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Valuating the Dutch Ecosystem Amenity Service using Hedonic House Pricing

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Abstract

This paper aims to estimate the effect of nearby natural space on Dutch house prices in 2021. This is done by comparing several spatial regression models. It is found that spatial difference regression using discrete intervals of distance to nature leads to the best in-sample model fit and most interpretable results. The model estimates an effect of 7.1% of living within 500 meters of attractive nature, decaying to an 0.6% effect for properties up to 6 kilometers away. Similarly, a 3.7% effect was found for living within 50 meters of ordinary nature, decaying to 0.2% for properties 250 meters away. Using these estimates, the value of the Dutch ecosystem amenity service is valuated at 818.2 million euro in 2021. It is also found that proximity effects are heterogeneous across different urbanization degrees, showing that attractive nature is valued more in densely populated areas, whereas ordinary nature was valued more in the least urban areas. Further, a comparison between the use of assessed values and market transactions shows that these do not lead to the same model estimates, although differences are limited. These findings have implications for public policy and urban planning, the use of hedonic models by statistical offices, and adds to the current literature on spatial econometrics and amenity value estimation.

Keywords: Spatial Econometrics, Hedonic Regression, Ecosystem Amenity Service

Contents

1 Introduction

Nature, economy, and society are inseparable from each other. Nature provides goods and services to the economy, it has impact on our health, and people enjoy being in nature, leading to both physical and intangible benefits (Statistics Netherlands & WUR, 2021). This paper focuses on the monetary valuation of such intangible benefits. This task, however, is not trivial. The value of goods that nature provides, such as wood and crops, can be calculated straightforwardly through market sales, given that consumer surplus is ignored. However, it is not immediately clear how one should put a monetary value on a walk in a nearby park, or being able to see nice trees outside of your home. Therefore, this study attempts to calculate the monetary value of nature proximity in the Netherlands in 2021 by estimating the added value of nature proximity to house prices.

A framework on ecosystem valuation can be found in the System of Environmental-Economic Accounting, Ecosystem Accounting (SEEA EA). It is a comprehensive statistical framework for organizing data about habitats and landscapes, measuring ecosystem services, tracking changes in ecosystem assets, and linking this information to economic and other human activity (United Nations et al., 2021). This framework is an attempt to move beyond the typical indicators of economic progress like gross domestic product. Based on this framework, Statistics Netherlands together with the Wageningen University & Research (WUR) publishes the Natural Capital Accounts (NCA), which is the ecological analogue of the System of National Accounts. The NCA serves as an important source for policy making on a national, regional, and local level (Statistics Netherlands & WUR, 2021).

The SEEA EA distinguishes three types of ecosystem services, namely provisioning, regulating, and cultural services. Provisioning services are those services which provide contributions to benefits extracted or harvested from ecosystems. Think of wood that comes from forests, or vegetables harvested from cropland. Regulating services are services resulting from the ability of ecosystems to regulate biological processes and to influence climate, hydrological, and biochemical cycles. For instance, the air and water filtering service trees provide. Lastly, cultural services are experiential and intangible services related to the perceived or actual qualities of ecosystems whose existence and functioning contributes to a range of cultural benefits (United Nations et al., 2021). These for instance entail the utility gained from a walk in nature, or the sight of green from your house. Our study focuses on valuating one specific cultural ecosystem service in the Netherlands, namely the amenity service.

The ecosystem amenity service is defined as the ecosystem contributions to local living conditions, in particular through the biophysical characteristics and qualities of ecosystems that provide pleasant conditions for living (Statistics Netherlands & WUR, 2022). Assuming that homeowners are willing to pay for these pleasant living conditions, the contribution of nearby nature on housing prices in a hedonic pricing setting is estimated. Our paper builds on the valuation methodology used in the Dutch NCA, examining several hedonic model specifications and definitions of nature proximity, combined with a distinction between nature which is perceived as attractive, and other nature.

Our study tries to answer the question: *What model specification can best estimate the value of the Dutch ecosystem amenity service in 2021?* To this end, the following sub-questions are answered: *What definition of nature proximity best captures the added value to house prices by nearby nature?* and *What spatial hedonic regression specification models the house prices for 2021 in the Netherlands best?* Additionally, estimation allowing for heterogeneous responses for different levels of urbanity is performed. Further, we try to answer the question *Do estimation results differ significantly when transaction values are used as dependent variables instead of assessed values?* This question is of importance, as most other studies make use of market sales, and thus the use of assessed value needs to be validated.

To answer these questions, two definitions of nature proximity are examined, namely by discrete distance intervals and nature density measures. Further, five hedonic model specifications are compared, namely standard OLS estimation, spatial differencing, fixed effects estimation, a spatial lag model, and a spatial error model. Lastly, the model is reestimated to allow for heterogeneity in the response to amenity services per urbanization degree, and the robustness of the model with respect to outliers and the definition of house price is studied.

We find that the spatial difference specification best models housing prices, attaining the highest adjusted R^2 and the lowest AIC of all specifications. Further, we find that both discrete distance intervals as a nature density specification lead to similar model fit, although the discrete distances are easiest to interpret, and therefore are preferred. Using the spatial difference specification, the value of the ecosystem amenity service in 2021 is found to be approximately 818.2 million euros. Further, we find that there is clear heterogeneity across urbanization degrees, showing that highly urbanized areas value attractive nature the most, whereas other nature is valued most in the lowest urbanization degree. Lastly, we find that estimation using market transactions leads to different estimation results than when using assessed values, although not all estimates differ significantly.

