A spatial analysis framework to assess responses of agricultural landscapes to climates and soils at regional scale

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Summary

This chapter describes the structure, datasets and processing methods of a new spatial analysis framework to assess the response of agricultural landscapes to climates and soils. Georeferenced gridded information on climate (historical and climate change scenarios), soils, terrain and crop management are dynamically integrated by a process-based biophysical model within a High Performance Computing environment. The framework is used as a research tool to quantify productivity and environmental aspects of agricultural systems. An application case-study using New Zealand spatial datasets and silage maize cropping systems illustrates the current framework capability and highlights key areas for enhancement in future gridded modelling research.

1. Introduction

Large-scale agricultural systems are highly sensitive to climate change. It is therefore critical to develop tools that can assess crop responses to climate by accounting for multiple combinations of soils, plant genotypes and managements that characterise agricultural systems. The productivity and environmental footprint of agricultural systems are strongly influenced by interactions among genotypes (G; e.g. crop species and cultivars), environments (E; e.g. climate and soils) and management (M; e.g. sowing dates and input resource amounts) conditions (Ewert et al., 2015a). The nature of GEM interactions can largely differ spatially and temporally (Teixeira et al., 2016), as farmers tactically combine G and M into technology bundles to respond to a changing E at both short- (i.e. inter-annual weather variability) and long-term (i.e. climate change). These responses can be estimated by process-based biophysical models such as the Agricultural Production Systems sIMulator (APSIM) framework (Holzworth et al., 2014). Biophysical models quantitatively consider GEM effects on underlying crop and soil processes which enables understanding mechanisms of response. For example, by representing water and nitrogen fluxes in crops and soils, biophysical models enable a quantitative exploration of crop performance under future scenarios of land use, farmer adaptation, resource availability and other research and policy aspects relevant to agricultural landscapes (Ewert et al., 2015a; Rosenzweig et al., 2013). Historically, biophysical models were developed and calibrated for local (point-based) simulations in which input data are assumed to be known. This contrasts with large-scale studies, particularly for climate change, in which biophysical models require gridded input data on climates and soils that need to be estimated by different methods (Ewert et al., 2015b). This fundamental change implies an additional layer of uncertainty being carried from input datasets into model structures and ultimately into output simulations (Grosz et al., 2017; Wallach and Thorburn, 2017). This has been the topic of investigation of many recent gridded-modelling studies which assembled different datasets and models to address specific research questions at different scales (Hoffmann et al., 2014; Müller et al., 2017; Zhao et al., 2016). In this chapter, we present a comprehensive methodological description and application of a nationwide gridded analyses framework under development for New Zealand as a case study. The need for analytical solutions to evaluate large-scale agricultural systems is particularly relevant for countries such as New Zealand. The nation's high reliance on the agricultural sector can be illustrated by the economic and environmental profile that largely differs from most nations with a similar degree of development. Specifically, around 6.5% of New Zealand's gross domestic product (GDP) and 50% of greenhouse gas emissions are derived from primary sector activities (MFE, 2018; Stats-NZ, 2017). This chapter describes the development of a spatial analysis framework to operate as a research tool for interdisciplinary science teams working on agricultural landscapes. The approach encapsulates a dynamic biophysical model within a High Performance Computing (HPC) environment to serve as the core-engine for integration of georeferenced information on climate (historical and future change projections), management, soils and terrain nationally. The technical challenges and solutions to implement the spatial analysis framework are illustrated with an example application using a prototype version.

These results provide original insights on the development of gridded-modelling frameworks which can be applied to other situations and locations.

2. Data flow and input datasets

The flow of information across the framework data pipeline is illustrated in Figure 1. The method can be described in three stages: an Input Database stage, which holds the base input data which is harmonised to a common spatial resolution; the Modelling stage, which encompasses the formatting of the data to serve as input for APSIM and running the simulations in a HPC environment; and the Output Database and Visualisation stage, where final outputs are stored and end-users can explore georeferenced simulated results.

