Development of a soil quality decision support tool to identify and support best management practices

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Abstract
Understanding and managing the effects of soil and crop management practices on soil quality and crop production is essential to maintaining profitable and environmentally sustainable farming enterprises. The Land Management Index (LMI) decision support tool was developed to assist land managers predict the effects of current management practices on soil quality and allows them to run "what if?" scenarios to support future paddock-scale management decisions. To achieve this, a total 14 different indicators of soil quality were measured on >700 paddocks representing the major soils orders and agricultural land uses across seven New Zealand regions. Detailed soil and crop management information (e.g. crop type, sowing/harvest dates, tillage type, irrigation) was also collected for the 10 years proceeding sampling for each paddock. The model was developed by first defining a minimum dataset of critical soil quality indicators and then establishing empirical relationships between these indicators and quantitative measures of the soil and crop management information. These empirical relationships formed the basis of the first generation LMI (ver 1.1) decision support tool that was released for use by farmers and resource managers in June 2009.

Key Words
Crop rotation, tillage, land use, aggregate stability.

Introduction
The soil and crop management practices applied to paddocks can be important determinants of changes in soil quality and the future productivity of agricultural production systems. Knowledge of these effects is important to establishing recommended best management practices and the development of tools that assist farmers and resource managers with on-farm management decisions. The ability to predict changes in soil quality and, by association, future productivity based on historic management information would be useful in undertaking "virtual" monitoring of soil quality changes and identifying real time management solutions to existing soil quality conditions based on modeled future "what-if" scenarios. The aim of this research was to develop and test methods for quantifying the effects of management history on soil quality properties across a wide range of soils and land uses in New Zealand and apply this knowledge to the development of a first generation soil management decision support tool.

Materials and methods
Soil quality and management history data were collected from >700 paddocks between June 2002 and July 2007. Data from a further 37 paddocks was also collected as an independent validation dataset. The paddocks sampled include a range of land uses and intensities (mixed and intensive arable and vegetable cropping, dairy pasture, intensive beef pasture and sheep pasture) and were located across seven New Zealand regions (Auckland, Waikato, Gisborne, Hawke's Bay, Manawatu, Canterbury and Southland). For each paddock, detailed soil and crop management information was collected, including crop types and rotation, sowing and harvest dates, residue management practices, individual tillage passes (e.g. mouldboard plough, harrow, roll), irrigation and fertiliser inputs, for the 10 years prior to soil quality assessment. No two paddocks monitored had exactly the same management over the 10 year history period. Much of the management history information was descriptive by nature and hence needed to be converted to a quantitative form before it could be used to derive coefficients for the LMI model. This was achieved by applying quantitative weightings to the individual tillage implements used to prepare seed beds and the crop types grown. A time weighting was also applied to account for the effects of time over the 10 years preceding each soil quality assessment. The details of these analyses and outcomes are discussed below.

Fourteen different indicators of soil quality were measured on each paddock, covering physical, chemical and biological aspects of soil quality. These included: total C and N (%, t/ha, 0-15 and 15-30 cm), hot-water extractable carbon (HWC)(µg C/g soil, 0-15 cm), C:N ratio (0-15 and 15-30 cm), bulk density (BD)(g/cm^3, 0-15 and 15-30 cm), penetration resistance (PR)(MPa, 0-15 and 15-25 cm), aggregate stability (MWD; mm,

%<1 mm, 0-15cm), aggregate size distribution (MWD mm, 0-7.5 cm), erodible aggregates (%<0.85 mm diameter, 0-7.5cm), large-dense aggregates (%>9.5 mm diameter, 0-7.5 cm), ideal aggregates (%0.85-9.5 mm diameter, 0-7.5 cm), Olsen P (µg /g, 0-15 cm), pH (0-15 cm) and soil texture (0-15 cm). Further supporting information was also collected for each paddock including soil series, soil order, soil texture, and the Land Environments New Zealand (LENZ) Level 1 climate layer descriptors (Leathwick et al, 2003). LENZ Level 1 descriptor is an environmental classification, which groups together those sites with similar environmental conditions). These factors (soil order, texture, LENZ level 1) are referred to here as the site/location factors.

Principal components analysis (PCA) and correlation analyses were applied to the indicator data to define a minimum dataset of critical indicators for use in development of the LMI decision support tool. Our aim was to 1) quantify the contribution of different indicators to explaining variability in the indicator dataset, 2) determine the inter-relatedness of different indicators, and 3) ensure that the indicators selected address a wide range of key soil management issues (e.g. soil organic matter storage, nutrient content, soil structure, soil compaction).

