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Erratum: On 26 May 2022: A) The original publication of this manuscript incorrectly stated that California's citrus-producing industry was worth $2.3 billion. The error was corrected to $3.63 billion. B) Formatting of the 10 hypotheses in the introduction and methods was adjusted.

Research

Collective action in the area-wide management of an invasive plant disease

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ABSTRACT. Area-wide management (AWM) is a strategy for invasive plant pests and diseases in which management actions are coordinated across property boundaries to target the entire pest or pathogen population in an area. Because some people may benefit from the actions of others without bearing the costs, but group-level contributions are required to achieve effective control, AWM suffers from free-riding, yet it has rarely been studied as a collective action problem. To foster collective action for the management of huanglongbing (HLB), California citrus stakeholders have adopted two distinct institutional approaches: Psyllid Management Areas (PMAs), in which coordinated treatments are voluntary, and Pest Control Districts (PCDs), in which coordinated treatments are mandatory. Through a survey distributed to citrus stakeholders in Southern California and a regression analysis of participation levels in AWM over nine seasons, we assess the impact that individual perceptions, institutional approaches, and group-level determinants have had on collective action. Our results show that although citrus stakeholders are confident about the benefits of AWM, they are aware of collective action problems and identified the lack of participation as the main barrier to AWM. Group size, grove size, and heterogeneity in grove size were found to significantly impact collective action. In addition, our analysis shows that the two institutional approaches that were developed for AWM have followed a different trajectory over time, leading to a discussion of the determinants that may enable and sustain collective action for invasive species management.

Key Words: *area-wide management; collective action; huanglongbing; invasive species; plant health*

INTRODUCTION

In recent years, there has been a growing interest in collective action problems associated with the management of invasive species (Bagavathiannan et al. 2019, Graham et al. 2019, Garcia-Figuera et al. 2021a) that threaten the sustainability of social-ecological systems across the globe (Simberloff et al. 2013, Bebber et al. 2014, Driscoll et al. 2014, Freer-Smith and Webber 2017, Faulkner et al. 2020). Pioneering studies suggested that invasive species management has the characteristics of a weakest-link public good, where the overall level of provision is conditioned by the least effective provider (Perrings et al. 2002). Recent reviews have reinforced the concept of invasive species management as a public goods collective action problem that requires contributions, i.e., adoption of management practices, by affected actors and generates environments free of invasive species that create mostly non-rivalrous benefits to users (Graham et al. 2019, Niemiec et al. 2020). Conceptualizing invasive species management as a collective action problem creates the potential of applying collective action theories originally inferred from case studies of common-pool resources (CPRs; Ostrom 1990, Baggio et al. 2016) to this emerging challenge.

Here we use collective action theory to guide analysis of participation in the area-wide management of an invasive plant disease, focusing on individual perceptions, institutional approaches, and group-level outcomes. Area-wide management (AWM), a strategy in which individual actors coordinate their management actions across property boundaries to target the entire pest or pathogen population within an area, is a common recommendation for plant pests and diseases that have high dispersal potential (Vreysen et al. 2007, Hendrichs et al. 2021). Many ecological studies have recommended the implementation of AWM for a broad range of plant pests and diseases (Anco et al. 2019, Laranjeira et al. 2020), yet little attention has been paid to the collective action problem associated with AWM (Kruger 2016, Mankad et al. 2017).

AWM invokes many of the variables that the broader literature on collective action hypothesizes as drivers of cooperation. These include the number of individuals involved (Olson 1965); whether benefits are rivalrous, i.e., CPRs, or non-rivalrous, i.e., public goods (Ostrom 2003); the heterogeneity of individuals (Gavrilets 2015); or the option to have face-to-face communication (Smith 2010). With repeated interactions between individuals, the availability of information about past actions; how individuals are linked; and whether they can enter or exit participation voluntarily can also impact collective action (Ostrom 2010). These external structural variables have been proposed to interact with an inner core of individual-level variables (reputation, trust, and reciprocity) to affect the level of collective action and benefits achieved (Ostrom 2010). In this study, we tested the impact of some of these variables on the AWM of huanglongbing (HLB).

HLB is an invasive disease of citrus trees that is threatening citrus production worldwide (Wang 2019). The most common type of HLB is associated with the bacterium "*Candidatus* Liberibacter asiaticus," which is spread by an insect vector, the Asian citrus psyllid (ACP), *Diaphorina citri* (Bové 2006). The bacterium reproduces in the vascular tissue of citrus trees causing fruit yield and quality loss (Bassanezi et al. 2009). Infected citrus trees eventually die because commercial varieties are not resistant (Ramadugu et al. 2016) and there is no available cure. Therefore, the only measures to prevent trees from getting infected with HLB are to identify and remove infected trees, to replace them with certified plant material, and to control the insect vector (Gottwald 2010). Many studies have shown that these three measures are most effective if they are applied on an area-wide scale (Bassanezi et al. 2013, Singerman et al. 2017, Yuan et al. 2021), yet

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participation in AWM in HLB-affected regions has been irregular (Singerman and Rogers 2020, Bassanezi et al. 2020).

The collective action problem associated with area-wide insecticide treatments against the insect vector of HLB poses a particularly significant challenge. Effective vector control requires time-coordinated insecticide sprays by all growers in a sufficiently large area to avoid dispersal of the insect vector, but because coordinated treatments benefit the whole group, any grower may be tempted to rely on others' treatments and avoid the cost of spraying (Singerman and Useche 2019). If a grower fails to coordinate, that property can sustain the insect population and spread HLB to the rest (Bassanezi et al. 2013). To face this collective action problem, citrus growers in different regions of the world affected by this disease have developed similar institutional approaches that remarkably follow many of Ostrom's design principles for long-enduring CPR institutions, especially in California (Garcia-Figuera et al. 2021a).

Case study: area-wide management of ACP in California

The current HLB epidemic in California offers an exceptional case study to advance the application of collective action theory to the management of invasive plant pests and diseases. California is the main citrus-producing state in the U.S., with a $3.63 billion citrus industry that is under threat from HLB (Babcock 2022). The insect vector was first detected in San Diego in 2008 and it quickly became established in Southern California (Bayles et al. 2017). The first HLB-positive tree was found in a residential neighborhood in Los Angeles in 2012 (Kumagai et al. 2013). Since then, more than 2500 HLB-positive citrus trees have been detected and removed from residential properties (CPDPD 2021). No HLB-positive trees have been detected in commercial citrus groves to date. To prevent spread to commercial citrus, an AWM program was implemented in Southern California (Imperial, Riverside, San Bernardino, San Diego, Santa Barbara, and Ventura Counties). The AWM program consists of two coordinated insecticide treatments per year, one in the late summer (August–September) and one in the winter (December–February), but the exact treatment window depends on the county, and some counties conduct additional treatments, particularly in the fall (Grafton-Cardwell 2020). Growers bear the cost of treatments using pesticides recommended by the University of California (UC ANR 2021). Participation in AWM is considered crucial to keep the insect vector population under control and avoid the kind of damage to California citrus experienced by Florida's industry, where efforts to control the disease failed.

Since HLB was first detected in Florida in 2005, citrus acreage and yield have declined by 38% and 74%, respectively (Graham et al. 2020). An AWM program was implemented, but it failed to achieve adequate collective action (Singerman and Rogers 2020). The Florida Department of Agriculture and Consumer Services and University of Florida researchers defined AWM units for growers to voluntarily coordinate insecticide treatments for the insect vector (Rogers 2011), but most growers were not used to coordinating activities with each other, participation in AWM was not monitored, sanctions were not imposed on noncompliant growers, and there was no state-level industry-led organization coordinating efforts (Garcia-Figuera et al. 2021a). A recent review of the AWM program in Florida recommended replacing this voluntary program with a mandatory component, suggesting: "the top-down regulation could be implemented from the state to the fruit-procuring companies (i.e., packinghouses and processors), requiring them to provide documentation that their processed/packed fruit has been subject to coordinated sprays. Fruit-procuring companies would, in turn, require such documentation to growers as part of their specifications for purchasing their fruit. In this way, growers would need to organize themselves locally to fulfill such a requirement, perhaps through their associations and be assessed charges (from a third party) for the sprays on a per-acre basis" (Singerman and Rogers 2020:5). To date there is no indication that this recommendation will be followed by the Florida industry.

California offers an alternative example of an AWM program for HLB that combines voluntary and mandatory components as part of a bottom-up, grower-led strategy to achieve collective action. To overcome the collective action problem associated with AWM and coordinate insecticide treatments, California citrus growers have adopted two distinct institutional approaches: Psyllid Management Areas (PMAs) and Pest Control Districts (PCDs).

PMAs are groups of approximately 20 neighboring growers who voluntarily coordinate insecticide treatments for the insect vector of HLB over a 2–3 week window. PMAs were established by the grower-led state-wide program as relatively small zones that share a landscape, similar environmental conditions, and most importantly, a social network of growers (Grafton-Cardwell et al. 2015). Some PMAs have a voluntary leader who is responsible for contacting the rest of the growers when it is time to spray, following instructions from their grower liaisons. In other PMAs, growers are contacted directly by grower liaisons who were hired by the program to coordinate the network of PMAs in a region, facilitate area-wide treatments, disseminate outreach and education materials, and act as knowledge brokers between the state-wide program, the regional task forces, and the growers. Task forces are voluntary groups of growers, county authorities, and other citrus stakeholders that operate at a county or larger scale with the aim of coordinating efforts among PMAs. In regions that rely on PMAs to coordinate treatments, task forces meet every 1–3 months and recommend AWM treatments based on the number of insects observed on yellow sticky traps distributed throughout the state and checked every two weeks. Scientists from the University of California, or other centers of expertise, are often involved in advising task forces on these decisions. The organizational hierarchy from individual growers to PMAs, task forces, and the state-wide program exemplifies the concept of nested enterprises, a feature of long-enduring CPR institutions identified by Ostrom (Ostrom 1990).

PCDs are special districts instated by local growers to have the legal authority to control, eradicate, or respond to the effects of pests and diseases affecting a specific crop (UCCE 2005). Citrus PCDs currently exist in Imperial, Riverside, and San Diego Counties. Some PCDs were set up to control other citrus pests before HLB and its insect vector were detected. In other cases, PCDs were newly created to manage these invasive species (Appendix 1, Table A1.1). Within a county, PCDs are established by majority vote of growers in the proposed district (a vote of ≥ 51% by area in favor is required), who become subject to the rules established by the PCD board of directors. Inside a PCD, treatments against a specific pest can be mandatory. If a grower does not comply, the California Food and Agricultural Code allows the PCD to treat the non-compliant property and send a bill to the owner. If the bill is not paid within a certain time, the County has the authority to sell that property, or part of it, to recoup the cost of the treatment (FAC 1988). The board of directors of each PCD is responsible for monitoring the insect vector population with yellow sticky traps and letting the grower liaison know when it is time to contact the growers for the area-wide treatments. PCDs are typically funded by assessments that growers pay proportional to their acreage inside the PCD (Appendix 1, Table A1.1) Some PCDs (Coachella, Hemet, and San Diego) incentivize coordination by providing a complete or partial reimbursement of grower assessments if they show proof of compliance with the AWM treatment within the recommended window.

Application of collective action theory

The main goal of this study was to use collective action theory to better understand the individual and group-level determinants that may impact participation in AWM. A motivation for carrying out this analysis comes from the role played by University of California scientists in providing scientific support to stakeholders involved in decision making in the state-wide program (McRoberts et al. 2019). Being able to place the tasks that decision makers face in a robust framework that generalizes the issues they are dealing with may provide them with a useful perspective on whether the benefits of operating such a large and complex program are high enough to justify the program's transaction costs.

In terms of individual determinants, previous studies of collective action have shown that when users share common knowledge of relevant system attributes and are aware of how their actions affect each other, they perceive lower costs of organizing (Ostrom 2009). In the context of invasive weed management, the belief that weeds were a cross-boundary problem was found to be significantly correlated with the willingness to engage in control behaviors (Lubeck et al. 2019).

Therefore, we used a survey to assess citrus stakeholders' beliefs in the benefits of AWM and their perceptions of the main barriers to AWM because these could be important individual determinants of participation in AWM. The state-wide program has promoted AWM as the main strategy for the insect vector of HLB for several years (Grafton-Cardwell 2020), so we assumed that citrus stakeholders would be familiar with it, and wanted to assess if they believed it was beneficial. In particular, we wanted to test if citrus stakeholders' intentions to stay informed and communicate with grower liaisons were positively correlated with their belief in the benefits of AWM because this would suggest a pathway to promote collective action. In addition, by asking stakeholders about what they thought were the main barriers to AWM, we aimed to gain insight into their perception of the collective action problem.

H1: Citrus stakeholders who are more likely to stay informed and communicate with grower liaisons have higher confidence in the efficacy of AWM

Trust and reciprocity have been found to impact collective action in many different systems (Ostrom 2010). Trust in others' contributions to the collective effort was found to significantly affect collective action in groundwater management (Niles and Hammond Wagner 2019) and collective pest management (Stallman and James 2017); and community reciprocity was a significant predictor of most behaviors related to collectively controlling an invasive plant (Niemiec et al. 2016). Based on these findings, we aimed to assess citrus stakeholders' belief that others would contribute to AWM. Moreover, because collective action studies have shown that face-to-face communication is essential to develop trust and reciprocity (Ostrom 2010), and communication has also been found to impact collective pest management (Maclean et al. 2019, Sherman et al. 2019), we aimed to assess the citrus stakeholders' intentions to stay informed and communicate with neighbors, with the hypothesis that it would be positively correlated with trust in neighbors.

H2: Citrus stakeholders who are more likely to stay informed and communicate with neighbors are more likely to believe that their neighbors will participate in AWM

In terms of group-level determinants of collective action, we used an empirical record of group-level participation in coordinated insecticide treatments from 93 AWM units in Southern California over nine seasons to test the influence that collective action variables have on AWM participation. The emergence of institutions for collective action and their evolution has been at the core of collective action theory since its inception (Ostrom 1990). In our case study, the two types of institutions that emerged for AWM have different histories and characteristics that might influence participation in AWM, but there is a key difference between them that might have the biggest impact on collective action, based on the available literature. Whereas PMAs are voluntary and require a lower degree of commitment from citrus stakeholders, PCDs are mandatory and require contributions on a per-acre basis, so the two institutions differ in their degree of local enforcement.

H3: PCDs have higher participation levels than PMAs (baseline), all other factors being equal

As the size of a group increases, the probability of achieving a public good decreases. The larger the group size, the easier it is for individuals to free ride on the efforts of others, which discourages effective collection action. Furthermore, costs of organizing collective action increase with group size, making it more difficult to justify collective efforts (Olson 1965). In the invasive species literature, several studies have discussed the difficulty of coordinating large populations of land managers (Graham et al. 2019).

H4: AWM units (either PCDs or PMAs) with fewer members have higher participation levels

The size of the resource system is one of the key variables that impact the likelihood of collective action in social-ecological systems (Ostrom 2009). Forest commons with small to moderate sizes were found to be most conducive to self-organization, because very large forest commons have higher costs of defining boundaries, monitoring users, and gaining ecological knowledge about the system, while very small territories did not generate enough benefits (Chhatre and Agrawal 2008). In our system, the larger the unit, the more effective coordinated treatments will be, because the insect will have to fly longer distances to escape to untreated groves (Rogers et al. 2010, Flores-Sánchez et al. 2017). However, in larger AWM units the cost, effort, and time required

to assess the insect vector population and to apply insecticides will be potentially higher, and could lead to lower participation levels.
H5: Larger AWM units (in terms of total citrus acreage) have lower participation in AWM

The collective action literature suggests that when users are dependent on a resource for a substantial portion of their livelihoods or attach high value to the sustainability of the resource, they are more likely to self-organize (Ostrom 2009). Although we did not have any group-level measurement of dependency on citrus production, we assumed that it could be related to the size of citrus operations because people who manage larger operations may be more invested in citrus production (Mankad et al. 2019), and they may have more resources to fund treatments.
H6: AWM units with larger citrus groves have higher participation in AWM

Although there is some debate about the impact of heterogeneity on collective action, particularly relative to other factors (Poteete and Ostrom 2004), heterogeneity in assets, information, or payoffs has been found to negatively impact collective action, mainly because of the increased transaction costs of reaching an agreement and the conflicts that could arise over the distribution of benefits and costs to be borne (Ostrom 2010). Heterogeneity, i.e., thinking that the neighbors' farms or properties were different from one's own, was also found to negatively impact collective action for pest management (Stallman and James 2017).
H7: AWM units with higher heterogeneity (in the size of citrus groves) have lower participation in AWM

Finally, the use of a longitudinal dataset of overall participation in AWM at the group level allowed us to test if there had been an increase or decrease in participation over time. A priori, it was hard to hypothesize a general pattern across all AWM units, but we aimed to test if participation in AWM had grown over time, which could be viewed as a success of the state-wide program. More importantly, we aimed to test if there was an interaction between the type of institution and the age of the program, which would suggest that the evolution of participation has followed a different trajectory over time in PCDs and PMAs.
H8: Participation in AWM has grown over time
H9: Participation in AWM has followed a different pattern over time in PCDs and PMAs

METHODS

Research design

In this study we used two datasets: a survey dataset that measures individual stakeholder perceptions of AWM and a group-level dataset of actual participation of groups of stakeholders (organized in AWM units) in AWM treatments. The survey was used to assess citrus stakeholders' confidence in the benefits of AWM, the main barriers to AWM, and their confidence that their neighbors will participate. This information was intended to provide individual-level context to the analysis of participation in AWM, and to show how perceptions have evolved since the program was implemented. The second data set was a record of participation in AWM treatments in Southern California, where the unit of analysis is the AWM unit (PMA or PCD), composed of a group of stakeholders. This data set was used to estimate a statistical model to test hypotheses about participation in AWM. The dependent variable in the model was the level of participation in AWM. Independent variables included the institutional approach (PMA or PCD), group size, size of the resource system, size of citrus groves, heterogeneity in grove size, season of treatment, and age of program, as explained below.

Survey

Survey design
The questionnaire to assess citrus stakeholders' perception of the AWM program was designed by researchers as part of a broader study to assess citrus stakeholders' propensity to adopt recommended HLB management practices in California (Garcia-Figuera et al. 2021b). The questionnaire is provided in Appendix 2.

The most relevant questions for the present study focused on grower perceptions of AWM and collective action variables. To assess stakeholders' perception of their group efficacy (Niemiec et al. 2016, Lubeck et al. 2019) or response efficacy (Mankad and Loechel 2020), we asked for their perception of the likelihood that coordinated treatments against the insect vector would slow the spread of HLB more than uncoordinated treatments. The answers to this question were a 5-point Likert scale of "very unlikely," "unlikely," "maybe," "likely," or "very likely." This question was in line with a previous question asked in a similar survey in 2015 (Milne et al. 2018).

To gain insight into stakeholders' perception of the main barriers to AWM, and to determine if they perceived it as a collective action problem, we asked participants to indicate what they thought was the main barrier to area-wide management of the insect vector in their area, choosing among "preference to spray in one's own timing," "access to sprayers," "cost," "getting everyone to participate," or "worry about integrated pest management (IPM) disruption." These options were based on interactions with citrus stakeholders and conversations with grower liaisons, a previous survey by our group and collaborators in 2015 (Milne et al. 2018), and a study with citrus growers in Florida, which found that the main reason why growers did not participate in the AWM program was that "neighbors do not participate," followed by "I prefer to spray on my own timing" (Singerman et al. 2017).

To measure stakeholders' confidence that others around them were contributing to the collective effort, we asked them how likely they thought it was that their neighbors would apply insecticides within recommended treatment windows, choosing among "very unlikely," "unlikely," "maybe," "likely," and "very likely." We specifically asked this question after asking about the main barrier to AWM to prevent bias in responses to the question about barriers that could potentially arise once participants were asked about their neighbors.

To contextualize the three questions about AWM within the broader HLB control program in California, we asked participants about their self-reported intention to stay informed and communicate with the grower liaisons; their self-reported intention to communicate with neighbors (growers and homeowners); and their perceived vulnerability to HLB (how likely they thought it was that an HLB-positive tree would be detected in their grove in the next year). These questions were also assessed on a 5-point scale of "very unlikely," "unlikely," "maybe," "likely," and "very likely."

Controls for operator and operation demographics are based on previous agricultural surveys, including surveys about HLB (Stallman and James 2015, Singerman et al. 2017, Milne et al. 2018, Mankad et al. 2019). The research protocol was submitted to the Institutional Review Board (IRB) at UC Davis [1436590-1] and it was granted "Exempt" status because it entailed low risk to participants

Survey distribution

The survey was distributed at three grower meetings that were part of the Citrus Growers Educational Seminar Series, organized by the Citrus Research Board (CRB) in collaboration with the University of California Cooperative Extension (UCCE) in June of 2019 in Palm Desert (southeast California), Santa Paula (coastal California), and Exeter (San Joaquin Valley). These are annual seminars organized by the CRB and UCCE, for which attendees get Continuing Education units & Certified Crop Adviser hours. The availability of these credits tends to result in larger-than-usual attendance at grower workshops, reducing selection bias that could arise from sampling growers with more narrow interests. Selection bias was further limited by the fact that the annual election of citrus industry representatives for the CRB was scheduled on the day of the seminars in Palm Desert and Exeter. Nevertheless, as with most agricultural surveys, there likely remains some response bias toward more involved and larger growers, which limits the generalizability of our findings to the fringe of more disconnected, smaller growers.

To maximize participation, growers completed surveys during a designated time immediately after a presentation of best management practices for HLB that did not focus on AWM and did not mention collective action (Garcia-Figuera et al. 2021b). The survey was introduced as voluntary and anonymous, in compliance with IRB regulations. It was presented with the TurningPoint add-in for Microsoft PowerPoint (Microsoft, Redmond, WA, USA), and responses were collected using clicker handsets from TurningPoint (Turning Technologies, Youngstown, OH, USA) that had been given to each participant before the seminar started. Participants were given about one minute to answer each question. Once the polling time was closed for each question, a summary of the responses (percentage of participants that had chosen each response) was shown to the audience and briefly discussed before moving to the next question.

Analysis of participation in AWM

Dependent variable: participation in AWM

A regression model was used to quantify the impact of the institutional approach and group-level determinants on participation in AWM. The unit of analysis was the AWM unit (PMA or PCD). The dependent variable was the level of participation in coordinated insecticide treatments, measured as the percentage of the citrus acreage within each AWM unit treated within the designated treatment window. As mentioned, the grower liaisons and the state plant health agency have been tracking participation in AWM since coordinated treatments for ACP started to be recommended in Southern California in 2015 (Grafton-Cardwell et al. 2015). The task forces directing the PMAs or the board of directors of the PCDs determine the most appropriate window for treatment, and the grower liaisons collect the Pesticide Use Reports (PURs) submitted to the County Agricultural Commissioners (CACs) to determine the number of acres that were treated within the recommended window. Participation levels are then calculated as the percentage of the total citrus acreage within each AWM unit that was treated within the recommended window. These percentages are reported to the state plant health agency to determine which AWM units qualify for residential buffer treatments (CDFA 2020).

This unique data set of participation levels covers a total of 93 active AWM units in Southern California: 16 operating as part of a PCD and 78 operating as PMAs (Fig. 1). Although there are some areas within some of the counties with PCDs that are organizing AWM treatments voluntarily, participation in those treatments is not currently recorded. Thus, Southern California counties are either operating through PCDs or PMAs. Imperial County has a PCD with 7 growing zones; Riverside County has 2 PCDs (Hemet and Coachella) with a total of 6 growing zones; San Bernardino County has 19 active PMAs; San Diego County has a PCD with 3 areas; Santa Barbara County has 9 active PMAs; and Ventura County has 50 active PMAs. Participation levels from these AWM units were available for nine seasons: the fall of 2016, the winter of 2016–2017, the fall of 2017, the winter of 2017–2018, the fall of 2018, the winter of 2018–2019, the fall of 2019, the winter of 2019–2020, and the fall of 2020 (Appendix 1, Fig. A1.1). In total, the data set contains 840 observations corresponding to participation levels in 93 AWM units over nine seasons.

