An estimate of carrying capacity of land for ruminant livestock production across southern Australia, using gridded batch simulation modelling

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Abstract
We present the first gridded modelling of grazing systems across southern Australia to estimate the carrying capacity of land for ruminant livestock production in relation to climate, soil and pasture species characteristics. A static Merino sheep trading enterprise was simulated using GrassGro™ software across a 5 km continental grid. A batch processing wrapper was developed to select inputs by geolocation and transfer these data to the simulation engine. The key output was a continental map of the optimised stocking rate per winter-grazed pasture hectare, as determined through maximising gross margin ($/ha), constrained by a supplementary feeding limit (< 20% of total energy intake) and a ground cover threshold (>50% cover for more than 90% of the time). We use the study to highlight some likely sources of error in existing methods, and how our method can help to compare livestock carrying capacity across a wider geographic region.

Key Words
GRAZPLAN, feedbase, relative intake, temperate, subtropical, NPP.

Introduction
Many factors influence the productivity of a dryland grazing enterprise. These include: i) environmental factors such as soil type and climatic conditions, ii) sward characteristics related to the plant species that have been introduced and persist, and iii) the tactical and strategic business decisions that are made. This complexity makes it difficult to estimate and compare the capacity of farm land for livestock production (or carrying capacity) in a way that is applicable across enterprise types, regions and climatic zones. At the same time, it is obvious that large differences in the carrying capacity that are related to the farm's location do exist. This has led to the development of a range of methods to estimate the carrying capacity of a particular property. For example, French (1987) determined a linear relationship ($y=0.052x - 13$) between potential carrying capacity (y, sheep/ha) and annual rainfall (x, mm) based on research conducted in South Australia. However, the wide range of carrying capacity values used to establish this relationship at any given rainfall (particularly for high rainfall sites) suggests that other important drivers exist (French 1987). Experienced agronomists with access to the business records of many farms are able to advise livestock producers in their local areas based on their analysis and interpretation of these records. In these situations, factors such as high variability in management strategies, varying amounts of across enterprise integration, and year to year tactical decision making tend to result in poor correlations between actual stocking rates and growing season rainfall even within a region (The Sheep's Back, 2018). In Australia, simulation modelling software (e.g. GRAZPLAN) is widely used to test simplified livestock grazing scenarios at a range of stocking rates, generally for a particular farm system and location, and make an assessment of economic outcomes (Donnelly et al. 2002). A biophysical modelling approach makes it possible to optimise stocking rates around selected economic parameters. Our aim was to estimate the capacity of grazing land for ruminant production at high resolution across southern Australia with a purpose-built simulation modelling platform using climate, soil and pasture species data mapped to a continental grid.

Methods
GrassGro™ simulations (Moore et al. 1997) were batched and run on a daily time step over 30 years from 1 January 1988 to 31 December 2017 at a 5 square km resolution for the geographic area of the study (Figure 1). A generic livestock enterprise was used at all locations, based on wool production from Merino wether trading, where 18 month old replacements (45 kg, body condition score 2) were purchased annually on 1 January, and cast for age animals were sold on 31 December. Sheep were transferred to a feedlot and fed a 70:30 wheat chaff and wheat grain diet at 1.5 kg/head/day from 1 November to 1 February to reflect the animal's access to grazing of crop stubbles in mixed farming regions. Shearing of sheep was on 15 December annually. GrassGro pastures were built to represent typical pastures grown for livestock production in the project regions. The modelled pasture species were selected from the existing GrassGro

plant models, to represent pasture composition of a Statistical Local Area (SLA) described in the MLA Feedbase Audit (Donald, 2012). As the MLA Feedbase Audit was geographically restricted to the southern states, the combination of Gatton panic and white clover was used for all locations in Queensland. To represent the variation in pastures that may exist across a typical farm (e.g. improved and unimproved), two grazing paddocks were set up with a rule implemented in GrassGro^{TM} to identify and graze all animals on the best paddock, rotating animals between the two paddocks at a maximum of every 2 weeks.

