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Digital soil assessment of agricultural suitability, versatility and capital in Tasmania, Australia

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ABSTRACT

Digital soil assessment (DSA) is the application of interpretations to digital soil mapping (DSM). Since 2010, an operational DSA program has been underway in Tasmania, Australia, primarily for the assessment of agricultural land suitability for 20 different crops in newly commissioned irrigation schemes. This involves development of functional soil attribute and climate grids, initially undertaken in two pilot areas totalling 70,000 ha, with comprehensive soil sampling and temperature sensor networks. Through the Tasmanian State Government 'Water for Profit Program', this pilot land resource assessment has become operational and applied to the entire State (68,401 km^2), covering a total of 19 irrigation schemes. Using a combination of newly collected and legacy soil data and a suite of spatial explanatory covariates, a total of 218 80 m resolution 3D soil attribute grids were produced using the digital mapping approach, together with quantified prediction uncertainties. These grids have contributed to the 'Soil and Landscape Grid of Australia' and the 'GlobalSoilMap' projects. Using a similar approach, functional climate grids were generated for chill-hours, growing degree-days and frost risk. The digital soil and climate grids were applied to pre-defined enterprise suitability rulesets to produce 20 different maps of enterprise suitability, including opium poppies, and a range of perennial horticultural, cereal and vegetable crops, uploaded to a publically accessible spatial internet portal (Land Information Services Tasmania; LISTmap), which includes functionality to identify soil and climate limitations, as an indication of potential land management inputs. The suitability surfaces provide a regional indication of potential areas to expand or diversify into a range of cropping enterprises. However, some informative supplementary products were also developed to provide an overall spatial guide to the more versatile agricultural areas. This included an enterprise versatility index (by combining all suitability surfaces to identify areas more suited to more enterprises); and application of individual commodity 'financial gross-margins' to identify the highest-valued agricultural land in terms of earning potential. These products demonstrate the utility of functional soil property grids and the collective capacity of DSA to answer questions of agricultural potential; this can ensure the appropriate land is targeted for appropriate uses to stimulate agricultural markets and maintain food security.

1. Introduction

There is significant published literature and evidence demonstrating the proficiency of digital soil mapping (DSM) to provide functional soil property and class maps for a range of depths, across different soil and landscape types, and at different resolutions, depending upon need (Lagacherie, 2008; Lagacherie et al., 2007). DSM involves a variety of different disciplines, including the development of predictive spatial modelling functions of soil properties or classes using point-source calibration sites, along with spatial explanatory variables to map the spatial variation between sites. Popular DSM approaches employ environmental correlation (*scorpan*) utilising intensive computing capabilities and geostatistics to produce quantitative 3-dimensional grids of soil properties or classes, with the advantage of providing quantitative estimates of associated uncertainty (McBratney et al., 2003). DSM has perceived advantages over traditional polygonal soil mapping in that the process is quantitative, repeatable, objective, can be applied over large areas of sparse information, and routinely updated as new data is collected (Carré et al., 2007; Minasny et al., 2008). The raster outputs are better able to simulate the continuous and gradational variations of spatial soil properties, across multiple depths (MacMillan, 2008; McBratney et al., 2003). In recent years, this science has become increasingly operationalised, with GlobalSoilMap (Arrouays et al., 2014) being a globally significant example. DSM products, now largely accepted by mainstream soil science (Carré et al., 2007), are progressively being used for a variety of purposes to answer soil productivity and environmental assessments across a range of scales; locally,

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regionally and globally (Hartemink, 2015), including environmental processes and agricultural suitability (Harms et al., 2015). This is achieved through applying interpretations to functional DSM grids, and integrating with appropriate biophysical data such as vegetation, climate and terrain for quantitative decision making and support (McBratney et al., 2012); this process is referred to as digital soil assessment (DSA) (Carré et al., 2007). Finke (2012) surmised that DSM has reached an acceptable level of scientific maturity for the focus to now shift to DSA, and further into soil security and quality (McBratney et al., 2012, 2014).

The aims of this paper are to present a regional DSA for the whole of Tasmania for enterprise suitability assessment, and development of some preliminary spatial products to inform agricultural versatility and capital. The structure is as follows: first, we briefly review the operational DSA undertaken in the two pilot areas; describe how the pilot DSA approach was expanded using the soil and climate data collected in the pilot phase, and integrated with legacy soil data to generate state wide DSM surfaces to inform an Enterprise Suitability Assessment (ESA) for the whole State of Tasmania, for 20 different enterprises; describe, present and discuss preliminary state-wide maps produced for agricultural versatility and spatial gross-margins estimates; and examine the pros and cons of the suitability framework, and how this could be improved with a future sampling campaign.

1.1. Operational DSA

DSA was proposed by Carré et al. (2007) for assessing threats to soil (resulting in land degradation) and functions of soil, such as biophysical interactions, production and biodiversity, where DSM is a precursor to DSA. Therefore, DSA can be used to for identifying environmental risks and for land evaluation, such as agricultural land suitability for various crops, and integrated with other environmental or socio-economic data for tailored end-user requirements (Carré et al., 2007).

Examples of DSA, in an operational context, are demonstrating the functionality of DSM and producing credible and effective products when integrated into DSA. Van Zijl et al. (2014) evaluated a DSA approach for rapid land suitability assessment in the Namarroi area of Mozambique. A SoLIM (Soil Land Inference Model) approach (Zhu et al., 1997), integrating conceptual soil mapping units with pedometric inference techniques (Zhu et al., 1997) produced predictions of soil production potential, erosion risk, and compaction risk from a range of expert-based rulesets. The authors were able to demonstrate the relatively rapid production of functional soil property mapping to determine spatial land suitability from few field observations, with an absolute validation sample accuracy of 80%, and over 59% (with 95% confidence limits).

Thomas et al. (2015) and Harms et al. (2015) describe an application of operational DSA for agricultural land suitability assessment in Northern Queensland, primarily to explore opportunities for irrigated agriculture in an area of 155,000 km^2 in the Flinders and Gilbert catchment. The project used a combination of legacy and newly collected soils data, along with a suite of *scorpan* (McBratney et al., 2003) spatial covariates to predict of range of different soil properties using a robust regression tree (RT) approach (Breiman et al., 1984; Grunwald, 2009; McKenzie and Ryan, 1999; Moran and Bui, 2002). The validation diagnostics of DSM-derived functional soil property maps produced for this DSA were considered appropriate for the requirements of the regional-scaled suitability assessment, and were applied as input parameters to a range of land suitability rulesets to identify areas that were suitable for irrigated agricultural expansion. This operational DSA followed a similar exercise in Tasmania, Australia, producing land suitability maps for 20 different crops to inform irrigated agricultural expansion.

1.2. Tasmanian DSA

Tasmania is undergoing a period of agricultural expansion and investment in irrigation. As at June 2015, 19 irrigation schemes have been commissioned in addition to existing irrigation areas, funded by a combination of Federal, State and private investment; of these, 11 are now operational, 2 under-construction, and the remainder at the planning stage (Tasmanian Irrigation, 2015).

In 2010, the Tasmanian Department of Primary Industries Parks Water and Environment (DPIPWE), in collaboration with the University of Sydney Faculty of Agriculture and Environment and the Tasmanian Institute of Agriculture (TIA) launched the 'Wealth from Water' project (DPIPWE, 2015d), developing a land suitability framework based around operational DSM to stimulate investment and development of the irrigation schemes. The project covered two separate areas, totalling 70,000 ha (Kidd et al., 2014b). This was a 'proof of concept' pilot exercise which applied DSM for the generation of a suite of functional soil property and climate gridded surfaces to pre-defined 'enterprise suitability rule-sets' (developed by TIA) for 20 different enterprises, to inform an 'enterprise suitability assessment' (ESA) at 30 m resolution. The ESA was effectively a land suitability approach (FAO, 1976) of land evaluation, limited by the least suitable soil or climate parameter (Klingebiel and Montgomery, 1961). The TIA-derived rulesets all contain soil, terrain and climate parameters that were identified by industry workshops, available literature and agronomy experts to be the major limitations to each crop; many of these limitations can be effectively managed by various technologies, however, they would require either capital or ongoing investment, which will determine profitability. This inferred management underpins the ESA.

The term 'enterprise' was chosen over more commonly applied land use type (or land utilisation type) (FAO, 1976) due to the level of management inferred for each crop, identified by the parameter ranges of each rule-set. The basis the suitability framework provides a query-enabled list of limiting factors through DSM, identified to guide the management practices that could help overcome the limitations. In addition, market tools, financial modules, irrigation case studies and fact sheets were also developed (DPIPWE, 2015c, 2015d), which all infer that each land utilisation type should be considered in conjunction with the underpinning management requirements to manage limitations for an enterprise to become successful (profitable). The limitations requiring management were identified through the series of fact sheets; in addition, a 'default' or typical management was developed by industry and TIA for the purposes of identifying the suitability assessment parameters, and to provide the basis of the cropping gross-margins analysis. Finally, the term 'enterprise' was applied by the Tasmanian Government to the programme to identify each land use type as a business consideration, and is used throughout this paper to maintain consistency.