Results and discussion

Selecting a minimum dataset of critical indicators

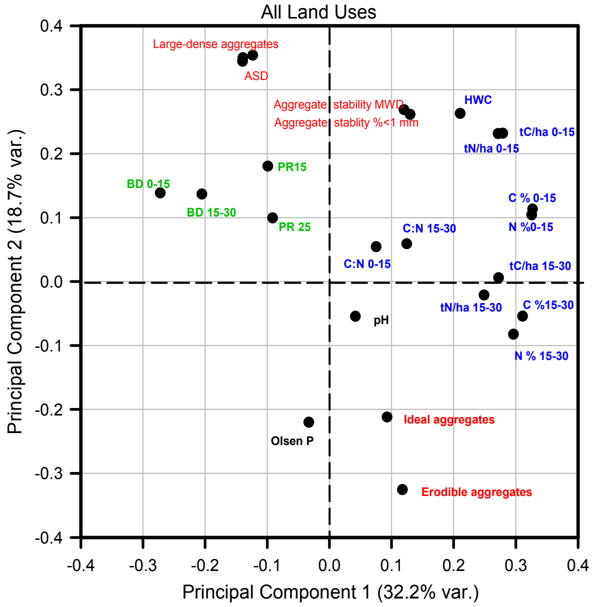
The latent vector loadings produced by the PCA analysis provided a measure of the contribution of each indicator to each PC axis. The aim was to identify indicators that make a relatively large contribution (i.e. have a high [+ or –] latent vector loading) to those principal components that explain a relatively high percentage (e.g. 70% or more) of the variation in the indicator data. Correlation matrices were also used to identify those indicators that are quantitatively related and therefore are likely to provide similar information about the state of the soil. The vector loadings for the first two principal components of the data set are plotted in Figure 1. The indicators with the highest loadings are shown as those points plotted the furthest from the centre point along one or both the PC axes. Just over 50% of the variation in the entire data set was explained by the first two PCs with a further 20% explained by PCs 3 and 4, and a total of 95% explained by the first 10 PCs. The indicators with the highest loadings to PC 1 (32.2% of the variation) were dominated by those that describe soil organic matter (e.g. total C and N % and t/ha, 0-15 and 15-30 cm) but also included biologically active carbon (HWC) and compaction (BD 0-15 and 15-30cm). The positive loadings for soil organic matter indicators and the negative loading for bulk density indicators are consistent with their established inverse relationship, i.e. bulk density tends to decrease with increases in soil organic matter content. The indicators with the highest loadings to PC 2 (18.7% of variation) were dominated by those that describe soil structure (e.g. aggregate size distribution [%] and aggregate stability [MWD, mm]) but also included some indicators of organic matter in the surface soil (e.g. tC/ha 0-15cm), biological activity (e.g. HWC) and chemical fertility (e.g. Olsen P). Most of the soil structure indicators also contributed high loadings to PC 3 (12.1% of variation), as did indicators of compaction (i.e. BD and PR) and chemical fertility (e.g. Olsen P). As a result of these analyses the minimum dataset of critical indicators was defined as; total carbon (t/ha, 0-15 cm), HWC, aggregate stability, erodible aggregates, large-dense aggregates, Olsen P, PR and C:N ratio.

Quantifying soil and crop management information

Tillage is generally accepted to have a neutral to negative effects on soil physical quality. The tillage practice used to establish a seed bed for a given crop is often based on a combination of implements. The LMI management dataset included 47 different tillage implements combined in different ways. We adapted the method used in the US 'Soil Conditioning Index' (National Agronomy Manual 509) developed by the United States Department of Agriculture Natural Resources Conservation Service to convert descriptive data into quantitative data. Each tillage implement was assigned a soil disturbance score based on the degree of disturbance (none, 0, to high, -5) associated with inversion, mixing, lifting, shattering, aeration and compaction (Table 1). The scores for different actions were then summed and multiplied by the proportion of each paddock affected by the implement to give the Soil Disturbance Rating (SDR). Where several tillage implements were used to prepare the soil for sowing a single crop, the SDRs for individual implements were summed to calculate the Total SDR for each crop sown (Table 2).

Crops are generally considered to have a neutral to positive effect on soil physical quality, as they provide the soil with protection against erosion by wind and rain, add organic matter to soil through root turnover, and release root exudates that stimulate biological activity and help to form and stabilize soil aggregates.

However the contribution of different crops to soil quality differs greatly. Hence different crop types were assigned positive weightings based on published literature and expert opinions on crop rooting characteristics, organic matter returns and nitrogen fixation potential (Table 3).



