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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 DCE 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. 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 a 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 survey 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. (2012), 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 is 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 second attribute is expressed similarly but relating to grassland and/or forest landscape (see Table 1). The level of (3) *risk of forest fires* is expressed as a percentage risk of forest fire (see Table 1), 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"* in order to be comparative with others studies in the region (see Table 1), the level of the fourth attribute (*stonewalls*) is stated for every 1 km how many "*meters* are *restored"* (see Table 1), (5) *cultural heritage* conservation presents "*rapid decline"*, "*no change"* or "*much better conservation"* levels and (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 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. 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*, of (2) *hedgerows*, of (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. Their corresponding meaning for each attribute is specified in Table 1. 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* and (3) *area of wetlands* and the (4) *payment*. These attributes' levels are showed as "*increases/decreases"* in the size of the corresponding area in hectares (more detailed in Table 1). The (4) *payment* is described in two different ways. First, as a "*levy on income tax*" over next five years. Second, respondents are 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 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*" up to "*moderate improvement*", (2) *surface and ground water quality* evened as "*low*", "*medium*" or "*high*" quality, (3) *flora and fauna quality* which can be "*poor*", "*medium*" or "*good*", (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).

In Table 1 are summarised the different analysed DCE applications for landscape valuation. 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* or *rough grassland*, *hedgerows or area of moorland* and *scrublands* are applied. However, a common attribute in almost all the studies is *area of woodlands*, differently named; *area of mixed and broadleaf woodlands, mountain land, area of grassy woodlands* or *surrounding vegetation*. Another common attribute among these studies is *wildlife*, interpreted from *endangered wildlife*, *wildlife habitats*, *flora and fauna quality* or even *biodiversity* attributes. Apart from the most common attributes (*area of woodlands* and *wildlife*), there is another widely used attribute for valuing landscapes which is *cultural heritage*. For example, in Domínguez-Torreiro and Soliño (2011) 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 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. Finally, some DCEs make a mention to water; from *rivers and lakes*, *area of wetlands* up *to surface and ground water quality* or *fish*.

What we can see clearly 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 and Colombo et al., 2005), 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 is clearly a challenge for future research.

Regarding the levels used for describing the attributes, it can be seen that choice tasks employ numeric description of the attributes; either through dummy variables (e.g. surface and ground water quality: low, medium or high), through percentages (e.g. area of rough grassland: -10%, +5%, +10%) or actual values (e.g. rural jobs: 0, 100, 200). It is worth noting that 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. In fact, 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. 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.

On the other hand, between two and four levels are employed although most of them use three levels including the cost attribute. 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. 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. Domínguez-Torreiro and Soliño (2011) and Carlsson et al. (2003) employ only two levels (including the cost) 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.

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

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. 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. Nonetheless, Morrison et al. (2000) argue that simple tests of convergent validity are not accurate indicators of the existence of payment vehicle bias because they may simply detect differences in the effects of payment vehicles. So, more refined tests 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.

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 or extra taxes collected by the government in question. As Table 1 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) take into account six possible levels for the tax in question. To represent cost attribute, levels in Table 1 range from 2€ (excluding the no cost) of Colombo and Hanley (2008) to the 95€ of Carlsson et al. (2003). Moreover, in some studies the tax increases progressively, whereas others follow a different pattern.

However, 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. This vehicle is used 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.