Independent variables

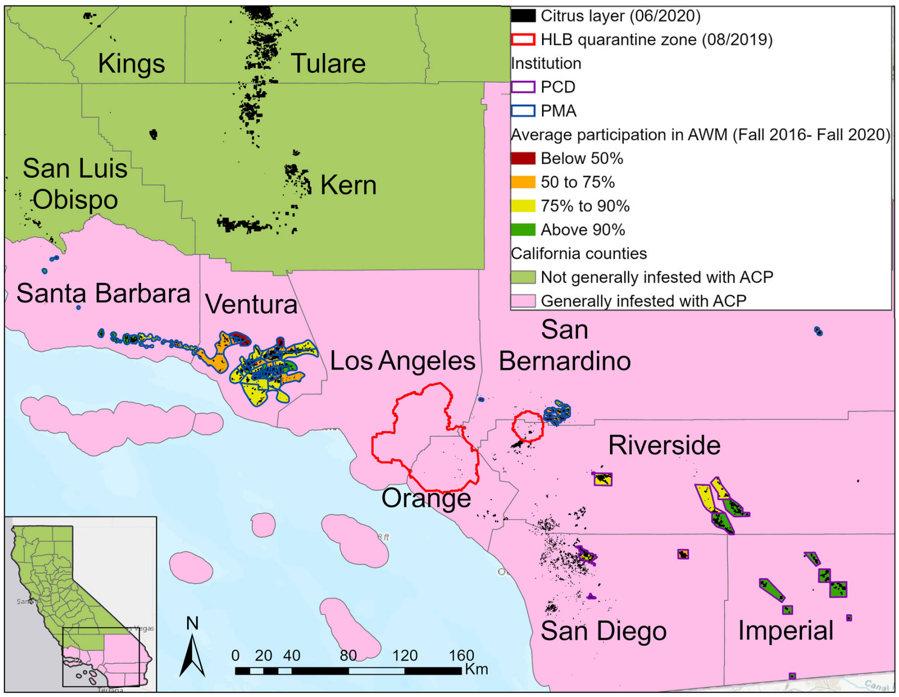
Independent variables that could impact participation in AWM were selected from recent studies related to collective action and invasive species management (Graham et al. 2019, Lubeck et al. 2019, Mankad and Loechel 2020), as well as information gathered through years of interaction with the grower liaisons and the state-wide program managers (McRoberts et al. 2019). Seven independent variables were considered:

1. Institutional approach: PMA (baseline) or PCD.
2. Group Size of each PMA or PCD, measured as the number of different pesticide use permits in each AWM unit, based on the information recorded in the database of citrus operations in California maintained by the CRB (Appendix 3).
3. Size of the resource system, i.e., total citrus acreage under each AWM unit, based on the information in the CRB citrus database (Appendix 3).
4. Size of citrus groves, measured as the average grove size in each AWM unit, based on the information in the CRB citrus database (Appendix 3).
5. Heterogeneity in grove size, measured in terms of the standard deviation of the size of citrus groves in each AWM unit, based on the information in the CRB citrus database (Appendix 3).
6. Season of treatment: fall (baseline) or winter.
7. Age of program, i.e., consecutive season (1-9), from 2016 to 2020.

Hypotheses

As explained in the Introduction, collective action theory and previous studies on the collective management of invasive species

Fig. 1. Geographical location of Psyllid Management Areas (PMAs) and Pest Control Districts (PCDs) for area-wide management of the Asian citrus psyllid (ACP) in Southern California. The outline of PMAs is shown in blue and the outline of PCDs is shown in purple. Each PMA and PCD has been filled with colors corresponding to the average coordination levels in the AWM program for ACP from the fall of 2016 to the fall of 2020. The red polygon that encompasses parts of Los Angeles, Orange, Riverside, and San Bernardino counties corresponds to the huanglongbing (HLB) quarantine zone, where HLB-positive trees have been detected and removed from residential properties. Counties colored in pink are considered to be generally infested with ACP, whereas counties colored in green are considered to be free of ACP (only localized detections where the population has been eradicated).



guided our hypotheses about the impact of institutional approaches and group-level determinants on participation in AWM (summarized in Table 1). In addition to those variables, we added one variable specific to our system. Because vector populations tend to peak at the end of the summer or the beginning of fall in California, entomologists have emphasized the importance of fall treatments to reduce the insect vector population (Grafton-Cardwell 2020). Therefore, we hypothesized that fall treatments would have higher participation than winter treatments, which are mostly preventive and aimed at targeting adults that may have survived through the coldest months of the year before the spring flush, i.e., young leaf growth

H10: Participation in AWM is higher in the fall than in the winter.

Analytical approach: zero-and-one-inflated beta regression model

Participation in the AWM program in California is measured as the proportion of the citrus acreage within each AWM unit that was treated within a 21-day window. Thus, it is a continuous variable that falls within the closed interval [0,1]. The participation dataset contains 11 observations at 0 (all PMAs), 668 observations in the interval (0,1) and 112 observations at 1 (60 PCDs and 101 PMAs). Given these characteristics, we chose to use a zero-and-one-inflated beta (zoib) regression model implemented through the R package "zoib" (Liu and Kong 2015). More information about the analytical approach can be found on Appendix 3.

RESULTS

Descriptive statistics of survey participants

A survey distributed at three citrus grower meetings aimed to assess their individual perceptions of their group efficacy, the main barriers to AWM, and their trust in others' participation in AWM. We collected responses from 98 individuals who indicated that they had groves in the Southern California counties that are routinely coordinating insecticide treatments for the insect vector of HLB (Imperial, Riverside, San Bernardino, San Diego, Santa Barbara, and Ventura), and have thus been grouped in AWM units. This was a subset of a broader survey that involved 300 participants from citrus-growing areas in Southern California, the Coast and the Central Valley (Garcia-Figuera et al. 2021b). The socioeconomic characteristics of the participants that were selected for this study are shown in Appendix 1, Table A1.2.

Table 1. Independent variables and hypotheses in the area-wide management participation regression model. PMA, Psyllid Management Areas; PCD, Pest Control Districts.

Independent variable	Type of variable	Expected sign
Institutional approach	Categorical: PMA (baseline)/PCD	Positive
Group size	Numeric (min 1, median 10, max 65)	Negative
Size of the resource system	Numeric (min 11 acres, median 404 acres, max 3652 acres)	Negative
Size of citrus groves	Numeric (min 0.6 acres, median 9 acres, max 30 acres)	Positive
Heterogeneity in grove size	Numeric (min 2 acres, median 9 acres, max 99 acres)	Negative
Season of treatment	Categorical: Fall (baseline)/Winter	Negative
Age of program	Numeric (1-9)	?

Although the survey was based on a non-random sample of attendees at citrus stakeholder meetings, we believe that it was reasonably representative of citrus production in Southern California. Most participants were from Ventura County (53), followed by Riverside (14), Santa Barbara and Ventura (7), Riverside and San Diego (5), Santa Barbara (4), Imperial (2), and other combinations (13). To give an idea of the size of the industry in these counties, there are about 874 operations with bearing or non-bearing citrus trees in Ventura County, 590 in Riverside, 152 in Santa Barbara, 1254 in San Diego, 20 in Imperial County, and 271 in San Bernardino (USDA-NASS 2019). Total citrus acreage in 2018 was 18,447 acres in Ventura (Ventura CAC 2019), 17,333 in Riverside (Riverside CAC 2019), 1291 in Santa Barbara (Santa Barbara CAC 2019), 11,701 in San Diego (San Diego CAC 2019), 9231 in Imperial (Imperial CAC 2019), and 2435 in San Bernardino (San Bernardino CAC 2019).

Most of the survey respondents from these counties were grove owners (38), PCAs (18), or ranch managers (17). Although 18 self-identified as other, we did not detect any significant differences in the distribution of responses to the relevant survey questions among different types of stakeholders, so all of them were considered as a single sample for analyses and are referred to as "participants" or "respondents." In terms of grove size, there was an under-representation of small citrus groves in our sample (23%) compared with state-wide percentages (50%); and an over-representation of large groves (29% vs. 1%; USDA-NASS 2019). In terms of age, the sample was representative, with 52% of respondents between the ages of 35 and 64, compared with 55% of growers between those ages in their counties of origin (USDA-NASS 2019). Younger growers were slightly over-represented. Organic citrus production was also over-represented in the survey, as 8% of citrus operations and 3% of acreage in the state of California are estimated to be certified organic (USDA-NASS 2017, 2019), yet 13% of participants indicated that they grew citrus organically. Participants for whom citrus production represented less than a quarter of their income comprised 41% of the sample, compared with participants who depended on citrus for their livelihood (23%).

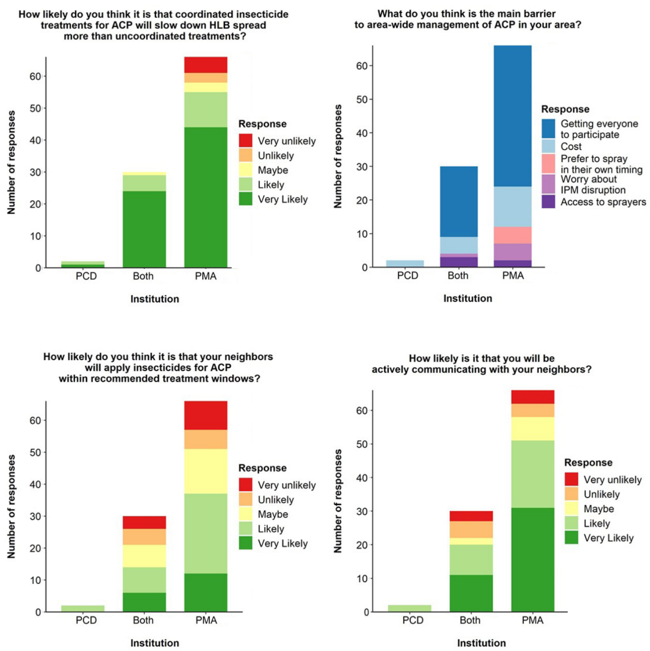
Individual-level perceptions of collective action in area-wide management

The majority of survey participants (87%) thought that it was "likely" or "very likely" that coordinated insecticide treatments for the insect vector would slow down the spread of the disease more than uncoordinated treatments, revealing a strong confidence in the benefits of collective action (Fig. 2). Participants with different socioeconomic backgrounds did not provide significantly different answers to this question, and confidence in AWM was consistent across PMAs, PCDs, and counties. Because participants were not asked specifically about the institutional approach that they were using for AWM, but about the county/ies where they grew citrus, counties that coordinate AWM exclusively through PCDs (Imperial) were grouped under the "PCD" category; counties that are coordinating AWM exclusively through PMAs (San Bernardino, Santa Barbara, Ventura, and combinations of these) were grouped under the "PMA" category, and the rest were grouped under "Both."

When participants were asked to identify the main barrier to AWM in their area, the majority thought that it was "getting everyone to participate" (64%). Therefore, although most participants believe that AWM is beneficial, many are worried that others might not contribute, clear evidence that there is a collective action problem. About a fifth thought that the main barrier was "cost" (19%), and a few thought that it was "worry about IPM disruption" (6%), "access to sprayers" (5%), or "preference to spray in their own timing" (5%; Fig. 2). The participants' role in citrus production, their age, their citrus acreage, or how much of their income came from citrus did not change these perceptions of the main barriers to AWM. However, respondents who grew citrus organically were significantly more worried about possible disruptions to their IPM program caused by repeated insecticide sprays than conventional producers, or those who grew citrus under both systems. Interestingly, we did not detect a significant difference between those who coordinated AWM through PCDs, PMAs, or both in the main barrier identified ($P = 0.22$ on the Kruskal-Wallis test).

Subsequently, participants were asked how likely they thought it was that their grower neighbors would apply insecticides within recommended treatment windows, which is a way of assessing their trust in neighbors. More than half (54%) thought that it was "likely" or "very likely"; about a fifth (21%) chose "maybe"; and a quarter (24%) thought that it was "unlikely" or "very unlikely" (Fig. 2). This reveals that many participants trust their grower neighbors to coordinate, but there is a certain degree of what has been called "strategic uncertainty," or uncertainty about the actions and beliefs of others. This was one of the main barriers for AWM in Florida (Singerman and Useche 2019). Participants' trust in neighbors did not significantly vary with their role in citrus production, their age, their management system, or their income

Fig. 2. Perception of area-wide management by citrus stakeholders in Southern California. The bars represent the percentage of participants who chose each response and indicated that they had citrus groves in counties that coordinate AWM treatments exclusively through Pest Control Districts (PCDs; n = 2), both PCDs or Psyllid Management Areas (PMAs; n = 30), or exclusively PMAs (n = 66). Responses have been color-coded according to the legends on the right of each plot. HLB, huanglongbing; ACP, Asian citrus psyllid; IPM, integrated pest management.



dependency on citrus. Nevertheless, a significantly higher proportion of small growers (with less than five acres of citrus) thought that it was "unlikely" or "very unlikely" that their neighbors would coordinate. Despite differences in AWM participation across Southern California, there was no evidence of divergent trust in neighbors among counties (P = 0.19) or institutional approaches (P = 0.68).

Among participants who thought that the main barrier to AWM was "getting everyone to participate," a third (33%) thought that it was "likely" or "very likely" that their neighbors would apply insecticides within designated treatment windows, while more than a quarter (14%) chose "maybe." Therefore, some participants seem to be concerned about people other than their grower neighbors. In other citrus-growing regions affected by HLB, residential neighbors with backyard citrus trees have been a major concern for citrus growers (Johnson and Bassanezi 2016, Sétamou 2020).

As expected, collective action was positively impacted by communication. Participants who were more likely to stay informed and communicate with the grower liaisons were also more likely to believe in the efficacy of AWM (ρ = 0.21, P = 0.045; Fig. A1.2). Therefore, engagement with the state-wide program may promote confidence in the efficacy of AWM, suggesting an avenue for outreach. Although we did not detect a significant positive correlation between the self-reported propensity to communicate with neighbors and trust in the neighbors' ability to coordinate (ρ = 0.18, P = 0.077; Fig. A1.3), this might be because the question about communication referred to both grower neighbors and homeowner neighbors. Overall, participants who indicated that they were more likely to communicate with their neighbors tended to think that their neighbors would coordinate insecticide treatments within recommended windows, suggesting that communication might be important to develop trust in others' contributions to achieve collective efforts. The participants' perceived vulnerability to HLB and their confidence in the benefits of AWM were not correlated, nor were their vulnerability and confidence in neighbors.

Finally, to provide historic context to the survey, we compared it with an equivalent one that was conducted in 2015, when the AWM program was getting started in California (Milne et al. 2018). At that time, participants were asked to rate the effectiveness of area-wide control of ACP. Some participants from Southern California thought it provided "excellent control" (17%), most thought that it provided "moderate control" (65%), and some (18%) considered it to be of "little effect" or "not effective" (Milne et al. 2018). Compared with our results, where 87% of participants think that AWM is beneficial, confidence in AWM seems to have increased over time. In 2015, the majority of respondents from Southern California indicated that "participation" was among their biggest concerns about AWM (54%), followed by "cost" (39%), "number of sprays" (26%), "pesticide resistance" (19%), "IPM program" (22%), "options for organic" (17%), and "access to sprayers" (11%; Milne et al. 2018). Therefore, the two main concerns that were identified in 2015, participation and cost, were still perceived to be the main barriers in 2019, with participation being the major concern by a majority in both surveys.

Group-level determinants of collective action in area-wide management

Individual beliefs and attitudes measured through surveys can be expected to influence decisions to participate (or not) in AWM, but it is the aggregate, group-level outcome that matters in relation to the objective of vector management. A zoib regression model was used to quantify the impact of several group-level variables on actual participation in AWM. The model with credibility intervals that did not include 0 for any of the independent variables and generated the lowest deviance information criterion included the institutional approach (PMA/PCD), the group size, the size of the resource system, the size of the citrus groves in the unit, the heterogeneity in grove size, the season of treatment (fall/winter), the age of the program (1–9), an interaction term between the institutional approach and the age of the program, and an interaction term between the size of the citrus groves and the heterogeneity in grove size (Table 2). Other fitted models are shown on Tables A1.3–A1.5 in Appendix 1.

In the selected zoib model, the signs of the coefficients of the independent variables were mostly as hypothesized (Table 1). Our first hypothesis was that mandatory PCDs would have higher participation than voluntary PMAs. The coefficient of the institutional approach was negative (Table 2), which may seem

Table 2. Posterior mean, 95% credible interval and potential scale reduction factors (psrf) for the parameters in the selected zoib regression model.

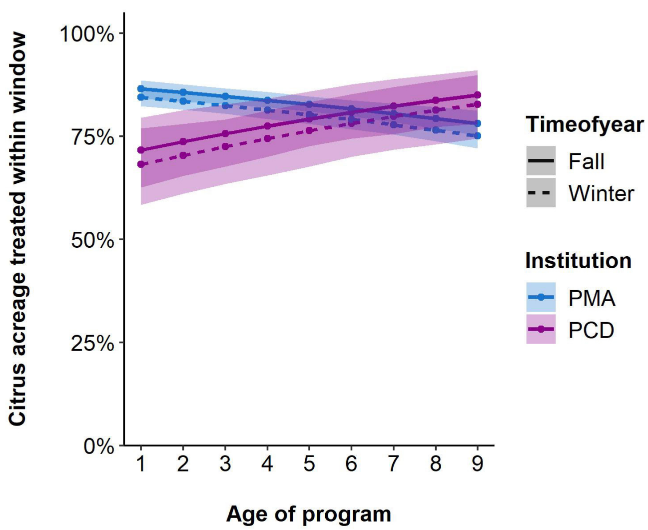
Model component	Parameter	Posterior mean	2.5% quantile	97.5% quantile	Point estimate of psrf	Upper CI of psrf
logit(mean)	Institutional approach (PMA/PCD)	-1.093	-1.653	-0.571	1.00	1.03
	Group size	-0.011	-0.016	-0.005	1.02	1.09
	Size of the resource system	0.000	0.000	0.001	1.00	1.02
	Size of citrus groves	0.104	0.064	0.141	1.00	1.01
	Heterogeneity in grove size	0.083	0.048	0.121	0.99	0.99
	Season of treatment (fall/winter)	-0.169	-0.298	-0.046	1.01	1.01
	Age of program	-0.074	-0.100	-0.048	1.00	1.00
	Institutional approach x Age of program	0.174	0.100	0.255	1.01	1.07
	Size of citrus groves x Heterogeneity in grove size	-0.006	-0.008	-0.004	1.00	1.02
	Intercept	0.426	0.108	0.792	0.99	1.00
log(dispersion)	Institutional approach (PMA/PCD)	-0.808	-1.305	-0.378	1.01	1.01
	Group size	0.034	0.024	0.043	1.01	1.06
	Size of the resource system	0.000	0.000	0.001	1.00	1.04
	Size of citrus groves	0.063	0.025	0.100	1.02	1.09
	Heterogeneity in grove size	-0.053	-0.083	-0.018	1.03	1.14
	Intercept	0.879	0.624	1.134	1.00	1.00
logit(Pr(y=0))	Institutional approach (PMA/PCD)	-67.449	-188.903	-4.659	1.01	1.06
	Group size	-0.580	-0.934	-0.302	1.00	1.00
	Intercept	-1.426	-2.380	-0.506	1.00	1.02
logit(Pr(y=1))	Group size	-0.319	-0.377	-0.266	1.00	1.03
	Heterogeneity in grove size	0.034	0.002	0.065	1.00	1.01
	Intercept	0.541	0.103	1.035	1.00	1.01
Observations	840					
Deviance information criterion	1679849					
psrf	1.1					

contradictory. However, we detected a significant interaction between the institutional approach and the age of the program, which means that the effect of the type of institution on participation depends on time, and cannot be interpreted in isolation (Brambor et al. 2006). The positive sign of the interaction term suggested that participation had been growing over time in PCDs, while it had been declining over time in PMAs. To illustrate the institutional differences, Figure 3 displays predicted levels of participation over time and in different seasons based on the type of institution, while fixing all other variables at their mean value. The predicted values clearly show an upward trajectory of participation in PCDs with a downward trajectory over time in PMAs. Even though PCDs started with lower participation levels, participation has been growing over time in this institution, while it has been declining in PMAs (Fig. 3).

The season when the AWM treatments are conducted also affects participation (Fig. 3). As hypothesized, winter treatments were found to have 0.84 times the odds of having higher participation than fall treatments (Table 2). Therefore, all other variables being equal, winter treatments tended to have slightly lower participation than fall treatments. This may have implications for vector and disease control because insecticide treatments during the winter dormant period, before the spring flush, were crucial for the management of the insect population in Florida (Qureshi and Stansly 2010) and Texas (Sétamou 2020).

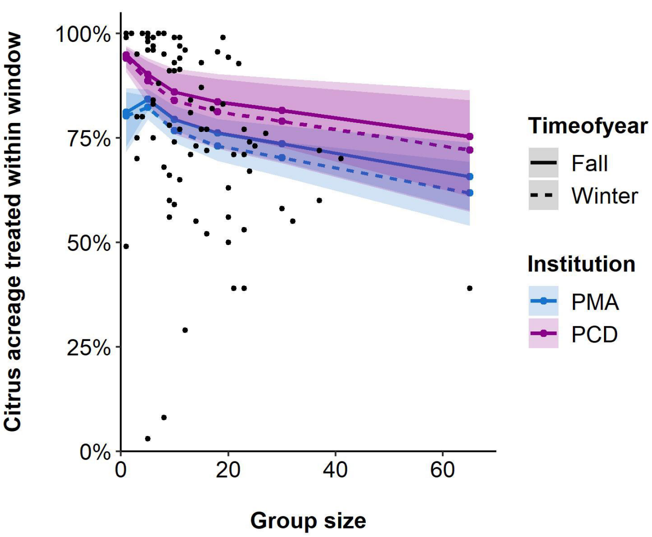
In line with the collective action literature, the model estimated that group size, i.e., the number of pesticide use permits in the AWM unit, had a negative effect on the mean of the beta distribution, the dispersion parameter of the beta distribution, the probability of having none of the citrus acreage

Fig. 3. Participation levels in area-wide management predicted by the zoib model depending on the institutional approach Psyllid Management Areas/Pest Control Districts(PMA/PCD), the season of treatment (fall/winter), and the age of the program. The dots show the mean of the predicted values in blue (PMAs) or in purple (PCDs), and the shaded areas correspond to the 95% CI of the mean. Predicted values for fall treatments are linked by solid lines and predicted values for winter treatments are linked by dashed lines.



treated within the window, and the probability of having all of the citrus acreage treated within the window. To illustrate how these effects would impact participation in AWM, the model was used to predict participation for a fall treatment during season number 9 based on the group size, while fixing all other variables at their mean value. Under these conditions, the model predicted that participation in a mandatory PCD would drop from 86% with 10 members to 82% with 30 members, and in a voluntary PMA it would drop from 79% with 10 members to 74% with 30 members. Interestingly, the model also suggested that the optimum number of members to maximize participation in a PMA would be around 5 for an average PMA size, with average grove sizes and average heterogeneity in grove size (Fig. 4). The current median number of members in a PMA in Southern California is 10, well above this suggested optimum.