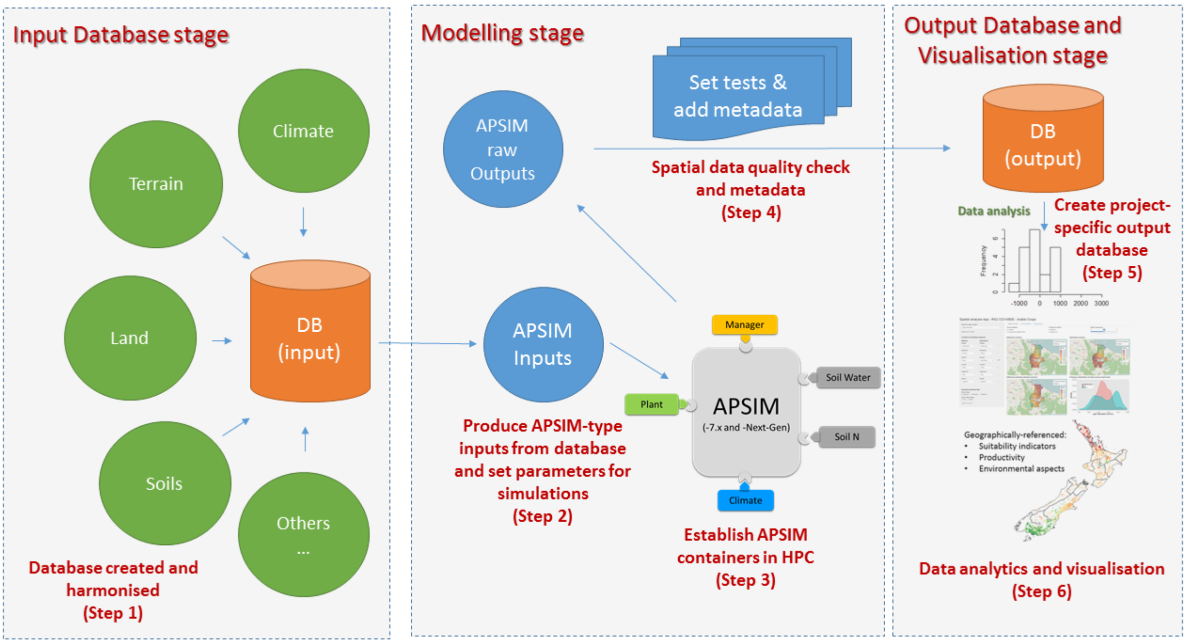

Figure 1. Schematic representation of flow of data across the spatial analysis framework. Input databases (DB) use data from Manaaki Whenua – Landcare Research (MWLR) for soils and terrain and from the National Institute of Water and Atmospheric Research (NIWA) for climate. APSIM is the Agricultural Production Systems sIMulator.

Input datasets are harmonised to a spatial resolution of 3 arc-minutes (~5 by 5 km). This resolution is defined by the gridded-datasets for daily climate variables provided in netCDF format by the National Institute of Water and Atmospheric Research (NIWA) of New Zealand. The climate raster resolution is based on NIWA's Virtual Climate Station Network (VCSN) grid system (NIWA, 2019). The netCDF climate datasets are converted into standard APSIM weather files (.met files in ASCII format) at daily time-resolution. Each file refers to an individual VCSN grid-cell containing all weather variables required by the model. These daily climate data were bias-corrected and downscaled across New Zealand (Tait et al., 2016). Two different climate datasets are currently considered in this version of the framework. An historical period (1971 to 2000) with interpolated weather station data from the ERA-40 dataset (Sood, 2015) is used for simulating absolute values of model outputs. For climate change assessments, climate data simulated by 6 General Circulation Models (GCMs) from the fifth phase of the Coupled Model Intercomparison Project (CMIP5) is used, available for baseline (1972 to 2005) and future (2006 to 2100) periods (Tait et al., 2016). The GCMs available from NIWA are HadGEM2-ES, BCC-CSM1.1, NorESM1-M, CESM1-CAM5, GISS-EL-R and GFDL-CM3. For each GCM, four different Representative Concentration Pathways (RCP) are considered (RCP 2.5, RCP 4.5, RCP 6.0 and RCP 8.5) to characterise climate change scenarios (Meinshausen et al., 2011). The minimum set of weather variables necessary to run APSIM are air temperature (maximum and minimum, $^{\circ}C$), rainfall (mm) and solar radiation (MJ/m^2) as illustrated for historical climate in Figure 2. For the CMIP5 data, vapour pressure (mbar) and wind speed (m/s) are also included to enable alternative evapo-transpiration calculations. In addition, the daily mean atmospheric CO_2 concentration from CMIP5 is included in the weather files. This is used as input for APSIM to adjust radiation use efficiency (RUE) and transpiration efficiency (TE), being necessary to account for the "CO_2 fertilization effect" depending on the photosynthetic pathway of specific crops (Vanuytrecht et al., 2016).

