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Digital soil mapping and assessment for Australia and beyond: A propitious future

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ABSTRACT

Digital Soil Mapping and Assessment (DSMA) has progressed from challenging traditional soil science paradigms, through small scale prototyping, to large-scale implementation capturing quantitative measures of soil attributes and functions. This paper considers the future for DSMA in the context of a highly uncertain world where high-quality knowledge of soil dynamics will be important for responding to the challenges of sustainability. Irrespective of whether the need is for survival, increased productivity or broadening the services provided from land management, or simply securing the soil itself, we see DSMA as a fundamental approach and essential tool. With a broadening need and a strong foundation in the practice of DSMA now in place, the theory, tools and technology of DSMA will grow significantly. We explore expected changes in covariate data, the modelling process, the nature of base data generation and product delivery that will lead to tracking and forecasting a much wider range of soil attributes and functions at finer spatial and temporal resolutions over larger areas, particularly globally. Equally importantly, we expect the application and impact of DSMA to broaden and be used, directly and collaterally, in the analysis of land management issues in coming decades. It has the capacity to provide the background to a soil and landscape 'digital twin' and the consequent transformation in monitoring and forecasting the impacts of land management practices. We envision the continued growth of DSMA skills amongst soil scientists and a much broader community of practice involved in developing and utilizing DSMA products and tools. Consequently, there will be a widening and deepening role of public-private partnerships in this development and application.

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Contents

1. Introduction

We see a future with several challenges facing humanity on this planet. These inter-related challenges include food and nutrition security, water security, energy security, climate change and human health. The trajectory of these challenges will be influenced by the security of soil itself (McBratney et al., 2014). The concept of soil security is a multidimensional framework that considers the components of soil capability, condition, capital, connectivity and codification. The soil security concept is similar to, but more extensive than notions of soil quality and soil health (McBratney et al., 2014). Our knowledge and understanding of future soil security will undoubtedly be informed by Digital Soil Mapping and Digital Soil Assessment (referred to as a collective DSMA in this document) as the means to assess the current conditions of our soil and the projected trends in condition and function (Carré et al., 2007b). Here, we explore a range of possible directions for DSMA as our soil knowledge needs increase and soil functions required by society change into the future.

The state of the near future is uncertain, that of the far future even more so. Casting back to the social, economic, environmental and climatic change experienced over the last century or so, reveals disastrous wars, economic collapses, regime change (Blainey 2005), inexorable temperature increases, habitat loss and revolutions in agricultural management (Pingali 2012). Given this, it is not unreasonable to assume such equally dramatic and unpredictable future scenarios. We cannot predict the future, but our expectations can be guided by the analyses of others. For example, the insurance marketplace Lloyds of London (Lloyd's, 2018) has introduced extreme risk scenarios to complement the more traditional and inductive actuarial assessment of risk and exposure, as the global insurance industry expect to deal with a wider range of natural and environmental risks in future decades.

Several Australian private industry groups working with the Commonwealth Scientific and Industrial Research Organisation (CSIRO) have used national outlook scenarios to guide societal discussions on the range of choices and options available (CSIRO and National Australia Bank, 2019). In exploring the range of possible futures for digital soil information approaches, we choose not to predict futures but to investigate the role of DSMA across contrasting futures. The second Australian National Outlook explored four plausible futures to 2060 and two of these, a "slow decline future" and "outlook vision", provide sufficiently contrasting specifications for our consideration of the future for, and the role of, DSMA.

A 'slow decline' future is characterized by stagnant productivity, continuing land degradation, limited change to the income sources currently driving land management and the growing threat of an increasingly variable and extreme climate. Primary producers will struggle to sustain productivity and profit levels from a declining soil resource and a changing climate (Ritchie et al. 2020; Sartori et al. 2019). The simple continuous decline trajectory that this suggests is unlikely. History suggests that the slow decline will lead to crisis reactions (Montgomery 2007), possibly in the form of Government interventions (McLeman et al. 2014), responses to which will require appropriate soil information, but which may not be readily available in appropriate detail.

An 'outlook vision' future assumes that there is a concerted effort to curtail climate change and that a series of productivity transformations are pursued, and some are successful. That will then entail a broader funding base for rural landscapes arising from societal investment in land-based carbon sequestration and mitigation, increased returns from more productive agricultural systems, more diversity (decommodification of agricultural produce through provenance tracking) and a stronger export and domestic market (CSIRO & National Australia Bank, 2019).

It is human nature to ponder the future. Although DSMA is a relatively new field of endeavor, practitioners have always had an eye to the future. Just over a decade ago Grunwald (2010) along with Carre and Boettinger (2008) summarized the progress of digital soil mapping (DSM) to that time and proffered suggestions for future directions of DSM, including moving to three dimensional predictions, a move towards Digital Soil Asssment, the incorporation of expert knowledge into DSM frameworks and bridging the gap between research and operational digital soil mapping. We contend that most of these aspirations have now been realized or at least well on the way to being so. If the coming decades deliver such impressive advances as the previous decade, practice of DSMA will be on sound foundations. More recently Arrouays et al. (2020) reflect on the contemporary challenges and opportunities for DSMA, including sensing data integration, improvements in uncertainty and validation methods, improved use of covariate data sources and better connections to end users and policymakers. We further explore these topics in this paper.

This paper considers a range of possibilities for a DSMA framework over a 10 to 50-year horizon and across plausible futures. Our discussion has a global emphasis but is influenced by the experiences of the authors in the Australian context (Kidd et al. 2020, this issue)

2. The potential pathways for DSMA

DSMA is not just an alternative system for soil survey and land evaluation. Rather it is a framework designed to meet a broad set of needs through fine resolution estimation of the key characteristics of soil. Over the past decade, DSMA has progressed from challenging traditional approaches and paradigms, through small scale prototyping and research applications, to the present, where we are seeing large-scale implementations capturing quantitative measures of soil attributes and function which are informing decision making and policy development.

It is now used by most land resource assessment agencies, and a growing cohort of private-sector players, around Australia. Typically, but not exclusively, DSMA products include attributes specified by GlobalSoilMap (Arrouays et al. 2014), consisting of maps of a range of soil attributes at 6 standard depth increments. DSMA products can be produced from new survey, legacy site data with covariates (Minasny and McBratney 2010) as well as the disaggregation of legacy soil maps of soil types and/or attributes (Odgers et al. 2014., Holmes et al. 2014) or from any combination of these. Most commonly, products are being generated as regular grids at resolutions between 30 and 250 metres (Fillipi, et al., 2020; Hengl et al., 2017; Mulder et al. 2016; Grundy et al., 2015) allowing regional to landscape scale applications. The breadth of DSMA applications is growing, with examples including land suitability mapping for agricultural commodities (Harms et al. 2015; Kidd et al. 2015a; Thomas et al. 2015; van Zijl et al. 2014,), and the parametrization of simulation models and decision support systems across scales from the individual farm to the entire continent (Freebairn et al. 2018; Lawes et al. 2018).

