Willingness to pay for soil information derived by digital maps: A choice experiment approach[1]

Published as:

Diafas I., Panagos P., Montanarella L. (2013). Willingness to Pay for Soil Information Derived by Digital Maps: A Choice Experiment Approach. Vadose Zone Journal Vol. 12, No.4 DOI: 10.2136/vzj2012.0198

Abstract

Soil surveys and the information they provide are commonly believed to be good investment, with significant benefits accrued to their users. To date, the empirical evidence for this comes from studies that have shown how enhanced soil information can alter agricultural practices in order to yield higher returns. This study attempts to estimate the economic value of soil information

---

[1] Iason Diafas*. Baarsjesweg 271/3, Amsterdam, Netherlands ; Tel : +31619422114 ; email : diafasj@gmail.com

Panos Panagos. European Commission, Joint Research Centre, Institute for Environment and Sustainability, Via E. Fermi 2749, I-21027 Ispra (VA), Italy; Tel : +390332783698; email: panos.panagos@jrc.ec.europa.eu

generated by a host of new proximal and in situ geophysical methods for the assessment of the following soil properties: carbon content, water content, clay content, bulk density and soil depth. The study also adopts a novel approach to the economic valuation of soil information by employing for the first time a choice experiment in order to estimate the willingness-to-pay (WTP) of potential users of the digital maps and their features. The choice experiment took the form of an online survey, administered to about a thousand individuals from the wider soil community. The results reveal significant WTP for maps of high resolution and accuracy that offer map interpretation in addition to a number of soil properties.

1 Introduction

It is a common claim within the soil community that soil surveys practically pay for themselves, an assertion that is backed up by a number of studies (Bie and Ulf, 1972; Carrick et al., 2010; Giasson et al., 2001). These studies have tried to quantify the economic value of soil information indirectly, by linking it with higher agricultural proceeds stemming from improved land management practices that are informed by enhanced information. For instance, Carrick et al.

(2010) estimated significant economic returns from a targeted application of a nitrogen leaching technology to N-leaching hotspots identified by a new soil map. Similarly, Giasson et al. (2001) and Bie & Ulf (1972) present tools for optimizing agricultural land use across soil types in a context of decision-making under uncertainty. They both demonstrate how higher payoffs can be associated with soil surveys of higher purity. Another way that the economic value of soil information has been demonstrated indirectly is through the development of such tools as *Green Credits* (Hunink et al., 2009). This is a financial mechanism that enables upstream farmers to practise water and management activities that benefit these farmers and downstream water users. As this mechanism draws heavilly on sound information regarding land use as well as soil properties, it can be argued that the payments made reveal, at least in part, the economic value of the soil maps involved.

The object of economic valuation of this study is not the information derived from traditional soil surveys but from a host of new sensing technologies for *non-invasive* characterization of the soil geophysical properties. These sensing technologies have been developed by DIGISOIL project (Grandjean et al., 2010), the main goal of which has been to develop an advanced soil mapping tool, by testing, assessing and integrating a range of new sensing tools capable of producing digital soil maps of high accuracy and fine resolution. The specific objectives focused on (i) adapting, testing, and validating the geophysical technologies, (ii) establishing correlations between measured geophysical parameters and soil properties involved in soil functions/threats such as erosion, compaction, organic matter decline, (iii) evaluating the technical feasibility and cost-effectiveness of the mapping tool. The identified sensing systems included the ground-penetrating radar (GPR), electrical resistivity tomography (ERT), electromagnetic induction (EMI), seismics, and airborne hyper-spectral.

The DIGISOIL mapping tool incorporates all the latest developments in proximal soil sensing techniques. Moreover, the DIGISOIL mapping tool is oriented to set up operational techniques useful for the implementation of the existing EU environmental policy such as the European Soil Thematic Strategy (CEC, 2006). In this context, the tool has been implemented to produce high resolution maps of soil properties such as soil organic carbon content and water content.

Digital soil mapping using proximal sensors is not a new affair of course. Similar sensing tools, generating soil information in the form of digital maps, have been employed on a commercial basis for over a decade (Viscarra Rossel et al, 2011). Therefore, one has to look no further than the money actually paid by users of such maps in order to estimate the value of the soil information. However, current market prices may only provide a rough, ballpark figure of the economic potential of the mapping tool of the current study. This is because the new mapping tool developed by DIGISOIL aimed at generating soil maps of superior quality by means of employing, as well as contributing to, the latest technological advancements in equipment (e.g. seismics) and signal processing.