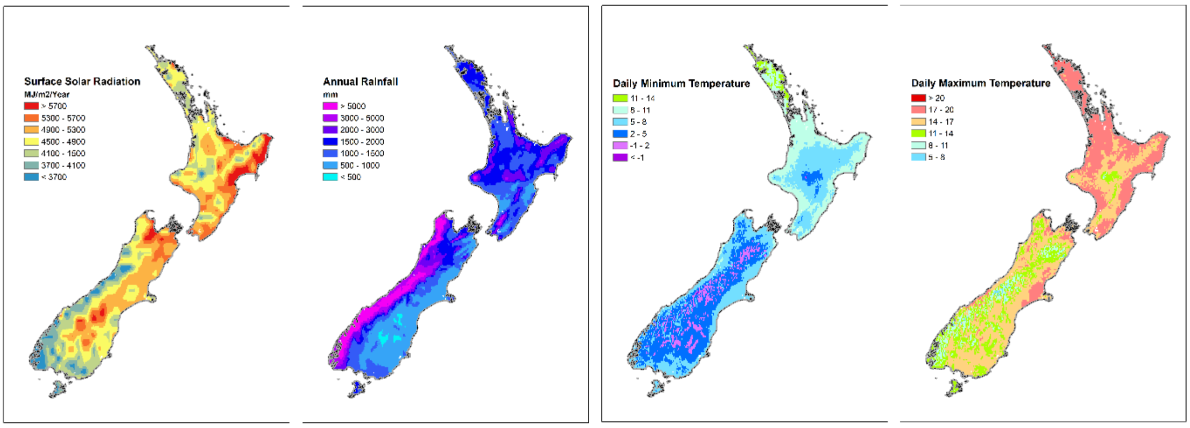

Figure 2. Maps illustrating the spatial variability in historical weather data (ERA-40; 1971 to 2000) across New Zealand. Minimum inputs required by APSIM include daily temperature (°C; maximum and minimum), annual rainfall (mm) and total surface solar radiation (MJ/m^2 per year).

The soil dataset is derived from the S-map database (S-Map, 2019), a new digital soil spatial information system for New Zealand (Lilburne et al., 2004; Webb and Lilburne, 2011). The aim of S-map, under development by Manaaki Whenua – Landcare Research (MWLR), is to provide consistent and comprehensive national coverage of digital data at 1:50000 scale. Soils in S-map are characterised by "families" which are subdivided into "siblings" on the basis of any unique combination of classes of drainage, stoniness, depth and texture (Webb and Lilburne, 2011). For input into APSIM, information on soil siblings is translated into a library (XML or JSON format) in which the required soil parameters are listed for layers in the soil profile (Figure *3*). Soil parameters are generated by pedotransfer functions (PTF) derived from observed and measured field data and expert knowledge. The PTFs range from simple look-up tables linked to soil classes to more complex algorithms considering various soil, land use, vegetation, climate or topographic attributes (Webb and Lilburne, 2011). The soil parameter library is automatically generated by a web-processing service developed by MWLR using 52°North infrastructure (52north.org). Information in the soil library is structured to meet the requirement of a cascading-type water balance module in APSIM (APSIM-SoilWat; Probert et al., 1998). Parameters are separated into physical, organic matter, and the soil-crop attribute groups. The physical attributes, for each functional horizon, include: BD (Mg/m^3, bulk density); AirDry (mm/mm, the water content at air-dry condition); LL15 (m^3/m^3, water content at the -1500 kPa); DUL (m^3/m^3, the soil water content at field capacity, assumed to be at -10 kPa); SAT (m^3/m^3, the saturated soil water content); and KS (mm/day, the hydraulic conductivity of the soil at saturation). The organic matter attributes are: OC (%, the organic carbon content), CNR (kg/kg, the carbon to nitrogen ration of the soil), FBIOM (kg/kg, the proportion of OC that is in the microbial biomass pool, fast turnover), and FINERT (kg/kg, the proportion of the remaining OC that is inert). The soil-crop attributes are: LL (m^3/m^3; the effective wilting point for the crop); KL (m^3/m^3, the maximum proportion of available water that a crop can take up each day) and XF (dimensionless, the root exploration factor that controls the rate at which roots can penetrate a soil layer).

