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\begin{document}

\title{Mapping soil slaking index and assessing the impact of management in a mixed agricultural landscape}

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%% The [] brackets identify the author with the corresponding affiliation. 1, 2, 3, etc. should be inserted.

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\firstpage{1}

\maketitle

\begin{abstract}
Soil aggregate stability is a useful indicator of soil physical health and can be used to
    monitor condition through time. A novel method to quantify soil aggregate stability,
    based on the relative increase in the footprint area of aggregates as they disintegrate
    when immersed in water, has been developed and can be performed using a smartphone
    application - SLAKES. In this study the SLAKES application was used to obtain slaking
    index (SI) values of topsoil samples (0 to 10 cm) at 158 sites to assess aggregate
    stability in a mixed agricultural landscape. A large range in SI values of 0 to 7.3 was
    observed. Soil properties and land use were found to be correlated with observed SI
    values. Soils with clay content >25\% and CEC:clay ratio >0.5 had the highest observed
    SI values. Variation in SI for these soils was driven by OC content which fit a
    segmented exponential decay function. An OC threshold of 1.1\% was observed below which
    the most extreme SI values were observed. Soils under dryland and irrigated cropping
    had lower OC content and higher observed SI values compared to soils under perennial
    cover. These results suggest that farm managers can mitigate the effects of extreme
    slaking by implementing management practices to increase OC content, such as minimum
    tillage or cover -cropping. A regression-kriging method utilising a Cubist model with a
    suite of spatial covariates was used to map SI across the study area. Accurate
    predictions were produced with leave-one-out cross-validation (LOOCV) giving an Lin's
    concordance correlation coefficient (LCCC)CCC of 0.85 and an RMSE of 1.1. Similar
    validation metrics were observed in an independent test set of samples consisting of 50
    observations (LCCC = 0.82; RMSE = 1.1). The potential impact of implementing management
    practices that promote soil OC sequestration on SI values in the study area was
    explored by simulating how a 0.5\% and 1.0\% increase in OC would impact SI values at
    observation points, and then mapping this across the study area. Overall, the maps
    produced in this study have the potential to guide management decisions by identifying
    areas that currently experience extreme slaking, and highlightingthose areas that are
    expected to have a significant reduction in slaking by increasing OC content.
\end{abstract}

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\introduction  %% \introduction[modified heading if necessary]
Objective and quantitative metrics are required to assess soil health and monitor soil
    condition through time. Development of simple accessible metrics to assess soil health
    will facilitate increased spatial and temporal sampling density, and will encourage
    farmers, consultants and even citizens to participate in soil health assessment.
    Acquisition of such metrics should be low cost, rapid and simple to facilitate
    sufficient spatial and temporal sampling density. Aggregate stability is an important
    indicator of physical condition that quantifies a soil's resistance to slaking and
    dispersion. Slaking is the disintegration of soil aggregates as a result of rapid
    wetting \citep{yoder,oades}. Slaking occurs when soil aggregates are unable to
    withstand the stress induced by water uptake derived from two main causes: swelling of
    clay minerals as water is adsorbed into the interstitial space; and internal pressure
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caused by compression of entrapped air bubbles as capillary action draws water into the small pores between soil particles \citep{emerson64}. Most cultivated soils in Australia are prone to some degree of slaking. The degree of slaking determines if the process produces a favourable or unfavourable environment for cultivation and plant growth, and has implications for soil conservation. A small degree of slaking can be beneficial and is associated with self-mulching - an ability to recover from disturbance by reforming small (<5 mm) aggregates at the soil surface following wetting and drying cycles \citep{selfmulch}; and mellowing - a partial disintegration of soil aggregates on wetting that results in increased friability \citep{mellow}. Slaking produces detrimental effects when aggregates disintegrate further into microaggregates (ø <0.25 mm). Detached microaggregates migrate and settle into pores, reducing pore volume, decreasing infiltration and percolation rates, and leading to increased surface runoff \citep{rengasamy1984}. Erosion susceptibility is exacerbated as greater run-off volumes increase erosive power and the slaked aggregates also provide suitably sized particles for translocation. Ultimately the soil has a lowered capacity to support plant growth as plant available water and soil-atmosphere gas exchange are both reduced . In severe cases, crusting or hard-setting occurs when slaked and dispersed aggregates coalesce and set hard on drying \citep{Mullins1990}. Soil strength increases as the soil dries producing difficulty in cultivation until the soil is rewetted, and shoot emergence and root growth may be restricted \citep{Mullins1990}.

The susceptibility of a soil aggregate to slake is related to texture, mineral composition and organic matter content \citep{Mullins1990}. Soils with high clay content, especially those containing smectite or vermiculite minerals, are more likely to slake as they expand on wetting and also contain a greater number of small diameter pores into which capillary action will draw water and compress entrapped air-bubbles \citep{emerson64}. High organic matter content improves soil structure by binding soil particles into stable aggregates and reducing susceptibility to slaking \citep{chenu2000organic}. Techniques that increase soil organic matter such as cover cropping, reduced tillage and application of organic amendments may reduce susceptibility to slaking. Agricultural management practices that increase susceptibility to slaking include: conventional tillage methods that destroy soil structure and accelerate organic matter decomposition; burning or removal of crop residues; and the application of pesticides and other chemicals that are harmful to soil biota and lead to disruption of organic matter cycling and reduced aggregation~~. ~~. T~~t~~he detrimental effects of soil slaking are more pronounced in areas with clear wetting and drying cycles, such as temperate Australia. \cite{collisGeorge} found that~~,~~ ~~as~~ the initial water content of soil affects the degree of slaking upon rewetting and soils of low initial water content are more prone to rapid and explosive slaking~~\citep{collisGeorge}~~.

Slaking and dispersion are quantified through aggregate stability tests that observe changes in soil aggregate morphology following immersion in water in an attempt to predict soil behaviour in the field. \cite{emerson67} developed a test to classify samples into eight classes based on the degree of slaking, swelling and dispersion observed when air-dried soil aggregates are immersed in distilled water. The Emerson Aggregate Test was extended by including a supplementary analysis whereby soil samples were wetted and moulded into cubes before immersion in the distilled water as a means to simulate the shear forces associated with raindrop impact and tillage on bare soil \citep{lovedayPyle,emerson91}. \cite{aswat} modified these tests further to include observations of slaking and dispersion at both ten minutes and two hours post submersion in the 'aggregate stability in water' (ASWAT) test. This greatly decreased the time-requirement from 20+ h required for previous tests, however, interpretation of the degree of slaking for the ASWAT test remained moderately subjective and scores were produced on an ordinal scale from 0 to 4 which limits statistical applications.

Established methods to quantify stability of aggregates subject to wet-sieving or simulated rainfall are also time-consuming and require specialist equipment \citep{yoder,schindelbeck}.

A new method has been developed to calculate degree of slaking using a time-series of digital photographs to quantify the increase of the footprint area of aggregates as they disintegrate when immersed in distilled water \citep{mario}. This method has been incorporated into a smartphone application, SLAKES, that is able to quantify aggregate stability in only ten minutes \citep{slakes}. The reduced assessment time was achieved as the authors found that the two hour reading can be reliably estimated from change in footprint area over the ten minute analysis period. The SLAKES application requires no specialty equipment and the automated nature of the application allows aggregate stability to be quantified with minimal~~um~~ training. These advances make the analysis more readily available to farm managers and citizen scientists. The method calculates an objective and continuous slaking index (SI), which reduces operator error and facilitates elucidation of contributing factors of observed slaking. For example, \cite{flynn} investigated aggregate stability of Vertisols under different agricultural management strategies and found that SI was significantly more sensitive at distinguishing the perennial, no-till and conventional tillage management treatments compared to the Cornell Wet Aggregate Stability Test \citep{schindelbeck}.

Few studies have mapped aspects of soil aggregate stability using digital soil mapping (DSM) techniques. \cite{odeh} used regression-kriging and indicator-kriging to model the electrochemical stability index (ESI) across an irrigated cropping region of western NSW, Australia. This resulted in a map of 'risks zones' that were susceptible to dispersion and which could be prioritised for increased monitoring and tactical management to abate immediate and future detrimental impacts on crop production. A study by \citep{ANNABI2017157} also utilised regression-kriging to produce accurate predictions of soil aggregate stability of an agricultural district in Tunisia. ~~-~~Fine-resolution maps of soil aggregate stability across fields and farms have considerable potential to aid farm managers in decision-making processes. Such maps could ~~help~~ guide farm managers to implement soil amelioration practices, such as tactical application of gypsum, or change in management practices, such as minimum tillage~~cultivation method~~ or use of cover ~~-~~crops. Tools that make aggregate stability quantification accessible, such as the SLAKES application, may facilitate the production of such maps.

The current study investigated the use of the SLAKES application and DSM techniques to assess variation in SI across a landscape with different agricultural and natural land uses. The contribution of both soil attributes and land management to slaking was investigated~~explored~~, and the potential impact of increasing soil OC levels on slaking was explored.

