Climate Resilience in Central America's 'Dry Corridor': Modelling the Effectiveness and Adoption of Water-Conserving Farming Practices

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Abstract

Smallholder farmers in Central America's Dry Corridor are vulnerable to the intensification of droughts in the region induced by climate change. These droughts lead to severe economic and humanitarian impacts. Widespread adoption of so-called Water Smart Agriculture (WSA) practices is a potential pathway to increased resilience to drought. We present an initial implementation of a coupled social-ecohydrological model of the spread of WSA practices in Central America's Dry Corridor. The model aims to understand how WSA adoption may be accelerated in light of further climate change. Both the social system and the ecohydrological model act on a computational grid where each cell represents a field. The agent-based social system model computes which fields use WSA based on farmers' desperation and perceived success of their neighbours. The ecohydrological model computes the evolution of soil moisture and plant biomass (representative of harvest) on each grid cell based on farmers' WSA decisions and inputs of temperature and rainfall using simple differential equations. Initial results suggest that if farmers can perceive the benefits of a neighbour using WSA, they will switch to WSA themselves, causing the practice to spread quickly through the social system. Exploring the effect of different climate scenarios, levels of farmer jealousy and varying numbers of farmers using WSA initially, we find that only the initial number of farmers has a statistically significant effect on the speed of the spread of WSA usage. However, significant limitations to the model remain, making these results highly preliminary.

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Project Report

1 Introduction

Climate change is intensifying droughts and leading to irregular or extreme rainfall patterns in Central America (Hannah et al. [2017]). The 'Dry Corridor', a mountainous region of tropical dry forest stretching across Guatemala, El Salvador, Honduras, Nicaragua, and Costa Rica, is particularly susceptible to these climactic changes. The social impact of warming in this region is severe. Between 54 and 67% of people in the Dry Corridor are smallholder farmers, who depend on the weather for their livelihoods (FAO [2021a]). As temperatures rise, the traditional farming practices used by these farmers are increasingly insufficient for delivering reliable crop yields. This diminishing food security is driving many people to emigrate, and pushing millions of others into food poverty (FUSADES [2021]).

Alternative farming practices offer ways of combating this problem by retaining soil moisture and protecting crop yields in hot conditions. One such practice is Water Smart Agriculture (WSA), promoted and funded by the NGO Catholic Relief Services (CRS) (Callahan [2023]). Starting from 400 farmers in 2015, WSA practices were implemented by 3000 farmers in 2020. WSA has been shown to increase soil moisture and crop yields relative to traditional practices - especially in hot years (FUSADES [2021]). It is CRS' stated aim for 500,000 farmers to implement WSA practices by 2030. Depending on uptake, alternative agricultural practices like WSA could play a vital role in maintaining Dry Corridor food production as the climate continues to heat up (Callahan [2023]).

In light of climate changes in the Dry Corridor, and the alternative farming practices that attempt to combat them, this modelling project aims to answer the following questions:

- How do different climate scenarios impact the effectiveness of Water Smart Agriculture?
- What social and environmental factors affect the uptake of Water Smart Agriculture?
- What conditions are necessary for Water Smart Agriculture to reach 500,000 farmers by 2030?

We approached these questions by developing a coupled ecohydrological/social model in Python and NetLogo. The ecohydrological component is adapted from existing ecohydrology packages, and simulates the ecohydrological effects of Water Smart Agriculture on the field level. The social model was developed from first principles, and simulates the social dispersal of farming practices between farmers. The success of WSA in maintaining soil moisture and crop yields as dictated by the ecohydrological model is perceived by the farmers in the social model and thus dictates the speed of dispersal.

Based on our simple model, we find that:

- WSA yields are higher than traditional yields across climate scenarios; and
- The number of lead farmers is the most important parameter for the rate of increase in

WSA usage.

2 Background

2.1 Social Context: The Dry Corridor

The Dry Corridor is a region 1600 kilometres long and 100-400 kilometres wide, stretching along the west coast of Central America (FAO [2022]). 7.5% of the region suffers severe droughts, while 50.5% suffers high drought and the remaining 42% suffers low drought conditions each year (FAO [2021a]). 11.5 million people live there, and at least half of these people own and work smallholder farms (FAO [2021a]).

Smallholder farms are approximately 1-2 hectares in size (equivalent to a square field with edges 100-140m in length). They are usually managed by a household, with the mean household size being 5.4 people. These farming families grow enough food to feed themselves, with a little left over to sell on international markets (Alpízar et al. [2020]). 80% of smallholder farmers live below the poverty line, and 30% live in extreme poverty (FAO [2021a]), while only 30% are literate (FUSADES [2021]). Because smallholders don't have the financial resources to invest in crucial technologies like suitable irrigation, their harvests depend heavily on the weather (Alpízar et al. [2020]).

Climate change projections indicate that over the next few decades, the Dry Corridor will become warmer. Rainfall patterns may also become increasingly erratic, although it's unclear whether more or less total rain will fall (Hannah et al. [2017]). These climactic changes will effect smallholder farmers and their livelihoods profoundly. Further, these changes have serious implications for wider food security, as 92% of basic food-crops in the region are produced by rain-fed farms (Beekman et al. [2014]). When smallholder farms fail, as they did in the severe droughts of 2018, millions of people require food assistance (Callahan [2023]).

Far from being an isolated problem, many of the challenges faced in the Dry Corridor will develop or worsen in other regions in coming decades (FAO [2021b]). Therefore it is crucial that sustainable, climate-resilient farming practices are developed now to tackle food insecurity both locally and globally into the future.

2.2 Water Smart Agriculture

A promising response to climate challenges in the Dry Corridor has been the promotion of regenerative farming practices, such as Water Smart Agriculture (Sain et al. [2017]). WSA (or ASA - *Agua y Suelo para la Agricultura* in Spanish) is a program designed and funded by the NGO Catholic Relief Services, who have been working in the Dry Corridor for over 60 years. The key tenets of WSA are:

- maintaining permanent soil cover and minimising tillage;
- diversifying crops and rotating crops between fields;
- using cover crops and trees;
- deliberate use of appropriate (and natural) fertilisers;
- coordinated watershed-level water management; and
- keeping messaging simple, actionable, and with farmer wellbeing at heart. (ASA [2023])

These practices go a long way to regenerating soil health and maintaining soil moisture even in the dry period. By keeping fields covered instead of stripping away old plant matter, and by shading the soil with cover crops, WSA retains water on the field. Further, by limiting the use of fertilisers and including diverse native plants, WSA enhances soil health. Ultimately, these practices lead to increased resilience and increased yield for farmers in worsening weather conditions. After four years of implementing WSA, smallholders' crop yields increased by approximately 40%, and soil moisture during the dry period increased by 23% (FUSADES [2021]).

Findings from the scientific literature broadly support the assertion that covering fields with mulches and the correct use of cover crops can improve crop yields (Adetunji et al. [2020]). Mulching decreases soil moisture loss to evaporation, while cover cropping can improve soil moisture as well as soil nutrient content and physical properties (Qi and Helmers [2010], Blanco-Canqui et al. [2011]). However, improvements to soil properties brought about by cover crops are not immediate, but rather emerge over several years (Van Dung et al. [2022]). Additionally, it is important to keep in mind that these changes are not automatic, and cover cropping that is poorly adjusted to regional soil properties and climate might lead to the cover crop competing with the main crop for water and nutrients (Adetunji et al. [2020], Abdalla et al. [2019]).

CRS began implementing WSA in 2015. They trained over 60 extensionists from different countries in the Dry Corridor. These extensionists went on to work closely with 400 lead farmers, who implemented WSA on demonstration plots to display its effectiveness. Then the lead farmers and extensionists together ran field schools, which expanded knowledge of WSA to nearby farmers. By 2020, the number of farmers implementing WSA had climbed to 2914. The WSA program was found to be cost effective, to efficiently generate ecosystem services such as carbon sequestration, and to improve climate resilience for smallholder farmers (FUSADES [2021]).

However, WSA adoption rates are often lower than anticipated, and many farmers revert to traditional practices after NGOs recede. Crucial factors in the adoption of WSA are the conditions specific to an individual farm, the quality and abundance of extension services, and social network effects such as peer pressure and group membership. For WSA practices to continue to expand, greater attention must be paid to these issues (GWI [2015]).

Catholic Relief Services aim for 500,000 hectares and 500,000 smallholder farmer families to implement WSA by 2030 (Callahan [2023]). This represents roughly 7% of smallholder farmers in the Dry Corridor, but only 1.5% of the landmass due to large farms holding disproportionately much of the land (FAO [2022]). Nonetheless, WSA implementations may significantly increase food security in the region. Farmers implementing WSA during the extreme droughts of 2018 produced 41% more maize than those using traditional methods (Callahan [2023]). Thus, regenerative farming practices such as Water Smart Agriculture have a crucial role to play in mitigating the impacts of climate change.

2.3 Theories Informing Model Design

Water Smart Agriculture operates in two spheres. The first is the ecohydrological sphere, where the implementation of WSA practices generates biological impacts on soil moisture, crop yields, and farm resilience. The second is the social sphere, in which human actors gain knowledge of WSA practices and choose whether to implement them, as well as passing this knowledge onto others. To approach the design of a computer model representing this complex socio-ecohydrological system, we draw on established practices in sociological and ecohydrological research. What follows is a brief description of social network theory, and an exploration of an existing ecohydrological model, CATGraSS.

2.3.1 Social Network Theory

Following social network theory, we conceptualise the social system of farmers embedded in communities as a network of nodes (farmers) connected by edges (social relations). Understood in this way, the social network facilitates the sharing of resources (and information) along connected edges. As such, farmers' positions in the network dictate their access to resources (Light and Moody [2020]).

2.3.2 The CATGraSS Ecohydrological Model

Turning now to ecohydrological processes, we draw on the design of CATGraSS, a model of soil moisture and vegetation. The individual components of CATGraSS are available as part of the Landlab Python package. CATGraSS was developed to simulate the establishment of different plant types in a semi-arid environment based on soil moisture availability and solar radiation varying across a landscape depending on slope and orientation of the land surface. It explicitly models soil moisture dynamics following an approach introduced by Laio et al. [2001]. The soil moisture module assumes that rainfall and temperature are inputs, i.e., neglects moisture recycling through atmospheric processes. In addition, interactions between cells such as moisture diffusion and run-on are ignored. Soil moisture is solved for using a vertically lumped (i.e., no explicit representation of the vertical dimension) differential equation on each cell (Zhou et al. [2013]):

$$n\frac{ds}{dt} = \frac{1}{Z_r}(I_a - ET_a(s) - D(s)) \tag{1}$$

On the LHS, n is soil porosity, s is the soil moisture saturation fraction and t is time. I_a on the RHS is the rate of water infiltration, Z_r is root zone depth, $ET_a(s)$ is the rate of evapotranspiration from the soil and its vegetation and $D(s)$ is the rate at which water leaks out from the root zone. The evolution of soil moisture is thus driven by inputs of rainfall and temperature. The rainfall controls how much water can infiltrate and thus feeds into I_a, while temperature controls the maximum rate at which water can evaporate from a surface. That quantity is also called the potential evapotranspiration (PET) and feeds into the calculation of $ET_a(s)$. $D(s)$ is only indirectly affected by rainfall and temperature as it is calculated from the current soil moisture content.

Crucially though, all RHS terms also directly or indirectly depend on the vegetation, so the soil moisture is tightly coupled to plant growth. The presence and type of vegetation affects the resistance of the ground surface to evaporation, so $ET_a(s)$ is calculated from PET using available soil moisture, the plant leaf area and the fraction of ground covered by vegetation. The ground cover can also affect how quickly water can infiltrate the soil (I_a) and how quickly it is lost to deep percolation($D(s)$).

