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Current practice and future research reflections

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Landscape valuation through discrete choice experiments: Current practice and future research reflections

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Abstract

The Discrete Choice Experiments (DCEs) are a fast growing landscape valuation technique. This paper describes some recent applications implemented in this field and identifies their attributes, levels, payment vehicles, experimental designs, innovations and econometric models. From this basis some important areas for future research are reflected upon. These include: choice task complexity, experimental design, preference and scale heterogeneity or econometric models' behaviour. The purpose of this paper is to survey the state of current DCE applications, identify knowledge gaps and suggest some reflections for future research in landscape valuation through DCEs.

Keywords: landscape valuation, discrete choice experiment, review, choice task design, heterogeneity, econometric models.

JEL classification: Q51

1. Introduction

Many landscape policies have been adopted by decision makers of several countries over the last few decades in order to manage landscapes, most of them rural landscapes. Particularly, landscape conservation and protection aspects have dominated the discussion about landscape development (Marangon and Troiano, 2008) and are currently one of the priorities in the environmental policies. The conservation for the future of landscapes depends on national policy decisions which in turn will be shaped by the preferences of the general public (Howley et al., 2012).

The need for public intervention derives from the economic characteristics of the landscape. Landscapes fulfil many different functions by providing multiple benefits in terms of goods and services for human society, so policy-makers need to know the values of the different functions performed by them. The value of the different components of the landscape depends not only on objective aspects (e.g. mountains, forests and open spaces) but also on the vision of the world (i.e. cultural aspects) through which the landscape is interpreted (Goio and Gios, 2011).

As it is well known, the landscape is a public good[1] and an externality (positive or negative) of business activities that use and modify the territory. Additionally, the landscape can be considered a cultural good. For instance, agricultural landscape preserves important features of past farming activities and customs (Marangon and Tempesta, 2008). Thus, it can be considered a merit good. All in all, the landscape can be viewed as an economic resource and as a local public good in that it provides amenities and supports recreational as well as productive activities (Oueslati and Salanie, 2011). As a market price for landscape cannot exist, landscape valuation techniques for policy purposes need to be used.

There is an abundant literature on techniques for assessing and valuing landscapes and there are studies which review this corresponding literature (Daniel and Vinig, 1983; Palmer, 2003: García and Cañas, 2001; Macaulay Land Use Research Institute, 1997). It is possible to find different classification depending on the criteria under it is being valued (intrinsic characteristics, scenic beauty or preference...). However, Discrete Choice Experiments (DCEs) seems to be the most appropriate valuation method for policy purposes; as it allows

[1] A pure public good has non-rival and non-exclusion characteristics, that is, once it is produced, one person's consumption of the good does not diminish its availability to others.

estimating monetary values of landscape changes which is comparable to implementation costs, provides more detailed information and it is possible to measure the benefits associated with the implementation of multidimensional policies with an impact on non-use (passive-use) economic values; (Bateman et al., 2002; Adamowicz et al., 1998; Bennett and Blamey, 2001). DCE applications to landscape are expanding rapidly (Campbell, 2007; Sayadi et al., 2009; Blazy et al., 2011; Colombo et al., 2005; Domínguez-Torreiro and Soliño, 2011; McVittie et al., 2004).

A big problem that arises when applying DCEs for landscape valuation is that landscapes are complex and not easily understood. The term "landscape" has various and sometimes strongly contrasting meanings. For some people landscape is synonymous with environment or ecosystem and for others it has a purely aesthetic meaning. According to the European Landscape Convention (Art. 1, www.coe.int), ''the landscape is an area, as perceived by people, whose character is the result of the action and the interaction of natural and/or human factors''.

DCE presents individuals with landscape changes which they have little prior experience and consequently less familiar attributes and employs hypothetical market institutions which individuals have never previously encountered. So, if respondents in DCE surveys lack experience of the landscape and/or markets concerned then it is quite possible that they have been unable to form theoretically consistent preferences prior to their responses being collected (Bateman et al., 2009). Thus, the design of the survey (the design of the choice task and experimental design) is of great relevance in this kind of applications.

The reliability of the information obtained from a DCE, however, not only depends on the design of the survey, but also on the econometric treatment of the data. Researchers should be conscious of many econometric issues in order to conduct a more complete interpretation of data and consequently offer more reliable information to policy makers.

The aim of this paper is to identify current practice in the application of DCEs for landscape valuation and, from this, reflect on important areas for future research. An overview of approaches for assessing and valuing landscapes is also reported and DCEs are introduced. The contribution of this paper is to try to move DCEs for landscape valuation closer to best practice in the broader context of DCE applications more generally.

The paper is organised as follows. In the next Section it is carried out a brief review of different ways to assess landscape in the literature and DCEs are introduced. Section 3 describes the design of the survey of different DCEs for valuing landscapes' changes and section 4 is devoted to the econometric treatment of their data. Both Section 3 and Section 4 are completed with some future research reflections in the area. Finally, Section 5 provides some concluding remarks.

2. Approaches for assessing and valuing landscapes

Before analysing the different methods for assessing and valuing landscapes, it is important to distinguish between *evaluation* and *valuation*. *Evaluation* is the process of scoring or rating the quality of landscape, whereas *valuation* assigns an economic (i.e. monetary) value to a landscape or its attributes. These two things can diverge with implications for policy (Moran, 2005).

Although there is an abundant literature on landscape evaluation techniques, it does not offer a consensus measurement on it. There are different classifications in the literature about evaluating landscapes. Arriaza et al. (2004) and González and León (2003) explain two main approaches, *direct* and *indirect* methods pointed out by Briggs and France (1980) and *objectivist* and *subjectivis*t approach respectively.

Whereas in the *objectivist* approach, landscapes are valued by their objective and intrinsic characteristics (Daniel and Vinig, 1983), in the *subjectivist* approach landscapes' values depend on the characteristics of the observer (Briggs and France, 1980). That is, the landscape refers to visually perceived properties and its value is given by the satisfaction experienced in its contemplation. When both *objective* and *subjective* ideas are integrated, then *holistic* approach is used (Bishop and Hulse, 1994; Buhyoff et al., 1994) which is mainly focused on predicting the value of landscape changes due to the impact of human activities.

There has been also a large ongoing research program on landscape perception assessments (see Palmer, 2003) where the criterion is typically scenic beauty or preference (Parsons and Daniel, 2002) although other criteria are sometimes used (Palmer and Roos-Klein Lankhorst, 1998). In recent years the *visual or scenic landscape aesthetics* approach has been applied to determine the relationships that exist between landscape biophysical components and the scenic preferences of the observers (derived from a human perceptual/judgmental process) by using photographs (Arriaza et al., 2004; Terry C, 2001). A recent example can be found in Howley (2011) where respondents were asked to rate the various rural landscape images at an aesthetic level.

The use of photos in landscape preference studies has become generalised. The photos are capable of providing stimuli that enable the mind to associate sensory information with other knowledge and thus form opinions about what is perceived through intuitive recognition of an aesthetic quality (Bell, 2001). Barroso et al. (2012) highlight the need to engage in digital manipulation of the photographs to be used in preference studies since it emerges from the necessity to correct deficiencies on captured images (i.e. contrast, scale, view depth or cloud cover of the sky) and control and alter the content of the elements present in the images. However, although photographs of landscape are the most frequently used perception stimulus for aesthetic evaluation of landscape (Palmer and Hoffman, 2001), some authors consider that its use can be inadequate (e.g. Kroh and Gimblett, 1992; Zube et al., 1974).

Recently, *ecological aesthetics* have been included in this field. Qingjuan et al. (2011) propose strategies not only based on the assessment of aesthetics, but also on the evaluation of ecology in order to reserve landscape of a rural area of China. Moreover, Gobster et al. (2007) argue that landscape planning, design and management that address the aesthetics of future landscape patterns can be powerful ways to protect and enhance ecological goals. However, Parsons and Daniel (2002) conclude that ecological aesthetics are inappropriate to the extent that they are based on the presumed superficiality of perceptual and affective processing, as well as to the extent that they are based on the presumed easy malleability of environmental preferences.