We are at an exciting stage in the development of DSMA methods. Spatial coverage and resolution are improving as finer resolution environmental covariates relevant to describing soil spatial distributions have become more easily accessible (such as those from the Sentinal 2 platform) (Drusch et al. 2012). As DSMA skills within the soil science domain continue to increase, more sophisticated modelling techniques are being developed and more measured soil data are being collected. Importantly, DSMA now offers new capabilities that assist decision making across areas not previously feasible using traditional approaches (Thomas et al. 2018).

However, significant challenges remain. Contemporary DSMA approaches and products exist on a variety of different data storage systems and delivery platforms, produced by a wide range of practitioners using a variety of different modelling approaches, on different spatial supports. Thus, it is currently challenging to bring together a set of consistent, seamless DSMA products at the finest possible scale and lowest uncertainty to inform decisions across multiple scales. A challenge is to efficiently integrate these disparate products into a cohesive and seamless information source which can be efficiently updated over time.

Another challenge is for DSMA approaches to provide models of the dynamic nature of soil systems. This is yet to be realized. We envisage an automated system able to ingest new measured data as it becomes available to produce new versions of soil property estimates over time, allowing the trend of soil attributes and function to be quantified.

Yet another challenge, is to integrate or combine DSMA products together in innovative ways to increase their utility. Current DSMA products tend to be used to provide baseline estimates of key soil properties for assessing the current or historic state of the soil. Estimates of static soil attributes such as available water capacity are invaluable in an agriculture context, but the value grows when combined with other DSMA data layers such as soil horizon and profile thicknesses, hydraulic conductivity, and drainage to produce digital soil assessment to inform policy decisions concerning future land use (Kidd et al. 2015a).

In resolving these challenges, we will realise a much deeper potential for DSMA to contribute to improved societal outcomes.

2.1. Why will we need more DSMA?

All plausible futures require more soil information and the utility promised through DSMA. A focus on alternative futures allows us to explore the breadth of that potential need.

New options arise in the 'outlook vision' view. The breadth of land uses grows and the emphasis on matching those choices to a more nuanced understanding of soil capacity will be crucial. As corporate sustainability goals become increasingly common, consumer demands for sustainably produced food will increase (Thomson et al. 2020). The condition of the soil becomes a reported asset within the supply chain which will potentially grow sustainable producers' profit relative to those producing food in unsustainable ways. In both the slow decline and outlook vision scenarios, the focus on managing soil capacity and resilience, and thus the need for appropriate soil information, will need to increase but through different drivers, the former as a crisis or restoration need, the latter as part of the accent on information-led productivity and capacity optimization.

DSMA will be an essential tool to enable society to either cope with the breadth of challenges emerging within a slowly declining system or to realize the potential arising from a concerted societal investment in an 'outlook vision'. DSMA allows the elements of soil security to be identified, monitored over time and connected to the managed and natural ecosystems. It can also assist us to explore and test the management regimes needed to drive change or to respond to challenges. DSMA has yet to fully realize this potential, but we develop the case here that it is on the verge of so doing.

3. Possible impact pathways for an evolving DSMA

The Sustainable Development Goals (United Nations 2020) and similar national and regional goals (Australian Government., 2018) are the latest attempts to encapsulate the breadth of the ambition needed and the degree of integration required to secure a sustainable future for the planet. Frameworks to implement these goals and monitor progress are now emerging (Stafford-Smith et al. 2017) and soil management components are part of reporting on progress towards the UN Sustainable Development Goals (Bouma 2019; Bouma, 2014). These require a focus on ecosystem services (and therefore links to soil state and trend) and the delivery of goods and services ranging across the provision of food and fiber, clean air and water, scenic and cultural amenity. Evaluating the capital dimensions (including productive and natural) is a key component of soil security assessment (Bennett et al. 2019) and DSMA can provide a valuable set of tools to achieve this.

Beyond measures of state and trend, there is a need to value and account for such goods and services. The state of the soil resource (Robinson et al. 2017) is now part of the System of Environmental Economic Accounts (Bartelmus 2007; SEEA 2003), an international statistical standard using a systems approach to assess the impact of environment on the economy.

To inform these high-level accounting frameworks enacted at broad scales, DSMA will need to operate across scales. Although the SDGs will not be invoked at the individual farm level, the impacts of local actions undertaken at a farm scale will need to be aggregated, in a sensible manner, to assess progress towards these global goals.

Beyond these broad scale assessments DSMA will have a significant and varied role at and across all scales. We offer five examples below suggesting some possible future directions and applications of DSMA. In an 'outlook vision' future we would see DSMA being a key tool across all these possible impact pathways. DSMA would not only be able to provide information to support these applications, but DSMA methods would evolve to support optimal outcomes for these applications. In a 'slow decline' future we envisage that DSMA will still be utilized in these applications, but more so in a context of striving for maximum efficiency from a given effort, or to quickly provide information about an issue at a critical time, rather than being used as a strategic enabler of new discovery.

3.1. Agricultural soil management

As population increases over time, more food is needed from the same land base in a sustainable manner (Keating et al. 2014). Optimal management of the soil resource and understanding the interaction of agricultural management and biological systems is critical to support this production increase.

While general prescriptions for increasing agricultural productivity can be identified and can be on average accurate, each farm and possibly each field may require a specific management approach. New DSMA products need to be useful at the farm decision making resolution (in most cases within a field) and be current and available at the time key management decisions need to be made. DSMA products will need to estimate accurately the major drivers at the scale at which new generation farm machinery and equipment operate. Broad regional scale DSMA products will significantly improve in spatial resolution and accuracy into the future, but still may struggle to be useful at the field scale. We foresee, particularly in the 'outlook vision' that farm specific DSM mapping may begin to emerge, utilising data collected locally by farmers, agronomists and farm machinery. In the future, farm machinery may autonomously undertake management decisions and operations based on real-time feeds of crop requirements and the state of soil properties sourced directly from fine-scale DSMA. This will require infrastructure to capture real-time soil data to ensure continuous monitoring (Saqib et al. 2020). This outcome will most likely require several iterations of improving soil data sets to get to field and sub-field scale. Monitoring of soil attributes which directly influence crop growth will allow effective management of systems by simultaneously balancing inputs required for optimal crop and long-term sustainability of the system. This information will be supplied to land managers in forms relevant to timely decisions and to specific applications (Sciarretta et al. 2019).