For this reason, CATGraSS models vegetation dynamically instead of, e.g., just diagnosing it from soil moisture and environmental factors. Live (i.e., green) biomass B_l is modelled using the following differential equation (Zhou et al. [2013]):

$$\frac{dB_l}{dt} = \text{NPP} \cdot \phi_a - k_{sl}B_l - k_{sf}\xi B_l \tag{2}$$

where NPP is the plants' net primary productivity and ϕ_a is an allocation coefficient that determines how much of the productivity goes towards green biomass. k_{sl} is a senescence (death) parameter for live biomass, k_{sf} is the maximum drought-induced foliage loss rate and ξ is the mean water stress during the model time step, which depends on mean soil moisture. Similarly, the dead biomass is governed by the following equation (Zhou et al. [2013]):

$$\frac{dB_d}{dt} = k_{sl}B_l - k_{dd}\eta_{sd}B_d. \tag{3}$$

Here, k_{dd} is a decay constant for above-ground dead biomass, while η_{sd} is a function of maximum plant transpiration that accounts for the effect of temperature and humidity on decay rates. While we are not directly interested in the dead biomass itself, CATGraSS uses both live and dead Biomass to calculate vegetation cover fraction at the next time step. Therefore, solving Equation 3 is still relevant to our model: vegetation cover fraction influences the soil moisture component. More information on how CATGraSS solves these equations and how they are influenced by the functional type of the vegetation (e.g., grass, cover crop) can be found in the Soil Moisture and the Vegetation subsections of the ODD protocol in the appendix.

3 Model Formulation and Implementation

3.1 Model Overview

The purpose of this model is to answer our research questions:

- How do different climate scenarios impact the effectiveness of Water Smart Agriculture?
- What social and environmental factors affect the uptake of Water Smart Agriculture?
- What conditions are necessary for Water Smart Agriculture to reach 500,000 farmers by 2030?

We conceptualised the complex socio-ecohydrological system of farming practice impacts and uptake in the Dry Corridor as being composed of two separate systems. The first is the ecohydrological system. This captures the soil-level impacts of WSA practices such as the interactions between cover cropping, soil moisture, and crop yields. The second system is the social system, which captures how farmers are exposed to knowledge of farming practices, and why they choose to implement (or ignore) different practices.

The two models feed into one another, as shown in Figure 1. Farmers' decisions to implement WSA farming practices in the social model dictate where WSA effects appear in the ecohydrological model. The results of WSA practices as calculated by the ecohydrological model feed back into the social model. When these effects are sufficiently beneficial or detrimental to be of note, farmers will adapt their farming practices. These two submodels are now described in further detail.

3.2 Ecohydrology Model

Our ecohydrology model solves the equations introduced in section 2.3.2 on each cell of a 51x51 computational grid. But before we delve deeper inot how we adapted CATGraSS for modelling the ecohydrological impact of WSA decisions, we first need to establish a baseline cycle of a farming year in the dry corridor. We choose to model the ecohydrology on a daily time step in order to be able to capture the effects of the irregularity of precipitation. In light of the available time, we make use of a strongly simplified representation of seasonal precipitation patterns and farming practices in the dry corridor. We assume that there are very distinct dry and wet seasons, with the dry season taking up the first 3.5 months of the year. We neglect the midsummer drought ('Canícula') typical of the region, meaning the wet season in our model is uniform in its precipitation statistics (see e.g. Zhao et al. [2019] for a description of seasonal rainfall patterns and their drivers). Both dry and wet season rainfall are randomly generated

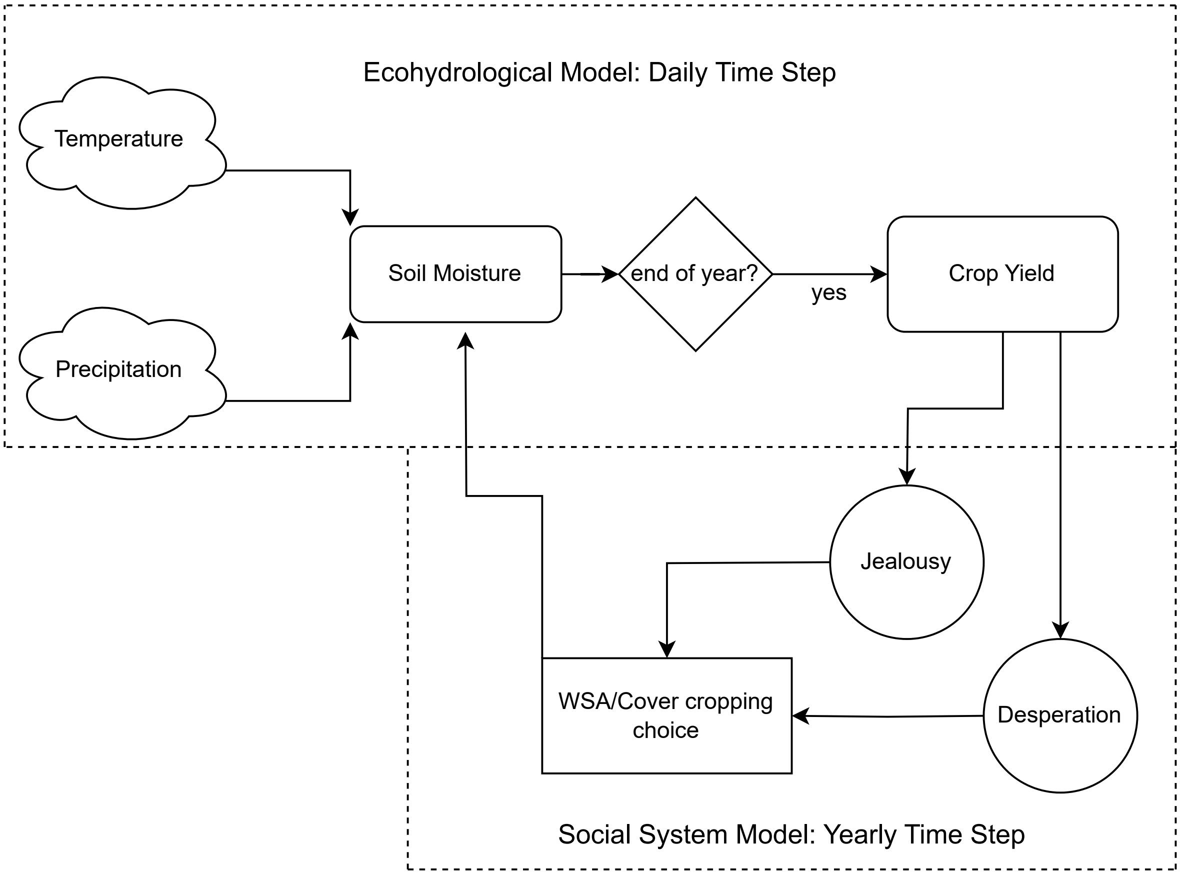


Figure 1: Simplified influence diagram summarising the model design

as a marked Poisson process, with parameter values of average rainfall event length, inter-event length and event size (i.e., precipitation depth per event). Those parameters are chosen for both seasons by trial-and-error such that accumulated annual rainfall is around 1000mm and the seasons are clearly distinguishable. Using randomly generated rainfall allows us to easily generate future climate scenarios where the total amount of rainfall stays roughly the same, but its statistics change. For the temperature input to the model, we use monthly temperature data from Berkeley Earth upsampled to a daily time series. For future climate scenarios, we can simply shift those temperature time series up by set amounts.

We assume that farmers traditionally leave their fields bare in the dry season, but employ mulching and cover cropping practices during the dry season if they have adopted WSA practices. In our model, farmers sow their fields at the beginning of the wet season and only harvest them once at the end of the wet season. We further assume that crops grown by the farmers have similar properties to the 'grass' plant functional type that Zhou et al. [2013] have implemented in CATGraSS. For the cover crop, we need to introduce a new plant functional type (PFT) with special properties: because we want its use to conserve soil moisture over the dry season, we need this PFT to inhibit evaporation as well as deep percolation. In CATGraSS however, any kind of live vegetation will increase evapotranspiration and will therefore have a negative impact on soil moisture. This means that our cover cropping PFT is modeled on the existing 'bare soil' PFT rather than any of the actual vegetation PFTs, and should more appropriately be called the mulching PFT. In contrast to bare soil, the mulch is three times more resistant to evaporation, so dry-season ET_a will be significantly smaller on WSA fields than on non-WSA fields for the same PET. For good measure, we also roughly halve the deep percolation loss constant for this PFT (see the appendix for more detail).

This new PFT that we apply to WSA-employing fields should allow farmers to start into the growing season with fields that have better soil moisture content. During the wet season itself, another change we make to CATGraSS takes effect. We make the assumption that improvements to soil properties brought about by WSA practices act to increase the plants' net primary productivity (NPP; see Equation 2). Therefore, we introduce a 'soil health' factor SH such that $\mathrm{NPP} = \mathrm{NPP}_{std} \cdot SH$, where NPP_{std} is the NPP implemented in CATGraSS by default. All fields start off with $SH = 1$. At the end of each model year, the value of SH on each field is calculated based on the current SH and the WSA status of the field: if the field is currently using WSA, SH is incremented towards a higher threshold of 1.3. If the field is currently not using WSA, SH is incremented towards a lower threshold of 1. In mathematical form, this means:

$$SH_{n+1} = SH_n + (T - SH_n) \cdot 0.5 \tag{4}$$

where n indicates the value in the current year, $n+1$ the value in the next year, and T is the WSA-status-dependent threshold that we let SH tend towards in that time step. Effectively, the factor of 0.5 that is applied each time means that it takes about three years until soil health improvements from WSA use take full effect (and vice versa with soil health deterioration if farmers switch away from WSA).

At the end of the wet season, the farmers harvest their crops. In our model, we simply use live biomass (which is expressed in grams of dry green biomass per square metre) on the last day of the wet season as a proxy for the harvest to pass back to the social system model. The value of the crop yield is therefore a qualitative measure and should not be taken to have any quantitative meaning.

Finally, we had to perform some parameter tuning in order to make differences between fields using WSA and fields not using WSA emerge. Those differences in end-of-year biomass only seemed to appear if plants experienced some degree of water stress during the wet season. To achieve this while retaining broadly realistic total rainfall, we decreased the water use efficiency parameter of the grass PFT by a factor of 10 (from 0.01 to 0.001). This parameter expresses the ratio of water used for photosynthesis (i.e., biomass growth) to water lost to transpiration. It linearly feeds into the calculation of NPP (plant net primary productivity).

3.3 Social System Model

We developed an agent-based model in NetLogo to replicate the social dynamics among farmers based on their crop yields and farming methods. At the onset of the simulation, an environment is created from a 51 by 51 two-dimensional grid comprising square cells. Each cell is overlaid by a field agent. 800 farmer agents are randomly assigned to these fields. Subsequently, nearest-neighbour clustering is used to associate each field with their closest farmer. Neighbouring farmers are linked if they had fields adjacent to one another.

Of these farmers, a set number of these agents are randomly selected to be lead farmers, who would only use WSA practices, without switching back allowed. This is to simulate the lead farmers paid by CRS to use WSA in their studies.

At any social step of the model, the farmers make decisions about which farming methods to use based on their yields, farming methods and the same information about their neighbours. Farmers are informed of each of their field's yields from the hydrological model.

If the farmer's best-performing neighbour uses a different farming method than them, and this difference is better than the jealousy tolerance, the farmer switches to this method and begins a grace period until they can switch back. Farmers with a total yield below a desperation threshold swap their farming methods to try and get enough yield to survive. We chose total yield as a metric because smallholder farmers provide for themselves, so smaller the farms provide less yield. The Grace Period was implemented to stop flipping between farming methods for desperate farmers.

Farmers can only switch to WSA if they have already been exposed to the farming technique via their neighbours. When a farmer switches to WSA methods, their neighbours are informed that WSA exists, which replicates word-of-mouth spreading in a social network.