This study provides an empirical contribution by estimating the value of the ecosystem amenity in the Netherlands, and showing how it has changed over time. Being able to identify the benefits derived from nature has several uses in policy making. It can be used in the cost-benefit analysis of a new nature project, or the decision to engage in nature renovation and preservation projects. It is especially relevant in the discussion on the current state of the Dutch housing market. The current housing shortage in the Netherlands is estimated at 401,000 houses (NOS, 2024). There is an important trade-off between the construction of new houses, and the preservation of natural ecosystems , both due to limited space, and the emission of harmful substances (Bulkely, Almassy, Fransen, Maia, & Toxope, 2023). Creating insights in the value of nature could aid in this debate to correctly assess this trade off. Outside of policy making, it is also a topic of interest for brokers when valuating real estate.

Furthermore, the value estimation of the amenity service is important for statistical offices across Europe. Eurostat, the official European statistical office, currently obligates national statistical offices to publish the non-monetary components of the NCA. However, in the future publishing the monetary components of the NCA will become mandatory. It is therefore important that the models behind these monetary valuations are accurate. Our study aims to do just that for the monetary valuation of the ecosystem amenity service.

The study adds to the current literature as it is one of the few studies focusing on a nation wide estimation of the effect of nature on housing prices. Only few other papers considered such a large scope (Daams, Sijtsma, & van der Vlist, 2016; Gibbons, Mourato, & Resende, 2014; Holt & Borsuk, 2020), but none of them observed the full population like in our study. Furthermore, two methodological contribtuions are made. First, a definition of nature proximity, namely the nature density using kernel density estimation, is used, which has not yet been used in comparable studies. Second, it directly compares several spatial models on in-sample fit, computational feasibility, and interpretability. Further, is the first study to directly compare the use of assessed values with the use of actual market transactions, which is relevant for the validation of the use of assessed values by Statistics Netherlands.

In the remainder of the paper, an overview of relevant literature is first given in Section 2, followed by a description of the used data in Section 3 and methodology in Section 4. Afterwards, the results of the model comparison are presented and discussed in 5, after which a heterogeneity analysis is performed in Section 6. Following this, the robustness of the results is verified in Section 7. Finally, a discussion of the results and some outlooks for further research are presented in Section 8 and 9, respectively.

2 Literature

2.1 The Effect of Nearby Nature

Before looking at the added value of nearby nature on house prices, it is important to argue why property buyers would or should value nature in their proximity in the first place. Nearby nature has a recreational function, as well as reducing air and noise pollution likely leading to improved (mental) health (Statistics Netherlands & WUR, 2022). An extensive stream of literature discusses and investigates the effect of nearby nature on health and welfare of residents. Hidaka (2012) highlights the importance of natural light exposure for the mental health of humans. However, the exposure to natural light is limited by the increased urbanization of our society, with more and higher buildings blocking the natural light, stressing the importance of open space. The authors further emphasize the value of physical activity, which is stimulated when this activity can be performed in attractive natural environments.

Astell-Burt, Mitchell, and Hartig (2014) find that the proximity of green space is associated with better mental health among older women and for men in their early to middle adulthood. Further, it was found that living in greener areas was correlated with better (perceived) health (De Vries, Van Dillen, Groenewegen, & Spreeuwenberg, 2013; Maas, Verheij, Groenewegen, De Vries, & Spreeuwenberg, 2006; Mitchell & Popham, 2007, 2008). However, not all existing literature is unanimous on the effect of green space amenity on health. Richardson and Mitchell (2010) only find positive effects for males, and one study even finds that mortality rates were higher in greener cities (Richardson et al., 2012).

A recent field of concern is heat stress in urban areas. Temperatures in urban areas sometimes are three degrees Celsius higher than in non-urban areas (Bowler, Buyung-Ali, Knight, & Pullin, 2010). One solution, but certainly not the only one, is urban greening. It was found that urban parks are in general close to one degree cooler than the built up area within towns (Bowler et al., 2010). However, Wang and Akbari (2016) find that these effects mainly affect temperatures during the day. Similarly, Jacobs et al. (2020) find that small water bodies within cities lead to a decrease in temperature during the day of approximately 0.6 degrees, but lead to a slight, negligible increase in temperature during the night. Chen et al. (2014) even find that an increase in vegetation coverage of 15% to 33% in Melbourne could reduce the average heat related mortality rate by 5% to 28%.

Starting in the 2010s, there has been a growing stream of literature concerning the relation between environmental amenities, such as air quality and proximity to nature, and house prices. The majority of these studies indeed find a positive relationship between the proximity (or absence) of positive (negative) environmental amenities and house prices (Bouwknegt & Schilder, 2023; Brander & Koetse, 2011; Conway, Li, Wolch, Kahle, & Jerrett, 2010; Gibbons et al., 2014; van Ruijven & Tijm, 2022). Furthermore, diminishing returns to the amount of nearby nature and a declining effect over distance are often found.

Since in our study a distinction between attractive and other nature is made, of specific interest are studies which also take into account the attractiveness and quality of nature. This attractiveness can be measured in either an objective or a subjective way, both of which have their merits. Objective measures ensure that quality is measured in the same way by everyone. However, since we expect the proximity and quality of nature to impact the prices of houses, this means that the property buyers should also see this value of nature, and should be allowed to assess nature importance in different ways, pleading for a subjective assessment of quality. Luttik (2000) was one of the first to include nature quality to assess the quality and accessibility of nature, by visiting the nature areas by bike. Panduro and Veie (2013) also assess the quality of nature by rating its accessibility, as well as incorporating the level of maintenance of the piece of nature. Poor, Boyle, Taylor, and Bouchard (2001) use both an objective and subjective measure of water quality in a hedonic pricing model, surprisingly finding that the objective measure could explain variance in house prices more than the subjective measure.