A complex classification of landscape evaluation is that enhanced by Daniel and Vinig (1983). They split the methods into *ecological*, *formal aesthetic*, *psychophysical*, *psychological* and *phenomenological models*. On the other hand, García and Cañas (2001) divide the methods into five categories: *direct* models, models to predict *public preferences*, *indirect* models, *mixture* models and *economic valuation* models.

It is also possible to find a detailed review of existing methods of landscape assessments and evaluations in Macaulay Land Use Research Institute (1997). In fact, the methods are split into *descriptive inventories*, *public preference* models and *quantitative holistic* techniques. Finally, recently emerge technique is the *life satisfaction* approach which is particularly used to value scenic amenity (Ambrey and Fleming, 2011).

Nevertheless, the devising of landscape policies involves the need for valuation methods - which assign an economic value to a landscape or its attributes - that can correctly guide public choices. The decision-makers of land management need to know the complete benefits (including those nonmarket benefits) they can expect for their policy (Jianjun et al., 2013). That is, an objective measurement of the impact of public action on landscapes is needed, which is comparable to implementation costs (Santos, 1998).

Thus, economic non-market valuation has developed several methods for estimating the monetary value of environmental changes which are mainly divided into revealed preference and stated preference methods. Moran (2005) presents a detailed discussion of the economic valuation of rural landscapes.

Most of the studies estimate preferences for preserving landscape by estimating willingness to pay (WTP) for the conservation and improvement of landscape using stated preference data. Additionally, the public good and non-market nature of landscapes favours the use of stated preference methodology (Contingent Valuation Method and Choice Modelling) where the estimates of existence benefits are sought (Campbell, 2007). This methodology directly asks respondents about their preferences for hypothetical transformation(s) of the considered landscape change.

Since landscapes are complex environmental goods involving several attributes, there has been a more recent interest in Choice Modelling's variant of choice experiments, which enables the estimation of attribute values and hence marginal effects. A DCE presents a survey to respondents with a series of options concerning the good in question. That good is described in terms of its defining attributes which are in turn varied across a range of levels to define each option. The respondent is asked to choose between two or more of these options (one of which may be the status quo). This choice process is then iterated so as to build up a set of trade-off preferences for each respondent. Repeating this process across a sample allows the researcher to efficiently gather a substantial data set concerning underlying preferences which can be analysed to extract the WTP for a given provision level of the specified good (Bateman et al., 2006).

Thus, DCEs provide more detailed information regarding the trade-offs and values associated with different policy designs (Campbell, 2007). Moreover, they are recommended for measuring the benefits associated with the implementation of multidimensional policies with an impact on non-use (passive-use) economic values (Bateman et al., 2002; Adamowicz et al., 1998); Bennett and Blamey, 2001). Agrarian and rural development multifunctional policies simultaneously influence the provision of a broad range of non-market goods and services originated in rural areas, such as, landscape and open space amenities, natural hazards prevention, biodiversity preservation, rural economic viability, cultural heritage, etc. (Abler, 2004).

The DCE method therefore seems to be more appropriate technique for landscape management purpose. Starting in the early 2000s, economists using stated preference methods to value farmland benefits turned their attention more toward DCE to analyze the relationships between WTP for farmland protection and specific farmland attributes (Bergstrom and Ready, 2008). In a recent study of Jianjun et al. (2013), the DCE is considered a reliable tool in the analysis of respondents´ preferences.

As it is going to be analysed bellow, most of the studies on valuing landscape use DCE to estimate how WTP for rural landscape preservations varies as a function of the characteristics of the respondents and landscape. They employ a DCE with the aim of helping policymakers to target protection programs according to public preferences. For example, Colombo and Hanley (2008), Campbell (2007) or Rambonilaza and Dachary-Bernard (2007). Nonetheless, it is also possible to find some contingent valuation studies in this field, such as, Sayadi et al. (2004), Morey et al. (2008) or González and León (2003) and even more in the nineties (see Moran et al., 2005).

3. Designing the survey

This section provides an analysis of the design of the survey in recent DCEs for landscape valuation, by using recent experiences on attributes and levels, payment vehicle, responsible institution for policy management and the experimental design. Moreover, the future challenges in this kind of applications are stood out.

3.1 Attributes/levels

The lack of affective connection with attributes and its levels used in the choice task for landscape valuation well compromise the reliability of the gathered information as the attributes and/or their measurement units usually is less familiar than in others fields. For instance, many DCE applications in the field of transport management comprise solely commonplace attributes.

However, DCE exercises in landscape valuation and environmental valuation in general, often present respondents with less familiar attributes and measurement units. Psychological insights suggest that in such situations individuals will tend to "construct preferences" using a variety of choice heuristics or "rules of thumb" (Slovic, 1995; Tversky and Kahneman, 1974; 1973).

Actually, whilst most DCE focus strongly on the precision of given information to survey respondents, psychological research tends to emphasise the "evaluability" of that information (Hsee, 1998; 1996a, 1996b; Slovic et al., 2004). The argument behind this is that unless individuals connect with and understand a piece of information on an emotional "affective" level, then that information will (at least to some degree) lack meaning.

All this discussion leads to believe that the attributes/levels, payment vehicles or institutions used in the DCE are of great relevance when valuing landscape changes, that is, the design of the choice task (definition of attributes and its levels and selection of the payment vehicle) ought to be done accurately in order to obtain reliable results for policy purposes.

Domínguez-Torreiro and Soliño (2011) designed a DCE survey to assess social preferences regarding the implementation of regional rural development programs in Cantabria (Spain). The included attributes in the choice task were: (1) *endangered wildlife*, (2) *rural landscape*, (3) *risk of forest fires*, (4) *quality of life in rural areas*, (5) *monuments and traditions at the villages* and (6) *cost*. The levels of the first attribute are defined as a "*loss of endangered species in mountain and coastal areas*" (base level), "*recovery & conservation of endangered species in mountain areas*", "*recovery & conservation of endangered species in coastal areas*" and "*recovery & conservation in mountain and coastal areas*". The levels for the second attribute are expressed similarly but relating to grassland and/or forest landscape. The levels of (3) *risk of forest fires* are defined as a "*percentage risk of forest fire*" (75%high risk; 25% low risk and 50% high risk; 50% low risk), while (4) *quality of life in rural areas'* levels are "*less*" than urban areas or "*similar*" to urban areas. "*Loss*" or "*recovery & conservation*" of cultural heritage are the levels for the (5) *monuments and traditions at the villages attribute.* Finally, the (6) policy *cost* is defined in terms of "*additional taxes"* (€ per individual and per year).

Colombo and Hanley (2008) estimated social benefits from preserving a rural mountain landscape in a Northwest region of England. The following attributes were chosen: (1) *area of heather moorland and bog*, (2) *area of rough grassland*, (3) *area of mixed and broadleaf woodlands*, (4) *length field boundaries (stonewalls),* (5) c*ultural heritage* and (6) *cost*. The levels of the first three attributes are expressed as a "*percentage changes"* (e.g. -10%, +5% and +10% for the *area of rough grassland*) in order to be comparative with others studies in the region; the level of the fourth attribute (*stonewalls*) is stated for every 1 km how many "*meters* are *restored"* (50, 100 and 200); (5) *cultural heritage* conservation presents "*rapid decline"*, "*no change"* or "*much better conservation"* levels and the (6) *cost* is expressed as "*extra* national and local *taxes*" (€ per individual and per year).