931 soil cores were sampled, including an independent validation set (30%) (Kidd et al., 2015a). The observations were modelled as a function of spatial covariates using Regression Tree (RT) combined with kriging of the model residuals where spatial-autocorrelation was sufficiently strong; that is, regression-kriging (RK) (Hengl et al., 2004, 2007; Odeh et al., 1995). The DSM methodology and results are presented and described in more detail in Kidd et al. (2012, 2014a, 2014b, 2015a). 271 temperature sensors were installed in optimum locations to ensure representation of the full terrain covariate distribution, and climate grids generated from this data using the terrain covariates, as described in Webb et al. (2015). The soil and climate grids, and resultant ESA maps from interpreting the outputs of the enterprise suitability rule-sets, were uploaded to a publically accessible spatial web-based portal (DPIPWE, 2015e), where growers or potential investors could view the ESA maps, and query any part of each map to determine what any limiting soil or climate factors might be.

Gross-margins economic data for each enterprise was also developed by DPIPWE into a set of Gross Margins Analysis Tools (GMAT) to assist business planning, to be used in addition to consideration of the ESA mapping (DPIPWE, 2015b). Gross margins provide estimates of the expected monetary returns from the sale of produce after taking into account the economic variables associated with production. Enterprises included:

> *barley; blueberries; carrot seed; carrots; cherries; hazelnuts; industrial hemp; linseed; lucerne; olives; onions; poppies; potatoes; pyrethrum; raspberries; rye grass for dairy; strawberries; wheat and wine grapes (pinot noir and chardonnay).*

This pilot project was considered successful in that acceptable diagnostics were obtained for the modelled soil and climate grids (Kidd et al., 2014b; Webb et al., 2015), suitability boundaries generally aligned with existing enterprises, with positive feedback obtained from industry and agricultural groups. Internet usage statistics showed that there were over 8500 viewings of the maps in the first 3 months after release. The operational process, having been refined and adapted during the pilot-phase was deemed suitable for full operational application to the remainder of the State.

In 2015, the Tasmanian Government launched the 'Water for Profit' (WfP) program (DPIPWE, 2015d), providing irrigation and cropping decision support tools through the provision of state-wide DSM and climate modelling, and the expansion of the pilot ESA to cover all irrigation and dryland agricultural areas at 80 m resolution. The DSM included those soil properties and depths as specified by GlobalSoilMap (Arrouays et al., 2014), contributing to both GlobalSoilMap and the Soil and Landscape Grid of Australia (CSIRO, 2015), in addition to the soil attributes required for the Tasmanian ESA (Kidd et al., 2014b); topsoil (0 to 15 cm) pH, electrical conductivity, clay %, exchangeable Ca (exCa), exchangeable magnesium (exMg), stone content, and whole-profile depth to sodic layer, drainage class, depth to sodic layer (exchangeable sodium percentage > 6 (Isbell, 2002)) and effective rooting depth. The DSM developed for the state-wide DSA is fully described and presented in Kidd et al. (2015b), which provides background to this paper. As per the pilot phase, climate grids included frost risk, chill-hours, growing-degree-days and extreme heat risk. These are defined and methodology presented in more detail in Kidd et al. (2014a, 2014b, 2015a, 2015b).

A heuristic integration of all 20 state-wide ESA grids was undertaken as a first-attempt to identify specific areas of the State that were suited to more enterprises than other areas. The resultant DSA product was referred to as an 'Enterprise Versatility Index' (EVI), which showed the areas that were capable of supporting a wider range of specific project enterprises, but considered different from the conventional definition of land capability (which generally refers to the potential for the land to support a wide range of agricultural practices (Klingebiel and Montgomery, 1961)) in that the EVI was specifically assessed in consideration of the 20 different program enterprises. The suitability maps are considered functional in that they spatially depict areas likely to be appropriate for development or intensification, depending on proximity to infrastructure. However, when combined, as per the EVI, or integrated spatially with economic potential gross-margin data, more powerful DSA interpretations and decision-support tools become possible, which provides a framework for initial identification of high-value agricultural land.

The EVI and GM mapping were developed to provide preliminary identification of general areas that could be targeted for new soil sampling to improve DSM, new enterprises, or intensification and diversification into existing irrigated land, stimulation for the uptake of water licence allocations, and to support and encourage regional prosperity in the Tasmanian agricultural sector. The mapping could also guide policy, and be used to inform the enhancement of legacy land capability mapping, used for the protection of agricultural land in Tasmania (Grose, 1999a, 1999b).

2. Method

2.1. Location

2.1.1. Study area

Tasmania is an island state covering approximately 68,401 km^2, located off the South-eastern coast of Australia. Its southern latitude affords a cool-temperate climate, with longitudinally trending average rainfall from West (>1800 mm yr^{-1}) to East (<450 mm yr^{-1}) (Australian Bureau of Meteorology, 2014). Population is approximately 0.5 million people, with agriculture being one of the largest and most important economic industries.

2.1.2. Dominant soils and land uses

The intensively-used Tertiary basalt soils on the north-west coast and north-east are the State's most agriculturally productive, maintaining a wide range of intensive vegetable cropping. These soils are also well suited to the production of opium poppies, an important industry in Tasmania. Classified as Red Ferrosols (Isbell, 2002) (Nitisols or Acrisols; IUSS Working Group WRB (2007)), they are generally highly fertile, freely draining (Spanswick and Kidd, 2000), and high in organic carbon (Cotching, 2012; Cotching and Kidd, 2010; Cotching et al., 2009b; Sparrow et al., 1999). The Midlands agricultural area (between Launceston and Hobart) is another important farming region for Tasmania, mainly accommodating cereal cropping, alkaloid poppies, and sheep grazing. The area contains wide-ranging texture-contrast soils, many of which are considered sodic (exchangeable sodium % > 6, Sodosols (Isbell, 2002) (Solonetz or Lixisols; IUSS Working Group WRB (2007))).

The most common geology is Jurassic Dolerite (Kirkpatrick, 1981), forming soils on undulating low hills and mountainous terrain as stony Brown Dermosols (Isbell, 2002) (Lixisols; IUSS Working Group WRB (2007)) used for grazing, forestry, and conservation (Cotching et al., 2009b). Sandy coastal plains (Aeric, Acquic and Semi-acquic Podosols (Isbell, 2002) (Podzols; IUSS Working Group WRB (2007)), are used for conservation, grazing and some cropping in the North East (Cotching et al., 2009b). Apples and vineyards are common in more marginal areas, including the Huon Valley, Coal River Valley, Tamar Valley, and Pipers River areas. The state's west and south-west is largely conservation land, listed as world heritage area. This wilderness covers rainforest, peat-lands and moorlands, button-grass plains and skeletal mountain peaks, with peat soils very high in organic carbon (Organosols (Isbell, 2002)), (Histosols; IUSS Working Group WRB (2007)), (Kidd et al., 2015b).

2.2. Digital soil mapping

2.2.1. Soil calibration data and covariates

Recently sampled site data from the DSM pilot project (Kidd et al., 2015a) was combined with legacy soil site data from the DPIPWE soils database, which included various soil chemical and morphological data at various depths. There were up to 5500 sites available, depending on soil attribute and depth (some data contained chemistry data, and/or morphological data only, such as drainage class and stone content (National Committee on Soil and Terrain, 2009)). Mass-preserving depth-splines (Malone et al., 2009, 2011) were fitted to the soils data to generate soil attribute values for required standard depths (0–5 cm, 5–15 cm, 15–30 cm, 30–60 cm, 60–100 cm, 100–200 cm, as per GlobalSoilMap guidelines (Arrouays et al., 2014), and 0–15 cm for the enterprise suitability rulesets (Kidd et al., 2014b)). Soil properties included pH, EC, exCa, exMg, clay %, sand %, silt %, stone %, ESP, soil drainage and effective rooting depth.

A collection of spatial covariates were re-sampled to a common 80 m grid, with terrain derivatives generated using SAGA GIS (SAGA GIS, 2015), based on the 3-arc second Shuttle Radar Topography Mission (SRTM) digital elevation model (DEM) (Gallant et al., 2011). (Due to the requirement of working in the Australian Map Grid (AMG) projected coordinate system, 80 m resolution was determined to be the optimum resolution for accurately re-projecting the grids back into the required geographic coordinate system). Terrain covariates included slope, plan curvature, low-lying topographic relief (TCI-Low; (SAGA GIS, 2015), multi-resolution valley-bottom flatness (MrVBF; (Gallant and Dowling, 2003), multi-resolution ridge-top flatness (MrRTF; (Gallant and Dowling, 2003), topographic wetness index, SAGA wetness index (SAGA GIS, 2015), vertical distance to channel network, eastness index, and northness index (to reduce modelling confusion due to aspect, where 1° and 359° are geographically close, but at opposite ends of the covariate value range). Climate covariates included annual average rainfall and average mean temperature. Remotely-sensed covariates included persistent-greenness (derived from LandSat imagery), and gamma-radiometrics (total count, radioactive thorium, uranium and potassium; (Viscarra Rossel et al., 2014), and a hybridised gamma-radiometric-geology (Mineral Resources Tasmania, 2008) surface, as described in Kidd et al. (2015b).

A raster-stack of all covariates was intersected with the soil calibration data for each individual soil attribute by depth to produce the model training inputs.

2.2.2. Modelling

Modelling was undertaken using cloud-based high-performance computing in the 'R' coding environment (R Development Core Team, 2015) using a regression tree (RT) approach, specifically Cubist (Quinlan, 2005) via the Cubist R package (Kuhn et al., 2012, 2013). Cubist uses a data-mining algorithm to partition the calibration data into a set of structured classifiers, based on the explanatory covariate values. The tree structure is formed through recursive partitioning into linear models until no significant variance in calibration results are established (McBratney et al., 2003).