Table 1. Survey design of DCE applications for landscape valuation

Reference	Aim	Attributes	Levels	Payment
Domínguez-Torreiro and Soliño (2011)	Implement rural development programs (Cantabria, Spain)	*Endangered wildlife*	**Loss** of endangered species in mountain and coastal areas**/** Recovery & conservation of them in mountain areas**/** Recovery & conservation of them in coastal areas**/** Recovery & conservation of them in both areas	Additional taxes (**€**/individual/year) **0**/ 10/ 25/ 40/ 55
		Rural landscape	**Deterioration** of forest and grassland landscape**/** Recovery & conservation of forest landscape**/** Recovery & conservation of grassland landscape**/** Recovery & conservation of both landscapes	
		Risk of forest fires	**75% high risk; 25% low risk/** 50% high risk; 50% low risk	
		Quality of life in rural areas	**Less** than urban **/** Similar to urban	
		Monuments and traditions	**Loss** of cultural heritage**/** Recovery & conservation	
Colombo and Hanley (2008)	Preserve rural mountain landscape (Northwest England)	*Area of heather moorland and bog*	-12%**/ -2%/** +5%	Extra taxes (**£**/individual/year) **0**/ 2/ 5/ 10/ 17/ 40/ 70
		Area of rough grassland	**-10%/** +5%**/**+ 10%	
		Area of woodlands	**+3%/** +10%**/** +20%	
		Length field boundaries (stonewalls)	50 meters**/ 100 meters/** 200 meters	
		Cultural heritage	**Rapid decline/** No change**/** Better conservation	
Campbell (2007)	Rural landscape improvement (Ireland)	**1 DCE:**		Income Tax and Value Added Tax Contributions (**€**/individual/year) **0**/ 15/ 20/ 35/ 40/ 50/ 65/ 80
		Mountain land	A lot of action**/** Some action**/ No action**	
		Stonewalls	A lot of action**/** Some action**/ No action**	
		Farmyard tidiness	A lot of action**/** Some action**/ No action**	
		Cultural heritage	A lot of action**/** Some action**/ No action**	
		2 DCE:		
		Wildlife habitats	A lot of action**/** Some action**/ No action**	
		Rivers and lakes	A lot of action**/** Some action**/ No action**	
		Hedgerows	A lot of action**/** Some action**/ No action**	
		Pastures	A lot of action**/** Some action**/ No action**	
Rambonilaza and Dachary-Bernard (2007)	Preserve agricultural landscape (Brittany, France)	*Scrublands*	**High reforestation/** Low reforestation**/** Trimmed scrubland	- 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
		Hedgerows	**Absence of hedges/** Slight presence **/** Hedgerows	
		Farm buildings	**No integration/** Partial integration**/** Good integration	

Morrison and MacDonald (2006)	Landscape biodiversity improvement	*Area of scrublands*	**66,000 ha/** 73,000 ha**/** 80,000 ha**/** 90,000 ha	-Levy on income tax (**$**/household/year) **0**/ 10/ 20/ 40/ 60/ 80/ 100 -Reallocation of government expenditure
		Area of grassy woodlands	**46,000 ha/** 51,000 ha**/** 56,000 ha**/** 63,000 ha	
		Area of wetlands	**73,000 ha/** 81,000 ha**/** 88,00 ha**/** 99,000 ha	
Colombo et al. (2005)	Off-farm impacts of soil erosion on landscape (Andalusia, Spain)	*Landscape desertification*	**Degradation /** Small improvement: reducing desertification risk in high erosion areas**/** Moderate improvement: reducing risk in all areas	Extra taxes (**€**/individual/year) **0**/ 6.01/ 12.02/ 18.03/ 24.04/ 30.05/ 36.06
		Surface & ground water quality	**Low** (water not potable, high turbidity, toxic materials**)/** Medium (potable water, turbidity problems, acceptable levels of toxic materials**/** High (potable water, turbidity absent, toxic materials absent)	
		Flora and fauna quality	**Poor** (reduction of ecological index by 20%)**/** Medium (increase in ecological quality index by 50%)**/** Good (increase in ecological quality index by 90%)	
		Rural jobs (number)	**0/** 100**/** 200	
		Area covered by the project	330 km^2 **/** 660 km^2**/** 990 km^2	
Carlsson et al. (2003)	Design a wetland (Southern Sweden	*Surrounding vegetation*	**Forest /** Meadow-land	Extra taxes (**SEK**/individual/year) **0**/ 200/ 400/ 700/ 850
		Biodiversity	**Low** different species**/** Medium**/** High	
		Fish	Improve condition for species Yes**/ No**	
		Fenced waterline	Surround the water Yes**/ No**	
		Crayfish	Introduce Swedish crayfish and allow fishing Yes**/ No**	
		Walking facilities	Walking tracks and information Yes**/ No**	

Note: Levels in bold correspond to the status quo alternative.

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. As Hoyos et al. (2010) point out; two main steps have to be addressed in the experimental design. The first step corresponds to the specification of the utility function, whereas the second step involves the construction of choice combinations. 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. Different designs can be considered. Therefore, the first aspect examined in this section is whether fractional or full factorial design is used in applications (see Table 2).