\section{Methodology}
\subsection{Site description}
The study was centred around a mixed farming property, L'lara (30\textdegree15'18" S, 149\textdegree51'39" E), which is located \textasciitilde11 km north-east of the township of Narrabri, NSW, Australia (Fig. \ref{fig:studyArea}). Climate at the study site is classified as humid subtropical (Cfa) under the K{\"o}ppen-Geiger system \citep{koppen}. The site experiences hot summers and cool winters. The long-term average annual precipitation for the study area is 658 mm~~,~~ and is slightly summer-dominant \citep{bom}. The landscape at L'lara and its surrounds can be broadly characterised into two distinct areas: sand covered hills derived predominantly from

Jurassic coarse-grained sediments of Pilliga sandstone covered by Quaternary sands and talus material; and floodplain areas derived from Quaternary alluvial deposits of basaltic materials washed from the western side of the Nandewar range. The soils of the floodplain area at L’lara aare~~ c~~ classified as Vertisols~~lassified as black and brown Vertosols according to the Australia Soil Classification~~ according to the World Reference Base for Soil Resources, with some expression of calcic horizons \citep{wrb~~isbell~~}~~, with small areas of grey Vertosols~~. The sand hill area is represented by ~~The soils on the sand hill area were predominately Chromosols, Dermosols, Kandosols, Rudosols and Tenosols \citep{isbell}~~Luvisol, Lixisol, Solonetz, Leptosol and Regosol soil groups.~~, the unifying feature of these soils was the presence of a relatively sandy topsoil.~~ L'lara encompasses a total area of 1,850 ha, with approximately 1,070 ha used for dryland~~, broadacre~~ cropping. Cropping is performed primarily on the Verti~~o~~sols, and occurs over both summer and winter periods with cotton (\textit{Gossypium hirsutum} L.), wheat (\textit{Triticum aestivum} L.), canola (\textit{Brassica napus} L.) and chickpea (\textit{Cicer arietinum} L.) grown in rotation. Lower lying floodplain areas close to creek lines and all of the sand hill area is used for grazing of beef cattle on unimproved native pastures (\textasciitilde704 ha) and remnant forest cover (\textasciitilde76 ha).

\begin{figure}[h]
\includegraphics[width=120cm]{fig01.PNG}
\caption{a) Location of L'lara farm and the wider study area in relation to the township of Narrabri, NSW, Australia. Sample locations used as a training set (n = 108) and test set (n = 50) are indicated. Satellite imagery sourced from Google Earth Pro V 7.3.2 .5776. (March 5, 2019). Narrabri, NSW, Australia. 30° 16’ 31.37”S, 149° 51’ 46.42”E, Eye alt 20.57 km. Image © CNES/Airbus 2020. http://www.earth.google.com [April 20, 2020]. b) MrVBF calculated at 30 m resolution using the SRTM digital elevation model. c) Pixel-wise 50th percentile of NDVI calculated from Landsat 7 scenes covering the time-period 2000 to 2018. d) Simplified land use across the study area \citep{abares_alum}. FR, forest reserve; Gr, grazing including understorey grazing and stock routes; DC, dryland cropping; IC, irrigated cropping; OW, open water; BU, built-up areas. The external perimeter boundary of L'lara is indicated by the thick black line and boundaries of cropping paddocks are indicated by thin black lines.}

\label{fig:studyArea}
\end{figure}

L'lara lies at the centre of a diverse landscape. Outside the property, dryland cropping and grazing occur on the floodplains and slopes to the east and south. Intensive irrigated agricultural production occurs on the lower floodplain to the south-west of the property, and the Killarney State Conservation Area lies directly to the north. This conservation area contains similar species as the remnant forest area found on L'lara which is dominated by white cypress pine (\textit{Callitris glaucophylla}), hickory (\textit{Acacia leiocalyx}), black cypress pine (\textit{Callitris endlicheri}), narrow-leaved ironbark (\textit{Eucalyptus crebra}), bulloak (\textit{Allocasuarina leuhmannii}) and dirty gum (\textit{Eucalyptus chloroclada}).

\subsection{Soil sampling}
A training set of 108 samples and a test set of 50 samples were defined (Table \ref{table:campaigns}). The training set comprised both on- and off-farm samples. ~~Sample sites were identified on L'lara and the surrounding area.~~ The~~ majority of~~ on-farm samples (n

= 58) were identified based on a random stratified sampling approach utilising soil type and land use as parameters (Fig. \ref{fig:studyArea}). This ensured representation of the major soil types and different land uses - dryland cropping, pasture and forest cover found on the property. The off-farm samples (n =~~o investigate slaking in the area surrounding L'lara, an additional~~ 50) samples were sourced from neighbouring properties found within a 5 km distance from the boundary of L'lara. As a soil type map was not available for off-farm locations t~~T~~he~~se~~ sites were identified through a random stratified approach utilising K-means clustering and rasters of elevation, multi -resolution valley bottom flatness (MrVBF) and airborne gamma radiometrics as input variables \citep{filippiUR}.~~ K-means clustering~~ F~~was utilised to split the data into f~~our strata were~~classes~~ identified whose geographic distribution were approximately~~roughly~~ equivalent to sand hill, transition, upper floodplain and lower floodplain landscape positions. Sample sites were randomly selected within each stratum . Five of the samples on the lower floodplain were under irrigated agriculture, a land use not represented on L'lara. The test set was constructed utilising 30 existing sites~~A supplementary dataset of 30 existing sites~~ on the dryland cropping areas of L'lara which are described in \cite{filippi}, and 20 sites on the pasture areas~~were also used as a test set for model predictions~~. At each of the 158 sites a topsoil (0 to 10 cm) sample was obtained by excavation using a shovel at a discrete location.

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\begin{table}[h]
\caption{Summary of sampling campaigns and land use for each dataset.}
\begin{tabular}{lllccccc}
\tophline
           &            &        &         \multicolumn{5}{c}{Observations   (n)}        \\
Sample set & Location   & Date   & Forest & Pasture & Dryland          & Irrigated    & Total \\
\middlehline
Training   & L'lara     & Dec-18 & 6       & 20       & 32                & -    & 58    \\
           & Surrounds & Aug-19 & 7       & 18        & 20                & 5    & 50    \\
Test       & L'lara     & Jul-18 & -       & -        & 30                & -    & 30    \\
           & L'lara     & Jul-18 & -       & 20       & -                 & -    & 20 \\
\bottomhline
\end{tabular}
\label{table:campaigns}
\end{table}
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\subsection{Sample preparation and l~~L~~aboratory methods}
All soil samples were air-dried at 40\textdegree C for 48 hours. ~~-~~A selection of 12~~0~~ to 15 soil~~30~~ aggregates (ϕ 5-10 mm) were isolated from the air-dried, bulk soil samples prior to grinding and sieving for laboratory analysis. If distinct aggregates were not immediately evident in the bulk soil then the sample was passed through a 5 mm sieve to isolate aggregates, this procedure was often required in sandy soils~~and retained after drying for use with the SLAKES application~~. The remaining sample was then ground to pass through a 2 mm sieve prior to laboratory analysis. Particle size analysis was performed using the hydrometer method \citep{geeBauder}. Organic carbon content was

quantified using the Walkley-Black method \citep{WB}. Soil pH and electrical conductivity (EC) was measured using a 1:5 soil:H\textsubscript{2}O suspension. As the soil samples did not contain significant quantities of carbonates or soluble salts, the cation exchange capacity (CEC) was assessed using the ammonium acetate method \citep{rayment}. Exchangeable sodium percentage (ESP) and Ca:Mg ratio were calculated from the relevant exchangeable cations, and CEC:clay ratio was calculated following correction for the CEC contribution of organic matter (OM). Laboratory data was obtained on the 108 samples of the training set only, for the test set only slaking index information was obtained.

\subsection{SLAKES slaking index}

~~A selection of 20 to 30 soil aggregates (ø 5-10 mm) were isolated from the air-dried, bulk soil samples prior to grinding and sieving for laboratory analysis. If distinct aggregates were not immediately evident in the bulk soil then the sample was passed through a 5 mm sieve to isolate aggregates, this procedure was often required in sandy soils.~~ A slaking index (SI) was obtained using the SLAKES application \citep{slakes}. Briefly, a smartphone (Galaxy J2 Pro, Samsung, Republic of Korea) with an 8 MP digital camera was fixed on an articulated stand to provide the camera lens an unimpeded view of the bench surface. The height of the stand was adjusted so that the field of view of the camera was filled by a 100 mm diameter petri dish placed on the surface of the bench directly below the camera. Three soil aggregates were placed into the petri dish and an initial image of the aggregates was acquired. The petri dish was then drawn back and replaced by an identical petri dish filled with sufficient deionised water to completely immerse the aggregates. The aggregates were held directly above the deionised water and dropped simultaneously into the petri dish with care being taken to preserve the order and orientation of the aggregates to that of the initial image. The start button of the SLAKES application was then immediately pressed and the setup left to process over a 10 minute period after which the SI was displayed on the screen of the smartphone. The experiment was performed on a white surface to increase contrast between the soil aggregates and the background surface. The experiment was also performed under diffuse and constant lighting to prevent the occurrence of shadows over the petri dish which could introduce errors during the image segmentation process. The procedure was repeated twice for each sample and if the difference between the duplicate readings was greater than one unit an additional reading was obtained. An additional reading was required for approximately 20\% of samples and was more commonly required for soils with higher slaking index values compared to samples which exhibited minimal slaking. When additional readings were taken the outlier reading was~~Outlier readings were~~ discarded and remaining~~plicate~~ readings averaged to provide the final SI for each sample.

