

DAESim: A Dynamic Agro-Ecosystem Simulation Model for Natural Capital Assessment

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Abstract

Threats to sustainable food production are accelerating due to climate change, depletion of natural capital, and global financial instability. This causes significant risks to farmers, consumers, and financial and policy institutions. Understanding agro-ecosystems, and how varying management styles impact long-term local and global risks, is critical to future wellbeing. To better understand and forecast alternative futures for agricultural production, we have developed a dynamic simulation model that accounts for the core natural capital components of agro-ecosystems, including climate, soil, carbon, water, nitrogen, phosphorus, microorganisms, erosion, crops, grazing, and trees. Dynamic Agro-Ecosystem Simulation (DAESim) model can be used to simulate dynamics of soil health and project it into the future to assess vulnerabilities and resilience. This knowledge can inform and guide investment decisions by financial institutions, insurance companies, farmers, and government agencies. Here, we describe the basic model structure, sensitivity, and calibration results. We then run a few scenarios to highlight the model's ability to analyze the results of alternative agro-ecosystem management options.

Keywords: Integrated modelling, modularity, ecosystem services, carbon sequestration, farming practices, regenerative agriculture.

1. Introduction

In a world of increasing population and consumption, changing climate, and decreasing availability of arable land, there is an urgent need to improve and preserve the quality of agro-ecosystems. Agriculture has always been particularly vulnerable to extreme weather patterns and other environmental hazards. With mounting pressures from climate variability, soil loss, and with many uncertainties in associated parameters and processes, threats to sustainable food production are increasing in frequency and intensity (IPCC Climate Change 2014; Shukla et al. 2019). These pose significant risks to farmers, consumers, and the financial and policy institutions supporting agro-ecosystems and concerned with food security. Risk and resilience are crucial factors in the management of farming systems (Meuwissen et al. 2019; Rotz & Fraser 2015). The growing risks are a strong incentive for the development of analytical and predictive methods to enable better-informed farm management. In addition to conventional ecological modelling, we should account for social drivers and mechanisms, which could potentially reward farmers for carbon sequestration and provision of other ecosystem services, which can offer new incentives for their sustainable production. The United Nations, Food Systems Summit 2021 (von Braun et al. 2021) is a recent compendium of studies about building food system resilience to vulnerabilities, shocks and stresses.

Agro-ecosystems are complex, dynamic systems that operate on local and regional scales influenced by local, national, and global economic frameworks. In these systems causal relationships between system variables are not simple – they are affected by contextual and exogenous factors and by positive and negative feedback loops, time delays, and non-linear dynamics (Sterman 2002). Moreover, they are embedded in hierarchical social systems, which come with their additional uncertainties and drivers. Complex dynamic systems modelling is one approach capable of incorporating these features.

A number of models have been developed to assess agricultural management decisions. For example, in the context of Australian farming, the Australian Bureau of Agricultural and Resource Economics and Sciences developed the Global Trade and Environment model (Pant et al. 2002). This is a general equilibrium model that takes the inter-linkages of the economy into account, among which supplies, access and transportation costs, taxes, investor and household behaviors are most important. It also includes two extension modules that appraise the costs and benefits of multiple scenarios. However, they have not considered recently marketed ecosystem services (e.g. carbon sequestration) and only focus on elements

that relate directly to the traditional market economy. In addition, their environment module only considers the effects of management decisions on greenhouse gas emissions, without key crop and environment specific features. Another example is the Investment Framework for Environmental Resources model (INFFER) (Pannell et al. 2012; Pannell et al. 2009), which was developed to assess and improve conservation and other types of environmental projects. It calculates the impacts and opportunities for policymakers and businesses in order to clarify investment opportunities. However, it does not consider agricultural land management in its framework. As a third example, the Australian Stocks and Flows model, assesses the sustainability of the grains industry and food security under different scenarios of climate change, but does not include the broader contributions of ecosystem services to agricultural productivity and societal wellbeing (Dunlop et al. 2004). FARMSIM (Richardson & Bizimana 2017) is another simulation model designed to inform decision-makers about the economic and nutritional impacts of various farming systems. Though it can provide estimates of empirical probability distributions for net income for crops and/or livestock, and nutrient intake by the farm family, there is no information provided about ecosystem services and the health of land.

The available models generally only cover a subset of agro-ecosystem types (Turner et al. 2016). There are many crop production models (e.g., Agricultural Production Systems sIMulator (APSIM) (Holzworth et al. 2014)), financial risk models (Katchova & Barry 2005; Pannell et al. 2012), and farmer behavior models (Martin et al. 2011; Robert et al. 2016). What is missing from the range of specialized models is integration. The category of natural capital incorporates a variety of other ecosystem services that include global climate regulation (via carbon sequestration), water supply, nutrient cycling, soil creation, pollination, recreation, and others. While these ecosystem services are vital to local and global populations (Assessment 2001; Costanza et al. 2014b; Reid et al. 2005), their dynamics and value are not fully recognized in most ecological models and conventional economic measures of wealth and productivity (Bateman et al. 2013; Costanza et al. 2014a; Dasgupta 2008). Accurate assessment of wellbeing requires analysis of a far more inclusive set of indicators beyond income level and economic productivity (Farley & Costanza 2010). This highlights the necessity for developing models that can encompass the natural and social capital considerations underlying individual and societal wellbeing. Furthermore, farmers, bankers, and government agencies need to know the value of farm assets, particularly natural capital in addition to built capital. They also need to include responses to future climate projections, along with individual performance and industry trends.

So far, no analytical models have been developed to assess natural capital on farms in collaboration with farmers and governments to maximize sustainable wellbeing (Turner et al. 2016). Besides, none of the existing models can assist major landowners, banks, and large corporations to make decisions about shifting from commercial exploitation to investment in sustainability targets (e.g., carbon sequestration and biodiversity). These gaps give rise to the need to build a comprehensive model to help understand the complex connections between natural, social, built, and human capital, ecosystem functions, and services; and forecast factors affecting farm seasonality, sustainability and resiliency.

As a first step in this process, we used STELLA modelling software to develop a dynamic simulation model of the natural capital component in farm agro-ecosystems. To create this model, we synthesised, extended and integrated components from several existing models of farm productivity (e.g., LHEM (Voinov et al. 2004), Century (Parton et al. 1994), DayCent (Parton et al. 1998), APSIM (Holzworth et al. 2014), etc.). We used data from an Australian agro-ecosystem to calibrate and test the model performance. Historical data on biophysical and environmental conditions were collected from publicly available geo-spatial databases including SoilGrid and Digital Agriculture Services. These data include climate, soil characteristics, erosion rates, groundcover, water quality, chemical inputs and other variables. We incorporated the effects of both fast variables (i.e., rainfall, fertilizer application rates, and short-term management decisions) and slow but changing variables (i.e., soil conditions, climate change, long-term farming practices and groundwater) on the indicators of soil function/health (e.g., water holding capacity/bulk density).

The rest of the paper is organized as follows: Section 2 describes the model framework and method as well as the details of our case study. Section 3 presents calibration and validation results, uncertainty analysis, and findings from the model. Finally, Section 4 reports the results of alternative, progressive management scenarios and Section 5 derives conclusions, some practical and managerial perspectives, and future directions for the model and its applications.

2. Materials and methods

Our Dynamic Agro-Ecosystem Simulation (DAESim) model has eight interconnected modules that are grouped in the following three broad categories: (1) Climate and management; (2) Natural Capital; and (3) Outputs. This modular approach allows for easy integration of additional modules in the future, namely human, social, and built capital. It is designed to explicitly account for ecosystem goods and services and factor them directly into the process of global economic production and human welfare development. In Figure 1, we

graphically show the structure of the model, and the interactions among the modules. We also color coded the diagrams such as green variables demonstrating inputs and orange filled ones indicating the empirical dynamic data. Access to the model is available here at <https://www.comses.net/codebase-release/a18a26d6-5a1d-4327-a7ec-31367939bc78/>.