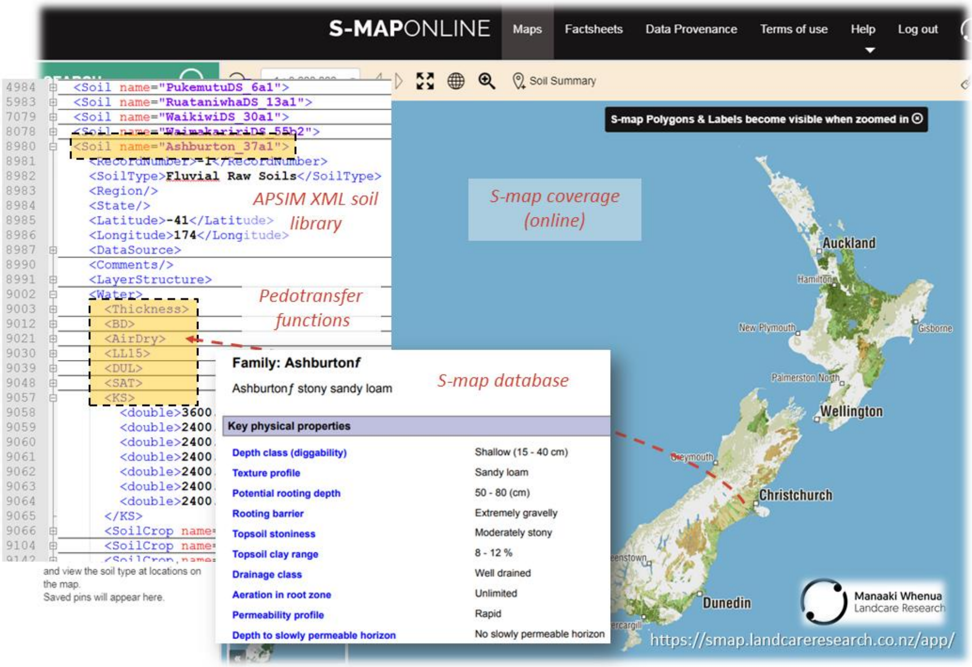

Figure 3. Illustration of the national soils database in S-map used as input by APSIM in the spatial model framework. Data by soil sibling name is available in the S-map database. Soil data are translated into XML format (in this example) used in APSIM, with parameters estimated across the soil profile, by a variety of pedotransfer functions.

The analysis framework uses logical rules to select which soil sibling(s) to consider within a VCSN grid. Soil siblings available per VCSN grid-cell are defined by spatially overlapping S-Map to generate metadata containing a list of S-map siblings per each VCSN grid. These metadata also include the share of area occupied by each sibling within a given grid-cell. This is used to select siblings for simulation based on their spatial representativeness. Additional soil metadata hold biophysical characteristics of individual siblings, such as average depth, drainage, texture, water holding capacity (WHC) and top soil stoniness. This enables selection of siblings by their biophysical attributes (e.g. most contrasting WHC). For other terrain attributes (elevation, slope, aspect and land capability class), summary statistics (minimum, maximum, mean, median, standard deviation and 10th and 90th percentile) are included as an additional database, for each VCSN grid, based on LRIS portal datasets (LRIS-Portal, 2019). Terrain characteristics enable the selection of grid-cells that are suitable for the presence of specific crops, regarding topography and other land information.

3 Biophysical model

The APSIM model

The APSIM model (Holzworth et al., 2014) is used as the core integrator of GEM information within the spatial analysis framework (Figure *4*). In brief, APSIM is a biophysical process-based dynamic model that simulates crop growth and development and corresponding carbon, water and nitrogen dynamics in the plant and the soil in response to daily weather input data. The model is composed of multiple modules that represent specific processes at the plant (e.g. canopy development and biomass growth), soil (e.g. drainage and N mineralization) and farmer management decisions (e.g. sowing time and cultivar selection). Currently the model exists as

(i) APSIM, hereafter referred to as APSIM-7.x (Holzworth et al., 2014), where “x” refers to a version number; and (ii) APSIM Next Generation, hereafter referred to as APSIM-Next-Gen (Holzworth et al., 2018). Both APSIM models are being currently calibrated and applied for a wide range of crops and environmental conditions in New Zealand (e.g. Brown et al., 2018; Khaembah et al., 2017) and worldwide (e.g. Gaydon et al., 2017).

