2.2.3. Regression analysis

We conducted two regression analyses on each outcome variable examining the effect of average farm size, farm size heterogeneity, and subsidy, which can be expressed with the following equations:

$$Y_i = \beta_F F + \beta_S S + \beta_{FS} FS + \epsilon$$
$$Y_i = \beta_H H + \beta_S S + \beta_{HS} HS + \epsilon$$

where Y represents the outcome variable, F represents farm size, H represents farm size heterogeneity, S represents subsidy, FS and HS represent the interaction terms, and ε represents the error term. The two models were estimated separately with non-parametric kernel regression, chosen for its ability to capture non-linearity (64).

RESULTS

3.1. Pest control strategy

We examine the number of farmers adopting the non-HS farm-level pest control strategy as an indicator of environmental outcomes for the provision of natural pest control ecosystem services. Subsidy levels for each NCH patch are from 1-10, equivalent to 10%-100% of the net production of an HS patch. We observe distinct responses across three ranges of subsidy levels. Without subsidy, the non-HS strategy is adopted by a minority of farmers (figure 3). Within this "baseline environment," the percentage of farms using the non-HS strategy is negatively correlated with average farm size (figure 3a, 3b). Noticeable changes in non-HS strategy adoption first occur around subsidy level 4 in Vietnam and level 5-6 in Cambodia. These points mark "inflection subsidy levels" for each context, where farmers first begin to allocate land for NCH integration (figure S4), reduce their HS patch usage (figure S5), and increasingly adopt the non-HS farm strategy (figure 3) in response to subsidies. Starting from the inflection subsidy levels, non-HS strategy adoption increases substantially as subsidy rises, remaining high through subsidy level

5-7 in Vietnam and 6-8 in Cambodia, after which it falls off. Within these “optimum subsidy ranges,” response to subsidy is strongly influenced by farm size in Vietnam and to a lesser degree in Cambodia.

Non-HS strategy adoption increases more sharply in landscapes with bigger average farm sizes (figure 3a, 3b). As a result, the baseline negative correlation between farm size and non-HS strategy adoption is reversed, becoming positive under optimum subsidies. Non-parametric regression analysis for non-HS strategy adoption through the optimum subsidy range reveals a positive β_S, a negative β_F, and a positive β_{FS} in both contexts (table 4). This confirms our observations: subsidies promote non-HS strategy adoption (β_S), and increased farm size negatively affects non-HS strategy in the absence of subsidies (β_F) but powerfully amplifies the function of subsidy in promoting non-HS strategy adoption at the farm level (β_{FS}) (table 4).

From the baseline environment through the optimum range, non-HS strategy and HS patches remain well-aligned, consistently showing opposite trends (figure 3, figure S5). However, as subsidy increases past the optimum range, non-HS strategy adoption and HS patches both decrease, showing a disconnect between farm-level strategic processes and patch-level decisions. With excessively high subsidies, the NCH subsidy becomes primarily a source of income for individual farmers, rather than an effective instrument to incentivize coordinated landscape-wide efforts to harness natural enemy services. Although more farmers allocate portions of their land for NCH, their motivation is driven by direct subsidy income rather than the shared production benefits from natural pest control. The role of spatial spillover and spatial cooperation in farm production planning fades, resulting in HS farms that allocate land for NCH and fewer non-HS farms. Farm size heterogeneity also affects farm-level strategies and the function of NCH subsidies, but in the opposite direction compared to average farm size (figure 3c, table 5).

Figure 3A

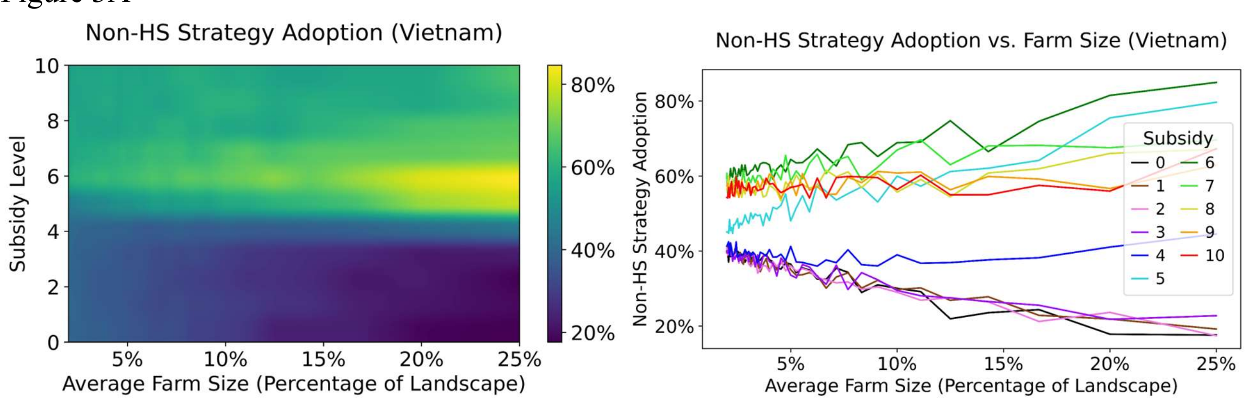

Figure 3B

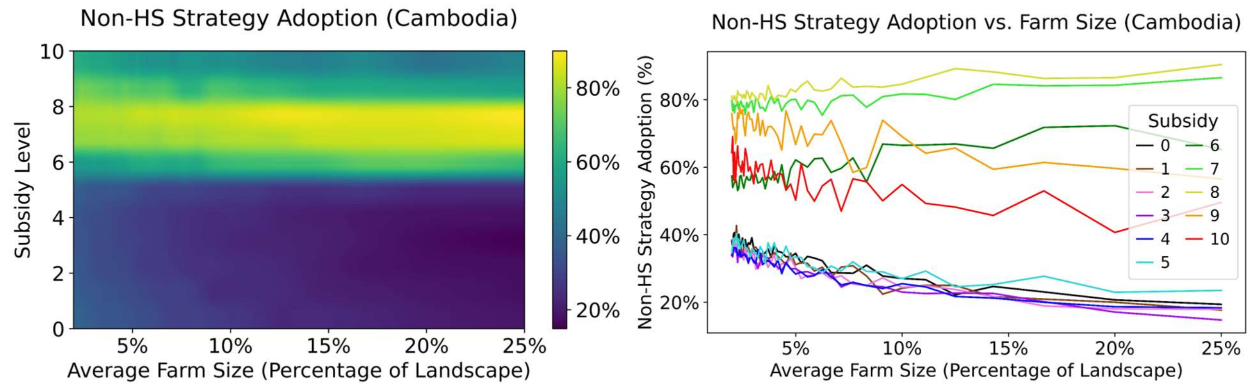

Figure 3C

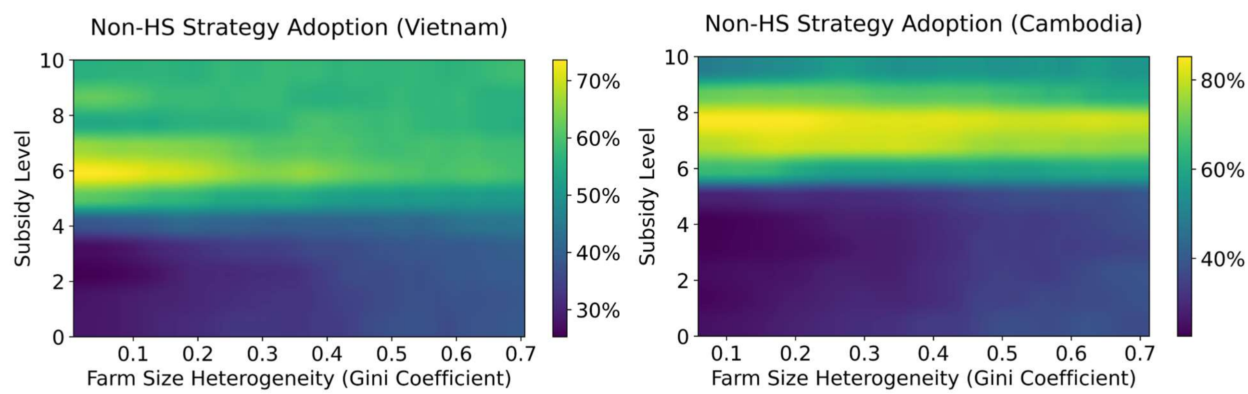

Figure 3. Average percentage of farms adopting the non-HS strategy in (A) Vietnam across varied subsidy level and average farm size, shown through heatmaps (left panel) and line plots (right panel); (B) Cambodia across varied subsidy level and average farm size, shown through heatmaps (left panel) and line plots (right panel); (C) Vietnam (left panel) and Cambodia (right panel) across varied subsidy level and farm size heterogeneity, shown through heatmaps.

3.2. NCH efficiency

We examine the production benefit provided per NCH patch as an indicator of coordination efficiency in harnessing natural enemy services. At low subsidy levels, NCH efficiency is poor across all landscapes (figure 4). NCH efficiency exhibits a large increase within the optimum subsidy range. Both contexts show a strong size-dependent response to subsidy, with peak NCH efficiency through the optimum subsidy ranges nearly double at the largest farm scale compared to the value at the smallest. This suggests that landscapes with fewer farms of larger holdings are much more efficient in coordinating to use natural enemy services through NCH integration. Furthermore, the similar degree of size-dependence observed between Vietnam and Cambodia suggests that the NCH efficiency is less influenced by contextual factors specific to each farming environment, compared to non-HS strategy adoption. Regression analysis for the production benefit per NCH patch reveals a positive β_S and a positive β_{FS} of similar magnitudes in both contexts, supporting that subsidies promote NCH efficiency and that this effect is consistently enhanced with increased average farm size (table 4). Farm size heterogeneity exhibits a mild negative overall effect in Vietnam and a negative effect on the function of NCH subsidies in Cambodia (figure 4c, table 5).