Campbell (2007) conducted two separate DCE in Ireland to estimate the WTP for rural landscape improvement measures within the Scheme. While in the first DCE the attributes were (1) *mountain land*, (2) *stonewalls*, (3) *farmyard tidiness*, (4) *cultural heritage* and (5) *annual cost*, in the second one, (1) *wildlife habitats*, (2) *rivers and lakes*, (3) *hedgerows*, (4) *pastures* and (5) *annual cost* were showed. In both experiments, the three levels of the attributes are used to depict each of these landscape attributes according to the effort made to conserve or enhance them. Furthermore, the levels for each one are labelled as *"a lot of action"* (high level of improvement), *"some action"* (intermediate level of improvement) and *"no action"* (unimproved or status quo) and visualised by digitally manipulating photograph in order to understand more easily the attributes' changes (for more detailed information see Campbell et al., 2006). The expected *annual cost* is specified as the value that respondents would personally have to pay per year, through their "*Income Tax and Value Added Tax contributions*", to implement the alternative. Depending on the survey phase different price levels were used (see Campbell et al., 2006).

Rambonilaza and Dachary-Bernard (2007) analysed preferences for preserving agricultural landscape of two categories of rural landscapes users - residents and visitors - at Brittany (France) by applying a DCE. For that purpose the condition of (1) *scrublands*, (2) *hedgerows*, (3) *farm buildings* and the (4) *cost* for visitors and residents were chosen as attributes. To control for respondent confusion, the levels for each landscape attribute are denoted using the same level: "*undesirable"*, "*intermediary situation"* (owning to partial public intervention) and "*optimal level"* of the attribute from the landscaping viewpoint. The corresponding detailed meaning for each attribute is specified in their study. The (4) *cost* takes the form of an increase tax which differed depending on the person interviewed. That is, for tourists, is an "*increase of the resort tax*" defined on a basis of € per person and per night, whereas for residents is an "*increase in municipal taxes*" (€ per household and per year).

Morrison and MacDonald (2006) conducted a DCE in South Australia for a landscape biodiversity improvement in terms of (1) *area of scrublands*, (2) *area of grassy woodlands*, (3) *area of wetlands* and the (4) *payment*. The levels of the attributes are showed as "*increases" or "decreases"* in the size of the corresponding area in hectares. For example, the levels of the *area of scrublands* are *66.000ha* (base level), *73.000 ha*, 80.000ha and *90.000 ha*. The (4) *payment* is described in two different ways. First, as a "*levy on income tax*" over next five years. Second, respondents were told that any expenditure on new biodiversity projects would require a reduction in other government programs, such as, health, transportation, education and policing. This is called "*reallocate expenditure*" away from government programs over the next five years.

Colombo et al. (2005) made use of a DCE to identify peoples' preferences towards the different characteristics (off-farm impacts) of soil erosion on a landscape of an Andalusia region (Southeast Spain). The attributes and levels used in the study were: (1) *landscape desertification* which levels are ranked from "*degradation*", "*small improvement*" (reducing desertification risk in high erosion areas) up to "*moderate improvement*" (reducing desertification risk in all areas); (2) *surface and ground water quality* evened as "*low*" quality (water not potable, high turbidity, toxic materials), "*medium*" quality (potable water, turbidity problems, acceptable levels of toxic materials) or "*high*" quality (potable water, turbidity absent, toxic materials absent); (3) *flora and fauna quality* which can be "*poor*" (reduction of ecological index by 20%), "*medium*" (increase in ecological quality index by 50%) or "*good*" (increase in ecological quality index by 90%); (4) *rural jobs created in watershed* expressed as a "*number"* (0, 100, 200); (5) *area covered by the project* which its levels are "*km^2 of catchment area treated against erosion*" (330, 660, 990) and (6) *payment* showed as "*extra taxes*" (€ per individual and year over next five years).

Carlsson et al. (2003) estimated individuals marginal WTP for different attributes of a wetland in Southern Sweden. Although a wetland is not strictly a landscape, it contributes to its diversity and that's why it is worth analysing it. They included the following attributes and levels in the choice task: (1) *total cost*; (2) *surrounding vegetation* which can be *"forest*" or *"meadow-land*"; (3) *biodiversity* with "low", "medium" or "high" species variety levels; (4) *fish* which is to improve (*"yes*") or *"no*" the condition of species; (5) *fenced waterline* expressed as the possibility to surround the water ("yes") or "no"; (6) *crayfish* which levels are *"yes*" or *"no*" depending on the chance to introduce Swedish crayfish and allow fishing and (7) *walking facilities* which presents the level "yes" if there are available walking tracks with information signs about the plant and animal life and *"no*" otherwise. About the (1) total *cost* is an extra tax (SEK per citizen and year).

Westerberg et al. (2010) employed also a DCE to elicit the public preferences for the potential land use and activity changes in the Marais des Baux wetland in Southern France. The attributes and levels are the following ones: (1) *size of wetland* which can take "*no restoration*" (current size), "*small-scale restoration*" (1/3 of original size), "*large-scale restoration*" (2/3 of original size) levels; (2*) tree hedges* attribute shows "*few*" (full view of Alpilles), "*more*" (partial view of Alpilles) and "*most*" (any view of Alpilles) levels; (3) *biodiversity* which is presented as "*low*" (low number of rare and common species), "*medium*" (rare and common species will increase) and "*high*" (rare and common species will increase and several species may return again); (4) *access and recreation* with "*no access facilities*" (only access to the publicly owned dyke from which hunting is allowed) , "*passive recreation*" (recreational and observational facilities but hunting is not allowed) and "a*ctive recreation*" (access to the wetland with walk and bike trails and hunting is allowed in certain areas) levels; and finally (5) *mosquito control* which was set up as "*no control*" (no effort to reduce it), "*natural control*" (strict water level management and biological control) and "*chemical control*" (from the Bt toxin, a selective naturally occurring bacteria). For the (6) *monetary* attribute an increase in the municipal tax is defined (€ per person and per year).

Concerning the selection of attributes for landscape valuation, Table 1 ranks and classifies the most common non-price attributes used in these DCEs for landscape valuation. A common attribute in almost all the studies is related with vegetation, such as, *area of woodlands*, *area of mixed and broadleaf woodlands, mountain land, scrublands, hedgerows, surrounding vegetation* or *tree hedges*.

Most of the DCE studies aim at preserving a rural landscape, so their application has become a factor of great importance in giving decision makers a picture of landscape management. In addition, rural landscape conservation and protection is one the priorities of the Common Agricultural Policy (CAP) and hence the attempt to estimate WTP for rural landscape improvement measures within it. So, it seems reasonable that attributes related to rural development or improvement programs, such as, *quality life in rural areas*, *rural jobs*, *farm buildings* or *farm tidiness* and attributes to describe a rural landscape like *pastures, rural landscape* or *rough grassland* are applied.

The third common attribute among these studies is wildlife, showed in these studies as *endangered wildlife*, *wildlife habitats*, *flora and fauna quality* or even *biodiversity*. Apart from the most common attributes related with vegetation, rural aspects and wildlife, there are other widely used attributes for valuing landscapes which are *water* and *cultural heritage*.

Water, on the one hand, is expressed differently among DCEs; from *rivers and lakes*, *area or size of wetlands* up *to surface and ground water quality* or *fishing*. On the other hand, cultural heritage in Domínguez-Torreiro and Soliño (2011), for example, is defined as monuments and traditions in the area, whereas in Colombo and Hanley (2008) is referred to maintenance of typical constructions, native breeds and traditional forms of grazing. This attribute is of great importance as culture changes landscapes and culture is embodied by landscapes. Nassauer (1995) explains broad culture principles for designing possible landscapes.

The attribute *stonewalls* is employed in two studies for preserving rural landscape although this kind of boundary varies with the location. In the case of Carlsson et al. (2003), *fenced waterline* is showed in the choice task for designing a wetland. The studies which are focused on a wetland take into account also the access and recreation services by presenting *walking facilities* and *access & recreation* attributes. And finally, there are some other attributes which are characteristic for each of the studies, such as, *risk of forest fires, landscape desertification* or *mosquito control*.