The economic estimation was carried out concurrently with the development and testing stages of this new mapping tool i.e. before the validation of the tested sensing tools and techniques and, therefore, before the final technological specifications and performance were established. To accomodate the open-ended nature of this process, this study took on a different approach to economic valuation by employing a survey, the aim of which has been to infer economic value directly from potential users of the said digital soil maps. The main assumption made under this approach is that the price that the user is willing to pay for a product or service is determined by her estimation of the returns she expects to achieve from the use of her purchase. For instance, the price that farmers would be willing to pay to acquire a high-quality digital soil map embodies their estimation of the extra returns that the use of the information will bring.

Given sufficient provision of information regarding the features of the digital map, it is reasonable to assume that users themselves know well how this information can benefit them and how big a value they place on the product. Thus, the novelty of this approach is twofold: first, it does away with the need for the researcher to engage in extensive assumption-making with regard to expected payoffs. Second, by surveying a range of different types of potential users and uses, it offers the chance to estimate the economic value of the soil information held by more than one category of users and for more than one intended use.

2 Methodology

2.1 Method description

The method used for the economic valuation is a Choice Experiment (CE), which belongs to the family of valuation techniques called Stated Preference Methods. This name reflects the way economic value is inferred, which is typically through the use of surveys and questionnaires that ask respondents –directly or indirectly- questions about their WTP (Bateman et al., 2002). The use of CEs originates in the field of marketing and transportation where it was first used in order to assess consumers' (commuters') preferences for different products, such astransport modes (Kjær, 2005). More recently it has been widely applied in the field of environmental economics in order to estimate the economic values held by the public for alternative environmental policies or for the provision of ecosystem services (Hoyos, 2010). The extensive use of CEs in such diverse fields of study highlights their versatility and adoptability.

In CEs, a sample of people who are expected to make use of a specific good, are asked a series of questions about their preferences for alternative versions of this good. Each question, called a 'choice set', usually consists of no more than three alternative versions of the described good. These alternatives typically share a common set of attributes and are differentiated one from the other by the attributes taking on different levels. In a choice experiment the attributes of the alternatives are assigned different levels according to an experimental design so that respondents are faced with an extensive range of possible alternative versions of the good. Respondents' choices of their preferred alternatives reveal their preference by demonstrating their willingness to trade-off one attribute against another. Provided that one of the attributes used to describe the alternatives is a monetary one (e.g.. price/cost), it is possible to estimate respondents' WTP for different alternatives[2]. More importantly, however, the choice trade-offs between different attribute levels, in combination with the monetary attribute, allows for the estimation of WTP for specific attributes.

---

[2] Each alternative has a price attached to it, just like in a real market situation. The *price* attribute is just like the other attributes in that it takes on a range of specific values each of which is assigned to individual alternatives that respondents are called to choose from in any given *choice set*

2.2 Econometric model

Choice experiments are an application of the characteristics theory of value (Lancaster, 1966), combined with random utility theory. According to this approach, the net benefit that each individual i associates with an alternative j is expressed as a utility function $U_{ij}()$, which is decomposed into two parts: a deterministic element, V, which is usually specified as a linear function of the attributes (*X*) of the j different alternatives in the choice set, a number of socioeconomic characteristics of the respondent (*S*) ; and a stochastic element (*e*) which represents unobservable influences on individual choice:

$$U_{ij} = V_{ij}\left(X_j, S_i\right) + e_{ij}\left(X_j, S_i\right) \tag{1}$$

Where the indirect utility function is generally expressed in the following linear form:

$$V_{ij} = \beta + \beta_{j1}x_1 + \beta_{j2}x_2 + ... + \beta_{jn}x_n + \delta_1 s_1 + \delta_2 s_2 + ... + \delta_n s_n \tag{2}$$

with β taking on the role of an alternative specific constant (ASC) which captures the average effects on utility of any factors not included in *V*. Thus, the probability that a particular respondent prefers option *h* in the choice set to any alternative option *g*, can be expressed as the probability that the utility associated with option h exceeds the probability associated with all other options:

$$P\left[U_{ih} > U_{ig} \forall g \neq h\right] = P\left[\left(V_{ih} - V_{ig}\right) > \left(e_{ig} - e_{ih}\right)\right] \quad (3)$$