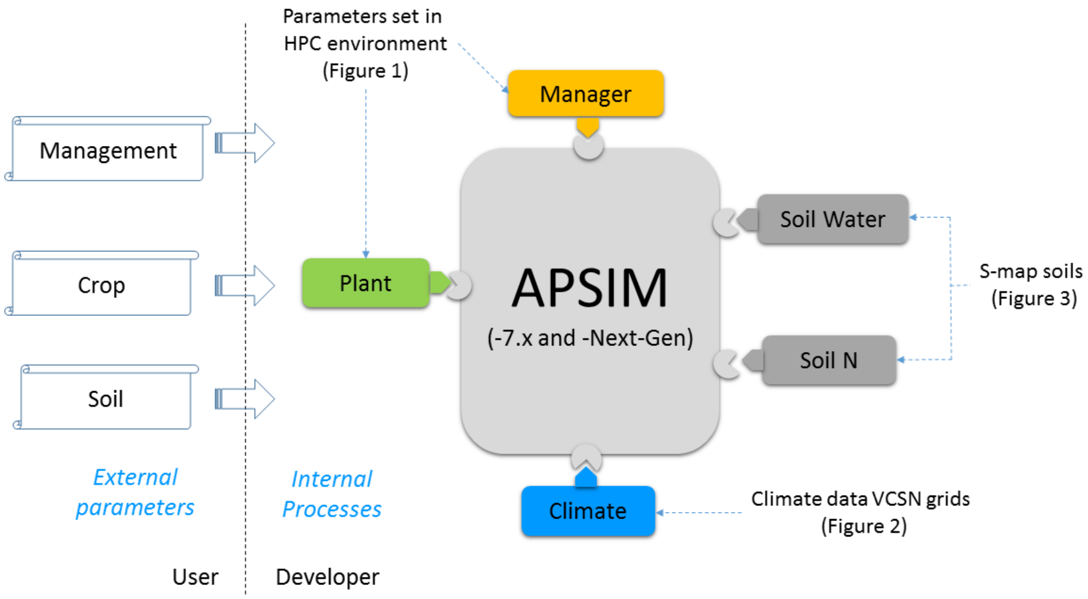

Figure 4. Representation of the modularity aspect of the APSIM model. APSIM is used as the core-engine to dynamically integrate georeferenced information on climates, soils, crops and managements in the analysis framework. Users can calibrate the model by providing parameters for simulations in the High Performance Computing (HPC) environment to characterise specific agricultural systems. Developers can select plant and soil processes and define how these respond to input parameters. In APSIM-Next-Gen, the distinction between users and developers is less strict than APSIM-7.x because the model user-interface enables developing new model representations. See http://www.apsim.info/.

The spatial analysis framework enables both APSIM-7.x and APSIM-Next-Gen to be run in an HPC Linux environment. For APSIM-7.x, the codebase complexity presents several challenges. The application achieves portability between Operating Systems (Microsoft Windows and GNU/Linux) by leveraging the Mono Project framework, requiring a number of external dependencies and workarounds to run in a Linux environment. These issues were solved by introducing containerization technologies which permit creating a stand-alone, self-contained *artifact* that can be run without changes in any HPC environment that supports running containers. An advantage of introducing software containers is that the project becomes more robust from a “reproducible research” perspective: software containers can be created in a *reproducible* way, and once created the resulting container images are both *portable* and *immutable*. These properties ensure that the exact state of the software stack used during the analysis is captured and distributed alongside the raw data to replicate the analysis in a different environment. The analysis framework had two container engines implemented: Docker (Docker Inc.) and Singularity (Sylabs Inc.). Docker containers however, were found to be unsuitable for multi-tenant HPC environments due to three primary concerns. Specifically (i) the security of the computer host could be compromised because operators must have *root* access, which allows full administrative control of the machine; (ii) by default, the data created from a Docker container are owned by the container-user instead of the operator running it; and (iii) container access to the persistent storage, where the raw data exist, must be explicitly declared by the operator at run-time. The Singularity container engine, which were developed for APSIM-7.x and APSIM-Next-Gen, addressed these limitations by restricting end-users to run commands inside a container using only their own user-identity, as well as automatically mapping the storage endpoints globally configured by the HPC administrator.