Consumers will increasingly demand certification that farming methods are sustainable by ensuring that land use and management is within the land's capability and that natural capital is maintained if not enhanced. Thus, it will be important to match the soil's inherent production capacity to the most appropriate agricultural systems, so as not to diminish its natural capital. DSMA methods will enhance the mapping and understanding of land suitability, thus assisting us to maintain natural capital of the soil resource. High temporal and spatial resolution remotely sensed data will document the current land use and the methods of land management to provide the evidence base for sustainability. The richness of the underlying data in the land suitability analyses can also be used to suggest alternative land uses or management strategies, where appropriate, to reduce the risk of diminishing natural capital.

Utilising innovative techniques to model soil attributes dynamically (McDermott and Wikle 2019, Stockman et al., 2015), DSMA has the potential to quantify trends of soil condition over time to provide evidence of sustainability, as well as potentially forecasting these trends into the future.

Additional applications where DSMA methods may contribute to decision making in an agricultural context might include:

- provision of information to support investment decisions by local authorities and private companies in various forms of logistics.; For example: new roads and rail linking areas with potential for high value produce to market, connecting value adding facilities such as processing factories to production area. (Integrated Food and Energy Developments Pty Ltd, 2013),
- optimizing the locations of high-level investments (e.g. water storages) to match land and production resources to the investment (Triantafilis et al. 2004),
- the supply of locally relevant soil information to support site specific agronomic advice delivered via decision support tools (Hochman et al. 2009),
- the provision of model parameter values used in regional scale, real-time prediction of crop and pastures yields (Kamir et al. 2020), for logistics planning and marketing strategy development,
- aiding in the real time estimate of global and regional food supplies to determine whether government intervention is necessary for food security (Kogan et al., 2019), and
- supporting the estimation, through modelling, of the magnitude of off of-site impacts of soil erosion, drainage and nutrient and sediment pollution risks at regional scales (Shaw et al. 2013).

3.2. Ecosystem enhancement and human health

DSMA to date has typically focused on supplying the information needed to support agricultural production, and avert associated land degradation; however, food production is only one of several ecosystem services soil provides (Adhikari and Hartemink 2016). Future DSMA assessments may increase our understanding of, and inform opportunities to enhance, soil-related ecosystem services. For example, spatial knowledge of soil infiltration rates is required for water-sensitive urban design. Soil also underpins other critical ecosystem services such as water filtration and storage, nutrient storage and biogeochemical cycling of C and N, supporting above and below ground biodiversity, waste decomposition amongst others (Baveye et al. 2016). Whilst these soil functions are ones that have not historically been the focus of DSMA methods, there is an obvious potential for DSMA approaches to be used into the future to inform our understanding and delivery of ecosystems services.

Recent studies have explored the relationship between human and animal health and the soil microbiome. DSMA may have a role to play in assisting us understand the emerging links between the soil microbiome and immunological responses in animals and consequent impacts on human and animal health. Liddicoat et al. (2018) showed that soil properties (from mapped DSM grids) could be used for forecasting locations where health could be compromised due to associations between a soil property (Cation Exchange Capacity) and the risk of infectious and parasitic disease. Liddicoat et al. (2020) found that biodiverse soils may represent an important supplementary source of butyrate-producing bacteria capable of resupplying the mammalian gut microbiome, with potential for gut health and mental health benefits. Yang et al. (2019) have used DSMA approaches to model the distribution of soil bacterial abundance and diversity. If areas and characteristics of 'healthier soils' can be understood and mapped, there is potential to leverage this understanding for gains in human health and also livestock health.

Many of the antibiotics that we currently use in medicine are derived from compounds naturally produced by bacteria or fungi in the soil (Roberts 2020). There are recent efforts to analyse the under-explored species of actinobacteria in the soil biome with the aim of finding novel leads for synthesising new drugs to combat multi-drug resistant bacteria (Talpur et al. 2020). DSMA can provide exciting new approaches to refine the location of prospective soil biomes, thus expediting new drug development.

3.3. Climate change abatement

DSMA products to date have been used to establish baselines for important policy frameworks to address climate change (Gray and Bishop, 2016). DSMA has been used to estimate baseline soil organic carbon (SOC) stocks and soil organic matter (SOM) fractions in Australia (Viscarra Rossel et al. 2014), and baseline inorganic soil carbon (Wilford et al. 2015), which provide the underpinning data layers needed to monitor changes in terrestrial carbon stores and fluxes.

Beyond these initial applications, DSMA has the potential to inform and guide policy development for soil carbon mitigation, abatement, and accounting. This will require fine resolution estimates of key soil properties such as soil texture, bulk density and soil organic carbon needed to determine baseline levels of SOC stock and SOC stock change over time at farm and individual field scales (30 m and less) (Paustian et al. 2019). As well as informing management at the farm field scale it is important that these carbon stock estimates can also be analyzed and summarized across scales to inform national accounts and inform policy development and implementation.

Local and regional DSMA models will be required, combined with optimized sampling schemes tailored to capture the spatial variability of soil in carbon (e.g. de Gruijter et al. 2016) along with cost-effective soil carbon measurement including *in situ* sensing (Viscarra Rossel et al. 2017). This information can be used to guide the approaches for abatement best suited to particular areas or enterprises and inform policy on the most effective way to achieve abatement goals as part of broader national and commercial accounting systems (Aslam et al. 2017). In addition, DSMA approaches may also help us to spatially model and test the carbon sequestration potential with the adoption of new management practices and land uses (Bryan et al. 2014).

3.4. Quality food production and provenance

Consumers are becoming increasingly interested in the environmental consequences of food production (Yue et al. 2011; Mirosa 2012) leading to potential change in markets and trade. DSMA approaches and products could support the quality assurance of food production, giving consumers confidence to make informed choices. This awareness and informed decision making may also enhance consumers "connectedness", as described by the soil security concept (Bennett et al. 2019), to the soils used to produce their food.

In the wine industry, Terroir is a term used to express the concept of 'taste of place'. Consumers are often willing to pay a premium, for products from specific regions with well-regarded Terroir. Coggins et al. (2019) developed a method using DSMA approaches to spatially delineate appellation boundaries through the creation of Terrons. It is envisaged that similar approaches will be used across a broad range of food production systems as the demand for food provenance information increases and produces of bulk commodities look to distinguish their products in crowded markets (Melini and Melini 2019).

Existing and future DSMA investment may also facilitate rapid provenance screening. Food products that are grown in the soil reflect the regional distribution of elements, through adsorption of bioavailable elements and mobilized nutrients from the soil into the plant or by feed intake into the animal (Danezis et al. 2016). By generating regional "signatures" of unique combinations of relevant soil attributes using DSMA methods, we can potentially determine if a specific food is likely to have been grown in a given region (Drivelos and Georgiou 2012).

We may also be able to utilise DSMA to assist us in further understanding the complex mechanisms behind the soil's influence on the qualities of agricultural products over broad areas at a fine scale. Plant available water capacity, soil organic matter, soil microbial diversity, porosity, pH, micro-climate, micro-relief, and micro-nutrients are amongst soil properties that may affect the quality of agricultural produce (Reeve et al. 2016). By having fine scale representations of the three-dimensional distribution of soil properties soil scientists may further our understanding of which soil properties are causative and the mechanisms by which they influence food quality.