Model inputs

Grid points were identified using a national fish-net to select locations at 5 x 5 km resolution, ensuring only mainland sites were selected. The extent of the area selected for simulation corresponds to the national Pastures from Space footprint (http://www.pasturesfromspace.csiro.au) representing the temperate to sub-tropical pasture growing region. Meteorological data were obtained from SILO gridded datasets for maximum and minimum temperature, rainfall, synthetic pan evaporation, radiation, and vapour pressure. Data for the SILO grid point (resolution of 0.05 degree) nearest the fish-net grid point was transformed into APSIM format for use in the simulations. Soil data for the GrassGro™ simulations were obtained via the "getApsoil" web service (http://www.asris.csiro.au/ASRISApi/api/APSIM/getApsoil) provided by the Australian Soil Resource Information System (ASRIS). This service generates a synthetic APSIM soil parameter file by applying pedotransfer functions to soil property values extracted from the TERN (Terrestrial Ecosystem Research Network) Soil and Landscape Grid of Australia (SLGA) (grid resolution of 90 metres). In addition, values for particle size distribution were obtained from direct queries to the SLGA and merged into the corresponding APSOIL description and a value for saturated hydraulic conductivity in each soil layer was estimated from the ASPOIL SWCON parameter. For model initialisation the distribution of available water in the soil profile was set to the amount at which the plant available water was 30% of the plant available water capacity for each soil layer. Simulations were run over a sufficient length of time to ensure that these initial conditions did not substantially affect the outcome.

Configuration of batch simulation wrapper and optimising stocking rate

To enable the configuration and simulation of the multiple scenarios, a dynamic program referred to as GGWrapper was built to interact with the GrassGro version 3.3.9 modelling engine. GGWrapper is a command-line application which enables the user to run a GrassGro simulation, with options for replacing the soil, weather, and pasture composition elements, and to implement rules enabling an "optimum" stocking rate for a scenario to be determined. The criterion set for this study was to maximise the gross margin of the enterprise, subject to two constraints: (1) that ground cover drops below 50% no more than on 10% of days in an average year; and (2) that ME from supplement be no more than 20% of total ME intake in an average year. Prices used for the gross margin analysis were sourced from industry benchmarking reports.

Results

Pasture production (Net Primary Production, kg/ha NPP) simulated from grazed pastures across the southern agricultural region of Australia is presented in Figure 1a. Overall, our method was successfully implemented with pasture production corresponding with expected trends across the national grid. Some edge effects are visible across statistical local area boundaries associated with different plant combinations selected for the modelling scenarios, particularly for NSW. The introduction of sub-tropical grass into the model at the Queensland border increased NPP in these scenarios. In the inland drier regions, where mean annual NPP was low, the variability in NPP from year to year was higher than for those regions with higher NPP (data not provided). In some areas, low productivity was due to the pasture species (e.g. native grasses) selected in the simulations. It should be noted that the composition of the simulated pastures may have performed unpredictably at some locations, as the performance of individual simulations was not analysed. Ongoing work could consider a diagnostic process to identify any instances and causes of poor model performance. At a minimum, the pasture composition selected in the model should be considered when interpreting results for a particular location. Across most of the region studied, profitability was the key driver that constrained the optimisation of stocking rate (Figure 1b). However in the drier inland agricultural regions ground cover and supplementary feeding optimisation limits constrained the simulations; that is, the rules implemented for maintaining ground cover and keeping supplementary feeding were more important determinants of optimal stocking rate than profitability. This was likely due to the different pasture types, greater seasonal variability and lower biomass of plant residues (dead plant material).

a) b)