Figure 4A

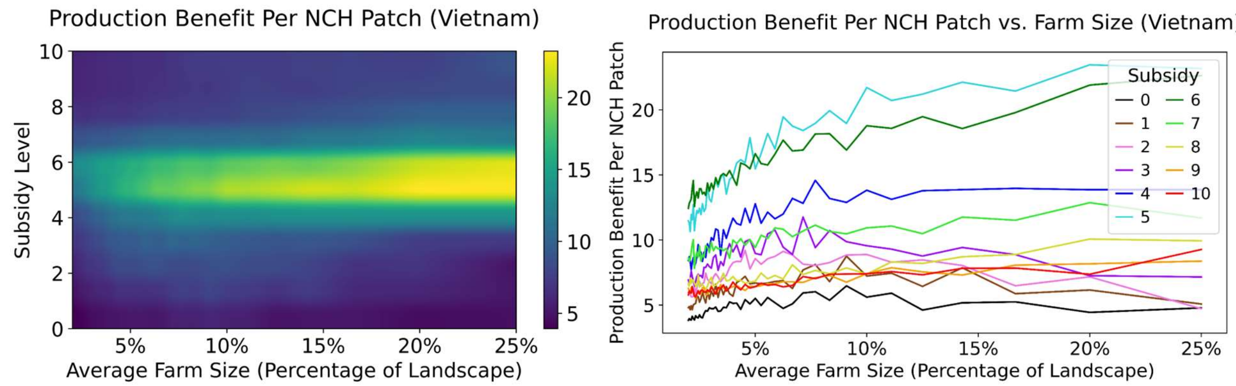

Figure 4B

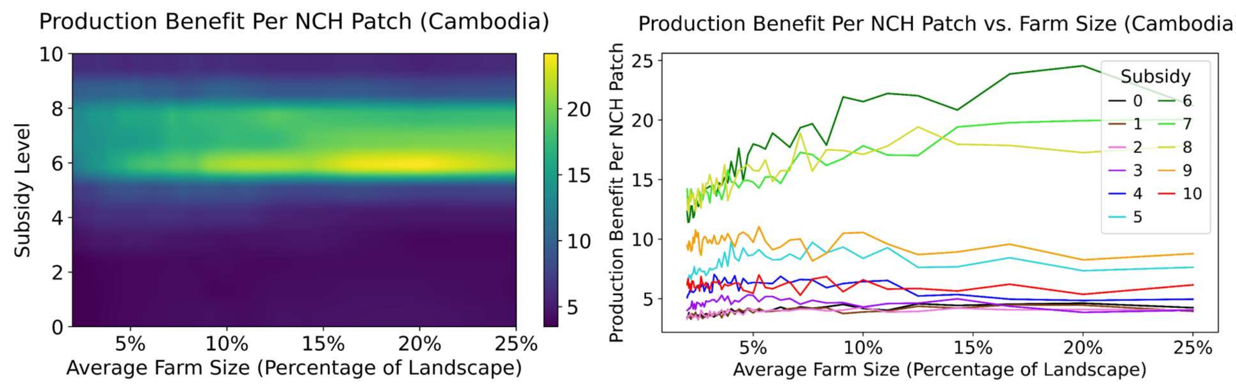

Figure 4C

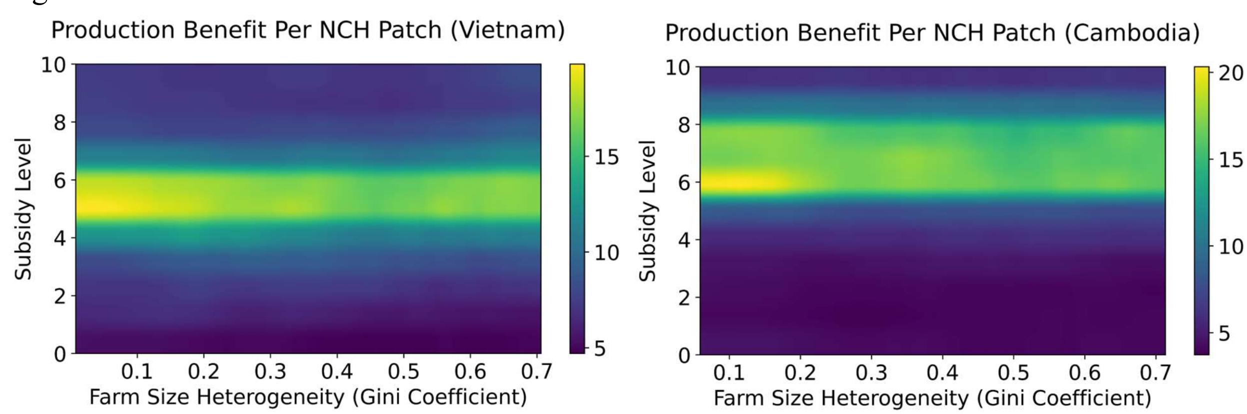

Figure 4. Average production benefit per NCH patch in (A) Vietnam across varied subsidy level and average farm size, shown through heatmaps (left panel) and line plots (right panel); (B) Cambodia across varied subsidy level and average farm size, shown through heatmaps (left

panel) and line plots (right panel); (C) Vietnam (left panel) and Cambodia (right panel) across varied subsidy level and farm size heterogeneity, shown through heatmaps.

3.3. Net production

Before the subsidy inflection points, both contexts display strong net production fueled by widespread HS usage (figure 5). Net production exhibits a slight dip around subsidy level 5 in Vietnam and level 6 in Cambodia. In this transition stage, NCH integration is efficient but limited, falling short of fully compensating for the production loss from reduced heavy spraying. Net production rebounds to slightly above baseline production in Vietnam around subsidy level 6 and returns to baseline production in Cambodia around subsidy level 7, and remains relatively high through the optimum ranges. This represents a well-balanced cooperative equilibrium where the total shared benefits provided by NCH offset or, in the case of Vietnam, exceed the production lost from reduced heavy spraying and less available cropland. We observe a positive β_{F} in both contexts, suggesting that larger average farm size correlates with higher production in the absence of subsidies. We observe a positive β_{F} in both contexts, but a small negative β_{S} (-0.275) and statistically insignificant β_{FS} in Vietnam and small negative values for both β_{S} (-0.516) and β_{FS} (-0.517) in Cambodia. These results suggest that production improves with larger average farm size and mildly decreases with subsidy.

Beyond the optimum range, net production sharply declines (figure 5), even as income continues to rise (figure S6) from increasing NCH subsidies. This shows that subsidies must be carefully moderated to ensure that farmers remain motivated by landscape production rather than primarily driven by provided incentives. However, within the optimum subsidy ranges, farm-level strategy, patch-level land use, and NCH efficiency are well-aligned in both contexts, leading to strong net production. This indicates that appropriately designed incentives can effectively reduce pesticide use without compromising production by encouraging efficient utilization of the natural enemy services provided through NCH integration.

Figure 5A

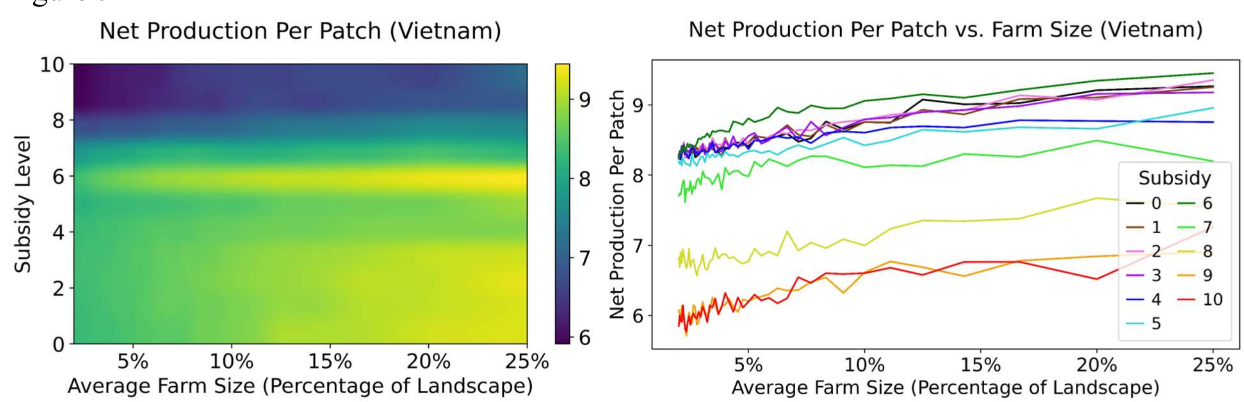

Figure 5B

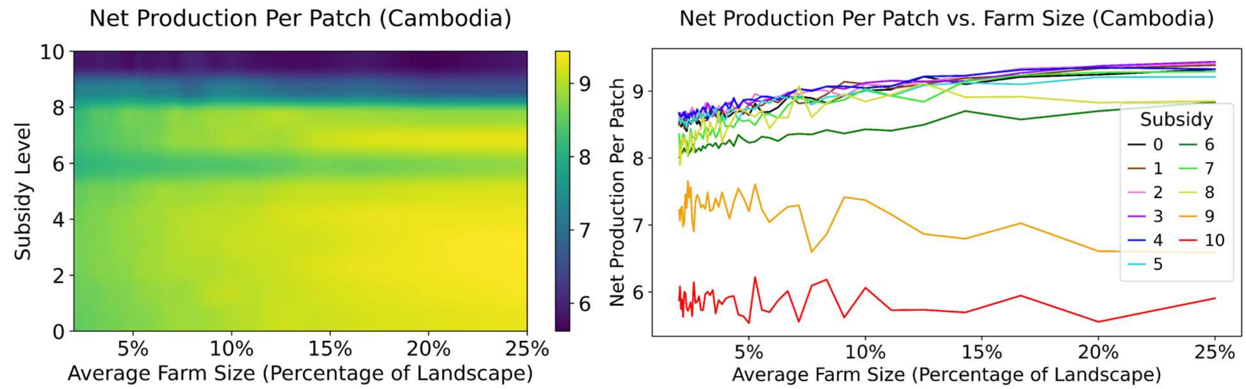

Figure 5C

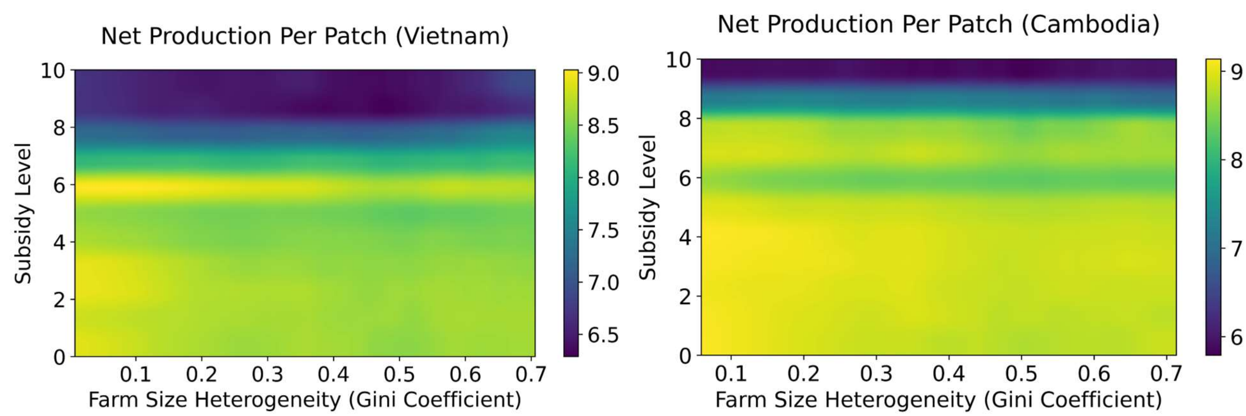

Figure 5. Average net production per patch in (A) Vietnam across varied subsidy level and average farm size, shown through heatmaps (left panel) and line plots (right panel); (B) Cambodia across varied subsidy level and average farm size, shown through heatmaps (left panel) and line plots (right panel); (C) Vietnam (left panel) and Cambodia (right panel) across varied subsidy level and farm size heterogeneity, shown through heatmaps.

