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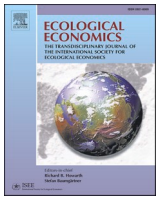

Do urban environmental inequalities influence demand for nature based solutions?

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ABSTRACT

Nature-based solutions (NBS) are currently being promoted for urban climate change adaptation. We argue that urban planners should account for the demand for NBS, which may be spatially heterogeneous and influenced by environmental inequalities. We develop a discrete choice experiment to evaluate preferences for two co-benefits (aquifer preservation and local climate regulation), as well as one potential negative effect of NBS policies (their impact on the reduction of space available for cars in cities). The survey in a large French city reveals a strong heterogeneity of preferences for local climate regulation and for the reduction of car space. We analyze the spatial heterogeneity of preferences, and find significant spatial autocorrelation and local clusters of high/low demand for local climate regulation and for the reduction of car space. In a subsequent post-estimation model, we identify that individual's exposure to heat islands affects positively their demand for NBS policies, which allows us to effectively create a city-wide demand map for local climate regulation. In addition, individual's reliance on car use influence their demand for NBS policies. Overall, our analysis highlight that analyzing environmental inequalities is important for planning sound NBS policies.

1. Introduction

In the coming decades, cities will need to adapt to a variety of challenges posed by climate change, and land use change, resulting in air, soil, and water pollution, heat island effects, and increased flood risks. Urban nature-based solutions (NBS) - e.g., urban greening, depaving, sustainable urban drainage systems (SuDS), preservation of natural areas- are increasingly considered by cities to tackle these issues. These challenges are unequally distributed in urban areas, therefore these solutions need to be implemented in areas where they are needed the most. Most cities have yet to design and implement spatially explicit NBS development strategies (Almenar et al., 2016; Elmqvist et al., 2013), rather most NBS are currently implemented based on available land opportunities that are usually located outside densely populated centers where the need for adaptation services is the highest (Kabisch et al., 2016). To avoid such outcomes, decision makers to account for the spatial patterns of supply and demand for the ecosystem services (ES) provided by NBS (Cortinovis and Geneletti, 2018; González-García et al., 2020), in order to maximize the benefits of public investments for society (Mader et al., 2011).

Most current NBS planning approaches are based on the study and modeling of biophysical indicators of ES supply (Elliot et al., 2019; Hu et al., 2015; Oraei Zare et al., 2012; Polasky et al., 2008). These approaches rely on a strong rationale for action: by mapping explicitly ES supply, they allow for the identification of spatial environmental inequalities (EI). Resulting spatial recommendations for NBS projects are thus designed to target areas of scarce ES supply, mitigate EI (Liotta et al., 2020). Environmental justice (EJ) has developed the thorough analyzis of EI in urban contexts as a means to inform policy makers. Indeed, identifying the spatial distribution of EI prior to the planning phase of NBS policies may improve their outcome.

However, supply-based approaches can encounter shortcomings by not accounting for urban dwellers' demand (Langemeyer et al., 2016; Nesshöver et al., 2017; Van Oijstaeijen et al., 2020). First, focusing exclusively on supply may not always capture the full extent of the spatial heterogeneity of the possible benefits of NBS policies, and can potentially lead to suboptimal choices of location (González-García et al., 2020). For instance, in the context of NBS policies aimed at mitigating heat islands, this could lead to prioritize commercial or industrial areas endowed with large parking lots and few green areas, but

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also with few residents, rather than selecting densely populated areas of the city where the demand for heat mitigation is higher. In addition, failure to analyze demand may leave unnoticed the potential existence of populations or areas strongly opposed to the implementation of NBS policies (Gould and Lewis, 2016; Laurent, 2011)(Blanco et al., 2019; Lyytimäki and Sipilä, 2009).

Stated preference methods, can be used to evaluate citizens' demand for contrasted NBS strategies and inform policy makers. Researchers have started using spatial econometric tools to analyze the spatial heterogeneity of demand for different types of environmentals: individual's willingness to pay (WTP) for environmental programs and goods are not distributed randomly, but 1) show national or regional spatial disparities (Czajkowski et al., 2017; Pinto et al., 2016; Toledo-Gallegos et al., 2020), and 2) they display local clustering of low or high WTP (Johnston et al., 2015; Kim et al., 2022; Toledo-Gallegos et al., 2020).

However, few studies have established a clear link between the spatial heterogeneity of demand for NBS and the distribution of EI. Clarifying this link will provide generic insights - beyond individual case studies - into the rationales behind the spatial heterogeneity of demand for NBS. This link has only been studied implicitly, when analyzing how preferences for urban green areas are ordered along an urban-rural gradient (Hérivaux and Le Coënt, 2021; Zhou et al., 2018), since the urban-rural gradient can encompass the distribution of EI. However, the degree to which EI are themselves determinants of the spatial heterogeneity of demand has yet to be explicitly investigated.

In this paper, we evaluate the influence of distributional EI on the demand for NBS. We implemented a choice experiment to evaluate the preferences for contrasted alternatives of development of infiltration infrastructures (including NBS), aimed at protecting groundwater resources as well as at providing other urban ES. This choice experiment was led in the Bordeaux Metropolitan (BM) area, France, where the local government is currently designing a plan to develop infiltration infrastructures.

Our analysis addresses two research questions:

- Are preferences for NBS spatially heterogeneous?
- Are preferences for NBS influenced by EI?

The novelty of this paper lies in three points:

Firstly, while the spatial distribution of EI and the spatial heterogeneity of demand for urban ES have been both explored, to our knowledge very few studies have actually bridged the gap between these questions (Jacobs et al., 2016), and analyzed how EI may impact preference for NBS at city scale. The goal of this paper is to address this point in order to 1) characterize the spatial distribution of preferences, 2) identify rationales for these distributions, and 3) predict maps of demand for NBS benefits and negative effects.

Secondly, although preferences for the multiple benefits provided by NBS, urban green areas, and sustainable urban drainage systems (SuDS) have been thoroughly studied, this work focuses on a different type of NBS that provides a particular benefit that has not been extensively evaluated in this literature: the preservation of groundwater resources.

Thirdly, this paper focuses on the relatively unexplored spatial dilemma at the core of many urban planning debates, between NBS development and availability of space for cars in cities (Cortinovis and Geneletti, 2018; European Commission, 2015). In particular, we explore how this trade-off impacts demand for NBS.

2. State of the art

Distributional justice is one dimension of EJ that classically focuses on the distribution and allocation of environmental costs, burdens and benefits between individuals and groups (Walker, 2012). In this paper we analyze three dimensions of distributional environmental inequalities that are particularly salient in the context of NBS policies (Kato-Huerta and Geneletti, 2022), and that may impact demand for urban ES: inequality in exposure to environmental hazards, inequality in access to urban green areas, and inequality caused by the adverse effects of greening policies. In this section, we look at how these dimensions of inequalities can affect demand for NBS.