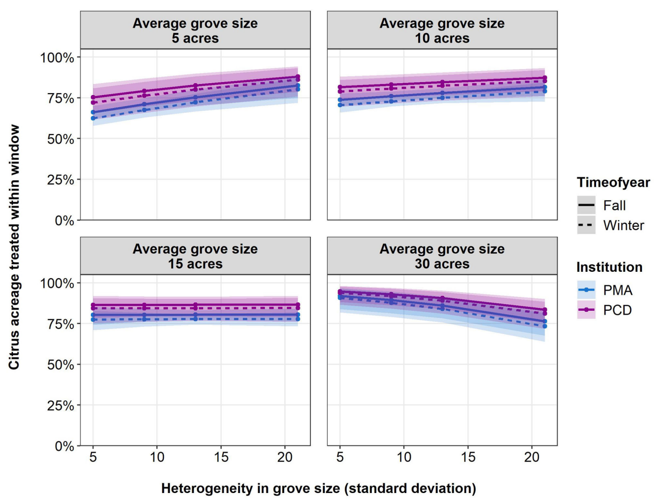
Fig. 4. Participation levels in area-wide management predicted by the zoib model depending on the number of pesticide use permits. The mean of the predicted values for season number 9 is shown in blue (Psyllid Management Areas; PMAs) or in purple (Pest Control Districts; PCDs). Predicted values for the fall treatments are linked by solid lines and predicted values for the winter treatments are linked by dashed lines.The black dots correspond to the observed participation values and their corresponding number of permits during the last season (the fall of 2020).



The size of the resource system, i.e., the total citrus acreage treated in the AWM unit, was not a limiting factor for participation in AWM. As shown in Table 2, the coefficient of the size of the resource system was estimated to be zero, so once the size of the group and other variables were considered, the size of the resource system by itself did not impact the level of participation in AWM.

As hypothesized, the model showed that the average size of citrus groves and the heterogeneity in grove size had an impact on participation (Table 2). More importantly, these factors interacted, so the effect of heterogeneity on participation depended on the size of citrus groves, and vice versa. As shown in Fig. 5, when the groves were mostly small (with an average size of 5 acres), the presence of a few large groves could have a beneficial effect on participation, but if the groves were mostly large (with an average size of 30 acres), participation could decline in the presence of a few small groves. This suggests that large growers might be acting as opinion leaders in areas predominated by smaller groves, helping promote collective action; while in areas predominated by large groves, a few small operations that might be owned by hobbyists or less engaged growers could lead to a decline in participation. This could be interpreted as evidence of a weakest-link collective action problem.

Fig. 5. Participation levels in area-wide management predicted by the zoib model depending on the average size of the citrus groves and the heterogeneity in grove size. The mean of the predicted values for season number 9 is shown in blue (Psyllid Management Areas; PMAs) or in purple (Pest Control Districts; PCDs). Predicted values for the fall treatments are linked by solid lines and predicted values for the winter treatments are linked by dashed lines. The panels show different average sizes of the citrus groves in a management unit. The plots corresponding to other values of the age of the program are shown in Figs. A1.4–A1.11 in Appendix 1.



DISCUSSION

Citrus stakeholders in Southern California are aware of the collective action problem associated with HLB management. Our survey showed that there was a high level of confidence in the benefits of coordinated insecticide treatments for HLB management, but also a widespread opinion that getting everyone to participate is the main barrier to successful AWM, and some worry that neighbors may not contribute to the collective effort. The high level of agreement about the benefits of AWM may predispose citrus stakeholders to achieve collective action, as collective responses were found to be enhanced when stakeholders acknowledged the cross-boundary nature of invasive species management and were aware of the benefits associated with collective action (Graham et al. 2019). In the context of collective weed control, awareness of cross-boundary interrelationships or confidence that collective efforts can achieve desired outcomes were also found to influence engagement (Lubeck et al. 2019).

Although only a quarter of the survey participants believed that it was “unlikely” or “very unlikely” that their neighbors would coordinate, this level of mistrust could jeopardize collective action if efforts are not made to promote engagement with the state-wide HLB control program and to encourage communication between neighbors. In a previous study about the management of an invasive tree in Hawaii, people felt discouraged about controlling it because they perceived a lack of participation or coordination among neighboring landowners (Niemiec et al. 2016). Similarly, among crop farmers in Missouri, the perceived trustworthiness of their neighbors did not affect their willingness to participate in cooperative pest control (Stallman and James 2015), but farmers whose farms were dissimilar from their neighbors’ were significantly more willing to cooperate if they trusted their neighbors, suggesting that trust is important in countering the potential negative effects of heterogeneity on coordination (Stallman and James 2017). Although we did not detect a significant correlation between communication with neighbors and trust in neighbors, there was a positive trend, in line with previous studies that showed that face-to-face communication is essential to develop trust and reciprocity in collective efforts for pest and disease management (Maclean et al. 2019, Sherman et al. 2019).

Mistrust in neighboring growers was an important factor behind the failure of the AWM program for HLB in Florida. An experimental voluntary contribution game conducted with Florida citrus growers in 2016 showed that the most limiting factors for participation in AWM were the threshold required for collective action to have a successful outcome, the beliefs about others not coordinating, and risk aversion (Singerman and Useche 2019). When the threshold for coordination in the game was high, growers chose to coordinate less as the group size increased. However, once they were shown an empirical study that proved that participation in AWM was beneficial, 30% of the growers chose to coordinate more (Singerman and Useche 2019). The authors concluded that future studies that clarified what participation thresholds would be required for successful HLB management could increase the success of collective efforts (Singerman and Useche 2019), but those studies remain to be conducted.

Compared with Florida, California offers an alternative example of an AWM program for the insect vector of HLB that combines voluntary and mandatory institutions to achieve collective action. Although there are precedents of successful AWM programs for other plant pests and diseases in the state (Haviland et al. 2021, Simmons et al. 2021), the level of mobilization that HLB has imposed on citrus growers is extraordinary, and justified by the devastating consequences of the HLB epidemic in Florida and other citrus-growing areas (Bassanezi et al. 2020, Graham et al. 2020). Soon after the insect vector was detected in California, citrus growers partnered with the state plant health agency to establish a state-wide program for HLB. They organized themselves in PMAs, or took advantage of existing PCDs, expanded them, or even created new PCDs to coordinate insecticide treatments and suppress the insect population, in an attempt to limit the spread of the disease. A key difference between PMAs and PCDs is that treatments are voluntary in PMAs while they are mandatory in PCDs, and this difference appears to have had meaningful impacts on participation. Although PCDs had lower participation levels in the beginning of the AWM program, perhaps because in some counties they were created precisely to avoid free-riding, our analysis shows that PCDs have been growing in participation over time, while participation has been declining in PMAs, all other variables being constant. This raises the question of whether a voluntary institutional approach will be able to sustain collective action for HLB management in California in the long term.

The other group-level determinants considered in our regression analysis may help answer this question. In line with collective action theory, the size of the group was found to be a limiting factor for AWM. This agrees with case studies of CPRs in which the number of social-ecological system users was one of the factors that determined self-organized collective action (Ostrom 2009), and it was also one of the most commonly cited factors for collective action in invasive species management (Graham et al. 2019). Because there are higher transaction costs associated with organizing larger groups and the probability of free-riding is higher (Graham et al. 2019), we expected participation in AWM to go down as the number of people who needed to coordinate treatments increased, and it did. This was one of the reasons why PMAs were designed on the basis of social criteria, so that they would comprise relatively small groups of growers that were part of the same social network, where one grower could drive around and reach the rest of the group within one day (Grafton-Cardwell et al. 2015). In Florida, AWM units were designed to comprise a sufficiently large area to suppress the insect population and prevent the spread of the disease (Rogers 2011), and similar epidemiological criteria were followed in Mexico (SENASICA 2012). From a collective action perspective, the total size of the resource system was found to have no effect on participation once the institutional approach, the group size, the size of citrus groves and other variables were considered.

We detected a positive effect of heterogeneity in grove size when the majority of citrus groves in the AWM unit were small, and a negative effect when the majority of citrus groves were large. Therefore, the collective action problem associated with AWM might be more difficult to overcome when there is a large mass of large commercial growers and a few small growers who might not have the resources or interest in coordinating insecticide treatments. This analytical result is in line with years of discussions within the state-wide HLB program about the risk of small growers being the weakest link in the collective action problem. Properties with 25 citrus trees or more are considered to be commercial citrus groves in California, but many of them are residential properties whose owners may not be willing to spend resources to care for their citrus trees. These owners rarely participate in citrus grower meetings, and it has been difficult to motivate them to participate in AWM. In our survey sample, small growers (less than five acres of citrus) were less likely to trust their neighbors than big growers, probably suggesting a higher prevalence of weakest links in communities predominated by smaller groves. Considering that around 34% of the citrus groves in Southern California that are routinely conducting AWM treatments have less than five acres (USDA-NASS 2019), heterogeneity may not have had a negative impact to date, but it could become relevant in parts of California predominated by big groves intermixed with a few small operations, such as the Central Valley.

The lower participation detected for winter treatments compared to fall treatments could be a target for outreach from the statewide program because it may be related to the generally lower adoption of preventive treatments compared with suppressive treatments, which has been observed in other plant disease systems (Hillis et al. 2017). Apart from the variables captured in the regression model, the lack of sufficient equipment to conduct all insecticide treatments within the 21-day window has also been a limiting factor for participation in parts of Southern California. In addition, unfavorable weather events (strong winds, mud slides, wildfires) have had a negative impact on participation and may explain some of the 0 values recorded for some PMAs. Finally, the allocation of water to apply systemic insecticide treatments through the irrigation system has also been a limiting factor, particularly in San Bernardino County.

As ACP and HLB continue to spread in Southern California, it is likely that an HLB-positive tree will be detected in a commercial grove in the near future. Participation in AWM will then become more crucial to keep the insect populations under control and limit disease spread. Although our results suggest that citrus stakeholders are aware of the benefits of coordinated insecticide sprays, more research will be needed to determine the specific benefits and costs of area-wide management; to estimate the participation threshold required for effective control under different ecological and social conditions; to evaluate the impact that this information may have on the growers' intentions to coordinate efforts; and to determine how individual intentions will translate into group-level outcomes. Previous studies have shown that fostering community-building activities and learning opportunities that build trust among participants, highlighting participants' positive experiences and employing multiple forms of incentives can help sustain collective action (Graham et al. 2019). This could be particularly beneficial for the type of "co-managed" collective action adopted in California, where private landowners entered in a cooperative arrangement with the state plant health agency to promote AWM. The growing interest in addressing invasive species management as a collective action problem will likely lead to additional studies in other social-ecological systems that will enhance our understanding of the factors and strategies that might sustain collective action in AWM.

CONCLUSION

In this study, we provide evidence of how individual perceptions and group-level variables may impact collective action in the area-wide management of an invasive plant disease. We contribute to the emergent application of collective action theory to invasive species management by showing that confidence in the benefits of the collective effort, trust in neighbors' contributions, the size of the group, the size of the properties, and the heterogeneity in property size may be key factors to consider when designing an area-wide management program for an invasive plant pest or disease. In addition, we show that voluntary vs. mandatory institutional approaches may lead to distinct collective outcomes over time. Further studies in different social-ecological systems that clarify the benefits of collective action and combine surveys with quantitative analyses of collective outcomes will likely improve our understanding of the social dimensions of biological invasions, helping societies to better face the threat of invasive species.

Responses to this article can be read online at:
https://www.ecologyandsociety.org/issues/responses.php/13217

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Data Availability:

The data sets and R code that support the findings of this study will be openly available in a Github repository at https://github.com/nmcr01?tab=repositories upon publication of this article. Ethical approval for this research study was granted by the Institutional Review Board at the University of California, Davis.

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Appendix 1: Supplementary figures and tables

Table A1.1: Institutions coordinating area-wide management of ACP in Southern California.

County	Institution	History	Citrus acreage	Assessment rate (2018)	Coordinated treatments	Number of management units	Using PMAs?	Participation in AWM	Challenges	Other activities
Imperial	Imperial County Citrus Pest Control District	Formed in 1972 for California red scale (*Aonidiella aurantii*) control[†]. Expanded in 2013 to the whole county for ACP and HLB control[‡]	7,200	$15 / acre	Fall (Aug-Oct, Winter (Dec-Jan), Spring (Feb-Apr)	7 (6 after 2020)	No, PCD growing zones	High	ACP from across the Mexican border	Outreach, trap monitoring, coordination with Mexican authorities
Riverside	Citrus Pest Control District No. 2 (Coachella Valley)	Formed in 1946 for California red scale control[§]	8,000	$150 / acre	Fall (Sep-Oct), Winter (Dec-Jan)	4	No, four zones	High, reimbursing for treatments	Reinfestation from residential areas	Tree removal, biocontrol
	Citrus Pest Control	Formed in 2017 for ACP and	2,134	$100/acre	Fall (Sep), Winter (Dec-Jan)	2	No, two zones	Very high, three growers.	Reinfestation from	Funding some activities in

	District No. 3 (Hemet)	HLB control						Reimbursing for treatments	residential areas	residential areas
	Rest of the county	No entity directing the sprays	1,500	None	Fall, Winter			Low, not tracked	Absentee owners, small growers	UC Riverside promoting participation
San Bernardino	San Bernardino ACP/HLB Task Force	Formed in 2014[‖]	3,000	None	Fall (Oct-Nov), Winter (Nov-Dec), Spring (May-Jul)	19	Yes	Variable	Small growers, scarcity of PCOs, urban interface, water supply, bad actors	Grower liaison in contact with homeowners, reporting abandoned trees
San Diego	San Diego County Citrus Pest Control District	Formed in 2017 for ACP and HLB control[#]	4,500	$180 / acre	Fall (Aug-Sep), Winter (Jan), Spring (May-Jun)	3	No, three areas (Borrego Springs, San Pasqual, Pauma/Pala Valley)	Variable when it was voluntary. Now higher because of assessment reimbursements	Problems with organic treatments, small growers	County authorities monitor abandoned trees and try to remove them
Santa Barbara	Advisory committee	Formed in 2015 for ACP and HLB control[¶]	4,425	None	Fall (Sep), Winter (Jan)	12 (11 after 2019)	No, treating by cities	High	Weather, small properties	

Ventura	Ventura ACP/HLB Task Force	Formed in 2010 for ACP and HLB control[††]	25,000	None	Fall (Jul-Sep + Sep-Nov), Winter (Jan-Mar), Spring (Apr-Jun)	50	Yes	High	Spraying equipment shortage, continuous harvest, weather, movement of fruit	Outreach campaign in residential areas, reporting system for abandoned trees

[†] Margo Sanchez, pers. comm.

[‡] Mark McBroom, pers. comm.

[§] Baker, B. P. 1988. Pest Control in the Public Interest: Crop Protection in California. *UCLA Journal of Environmental Law and Policy* 8(1):31–71

[|] Bob Atkins, pers. comm.

[¶] Cressida Silvers, pers. comm.

[#] SDCCPCD. 2021. About Us. https://sdccpcd.specialdistrict.org/about-us.

[††] John Krist, pers. comm.

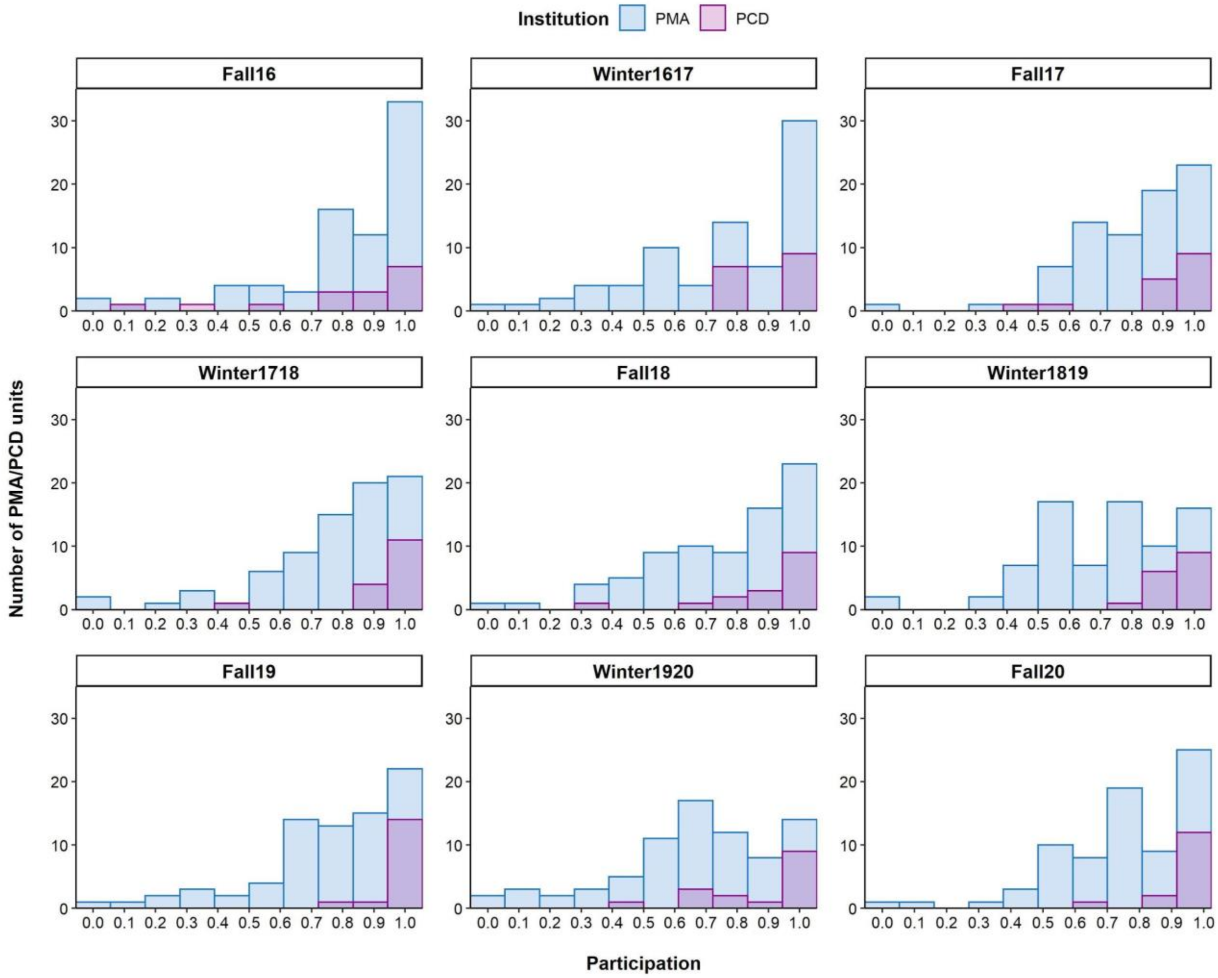

Fig. A1.1: Histogram of participation levels in area-wide management in Psyllid Management Areas (blue) and Pest Control Districts (purple) over nine seasons.

Table A1.2: Socio-economic characteristics of the survey respondents who indicated that they had citrus groves in Southern California (n =98).

Survey item	Responses
Role in citrus production	
Grove Owner	38
Ranch Manager	17
PCA	18
PCO	2
Other	18
NA	5
Farm size	
< 5 acres	23
5 – 25 acres	18
26 – 100 acres	11
101 – 500 acres	13
> 500 acres	28
NA	5
Age	
<35 years	12
35 - 50 years	14
51 – 65 years	37
> 65 years	35
Management system	
Conventional	59
Organic	13
Both	23
NA	3

Income from citrus	
< 25%	40
26 - 50%	13
51 - 75%	16
76 - 100%	23
NA	6

Note: Pest Control Adviser (PCA), Pest Control Operator (PCO), no answer (NA)

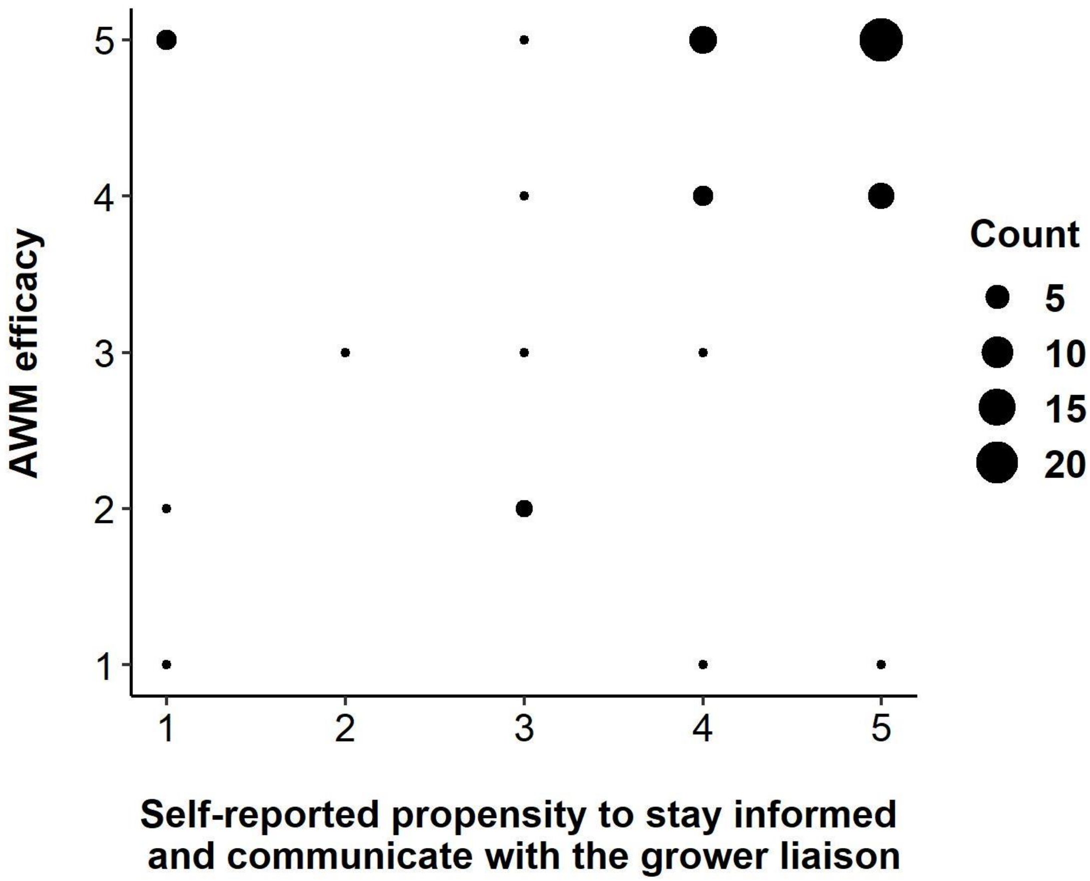

Fig. A1.2: Relationship between the self-reported propensity to stay informed and communicate with the grower liaison and the belief that coordinated insecticide treatments for ACP will slow down HLB spread more than uncoordinated treatments (AWM efficacy). Responses to the survey questions were transformed to numeric so that *very unlikely* = 1, *unlikely* = 2, *maybe* = 3, *likely* = 4, *very likely* = 5. The size of the points represents the number of participants who chose that combination of responses.