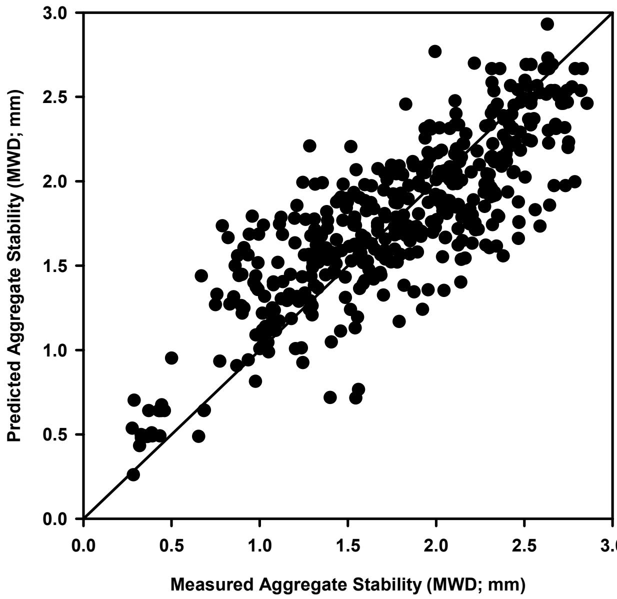


Figure 1. Vector loading for the first two principal components for the full LMI dataset.

Figure 2. LMI (version 1.1) predicted vs measured values of aggregate stability (MWD, mm) (454 paddocks).

Table 1. Examples of soil disturbance scores given to different tillage implements that were used to define their soil disturbance rating.

Tillage implement	Disturbance scores						Proportion of paddock affected	Soil Disturbance Rating
	Inversion	Mixing	Lifting	Shattering	Aeration	Compaction		
Direct drill	-1	-1	-2	-2	-1	-1	0.5	-4
Grubber	-4	-4	-3	-4	-4	-3	1	-22
Harrow	-2	-3	-1	-4	-3	-1	1	-14
Mouldboard plough	-5	-5	-5	-5	-5	-4	1	-29
Tyne	-1	-2	0	-2	-3	-3	1	-11

Table 2. Example calculation of the total soil disturbance rating (SDR) for a series of tillage passes used when establishing a barley crop.

	Pass 1	Pass 2	Pass 3	Pass 4	Pass 5	Total SDR
Implements used	Mouldboard plough	Maxi-till	Maxi-till	Harrow	Roll	
SDR of implement	-29	-18	-18	-14	-4	-83

Table 3. Examples of the crop type weightings applied.

Crop type group	Example	Weighting[1]
Fine root	Grass, triticale	4
Cereal	Barley, wheat	2.5
Brassica	Broccoli, pasja	2
Course root	Maize, sweetcorn	2
Tap root	Canola, mustard	2
Leafy vegetable	Lettuce, spinach	1
Root crop	Carrot, potato	1
Fallow/none	-	0

[1] values range from 0 to 4, with higher values having the greatest benefits on soil quality.

Recent management events have a stronger influence on soil quality than more distant events, hence a linear monthly time weighting was applied to all tillage SDR and crop weightings (based on 120 months). All tillage was assumed to occur in the month of crop sowing. All time-weighted tillage SDR values were summed to a single 'tillage score' and used in subsequent analysis, as were all time-weighted crop scores. Alternative time weighting relationships (exponential, logistic and Gompertz curves) were investigated, but the linear weighting was found to give the best fit to the data (results are not presented here).

Model development

The regression analysis procedures in GENSTAT were used to define the quantitative relationships between the site/location factors, the time-weighted tillage and crop scores and the soil quality indicators. Stepwise regression analysis was first used to identify which factors and variates contribute significantly and most importantly to describing variability in each indicator. Next multiple linear regression analysis was used to define the best case model and to establish how much of the variation was explained by the main effects and interactions (only first-order interactions were considered) that contributed significantly to the best fit model. Multiple linear regression was used to obtain the coefficients required to parameterise the LMI model.

Following this approach a first generation LMI (version 1.1) was developed based on data from arable and vegetable cropping and sheep pasture land uses (454 paddocks). The success of the method described for converting descriptive crop and tillage information to quantitative measures was determined by how much of the variability in certain soil quality indicators could be explained by the summarised management information. For most of the indicators, there was a relatively large and significant improvement in the amount of variability that could be explained by adding the time-weighted tillage and crop score information into the analysis. For example, in the case of aggregate stability, when location factors (texture, soil order, LENZ Level 1) alone were included in the regression analyses, only 20% of the variation in aggregate stability (MWD, mm) could be explained. When time-weighted crop and tillage scores were included in the regression analyses, along with the location factors, a further 44%, or a total of 64% of the variation was explained. The addition of the crop and tillage factors markedly improved the prediction of aggregate stability values for the cropping and pastoral land uses sampled. The relationship between measured aggregate stability and that predicted by the LMI model can be seen in Figure 2.

Conclusions

Our results indicate that the method used to quantify soil and crop management information can be useful in explaining variability in soil quality data and may be applied to the development of soil management decision support models operating at the paddock scale. Quantification of descriptive management information allows its incorporation in development of decision support tools. The LMI decision support tool allows land managers to predict soil quality following different management practices. This information will be useful in monitoring the effects of current land management practices on soil quality without the high cost of sampling and measuring changes in soil properties on paddocks over time. However, perhaps more importantly it will also help farmers and land managers to assess the likely effects of future management changes on soil quality helping support future on-farm management decisions. Further information on the LMI can be obtained from Plant and Food Research or the authors.

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