Table 1. Common attributes in landscape DCE applications

Attribute type 1	**Vegetation** (area of woodlands, mountain land, scrublands, hedgerows, surrounding vegetation, tree hedges)
Attribute type 2	**Rural** aspects (rural landscape, grassland, pastures, farmyard tidiness, farm buildings, rural jobs, quality life in rural areas)
Attribute type 3	**Wildlife** (endangered wildlife, wildlife habitats, flora and fauna, biodiversity, fish)
Attribute type 4	**Water** (rivers and lakes, area or size of wetland, surface and ground water quality, area of moorland and bog)
Attribute type 5	**Cultural heritage** (monuments and traditions, typical constructions, traditional forms of grazing)
Attribute type 6	**Boundaries** (stonewalls, fenced waterline)
Attribute type 7	**Access + Recreation** (walking facilities, bike trails, information panels, fishing)
Attribute type 8	**Others** (risk of forest fires, landscape desertification, area covered by the project, mosquito control)

In Table 2 there are summarised the different analysed DCE applications for landscape valuation, describing their aim, attributes, levels and payment vehicle. What we can see clearly in Table 2 is that the amount of attributes used is between five and seven (cost attribute included).

The study analysis shows that whilst three of the studies employ six attributes (Domínguez-Torreiro and Soliño, 2011; Colombo and Hanley, 2008; Colombo et al., 2005 and Westerberg et al., 2010), two applications use four (Rambonilaza and Dachary-Bernard, 2007 and Morrison and MacDonald, 2006) and only one DCE shows five (Campbell, 2007) and seven attributes (Carlsson et al., 2003).

In DCE literature there is no a clear consensus about how many attributes should be shown to respondents. Louviere (2001) argues that increasing the number of attributes will not significantly affect mean preference parameters. Moreover, he points out that there is no empirical evidence to suggest this but that increasing numbers of attributes (and other aspects of complexity) would impact on the random component variability. Hensher et al. (2001) note, whilst researchers agree that DCEs should not be too "complex", to date there is no guidance on what constitutes "complex". Coping with this in the survey design is clearly a challenge for future research.

Regarding the levels used for describing the attributes, it can be seen form Table 2 that choice tasks employ text description of the attributes which are coded using dummy variables (e.g. surface and ground water quality: low, medium or high), percentages (e.g. area of rough grassland: -10%, +5%, +10%) or actual values (e.g. rural jobs: 0, 100, 200).

Additionally, some studies complemented text information with visual description of attributes. In Campbell (2007) each level of improvement (a lot of action, some action, no action) is visualised by digitally manipulating a "control" photograph to depict either more or less of the attribute in question. Rambonaliza and Dachary-Bernard (2007) use scrublands, hedges and farm buildings photographs in the choice sets. Westerberg et al. (2010) employ also visual information in terms of GIS maps, photos and icons to reduce unfamiliarity with the attributes and the potential impact of heuristics.

In fact, some psychological insights suggest that a strategy for addressing anomalies within DCE, and non-market valuation in general, is to use visual information to reduce uncertainty and unfamiliarity with the good concerned (for example, landscape). Bateman et al. (2009) carry out a comparison among visual representations of land use change options by virtual reality software, a conventional DCE presented in numeric form and both the visual and numeric information seen by a sample of DCE participants. They conclude that the new virtual reality approach to DCE valuations reduces reliance upon response heuristics and consequent anomalies and allows underlying preferences to be more effectively measured.

Thus, future DCE applications for valuing landscapes should take into account this alternative for improving citizen understanding. However, future research ought to study more about to what extent the use of visualization techniques improves the individuals' choice task understanding. Some individuals might only pay attention to the photographs without attending the text information which in fact it is more detailed or the visual information can lead to bias choices since there are photos showed only in sunny days and so on. Therefore, a reflection on these issues needs to be done as when a practitioner is not sure about the consequences of introducing photographs, it might be preferred not implemented them.

For the different visualization techniques can be consulted Warren-Kretzschmar (2005). For example, a recent landscape preference study of Barroso et al. (2012) suggest showing manipulated photos using *Photoshop* to overcome the problems in photo interpretation by respondents. The photos are produced through manipulation in order to obtain a set of photographs that included all the desired land cover classes and different intensities of land use.

Between two and four levels are employed for describing the attribute in question although most of them use three levels (including the level for the status quo). This issue is again particularly important to keep respondents' concentration and understanding during the questionnaire. The analyst should weight up the number of attributes/levels showed in the choice task and the complexity of it.

Moreover, as Hoyos et al. (2010) point out, the more levels used and the greater the difference in the levels between the attributes, the higher the number of choice sets. So, on the one hand, more observations for econometric treatment will be available, but on the other hand, respondents would have to face more choice sets and consequently they might lose their concentration on the task. And they also highlight that in order to ensure that the application interval is broader and that the parameter estimates have smaller standard errors, the attribute level-range should be wide enough. But again, more research is needed to answer what wide enough is.

Domínguez-Torreiro and Soliño (2011) and Carlsson et al. (2003) employ only two levels (including the status quo level) for describing some of their choice tasks' attributes. The only one who employs four levels (three levels plus the status quo level) is Morrison and MacDonald (2006). The rest of the applications present three levels for each attribute which is quite typical in DCE´s applications.

In addition, in order to control for respondent confusion, in some applications (Campbell, 2007 and Rambonaliza and Dachary-Bernard, 2007) the levels of each landscape attribute are labelled using the same level (a lot of action, some action, no action and undesirable, intermediary situation and optimal level respectively).

Finally, the status quo treatment in the choice task design is studied by Domínguez-Torreiro and Soliño (2011). They test that different status quo treatments (Provided vs. Perceived) may have a substantial impact on individuals' stated preferences and on associated welfare measures to be used in subsequent policy analysis. They conclude that relevant differences are reported in the compensating surplus estimates from the status-quo provided and the status-quo perceived models. However, DCE applications in the literature tend to provide the status-quo alternative in the choice task. That is, they show the corresponding levels of the baseline scenario to the interviewees.

This analysis has showed the current state of the design of a choice task (common attributes and levels) for valuing a complex good as it is landscape and it has offered some reflections to bear in mind for future applications. Of course, this does not detract from having to consult with experts and to test with focus group to validate the choice task design and its credibility.

3.2 Payment vehicle, protests and institutional framework

The payment vehicle is a crucial element in DCE applications because it provides the context for payment. The monetary values of individual preferences for the different landscape attribute changes may be estimated by using a cost attribute which reflects the (hypothetical) price people would pay to benefit from a landscape change caused by a management policy as well as it allows the economic interpretation in terms of marginal utilities.

Nevertheless, the unfamiliarity with the cost can affect the plausibility of payment vehicles and lead to payment vehicle bias. As Morrison et al. (200) point out, payment vehicle bias may exist when implausible or objectionable payment mechanisms are applied or when payment vehicle presents an inadequate coverage. However, payment vehicle bias is not usually tested in applications, so future research should address this issue of determining whether payment bias exists.

The most commonly used approach for determining it is to use tests of convergent validity which examine whether there are differences in mean bids and protest rates. Nonetheless, simple tests of convergent validity are not accurate indicators of the existence of payment vehicle bias because they may simply demonstrate that different payment vehicles have different effect (Morrison et al., 2000). So, more refined tests able to determine whether payment vehicle bias exits are needed for future studies.

Morrison et al. (2000) analyse the results of three more tests apart from the traditional convergent validity test. These tests examine whether there are differences in protest rates, the effect of differences in coverage of payment vehicles, and the effect of respondents doubting that payment would be one-off. Finally, they found evidence of payment vehicle bias because of differences in the coverage of payment vehicles and doubts about payment being one-off.

The traditional way of dealing with respondents who have been identified as protesting against the payment vehicle is to delete from the sample. However, there is no a clear guidance for coping with this issue and it is clearly needed further research. Morrison et al. (2000), for example, propose the use of response recoding as a positive way of managing protests. Their obtained results suggest that response recoding is effective.