2.2.3. Uncertainty assessment

A k-fold cross validation was used to replicate the modelling process (where $k = 10$), holding back one-tenth of the data for validation, then looped to hold back a different data validation set for each iteration. As per Malone et al. (2014), the prediction limits (uncertainties) were calculated using the 5th and 95th quantiles of the residuals of each RT partition, based on leave-one-out cross-validation (Kohavi, 1995). The held-back data from each overall k-fold was tested within the upper and lower prediction limits for each k-fold loop to determine the percentage of values falling within the prediction intervals, that is, the percentage within prediction interval value (Malone et al., 2014). k-fold averaging produced the mean prediction values, prediction intervals and diagnostics for each soil attribute and depth.

Kriging of model residuals (regression-kriging; (Odeh et al., 1995) was assessed, however, autocorrelations were generally poor, with only minimal gains as indicated by the validation diagnostics. Due to the time taken to fit semi-variogram models and then performing kriging across the entire State, measured against the minimal improvements to modelling, RK was excluded from the version 1.0 modelling. Pedotransfer functions (PTF) (McBratney et al., 2002) were applied to the appropriate soil grids to spatially predict available water capacity (AWC), ECse (electrical conductivity of a saturated soil-water paste (Rayment and Lyons, 2011) and Bulk density.

The above selection of covariates, calibration data, DSM modelling, uncertainties and PTFs are described and presented in detail in Kidd et al. (2015b), which provides background DSM information to this paper.

2.3. Climate suitability parameters

Climate suitability inputs, such as frost-risk, chill-hours and growing-degree days were spatially derived using an array of 270 temperature sensors which were calibrated to grids generated from historical Bureau of Meteorology weather stations using least squares regression, then spatially modelled using terrain derivatives as explanatory spatial variables (Webb et al., 2015). Frost-risk was defined by industry-based temperature thresholds in critical phenological periods, for example, the probability of having at least one day below 2 °C at flowering. Chill-hours was also industry-defined as hourly low temperature accumulations that satisfy phenological chilling requirements for certain crops (Linvill, 1990); similarly, growing-degree days were defined as daily accumulation of sufficient temperatures to satisfy a crop's growth demands (Neild and Seeley, 1977). The climate modelling method and outputs are fully described and presented in Webb et al. (2014, 2015).

2.4. Enterprise suitability rulesets

Enterprise suitability rulesets form the framework for the initial DSA; that is, applying interpretations to the DSM outputs. The rulesets were produced for 20 previously listed enterprises by TIA, using a combination of research trials, available literature, and workshopped-consensus reached by industry experts and agronomists (DPIPWE, 2015a; Kidd et al., 2014b). Rulesets define the different soil property and climate variable ranges that constitute a degree of suitability for each enterprise. A 4 class system for suitability (comparable to the FAO suggested 5-class system (FAO, 1976; Manna et al., 2009) was based on the following:

- Well Suited — no limitations to productivity
- Suited — minor limitations to productivity
- Marginally suited — moderate limitations to productivity
- Unsuited — severe limitations to productivity

where limitations denote physical soil, climate and terrain constraints to enterprise productivity. The FAO (1976) 5 class system includes an additional class where the land is considered as unsuited, but with the potential to become suited with some form of improvement. The 4 class system was chosen instead, as the entire ESA framework is based around the implications of management, where even the unsuited class could become more suitable with effective management.

For the suitability analysis, the suitability rule-sets were applied to produce a suitability rating for each soil and climate property. The overall suitability rating for the output DSA mapping used a most-limiting-factor approach, where the lowest rated parameter becomes the overall suitability rating, as per Klingebiel and Montgomery (1961). For the purposes of this paper, demonstration examples of one tree-crop (hazelnuts) and one vegetable-crop (potatoes) are used. A sample suitability ruleset for Hazelnuts is shown in Table 1.

The rulesets for hazelnuts (*Corylus avellana L.*) include soil parameter ranges (depth, pH, EC, clay %, drainage and stone %), the tolerances for extreme frost events during winter months, optimum monthly maximum temperature ranges in January or February, chill hours (between April and August, to ensure cold enough conditions to optimise nut production), and <50 mm of mean rainfall in March (to avoid damage and deterioration of kernels at harvest) (DPIPWE, 2015c).

As an example of a vegetable-cropping enterprise, the rulesets for potatoes (*Solanum tuberosum L.*) are shown in Table 2.

The rulesets for potatoes include soil parameter ranges that affect productivity (pH, ECse, clay %, drainage and stone content). Temperature parameters for the occurrence of extreme minimum temperatures between the end of November and the end of February are the only climatic requirements to ensure optimum productivity. Low stone content is important for seed-bed preparation, harvesting rates, and machinery damage, while the slope limitations are necessary for consideration of soil erosion, machinery use and safety (DPIPWE, 2015f).

A further 18 ESA rulesets are available for the remaining enterprises, using comparable soil and climate parameters. The suitability rulesets were applied to the DSM and climate grids to produce maps for all 20 enterprises, displaying the overall suitability rating and the underlying

Table 1
Suitability ruleset — hazelnuts.

Suitability class	Soil depth (cm)	pH (0–15 cm)	EC (ds/m) (0–15 cm)	Clay % (0–15 cm)	Soil drainage class	Stone % (>20 cm) (0–15 cm)	Frost 0 days < −6 °C, June, July, August	Mean MONTH Tmax, January to February (°C)	Rainfall, mean March (mm)	Chill hours 0–7 ° C (April–August inclusive)
Well suited	>50	>6.5	<0.15	10–30	Well to moderately well	<10	4/5 years	20–30	<50	>1200
Suited	40–50	5.5–6.5	<0.15	30–50	Imperfect	10–20	3/5 to 4/5 years	30–33 or 18–20	<50	600–1200
Marginally suited	30–40	6.5–7.1	<0.15	30–50	Imperfect	10–20	2/5 to 3/5 years	33–35 °C	<50	600–1200
Unsuited	<30	<5.5 or >7.1	>0.15	>50 or <10	Poor to very poor	>20	<2/5 years	>35 or <18	>50	<600

soil and climate properties with individual parameter suitability ratings to provide identification of the associated biophysical limitations to cropping.

2.5. Enterprise versatility

A heuristic approach was used to spatially identify the areas of the state that are suited for a diversity of enterprises, (the most agriculturally versatile), where each of the 20 digital ESA surfaces were added together, presuming the nominal scale as linear. Each suitability class was assigned a numerical value, where;

$$\text{'Well−Suited'} = 4, \text{'Suited'} = 3, \text{'Marginally−Suited'} = 2, \text{ and 'Unsuited'} = 1$$

The additive grids for all 20 ESA surfaces would therefore have a range between 20 (implying a pixel is unsuited to all enterprises), to a maximum of 80 (implying a pixel is well-suited to all enterprises). The resultant map is a raster 'index' with a minimum-maximum stretch from 20 to 80, and is referred to here as the 'Enterprise Versatility Index' (EVI). This approach was used as a preliminary exercise to demonstrate the capacity of rasterised DSM and resultant DSA products into land use versatility analysis; this pragmatic approach was also used as it could be easily comprehended by end users as a product specifically tailored to the 20 enterprises considered under the WfP program.

2.6. Spatialisation of enterprise-specific gross-margins

A superior approach for assessing versatility can be achieved when spatially incorporating economic analysis into the overall land evaluation. To further refine the EVI and express economic potential, gross-margins (GM) analysis for each individual enterprise was applied to the ESA outputs to provide an indication of the potentially highest-earning, or most-valued land. GM data was developed as an official agency-based economic analyses (DPIPWE, 2015b), using the latest information for each enterprise in terms of management costs and achievable market prices, considering a typical, or default management regime. For example, hazelnut economic considerations included; nutrient inputs and liming application; pesticide application; grass maintenance; labour; harvesting; processing; and energy costs. Potato gross-margins considered; nutrient inputs; pesticides; irrigation; cultivation; planting; labour; harvesting; energy; levies; processing and cartage. The GM tools enabled users to manually adjust different management inputs, soils and climate variables, with the 'typical' GM displayed using default settings, for typical management, soils and climate ranges in the state. A simple approach was initially used that applied the 'typical' GM directly to the digital ESA grids, where the proportion of the allocated GM was applied to each pixel, for each enterprise, based on the ESA rating, such that;

$$\text{'Well−suited'} = 1.0 \text{ x GMi}, \text{'Suited'} = 0.75 \text{ x GMi}, \text{'Marginally−suited'} = 0.50 \text{ x GMi}, \text{ and Unsuited} = 0 \text{ x GMi}, \text{ and } \mathbf{i} = \text{each enterprise}$$

This was also a heuristic rule that presumed a high suitability rating for an enterprise infers fewer management inputs would be required (in terms of soils and climate), with greater potential to achieve high yields and full GM. Inversely, lower classed suitability areas would require greater management inputs to realise adequate productivity, lowering GM potential due to the costs involved in such management, or lower yields. Based on the general potential to achieve full GM centred on the ESA rating, GM maps were produced for 19 enterprises, (GM analysis for industrial hemp was not available at the time of publishing). The 19 individual GM maps were then combined by taking the median GM from each intersected pixel to produce a 'median potential GM' (MPGM) map for the state, where potential is with respect to all enterprises that could be undertaken. The median value was chosen due to the large differences between high value GM crops such as strawberries (\$66,416 AUD ha^{-1} yr), compared to broad-acre commodities such as barley (\$780 AUD ha^{-1} yr^{-1}). GM analysis provided estimates for both higher rainfall areas (>700 mm yr^{-1}), and lower rainfall areas (<700 mm yr^{-1}) to account for irrigation costs, which were applied to the spatial enterprise GM map calculations accordingly.

