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European Journal of Agronomy

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https://doi.org/10.1016/j.eja.2023.126853

European Journal of Agronomy 148 (2023) 126853

Contents lists available at ScienceDirect

European Journal of Agronomy

journal homepage: www.elsevier.com/locate/eja

Assessing land suitability and spatial variability in lucerne yields across New Zealand

Edmar Teixeira [a,b,*], Jing Guo [c], Jian Liu [a,d], Rogerio Cichota [a], Hamish Brown [a], Abha Sood [e], Xiumei Yang [f], David Hannaway [g], Derrick Moot [f]

[a] The New Zealand Institute for Plant & Food Research Limited, Lincoln, New Zealand
[b] International Institute for Applied Systems Analysis (IIASA), Laxenburg, Austria
[c] Manaaki Whenua - Landcare Research, New Zealand
[d] Wageningen University, Wageningen, The Netherlands
[e] The National Institute of Water and Atmospheric Research, New Zealand
[f] Dryland Pastures Group, Faculty of Agriculture and Life Sciences, Lincoln University, Canterbury, New Zealand
[g] Department of Crop & Soil Sciences, College of Agricultural Sciences, Oregon University, USA

A R T I C L E I N F O

Keywords:
APSIM
Crop modelling
GIS
Spatial modelling
Gridded modelling

A B S T R A C T

Lucerne (*Medicago sativa* L.) is a widely grown perennial legume worldwide which can provide high biomass and protein yields, biological N fixation, deep soil water extraction and a range of ecosystems services relevant to current and future agricultural systems. The potential to expand lucerne beyond its current cultivated areas in New Zealand, and its potential productivity across the country's contrasting climate zones, are currently unknown. To gain such insights, we estimated land suitability and spatial distribution of lucerne above-ground biomass across New Zealand lands considering contrasting growth conditions (rain-fed or irrigated for different soils types) and two simulation methods of different complexity (process- and GIS-based approaches). This aimed to assess yield-estimate spatial patterns and sensitivity to model selection for a wide range of combinations of water supply (i.e. irrigation and soil water storage) across New Zealand climate zones. For example, highly suitable areas for lucerne cultivation, were estimated in ~21 thousand km^2 when considering the exclusion of steep slopes, poor soil drainage and excess annual rainfall. The two crop-yield models were applied in response to 30 years of daily historical (1971–2000) weather data downscaled at 5 km resolution on suitable areas. Simulated average lucerne yields ranged from ~4.5–28 t dry matter/ha per year. Simulations showed a distinct spatial pattern of yield decline from north to south, mainly in response to decreasing temperatures. Temporally, water limited yields were up to 4-fold more variable than under irrigation, depending on the degree of drought stress across different years. Results also unveiled systematic spatial patterns of model uncertainty quantified as yield sensitivity to model selection. For instance, simulated yields were most sensitive to model selection (6–31% of total variability, T_i) within high abiotic-stress environments (e.g. low temperature and limited water supply). Overall, soil type selection accounted for most of yield variability (58–78% T_i), being particularly important in warmer environments with variable seasonal rainfall regimes (e.g. northern regions). As expected, water supply (i.e. rain-fed or irrigated systems) was relatively more impactful on yield (8–20% T_i) for limited rainfall areas, where crops are most drought prone (e.g. east coast and central southern regions). Long-term regional scale comparisons of annual lucerne yield, between 30-year simulated distributions and point-based observations from the AgYields database, helped identify hotspots of yield overestimation. Such insights are useful to guide future research on high yield gap areas (e.g. southern colder and drier locations) and highlight key areas for model improvement (e.g. representation of multiple biotic stresses). Overall, our results provide a first gridded-model assessment of lucerne suitability and yield at national scale and quantify the share of variability explained by key climatic, management and methodological components in spatial analysis studies. These insights can inform future modelling efforts and support agricultural planning that considers the expansion of lucerne and other perennial legumes.

* Corresponding author at: The New Zealand Institute for Plant & Food Research Limited, Lincoln, New Zealand.
E-mail address: edmar.teixeira@plantandfood.co.nz (E. Teixeira).

https://doi.org/10.1016/j.eja.2023.126853
Received 5 April 2022; Received in revised form 6 December 2022; Accepted 28 April 2023
Available online 6 May 2023

1. Introduction

The strategic expansion of perennial crops and legumes have been identified as key strategies to improve environmental sustainability of future agricultural systems (Cusworth et al., 2021; Sheaffer and Seguin, 2003; Stagnari et al., 2017). Globally, lucerne (*Medicago sativa* L.) is the most broadly cultivated perennial legume, with an estimated area of around 30 million ha (Monfreda et al., 2008; Moot et al., 2012). Its presence spans contrasting climate zones and agricultural production systems of different intensity of production (Michaud et al., 1988; Moot et al., 2012). The crop is mainly used to support livestock production but novel uses, such as for bioenergy and protein extraction, have recently been explored (Bouton, 2012; Filippa et al., 2020). The competitiveness of lucerne as a forage is explained by its adaptive capacity to low water and N input conditions, being a deep-rooted perennial legume with the ability to produce high biomass and protein yields through symbiotic nitrogen fixation (Issah et al., 2020). The lucerne taproot system allows access to soil water in deep soil profile which confers a competitive advantage over other shallow-rooted herbage species in drought prone environments with soils that enable high water storage (Brown et al., 2003). This adaptive capacity is particularly important in regions with limited water availability. This is a constraint of global relevance to current, and increasingly for future, agricultural production due to climate change (Tait et al., 2016), particularly where irrigation is not economically or environmentally viable (Rosa et al., 2018).

In New Zealand, lucerne competitiveness under limited water supply was the key motivation for an area expansion during the middle of the 20th century, peaking at 220,000 ha in 1976 (Purves and Wynn-Williams, 1989). After that, lucerne areas declined to ~84,000 in the late 80's. Causes of decline included poor defoliation management, biotic stress pressures and, similar to other legumes in Europe (Cusworth et al., 2021), the intensification and specialisation of competing production systems through the use of high N fertiliser and irrigation-water (Dunbier et al., 1982). More recently, the potential to further expand lucerne areas in New Zealand has been revisited given the availability of improved management and modern cultivars (Moot et al., 2003), which may explain the slight increase of 10,000 ha since 2012 to reach ~50, 000 ha in 2017 (Agricultural Production Census., 2017).

The potential to expand lucerne areas in New Zealand, and its productive potential in different regions, is currently unclear. This knowledge is particularly important when considering New Zealand's variable climate (Teixeira et al., 2017) and soil characteristics (Webb, 2003) because, despite the ability to assess water deeper in the soil profile, lucerne yields are sensitive to lack of water availability and drastically decline when soil moisture drops below critical thresholds in the root zone (Moot et al., 2012). As highlighted by a number of previous studies, it is therefore important to assess yield estimates for both potential (Y_P) and water-limited (Y_W) conditions (van Ittersum et al., 2013). For forage crops like lucerne, the Y_P represents above-ground biomass yield at unconstrained conditions determined by local solar radiation interception and regulated by temperature profiles, considering best agronomic management practices (i.e. non-limiting nutrient and water supply, biotic stress control and defoliation regimes). For Y_W, the same conditions are assumed but without considering additional water supply from irrigation. The assessment of both Y_P and Y_w are important because rain-fed systems are the most vulnerable to environmental changes, both under current climate (Asseng and Pannell, 2013; Eigenbrode et al., 2018) and considering future projections of climate change (Elliott et al., 2014) for New Zealand. Such understanding is critical to inform yield potentials which are a key component of agricultural assessments of yield-gaps and climate impact and adaptation of cropping systems across regions and timeframes (Jáuregui et al., 2022; van Ittersum et al., 2013). For such assessments, it is not feasible to solely rely on observational datasets because of the paucity of spatially-explicit yield information across the multitude of possible weather, management and soil combinations. In this regard, crop yield models can expand our current understanding by quantitatively simulating both Y_P and Y_W in response to gridded data on climates and soils to represent spatial and temporal variability (Rosenzweig et al., 2013; van Ittersum et al., 2013). Nevertheless, models are always imperfect representations of reality and the choice of model complexity (e.g. model structure and parameterisation) is an important component contributing to total uncertainty (Tao et al., 2018) and potential biases of simulated results (Saltelli, 2019). In contrast to gridded model simulations for major agricultural crops (Müller et al., 2017), to the best of our knowledge, lucerne Y_P and Y_W assessments have not yet been performed with different models at national scale to understand spatial and temporal yield variability patterns and key uncertainty sources for yield-estimates in this crop.