Table 4. Non-parametric regression results for effects of subsidy and average farm size

Dependent variables		Non-HS strategy	Production benefit per NCH patch	Net production	NCH patches	HS patches	Income	Income deviation
Vietnam	**Subsidy (β_S)**	1.063	1.634	-0.275	1.870	-1.186	1.704	-1.973
		(0.027)	(0.043)	(0.022)	(0.022)	(0.028)	(0.021)	(0.029)
	Farm size (β_F)	-1.843	0.243	1.114	0.150	1.509	1.039	-3.982
		(0.053)	(0.061)	(0.035)	(0.036)	(0.046)	(0.036)	(0.099)
	Farm size x Subsidy (β_{FS})	4.639	3.674	-0.084^{ns}	-0.196^{ns}	-3.753	-0.004^{ns}	0.924
		(0.131)	(0.190)	(0.103)	(0.082)	(0.138)	(0.105)	(0.195)
	R-squared	0.521	0.537	0.332	0.941	0.61	0.758	0.589
Cambodia	**Subsidy (β_S)**	1.936	1.745	-0.516	1.812	-1.888	2.359	-0.177^{ns}
		(0.554)	(0.084)	(0.028)	(0.034)	(0.043)	(0.063)	(0.091)
	Farm size (β_F)	-2.626	0.055^{ns}	1.004	0.496	1.935	1.156	-3.850
		(0.166)	(0.340)	(0.044)	(0.108)	(0.152)	(0.192)	(0.230)
	Farm size x Subsidy (β_{FS})	3.143	3.435	-0.517	-1.002	-2.320	-0.017^{ns}	-2.446
		(0.311)	(0.491)	(0.114)	(0.156)	(0.286)	(0.298)	(0.449)
	R-squared	0.793	0.691	0.254	0.936	0.824	0.807	0.397

Standard errors in parentheses. "ns" indicates p-value≥0.001.
Effect estimates are averages of derivatives from multivariate non-parametric kernel regression bootstrapped across 50 replications. Regression conducted through the "optimum subsidy ranges" for each context to capture only landscapes where farmer decisions strategically align with production outcomes. 18,800 total observations for Vietnamese context regression (subsidy 0-7). 21,140 total observations for Cambodian context regression (subsidy 0-8).
Non-HS strategy: average percentage of farmers in the non-heavySpray strategy; Production benefit per NCH patch: average production benefit to neighboring patches provided per non-crop habitat patch; Net production: average yield (not including subsidy) - pesticide cost per patch; HS patches: percentage of patches that are heavySpray; NCH patches: percentage of patches that

are non-crop habitat; Income: average yield + subsidy - pesticide cost per patch; Income deviation: $\frac{1}{N}\sum_{i=1}^{N}\left|\frac{income_i}{size_i \times \overline{income}}\right|$

Table 5. Non-parametric regression results for effects of subsidy and farm size heterogeneity

Dependent variables		Non-HS strategy	Production benefit per NCH patch	Production per patch	NCH patches	HS patches	Income	Income deviation
Vietnam	Subsidy (β_S)	3.238	2.396	-0.310	2.037	-2.284	1.827	-1.297
		(0.104)	(0.136)	(0.074)	(0.053)	(0.092)	(0.067)	(0.102)
	Farm size heterogeneity (β_H)	0.881	-0.249	-0.062^{ns}	0.007^{ns}	0.005^{ns}	-0.042^{ns}	1.949
		(0.057)	(0.053)	(0.041)	(0.031)	(0.005)	(0.037)	(0.073)
	Farm size heterogeneity x Subsidy (β_{HS})	-1.892	0.1999^{ns}	-0.122^{ns}	-0.013^{ns}	-0.143^{ns}	-0.100^{ns}	1.196
		(0.145)	(0.196)	(0.111)	(0.064)	(0.125)	(0.092)	(0.152)
	R-squared	0.409	0.491	0.165	0.914	0.604	0.672	0.365
Cambodia	Subsidy (β_S)	4.102	3.570	-0.348	1.691	-2.959	2.053	-0.920
		(0.093)	(0.105)	(0.078)	(0.034)	(0.065)	(0.075)	(0.195)
	Farm size heterogeneity (β_H)	1.229	0.124^{ns}	-0.182	-0.027^{ns}	-0.261	-0.161	3.788
		(0.051)	(0.045)	(0.037)	(0.019)	(0.041)	(0.045)	(0.118)
	Farm size heterogeneity x Subsidy (β_{HS})	-1.828	-0.622	-0.083^{ns}	0.067^{ns}	0.409	-0.004^{ns}	1.303
		(0.123)	(0.147)	(0.113)	(0.046)	(0.091)	(0.097)	(0.261)
	R-squared	0.685	0.629	0.112	0.926	0.795	0.772	0.357

Standard errors in parentheses. "ns" indicates p-value≥0.001.

Effect estimates are averages of derivatives from multivariate non-parametric kernel regression bootstrapped across 50 replications. Regression conducted through the "optimum subsidy ranges" for each context to capture only landscapes where farmer decisions strategically align with production outcomes. 15,392 total observations for Vietnamese context regression (subsidy 0-7). 17,343 total observations for Cambodian context regression (subsidy 0-8).
Non-HS strategy adoption: average percentage of farmers in the non-heavySpray strategy; Production benefit per NCH patch: average production benefit to neighboring patches provided per non-crop habitat patch; Net production: average yield (not including subsidy) - pesticide cost per patch; HS patches: percentage of patches that are heavySpray; NCH patches: percentage of patches that are non-crop habitat; Income: average yield + subsidy - pesticide cost per patch; Income deviation: $\frac{1}{N}\sum_{i=1}^{N}\left|\frac{income_i}{size_i \times \overline{income}}\right|$

DISCUSSION AND CONCLUSION

Our model involves two types of spatial spillover: pesticide drift and the spread of natural enemy services, which together define spatial complexity within the model. We observed in the NonCropShare data that farmers often shifted farm strategies collectively within a group (figure 1b), and we interpreted this as farmers proposing and conforming to group strategies within their social clusters, which creates social complexity within our model. The scale of the landscape in our model is fixed, so as average farm size increases, the landscape shifts from many farmers with smaller holdings to fewer farmers with larger holdings. This change reduces the portion of land on each farm providing or receiving spillover effects from other farms, resulting in greater ability to internalize spillover consequences, both positive from NCH and negative from HS. Additionally, farmers face less social pressure to conform to group choices by being part of fewer social clusters, reducing the number of strategy suggestions they receive. We observe that larger average farm size is correlated with lower non-HS strategy and higher HS patches in the absence of subsidies, but this trend reverses within the optimal subsidy range (figure 3, figure S5, table 4). Before the inflection point, farmers favor heavy spraying because it offers stable high production. With optimum subsidies, substantial financial incentive plus natural enemy services make NCH-focused strategies more attractive. Across both subsidy ranges, reduced spatial and social pressure gives farmers freedom to more widely implement the preferred strategy. Farm size heterogeneity has the reverse effect compared to farm size. The effect appears to be less pronounced, suggesting that spatial and social complexity is less influenced by farm size heterogeneity than average farm size (table 4, table 5). The spatial spillover effects in our model are stylized to closely represent the spatial coordination challenge of provision of natural pest control ecosystem services. It would be interesting to compare our results with studies focused on ecosystem services involving different spatial spillover effects, such as pollinator services (65).

Experimental behavioral research shows that economic inequality strongly discourages cooperation and hampers the establishment of social capital within groups (66), both of which are essential for the success of landscape-scale agri-environmental incentive programs (42, 67-69). In our study, larger average farm size and lower farm size heterogeneity are associated with significantly lower levels of income inequality (figure S7), which may contribute to the observed differences in response to subsidy in addition to changes in spatial and social complexity.

The two contexts we studied exhibit similar overall responses but also show some differences, likely driven by a combination of economic, social, cultural, institutional, and cognitive factors (70, 71). This speaks to the varied responses to agri-environmental programs across different farming contexts and highlights the importance of considering regional variation when designing payment schemes. Global sensitivity analysis showed that all model parameters significantly influence landscape outcomes, with impact varying depending on the outcome (table S3). Further analysis indicated that placing more weight on outcomes for the entire farm rather than individual land patches is associated with greater NCH receptivity (figure S8). With only two contexts to compare, we did not clearly identify the mechanisms driving the difference in size-dependence of response to subsidy between the contexts. According to the accompanying survey data, participants in the Vietnam field game had larger average real-life landholdings (table S2). We hypothesize that larger real-life landholdings conferred greater ability to prioritize farm-level outcomes during the NonCropShare game experiment in Vietnam, leading to an earlier subsidy inflection point for NCH adoption in the model simulation. However, additional field experiments across diverse contexts are needed to verify this hypothesis and provide insights to help assess the overall generalizability of our model.

Our model simulation suggests that landscape-scale payments for ecosystem services face fewer obstacles to work as incentive-based mechanisms in landscapes of larger, more homogeneous farms. The growth of farm scales due to cropland consolidation has contributed to significant biodiversity loss and ecosystem degradation (72, 73). Agri-environmental interventions are especially important to mitigate the decline in biodiversity and ecosystem services in landscapes of increasing farm sizes toward which many regions are shifting (74, 75). To date, improving biodiversity and reducing pesticide reliance have mostly been approached separately. Meanwhile, pesticide consumption continues to rise (76), underscoring the need for a paradigm shift in pest management to emphasize biodiversity-driven agroecological crop protection, moving the focus from treating target pests to holistically considering hosts, pests, and enemies (77, 78). We argue that it is urgent and prudent to prioritize landscape-level incentive programs to encourage NCH-based natural pest control, especially in regions with medium to large farms, for two reasons: to significantly alleviate pesticide reliance and improve biodiversity simultaneously, and to enable empirical data collection for ex-post ecological and economic evaluations, providing much-needed information to policymakers, researchers, farmers, and other stakeholders globally.

We apply the novel field-to-laboratory, data-driven method of extracting common patterns from large-scale field game datasets across different contexts to inform ABM development. Our approach allows the assessment of market-based policy instruments at a scale unattainable with real-world field experiments. This method is applicable to a wide range of problems where coordination and a spatially explicit flow of services and disservices determine the performance of policy instruments. However, it is important to recognize several simplifications made to facilitate game play and model simulation. The model does not account for the variability of habitat management in the provision of natural enemy services, a key factor in production benefits. Additionally, our cost and yield parameters are not calibrated to local markets but are instead designed to provide key equilibria. The model also does not consider other potential variables that could influence the function of subsidies, independently or in conjunction with farm size. Our results, derived from modeling abstracted agricultural environments, provide qualitative rather than quantitative insights and should be further validated with empirical data. To our knowledge, we are among the first to explore how farm size influences the function of payments for ecosystem services at the landscape level, adding to the growing but still limited understanding of landscape-scale interventions.