A purely subjective approach was employed by Daams et al. (2016), who estimate the effect of nature on Dutch property prices while accounting for perceived attractiveness of nature areas. They let respondents of a survey pin-point places on a map of the Netherlands which they find attractive areas of nature, and use these responses to construct clusters of perceived attractive nature. The benefit of this survey is that it incorporates the opinion of economic agents, who are also the ones buying the houses. The importance of subjective judgement by economic agents in hedonic models is emphasized by Palmquist (2005). Further, looking back at the definition of cultural services given earlier: "the experiential and intangible services related to the perceived or actual qualities of ecosystems whose existence and functioning contributes to a range of cultural benefits", we see that this definition considers both perceived and actual qualities of ecosystems. However, surveys can also come with difficulties, such as selection bias in the respondents and inaccurate measurements. Nevertheless, given the importance of subjective judgement in the formation of house prices, our study utilizes the same survey results as Daams et al. (2016). This is also the data used by Statistics Netherlands for their valuation of the ecosystem amenity service.

2.2 Hedonic Models

When it comes to the valuation of amenity services through house prices, there are two methods which are regularly employed, namely the Contingent Valuation Method (CVM), and the Hedonic Pricing Model (HPM) (De Groot, Wilson, & Boumans, 2002). The main difference between these methods lies in the type of preference measured. CVM measures stated preferences by employing surveys in an experimental setting, whereas HPM uses revealed preferences by using observed prices of product sales. The main power of CVM is that in an experimental setting the researcher can control external variables, easily allowing for causal inference. The downside, however, is that experiments are costly, both in terms of time and money. Furthermore, it is nearly impossible to get a perfectly representative sample of the population when performing an experiment. In addition, as stated preference methods measure preferences in a hypothetical settings, it is unlikely that results would directly translate to market behaviour.

Since HPM uses observed market behaviour, there is no need to set up an experiment. The issue, however, comes from the many external factors influencing the sales price, various of which can not be controlled for or are even unobserved. How to deal with these issues will be discussed in Section 4.2. Hedonic models are the staple for the estimation of amenity effects on house prices, and are also employed in our analysis. Hedonic models are based on the consumer theory formulated by Lancaster (1966), later extended by Rosen (1974). These models are built on the assumption that the value of a good comes from its separate characteristics, rather than the good as a whole. It therefore expresses the value of a good, often the market price, as a combination of characteristics. For houses, these characteristics are for instance the physical structure of the house, the neighbourhood characteristics, and the environmental amenities (Mendelsohn & Olmstead, 2009). In the original paper by Lancaster (1966) it was emphasized that this relation between price and characteristics is not necessarily linear. In fact, it most likely is not. However, in practice it is common to use a linear functional form (Bouwknegt & Schilder, 2023; Daams et al., 2016; van Ruijven & Tijm, 2022). Possible non-linearities are incorporated by using polynomials or logarithms of explanatory variables, or defining characteristics in terms of intervals rather than as a continuum.

Recent advancements in the hedonic pricing literature focus on the use of non-linear models, with emphasis on the use of machine learning models. Machine learning models show a considerable improvement in predictive performance, but they are generally lacking in explanatory power (Rico-Juan & de La Paz, 2021). Attempts have been made to make machine learning predictions more understandable, for instance with the use of generalizations of Shapley values. However, the existing implementations of these

Shapley values are based on crude approximations, and perform poorly under correlated regressors (Lundberg, Erion, & Lee, 2018; Slack, Hilgard, Jia, Singh, & Lakkaraju, 2020). Contrarily, linear models are easily interpretable, which is desirable for the purpose of our study, and therefore preferred for the valuation exercise in our paper.

2.3 Identification

This paper is concerned with hedonic models in the housing market, meaning we operate in the domain of spatial econometrics. A parallel can be drawn between spatial econometrics and time series analysis. In time series analysis, an observation is dependent on the previous observations, mainly those close to the current observation. In spatial econometrics, observations that are nearby each other are spatially correlated. The main difference is thus the direction of correlation, in time series it is one sided (past to future), and in spatial analysis correlation goes both ways. This two sided correlation could lead to difficulties in identifying the causal effect of nature proximity when not taken care of, as omission of these spatial correlations might lead to spurious regression. For instance, some neighbourhood characteristics may be correlated with the proximity of nature, although they may not directly affect treatment. Not accounting for these neighbourhood characteristics would lead to a biased estimate of the treatment effect. Furthermore, not taking spatial correlation into account would lead to incorrect standard errors due to correlation in the OLS residuals (Anselin & Rey, 1991; Von Graevenitz & Panduro, 2015). In order to deal with these issues, spatial regression models have been developed.

The next assumption needed for identification of causal effects is the assumption that assigned treatment should not influence the way an individual responds to the treatment. In case of continuous treatment (or a multi-valued discrete treatment), denote the value of treatment by $d \in D$, where D is the set of all possible treatments. Then the observed outcome for individual i who received treatment d is given by $Y_i(d)$. The potential outcome under treatment d' for individual i who received treatment d is then given by $Y_{id'}(d)$. In practice, we only observe $Y_{id}(d)$, so we only observe $Y_{id'}(d)$ where $d' = d$. All other values for $Y_{id'}(d)$ are unobserved potential outcomes or counterfactuals. In order to identify a causal effect, we need $\mathbb{E}\left[Y_{id'}(d)\right] = \mathbb{E}\left[Y_{id'}(d')\right]$ for $d \neq d'$. In other words, response to treatment should be independent of treatment assignment itself (Bareinboim & Pearl, 2012).