Inequality in exposure to environmental hazards is the most widely studied aspect in classical EJ studies (Calderón-Argelich et al., 2021), and focuses on revealing the contrasted exposure of different groups and populations to sources of pollution (Boyce et al., 2016; Diekmann et al., 2022; Samoli et al., 2019), to flood risks (Fielding and Burningham, 2005), or to the heat island effect (Darrel et al., 2011; Hsu et al., 2021; Wong et al., 2016). The closer previous studies have approached to identifying the relation between these exposures to environmental hazards and the demand for NBS can be found in environmental geography studies which have mapped the spatial mismatches between ES supply and demand (Baró et al., 2015, 2017; González-García et al., 2020; Herreros-Cantis and McPhearson, 2021). However, these studies have relied on using population density as a proxy for demand, and thus do not explicitly analyze individual demand heterogeneity. Therefore, although it is commonly assumed that exposure to environmental hazards increases demand for ES, this relation remains to be studied.

The second type of inequality that may affect demand for ES is inequality in access to green areas, which is stratified along many sociodemographic characteristics (Chen et al., 2022; Nghiem et al., 2021; Nyelele and Kroll, 2020; Wolch et al., 2014). To date, studies have investigated the link between access to green areas and demand for it mainly through a single entry: by analyzing how increased distance to environmental goods reduces WTP for environmental programs, i.e. the "distance decay" effect (Glenk et al., 2020). This effect has been identified in stated preference studies by including distance-based attributes, (Badura et al., 2020; Jørgensen et al., 2013; Pate and Loomis, 1997; Schaafsma et al., 2012; Tu et al., 2016), or by analyzing respondent locations and their distance to environmental goods in spatial econometrics model(Johnston and Ramachandran, 2014). However, the above works focus exclusively on large-scale environmental goods (parks, lakes, etc.), not on small urban NBS. The impact of EI in access to green areas on demand for NBS remains to be investigated.

Finally, NBS policies may amplify inequalities through their implementation (Calderón-Argelich et al., 2021). These negative effects have been overlooked in NBS valuation (Langemeyer and Connolly, 2020); instead ecosystem disservices have been the main center of attention as one of the main possible negative policy implications of NBS (Blanco et al., 2019; Gómez-Baggethun and Barton, 2013; Soto et al., 2018). In the context of urban NBS plannig, a direct short-term possible negative impact of these policies - and, we would argue, one that may be more impactful for urban populations than ecosystem disservices - may be the reduction in car-related infrastructure such as roads and parking areas (Gundlach et al., 2018; Lyytimäki and Sipilä, 2009). Some populations – especially suburban populations - may depend to a great extent on individual car use for their livelihood, and feel a loss of well-being due to policies that constrain car transport, especially in the absence of suitable alternatives (Gundlach et al., 2018). Hérivaux and Le Coënt (2023) showed that these populations may in consequence reject such NBS policies when this is not anticipated. The influence on demand for NBS of the impact of NBS policies on car space has not yet been estimated directly.

Based on these findings, we hypothesize that these three types of EI influence individual demand for ES.

3. Method

3.1. The survey

3.1.1. The survey design: Water infiltration NBS in Bordeaux metropolitan area, France

The Bordeaux metropolitan area (814,000 inhabitants) is located in the southwest of France, and covers 28 municipalities. For its public

water supply, the area depends largely on deep aquifers that are currently overexploited due to rapid demographic growth. The city is also experiencing increasingly strong heat waves that are predicted to increase from a mean of 8.4 days/year to 20.7 days/year by 2050 (Artelia., 2015). To mitigate these two adverse effects, the local government aims to develop infiltration infrastructure and urban greening as a way of combining two objectives, the preservation of deep aquifers, and adaptation to urban climate change, mainly though heat island mitigation. To this end, both NBS and grey infrastructure are being considered. Their main purpose will be to enable infiltration and storage of rainwater in shallow aquifers so it can later be reused for uses that are currently covered by drinking water even though lower quality water would suffice (irrigation of green spaces, street cleaning, industrial uses, etc.). The goal of this water use substitution is therefore to help preserve deep aquifers. The other main objective of this policy is to address heat island effects.

We conducted a choice experiment survey to assess both the resident population's preferences for various alternative implementations of infiltration infrastructure, and demand for their benefits. The choice experiment attributes and their levels were constructed in a participatory process with stakeholders. We held two workshops with members of the local administration involved in the management of the different issues at stake: water basin authorities, water service and urban greening personnel, and public developers. The first workshop (January 2022) aimed at (i) identifying available urban spaces that could be used for the development of infiltration infrastructure; (ii) discuss their main benefits, and negative effects, (iii) select which of these benefits and negative effects should be included in the choice experiment. The aim of the second workshop (March 2022) was to validate the range of levels for these effects.

The choice experiment was designed to both (i) respond to the policy questions identified during the participatory process on the preference for the benefits and negative effects generated by infiltration infrastructure, and (ii) test the impact of the three types of EI discussed in the state of the art section on preferences. The selection of attributes in particular was the result of these two objectives.

3.1.2. Attributes and levels

The attributes included in the choice sets were the following:

- The first attribute is the preservation of deep aquifers enabled by replacing the water currently used by infiltrated rainwater. This attribute is the main benefit attributed to infiltration infrastructure by workshop actors for which they expect to estimate preferences. It is formulated as the percentage of achievement of the official local deep aquifer water saving goals.
- The second attribute is linked to the regulation of local climate by reducing heat-island effects resulting from NBS. It is the second objective attributed to infiltration infrastructure by local actors. It is expressed as the total city-wide proportion of reduction in heat islands area due to NBS projects. This attribute is also well suited to test the impact of the inequality to exposure to environmental hazards on preferences.
- The third attribute is the impact of developing infiltration infrastructure on urban space dedicated to cars. This attribute may be perceived as either a negative effect, for instance by car-dependent citizens; but it can also involve other services and benefits, such as noise reduction or improved air quality due to reduced use of cars. It is considered by local actors as the potential main source of opposition to the development of infrastructure. As the authors, we also expect that inequality regarding the adverse effects of NBS policies may strongly affect preferences for this attribute.
- The fourth attribute is the distance of inhabitants to the closest NBS. It is expressed as a simple distance between the respondent's home and an NBS. We included this attribute to estimate the distance decay associated with infiltration infrastructure. We also expect that it may be affected by the inequality in access to green areas.
- The payment vehicle is an annual increase in water bills for a duration of 10 years. Respondents were given the explanation that implementing infiltration policies may require using this source of financing, as part of the water bills is dedicated to financing rainwater policies in the Bordeaux metropolitan area.

To identify plausible levels for the deep aquifer preservation and local climate regulation attributes, we estimated potential future benefits of infiltration infrastructure using a simple GIS modeling approach. We identified and mapped urban spaces that are really available for NBS projects in collaboration with workshop actors, and quantified the maximum possible levels for both of these benefits. The method is described in supplementary materials. The final attributes and their levels are listed in Table 1.

3.1.3. Hypotheses

We aim to assess the impact of inequality in exposure to environmental hazards, inequality in access to green areas, and inequality regarding the adverse effects of NBS policies on preferences for NBS. We transformed these questions into testable hypotheses in our case study:

- High exposure to heat island risks increases demand for local climate regulation (inequality in exposure to environmental hazard) (H1);
- Poor access to green spaces leads to a higher demand for NBS close to the individual's residence (inequality in access to green areas) (H2);
- Dependence on car use lowers demand for NBS policies that reduce car space (inequality regarding the adverse effects of NBS policies) (H3).