The SLAKES application uses an image segmentation approach to calculate the footprint area of each aggregate, expressed as pixel count, and tracks the relative increase in area of individual aggregates as they breakdown over time \citep{mario}. The SI of an individual aggregate at a given time after immersion is calculated as:
\begin{equation}
SI_t = \frac{A_{t}-A_{0}}{A_{0}}
\end{equation}
where, the \textit{A\textsubscript{0}} is the initial footprint area of the aggregate and \textit{A\textsubscript{t}} is the footprint area if the aggregate at time, \textit{t}. An SI of 0 means that the footprint area of the aggregate has not increased at all, an SI of 1 means that the footprint area has increased in size by 100\%, an SI of 2 means

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that the footprint area has increased in size by 200\%, etc. The change in SI over the course of the analysis is used to fit a Gompertz function on a log time-scale and calculate parameters \textit{a}, \textit{b}, \textit{c}:
\begin{equation}
SI_t = ae^{-be^{-c\cdot{}log(t)}}
\end{equation}
where, as described in \cite{mario}, \textit{a} is an asymptote representing the maximum SI after an indefinite period of time, \textit{b} describes displacement along the time axis and is associated with initial slaking, \textit{c} describes the growth rate and is associated with ongoing slaking of the aggregate. The SI value returned from the SLAKES application is the average of the \textit{a} parameter calculated individually for each aggregate. A major benefit of this approach is that this value can be estimated after only 10 minutes of immersion, unlike ~~othe~~ ASWAT test~~r approaches~~ that requires ~~$\geq{2}$~~ hours of immersion.

\subsection{Spatial covariates for modelling and mapping slaking index}
A range of publicly available spatial datasets were used as input variables to model SI across the study area (Table \ref{table:covars}). This included satellite imagery, a digital elevation model, terrain attributes, air-borne γ-radiometric maps, and a lithology indicator. Landsat 7 tier 1 surface reflectance satellite imagery from 2000 to 2018 was accessed through Google Earth Engine \citep{gorelick2017google}. To remove pixels that were affected by cloud cover or shading, a cloud-masking filter was applied to all images. The Normalized Difference Vegetation Index (NDVI) was then calculated for each pixel in each image. The 5\textsuperscript{th}, 50\textsuperscript{th} and 95\textsuperscript{th} percentile of the time-series of NDVI values were then determined for each pixel. The reason for using different NDVI percentiles was to characterise spatial variability in vegetation cover and vigour over the nineteen year period. For example, the median (50\textsuperscript{th} percentile) gives a value of typical greenness and the 95\textsuperscript{th} percentile gives peak plant greenness. The 5\textsuperscript{th} percentile would likely be low and represent soil variability for areas that are tilled or heavily grazed, and remain higher for areas of perennial cover such as forests.

\begin{table}[h]
\caption{Description and source of covariates used for digital soil mapping.}
\begin{tabular}{llcl}
\tophline
Type                & Description         & Resolution & Source \\
\middlehline
Satellite imagery$^\dag$ & Landsat 7 NDVI 5\%  & 30 m       & Google Earth Engine    \\
                    & Landsat 7 NDVI 50\% & 30 m       & Google Earth Engine    \\
                    & Landsat 7 NDVI 95\% & 30 m       & Google Earth Engine    \\
Terrain             & DEM (m)             & 5 m        & NSW Government   \\
                    & Slope (\%)          & 30 m       & CSIRO  \\
                    & Aspect (\textdegree)& 30 m       & CSIRO  \\
                    & MrVBF               & 30 m       & CSIRO  \\
                    & MrRTF               & 30 m       & CSIRO  \\
γ-radiometrics      & Total dose          & 100 m       & Geoscience Australia  \\
                    & Potassium (\%)      & 100 m     & Geoscience Australia  \\
Lithology           & Silica (\%)         & \textasciitilde{}125 m  & \cite{gray}   \\
\bottomhline
\end{tabular}
```

\belowtable{†Landsat 7 NDVI values represent percentiles computed over the 2000 to 2018 time-period} % Table Footnotes
\label{table:covars}
\end{table}

A 5 m digital elevation model (DEM) was accessed through the ELVIS (ELeVation Information System) platform \citep{elvis}. This DEM was derived from photogrammetry and generated via airborne imagery, it gives an accurate point estimate of elevation though it is not hydrologically enforced. Shuttle Radar Topography Mission (SRTM) derived terrain attributes at 30 m resolution were also accessed through CSIRO's Data Access Portal \citep{csiro}. The specific terrain attributes obtained included aspect, multi-resolution ridge-top flatness (MrRTF), multi-resolution valley bottom flatness (MrVBF), and slope. Gridded gamma radiometric data at 100 m spatial resolution derived from an air-borne gamma ray spectrometer was obtained through the Geophysical Archive Data Delivery System (GADDS) \citep{GA}. Variation in the concentrations of the radioelements in this product are indicative of change in soil type or parent material. The individual datasets used included dose rate, and potassium concentration data, which were processed with low-pass filtering \citep{minty}. A map of silica index, which is essentially a map of silica content of soil parent material, was also used as a covariate \citep{gray}. The silica index is known to relate to soil texture and other important soil physical properties, such as water holding capacity.

\subsection{Modelling and mapping procedure}
A regression-kriging approach was utilised to map SI across the study area. All data handling and processing was performed in the~~ open software~~ R platform for statistical computing \citep{R}. The data set was split into a training set (n = 108) and a test set (n = 50) as previously defined. At each of the 108 sampling sites in the training set, the spatial covariates described in Table 1 were extracted using the nearest neighbour method. A Cubist model was then used to build a relationship between SI and the spatial covariates at each observation point \citep{cubist}. A 20 m grid of the study area was created and the spatial covariates were then extracted using the nearest neighbour method at each grid point. The developed Cubist model was then used to predict SI on this grid of the study area. The residuals (difference between the observed and predicted SI values) at observation points showed a weak spatial autocorrelation. A Gaussian function fit to the empirical semivariogram had a relatively large nugget of 0.81, sill of 1.11 and a range of 1.92 km.~~were~~ A~~kriged onto the same 20 m grid to account for spatial auto-correlation of residuals.~~ grid of~~The~~ kriged residuals was constructed and added to the mapped output of the Cubist model to obtain the final SI prediction map of the study area. The complexity of the Cubist model was fine-tuned using a leave-one-out cross-validation (LOOCV) approach on the training set. The external validation test set consisting of 50 sites was used to assess the final model. Validation metrics used to assess the prediction performance were the Lin's concordance correlation coefficient (LCCC), root-mean-square error (RMSE), bias and the coefficient of determination (R^{2}).

\subsection{Mapping the simulated effect of increased soil organic carbon on slaking index}
~~Options to reduce soil slaking were investigated as a means to inform management practices. To achieve this the~~ R~~r~~elationships between SI and measured soil properties were~~as~~ explored to identify potential contributing~~ausal~~ factors ~~of slaking~~as a means to inform management practices to reduce excessive slaking. Two classes of soils were evident in the samples, soils with clay content $\geq{25\%}$ and CEC:clay ratio $\geq{0.5}$ which consistently exhibited excessive slaking, and other soils~~and allocate observation points into classes with similar behaviour~~. Class-based regression was~~ then~~ used to construct individual predictive models between SI and~~ these~~ other measured soil attributes for each class using either multiple linear regression or segmented, non

-linear regression for more complex relationships \citep{nlstools}. The effect of increasing soil OC levels on SI was investigated by simulating ~~a~~ increases of 0.5\% and 1.0\% ~~increase in~~ OC and applying the relevant class-based regression equation using the laboratory data at each point. These modified SI values were then extrapolated across the study area using the same regression-kriging approach as described above and validated using a LOOCV approach.

\section{Results and discussion}
\subsection{Investigating slaking index variation}
\subsubsection{Slaking index and soil properties}
A large range in SI was observed for the samples analysed in this study (Table \ref{table:lab_data}). A minimum SI of 0 was observed for nine samples, meaning that no slaking or swelling occurred and the footprint area of these soil aggregates did not increase. A maximum SI of 7.3 was observed, meaning that the average footprint area for these aggregates is projected to increase~~ncreased~~ in size by 730\%. This indicates an extreme level of aggregate disintegration, although it remains below the maximum theoretical SI of 7.8 suggested by \cite{mario}. Organic C had an observed range of 0.33 to 2.97\% and a median value of 0.88\%, demonstrating that many of the sampled locations had low levels of OC. Other measured soil properties ranged widely, demonstrating the diversity of soils sampled, e.g. clay ranged from 2.5 to 60.2\% and pH ranged from 4.8 to 9.2.

\begin{table}[h]
\caption{Summary statistics of slaking index and laboratory derived soil properties.}
\begin{tabular}{lcccccc}
\tophline
Property & Min. & 1st Qu. & Median & Mean & 3rd Qu. & Max. \\
\middlehline
Slaking index & 0.0 & 0.4 & 2.6 & 2.7 & 4.8 & 7.3 \\
Organic carbon (\%) & 0.33 & 0.74 & 0.88 & 1.07 & 1.22 & 2.97 \\
Clay (\%) & 2.5 & 11.1 & 29.1 & 28.1 & 42.1 & 60.2 \\
pH(1:5 H\textsubscript{2}0) & 4.8 & 6.0 & 6.8 & 7.0 & 8.3 & 9.2 \\
EC (dS m^{-1}) & 0.01 & 0.04 & 0.12 & 0.15 & 0.19 & 0.81 \\
Exch. Ca^{+2} (cmol\textsubscript{c} kg^{-1}) & 0.0 & 1.7 & 10.5 & 11.3 & 19.8 & 34.0 \\
Exch. Mg^{+2} (cmol\textsubscript{c} kg^{-1}) & 0.0 & 0.7 & 5.1 & 6.0 & 11.0 & 17.0 \\
Exch. K^{+} (cmol\textsubscript{c} kg^{-1}) & 0.1 & 0.4 & 0.8 & 0.9 & 1.4 & 2.2 \\
Exch. Na^{+} (cmol\textsubscript{c} kg^{-1}) & 0.0 & 0.0 & 0.2 & 0.5 & 0.6 & 3.6 \\
CEC (cmol\textsubscript{c} kg^{-1}) & 0.2 & 2.8 & 15.6 & 18.8 & 32.8 & 52.8 \\
ESP (\%) & 0.2 & 1.0 & 1.8 & 2.9 & 3.6 & 19.4 \\
Ca:Mg ratio & 0.1 & 1.5 & 1.9 & 2.2 & 2.5 & 10.8 \\
CEC:clay ratio & 0.01 & 0.08 & 0.44 & 0.43 & 0.70 & 1.09 \\
\bottomhline
\end{tabular}
\label{table:lab_data}
\end{table}

Slaking index ~~(SI)~~ was positively correlated with clay content (r = 0.84), pH (r = 0.70), electrical conductivity (r = 0.44), CEC (r = 0.87), CEC:clay ratio (r = 0.84) and all