To empirically estimate this expression, assumptions are made about the random component of the model. A typical assumption is that these stochastic components are independently and identically distributed (IID) with a Gumbel or Weibull distribution. This leads to the use of multinomial logit (MNL) models to determine the probabilities of choosing h over g options (Hanley, Mourato and Wright, 2001).

$$P(U_{ih} > U_{ig}) = \frac{e^{(\mu V_h)}}{\sum_g e^{(\mu V_g)}}, \quad \forall g \neq h \quad (4)$$

Here, μ is a scale parameter, inversely related to the standard deviation of the error term and commonly normalised to 1 for any dataset. The estimated coefficients of the attributes are linear parameters, and therefore can be used to estimate the tradeoffs between the attributes that respondents would be willing to make. The IID assumption of the error terms leads to the behaviorally comparable assumption of independence of irrelevant alternatives (IIA) assumption. Simply stated, the relative odds of choosing alternative *h* over alternative *g* are not affected by the availability of other alternatives in the choice set.

In choice experiments, the price coefficient can be used in conjunction with the other attribute coefficients to determine the willingness to pay of respondents for gains or losses in attribute levels. This WTP is called the "implicit price" or part-worth of the attribute and is calculated as follows[3]:

$$WTP_{attribute} = \frac{\beta_c}{\beta_y} \tag{5}$$

where β_c is the coefficient of any of the attributes and β_y gives the marginal utility of income and is the coefficient of the cost attribute (Train, 2003). By extension, it is possible to calculate the overall WTP for complete alternatives. This can be calculated using the following equation (Abou Ali & Carlsson, 2004):

$$WTP_{alternative} = \frac{V_1 - V_0}{\beta_y} \tag{6}$$

[3] WTP can be defined as the maximum amount someone is willing pay for a good that, when combined with the acquisition of the good, leaves the person just as well off as before the payment and the acquisition happened. In other words, it is the maximum amount that leaves the person's utility unchanged. Equation 5 is derived by taking the total differential of equation 2, setting it to zero and assuming only changes in the attribute of interest and the monetary attribute.

where V_1 is the utility associated with the purchase of a specific alternative and V_0 represents the utility of not choosing any of the offered alternatives in a choice set.

This study applies a Random Parameter Logit (RPL) model. Compared with the standard MNL model, the RPL has the distinct advantages that it does not exhibit the IIA property and that it can explicitly model unobserved heterogeneity by allowing for a distribution of preferences within the population. Like in the MNL model, the utility that respondent *n* obtains from alternative *j* in choice situation *t* is:

$U_{njt} = \boldsymbol{\beta}_n \, \boldsymbol{x}_{njt} + \varepsilon_{njt}$

(7)where $\boldsymbol{x}_{njt}$ is a vector of observed variables with coefficient vector $\boldsymbol{\beta}_n$, representing peoples' tastes. $\boldsymbol{\beta}_n$ is unobserved for each person and varies in the population with density $f(\beta_n \mid \theta)$, where $\boldsymbol{\theta}$ are the (true) parameters of this distribution. ε_{njt} is an unobserved random component that, similarly to the MNL model, is distributed iid extreme value, independent of $\boldsymbol{\beta_n}$ and $\boldsymbol{x}_{njt}$. The goal of the estimation procedure is to estimate $\boldsymbol{\theta}$, that is, the population parameters that describe the distribution of individual parameters.

2.3 Choice experiment design and application

The first step in designing a choice experiment is the selection of the attributes that comprise the assessed product or service. For the purposes of the current study, the product has been defined in terms of a digital map that provides information on several soil properties. The decision to frame the product in such a way was shaped by the finding of a preliminary survey that suggested that the vast majority of potential users were interested in obtaining the soil map rather than purchasing the necessary equipment and software and performing the analysis themselves. This finding confirmed a prior belief held by the authors that, because of the highly technical nature of the required mapping task and the associated skills set required, most respondents would opt for the complete maps.

The soil properties included as attributes are: water content, carbon content, clay content, bulk density and soil depth. These properties are the ones originally chosen for study and estimation by the DIGISOIL project. This means that there was little leeway in terms of which of them to include as attributes in the choice experiment. However, what is valued in this choice experiment is not merely the chosen soil properties per se but, rather, the measurement accuracy of each property. Measurement accuracy was defined in terms of percentage deviation from the true value of a soil property measured. So, for instance, a map might be capable of displaying carbon content with +/-5% accuracy. Expressing accuracy in this manner was preferred over other more technical ways, such as the Root Mean Square Error (RMSE), as it presented a simpler and more intuitive way that could be readily understood by all respondents, some of whom may lack technical knowledge.