3. Analysis and visualization

The volume of georeferenced outputs generated by the framework is potentially large, and inherently complex, due to the multiple combinations of G (e.g. crop species and cultivars) and M (e.g. use of irrigation, rate of fertiliser application and sowing dates) scenarios within thousands of E (e.g. grid-cells with many soils and climates). Grid-cell output data are visualised as raster images overlaid on maps by an application developed in R-Shiny (R-Shiny, 2019). The main functionality of the Shiny app is to spatially enable the comparison of two user-defined scenarios (*reference* versus *alternative*) in the main page and to further analyse rasterised outputs (Figure 5). The scenarios are constructed by selecting levels of factors that characterise climates (e.g. GCMs, RCPs and time-slices), soils (e.g. S-map sibling name), crop species/cultivars and any other experimental treatment (e.g. irrigation or fertiliser treatment) specific to a project. Original model results are produced in ASCII format for APSIM-7.x and SQLlite relational databases for APSIM-Next-Gen. During the processing, results are combined with metadata (e.g. variables units, names and acceptable ranges) and loaded into a project-specific PostgreSQL database accessed by the Shiny app. The Shiny app user-interface adjusts its configuration to include project-specific factors and factor-levels in the scenario menu (left side in Figure *5*). Results are displayed as raster images of multi-year averages or coefficients of variation and differences between the two scenarios per grid-cell. Various libraries from the R statistical package (R Core Team, 2017) are used to generate additional analysis capability such as graphs of regional distributions, variability within grid-cells and the relationship between selected output variables.

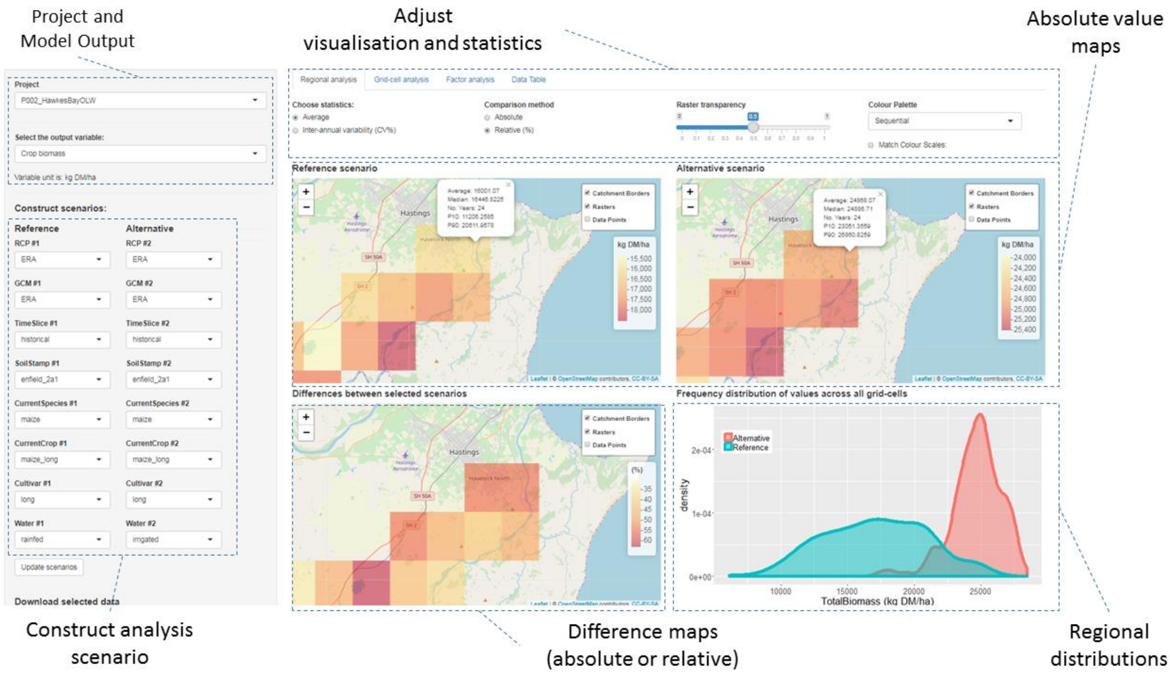

Figure 5. Illustrative example of the main user interface page of the Shiny app for analysis of large areas. Grid-cells illustrate the 3 arc-minute spatial resolution for the climate data in southern Hawkes Bay region. Scenarios show a comparison between rain-fed (*Reference*) and irrigated (*Alternative*) scenarios for biomass of silage maize crops using historical climate (ERA-40 dataset, 1971-2000).