Based on these hypotheses and on our set of attributes and levels, we created a questionnaire and the experimental design for the choice experiment.

3.1.4. Survey administration

The questionnaire comprised three parts. The first part explained the urban challenges faced by the Bordeaux metropolitan area regarding the preservation of water resources, as well as adaptation to climate change (heat island effects) and the benefits of infiltration. The second part contained the choice sets (for an example of a choice set, see Fig. 1), in which respondents chose between NBS alternatives defined by the attributes listed in Table 1. The third and final part was a series of questions regarding the individual's lifestyle and environment (e.g. type of residence, car use, distance to existing green areas, etc.), and socio-demographic variables (e.g., gender, age, employment, education, income).

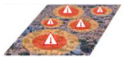
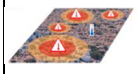
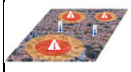
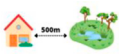
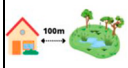
A first round of face-to-face pre-tests of the survey ($n = 34$) was implemented in June 2022 to be sure the questionnaire was clear, and to establish priors. The final levels of payment were raised after these pre-tests, as it appeared that we did not capture the full range of WTP.

The survey was then administered online by a polling company and sent to residents of all the municipalities that make up the Bordeaux metropolitan area in September 2022.

3.1.5. Survey design

We used a fractional D-efficient design for the experiment. Each choice set featured 2 alternatives resulting from different levels of implementation of infiltration infrastructure, and a 'status quo' option representing the absence of development of infiltration infrastructures - whether NBS or grey infrastructures - and was characterized in terms of all attributes. With this design, 10 parameters had to be estimated (2 for deep aquifer preservation, 3 for local climate regulation, 1 for car space reduction, 3 for the distance attribute, and 1 for payment). Based on general guidelines (Hensher et al., 2005), we decided on 12 choice sets to be on the safe side for model estimation and guarantee a balanced

Table 1
Attributes and levels.

Attributes	Levels							
Preservation of deep aquifers	**No** groundwater savings due to infiltration (status quo-only level)		**25%** of groundwater savings goal thanks to infiltration		**50%** of groundwater savings goal thanks to infiltration		**100%** of groundwater savings goal thanks to infiltration	
								
Local climate regulation	**No reduction** of heat island areas (status quo level)		**20%** decrease of heat island areas		**40%** decrease of heat island areas		**60%** decrease of heat island areas	
								
Impact on urban space dedicated to car use	**No reduction** of space dedicated to cars (status quo level)				**Reduction** of space dedicated to cars			
								
Distance to the nearest green infrastructure	**No** new green infrastructure in the vicinity of your home (status quo)		Nearest green infrastructure located **500 m** from you home		Nearest green infrastructure located **100 m** from your home		Nearest green infrastructure is located **right next** to your home	
								
Increase in annual water bill	0€ (status quo level)	30€	60€	90€	120€	150€	180€	

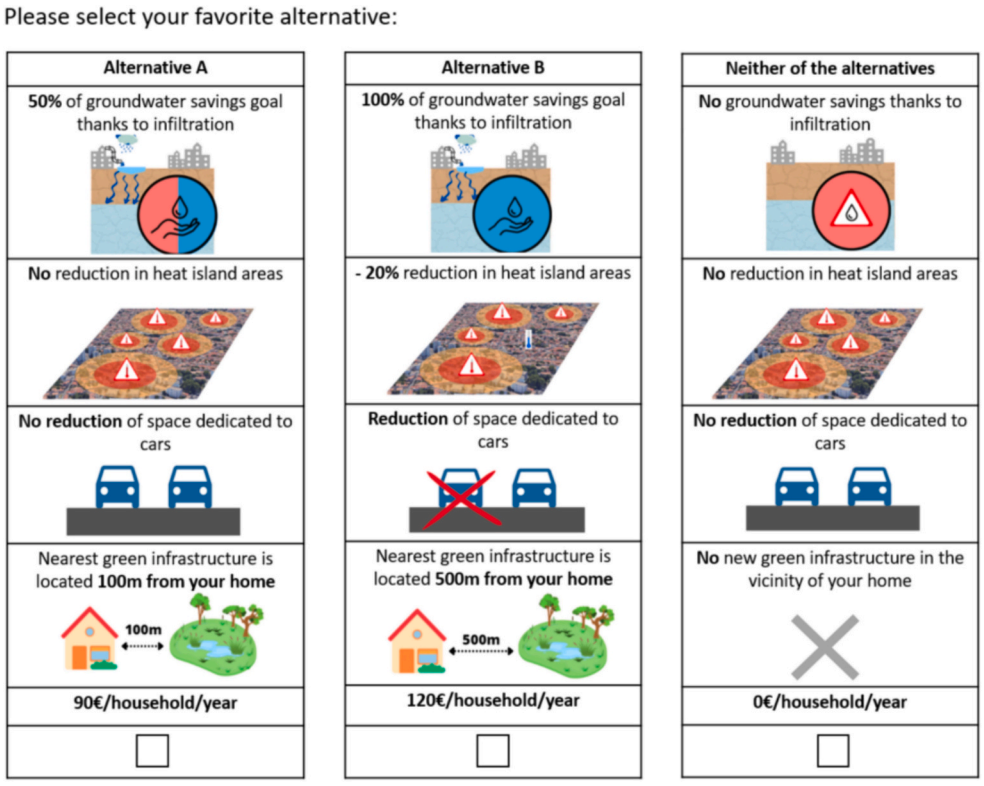


Fig. 1. Example of a choice set.

attribute level. We chose a hybrid blocking design, where 6 random sets out of the 12 would be presented to each respondent.

This design has a specificity: the attribute for deep aquifer preservation has a level that only appears in the status quo option ("no groundwater savings"), while all other non-payment attributes have a status-quo level that can also appear in the choice cards. It would have been illogical to present alternatives in which infiltration infrastructures are implemented, but do not improve groundwater preservation. Consequently, preference for the first level of aquifer groundwater preservation is combined with the preference for the status quo. In contrast, the heat reduction attribute featured a status quo level within the choice sets, as only grey infrastructure can be constructed for these infiltration policies, which would not result in delivering urban cooling ecosystem services. The levels and their coding are detailed in supplementary material.

3.2. Overall econometric approach

Our overall econometric approach aimed first to analyze preference heterogeneity, and then to test how EI impacts demand for NBS. The analysis is done in four stages:

- First, we used a mixed logit (MXL) model in preference and WTP space in order to estimate average and individual-specific coefficients and WTP (Section 3.2.1).
- For variables that present heterogeneity in the MXL model, we tested for spatial dependence of estimated individual WTP; and mapped hot/cold spots of individual WTP (Section 3.2.2).
- In order to analyze EI, and to identify potential predictors of spatial preference heterogeneity, we created indicators of EI and tested their spatial dependence (Section 3.2.3).
- Finally, we performed a post-estimation regression model, in which the individual WTP_n estimates from the MXL model are explained using environmental indicators and individual socio-demographic variables (Section 3.2.4).