3.4 Coupling Between the Social and the Ecohydrological Model

The interactions between the models are handled in Python by a driver file. We use PyNetLogo, a Python package allowing integration with NetLogo to allow both models to function together as the hybrid model depicted in Figure 1.

The driver file first initialises both models. The file creates a link with an instance of the NetLogo model and runs the setup methods with the parameters specified for the hybrid model run, feeding the field information back to the driver file. The ecohydrological model is also instantiated and run as described above to 'spin up' the model.

A single model step consists of a ecohydrological model step, and then a social model step. The driver file provides two inputs to the ecohydrological model, the first being a 51 by 51 array of the fields from the NetLogo model, with 0 or 1 to indicate if a field is using WSA methods. The second input is daily temperature data for the year of simulation, average, maximum and minimum of each day, with a shift corresponding to the climate scenario used in the model. The ecohydrological model is then run for a year of simulation and returns the biomass produced in each field as the yield.

The driver file updates the field agent information with this new yield and then writes this information back to the NetLogo model using the PyNetLogo link. After this, one social step is run, and farmers will make decisions on their farming methods based on this new information. The driver then obtains the field information from the model again, with the new decisions on WSA implementation.

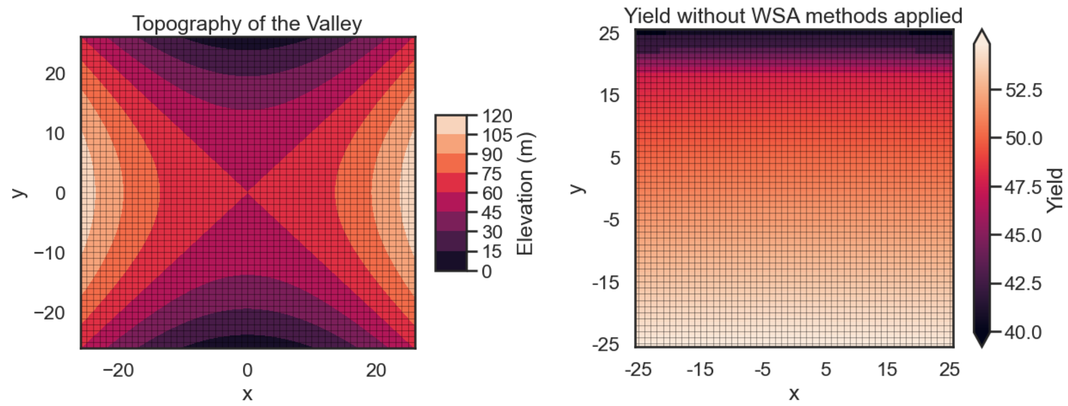
3.5 Experiments

In oWe varied three parameters between runs: social scenario, climate scenario, and number of lead farmers (5, 10 or 20). Social and climate scenarios are detailed in Tables 1 and 2 respectively. We ran 10 model runs for each combination of the three parameter options in order to minimise errors. If the time permitted, we would've liked to run more than 10 runs to further minimise errors. This resulted in a total of 180 model runs.

After each meta-step, the updated biomass from the hydrology model and the following farming methods decisions from the social model were recorded. This created a data frame detailing every field at every year for every model run for every parameter combination. This allowed for deconstruction of the model after each time step.

When writing the data to csv format, for each model we grouped the fields by year and farmer to minimise the size of the data output. This allowed us to maintain more of the same information at a smaller size, with the exception of the individual field coordinates.

For all of our experiments, we initialised the hydrology model with the topography of a valley as seen in Figure 2. The addition of topography allows to to explore the effects of varying amounts of sunlight: south-facing farmers receive more solar radiation, which should increase plant growth, but may also increase water stress due to evapotranspiration. These topographic



(a) Topography of the hydrology valley with elevation $0.08x^2 - 0.08y^2 + 60$, where x and y are cell indices.

(b) Yield of each of the fields in this valley without WSA methods implemented. X and y are cell indices.

Figure 2

effects may have impacts on how WSA spreads.

Social Scenario	**Jealousy Tolerance**	**Desperation Threshold**	**Grace Period Length**
No Desperation	5	0	3
Low Jealousy Tolerance	2	5	3
High Jealousy Tolerance	10	5	3

Table 1: Social scenario variables.

	Current Climate	**Warm Climate**
Temperature Shift (deg. C)	0	2
Actual Dry Period Start (Julian Day)	1	1
Actual Dry Period End (Julian Day)	140	160
Expected Dry Period Start (Julian Day)	1	1
Expected Dry Period End (Julian Day)	140	140
Rainfall Avg. Event Time (Dry Period, days)	0.5	0.5
Rainfall Avg. Event Time (Wet Period, days)	2	3
Rainfall Avg. Inter-Event Time (Dry Period, days)	10	10
Rainfall Avg. Inter-Event Time (Wet Period, days)	4	8
Avg. Rainfall Depth per Event (Dry Period, mm)	1	1
Avg. Rainfall Depth per Event (Wet Period, mm)	10	15

Table 2: Climate scenario variables. The expected dry season end date is the date on which the farmers sow their crops. Farmers harvest the day before the expected dry season start date.

4 Results and Exploration

Our results show that:

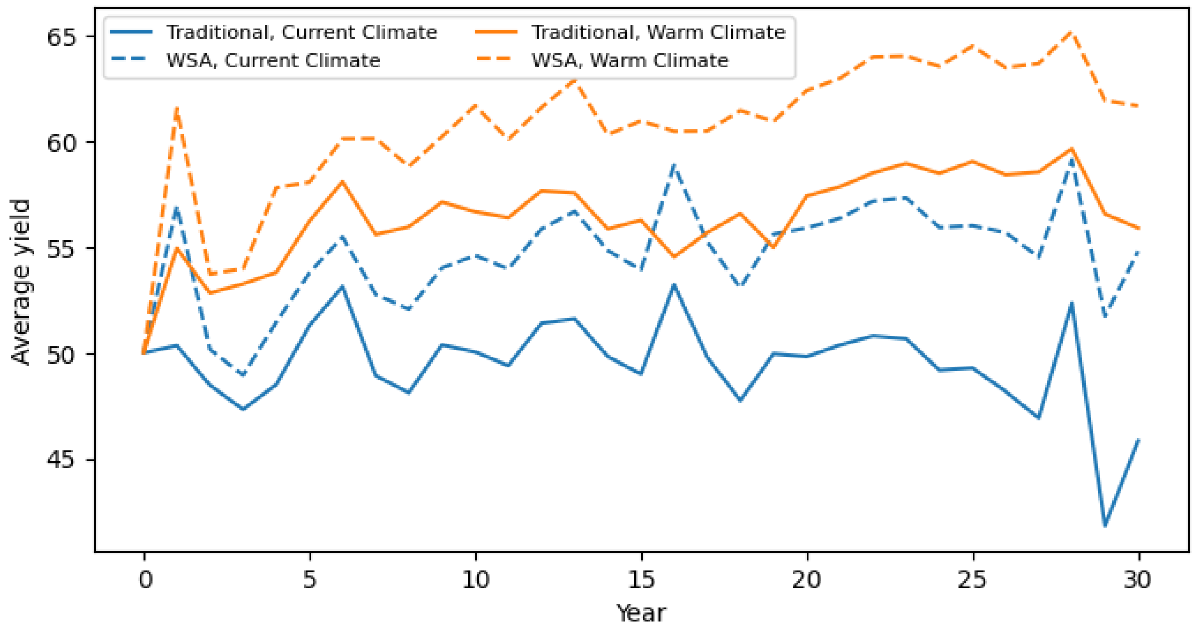


Figure 3: Average yield per year for WSA and non-WSA fields in the two climate scenarios, for when jealousy tolerance is high and lead farmers are 10.

- WSA yields are higher than traditional yields in both climate scenarios;
- The social scenario without desperation leads to the fastest increase in WSA usage; and
- The number of lead farmers is the most important parameter for the rate of increase in WSA usage.

They also reveal a prominent stepping pattern due to the jealousy tolerance behaviour. These findings are now explored in more detail.

4.1 Average Yield Across Social and Climate Scenarios

Figure 3 shows how average yield across 10 model runs varies between WSA and traditional farming practices in each climate scenario, when there are 10 lead farmers in the high jealousy tolerance social scenario. This graph is reproduced for each lead farmer and social scenario combination in Appendix Figure 8. From these graphs, we observe that average WSA yields are higher than average traditional yields in every climate and social scenario. This indicates that WSA is an effective way of increasing crop yields.

We also see that both traditional yields and WSA yields are higher in the warm climate scenario. This is because increased radiation leads to increased plant growth, up to the point of drought where plant biomass suddenly collapses. Our parameterisation of the warm climate does not appear to have reached drought levels, and therefore crops actually prefer the warm climate.

WSA yields and traditional yields tend to rise and fall at the same points across parameterisations. This suggests that both farming practices respond to climate conditions in similar ways. One notable exception of this is the peak in period 16 which appears across traditional yields, but does not appear in WSA yields. It is unclear why this peak occurs. While it is possible this inverted correlation would arise due to a large number of low-yield farmers transitioning from traditional practices to WSA, there doesn't appear to be a reason for many low-yield farmers

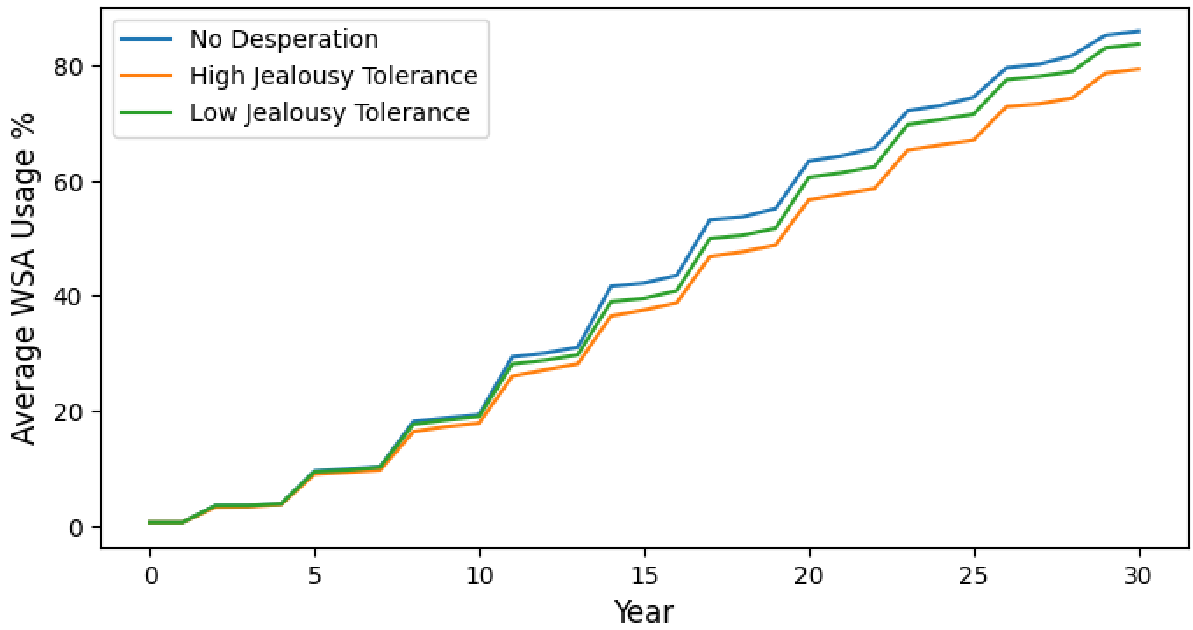


Figure 4: Average Water Smart Agriculture usage per year for each of the three social scenarios in the current climate and when lead farmers are 5.

to transition at this point across simulations. Therefore it is more likely that this phenomenon is the result of a weather event which differentially affects WSA and traditional practices.