Moreover, treatment must be (conditionally) unconfounded with other exogenous variables impacting the outcome variable. In this study, the outcome Y is the natural logarithm of assessed value of a dwelling. As for the set of possible treatments D, two sets are considered. The first set contains several binary treatment variables, which are discrete intervals of distance to (attractive) nature. The other set contains two variables indicating continuous treatment, namely the nature density score. See section 4.1 for a more precise definition of these variables. Unconfoundedness implies that no variable should be able to both affect the treatment variable and the outcome variable simultaneously and directly. If there exists such a variable it is important to include this variable in the estimating equation, given that it is observed. Otherwise the parameter of interest, which measures the treatment effect, will absorb (part of) the effect of the exogenous variable due to them being correlated, and the estimated parameter will not reflect the true treatment effect (Spirtes, Glymour, & Scheines, 2001). Examples of possible confounding variables are distance to the closest train station or highway, which are usually negatively correlated with distance to nature, but positively with assessed value. Ultimately, we are interested in the average treatment effect $E[Y_{id} - Y_{i\bar{d}} \mid X_i]$. In other words, the increase in log assessed value given treatment compared to the reference treatment $\bar{d}$, while keeping all other explanatory variables constant. For the discrete treatments, $\bar{d}$ is some reference category, whereas for the continuous treatment, $\bar{d} = 0$.

2.4 Spatial Models

Most of the confounding variables in this analysis will likely be spatial effects such as neighbourhood characteristics and other proximity variables. In order to deal with such spatial effects, there are several possible model adjustments. Firstly, one could explicitly incorporate spatial characteristics such as the number of schools and stores in the neighbourhood, or the local crime rate. However, the number of characteristics one can add to a model is limited, and never exhaustive. Furthermore, many spatial factors are unobserved. It is therefore impossible to fully remove omitted variables bias in this manner. An often employed solution is the use of regional fixed effects, for instance on postal code level (Bouwknegt & Schilder, 2023; Gibbons & Overman, 2012; van Ruijven & Tijm, 2022).

A more traditional approach of implicitly incorporating local characteristics is the use of spatial lag or spatial error models. The spatial lag model incorporates spatial effects by directly relating the outcome variable to outcomes of observations that are close (Anselin, 1988). This method can be seen as the spatial version of an autoregressive model in time series analysis. The inclusion of prices of other observations in order to determine the price of a house is close to the way realtors and governments assess housing values in practice, as they often refer to the prices of nearby estates to assess the value of a property (Can, 1990). Anselin (1988) shows that omitting the spatial structure leads to biased and inconsistent parameter estimates when spatial autocorrelation is present. On the other hand, the spatial error model assumes that spatial correlations come from misspecifications. Therefore, instead of modeling a direct relation between the outcomes, it models a relation between the error terms across observations, similar to moving average models.

A last method to account for spatial correlation is a spatial first difference model. Observations located in the same neighbourhood are modeled relative to one reference house in that neighbourhood. By taking this difference, local effects cancel out, as well as the effect of possible correlation in housing characteristics in the neighbourhood. Examples of studies discussing and using this method are Daams, Proietti, and Veneri (2019), Daams, Sijtsma, and Veneri (2019), and Gibbons and Overman (2012). This model is also currently employed by Statistics Netherlands for the estimation of the ecosystem amenity service.

The main complication with all of these models is the choice of neighbourhood scale. Picking a scale that is too large robustly estimates the average effect within the cluster, but disregards lower spatial variation, likely leading to overestimation of the nature proximity effect (Sommervoll & Sommervoll, 2019). This has also been found in an internal study of Statistics Netherlands, which for instance finds effects twice the size when estimating on sub markets, of which 76 exist in the Netherlands, instead of neighbourhoods, of which 2,623 exist in the Netherlands. Contrarily, when the scale is too small, variation within neighbourhoods might be too small, leading to overabsorption of the effect of interest in the spatial control, which possibly results underestimation of the parameter of interest (Von Graevenitz & Panduro, 2015). The mathematical details on spatial models, and the preferred scale of spatial control, are discussed further in Section 4.2.

3 Data

3.1 The Types of Nature

We first define what is considered as natural or green environment in the context of this study. To this end, we make use of the ecosystem type classification presented in Statistics Netherlands and WUR (2022), see Table I. Appendix A gives a more detailed description of all the ecosystem types.

TABLE I. Ecosystem types in the Netherlands

Natural	**Water**
Grassland*	Streams and Rivers*
Forest Area*	Lakes and Reservoirs*
Heathland and Driftsand*	Marine*
Bogs and Fens*	
Coastal and Dune Area*	
Agriculture	**Urban and Other (Semi-)built-up Area**
Cropland and Horticulture	Built-up Area
Grassland	Urban Green and Recreation(*)

Note. A * indicates that the ecosystem type is considered as nature in this study, (*) indicates that only part of the subcategory is considered nature.

The four overarching ecosystem categories are natural land, water, agricultural land and urban land. In our definition of nature for this study, we exclude all agricultural land as well as all urban land, except for public green spaces (such as public parks and other green space). The choice not to include agricultural land like meadows or cropland, is due to identification issues. Since approximately 45% of the Netherlands is covered by agricultural land. Combined with the fact that the other green and natural area cover approximately 36% of the Netherlands, the distance to nature would likely become extremely low for a majority of the houses, resulting in too little variability.

In order to identify the land cover of nature, we make use of a rasterized map of the Netherlands, with raster cells of 10x10 meters. For an area to be considered nature, it has to have an area of at least one hectare, of which more than 80% consists of at least one of the ecosystem types indicated with a * in Table I. All ecosystem types will be pooled together. Although it is likely that not all ecosystem types have the same value to home buyers, separating them could lead to significant multicollinearity, as often ecosystem types are found together. However, to still allow for a distinction between influential ecosystem types and less influential ones, we consider a measure of nature quality, namely perceived attractiveness.