In this study, we selected two lucerne yield models of contrasting complexity, previously developed and calibrated for New Zealand conditions. The intent was to quantitatively assess potential spatial patterns of model divergence (i.e. model uncertainty) when simulating lucerne above-ground yields across contrasting climate zones. Specifically, we used a GIS-based temperature-driven growth model (TGM; Moot et al., 2021b) and a process-based lucerne prototype model (APSIM Next-Gen lucerne; Yang et al., 2023, 2021) from the Agricultural Production Systems sIMulator (APSIM; Holzworth et al., 2014) framework. The GIS-based model is aimed for yield estimation at a field scale by lucerne growers and farm-consultants to budget feed supply, with minimal demand on input parameters. In contrast, the prototype APSIM-NextGen lucerne is a research tool under development to help understand underlying yield forming processes, through a detailed representation of the crop physiology, soil characteristics, management choices and their interactions with multiple environmental factors. The objectives of this study are therefore to (i) estimate potentially suitable areas for lucerne growth across New Zealand regions (ii) quantify spatial and temporal patterns of Y_P and Y_W variability within suitable areas and (iii) explore sensitivity of results to model selection and a range of growth conditions from interacting factors (climate, soil and management). These insights are expected to inform impact assessments that explore potential expansion of lucerne and other perennial legumes within agricultural regions through the use of gridded modelling approaches.

2. Materials and methods

2.1. Climate datasets

Regional climate simulations were performed from 1971 to 2000 using the ERA-40 dataset which is bias-corrected and downscaled at ~5 km resolution by the National Institute of Water and Atmospheric Research (NIWA) across New Zealand (Sood, 2014; Tait et al., 2016). The climate dataset (Fig. 1) included air temperature (°C, maximum and minimum), total solar radiation (MJ/m^2) and rainfall (mm). Evapotranspiration (ET) was estimated using the Priestley-Taylor approach in which vapour deficit and convection terms are accounted for by an empirical constant (α) to simplify the FAO Penman-Monteith equation (Allen et al., 1998). In our study, α was assumed as 1.37 for TGM estimates, as this value gave nearly identical daily ET estimates by APSIM (R^2 = 0.99) that dynamically estimates α and ET.

2.2. Description of soil types

Three generic soil descriptions representing a wide range of possible differences in profile available water (PAW) content for New Zealand soils were set up for the simulations. These were a PAW of 75, 300 or 525 mm over a whole profile of 2000 mm depth assumed to have no significant impediment to root growth. The value for PAW is the only soil parameter needed for TGM; its water balance calculations were set to start with full soil water storage on 1-July (mid-winter) every year. For APSIM, a more detailed characterisation of soil properties for each horizon across the profile is needed (Cichota et al., 2021). The required parameters for each soil type were defined based on data from representative soils of similar PAW found in the NZ National soils Database (Wilde, 2003), and complemented by pedo-transfer functions (Cichota et al., 2013). These soils represent a very stony coarse textured soil, excessively well-drained and with very low PAW (75 mm); a well-drained, with a medium loamy texture and medium PAW (300 mm); and a medium- to fine-textured soil, moderately-drained and with very high PAW (525 mm). The parameters defined for each soil horizon are illustrated for the PAW 300 mm soil (Table 1) and for all soils in the Supplementary Material. The values for the two parameters controlling soil evaporation rate (U and ConA) were set to 8.0 and 4.0 for summer and 4.0 and 1.5 for winter, respectively. These were adapted from typical approaches used for this model (Foley and Fainges, 2014; Ritchie and Crum, 1989). The curve number for runoff calculations was set to 60 for all soils. In all simulations, the soil was initialised with water content at field capacity, 2000 kg/ha of fresh organic matter (roots and crop residues), and 57.5 kg N/ha of mineral nitrogen.

2.3. Non-climatic lucerne suitability assessment

As a first step in the analysis, without considering temperature constraints later accounted for within TGM and APSIM, land suitability for lucerne was estimated based on terrain steepness, soil drainage class and annual rainfall regimes using the GAIA (Geospatial Assessment of suitability-Indexes for Agricultural systems) framework (Thomas et al., 2022). The GAIA framework is used as an interface to heuristically assimilate expert knowledge on land classification into four suitability classes (Unsuitable, Marginally-suitable, Suitable and Highly-suitable). The framework uses georeferenced climate and soil datasets as input to draw maps of crop suitability based on heuristic criteria following the approach by Kidd et al. (2015). In brief, the identification and parametrisation of suitability criteria metrics is developed iteratively through a sequence of expert interviews to scrutinise maps in GAIA user interface. Empirical knowledge is assimilated during the analysis of resulting national suitability maps from previous iterations and translated into metadata (Supplementary Material). For simplicity, only three criteria were used in this study (i) soil drainage class (poor- to well-drained), (ii) terrain slope (degree) and (iii) annual rainfall (mm). The parameters for each criterion was obtained during three iterations, first from published literature and then through two reviews with New Zealand experts on lucerne agronomy. Specifically, all grid-cells classified as "unsuitable" for any of the three criteria were excluded from the analysis. These included soil classes with "poor or very poor" drainage characteristics based on the LENZ dataset (www.lris.scinfo.org.nz/layer/48085-lenz-soil-drainage/). For terrain slope, we used zonal statistics at 25 m resolution to create a GIS layer with the percentage of slopes > 15 degrees within each 5 km VCSN grid cell to be excluded (Deng et al., 2014). The rationale is that steep areas are unsuitable for cultivation due to the difficulty and costs for mechanised operations. Therefore, only grid-cells with > 50% of the area with slopes < 15 degrees were classified "suitable" for lucerne. For the third criteria, a 30-year mean annual rainfall GIS layer was created and grid-cells where annual rainfall is > 1700 mm were excluded (Alemayehu et al., 2020; Kim et al., 2018). The rationale is that too wet conditions increase the risk of biotic stresses (e.g. root rot with *Pythium* spp.) that compromise stand survival and economic viability of lucerne (Berg et al., 2017; Samac et al., 2016). Finally, areas with waterbodies were also excluded (e.g. 24 larger lakes).