```
exchangeable cations (Table \ref{table:lab_cor}). Weak negative correlations were observed for SI with OC (r = -0.31) and Ca:Mg (r = -0.26). These observations support \cite{mario} findings that SI was positively correlated with pH, clay content and exchangeable Na\textsuperscript{+} and Mg\textsuperscript{+2}, and negatively correlated with Ca:Mg. The strongest correlation with SI in this study was observed with exchangeable Mg\textsuperscript{+2} (r = 0.90). This is in contrast to a recent study that demonstrated exchangeable Mg\textsuperscript{+2} played a negligible role in flocculation of soil particles and aggregate stability \citep{ZHU2019422}. It is believed that the observed correlation in our study is due to the dependence of exchangeable Mg\textsuperscript{+2} on clay content, CEC and shrink-swell minerals, such as smectite, rather than a direct causal effect. Clay content was a strong indicator of SI potential. Only one sample with clay content <25\% had an observed SI greater than 1, in contrast only three samples with clay content $\geq{25\%}$ had an observed SI less than 1. Clay soils are often more susceptible to slaking as they have both a higher concentration of shrink-swell minerals and also a greater concentration of smaller pores that may trap and compress air bubbles \citep{emerson64}. The majority of clay soils had a high~~high~~ CEC:clay ratio~~s observed in these samples and correlation with clay content~~ indicating~~e~~ that the dominant phyllosilicate in many of the clay soils studied is smectite. No correlation was observed between SI and ESP in our study. \cite{churchman} reviewed causes of swelling and dispersion in Australian soils and identified that exchangeable Na\textsuperscript{+} increased swelling, but only for high ESP values. Most of the samples in our study had low ESP values, which explains the lack of correlation with SI values. The low ESP values resulted in minimal dispersion observed in these samples, which was beneficial for this study as the SLAKES application currently cannot distinguish between slaking and dispersion \citep{mario}.

\begin{table}[h]
\caption{Pearson correlation coefficient (r) between soil properties.}
\begin{tabular}{lcccccccccc}
OC         & -0.31 &       &          &       &          &          &         &          &       &        &        \\
Clay       & \textbf{0.84}  & -0.13 &          &       &          &          &         &       &        &        &       \\
pH         & \textbf{0.70}  & -0.20 & \textbf{0.85}    &       &          &          &         &          &        &        &        \\
EC         & \textbf{0.44}  & 0.07  & \textbf{0.58}    & \textbf{0.47}  &          &          &       &        &        &        &        \\
Exch. Ca   & \textbf{0.83}  & -0.15 & \textbf{0.84}    & \textbf{0.83}  & \textbf{0.45}     &          &        &          &       &       &        &       \\
Exch. Mg   & \textbf{0.90}  & -0.22 & \textbf{0.85}    & \textbf{0.74}  & \textbf{0.45}     & \textbf{0.92}     &        &          &       &       &       &       \\
Exch. K    & \textbf{0.59}  & 0.19  & \textbf{0.65}    & \textbf{0.60}  & \textbf{0.63}     & \textbf{0.67}     & \textbf{0.65}    &          &       &       &       \\
Exch. Na   & \textbf{0.64}  & -0.25 & \textbf{0.68}    & \textbf{0.65}  & \textbf{0.63}     & \textbf{0.60}     & \textbf{0.65}    & \textbf{0.52}     &       &       &       &        \\
CEC        & \textbf{0.87}  & -0.17 & \textbf{0.87}    & \textbf{0.82}  & \textbf{0.49}     & \textbf{0.99}     & \textbf{0.97}    & \textbf{0.70}     & \textbf{0.66}  &       &       &       \\
ESP        & 0.01  & 0.04  & 0.01     & -0.10 & 0.16     & -0.09    & -0.04   & -0.10    & \textbf{0.40}  & -0.06 &       &       \\
```

```
Ca:Mg       & -0.26 & 0.22  & -0.20   & -0.04 & -0.07    & -0.10    & -0.27   & -0.04    &
    -0.18 & -0.16 & -0.24 &       \\
CEC:clay   & \textbf{0.84}  & -0.21 & \textbf{0.74}    & \textbf{0.72}  & \textbf{0.38}
    & \textbf{0.94}     & \textbf{0.91}    & \textbf{0.62}     & \textbf{0.53}  &
    \textbf{0.94}  & -0.14 & -0.16 \\
           & SI    & OC    & Clay    & pH    & EC        & Exch. Ca & Exch. Mg & Exch. K &
           Exch. Na & CEC   & ESP & Ca:Mg \\
\end{tabular}
\belowtable{Bold font indicates significance at p < 0.05. SI, slaking index; OC, organic
    carbon; pH, pH(1:5 H\textsubscript{2}O); EC, electrical conductivity (1:5
    H\textsubscript{2}O); CEC, cation exchange capacity; ESP, exchangeable sodium
    percentage; Ca:Mg, ratio of exchangeable Ca\textsuperscript{+2} to Mg\textsuperscript{
    +2}; CEC:clay, ratio of organic matter corrected CEC to clay content.}
\label{table:lab_cor}
\end{table}