Across scenarios, WSA yields appear to be less volatile than traditional yields. This is unsurprising in the final years, when most farmers implement WSA leading to increased stability. However, WSA yields appear to be more stable even in years 0-20, when substantial numbers of farmers still implement traditional practices. This suggests WSA practices offer more consistent yields across yearly weather conditions.

4.2 WSA Usage Across Social and Climate Scenarios

To explore the rate of increase in WSA usage across social and climate scenarios, we turn to Appendix Figure 9, an example panel of which is shown in Figure 4. These figures demonstrate how the percentage of farmers using WSA changes over the years across our parameterisations. As shown, the percentage of farmers implementing WSA approaches 100% by year 30 across social and climate scenarios.

Across parameterisations, and especially for low numbers of lead farmers, WSA use increases faster in the ‘low jealousy tolerance’ social scenario than in the ‘high jealousy tolerance’ scenario. This is unsurprising. When jealousy tolerance is low, farmers are more responsive to their neighbours’ use of WSA practices, and therefore choose to implement WSA sooner. This indicates that farmers who are more sensitive to the gains of WSA will be more likely to take up these practices.

However, the ‘no desperation’ scenario shows a faster increase in WSA use in many parameterisations. This is counterintuitive, as we might expect desperation to offer a second pathway into WSA use, increasing its uptake. Instead we see that the presence of the desperation pathway diminishes WSA use. This is an artifact of the model implementation. Farmers who have fields with very low yields are unable to produce above the desperation threshold regardless of their farming practice. Therefore these farmers continue switching practice throughout the simulation, and desperation becomes a primary pathway *away* from WSA practices. For this

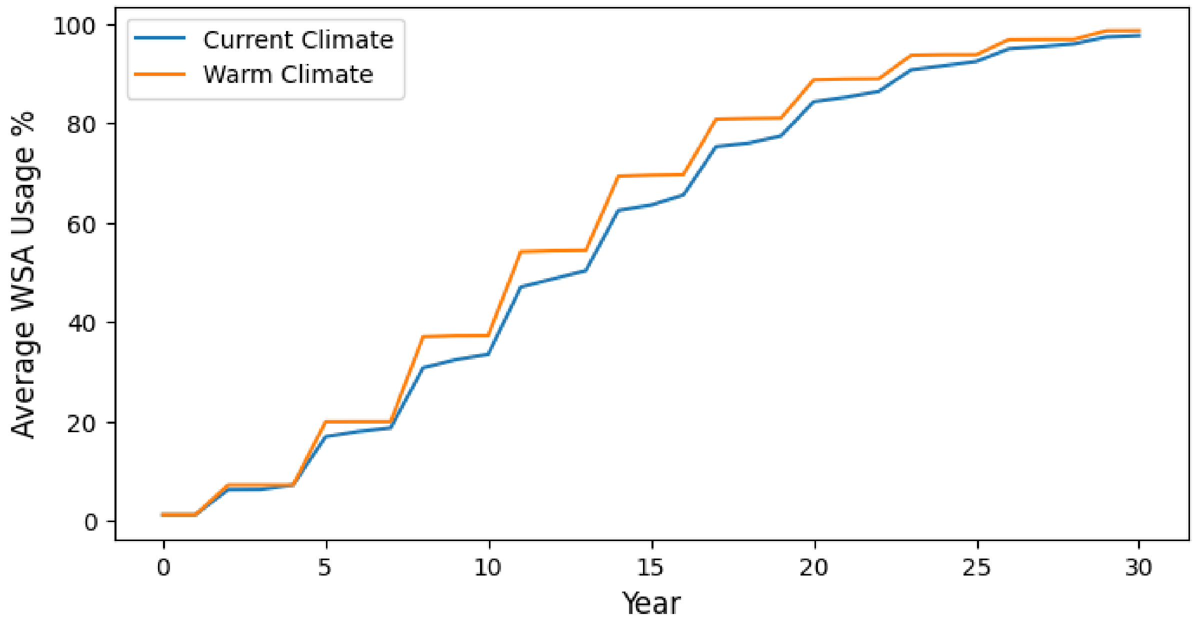


Figure 5: Average Water Smart Agriculture usage per year for both climate scenarios when farmers have low jealousy tolerance and lead farmers are 10.

reason, the 'no desperation' scenario outperforms the others.

Despite these differences between social scenarios, by far the most significant driver of WSA use is the number of lead farmers. As seen, the parameterisations with 20 lead farmers reach near 100% WSA implementation much faster than those with 5 lead farmers. This indicates that the most important feature of WSA promotion in the real world is the number of farmers who can be directly engaged with the project by CRS.

4.3 Investigating the impact of the parameters on WSA usage

Following the obvious differences in WSA uptake by the end of the 30 years of simulation between the different parameter groups, we decide to perform statistical tests to investigate if these differences are statistically significant (p value less than 0.05). For each of the parameters; climate scenario, social scenario and number of lead farmers, we get the proportion of uptake for each model run that had this parameter, then use this to perform ANOVA tests between different parameter values.

From Table 3, we can see the means and standard deviations across all parameter groups. We can note that only within the climate scenario parameter do both groups have similar standard deviations. For this reason, we decide to use Welch's ANOVA to compare the WSA implementation mean due to group sizes (2 and 3) and differing standard deviations making this test suitable.

Using SciPy's stats package, we can perform t-tests inbetween groups from the same parameter, resulting in the following output.

Social Scenarios

- No Desperation and Low Jealousy means have T-statistic 1.07, with a p-value of 0.286
- No Desperation and High Jealousy means have T-statistic 1.92, with a p-value of 0.0574

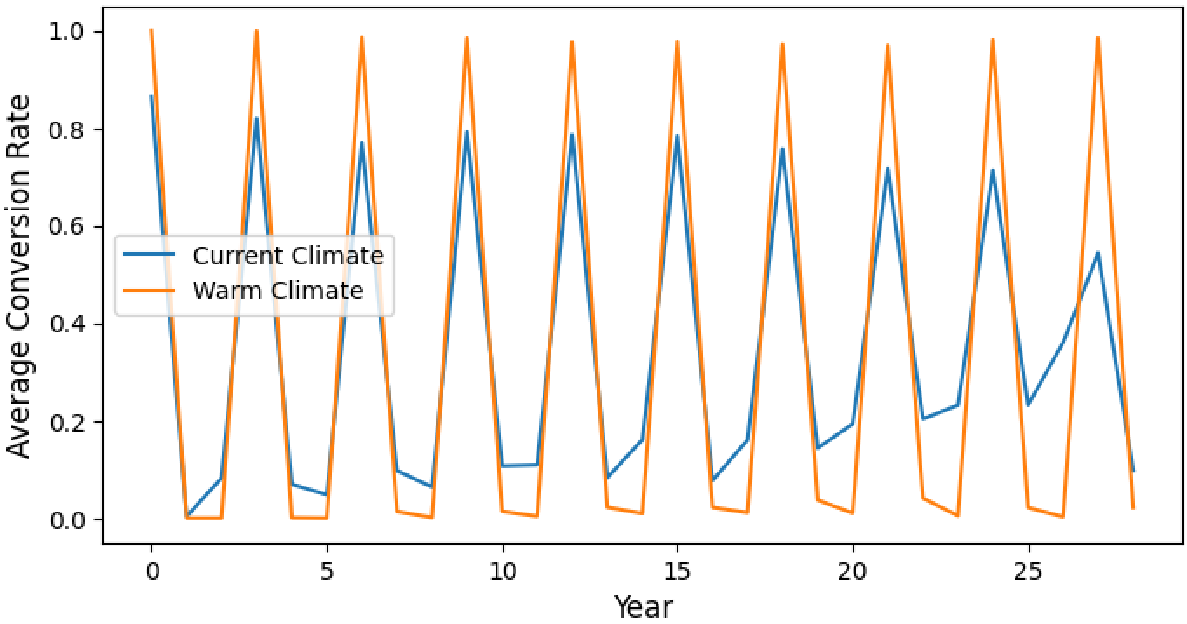


Figure 6: Average Conversion Rates per year for for the two climate scenarios, when jealousy tolerance is low and lead farmers are 10.

- Low Jealousy and High Jealousy means have T-statistic 0.842, with a p-value of 0.402

We can see from the p values that none of parameters have statistically significant differences between groups. No Desperation and High Jealousy social scenarios differences are close to being significant which can be seen in the Figures demonstrating WSA usage. If a subset of the dataset was selected, for example only simulations where 5 Lead farmers are initialised, we would expect differences to be more significant, as we see more divergence between usage rates in the graph.

Climate Scenarios

- Current Climate and Warm Climate means have T-statistic 0.988, with a p-value of 0.324

We can see from the high p value that there seems to be no significant difference between means of climate scenarios. It must be noted that since there are only two climate scenarios, a large variety of model runs are summarised for each group which could explain why it looks like there are differences in figures but no statistically significant differences.

Number of Lead Farmers

- 20 Lead Farmers and 10 Lead Farmers means have T-statistic 5.59, with a p-value of $5.66 * 10^{-7}$
- 20 Lead Farmers and 5 Lead Farmers means have T-statistic 11.44, with a p-value of $1.23 * 10^{-16}$
- 10 Lead Farmers and 5 Lead Farmers means have T-statistic 9.11, with a p-value of $1.35 * 10^{-13}$

For all of the group combinations, we can see p values lower than 0.05, which suggests statistically significant differences between all WSA usage means. This supports our interpretation that number of lead farmers is the dominating factor with regards to increasing WSA usage.

Social Scenario	Number of Model Runs	Mean	Standard Deviation
No Desperation	60	0.952	0.0701
Low Jealousy Tolerance	60	0.935	0.101
High Jealousy Tolerance	60	0.918	0.116

Climate Scenario	Number of Model Runs	Mean	Standard Deviation
Current Climate	90	0.930	0.0977
Warm Climate	90	0.941	0.0984

Number of Lead Farmers	Number of Model Runs	Mean	Standard Deviation
20	60	0.999	0.00493
10	60	0.972	0.0364
5	60	0.835	0.110

Table 3: Summary statistics of model runs grouped by parameters.

This may seem obvious as having more lead farmers will cause more neighbouring farmers to be exposed to WSA however this emphasises the importance of training more farmers in Central America to use WSA methods.

4.4 Understanding Stepping and Cyclic Behaviours in the Model

Finally, one striking feature of the model across results in the distinct stepping pattern which appears in WSA uptake (for example, see Appendix Figure 10). This is due to the inclusion of the 'jealousy tolerance' behaviour in the model. Because farmers only adapt their practice to neighbouring practices that are suitably better than their own, we see a delayed uptake of WSA practices.

In particular, since all lead farmers begin implementing WSA practices at the same moment, these practices become suitably attractive at exactly the same moment (year 3). Therefore the next generation of WSA farmers also reach maturity exactly three years later, and the stepping pattern persists throughout the model. It is surprising that both jealousy scenarios exhibit this three year stepping pattern, however this is presumably because WSA yields surpass both jealousy tolerance levels in their third year of implementation. More research into how this stepping pattern varies by jealousy tolerance level would be valuable.

Figure 6 shows the conversion rates of farmers to WSA practices each period, for different climate scenarios. The stepping pattern is particularly visible here, with spikes in conversions every three years. However this graph also reveals the smoothing-out of conversion rates in the current climate scenario. This occurs because WSA is slightly less attractive in the current climate scenario, so a small fraction of farmers don't transition to WSA until the 4th year. This means they desynchronise from the stepping pattern. This effect compounds each year, leading conversion rates to smooth out in the current climate scenario.