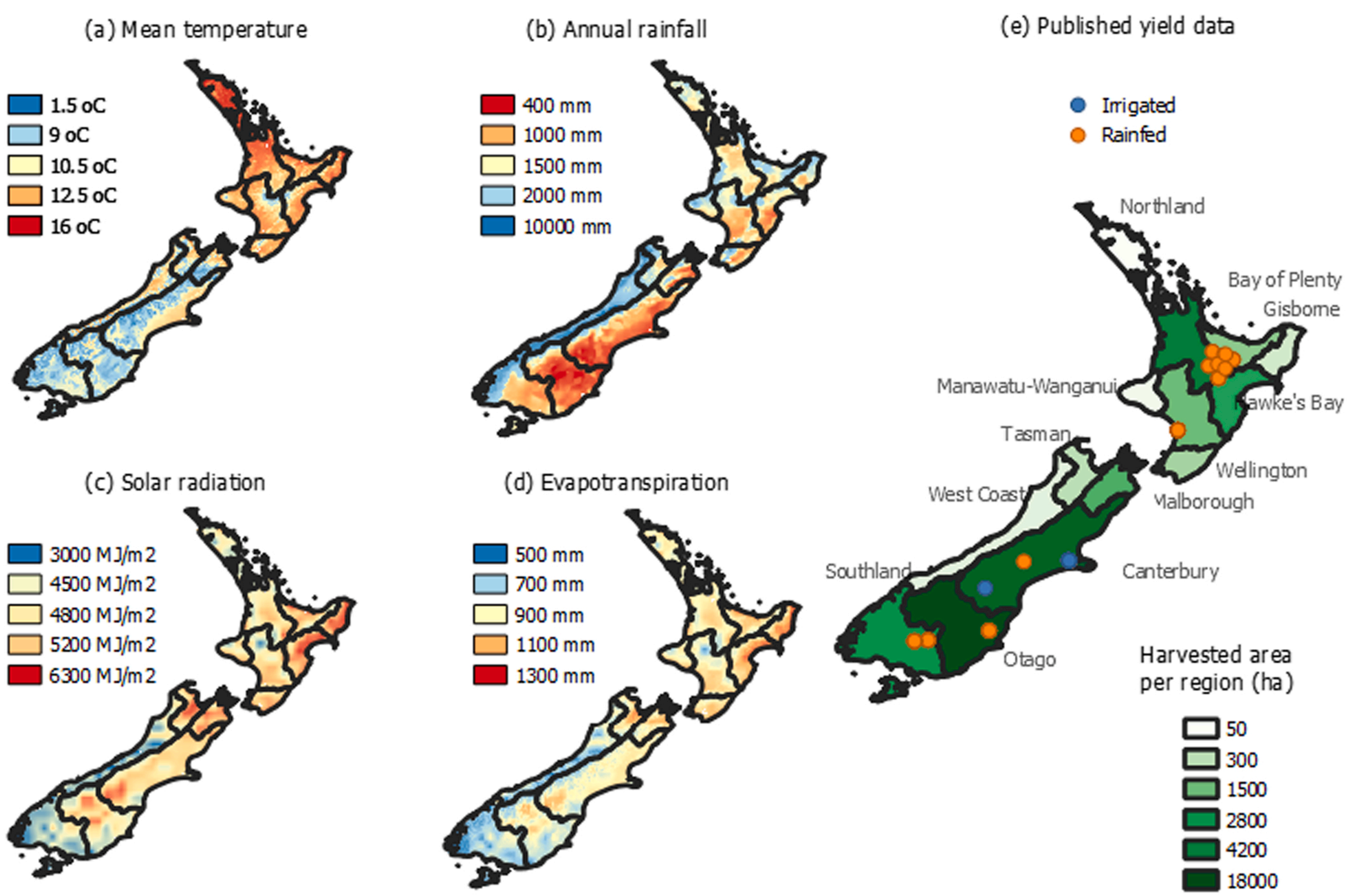

Fig. 1. Average historical climate conditions (a - d) and approximate location of published lucerne yield data (e) used for regional model testing (irrigated and rainfed) with area harvested per region (Agricultural Production Census, 2017).

Table 1
Soil parameterisation for a generic loamy texture soil with medium PAW (300 mm over the profile) used in APSIM simulations: BD is bulk density; LL15 is the lower limit for water uptake; DUL is the drained upper limit; SAT is water content at saturation; Ks is the saturated hydraulic conductivity, swCon is the drainage coefficient, OC is organic carbon content; FBiom and FInert are the microbial and the inert fractions of soil organic matter.

Depth (cm)	Stones (%)	Sand (%)	Clay (%)	BD* (g/cm^3)	LL15 (cm^3/cm^3)	DUL (cm^3/cm^3)	SAT (cm^3/cm^3)	Ks (mm/day)	swCon (/day)	OC (%)	FBiom (-)	FInert (-)
0–10	0	32.0	17.5	1.100	0.173	0.368	0.524	1199.9	0.592	3.00	0.080	0.314
10–25	0	33.0	18.5	1.200	0.163	0.350	0.503	887.6	0.554	2.10	0.050	0.475
25–50	0	35.0	18.0	1.350	0.134	0.316	0.455	377.0	0.481	0.75	0.008	0.779
50–75	0	47.5	15.5	1.450	0.108	0.288	0.421	482.2	0.495	0.30	0.008	0.937
75–100	0	48.0	15.0	1.450	0.104	0.275	0.423	611.1	0.503	0.20	0.008	0.967
100–125	0	50.0	14.0	1.450	0.099	0.242	0.422	453.3	0.488	0.20	0.008	0.989
125–150	0	54.0	12.0	1.420	0.092	0.225	0.415	681.7	0.509	0.20	0.008	0.992
150–175	0	55.0	12.0	1.400	0.094	0.205	0.417	705.7	0.517	0.20	0.008	0.993
175–200	0	55.0	12.0	1.400	0.097	0.192	0.411	766.9	0.529	0.20	0.008	0.994

2.4. Lucerne yield simulations

We used two already existing lucerne yield models with a contrasting degree of complexity to account for model uncertainty, potentially an important component of total uncertainty in gridded assessments (Tao et al., 2018). These were the temperature-driven lucerne growth model (TGM; Moot et al., 2021) and the lucerne model prototype from the process-based Agricultural Production Systems sIMulator (APSIM; Holzworth et al., 2014) framework. Following specifications previously suggested for the estimation of potential yield (Y_P) and water-limited (Y_W) yield (van Ittersum et al., 2013), both models use daily time steps and were originally calibrated under New Zealand conditions. The complexity in model structure and parameterisation is greater for APSIM, as it considers different underlying crop physiology processes that influence yield formation (e.g. canopy expansion and carbon assimilation and biomass partitioning among plant organs) in response to environmental drivers and soil conditions (Fig. 2). In contrast, TGM empirically represents aggregated effects of temperature and water supply on crop growth rates, which are seasonally adjusted to account for differences in carbon partitioning between storage organs (taproots and crowns) and above-ground shoot biomass (Moot et al., 2021). This is a critical physiological aspect to be considered when modelling seasonal lucerne productivity (Moot et al., 2015; Teixeira et al., 2009, 2008). Details are given for both models in the next sections.

