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Evaluation of the DIGISOIL mapping tool according to end users' needs

FP7 – DIGISOIL Project Deliverable D4.1

N° FP7-DIGISOIL-D4.1 April 2011



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I. Diafas (JRC)

With the collaboration of P. Panagos (JRC)

Checked	by:
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Name: Mélanie FONTAINE

Date: 5 May 2011

Approved by:		
Name: Gilles GRANDJEAN		
Date: 19 May 2011		

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Synopsis

The current deliverable pertains to the first task of DIGISOIL's Work Package 4, "Evaluation of the DIGISOIL mapping tool according to end-users' needs". The main objectives of this task are to identify potential end-users, determine the main areas that the end-users are interested in applying the mapping tool and, most importantly estimate the willingness to pay for the various features of the tool. These objectives have been addressed through the use of an online survey.

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1. Introduction

It is a common claim in the literature that digital soil mapping (DSM) holds the potential to deliver substantial cost savings compared to traditional soil survey methods, as it is less time-consuming and labour-intensive (Grunwald, 2010). Despite this potential, very little effort has gone into systematically assessing the economics of DSM. This is mainly due to the relatively nascent stage and rapidly evolving nature of DSM technology. DSM is still quite research-oriented, with a multitude of approaches and techniques employed for the characterization and prediction of a diverse range of soil properties. This means that there are still no standardized and mature DSM protocols on which to base an economic analysis.

In order to assess the economic potential of a DSM product it is necessary to estimate the costs and benefits associated with its development and application. This being an emerging technology however, data on both costs and benefits are not readily available. To overcome this, one can approach the issue through the process of new product development (NPD). This term is used to describe the process of introducing a new product or service into the market and its purpose is to address in a holistic way the issues affecting production and marketing of the product. In NPD, commercialization of a product is the last of several steps, beginning with idea generation and screening, followed by concept testing, business analysis and prototype development/testing. Concept testing and business analysis are closely related to each other. Concept testing involves evaluation of the product by consumers, usually by employing some sort of marketing research. If the product is to succeed, the spatial soil information it provides must be perceived as highly relevant to potential users. Business analysis seeks to determine the marketability of the product in terms of likely selling price compared with the costs of production. In other words, it is a type of cost benefit analysis.

The aim of this report is to shed light on the economic potential of introducing the new DIGISOIL mapping tool into the market. It does so by focusing on the concept testing stage, the main objective of which has been to assess the end-users' needs from an economic perspective. Specifically, it has sought to address the following questions :

- What is the target market i.e. who are the end-users?
- What is the intended use of the mapping tool by the end-users?
- What product features must the product incorporate?
- What are the economic benefits provided by the product?

The next sections of the report discuss the methodology chosen to assess end-users' needs, how this methodology has been applied and what the main findings are.

2. Methodology and survey design

2.1. METHODOLOGY

Testing of the product concept has been approached by employing a form of marketing research technique, called choice modelling. Choice modelling (or choice experiments) typically involves a sample of people, who are expected to make use of a specific good, being asked a series of questions about their preferences for alternative versions of this good. Each question, called a 'choice set', presents to respondents no more than three alternative versions of the good. These alternatives are described in terms of a common set of attributes and are differentiated one from the other by the attributes taking on different levels. The levels of the attributes in the alternatives are distributed according to an experimental design so that respondents are faced with a wide range of possible alternative versions of the good. Respondents' choices of their preferred alternatives demonstrate their willingness to trade-off one attribute against another. So long as one of the attributes used to describe the alternatives is monetary (i.e. price), it is possible to estimate respondents' willingness to pay (WTP) to obtain additional units of the other attributes. It is also possible, using the choice data, to estimate respondents' WTP for complete versions of the good.

Choice experiments are an application of the characteristics theory of value (Lancaster, 1966), combined with random utility theory. According to this approach, the indirect utility function for each respondent *i*, (U), can be 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:

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

Where the indirect utility function generally takes the linear form:

$$V_{ij} = \beta + \beta_{j1} x_1 + \beta_{j2} x_2 + \dots + \beta_{jn} x_n + \delta_1 s_1 + \delta_2 s_2 + \dots + \delta_n s_n$$
(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*. Since any socio-economic and attitudinal characteristics do not vary across choices for any given respondent, they only enter the utility function as interaction terms with the X attributes

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:

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

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

2.2. SURVEY DESIGN

The four questions mentioned in the introduction have been pursued through the use of an online survey, which was communicated to potential end-users via email. This task was greatly facilitated by an extensive contact list, maintained by the Soil Action of the Joint Research Centre of the European Commission, of numerous stakeholders coming from various fields, including academic and research institutes, governmental agencies and the private sector. Information on the first two questions was obtained by asking questions regarding the respondents' line of work and intended use of DSM. The other two questions have been jointly addressed by a choice experiment.