Two other map features were also included as attributes: *spatial resolution* and *map interpretation*. The former was included in order to gauge respondents' preferences with respect to different map resolutions. The latter has been defined as the option to offer map interpretations and recommendations catering to the prevailing or intended land use. As different stakeholders can be interested in different types of map interpretation, the type of interpretation was not explicitly spelled out and it was decided that the term be kept generic. This way the information was kept flexible enough to fit the modelling purpsoses, yet specific enough in order to conform to each respondents' notion of what kind of map interpretation they need The inclusion of map interpretation adds a layer of information that goes beyond just measuring soil properties to offering interpretation based on the needs of the user. Table 1 presents the attributes chosen to depict each alternative version of the digital map, as well as the various levels of each attribute.

A *price* attribute completed the set of attributes that were chosen to describe the product. The inclusion of a "price" attribute as a feature of each map version means that respondents are required to make tradeoffs between better map quality (this being described by higher levels of spatial resolution, measurement accuracy and inclusion of map interpretation) and higher cost of purchasing the map. Analysis of the series of choices made by respondents reveals their preferences in terms of making tradeoffs between map features. In other words, it allows measuring how much of one feature they are willing to give up in order to gain a bit more of another. Because one of the evaluated features is price, the tradeoffs reveal respondents' average willingness to pay for different levels of provision of each of the other features.

After attribute selection, the next step is the choice experiment design. This is normally done with aid of special software that combine the number of attributes and levels to form alternatives. The experimental design for this study was performed with the help of Sawtooth software which is capable of producing nearly optimal designs as these are defined by the properties of minimum attribute-level overlap, level balance and orthogonality (Chrzan and Orme, 2000). Twenty different versions of the experiment were created, with four choice sets comprising each version presented to a respondent. These 20 versions were randomly assigned across the sample of individuals that took part in the survey. Each of the four choice sets consists of two different hypothetical versions (alternatives) of the offered map, as well as an opt-out alternative which respondents could choose if they were not satisfied with the other two alternatives. In addition to the choice experiment, information was also collected on respondents' field of employment and of the type of map use they would be interested in.

The choice experiment took the form of a web-based survey, communicated to just over a thousand (1085 at the moment of the study) potential end-users via email. The task of finding potential end-users was greatly facilitated by an extensive contact list, maintained by the European Soil Data Center (ESDAC) of the Joint Research Centre of the European Commission and containing numerous stakeholders coming from various fields, such as academic and research institutes, governmental agencies and the private sector (Panagos et al. 2012). In order to encourage truthful and accurate disclosure of WTP, it was emphasized to the respondents that they should fill out the survey only if they, on behalf of the institute/company they work for, were seriously interested in this kind of maps and they would consequently wish to pay for it. This requirement may explain the somewhat low response rate received. The final sample numbered 166 respondents. Ten more responses were received but not included in the analysis as they arrived after the data collection cut-off date.

3 Results

3.1 Descriptive statistics

Only information on respondent's field of work and intended use of the digital maps was collected on top of the choice experiment in order to keep things short and encourage people to participate. Figure 1 shows the distribution of these two characteristics across the sample. These figures provide a picture of who are the main target end-users and what is their intended use of the mapping tool. As figure 1 shows, the overwhelming majority of the potential end users come from the research arena, be it a university (42%) or another type of research institute (36%). The third largest group of potential end-users represents public administration entities (11%), followed by the private sector (9%), such as agribusiness companies and consultancies. In terms of the intended use of the maps, the bulk of the responses are divided roughly equally amongst pure soil research (33%), agriculture (25%) and environmental monitoring (30%).

3.2 Model Results

Based on the attributes included in the choice experiment, the basic form of the utility function of a typical respondent[4] can be written as:

---

[4] , The utility expression (8), from which WTP is calculated, is assumed to reflect the institute's utility, rather than the individual's

$$U = b_0 + b_{resolution}\text{Resolution} + b_{depth}\text{Depth} + b_{density}\text{Density} + b_{carbon}\text{Carbon} + b_{water}\text{Water} + b_{clay}\text{Clay} + b_{degradation}\text{Degradation} + b_{price}\text{Price} + e \quad (8)$$

Parameter b_0 represents the alternative-specific constant (ASC), whose role is to pick up the average influence on utility of unobserved factors. Given the generic nature of the alternatives, the variable accompanying the ASC was set equal to one for the two alternatives in each choice set and zero for the opt-out alternative. The term e is the same random parameter as in equation 1 and it represents all the unobserved factors that are assumed to influence respondents' choices but are not included in the utility function.