3.5. Integration of DSMA into complex systems analysis

The soil and its functions have always been a key part of our economic, social, and environmental systems but the ability to include it effectively in whole-system studies has been limited by the challenge of obtaining the required soil information at suitable scales over large areas in usable forms. With improvements in computing power, the generation of spatially continuous high resolution and high accuracy soil information is possible. This data can be used to parameterize sophisticated deterministic land process models. We are beginning to see studies utilising complex point-based models such as the agricultural system simulator APSIM (Holzworth et al. 2018.), being run at vast numbers of locations over large areas to investigate complex biological interactions in a quasi-spatial sense (Hochman et al. 2016). DSMA is beginning to support this (Kidd et al. 2018), however to realise the full potential of these approaches we need to further improve DSMA. As the resolution of products generated using DSMA becomes finer and their spatial accuracy and delivery methods improve, integrated systems studies and the prescriptions they elicit for improved landscape management will improve.

Deterministic modelling approaches are not just restricted to site specific application but are also increasingly being used to substantially improve our understanding of the off-site impacts of land management practices. A relevant example of this the Australian Government's Reef 2050 Water Quality Improvement Plan (Queensland Government 2018), which aims to improve the water quality in the Great Barrier Reef Lagoon. These policies are strongly influenced and guided by the outputs of complex deterministic models used to estimate current and future water quality scenarios (Carroll et al., 2012, Wilkinson et al. 2014). Reference or initial soil property states are important parameters in this modelling. Often these parameters are derived from broadscale two-dimensional legacy maps with generalized and spatially lumped estimates of soil attribute values. There is the prospect of improving future water quality estimates over time as finer scale four dimensional spatio-temporal estimates of key soil properties become available through the application of DSMA approaches.

We suggest that the links between DSMA and deterministic modelling approaches will become relatively common into the future as limitations on processing continue to diminish and the demand for quantifiable management action outcomes increases.

The replacement of complex models by statistically based emulators is becoming a common approach in environmental science to reduce processing time and provide instantaneous answers that are difficult to achieve from long running deterministic models. (Gladish et al. 2018; Owen and Liuzzo 2019). DSMA and model emulators use many of the same data sources and statistical techniques, such as such as design-based sampling and machine learning. It is conceivable that the estimation of requisite soil properties may one day be integrated directly into the emulation methods potentially further improving estimation efficiency.

4. Evolving digital soil mapping and assessment

DSMA requires a multi-disciplinary approach to the estimation of soil attributes and function built around data, modelling approaches, and the delivery, access and use of soil data. We see improvement in each of these elements regardless of the realized future scenario. Most of these elements of DSMA methodologies have drivers of development that do not rely on their use in DSMA methods. In a 'slow decline' future we predict that all these elements will continue to advance and improve irrespective of the requirements of DSMA. They will advance to meet other business and political imperatives. In an 'outlook' scenario, we can imagine that the methodological requirements of DSMA will have some influence in the types and rate of improvements in the individual elements. DSMA will drive and shape the improvements of data sources, statistical methods and technology platforms rather than just 'piggy backing' on developments in other domains.

4.1. Spatial and temporal resolution

While spatial resolution needs are user and context-dependent, future soil data systems will be specified by the needs of its most demanding users. Capacity development will, therefore, build towards the support of extremely fine-scale outputs, as input data improves in resolution. Future DSMA will apply seamlessly across all scales from national to local, enabling application at the most appropriate scale for any given decision. Potential users with particularly fine resolution data needs include:

- Precision agriculture: In cropping, row spacings define a minimum cell size. Remote sensing imagery and EM-sensing devices already supply information at the sub-meter scale, a wide range of other datasets will be similarly detailed and available (Filippi et al. 2019; Iticha and Takele 2019). Fine resolution soils information will enable targeted management actions; however the size of current equipment may restrict the scale at which management can be implemented.
- Contaminated land remediation: Contamination hotspots are commonly 'human-scale', i.e. a few meters across (e.g. petrol dump, old sheep-dip area, point leak from a pipe, microplastics). Contaminated land sampling can be highly dense within a parcel of land and resultant maps are commonly 'engineering scale', i.e. 1:10000 or larger to support clean-up works with resolutions between 1-5 m desired. Horta et al. (2015) have suggested potential applications of DSMA in contaminated land studies.

Most fine-scale demands are concentrated around urban, peri-urban areas, and agricultural cropping land. Other resolution needs will be driven primarily by the needs of environmental modelers. Environmental modelling needs to operate on the landscape scale of the processes being modelled in order to achieve acceptable levels of reliability (McKenzie et al. 2008). It is probable that a resolution of 20 m or finer is required to accurately represent terrain parameters (Cavazzi et al. 2013). While regional or catchment-scale models such as the land surface model Community Atmosphere and Biosphere Land Exchange (CABLE) (Kowalczyk et al. 2006) or catchment water quality models such as SedNet (Prosser et al. 2001) commonly only require soil parameters at a lumped catchment level, they can benefit from parametrization schemes using fine scale data that has been aggregated to the catchment scale unit (Searle and Ellis 2009).

We see the provision of temporal data as an important focus for the next stages of DSMA. The emphasis is likely to be on time-steps relevant to land management decisions or to the need to respond to significant events (e.g. a major storm leading to a significant soil erosion event. While regular timestep data are needed for some forecasting applications (especially as new modelling approaches are developed that require high temporal intensity), the greater demand will be for soil information at critical decision times within the season or as decisions are needed. This elevates the importance of system architecture/infrastructure and user experience well beyond spatial resolution.

Digital soil input datasets would be stored at the resolution at which they were gathered. Modelling at the end user's requested level of spatial detail would then involve disaggregation or aggregation of the source datasets to a common grid cell size, with quantification of the imprecision resulting from those processes. Modelling would then be undertaken at the chosen resolution, adding imprecision from the fitted model itself. Set procedures would be defined for up and down scaling each potential input dataset and for quantifying the uncertainties introduced in doing so.

4.2. Data

4.2.1. Field sampling and measurement of soil attributes

Geospatially referenced soil observations with known soil properties are integral to DSMA. These observations are needed to train the predictive models, which are then used to interpolate and extrapolate soil variables over space. High quality modelling requires a sufficient sampling of the environmental space: samples that are well spread in the feature space coupled with appropriate density and geographical coverage (Ma et al. 2019; Wadoux et al. 2019a).