A typical payment vehicle includes levies on income taxes, water or land rates, increased park entrance fees and increased sales taxes. In analysed landscape applications' review, it can be clearly seen that the cost attribute takes the form of an increase in taxes collected by the government in question.

As Table 2 shows, between three and seven possible levels (excluding no cost of the status quo alternative) are defined for the cost. Three studies (Colombo and Hanley, 2008; Morrison and MacDonald, 2006; Colombo et al. 2005; Westerberg et al., 2010) take into account six possible levels for the tax in question. To represent cost attribute, levels in Table 2 range from 2€ (excluding the no cost) of Colombo and Hanley (2008) to the 95€ of Carlsson et al. (2003).

Nonetheless, future applications ought to take into account that the use of taxes in not the only way to secure improvements in landscape quality. Others alternatives are also possible, such as, an annual payment to a foundation which is used for example, in Hoyos et al. (2009) and Hoyos et al. (2011).

On the other hand, Morrison and MacDonald (2006) point out that because respondents may not need to pay (if there is already sufficient government revenue and a reallocation only is needed), may not be able to pay (if budget constrained), may refuse to pay (if they believe they have already paid sufficient taxes or if they believe it is simply the government's responsibility) or other factors, the credibility or acceptability of a tax-based payment vehicle may be constrained. So, in any of these contexts, they propose an alternative; instead of compensating surplus, estimate compensating tax reallocation where respondents are asked to indicate whether they would support specified amounts of government expenditure on the provision of additional public goods, given that there will be explicit opportunity costs. However, the main drawback of its application is that it is very difficult to provide an economic interpretation.

Another important aspect in a valuation study that has not received much attention in the literature is the institution responsible for the provision and management of the public good in question. The significance of selecting an appropriate institution is often overlooked in DCE applications. For instance, most of the studies in this review do not specify the proposed institution responsible for policy management although in some of them it seems that the national or regional government is the chosen managing institution. By contrary, Westerberg et al. (2010) propose an inter-municipal association as the responsible institution for the wetland restoration works.

The institutional framework may affect stated preferences (or choices) and WTP estimates (Remoundou et al., 2012; Bateman et al., 2002) because respondents' low trust in the institution's ability to manage the project and provide the good in question. Furthermore, Remoundou et al. (2012) stand out that the choice of the institutional context becomes more important in times of financial and political crisis as well as in those regions with high corruption incidence and poor government performance.

Given this, future research should take into account the possible effects of the institutional framework especially when applying a DCE where policies under evaluation are hypothetical and the institutional framework has to be specified based on prior knowledge, feedback with focus groups and personal judgment.

For example, Remoundou et al. (2012) examine whether stated preferences and WTP estimates obtained in a DCE are sensitive to the institutional context in which the good is offered. They employ two different institutions as responsible for the design and implementation of a forest restoration project in Greece: an authority under the supervision of the National government and an authority under the supervision of an international body (the European Commission). Their results reveal the coefficients of the utility model and the WTP estimates for all attributes are not statistically different between the two treatments although there are significant differences in the trust levels (European Commission shows significantly

Table 2. Survey design of DCE applications for landscape valuation

Reference	Aim	Attributes	Levels	Payment vehicle
Domínguez-Torreiro and Soliño (2011)	Implement rural development programs (Cantabria, Spain)	*Endangered wildlife*	Text (dummy)	Additional taxes (**€**/individual/year) **0**/ 10/ 25/ 40/ 55
		Rural landscape	Text (dummy)	
		Risk of forest fires	Numeric (%)	
		Quality of life in rural areas	Text (dummy)	
		Monuments and traditions	Text (dummy)	
Colombo and Hanley (2008)	Preserve rural mountain landscape (Northwest England)	*Area of heather moorland and bog*	Numeric (%)	Extra taxes (**£**/individual/year) **0**/ 2/ 5/ 10/ 17/ 40/ 70
		Area of rough grassland	Numeric (%)	
		Area of woodlands	Numeric (%)	
		Length field boundaries (stonewalls)	Numeric (actual values- meters-)	
		Cultural heritage	Text (dummy)	
Campbell (2007)	Rural landscape improvement (Ireland)	**1 DCE:**	*Labelled*	Income Tax and Value Added Tax Contributions (**€**/individual/year) **0**/ 15/ 20/ 35/ 40/ 50/ 65/ 80
		Mountain land	Text (dummy) + Visual (photo)	
		Stonewalls	Text (dummy) + Visual (photo)	
		Farmyard tidiness	Text (dummy) + Visual (photo)	
		Cultural heritage	Text (dummy) + Visual (photo)	
		2 DCE:	*Labelled*	
		Wildlife habitats	Text (dummy) + Visual (photo	
		Rivers and lakes	Text (dummy) + Visual (photo)	
		Hedgerows	Text (dummy) + Visual (photo)	
		Pastures	Text (dummy) + Visual (photo)	
Rambonilaza and Dachary-Bernard (2007)	Preserve agricultural landscape (Brittany, France)		*Labelled*	- For tourists: increase of the resort tax (**€**/person/night) **0**/ 0.10/ 0.20/ 0.30 - For residents: increase in local taxes (**€**/household/year) **0**/ 15/ 30/ 45
		Scrublands	Text (dummy) + Visual (photo)	
		Hedgerows	Text (dummy) + Visual (photo)	
		Farm buildings	Text (dummy) + Visual (photo)	
Morrison and MacDonald (2006)	Landscape biodiversity improvement	*Area of scrublands*	Numeric (actual values-hectares-)	-Levy on income tax (**$**/household/year) **0**/ 10/ 20/ 40/ 60/ 80/ 100 -Reallocation of government expenditure
		Area of grassy woodlands	Numeric (actual values-hectares-)	
		Area of wetlands	Numeric (actual values-hectares-)	

Colombo et al. (2005)	Off-farm impacts of soil erosion on landscape (Andalusia, Spain)	*Landscape desertification*	Text (dummy)	Extra taxes (**€**/individual/year) **0**/ 6.01/ 12.02/ 18.03/ 24.04/ 30.05/ 36.06
		Surface & ground water quality	Text (dummy)	
		Flora and fauna quality	Text (dummy)	
		Rural jobs	Numeric (actual values-number-)	
		Area covered by the project	Numeric (actual values-km^2-)	
Carlsson et al. (2003)	Design a wetland (Southern Sweden	*Surrounding vegetation*	Text (dummy)	Extra taxes (**SEK**/individual/year) **0**/ 200/ 400/ 700/ 850
		Biodiversity	Text (dummy)	
		Fish	Text (dummy)	
		Fenced waterline	Text (dummy)	
		Crayfish	Text (dummy)	
		Walking facilities	Text (dummy)	
Westerberg et al. (2010)	Restore or not a wetland (Southern France)	*Size of wetland*	Text (dummy) + Visual (maps, icons, photos)	Increase in municipal taxes (**€**/individual/year) 0/ 3/ 5/ 10/ 20/ 30/ 50
		Tree hedges	Text (dummy) + Visual (maps, icons, photos)	
		Biodiversity	Text (dummy) + Visual (maps, icons, photos)	
		Access and recreation	Text (dummy) + Visual (maps, icons, photos)	
		Mosquito control	Text (dummy) + Visual (maps, icons, photos)	

3.3 Experimental design and choice sets

An experimental design is a combination of attributes and levels used to construct the alternatives included in the choice sets. Respondents´ stated alternative choices in every choice set are used to estimate parameter weights for each of the attributes (Hoyos, 2010). As Hoyos (2010) point out, the model and the parameters to be estimated need to be specified before creating an experimental design which involves two steps.

The first step corresponds to the specification of the utility function, whereas the second step involves the construction of choice combinations. The former requires the consideration of the number of alternatives and attributes, the consideration of generic or alternative-specific attributes (including alternative-specific constant issues), the inclusion of interaction effects between attributes, and the consideration of non-linear effects via dummy-coded or effects-coded variables. In the latter, several aspects should be taken into account: from the use of labelled or unlabeled alternatives, the consideration of attribute-level balance, the number of attribute levels up to the attribute-level range.