3.2.1. Choice modeling

The econometric models are based on the random utility model. Respondent n faces T choice sets, where each choice situation t is made of J alternative. The respondent would choose alternative j based on its utility U_{njt}, which is made of both deterministic and random parts. The observable component of U_{njt} comprises the set of attributes X_{njt}, the corresponding coefficient for the vector of attributes β_n, and the unobserved error term ε_{njt}:

$$U_{njt} = \beta_n X_{njt} + \varepsilon_{njt} \tag{1}$$

The standard conditional logit model assumes homogeneous distribution of preferences among individuals, so it does not allow the study of preference heterogeneity. In contrast, the mixed logit model accounts for the heterogeneity of preferences by allowing the β_n coefficients to vary randomly across individuals according to a continuous distribution $f(\beta_n|\theta)$.We specify the parameters θ of this distribution to have preference coefficients follow a normal distribution across the population. The mixed logit model estimates the probability that the individual n makes the sequence of T choices, selecting alternative i_{nt} among J alternatives in choice situation t. The probability of this sequence of choices, conditional on knowing the individual taste coefficient β_n is given by:

$$P_n(j_{n1}, \ldots, j_{nT}|\beta_n) = \prod_{t=1}^{T} P_n(j_{nt}|\beta_n) = \prod_{t=1}^{T} \frac{exp(\beta_n X_{int})}{\sum_{j\in J} exp(\beta_n X_{jnt})} \tag{2}$$

However, β_n is random and therefore unknown, therefore from Eq. (2), we express the unconditional probability P_{nT} that individual n makes the observed sequence of choice j, by integrating over the known distribution of β_n. This gives us the final specification of our first model:

$$P_{nT} = \int \prod_{t=1}^{T} \frac{exp(\beta_n X_{int})}{\sum_{j\in J} exp(\beta_n X_{jnt})} f(\beta_n|\theta) d\beta \tag{3}$$

We used also a second mixed logit model, this time in 'WTP space', by reformulating the first model. In this way, the WTP of attribute coefficients are the direct results of the econometric model. Indeed, this method is better than the traditional method used to estimate WTP, i.e., calculating the ratio between attribute and payment coefficients, which leads to a skewed distribution of WTP as two randomly distributed parameters are associated (Train and Weeks, 2005). In Eq. (1), we separate the payment attribute p_{njt} from the other attributes X'_{njt}, hence the utility of the respondent n in choosing alternative i in choice situation t is:

$$U_{njt} = \alpha_n p_{njt} + \beta'_n X'_{njt} + \varepsilon_{njt} \tag{4}$$

with α_n a random parameter for payment, and β'_n individual random parameters for the other attributes. β'_n are again following a random distribution $f(\beta'_n|\theta)$, but not the payment attribute coefficient α_n, which is specified to have a uniform distribution across the population.

ε_{nit} is a random term that follows a Gumble distribution with a variance of $k_n^2(\pi^2/6)$, k_n is a scale parameter associated with individual n. By dividing Eq. (4) by k_n, we obtain the equation of utility in WTP space:

$$U_{njt} = \lambda_n \left[p_{njt} + \gamma_{njt} X'_{njt} \right] + \varepsilon_{njt} \tag{5}$$

with $\lambda_n = \alpha_n / k_n$ and $\gamma_{njt} = \beta'_n / \alpha_n$.

Following the same logic, the unconditional probability P_{nT} with this new specification gives us the second model in WTP space:

$$P_{nT} = \int \prod_{t=1}^{T} \frac{exp\left(\lambda_n \left[p_{njt} + \gamma_{njt} X'_{njt} \right]\right)}{\sum_{j\in J} exp\left(\lambda_n \left[p_{njt} + \gamma_{njt} X'_{njt} \right]\right)} f(\beta'_n|\theta) d\beta' \tag{6}$$

In both models, the expression cannot be solved analytically, and are thus approximated using maximum simulated likelihood method (using 500 Halton draws). This was done after dummy-encoding the choice dataset (the coding scheme is presented in appendix), using the STATA 12′ "gmnl" package. Finally, in order to further test spatial dependance of WTP estimates and the impact of environmental indicators on them, we also simulate the vector of conditional individual-specific WTP_n estimates, by using Bayes Theorem as shown by Train (2009):

$$WTP_n = \int \gamma_{njt} \frac{p(j_{nt}|X'_{nt}, \theta, \gamma_n, \alpha_n) f(\gamma_n, \alpha_n|\theta)}{p\left(j_{nt}|X'_{nj}, \theta\right)} d(\gamma_n, \alpha_n) \tag{7}$$

These WTP_n estimates are not strictly speaking individual set of estimates, which are impossible to observe and establish. Instead, they are rather mean estimates of WTP for the subpopulations who made the same series of choices, and they are as such, an approximation of individual WTP.

3.2.2. Test for spatial dependence of estimated WTP_n

We tested for spatial dependence of the estimated vector WTP_n from the MXL model. The goal of this step is to identify which attributes may present spatial clustering, thus indicating which attribute or attribute levels can be explained by spatially varying variables including environmental indicators. We used the R package "spdep".

We first constructed a neighborhood matrix to characterize the connections between respondents' geographical coordinates (specifically, centroids of their respective streets) using Gabriel's graph methodology (Gabriel and Sokal, 1969) and calculating the weight matrix. Gabriel's graph establishes links between two points, n and k, only if all other points lie outside the circle defined by their diameter [n, k]. Subsequently, we computed the weight matrix, to serve as a formal representation of spatial interdependence among observations: it is the

"formal expression of spatial dependency between observations" (Anselin et al., 1988). The weight matrix w_{nk} is a binary contiguity matrix:

$$w_{nk} = \begin{cases} 1 \text{ if } n \text{ and } k \text{ are kinked in space} \\ 0 \text{ otherwise} \end{cases} \quad (8)$$

We then used the Moran index to test for global spatial dependence, i.e. whether variables are distributed significantly differently from random, thus suggesting an underlying phenomenon of spatial association. It has been used in non-parametric approaches to identify significant WTP clustering phenomena (Campbell et al., 2008; Toledo-Gallegos et al., 2020). The Moran index considers the variances and covariances taking into account the difference between each observation and the average of all observations.

$$I = \frac{N \sum_{n=1}^{N} \sum_{k=1}^{N} w_{nk} (WTP_n - \overline{WTP})(WTP_k - \overline{WTP})}{\sum_{n=1}^{N} \sum_{k=1}^{N} w_{nk} \sum_{k=1}^{n=N} (WTP_n - \overline{WTP})^2} \quad (9)$$

with WTP_k the observation for individual k, N the total number of observations, $\overline{WTP}$ the sample mean.