The limitations of legacy soil data in DSMA applications are well established, including variable spatial accuracy and coverage (Vaysse and Lagacherie 2015, Carré et al., 2007a). Often by necessity, new sampling is used to augment existing observations. While existing soil data have been critical to the initial operational forays in DSMA around the world, we see future DSMA approaches driving the development of more effective and efficient ways to collect field data. Increasingly, these additional data will be collected following appropriate statistical sampling methods. (such as de Gruijter et al. 2006, and Brus 2019) while also giving sound alternatives when access restrictions are encountered (Clifford et al. 2014).

In the near future, soil sampling will be more strategic and coordinated to gain optimum value from each sample. Past sampling will be readily available and analyzed to plan and coordinate future data collection efforts. For example, Fig. 1 shows the environmental coverage of the Australian site data collation (Searle 2014). This map indicates the relationship between observational data and the environmental covariate feature space that those samples cover. Areas colored yellow are those that have been sampled more intensively in the covariate feature space associated with those locations.

We envisage real-time visualization of sample coverage, including consideration of sample type and sample quality, to guide sampling campaigns and coordinated across individual sampling efforts. New investment in soil sampling will be optimized to fill data gaps and data collectors will monitor and report on their cumulative sampling and survey efforts in near real time. Iterative DSMA modelling would be undertaken during a sampling campaign, so that DSMA uncertainties will be adaptively calculated with each new sampling region, guiding near-future sampling to optimize DSMA output accuracy (Bui, et al., 2020, in this issue). In addition, the status of the national or shared site data resource will continually improve and be readily available.

New technology will allow sampling time to be minimized at each site so that the number of sites measured per unit of time can be increased. Proximal sensing methods (e.g. infrared and X-ray fluorescence spectroscopies) will be integral in new data acquisition. It is becoming common in DSMA workflows to utilize lab-based mid-infrared spectroscopy to measure soil attributes on samples collected in the field (Kidd et al. 2015b; Thomas et al. 2018). These developments have significantly reduced the burden and costs associated with doing lab-based analytical measurement, and ultimately improve the granularity

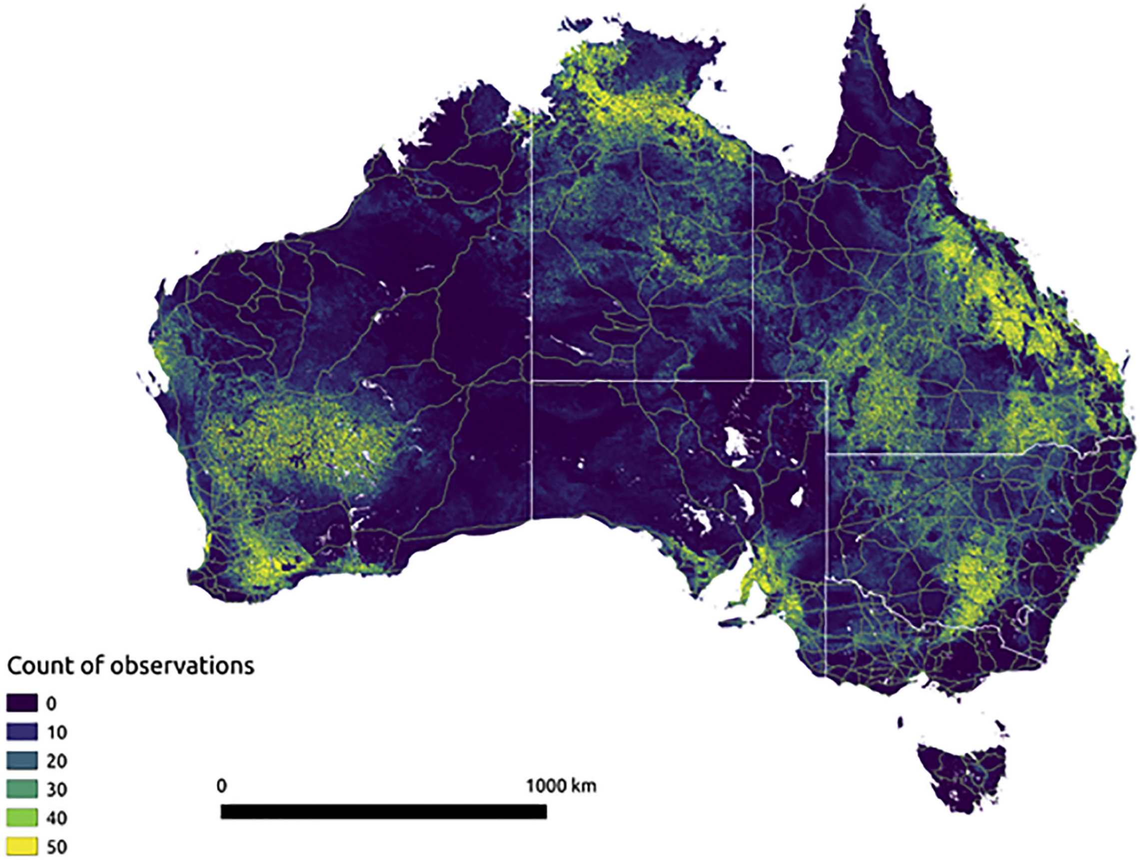

Figure 1. The spatial distribution of the relationship between samples and the environmental covariate feature space that those samples cover. i.e. A measure of how well areas of the environmental feature space have been sampled.

of information that is fed in spatial soil modelling workflows. These proximal sensing instruments that have, until recently, been stuck on laboratory benches are now becoming available as portable versions. X-ray diffraction (XRD) instruments can now be carried into the field (Sarrazin et al. 2005) and in the case of X-ray fluorescence (XRF) and visible-near-infrared (vis-NIR) spectrometry, they are available as hand-held devices (Weindorf et al., 2014; Stockmann et al., 2018). These instruments will cost less and increase in resolution and capacity. Lower cost devices with user-friendly interfaces and appropriate internal calibrations currently exist for the infrared region of the electromagnetic spectrum, but their spectral range is at present limited for estimating a range of soil properties reliably. Calibration algorithms for these instruments will move beyond the current focus on quality assessments of food products or plant materials and be tailored more specifically for soil measurement applications. More effective sharing of spectral libraries and prediction algorithms specifically calibrated for soil attributes will improve the accuracy of these measurements.

In-situ sensors will become integral for temporal data capture and the production of near-real-time soil property maps over small areas, using cloud computing and wireless networks enabled by cellular communications technology (Hedley et al. 2013). Along with developments in field deployed robotics, the new generations of sensors will measure a wider suite of soil attributes (towards the full Mendeleyev table and biological indicators including DNA identification).

A harmonized, standardized, and well governed soil site information infrastructure will underpin future DSMA. Submission of new soil data to managed data systems would be mandated for activities supported by public funding, or subject to government approval processes, and recommended for other private initiatives. This shared infrastructure will be based on a national standard data exchange model and offer quality-flagged bulk data upload options to cater for soil experts through to citizen science applications. User account-associated data sharing permissions will allow discrimination between public and restricted-use-only data. We see commercial and research labs becoming linked to a universal system achieving cost savings and efficiencies from a seamless process of assigning lab method codes and reconciling disparate data from various sources.