\subsubsection{Slaking index and land use}
Land use at sampling sites was~~ere~~ categorised into four classes: forest, predominately
    remnant vegetation cover on sand hills; pasture, encompassing improved/unimproved
    pastures but also stock routes and other areas of perennial grass cover; dryland
    cropping; and irrigated cropping. Clear differences in SI values were observed under
    these different land uses, which were accentuated after separating based on clay
    content (Fig. \ref{fig:landuseVsSI}). For samples with clay content $\geq{25\%}$,
    irrigated cropping had the highest SI values, followed by dryland cropping (which
    showed a large range of SI values), and then pasture. No samples with clay content
    $\geq{25\%}$ were observed under forest cover, nor soils with clay content <25\% under
    irrigated cropping. These findings are supported by the few existing studies
    investigating SI values of aggregates under cultivated sites compared to paired sites
    under natural vegetation \citep{mario, flynn}. Decreased aggregate stability of soils
    under cropping compared to pasture or natural vegetation has also been observed by
    other indicators of aggregate stability, such as mean weight diameter and water stable
    aggregates \citep{saygin,YE201871}. The marked differences in soil aggregate stability
    between land uses may be attributable to the impact of cultivation on the soil - both
    the direct destruction of aggregates through cultivation and associated increase in
    soil respiration and loss of OC. ~~In a review of ~~The natural disposition of these soils
    to slake is evident with an average SI of 2.8 observed for soils with $\geq{25\%}$ clay
    content under perennial ground cover in the pasture land use. This natural disposition
    had been significantly exacerbated by cultivation with an average SI value of 4.8
    observed for sites under dryland cropping, and 5.0 for sites under irrigation.~~-~~ The
    difference in mean SI value between irrigated and pasture land uses for clay soils was
    not found to be significant at the 95\% confidence level (p=0.07) but given the large
    difference in means this is assumed to be due to the small number of observations for
    the irrigated clay soils (n=5). The higher level of slaking under irrigation may be due
    to the fact that irrigated cropping represents a further level of cultivation
    intensification compared to dryland sites and sampled irrigated sites also only
    occurred on soils with clay content >50\%. For those sites with clay content <25\% SI
    values were predominately <1. Differences between land use were ~~not as distinct ~~not
    significant for these low clay content soils although increases in mean values were
    observed from forest to pasture and then dryland agriculture. A wide range of SI values
    was observed for samples with $\geq{25\%}$ clay content, warranting further
    investigation.
```

```latex
\begin{figure}[h]
\includegraphics[width=8.312cm]{fig02.PNG}
\caption{Boxplots of slaking index grouped by land use (forest, pasture, dryland cropping
    or irrigated cropping) and clay content (<25\% or $\geq{25\%}$) for the training set.
    Significant differences between means (p<0.05) of each class calculated using Tukey's
    Honest Significant Difference test are indicated by a lowercase letter above each plot.
    The number of observations for each class are indicated in brackets below each plot.}
\label{fig:landuseVsSI}
\end{figure}

\subsubsection{Effect of organic carbon on slaking index}
Organic C has been shown to increase soil aggregation and decrease susceptibility to
    slaking \citep{six2000soil}. \cite{chenu2000organic} found OC to be a good predictor of
    soil aggregate stability (R\textsuperscript{2} = 0.72) when investigating the effects
    of tillage management on humic loamy soils in southwest France. The diverse range of
    soils used in this study are assumed to have confounded this relationship as only a
    weak negative correlation (r = -0.31) between SI and OC was observed while much
    stronger correlations were observed for other soil properties such as clay content or
    CEC:clay ratio (Table \ref{table:lab_cor}). To investigate these correlations further,
    the relationship between clay content, CEC:clay ratio and SI was visualised (Fig.
    \ref{fig:clay_ratio}). CEC:clay ratio was chosen as an important parameter as it is a
    useful indicator of clay mineral type which affects slaking through contribution to the
    shrink-swell characteristics of a soil. A correlation between clay content and CEC:clay
    ratio was observed (Table \ref{table:lab_cor}). This relationship was related to
    landscape position in the study area, as high clay content soils found on floodplain
    areas also contained a higher proportion of shrink-swell clay minerals, such as
    smectite. Meanwhile, topsoil samples from the hills and slopes had lower clay content
    and also a lower CEC:clay ratio, indicating the dominance of low CEC phyllosilicates,
    such as kaolinite or illite. As identified previously, samples with clay content <25\%
    showed minimal slaking. For samples with a clay content $\geq{25\%}$, CEC:clay ratio
    was an important predictor of slaking. For example, soils with a clay content
    \textasciitilde40\% showed low to moderate slaking for CEC:clay ratio <0.5 and moderate
    to extreme levels of slaking for CEC:clay ratio >0.5 (Fig. \ref{fig:clay_ratio}). Clear
    threshold values were observed with extreme slaking values only occurring for soils
    clay content $\geq{25\%}$ and CEC:clay ratio >0.5. This observation was used to
    allocate samples into two classes: samples with clay content $\geq{25\%}$ and CEC:clay
    ratio >0.5; and all remaining samples. Relationships between measured soil properties
    and observed SI values were modelled independently for each class as different critical
    values were expected to control behaviour of different soil classes \citep{loveland}.

\begin{figure}[h]
\includegraphics[width=8.39.9cm]{fig03.PNG}
\caption{Relationship between clay content, CEC:clay ratio and slaking index (SI). Land use
    at sample site is indicated as either forest, pasture, dryland cropping or irrigated
    cropping. Dashed lines indicate clay content of 25\% and CEC:clay ratio of 0.5 above
    which extreme slaking was observed.}
\label{fig:clay_ratio}
\end{figure}