In the third step, we identified hot/cold spots of individual WTP_n using the standardized Getis-Ord Gi* statistic (Ord and Getis, 1995). It detects local spatial dependencies that do not appear in the global Moran I's analysis (Glenk et al., 2020). The significance of the Getis and Ord, 1992 indicator can be tested by making the assumption, in the absence of local spatial dependency, of a normal distribution. In essence, the Gi* is a z score for each point. When statistically significant, the smaller the z score is, the more intense the clustering of low values, i.e. cold spot, and vice versa for hot spots. Under our specifications:

$$G_n^* = \frac{\sum_{k=1}^{N} w_{nk} WTP_k - \overline{WTP} \sum_{k=1}^{N} w_{nk}}{\widehat{\sigma_{WTP}} \sqrt{\frac{\sum_{k=1}^{N} w_{kn}^2 - \left(\sum_{k=1}^{N} w_{nk}\right)^2}{N-1}}} \quad (10)$$

with $\widehat{\sigma_{WTP}}$ the sample variance.

We also provide a visual representation of these hot/cold spots using ordinal regression Kriging as in Campbell et al. (2008). The purpose of this analysis was to create informative maps of hot/cold spots of WTP, and to help identify the most suitable explanatory variables for the following step in the parametric approach.

3.2.3. Analysis of environmental inequalities

We used three indicators to describe EI in the Bordeaux metropolitan area and test our hypotheses. These indicators were used to describe EI, and then to further analyze individual preferences in the post-estimation phase and test our hypotheses. The first two indicators were estimated at the "IRIS" unit scale (IRIS is an infra-municipal "neighborhood" geographical unit used by the French National Institute of Statistics) to represent the environment in which respondents live. The third was estimated at the individual respondent level because no data existed at the IRIS scale.

The first indicator describes exposure to heat island effects: it is the mean surface temperature of the IRIS of the respondent during a heat wave. We used it to test H1. We calculated the mean surface temperature for each IRIS unit during a heatwave using thermal satellite imagery (*Landsat 7 Band 6, 07/08/2018)*. The second indicator describes access to green areas and was used to test H2. It is the sum of the surface area of "managed" green areas - parks and urban green areas – and tree cover, divided by the number of inhabitants per IRIS unit. Finally, the questionnaire included a series of questions about respondents' use of a car, including how frequently they use their individual car every week, as a way to measure individual dependency on car use, and to test H3.

Similarly to 3.2.2 we then tested the global spatial dependence all three of these indicators using a neighborhood matrix describing the links between the IRIS (using their centroids) and the Moran index. This analysis tests the extent to which the environmental indicators represent real spatial inequalities. These indicators were then used as explanatory variables in the post-estimation stage.

3.2.4. Post-estimation of WTP

In the final stage, the individual WTP_n estimated with the MXL model in WTP space were analyzed using each respondent's socio-demographic variables, exposure to heat island, access to green areas, and car use. Three distinct OLS regressions were performed, for each attribute level for which significant spatial autocorrelation was detected. In this specification, each WTP_n is of the following form:

$$WTP_n = c_n + \sum_{k=1}^{K} z_{kn} L_{kn} + \varepsilon_n \quad (11)$$

where c_n is the constant term, ε_n the error term, z_{kn} is the k^{th} coefficient associated to the L_{kn} explanatory variable. For each WTP estimate, the independent variables included one of the indicators of environmental inequality, as well as 3 socio-demographic variables (age, income and education level). These 3 variables were selected as they can influence WTP. All three variables showed no significant collinearity, so their simultaneous inclusion in the models was not problematic.

Upon performing these post-estimations, we systematically tested for spatial dependence the errors (ε_n) using Moran's index, which would indicate that the independent variables do not account for all existing possible spatial autocorrelation, hence that some spatial phenomenon were missing in the explanation of WTP_n. (Anselin et al., 1988). In all cases, the tests indicated no significant spatial dependence in the errors of the model. In other words, all spatial heterogeneity was captured by the independent variables. For this reason, we did not deem it necessary to expand the modeling approach to include spatial models as there was no reason to assume an impact of WTP feedback effects (spatial lag models), or of a missing lagged spatial variable (spatial error models).

4. Results

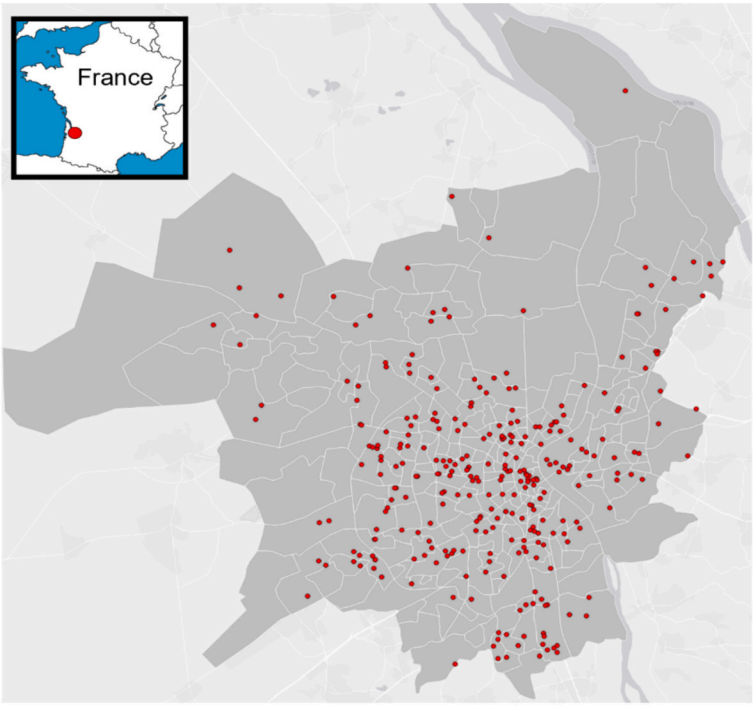
We obtained 302 answers from people living in the Bordeaux metropolitan area. From this sample, we excluded 9 protest respondents using guidelines from Johnston et al. (2017). The representativeness of the sample for the population of the Bordeaux metropolitan area was generally good in terms of gender, age and employment rate, despite under-representation of unemployed individuals and individuals of primary education levels, and higher income levels (Fig. 2). The sampling strategy was designed to ensure representation from each municipality, proportional to its population, resulting in data points concentrated predominantly in and around Bordeaux's core.

4.1. Heterogeneity of preferences

4.1.1. MXL preference heterogeneity

The results of the MXL model (Table 2) in both preference and WTP space showed the coefficients of all levels to be significant. Overall, mean coefficients and WTP were higher for the highest levels of both benefits, aquifer preservation and local climate regulation. Mean yearly WTP for the highest level of aquifer preservation ("Inf_100") was about 94€ per household and about 179€ for the highest level of local climate regulation ("Heat_60"). The SD were significant for both of these levels in WTP space, suggesting that our sample includes heterogeneity of preferences in the population that requires further investigation.

On average, car space reduction was perceived as a negative effect, with a mean WTP at −26€ per household. However, the SD was significant and was the highest for this attribute in both preference and WTP space. In fact, the magnitude of the SD indicates that there are both



	Sample Average	Bordeaux Metropolitan Area
Sample size	293	814,049
Age		
18-29 (%)	16.9	27.4
30-44 (%)	24.2	20.2
45-59 (%)	31.5	18.1
60-75 (%)	24.8	13.5
Gender (% of female)	55.2	52
Unemployed (%)	8.9	20
Retired (%)	22.2	21.3
Education		
Primary (%)	1.7	15
Lower Secondary (%)	14.2	5.1
Upper secondary (%)	25.8	37.1
Tertiary (%)	58.3	42.6
Median net monthly income (%)	2556	2030
Private car ownership (%)	85.4	77.1

Fig. 2. Sample description and respondent location.

individuals with highly positive and highly negative WTP for this attribute. Car space reduction is a strong source of heterogeneity, a polarizing factor in the sample.