In order to capture some of the heterogeneity of respondents' preferences, the *price* attribute was interacted with dummy variables representing respondents' line of work and intended use of the map. It has not been assumed that only these two variables are responsible for the observed choices and for the variance in WTP. In fact, one could include several other variables on things such as individuals' attitudes toward digital soil-mapping and previous experience with similar technologies. However, data only on the aforementioned two variables were collected in an effort to keep the survey as short as possible while still including some key variables that were believed to hold sway over respondents' choices.

As explained previously, the RPL model was chosen over the simple MNL model due to the latter's inability to capture preference heterogeneity among respondents. In RPL models the analyst specifies a probability distribution for each attribute coefficient that is hypothesized to vary across the population (Hensher et al., 2005). For this model, extensive experimentation with different distributions for each of the attributes suggested that preference heterogeneity was present only in the "cost" attribute, which was assigned a normal distribution. Table 2 presents the results of the statistical analysis of the responses to the choice experiment part of the survey. It shows the values of the estimated parameters of the respondents' hypothesized utility function (eq. 8)

First, the log-likelihood ratio test is carried out in order to determine the overall significance. For 19 degrees of freedom, the value of P(Chi^2) means that the RPL is an improvement over a constants-only model. With regard to data fit, the value of *Adj.* R^2 is 0.35413, indicating a very good fit to the data. According to Hensher et al. (2005), the R^2 of a choice model is not exactly the same as the R^2

of linear regressions, so what would pass as a barely acceptable linear model in terms of the R^2 may well represent a very good choice model. In particular, Hensher et al. (2005) point out that in a choice model, values of R^2 in the range of 0.3 to 0.4 can be translated as an R^2 of about 0.6 to 0.8 for the linear model equivalent.

What stands out from the above results is the fact that all the attribute parameters are statistically significant, which means that they have significantly influenced respondents' utility and thus choices. Moreover, they take on the expected sign. The coefficients corresponding to map resolution, measurement accuracy of the soil properties and inclusion of map interpretation have positive signs, meaning that higher levels of these attributes impact positively on respondents' utility, i.e. they are desirable attributes. An inspection of these estimates reveals that the attribute that weighed most heavily in respondents' choices is the option of having map interpretation, followed by estimates of clay and carbon content.

On the other hand, the price attribute coefficient is negative, as one would expect that higher prices reduce utility and thus the chance of choosing a more expensive alternative. Moreover, the significant standard deviation coefficient for this attribute is evidence of heterogeneity of respondents' sensitivity to the price of the maps. The sources of such heterogeneity are not, however, explicitly accounted for. In order to detect any such sources, one needs to include individual-specific traits by interacting them with the random coefficient. To that effect, the respondents' line of work and their intended use of the maps have been interacted with the *price* attribute. Their values, shown in Table 2, can be interpreted as deviations from the mean estimate of the *price* parameter. What the values of these interactions show is that, for instance, on the average, respondents representing universities exhibited a higher sensitivity to cost, whereas respondents from the private sector (e.g. agribusiness) had a somewhat lower cost sensitivity.

The parameter estimates in Table 2 provide crucial information and make up the most significant findings of this work. Their importance lies in the fact that not only do they reveal respondents' preferences over the several attributes, but also they can translate these preferences into monetary figures. Using equation 5, the average WTP for each level of provision of the various attributes has been calculated and is presented in Table 3. Similarly, Table 4 shows the average WTP of respondents from the private sector, calculated by adding the significant parameter value of the interacted term *price* x *private* to the value of the price parameter in the denominator of equation 5.