At the time of publishing, the value of the GM data was presented in Australian dollars (\$AUD), where \$1 AUD = \$0.77 USD = \$0.69 EUR. Potential GM analysis of availability and distance to markets were outside the scope of this DSA example, and not included.

For expensive to establish enterprises, for example, perennial horticultural crops such as hazelnuts, establishment costs will affect profitability over many years until fully productive. Example establishment costs are for deep-ripping, tree-stock, irrigation systems, and drainage infrastructure. For the purposes of this DSA example, the MPGM mapping was considered as 'once established', that is, potential earnings for fully matured and productive systems. It is therefore difficult to provide direct comparisons against broad-acre cropping with much lower establishment costs. A better measure that incorporates establishment and direct future comparisons between enterprises would incorporate Net Present Value (NPV) (Rossiter, 1995), which takes into account establishment, inflation, interest rates and net returns over a given period; however, comparisons become difficult to implement of crops with different temporal outlooks. NPV effectively compares the present day value against a future point in time and will be spatially tested in future iterations.

The framework is summarised in Fig. 1 as a schematic of the different steps involved in the entire DSA.

3. Results and observations

3.1. Suitability mapping — hazelnuts and potatoes

Fig. 2 shows the ESA map for hazelnuts, based on v1.0 DSM outputs (Kidd et al., 2015b). The map is tenure-independent, meaning that all land (public and private) is included in the analysis.

Certain land tenures, such as World-Heritage listed conservation areas (WHA), reserves, or conservation covenants are prohibited for agricultural development; however, they are included in this spatial analysis in order to demonstrate the proportion of conservation area that is not suited to agriculture. The mapping shows that large areas of the state are suited, but not well-suited, to hazelnuts, predominantly in the agricultural zones of the state across the north and central midlands. Fig. 3 shows the graphical proportions of the ESA input parameters as a percentage of total state area (68,401 km^2). The graph

Table 2
Suitability ruleset — potatoes.

Suitability class	Depth to heavy clay (cm)	pH (0–15 cm)	ECse (0–15 cm)	Clay % (0–15 cm)	Soil drainage class	Stone % (>6 cm) (0–15 cm)	Slope (%)	Temperature (>0 days Nov to Feb with $T_{min} < 0$ °C)	Temperature (>0 days Nov to Feb with $T_{min} > 20$ °C)
Well Suited	>25	>5.0	<1.2	>25	Well	<2	<10	<1 year in 5	<1 year in 5
Suited	>25	>5.0	1.2–2.0	>5	Excessive; Mod Well	2–10	10–25	1/5 to 2/5	1/5 to 2/5
Marginally Suited	15–25	>5.0	2.0–4.0	<5	Imperfect	10–20	10–25	2/5 to 3/5	>2/5
Unsuited	<15	<5.0	>4.0	<5	Poor to very poor	>20	>25	>3/5	>3/5

shows that most soil and climate parameters are suited to hazelnut production, with the exception of pH, with over 60% classed as 'unsuited', and over 70% unsuited due to excessive rainfall in March.

Fig. 4 shows the ESA mapping for potatoes, also based on v1.0 DSM. Relatively small areas of well-suited land are evident across the north-west and north-east of the state, generally surrounded by 'suited' land. Much of the central northern-midlands area is only considered marginally suited, with most of the central highlands and west coast classed as 'unsuited'.

Fig. 5 shows the graphical proportions of the state's area for the individual ESA soil and climate parameters. Up to 30% of the area is unsuited due to pH, with some minor limitations due to topsoil clay content, although almost 75% is classed as suited. Drainage is another limitation, with almost 35% classed as marginally-suited, with similar areal proportion of the state limited by stone content, frost-risk and slope.

The EVI map derived from all 20 ESA outputs is presented in Fig. 6, which ranges from 20 (lowest possible) to 71 (out of a maximum 80). The least versatile areas are displayed as the south-west and central highlands of the state, while the midlands are moderately versatile (EVI between 40 and 60). The most versatile areas (EVI > 60) are in the north-west and north-east. Mean EVI value is 31.6, with a standard deviation of 8.8.

Fig. 7 shows the overall MPGM mapping for the entire state, independent of tenure, for 19 enterprises (no industrial hemp). This map is in general agreement with the EVI grid; however, some areas of higher GM potential are evident in the far north-east and into the east coast, indicating the potential for high-valued enterprises in these areas, which are not necessarily suited to lower GM broad-acre cropping. Again, the west coast and central highlands have very low MPGM values. The MPGM values range from \$0 AUD ha^{-1} yr^{-1} to \$4054 AUD ha^{-1} yr^{-1}, while the mean MPGM is \$477 AUD ha^{-1} yr^{-1}.

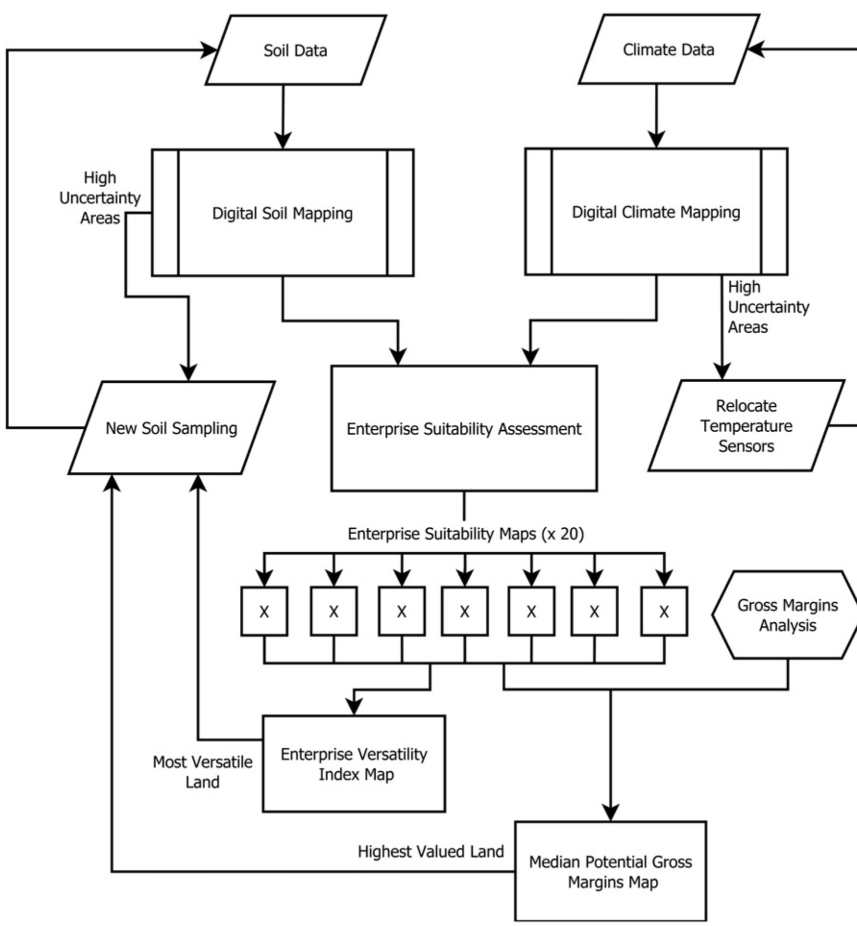

Fig. 1. Digital soil assessment process — Tasmania.

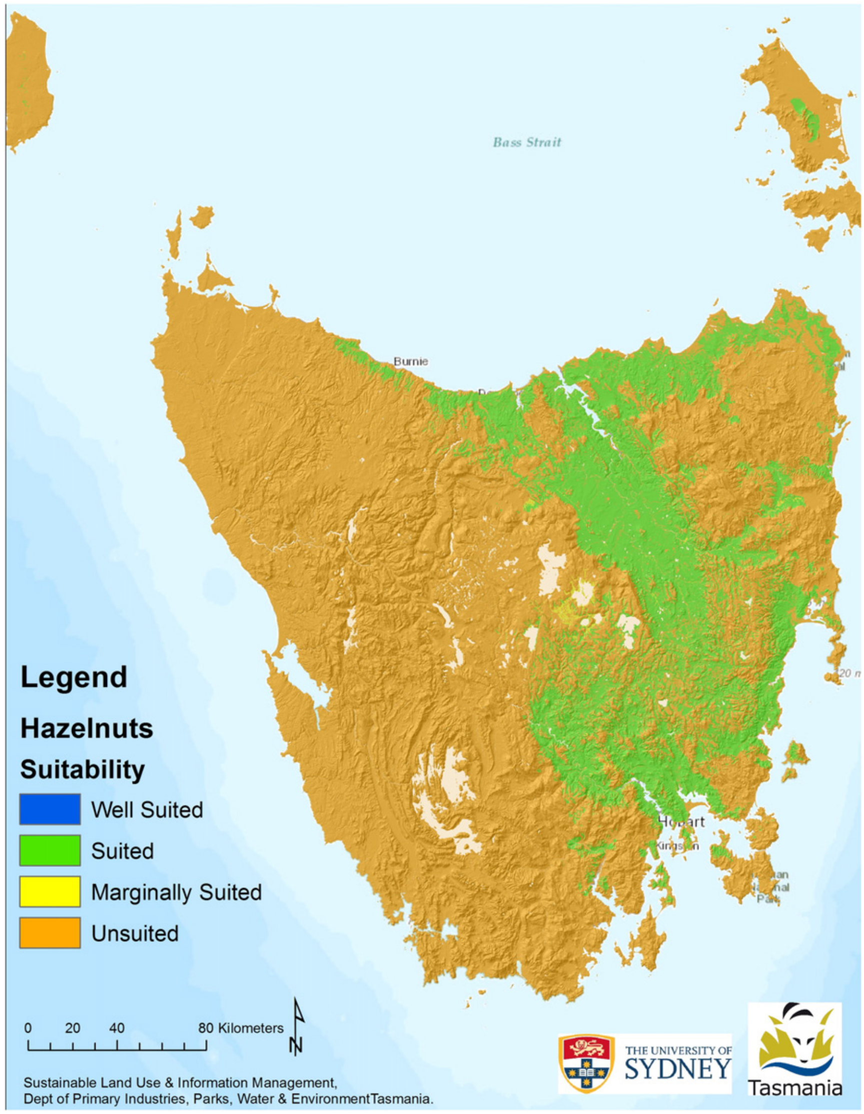

Fig. 2. Suitability — hazelnuts.