Regarding the distance attributes, respondents preferred overall proximity to new green infrastructures over no NBS close to their residence. However the difference between immediate proximity, 100 m and 500 m from their home was not significant, suggesting no distance decay effects under 500 m. Furthermore these attributes had no significant SD, suggesting no heterogeneity among respondents.

The status quo option (SQ) had negative coefficients, revealing that respondents had a strong preference for the implementation of infiltration scenarios. However, this preference was confounded with the base level of infiltration ("Inf_25"), leading to an upward bias: the real coefficient for status quo should be even lower. As expected, the payment coefficient had a negative sign.

4.1.2. Spatial preference autocorrelation

Based on the MXL model estimates, we tested for the spatial autocorrelation of preferences. We identified spatial autocorrelations only for the individual WTP_n of the highest level of the local climate regulation level "Heat_60", with a Moran's I of 0.0878 (p-value 0.0311). We also identified significant hot/cold spots for "Heat_60" and "Red_Car" (see Fig. 3). Based on this finding, we decided to test the impact of our indicators of EI for these attribute levels.

The hot spot for "Heat_60" is located in the city center, in an area where mean temperature during heat waves is potentially particularly high, as is the case in many large cities, suggesting a link between preferences for heat reduction and the mean temperature per IRIS unit. Because spatial autocorrelation was previously identified for this level, this hot spot is interpreted as playing a significant role in the phenomenon of spatial autocorrelation. In contrast, the hot and cold spots for the car space reduction attribute are to be interpreted only as being significant local clusters of similar WTP, which do not reflect on the more general spatial distribution of this variable. In the post-estimation step, we thus tested the relationship between these levels and the EI indicators. Considering the lack of spatial dependence of the aquifer preservation and distance attributes, we disregarded them in the following stage.

4.2. Analysis of environmental inequalities

We identified significant spatial autocorrelation for all three EI indicators (see Fig. 4). It appears that centric populations are significantly more exposed to heat island effects, and have less access to green areas.

Table 2
Results of MXL models. "Inf_50" and "Inf_100" are the variables for the two levels of groundwater preservation, "Heat_20," "Heat_40" and "Heat_60" the thee levels of climate regulation, "Red_Car" is the level of car space reduction, "Dist_0", "Dist_100" and "Dist_500" the three distance levels, "SQ" the status-quo attribute, and "Payment" is the payment attribute. Significance of the coefficients are marked by asterisks: *** p value <1%, ** p value in [1, 5%), * p value in [5, 10%): n (observations) = 5238.

	MXL (preference space)		MXL (WTP space)	
	Coef (mean)	SD	WTP(mean €/year/household)	SD
Inf_50	0.546***	0.047	79.584***	1.656
Inf_100	0.761***	0.535***	94.668***	−90.906***
Heat_20	0.765***	−0.028	101.483***	2.606
Heat_40	1.122***	0.344	156.1***	52.326
Heat_60	1.327***	0.403	179.758***	−68.899*
Red_car	−0.208**	1.148***	−26.940*	161.808***
Dist_0	0.708***	0.042	103.287***	6.828
Dist_100	0.632***	−0.059	83.039***	−1.191
Dist_500	0.705***	0.188	95.546***	9.640
SQ	−3.530***	2.959***	−411.677***	412.741***
Payment	−5.399***	1.537***	–	–
Log-likelihood	−1407.77		−1454.1457	
LR chi^2(11)	386.55	–	–	–
Wald chi2 (11)	–	–	3155.13	–
AIC	2859.544		2959.291	–
BIC	3003.946		3096.693	–

In fact, the map shows that there is a clear distinction between rural and periurban IRIS on the one hand, and inner city centric IRIS on the other, indicating an urban-rural gradient for these EI. The frequency of car use indicator indicates that overall, in our sample, centric respondents and residents of the city of Bordeaux use their cars less then respondents who live in other parts of the Bordeaux metropolitan area. A policy that impacts car use would therefore affect periurban and rural areas more, suggesting potential inequality with respect to an adverse effect on the outcome of the NBS policy.

The following regression model is only presented for the attribute levels for which significant heterogeneity (in MXL model) and some spatial autocorrelation phenomenon - either global autocorrelation or local clustering - were detected, i.e. the attribute levels "Heat_60" and "Red_car". Regarding the distance attributes, the tests for spatial autocorrelation were inconclusive, nor did we identify any significant link between the indicator access to green areas and the preference for alternatives that include neighboring new green infrastructures. Not only did we not observe an impact of access to green areas on the distance attribute, but in our study, no distance decay was observed under 500 m.

Regarding the post-estimation model, as expected, the WTP for the level "Heat_60" depended to a great extent on the mean temperature in the respondent's neighborhood (Table 3), and, to a lesser extent, on the respondent's age. The other sociodemographic variables were not significant. The individual WTP_n estimated for the level "Red_car" depended solely and negatively on the respondent's frequency of car use. Individuals who rely on using their car are indeed more likely to consider the reduction of car space as a negative effect and have a negative WTP for this level. Most socio-demographic variables, including income, were not significant in either case.

In the following section, we discuss these results in relation to our hypotheses.

5. Discussion

5.1. Result interpretation

The analysis of the spatial patterns of demand for NBS and the influence of environmental inequalities on WTP allowed us to answer our three questions about the influence of the three types of environmental inequalities considered in this work.

Our first hypothesis (H1) was confirmed: exposure to high temperatures leads to a preference for alternatives with the most ambitious levels of local climate regulation. Individual WTP_n estimates for the highest level ("Heat_60") were spatially autocorrelated, and a cluster of high WTP for local climate regulation was identified in the city center, where the mean temperature is particularly high (see Fig. 4). Post estimation indicated that WTP_n estimates for heat reduction depend on mean temperature of the resident's neighborhood. The result of the post-estimation can thus be used to estimate WTP for each neighborhood of the city, and to create a demand map (Fig. 5). Furthermore, mean temperatures were themselves auto-correlated and revealed an urban-rural gradient.

This result suggests that the urban-to-rural gradient of exposure to environmental hazards, illustrated here by the 'mean temperatures in

Fig. 3. Hot/cold spot analysis for the individual WTP_n associated with the highest level of heat island reduction "Heat_60" (1) and the reduction of car space "Red_car" (2).