The DCE design objectives should be identification and efficiency. Identification determines which model effects can be independently estimated, and informs practitioner about the specification of the indirect utility function. Efficiency, on the other hand, refers to the precision with which the effects that are identified can be estimated, and more efficient designs give more precise parameter estimates for a given sample size. Different experimental designs can be considered. Therefore, the first aspect examined in this section is whether fractional or full factorial design is used in reviewed applications (see Table 3).

A full factorial design includes all possible combinations of attributes and levels. Although it is more robust and it allows estimation of all main effects (effect of each attribute) and interaction effects (effect of interaction between two or more attributes) independently of one another, the price paid is potentially large numbers of scenarios to be examined by respondents. Thus, this kind of design is usually only possible if there are a small number of attributes and levels. None of the studies of the review makes use of the full factorial design. So, given that the number of combinations may become too large in this kind of DCE applications, fractional factorial design is implemented in all the analysed applications (see Table 3).

A fractional factorial design is a sample of the full design and it allows the estimation of all the effects of interest which usually are main effects only (e.g. in Domínguez-Torreiro and Soliño, 2011; Colombo and Hanley, 2008) or main effects plus some higher-order interaction effects (e.g. in Colombo et al., 2005). This in turn is usually blocked into different versions to which respondents are randomly assigned. As Table 3 shows, for example, in Domínguez-Torreiro and Soliño (2011), the sixteen choice sets obtained with the initial fractional factorial design were subsequently divided into two blocks of eight choice cards to be confronted by each respondent; Colombo et al. (2005) divided the 108 combinations into 27 groups of four choices using a blocking factor, or in Carlsson et al. (2003) the 60 choice sets were blocked into 15 versions each containing four choice sets.

As it can be seen from Table 3, the number of choice sets confronted by an individual is between four and nine. Nevertheless, the appropriate number of choice sets is context specific. The issue of how many choice cards present to the individual is also an open debate in the literature of DCEs. Whilst Hanley et al. (2002) find that increasing the number of choice tasks influence estimated model parameters; Hensher et al. (2001) conclude the opposite. In this case, most of the applications present six choice sets to the respondent.

In addition, fractional factorial design can be orthogonal (i.e. those pursuing no correlation between the attribute levels) or so-called efficient or optimal designs (i.e. those pursuing the minimum predicted standard errors of the parameter estimates). Another difference between them is the amount of information required since efficient designs rely on prior information about the parameter estimates.

Although the empirical applications in the field of environmental economics have mainly relied on the use of orthogonal designs (Louviere et al., 2000), its use has been recently challenged (Huber and Zwerina, 1996; Kessels et al., 2006). A recent trend in the literature has started to move away from orthogonal designs towards designs that relate to the econometric models used in fitting DCE data (Hoyos, 2010). The central argument against the use of orthogonal designs is that their statistical properties do not hold for the non-linear models used in DCEs (see Hoyos, 2010).

Efficient or optimal designs attempt to link the experimental design-generation with the smaller asymptotic standard errors of the parameter estimates, based on the idea that the concern in DCEs is not the correlation between the attributes but the correlations of the differences in the attributes (Huber and Zwerina, 1996). A widely used efficiency criterion is D-efficiency. It is important to use an experimental design that maximises an efficiency criterion or equivalently minimises an error criterion, such as *D*-error (Campbell, 2007). Typically, this gives reasonably robust designs for most DCE applications, but there may be cases where one wants to optimise more specific criteria for one or more model parameters. In order to increase sampling efficiency, Campbell (2007) employs a sequential experimental design approach with a Bayesian information structure.

Efficient designs outperform orthogonal designs if any prior information about the parameters is available. The pro of efficient designs is that this prior information can help in developing experimental designs where either parameter estimates have lower standard errors or the sample size required is smaller. Although some authors have been concerned about the impact of priors parameter estimates on the final model results, Bliemer et al. (2009) argue that "*misspecification of priors may decrease the efficiency of the design but the efficiency will in general still be better than assuming zero priors*".

Huber and Zwerina (1996) distinguish four characteristics for an efficient experimental design: (1) orthogonality; (2) level balance; (3) minimal overlap; and (4) utility balance. However, Street and Burgerss (2007) note that satisfying these properties does not guarantee an optimal design and some designs that satisfy these criteria may not be identified. The determination of priors used for generating the efficient design and the fact that the final model should be known in advance constitute the main challenges of efficient designs. Optimal efficient design is a research field in constant progress during the last few years.

Table 3. Experimental design of DCE applications for landscape valuation

Reference	Design	Choice sets
Domínguez-Torreiro and Soliño (2011)	D-Optimal main effects orthogonal fractional factorial (16 choice sets)	8
Colombo and Hanley (2008)	Main effects orthogonal fractional factorial (18 choice sets)	6
Campbell (2007)	Efficient sequential	At least 6
Rambonilaza and Dachary-Bernard (2007)	Efficient + orthogonal fractional factorial (9 choice sets)	6
Morrison and MacDonald (2006)	Fractional factorial (54 choice sets)	6
Colombo et al. (2005)	Main effects and two-way interactions orthogonal fractional factorial (108 choice sets)	4
Carlsson et al. (2003)	D-Optimal fractional factorial (60 choice sets)	4
Westerberg et al. (2010)	D-Optimal fractional factorial (18 choice sets)	9

The empirical evidence on task complexity suggest that experiments should be very carefully designed and estimated, and that it should be no more complex than the market it aims to simulate (Lancsar and Louviere, 2008). That is, there may be a trade-off between optimality and plausibility.

From a statistical perspective optimal design is desirable, but from an empirical point of view some other issues need to bear in mind, such as, task complexity, heuristics or the inclusion of a base scenario or status quo option (Lancsar and Louviere, 2008). In other words, experimental designs, DCE tasks, DCE task instructions, layouts, formats, and so on, may all impact unobserved variability, decreasing statistical efficiency (Louviere and Lancsar, 2009). More research is needed into the trade-off between better statistical efficiency and more choice variability.

Despite progress, efficient or optimal DCE design in environmental valuation is still in its infancy, with some unresolved challenges noted above. Whilst there is no one correct way to design DCEs and to decide the number of choice sets to be presented, greater attention should be given to reporting the properties of designs. As Louviere and Lancsar (2009) argue, frequently the key aspects of experimental designs are not disclosed or are insufficiently disclosed in academic papers and they call researchers to address this issue.

All in all, the experimental design is perhaps the most important aspect of DCEs as it determines what model(s) can be estimated with what levels of precision (Louviere and Lancsar, 2009). Closer collaboration with design experts would help to improve designs and consequently, to obtain more reliable results.

4. Econometric modelling

In this section, it is addressed the current use of econometric models to analyse the DCE data for landscape valuation. As it has been done in previous Section 3; what needs to be done, unresolved issues and potentially fruitful areas for ongoing research are also pointed out.

4.1 Model specification

Once designed the survey and collected the responses, the next step of the landscape valuation process through DCE consists in estimating the choices. However, which model specify is not an easy task and several aspects have to bear in mind. In order to estimate discrete choices in a utility maximising framework, the DCE employs the behavioural framework of Random Utility Theory (RUT) developed by McFadden (1974). The utility function for individual *n* choosing the alternative *j* is:

$$U_{nj} = V_{nj} + \varepsilon_{nj}, \tag{1}$$

where V_{nj} is the deterministic part of the latent utility that contains factors observable by the analyst and ε_{nj} is a random component that represents determinants of respondent´s choice that are not observable.