4. Application of the spatial analysis framework

This section illustrates a case-study application of the spatial analysis framework prototype adapted from Rutledge *et al.* (2017). In this example, we investigate the influence of climate change impacts on irrigated silage maize yields across arable lands in New Zealand. APSIM-7.9 runs used interpolated weather station data for historical climate (ERA-40 database, 1971 to 2000) to simulate absolute silage yields in each VCSN grid-cell. Relative climate change impacts were then calculated based on model runs for baseline (1985–2005) and future (2080–2099) periods from the CMIP5 dataset for the RCP 8.5 with the GCM HadGEM2-ES. Simulations assumed fully irrigated conditions and a single hypothetical soil type with high water holding capacity (160 mm/m), so the effect of high spatial resolution soil databases was not considered in this case-study. Model runs were done with or without tactical farmer adaptation of using long-cycle genotypes and sowing earlier in response to the early onset of warmer spring temperatures. Simulation results showed a consistent north-south decreasing gradient of absolute maize silage yields for the historical climate (Figure 6). Silage biomass estimates ranged from 7 t dry matter (DM)/ha in southern regions to up to 27 t DM/ha in northern regions. Silage quality was characterised by the percentage of grains in total biomass (i.e. Harvest Index, HI) which relates to the forage metabolisable energy. The HI declined from 46% in the warmer regions of the North Island to 17% in New Zealand's cooler southern regions. These differences were mainly caused by a reduction in the length of time available for maize to grow due to low temperatures, which shortened the grain filling period.

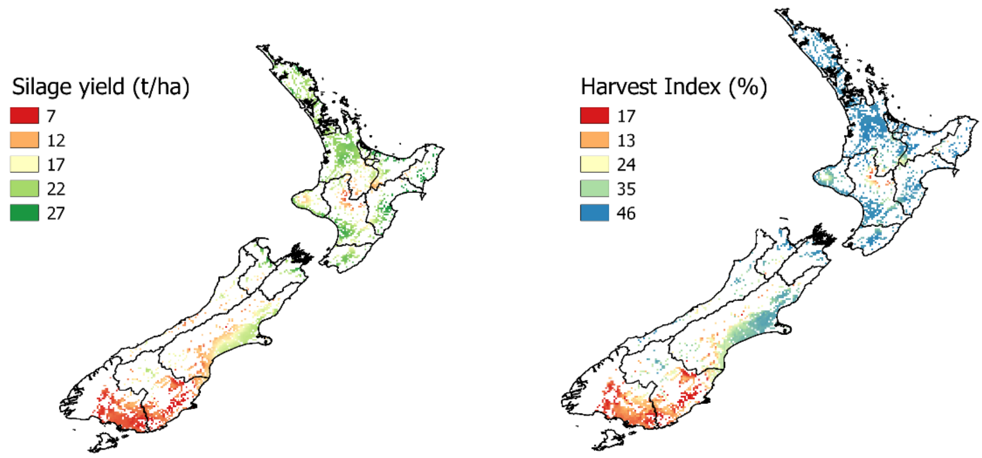

Figure 6. Simulated total biomass yield of silage maize (t dry matter DM/ha) and grain content (% yield) of silage maize in arable lands for the period 1971–2000 (ERA-40 historical climate) using the Agricultural Production Systems sIMulator (APSIM). Adapted from Rutledge et al. (2017).

Simulated climate change impact on irrigated maize silage yield is shown in Figure *7*. Negative impacts occurred mainly in the North Island. In contrast, southern regions showed potential for an increase in climatic suitability for the growth of maize silage. Adaptation of sowing dates and maize genotypes partially counteracted negative impacts in northern and central regions. In southern regions, there was a further increase in positive yield responses when adaptation options were considered.