A full factorial design includes all possible combinations of attributes and levels. Although it is more robust and it allows investigation of all interaction effects, 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 almost all the analysed applications (see Table 2).

A fractional factorial design is a sample of the full design and it allows 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 2 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 2, the number of choice sets confronted by an individual is between four and eight. 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 designs (i.e. those pursuing the minimum predicted standard errors of the parameter estimates). 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). However, the construction of efficient experimental designs requires knowledge of the parameter values and in most cases these are unknown at the time the design is constructed. In order to increase sampling efficiency, Campbell (2007) employs a sequential experimental design approach with a Bayesian information structure (see Table 2).

Table 2. Experimental design of DCE applications for landscape valuation

Reference	Design	Block into:	Choice sets
Domínguez-Torreiro and Soliño (2011)	D-Optimal main effects orthogonal fractional factorial (16 choice sets)	2	8
Colombo and Hanley (2008)	Main effects orthogonal fractional factorial (18 choice sets)	3	6
Campbell (2007)	Efficient sequential	x	At least 6
Rambonilaza and Dachary-Bernard (2007)	Efficient fractional factorial (9 choice sets)	x	6
Morrison and MacDonald (2006)	Fractional factorial (54 choice sets)	9	6
Colombo et al. (2005)	Main effects and two-way interactions orthogonal fractional factorial (108 choice sets)	27	4
Carlsson et al. (2003)	D-Optimal fractional factorial (60 choice sets)	15	4

Despite progress, optimal DCE design in environmental valuation is still in its infancy, with some unresolved problems 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. Closer collaboration with design experts would help to improve designs and consequently, to obtain more reliable data.

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. Offered in the DCE different options defined in terms of these attributes, individuals will maximise their utility choosing the alternative which gives them the highest level of utility: that is, individual *n* will chose alternative *j* over some other option *i* if $U_{nj} \succ U_{ni}$. The random utility approach developed by McFadden (1974) is used to link the deterministic model with a statistical model of human behaviour. Thereby, the conventional utility function $U(\bullet)$ is split into two parts: one deterministic $V(\bullet)$ that contains factors observable by the analyst, and a random component $\varepsilon(\bullet)$ that represents determinants of respondent´s choice that are not observable. In other words, the utility function for individual *n* choosing the alternative *j* is:

$$U_{nj} = V_{nj} + \varepsilon_{nj}. \quad (1)$$

The randomness of the utility function (utilities are unobserved) 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 3. 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)	MNL
Morrison and MacDonald (2006)	RPL
Colombo et al. (2005)	MNL
Carlsson et al. (2003)	RPL

Table 3 reports the use of econometric models to analyse DCE data. The majority of the studies specify a RPL model, thus allowing for heterogeneous preferences. 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.

In the landscape applications' study, Rambonilaza and Dachary-Bernard (2007) and Colombo et al. (2005) are the only ones who use a simple Multinomial Logit (MNL) model to analyse the choice data. The former bases their estimation on a conditional logit model by maintaining a strong assumption of "Independence of Irrelevant Alternatives"[2] (IIA) property. They argue that the inclusion of a large set of *cross*cutting variables of choice attributes with socio-demographic attributes meet this requirement. The latter, on the other hand, tests whether MNL specification was appropriate using the Hausman and McFadden (1984) test for the IIA property. Under MNL model the utility to person *n* from choosing alternative *j* is given by:

[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.

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

Here, the vector of utility weights β is homogeneous across consumers and as 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. 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 RPL (Domínguez-Torreiro and Soliño, 2011; Colombo and Hanley, 2008; Campbell, 2007; Morrison and MacDonald, 2006; Carlsson et al., 2003). 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:

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

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. 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 conditional logit 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. 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 3 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:

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

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 (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:

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

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 3 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:

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

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.

Table 4. 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 improve the individuals' choice task understanding in DCEs for valuing landscapes?
• Which one is the most appropriate payment vehicle?
• 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?

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 normally 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.

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 there are the DCEs that 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 4 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 institution. A review of the attributes/levels, payment vehicle and applied innovations of recent studies shows that most experiments aim at preserving a rural landscape. In general, between five and seven attributes are used (including the cost) and *the area of woodlands*, *wildlife* and *cultural heritage* 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 - which range from 2€ to 95€ taking into account all analysed landscape applications. 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. 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 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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