The way to interpret the numbers in Tables 3 and 4 is the following: each number represents the average WTP for obtaining an extra level of the respective attribute. For instance, for the measurement of carbon content, the average respondent would be willing to pay about 25€ for obtaining a low-accuracy measurement. In order to have a measurement of high accuracy for the carbon content respondents would be willing to pay 74,4€ (3 times 24,8€). The same applies for the other features of the DIGISOIL mapping tool, such as map resolution and inclusion of map interpretation. It is evident from these WTP figures that the feature of the DIGISOIL mapping tool that is most highly valued by respondents is the provision of map interpretation. In addition, the observed variance in the random coefficient of the price attribute translates into variance in the estimated WTP of the several other attributes. By making use of equation

6, it is possible to calculate the overall WTP for complete alternative versions of the mapping tool. For instance, it is possible to calculate respondents' WTP for a high-resolution map, with high measurement accuracy for all the soil properties and with soil map interpretation included. In the case of the best possible map alternative as the one described above, it can been seen in Table 4 that the average WTP is €447/ha. For a medium resolution map, with medium accuracy and map interpretation, WTP would be €324/ha, while for a map with low resolution, low measurement accuracy and no interpretation, WTP is just €123/ha.

4 Conclusions and discussion

This paper has presented the findings of a study carried out with the aim of estimating the economic value residing in the maps produced by new digital soil-mapping technologies. The method employed is a *choice experiment* and it is the first of its kind in the valuation of soil information. The novel character of this approach, however, does not mean that it is better than alternative ones or that it should be adopted ubiquitously by the soil community. It merely presents an alternative way to value soil information in the context of a new digital soil-mapping tool. Thus, the goal of the current work has been not to merely estimate the economic potential of a specific digital soil-mapping tool, but also to demonstrate the suitability of CEs as a technique in valuing soil information provided by innovative new technologies in general.

The findings reflect the analysis undertaken on a number of replies to the choice experiment, administered to a large number of stakeholders in the wider soil community. The purpose of the survey has been to identify potential end-users and assess their needs and preferences with regard to the features of the DIGISOIL mapping tool and to produce an estimate of the maps' economic value, expressed in terms of end-users' willingness to pay for the various map features.

The survey has helped paint a picture of who the potential end-users may be and for what purpose they would want to use the DIGISOIL maps for. What is interesting to note is that a healthy majority of the respondents stated as intending to use the map in areas other than in agriculture; areas such as environmental monitoring and pure soil research. This finding seems to confirm the acknowledgement of the multi-dimensional role of soils and of the need of stakeholders, other than from the agricultural sector, for quality soil information. (Montanarella, 2010; McBratney et al. 2010).

Further analysis of the survey results has shown that there is a positive and significant economic value associated with the use of DIGISOIL's mapping tool which, for a high-definition, high-accuracy map with interpretation, could be as high as €447/ha. . It is reasonable to ask how reliable or valid these estimates are. As mentioned previously, soil mapping tools of varying technological maturity are already sold in the market. Information gathered through personal communication with two major companies in the field of digital soil mapping revealed that prices for similar mapping products are in the range of €100-300/ha and are, therefore, broadly in line with the findings of this study. This convergence is crucial as it nullifies criticisms against the use of surveys (due to their hypothetical nature) for the estimation of economic values.

Moreover, end-users' WTP for individual features of the maps has been estimated, pointing to a particularly strong preference for the inclusion of map interpretation. This finding reinforces the recognition of the growing need for interpreted soil information for a range of anticipated land uses. For example, a catchment hydrologist may want to know the parameters of the infiltration curve, and the hydraulic conductivities with depth. Agronomists wish to know the available nutrient content and the retention capacity for applied nutrients, the quantity and type of salts, and trace metal content. A civil engineer would be interested in the bearing capacity, plasticity, and Atterberg limits, while an urban planner would want to know areas which are too contaminated to be used for gardens, housing or sports fields (Rossiter, 2005). The fact that the highest WTP has been expressed for the option to have map interpretation highlights the preponderance of this feature amongst the soil community.

In addition, analysis of the data reveals that the responsiveness of respondents to the asked map price is not uniform across the sample but varies significantly. In order to capture some of the heterogeneity of respondents' preferences, the *price* attribute was interacted with dummy variables representing respondents' line of work and intended use of the map. It has not been assumed that only these two variables are responsible for the observed choices and for the variance in WTP. In fact, one could include several other variables on things such as individuals' attitudes toward digital soil-mapping, previous experience and planned future use. However, data only on the aforementioned two variables were collected in an effort to keep the survey as short as possible while still including some key variables that were believed to hold sway over respondents' choices.