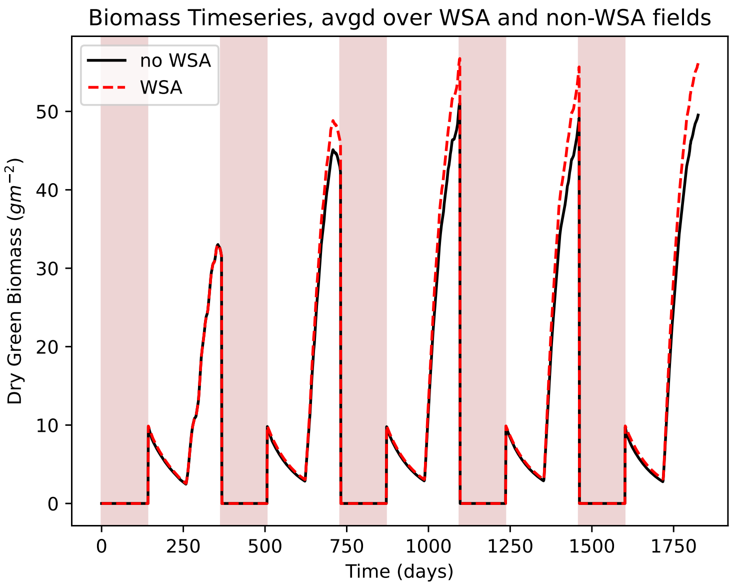


Figure 7: Daily time series of biomass from the Ecohydrology model run on its own for five years in the 'current' climate configuration. 20 WSA fields are randomly allocated and remain the same throughout the model run. Brown shading indicates the dry season; biomass is intentionally zero during this period.

Conversion rates diminish in the final few years of simulation, as the only remaining traditional farmers are those with particularly good yields, who take especially long to transfer to WSA practices.

5 Significance of Results and Limitations

5.1 Ecohydrology Model Limitations

Running the ecohydrological model on its own in order to better understand the full model outputs reveals some unexpected and unexplained behaviour suggests that the ecohydrological model in its current configuration does not yet fully work as intended. Most striking are patterns observed in daily outputs of spatially averaged biomass (Figure 7). In the first approximately 120 days after sowing, the crops do not seem to grow much. Then, they suddenly start growing explosively. This pattern can also be observed when changing the time of year in which the crops are sown and thus appears to be independent of environmental conditions. Therefore, there is good reason to believe that this behaviour is not physical and due to a fault with the model.

One unfortunate effect of this is that soil moisture at the end of the dry season does not really seem to affect biomass outcomes at the end of the wet season. The initial decay in biomass after sowing occurs regardless of environmental conditions - so by the time plant growth kicks in, soil moisture on both WSA and non-WSA fields will have been replenished by wet season rain and bear no significant difference anymore. Inspecting daily outputs of soil moisture (Figure 12) further supports this assertion that end-of-dry-season soil moisture does not matter as much as we would like. In the 'warm' climate (Figure 12b), soil moisture on fields using WSA drops significantly more during the dry season than it does in the 'current' climate (Figure 12a): in the 'warm' climate, end-of-dry-season soil moisture on WSA fields is not dramatically different from non-WSA fields. This would suggest that the soil moisture conserving properties of mulching/cover cropping become much less effective in the warm climate, which is at odds with our previous finding that WSA is overall not significantly less effective in the warm climate. We may conclude that the modelled improved yields on WSA fields are currently mostly due to the increased primary productivity of the plants rather than dry-season soil moisture conservation.

Figures 7 and 12 also illustrate how the ecohydrology model needs a few years to spin up and properly equilibrate: yields and soil moisture in the first couple of years are significantly lower than they are later on. This is largely due to the rainfall, which curiously appears to be persistently lower in the first few model years before stabilising after three or four model years. This should not happen as precipitation is randomly generated and points to further undiscovered model issues. In our coupled experiments, we mitigate against this problem by always letting the ecohydrology model run on its own for five years before coupling in the social system model.

5.2 Social Model Limitations

The most important limitation of the social model is its lack of correspondence with conditions in the real world. Farmers implementing WSA practices in reality are usually very few and far between, with only one or two farms using WSA practices in each watershed ((GWI [2015]). As described above, CRS' stated goal is for roughly 7% of smallholders and 1.5% of landmass in the Dry Corridor to implement WSA by 2030 (Callahan [2023]). The model, in contrast, shows a very dense uptake of WSA, with 800 farmers in a 3.5km square implementing WSA practices by the end of 30 years. In this sense, it does not capture the social dynamics of WSA well.

This is particularly problematic when considering a wider range of social network effects which were not included in the model. For example, many farmers implementing WSA in the real world revert to traditional practices when NGOs recede. This is due, among other things, to the social network pressures of isolation. Going further, farmers' lack of familiarity with WSA practices even after having implemented them for a few years presents a second stumbling block which can inhibit the continued use of WSA (GWI [2015]). These two features of isolation and unfamiliarity are not well captured in the model. Nevertheless they are highly relevant to WSA uptake rates, and thus are an important oversight.

One way that CRS tackles the problems of isolation and unfamiliarity in the real world is through social group membership. Knowledge of WSA practices is dispersed through churches and prominent church figures, meaning these technical knowledges are immediately situated in well-established communities of mutual support. Further, CRS helps establish farmer learning groups who support one another to maintain and develop WSA practices in the future (Johnson and Blumberg [2021]). Crucially, these social relations are only loosely informed by spatial distance. This allows pockets of WSA implementation to share support and learning with one another across geographical separation. In the model, social relations can only exist due to spatial proximity. This means the model cannot represent these long-distance support networks, severely limiting its ability to capture the uptake of WSA by small pockets of farmers across the large Dry Corridor.

A further limitation is the uniform nature of the social network. Social relations in the model are (mostly) very uniform, with the network extending with identical density in all directions. This neglects some of the most basic findings of social network theory, such as clustering and bridging/bonding capital (Granovetter [1999]), as well as the identification of some network members as 'brokers' who connect otherwise disparate communities (Light and Moody [2020]).

Relatedly, the model implementation has the unintended consequence of correlating ownership of low-yield fields with poorly connected positions in the social network. Due to the elevation profile we used, fields in the north of the region perform particularly poorly on crop yields because they receive much less sunlight. Additionally, farmers close to the edges of the grid are likely to be poorly connected with lead farmers, as these connections can only come from two directions rather than all four. For this reason, social network connectivity and crop yields both diminish near the edges of the grid. We were unable to allocate time to explore the extent to which this phenomenon impacts our model outputs, however it may have important implications. For example, this correlation might mean that the average farmer who transitions from traditional methods to WSA methods in any period will have *higher* yield per-field than the average traditional farmer in that period. Due to these various limitations, the outputs of this model should only be understood as indications of potential processes, rather than evidence of these processes' existence.

6 Further Work

The ecohydrology model in particular deserves more attention in order to make our coupled model more useful and trustworthy. After addressing the issues outlined in section 5.1, a major improvement would be to properly take the mid-summer 'Canícula' drought typical of the dry corridor into account. This would require the implementation of inter-cropping (i.e., using cover crops to cover the bare soil between main crops) for WSA fields. This means changing the plant functional type without losing information on main crop biomass and vegetation cover, which would be a significant amount of work and hence was out of scope for this project.

Secondly, it would be valuable to further tune CATGraSS to its use in an agricultural setting. For example, crops may be particularly sensitive to water stress in certain periods, such as immediately after sowing or when they are flowering. Including these effects could lead to a much more realistic model response to drought and make soil moisture conservation have a more pronounced effect on yield.

Thirdly, we might want to add some stochasticity to the soil health factor acting on NPP. This would provide an additional pathway for farmers to switch back to non-WSA, and would more accurately represent the fact that soil properties only improve if cover cropping and crop rotations are implemented correctly.

Finally, we should consider whether a daily time step is really needed for the ecohydrology model in order to capture variability of precipitation patters. A longer time step could save vast amounts of computation time and enable running more and larger experiments: we could properly explore the parameter space rather than having to focus on a few plausible scenarios. Since all equations are solved analytically rather than numerically, there are no stability restrictions on the time step length.

7 Summary and Conclusion

Using an initial implementation of a coupled social-ecohydrological model, we explore the field-level effectiveness and social dispersal of Water Smart Agriculture (WSA) practices in Central America's Dry Corridor, which promise to improve the resilience of smallholder farmers to droughts.

While this initial implementation produces some interesting results, the model suffers from severe limitations on both the ecohydrological and social sides. Therefore, all results should be regarded as highly preliminary. Nonetheless, our answers to the research questions posed at the start of this paper are as follows:

How do different climate scenarios impact the effectiveness of Water Smart Agriculture? In our model, there is no statistically significant difference in the speed of WSA adoption between a ‘current’ and a ‘warm’ climate. However, we expect this finding to be particularly sensitive to the deficiencies of the ecohydrological model.

What social and environmental factors affect the uptake of Water Smart Agriculture? The number of lead farmers is crucial to uptake rates. In our initial limited parameter exploration, we have not been able to identify environmental factors that significantly affect the usage of WSA.

What conditions are necessary for Water Smart Agriculture to reach 500,000 farmers by 2030? The benefits of WSA practices must be visible for WSA to spread, and the number of lead farmers must be high.

Appendix: ODD

1 Purpose and Patterns

Intensifying droughts and irregular rainfall conditions due to climate change present increasing challenges to smallholder farmers in Central America's Dry Corridor. 'Water Smart Agriculture' [WSA] is an approach to farming promoted by the NGO Catholic Relief Services [CRS] which combats these issues by retaining soil moisture (FUSADES [2021]).

The purpose of this model is to explore how WSA practices impact soil moisture and crop yields in a hydrological model, and how WSA outcomes lead to the dispersal of farming practices in a paired social model. These two models are combined into a 'meta-model', which aims to replicate the empirical spread of WSA methods from 2015 to 2020 as seen by CRS. This meta-model will then be used the predict the viability of CRS' stated goal to reach 500,000 farmers by 2030 (Callahan [2023]).

2 Entities, State Variables and Scales

2.1 Temporal and Spatial Scales

One timestep of the meta-model represents one year. This meta-step is comprised of 365 hydro-steps which calculate daily hydrological outcomes of the current configuration of farming practices, followed by 1 social-step in which farmers adapt their practices based on the year's outcomes. In total, 30 years are simulated in this way.

The environment modelled is taken to be a representative sample of the Dry Corridor, of size 3.57x3.57km, represented by a 51x51 non-toroidal grid. Each cell represents a field of size 70x70m. Most farmers own between 1 to 5 fields, with a few owning as many as 12, mimicking the real-world scale of smallholder farms in the Dry Corridor (Alpízar et al. [2020]).

2.2 Ecohydrological Model

The entities in the ecohydrological model are:

- The cells of the computational grid, each with specific soil properties
- The vegetation or ground cover on each of those cells

Table 4 outlines the state variables associated with each grid cell's soil and ground surface. Table 5 describes variables associated with ground cover and vegetation on each cell, and Table 6 describes global state variables that are set uniformly for all cells. Some variable descriptions are taken from their description in the Landlab code. Note: CATGraSS works with more state variables than those listed here, but we only list those relevant for the evolution of our implementation.

Variable Name	Type	Meaning	Init.
Soil Moisture Saturation Fraction	Float	Water saturation of the soil, ranging from 0 (no water) to 1 (fully saturated)	0.75
Soil Health	Float	Scaling factor on plant net primary productivity that parameterises the improvement of soil nutrient levels through the use of WSA practices. Range: (1, 1.3)	1
Topography (Elevation, Slope and Aspect)	Float	Elevation in m of each cell. Together with elevations of surrounding cells, this determines the slope and aspect of that cell. Elevation described by $70 * 0.08(x - 70 * 25)^2 - 70 * 0.08(y - 70 * 25)^2 + 60$	

Table 4: State variables for ground surface. All of these are fields, i.e., set on each grid cell individually. Initial Conditions are applied uniformly across all fields.