Accuracy and fit for purpose statements will emerge from the data infrastructure to ensure unambiguous interpretations and clear intended use of data products.

Alongside and complementary to this data management process, we envisage the possible application blockchain (distributed ledger) technology (Padarian and McBratney 2019) allowing decentralized collection of data (with standard procedures and data model).

4.2.2. Environmental covariates

Access to finer scale and more detailed environmental covariates has provided the impetus for operational DSMA. We see substantial opportunities to improve DSMA with the continued improvement in temporal and spatial resolutions of environmental covariates and an increase in the number and types of remote sensing platforms measuring an increasingly broad range of landscape variables.

Almost certainly satellite and airborne remote sensing of soil and related properties will have a finer resolution in space and time with a wider range of sensor and spectral wavelengths. Contemporary examples of such platforms currently in development include the Environmental Mapping and Analysis Program (ENMAP) (Guanter et al., 2015), the HYMAP Group Shoot (Kruse et al. 2000) and the NASA-ISRO Synthetic Aperture Radar Mission. (NISAR) (Hoffman et al. 2016). The data will become more accessible, as will the algorithms to efficiently process the data (Chabrillat et al. 2016).

Specific sensing will be developed to better estimate currently challenging aspects of soil function. We see the creation and development of new sensor technologies that characterize subsoil variability based on electro-magnetic like, non-invasive sensing technology to characterize soils to at least one metre with high resolution depth discretization. Increase granularity of gravity anomaly via satellite measurement has the potential to inform on subsoil water storage.

Unmanned aerial systems (UAS) including drones and similar unmanned aerial vehicles (UAVs) and their associated sensing platforms will transform the collection of field data (Van der Merwe et al. 2020). They will increasingly provide vis-NIR and thermal imagery (Bokolonga et al. 2016; Saha et al. 2018) and fine granular land surface mapping. The next stage will see platforms for conductivity sensors (Barrowes et al. 2019), ground penetrating radar (Wu et al. 2019) and gamma-ray spectrometers (Šálek et al. 2018) flown with the required frequency for a given application. Improvements in payload capacity and a broader range of sensors will facilitate the integration of plant and soil dynamics at field scales at appropriately frequent time-steps. UAS will also be used to map change over time and across landscapes including extreme events such as flooding and erosion extent.

Our ability to process and manage the vast amount of data collected by UAS will continue to grow apace. Data will be stored, processed and accessed in cloud-based systems. Continually increasing processing power will allow us to unlock the vast amounts of information stored in these data sets.

4.3. Estimation/modelling methods - Is it all machine learning?

Machine learning (ML) approaches will continue to evolve and become invaluable for synthesizing vast amounts of soils data into understandable and useable products. More sophisticated and complex methods will be easier to apply computationally. The challenge will be to use these models to increase our pedological understanding.

A key to the successful implementation of ML in developing and furthering pedological knowledge is to bridge the gap between data and data needs of models and the products delivered. Most commonly in current DSMA approaches, the ML models are treated as a “black box”. The models provide no new knowledge of the relationship of the input data to the products produced. DSMA needs to develop methods for generating new soil process understanding from modelling methods (Wadoux et al. 2020).

The integration of process models with empirical spatial data modelling is intuitively a well resolved pathway to apply pedological knowledge. Examples exist already in nowcasting and forecasting of soil moisture (e.g. Wimalathunge and Bishop 2019). We expect to see greater integration of empirical modelling with comprehensive pedogenesis models that simultaneously encapsulate multiple soil processes such as SoilGen (Finke 2012) and MILESD (Vanwalleghem et al. 2013), which both challenge and engage the users of these models to think more deeply about why soils are the way they are at a given location in terms of their physical and chemical profile. These quantitative modelling frameworks represent a considerable amount of hard-earned experimental effort and knowledge that the DSMA community will build upon. Recent work on coupling landscape evolution and pedogenesis with empirical modelling by Ma et al. (2019) suggest new approaches to ensure that DSMA delivers meaningful products into the future. Both process and empirical modelling have their own benefits and limitations, and there is value in fusing these approaches to capture the best components of each.

New insights and useful products will emerge from close collaboration between domain experts (hydrologists, pedologist, geologists) and ML practitioners. This integration will support the development and implementation of models that reflect a continuing supply of increasingly pertinent data. ML technicians will be engaged in the critical interrelationships between domains and ensure new conceptual models elucidate and validate existing understanding. We expect that machine learning algorithms will be customized so that they better complement DSMA, through awareness of spatial context (e.g. Georganos et al. 2019; Myer et al. 2019; Padarian et al. 2019; Wadoux et al. 2019b), or through design to explicitly recognize the soil-landscape relationship context. While interpretability is a desirable outcome of ML methods, we cannot expect to obtain easily interpretable parameters from complex 4-D models. Instead, we need to develop new techniques to understand the internal mechanisms of complex models. While we develop these new techniques, the simplest way of assuring interpretability, given a limited, sensible number of inputs (i.e. covariates), is for domain experts to evaluate the output maps. This will require iterative workflows that enable interpretation. Prediction without immediate understanding can be seen as a form of conceptual extrapolation. Unusual or unexpected map predictions may lead to new knowledge where maps do not fit preconceived ideas.

4.4. Delivery

4.4.1. Integrated platforms

DSMA offers the opportunity to effectively include soil function in integrated decision-support and assessment platforms. As the use of decision support tools increases so will the demand for local scale soil information. There will be increased incentives for localized data capture built around community knowledge of soils, incorporating for example automated DSMA algorithms for small-extent local predictive maps. Applications are likely to include dedicated platforms targeting uses such as soil carbon assessment or market-oriented sustainable land use accreditation schemes. These would integrate both expert national DSMA products (as covariates and to guide sampling designs) and inbuilt DSMA algorithms (to produce local maps) together with multiple other data sources as part of an integrated user-friendly platform.

Nationally, we foresee a coherent and well managed data access system that not only serves the scientific community, but also facilitates the operational application of DSMA products by landholders. Smartphone applications drawing from this system would facilitate presentation and delivery of DSMA data and include a range of user-friendly tools to showcase the available datasets over an area. Each tool would use geolocation to identify an area of interest for the landholder and show a combination of snapshots and dynamic products. Snapshot layers could include crop-specific land suitability and soils maps, where dynamic tools could include plant available water calculations and forecasts similar to the SoilWaterApp, (http://soilwaterapp.net.au/) (Freebairn et al. 2018).