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Supplementary Information

Section S1 has additional methods (ODD protocol and sensitivity analysis). Section S2 has all additional results.

S1. Additional methods

S1.1. ODD Protocol

1. Purpose and patterns

The purpose of this model is to explore how subsidies interact with varied farm size and farm size heterogeneity to influence farmers' decisions about sharing natural enemy service to reduce pesticide use in a spatially explicit environment. The model is informed by strategic and behavior patterns in NonCropShare game data and theories of bounded rationality (58-60) and case-based reasoning (61, 62).

2. Entities, state variables, and scales

The model contains entities of patches, farmers, social clusters, and the global environment.

2.1. Patches

Patches are square grid cells that comprise the landscape. Patches are characterized by state variables of land use choice (NCH, NS, LS, HS), yield (including boosts from adjacent NCH patches), cost, and income (possibly different from net production if subsidy is provided for NCH patches). Land-use choice is selected by the farmer owner of the patch, and this land-use choice and its interaction with the spatial spillover from other patches in the landscape determines the other state variables. Yield is calculated as the total production of the land-use choice (described in table 1), including boosts from adjacent NCH patches. Cost is incurred based on the degree of pesticide usage. Income is calculated as the yield - cost + subsidy.

2.2. Farmers

Farmers are the autonomous decision-making agents within the landscape. They are characterized by state variables involving strategy, memory states, behavioral preferences, social cluster membership, and trust. The primary farmer state variable is farm-level strategy, either HS or non-HS. These strategies determine which land-use choices are available to farmers: farmers under the non-HS strategy will not use heavy spraying while farmers under the HS strategy will use all patch types.

The model exists at three geometric scales: patch (individual piece of land), farm (area of adjacent patches controlled by one farmer), and landscape (the entire collection of farms). Farmers maintain four memory states for each patch they own, one for each land use choice in which they "remember" the history of the income generated at each geometric scale (memory state structure shown in figure S1). For each geometric scale, farmers also have corresponding state variables (*carePatch*, *careFarmer*, and *careLandscape*) that determine how heavily they weigh recorded outcomes at each geometric scale in determining their future land-use decisions. Similarly to the patch-scale land-use memory states, farmers maintain two farm-level memory states associated with the two farm-level strategies (non-HS and HS) in which they record the income generated by their entire farm when they adopted a given strategy.

Farmers also have state variables of the list of social clusters they can potentially join and which social cluster, if any, they are currently a part of. Farmers have trust values with each neighboring farmer with whom they share at least one border or corner. These trust values influence the likelihood that a farmer will discuss and adopt group strategy coordination.

Figure S1

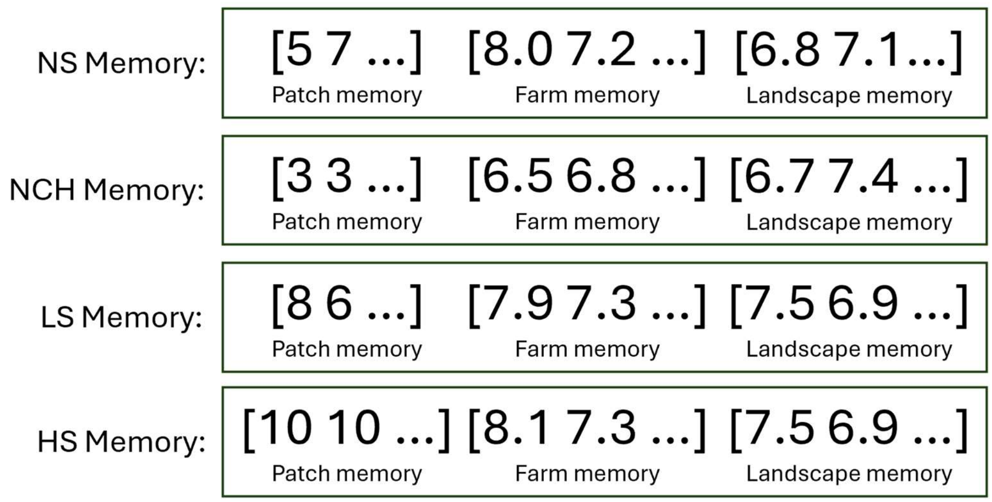

Figure S1. Example visualization of the memory state of a single patch containing information on past outcomes. In this example, the last time the farmer chose NS for this patch, they earned an income of 7 directly from the patch, their entire farm earned an average income of 7.2 per patch, and the landscape outside of their farm earned an average income of 7.1 per patch. Each memory array is truncated if it grows longer than the *memory* parameter.

2.3. Social clusters

Social clusters have the state variables of the list of farmers who can join the cluster and the current group coordination strategy, which is proposed by a member farmer.

2.4. Global environment

The global environment has state variables of *subsidy*, *nonHSPercent*, *initialExperience*, and *memory*. The *subsidy* functions the same as in the nonCropShare game and adds a financial incentive to use NCH patches. The environment *nonHSPercent* determines the proportion of farmers initialized to the non-HS strategy. The environment *initialExperience* is the per-patch income that farmer memory is initialized with at the start of a model run. Global *memory* is the maximum number of harvest seasons farmers will record in their memory state before truncating.

2.5. Scale
The model represents an abstracted farming environment, with each time step corresponding to a single agricultural season of planting and harvesting. In all experiments, the model runs for 50 time steps to capture long-term landscape trends. The model is spatially explicit, with the landscape represented as a grid of square cropland patches. When calibrating to NonCropShare game data, the modeled landscape is a 6x6 uniform distribution. In all other experiments, the modeled landscape is a 15x15 grid, allowing for greater flexibility in landscape distribution.

3. Process overview and scheduling
Our model is designed to simulate farmer planting decisions over agricultural seasons. Farmer decisions occur at two scales: farm-level strategy and patch-level land use. Farmers first decide on farm-level strategy, which then guides what land use choices they are willing to make on their individual patches.

Time steps are discrete and start with farmer agents deciding whether to coordinate with neighbors on farm-level strategy (see *Submodel: Cluster interaction* below). Farmers who decide not to coordinate simply choose the strategy with the highest average income in their memory state. Then, for each patch they own, farmers calculate three certainty equivalents (one for each geometric scale) for each of the four land-use choices based on patch-level memory states (see *Design Concepts: Objectives* below). For each patch they own, farmers select the land-use choice with the greatest calculated certainty equivalent. After choices are made for all patches, farmers harvest and receive income based on landscape composition. Farmers then update their farm-level strategy memory states with their total income and their patch-level land-use choice memory states with the income earned at each geometric scale. If the length of any memory state exceeds the global *memory* parameter, that memory state is truncated to drop the first (oldest) value. Outputs for tracked landscape outcome variables are updated at this point (see *Design Concepts: Observation* below).

4. Design concepts
The model environment is structured with the rules of NonCropShare game, stylized to represent the spatial coordination dynamic between pesticide spraying and mobile enemy services. Agent behaviors are broadly informed by theories of bounded rationality (58-60) and case-based reasoning (61, 62). Farmer agents' decisions are primarily driven by case-based reasoning driven by their memory of previous income earned when they made different choices. Still, farmers are not perfect income-optimizing agents, displaying bounded rationality limited by information, strategy, social pressure, and spatial spillover. Agent behaviors and model structure are further informed by patterns observed from game data clustering. To represent how farmers flexibly

experimented with strategy within the game, we structured farmer agents so that current strategy has no impact on strategy selection, aside from current harvest yield contributing to the expected value of their current strategy. To capture farmer strategic coordination with neighbors, we encoded social group interactions where farmers potentially adopt group strategies based on trust with other farmers. Collectively, these general theories and data-based findings drive the model's core structure.

4.1. Emergence

We track several key emergent results from the model: non-HS strategy adoption, HS patches, NCH patches, net production (income minus subsidy), production per NCH patch, income, and income deviation (average farmer deviation from mean landscape income) (table S1). Of these, only non-HS strategy adoption emerges from internal farmer agent processes driven by social interaction and strategic preference. All other results emerge directly from landscape patch composition and the resultant earned yield and subsidy. Land-use choices are determined by farmer agents, whose driving mechanisms are described in *Objectives*.

4.2. Adaptation

The adaptive behaviors of farmers are patch-level land-use choice and farm-level strategy. Farmer adaptation is primarily driven by maximizing expected utility, derived from case-based memory of previous income earned when they made certain choices, both at the patch- and farm-level. Farmer adaptation of farm-level strategy also occurs in coordination with other farmers through interactions within social clusters. Farm-level strategy then partially drives patch-level decisions by determining which land-use choices farmers are willing to implement.

4.3. Objectives

Farmers evaluate patch-level land use choices and farm-level strategy options by an objective measure based on net income. It is worth noting that due to financial incentives, this is related but separate from net production. For each patch they own, farmers calculate an objective measure for each land-use choice (NCH, NS, LS, HS) according to the following expression:

$$c_{patch}\,\overline{x}_{patch} + c_{farm}\,\overline{x}_{farm} + c_{landscape}\,\overline{x}_{landscape}$$

where c represents the farmer behavioral weight on that geometric scale and $\overline{x}$ represents the mean income value in the farmer's memory state for that land-use choice and geometric scale (see *Entities, state variables, and scales: Farmers* above). For each farm-level strategy, farmers calculate the objective measure as the mean income value in the farmer's memory state for that strategy.

4.4. Learning

Farmer learning is memory-based following the theory of case-based reasoning, which states that agents make decisions by drawing on memory of previous outcomes of when they made similar choices (4, 5). Farmers use their patch-level and farm-level memory states to inform their decisions at each round.

4.5. Prediction

The objective utility measure is based on the explicit prediction that future income from making a certain decision can be reasonably predicted through previous outcomes when that same decision was made, in accordance with case-based reasoning theory.

4.6. Sensing

Farmers sense the income they earn from each of their own patches and the average income of the landscape outside their own farm. However, they do not sense explicitly that NCH provides benefits or that HS cancels those benefits. Thus, measured income from an NCH cell is always the provided subsidy, regardless of how much boost it provides to surrounding cells. Measured income from a base cell includes any received NCH boosts. Farmers cannot sense the farming strategy of their neighbors; strategy information-sharing occurs with proposing group strategies within social clusters.

4.7. Interaction

Our model includes two types of interactions: spatial (mediated) and social (direct). Spatial spillover interactions occur with the usage of HS and NCH patches. Spillover effects across farm boundaries create inter-farm spatial interactions that affect the income of neighboring farms. NCH has a larger effect radius and can boost production for neighboring farms, but HS patches can cancel out those natural pest control benefits, creating a spatial dichotomy. Social interactions occur between farmers who share borders and/or corners to propose and coordinate farm-level strategy (see *Submodel: Cluster interaction* below).