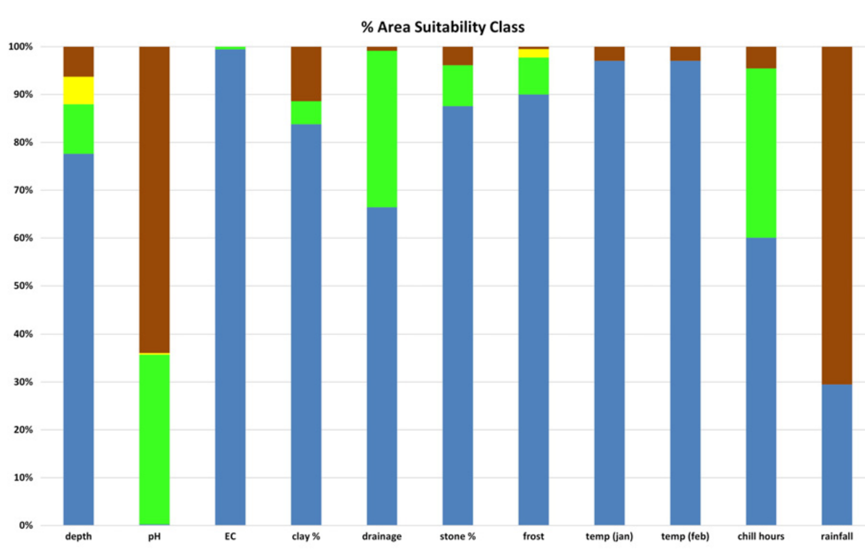

Fig. 3. % area of suitability class by parameter — hazelnuts.

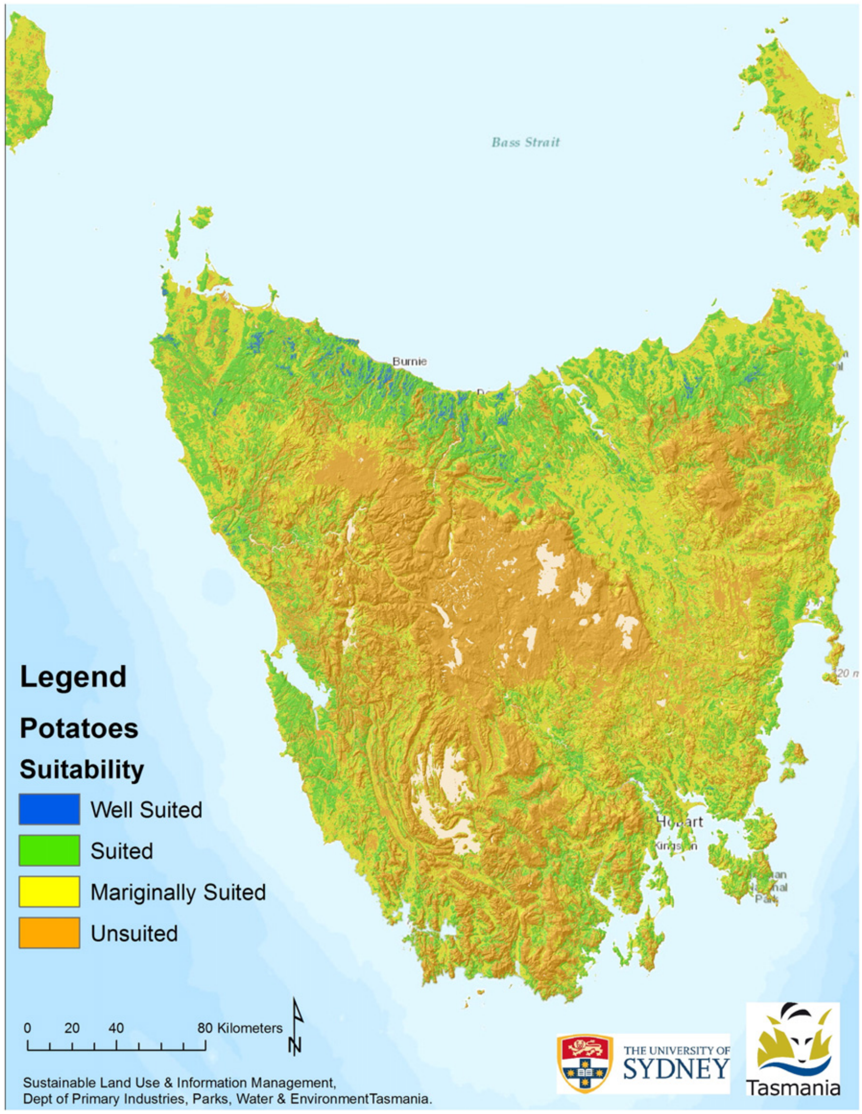

Fig. 4. Suitability — potatoes.

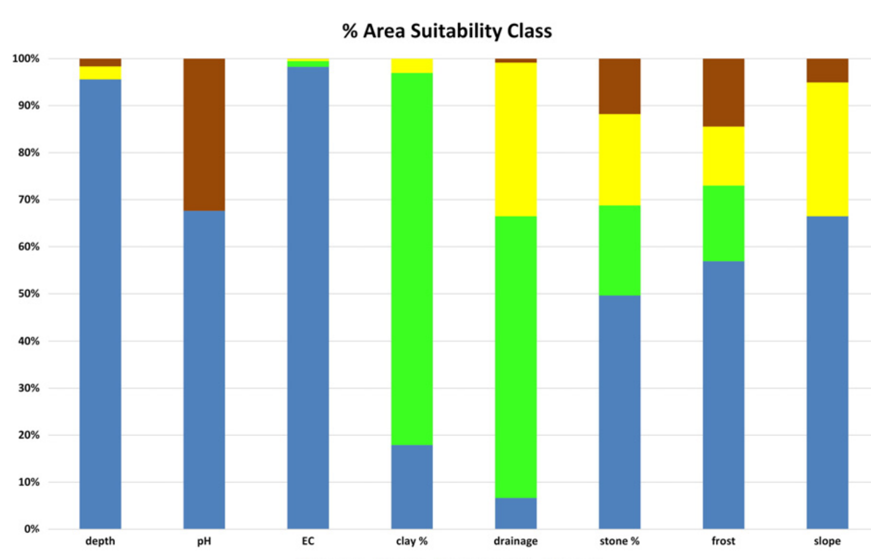

Fig. 5. % area suitability by parameter — potatoes.

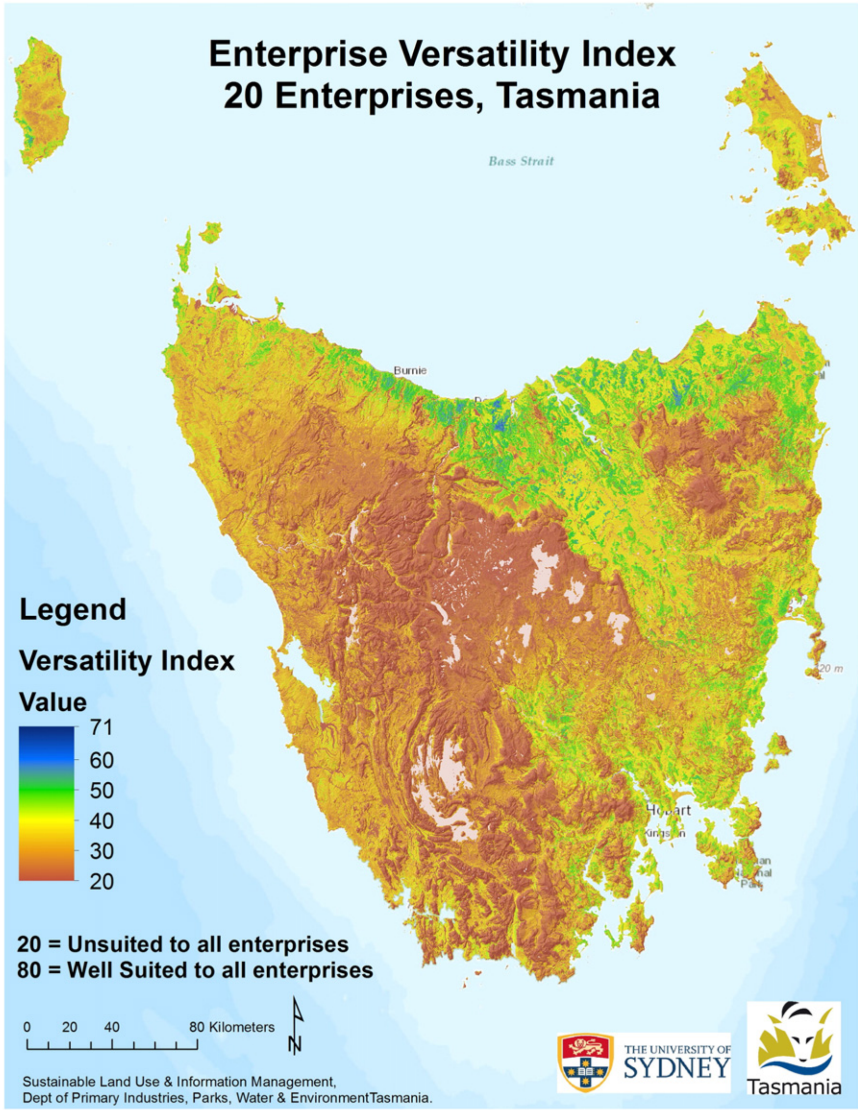

Fig. 6. Enterprise versatility index.