Unfortunately, not all of the hypothesized determinants of respondents' choices have been identified, as only some types of employment and intended use of the maps seem to have a significant effect on choice. The statistical insignificance of the other attributes does not mean that they exert no influence on choices. Rather, it is likely that the problem lies in the sample and its relatively small size. A larger sample would have been more likely to capture most of the variation in preferences. Focusing on the interaction terms that came out significant, the data suggest that the WTP of the education sector and for purposes of pure soil research is lower than the overall average. On the other hand, the private sector exhibits a higher than average WTP. This is an entirely reasonable conclusion which reflects the willingness of private companies in the agricultural sector to invest more in the acquisition of high-quality, reliable soil data that will help them maximise returns from activities such as precision agriculture. If we were to ignore the insignificance of the other interaction terms, their signs seem to suggest that respondents interested in making use of the maps in agriculture and environmental monitoring have higher average WTP than those intending to use them in forestry and engineering/construction, an observation that may again reflect the higher added-value of the soil information to these activities. Again, these results should be read with caution, in light of the potential problems associated with the small sample size.

This drawback aside, the current work is still quite important. It has shown that apart from producing reliable estimates of the economic value of soil information generated by new, state of the art sensing systems, CEs have the potential to shed light to a plethora of effects and relationships. By including information on consumers' characteristics, CEs can reveal the WTP for individual map properties (including map interpretation) according to consumer categories. Such information is crucial in the eventual commercialization of new mapping tools as it can provide better, customised solutions to potential end-users according to their specific needs and requirements.

Acknowledgements

The authors would like to acknowledge the kind collaboration and contributions of the partners of DIGISOIL: Integrated system of data collection technologies for mapping soil properties. EC Proposal Reference No.: FP-7- 211523

5 References

Abou Ali, H. and Carlsson, F., (2004), Evaluating the welfare effects of improved water quality using the choice experiment method, *Working Papers in Economics*, 131, Gothenburg University

Bateman, I., Carson, R., Day, B., Hanemann, M., Hanley, N., Hett, T., Jones-Lee, M., Loomes, G., Mourato, S., Ozdemiroglu, E., Pearce, D., Sugden, R. and Swanson, J., (2002), *Economic valuation with stated preferences techniques: a manual*. Cheltenham, UK, Edward Elgar

Bie, S. and Ulph, A., 1972. The economic value of soil survey information. *Journal of Agricultural Economics*. 23 (3), pp285-297

Carrick, S., Vesely, E-T., Hewitt, A., 2010. Economic value of improved soil natural capital assessment: a case study on nitrogen leaching. 19th World Congress of Soil Science, Soil Solutions for a Changing World, 1– 6 August 2010, Brisbane, Australia.

Chrzan, K. and Orme, B., (2000). An Overview and Comparison of Design Strategies for Choice-Based Conjoint Analysis, *Sawtooth Software Technical paper*, http://www.sawtoothsoftware.com/techpap.shtml

EC, (2006), Communication from the Commission to the Council, the European Parliament, the European Economic and Social Committee of the Regions, Thematic Strategy for Soil Protection, (COM(2006) 231 final).

Giasson, E., van Es, C., van Wambeke, A., Bryant, R.B., 2010. Assessing the economic value of soil information using decision analysis techniques, *Soil Science,* 165 (12), pp971-978.

Grandjean, G., Cerdan, O., Richard, G., Cousin, I., Lagacherie, P., Tabbagh, A., Van Wesemael, B., Stevens, A., Lambot, S., Carré, F., Maftei, R., Hermann, T., Thörnelöf, M., Chiarantini, L., Moretti, S., McBratney, A. and Ben Dor, E., (2010), DIGISOIL: An Integrated System of Data Collection Technologies for Mapping Soil Properties., *Progress in Soil Science*, 1, pp89-101

Hanley, N., Mourato. S., Wright, R.E., 2001. Choice modelling approaches: A superior alternative for environmental valuation?. *Journal of Economic Surveys*, 15 (3), pp435-462

Hensher, D., Rose, J. and Greene, W., (2005) Applied choice analysis: a primer.,Cambridge University Press, New York, 717pp.

Hoyos, D., (2010), The state of the art of environmental valuation with discrete choice experiments, *Ecological Economics*, 69, pp1595-1603

Hunink, J.E., W.W. Immerzeel, and Droogers, P., (2009), Green Water Credits for the Upper Tana Basin, Kenya. Phase II – Pilot Operations: Biophysical assessment using SWAT. Report FutureWater: 84

Kjær, T., (2005), A review of the discrete choice experiment with emphasis on its application in health care, *Health Economics Papers,* 1, University of Southern Denmark

Lancaster, K. J. (1966), A new approach to consumer theory, *Journal of Political Economy*, 74 (2), pp132-157

McBratney, A., Mendonça Santos, M., Minasny, B., 2003. On digital soil mapping, *Geoderma*, 117, pp3–52.