Soil organic carbon was the only significant predictor of SI for soils with clay content
    $\geq{25\%}$ and CEC:clay ratio >0.5. The relationship between SI and OC fit a
    segmented, exponential decay function (Fig. \ref{fig:si_oc}). This equation was
    developed by optimising a four parameter nonlinear regression model to minimise
    residual sum of squares using the \emph{nls} functions from the \emph{nlstools} R
    package \citep{nlstools}. The model contained: a constant value that characterised SI
```

behaviour under low OC levels; a threshold value above which the relationship was characterised by exponential decay; and two parameters that characterised exponential decay behaviour at high OC levels. A threshold value of 1.1\% OC was identified. The average observed SI values for samples below this threshold was 5.01~~ - the highest observed SI values in this study~~. Extreme SI values were uniquely observed for samples with OC content under this threshold value. As the constant value indicates, no relationship between OC and SI was identified for these samples, nor could a relationship be developed between SI and other measured soil properties~~ be identified~~. As such the factors responsible for the large range in observed SI values for these soils remains unidentified. To identify causal factors future research should investigate potential relationships between SI and OC fractions, OC type, microbial activity or crop species that have been previously~~ been~~ identified as influencing aggregate stability \citep{six2,morel,six3}. The 1.1\% threshold value also effectively separated observed differences in OC content between pasture and cropping land use activities. Interestingly, pasture sites with \textasciitilde{1.0\%} OC had lower observed SI values than corresponding dryland agriculture sites indicating that direct effects of cultivation, extended fallow or monoculture production may influence observed SI values although the number of samples is too few for statistical analysis. Similar critical OC content values ranging from 1.1 to 2\% have been identified when considering a soil's ability to provide nutrients for crop growth, or support microbial diversity \citep{aune1997agricultural,Zvomuya,yan2000functional}. For this study the 1 .1\% OC value should not be interpreted as a target value for farm managers to achieve but rather it describes an absolute minimum threshold below which slaking is unpredictable and can result in extreme values. To abate potentially detrimental effects of slaking farm managers should aim to increase OC levels above this minimum threshold. The exponential decay component of the equation provided a weak fit to the available data (R^{2} = 0.27). The function suggests that slaking can be reduced, but not completely eliminated, by increasing OC content for the range of OC contents observed in this study. The constant parameter of 2.76 in the exponential decay function suggests a minimum obtainable SI value for these soils, however this model was based on few observations and limited samples of >2\% OC. Future investigation should prioritise identification of sites with higher OC content to better characterise this relationship.

The relationship between SI and OC for those soils that did not meet the criteria of \$\geq{25\%}\$ clay content and CEC:clay ratio >0.5 were modelled separately using multiple-linear regression. For these soils, SI was explained with the following equation: \emph{SI} = -0.22 - 0.19\$\times{OC}\$~~*OC~~ + 0.09\$\times{clay}\$~~*clay~~ (R^{2}= 0.77, RMSE = 0.7, p = 0.000). This regression equation indicates~~sult demonstrates~~ that while OC content still had a significant effect on observed SI values, the magnitude of the effect is lesser~~relative effect was smaller~~ for these soils. For example, soils with clay content \$\geq{25\%}\$ and CEC:clay ratio >0.5 are expected to see a reduction in SI of 1.59 units if OC is increased from 0.7\% to 1.7\%, meanwhile if OC is increased from 0.7\% to 1.7\% in other soils a decrease in SI of only 0.19 is expected to occur. These two equations were used to model the effect on SI of~~ a~~ simulated 0.5\% and 1.0\% increases in OC at the sample sites, which were~~as~~ then mapped across the study area. The results of the~~i~~se analyses are shown in Section 3.2.4.

\begin{figure}[t]
\includegraphics[width=8.3~~12~~cm]{fig04.PNG}
\caption{Relationship between slaking index (SI) and organic carbon (OC) for soil samples

with clay content $\geq{25\%}$ and CEC:clay ratio >0.5. A segmented, exponential decay function containing a lag phase and threshold value of 1.1\% OC was fit to the observed data points. Land use at each observation point is indicated.}
\label{fig:si_oc}
\end{figure}

\subsection{Mapping results}
\subsubsection{Importance of predictor variables}
Investigation of the use of covariates as conditions and predictors in the Cubist model showed that MrVBF and the NDVI 5th, 50th and 95th percentiles were the most important predictor variables of SI values. The NDVI data used in this study largely represent variation in vegetation cover, and hence land use. The 5th percentile NDVI was used as both a condition and a predictor in the model. The 5th percentile NDVI represents the lower distribution of vegetation over the 2000-2018 period with low values indicating cultivated sites \citep{ndvi_crop}, and variation within cultivated sites representing topsoil variability. Low values of 5th percentile NDVI indicate areas of bare-earth from cultivation or extended fallow, facilitating the identification of cropping sites. For cropping sites, the 5th, 50th, and 95th percentile values would be vastly different due to the seasonal nature of cropping. This would be similar in the pastures due to seasonal 'browning off' of~~in~~ the perennial grass cover. In contrast, the different NDVI percentiles for forest cover would be high and relatively similar due to the more constant biomass throughout different seasons. The importance of NDVI percentiles in the model, and known relationships with land use support previous findings that land use has a considerable influence on observed SI values (Fig. \ref{fig:landuseVsSI}). The importance of MrVBF may be attributed to the information it contains on landscape position, which is related to clay content and CEC:clay ratio \citep{mrvbf}. The lowest MrVBF values were found on the sand hills, increasing through a transition zone to the upper floodplain. The highest MrVBF values were found on the lower floodplain, which also corresponded to the highest clay content in the study area . Slope and gamma radiometric potassium data were used as predictors in the model~~for some models~~. The important predictors in the model reflect those used by \cite{YE201871} to map aggregate stability in a small catchment of the Loess Plateau which the authors found was explained by intrinsic factors (parent material, terrain attributes and soil type) and extrinsic factors (land use and farming practice). The covariates that were the least important predictors included elevation, MrRTF and aspect.

\subsubsection{Mapping accuracy}
The quality of the predictions of SI from the regression-kriging approach was assessed using two validation techniques. The first technique involved using LOOCV on the training dataset (n = 108). This method showed that SI could be predicted to a relatively high degree of accuracy, with an LCCC of 0.85, R^{2} of 0.75, RMSE of 1.1 and a bias of 0.0 (Fig. \ref{fig:goof}). The second approach involved comparing SI values observed for an independent test set (n = 50) with SI values extracted from the final map product. The second approach demonstrated the robustness of the model, as SI was predicted with similar accuracy to that of the training set, with an LCCC of 0.82, R^{2} of 0.78, RMSE of 1.1 and a bias of 0.6 (Fig. \ref{fig:goof}). This demonstrates that SI can be accurately spatially predicted when using DSM techniques and ancillary spatial information. The successful prediction of SI

can be attributed to availability of ancillary spatial information that explain the main factors controlling slaking, such as the different NDVI percentiles representing land cover and use, and MrVBF representing clay content and the accumulation of water /soil. While there are no other published studies to our knowledge that have modelled and mapped SI across a study area, these validation statistics are comparable to other DSM studies that have modelled other aspects of soil stability such as \cite{ANNABI2017157} who modelled aggregate stability using three different indices in a study region in Tunisia, with an accuracy of 0.62 to 0.74 R^{2} when tested with LOOCV.

\begin{figure}[H]
\centering
\includegraphics[width=8.3cm]{fig05.PNG}
\caption{Plot of observed and predicted slaking index (SI) values from regression-kriging for two validation methods: (1) leave-one-out cross validation (LOOCV) on the training set (n = 108), and (2) external validation on an independent test set (n = 50).}
\label{fig:goof}
\end{figure}

\subsubsection{Spatial variability of slaking index}
The map of soil SI across the study area shows considerable variation (Fig. \ref{fig:SImap}). The model was very effective at mapping high clay content soils that had a natural tendency to slake and also at identifying tillage practices that exacerbated this effect. It is clear that SI values were higher on arable areas, particularly on the cropped fields at L'lara, as well as the dryland and irrigated cropping areas lower down the floodplain to the south-west of L'lara. The forested areas showed the lowest SI values in the study area. The spatial patterns of the maps are clearly driven by vegetation cover/land use, and MrVBF, as indicated by the variables used as conditions and predictors in the Cubist model. The unique features~~patterns~~ of MrVBF can be seen, as low SI values are found where deposition would be low, whereas high SI values are found where deposition is~~would~~ expected to be high. The NDVI 5th percentile covariate provides a good indication of whether a field has undergone tillage or been left in a bare fallow but provides no insight into the frequency, timing or intensity of tillage events. An aspect for further improvement to this approach would be to include a more sensitive method able to characterise the frequency of tillage events or quantify the amount of time left under bare fallow.

\begin{figure}[H]
\centering
\includegraphics[width=12cm]{fig06.PNG}
\caption{Prediction of slaking index (SI) across the study area using regression-kriging. Slaking index (~~The boundaries of L'lara farm are indicated as well as~~ SI) values at observation sites for the training set (n = 108) and test set (n = 50) are provided. The external perimeter boundary of L'lara is indicated by the thick black line and boundaries of cropping paddocks are indicated by thin black lines.}
\label{fig:SImap}
\end{figure}

\subsubsection{Mapping~~apping change~~ ~~in~~ slaking index after modelled~~for a 1\%~~ increase in organic carbon}
The impact of increasing soil OC levels by 0.5\% and 1.0\% on SI values was assessed and mapped across the study area (Fig. \ref{fig:SI change}). When tested with LOOCV, the