4. Discussion

For this study, DSA was essentially considered as the application of various interpretations to DSM, such that

DSA = **DSM** + **DSI** + (**DEI** + **SEI**)

where DSI = Digital Soil Interpretation, DEI = digital environmental interpretations, and SEI = socio-economic interpretations. In this case, interpretations are the different ranges of soil attributes that a particular enterprise can tolerate to be considered suitable, and is considered digital in that the interpretations can be applied 'pixel-by-pixel' to produce a suitability assessment of each pixel. However, the interpretation component not only involves interpretation of soil attributes, but also integration with other environmental (DEI) or socio-economic information ranges (SEI), such as climate, terrain and economic analysis. This example of an operational DSA (in the sense that it is part of government funded core-business) was derived from products based on first versions (v1.0) DSM surfaces of Tasmania (Kidd et al., 2015b), and provides some additional and potentially powerful decision-support spatial tools that can be generated from functional soil (and climate) grids. DSM products have been shown to provide many functional uses by direct query of soil attribute values alone (Carré et al., 2007); however, when combined with information such as climate, management inputs and market information (GM), spatial information such as yield potential, agricultural capital, and potential for diversification or intensification can be revealed (McBratney et al., 2012).

4.1. EVI and ESA mapping

The EVI and ESA mapping (for all enterprises) generally agrees with expert-based knowledge of spatial extent of land use and productivity in Tasmania (Cotching and Kidd, 2010; Cotching et al., 2009b). Despite the heuristic approach to the preliminary EVI mapping, the more versatile areas (EVI > 50) show general correlation with the Red Ferrosols (Isbell, 2002), (Nitisols or Acrisols (IUSS Working Group WRB, 2007)) in the north-east of the State around Scottsdale, and the north-west from Sassafras to Forest. These areas have been traditionally used for intensive vegetable production, in agreement with the ESA mapping. Fig. 6 shows that the south-west world heritage listed parts of the state, even though prohibited for agricultural development due to conservation status, are unsuited to most if not all enterprises. Suitability of hazelnuts (Fig. 2) is not necessarily restricted to the high production areas, highlighting parts of the Southern Midlands and east coast as suitable, which are not historically intensive agricultural

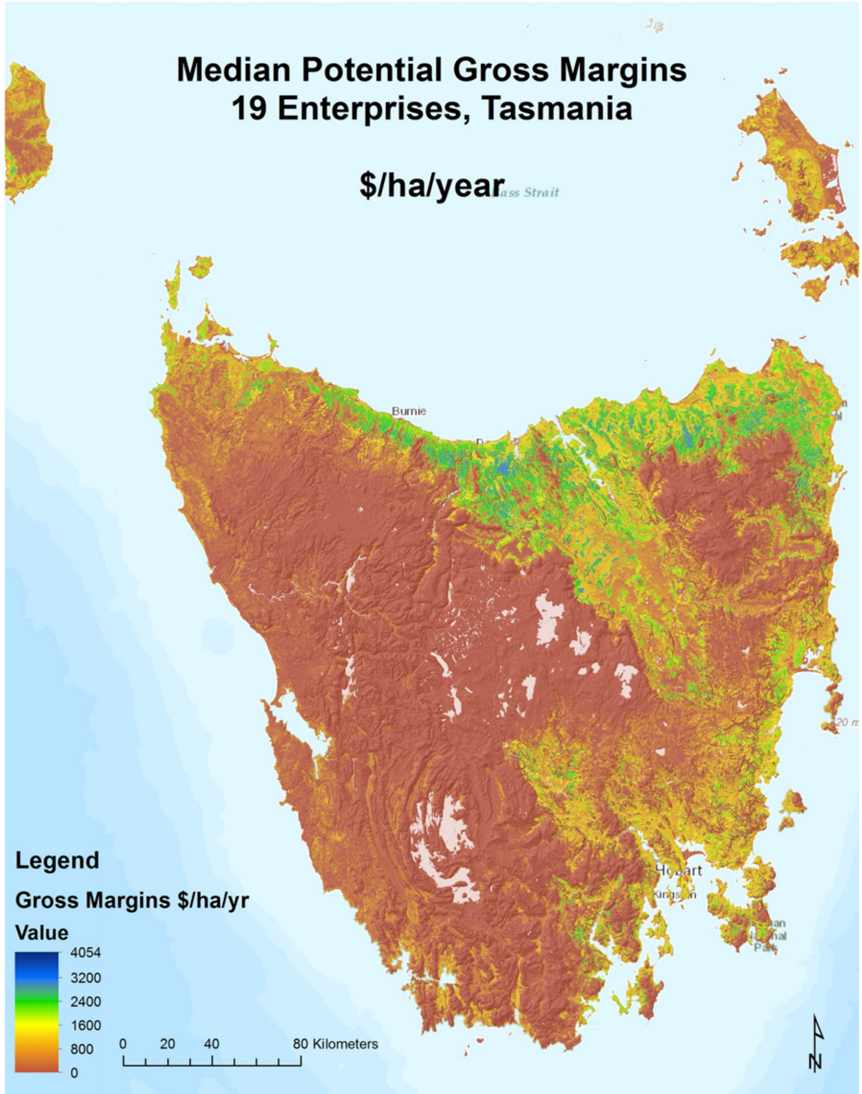

Fig. 7. Median potential gross margins ($AUD).

areas. Much of the central and south-west areas unsuited to hazelnuts are limited by excessive rainfall, poor drainage, shallow soils, and severe frosts in high-elevated areas. However, lack of soil sample sites (as well as temperature logger sites) have contributed to model uncertainty in these areas (refer to Kidd et al. (2015b)), which could lead to some misclassification of suitability ratings. The suitability for potato cropping (Fig. 3) is better aligned with the Ferrosols and higher production areas in the north, and are limited in the midlands due to 'duplex' soils (sharp texture-contrast between the A and B horizons) and drainage. Stone content, excessive slope and sub-optimal temperature regimes severely limit this crop in the central highlands, and other mountainous areas in the central north-east around the Ben Lomond mountain ranges.

The EVI product would be considered useful for investors looking at land suited to a wide variety of enterprises, and to inform protection of agricultural land from non-agricultural development. However, an EVI > 60 doesn't definitively signify that an area is suited to all enterprises (that is, 20 x 3 (suited)); it may imply that the pixel was well-suited to some enterprises (for example, perennial horticulture), but only marginally suited to others, such as broad-acre crops. Further interpretation of the EVI is warranted, or development of alternative products where a count of enterprises per pixel per suitability class could provide more specific information. The EVI shows areas more suited to more enterprises, independent of monetary value, whereas the application of GM can differentiate between areas suited to a range of lower-earning crops, in comparison to areas potentially suited to higher-valued commodities that could require greater infrastructure costs to develop (and therefore greater economic-risk per unit area).

4.2. GM mapping

The individual GM maps produced for each individual enterprise would be useful for investors or farmers interested in specific commodities, however, when combined into the MPGM product, the earning potential and value of different parts of the state become apparent. The mapping shows that again, the Ferrosols have the potential to not only support a wide-variety of crops, but those of highest value (once established). However, parts of the northern midlands, traditionally used for broad-acre cereal cropping, show lower economic potential per area, due to the soil and climate limitations to higher-valued intensive vegetable production (mainly drainage and frost-risk).

The default GM values applied to the suitability mapping presume adequate management, for example, pH limitations ameliorated by liming. Lower suitability classes would imply that extra management inputs (and costs) would be required to achieve default management, and the full GM value. Further refinement of the GM application to the spatial analysis is possible, where, using the pH limitation example for lower suitability classes, the typical cost per hectare (or pixel) of adding required quantities of lime to increase suitability could be calculated and subtracted from the expected spatial GM value, as a more realistic measure than the heuristic scaling. Further GM costs could be refined if the pH buffering index was also spatially modelled. If drainage was a limiting factor, the costs of drainage infrastructure establishment could also be incorporated, based on the severity of the predicted drainage class that needs managing, although as a capital expenditure, this wold not be considered within the GM analysis, but in establishment costs. Harder to overcome limitations, such as EC, or temperature regimes, would be more likely to impact on potential crop yields, and would need research to estimate this based on reduction in GM, or alternative biophysical modelling for land evaluation. Rainfall was incorporated into the GM products and spatial analysis, where, for irrigated cropping, lower rainfall areas will potentially require increased irrigation, reducing the potential GM due to the irrigation expenses. The economic analysis would be considered more realistic for potatoes, as crop establishment costs are minimal compared to that of hazelnuts, as previously discussed. DPIPWE analysis shows that 'start-up' value of establishment can be as high as $21,093 per hectare for hazelnuts, with NPV running at a loss until around 14 years after establishment (DPIPWE, 2015c).