Variable Name	Type	Meaning	Init.
Vegetation Cover Fraction	Float	Fraction of grid cell covered by vegetation	0.5
Live Leaf Area Index	Float	One-sided green leaf area per unit ground surface area	1
Plant Functional Type (PFT)	Integer	Classification of plant or ground cover inhabiting that grid cell, coded by an integer value. 0 = grass, 3 = bare soil, 6 = WSA dry-season cover crop/mulch. Other PFTs are available, but were not used here.	0
Live Biomass	Float	Weight (in grams) of green organic mass per square metre - measured in terms of dry matter	10
Dead Biomass	Float	Weight (in grams) of dead organic mass per square metre - measured in terms of dry matter	450 (Landlab default)

Table 5: State variables for vegetation and ground cover. All of these are fields, i.e., set on each grid cell individually. Initial Conditions are applied uniformly across all fields.

Variable Name	Type	Meaning	Init.
Julian Day	Integer	Julian Day, going from 0 to 364	0

Table 6: Global Ecohydrological variables applied equally to all fields

2.3 Agent-Based Social Model

The entities present in the social model are:

- farmers, who make farming practice decisions each social-step;
- fields, which are owned by farmers and represent crop-growing plots; and

- the global environment, which holds global social parameters.

Tables 7, 8 and 9 describe the state variables of these agents respectively.

Variable Name	**Type**	**Meaning**	**Init.**
Lead Farmer	Boolean	Farmer is a 'lead farmer'. Lead farmers use WSA methods throughout the model run, representing those who are funded to use WSA by campaigns	False. See Assign Lead Farmers
Grace Period	Integer	Remaining years before a farmer can change farming method again	0
Total Yield	Float	Yield of all fields owned by the farmer	[not set]
Average Yield	Float	Average yield per field owned by the farmer	[not set]
Using WSA	Boolean	Farmer is using WSA on their fields this year	False
Knows WSA	Boolean	Farmer has been previously exposed to WSA	False
Next Practice	Boolean	Farmer will use WSA next year	False

Table 7: State variables for farmer agents.

Variable Name	**Type**	**Meaning**	**Init.**
Yield	Float	Amount of crops the field produced this year	[not set]
Owner ID	Integer	ID of farmer that owns the field	See Allocate Fields
Implements WSA	Boolean	Owner is using WSA this year	False

Table 8: State variables for field agents.

Variable Name	**Type**	**Meaning**	**Init.**
Number of Farmers	Integer	Number of farmers in this model run	800
Number of Lead Farmers	Integer	Number of lead farmers who use WSA methods throughout the model run	20
Desperation Threshold	Float	When farmers' total yield falls below this threshold, they switch farming practice 'out of desperation'	5
Jealousy Tolerance	Float	When a neighbour's average yield exceeds a farmer's average yield by more than the jealousy tolerance, the farmer will mimic that neighbour's farming practice 'out of jealousy'	10
Grace Period Length	Integer	The length of the cooldown period for changing farming method	3

Table 9: Global Environment Variables.

3 Process Overview and Scheduling

Each meta-step represents the passage of one year. The processes involved in completing a meta-step are as follows:

- Retrieve Fields - the meta-model retrieves which fields currently implement WSA from the social model, and passes this information to the hydrological model.
- Hydrological Cycle - the meta-model triggers 365 hydro-steps, simulating a year of rainfall and temperature conditions and calculating daily soil moisture outcomes of these conditions given the farming practices on each field.
- Retrieve Yields - the meta-model retrieves biomass levels for each field from the hydrological model, converts these into crop yields, and passes this into the social model.
- Social-step - the meta-model triggers one social-step, where farmers change their farming practices based on the years outcomes.

A hydro-step comprises:

- Check if the Julian day corresponds to that on which farmers expect the dry season to start. If it is, set the PFT to 3 (bare soil) on non-WSA fields and 6 (mulching/evaporation-resistant cover crop) on WSA fields. This means removing all the biomass that was on the field before.
- Check if the Julian day corresponds to that on which farmers expect the dry season to end. If it is, set the PFT to 0 (grass) and re-initialise the vegetation component.
- Calculate incident Radiation for each field.
- Calculate Potential Evapotranspiration (PET).
- Call Soil Moisture calculate soil moisture at the next time step. This also advances time by one day.
- Call Vegetation to calculate live and dead biomass as well as vegetation cover at the new time step.
- at the end of the model year, we do the following:
  - Update the soil health variable based on each field's WSA status and the current value of the soil health value
  - Record the current live biomass and output it. This assumes that the start of the model year and the start of the dry season coincide.

A social-step comprises:

- Gather Yield - farmers calculate yield from the total yields of their fields.
- Make Farming Practice Decisions - farmers who have been exposed to WSA have the opportunity to change practice either out of jealousy or desperation.
- Change Practice - practice changes take effect, and farmers who changed are put into a grace period.
- Share Knowledge - farmers implementing WSA spread knowledge of WSA to their neighbours.

These processes are described in further detail in the Submodels section.

4 Design Concepts

4.1 Basic Principles

The basic principle underpinning the model is the viability of farming practices in worsening climate conditions. As temperatures rise and rainfall becomes less predictable, WSA farming methods are assumed to be increasingly better than traditional methods. However the uptake of WSA is constrained by social network processes. That is, farmers can only adapt if they have gained knowledge of alternative strategies through the social network. Finally, farmers want to maximise production, but they do this only by mimicking successful neighbours. As such, the discovery of optimal choices is highly contingent on social processes.

4.2 Emergence

The interactions of WSA methods with temperature and rainfall data in the hydrological model lead to an emergent viability of WSA methods. In turn, the level of success of WSA relative to traditional methods, as well as the manner in which knowledge spreads, lead to emergent WSA implementation rates.

4.3 Adaptation

Farmers adapt their farming practices according to their knowledge of WSA, current yield, and the relative success of their neighbours. When a farmer does particularly poorly, or their neighbours do particularly well, the farmer switches farming practice.

4.4 Objectives

Each farmer aims to produce as much yield as possible by altering their practices. However this maximisation is imperfect as farmers only make changes when they are sufficiently desperate or jealous.

4.5 Learning

Farmers learn about WSA when one of their neighbours implements it. From this point onwards, they are able to choose between implementing WSA or traditional farming practices.

4.6 Sensing

Farmers can sense their neighbours, their average yield and their farming method. They use this information to determine whether they will switch farming practice.

4.7 Interaction

Farmers interact by sharing knowledge of WSA practices with one another.

4.8 Stochasticity

Farmers are placed randomly within the 51x51 grid. Fields are randomly allocated to one of the farmers closest to them. Lead farmers are randomly selected from the pool of farmers. The rainfall input is randomly generated for each year as a marked Poisson process from inputs of average rainfall event length, average inter-event time, and average depth of precipitation per event.

4.9 Collectives

Farmers own a group of fields, forming their farm. The yields of these fields are combined to produce the farmer's total and average yields which inform decision-making. For this reason, farmers with fewer fields may behave differently than farmers with more.

4.10 Observation

Information is gathered by the meta-model each meta step on fields. Each field has a fixed Owner ID, and fixed inbuilt unique ID, X coordinate and Y coordinate. Each timestep updates the Yield and Implements WSA boolean if changes are made, with the year corresponding to the meta step being recorded. The hydrological step has the previous years Implements WSA information input for each field and returns the Yield for each field which is recorded for this year of simulation. The field Yield is input into the social model and returns the Implements WSA information for this year.

The model parameters for the run are recorded alongside the total cumulative rainfall for each year.

5 Initialisation

To initialise the meta-model, we set up the Python-NetLogo connection and initialise the data frames that will be used for passing results back and forth between model components. Once that is finished, we let the ecohydrological model run for five 'spin-up' years using the initial random seed of WSA fields and the first year of temperature data in order to allow the model to properly equilibrate before we start coupling in the social system model.

To initialise the hydrological model, the following processes are followed:

- Define the model grid and assign elevation field.
- Read precipitation parameters from climate configuration (dry season beginning and end as well as rainfall event time, inter-event time, and average precipitation depth per event for both wet and dry season) and initialise the Poisson rainfall generator from those.
- Initialise radiation, potential evapotranspiration, soil moisture and vegetation submodels.

To initialise the social model, the following processes are followed:

- Initialise Fields and Farmers - create fields and farmers.
- Allocate Fields - allocate fields to be owned by nearby farmers.
- Find Neighbours - from field allocations, identify which farmers share neighbouring plots.
- Assign Lead Farmers - select a random subset of farmers to be lead farmers.

These processes are described in more detail in the Submodels section. The initial variables for each entity, and how they were varied across model runs, are described in Tables 7, 8, and 9.

6 Input Data

The model takes daily average, maximum and minimum temperature data (in degrees Celsius) as input. These are then passed into the Ecohydrology model.

After extensive research we couldn't find a big enough dataset that contained daily temperature readings from a region in Central America. Instead, we decided to use monthly temperatures in Costa Rica from Berkley Earth (https://berkeleyearth.org/data/). We extrapolated the monthly data to daily readings using a different Uniform distribution for each month, where low was average temperature of that month minus two and high was average temperature of that month plus 2. After getting the daily readings and studying Costa Rica's climate, we set the maximum and minimum daily temperatures to be the average plus and minus four degrees respectively.

7 Submodels

7.1 Meta-model

7.1.1 Retrieve Fields

This submodel is coded up in the `modelScript.py` script. In the script, the function reportsToDataFrame is called and provided with the NetLogo link. This method uses the get-info function defined in NetLogo to obtain all field agents and their variables. Variables comprised of all defined and inbuilt variables for the field agents. The function then sorts the field information into the correct order based on their position on the grid (from top left to bottom right, going right to start). This is then formatted as a Pandas data frame.

The column corresponding to whether a field is using WSA methods is extracted from the dataframe then converted to a 2D array of dimension 51 by 51, replicating the rows from the NetLogo grid. This is now the correct format to be provided into the ecohydrological model.

7.1.2 Retrieve Yields

This submodel is coded up in the `modelScript.py` script. In the script, convertHydrologyToDF unravels the 51 by 51 2D array into a singular list. This list is then used to update the yield information for each field in the field data frame. The field information is then passed back to the NetLogo model using the PyNetLogo command, write_NetLogo_attriblist.

7.2 Ecohydrological Model

7.2.1 Radiation

This submodel is coded up in the `radiation.py` script in the Landlab distribution (see here for the documentation). In our configuration of the model, we use it to calculate the net incoming shortwave radiation incident on a flat surface R_f, which is the same on each cell, and a true radiation factor F_R. F_R accounts for the slope and aspect of the cell and is a float that expresses the ratio of actual net incoming radiation incident on a cell to what it would be if that cell were flat. The true net incoming shortwave radiation is then available as the product $R_{nsw} = R_f * F_R$. F_R and R_f are calculated from the surface albedo $A = 0.2$, the cloudiness fraction $N = 0.2$, the solar altitude α (which is dependent on inclination angle at noon δ, which in turn is determined by the latitude ϕ - 10 degrees - and the day of the year), the solar constant $I_0 = 1366.67\text{Wm}^{-2}$

and the clear-sky turbidity $n = 2$. Apart from the latitude, which was chosen to approximately match the location of northern Costa Rica, those parameter values are the Landlab defaults.

7.2.2 Potential Evapotranspiration

This submodel is coded up in the `potential_evapotranspiration_field.py` script of the Landlab distribution (see here for the documentation). The surface potential evapotranspiration here is calculated using the Priestley-Taylor equation from inputs of net radiation as well as minimum, maximum and average daily temperatures. The temperature inputs are used to calculate saturation vapour pressure e_s, approximate actual vapour pressure e (and thus obtain its slope δe w.r.t. temperature) as well as net outgoing long-wave radiation R_{nlw} (from black-body radiation of the soil). This allows the model to solve for the potential evapotranspiration:

$$PET = \max\left(a\frac{\delta e}{\delta e + \gamma}\frac{R_{net}}{L_v}, 0\right) \tag{5}$$

where $a = 1.26$ is the Priestley-Taylor constant, $\gamma = 0.066$ is the psychrometer constant and $R_{net} = R_{nsw} - R_{nlw}$ is the total net radiation.