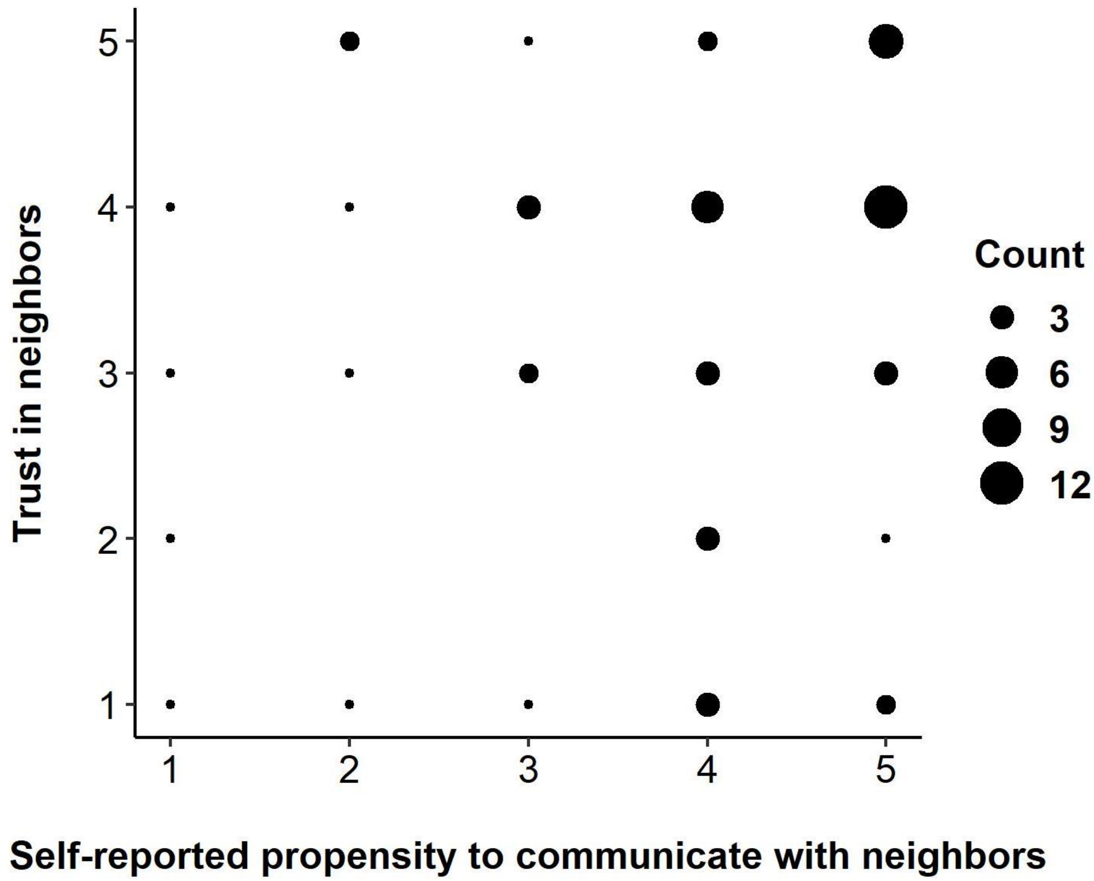

Fig. A1.3: Relationship between the self-reported propensity to communicate with neighbors and the belief that neighbors will apply insecticides for ACP within the recommended treatment window (trust in neighbors). Responses to the survey questions were transformed to numeric so that *very unlikely* = 1, *unlikely* = 2, *maybe* = 3, *likely* = 4, *very likely* = 5. The size of the points represents the number of participants who chose that combination of responses

Table A1.3: Posterior mean and 95% credible interval for the parameters in the zoib regression models evaluated that were more complex than the selected model (SD28).

		SD22 mean	SD22 2.5%	SD22 97.5 %	SD23 mean	SD23 2.5%	SD23 97.5 %	SD24 mean	SD24 2.5%	SD24 97.5 %	SD19 mean	SD19 2.5%	SD19 97.5 %	SD28 mean	SD28 2.5%	SD28 97.5 %
logit (mean)	Institutional approach†	-1.08	-1.67	-0.52	-1.08	-1.61	-0.53	-1.06	-1.63	-0.50	-0.68	-1.21	-0.13	-1.09	-1.65	-0.57
	Group size	-0.01	-0.02	0.00	-0.01	-0.02	0.00	-0.01	-0.02	0.00	-0.01	-0.02	-0.01	-0.01	-0.02	0.00
	Size of resource system	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Grove size	0.10	0.06	0.14	0.10	0.07	0.14	0.10	0.06	0.15	0.08	0.04	0.12	0.10	0.06	0.14
	Heterogeneity	0.08	0.05	0.12	0.09	0.05	0.12	0.09	0.05	0.12	0.12	0.08	0.15	0.08	0.05	0.12
	Season‡	-0.18	-0.32	-0.04	-0.17	-0.30	-0.04	-0.17	-0.29	-0.03	-0.16	-0.29	-0.03	-0.17	-0.30	-0.05
	Age	-0.07	-0.10	-0.04	-0.07	-0.10	-0.05	-0.07	-0.10	-0.05	-0.07	-0.10	-0.05	-0.07	-0.10	-0.05
	Institution† x Age	0.17	0.10	0.25	0.17	0.09	0.25	0.17	0.09	0.25	0.18	0.09	0.26	0.17	0.10	0.25
	Grove size x Heterogeneity	-0.01	-0.01	0.00	-0.01	-0.01	0.00	-0.01	-0.01	0.00	-0.01	-0.01	0.00	-0.01	-0.01	0.00
	Intercept	0.43	0.06	0.78	0.40	0.07	0.73	0.42	0.07	0.77	0.46	0.12	0.81	0.43	0.11	0.79
log(dispersion)	Institutional approach†	-0.81	-1.32	-0.30	-0.81	-1.32	-0.33	-0.80	-1.30	-0.31				-0.81	-1.30	-0.38
	Group size	0.03	0.02	0.04	0.03	0.02	0.04	0.03	0.02	0.04	0.03	0.03	0.04	0.03	0.02	0.04
	Size of resource system	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00				0.00	0.00	0.00
	Grove size	0.06	0.02	0.11	0.06	0.02	0.11	0.06	0.01	0.10				0.06	0.02	0.10
	Heterogeneity	-0.05	-0.09	-0.01	-0.05	-0.09	-0.02	-0.05	-0.09	-0.01				-0.05	-0.08	-0.02

	Season[‡]	-0.07	-0.27	0.13												
	Age	0.00	-0.03	0.04												
	Intercept	0.90	0.56	1.27	0.88	0.60	1.15	0.89	0.60	1.17	1.07	0.91	1.23	0.88	0.62	1.13
logit(P(1))	Institutional approach[†]	-92.64	-221.71	-6.68	-34.93	-85.72	-3.62	-46.39	-119.37	-3.70				-67.45	-188.90	-4.66
	Group size	-0.69	-1.21	-0.29	-0.61	-1.01	-0.31	-0.59	-1.07	-0.28	-0.49	-0.87	-0.22	-0.58	-0.93	-0.30
	Size of resource system	0.00	0.00	0.00												
	Grove size	-0.02	-0.15	0.10												
	Heterogeneity	0.04	-0.12	0.19							-0.01	-0.13	0.10			
	Season[‡]	0.51	-0.86	1.85												
	Age	-0.13	-0.40	0.13												
	Intercept	-1.06	-3.25	0.93	-1.37	-2.35	-0.43	-1.41	-2.45	-0.37	-2.13	-3.42	-0.96	-1.43	-2.38	-0.51
logit(P(0))	Institutional approach[†]	-0.22	-0.91	0.49												
	Group size	-0.31	-0.39	-0.24	-0.30	-0.37	-0.24	-0.32	-0.39	-0.26	-0.28	-0.34	-0.23	-0.32	-0.38	-0.27
	Size of resource system	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00						
	Grove size	0.08	0.04	0.13	0.08	0.04	0.13	0.05	0.02	0.08	0.07	0.05	0.10			
	Heterogeneity	-0.05	-0.11	0.00	-0.05	-0.10	0.00							0.03	0.00	0.06
	Season[‡]	-0.36	-0.82	0.08												
	Age	-0.08	-0.17	0.00												
	Intercept	0.50	-0.27	1.30	-0.13	-0.74	0.46	-0.20	-0.77	0.36	-0.34	-0.91	0.22	0.54	0.10	1.04
	DIC	1679813			1679811			1679814			1679852			1679849		

Multivariate psrf	1.39	1.05	1.20	1.01	1.10

Note: deviance information criterion (DIC), potential scale reduction factor (prsf)

† Institutional approach was modeled as a factor, considering PMA as the baseline

‡ Season of treatment was modeled as a factor, considering Fall as the baseline

Table A1.4: Posterior mean and 95% credible interval for the parameters in the zoib regression models evaluated that were less complex than the selected model (SD28).

		SD27	SD27	SD27	SD29	SD29	SD29	SD30	SD30	SD30	SD31	SD31	SD31	SD13	SD13	SD13	SD21	SD21	SD21	SD0	SD0	SD0
		mean	2.5%	97.5%	mean	2.5%	97.5%	mean	2.5%	97.5%	mean	2.5%	97.5%	mean	2.5%	97.5%	mean	2.5%	97.5%	mean	2.5%	97.5%
logit (mean)	Institutional approach†	-1.08	-1.64	-0.51	-1.34	-1.89	-0.83	-0.24	-0.68	0.20	-0.54	-0.97	-0.13	-0.67	-1.17	-0.13	-0.58	-1.13	-0.03			
	Group size	-0.01	-0.02	0.00	-0.02	-0.02	-0.01	-0.01	-0.02	0.00	-0.02	-0.02	-0.01	-0.01	-0.02	-0.01	-0.02	-0.03	-0.01			
	Size of resource system	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00			
	Grove size	0.10	0.07	0.14	0.03	0.00	0.06	0.10	0.06	0.14	0.03	0.00	0.05	0.08	0.04	0.12	0.09	0.05	0.12			
	Heterogeneity	0.08	0.04	0.12	0.02	-0.01	0.05	0.08	0.05	0.12	0.02	-0.01	0.05	0.12	0.08	0.15	0.13	0.09	0.16			
	Season‡	-0.17	-0.29	-0.04	-0.15	-0.28	-0.02	-0.17	-0.30	-0.04	-0.15	-0.28	-0.03	-0.16	-0.29	-0.03	-0.16	-0.30	-0.02			
	Age	-0.07	-0.10	-0.05	-0.07	-0.10	-0.05	-0.06	-0.08	-0.03	-0.06	-0.08	-0.03	-0.07	-0.10	-0.05	-0.07	-0.10	-0.04			
	Institution† x Age	0.17	0.09	0.25	0.16	0.08	0.24							0.18	0.09	0.26	0.17	0.08	0.26			
	Grove size x Heterogeneity	-0.01	-0.01	0.00				-0.01	-0.01	0.00				-0.01	-0.01	0.00	-0.01	-0.01	0.00			

	Intercept	0.41	0.07	0.76	1.05	0.79	1.30	0.34	-0.01	0.69	0.96	0.71	1.23	0.47	0.12	0.81	0.51	0.17	0.86	1.06	0.98	1.15
log (dispersion)	Institutional approach†	-0.82	-1.32	-0.33	-0.88	-1.38	-0.40	-0.89	-1.38	-0.41	-0.95	-1.44	-0.44									
	Group size	0.03	0.02	0.04	0.03	0.02	0.04	0.03	0.02	0.04	0.03	0.02	0.04	0.03	0.03	0.04						
	Size of resource system	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00									
	Grove size	0.06	0.02	0.11	0.06	0.02	0.10	0.07	0.03	0.11	0.07	0.03	0.11									
	Heterogeneity	-0.05	-0.09	-0.02	-0.06	-0.10	-0.02	-0.06	-0.09	-0.02	-0.06	-0.10	-0.03									
	Season‡																					
	Age																					
	Intercept	0.88	0.60	1.16	0.87	0.60	1.16	0.87	0.59	1.14	0.87	0.59	1.14	1.07	0.91	1.23	1.53	1.42	1.63	1.24	1.14	1.34
logit (P(1))	Institutional approach†																					
	Group size	-0.47	-0.83	-0.23	-0.48	-0.89	-0.23	-0.47	-0.84	-0.22	-0.51	-0.91	-0.24	-0.49	-0.85	-0.22						
	Size of resource system																					
	Grove size																					
	Heterogeneity																					
	Season‡																					
	Age																					
	Intercept	-2.22	-3.12	-1.36	-2.17	-3.10	-1.31	-2.21	-3.12	-1.35	-2.14	-3.06	-1.27	-2.17	-3.10	-1.30	-4.37	-5.00	-3.79	-4.37	-5.03	-3.79
logit (P(0))	Institutional approach†																					
	Group size	-0.32	-0.38	-0.27	-0.32	-0.38	-0.26	-0.32	-0.38	-0.26	-0.32	-0.38	-0.26	-0.31	-0.37	-0.26						
	Size of resource system																					

Grove size																					
Heterogeneity	0.03	0.00	0.07	0.03	0.00	0.07	0.03	0.00	0.07	0.03	0.00	0.07									
Season[‡]																					
Age																					
Intercept	0.53	0.06	1.01	0.53	0.05	1.00	0.53	0.05	1.02	0.53	0.05	1.03	0.89	0.55	1.25	-1.43	-1.61	-1.25	-1.43	-1.60	-1.26
DIC	1679860			1679885			1679877			1679900			1679883			1680225			1680402		
Multivariate psrf	1.04			1.02			1.05			1.05			1.02			1.05			1		

Note: deviance information criterion (DIC), potential scale reduction factor (prsf)

[†] Institutional approach was modeled as a factor, considering PMA as the baseline

[‡] Season of treatment was modeled as a factor, considering Fall as the baseline

Table A1.5: Posterior mean and 95% credible interval for the parameters in the selected zoib regression model (SD28) with the size of the resource system, and the model without this independent variable (SD32).

		SD28 mean	SD28 2.5%	SD28 97.5%	SD32 mean	SD32 2.5%	SD32 97.5%
logit(mean)	Institutional approach†	-1.09	-1.65	-0.57	-0.65	-1.17	-0.13
	Group size	-0.01	-0.02	0.00	-0.01	-0.01	0.00
	Size of resource system	0.00	0.00	0.00			
	Grove size	0.10	0.06	0.14	0.13	0.09	0.16
	Heterogeneity	0.08	0.05	0.12	0.10	0.07	0.13
	Season‡	-0.17	-0.30	-0.05	-0.17	-0.31	-0.04
	Age	-0.07	-0.10	-0.05	-0.07	-0.10	-0.05
	Institution† x Age	0.17	0.10	0.25	0.17	0.09	0.26
	Grove size x Heterogeneity	-0.01	-0.01	0.00	-0.01	-0.01	-0.01
	Intercept	0.43	0.11	0.79	0.26	-0.06	0.58
log(dispersion)	Institutional approach†	-0.81	-1.30	-0.38	-0.42	-0.82	0.01
	Group size	0.03	0.02	0.04	0.04	0.03	0.05
	Size of resource system	0.00	0.00	0.00			
	Grove size	0.06	0.02	0.10	0.07	0.03	0.11
	Heterogeneity	-0.05	-0.08	-0.02	-0.05	-0.08	-0.02
	Season‡						
	Age						

	Intercept	0.88	0.62	1.13	0.88	0.62	1.15
logit(P(1))	Institutional approach†	-67.45	-188.90	-4.66	-53.65	-126.63	-3.99
	Group size	-0.58	-0.93	-0.30	-0.58	-0.94	-0.30
	Size of resource system						
	Grove size						
	Heterogeneity						
	Season‡						
	Age						
	Intercept	-1.43	-2.38	-0.51	-1.42	-2.39	-0.47
logit(P(0))	Institutional approach†						
	Group size	-0.32	-0.38	-0.27	-0.32	-0.37	-0.27
	Size of resource system						
	Grove size						
	Heterogeneity	0.03	0.00	0.06	0.03	0.00	0.07
	Season‡						
	Age						
	Intercept	0.54	0.10	1.04	0.54	0.06	1.04
	DIC	1679849			1679861		
	Multivariate psrf	1.10			1.33		

Note: deviance information criterion (DIC), potential scale reduction factor (prsf)

† Institutional approach was modeled as a factor, considering PMA as the baseline

‡ Season of treatment was modeled as a factor, considering Fall as the baseline

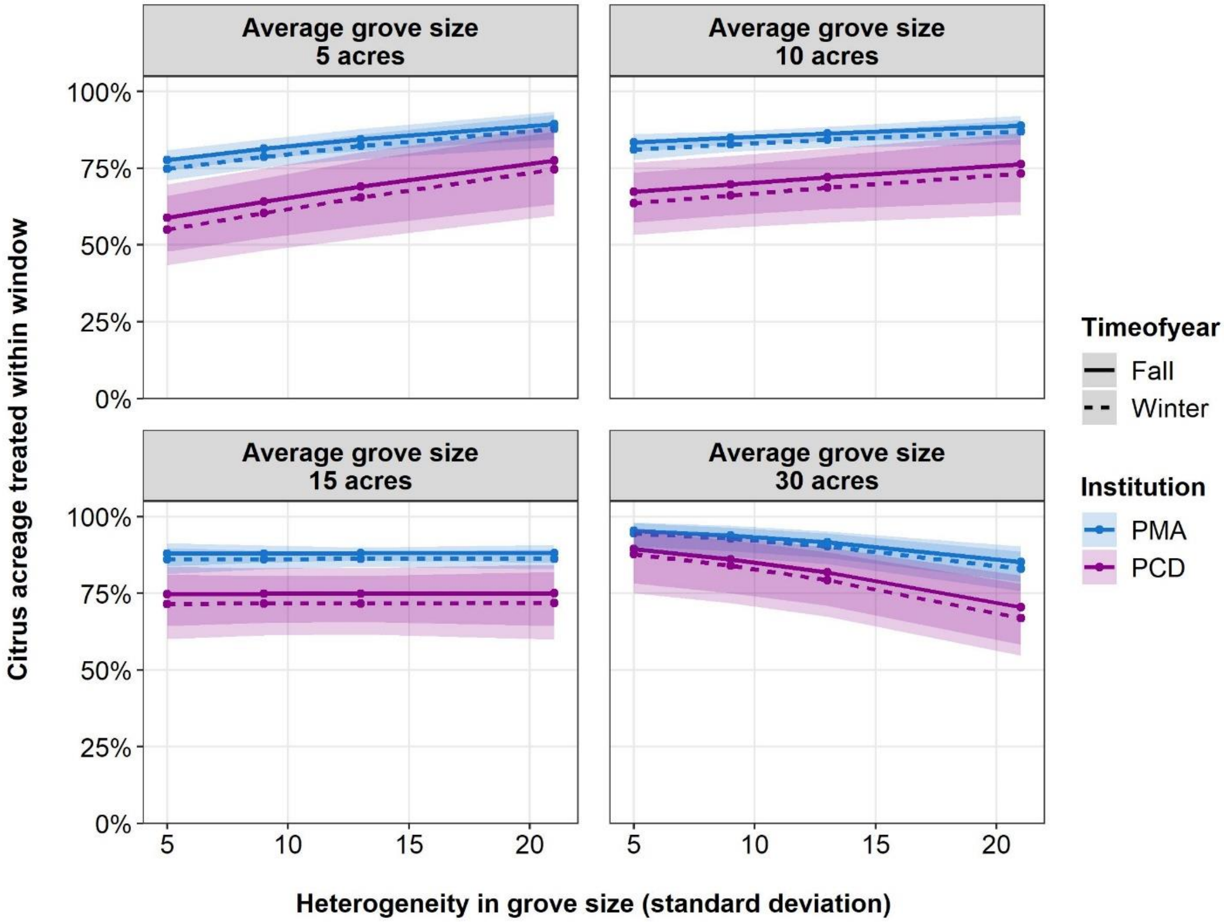

Fig. A1.4: Participation levels in AWM predicted by the zoib model depending on the average size of the citrus groves and their heterogeneity. The mean of the predicted values for season number 1 is shown in blue (PMAs) or in purple (PCDs). Predicted values for the fall treatments are linked by solid lines and predicted values for the winter treatments are linked by dashed lines. The panels show different average sizes of the citrus groves in an AWM unit.

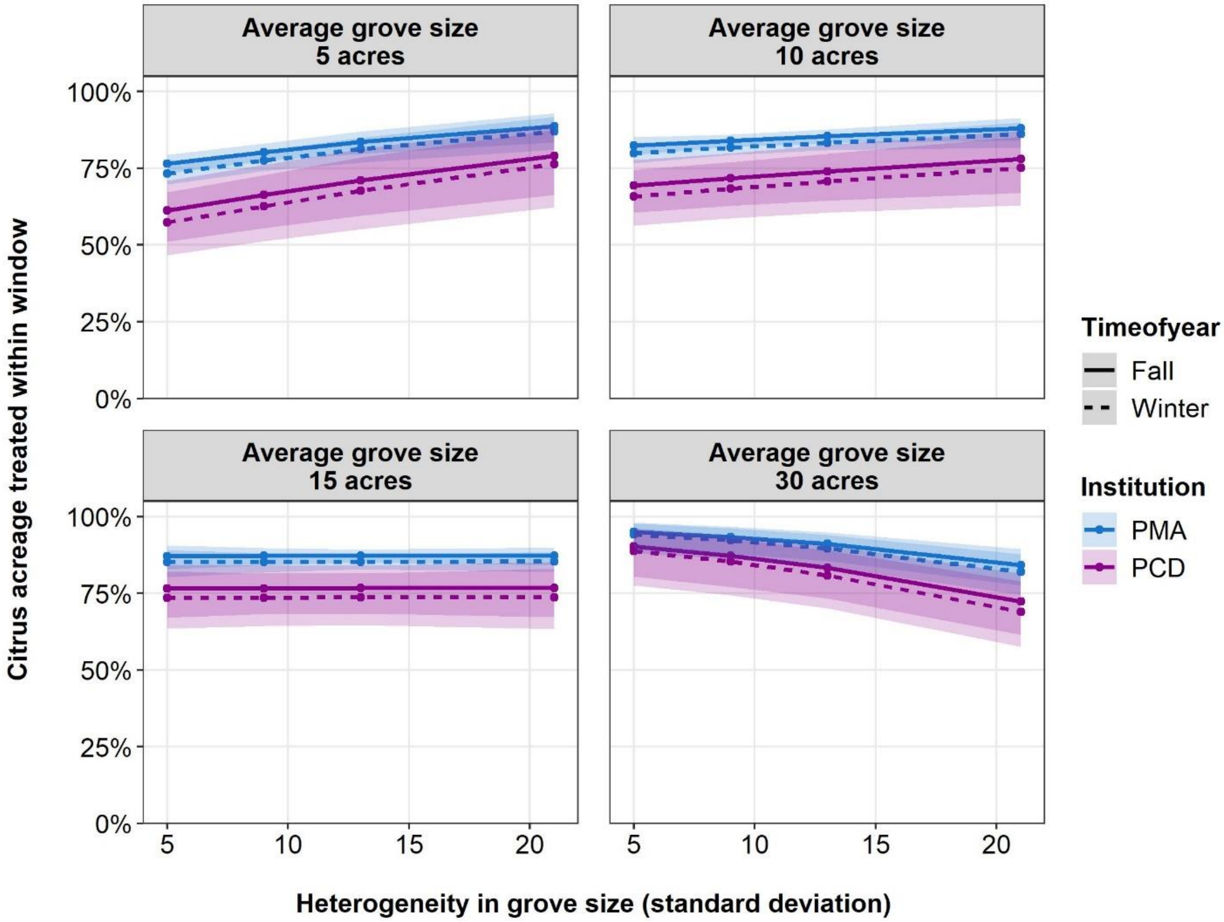

Fig. A1.5: Participation levels in AWM predicted by the zoib model depending on the average size of the citrus groves and their heterogeneity. The mean of the predicted values for season number 2 is shown in blue (PMAs) or in purple (PCDs). Predicted values for the fall treatments are linked by solid lines and predicted values for the winter treatments are linked by dashed lines. The panels show different average sizes of the citrus groves in an AWM unit.