Once all nature areas are defined on the rasterized map, we wish to identify which of these natural areas people consider attractive. To this end, we make use of the online survey Greenmapper (www.greenmapper.org). In this survey, respondents are shown a map, starting at their home, and are asked to pinpoint pieces of nature which they find attractive on four levels, namely on a local (max. 2 km from their home), regional (max. 20 km from their home), national, and global level. The results for the national level align with the objective of this research, and are therefore used. This results in many points on the map of the Netherlands which respondents consider attractive, called hotspot markers. These markers then need to be aggregated into clusters of nature. Daams et al. (2016) use a spatial clustering technique to accomplish this goal. In this procedure, the density of markers is calculated per 250 m x 250 m raster cell, with a 1250 m search radius. Raster cells of which the density exceeds a certain cut-off value are kept, and other cells are set to non-attractive. The remaining raster is then laid over a land use map, and all clusters which coincide with natural land use area remain, and form the Clusters of Attractive Nature Area (CANA). This procedure ensures that relatively isolated markers do not create unlikely or incoherent clusters of attractive nature. This method is adopted in this study. Nature areas which are not considered as CANA, are refered to as Other Nature Area (ONA). For a more in-depth description of the methodology, see (Daams et al., 2016).

The resulting CANA and ONA clusters are visualized in Figure I. We see that in general, beaches and the Wadden Islands are seen as attractive nature. Furthermore we see that the majority of the Veluwe are considered as attractive, as well as the hilly landscapes in Utrecht and Zuid-Limburg.

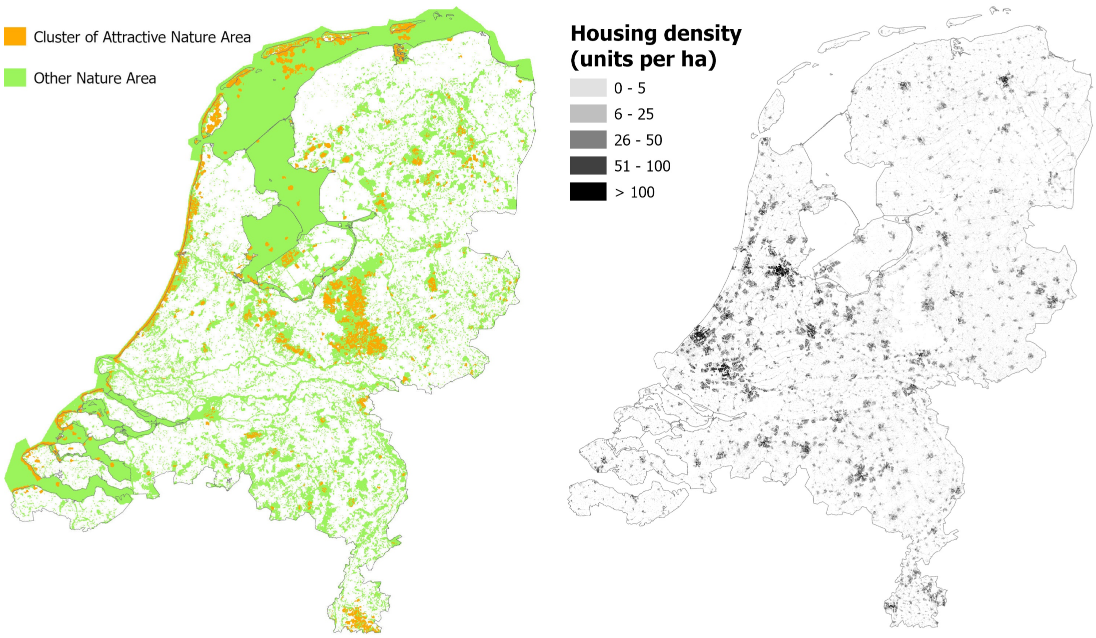

FIGURE I. Dutch land cover by CANA and ONA (left), and Housing Density (right)

3.2 Housing Values and Characteristics

In this study we make use of data on the assessed value (WOZ-waarde in Dutch) of all houses and apartments in the Netherlands in the year 2021. The assessed value is an approximation of the market value of a dwelling used for several national and local taxes, based on sales of similar dwellings in the neighbourhood. Important to note is that only properties with a pure residential function, that are currently in use, are considered. For all of these dwellings we have information on the construction year, dwelling type (detached, semidetached, terraced, end of terrace), floor space (m^2), and a rental property dummy. Lastly, we have the distance to nature as described in the previous subsection as explanatory variables. Summary statistics can be found in Table II. We have full information on approximately 7.3 million dwellings in the Netherlands. One important characteristic, namely plot area, is not included. Besides the fact that data on plot area for dwellings is hard to obtain, for apartments and properties owned by housing corporations it is not clear how plot area should be divided among the individual dwellings. For an apartment complex, many dwellings lie on the same plot, and the same goes for houses owned by housing corporations. However, in many practical applications, log-linear models tend to perform well in the absence of plot area as explanatory variable, and thus this should not lead to problems (Eurostat, 2013).

TABLE II. Summary statistics of housing characteristics and distance to nature ($n = 7,321,072$).