mapping procedure used for the simulated 0.5\% increase in OC scenario was found to have an LCCC of 0.94, R^{2} of 0.90, RMSE of 0.6 and a bias of -0.1, and the simulated 1.0\% increase in OC scenario had~~resulting simulated SI values could be predicted accurately, with~~ an LCCC of 0.95, R^{2} of 0.92, RMSE of 0.4 and a bias of 0.0. The validation metrics for the~~a~~ simulated 0.5\% and 1.0\% increases in OC were better than those~~ under~~ derived from modelling under current conditions. This may be attributed to the simulated map showing a bimodal distribution of SI values , with approximately half of the study area predicted to~~ be~~ have SI values of \textasciitilde{}0, and the other half predicted to have SI values of \textasciitilde{}3 under the 1.0\% increase in OC scenario. The reason for this is likely due to SI values returning to their natural, or expected values, that are primarily driven by clay content and clay type as opposed to land use and management. Another contributing factor for the improved validation metrics under increased OC scenarios is due to the SI values being based on modelled data from which unexplained error has been removed. Future efforts should account for the error of the underlying regression equations and quantify the uncertainty of the resultant maps by bootstrapping and applying random error based on the the prediction variance of the underlying regression equations. The change maps show~~s~~ the difference between the current observed SI values, and the simulated SI under increased OC content scenarios~~with an increase of 1\% OC~~. These~~is~~ map reveals a much larger expected decrease in SI values for the 1.0\% increase in OC scenario and that the~~that the~~ largest decreases in SI values were predicted to occur on dryland and irrigated cropping areas on L'lara and surrounds. Some of these areas were predicted to have their SI value decreased by up to 3 units. Much of the forested and pasture areas with lower current SI values were predicted to have their SI value largely unchanged even by a 1.0\% increase in OC content. The produced maps~~results of this analysis~~ highlight areas~~clearly show the benefit~~ ~~of~~that are expected to have~~ increasing soil OC on SI and aggregate stability~~ lower SI when OC levels are increased. This could encourage farmers and land managers to implement management practices that increase soil OC levels in cultivated areas, such as minimal tillage and cover cropping.

\begin{figure}[H]
\centering
\includegraphics[width=12~~7~~cm]{fig07.PNG}
\caption{Prediction of slaking index~~ (SI)~~ across the study area using regression-kriging after~~ a~~ modelled~~ 1\%~~ increases in organic carbon: a) slaking index after a modelled 0.5\% increase in organic carbon; change in slaking index after a modelled 0.5\% increase in organic carbon; c) slaking index after a modelled 1.0\% increase in organic carbon; change in slaking index after a modelled 1.0\% increase in organic carbon~~ (left), and change in SI compared to current conditions (right)~~. The external perimeter boundary~~ies~~ of L'lara is indicated by the thick black line and boundaries of cropping paddocks are indicated by thin black lines.~~form are indicated~~}
\label{fig:SI_change}
\end{figure}

\conclusions %% \conclusions[modified heading if necessary]
Soil slaking index (SI) values were obtained through the use of the SLAKES smartphone application across a mixed farming landscape to assess aggregate stability of the topsoil in a mixed agricultural landscape. Land use had a clear impact on SI values, with sites under irrigated and dryland cropping showing higher SI values than those under pasture and forested areas. Clay content, CEC:clay ratio and organic carbon

content had a considerable impact on SI values of soil samples. Samples with low OC and high clay content combined with high CEC:clay ratio were the most prone to slaking. An OC threshold of 1.1\% was observed, below which slaking behaviour was not correlated with any of the measured soil properties and the most extreme SI values were observed. A regression-kriging approach utilising a Cubist model and diverse spatial covariates proved to be successful in spatially modelling SI values. The model had high predictive power, with an LCCC of 0.85 and RMSE of 1.1, when using a LOOCV approach on the training dataset (n = 108). The results were also of high quality when assessed using an independent test set (n = 50), with an LCCC of 0.82 and RMSE of 1.1. The decrease in SI expected from ~~a~~ a 0.5\% and 1.0\% increase in OC content was also simulated and mapped across the study area. The results of these~~is~~ simulations suggested that considerable improvements in SI and soil aggregate stability could be achieved if practices that promote the sequestration of OC were implemented, particularly on cultivated areas. Overall, this study demonstrated that novel approaches to cheaply and rapidly assess the aggregate stability of soil samples could be combined with DSM approaches to create accurate, fine-resolution maps of aggregate stability. These maps have the potential to guide management decisions, whether that be to determine land use and management, such as avoiding cultivation/cropping in areas that are prone to slaking, or to increase OC in areas of extreme slaking through the use of minimum tillage or cover -cropping.

\authorcontribution{
EJ, PF and AM designed the experiment and the data analysis method. EJ, PF, RW and VP performed the field sampling campaigns. RW and MF collected the slaking index data. EJ and PF analysed the data. EJ prepared the paper with contribution from all co-authors.
} %% this section is mandatory

\competinginterests{The authors declare they have no competing interests.} %% this section is mandatory even if you declare that no competing interests are present

\begin{acknowledgements}
The authors would like to thank the Grains Research and Development Corporation (GRDC) and the Australian Government's National Landcare Program for ~~partly~~ funding this research. The authors would also like to thank Ms Blandine Lemercier and A/prof. Sébastien Salvador-Blanes for their review and valuable suggestions to improve the manuscript, and~~We would also like to acknowledge the contributions of~~ Ms Alessandra Calegari, Ms Vita Ayu Kusuma Dewi, Ms Zhiwei (Vera) Wang, Mr Bradley Ginns, Ms Hannah Lowe and Ms Victoria Pauly for their assistance~~assisting~~ in gathering~~-~~ and analysing ~~the~~ soil samples~~data~~.
\end{acknowledgements}

%% REFERENCES

\bibliographystyle{copernicus}
\bibliography{example.bib}

%%

Author's response to RC1

Specific comments

Line 22: Development of simple accessible metrics to assess soil health facilitate spatial and temporal sampling density but should also support the implication of farmers, consultants and even citizen in soil health assessment.

Sentence has been reworded to incorporate suggestions.

Line 28-29: The degree of slaking determines if the process produces a favourable or unfavourable environment for cultivation and plant growth. It is true but not sufficient. It also determines the degree of soil conservation because the aim is to cultivate but likewise to protect this resource.

Added "and has implications for soil conservation."

Line 45: The authors focus on agricultural practices that increase soil susceptibility to slaking, but what about practices limiting susceptibility to slaking? Carbon management, crop successions, superficial or "light" tillage. . .

Added "Techniques that increase soil organic matter such as cover-cropping, reduced tillage and application of organic amendments may reduce susceptibility to slaking"

Line 59: Another group of widely used method to estimate aggregate stability (that is the contrary of slaking) is the Mean Weight Diameter (MWD) after wet sieving of soil aggregates. You should mention this reference method.

Added "Established methods to quantify stability of aggregates subject to wet-sieving (Yoder, 1936) or simulated rainfall (Schindelbeck et al., 2016) are also time-consuming and require specialist equipment."

Line 93-95: Please, provide the equivalent of soil references according to the World Base Reference for soil classification.

Australian Soil Classification has been removed and text changed to: The soils of the floodplain area at L'lara are classified as Vertisols according to the World Reference Base for Soil Resources, with some expression of calcic horizons (IUSS Working Group WRB, 2015). The sand hill area is represented by Luvisol, Lixisol, Solonetz, Leptosol and Regosol soil groups.

Line 96: Please define "broadacre".

The term ‘broadacre’ has been removed to prevent any ambiguity as the term has limited use outside of Australia. The remaining sentence still conveys the same meaning.

Line 96: Is L’Iara covered with a soil map? If yes it and if it is relevant, it could interesting to add this map (near figure 1 for instance). It not, a land use map could also be helpful to interpret figures 6 and 7.

A soil type map was produced but unfortunately only covers L’lara and it is in the Australian Soil Classification and we have been requested to use WRB. MrVBF, NDVI and land use maps have been added to Figure 1. The MrVBF map gives a good indication of the distribution of Vertisols versus other soil with a sandy topsoil.

Line 111: “in the area surrounding L’Iara, an additional 50 samples. . .” or “50 additional samples”?

Text has been modified at request of RC2.

Line 108-119: Sampling scheme: collection of datasets with various sampling approach. I guess they came from various field campaigns and programmes. What are the dates for each one? A summary of the distribution of land use at the observation points is missing. It could be a table or a sentence in the text.

Text has been modified for clarity and a table added summarising the sampling dates and number of observations for each land use for each campaign.

Line 121: What was the size of the 20 to 30 aggregates? I suppose that it was for each soil sample. Please mention that.

Target diameter of “(ø 5-10 mm)” given in text.

Line 130-132: These 2 sentence could be move to the 2.3 section and replace the 2 first sentences of this section. I suggest renaming this 2.3 section: “soil sample preparation and laboratory methods” (or something like that).

Lines 130-132 moved to section 2.3 and section 2.3 renamed “Sample preparation and laboratory methods”. Note number of samples changed to “12 to 15” at the request of RC2.

Line 141: ‘10 minutes’

Existing grammar is correct, suggestion not incorporated.

Line 145: It the difference between replicates was more than one, only the unique additional reading was considered for the final result of SI? And what would happen if this additional reading was an outlier one? How many times a third observation was necessary?

Modified text: "An additional reading was required for approximately 20\% of samples and was more commonly required for soils with higher slaking index values compared to samples which exhibited minimal slaking. When additional readings were taken the outlier reading was discarded and remaining readings averaged to provide the final SI for each sample."

When an additional reading was taken it was always within one unit of one of the original duplicates. The additional sample and the duplicate within one unit were then averaged to give the final slaking index value and the other duplicate was treated as an outlier and not used in the calculation.

Line 160: Please name other approaches.

Text has been modified "unlike the ASWAT test that requires 2 hours of immersion."

Line 174: All terrain attributes are not at the same spatial resolution. Slope, aspect, MrVBF and MrRTF could have been obtained from the 5m DEM since it was available.

The 5 m photogrammetry DEM provides the most accurate point estimate of elevation but it is not hydrologically enforced and for this reason we prefer to use the elevation derivatives calculated from the 30 m SRTM DEM.

Added "and gives an accurate point estimate of elevation though it is not hydrologically enforced".

Line 178: Why potassium concentration is of particular interest?

Added "Variation in the concentrations of the radioelements are indicative of change in soil type or parent material".

Line 184: How was made the split between training and test datasets?

Text has been updated in section 2.2. to clarify this.

Line 190: "The kriged residuals was were added. . .". There is non information in the text about the variogram of the residuals? Were residuals spatially structured?

Added information about kriging of the residuals: "The residuals (difference between the observed and predicted SI values) at observation points showed a weak spatial autocorrelation. A Gaussian function fit to the empirical semivariogram had a relatively large nugget of 0.81, sill of 1.11 and a range of 1.92 km."

Line 196: The first sentence is not clear. Please reword. You could also rephrase the second sentence. Line 198: Observation points are allocated into classes having similar behaviour. How many classes? How the choice of classes and allocations of observations was done?

Start of paragraph reworded "Relationships between SI and measured soil properties were explored to identify potential contributing factors as a means to inform management practices to reduce excessive slaking. Two classes of soils were evident in the samples, soils with clay content ≥25% and CEC:clay ratio≥0.5 which consistently exhibited excessive slaking, and other soils.