7.2.3 Soil Moisture

We adapted this submodel from Landlab's `soil_moisture_dynamics.py` script (documentation here). Our contributions are adding a cover cropping/mulching plant functional type (PFT) and separating canopy interception capacity from evaporative inhibition (see below for explanation). The cover cropping functional type is largely equal to bare soil in its parameter values, but has a lower loss rate to deep percolation (7 instead of 13.8) and a higher evaporative inhibition parameter (3 instead of 1).

The soil moisture component solves Equation 1. It begins by calculating the effective precipitation during that time step:

$$P_{eff} = \max(P - Ic_{agg}, 0) \tag{6}$$

where Ic_{agg} is the aggregated interception capacity on the cell and P is the precipitation on that day (read from input). Ic_{agg} is the product of the ground cover interception capacity I_c, which is set to 1.0 for all PFTs used in this work, and the vegetation cover fraction.

The model works on the assumption that this rain falls as an impulse at the beginning of the time step that is absorbed by the soil at a rate depending on its porosity, root depth and the infiltration capacity I_v. I_v depends on fixed infiltration capacity parameters for vegetated (24) and bare (20) soil as well as vegetation cover fraction. The soil absorbs moisture up to total saturation, after which the remainder is partitioned off as runoff - which, interestingly, does not affect neighbouring cells. The soil moisture at the end of the time step is then computed from the rate of absorption and the rate of soil moisture decay. Moisture decay is controlled by the evapotranspiration of the plants and the soil.

To be able to work out actual evapotranspiration rates later, the model then calculates the maximum surface evapotranspiration ET_m - the evapotranspiration rate that occurs when all plants are transpiring at full capacity:

$$ET_m = \max\left((PET \cdot F_r + PET \cdot f_b \cdot (1 - F_r)) - I_c, 0.0001\right) \tag{7}$$

where F_r is the ratio of actual live leaf area index LAI to the maximum leaf area index LAI_{max} of that PFT ($LAI_{max} = 2.88$ for grass and 0.01 for our other PFTs) and $f_b = 0.7$ is the fraction of bare soil. For the cover crop/mulching PFT, we replace I_c in this equation with an evaporative inhibition constant set to 3.

We can now get to work properly and calculate soil moisture at the next time step. The actual equations and logic used for this are not easily tractable from the Landlab code, but we will try to give a heuristic overview of the workings of the soil moisture calculations.

The algorithm chosen to calculate the final soil saturation depends on the soil saturation at the beginning of the time step s_{ini}: s_{ini} may be larger or smaller than the soil saturation at field capacity $s_{fc} = 0.56$, the soil saturation at stomatal closure $s_{sc} = 0.33$ and the soil saturation at wilting point $s_{wp} = 0.13$ respectively. Real evapotranspiration and hence soil moisture decay is assumed to be dependent on the value of s relative to these thresholds.

Once the decision which algorithm to use is made, the maximum evapotranspiration rate (and, if $s_{ini} > s_{fc}$, deep percolation loss) is used to calculate how much time is left before each of the lower soil saturation thresholds would be reached. If $s_{ini} < s_{wp}$ already, then all of those times are of course zero. The relationship between those calculated times and the length of the time step dt (i.e., if dt is larger or smaller than each of the times) then leads to a choice of a specific forecast equation for soil moisture at the end of the time step. Depending on the case, that forecast equation may depend on the maximum evapotranspiration, the thresholds described above, the time step length and the time it will take to reach lower thresholds. For the case that s is projected to drop below s_{wp}, the forecast equations make use of an additional, lowermost threshold: the soil saturation degree at the hygroscopic point $s_{hgw} = 0.1$.

7.2.4 Vegetation

We adapted this submodel from Landlab's `vegetation_dynamics.py` script (documentation here). Our contribution is to add a factor SH to the equation for net primary productivity (NPP) that parameterises the improvements to soil nutrients that may be achieved by correctly implementing WSA practices. In accordance with the soil moisture component, we also added a cover cropping/mulching PFT, but because that PFT needs to have its biomass set to 0 in order to be effective at conserving soil moisture, it is no different from bare soil in terms of vegetation dynamics and only needed in order to enable the model code to run.

The vegetation component solves Equations 2 and 3. The solutions to these equations (i.e., live and dead biomass) are then used to diagnose the remaining state variables, i.e., live leaf area index and vegetation cover fraction. Those than indirectly feed back on the vegetation by having an effect on soil moisture calculations (see previous section).

For the 'bare soil' and 'cover crop/mulching' PFTs, the case is clear: both live and dead biomass are always set to zero for simplicity. For grass, the calculation is of course more complicated.

For brevity, we shall focus on the equation for live biomass, as that is what we are directly interested in. The model simply uses the analytical solution to Equation 2:

$$B_l = (Bl_{\text{init}} - Y_{\text{const}}) \cdot \exp\left(-(k_{sl} + k_{sf}\xi) \cdot dt\right) + Y_{\text{const}} \tag{8}$$

where Bl_{init} is the initial live biomass and dt is the time step length in days. We also have

$$Y_{\text{const}} = \frac{\text{NPP} \cdot \phi_a}{k_{sl} + k_{sf}\xi}. \tag{9}$$

All other variables and constants are defined as in Equation 2. NPP is calculated as follows:

$$\text{NPP} = \max((ET/dt) \cdot \text{WUE} \cdot 24 \cdot w \cdot \rho_w, 0.001) \cdot SH \tag{10}$$

Here, dt is the time step in hours, WUE is the water use efficiency of the vegetation (0.001 for grass - 10 times smaller than the Landlab default setting), $w = 0.55$ is the conversion factor of CO_2 to dry biomass and $\rho_w = 1000$ kg m^{-3} is the density of water. SH is the soil health factor introduced by us and takes on values between a lower threshold of 1 and an upper threshold of 1.3. Each model year, the value of SH on each field is calculated based on the current SH and the WSA status of the field: If the field is currently using WSA, SH is incremented towards the higher threshold. If the field is currently not using WSA, SH is incremented towards the lower threshold. In mathematical form:

$$SH_{n+1} = SH_n + (T - SH_n) \cdot 0.5 \tag{11}$$

where n indicates the current year, $n + 1$ the next year, and T is the WSA-status-dependent threshold that we let SH tend towards in that time step.

7.3 Social Model

7.3.1 Initialise Fields and Farmers

For every tile in the grid, one field agent is created and positioned at that tile. Then, a number of farmer agents as determined by the ‘number of farmers’ parameter of this model run are produced. Each farmer is positioned on the map by randomly selecting a tile which does not have a farmer already in it, and moving there. All fields and farmers are initialised with identical values, as described in Initialisation.

7.3.2 Allocate Fields

Each field finds the farmer closest to it. Where farmers are equidistant to a field, a random choice is made. The chosen farmer is declared to be the owner of this field.

7.3.3 Assign Lead Farmers

A number of existing farmers, according to the ‘number of lead farmers’ parameter of this model run, are randomly selected. These farmers are declared ‘lead farmers’, meaning they are forced to use WSA practices in every year. The fields owned by these farmers are set to use WSA in the first year.

7.3.4 Find Neighbours

Each field identifies its neighbouring fields in the orthogonal directions (up, down, left, right). If a neighbour field is owned by a different farmer than this field, those two farmers are recorded as neighbours.

7.3.5 Gather Yield

Each farmer calculates the total and average yields from their owned fields, and makes this information accessible to neighbouring farmers.

7.3.6 Make Farming Practice Decisions

Each farmer who is a lead farmer is disregarded, as they must continue using WSA. Remaining farmers who have not yet encountered WSA are disregarded, as they are not able to change their farming methods. Remaining farmers who are currently in a grace period reduce their remaining grace period by 1 and are disregarded. The farmers that remain are able to make farming practice decisions.

First, these farmers consider whether their total yield this year is below the 'desperation threshold' parameter of this model run. If it is, this means that the farmers are not able to provide for themselves, and will try something new 'out of desperation'. These farmers indicate that they will switch practice next year.

Those farmers who don't switch out of desperation compare their average yield to the highest average yield among their neighbours. If the neighbour's yield exceeds the farmer's yield by more than or equal to the 'jealousy tolerance' parameter of this model run, this means the difference is sufficiently high that the farmer is motivated to change. These farmers indicate that they will mimic the neighbour's farming practice next year.

Note, farmers indicate that they will switch practice, rather than switching practice immediately. This is to ensure that practice mimicking is not impacted by the order in which farmers make practice decisions.

7.3.7 Change Practice

Each farmer with an indicated next practice not equal to their current practice is put into a grace period according to the 'grace period length' parameter of this model run. Each farmer then changes their practice to that indicated.

7.3.8 Share Knowledge

All farmers who will use WSA practices in the next year inform their neighbours of the existence of WSA, meaning those neighbours are able to make farming practice decisions in the future.

Appendix: Graphs in Whole Parameter Space

Figure 8: Average Yield by Farming Practice per year in the whole parameter space.

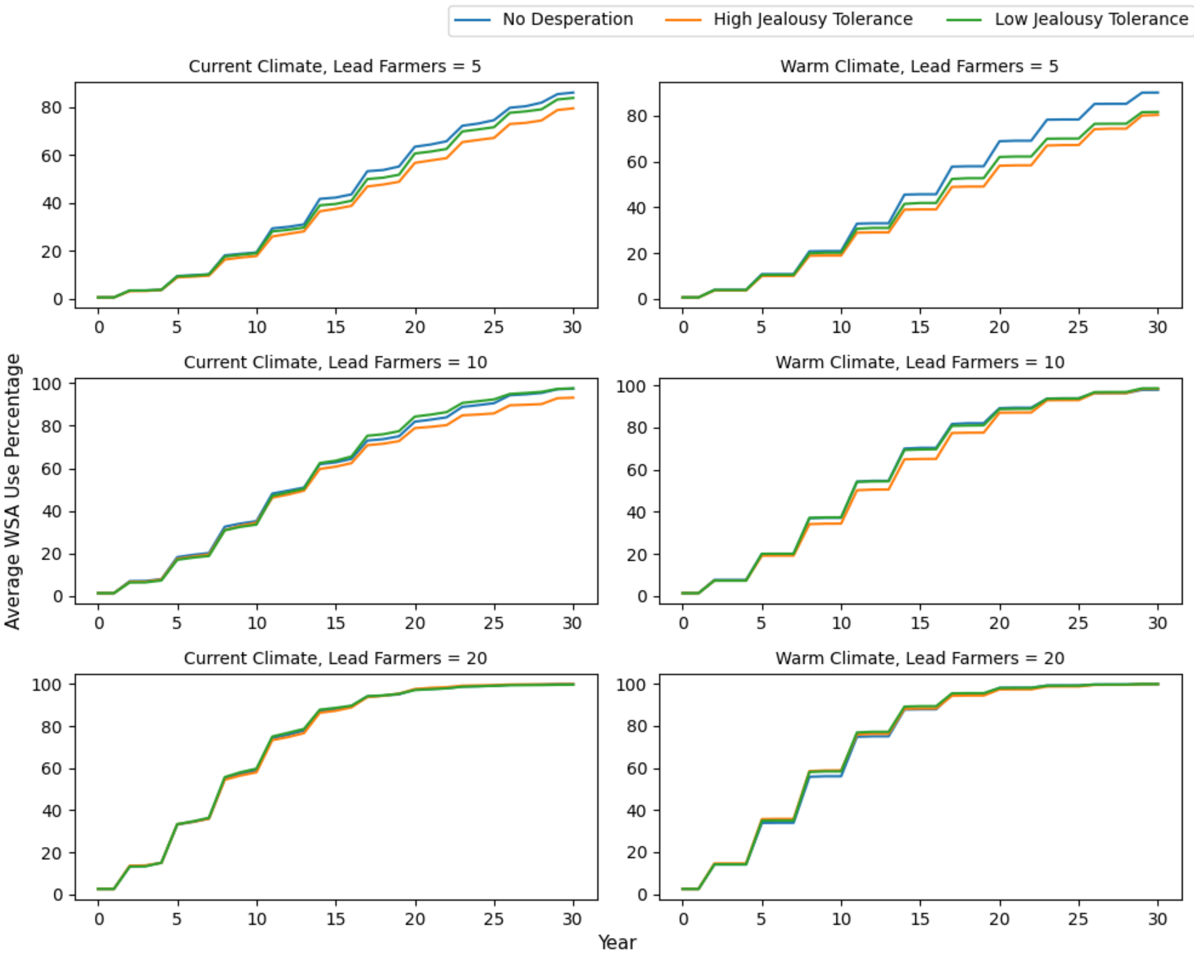


Figure 9: Average Water Smart Agriculture uptake per year for each of the three Social Scenarios in the whole parameter space.