For the purposes of the choice experiment, the product has been described to respondents as a digital soil map, capable of estimating a number of soil properties with high degrees of accuracy and spatial resolution. Each respondent has been presented with four choice sets, each consisting 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. Respondents were asked to evaluate these alternatives with regard to varying levels of map resolution and measurement accuracy of the following soil properties: soil depth, bulk density, carbon content, water content and clay content, which are the main soil properties estimated by the techniques developed under DIGISOIL. 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

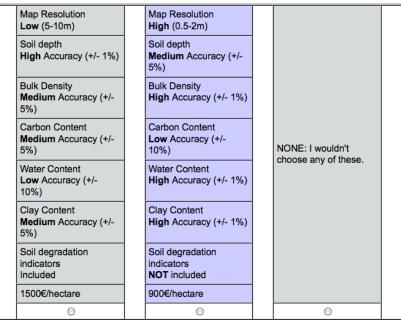
presented a simpler and more intuitive way that could be readily understood by all respondents, many of whom may lack knowledge of statistical terms. In addition to the soil properties estimated by the mapping tool, the option of providing indicators of soil degradation has been included in the assessed map versions. Table 1 presents the attributes chosen to represent each alternative version of the mapping tool, as well as the various levels of each attribute.

Attributes	Levels
On atial reachution	Low (5-10m)
Spatial resolution	Medium (2-5m) High (0.5-2m)
	Low measurement accuracy (+/-10%)
Soil depth	Medium measurement accuracy (+/-5%)
	High measurement accuracy (+/-1%)
Dull density	Low measurement accuracy (+/-10%)
Bulk density	Medium measurement accuracy (+/-5%) High measurement accuracy (+/-1%)
	Low measurement accuracy (+/-1%)
Carbon content	Medium measurement accuracy (+/-10%)
Carbon content	High measurement accuracy (+/-1%)
	Low measurement accuracy (+/-10%)
Water content	Medium measurement accuracy (+/-5%)
	High measurement accuracy (+/-1%)
	Low measurement accuracy (+/-10%)
Clay content	Medium measurement accuracy (+/-5%)
	High measurement accuracy (+/-1%)
Soil degradation	Not included
indicators	Included
Price per hectare (euros)	700, 900, 1200, 1500, 2000, 2500, 3500

Table 1: Attributes and levels

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 degradation indicators) 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. Figure 1 depicts a typical choice set, one of many presented to respondents.



If these were your only options, which would you choose? Choose by clicking one of the buttons below:

Figure 1: Example of a choice set

Based on the above selection of attributes, the utility function of a typical respondent can be written as:

 $U = b_0 + b_{resolution} Resolution + b_{depth} Depth + b_{density} Density + b_{carbon} Carbon + b_{water} Water + b_{clay} Clay + b_{degradation} Degradation + b_{price} Price + e$ (5)

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 represents all the unobserved factors that are assumed to influence respondents' choices but that are not included in the indirect utility function.

In addition to the design attributes, respondents' type of employment and their intended use of the mapping tool were assumed to influence choices. Thus, they were included in the utility function as dummy variables, interacting with the main attributes.

2.3. RESULTS

The survey was administered via email to about a thousand individuals, 166 of whom chose to take part. It is hard to say to what extent this is a good response rate since there is no generally agreed upon figure in the literature as to what constitutes an acceptable threshold, below which response rates are deemed insufficient. Given that this is the first survey of its kind, the response rate can be taken to be a decent starting point on which future research can build upon.

The survey began by asking questions on respondents' line of work and on their intended use of the mapping tool. Figures 2 and 3 show the percentage of respondents falling in the various categories chosen for each question.

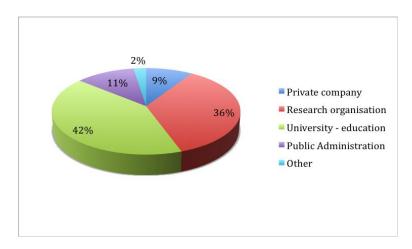


Figure 2: Type of organisation

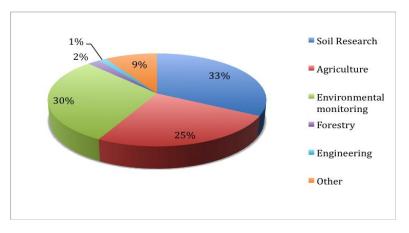


Figure 3: Intended use

These figures provide a picture of who are the main target end-users and what is their intended use of the mapping tool. As these figures show, 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 DSM, the bulk of the responses are divided roughly equally amongst pure soil research (33%), agriculture (25%) and environmental monitoring (30%).