4.8. Stochasticity

The model involves stochasticity in initializing farmer agent characteristics and in generating non-uniform landscapes (see *Initialization* below). This allows for variation among individual agents and the generation of pseudo-random landscape configurations. Stochasticity also exists during model iteration with the likelihood that farmers will engage in discussion with neighbors and adopt proposed strategies (see *Submodel: Cluster interaction* below).

4.9. Collectives

Farmers form collectives around shared borders and corners, called social clusters. Within these collectives, farmers propose and adopt group strategies based on trust, allowing for the coordination and dissemination of strategies (see *Submodel: Cluster interaction* below).

4.10. Observation

Several primary landscape outcomes are tracked from the model, described in table S1. Landscape outcomes are calculated at the end of each time step and averaged across all 50 time steps of model iteration.

Table S1. Observed landscape outcomes.

Landscape Outcome	Calculation
Non-HS strategy adoption	$\frac{\sum F_{non-HS}}{F_{tot}}$
HS patches	$\frac{\sum P_{HS}}{P_{tot}}$
Production benefit per NCH patch	$\frac{\sum(production\ bonus\ from\ NCH)}{\sum P_{NCH}}$
Net production	$\frac{\sum[yield\ (not\ including\ subsidy) - pesticide\ cost]}{P_{tot}}$
NCH patches	$\frac{\sum P_{NCH}}{P_{tot}}$
Income	$\frac{\sum(yield\ + subsidy - pesticide\ cost)}{P_{tot}}$
Income deviation	$\frac{1}{F_{tot}}\sum_{i=1}^{F_{tot}}\left\lvert\frac{income_i}{size_i \times \overline{income}}\right\rvert$

In equations, F represents farmers and P represents patches.

5. Initialization

Landscape distribution is determined by the number of farms and the parameter *heterogeneityIndex*. Farmers are iteratively initialized with a *growthWeight* starting at 0.001. Each farmer's *growthWeight* is iteratively defined by the following equation:

$$w' \times (1 + rand(0, heterogeneityIndex))$$

where w' is the *growthWeight* assigned to the previous farmer. Farmers are each allocated a certain number of patches proportional to their *growthWeight*. Thus, a higher *heterogeneityIndex* corresponds with a greater degree of farm size heterogeneity.

Farmers are iterated through in descending order of *growthWeight* (to avoid having large farms grow to completely circle smaller farms initialized earlier). The current farmer selects an unowned patch as their first patch. Then, their farm begins growing outward from that starting patch. Any patch which is surrounded by 3 or 4 of the farmer's existing patches is prioritized to be added to the farmer's farm (to avoid encircling "islands" of unclaimed patches). If there are no patches that satisfy that criteria, one patch that directly borders the farmer's farm is added to the farm. This continues until either the farmer's allocated patch limit is reached or they have no remaining unclaimed bordering patches. If the entire landscape is filled before every farm is initialized, the model run terminates and initialization resets. If any patches remain unclaimed after this process occurs for every farmer, they are each allocated randomly to a bordering farm.

Clusters form around shared corners and borders. For each patch, a list is generated for each of the patch's four corners, each containing the unique farmers who own a patch sharing that corner. Any non-duplicate list of multiple farmers is added to the landscape list of all potential clusters and to the personal list of potential clusters for the farmer owner of the patch. In this way, farmers can potentially join any unique group of farmers who are all adjacent to each other (clusters thus range in size from two to four farmers).

Farmers are initially seeded with the non-HS strategy proportionally to *nonHSPercent*. Patches are then randomly seeded with land-use choices. Patches owned by a non-HS strategy farmer cannot be seeded with heavy spraying. Farmers are each seeded with one memory value of *initialExperience* for each land-use choice and geometric scale on all of their patches. Prior to normal process iteration, farmers calculate income from the seeded landscape and update memory states, providing them with real landscape outcomes to inform early choices.

6. Input data
The model does not use input data to represent time-varying processes.

7. Submodel: Cluster interaction
Farmers each have social clusters with neighboring farmers that they can potentially participate in. In random order, farmers begin joining social clusters. The current farmer first ranks clusters that already have at least one member by their total trust with all the other farmers that could join that cluster. Then, they rank all other potential clusters by their total trust with the other farmers in that cluster. Thus, farmers primarily prioritize clusters with existing members, then prioritize larger, more trusted social clusters. The current farmer then iterates through their ranked cluster list, and for each cluster, their chance of joining is equal to their average trustIndex with all other potential members. If the farmer goes through every cluster without joining or is the only farmer to join their cluster, they do not participate in discussion for the season and simply choose the strategy that has the highest mean income in their memory. After every farmer has gone through this process, within each cluster with multiple members, each member proposes the strategy for which they have the highest mean income memory. The cluster adopts the strategy with the highest proposed value as their group strategy. For each member of the cluster who currently uses the opposite strategy, their chance to coordinate by adopting the group strategy is their trustIndex with the proposing farmer.

Figure S2

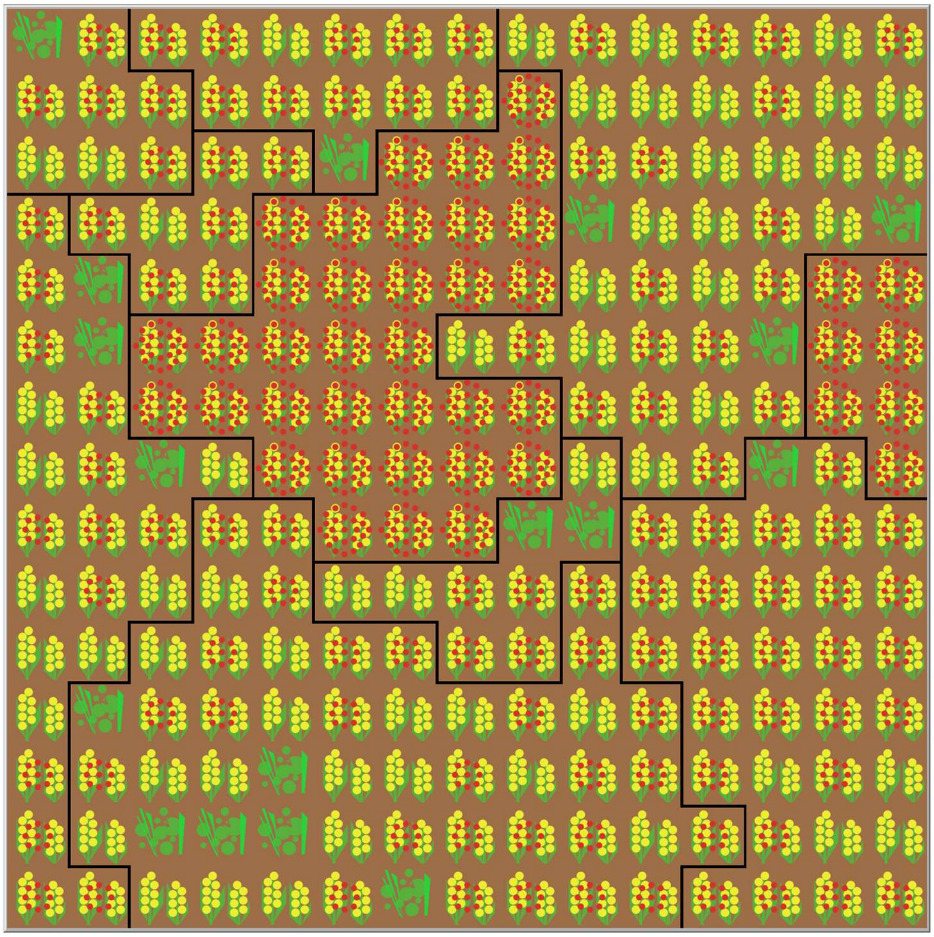

Figure S2. Example landscape generated non-uniformly with *heterogeneityIndex* of 0.

S1.2. Global sensitivity analysis

We conducted a global sensitivity analysis on the effect of each model parameter on landscape outcomes. For sensitivity analysis, we varied subsidy from 0 to 10 and varied number of farms from 4 to 50. For each combination of subsidy and number of farms, 1000 parameter sets were initialized with Monte Carlo sampling across full parameter ranges (Table 3**)**. By initializing this volume of parameter sets, we generated data spanning the model's full parameter range, allowing analysis of the overall effect of each parameter. We ran the model across each parameter set. We scaled all variables, both inputs and outputs, to Z-score and conducted Ordinary Least Squares regression on the resulting data according to the following equation:

$$Y = \sum_i \beta_i x_i + \sum_i \sum_j \beta_{ij} x_i x_j,$$

where Y is the outcome variable, β is a regression coefficient, and x is a parameter variable. In this way, the model accounts for regression terms on each individual parameter and for the product of each pair of parameters, allowing exploration of the interaction effects between parameters.

S2. Additional results

Table S2. Survey data of field game participants

Description	Cambodia		Vietnam	
	Mean	SD	Mean	SD
Average fraction of farms owned across group	0.42	0.24	0.91	0.12
Average farm holding size across group	2.58	3.1	13.22	24.15
Average fraction of crops sold (by mass) across group	30.84	18.33	27.29	20.6
Fraction of group using chemical fertilizers	0.69	0.33	0.998	0.02
Fraction of group using pesticides	0.29	0.28	0.85	0.27
Fraction of the group that is female	0.46	0.29	0.45	0.26
Average age across group	43.22	6.69	49.24	7.16
Average years of formal education across group	2.19	0.66	3.94	0.57
Fraction of group received instruction on pesticides	0.21	0.23	0.83	0.21
Fraction of group aware of pesticide hazards	0.63	0.24	0.97	0.08
Average (self-reported, scale of 1–5) relationship across group	3.75	0.74	4.17	0.69

Adapted from Andrew Bell and Wei Zhang 2016 *Environ. Res. Lett.* 11 114024.