This type of spatial monetary product demonstrates the low agricultural economic potential in current conservation areas, and will better inform the process of identifying areas for conservation covenants, or development-conservation conflicts in marginal areas.

4.3. Validation and refinement

The preliminary DSA products were developed as a regional guide to indicate most-likely suitability and biophysical limitations, where paddock-scaled investigations are encouraged before any investment due to the uncertainty ranges of the DSM inputs. In addition to the DSM validation process discussed and presented in Kidd et al. (2015b), the state-wide ESA surfaces are being further assessed to identify any conflicting land uses (that is, identified examples of a particular enterprise occurring in an area mapped as 'unsuited' to that enterprise). This will provide an indication of whether specific rule-sets require 'relaxing' of any input parameter ranges, or whether the v1.0 DSM products are poorly predicting in some areas. However, non-spatially-aligned occurrences of land uses with ESA mapping can occur where some management has already been applied, such as drainage infrastructure, raised-beds, liming or addition of fertilisers, or utilisation of climate-tolerant crop-species to overcome temperature restrictions; therefore, these anomalies can be explained.

4.3.1. Legacy land capability and enterprise versatility

Legacy Land Capability Mapping (FAO, 1976; Klingebiel and Montgomery, 1961) was previously undertaken in Tasmania using a traditional approach, assessing the capacity of the land to sustainably support broad-acre agriculture based on a range of soil characteristics, climatic ranges, terrain and parent material. These criteria were described by Grose (1999b), with mapping derived by aerial photo interpretation and free-survey of soil and terrain characteristics. The EVI surfaces generally agree with the traditionally mapped land capability of Tasmania (Grose, 1999a, 1999b), but show slightly different boundaries due to the different applied criteria and resolution of (traditional) mapping. For example, Fig. 8 shows that the Class 1, 2 and 3 land (defined as prime-agricultural land in Tasmania (Grose, 1999b)) are in general agreement with the higher EVI areas around Devonport when EVI values > 50 are highlighted. The discrepancy between the EVI > 50 and land capability mapping in the city of Devonport is due to the land capability being excluded by an 'urban mask'. However, small EVI > 50 areas outside the legacy mapping are also evident further up the Mersey Valley, south of Latrobe, and in the east. Anomalies could exist as some enterprises, for example, perennial horticulture (wine grapes, tree-crops) are suited to growing in non-prime-agricultural areas (Class 4 or lower), which will increase the EVI values in these areas. Some enterprises will also have conflicting optimal soil and climate requirements, and public land tenures were also excluded from the traditional land capability mapping. For quantitative comparisons to the existing land capability mapping, conventional broad-acre cropping enterprises (especially vegetable cropping) would need to be considered in the EVI only, as these more closely align within the Tasmanian land capability considerations (where perennial horticulture was not included) (Grose, 1999b). Small areas of high EVI present outside the capability class 1 to 3 polygons are due to the DSM/ DSA capacity at 80 m resolution to identify small areas beyond the minimum mapping area (40 ha (McKenzie et al., 2008)) of the traditionally derived land capability mapping at the 1:100,000 scale. Areas not mapped as high EVI within the land capability polygons could again be due to the limitations of the traditional scale, where complexes of capability classes were applied to polygons where delineation of these classes could not be made at the nominal scale (Grose, 1999b), or even mis-mapping of some areas. However, the visual spatial correlation of the preliminary EVI with known areas of versatile land, despite being developed using different approaches, criteria, and end-uses indicates that this simple additive approach shows potential, and also demonstrates the potential of incorporating rasterised 'building block' DSM inputs into the DSA.

Whereas the legacy land capability mapping is used to identify broad areas of the capacity of the land to support conventional, broad-acre agriculture, the DSA/EVI/MPGM mapping described here was developed as a component of the overall WfP program package specifically in consideration of the 20 listed enterprises, management considerations, and economic analyses. In Tasmania, a major function of the legacy land capability mapping is for the identification of prime agricultural land (as per the FAO framework FAO (1976)) to ensure these areas are not 'lost' to other non-agricultural activities and development. This is enforced by local government through local planning schemes and development approvals under the *State Policy on the Protection of Agricultural Land, Tasmania* (Tasmanian Government, 2009). However, local Government has had to rely on the 1:100,000 capability mapping; the DSM could potentially be used to refine and enhance the spatial accuracy of this product.

High EVI areas can be used for identification of potential areas for investment and infrastructure development, protection of agricultural land to conserve agricultural economy and food-security; also to determine economic risk for financial and insurance institutions, and set local government land rates (levies). Many of the low-versatility areas contain soil properties unsuited to many agricultural uses, but still have high environmental or aesthetic value. These less agriculturally-diverse areas can be assessed for conservation value, and if appropriate, have land tenure adjusted to protect environmental assets without reducing agricultural potential, but facilitating protection from failed development, environmental degradation, loss of conservation value, loss of aesthetic quality, and potential off-site effects such as water-quality reduction due to erosion.

As previously discussed, the MPGM mapping shows the potential median GM in consideration of all the 19 enterprises that could be undertaken, where the constituent GM mapping is calculated as if;

- the enterprise was in full production, without consideration of establishment costs or losses due to maintenance of stock,
- for default management, and
- with heuristic scaling with respect to suitability class

A better indication of the true earning potential and land versatility, in consideration of establishment, inflation, interest rates and maintenance would be to incorporate NPV into the spatial analysis. Future analysis for versatility will incorporate NPV as it becomes available during the WfP program, incorporating internal rate of return as a

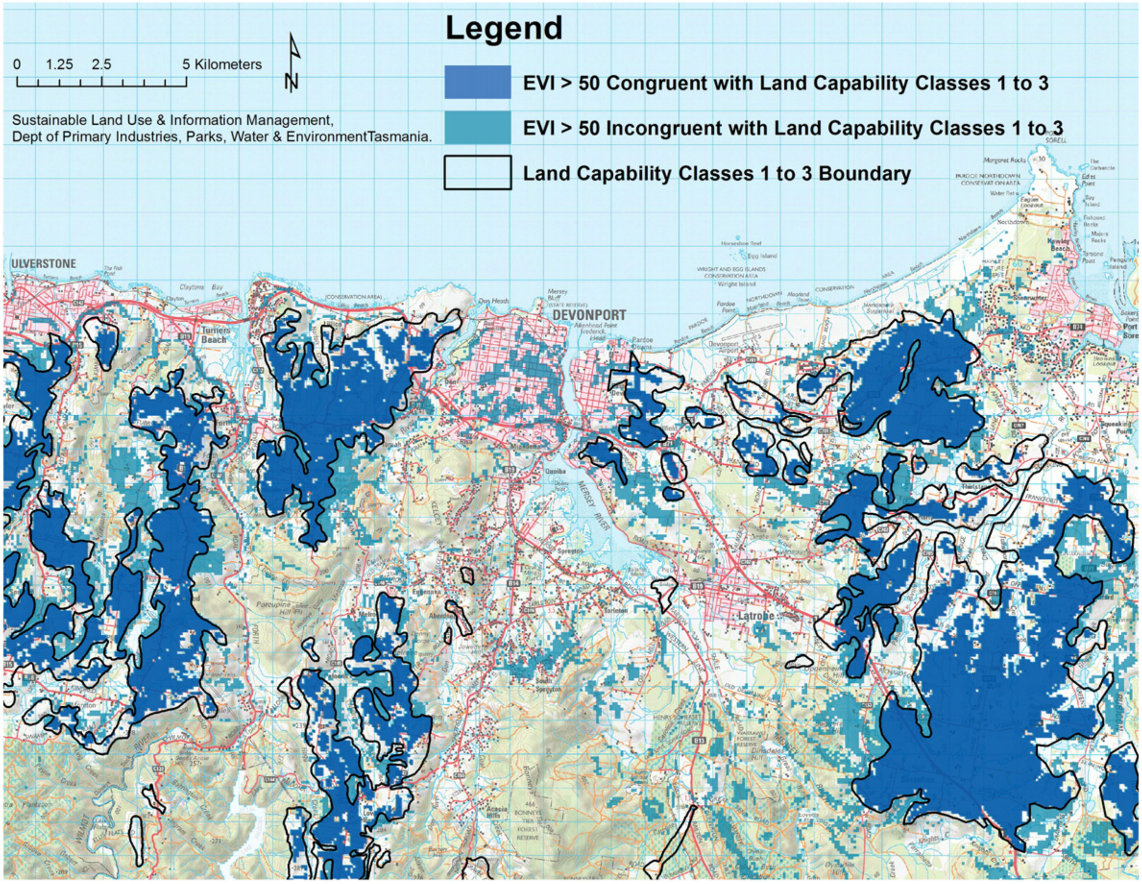

Fig. 8. Enterprise versatility index against land capability (classes 1 to 3).

weighting for each pixel, as a weighted proportion of each suitability class for each enterprise or land use type, as described in Rossiter and Van Wambeke (1997).