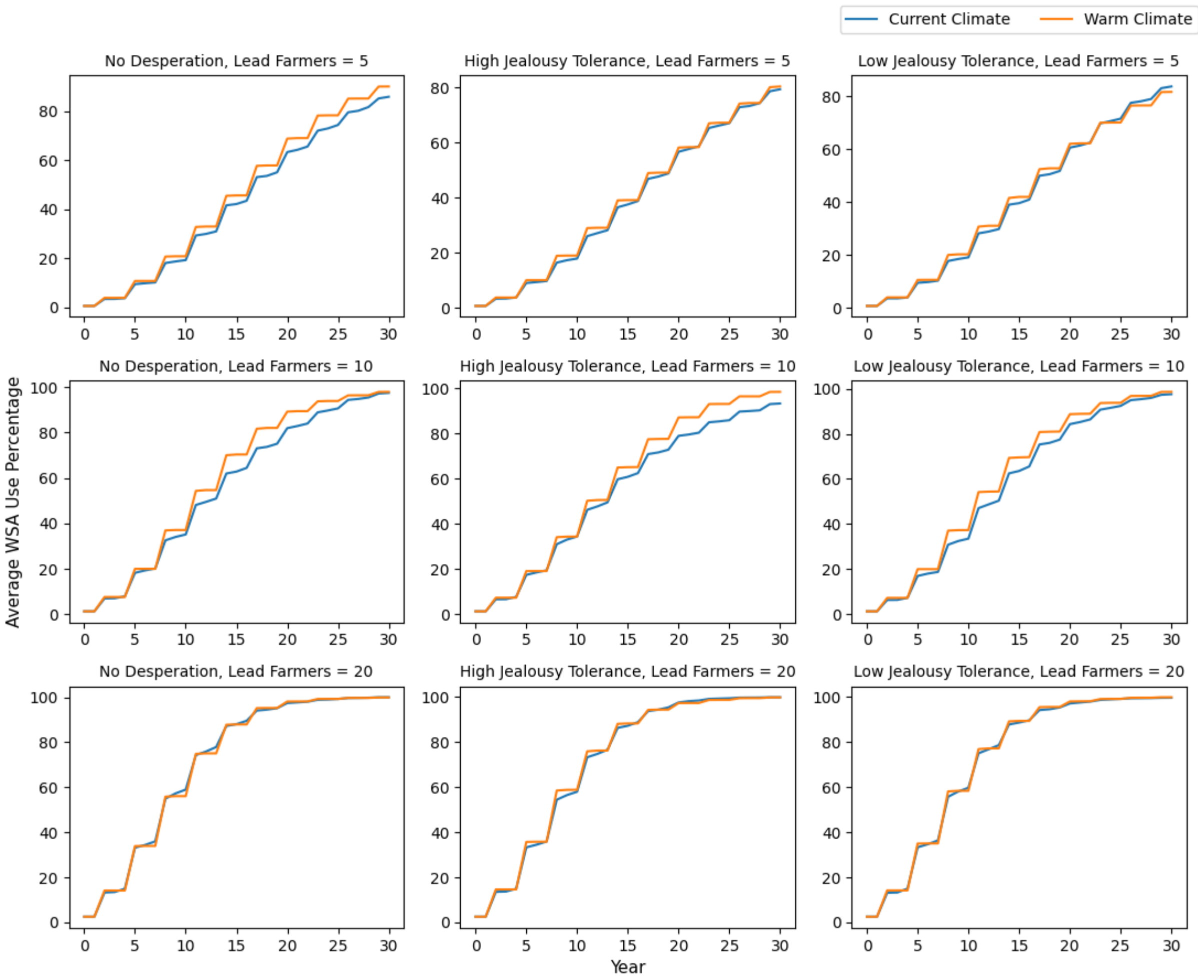


Figure 10: Average Water Smart Agriculture uptake per year for each of the two Climate Scenarios in the whole parameter space.

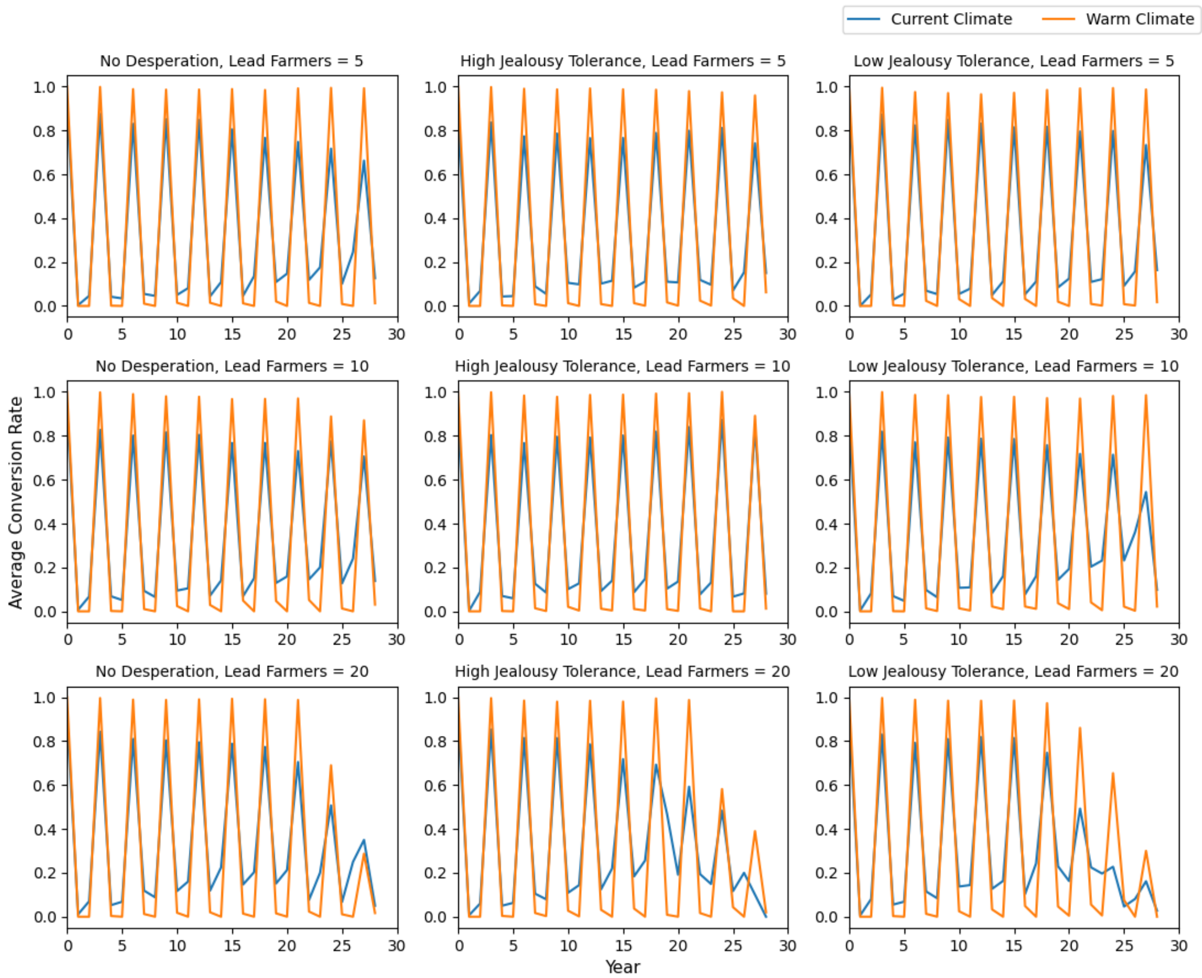
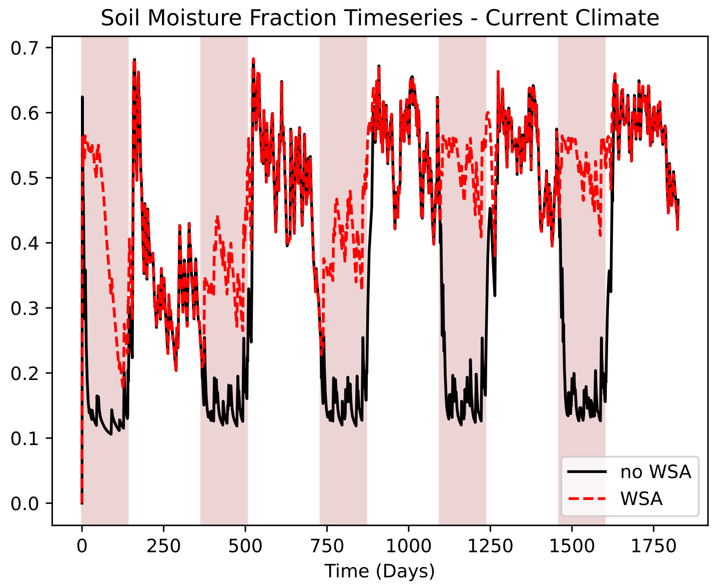
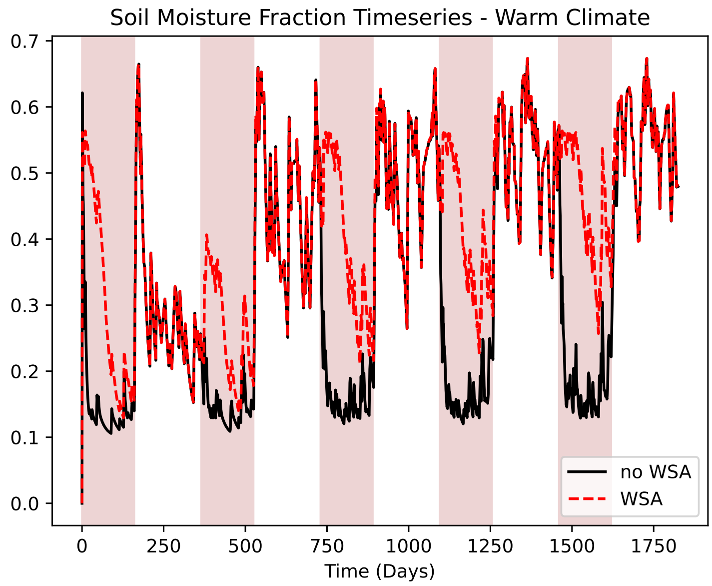


Figure 11: Average conversion rate to Water Smart Agriculture per year for each of the two Climate Scenarios in the whole parameter space.



(a)



(b)

Figure 12: Daily time of Soil Moisture from the Ecohydrology model run on its own for five years in both the 'current' (top) and the 'warm' (bottom) climate configurations, spatially averaged over fields using WSA and fields not using WSA. 20 WSA fields are randomly allocated and remain the same throughout the model run. Brown shading indicates the dry season. WSA field soil moisture drops significantly more in the dry periods when the climate is warmer.

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