Variable	Mean	Std. Dev.	Variable	Mean	Std. Dev.
Assessed value (€)	288,177.946	178,292.022	500-1,000 m	0.080	
Living area (m^2)	115.787	108.988	1,000-2,000 m	0.086	
Freehold	0.584		2,000-3,000 m	0.088	
Housing corporation	0.297		3,000-4,000 m	0.086	
Other leasehold	0.119		4,000-5,000 m	0.082	
Detached	0.119		5,000-6,000 m	0.073	
Semidetached	0.090		6,000-7,000 m	0.066	
End-of-terrace	0.134		7,000-8,000 m	0.057	
Terraced	0.311		>8,000 m	0.160	
Multi-family home	0.347		*Dist. (m) to ONA*	395.756	290.165
Constructed < 1905	0.041		0-50 m	0.055	
Constructed 1906-1930	0.084		50-100 m	0.078	
Constructed 1931-1944	0.049		100-150 m	0.177	
Construced 1945-1959	0.089		150-200 m	0.146	
Constructed 1960-1974	0.220		200-250 m	0.100	
Constructed 1975-1989	0.221		250-300 m	0.089	
Constructed 1989-2000	0.131		300-350 m	0.079	
Constructed 2001-2010	0.093		350-400 m	0.061	
Constructed > 2010	0.071		400-450 m	0.054	
Dist. (m) to CANA	4459.337	3691.979	450-500 m	0.057	
0-500 m	0.065		>500 m	0.277	

The variables assessed value and living area are right skewed, with a sample skewness of 6.87 and 1429.03 respectively (also see Appendix B). Since a skewed dependent variable could lead to heteroskedasticity in the residuals of regression, this suggests transforming these variables by the natural logarithm (Diewert, 2003). Additionally, it is unlikely that the relation between the assessed value and property characteristics is a constant relation (Bouwknegt & Schilder, 2023; Daams et al., 2016). Therefore, in the analysis, we take the natural logarithm of the assessed value and living area. A positive added effect is that after taking the logarithm of these variables, they are close to normally distributed around the center of observations (see Appendix B). This allows for a proper assessment of outliers in the data, as described in the next paragraph.

Furthermore, in the spatial fixed effect model (to be defined in Equation (10)), several neighbourhood characteristics defined on the PC4 (the four numbers in a Dutch postal code) level are used. These include the average distance to the nearest:

- General Practitioner
- General Practice Center

- Hospital without outpatient clinic
- Hospital with outpatient clinic
- Pharmacy
- Fire Department
- Driveway
- Train Station
- Transfer Station.

3.3 Outliers

A thorough evaluation of outliers is of importance, as regression coefficients might be heavily influenced by even a single outlier. In fact, the asymptotic breakdown point of linear regression, as described by Donoho and Huber (1983), is 0% (Rousseeuw & Leroy, 2005). This means that the estimates can have an arbitrarily large bias, caused by even a single outlier. Besides, statistical tests may lose power under the presence of outliers (Seo, 2006). We focus on outliers with respect to the assessed value, floor space, and the ratio of assessed value to floor space. These variables are considered most important for the outlier treatment, as measurement error is most likely to appear in these variables. Examples of possible outliers or incorrect measurements in the data are a dwelling with an assessed value of 1 euro, and one with an assessed value of 42 million euro.

Outliers will be detected in the following way. For a variable Y, robustly estimate the mean μ and variance σ by $\hat{\mu} = \text{med}(\ln(Y_i))$ and $\hat{\sigma} = c \cdot \text{med}|\ln(Y_i) - \text{med}(\ln(Y_i))|$, respectively. Here, med is the median, and the constant c is necessary to ensure Fisher consistency for the standard deviation at the normal distribution. Assuming normality, consistency is achieved by setting $c = \frac{1}{\Phi^{-1}(0.75)} \approx 1.4826$ (Pham-Gia & Hung, 2001). Next, we label an observation i as an outlier in variable Y_i when

$$\begin{aligned} |\ln(Y_i) - \hat{\mu}| &> z_{1-\frac{\alpha_n}{2}}\hat{\sigma}. \\ \text{with } \alpha_n &= 1-(1-\alpha)^{1/n}. \end{aligned} \tag{1}$$

Here, n is the total number of observations, z_q indicates the qth quantile of the standard normal distribution, and α_n is the Šidák correction of the level for multiple testing (Šidák, 1967). We test on a level of $\alpha = 0.001$. We remove all observations from our data which were flagged as an outlier for at least one of the tested variables. Although removing outliers is not optimal, it simplifies the estimation of the models described in Section 4.2, especially for Equation (6) and (8). These are estimated using maximum likelihood, of which a robust estimation leads to unnecessary complications. To verify if removing these outliers heavily influences results, the preferred model specification in Section 4.2 will also be estimated with the full dataset, using OLS and the robust MM-type estimator. Results are in Appendix D.

The above described procedure leads to the removal of 3,784 outliers, which equals roughly 0.05% of the initial dataset. In Table III the summary statistics of the reduced dataset are shown.

TABLE III. Summary statistics of housing characteristics and distance to nature after outlier treatment ($n = 7,317,288$).

Variable	Mean	Std. Dev.	Variable	Mean	Std. Dev.
Assessed value (€)	288,017.660	174,450.244	500-1,000 m	0.078	
Living area (m^2)	115.477	57.548	1,000-2,000 m	0.177	
Freehold	0.584		2,000-3,000 m	0.146	
Housing corporation	0.297		3,000-4,000 m	0.100	
Other leasehold	0.119		4,000-5,000 m	0.089	
Detached	0.119		5,000-6,000 m	0.079	
Semidetached	0.090		6,000-7,000 m	0.061	
End-of-terrace	0.134		7,000-8,000 m	0.054	
Terraced	0.311		>8,000 m	0.160	
Multi-family home	0.347		*Dist. (m) to ONA*	395.758	290.126
Constructed < 1905	0.041		0-50 m	0.065	
Constructed 1906-1930	0.084		50-100 m	0.065	
Constructed 1931-1944	0.049		100-150 m	0.080	
Construced 1945-1959	0.089		150-200 m	0.086	
Constructed 1960-1974	0.220		200-250 m	0.088	
Constructed 1975-1989	0.221		250-300 m	0.086	
Constructed 1989-2000	0.131		300-350 m	0.082	
Constructed 2001-2010	0.093		350-400 m	0.073	
Constructed > 2010	0.071		400-450 m	0.066	
Dist. (m) to CANA	4459.207	3691.775	450-500 m	0.057	
0-500 m	0.055		>500 m	0.277	

Note that many of the values remain largely unchanged, except for assessed value and living area. For these variables, the mean decreased slightly, but the standard deviation decreased substantially, especially for living area.