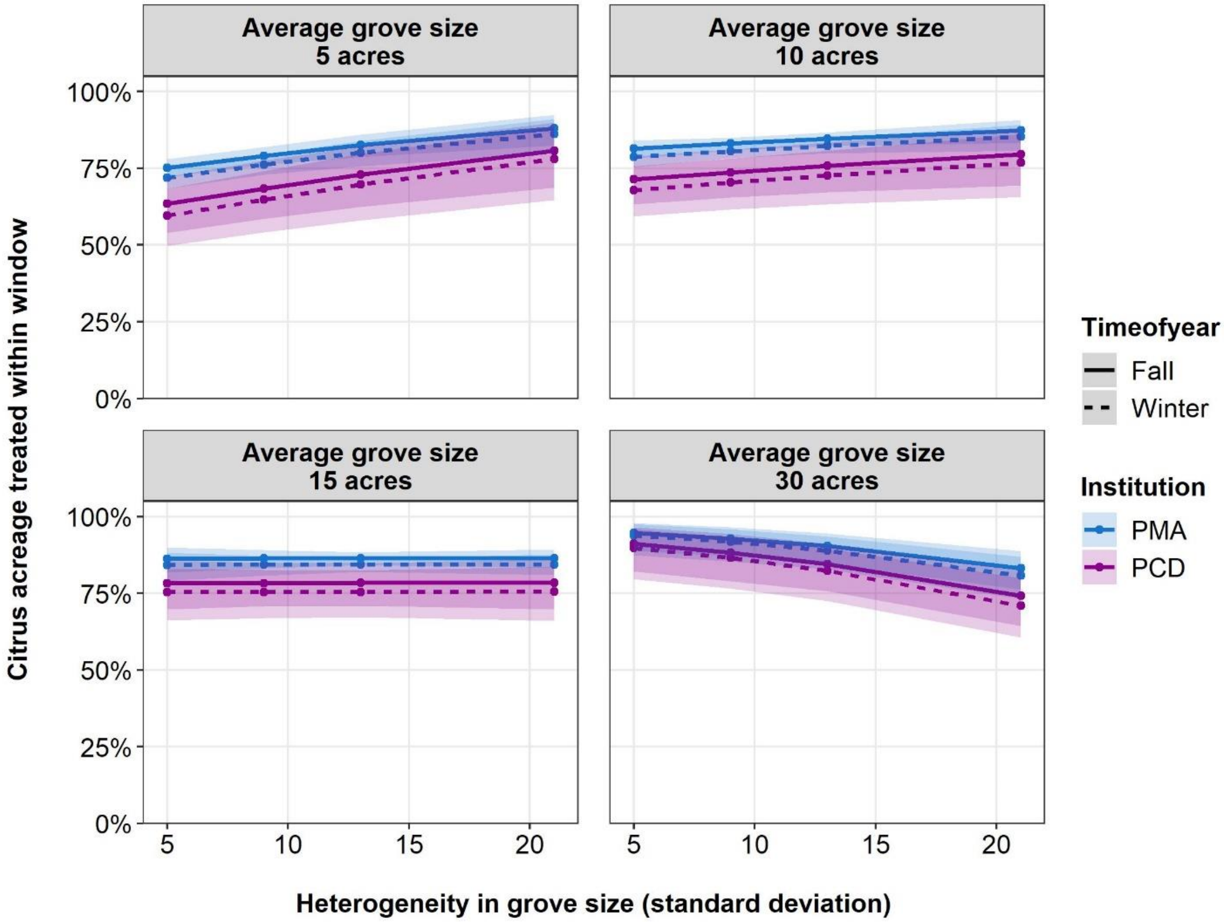

Fig. A1.6: Participation levels in AWM predicted by the zoib model depending on the average size of the citrus groves and their heterogeneity. The mean of the predicted values for season number 3 is shown in blue (PMAs) or in purple (PCDs). Predicted values for the fall treatments are linked by solid lines and predicted values for the winter treatments are linked by dashed lines. The panels show different average sizes of the citrus groves in an AWM unit.

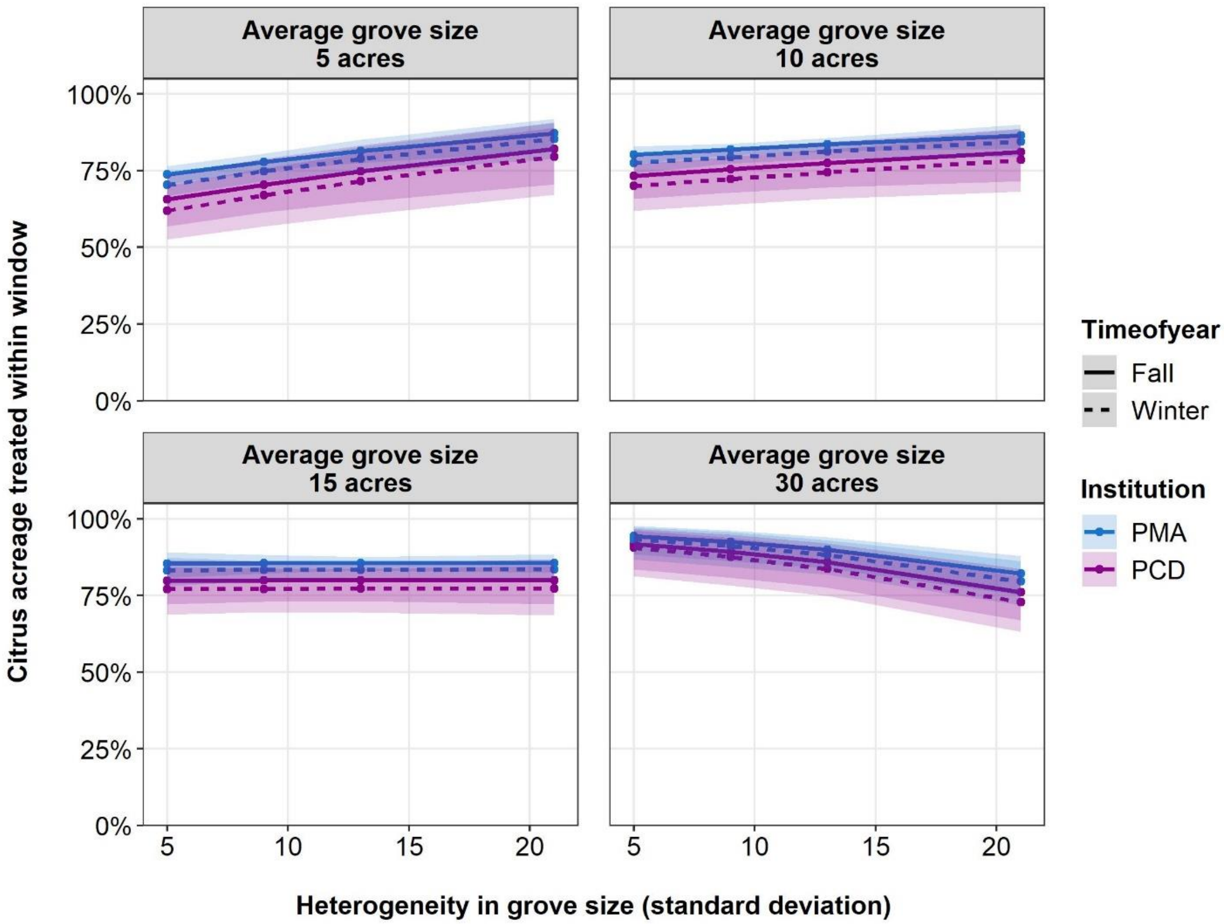

Fig. A1.7: Participation levels in AWM predicted by the zoib model depending on the average size of the citrus groves and their heterogeneity. The mean of the predicted values for season number 4 is shown in blue (PMAs) or in purple (PCDs). Predicted values for the fall treatments are linked by solid lines and predicted values for the winter treatments are linked by dashed lines. The panels show different average sizes of the citrus groves in an AWM unit.

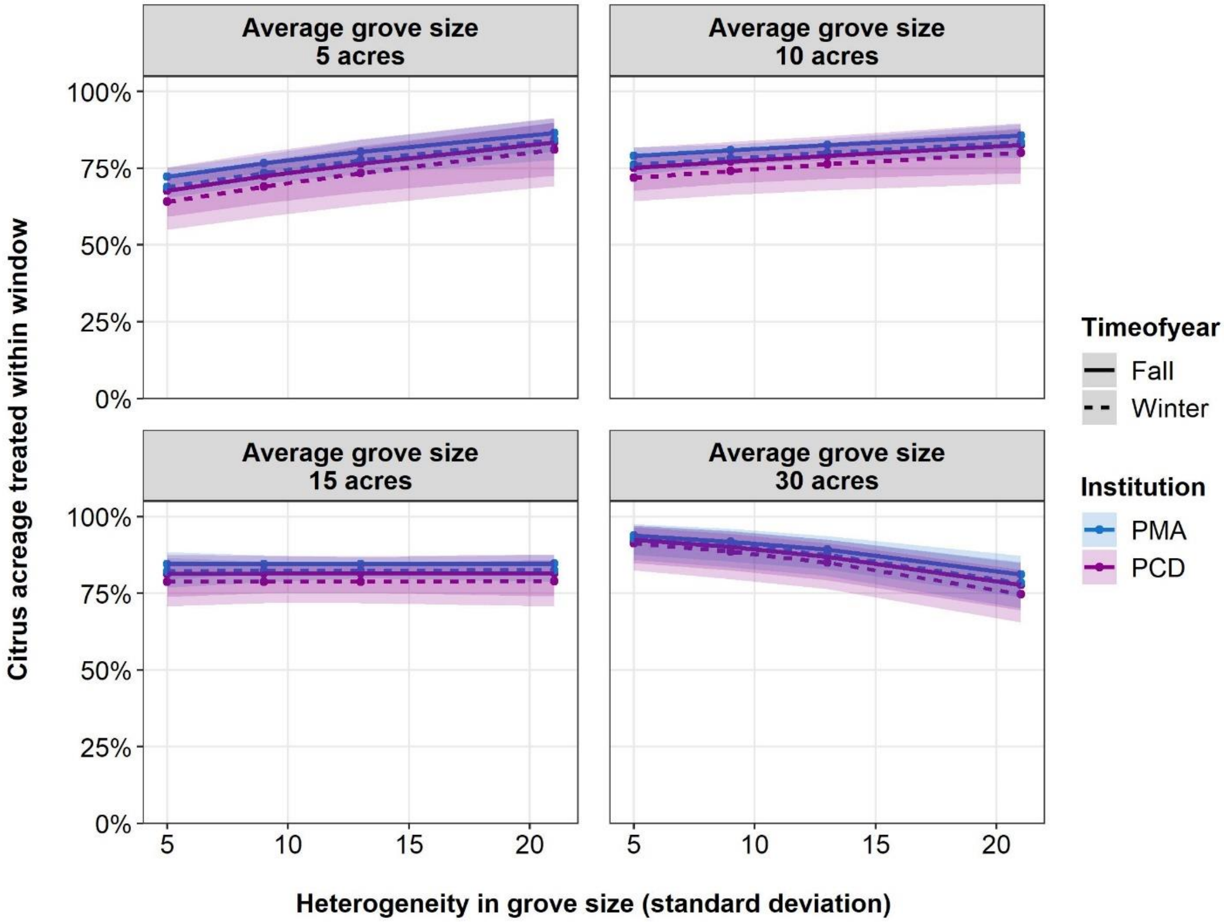

Fig. A1.8: Participation levels in AWM predicted by the zoib model depending on the average size of the citrus groves and their heterogeneity. The mean of the predicted values for season number 5 is shown in blue (PMAs) or in purple (PCDs). Predicted values for the fall treatments are linked by solid lines and predicted values for the winter treatments are linked by dashed lines. The panels show different average sizes of the citrus groves in an AWM unit.

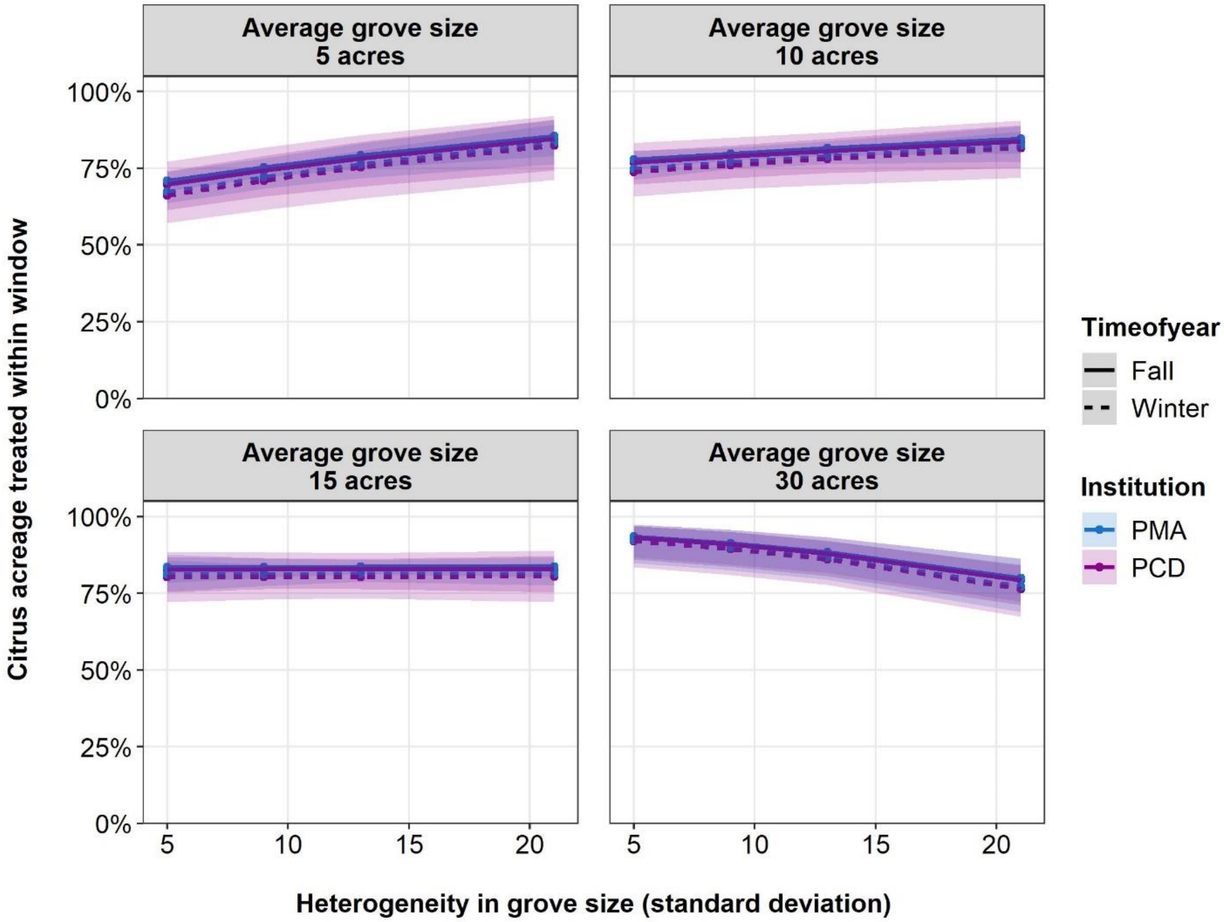

Fig. A1.9: Participation levels in AWM predicted by the zoib model depending on the average size of the citrus groves and their heterogeneity. The mean of the predicted values for season number 6 is shown in blue (PMAs) or in purple (PCDs). Predicted values for the fall treatments are linked by solid lines and predicted values for the winter treatments are linked by dashed lines. The panels show different average sizes of the citrus groves in an AWM unit.

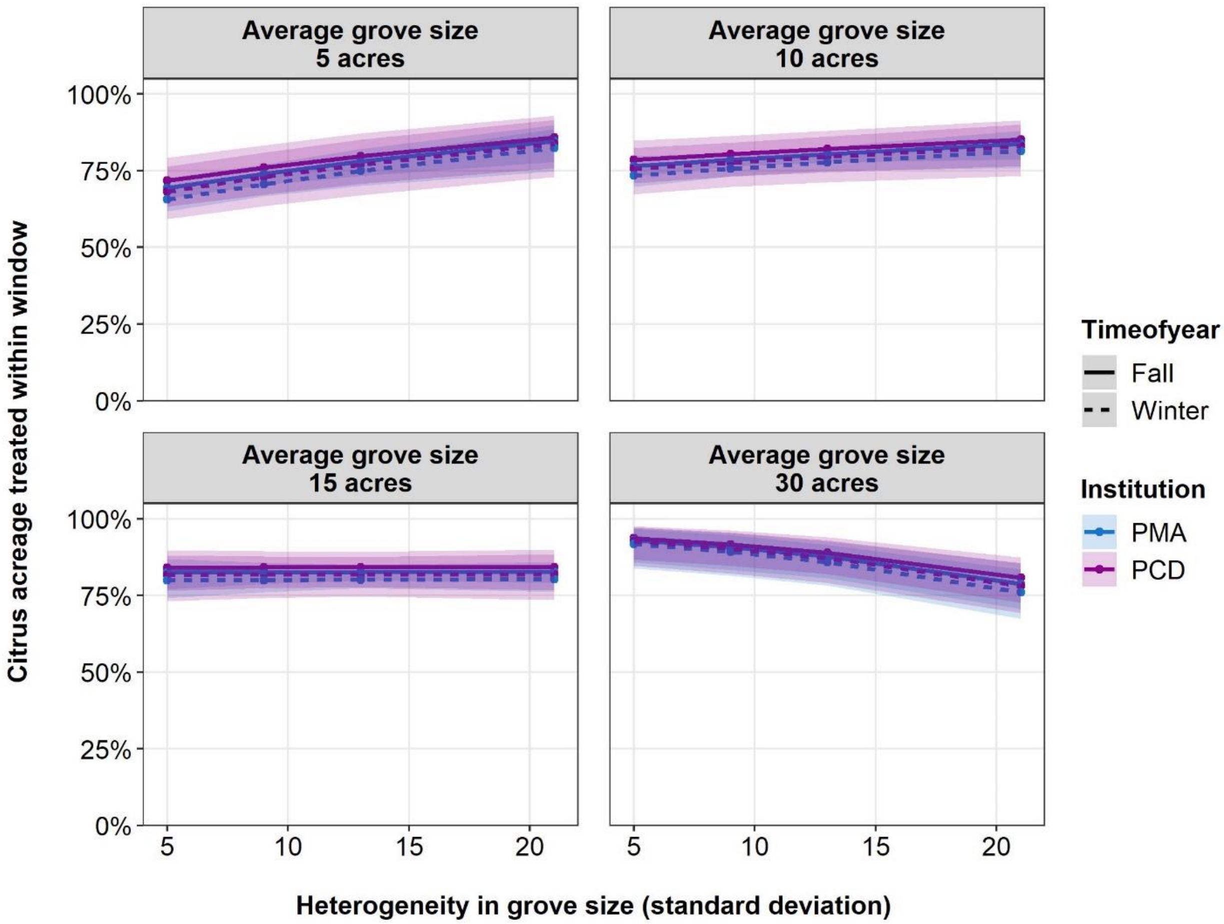

Fig. A1.10: Participation levels in AWM predicted by the zoib model depending on the average size of the citrus groves and their heterogeneity. The mean of the predicted values for season number 7 is shown in blue (PMAs) or in purple (PCDs). Predicted values for the fall treatments are linked by solid lines and predicted values for the winter treatments are linked by dashed lines. The panels show different average sizes of the citrus groves in an AWM unit.

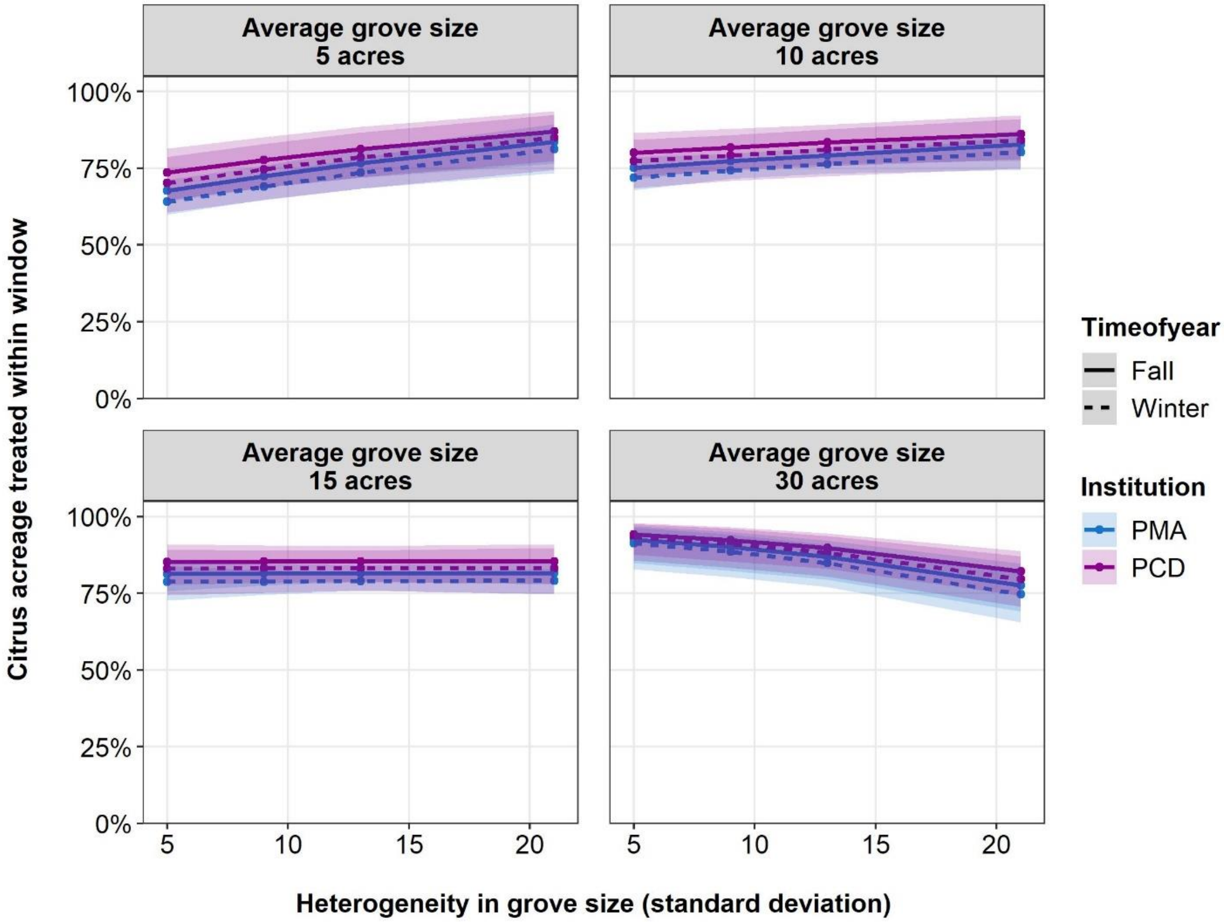

Fig. A1.11: Participation levels in AWM predicted by the zoib model depending on the average size of the citrus groves and their heterogeneity. The mean of the predicted values for season number 8 is shown in blue (PMAs) or in purple (PCDs). Predicted values for the fall treatments are linked by solid lines and predicted values for the winter treatments are linked by dashed lines. The panels show different average sizes of the citrus groves in an AWM unit.

Appendix 2: Survey questionnaire

1. What is your main role in citrus production?

a. Grove owner

b. Ranch manager

c. Pest Control Adviser (PCA)

d. Pest Control Operator (PCO)

e. Other

2. How many acres of citrus do you grow or manage?

a. <5 acres

b. 5-25

c. 26-100

d. 101-500

e. >500

3. What age group are you in?

a. <35 years

b. 35-50

c. 51-65

d. >65 years

4. Where are your groves located? (click all that apply)

a. Fresno

b. Imperial

c. Kern

d. Madera

e. Riverside

f. San Bernardino

g. San Diego

h. Santa Barbara

i. Tulare

j. Ventura

5. How do you grow citrus?

a. Conventionally

b. Organically

c. Both

6. What percentage of your income comes from citrus?

a. 0-25%

b. 26-50%

c. 51-75%

d. 76-100%

7. How likely do you think it is that an HLB-positive tree will be detected in your grove in the next year?

a. Very unlikely

b. Unlikely

c. Maybe

d. Likely

e. Very likely

8. How likely is it that you will stay informed about HLB and actively communicate with your grower liaison?

a. Very unlikely

b. Unlikely

c. Maybe

d. Likely

e. Very likely

f. I don’t know who my liaison is

9. How likely is it that you will be actively communicating with your neighbors (growers and homeowners)?

a. Very unlikely

b. Unlikely

c. Maybe

d. Likely

e. Very likely

11. How likely do you think it is that <u>coordinated</u> insecticide treatments for ACP will slow down HLB spread <u>more than uncoordinated</u> treatments?

a. Very unlikely

b. Unlikely

c. Maybe

d. Likely

e. Very likely

12.What do you think is <u>the main barrier</u> to area-wide management of ACP in your area? (read the whole list before you choose)

a. Preference to spray in one’s own timing

b. Access to sprayers

c. Cost

d. Getting everyone to participate

e. Disruption of IPM

13. How likely do you think it is that your neighbors will apply insecticides for ACP within recommended treatment windows?

a. Very unlikely

b. Unlikely

c. Maybe

d. Likely

e. Very likely

Text A2.2: Data analysis

All statistical analyses were done in the R programming environment version 4.0.3 (R Foundation for Statistical Computing 2020) with a Windows 10 Pro version 1909, 64-bit operating system (Microsoft, Redmond, WA, U. S. A.). Data manipulation and descriptive statistics were conducted using the R package "dplyr" (Wickham et al. 2021) and base R. Plots were generated with the R package "ggplot2" (Wickham 2016).