4.4.2. Federated data systems

Easy access to high quality georeferenced soil property data is a key enabler of DSMA. There are a range of approaches that can be used to achieve this from creating a centralised aggregation of data by a single intermediary (Batjes et al. 2017) through to federating data from existing data providers. In the data federation approach, the data custodians provide a view of their data according to a community agreed model. End users access web services from multiple data custodians, that conform to the standard (community) structure and semantics (Box et al., 2015) on the fly as data is required.

Data aggregation approaches are generally created for a specific purpose typically with a finite life cycle (eg the National Soil Site Collation, Searle 2014). The advantage of the data federation approach is that it leverages existing datasets already maintained by custodians and requires very little additional resourcing. It also gives users access to the most up to data from each of the individual repositories. We expect in the future, data federation will become the norm, but in the near term DSMA will continue to exploit purpose specific aggregated data sets. This would also include other related data such as infrared spectra and outputs from soil sensing devices.

Substantial gains will be made when data federation extends to soil information collected by private enterprise (eg. fertilizer companies or agricultural consultants) or by citizen scientists. By adding previously privately held data sets to a much larger pool of data, improved insights can be developed that will benefit all stakeholders – the whole is greater than the sum of the parts.

4.5. Human capital/pedological knowledge/knowledge community

We expect that DSMA practitioners will be teams based around individuals with specific disciplinary knowledge, who are adept at a broad range of analytical techniques. Because the skill demands will continue to increase and broaden, it will be essential multi-disciplinary teams include the traditional expertise in the biophysical sciences and a growing sophistication in the use of numerical and technological skills.

As artificial intelligence and machine learning approaches improve prediction and decision making, pedological skills must be retained and connected to the estimation processes to provide the soil landscape understanding that not only ensures DSMA products are realistic, but also that digital soil survey increases our landscape knowledge.

Regardless of the which plausible future scenario is realized we find it difficult, in the Australian context, to imagine that a centralized agency to bring together the human capital required for DSMA, such as a national soil survey agency, will materialize. Instead we think that a collaborative approach founded in the strong community of practice that currently exists (Kidd et al. 2020, this issue) will continue to support DSMA developments going forward, possibly with more high-level support and coordination, relying less on the current 'bottom-up' approach. This collaborative approach will allow for more flexibility in bringing together the requisite human capital and allow us to be agile with the directions we explore.

4.6. A broader community involved in DSMA

DSMA stakeholder profiles will range from individuals and citizen scientists to multinational corporations. These groups will be involved in a range of activities including funding, collecting and analyzing data, and interpretation, product generation, policy delivery, and decision making. The breadth of involvement will come from the value of information for an extensive number of purposes and so access to and use of soil data will broaden. We see the stakeholder community consisting of:

- The general public using the data as their part in community planning and growth (eg. evidence-based input into opportunities for public consultation such local environment plans and development applications),
- Landholders, individually or in groups, refining the myriad of decisions from overall strategy to tactical choice within an enterprise mix,
- Local authorities and councils using DSMA to guide planning decisions and implementation more effectively and at scale,
- Local natural resource management communities, environmental groups using the data for guiding funding and extension activities,
- Government agencies that will increasingly rely on DSMA products for assessing and improving ecosystem services and climate adaptation, including natural disaster prediction, prevention, and mitigation,
- Companies and the corporate world using DSMA to guide investment decisions, and
- State and Federal Governments applying the data in regional planning and broad policy and strategy developments.

The DSMA practitioner community will experience a future of transformation and growth, building on experience gained from our current approaches and products and realizing these new opportunities.

Consequently, the soil information community will be more closely connected to the use of soil information and therefore to other communities of practice seeking impact across new applications. DSMA will increasingly be part of an integrated solution targeted at complex social and economic issues.

4.6.1. Business models

New business models will emerge around DSMA. New avenues of data supply to support DSMA will emerge from individual and community suppliers (eg. citizen scientists, or farmer scientists), and from a new set of commercial arrangements. Both data supply groups require a clear value proposition to encourage data supply. While citizen scientists may often be driven by curiosity and interest, they will expect to see their contribution effectively used to address an environmental or community issue. The farmer-scientist may be motivated either by the increased information returns drawn from the farm data or by the value in sharing amongst farmer groups.

The principle commercial data providers will be the agricultural services industries, including agronomic consultants and soil testing laboratories. A sufficiently compelling value proposition has yet to be developed in Australia for these commercial companies to be fully engaged in data sharing activities. There are likely to be elements of 'good corporate citizen', specific data sharing arrangements that return value to data supply, methods of ensuring maintenance of intellectual property, opportunities to join new high value industries and the need to respond to community expectations around agreed priorities (eg. the health of the Great Barrier Reef). An example of data sharing across states and from the corporate sector that is relevant here is the Australian National Geoscience Agreement based around a clear understanding of what constitutes pre-competitive information where there is a common interest in data collaboration. A similar arrangement is likely with fertilizer companies as they have an increasing interest in the development and availability of DSMA products and the availability of data on-line in an easy to acquire and applied format for farmers and consultants to use. Coupled to recommendation guidelines for nutrients and ameliorants, funding from these companies would seem an appropriate investment.

New players will include large fiduciary institutions that need to meet societal expectations for ethical and sustainable investment (Edwards et al. 2019; Abeysekera 2013). Superannuation and pension funds looking for long-term growth will be willing to invest in understanding how soils can contribute to sustained investment outcomes and be willing to support DSMA activities. The National Australia Bank states "We need to manage our natural capital with the same diligence that we manage our financial capital. This means accounting for the availability of clean water, investing in biodiversity and putting a value on soil conservation." (NAB web site, accessed May 2020). Natural capital rarely appears on the balance sheets of corporations and is seldom taken into account in financial decision-making. These practices can ultimately translate into unpriced material risks for financial institutions that may emerge at either local or systemic levels (Ascui and Cojoianu 2019). DSMA has the opportunity to provide tools to financial institutions with significant agricultural investments to monitor the condition of these investments in natural capital.

4.6.2. Communities of practice

We expect a much broader and more impactful DSMA community of practice than the current research/government axis (Universities/ Federal agencies/States agencies) to include industry (providing the user-driven perspective, stakeholder) and (new) data suppliers (industry, communities, individuals). Institutional investors will play a prominent role in their activities; for example, in supporting the development of new standards, data platforms, and in many instances research.

Citizen scientists will improve DSMA by accessing contributing large amounts of data not previously obtainable. Examples of current citizen science programs collecting soil samples, the kind from which DSMA may benefit from in the future, include the "Swab and Send" initiative (Roberts 2020) where the community collects soil microbial samples for new antibiotic developments and the global Land-Potential

Knowledge System which has developed a richly featured mobile app for collecting and interpreting soil data by soil scientists, citizen scientists, land owners, and land managers (Herrick et al. 2013). Another relevant example is the soil citizen science program in Western Australia, MicroBlitz (Gruber 2015) which is collecting soil microbial data. These examples demonstrate a potential alternative way to collect soil data relevant to DSMA approaches into the future. While there are complications with citizen science (the development of the data collection infrastructure, privacy and data availability and governance), the breadth of data collection possible is potentially transformative. Privacy rules are needed to ensure contribution from those landholders concerned with the use of the data. There would also be a need to monitor the quality of such data.