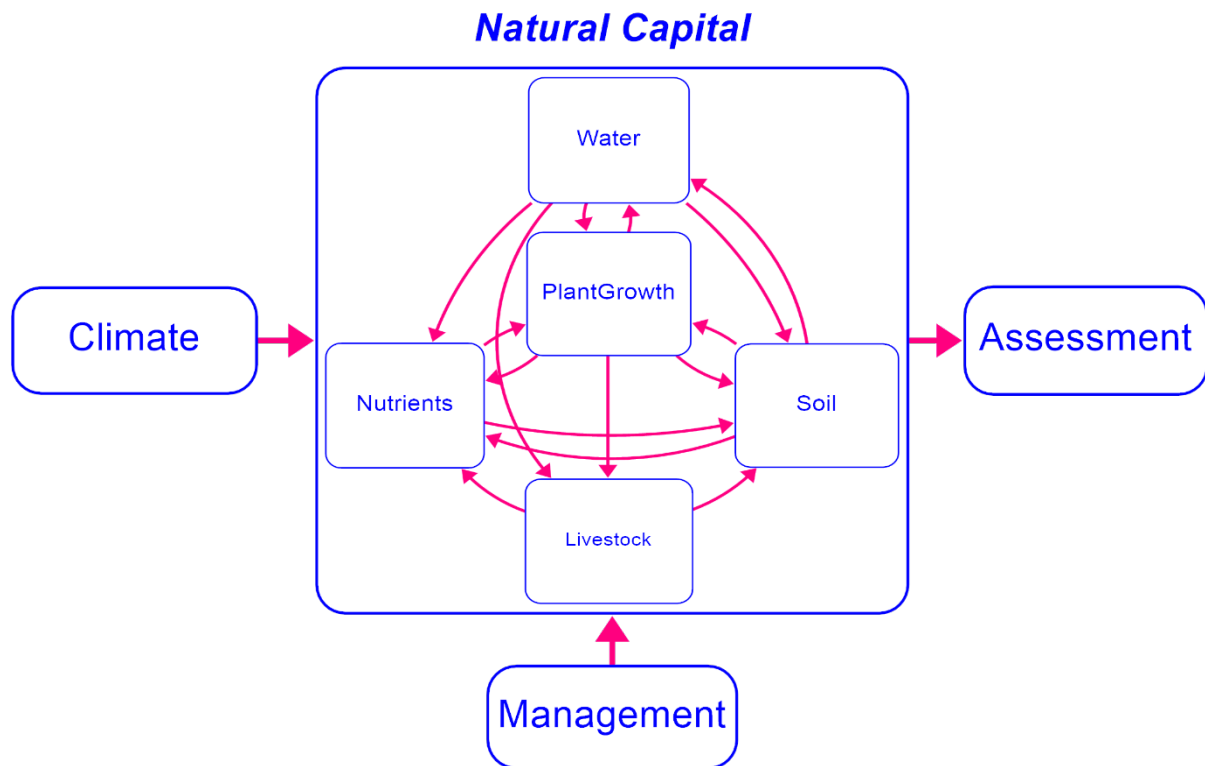


Figure 1. A graphical representation of the modules in DAESim illustrating the interactions among the ecosystem functions.

2.1. Climate

This module does not have any state variables. It is designed primarily to simplify data pre-processing. It encompasses variables that describe the climatic factors, such as precipitation, temperature, humidity, wind speed, solar radiation as well as day length, elevation, and Julian days (Figure 2). Appendix A1 provides further details about data sources and unit conversions in the climate module. In this model, macro climate variations are considered representing climates from different locations.

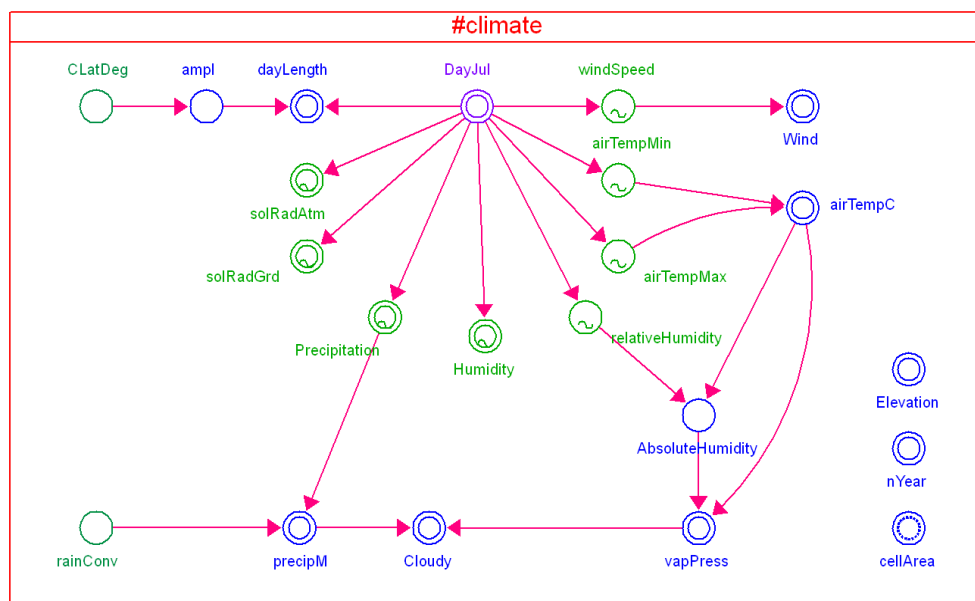


Figure 2. STELLA diagram of climate module.

2.2. Management

Agricultural management practices considered in this study are presented in Figure 3. They drive short and long term variability in soil properties and processes related to water retention, crop growth dynamics, sediment and nutrient loss, etc.

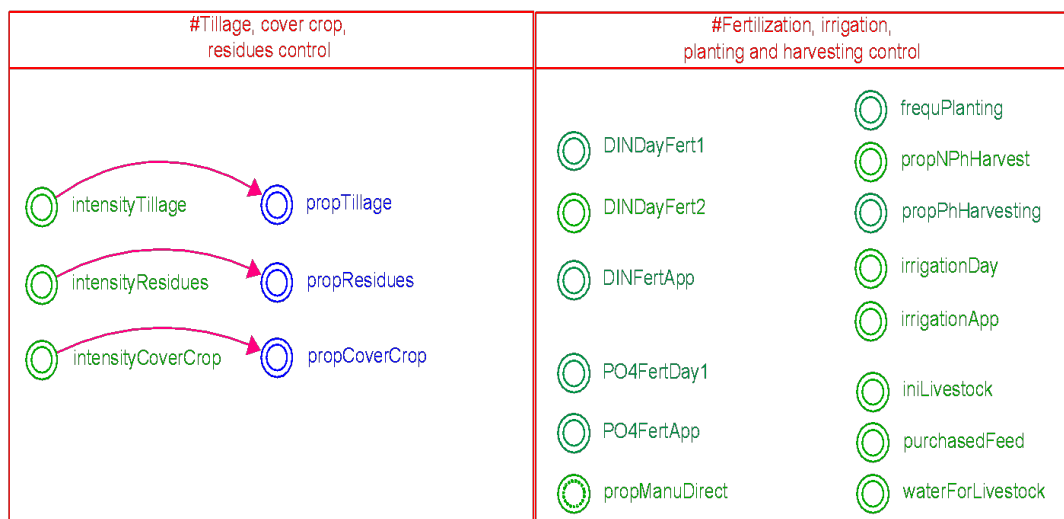


Figure 3. STELLA diagram of management module.

Farm management practices directly influence different processes related to nutrient availability, crop growth, soil health, and water retention. There are two general categories of farming practices: conventional and ecological. In general, conventional farming practices focus on near term yields and inputs. Whereas, ecological farming has a focus on also regenerating natural capital to balance long term food production with ecosystem health. The

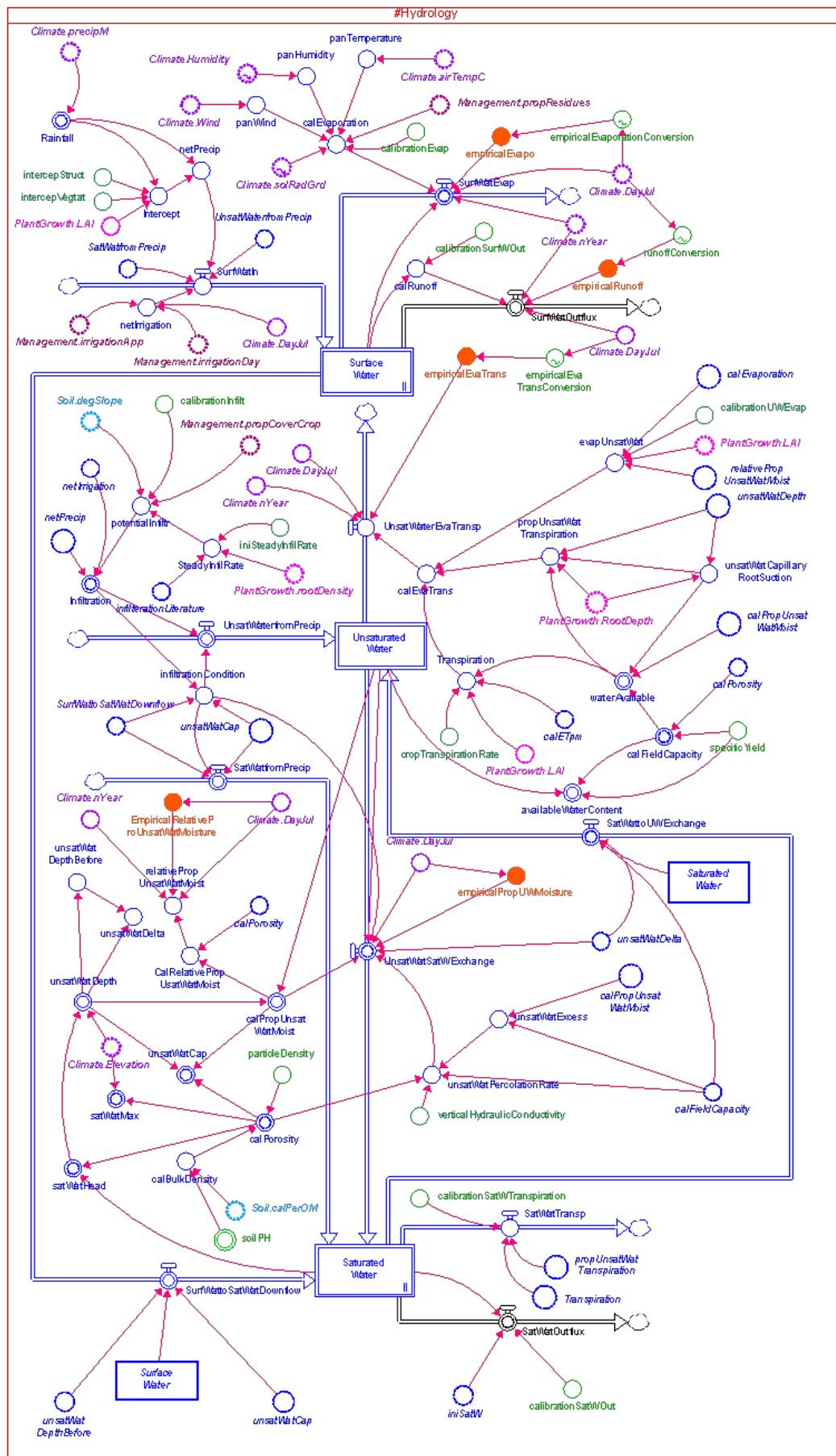
potential benefits for ecological practices are not only limited to carbon sequestrations and biodiversity preservation, but also building farming community well-being as well as improving farming livelihoods and the social reproduction of culture. More details on the convergence and divergence of agriculture practices and definitions are provided by Schreefel et al. (2020). Regeneration International summarises a list of practices that are supposed to be important in establishing a truly ecological and climate-resilient farm¹. Read more about Regeneration International here. In DAESIM, we specifically consider a set of management practices such as reduced tillage, cover crops and plant residues and their impact on the health of ecosystem services. The values for these control parameters vary between 0 and 1 indicating the fraction of land with conventional/conservation/no till, intensity of crop residue inputs to the soil, and intensity of cover crop adoption. This module allows the user to control other management practices in agriculture including planting, harvesting, fertilizing (including chemical fertilizer and manure compost) and irrigation, grazing and potential manure application.