Analysis of survey data

Correlations between ordered categorical variables from the survey were tested using Spearman's rank correlation test.

Analysis of participation in AWM

Four of the independent variables in the regression model (group size, size of the resource system, size of citrus groves, heterogeneity in grove size) were based on information recorded in the database of citrus operations in California maintained by the Citrus Research Board (CRB), hereafter referred to as the *citrus layer*. We obtained access to the June 2020 version of the citrus layer (Rick Dunn, personal communication) and the outlines of each AWM unit in the state of California (Rick Dunn and Robert Johnson, pers. com.). The software ArcGIS Pro (ESRI, Redlands, CA, U. S. A.) was used to overlay the citrus layer and the institutional layer in order to calculate the group size, size of the resource system, size of citrus groves and heterogeneity in grove size in each AWM unit using the "Dissolve" tool. Correlations between numeric independent variables in the regression model were tested using Pearson's correlation test.

- Group size: It was calculated as the number of different PURs within each AWM unit on the CRB citrus layer, which was compared with the number of PURs routinely collected by the grower liaisons and found to be highly correlated (ρ=0.72, *P*=2E-15).
- Size of the resource system: It was calculated by aggregating all of the citrus properties in each PMA/PCD and calculating the sum of the grove acres. The calculated total citrus acreage under each management unit was highly correlated with data provided by the grower liaisons (ρ=0.97, *P*<2.2E-16) and with the citrus acreage recorded in the California Statewide Crop Mapping database (ρ=0.98, *P*<2.2E-16) (Department of Water Resources 2020).
- Size of citrus groves: It was calculated with the "Dissolve" tool from the software ArcGIS Pro by aggregating all of the citrus properties in each PMA/PCD and calculating the mean of the grove acres.
- Heterogeneity in grove size: It was calculated with the "Dissolve" tool from the software ArcGIS Pro by aggregating all of the citrus properties in each PMA/PCD and calculating the standard deviation of the grove acres.

Some preliminary statistical analyses were conducted to guide the hypotheses tested with the zoib regression model.

- Institutional approach (PMA/PCD): there was significantly higher participation in AWM in PCDs than PMAs in every season ($P \leq 0.043$ on t-tests), except the Fall of 2016 ($P=0.99$).
- Group size: there was a significant negative correlation between the number of pesticide use permits and participation in AWM ($\rho=-0.28$, $P<2.2E-16$).
- Size of citrus groves: there was a significant positive correlation between the average size of citrus groves and participation in AWM ($\rho=0.27$, $P \leq 2.2E-16$).

Zero-and-one-inflated beta regression models were constructed using the R package "zoib" (Liu and Kong 2015). A zoib model assumes that the dependent variable *y* (the percentage of citrus acreage in each PMA/PCD treated within the recommended window) follows a piecewise distribution such that

$$f(y_i) = \begin{cases} p_i & \text{if } y_i = 0 \\ (1-p_i)q_i & \text{if } y_i = 1 \\ (1-p_i)(1-q_i)\text{Beta}(\alpha_{i1}, \alpha_{i2}) & \text{if } y_i \in (0,1) \end{cases}$$

where p_i represents the probability $\Pr(y_i=0)$, q_i represents the conditional probability $\Pr(y_i=1|y_i\neq 0)$, and α_{1i} and α_{2i} represent the shape parameters of the beta distribution for $y_i \in (0,1)$. These distributions are combined to derive the unconditional estimate of the response $E(y_i)$:

$$E(y_i) = (1-p_i)(\,q_i + (1-q_i)\mu_i^{(0,1)}$$

The zoib regression model estimates the logit [*i.e.*, the log(odds)] of the expected value of the beta distribution, the logit of $P(0)$ and $P(1)$ and the log of the dispersion of the beta distribution as linear functions of fixed and/or random effects. The coefficients of the effects on the mean of the beta regression can be interpreted as the expected change in the logit of participation with a one unit change in the corresponding variable. The coefficients of the effects on P(0) and P(1) are interpreted as the change in the logit of either having Participation=0 or Participation=1 with a one unit change in the corresponding variable. The coefficients of the effects on the dispersion of the beta distribution indicate the change in the log of the dispersion with a one-unit change in the corresponding variable (van Woerden et al. 2019). Based on a Bayesian framework, the coefficients are estimated through a Markov Chain Monte Carlo (MCMC) approach (Liu and Kong 2015). Two independent MCMC chains were run per model, each with 5000 iterations, including 200 iterations for burn-in, and thinned by a factor of 2. We assumed a Normal prior distribution N(0, 0.001) for each regression coefficient.

MCMC convergence was visually checked with trace plots and autocorrelation plots. The potential scale reduction factor (psrf) was calculated for each model parameter and the threshold psrf≤1.1 was used to determine that convergence had been reached (Gelman et al. 2021). In cases where psrf>1.1, we repeated the MCMC process with three chains, 10000 iterations per chain, 1000 for burn-in and thinned by a factor of 50. Posterior inferences for each parameter are reported as the mean and 95% credible interval (CI). Model selection was based on the deviance information criterion (DIC) (Liu and Kong 2015). Starting with the most complex model including the seven independent variables mentioned in the previous section, we examined the results and iteratively removed variables for which the CI of the posterior estimates was bounded by a negative and a positive value, and therefore comprised zero. Among competing models that fulfilled the previous condition, we chose the one with the lowest DIC (Table A4.1, Table A4.2).

Finally, the participation levels predicted by the zoib regression model were calculated using the pred.zoib function in the R package "zoib" (Liu and Kong 2015). Predictions were based on a new dataset where the independent variable under evaluation was allowed to vary within the range observed in the original dataset and the rest of the independent variables were fixed at their mean value, except in the case of interaction terms, where both variables were allowed to vary within the observed range.

All the R code used in this study will be posted in a repository at the following URL after publication: https://github.com/nmcr01?tab=repositories.

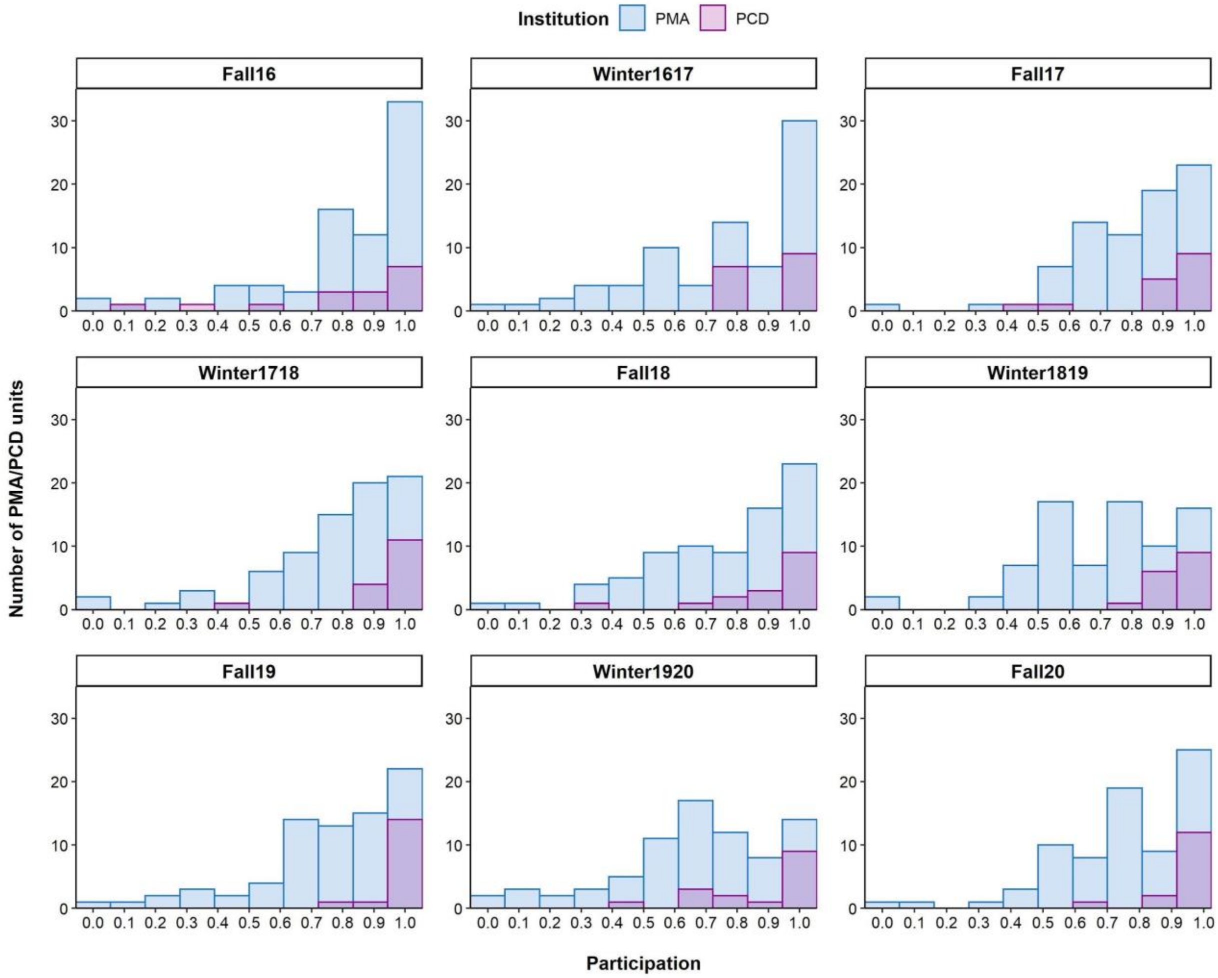

Fig. A2.1: Histogram of participation levels in area-wide management in Psyllid Management Areas (blue) and Pest Control Districts (purple) over nine seasons.

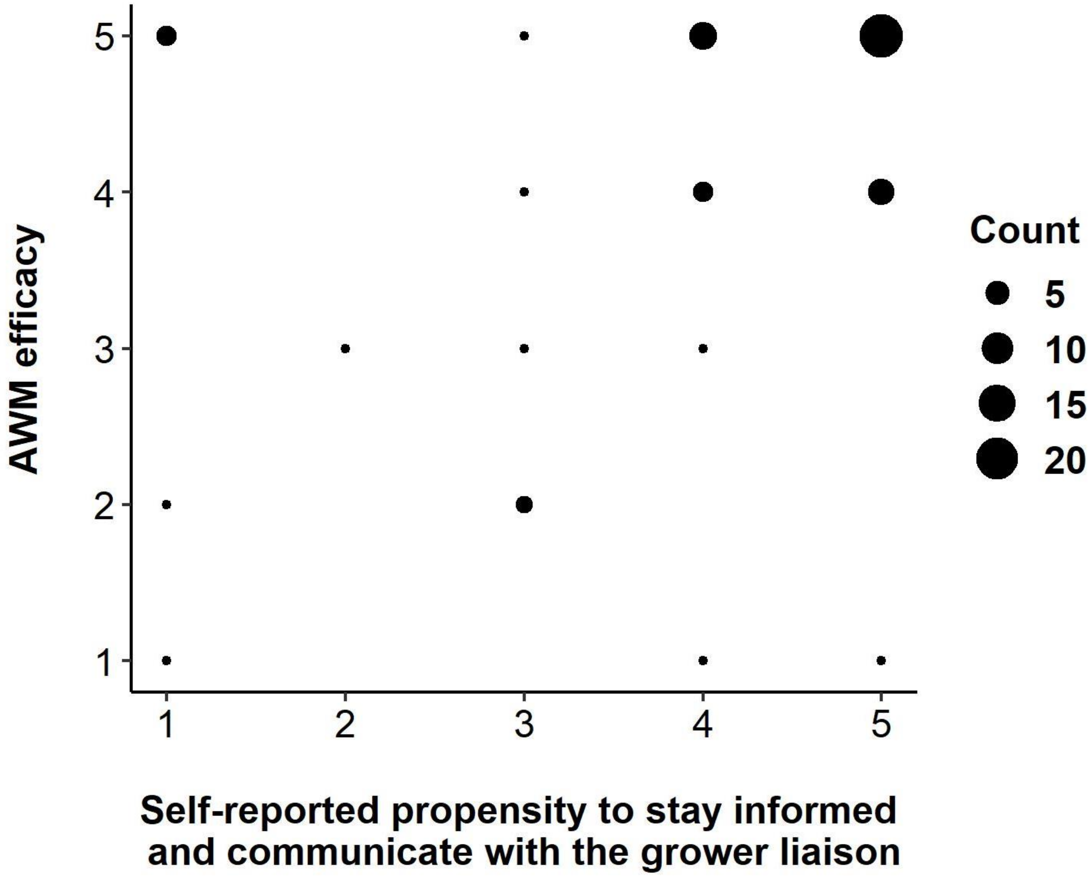

Fig. A2.2: Relationship between the self-reported propensity to stay informed and communicate with the grower liaison and the belief that coordinated insecticide treatments for ACP will slow down HLB spread more than uncoordinated treatments (AWM efficacy). Responses to the survey questions were transformed to numeric so that *very unlikely* = 1, *unlikely* = 2, *maybe* = 3, *likely* = 4, *very likely* = 5. The size of the points represents the number of participants who chose that combination of responses.

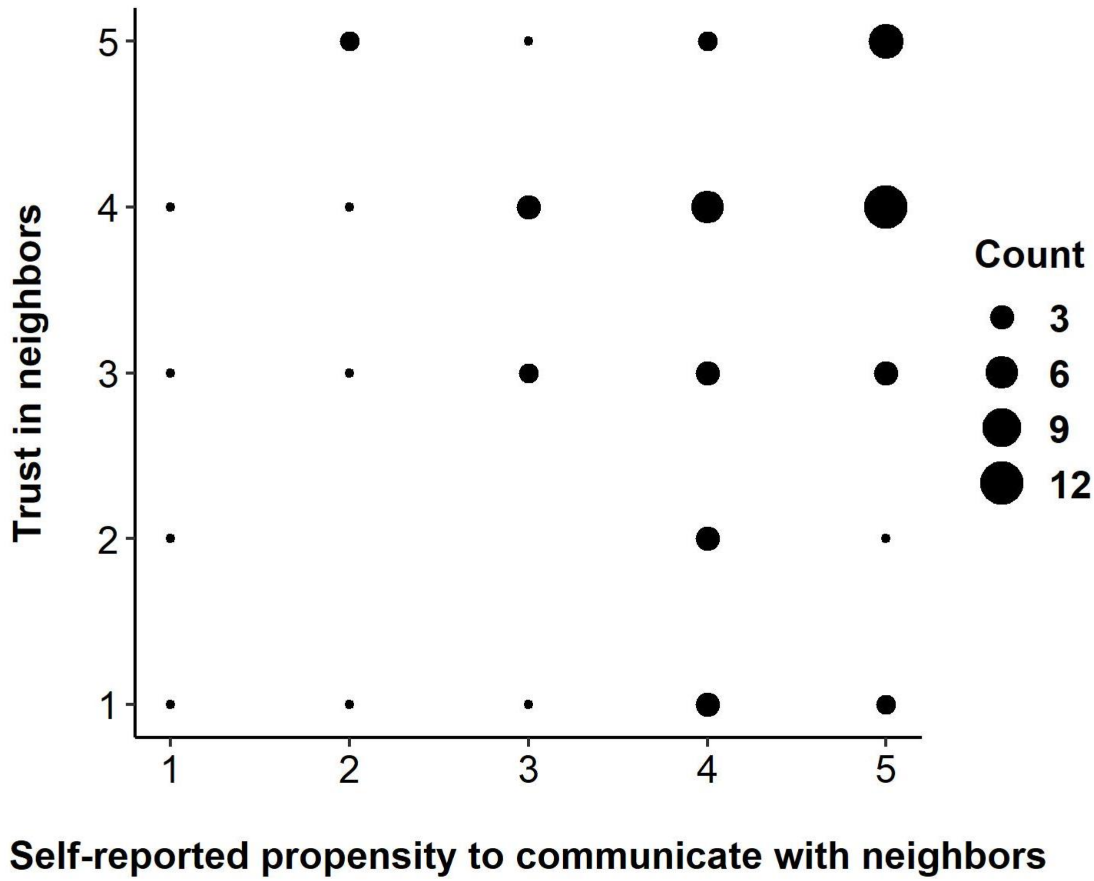

Fig. A2.3: Relationship between the self-reported propensity to communicate with neighbors and the belief that neighbors will apply insecticides for ACP within the recommended treatment window (trust in neighbors). Responses to the survey questions were transformed to numeric so that *very unlikely* = 1, *unlikely* = 2, *maybe* = 3, *likely* = 4, *very likely* = 5. The size of the points represents the number of participants who chose that combination of responses.

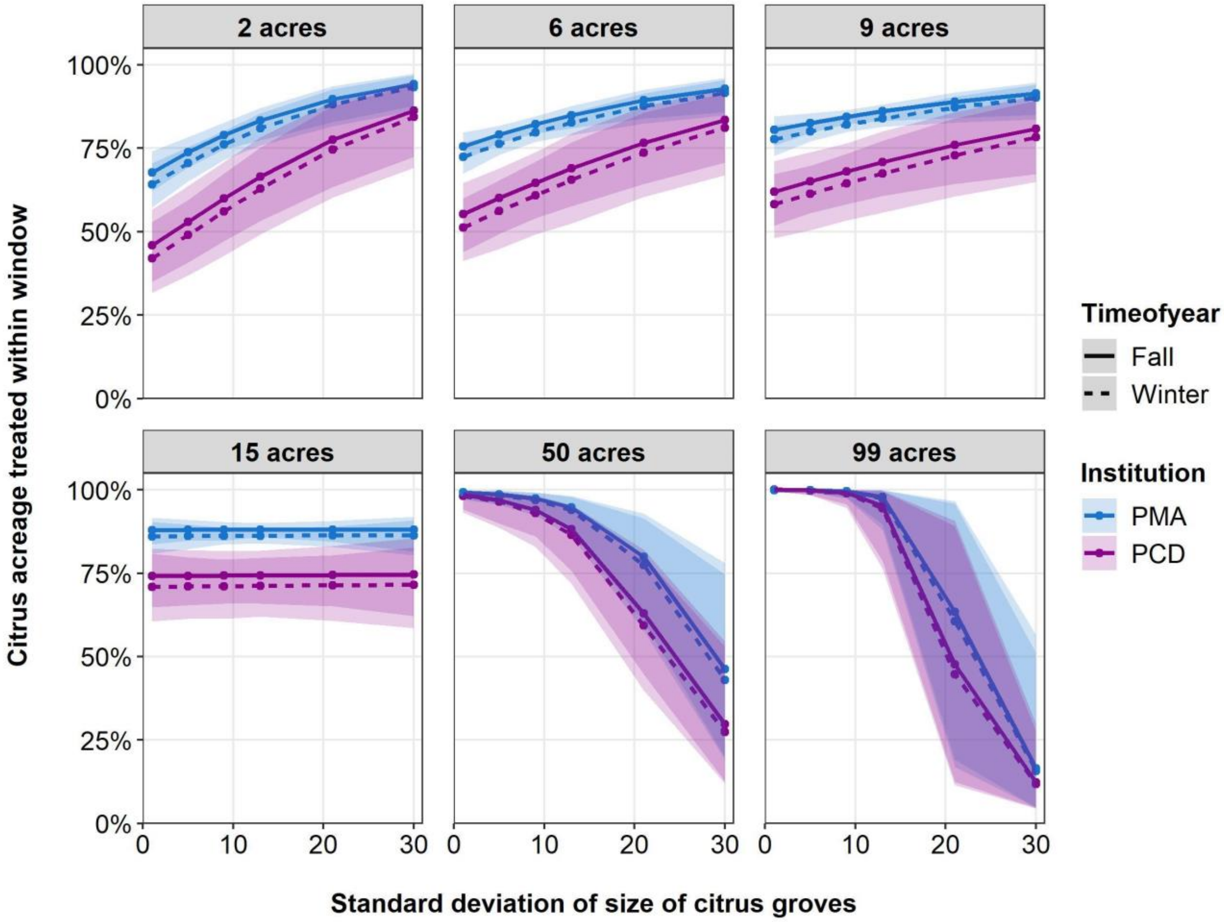

Fig. A2.4: Participation levels in AWM predicted by the zoib model depending on the average size of the citrus groves and their heterogeneity. The mean of the predicted values for season number 1 is shown in blue (PMAs) or in purple (PCDs). Predicted values for the fall treatments are linked by solid lines and predicted values for the winter treatments are linked by dashed lines. The panels show different average sizes of the citrus groves in a management unit.

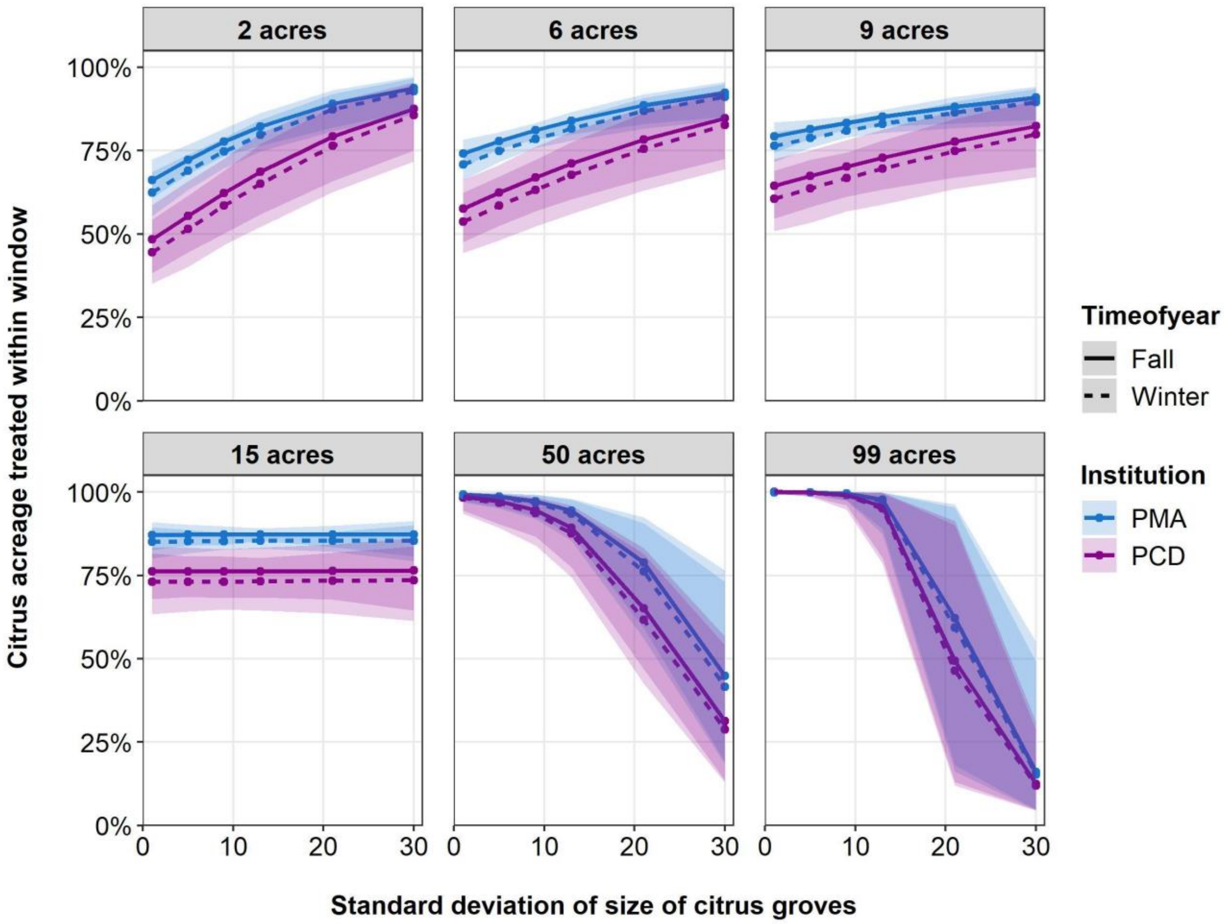

Fig. A2.5: Participation levels in AWM predicted by the zoib model depending on the average size of the citrus groves and their heterogeneity. The mean of the predicted values for season number 2 is shown in blue (PMAs) or in purple (PCDs). Predicted values for the fall treatments are linked by solid lines and predicted values for the winter treatments are linked by dashed lines. The panels show different average sizes of the citrus groves in a management unit.