4 Methodology

4.1 Identifying the Nature Proximity

In this study, two measures of proximity to nature will be considered: discrete distance intervals, and nature density. The first measure is used in many comparable studies (Conway et al., 2010; Daams et al., 2016; van Ruijven & Tijm, 2022). We define the distance between a house and CANA/ONA as the euclidean distance to the closest piece of CANA/ONA. Hypothesizing that the effect of attractive nature extends further than that of remaining nature, we use the following intervals for CANA: 0-0.5 km, 0.5-1 km, 1-2 km, 2-3 km, 3-4 km, 4-5 km, 5-6 km, 6-7 km, 7-8 km, and >8 km. For ONA, we use the intervals 0-50 m, 50-100 m, 100-150 m, 150-200 m, 200-250 m, 250-300 m, 300-350 m, 350-400 m, 400-450 m, 450-500 m, and >500 m. These distance measures are included as dummy variables in the regression model, which will be specified later in Section 4.2.

It is likely that not only distance to nature, but also the area of nearby nature influences the house price. In previous studies, area is often included as the total area within a certain distance of the dwelling (Bouwknegt & Schilder, 2023; Daams et al., 2016; van Ruijven & Tijm, 2022). In this paper, a new measure is introduced, namely the nature density score. This score will be calculated using kernel density estimation, and will increase for a dwelling when distance to nature for the dwelling is lower, as well as increasing when there is more natural area near that dwelling.

The nature density score of a dwelling will be calculated separately for both CANA and ONA. The nature density score ND of a dwelling i is calculated as:

$$ND_i = \frac{1}{r^2} \sum_{k=1}^{K} \left[\frac{3}{\pi} \left(1 - \left(\frac{d_{ik}}{r} \right)^2 \right)^2 \right] \quad \text{For all } k \text{ such that } d_{ik} < r. \tag{2}$$

Here, r is the search radius, k is the index for a raster cell which is flagged as CANA/ONA, K is the total number of raster cells containing nature, and d_{ik} is the distance from the center of the raster cell in which house i is located to the center of raster cell k. The kernel in Equation (2) is the Quartic kernel as described by Silverman (1986). The center of each raster cell will receive a nature density based on this kernel, which is then multiplied by the total number of cells flagged as nature. The resulting score can be seen as the intensity of nature around this cell, which is based on both distance to nature, as well as the area of the nature around the cell. All houses will get assigned a nature density score based on the cell they are in. Figure II shows a simple example of the density around a nature raster cell located at $(0, 0)$. From this figure, it is clear that the density around a nature cell is smoothed non-linearly into space around the nature cell, which is in line with the notion of Lancaster (1966) that characteristics likely do not enter the hedonic regression equation linearly.

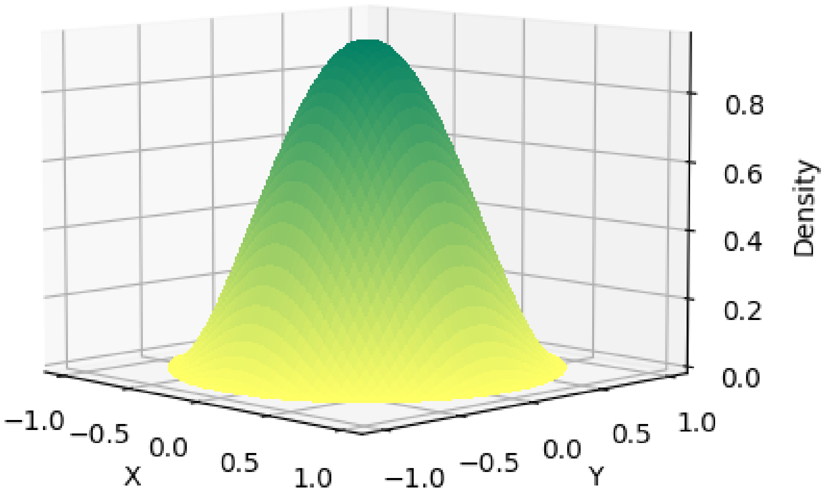

FIGURE II. Surface plot of the two dimensional Quartic kernel with unity radius

The search radius r will be calculated based on Silverman's rule-of-thumb for bandwidth calculation in kernel density estimation, extended to the multivariate case. It is calculated with the procedure described in Algorithm 1.

Algorithm 1 Procedure for calculating the search radius in kernel density estimation

1. Calculate the mean center of the input points (the center points of all raster cells containing nature).
2. Calculate the distance from each input point to the mean center calculated in step 1.
3. Calculate the median of the distances in the previous step (D_m).
4. Calculate the search radius r by

$$r = 0.9 \cdot \min\left(SD, \sqrt{\frac{1}{\ln(2)}} \cdot D_m\right) \cdot n^{-0.2}.$$

Here, SD is the standard distance, which is calculated as

$$SD = \sqrt{\frac{\sum_{k=1}^{K}(x_k - \bar{X})^2}{K} + \frac{\sum_{k=1}^{K}(y_k - \bar{Y})^2}{K}}, \tag{3}$$

where k and K are defined as before, x_k and y_k are the x and y coordinate of the center of nature raster cell k, and $\bar{X}$ and $\bar{Y}$ are the x and y coordinates of the mean center.