2.3. Natural capital

2.3.1. Water module

In line with the LHEM (Voinov et al. 2004) hydrologic module, the water module of DAESim has three state variables to mimic the vertical movement of water: surface water, unsaturated groundwater of soil, and saturated groundwater storage. It calculates the associated fluxes related to physical (such as evaporation, runoff, and percolation into groundwater storage) and biological (interception, infiltration into soil water, plant transpiration) processes to simulate the water exchange between the state variables (Figure 4). Water plays a crucial role in regulating most of the ecosystem functions, and as such, the outputs of this module are used as inputs in all the other modules. It is these multiple water process features that distinguish DAESim from other common plant growth models (e.g. DAYCENT). The main function of water is to enhance plant growth, but also to aid decomposition by microbes and trigger the nutrient and mineral cycles to sustain plant life.

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Infiltration is the process by which water on the ground surface enters the soil. We used an established empirical model for predicting the infiltration rate based on soil properties (percentage of sand, silt, clay and organic matter as reported in the erosion module) and moisture content (Patle et al. 2019). Additionally, the infiltration rate can be modified by the habitat type (ground cover as defined in the management module), vegetation type, and root system. Vegetation has a positive influence on infiltration by increasing the rate of water penetration into the soil. This is a key feedback that many farmers know, as establishing good plant ground cover leads to a virtuous cycle by holding more runoff, which aids plant growth. Conversely, overgrazing and loss of ground cover increases runoff, erosion, and loss of plant growth. Our model captures these particular benefits in reducing soil erosion by protecting the soil surface so water tends to infiltrate instead of running off. In addition, relying on the findings of Xie et al. (2020), the model considers the direct impact of the crop root system on the infiltration rate.

The bulk density of a soil sample is estimated as the mass of the sample divided by the volume of the sample. When dealing with soil samples, the average bulk density of soil is 2 g/cm³ (but ranges from 1-3g/cm³ from topsoil to subsoil). This is a key value that is unfortunately not measured often enough and lacks depth and spatial resolution, especially as soil bulk density changes with management (Gajda et al. 2016). Here bulk density is assumed to be the initial bulk density of soil samples unless otherwise specified. To monitor the changes of the bulk density over time, we refer to the study of Yue et al. (2017) to estimate the dynamics of bulk density based on soil pH and the percentage of organic matter, which states how bulk density goes down and organic matter goes up. This dynamic bulk density feedback is also a key addition in DAESim that would show accelerating positive or negative multi-year effects on plant growth.

Field capacity - the proportion of total soil volume capable of holding water - is important for measuring the dynamics of water storage over time. The value of field capacity changes in time depending on the specific yield (referring to the wilting point water) and porosity (referring to the total soil volume that is taken up by the pore space) (Rab et al. 2011). See Appendix A2 for equations and further explanation.

2.3.2. Plant growth module

We developed the DAESim crop growth module using similar assumptions and processes to those in the LHEM plant module (Voinov et al. 2004) and APSIM (Holzworth et al. 2014), including net primary production in photosynthetic tissue, translocation to non-photosynthetic tissue, and decomposition (refer to Figure 5). Photosynthetic (leaves) and non-photosynthetic

biomass (stems and roots) are the main components of plant biomass and translocation moves carbon sugars from leaves to stems and roots. Water and nutrients are translocated from the roots and stems to the leaves. The module imports driving variables (solar radiation, day length, and min/max temperature, humidity data) from the climate module, nutrient availability from the nitrogen and phosphorus modules, and water availability from the water module to simulate the plant growth. Recent studies suggest that a greater allocation to root mass provides a greater rooting depth later in the season leading to drought tolerance and increased yield under water-limiting conditions (McNally et al. 2015). To consider this effect, we allow two genetic states with more or less the root biomass allocations affecting root depth equations. The plant module data sources are available in Appendix A3.

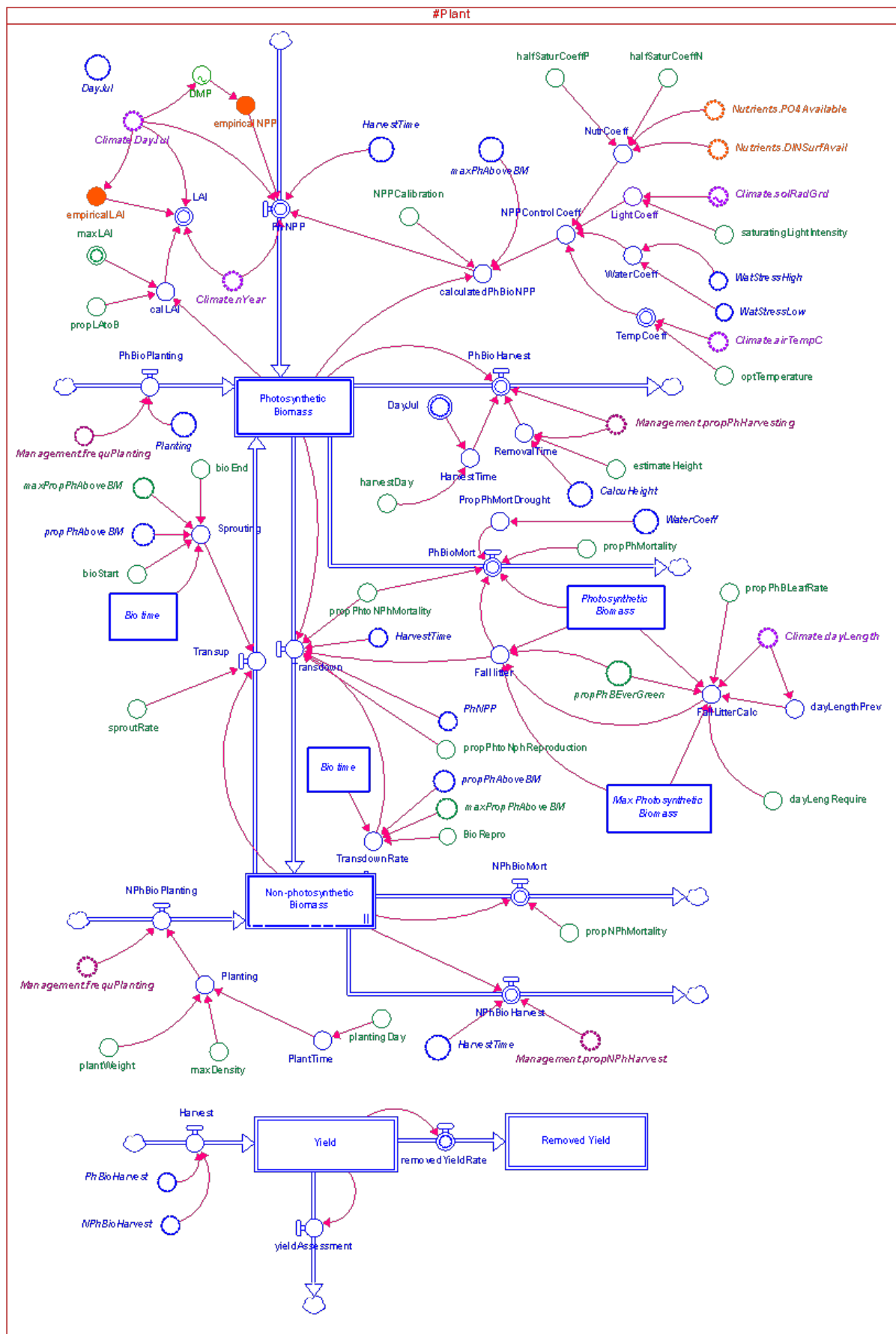


Figure 5. STELLA diagram of plant growth module.

2.3.3. Soil module

We developed the soil module based on the Millennia, APSIM, and LHEM models. It encompasses both organic matter decomposition process and soil erosion by water (Figure 6). The decomposition process includes four state variables related to stable detritus, labile detritus, minerals, and microbial biomass. The inclusion of microbes serves predominantly to close the nutrient and mineral cycles in the system. Compared to the existing models, our model adds the manure/detritus decomposition process, calculates CO₂ emissions from soil, explores the dynamics of microbial activities, and estimates nutrient loss due to water erosion. We modify the inflows of soil organic matter (SOM) to the stable and labile pools of carbon by adding manure/compost as a source of SOM. This also adds to the nitrogen pool. For example, when the biomass decomposes and/or is consumed by an animal and released as manure, part of the biomass turns into stable detritus and part is released as CO₂. For estimating the initial amount of organic matter stock, we incorporated an equation using total carbon stock, proportion of carbon in different pools (Srivastava et al. 2016), and the conversion factor for estimating organic matter from soil organic carbon (Edwards 2021).