2.4.1. Process-based model: The APSIM-NextGen Lucerne prototype

The process-based biophysical simulations were performed with the Agricultural Production Systems sIMulator framework (APSIM; Holzworth et al., 2014). In brief, APSIM simulates processes for plants (e.g. growth and development) and soil (e.g. carbon, water and nitrogen balances) at daily time steps driven by weather and soil parameters with management related inputs. We represented the lucerne cultivar 'Kaituna', a FD5 semi-dormant genotype extensively assessed and previously calibrated for APSIM under New Zealand conditions (Moot et al., 2015; Ta et al., 2020; Teixeira et al., 2009). The current prototype model is under development within the Plant Modelling Framework (Brown et al., 2014) which is part of the Next Generation APSIM model, APSIM-NextGen (Holzworth et al., 2018). The model parameterisation and testing performance across multiple location and lucerne genotypes is available at github.com/APSIMInitiative/ApsimX/-tree/master/Prototypes/Lucerne. In brief, the prototype version selected (version 2021.10.8.6835) estimated shoot yield components of lucerne with similar accuracy for leaves (R^2 = 0.62 and NSE = 0.47, n = 631) and stem (R^2 =0.67 and NSE=0.66, n = 618) fractions at the time of model application. For model application, APSIM requires a detailed description of agronomic management which for lucerne in this study implies setting the dates of individual harvests and irrigation events. Both management events were set to occur automatically in response to plant and soil indicators assuming best practice decision making under optimal conditions. This does not account for real world

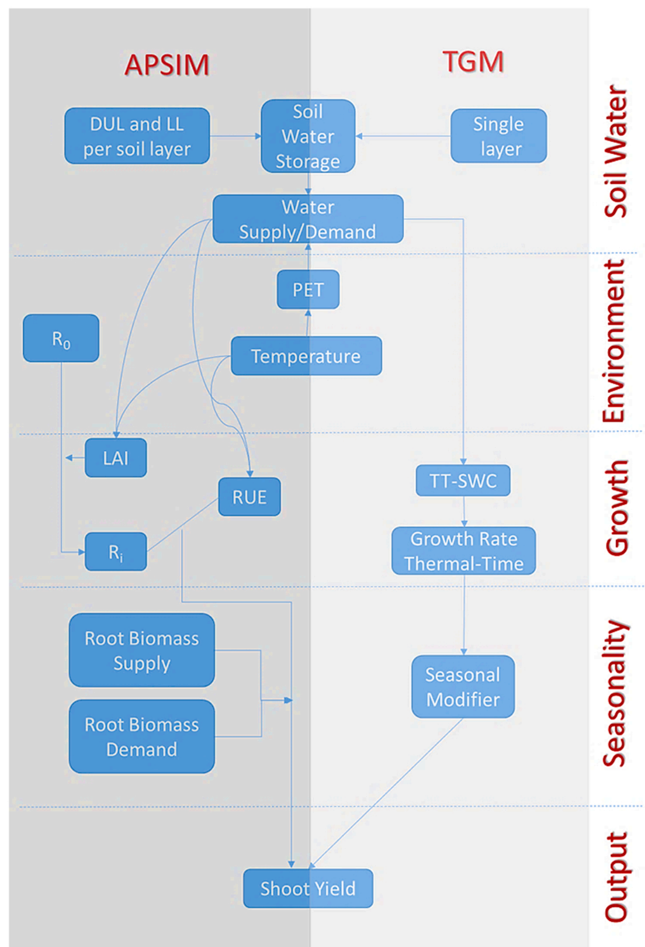

Fig. 2. Illustrative representation of parameter and structural complexity differences between APSIM and TGM through selected components required to simulate lucerne yields such as potential evapotranspiration (PET), radiation use efficiency (RUE) and intercepted solar radiation (R_i). TT-SWC is the parameter representing the soil moisture threshold of 20 mm required to restart daily thermal-time accumulation after summer moisture deficits. Soil Water parameters include drained upper limit (DUL) and lower-limit (LL) for each soil layer.

complexity where the timing of events is subject to climatic and operational uncertainty. Specifically, the crop was set to be harvested when reaching 3 t DM/ha recommended for grazing (Moot et al., 2016) or at the flowering stage (stage 6.0), if the target yield was not achieved, to mimic a harvest prior to the decay in nutritive value at advanced phenology (Fick and Onstad, 1988). This implied a greater number of harvests per year in grid-cells and years with favourable weather conditions for crop growth and development. Similarly, for non-limited water supply (i.e. Y_P), irrigation was applied as per crop demand in response to environmental conditions. This resulted in a different number of irrigation events and amounts depending on soil characteristics, precipitation patterns and seasonal evapotranspiration. The initial soil conditions were reset annually on 1-July (mid-winter) to default water, carbon and nitrogen amounts (Table 1) to ensure that the main drivers of yield variability were annual weather conditions and regional climate, following methodological considerations from Teixeira et al. (2018). Spatial APSIM-NextGen simulations at 5 km resolution were performed using the ATLAS (Assessment Tool for Landscape Agricultural Systems) framework (Teixeira et al., 2020).

2.4.2. The GIS-based model: the Temperature-driven Growth Model (TGM)

The empirical GIS-based yield modelling approach developed for New Zealand conditions uses only maximum and minimum daily temperatures as input for Y_P estimates (Moot et al., 2021). The model is used to estimate potential lucerne above-ground biomass yield (Eq. (1)) by multiplying daily thermal-time accumulations and seasonal standardised growth rates (kg DM/°Cd). For increasing photoperiods from mid-winter to mid-summer (1 July to 31 December in New Zealand), the growth rate is assumed to be 9.68 kg DM/°Cd from 181° to 1500°Cd, whereas in a decreasing photoperiod, it declines to 5.40 kg DM/ha/°Cd to account for increased partitioning to roots in autumn.

$$y = \begin{cases} \sum_{i=D_{start}}^{31Dec} r_1 \cdot tt_i \\ \sum_{i=1jan}^{30Jun} r_2 \cdot tt_i \end{cases} \tag{1}$$

Where y is the accumulated lucerne yield through an agricultural year starting on 1-July. The seasonal growth rates are for increasing (r_1) and decreasing (r_2) photoperiods, respectively; tt_i is daily thermal-time accumulation.

Under water-constrained conditions, a soil water availability adjustment is applied to restrict thermal-time accumulation in periods of water stress, reducing yields from their potentials. Evapotranspiration (ET) using the Priestley-Taylor method, consistent with APSIM-NextGen calculations, is subtracted daily from available soil water storage plus precipitation inputs. Multiple values of maximum soil water storage capacity were considered to represent contrasting soil types (75, 300 and 525 mm PAW). If available soil storage is totally exhausted (i.e. drought situation), the model stops accumulating thermal-time for yield calculation. Crop growth only recommences once rainfall has increased soil water storage to greater than 20 mm, when the model again restarts thermal-time accumulation for yield calculation. The soil water storage calculation is represented in the function below (Eq. (2)).

$$SWC_i = SWC_{i-1} + PCP_i - ET_i \tag{2}$$

Where SWC_i is the soil water content on day i. Full soil water storage capacity is assumed every year on 1-July. PCP is daily precipitation and ET is daily evapotranspiration, both in mm/day.

The thermal-time calculation was averaged from 8 estimations during the day (i.e. every 3 h) using a sinusoidal approach (Jones et al., 1986) and cardinal temperatures for average temperature input (0, 1, 15, 30, 40°C). The resultant thermal-time daily estimates (0, 0, 10, 25, 0°Cd) are consistent with those used in APSIM-NextGen methods.

A schematic representation of key components in APSIM and TGM, simplified for comparative purposes, is shown in Fig. 2. In brief, both models rely on identical thermal-time and potential evapotranspiration calculations, but these drive growth and water demand rates through different algorithm implementation complexities. In APSIM, growth rates are a product of intercepted light and radiation use efficiency which is then retained in shoots depending on biomass demands by below-ground organs. In contrast, TGM adjusts temperature-driven growth rate parameters seasonally to account for differential allocation of biomass to perennial organs (Fig. 2).