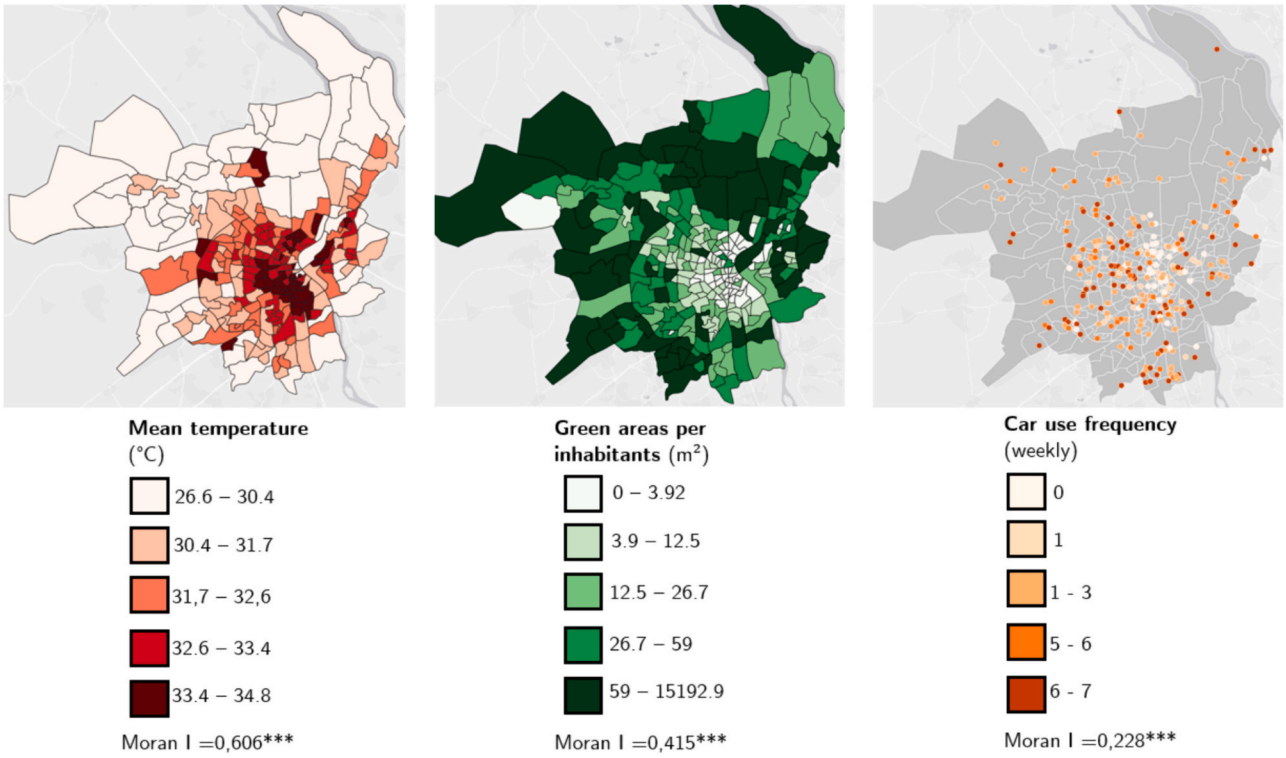


Fig. 4. Environmental indicators and Moran test. Significance of the Moran I marked by asterisks: *** p value <1%, ** p value in [1, 5%), * p value in [5, 10%).

Table 3
Post-estimation regressions.

	Heat_60 (WTP)	Red_car (WTP)
Constant	93.332	23.418
Mean temperature	2.823***	–
Car use frequency	–	−12.086***
Age	−2.607*	2.149
Income	0.350	−6.289
Education	0.580	6.596
F-statistic	5.07***	2.835**
Adjusted R^2	0.0779	0.0246

Significance of the coefficients marked by asterisks: ***p value < 1%, **p value in [1, 5%), *p value in [5, 10%); n (observations) = 291. Only the appropriate indicator was used each time to test each hypothesis: car use frequency is not included as an explanatory variable in the regression for Heat_60, and mean temperature is not in the regression for "Red_car".

heat wave episodes' indicator is matched by a similar gradient of demand for NBS. Inner city dwellers may have higher WTP for the implementation of urban climate change adaptation strategies than peri-urban and rural inhabitants who are less exposed to environmental hazards. This demand gradient for ecosystem services is in line with the results of other studies (Baró et al., 2017; Hérivaux and Le Coënt, 2021). Overall, this analysis suggests that inequality in exposure to environmental hazards may be a strong driver in the spatial heterogeneity of demand for NBS.

The second hypothesis (H2) was invalidated. Thus our general assumption of distance decay must also be rejected, like in Lizin et al. (2016). A possible explanation is that there is no distance decay at such a small scale and for such small-scale infrastructure. Stated preference studies that do identify distance decay appear to be carried out at much larger scales, i.e., country wide (Badura et al., 2020; Czajkowski et al., 2017), or at least region wide (Schaafsma et al., 2012). We may also lack statistical power to analyze this effect (n = 293). Consequently, we cannot draw any firm conclusions concerning the impact of the inequality in access to green areas on demand for NBS.

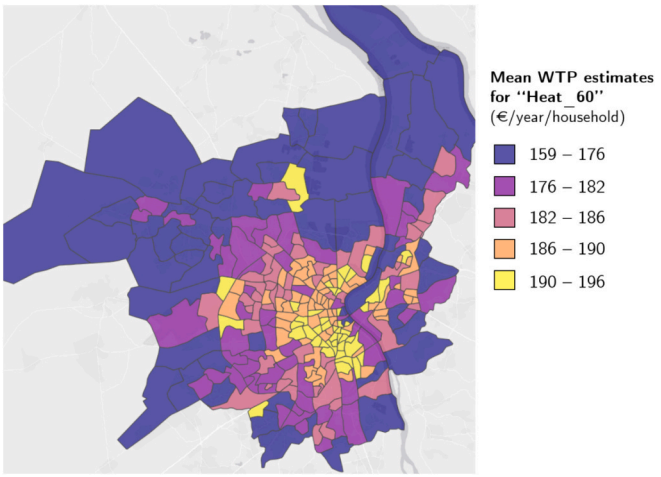


Fig. 5. WTP post-estimation for heat island reduction at 60%. The map was made using the relation between mean temperature and WTP estimated in the post-estimation.

Our third hypothesis (H3) was confirmed: strong dependence on car transport led respondents to favor alternatives that do not require reducing the space dedicated to cars, and vice versa. In fact, the attribute "Red_car" seemed to be the main source of preference heterogeneity, and was a polarizing attribute in our sample. We argue that this reflects the impact of environmental inequalities caused by NBS and urban greening policies on individual preferences: reducing car space can have either a strong negative or a strong positive impact on individuals, depending on how much they are dependent on car use and subject to external benefits of car traffic reduction (air quality improvements, noise reduction, increased city walkability, increased safety for cyclists, etc.). Based on this finding, it appears critical to include this kind of spatial tradeoff in future valuation studies. To our knowledge, no other

study has focused on evaluating the possible negative effect of consumption of space by urban green infrastructure. Yet our result is in line with that of another stated preference study showing that preference for changes toward car-free city centers may depend on individual's transport practices (Gundlach et al., 2018).