Ecological/conservation agriculture seeks to regenerate and build organic matter stocks in soil to sequester carbon from the atmosphere (Schreefel et al. 2020). Increased soil organic matter aids water holding capacity and cation exchange capacity. Decomposition of biomass via active microbes is key to nutrient cycling. This natural decomposition process provides nutrients but also releases CO₂ and other greenhouse gases. Microbial abundance and type can accelerate soil nutrient cycles and soil organic matter regeneration (Wang et al. 2011). The decomposition processes of stable and labile detritus are defined with nonlinear functions to account for the influence of microbes, humidity, and temperature. The level of soil moisture (from the water module) should be suitable for the microbes to continue to accelerate the biological decomposition process. The soil temperature for microbial activities is calculated based on the average daily temperature.

Microbes consume a proportion of plant matter for growth and release organic matter when they break them down, shifting carbon from the labial to the stable pool. Various microbe types have different growth rates, consumption rates, decomposition rates and survival rates in times of stress. In this model, however, due to the unavailability of empirical data, we simplify the process and consider microbes as one aggregate group. So, we assume these rates to be identical for all soil microbes. This is a reasonable assumption since soil microorganisms can decompose organic matter, cycle nutrients and fertilize the soil only as part of the microbial community (Johns 2017).

Stable and labile detritus can be lost through the process of oxidation to CO₂ and leaching as dissolved organic carbon. The amount of litter and detritus returned to the soil depends on the leaf biomass and amount harvested with the rate of decomposition influenced by mechanical incorporation and tillage. Selection of farming methods can influence the rate of oxidation process. In conventional farming, losing carbon-rich organic matter from soils can happen at a higher rate, releasing the carbon captured by photosynthesis. The loss of stubble also results in increased evaporation. This effect is reflected in the soil oxidation rates in the model. We used the Universal Soil Loss Equation (USLE) (Wischmeier & Smith 1978), one of the most widely used models for estimating daily soil erosion in cropland. This model uses four factors, including: Soil Erodibility Factor (K), Slope Length and Steepness Factor (LS), Cover Management Factor (C), and the Support Practice Factor (P), for predicting soil loss (See Figure 6). In the original model, these factors are assumed to be constant in time. However, as farming practices and land management decisions can indirectly affect the values of K and C, we modify USLE to account for these effects.

Soil erodibility factor, K, represents runoff rate and soil susceptibility to erosion events. To account for the dynamics of K, we use the findings of Wischmeier and Smith (1978) and Renard and De Marsily (1997) about the influence of SOM, bulk density, and permeability on the soil erodibility factor. Regarding the C factor dynamics, we include the influence of land use and management on reducing the soil loss rate. The loss of topsoil due to erosion events is reflected in the model. Further explanations about the soil module are available in Appendix A4.

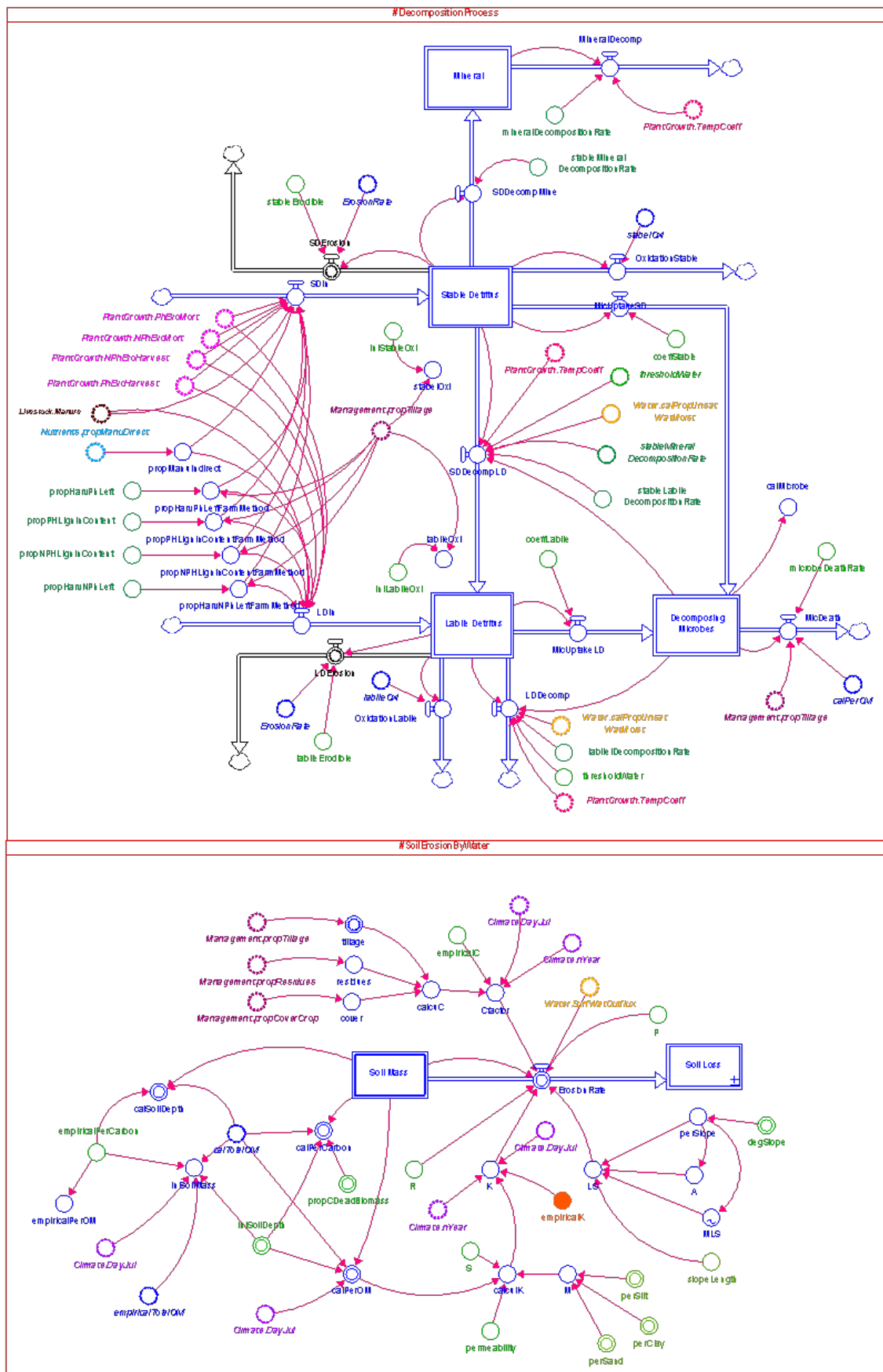


Figure 6. STELLA diagram of soil module including the decomposition process and water erosion.

2.3.4. Nutrient module

We incorporated the nutrient cycle defined in GEM (Panagos et al. 2014) to simulate the dynamics of nitrogen (Figure 7) and phosphorus in topsoil (Figure 7). We considered four major sources of nitrogen in the system, including atmospheric deposition, fertilizer application, natural decomposition of organic material, and manure. N is provided via the manure decomposition process but soluble N is also lost to denitrification. N fixation by legumes or free living N fixing microbes eating detritus is included. Nitrogen fixation is the amount of atmospheric nitrogen that is converted to soluble forms such as ammonia by enzymes to be ready for plant uptake. Denitrification is the process that converts nitrate to nitrogen gas (N_2 , N_2O and NO_2), thus removing bioavailable nitrogen and returning it to the atmosphere. We use the study of Holzworth et al. (2014) for defining the nitrification process. In DAESim, the incoming fluxes of phosphorus are the same as nitrogen fluxes except for the nitrogen fixation and denitrification processes.

The nutrient cycle outflows are based on the hydrologic fluxes calculated in the water module as well as net primary productivity defined by the plant module. For estimating the nutrient levels, GEM and LHEM closely follow the water fluxes and measure plant available nutrients on the surface, in the unsaturated storage, and the saturated layer. Our model currently focuses only on the nitrogen and phosphorus stored in the upper soil layer that is available for plant uptake. Thus, the vertical transportation of nutrients, as well as the sorption process, are excluded from the model analysis and replaced by two equations. The first one measures the amount of nutrients that can be carried away in moving water. The second equation refers to nutrient leaching, the downward movement of dissolved nutrients in the soil profile with percolating water. The nutrients in the surface storage are assumed to be available for plant uptake when there is water in surface soil or when the water is available to the plant root system to dissolve them. This assumption allows us to monitor the availability of nutrients for plant growth. Further details for the nutrient module can be found in Appendix A5.

2.3.5. Livestock module

At present, this module predominantly feeds into the nutrient and soil modules in the system, but does not go into all the details of livestock rotations (such as animal movement), the economic (e.g., profitability for farmers) and social (e.g., food security) considerations. Demographic composition and the availability of feed and water are important determinants for analyzing and understanding the dynamics of livestock populations. We consider the seasonal fluctuations in the number of births (Birth) and deaths (Death) of animals, depending on the population and gender, while the influence of animal age on the dynamics of the population is excluded.