Montanarella, L., 2010. Foreword, in: Boettinger, J.L., Howell. D.W., Moore, A.M., Hartemink, A.E., Kienast-Brown, S. (Eds), Digital Soil Mapping: Bridging Research, Production, and Environmental Application, Springer Dordrecht, pp v-vi

Panagos, P., Van Liedekerke, M., Jones, A., Montanarella, L. ,2012. European Soil Data Center: response to European policy support and public data requirements. *Land Use Policy* 29 (2), pp329–338.

Train, K., (1999), Mixed logit models for recreation demand, in: Herriges, J., Kling, C., (eds.), Valuing Recreation and the Environment, Edward Elgar, Cheltenham.

Rossiter, D., (2005), Digital soil mapping: towards a multiple-use soil information system, *Análisis Geográficos*, 32 (1), pp7-15

Train, K., (2003), *Discrete Choice Methods with Simulation*, Cambridge University Press, New York.

Viscarra Rossel, R., Adamchuk, V., Sudduth, K., Mckenzie, N. and Lobsey, C., (2011), Proximal soil sensing: an effective approach for soil measurements in space and time, *Advances in Agronomy*. 113, pp237-282.

Table 1. Choice Experiment atrributes and their levels

Attributes	Levels
Spatial resolution	Low (5-10m) Medium (2-5m) High (0.5-2m)
Soil depth	Low measurement accuracy (+/-10%) Medium measurement accuracy (+/-5%) High measurement accuracy (+/-1%)
Bulk density	Low measurement accuracy (+/-10%) Medium measurement accuracy (+/-5%) High measurement accuracy (+/-1%)
Carbon content	Low measurement accuracy (+/-10%) Medium measurement accuracy (+/-5%) High measurement accuracy (+/-1%)
Water content	Low measurement accuracy (+/-10%) Medium measurement accuracy (+/-5%) High measurement accuracy (+/-1%)

Clay content	Low measurement accuracy (+/-10%) Medium measurement accuracy (+/-5%) High measurement accuracy (+/-1%)
Map interpretation	Not included Included
Price per hectare (euros)	100, 300, 600, 900, 1200, 1500

Table 2. Model Results

Variables	Coefficients	Std. Deviation
Map resolution	0.1509*	Fixed
Soil Depth	0.1745**	Fixed
Bulk Density	0.2075***	Fixed
Carbon Content	0.2481***	Fixed
Water Content	0.1927**	Fixed
Clay Content	0.2542***	Fixed
Map interpretation	0.7867***	Fixed
Price/ha	-0.01***	0.0006***
ASC	-0.8986^{ns}	Fixed
Price*Private	0.004**	
Price*Research Institute	0.002^{ns}	
Price*University	-0.003**	
Price*Government	0.002^{ns}	
Price*Pure soil research	-0.006***	
Price*Agriculture	0.0008^{ns}	
Price* Environmental Monitoring	0.002 ^{ns}	
Price*Forestry	-0.004 ^{ns}	
Price*Engineering	-0.005 ^{ns}	
Log-likelihood	-604.2686	
P(Chi²); DF	0.0000; 19	

Adj. R^2 (Pseudo-R^2)	0.35413

***: significant at $p \leq 0.01$; **: significant at $p \leq 0.05$; *: significant at $p \leq 0.1$; ^{ns}: not significant

Table 3. Average WTP for the several features of the map

Attribute	**WTP**	**Attribute**	**WTP**
Map Resolution	15,1€	Water Content	19,3€
Soil Depth	17,4€	Clay Content	25,4€
Bulk Density	20,7€	Soil Degradation Indicators	78,7€
Carbon content	24,8€		

Table 4. Average WTP of private companies

Attribute	**WTP**	**Attribute**	**WTP**
Map Resolution	€25,2/ha	Water Content	€32.1/ha
Soil Depth	€29.1/ha	Clay Content	€42,4/ha
Bulk Density	€34,6/ha	Map interpretation	€131,1/ha
Carbon content	€41.4/ha		

Table 5. WTP for three alternative maps

Map Type	**WTP**
High-resolution, high-accuracy with interpretation	€447/Ha
Medium-resolution, medium-accuracy with interpretation	€324/Ha
Low-resolution, low-accuracy without interpretation	€123/Ha

Figure 1. Respondents' employment and intended map use