The v1.0 surfaces for pH includes all calibration sites regardless of temporal distribution (as per guidelines for first GSM products (Arrouays et al., 2014)), and encompasses both agriculturally-used and non-production areas; the DSM outputs can essentially be considered representative of the natural (non-limed) condition in some areas, and are useful in indicating that management of soil pH will be need consideration for many enterprises in most parts of Tasmania. While pH is shown to be a common limitation to many enterprises, it is potentially one of the most difficult soil attributes to effectively model due to temporal land management induced spatial variation in the topsoil, most pronounced in the top 30 cm (Kidd et al., 2015b; McKenzie et al., 2002). Future work is needed to reduce the temporal modelling uncertainties by eliminating older calibration data (as discussed in Kidd et al. (2015b)), or incorporating updated land-use layers to spatially explain changes in pH based on land-use. However, pH is considered an easily managed agricultural limitation in Tasmania, with a good and affordable lime supply-chain (Cotching et al., 2009a; Cotching and Kidd, 2010; Hamlet, 2002), so can be considered a 'soft' limitation to most enterprises and areas (depending upon actual starting pH, land-use history and the soil buffering capacity), or could even be removed completely from the ESA frame-work in future versions if modelling diagnostics are not improved (Carré et al., 2007; Kidd et al., 2015b). It is also arguable that easily mitigated suitability constraints such as soil pH should be included in land evaluation; of the soil properties listed, exchangeable calcium would be another that could effectively be removed from the rule-sets as low-levels can also be effectively ameliorated. Soil drainage is also considered a relatively easy to mitigate suitability parameter; however, this was considered an important parameter in the Tasmanian ESA, as the midlands agricultural area contains a range of challenging (in terms of management) texture-contrast soils, limited for production, cultivation and harvesting due to poor drainage and perched water (Cotching et al., 2009a; Hamlet, 2002). As an alternative land evaluation method, suitability could be modelled directly from each location; however, this would not provide an indication of soil or climate limitation. Modelling each individual soil attribute was the preferred option, which affectively developed a new soils resource that will be used for a variety of additional agricultural and environmental modelling assessments (Kidd et al., 2015b). However, several additional spatial suitability parameters will need developing now that ESA mapping has moved from the pilot areas, to state-wide. The original rule-sets were developed for the Meander and Tunbridge areas of Tasmania; additional parameters such as humidity (a known issue for opium poppy productivity and disease risk on the Tasmanian East coast), or temporal wind direction and speed for areas in the far north west will require further research, application and testing. These suitability rulesets are also largely productivity based, with little regard for environmental sustainability, as opposed to the land capability assessment previously undertaken in Tasmania (Grose, 1999a, 1999b). Future refinements of the rulesets are planned to determine parameter ranges based on assessment of soil and water conservation inputs (for example, RUSLE (Lu and Yu, 2002; Millward and Mersey, 1999; Renard et al., 1997; Renard et al., 1991) erodibility potential). This could also include economic and strategic factors such as market requirements, and proximity to processing infrastructure and transport (D'haeze et al., 2005).

4.4. DSM, uncertainties and future soil sampling

The 80 m resolution DSA products should be considered as a preliminary regional guide to crop suitability, agricultural versatility and capital, with further paddock-scaled and market investigations recommended before future agricultural development due to DSM uncertainties. As the future DPIPWE program of soil sampling is continued in 2015, the aim is to reduce DSM uncertainty ranges in important areas. From the v1.0 products developed for Tasmania (ESA, EVI and MPGM), a major use will be to inform new soil sampling campaigns to enhance the ESA in new irrigation schemes, targeting those areas of high versatility and earning potential, combined with areas of highest uncertainties (in terms of DSM, as discussed in Kidd et al. (2015b)). This will ensure that sampling resources will target the most important agricultural land with large DSM prediction intervals (see Fig. 1). There is further work underway to test and produce DSM and DSA at 30 m resolution, with anticipated potential to show greater farm-scaled variations in soil properties, such as the subtle terrace-association features in the Launceston Tertiary Basin (Doyle, 1993), more pronounced with the 30 m resolution STRM-DEM. This would have implications to spatial economic analysis, but improve the functionality of the DSM and ESA products to better inform the high spatial variability of Tasmanian soils, and consequential small management units when compared to mainland Australia (Kidd et al., 2007).

4.5. Consideration of uncertainties in ESA

The ESA mapping was developed using the predicted value for each DSM and climate parameter, however, each of these parameters have also had upper and lower prediction limits (uncertainties) calculated, which have not (as yet) been considered in the ESA framework. The propagation of uncertainties from DSM through the DSA process is necessary to fully realise the quantitative DSM benefits to the DSA approach (Carré et al., 2007). Future ESA modelling will incorporate an uncertainty or 'sensitivity' analysis (Harms et al., 2015) to these uncertainty ranges, to determine how this might affect each suitability rating, based on the uncertainty range on the parameter threshold values, as discussed in Kidd et al. (2015b). Recent unpublished analysis has demonstrated that for the ESA of hazelnuts in the Meander Study area, the overall spatial distributions of suitability can change substantially when considering uncertainties, especially for soil properties which have modelled poorly with large prediction intervals, and that discrete threshold land suitability assessments have limitations to meaningful interpretation. This will, in turn, have implications for the EVI and MPGM maps; however, research will need to determine whether a suitability classification is due to the actual limitation, or as a result of high uncertainty of a DSM-derived suitability range. Ongoing sampling coupled with the updating of DSM outputs should resolve or reduce the uncertainty propagation into the ESA.

As also discussed, some additional parameters will be developed for the ESA rule-sets, as well as re-assessing some parameter ranges, and the addition of extra enterprises to the current list of 20. Another approach will be to 'back-model' the instances of new, known and successful enterprises, where the location of these will refine the soil and climate parameter ranges; however, this would need to be considered with analysis of any management inputs into these areas, such as planting and harvesting times, or parameter-tolerant crop species, to determine whether these areas would still be comparable, management-wise, with the default-management regimes used to develop the original suitability rulesets. This will, to a certain extent, reduce the error in suitability class interpretation, as the rule-sets will be adjusted to take into account the potential uncertainty of the DSM input parameters; however, improving the DSM uncertainties through additional sampling, modelling, and covariate generation is the preferred option.

A spatially-referenced database containing detailed soil and climate predictions for each pixel would also be a useful development, which will allow end-users to input their own suitability parameters and interpretations. We were unable to modify the suitability system used in the pilot phase as that was the format chosen and developed by TIA and industry at the time; however, there is now opportunity and impetus through the 'Water for Profit' program to test alternative systems. Multi-parameter type suitability assessments will be tested, where combinations of soil and climate input parameters are used to define suitability, for example, imperfect drainage for opium poppies as an issue in the northern midlands if the likelihood of above-average March rainfall is high. This would also involve 'weighting' different parameters depending upon importance, possible management costs or effective limitation to suitability, such as the multi-parametric approaches presented by Rabia and Terribile (2013).

4.6. Biophysical modelling

Once functional soil grids are produced with acceptable levels of validation and uncertainty for a region, many new spatial biophysical assessment products become feasible. Using biophysical models within a DSA, temporal effects of land management and present and forecast climate conditions can be integrated to facilitate the production of temporal and spatial estimates of yield (Rossiter, 2003). Biophysical modelling could be applied directly to the soil grids, such as APSIM (Keating et al., 2003) crop-based simulations. From the predicted spatial yields (based on typical management), higher yields can be considered more suited to an enterprise, with variations in management and yield outputs used to spatially identify the soil or climate limitations requiring consideration in specific areas. This would be useful for forecasting commodity outlooks, production planning and forecast earnings, and demonstrating beneficial land management practices and required nutrient inputs. The spatial yield outputs could be integrated with climate change or extreme weather forecast scenarios to provide a tool for risk-mitigation strategies, or estimation of agricultural insurance premiums. This will potentially become a superior ESA product to traditional land evaluation frame-works as a range of simultaneously occurring biophysical inputs and managements can be spatially modelled to show areas expected to produce better production outcomes per unit area.

5. Conclusions

This paper presents some preliminary uses of Tasmanian v1.0 DSM surfaces; incorporating DSM into a conventional land suitability framework as part of a DSA to assess land suitability for 20 different enterprises for newly commissioned irrigation schemes. The suitability maps provide underlying data in the form of soil and climate limitations, and were combined to provide a spatial indication of agricultural versatility. The suitability maps were also integrated with gross-margins analysis for each enterprise to spatially indicate the economic potential for different parts of the State. The simple and preliminary process to derive the versatility and economic maps demonstrates the benefits of digitally-derived spatial predictions for the application of interpretations 'pixel-by-pixel' (DSA).

These are early products that will be refined as soil sampling and DSM (v1.0+) program is continued during 2015 and 2016, the suitability frame-work is enhanced, and biophysical modelling tested. The mapping generally aligns with traditional, coarse-scaled land capability mapping and expert knowledge of the State's soils, emphasizing the Tertiary Basalt-derived soils in the north-east and north-west of the State as potentially being the most versatile, and valued (economically), and indicates the potential of this approach. The mapping also shows that Tasmanian conservation areas are also less versatile and suitable for agriculture, and therefore non-productive and potentially environmentally fragile, justifying their conservation status. The DSA has identified soil attributes that will require effective management to maintain productivity, with future work to integrate vulnerable soils into the suitability assessment to ensure appropriate environmental management and sustainability.

Now that many countries and jurisdictions around the world are developing functional DSM grids, (many with impetus from GlobalSoilMap), innovative agricultural and environmental modelling and assessment is emerging, with new opportunities to identify, utilise and protect the most important agricultural land and ensure food security for future generations. However, predictive uncertainties need to be incorporated and tested as part of future land evaluation to fully utilise the quantitative potential of DSM.

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Appendix A. Supplementary data

Supplementary data associated with this article can be found in the online version, at http://dx.doi.org/10.1016/j.geodrs.2015.08.005. These data include the Google map of the most important areas described in this article.

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