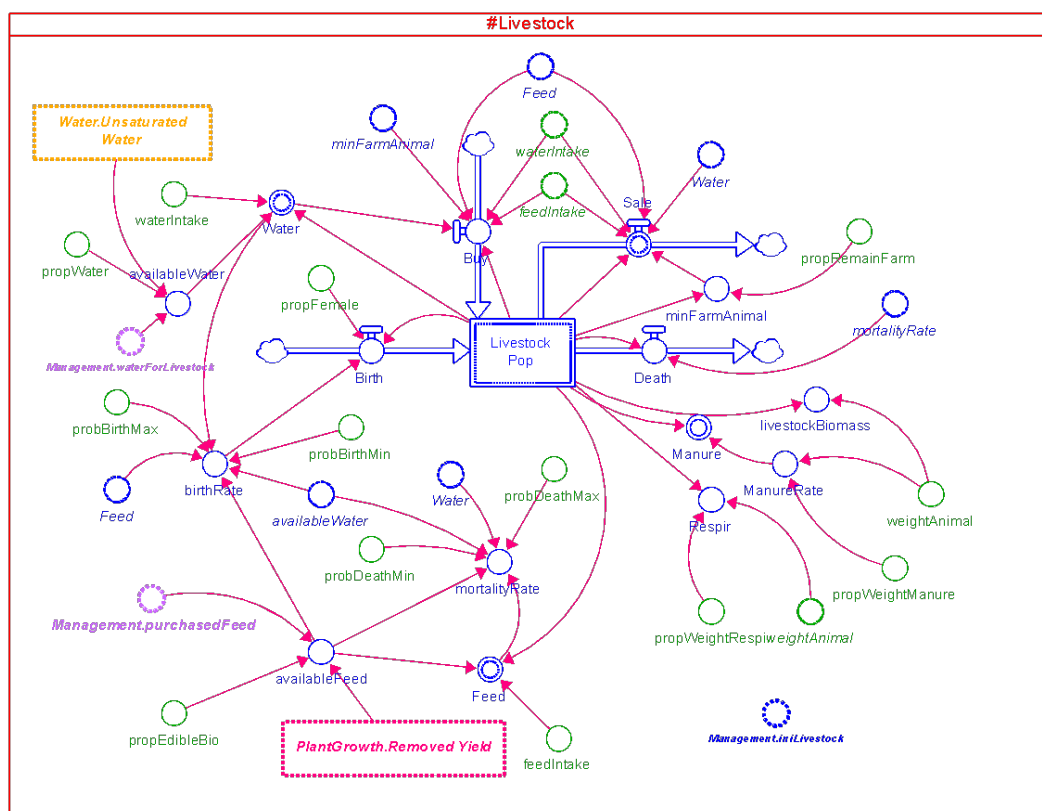


Figure 8. STELLA diagram of livestock dynamics.

Factors such as the availability of feed² and water can influence the fertility rate. Regarding the risk factors associated with animal mortality (mortalityRate), we only consider the influence of drought and ignore the role of other factors such as disease and age³. Note that we did not consider the different nutrient aspects of feedstock. The trade of livestock depends on whether there is enough feed and water available, and the minimum number of animals on the farm. Manure³ is an inevitable by-product of livestock production. The word manure used

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in this context refers to animal waste. It is a valuable material that can be used as a source of organic material and fertilizer for crops and pasture. We define the composition of manure as excreted material from the animal faeces and urine only and exclude the amount of bedding used for manure collection. In our case, the quantity of manure depends on the animal's weight. It is to be noted that the livestock module takes inputs from the plant growth and water modules. The impacts of different grazing techniques and their pressures on land were not the focus of this study and were left out of this module. Further details are available in Appendix A6.

2.4. Assessment

Soil health assessment is defined by measuring the biological, physical and chemical functionalities of soil as a living system to inform land management decisions and ensure nutrition security, environmental quality, as well as climate change resilience (Maikhuri & Rao 2012). In this module, we aim to introduce a set of measurable soil parameters to indicate the effectiveness of farming management practices and quantify their efficiency (Figure 9). A comprehensive list of indicators, their definitions and references is provided in the study of Bennett et al. (2010) and Karlen et al. (2019). The selected soil health indicators for this study include the following factors.

The importance of soil structure and fertility is presented in

- *Carbon stock*: the total carbon in soil, mineral, labile and stable detritus (linked to the soil module);
- *Soil organic carbon*: the percentage of organic carbon in soil (linked to the soil and erosion modules);
- *Soil erosion potential*: the amount of soil eroded (linked to the erosion module);
- *Crop yield*: farm production (linked to plant module);

Microbial activity and potentials of nutrients to support plant development are reflected in

- *Fungal microbes*: the microbial biomass (linked to the soil module);
- *Phosphorous*: The total amount of phosphorus in the topsoil (linked to the phosphorous and erosion modules);
- *Nitrogen*: The total amount of nitrogen in the topsoil (linked to the nitrogen and erosion modules).

The water retention, moisture to support plant growth and pollutants are measured in

- *Water quality*: total nitrogen concentration in surface water to indicate potential water pollution (linked to the water and nitrogen modules);
- *Water quantity*: the total amount of water a soil can hold at field capacity (linked to the water modules).

The main objective is to maximize the ecosystem health, which can be only achieved through finding a balance between soil water, nutrients, structure, and production. Finding the optimality in this case is a challenging task as, for example, an increase in the amount of nutrients (e.g., nitrogen and phosphorus indicators) can cause water pollution problems (in conflict with the water quality indicator).

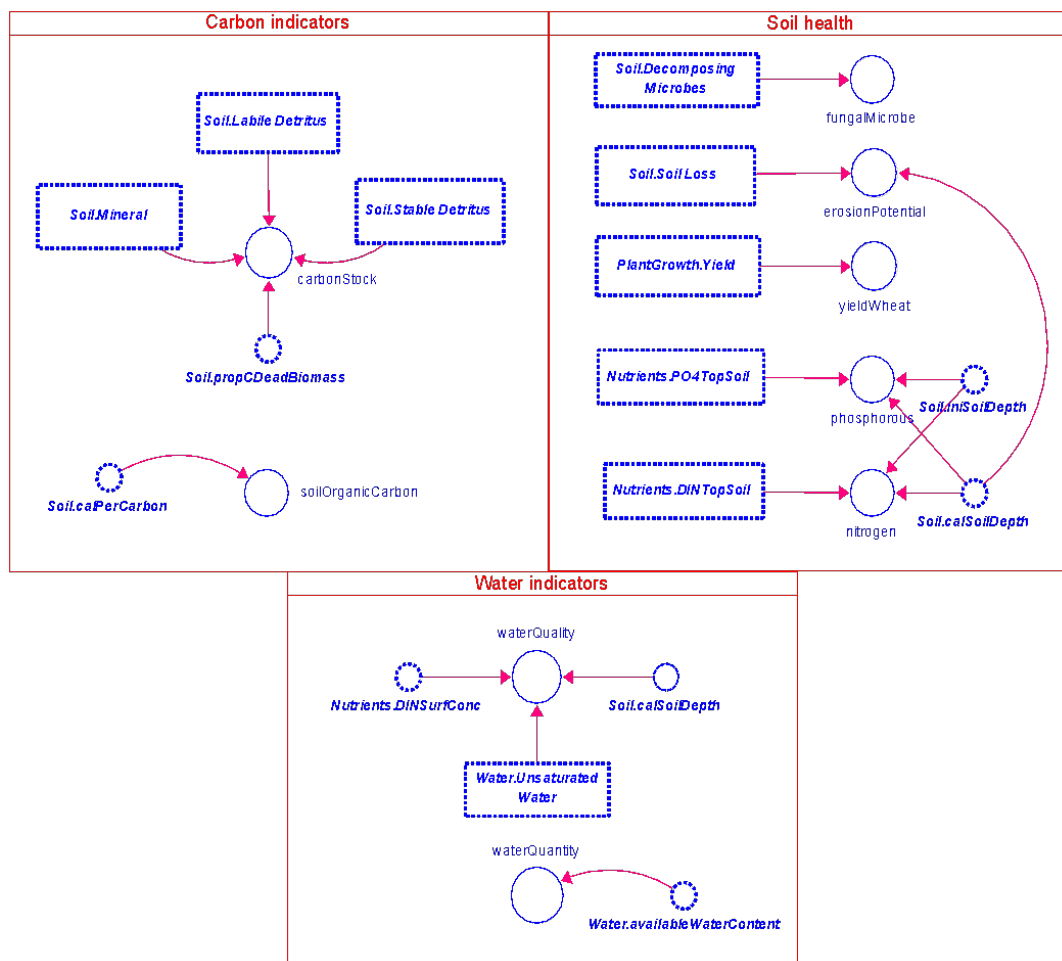


Figure 9. STELLA diagram of farm health assessment.

In this study, we avoided indicator aggregation to provide users with the flexibility of selecting indicators of interest to be included in their soil health assessment and land management decision-making. In the future, we can use interactive multi criteria analysis methods to aggregate all these indicators for a more general and understandable ecosystem service assessment.

3. Sensitivity, calibration and validation

- **Sensitivity**

To assess the model sensitivity, we use the one-factor-at-a-time (OFAT) method in which each parameter is varied solely utilizing a range from minimum to maximum of the possible value from the STELLA model, divided into 50 runs. For each value, the resulting absolute change in the outputs is compared to the baseline. We categorize parameters as highly sensitive, averagely sensitive, and low sensitive parameters. Overall, the soil module has the highest sensitivity, whereas the phosphorus module has the lowest sensitivity (see Appendix B1).