5.2. Limitations and perspective

The first improvement pathway related to our econometric approach. The estimation strategy to analyze the influence of EI on preferences, is based on a two-step approach with first the estimation of individual WTP_n with a MXL model followed by the estimation of the influence of several variables (including EI) with a simple OLS regression. This approach does not avoid the potential loss of efficiency caused by the dependent variable (WTP_n) being conditional on the estimated parameters from the MXL model. Moreover, the WTP_n are not the actual unique set of estimates of each individual, but rather an estimation of the mean individual-specific WTP_n, derived from the individual's conditional distribution. However, it enables the inclusion of a large number of variables to predict preferences (Glenk et al., 2020) and has been used in a number of studies thanks to its tractability (Broch et al., 2013; De Valck and Rolfe, 2018; Johnston and Ramachandran, 2014; Tu et al., 2016; Yao et al., 2014). The alternative, i.e. to focus the analysis more on the spatial heterogeneity of preferences would have meant using another choice modeling framework, namely a geographically weighted multinomial logit model (Budziński et al., 2018). However, this approach assumes that all heterogeneity is location-specific, i.e., that individuals in the same location have homogeneous preferences. With these specifications, heterogeneity is not individual-specific, in other words, it does not allow testing of specific hypothesis on the influence of other sociodemographic characteristics (for instance income, or individual car use in our case). Considering all these factors, we decided that our two-step approach was the best available option to test our hypotheses.

The second limitation comes from data availability. We did find that self-declared individual car use frequency influences negatively WTP for substituting urban space dedicated to car transportation with NBS. Yet, we did not identify global spatial autocorrelation for this indicator but only local hot/cold spots. The lack of spatial database on transportation choices prevented us from drawing conclusions that are more general on the spatial influence of car use frequency on the support to NBS development policies, which could be valid for other cities. It also prevented us from replicating Fig. 4 for this attribute. Replicating this type of choice experiment in a city where this data is readily available may provide an opportunity to provide relevant complements on the influence of this inequality. Additionally, this tradeoff related to urban space competition could be explored more thoroughly by including different levels of attributes, and explore related preferences such as: pedestrian space, housing space, infrastructure space…

A final progression route relates to the way we account for inequalities. We use simple indicators of exposure to hazards, access to green areas and car use to characterize EI. EI may nevertheless be the results of more complex interactions with socio-economic inequalities e.g. income levels or other sociodemographic characteristics(Gould and Lewis, 2016; Walker, 2012). In addition, the effect of inequalities on demand levels has been shown to depend on whether the environmental goods at play are substitutes for manufactured consumer goods(Meya, 2020). In our case, we did not explore these dimensions: the income variable was not a significant factor of individual WTP, and the sociodemographic variables (income, education, age) did not present any significant spatial autocorrelation, i.e., they did not represent significant spatial inequalities. Analyzing the interactions between income levels and EI could advance our understanding of the effect of environmental inequalities on demand. Another possible perspective for further research is to adopt a "horizontal" perspective on EI i.e. inequalities as a measure of between-group differences (Boyce et al., 2016)We would divide the sample into groups - e.g. by income categories – and then analyze variations in demand across these groups. This would allow - for instance - the explicit identification of populations or communities with low or high demand for NBS.

5.3. Scientific and policy implications

This work contributes to the urban ES valuation literature by revealing the importance of analyzing the spatial heterogeneity of demand for NBS combined with the analysis of the underlying factors that systematically explain this heterogeneity, e.g. environmental inequalities. Exploring this line of research advances our understanding of the spatial heterogeneity of demand for NBS, thereby making it possible to draw conclusions that are more generic than those that can be drawn from individual case studies. The positive correlation we, for example, demonstrate between heat exposure and demand for NBS (with significant heat regulation effects) is most likely to be transferable to other cities, and strengthens the rationale, for urban planners, to target NBS development in these areas. This criterion is nevertheless only one of the spatial criteria to consider in NBS planning and needs to be integrated with other ones to identify optimal patterns of NBS development (Farina et al., 2024).

Our analysis also reveals that (i) NBS policies may lead to the emergence of environmental inequalities as they have adverse effects that affect specific vulnerable populations, which influence their demand for these policies. This phenomenon has been largely overlooked by NBS planning and assessment tools to date (Van Oijstaeijen et al., 2020). While this type of analysis of preference heterogeneity allows policy makers to more efficiently target areas and populations in a way that reduces the impact on inequalities as much as possible, there may be cases where affecting the well-being of a proportion of citizens is unavoidable. For instance, in our case, many individuals with a high reliance on car use may reside in areas with an overall high demand for car space reduction. Targeting these areas would penalize these very individuals. This indicates that for such policies to be accepted, (monetary) transfers may be necessary to plan and include in these policies, e.g. paying compensation for the use of other modes of transport. This result also underlines the need to combine urban NBS development policies with ambitious mobility policies aimed at reducing dependence on cars.

This work finally contributes to NBS planning by incorporating the current debate surrounding environmental justice. Environmental inequalities have mostly been studied from the point of view of "distributional justice", i.e. the exposure of individuals and communities to environmental risks and the equitable allocation of wealth and ES (Calderón-Argelich et al., 2021). Based on this observation, several authors have argued that urban NBS decision making approaches need to push further toward a recognitional and procedural conception of justice (Langemeyer and Connolly, 2020). The former term means acknowledging and accounting for the different needs, preferences and values of citizens; the latter allows the involvement and participation of citizens in decision-making procedures. Indeed, individuals may have contrasted needs, preferences and aspirations (Jacobs et al., 2016), which may strongly affect the well-being to be obtained from NBS policies (Turkelboom et al., 2018), and distributional analyses overlook these complexities (Langemeyer and Connolly, 2020). Our work contributes to the adoption of a recognitional justice perspective in NBS policy-making: it illustrates the importance of broadening the vision of environmental justice in urban ES studies to include citizen's heterogeneous demand for nature, their preferences and constraints, which can be strongly influenced by their living environment and individual practices (Jacobs et al., 2016).

6. Conclusion

This paper presents the results of a discrete choice experiment implemented in the metropolitan area of Bordeaux, France. It investigates the preferences of the population for multiple cobenefits and outcomes of urban NBS policies. Residents have a strong demand for the cobenefits of NBS, and perceive negatively the potential reduction of car space induced by urban NBS policies. Our results show significant preference heterogeneity, which we further investigate in the form of spatial heterogeneity. We identify a phenomenon of global spatial dependence of the demand for local climate regulation, and we identify hot/cold spots for the willingness to pay associated to the outcome on car space reduction. This spatial heterogeneity of demand is then analyzed as resulting from the impact of environmental inequalities: high exposure to heat islands heightens individual's demand for scenarios offering greater urban cooling benefits; and dependence on car use impacts negatively their demand for policies that may reduce car space availability.

To our knowledge, this is one the first studies to highlight the link between environmental inequalities and demand for urban NBS. NBS policies may lead to the emergence of environmental inequalities as they have adverse effects that essentially target specific vulnerable populations, and that these environmental inequalities have a dramatic influence on the demand for these policies. These findings offer valuable insights to urban NBS planning, as they highlight the need to account for preference heterogeneity and analyze environmental inequalities to maximize the welfare of NBS policies.

CRediT authorship contribution statement

Georges Farina: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Philippe Le Coënt:** Writing – review & editing, Supervision, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Cécile Hérivaux:** Writing – review & editing, Validation, Supervision, Methodology, Investigation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ecolecon.2024.108298.

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