Figure S3A

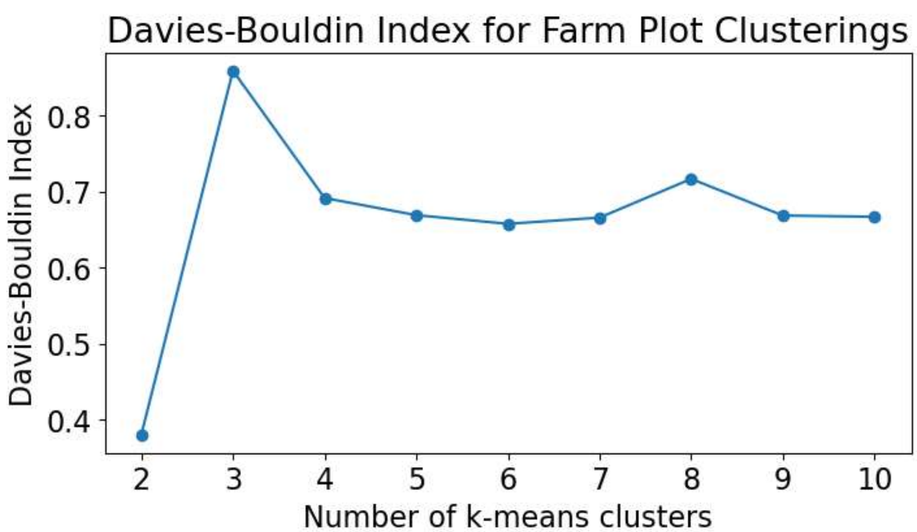

Figure S3A. Davies-Bouldin index (DBI) for k-means clusters of NonCropShare data from 2-10 clusters. DBI measures the average similarity of each cluster with its most similar cluster, with similarity calculated as the ratio of within-cluster distances to between-cluster differences. Thus, lower DBI represents better fitness. Clustering into two k-means clusters minimizes DBI and achieves best fitness.

Figure S3B

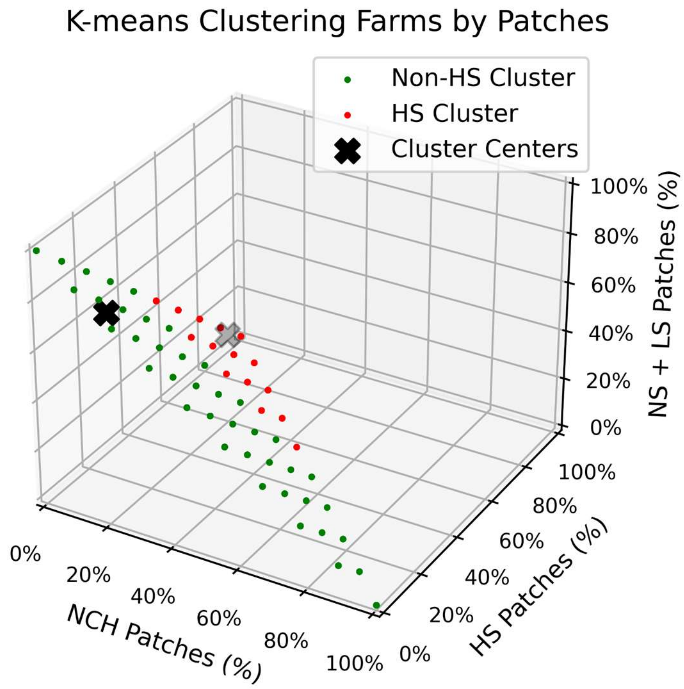

Figure S3B. 3-dimensional visualization of k-means clustering of NonCropShare field experiment data by factors of NCH patches, HS patches, and NS + LS patches.

Figure S4A

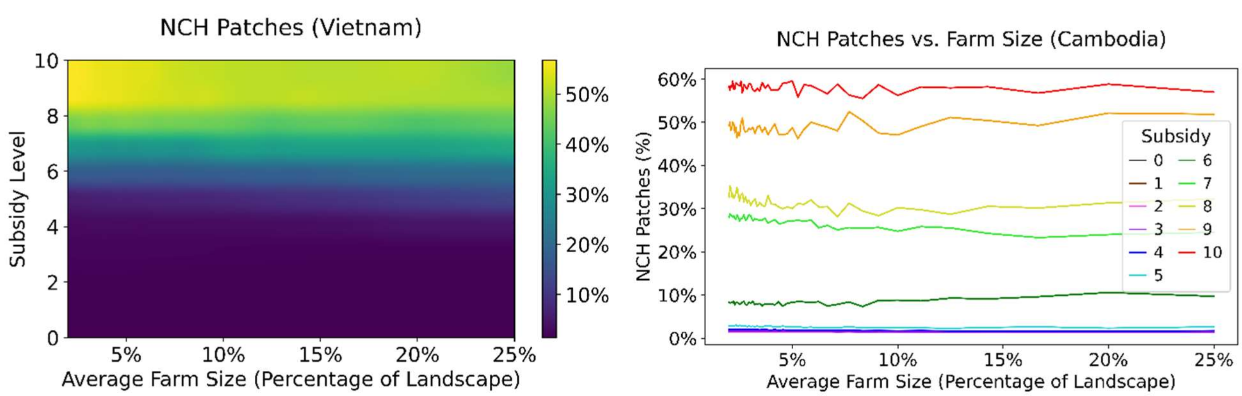

Figure S4B

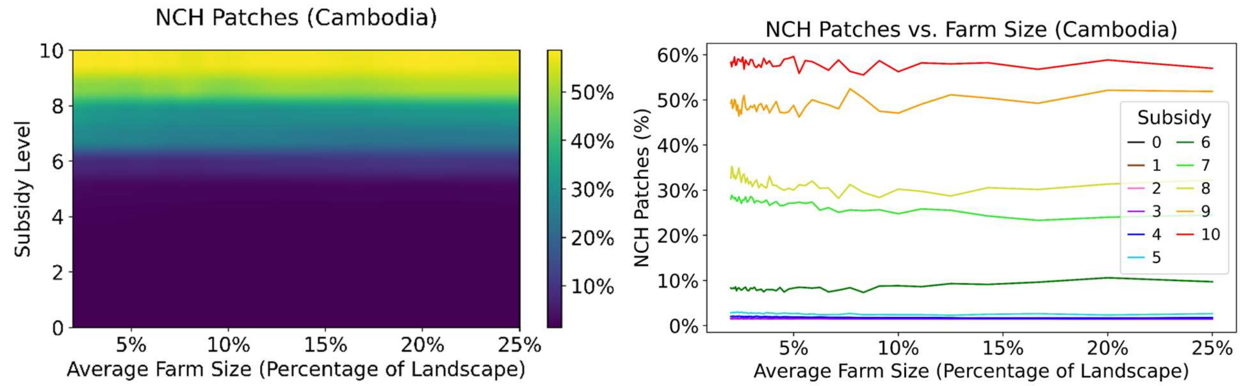

Figure S4C

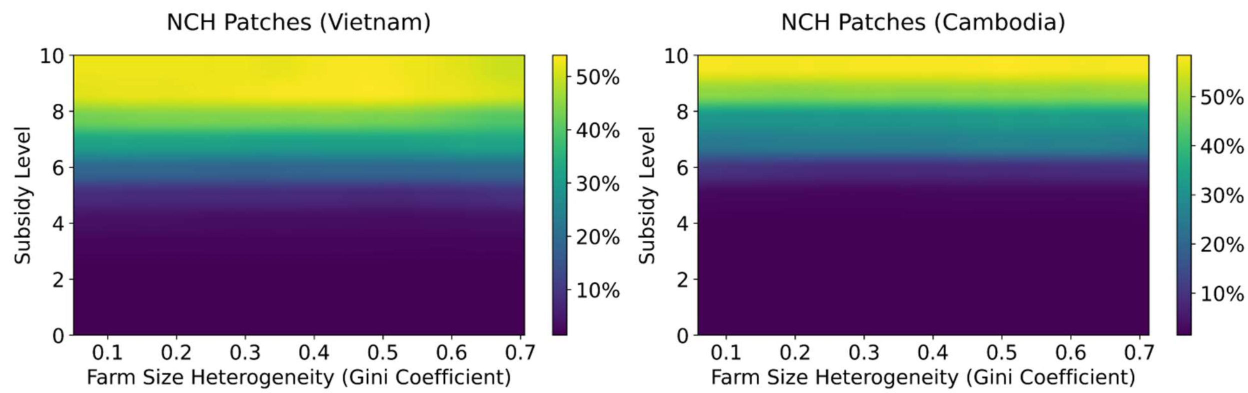

Figure S4. Average percentage of non-crop habitat (NCH) patches in (A) Vietnam across varied subsidy level and average farm size, shown through heatmaps (left panel) and line plots (right panel); (B) Cambodia across varied subsidy level and average farm size, shown through heatmaps (left panel) and line plots (right panel); (C) Vietnam (left panel) and Cambodia (right panel) across varied subsidy level and farm size heterogeneity, shown through heatmaps.