Table 2: It would be relevant to distinguish training and test datasets to confirm that they cover a similar range of soil attributes values, especially because of the difference in location between the 2 datasets: training data only located within L'Iara boundaries.

As indicated in Figure 1 the test set is located entirely within L'lara and is inter-mixed with samples from the training set. In this instance I don't believe it is necessary to confirm that the samples occupy the same covariate space.

Line 225: ". . .in these samples. . ." which ones? With clay content >25%?

Text modified "The majority of clay soils had a high CEC:clay ratio indicating that the dominant phyllosilicate in the clay soils studied is smectite."

Figure 2: It would be useful to know the number of samples in each of the classes land use/clay by adding this information in the figure. What about statistical significance of the differences between classes?

The number of observations for each class and significant differences ($p<0.05$) between means calculated using Tukey's HSD have been added to the plot and discussed in the text.

Line 267: I guess "3)" has to be suppressed.

"3)" was an incomplete reference to "(Fig. 3)". Corrected in text.

Line 301: The scenario of an increase of SOC by 1% conduces to predict a reduction of SI of 1.59 units for soils with clay content >25% and CEC:clay ration >0.5 according to the decay function. Values of SI depending on OC are widely dispersed around the model (figure 4). Nevertheless, the map of change in SI after increase of C is based on this weak model. I suggest the authors to be more cautious in their conclusions concerning the effect of OC change on SI. Some elements of discussion about uncertainty are expected.

Added – “provided a weak fit to the available data”

Additional discussion points added to section 3.2.4 - “Another contributing factor for the improved validation metrics under increased OC scenarios is due to the SI values being based on modelled data which has had all unexplained error removed. Future efforts should account for the error of the underlying regression equations and quantify the uncertainty of the resultant maps by bootstrapping and applying random error based on the the prediction variance of the underlying regression equations.”

Line 321: “. . .for some models”. How many models were run? Please complete the section 2.6.

Changed to “in the model”. A single cubist model was calibrated and LOOCV used for validation.

Line 345: ‘patterns’

Changed to ‘features’

Line 353-354: The accuracy of the mapping process was assessed, but not the real effect of increasing SOC content by 1% because uncertainty of the decay function of SI with SOC (the map was based on) was not estimated. This must be specified to avoid misunderstanding of this result.

Stipulated that the validation metrics refer to the “mapping procedure” and also added “Another contributing factor for the improved validation metrics under increased OC scenarios is due to the SI values being based on modelled data from which unexplained error has been removed.”

The authors would like to thank RC1 for their constructive review, we have also simulated the change in slaking index under a 0.5% increase in OC as suggested.

Author's response to RC2

Abstract :

Line 13 : explain in full words the term LCCC

LCCC explicitly defined as Lin's concordance correlation coefficient

Introduction :

Lines 48-49 : state (if relevant) that an initial low soil water content increases slaking.

Added "and soils of low initial water content more prone to rapid and explosive slaking"

Lines 76-78 : add that in the paper by Annabi et al., 2017 the method used to measure soil aggregate stability is the normalized method(ISO/DIS 10930, 2012), which is time and cost consuming, which is not the case of the SLAKES approach.

Added "Tools that make aggregate stability quantification accessible, such as the SLAKES application, may facilitate the production of such maps." Detractions of wet-sieving and simulated rainfall techniques were added at line 59 at the request of RC1.

Methodology

Lines 93-95 : please refer to the WRB soil classification as the Australian classification is unknown by most of readers.

Australian Soil Classification has been removed and text changed to: The soils of the floodplain area at L'lara are classified as Vertisols according to the World Reference Base for Soil Resources, with some expression of calcic horizons (IUSS Working Group WRB, 2015). The sand hill area is represented by Luvisol, Lixisol, Solonetz, Leptosol and Regosol soil groups.

Lines 93-100 : it would be interesting to present the soil and landuse maps of the study area, as they are primary drivers of soil aggregate stability. These maps would be very useful to help the reader interpret the SI maps you present later in the paper. These data are moreover used for soil sampling as input parameters.

A soil type map was produced but unfortunately only covers L'lara and it is in the Australian Soil Classification and we have been requested to use WRB. MrVBF, NDVI and land use maps have been added to Figure 1. The MrVBF map gives a good indication of the distribution of Vertisols versus other soil with a sandy topsoil.

Lines 108-119 : the reading of this paragraph is not straightforward, as the sampling strategy is quite complex. I think the 108 samples described lines 108 to 116 should be introduced by a short sentence line 108, such as for example : "A training set of 108 samples and a test set of 50 samples were defined. The training set comprises 58 on- and 50 off-farm samples."

Text has been modified for clarity.

Lines 112-113 : why are the input parameters for the sampling strategy different for off-farm samples ? Is it due to the fact that a soil map is not available ? This could be mentioned.

Correct, the soil map was only available on-farm. Text has been adjusted accordingly.

Lines 113-114 : I do not understand on which sampling set the K-means clustering is applied, and for what purpose.

K-means was the stratification method for stratified random sampling to identify off-farm samples. Text has been updated for clarity.

Line 130 : why are 20 to 30 soil aggregates necessary for the slaking test, as only 3 aggregates are necessary for the test, and the test is repeated three times at most ?

Text has been changed to "12 to 15" aggregates. While we did not need to repeat the test more than three times, however the application did crash sometimes and the test could be compromised if a shadow was inadvertently cast over the sample while analysing so it is recommended to have some spare aggregates to run additional tests. Note this has been moved to section 2.3 at the request of RC1.

Lines 144-146 : I think it is important to provide information on the repeatability of the measurements, e.g. to ensure the average value calculated for the SI is representative of the whole sample SI. Indeed, the SI is calculated on 3 aggregates, which could be considered as a low number. It is therefore important that you provide at least a graph with the distribution of the differences in SI values for the 108 samples, including 'outlier readings'. In that respect, and to further explore the representativity of the measured aggregates, it would be interesting to present the values of the 'a' coefficient for each aggregate that is tested.

Modified text: "An additional reading was required for approximately 20\% of samples and was more commonly required for soils with higher slaking index values compared to samples which exhibited minimal slaking. When additional readings were taken the outlier reading was discarded and remaining readings averaged to provide the final SI for each sample."

The graph you mention would be great to have but unfortunately the data was collected by different people over a number of months. Some reported every scan taken including replicates and outliers for each sample, others only the final two replicates used, and others only reported the final averaged value. I will ensure that all scans are recorded and look to include such a graph in future publications, but I am reluctant to publish the incomplete dataset here.

The version of the app used reports the slaking index for each aggregate after the 10 minute analysis time but not the ‘a’ coefficient for each aggregate, this may be introduced in later versions of the app though.

Line 145 : I do not understand what are these 'outlier readings', and on what basis they could be discarded.

When an additional reading was taken it was always within one unit of one of the original duplicates. The additional sample and the duplicate within one unit were then averaged to give the final slaking index value and the other duplicate was treated as an outlier and not used in the calculation.

Line 175 : what is the unit of the aspect ? How did you go around the circular nature of the variable ?

Degrees symbol added to the table. The variable was not found to be a significant predictor when left in degrees or when aspect was investigated as a cardinal direction factor.

Results :

Line 209 : you state that some aggregates "increased in size by 730%". As I understand it, it is not the actual increase that is measured after 10 mn of immersion at the end of the SLAKES experiment, but rather a final aggregate size using the Gompertz function at $t=\infty$.

Correct. Added “is projected to increase”.

Line 210-211 : you mention that all SI values are below the maximum theoretical value of 7.8 suggested by Fajardo et al. (2016). What about the 'outlier readings' you mentioned line 145 ? This should be clarified.

All reasonable results were below this threshold. At times when a shadow was inadvertently cast over the petri dish values of >1,000 were reported but these were discarded.

Line 246 : just to make sure, you mention average SI values, is it an average or a median value ?

It is average value. The value returned from the app is the average of the three aggregates analysed and then we average the value from duplicate tests to achieve the final value.

Line 261 : make reference to Table 2.

Reference to Table 3 added

Lines 302-304 : is there a way to account for the uncertainty due to the (relatively weak) regression applied for the mapping ?

Points added to the discussion – “Another contributing factor for the improved validation metrics under increased OC scenarios is due to the SI values being based on modelled data from which unexplained error has been removed. Future efforts should account for the error of the underlying regression equations and quantify the uncertainty of the resultant maps by bootstrapping and applying random error based on the the prediction variance of the underlying regression equations.”

Lines 340-341 : this assumption is not straightforward, and requires to provide a soil and landuse map.

Land use, MrVBF and NDVI maps have been added to Figure 1 to facilitate interpretation.

Lines 345-346 : the same deals for MrVBF : a MrVBF map would help the reader.

Land use, MrVBF and NDVI maps have been added to Figure 1 to facilitate interpretation.

Lines 362-363 : I do not think the mapping of SI change is the main result that "shows" the benefit of increasing soil OC on SI values. This was shown by the results leading to Figure 4. Here, the mapping allows to precisely locate where there is a real benefit to increase soil OC to increase aggregate stability.

Correct. Sentence changed to “The produced maps highlight areas that are expected to have lower SI when OC levels are increased”.

Figures, tables :

Figure 1 : the black lines (bold and not bold) on the map are not defined in the legend.

Description of lines has been added to the Fig. 1 caption as well as for Figs 6 and 7.

Table 3 : for readability, emphasize in bold characters the correlations that are significant at a given confidence level.

Bold font has been used to indicates correlation with significance at $p < 0.05$ and the table caption updated accordingly.

Minor edits :

Line 200 : "[...] on SI has been investigated"

Amended

Line 240 : "[...] natural vegetation (Fajardo et al., 2016 ; Flynn et al., 2020)."

Amended

Line 244 : remove "In a review of"

Amended

Line 267 : remove "3)"

Amended. This was an incomplete reference to Fig. 3

Line 283 : remove one "been"

Amended

Line 354 : remove"under"

Amended

Line 356 : remove "be"

Amended

Line 381 : "through the use of"

Amended