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.5).

Variables	Coefficients	p-value
Map resolution	0.1831	0.0207
Soil Depth	0.1573	0.0379
Bulk Density	0.2099	0.0078
Carbon Content	0.2631	0.0006
Water Content	0.1977	0.0107
Clay Content	0.2640	0.0007
Degradation Indicators	0.8112	0.0000
Price/ha	-0.001	0.0000
ASC	-1.067	0.0242
Log-likelihood	-611.92	
Restricted Log-likelihood -729.48		9.48
P(Chi ²); DF	0.0000; 10	
Adj. R ² (Pseudo-R ²)	0.34	490

Table 2: Econometric results

First, the Adj. R^2 is 0.349, indicating a good fit to the data. According to Hensher et al., 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. 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 R2 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 parameters are statistically significant at p<0.05, 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 soil degradation indicators have positive signs, meaning that higher levels of these attributes impact positively on respondents' utility, i.e. they are desirable attributes. 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. An inspection of these estimates reveals that the attribute that weighed up most heavily in respondents' choices is the option of having indicators of soil degradation, followed by estimates of clay and carbon content.

The negative sign of the ASC coefficient indicates that there were probably other, unobserved influences, which, on average, had a negative impact on respondents' utility of choosing either of the two alternatives. One can only speculate on the sources of these influences. For instance, they might have stemmed from a lack of certain features or attributes of the mapping tool that respondents might have been interested in obtaining. Alternatively, they may reflect a general dissatisfaction with the overall level of requested prices.

What is missing from table 1, are estimates of the coefficients of the interaction terms. These were meant to capture the effect on choice of respondents' type of employment and intended use of the mapping tool. However, most of the parameters of the various dummy variables representing these interactions came out insignificant. Moreover, their inclusion in the model resulted in lower values of Adj. R², indicating worse data fit.

Nevertheless, the parameter estimates in Table 1 provide crucial information and make up the most significant findings of this work package task. 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. In choice experiments, the price attribute can be used in conjunction with the other attributes to determine the willingness to pay of respondents for gains or losses of attribute levels. This WTP is called the "implicit price" or part-worth of the attribute and is calculated as follows:

$$WTP = -\frac{\beta_c}{\beta_y},\tag{6}$$

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. Using this formula, the WTP for each level of provision of the various attributes has been calculated and is presented in the following table.

Attribute	WTP	Attribute	WTP
Map Resolution	183€	Water Content	198€
Soil Depth	157€	Clay Content	264€
Bulk Density	210€	Soil Degradation Indicators	811€
Carbon content	263€		

Table 3: WTP for the several features of the DIGISOIL mapping tool

The way to interpret the above numbers is this: 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 $263 \in$ 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 $789 \in (3 \text{ times } 263 \in)$. The same applies for the other features of the DIGISOIL mapping tool, such as map resolution and inclusion of degradation indicators. 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 degradation indicators.

By extension, 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 degradation indicators included. This can be calculated using the following equation:

$$CS = -\frac{-1}{\beta_y} \left(V_0 - V_1 \right) \tag{7}$$

Where β_y is the utility of income, V_o is the utility of the opt-out alternative and V_1 is the utility of a proposed alternative version. In the case of the best possible map version, (the one described above) the WTP is calculated to be $3570 \notin$ /ha. For a medium resolution map, with medium accuracy and degradation indicators, WTP would be $2270 \notin$.

3. Conclusions

This deliverable has presented the findings of Task 1 of DIGISOIL Work Package 4, "Evaluation of DIGISOIL's mapping tool according to end-users needs". The findings reflect the analysis undertaken on a number of replies to a survey, administered to a large number of individuals who have registered to receive the monthly newsletter of JRC's Soil Action. The purpose of the survey has been to assess end-users' 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 what purpose they would want to use the DIGISOIL maps for. 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 that includes indicators of soil degradation, could be as high as 3570. Moreover, end-users' WTP for individual features of the maps has been estimated, pointing to a particularly strong preference for the inclusion of soil degradation indicators.

Unfortunately, the determinants of respondents' choices have not been identified, as the type of employment and intended use of the maps did not seem to have any meaningful effects on choice. If indeed there were such effects, ability to detect them would have helped better understand respondents' choice patterns and consequently help enhance the development of the mapping tool in order to better meet end-users' needs. Nevertheless, the knowledge generated by this research with regard to the economic value of the DIGISOIL's mapping tool is very useful because it provides valuable input for the task of estimating the cost-effectiveness of this technology and thus determining its economic viability.

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Scientific and Technical Centre RNSC Division 3, avenue Claude-Guillemin - BP 36009 45060 Orléans Cedex 2 – France – Tel.: +33 (0)2 38 64 34 34