Figure S5A

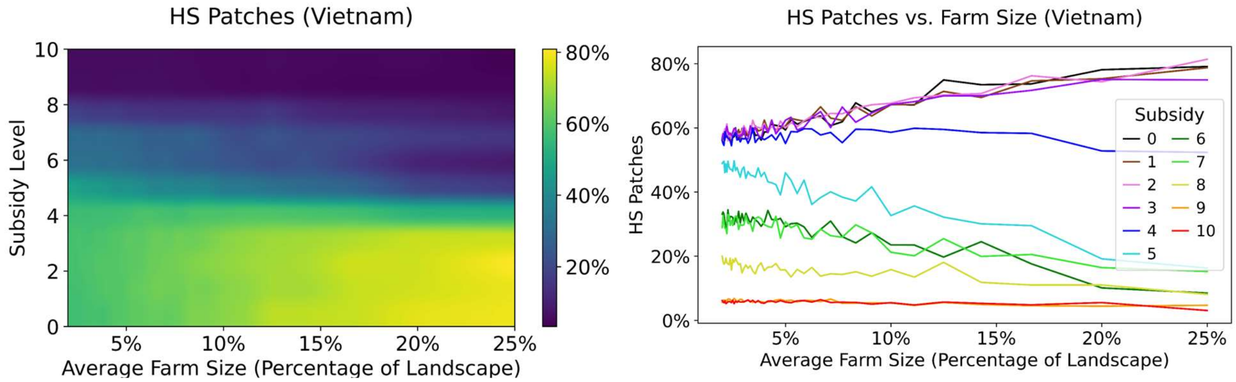

Figure S5B

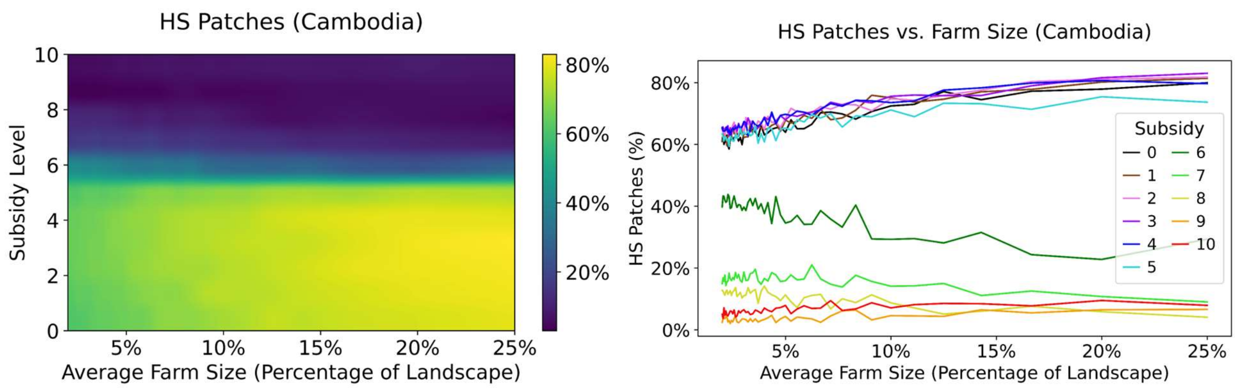

Figure S5C

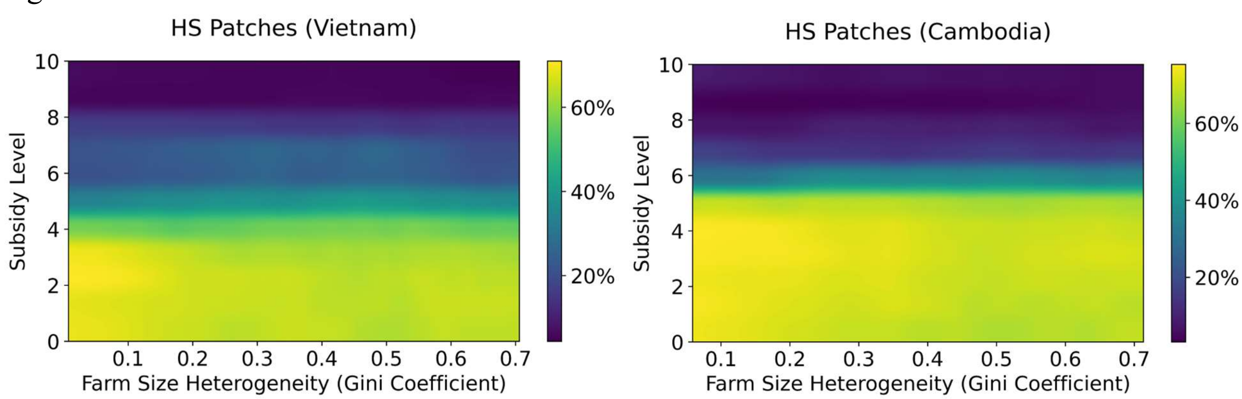

Figure S5. Average percentage of heavySpray (HS) patches in (A) Vietnam across varied subsidy level and average farm size, shown through heatmaps (left panel) and line plots (right panel); (B) Cambodia across varied subsidy level and average farm size, shown through heatmaps (left panel) and line plots (right panel); (C) Vietnam (left panel) and Cambodia (right panel) across varied subsidy level and farm size heterogeneity, shown through heatmaps.

Figure S6A

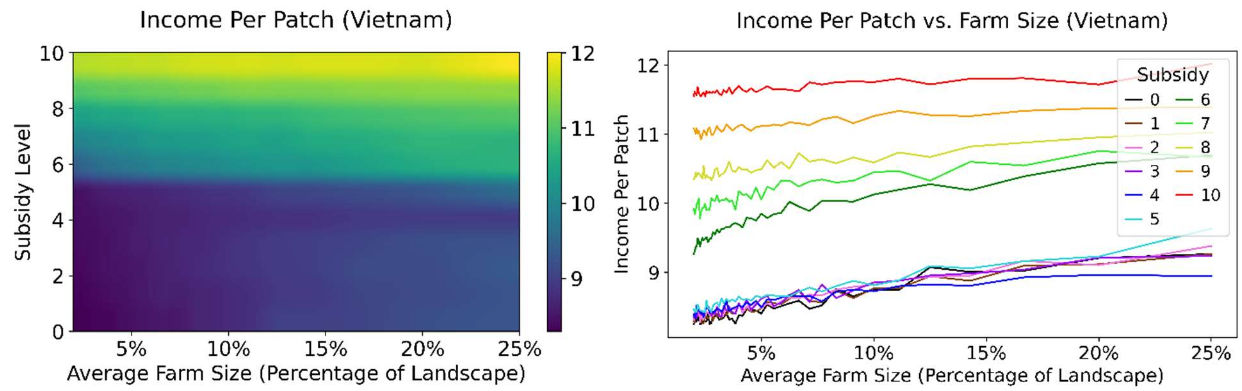

Figure S6B

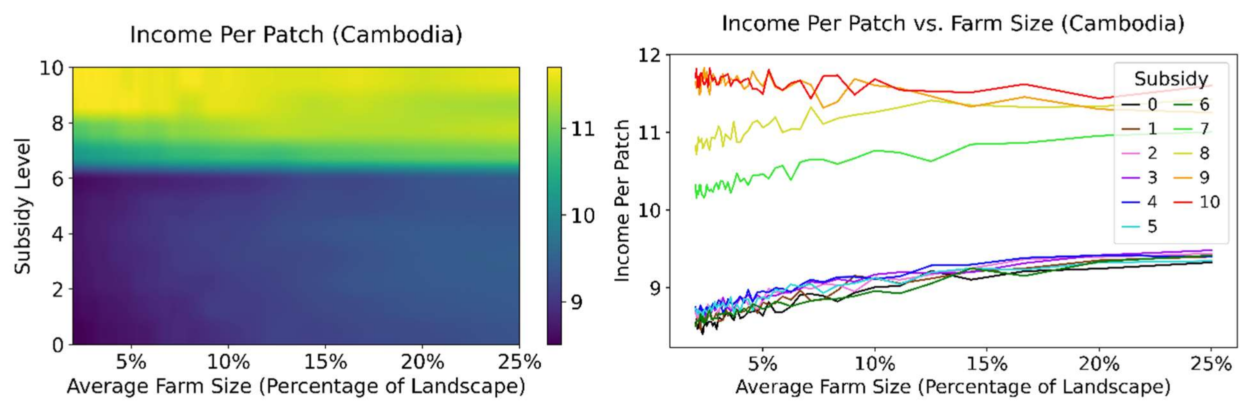

Figure S6C

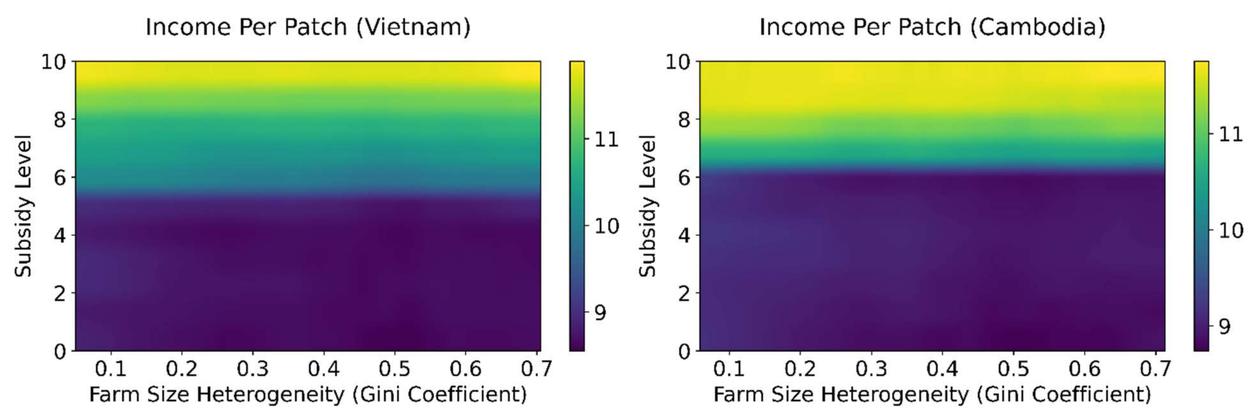

Figure S6. Average income per patch in (A) Vietnam across varied subsidy level and average farm size, shown through heatmaps (left panel) and line plots (right panel); (B) Cambodia across varied subsidy level and average farm size, shown through heatmaps (left panel) and line plots (right panel); (C) Vietnam (left panel) and Cambodia (right panel) across varied subsidy level and farm size heterogeneity, shown through heatmaps.