- **Calibration**

Calibration is a vital step in tuning the model to reproduce empirical data by tweaking the values of unknown and sensitive model parameters. There is a set of data related to plant, water, and erosion dynamics available in geospatial databases that can be used for this purpose as described below. We selected the Woodstock (long season) wheat farm in New South Wales, Australia (-33.715014, 149.071208) as the case study site. The data are collected by the National Variety Trials (NVT) program on a yearly basis, to assist Australian grain growers in varietal decision making. The trial sites are chosen in consultation with stakeholders (agronomists, growers, etc.) to represent soil types, crop prevalence, and environments within a region. Contracted providers sow, maintain and harvest the woodstock trial site and assure that no limiting factors like nutrition or disease affect the result of experiments. Complementary information about the NVT program can be found [here](#). We ran the model over the time period of Jan 2018 to Jan 2020. The list of DAESim input parameters and their values is available in Appendix B2.

For the Plant module calibration, we collected dry matter productivity (DMP) data from the [Copernicus Global Land Service](#)⁴ for every 10 days and converted it to daily NPP data (using $DMP \times 0.45 \times 0.1 / 1000$) to match the model time step. Besides, LAI data are collected from the same database and scaled (values are divided by 40) to be consistent with the model parameter. Figure 10 shows that the simulated NPP and LAI are replicating the empirical data quite closely. The spring and autumn growing seasons increase in leaf area and net photosynthetic productivity, with decreases in dry summers and colder winters. This shows the carbon capture and translocation potential of the plants to soil and to yield.

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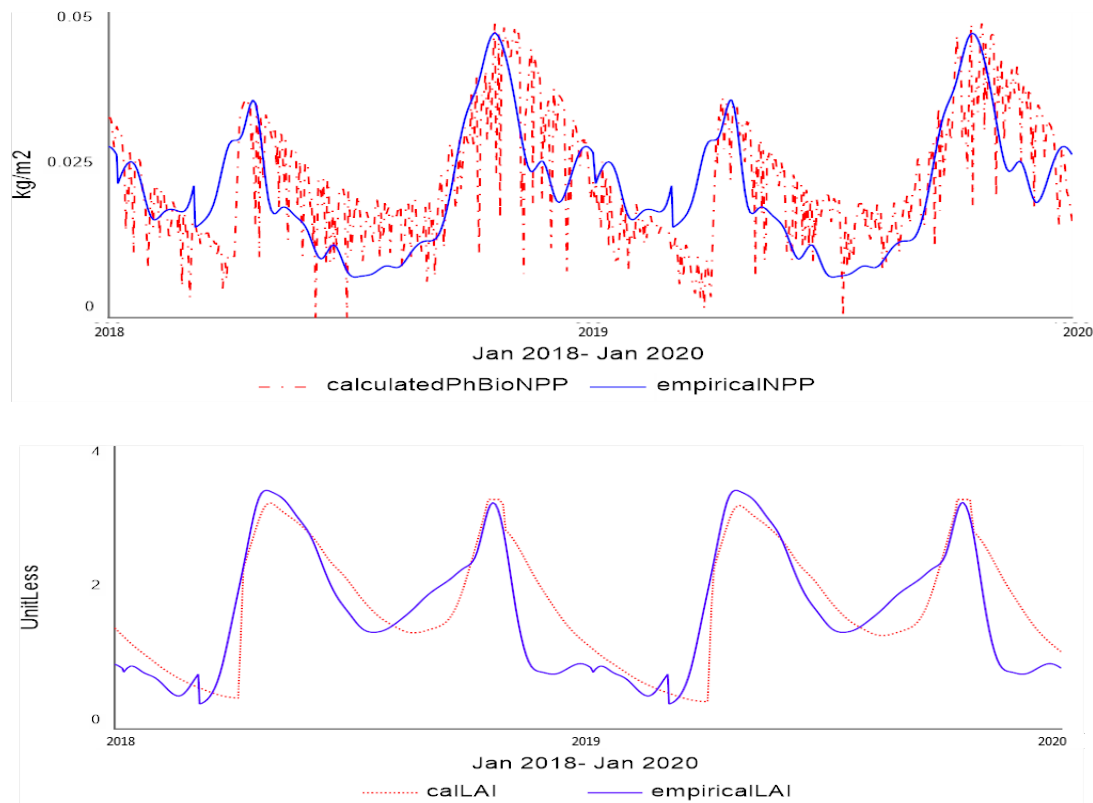


Figure 10. Comparing the empirical data of NPP and LAI with those calculated by the model.

For calibrating the soil module, we focus on estimating different pools of carbon in soil - labile, mineral and stable - and microbial biomass. According to (Srivastava et al. 2016) the SOM consists approximately of 10% labile (active), 40-80% stable (slow) and 10-50% mineral (passive) detritus, with differential turnover rate ranging from months to over several hundred to thousands years. We multiplied these proportions in the amount of SOM collected from [SoilGrid](#)⁵. Regarding microbial biomass, we rely on the empirical findings of Bastida et al. (2021) to estimate the initial amount of microbes in the soil, as well as their reproduction and death rates. Figure 11 compares the empirical and model generated dynamics of microbes.

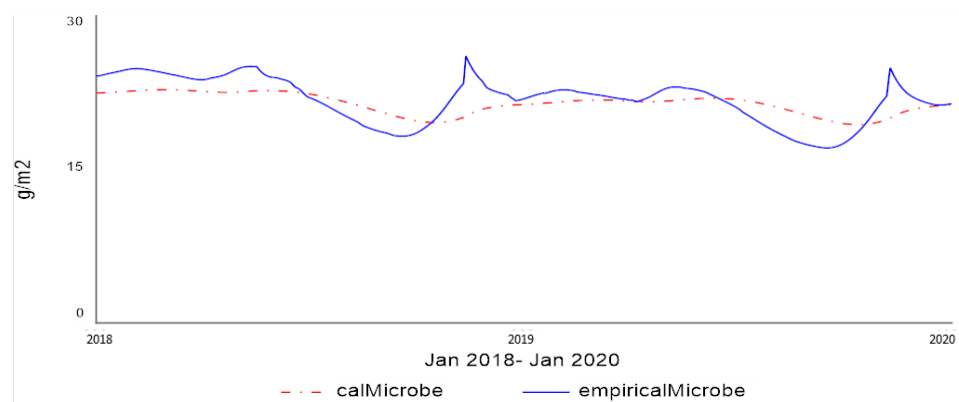


Figure 11. Comparing the microbial biomass dynamics calculated by the DAESim model and empirical equation derived by Bastida et al. (2021).

We calibrate the evaporation and transpiration in the water model. The required data are collected from the Australian Bureau of Meteorology website⁶. To be directly used for calibration, we make the units of data consistent with the units of the model variables (the units of evaporation and transpiration data are divided by 1000). Figure 12 demonstrates the model can replicate the values and trends observed in the empirical data.

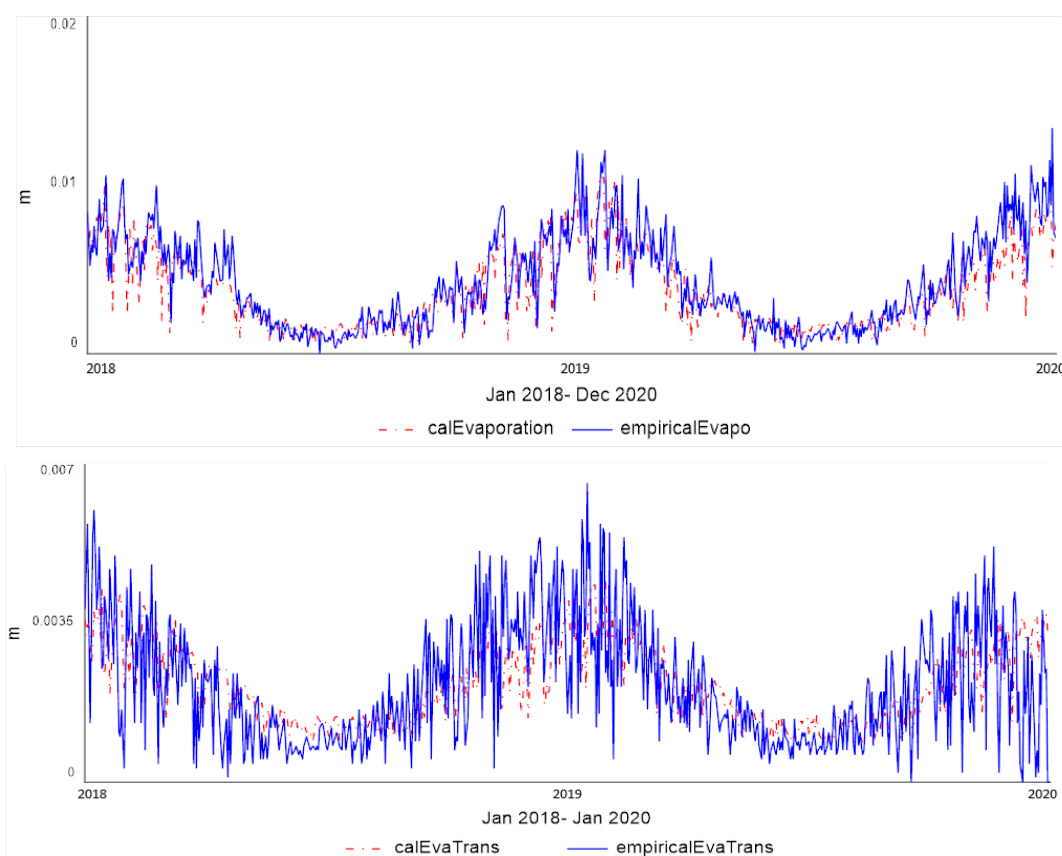


Figure 12. Comparing the empirical data of evaporation with those calculated by the model.