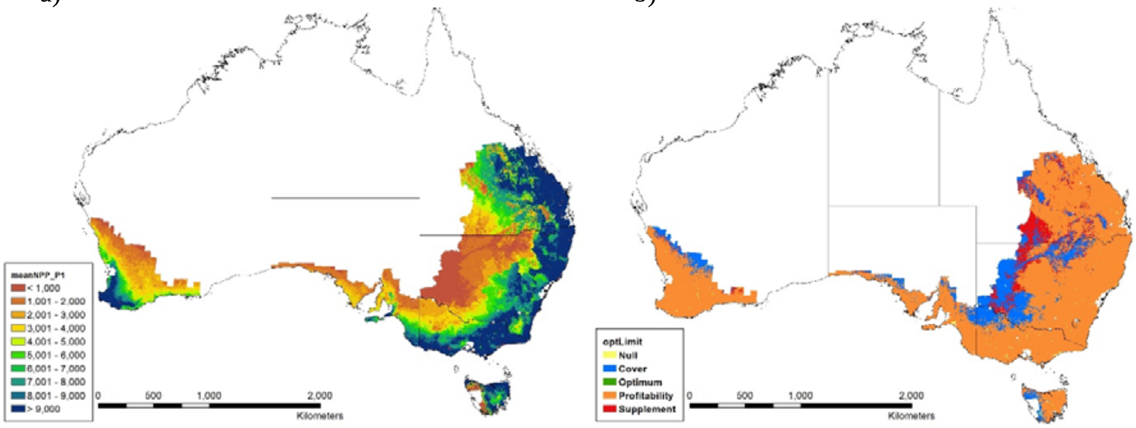

Figure 1. The spatial distribution of a) Net Primary Production (NPP kg/ha) and b) the limiting optimisation constraint for a GrassGro® simulated grazing enterprise for the southern agricultural region of Australia at 5 km grid resolution.

Optimised stocking rates for the agricultural regions of Australia are presented in Figure 2. Estimated stocking rates appear to be lower in parts of inland Qld compared with both rainfall and NPP trends. There may be lower utilisation or feed conversion efficiency of the sub-tropical forage, indicated by a clear bimodal clustering in the relationship between NPP and optimised stocking rate (data not presented). Consistent with the changes in NPP (Figure 1a), the optimal stocking rates determined for Qld were higher with the inclusion of Gatton panic based pastures, more suited to the sub-tropical conditions. However, there is a high level of variability in optimised stocking rate for similar geographic areas in Qld, compared with the other states.

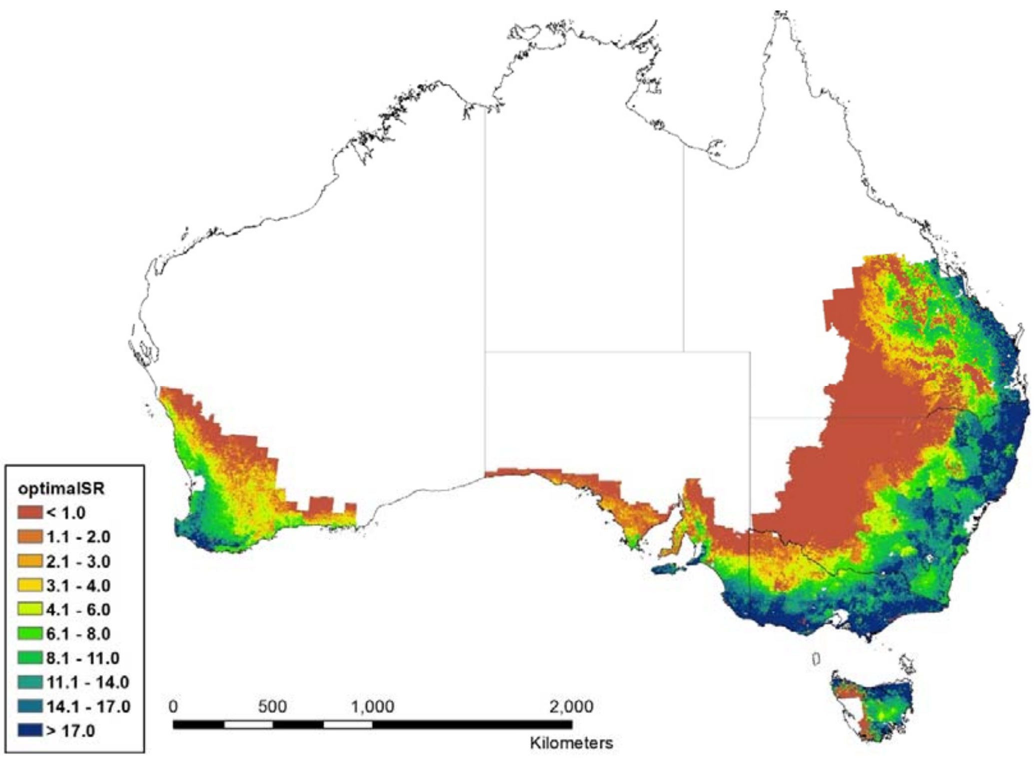

Figure 2. Optimised stocking rate of a Merino wether trading enterprise estimated for MLA feedbase audit derived pasture combinations 1988 – 2017 for the southern agricultural region of Australia at 5 km resolution.