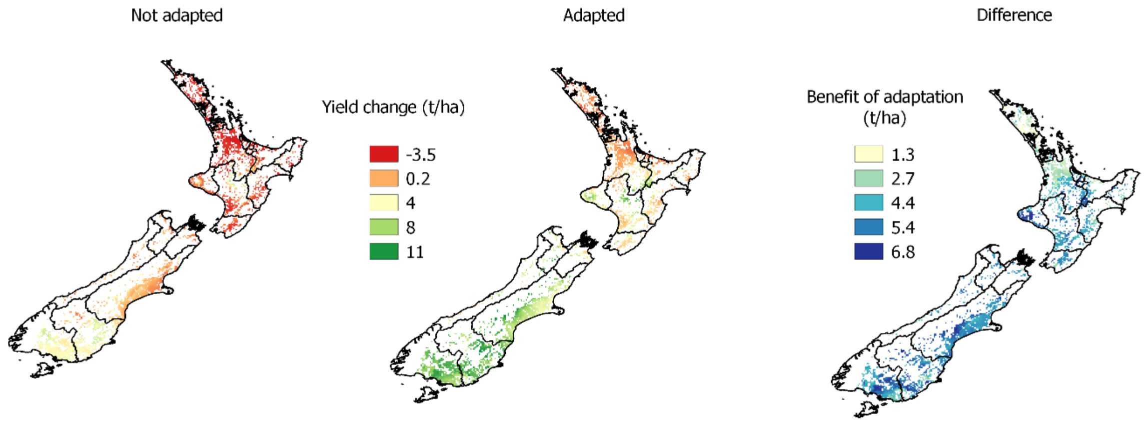

Figure 7. Simulated climate change impact on silage maize yields for end-of-century climate (2080–2099, Representative Concentration Pathway RCP 8.5 using the HadGEM2-ES climate model) and the effect of adapting sowing dates and genotypes across New Zealand's arable lands. Adapted from Rutledge et al. (2017).

The main implication of these results is that adaptation to climate change is possible through a shift or expansion of cropping areas to southern regions in New Zealand. This is because low temperature stress that currently limits maize growth is minimised in the climate change scenario considered. However, such analysis does not consider logistical and economic aspects that might play an important role on the viability of industry expansion at regional scales. Also, access to irrigation and soil types were not considered in the study, as these would require georeferenced information across all arable lands, not yet available and incorporated into the framework. The expansion of S-map databases (Figure *3*) across New Zealand in the future will enable more accurate and comprehensive investigations for multiple soils types, which is particularly important for rain-fed production systems. Finally, our results indicate that adaptation of current agronomic practices are likely to be required to minimise yield losses and exploit yield increase potentials under climate change. The spatial variability in the magnitude of adaptation effects suggest that local studies on management interventions are necessary to properly identify those adaptive measures that confer resilience to climate change. The biophysical aspects considered in this framework require further integration with socio-economic elements for a more comprehensive evaluation of adaptive strategies.

5. Outlook and conclusions

This chapter describes the development of a spatial analysis framework to investigate crop and soil processes in agricultural landscapes, with New Zealand as a case study. It uses a biophysical model as the core-engine to dynamically integrate national georeferenced datasets on climates, soils, terrain and simulate response to contrasting crop genotypes and management interventions. A key strength of the framework is the combination of the spatial resolution (5 x 5 km grids) able to address regional-scale questions and the high temporal resolution of simulations (daily time steps, reported annually). This enables sufficient depth of analysis to investigate inter-annual variability and also plant/soil processes that operate in short time-scales to influence crop productivity (e.g. canopy development) and environmental aspects (e.g. water and N uptake). There are limitations and aspects that require attention in the prototype stage of the analysis framework. For instance, the trade-off of high spatio-temporal resolution is the large demand for data storage and computing power, which requires the HPC environment to run APSIM. Also, the use of large georeferenced data as model input (climate, soil and terrain) may introduce significant uncertainty because such datasets are often created by other modelling approaches such as interpolations, downscaling methods and transfer functions. This uncertainty permeates through the data pipeline to the model calculations and model results (Wallach and Thorburn, 2017). Our approach to reduce this risk is to connect biophysical modellers and data providers who all work using a single cloud source-code repository to develop the framework, so input data issues are quickly reported and made visible across developers. Additional uncertainty comes from the use of a single biophysical model, instead of model ensembles that account for differences in model structure (Rodríguez et al., 2019). The current strategy to deal with this uncertainty source is to intensively calibrate APSIM-7.x and APSIM-Next-Gen for local conditions (crops, soils and management) which minimises the need for extensive multi-model expertise. The model testing and calibration process is largely facilitated with APSIM-Next-Gen because the version control system evaluates model performance in an automated way, at each request for model update, by comparing results against worldwide datasets in the APSIM-Next-Gen repository (Holzworth et al., 2018). Finally, although the current spatial framework uses georeferenced information to generate APSIM simulations that can cover an entire region or country, the simulations themselves are not spatially aware and do not interact with each other. This implies that some questions, such as nutrient transfer within large farms or catchments, cannot yet be addressed with the analysis framework.

In conclusion, this chapter provides a comprehensive description of the development and application of a spatial analysis framework, still in the prototyping stage, to address research and policy questions in agricultural landscapes. The technical solutions to enable the framework to remain useful as an analysis tool rely heavily on a multi-developer environment, with collaboration within and across research organizations, due to the interdisciplinary nature of the research and the requirements on specialised georeferenced datasets. The insights and solutions provided can contribute to advances in state-of-the-art gridded modelling of agricultural landscapes.

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