2.5. Regional model comparison and sensitivity analysis

2.5.1. Observed data

A regional comparison between "simulated" 30-year yield distributions and "observed" yield data from the AgYields National Database (Moot et al., 2021a) was performed using grid-cell scale datapoints. In brief, the AgYields database is a systematic compilation of geo-referenced yield data for multiple crop species, including lucerne, from published experimental datasets. The AgYields lucerne dataset provided 121 data points (99 for rain-fed and 22 for irrigated crops) of annual above-ground biomass yield (t dry matter /ha per year), available within 17 different grid-cells across five New Zealand regions. We applied existing models to assess the degree of overlap between (i) simulated 30-year distributions within a 5 km grid-cell by both models and (ii) all observed datapoints in the same grid-cell from AgYields. The aim was to evaluate spatial patterns of model divergence (i.e. model uncertainty) in relation to long-term published datasets for a given location. It is important to note that this analysis was not aiming to further test model accuracy, as this was not technically possible due to contrasting nature and spatio-temporal scales of simulated and observed datasets. Specifically, simulations used interpolated long-term ERA-40 weather reanalysis (1971–2000) at a 5 km grid-cell scale as model input. In contrast, observed AgYields datasets represent real-world yield data in response to local weather during specific years. These contrasts therefore allowed only comparison of long-term distributions at grid-cell and regional scales with the intent of identifying systematic patterns of divergence. In addition, other growth conditions that influence observed yields such as soil characteristics and lucerne defoliation management were not associated with AgYields data, and therefore could not enable a formal set up of model simulations for further accuracy assessment. Nevertheless, both models have been formally tested using point-scale observed datasets (Moot et al., 2021b; Yang et al., 2023, 2022, 2021), so our analysis using AgYields data solely aimed to provide insights on the magnitude of distribution divergences among model outputs and in relation to reported yields across regions.

For that, only data-points from unconstrained growth conditions, apart from water-limited when evaluating Y_W, were selected. For each available data-point coordinate, 30-year simulation distributions from the respective VCSN grid-cell were considered for comparison. When coordinates were not provided in publications, these were assumed from arable land identified near the reported trial locations.

The selected test dataset gave median yields (and 25th to 75th percentiles) of 14 t DM/ha (11–17 t DM/ha) for rain-fed and 18 t DM/ha (15–19 t DM/ha) for irrigated crops.

2.5.2. Sensitivity analysis

A variance-based sensitivity analysis procedure (Pianosi et al., 2016; Santner et al., 2003; Welch et al., 1992) was applied to quantify the share of total variability in yield estimates attributable to each input factor (model selection, soil type and water supply management). Briefly, the variation in 30-year median yield estimates for each grid-cell was attributed to each main factor using ANOVA decompositions by quantifying variances for each factor and interactions. The normality of yield data distributions, as a requirement for ANOVA, was found in around 99% of the ~3600 grid-cells that showed a median p-value greater than $\alpha = 0.05$ quantified through a Shapiro-Wilk test (Shapiro and Wilk, 1965) across individual model/water-supply/soil combinations. The sums of squares for each main factor, plus its interaction components, were normalised by the total sums of squares and presented as percentages per grid-cell. The greater the normalised value, the higher is the sensitivity of lucerne yields variable to a given factor. Statistical analyses were performed using the statistical software R (R

Core Team, 2020). Multi-year simulation results are graphically presented through box-and-whisker plots. The upper and lower box edges represent the 25th and 75th quartiles while the whiskers (vertical lines outside the boxes) represent the 5th and 95th percentiles. Maps were produced with QGIS software (QGIS Geographic Information System, 2022).

3. Results

3.1. Lucerne grid simulation in comparison with regional yield datasets

Distributions of 30-year lucerne yield simulations for both models using the ERA-40 reanalysis climate dataset were compared with available yield data published for specific regions in New Zealand (Fig. 3).

The comparison with AgYields data showed a systematic variation in model agreement depending on climatic regions. For example, 30-year yield simulations were closer to published data in Canterbury (70–98% overlap) where both models were mostly developed and tested (i.e. triangles representing calibration-data in Fig. 3). In other regions, where most the data-points were independent from previous development/calibration studies (circles in Fig. 3), there was less agreement between simulated yield distributions and AgYields data-points. Differences were particularly larger for Southland (15–35% overlap), followed by Waikato (40–80%), Manawatu-Wanganui (79%) and Bay of Plenty (83–92%). Otago showed underestimation with 74% overlap by both models but also overestimation by APSIM. Across all regions, median yields were slightly lower for TGM than APSIM, from 1% to 12%, depending on location.

3.2. Spatial patterns of suitability and yield estimates across New Zealand

The overlaying of slope, rainfall and soil drainage GIS layers gave ~21 thousand km^2 of highly suitable land for lucerne cultivation (Fig. 4), without consideration of other limitations such as low temperature or economic yields which were accounted for by TGM and APSIM in the subsequent analysis.

Both models estimated similar spatial patterns of yield distribution across the land classified as suitable for lucerne growth (Fig. 5). With irrigated conditions and ample soil water storage (525 mm PAW soil), Y_P values > 25 t DM/ha were estimated for the northern areas of the country while lowest values were found to be < 10 t DM/ha in the southern regions. Model divergence was minimal for irrigated conditions.

For rain-fed conditions, Y_W estimates illustrated for the lowest water holding capacity soil (75 mm PAW) in Fig. 5, also showed a north-south decline with both models identifying similar spatial patterns and hotspots of low yields. Nevertheless, models diverged the most under these conditions, particularly for the coldest and driest regions (e.g. central southern areas). This was further highlighted by the sensitivity analysis (Fig. 6) that shows model selection being relatively more important in the southern (22%) than northern (10%) regions, with the two most southern locations showing model selection explaining ~30% of total variability. In these locations, yields are limited by simultaneous abiotic stresses from both low temperatures and limited water supply. In contrast, yield sensitivity to soil type was overall the highest share of total variability (65% on average), particularly in the warmer northern regions (~70–78%) where temperature and rainfall amounts are relatively less limiting to lucerne growth than in the South Island (~55–69%). As expected, the relative sensitivity of yield to water supply was highest in predominantly water-limited environments (e.g. east coast regions of both islands) with an overall average of ~15% of total variability in both islands.

As a consequence, the estimates of Y_W systematically diverged the most between models for the lowest water holding capacity soil (75 mm PAW) when yields are mostly limited by water deficit (Fig. 7).

4. Discussion

4.1. Spatial patterns of lucerne suitability and yield across New Zealand

Advancing approaches to quantify spatial variability in lucerne yields is critical given the global significance of the crop (Moot et al., 2012) and the benefits of assessing expansion potential of perennial legumes to diversify agricultural systems into more sustainable crop mixes (Asbjornsen et al., 2014). For New Zealand, our preliminary estimates of suitable areas for lucerne growth offer an initial indication of potentials but cannot accurately capture economically and environmentally viable areas to cultivate the crop within each region. For example, although we accounted for terrain steepness with a single parameter threshold (Brejea et al., 2021), individual growers might find it important to restrict operations to even flatter lands while others, who rely on grazing operations, might make use of steeper terrain. Similarly, risk of yield losses due to biotic-stress was only accounted for by