Figure S7A

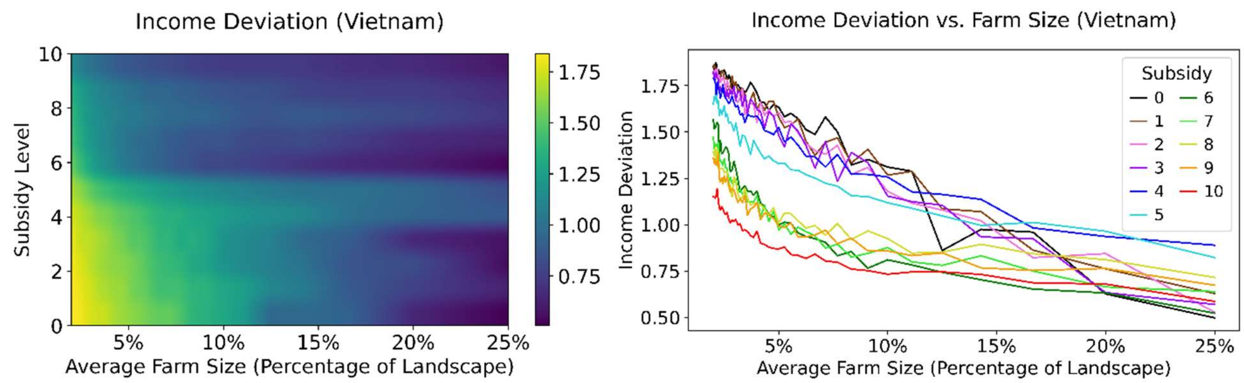

Figure S7B

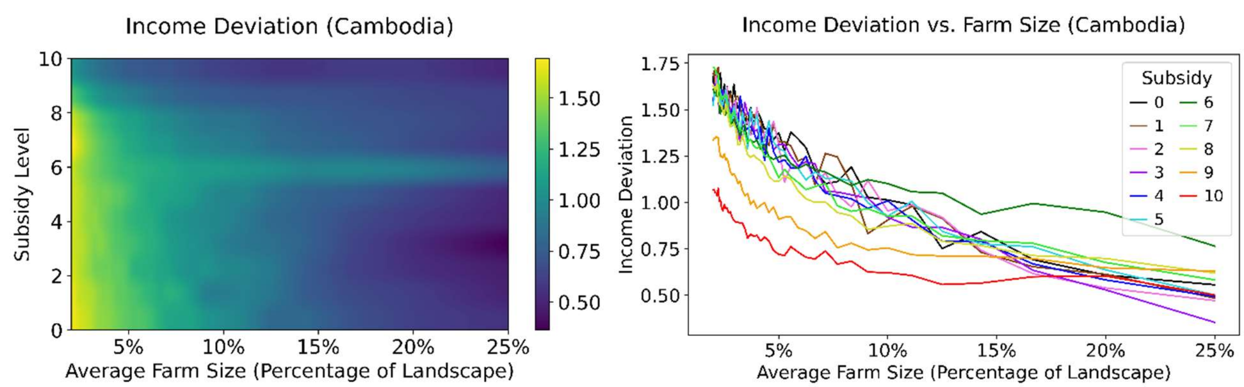

Figure S7C

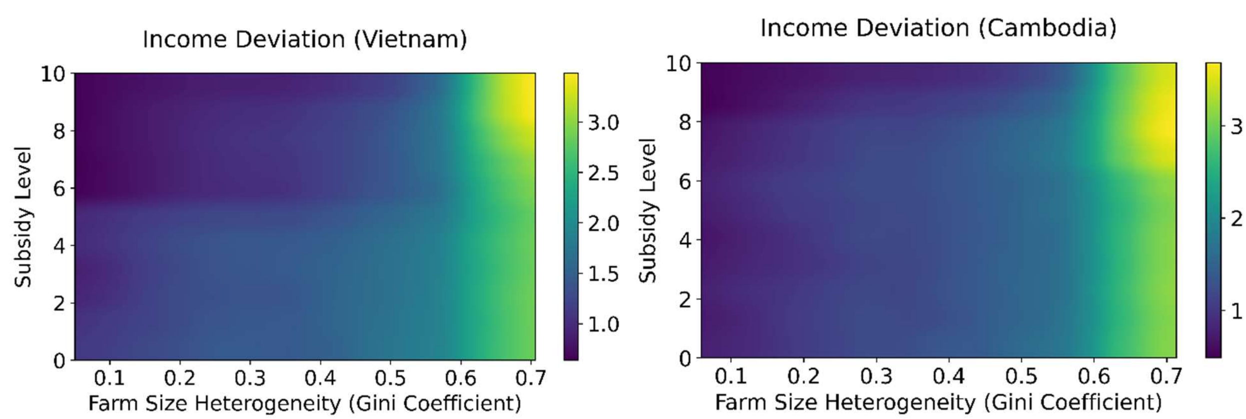

Figure S7. Average income deviation per farmer in (A) Vietnam across varied subsidy level and average farm size, shown through heatmaps (left panel) and line plots (right panel); (B) Cambodia across varied subsidy level and average farm size, shown through heatmaps (left panel) and line plots (right panel); (C) Vietnam (left panel) and Cambodia (right panel) across varied subsidy level and farm size heterogeneity, shown through heatmaps.

Figure S8

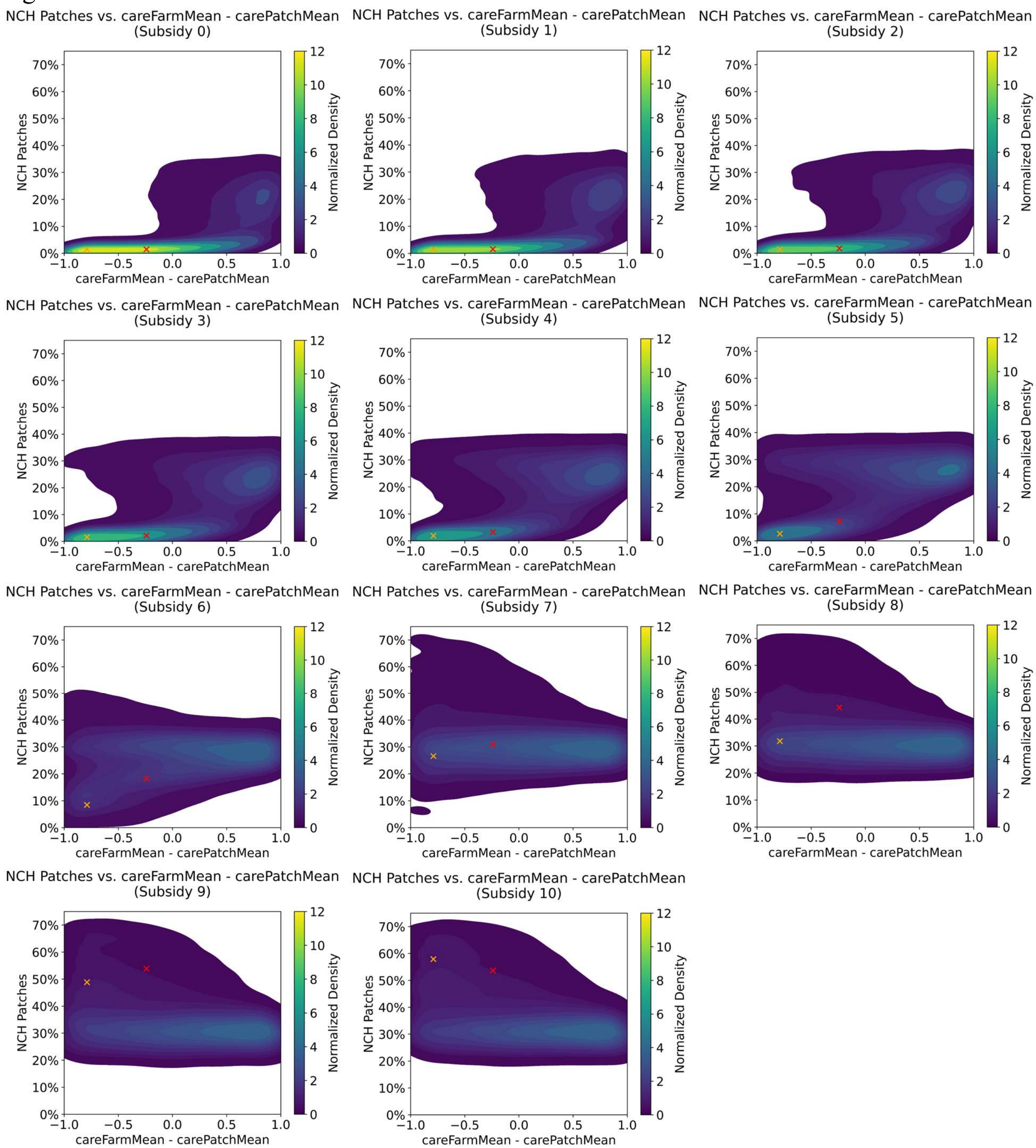

Figure S8. Density plots showing the distribution of average NCH patches at each subsidy level as a function of the difference between *careFarmMean* and *carePatchMean* (*careFarmMean - carePatchMean*). Distributions are taken over full global sensitivity analysis and normalized to x-axis density. Average values across all calibrated environment experiments at each subsidy level are shown for Vietnam (red) and Cambodia (orange).

Table S3. Global sensitivity analysis results

	Non-HS Strategy	Production Benefit Per NCH Patch	Net Production Per Patch	NCH Patches	HS Patches	Income Per Patch	Income Deviation
careFarmMean	-0.071	0.03	0.059	0.069	0.108	0.044	0.018
careLandscapeMean	0.042	0.025	0.045	0.088	-0.056	0.021	0.074
carePatchMean	0.153	0.081	-0.047	-0.07	-0.393	-0.015	-0.106
initialExperience	1.558	0.892	0.827	0.036	-0.064	0.68	0.15
memory	-0.018^{ns}	-0.004^{ns}	-0.007^{ns}	0.014^{ns}	0.018^{ns}	-0.000^{ns}	-0.010^{ns}
nonHSPercent	2.496	0.952	0.741	0.325	-0.797	0.653	0.26
trustIndexMean	0.001^{ns}	0.106	0.093	0.013^{ns}	-0.075	0.079	0.051
careFarmMean × *careLandscapeMean*	-0.05	-0.066	-0.033	-0.025	0.092	-0.023	-0.01
careFarmMean × *carePatchMean*	0.026	0.044	-0.014	-0.014	-0.005^{ns}	-0.016	0.024
careFarmMean × *initialExperience*	0.166	0.132	-0.015	-0.051	-0.338	-0.017	-0.047
careFarmMean × *memory*	-0.006^{ns}	-0.003^{ns}	0.002^{ns}	-0.001^{ns}	0.007^{ns}	0.001^{ns}	0.003^{ns}
careFarmMean × *nonHSPercent*	0.019	-0.025	0.012	0.041	0.012	0.025	0.019
careFarmMean × *trustIndexMean*	0.028	0.014	0.001^{ns}	0.007^{ns}	-0.028	0.003^{ns}	-0.004^{ns}

careLandscapeMean × carePatchMean	-0.006$^{\text{ns}}$	0.024	0.011	-0.04	0.010$^{\text{ns}}$	0.002$^{\text{ns}}$	-0.015
careLandscapeMean × initialExperience	0.019$^{\text{ns}}$	0.056	-0.03	-0.08	-0.107	-0.02	-0.065
careLandscapeMean × memory	-0.012$^{\text{ns}}$	-0.008$^{\text{ns}}$	0.006	0.000$^{\text{ns}}$	0.011$^{\text{ns}}$	0.005$^{\text{ns}}$	0.001$^{\text{ns}}$
careLandscapeMean × nonHSPercent	0.001$^{\text{ns}}$	-0.049	-0.002$^{\text{ns}}$	0.066	0.033	0.021	0.01
careLandscapeMean × trustIndexMean	0.015	0.006$^{\text{ns}}$	0.002$^{\text{ns}}$	0.001$^{\text{ns}}$	-0.006$^{\text{ns}}$	0.003$^{\text{ns}}$	0.016
carePatchMean × initialExperience	-0.375	-0.431	-0.010$^{\text{ns}}$	0.054	0.861	-0.013	0.097
carePatchMean × memory	0.036	0.016	-0.009	0.000$^{\text{ns}}$	-0.028	-0.007	-0.001$^{\text{ns}}$
carePatchMean × nonHSPercent	-0.004$^{\text{ns}}$	0.086	0.014	-0.079	-0.043	-0.02	-0.013
carePatchMean × trustIndexMean	-0.036	-0.016	-0.008	-0.002$^{\text{ns}}$	0.027	-0.006	-0.008
initialExperience × memory	0.039	0.029	-0.001$^{\text{ns}}$	-0.020$^{\text{ns}}$	-0.044	-0.008$^{\text{ns}}$	0.019
initialExperience × nonHSPercent	-2.758	-1.177	-0.857	-0.373	0.917	-0.753	-0.286
initialExperience × trustIndexMean	0.017$^{\text{ns}}$	-0.096	-0.084	-0.021	0.09	-0.075	-0.062
memory × nonHSPercent	-0.02	-0.014	0.003$^{\text{ns}}$	-0.004$^{\text{ns}}$	0.012$^{\text{ns}}$	0.000$^{\text{ns}}$	-0.008
memory × trustIndexMean	0.003$^{\text{ns}}$	0.001$^{\text{ns}}$	-0.002$^{\text{ns}}$	0.003$^{\text{ns}}$	-0.009$^{\text{ns}}$	-0.001$^{\text{ns}}$	0.008
nonHSPercent × trustIndexMean	-0.029	0.007$^{\text{ns}}$	0.021	-0.003$^{\text{ns}}$	0.007$^{\text{ns}}$	0.015	-0.023

“ns” indicates p-value≥0.001.
Regression conducted via Ordinary Least Squares.