Citizen scientists will emerge as not only significant contributors of legacy or contemporary soils data but as active participants in the DSMA process. The current focus of citizen science as collectors of observation data used to model phenomena like species occurrence or changes (e.g. Harley et al. 2019) or threats to the environment will broaden as the need to adaptively manage soil locally grows with more challenging climates. They will fill temporal and spatial gaps and support policy interventions and management to address soil management issues. New governance and stewardship frameworks for soils data and vocabularies will benefit harmonization of these many data sources; on-line estimation engines using DSMA will allow immediate use of new data and a broader community will connect and grow soil and scientific literacy.

4.6.3. The role of the soil scientist

Soil science knowledge will remain a fundamental cornerstone of DSMA into the future. While automation will increase in DSMA, the systems will be designed by multi-disciplinary teams that will require the knowledge and interpretation of experienced soil scientists (Bui et al., 2020, in this issue). The outputs of automated systems will be constantly evaluated and improved, paying special attention to systems that are more dynamic, where newly acquired data can generate unexpected outputs. As with most autonomous systems, human oversight and expert evaluation will be critical.

One of the great benefits of a modelling-based approach is the ability to analyse large data and handle complex processing tasks to build sophisticated relationships with measured data, rivalling or exceeding human capacity to do so. This may alter the role soil scientists play into the future, potentially being more focused on the interaction between people, the soil and the desired outcomes, what we have traditionally referred to as science extension.

4.7. A digital twin for soil?

Fundamentally, different models and representations of soil will become possible and effective through an intimate connection between the soil and its digital representation – a concept known more generally as digital twinning. Haag and Anderl (2018) define a digital twin as, the comprehensive digital representation of an individual product. It includes the properties, condition and behavior of the real-life object through models and data. DSMA will enable digital twins to be developed using the explicit digital representation of knowledge of the soil at specified spatial locations, to depth, and at specified times. Then as the soil changes, DSMA will enable its digital representation to change with it. Applications will include accounting for SOC stocks with soil physical changes in time (e.g. due to high temporal variability of bulk densities in shrink-swell soils, or to erosion processes), meeting the need for the definition of stocks on an equivalent soil mass basis (Ellert and Bettany 1995). New approaches to simulation will then evolve and change our understanding of land management effects and short-range variation. Predictions and forecasts will be more effective and testable. This could provide new spatial and temporal dimensions to the Digital Soil concept, an important component of Soil Security. The twinning approach will use the capacity of DSMA to describe the complex nature of soil variation and inform the management of soil with knowledge of this variation.

5. A DSMA snapshot – the next 10 years of change

We consider we are at the beginning of significant enhancement in the contribution of DSMA and envisage the following specific plausible pathways for DSMA over the next 10 years.

Government, industry and the community will commission DSMA studies as the established approach to understand the role of soil in the function of land ecosystems at a range of scales and across use cases – such is the capacity of this approach to characterize the key aspects of the system under consideration. The investment and infrastructure to support this is recognized and valued.

DSMA draws from advanced technologies that increase the number and variety of data, such as infrared (NIR/MIR) integrated in mobile phone applications. All soil analysis labs include the use of MIR spectra in their product offerings and continuously contribute to a common spectral library (based on the approach described in Saby et al. 2017). Because this then substantially increases the number of field observations, farmers agree to deliver their data as part of a national data commons from which all benefit. Privacy issues have been solved by data system innovation and agreed protocols and data are readily shared in federated information systems.

New satellites now provide high frequency and precise information on land use and management. DSMA has evolved to produce real-time monitoring of soil properties and the management impact on these properties and on crop yields. Data accumulation over time now allows space-time modelling. A new generation of soil-data-scientists use space-time modelling and understand and interpret the result from a soil science point of view.

Most countries now deliver national DSMA products in a bottom-up process for global assessments. Increased regional scale mapping has substantially improved the data and mapping coverage of Australia but due to various funding priorities and access issues there are still large areas of Australia with sparse site data and broad-scale land systems mapping. These input data gaps will be sensibly filled, being informed by DSMA methods, and appropriate products will produced to fill information gaps.

Harmonization of traditional soil polygon maps DSM products may still be challenging for some purposes, but practitioners are developing ways for datasets to coexist and have set standards for comparing accuracies between the differing methods. While there are a range of differences between these products, there is no longer a complete separation between them.

Increasingly, DSMA works on new and emerging applications such as peri-urban areas, human health (emerging contaminants, antibiotics, various diseases) and on improved land use planning. Soil biology mapping has emerged and provides an opportunity for collaboration between DSMA practitioners and biologists. The interactions between soil attributes including available water content, pH and salinity and the spatial distribution of micro-organisms is now available at fine scale around the country. Soil microbiologists have standardized their methods (Thiele-Bruhn et al., 2020), and this establishment of operationalized soil biology measurements has opened a pathway to spatializing this information.

The DSMA research and development community is focusing on increasingly publishing more of its work in open-access journals to promote wider uptake of cutting-edge work. DSMA methodologies, standards and guidelines are being published in freely available online texts, and reproducible software code and data are hosted in public online repositories.

Aligned with these changes the products generated by DSMA are publicly and freely available online via a range of open standards web delivery mechanisms in open data formats. Soils data tailored to meet the needs of specific applications is also being made available via purpose-built web application programming interfaces.

6. Conclusions

Digital Soil Mapping and Assessment are in the middle stages of a soil information transformation. Its use has moved beyond proof of concept to large scale operations. Its impact will grow substantially – because soil information in this high-utility form has applications and potential users that have yet to be satisfied and will be part of a community-wide response to future conditions with unknown but challenging dimensions. Investment in DSMA will therefore grow as the data streams increase and are used.

The components of DSMA (sampling and measurement, data systems, modelling and estimation methods, computation, and information access and integration) are individually increasing in capacity as part of the ICT revolution. We see the integration of improvements in these individual components into DSMA, will lead to substantial improvements in products generated from DSMA approaches and an increased uptake of DSMA derived knowledge used in decision making. Decision systems of all kinds will access this improved knowledge so that the key elements of the soil will be embedded in an improved integrated understanding of the landscape trends and the options and consequences of land management. The soil will no longer be hidden.

We see DSMA moving towards providing a digital twin of the soil and its function that allows a level of understanding and prediction that is both currently lacking and sorely needed.

Regardless of the plausible future scenario realized, be that 'slow decline' or 'outlook vision', we postulate that DSMA has a propitious future.

Declaration of Competing Interest

None.

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