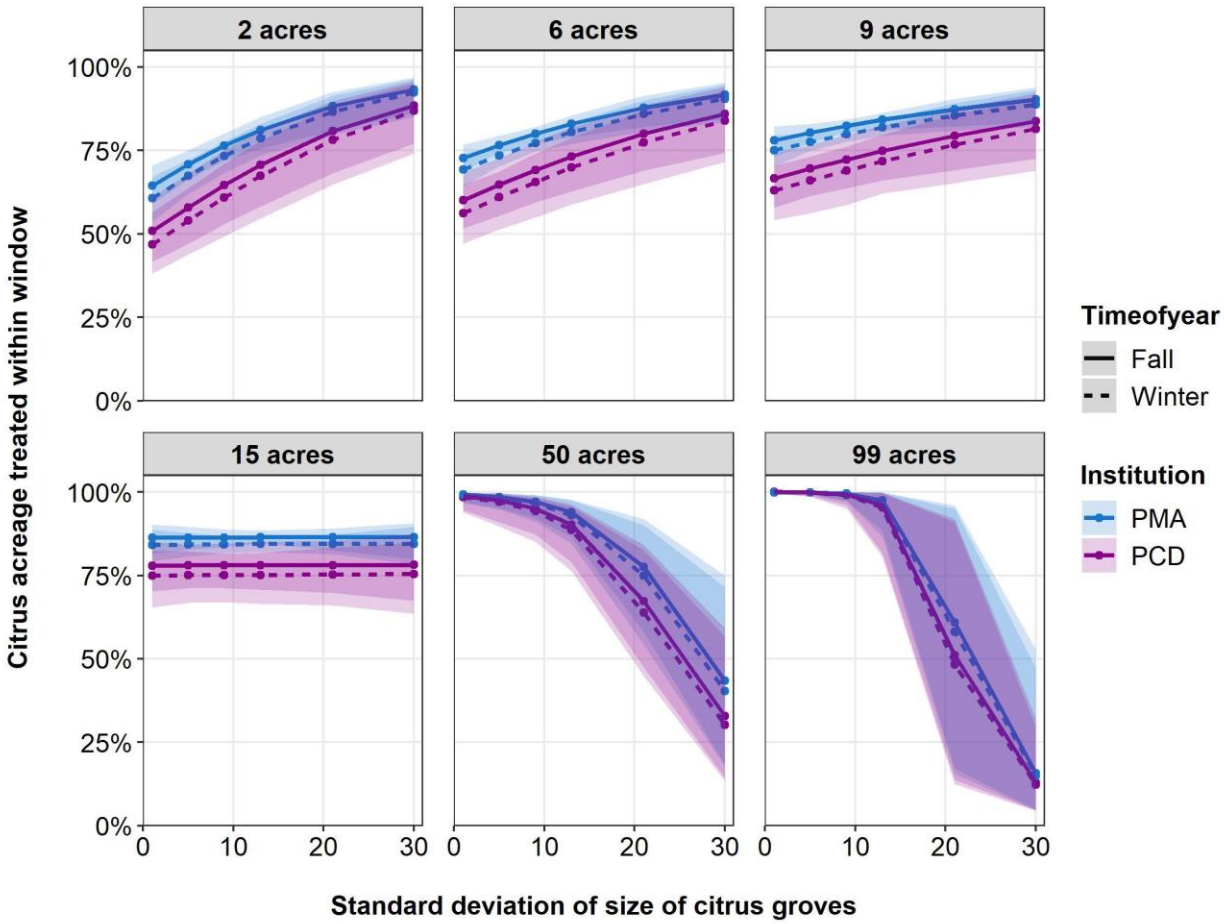

Fig. A2.6: Participation levels in AWM predicted by the zoib model depending on the average size of the citrus groves and their heterogeneity. The mean of the predicted values for season number 3 is shown in blue (PMAs) or in purple (PCDs). Predicted values for the fall treatments are linked by solid lines and predicted values for the winter treatments are linked by dashed lines. The panels show different average sizes of the citrus groves in a management unit.

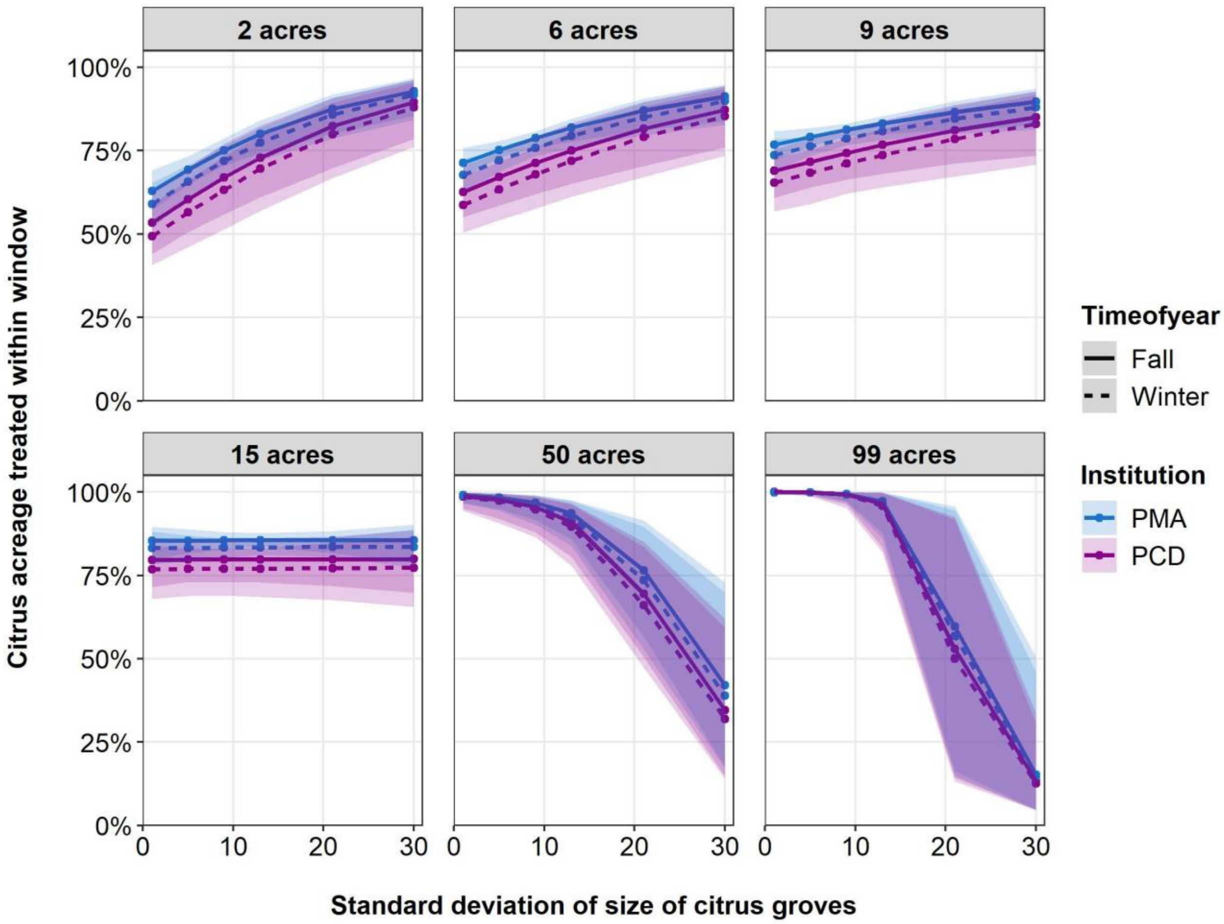

Fig. A2.7: Participation levels in AWM predicted by the zoib model depending on the average size of the citrus groves and their heterogeneity. The mean of the predicted values for season number 4 is shown in blue (PMAs) or in purple (PCDs). Predicted values for the fall treatments are linked by solid lines and predicted values for the winter treatments are linked by dashed lines. The panels show different average sizes of the citrus groves in a management unit.

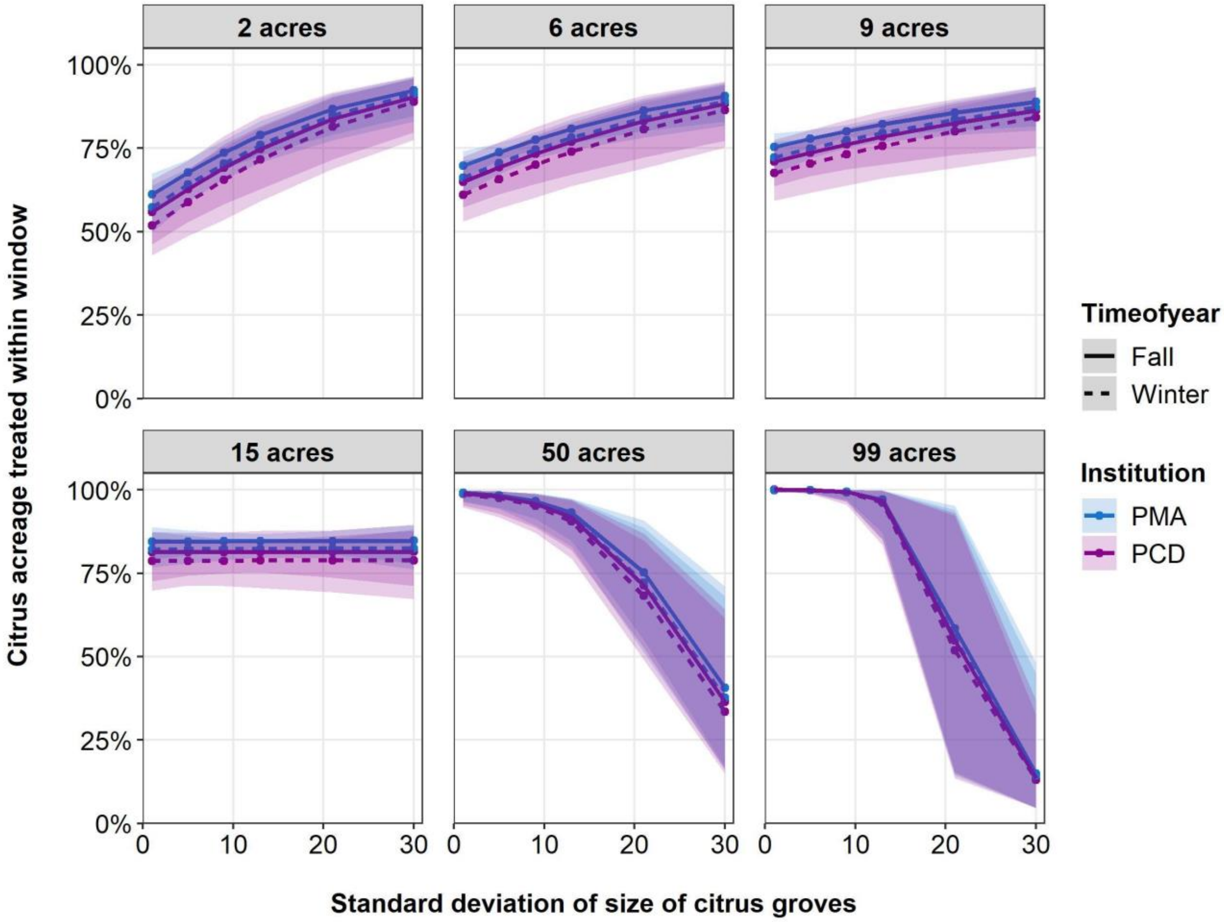

Fig. A2.8: Participation levels in AWM predicted by the zoib model depending on the average size of the citrus groves and their heterogeneity. The mean of the predicted values for season number 5 is shown in blue (PMAs) or in purple (PCDs). Predicted values for the fall treatments are linked by solid lines and predicted values for the winter treatments are linked by dashed lines. The panels show different average sizes of the citrus groves in a management unit.

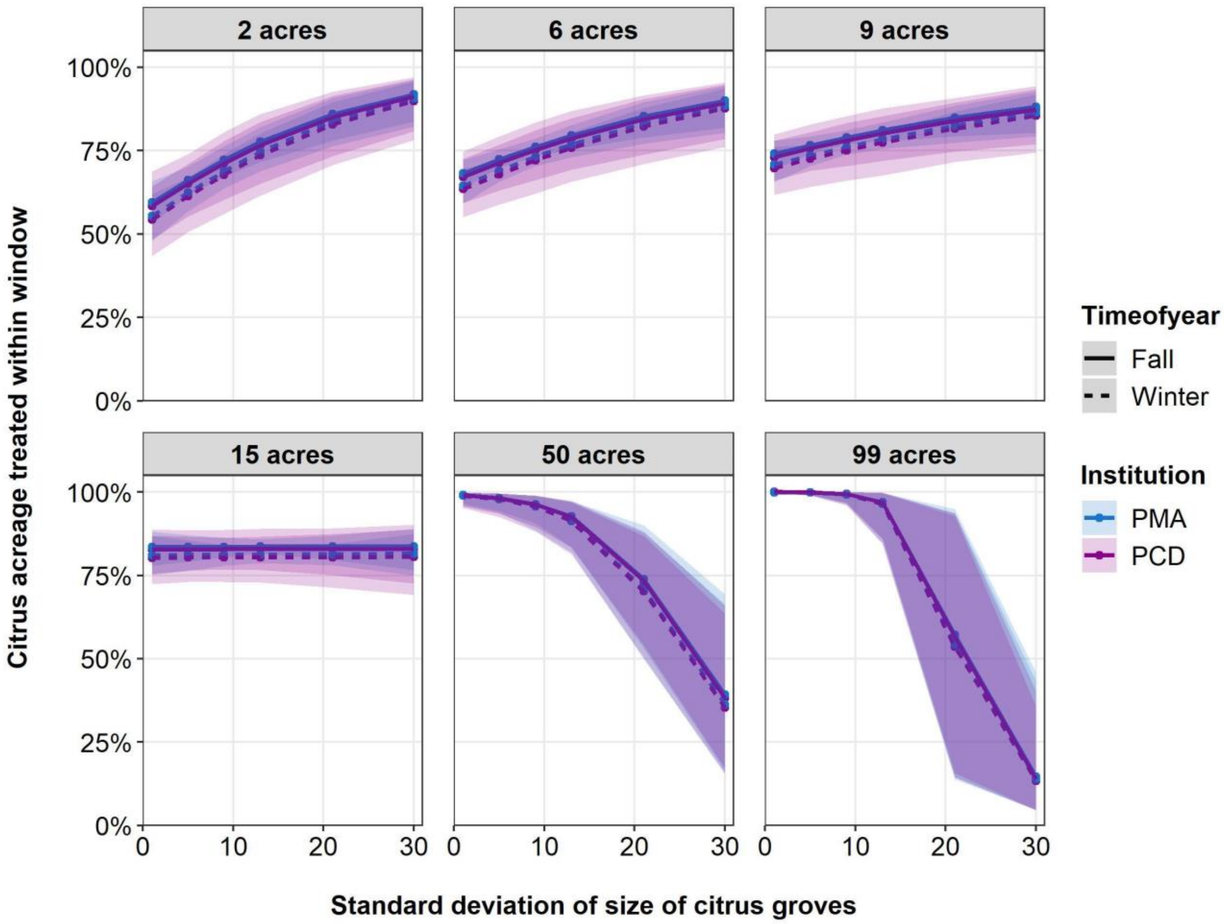

Fig. A2.9: Participation levels in AWM predicted by the zoib model depending on the average size of the citrus groves and their heterogeneity. The mean of the predicted values for season number 6 is shown in blue (PMAs) or in purple (PCDs). Predicted values for the fall treatments are linked by solid lines and predicted values for the winter treatments are linked by dashed lines. The panels show different average sizes of the citrus groves in a management unit.

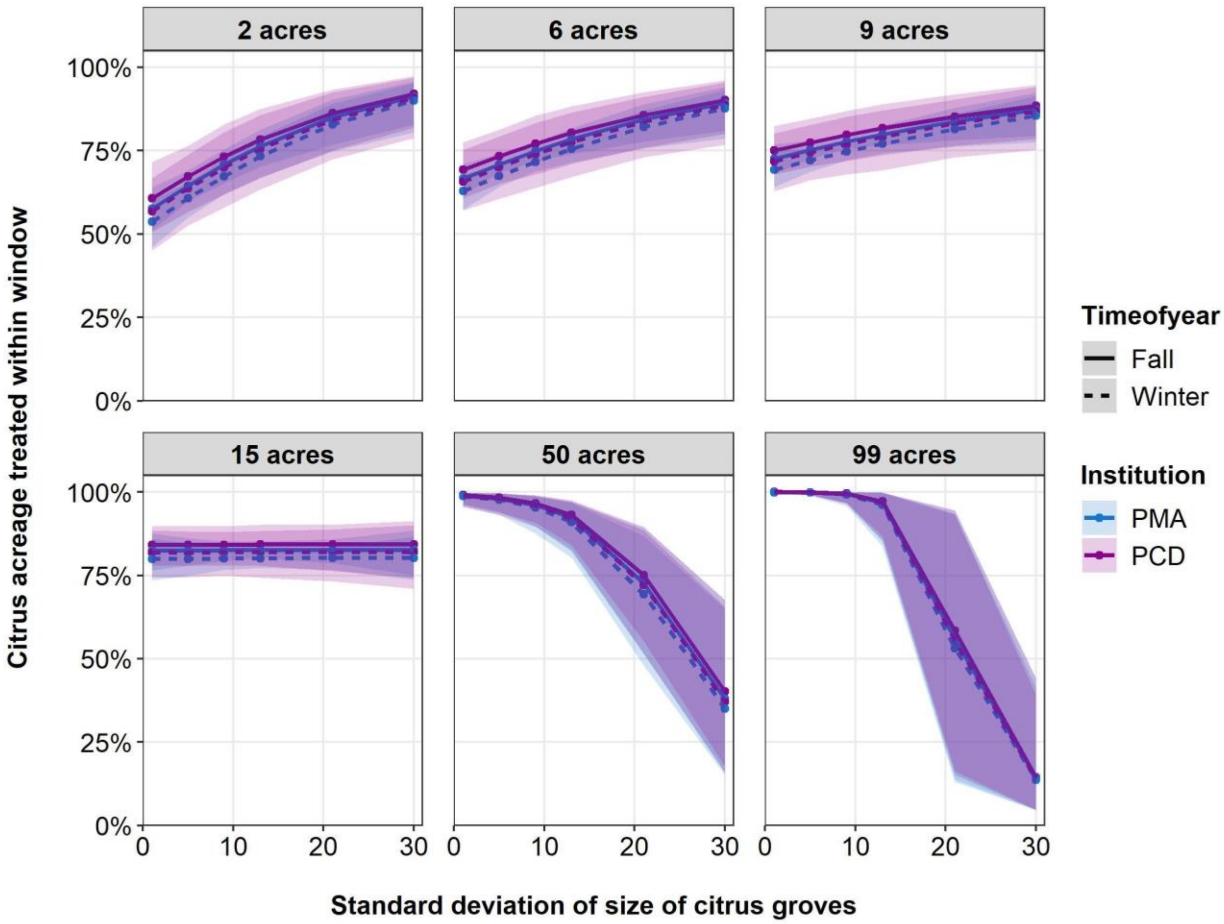

Fig. A2.10: Participation levels in AWM predicted by the zoib model depending on the average size of the citrus groves and their heterogeneity. The mean of the predicted values for season number 7 is shown in blue (PMAs) or in purple (PCDs). Predicted values for the fall treatments are linked by solid lines and predicted values for the winter treatments are linked by dashed lines. The panels show different average sizes of the citrus groves in a management unit.

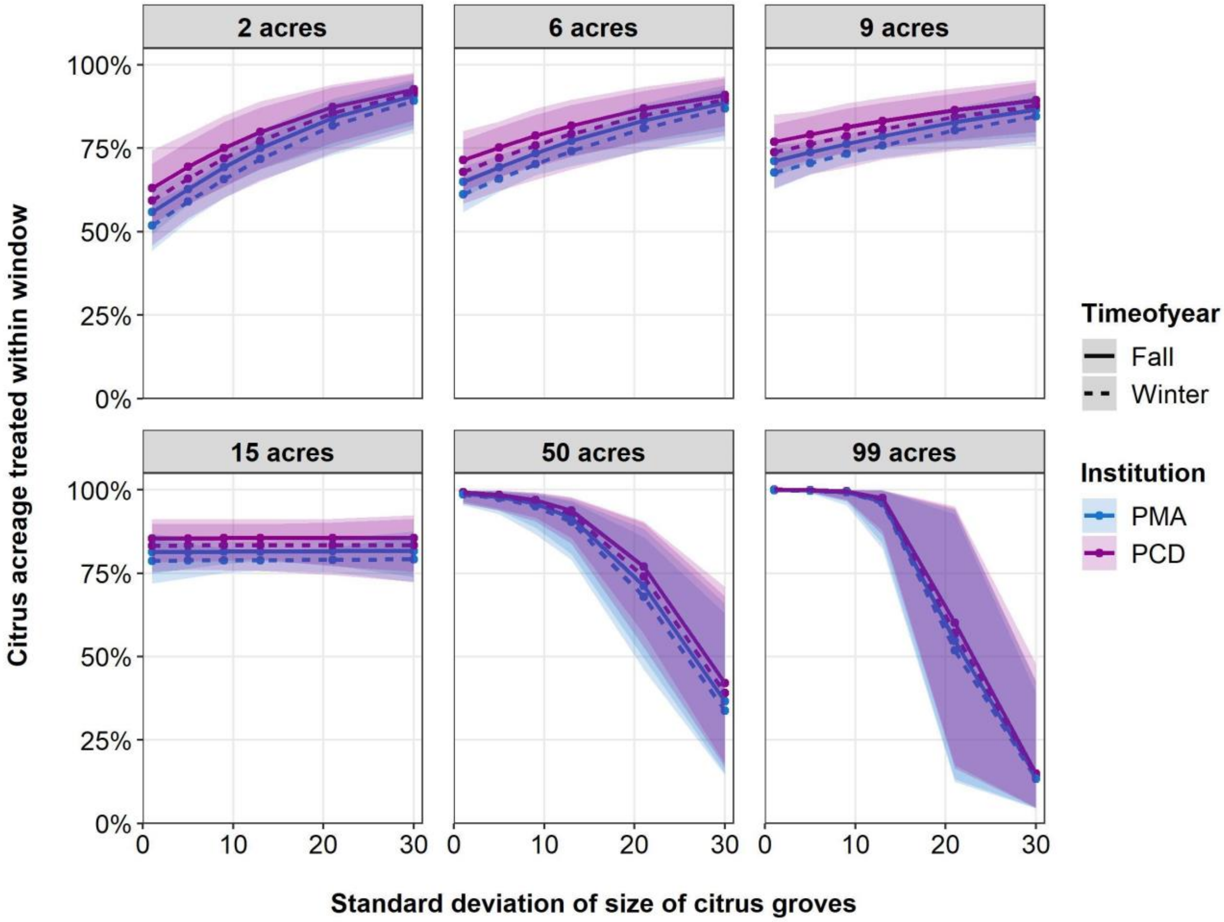

Fig. A2.11: Participation levels in AWM predicted by the zoib model depending on the average size of the citrus groves and their heterogeneity. The mean of the predicted values for season number 8 is shown in blue (PMAs) or in purple (PCDs). Predicted values for the fall treatments are linked by solid lines and predicted values for the winter treatments are linked by dashed lines. The panels show different average sizes of the citrus groves in a management unit.