We use the amount of nitrogen and phosphorus reported by [NVT program](#)⁷ to calibrate the total nitrogen and phosphorus in the topsoil. In the erosion module, we tune the value of soil permeability to make the calculated erodibility factor (K) as close as possible to the value of K collected from the Maps of Australian soil loss by water erosion derived using the [RUSLE](#)⁸. The difference between calculated and empirical K is less than 0.01.

⁶ <http://www.bom.gov.au/water/landscape/#/qtot/Actual/day/-28.4/130.4/3/Point////2020/8/14/>

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⁸

- **Validation**

After the model calibration with available data, the model delivers an overall assessment of the soil health as presented in Figure 13. With regards to the microbe indicator, the estimated microbial biomass (on average 25 g/m²) and its dynamics in time are consistent with the microbial biomass (23 g/m² in topsoil) reported by [Soil Quality Organization](#)⁹. Looking into NVT reports (2017-2019) for Woodstock, the predicted annual wheat yield (0.6-0.7 kg/m²), total nitrogen (35 g/m³), and total phosphorus (25 g/m³), and percentage of soil organic carbon (1.8%) are completely in line with the measured values in Woodstock (0.644-0.675 kg/m² yield, 40-60 g/m³ nitrogen, 20-30 g/m³ phosphorus, and 1.2-1.9% organic carbon). The estimated total carbon stock at around 48000 g/m² is in agreement with the values reported by SoilGrids at 46000 g/m². Comparing the annual average of erosion rate (4 g/m³) with the data collected from CSIRO Data Access Portal (Maps of Australian soil loss by water erosion) (3 g/m³), we observe a high accuracy in the erosion predictions (estimation error less than 5%).

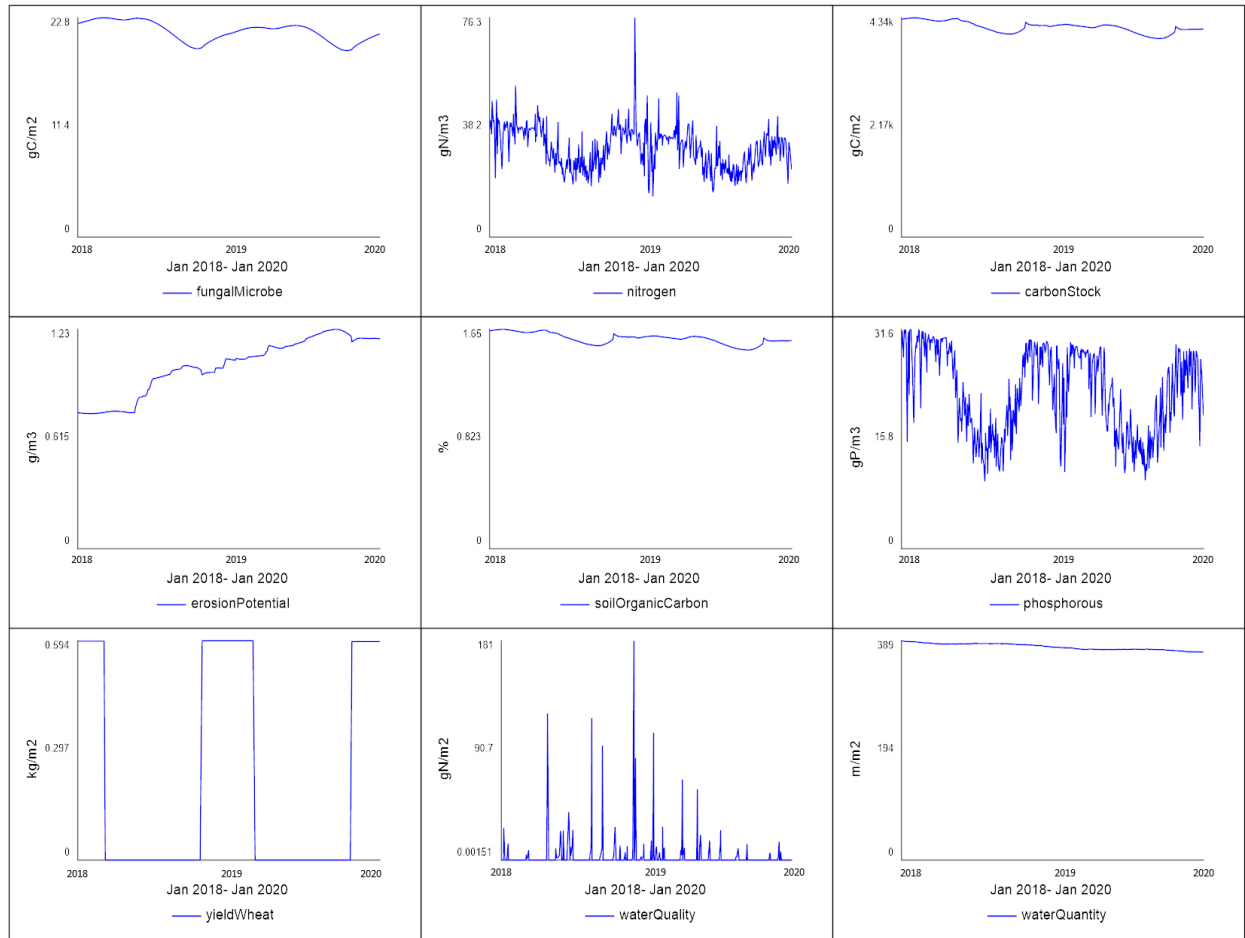


Figure 13. Woodstock soil health as assessed by DAESim.

Beside, a comparison between the estimated root depth and the empirical data from the literature (Thorup-Kristensen et al. 2009) shows that the simulation model can estimate the depth of the wheat crop with high accuracy within the ranges (between 1 and 2 meters) reported by Lilley and Kirkegaard (2016) and Kirkegaard and Lilley (2007). We also compare the estimated and empirical values of soil moisture (from Copernicus Global Land Service) to check the validity of the water module further. As shown in Figure 14, the simulation model can estimate the dynamics of moisture level with high accuracy and indicate that in very wet years, soil is saturated all the time and there is no benefit of irrigation.

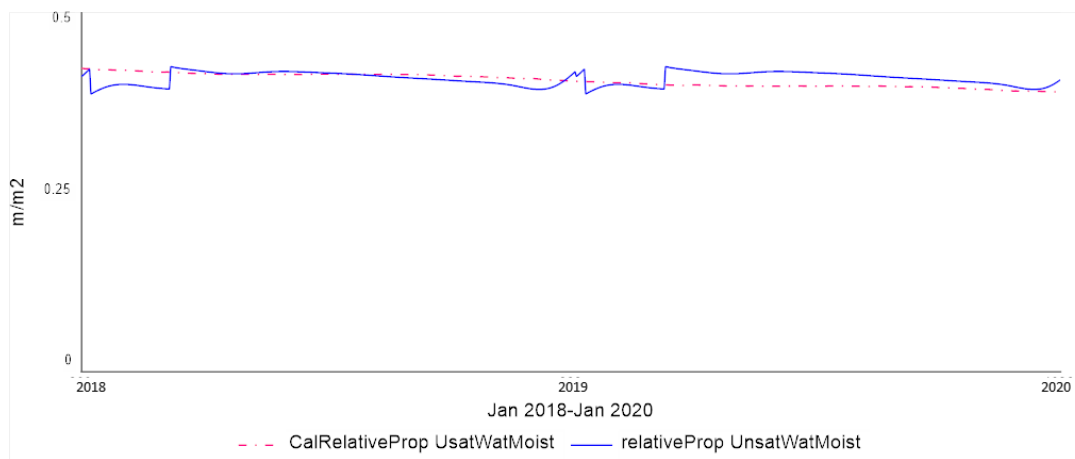


Figure 14. Comparing the empirical and simulated values of soil moisture over 2.8 years

4. Scenario analysis: alternative farming practices

• Scenario description

This subsection outlines the scenarios, from climate change to management options regarding agriculture. Table 1 indicates the variables changing in each scenario and their assumed values. For the purpose of this initial study, we only consider the scenario of changing farming practices and exclude possible climate scenarios (it is not being treated in this paper). In conventional farming, losing carbon-rich organic matter from soils can happen at a higher rate, accelerating climate warming. But by regenerating, rehydrating, and covering soils, farmers sequester more carbon underground. For conducting the model experiments, we changed the variables of the management module assuming all the other model parameters stayed the same. In scenario 1 (Run 1), the farmer uses recommended fertilizer rates for the reference crop, and conventional management practices (conventional tillage, low intensity cover crop, and low amount of crop residues) to achieve higher yield. In scenario 2 (Run 2), the farmer applies the same fertilizer but switches to conservation practices by applying conservation tillage, leaving higher residues on the land, and keeping the land covered with all-season crops.

Table 1. The list of parameters and their values that change in each scenario.