The lessened edge effect on the Queensland border for optimal stocking rate appears to be a result of higher NPP levels not supporting higher livestock production potential due to poorer utilisation of this forage. This modelling platform has not been well tested under northern grazing conditions, where diet selectivity is higher with greater divergence from the available forage components. Under these conditions, relative intake values for the same NPP may vary substantially, affected by plant nutritive value and other sward characteristics that affects the rate at which forage is ingested.

In Table 1, locations with approximately 500 mm annual rainfall (1988-2017) were selected as a case study to demonstrate how the inter-related farm systems factors affect the potential for livestock production. Net primary productivity at Baradine and South Stirling were the lowest, which was likely due to the slower growing perennial grass species selected for these sites. Across other sites, total NPP was reasonably consistent (5716 – 7105 kg/ha). In WA, NPP at two sites (Badgingarra and Williams) with the same pasture composition and rainfall differed by about 1000 kg/ha. This was likely due to the cooler climate and longer growing season at Williams, which is 300 km further south. As would be expected, the higher production and extended growing season at Williams resulted in a higher optimal stocking rate compared with Badgingarra (11.4 versus 7.6 sheep/ha). At Ombersley, the higher stocking rate (15.0 sheep/ha) may be due to an extended growing season with more evenly distributed annual rainfall. Gross Margins generally reflected the stocking rates at the sites. However, where energy required from supplementary feeding was higher (e.g. Morven and Baradine) Gross Margins were lower relative to other sites with comparable stocking rates. This demonstrates that while rainfall is important for the total and distribution of NPP, other environmental factors have a large influence on ruminant carrying capacity in a particular location.

Table 1. Simulation outputs for a Merino wether trading enterprise at a selection of Australian locations with a mean annual rainfall (1988-2017) of 500 ± 5.0 mm.

Location	Pasture type	Net Primary Production (kg/ha/year)	Net Primary Production CV (%)	Optimal stocking rate (sheep/ha)	Gross Margin ($/ha)	Energy from supplement (%)
Badgingarra, WA	Annual grass/legume	5716	28.2	7.6	127	7.7
Baradine, NSW	Native perennial grasses	3334	63.5	4.0	-11	14.3
Coolamon, NSW	Improved perennial/annual	6218	45.8	10.0	155	10.6
Morven, Qld	Perennial grass/legume	6211	62.8	2.7	-34	24.4
Mt Torrens, SA	Annual grass/legume	6107	46.0	8.2	117	8.7
Ombersley, Vic	Improved perennial	7105	42.2	15.0	258	8.1
South Stirling, WA	Improved perennial/annual	5138	38.5	4.5	33	10.3
Williams, WA	Annual grass/legume	6707	29.1	11.4	205	8.4

Conclusion

To our knowledge this is the first time that gridded simulation modelling has been used to estimate the capacity of land for ruminant livestock production across southern Australia. Further, we demonstrate the limitations of using a simple function based on rainfall to estimate carrying capacity. At a local scale, we expect that there may be some inconsistencies in the local accuracy and relevance of the results. Individuals may perceive different optimal stocking rates for their particular farm and farming system and may have different approaches to risk that may mean they 'push the boundaries' of their system more or less. There will also be differences in enterprise structures, management decisions and/or pasture production that affect optimal (profit maximising) stocking rates, as well as non-financial priorities. Nonetheless, we have presented a method for a broadly applicable estimate of carrying capacity and excludes variability associated with the management philosophies of individual businesses, which are inherent in benchmarking studies.

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