Table A2.1: Institutions coordinating area-wide management of ACP in Southern California.

County	Institution	History	Citrus acreage	Assessment rate (2018)	Coordinated treatments	Number of management units	Using PMAs?	Participation in AWM	Challenges	Other activities
Imperial	Imperial County Citrus Pest Control District	Formed in 1972 for California red scale (*Aonidiella aurantii*) control[1]. Expanded in 2013 to the whole county for ACP and HLB control[2]	7,200	$15 / acre	Fall (Aug-Oct, Winter (Dec-Jan), Spring (Feb-Apr)	7 (6 after 2020)	No, PCD growing zones	High	ACP from across the Mexican border	Outreach, trap monitoring, coordination with Mexican authorities
Riverside	Citrus Pest Control District No. 2 (Coachella	Formed in 1946 for California red scale	8,000	$150 / acre	Fall (Sep-Oct), Winter (Dec-Jan)	4	No, four zones	High, reimbursing for treatments	Reinfestation from residential areas	Tree removal, biocontrol

	Valley)	control[3]								
	Citrus Pest Control District No. 3 (Hemet)	Formed in 2017 for ACP and HLB control	2,134	$100/ acre	Fall (Sep), Winter (Dec-Jan)	2	No, two zones	Very high, three growers. Reimbursing for treatments	Reinfestation from residential areas	Funding some activities in residential areas
	Rest of the county	No entity directing the sprays	1,500	None	Fall, Winter			Low, not tracked	Absentee owners, small growers	UC Riverside promoting participation
San Bernardino	San Bernardino ACP/ HLB Task Force	Formed in 2014[4]	3,000	None	Fall (Oct-Nov), Winter (Nov-Dec), Spring (May-Jul)	19	Yes	Variable	Small growers, scarcity of PCOs, urban interface, water supply, bad actors	Grower liaison in contact with homeowners, reporting abandoned trees
San Diego	San Diego County Citrus Pest Control District	Formed in 2017 for ACP and HLB control[5]	4,500	$180 / acre	Fall (Aug-Sep), Winter (Jan), Spring (May-Jun)	3	No, three areas (Borrego Springs, San Pasqual, Pauma/Pala)	Variable when it was voluntary. Now higher because of assessment reimbursements	Problems with organic treatments, small growers	County authorities monitor abandoned trees and try to remove them

							Valley)			
Santa Barbara	Advisory committee	Formed in 2015 for ACP and HLB control[6]	4,425	None	Fall (Sep), Winter (Jan)	12 (11 after 2019)	No, treating by cities	High	Weather, small properties	
Ventura	Ventura ACP/ HLB Task Force	Formed in 2010 for ACP and HLB control[7]	25,000	None	Fall (Jul-Sep + Sep-Nov), Winter (Jan-Mar), Spring (Apr-Jun)	50	Yes	High	Spraying equipment shortage, continuous harvest, weather, movement of fruit	Outreach campaign in residential areas, reporting system for abandoned trees

[1] (Margo Sanchez, pers. comm.), [2] (Mark McBroom, pers. comm.), [3](Baker 1988), [4](Bob Atkins, pers. comm.), [5](Cressida Silvers, pers. comm.),[6](SDCCPCD 2021), [7](John Krist, pers. comm.)

Table A2.2: Socio-economic characteristics of the survey respondents who indicated that they had citrus groves in Southern California (n =98).

Survey item	Responses
Role in citrus production	
Grove Owner	38
Ranch Manager	17
PCA	18
PCO	2
Other	18
NA	5
Farm size	
< 5 acres	23
5 – 25 acres	18
26 – 100 acres	11
101 – 500 acres	13
> 500 acres	28
NA	5
Age	
<35 years	12
35 - 50 years	14
51 – 65 years	37
> 65 years	35
Management system	
Conventional	59
Organic	13
Both	23
NA	3

Income from citrus	
< 25%	40
26 - 50%	13
51 - 75%	16
76 - 100%	23
NA	6

Note: Pest Control Adviser (PCA), Pest Control Operator (PCO), no answer (NA)

Table A2.3: Posterior mean and 95% credible interval for the parameters in the zoib regression models evaluated that were more complex than the selected model (SD28).

		SD22 mean	SD22 2.5%	SD22 97.5%	SD23 mean	SD23 2.5%	SD23 97.5%	SD24 mean	SD24 2.5%	SD24 97.5%	SD19 mean	SD19 2.5%	SD19 97.5%	SD28 mean	SD28 2.5%	SD28 97.5%
logit (mean)	Institutional approach[†]	-1.08	-1.67	-0.52	-1.08	-1.61	-0.53	-1.06	-1.63	-0.50	-0.68	-1.21	-0.13	-1.09	-1.65	-0.57
	Group size	-0.01	-0.02	0.00	-0.01	-0.02	0.00	-0.01	-0.02	0.00	-0.01	-0.02	-0.01	-0.01	-0.02	0.00
	Size of resource system	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Grove size	0.10	0.06	0.14	0.10	0.07	0.14	0.10	0.06	0.15	0.08	0.04	0.12	0.10	0.06	0.14
	Heterogeneity	0.08	0.05	0.12	0.09	0.05	0.12	0.09	0.05	0.12	0.12	0.08	0.15	0.08	0.05	0.12
	Season[‡]	-0.18	-0.32	-0.04	-0.17	-0.30	-0.04	-0.17	-0.29	-0.03	-0.16	-0.29	-0.03	-0.17	-0.30	-0.05
	Age	-0.07	-0.10	-0.04	-0.07	-0.10	-0.05	-0.07	-0.10	-0.05	-0.07	-0.10	-0.05	-0.07	-0.10	-0.05

	Institution† x Age	0.17	0.10	0.25	0.17	0.09	0.25	0.17	0.09	0.25	0.18	0.09	0.26	0.17	0.10	0.25
	Grove size x Heterogeneity	-0.01	-0.01	0.00	-0.01	-0.01	0.00	-0.01	-0.01	0.00	-0.01	-0.01	0.00	-0.01	-0.01	0.00
	Intercept	0.43	0.06	0.78	0.40	0.07	0.73	0.42	0.07	0.77	0.46	0.12	0.81	0.43	0.11	0.79
log(dispersion)	Institutional approach†	-0.81	-1.32	-0.30	-0.81	-1.32	-0.33	-0.80	-1.30	-0.31				-0.81	-1.30	-0.38
	Group size	0.03	0.02	0.04	0.03	0.02	0.04	0.03	0.02	0.04	0.03	0.03	0.04	0.03	0.02	0.04
	Size of resource system	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00				0.00	0.00	0.00
	Grove size	0.06	0.02	0.11	0.06	0.02	0.11	0.06	0.01	0.10				0.06	0.02	0.10
	Heterogeneity	-0.05	-0.09	-0.01	-0.05	-0.09	-0.02	-0.05	-0.09	-0.01				-0.05	-0.08	-0.02
	Season‡	-0.07	-0.27	0.13												
	Age	0.00	-0.03	0.04												
	Intercept	0.90	0.56	1.27	0.88	0.60	1.15	0.89	0.60	1.17	1.07	0.91	1.23	0.88	0.62	1.13

logit(P(1))	Institutional approach[†]	-92.64	-221.71	-6.68	-34.93	-85.72	-3.62	-46.39	-119.37	-3.70				-67.45	-188.90	-4.66
	Group size	-0.69	-1.21	-0.29	-0.61	-1.01	-0.31	-0.59	-1.07	-0.28	-0.49	-0.87	-0.22	-0.58	-0.93	-0.30
	Size of resource system	0.00	0.00	0.00												
	Grove size	-0.02	-0.15	0.10												
	Heterogeneity	0.04	-0.12	0.19							-0.01	-0.13	0.10			
	Season[‡]	0.51	-0.86	1.85												
	Age	-0.13	-0.40	0.13												
	Intercept	-1.06	-3.25	0.93	-1.37	-2.35	-0.43	-1.41	-2.45	-0.37	-2.13	-3.42	-0.96	-1.43	-2.38	-0.51
logit(P(0))	Institutional approach[†]	-0.22	-0.91	0.49												
	Group size	-0.31	-0.39	-0.24	-0.30	-0.37	-0.24	-0.32	-0.39	-0.26	-0.28	-0.34	-0.23	-0.32	-0.38	-0.27

Size of resource system	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00						
Grove size	0.08	0.04	0.13	0.08	0.04	0.13	0.05	0.02	0.08	0.07	0.05	0.10			
Heterogeneity	-0.05	-0.11	0.00	-0.05	-0.10	0.00							0.03	0.00	0.06
Season‡	-0.36	-0.82	0.08												
Age	-0.08	-0.17	0.00												
Intercept	0.50	-0.27	1.30	-0.13	-0.74	0.46	-0.20	-0.77	0.36	-0.34	-0.91	0.22	0.54	0.10	1.04
DIC	1679813			1679811			1679814			1679852			1679849		
Multivariate psrf	1.39			1.05			1.20			1.01			1.10		

Note: deviance information criterion (DIC), potential scale reduction factor (prsf)

† Institutional approach was modeled as a factor, considering PMA as the baseline

‡ Season of treatment was modeled as a factor, considering Fall as the baseline

Table A2.4: Posterior mean and 95% credible interval for the parameters in the zoib regression models evaluated that were less complex than the selected model (SD28).

		SD27 mean	SD27 2.5%	SD27 97.5%	SD29 mean	SD29 2.5%	SD29 97.5%	SD30 mean	SD30 2.5%	SD30 97.5%	SD31 mean	SD31 2.5%	SD31 97.5%	SD13 mean	SD13 2.5%	SD13 97.5%	SD21 mean	SD21 2.5%	SD21 97.5%	SD0 mean	SD0 2.5%	SD0 97.5%
logit (mean)	Institutional approach†	-1.08	-1.64	-0.51	-1.34	-1.89	-0.83	-0.24	-0.68	0.20	-0.54	-0.97	-0.13	-0.67	-1.17	-0.13	-0.58	-1.13	-0.03			
	Group size	-0.01	-0.02	0.00	-0.02	-0.02	-0.01	-0.01	-0.02	0.00	-0.02	-0.02	-0.01	-0.01	-0.02	-0.01	-0.02	-0.03	-0.01			
	Size of resource system	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00			
	Grove size	0.10	0.07	0.14	0.03	0.00	0.06	0.10	0.06	0.14	0.03	0.00	0.05	0.08	0.04	0.12	0.09	0.05	0.12			
	Heterogeneity	0.08	0.04	0.12	0.02	-0.01	0.05	0.08	0.05	0.12	0.02	-0.01	0.05	0.12	0.08	0.15	0.13	0.09	0.16			
	Season‡	-0.17	-0.29	-0.04	-0.15	-0.28	-0.02	-0.17	-0.30	-0.04	-0.15	-0.28	-0.03	-0.16	-0.29	-0.03	-0.16	-0.30	-0.02			

	Age	-0.07	-0.10	-0.05	-0.07	-0.10	-0.05	-0.06	-0.08	-0.03	-0.06	-0.08	-0.03	-0.07	-0.10	-0.05	-0.07	-0.10	-0.04			
	Institution† x Age	0.17	0.09	0.25	0.16	0.08	0.24							0.18	0.09	0.26	0.17	0.08	0.26			
	Grove size x Heterogeneity	-0.01	-0.01	0.00				-0.01	-0.01	0.00				-0.01	-0.01	0.00	-0.01	-0.01	0.00			
	Intercept	0.41	0.07	0.76	1.05	0.79	1.30	0.34	-0.01	0.69	0.96	0.71	1.23	0.47	0.12	0.81	0.51	0.17	0.86	1.06	0.98	1.15
log (dispersion)	Institutional approach†	-0.82	-1.32	-0.33	-0.88	-1.38	-0.40	-0.89	-1.38	-0.41	-0.95	-1.44	-0.44									
	Group size	0.03	0.02	0.04	0.03	0.02	0.04	0.03	0.02	0.04	0.03	0.02	0.04	0.03	0.03	0.04						
	Size of resource system	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00									
	Grove size	0.06	0.02	0.11	0.06	0.02	0.10	0.07	0.03	0.11	0.07	0.03	0.11									

	Heterogeneity	-0.05	-0.09	-0.02	-0.06	-0.10	-0.02	-0.06	-0.09	-0.02	-0.06	-0.10	-0.03									
	Season‡																					
	Age																					
	Intercept	0.88	0.60	1.16	0.87	0.60	1.16	0.87	0.59	1.14	0.87	0.59	1.14	1.07	0.91	1.23	1.53	1.42	1.63	1.24	1.14	1.34
logit (P(1))	Institutional approach†																					
	Group size	-0.47	-0.83	-0.23	-0.48	-0.89	-0.23	-0.47	-0.84	-0.22	-0.51	-0.91	-0.24	-0.49	-0.85	-0.22						
	Size of resource system																					
	Grove size																					
	Heterogeneity																					
	Season‡																					
	Age																					

	Intercept	-2.22	-3.12	-1.36	-2.17	-3.10	-1.31	-2.21	-3.12	-1.35	-2.14	-3.06	-1.27	-2.17	-3.10	-1.30	-4.37	-5.00	-3.79	-4.37	-5.03	-3.79
logit (P(0))	Institutional approach†																					
	Group size	-0.32	-0.38	-0.27	-0.32	-0.38	-0.26	-0.32	-0.38	-0.26	-0.32	-0.38	-0.26	-0.31	-0.37	-0.26						
	Size of resource system																					
	Grove size																					
	Heterogeneity	0.03	0.00	0.07	0.03	0.00	0.07	0.03	0.00	0.07	0.03	0.00	0.07									
	Season‡																					
	Age																					
	Intercept	0.53	0.06	1.01	0.53	0.05	1.00	0.53	0.05	1.02	0.53	0.05	1.03	0.89	0.55	1.25	-1.43	-1.61	-1.25	-1.43	-1.60	-1.26
	DIC	1679860			1679885			1679877			1679900			1679883			1680225			1680402		

Multivariate psrf	1.0 4	1.0 2	1.0 5	1.0 5	1.0 2	1.0 5	1

Note: deviance information criterion (DIC), potential scale reduction factor (prsf)

† Institutional approach was modeled as a factor, considering PMA as the baseline

‡ Season of treatment was modeled as a factor, considering Fall as the baseline

Table A2.5: Posterior mean and 95% credible interval for the parameters in the selected zoib regression model (SD28) with the size of the resource system, and the model without this independent variable (SD32).

		SD28 mean	SD28 2.5%	SD28 97.5%	SD32 mean	SD32 2.5%	SD32 97.5%
logit(mean)	Institutional approach†	-1.09	-1.65	-0.57	-0.65	-1.17	-0.13
	Group size	-0.01	-0.02	0.00	-0.01	-0.01	0.00
	Size of resource system	0.00	0.00	0.00			
	Grove size	0.10	0.06	0.14	0.13	0.09	0.16
	Heterogeneity	0.08	0.05	0.12	0.10	0.07	0.13
	Season‡	-0.17	-0.30	-0.05	-0.17	-0.31	-0.04
	Age	-0.07	-0.10	-0.05	-0.07	-0.10	-0.05
	Institution† x Age	0.17	0.10	0.25	0.17	0.09	0.26
	Grove size x Heterogeneity	-0.01	-0.01	0.00	-0.01	-0.01	-0.01
	Intercept	0.43	0.11	0.79	0.26	-0.06	0.58
log(dispersion)	Institutional approach†	-0.81	-1.30	-0.38	-0.42	-0.82	0.01
	Group size	0.03	0.02	0.04	0.04	0.03	0.05
	Size of resource system	0.00	0.00	0.00			
	Grove size	0.06	0.02	0.10	0.07	0.03	0.11
	Heterogeneity	-0.05	-0.08	-0.02	-0.05	-0.08	-0.02
	Season‡						

	Age						
	Intercept	0.88	0.62	1.13	0.88	0.62	1.15
logit(P(1))	Institutional approach†	-67.45	-188.90	-4.66	-53.65	-126.63	-3.99
	Group size	-0.58	-0.93	-0.30	-0.58	-0.94	-0.30
	Size of resource system						
	Grove size						
	Heterogeneity						
	Season‡						
	Age						
	Intercept	-1.43	-2.38	-0.51	-1.42	-2.39	-0.47
logit(P(0))	Institutional approach†						
	Group size	-0.32	-0.38	-0.27	-0.32	-0.37	-0.27
	Size of resource system						
	Grove size						
	Heterogeneity	0.03	0.00	0.06	0.03	0.00	0.07
	Season‡						
	Age						
	Intercept	0.54	0.10	1.04	0.54	0.06	1.04
	DIC	1679849			1679861		
	Multivariate psrf	1.10			1.33		

Note: deviance information criterion (DIC), potential scale reduction factor (prsf)

[†] Institutional approach was modeled as a factor, considering PMA as the baseline

[‡] Season of treatment was modeled as a factor, considering Fall as the baseline

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Appendix 3: Data analysis

All statistical analyses were done in the R programming environment version 4.0.3 (R Foundation for Statistical Computing 2020) with a Windows 10 Pro version 1909, 64-bit operating system (Microsoft, Redmond, WA, U. S. A.). Data manipulation and descriptive statistics were conducted using the R package "dplyr" (Wickham et al. 2021) and base R. Plots were generated with the R package "ggplot2" (Wickham 2016).

Analysis of survey data

Correlations between ordered categorical variables from the survey were tested using Spearman's rank correlation test.

Analysis of participation in AWM

Four of the independent variables in the regression model (group size, size of the resource system, size of citrus groves, heterogeneity in grove size) were based on information recorded in the database of citrus operations in California maintained by the Citrus Research Board (CRB), hereafter referred to as the *citrus layer*. We obtained access to the June 2020 version of the citrus layer (Rick Dunn, personal communication) and the outlines of each AWM unit in the state of California (Rick Dunn and Robert Johnson, pers. com.). The software ArcGIS Pro (ESRI, Redlands, CA, U. S. A.) was used to overlay the citrus layer and the institutional layer in order to calculate the group size, size of the resource system, size of citrus groves and heterogeneity in grove size in each AWM unit using the "Dissolve" tool. Correlations between numeric independent variables in the regression model were tested using Pearson's correlation test.

- Group size: It was calculated as the number of different PURs within each AWM unit on the CRB citrus layer, which was compared with the number of PURs routinely collected by the grower liaisons and found to be highly correlated (ρ=0.72, *P*=2E-15).
- Size of the resource system: It was calculated by aggregating all of the citrus properties in each PMA/PCD and calculating the sum of the grove acres. The calculated total citrus acreage under each management unit was highly correlated with data provided by the grower liaisons (ρ=0.97, *P*<2.2E-16) and with the citrus acreage recorded in the California Statewide Crop Mapping database (ρ=0.98, *P*<2.2E-16) (Department of Water Resources 2020).
- Size of citrus groves: It was calculated with the "Dissolve" tool from the software ArcGIS Pro by aggregating all of the citrus properties in each PMA/PCD and calculating the mean of the grove acres.

- Heterogeneity in grove size: It was calculated with the "Dissolve" tool from the software ArcGIS Pro by aggregating all of the citrus properties in each PMA/PCD and calculating the standard deviation of the grove acres.

Some preliminary statistical analyses were conducted to guide the hypotheses tested with the zoib regression model.

- Institutional approach (PMA/PCD): there was significantly higher participation in AWM in PCDs than PMAs in every season ($P \leq 0.043$ on t-tests), except the Fall of 2016 ($P=0.99$).
- Group size: there was a significant negative correlation between the number of pesticide use permits and participation in AWM ($\rho=-0.28$, $P<2.2E\text{-}16$).
- Size of citrus groves: there was a significant positive correlation between the average size of citrus groves and participation in AWM ($\rho=0.27$, $P \leq 2.2E\text{-}16$).

Zero-and-one-inflated beta regression models were constructed using the R package "zoib" (Liu and Kong 2015). A zoib model assumes that the dependent variable *y* (the percentage of citrus acreage in each PMA/PCD treated within the recommended window) follows a piecewise distribution such that

$$f(y_i) = \begin{cases} p_i & \text{if } y_i = 0 \\ (1-p_i)q_i & \text{if } y_i = 1 \\ (1-p_i)(1-q_i)\mathrm{Beta}(\alpha_{i1}, \alpha_{i2}) & \text{if } y_i \in (0,1) \end{cases}$$

where p_i represents the probability $\Pr(y_i=0)$, q_i represents the conditional probability $\Pr(y_i=1|y_i\neq 0)$, and α_{1i} and α_{2i} represent the shape parameters of the beta distribution for $y_i \in (0,1)$. These distributions are combined to derive the unconditional estimate of the response $E(y_i)$:

$$E(y_i) = (1-p_i)(\,q_i + (1-q_i)\mu_i^{(0,1)}$$

The zoib regression model estimates the logit [*i.e.*, the log(odds)] of the expected value of the beta distribution, the logit of $P(0)$ and $P(1)$ and the log of the dispersion of the beta distribution as linear functions of fixed and/or random effects. The coefficients of the effects on the mean of the beta regression can be interpreted as the expected change in the logit of participation with a one unit change in the corresponding variable. The coefficients of the effects on P(0) and P(1) are interpreted as the change in the logit of either having Participation=0 or Participation=1 with a one unit change in the corresponding variable. The coefficients of the effects on the dispersion of the beta distribution indicate the change in the log of the dispersion with a one-unit change in the corresponding variable (van Woerden et al. 2019). Based on a Bayesian framework, the coefficients are estimated through a Markov Chain Monte Carlo (MCMC) approach (Liu and Kong 2015). Two independent MCMC chains were run per model, each with 5000 iterations, including 200 iterations for burn-in, and thinned by a factor of 2. We assumed a Normal prior distribution N(0, 0.001) for each regression coefficient.

MCMC convergence was visually checked with trace plots and autocorrelation plots. The potential scale reduction factor (psrf) was calculated for each model parameter and the threshold psrf≤1.1 was used to determine that convergence had been reached (Gelman et al. 2021). In cases where psrf>1.1, we repeated the MCMC process with three chains, 10000 iterations per chain, 1000 for burn-in and thinned by a factor of 50. Posterior inferences for each parameter are reported as the mean and 95% credible interval (CI). Model selection was based on the deviance information criterion (DIC) (Liu and Kong 2015). Starting with the most complex model including the seven independent variables mentioned in the previous section, we examined the results and iteratively removed variables for which the CI of the posterior estimates was bounded by a negative and a positive value, and therefore comprised zero. Among competing models that fulfilled the previous condition, we chose the one with the lowest DIC (Table A4.1, Table A4.2).

Finally, the participation levels predicted by the zoib regression model were calculated using the pred.zoib function in the R package "zoib" (Liu and Kong 2015). Predictions were based on a new dataset where the independent variable under evaluation was allowed to vary within the range observed in the original dataset and the rest of the independent variables were fixed at their mean value, except in the case of interaction terms, where both variables were allowed to vary within the observed range.

All data sets and R code used in this study will be posted in a repository at the following URL after publication of this manuscript: https://github.com/nmcr01?tab=repositories.

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