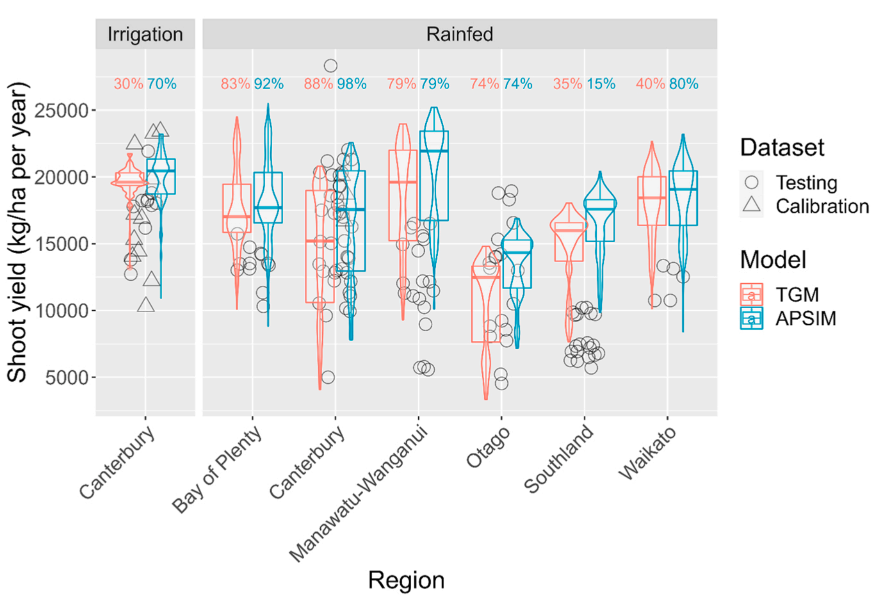

Fig. 3. Comparison between 30-year simulated distributions of lucerne yields (ERA-40 reanalysis climate data) and observed yields (actual point-based weather) within similar 5 km grid-cells and across New Zealand regions in which AgYields data is available for comparison with long-term simulations. Values show the percentage of total observed data-points captured within the 1st to 99th percentile of 30-year simulations, considering three possible soil water holding capacity for each model. Triangles represent data-points originally used in model development (calibration), while circles represent data-points which were not previously used in model development for the process- (Yang et al., 2021) and GIS-based (Moot et al., 2021b) models .

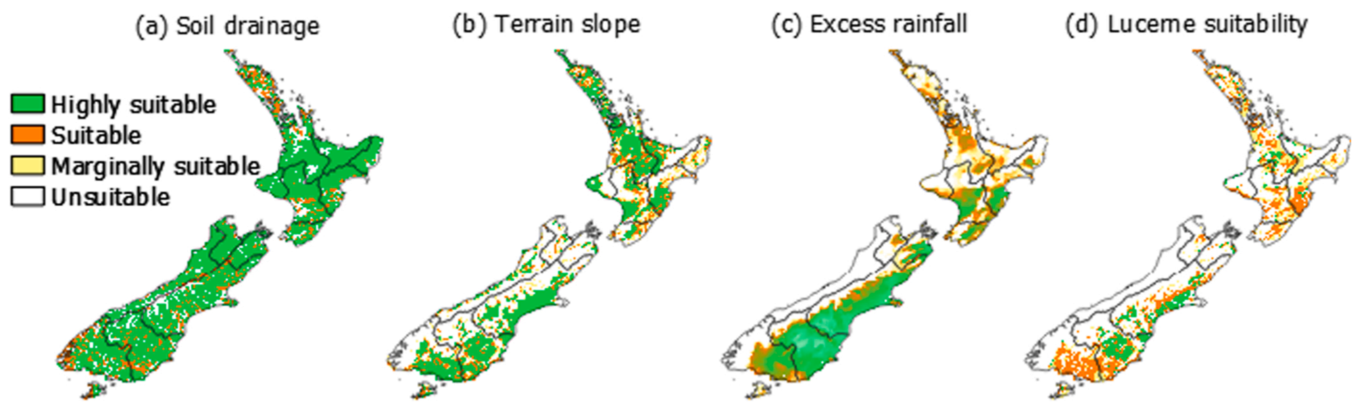

Fig. 4. Potential land suitability estimates for lucerne growth across New Zealand excluding limited soil drainage (poor/very-poor classes), steep terrain slope (>15 degrees in >50% of the grid-cell area) and excess rainfall (annual precipitation > 1700 mm) for selection of grid-cells.

assuming high rainfall and poor-drainage soils, as proxies for high risk of pest damage (Close et al., 2015). In the future, these and other aspects can be more mechanistically introduced into models depending on specific research questions and the balance between gains in accuracy and potential biases from additional model complexity (Saltelli, 2019). Similarly, other commonly used criteria to assess land suitability for lucerne, such as soil chemical and physical (e.g. salinity, drainage, pH) characteristics (Alemayehu et al., 2020; Deng et al., 2014; Kim et al., 2018), were outside of the scope of this study but can be implemented depending on localised data availability and research objectives.

In addition to suitability, our study provided a first quantification of spatial variability in lucerne yields at a wide landscape-scale using both process- and GIS-based models. The responses of lucerne yield to temperature and rainfall gradients found across New Zealand with these two models agree with patterns estimated in a recent assessment in Canada using the lucerne EPIC model (Wang et al., 2021). Absolute yield estimates were however higher in New Zealand than Canada, particularly in the warmer climate zones of the country likelly due to the longer growth cycle length. Expanding the understanding of drivers of spatial variability previously observed for lucerne crops at field (Kayad et al., 2016), regional (Brejea et al., 2021) and national scales (Wang et al., 2021), our results highlighted a north-south pattern of decline in potential lucerne yields (Y_P) across the country, which was consistently captured by both models that converged the most under non-limited water conditions. This is similar to the pattern observed in other irrigated cropping systems in New Zealand, such as silage maize, in which temperature gradients become the main driver of spatial yield variability across the country (Teixeira et al., 2017). Optimum temperatures for different lucerne physiological processes are ~20 ^oC (Pearson and Hunt, 1972) which is above the current gradient observed in the oceanic temperate climates of New Zealand. The yield reductions estimated for colder southern regions occur primarily due to the sensitivity of canopy expansion and photosynthesis to sub-optimal temperatures, by limiting both plant development (e.g. main-stem node appearance and branching) and growth (e.g. carbon assimilation) rates (Brown et al., 2006; Teixeira et al., 2007). This is captured by a decline in both radiation interception (R_i) and radiation use efficiency (RUE) considered in the process-based model (Fig. 2). Nevertheless, the GIS-based model "bundled" representation of such processes into a single parameter set (i.e. seasonal growth rates per thermal-time unit) was also sufficient to capture similar yield spatial patterns of non-stressed crops. This was illustrated by a relatively small model divergence between models for Y_P (± 7%). Implicit here is the empirical climate-specific estimation of aggregated parameters in the GIS-based model, that assimilates the inherent relationship between temperature and incoming radiation within a given environment (Bristow and Campbell, 1984). In contrast, although the overall north to south yield decline with lower temperatures was still captured by both models for rain-fed conditions (Y_W), the extent and intensity of water-stress hotspots identified by each model differed. This was particularly important at low yields in the east- and central-southern regions of New Zealand, where average rainfall is less than 600 mm/year. Such increase in model divergence under extreme summer-dry conditions is expected due to the additional complexity required for calculations of daily water supply and demand, and the translation of these into yield decline magnitude. Although both models rely on a similar method to calculate water demand (i.e. Pristley-Taylor evapotranspiration), yield decline is an emergent property of interacting canopy and photosynthesis responses in the process-based model, while for the GIS-based the accumulation of thermal-time (i.e. the main driver of growth) is stopped and restarted based on empirical soil moisture thresholds. As a consequence, uncertainty due to model selection was particularly high in locations where abiotic stresses interact, such as the central South Island because dry and cold conditions occur simultaneously. Therefore, the representation of lucerne responses to multiple interacting yield-constraining conditions is suggested as a critical area for future model improvement targeting spatial applications. Such insights and considerations may help address the limited representativeness of perennial legumes in current gridded agricultural climate-impact studies, still largely dominated by cereal crop commodities (Müller et al., 2019; White et al., 2011). The regional divergences found between models, and between simulations and observations (Fig. 3), can be attributed to different sources of biases that occurr simultaneously. These are likely a combination of imperfections in model structure/parameterisation and also on how agronomic and experiential aspects (e.g. measurement method, stand density/age, defoliation regime, biotic and abiotic stresses), that largely influence yield observations, are known and represented in model configurations. Both sources of biases are discussed in the following section.