The randomness of the utility function suggests that only analysis of the probability of choosing one alternative over another is possible. In addition, since the random element of utility is by definition not observable, the analyst must make assumptions about the nature of the error component if they wish to estimate the choice probability, thus, resulting in different Random Utility Models (RUMs): from the simple Multinomial Logit (MNL) model, Generalised Extreme Value (GEV) models and its variants, Multinomial Probit (MP), Mixed Logit model (MXL) - and Random Parameter Logit model, RPL-, Latent Class (LC) model up to Scale Heterogeneity model (S-MNL) and Generalised Multinomial Logit (G-MNL) model among others.

Table 4 reports the use of econometric models to analyse DCE data. The majority of the studies specify a RPL model, thus allowing for heterogeneous preferences (or unobserved heterogeneity). Actually, the fact that an individual makes a choice depending on his/her tastes, experiences, attitudes and perceptions, gain a special relevance for landscape valuation. Landscape is a complex good and differently understood. In other words, people tend to have different perceptions towards landscape. For example, for some people landscape is synonymous with environment or ecosystem and for others it has a purely aesthetic meaning.

The inclusion of heterogeneity provides more information, regarding the influence of socio-economic and demographic factors in respondents' decision making during the experimental design. If such variations are ignored when carrying out welfare and preference estimations, then this leads to biased results. In last years, there has been a large ongoing research program on how best to model heterogeneity.

Table 4. Model specifications in DCEs for landscape valuation

Reference	Model specification
Domínguez-Torreiro and Soliño (2011)	RPL
Colombo and Hanley (2008)	RPL; LC; S-MNL
Campbell (2007)	RPL combined with Random-Effects model
Rambonilaza and Dachary-Bernard (2007)	CL
Morrison and MacDonald (2006)	RPL
Colombo et al. (2005)	MNL
Carlsson et al. (2003)	RPL
Westberg et al. (2010)	CL, RPL1, RPL2

In the landscape applications' study, Rambonilaza and Dachary-Bernard (2007) bases their estimation on a Conditional Logit (CL) model by maintaining a strong assumption of "Independence of Irrelevant Alternatives"[2] (IIA) property. Colombo et al. (2005) and Westerberg et al. (2010), on the other hand, test whether MNL specification was appropriate using the Hausman and McFadden (1984) test for the IIA property. Since Westerberg et al. (2010) found that the model suffer from violation of the IIA property, it was used as a benchmark for the following RPL specification. Under Multinomial Logit (MNL) model the utility to person *n* from choosing alternative *j* is given by:

$$U_{nj} = \beta' x_{nj} + \varepsilon_{nj} \qquad (2)$$
$$n = 1,\ldots,N; \qquad j = 1,\ldots,J.$$

Here, the vector of utility weights β is homogeneous across consumers, x_{nj} is a *K*-vector of observed attributes describing the alternative *j* for individual *n* and the error term ε_{nj} is i.i.d. Extreme Value. In this model, the heterogeneity tastes for unoberserved attributes are captured by the error term, whereas tastes for observed attributes are homogeneous.

[2] The "Independence of Irrelevant Alternatives" (IIA) property states that the relative probabilities of two options being selected are unaffected by the introduction or removal of other alternatives.

Other models that also have a uniform appreciation of attributes are the Generalised Extreme Value (GEV) models in spite of assuming a Generalized Extreme Value for the error term. Models like Nested Logit (NL), Combinational Nested Logit (CNL) or Paired Combinational Logit (PCL) among others, account also for homogenous preferences.

Most works focuses on extending these models to also allow for heterogeneous tastes over observed attributes by specifying a Random Parameter Logit (RPL) (Domínguez-Torreiro and Soliño, 2011; Colombo and Hanley, 2008; Campbell, 2007; Morrison and MacDonald, 2006; Carlsson et al., 2003; Westerberg et al., 2010). They handle the case of coefficient heterogeneity by assuming that (some of) the weighting coefficients vary in the population according to some distribution and estimating the parameters of those distributions. In RPL the utility to person *n* from choosing alternative *j* is given by:

$$U_{nj} = (\beta + \eta_n)' x_{nj} + \varepsilon_{nj} \qquad (3)$$
$$n = 1, \ldots, N; \qquad j = 1, \ldots, J.$$

Here, β is the vector of mean attribute utility weights in the population, whereas η_n is the vector of person *n*-specific deviations from the mean. The error term ε_{nj} is still i.i.id. Extreme Value. The main task when applying this model is to find variables and a mixing distribution that takes into account the other components of utility, which correlate over alternatives or are heteroskedastic (Train, 2003).

The two used tests to select random parameters are the Lagrange Multiplier (LM) test proposed by McFadden and Train (2000) and the *t*-statistic of the deviation of the random parameter. In the reviewed DCE applications in landscape valuation most of the studies do not make use of any test for selecting random parameters and one of them apply only the *t*-statistic test. Researcher should pay more attention to the relevance of randomness assumptions and the limitations of available statistical tests. Some tips about the issue of selecting random parameters can be found in Mariel et al. (2011).

Another important issue in the specification of a RPL in DCEs is the choice of an appropriate mixing distribution in the absence of information on the actual shape of that distribution in the sample population (Hess, 2010). In fact, an inappropriate choice of the distribution type may bias the estimated means of the random parameters. Nevertheless, in spite of having considerable impact on results, little evidence exists to guide this choice (Fosgerau, 2006). This is clearly an important area for future research.

In practice, researchers have tended to specify a parametric distribution and estimate its parameters testing alternative distributions. The most popular distributions in the context of DCE are normal, triangular, uniform and lognormal, each one with its strengths and weaknesses. Apart from these typical distributions, there are other kinds of distributions and methods to select the distribution more specifically: distributions bounded on either side, with bounds directly estimated from the data (Hess et al., 2005), empirical distributions (Hensher and Greene, 2003a), censored distributions (Train and Sonnier, 2005), constraints on the distribution (Hensher and Greene, 2003a), conditional distributions (Hess, 2010), the assessment of shape of distribution (Sørensen, 2003), non-parametric alternative (Fosgerau, 2006) or Fosgerau and Bierlaire (2007) procedure.

Returning to the analysed landscape applications, in Domínguez-Torreiro and Soliño (2011), preferences for all attributes are assumed to be independently normally distributed but for the *cost* attribute and the attribute level "*recovery and conservation of endangered species in mountain areas*" are assumed to be homogenous to facilitate interpretation and because an initial analysis respectively. Similarly, Colombo and Hanley (2008) employ a normal distribution for considered attributes. Nevertheless, the monetary attribute (*cost*) and the preferences towards the attribute *area of heather moorland and bog* are kept fixed. Again, the reasons behind that are for facilitating welfare measure's interpretation and due to the outcome of a previous analysis respectively.

Carlsson et al. (2003) assume non-price attributes randomly distributed with a normal distribution, with the exception *surrounding vegetation* because it was insignificant in the CL model. They explain two reasons of letting the cost variable be fixed: (i) the distribution of the marginal WTP for an attribute is then simply the distribution of that attribute's coefficient, and (ii) the wish to restrict the *price* variable to be non-positive for all individuals.

Westerberg et al. (2010) make use of the *t*-statistic test to select random parameters in their RPL specification. They conclude that five parameters are subject to significant preference heterogeneity (random parameters) which are specified as normally distributed. The cost parameter is also treated as fixed for simplicity reasons.

In contrast, although in Campbell (2007) the RPL specification it is also used (combined with Random-Effect model), in this application all attributes parameters are specified as random, including the *expected annual cost*. Furthermore, it is opted for bounded triangular distributions in which the location parameters are constrained to be equal to the scales.

Another model that allows also for heterogeneity but only among classes of people is the Latent Class (LC) model. In Table 4 it can be seen that Colombo and Hanley (2008) estimate a LC model among others. The utility to person *n*, who belongs to *m* class, from choosing alternative *j* is the following:

$$U_{nj} = \beta_m' x_{nj/m} + \varepsilon_{nj/m} \qquad (4)$$
$$n = 1,\ldots,N; \qquad j = 1,\ldots,J,$$

where *m* is the class of individuals or segment. In this case, each class has homogenous preferences, but segments differ in preference structure (i.e. there is preference heterogeneity among *m*).