	Intensity of tillage	Intensity of cover crop	Intensity of residues
Scenario 1	5	1	1

Scenario 2	3	3	3
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● Scenario result

We run the model for 10 years and compare the scenarios. The results in Figure 15 show that in the conservation farming scenario, all soil health indicators perform better than in the conventional scenario; though compared to the conventional farming, the yield drops slightly in the first few years, and it bounces back to the initial state in the later years. No-till farming minimizes soil disturbance, while cover cropping, and residue adoption retain water and rehydrate land. Hence, they are expected to build healthier, more structurally stable, and resilient soil for plants. Changing tillage practices was shown to significantly increase levels of soil organic carbon (from 1.4 to 1.6% in 10 years) and soil microbes (18 to 26 g/m² in 10 years) over time. This is in line with other studies that have shown that a combination of reduced tillage, cover cropping, and stubble retention can increase soil organic carbon by up to 10-20% after less than 10 years (Institute 2014)¹⁰. This result thus predicts the potential of the conservation scenario, in which we observe a 14% increase in soil organic carbon, with minimal yield losses.

¹⁰ <https://rodaleinstitute.org/wp-content/uploads/Regenerative-Organic-Agriculture-White-Paper.pdf>.

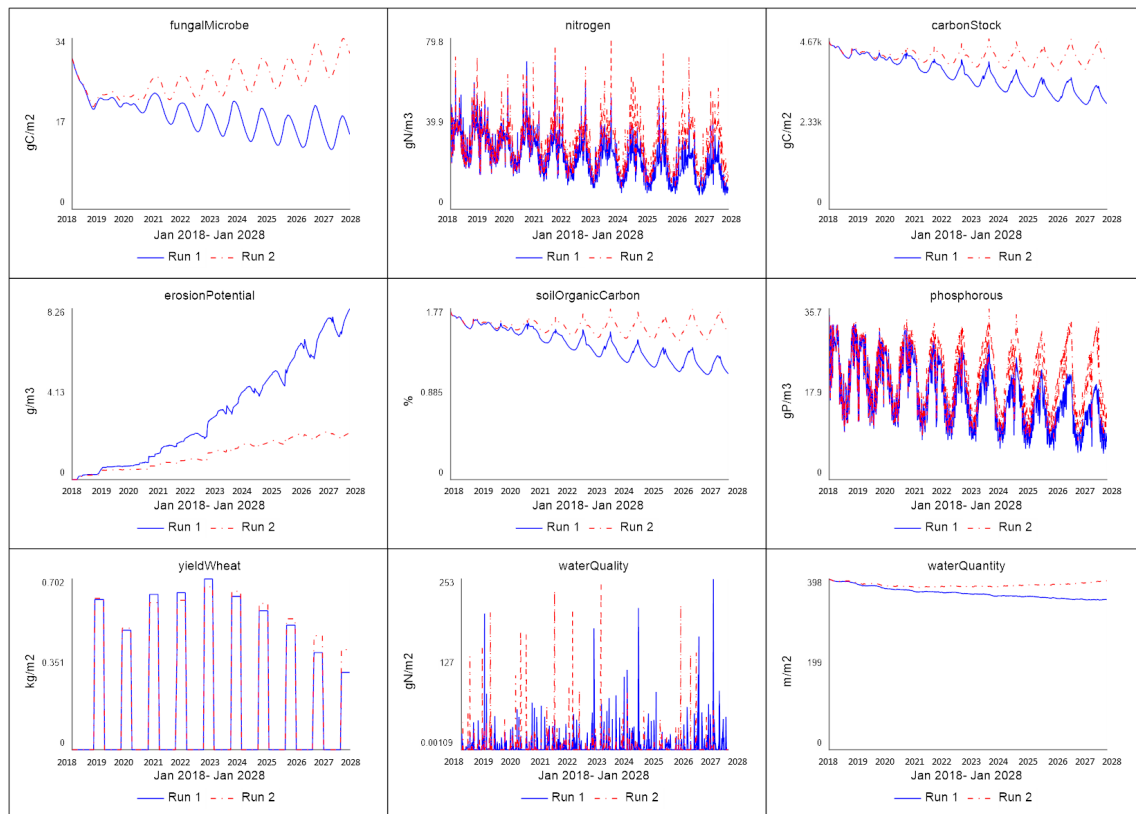


Figure 15. A comparison between the influence of conventional (blue/solid-Run1) with conservation (red/dotted-Run2) farming practices on soil health indicators. In the conventional scenario, there are clear downward trends in the carbon stock, microbial biomass, and water holding capacity.

Another critical management factor in conservation farming is the strategic use of crop rotation and cover cropping. It can effectively protect soil from erosion and preserve the nutrient levels for successful plant growth (Bolinder et al. 2020). It also helps balance soil nutrients (about 20% increase in topsoil nitrogen and phosphorus) and build a diverse SOM. The other influential practice used to help maintain and support soil biology is residue mulching and retention. Leaving plant residue evenly across the ground serves as mulch protecting the soil and supporting the fungal relationships essential for nutrient uptake and carbon sequestration. In this case, a higher level of soil moisture (5% more) was observed. From our analysis, we conclude that a combination of conservation farming practices reduces the risk of soil erodibility (from 3.2 to 1.2 g/m³ in 10 years) due to the reduction in C factor (-42%) and increase in percentage of soil carbon. The changes observed in the C factors are in line with Panagos et al. (2015) estimations of C factors decrease due to management practices in a 10 year period. Hence, using soil conservation as the entry point can considerably contribute to multiple ecosystem services.

5. Discussion and conclusions

Soil naturally stores carbon but if its carbon is exposed to oxygen in the atmosphere, it transforms into carbon dioxide, and is lost from soil contributing to the greenhouse gas emissions that warm the planet. Conservation farming is a set of practices that aims to regenerate soils and at scale ultimately help to compensate for historical farming emissions and reverse climate change by drawing more carbon from the atmosphere. We built an integrated, dynamic simulation model of an agro-ecosystem that can be used to examine the relationship between natural capital, resilience, and risk. The model includes a range of variables potentially affecting the short and long-term behavior of natural capital. It is a synthesis and expansion of several previous and ongoing agro-ecosystem modeling efforts and is intended to be applicable worldwide. The model runs on a daily time step and has been calibrated with historical data for a farm in New South Wales, Australia.

It is important to compare the structure of DAESim with other popular agriculture models. For example, consider APSIM, which is a well-known modelling and simulation tool for farming systems. It contains a set of modules including plant, animal, soil, and climate to simulate systems for a diverse range of practices (Holzworth et al. 2014). Both DAESim and APSIM explicitly simulate water, nitrogen, and soil cycles. Looking into the details of APSIM's soil and nitrogen modules, we note that soil microbes and their role in decomposing organic matter, cycling nutrients and fertilizing the soil are not included. Despite the vital role of microbes in carbon storage and land sustainability, little is known about their biodiversity, interactions within an ecosystem, or factors affecting their growth/degrowth. As a result, they are also rarely considered in simulation models. The Millennial model, developed by Abramoff et al. (2018), is one of the very few models that incorporated microbial processes in soil organic matter predictions. With regards to the soil modules, DAESim is conceptually different from Millennial, and considers microbial pools as measurable entities in the soil, directly influencing the decomposition rate.

DAESim has important implications for both theory and practice. From a theoretical perspective, it can significantly advance understanding and management of agro-ecosystems. This model uses data from spatial databases, other online sources and literature. It can also be used as part of an integrated mobile application that can be user-friendly and easily used by stakeholders. This will improve resilience, long-term prosperity, and well-being for farmers, bankers, and society as a whole. It incorporates social/conservation farming system scenarios to evaluate and forecast potential outcomes. It addresses the soil and water science and research priorities by providing a modelling framework across the soil-atmosphere-water

system. It also enhances understanding of the sustainable limits for productive use of soil, freshwater, river flows and water rights, and developing solutions for restoration and remediation of soil and water.

This tool can also support financial institutions, insurance companies, and government agencies for decision-making. It allows farmers, bankers, and land managers to improve the value assessment of natural capital assets on farms and make more-informed investment decisions. The model assists banks, development agencies, and investors in developing new mechanisms that incorporate accurate natural capital measures by understanding and quantifying its contribution to farm productivity and financial risk. It has the potential to help banks better account for the risks incurred when providing loans to farmers. By improving the ability of farmers to produce consistent financial performance and a more reliable source of income, the model would generate a lower-risk profile and more dependable interest payments on their loans. It addresses the Australian government's priorities around low emissions technologies - DISER 2020 (Government 2020) - by providing a carbon modeling framework across the soil-atmosphere-water system. It also allows the governments to track their international pledges and targets (Höhne et al. 2017) by understanding the carbon sequestered and emitted by their soils. Additionally, it explores the influence of key levers for transitioning to ecological agriculture including increasing financial investment in regenerative farmers and reforming crop insurance to incentivize regenerative practices that regenerate soil as natural capital.

6. Future Research

This study suggests several potential directions for future research. Firstly, the model is generic enough to be used for soil health assessment of any arable land used for cultivating wheat (which is also used as feed for livestock). With minor modifications, the model can be easily adapted for other crops (such as barley, lentil, and pasture) as well as woodland-grassland ecosystems (such as forest and tropical savannah). Secondly, the model validation process was not straightforward and can certainly be improved in the future, as more field data related to soluble nitrogen, and phosphorus becomes available, and the model undergoes further calibration, validation, and testing. Thirdly, the model can be implemented in a spatially explicit way for investigating landscape scale dynamics (Costanza & Voinov 2003). Micro and macro climate variation can be considered by varying the inputs either as a grid of related climate vectors within a landscape or as a set of variables representing climates from different locations, past and future conditions. Finally, the model can be used in future to explore the influence of key levers for transitioning agriculture to regenerate soils including increasing

financial investment in soil carbon. A multi-objective optimization model can help with the farm management decisions under different climate conditions and environmental constraints.

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