4.2. Scope, implications, and limitations of this study

The land suitability "potential" estimates for lucerne (Fig. 4) in our study are likely to represent an upper limit which overestimates "actual" viable land for lucerne cultivation across the country. This is because we considered biophysical drivers, without accounting for additional socio-economic limiting factors (e.g. competition with other agricultural or non-agricultural land uses; absence of infrastructure/markets and exclusion of environmentally/culturally protected areas). At the other extreme, this study across New Zealand climate zones also cannot capture the much wider range of environmental conditions where lucerne is reported to grow. For instance, the crop is cultivated from cold to semi-arid conditions where genotypes with different phenotypical traits (e.g. degree of fall dormancy) are locally adapted (Annicchiarico et al., 2011; Djaman et al., 2020). Depending on the environment, specific physiological processes, not necessarily accounted for in the models here considered, may become more critical for estimation accuracy. For

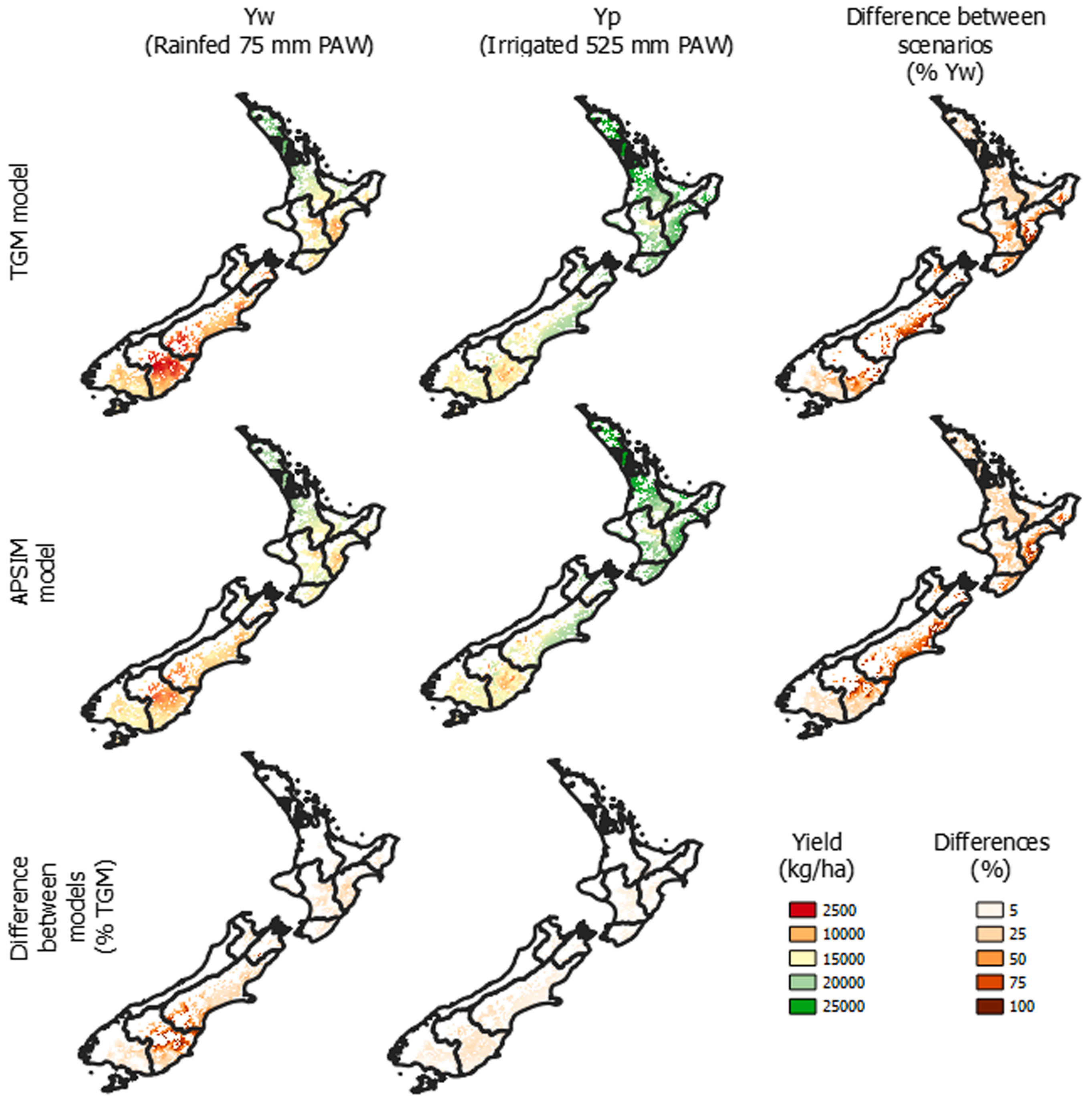

Fig. 5. Above-ground annual yield estimates for lucerne crops (dry matter t /ha) simulated by two models (APSIM and TGM) under two contrasting water supply conditions (rain-fed with 75 mm soil and irrigated with 525 mm of potentially available water, PAW) across New Zealand.

instance, in the harsh winter conditions of Canada it is critical to correctly simulate crown-level temperatures under snow cover to capture differences in stand survival (Jing et al., 2020). This is not required or accounted for in the models applied in this study. Such considerations, and other more sophisticated filtering logic (e.g. considering different weights for specific suitability factors), could be explored in future analysis depending on climatic conditions and research questions of interest.

A key implication of our findings is that greater confidence on yield simulations is expected for Y_P than $Y_{W;}$ and also when comparing relative yield differences (e.g. across locations and years) instead of absolute yield values. This is illustrated by the better agreement for Y_P both with the AgYields irrigated data-points (Fig. 3) and between models (Fig. 5). However, by definition, Y_P calculations assume optimal growth conditions, which are not commonly achieved in the field even under best agronomic practices. Even under fully watered conditions other yield-constraining factors, such as biotic stress damage facilitated by to frequently wet soils, might reduce stand longevity and lucerne productivity by affecting self-thinning patterns across years (Teixeira et al., 2007). In contrast, for water limited conditions there was a larger model divergence which may be caused by the difficulty to realistically represent edapho-climatic and management conditions, particularly defoliation regimes for lucerne, at fine resolutions (i.e. field scale at daily time-steps) a key source of uncertainty in crop model simulations (Wang et al., 2021). This aspect is further illustrated by the comparison with the AgYields database, which highlighted a yield overestimation