People belong to one class *m* depending on its latent preferences, its latent acts and its personal characteristics. However, the researcher does not know to which class the individual belong. So, the probability to belong to class *m* has to be defined, where many specifications are possible (see Birol et al., 2006 and Hensher and Greene, 2003b). Colombo and Hanley (2008) use Akaike Information Criterion (AIC) and its corrected version (CAIC) and conclude that three is the optimal number of classes, so that finally three classes are estimated in the econometric model.

Recent emphasis has been given to the treatment of scale; in particular recognition of variance in utility over different choice situations (Greene and Hensher, 2010) although it is seems uncommon in landscape studies, and in general in environmental applications. Many authors have argued that much of the taste heterogeneity in most choice contexts can be better described as “scale” heterogeneity.

In other words, for some individuals, the scale of the idiosyncratic error term is greater than for others. Particularly, Louviere et al. (2008) argue that much of the heterogeneity in discrete models would be better captured by the scale heterogeneity (S-MNL) model than by RPL, as (i) distributions in RPL do not appear to being normal like is assumed in most applications and (ii) when comparing coefficient vectors across individuals, something close to the scaling property seems to hold.

In a simple logit model, the scale of the error term (σ) is commonly normalized to 1 due to identification issues. Nonetheless, under the S-MNL context, σ is heterogeneous in the population and its value for individual *n* is denoted σ_n. In this way, the utility function under S-MNL becomes:

$$U_{nj} = (\beta\sigma_n)' x_{nj} + \varepsilon_{nj} \tag{5}$$
$$n = 1,\dots,N; \qquad j = 1,\dots,J.$$

In equation (5) the vector of utility weights β is scaled up or down proportionally across individuals *n* by the scaling factor σ_n. Thus, the statement that all heterogeneity is in the scale of the error term is observationally equivalent to the statement that heterogeneity takes the form of the vector of utility weights being scaled up or down proportionately as one "looks" across consumers (Fiebig et al., 2009).

As Table 4 shows, Colombo and Hanley (2008) not only estimate a RPL and LC model, but they also specify a S-MNL model in order to make a comparison among them. The scale parameter σ_n is estimated as a function of attributes and socio-demographic characteristics of the individuals.

Another relatively new interest is in establishing a mechanism to account for scale heterogeneity across individuals, in addition to the more commonly indentified taste heterogeneity (also called "coefficient heterogeneity") in RPL models. So, an alternative approach noted by Keane (2006) and Fiebig et al. (2009) is to accommodate both: the coefficient heterogeneity of RPL and the scale heterogeneity of S-MNL. In other words, RPL and S-MNL could be nested to obtain a Generalized Multinomial Logit (G-MNL) model. Thus, estimating a G-MNL the analyst would know whether the heterogeneity is better described by scale heterogeneity, the assumed distribution in RPL, or some combination of the two.

In the G-MNL model, the utility to person *n* from choosing alternative *j* is given by:

$$U_{nj} = \left[\sigma_n\beta + \gamma\eta_n + (1-\gamma)\sigma_n\eta_n\right]' x_{nj} + \varepsilon_{nj} \tag{6}$$
$$n = 1,\dots,N; \qquad j = 1,\dots,J,$$

where γ is a weighting parameter between 0 and 1 which governs how the variance of coefficient taste heterogeneity varies with scale in a model that includes both. In other words, it controls the relative importance of the overall scaling of the utility function, σ_n, versus the scaling of the individual preference weights, η_n.

However, several issues are found when computing and estimating a G-MNL: choosing a distribution for η_n and σ_n, constraining the scale parameter σ_n (necessary normalization due to identification issues), treating Alternative Specific Constants (ASCs) or choosing the amount of random draws among others (see Fiebig et al., 2009). None of landscape applications make use of this model; in fact, it is difficult to find an application in environmental DCE literature which applies a G-MNL. So, there seems to be a need for analysing the behaviour of this model in this kind of applications.

At this point, it can be seen that DCEs for landscape valuation in general make use of RPL assuming a normal distribution for randomly distributed variables which usually are associated with non-price attributes. Thus, when valuing a less familiar change as landscape changes, DCE applications tend to assume that the heterogeneity in preferences goes far beyond what can be explained solely with respondent´s characteristics. That is, they assume that an individual makes a choice depending on his/her tastes, experiences, attitudes and perceptions towards a landscape change by randomly distributed coefficients in the econometric model.

However, as it has been argued before, the success of the RPL is subject to the selection of random parameters and their mixed distribution. The S-MNL and G-MNL models have also been analysed although further research is still needed for establishing them more seriously in the literature.

Table 5. Reflections on future research questions

Design questions
• What is the most manageable number of attributes, levels and choice sets to include in a DCE?
• To what extent the use of visualization techniques improves the individuals' choice task understanding in DCEs for valuing landscapes?
• Which one is the most appropriate payment vehicle? And institutional framework?
• How can be tested payment vehicle bias?
• Can analysis be more discerning in their treatment of protest responses?
• Can good practice criteria be developed to promote strong quality experimental designs?
Econometric questions
• Which is the most suitable way to account for preference heterogeneity?
• How to cope with random parameters and mixing distributions in RPL specification?
• Should be taken into account the scale heterogeneity?
• How do alternative models to RPL specification behave?

5. Conclusions

Landscape conservation and protection aspects are currently one of the priorities in the environmental policies. There is an abundant literature on landscape evaluation techniques, but DCEs are expanding rapidly as a method for landscape valuation. Thus, this paper has reviewed different applications in this field in order to discuss its current practice and future research reflections not only corresponding to the design of the survey but also to the estimation stage of the data. Table 5 reflects design and econometric issues for future research.

As DCE presents individuals with landscape changes which they have little prior experience and consequently less familiar attributes and employs hypothetical market institutions, researchers should pay attention to the selection and definition of attributes and its levels as well as the payment vehicle and the institutional framework.

An analysis of the design of the survey in recent DCEs for landscape valuation shows that most experiments aim at preserving a rural landscape. In general, between five and seven attributes are used (including the cost) and *vegetation*, *rural aspects* and *wildlife* are the most used attributes among these studies. The attributes are described in numeric levels (percentages, dummy variables or actual values) which most of them present three levels. However, it is highlighted for the need of visualization innovation which may help to reduce uncertainty and unfamiliarity with landscape´s changes. Future research should address the issue of comprehension in landscape studies within the context of alternative survey designs; varying number of attributes, levels and presentation of scenarios (text versus visual).

The cost attribute usually takes the form of an increase in taxes or extra taxes collected by the government in question. There seems to be a clear need to guide researchers in finding the most appropriate payment vehicle, in determining whether payment bias exists and in dealing with protests. On the other hand, the selection of the institution responsible for the policy is usually overlooked in DCE applications. In fact, no one of the analysed applications make reference to it. Since this decision could affect choice and WTP estimates and more nowadays because the financial crisis that we are living, future research should take into account the possible effects of the institutional context.

Regarding the experimental design, it has been concluded that most reviewed studies carry out a fractional factorial blocked design and present six choice sets to the respondent.

However, major developments are needed in this area in order to improve the design and test its properties.

Largely unrelated to progress in experimental design, major developments have occurred in types of choice models that can be estimated from choices in DCEs. Generally, DCEs for landscape valuation estimate choice responds by a RPL model. Thereby, the heterogeneity among individuals is generally included by randomly distributed coefficients which usually follow a normal distribution. However, RPL specification involves the need to make certain decisions, mainly corresponding to the selection of parameters and mixing distribution. Additionally, there are also other models available to estimate choices (S-MNL and G-MNL) although it is required further research about their performance.

Further research might complete this study with more DCE applications for valuing landscapes´ changes and add more key issues needing further research and emerging research trends, such as, preference stability, validity and reliability, attribute non-attendance and latent attitudes.

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