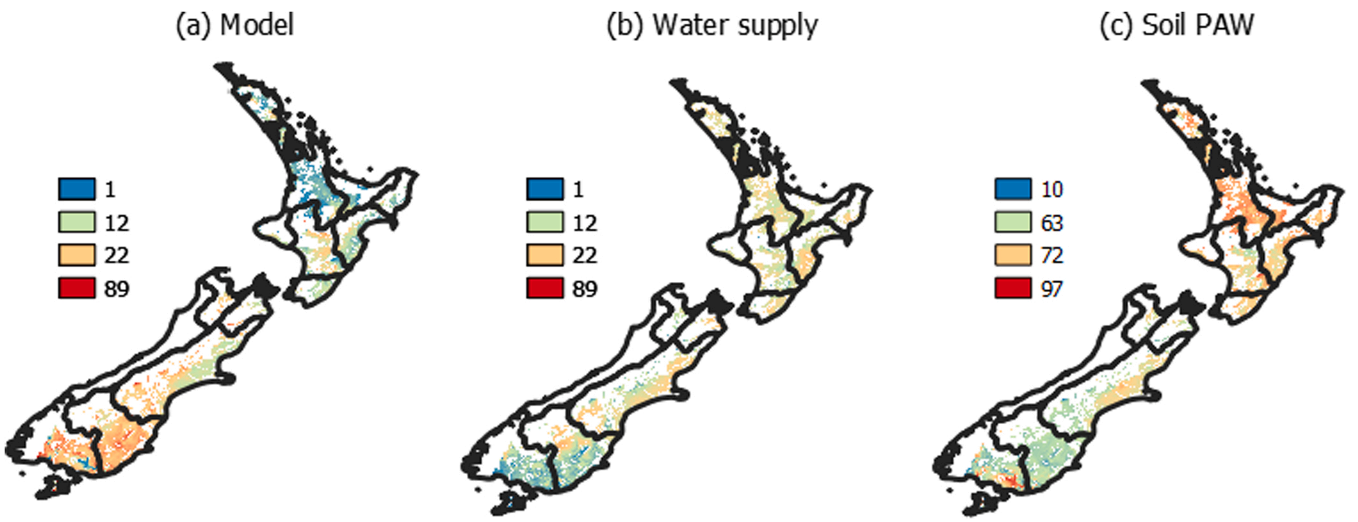

Fig. 6. Spatial patterns of sensitivity for lucerne yield estimates, as percent of total variance, for the selection of (a) model, (b) water supply and (c) soil PAW per grid-cell for the 30-year lucerne yield simulations.

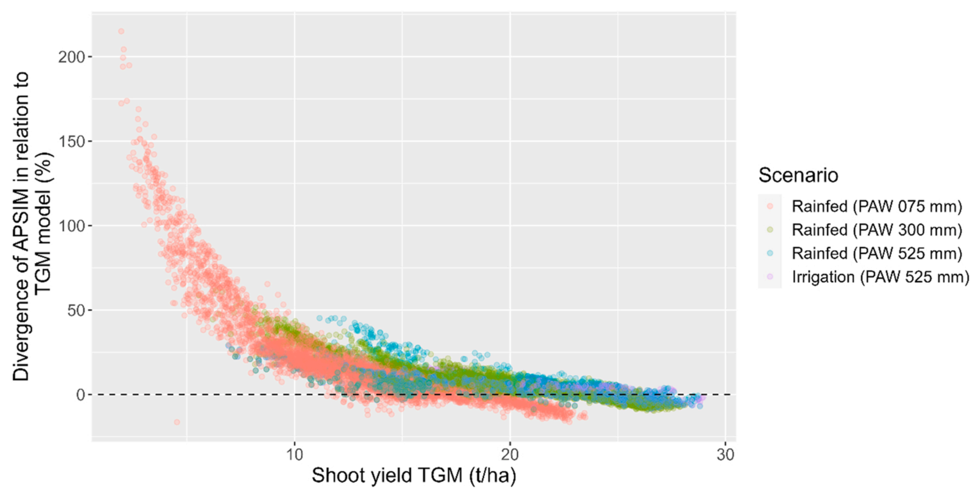

Fig. 7. Relative difference between yields simulated by TGM and APSIM-NextGen models for irrigated (IRR) and rainfed (RAIN) conditions under hypothetical soil types with Plant Available Water (PAW) ranging from 75 to 525 mm.

response of both models in cooler and drier regions (e.g. central South Island). Our analysis was able to unveil spatial yield divergence patterns but it cannot isolate the underlaying causes of disagreement neither between models, nor in relation to observed yields to identify the fittest model for different situations. This is because the yield overestimation in southern regions can be an indication of regional yield-gaps and/or be caused by systematic biases in model structure or parameterisation that mainly emerge at high abiotic stress environments. The disentangling of possible disagreement drivers requires further investigation. As highlighted in Section 2.4.1 although it was not possible to formally further test the models, given contrasting spatial resolution and climate data between simulated and observed datasets, the use of already existing model formulations allowed the identification of systematic patterns of disagreement between models and with observed data, that can be explored at greater depth in the future by focusing on hotspots where multiple stresses coincide such as central South Island.

Finally, it is important to note that the historical reanalysis of climate data does not capture shifts in land suitability neither due to biophysical and socio-economic drivers of land use (Costa et al., 2019; Puy et al., 2020) nor due to already occurring climate change. In particular, observed warming and changes to rainfall patterns (amounts and frequency) in recent years (Masson-Delmotte et al., 2021), and projected for the future (Meinshausen et al., 2011), are likely to influence spatiotemporal distribution of land suitability and yield for lucerne across New Zealand. The disentanglement of such uncertainties and potential biases require further investigation, particularly through the collection of data tailored for model testing and improvement purposes across more extreme climate conditions (Kersebaum et al., 2015; Rosenzweig et al., 2013). These can also be investigated in the future through an expansion of the current modelling approaches by considering gridded climate change projections that account for uncertainty in emission scenarios and climate projections downscaled for New Zealand (Tait et al., 2016; Teixeira et al., 2021).

5. Conclusions

Our analysis shows a consistent north-to-south declining spatial pattern of lucerne yields across New Zealand. These were driven in large part by temperature gradients that influence crop growth and development rates and were captured by two models with different complexity, particularly for higher yields under unconstrained growth conditions. In contrast, there was greater model divergence, and model overestimation of reported regional data, for low yields under high stress conditions due to low temperature (e.g. southern regions) and limited water supply (e.

g. rain-fed conditions with low water holding capacity soils). This highlights a need to focus research efforts to develop and test lucerne models under conditions where multiple stresses interact. This first spatial assessment of lucerne yields can serve as the foundation for future regional and national yield gap analyses and inform similar approaches considering other agricultural systems with perennial legumes.

CRediT authorship contribution statement

Edmar Teixeira was responsible for the study Conceptualization, Data analysis and writing. Spatial analysis and development/set-up of the TGM model were done by Jing Guo and Derrick Moot. The suitability assessment was conceptualised by David Hannaway and Derrick Moot and performed by Jing Guo. The ATLAS parameterisation and HPC runs were done by Jian Liu and Rogerio Cichota. APSIM lucerne prototype parameterisation was done by Xiumei Yang, Rogerio Cichota and Hamish Brown. Climate data curation was done by Abha Sood. All authors contributed to the review and editing of drafts and the final version.

Declaration of Competing Interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests Edmar Teixeira reports financial support was provided by New Zealand Ministry of Business Innovation and Employment. Jing Guo reports financial support was provided by New Zealand Ministry of Business Innovation and Employment. Derrick Moot reports financial support was provided by New Zealand Ministry of Business Innovation and Employment. Hamish Brown reports financial support was provided by New Zealand Ministry of Business Innovation and Employment. Jian Liu reports financial support was provided by New Zealand Ministry of Business Innovation and Employment. Rogerio Cichota reports financial support was provided by New Zealand Ministry of Business Innovation and Employment.

Data availability

The authors do not have permission to share data.

Acknowledgements

This study is part of the 'Hill Country Futures' research programme (Biodiversity in landscapes) funded by Beef + Lamb New Zealand, the Ministry of Business, Innovation and Employment (MBIE), Seed Force New Zealand and PGG Wrightson Seeds (BLNZT1701).

Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.eja.2023.126853.

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