4.2 The Hedonic Price Model

Base Specification

The starting point of the hedonic price analysis in this study is the following model:

$$\ln(AV) = X\beta + N\gamma + \varepsilon. \tag{4}$$

Here, $\ln(AV)$ denotes the natural logarithm of assessed value, X is a matrix of property characteristics as described in Section 3.2 and also includes the regression constant, N contains the variables related to nature proximity, and ε is the i.i.d. error term. As described in the previous section, we have two different distance measures. All models described in this section will be estimated twice, each with one of these measures. In other words, we estimate one model where N consists of dummy variables for all discrete distance intervals mentioned in Section 4.1, and one model where N consists of only the two nature density scores (one for CANA and one for ONA). Both β and γ are parameters to be estimated. This simple model does not take spatial autocorrelation into account. Next, models controlling for spatial autocorrelation are discussed.

Spatial Difference Model

The first spatial model is the spatial difference model. This model is defined as follows

$$\ln(AV_{iz}) - \ln(AV_{jz}) = (X_{iz} - X_{jz})\beta + (N_{iz} - N_{jz})\gamma + \varepsilon_{ijz}. \tag{5}$$

Here, i and j are indices of houses both located in neighbourhood z. In other words, the log of assessed value is modeled relative to an arbitrary reference house in the same neighbourhood, eliminating neighbourhood effects. In fact, it is even stricter than common fixed effects models, as it also eliminates similarities in unobserved characteristics of houses. The differencing is done on PC4 level. Important to note is that due to the differencing, the shocks will not be uncorrelated. Therefore, standard errors are clustered on PC6 level. This model specification is currently used by Statistics Netherlands for the valuation of the ecosystem amenity service.

Spatial Lag and Spatial Error Model

Now, two traditional methods of spatial regression are discussed. First, the spatial lag model is defined in the following way

$$\ln(AV) = \rho W \ln(AV) + X\beta + N\gamma + \varepsilon. \tag{6}$$

Here W is a weight matrix relating observations with each other based on some spatial contiguity measure, and all other symbols are as defined in Equation (4). The parameter ρ needs to be estimated alongside β and γ. ρ is the spatial parameter, signifying the degree of spatial correlation between outcome variables. During estimation, which is done using maximum likelihood, this parameter is restricted to the interval $[0, 1]$. This parameter needs to be bounded to avoid singularity of the matrix $[I - \rho W]$. To avoid this issue, the parameter needs to be bounded below by $1/\omega_{min}$, and bounded above by $1/\omega_{max}$, where ω_{min} and ω_{max} are the smallest and largest eigenvalue of W, respectively. When W is row standardized, as done in this study, $\omega_{max} = 1$ and $\omega_{min} < -1$ (Baltagi, 2001). However, we expect spatial correlation to be positive, and therefore bound ρ below by 0, also for improved computation time. Details on how to define the weight matrix W will follow shortly. Note that his model can be rewritten as

$$\ln(AV) = [I - \rho W]^{-1} X\beta + [I - \rho W]^{-1} N\gamma + [I - \rho W]^{-1} \varepsilon. \tag{7}$$

The effect of an explanatory variable x_k on the dependent variable is given by the partial derivative. The partial derivative of $\ln(AV)$ with respect to variable x_k is given by $\frac{\partial \ln(AV)}{\partial x_k} = [I - \rho W]^{-1} \beta_k$, which is an $n \times n$ matrix, also called the impact matrix. The average value of the diagonals of the impact matrix gives the direct impact of variable x_k on $\ln(AV)$. The mean value of the off diagonal entries gives the indirect impact. Averaging all values of the impact matrix gives the total impact of variable x_k. We are interested in the total impact for this study. Standard errors and p-values for the total impacts are computed using simple simulation techniques.

In the spatial error model, the error term in (4) is specified in a spatially lagged form, namely $\varepsilon = \lambda W \varepsilon + \nu$, where ν is a vector of i.i.d errors. This expression can be rewritten as $\varepsilon = (I - \lambda W)^{-1} \nu$. The resulting spatial error model is

$$\ln(AV) = X\beta + N\gamma + (I - \lambda W)^{-1} \nu. \tag{8}$$

Where the coefficients β, γ, and λ have to be estimated, and all other terms are defined as before. The parameter λ measures the degree of spatial correlation, and is also estimated using maximum likelihood. During estimation it is restricted to the interval $[0, 1]$, for the same reasons as the parameter ρ in the spatial lag model.

The spatial lag and error model have been used in a similar context by Holt and Borsuk (2020), Hoshino and Kuriyama (2010), and Sohn, Kim, Kim, and Li (2020). Note that Equation (6) and (8) look quite similar, especially in terms of model errors. However, the difference comes from the explanatory variables. Whereas the spatial error model only models correlated shocks, the spatial lag model also assumes indirect effects of variables through correlated observations.

A key part of the spatial regression models is the definition of the weight matrix W. This matrix defines the degree of correlation between houses. There are many possible choices of the weight matrix, for which we refer to Getis and Aldstadt (2004). In this study, we consider the following weight structure:

$$w_{ij} = \begin{cases} 1 & \text{if } PC4_i = PC4_j, \quad i \neq j \\ 0 & \text{otherwise,} \end{cases} \tag{9}$$

where $PC4_i$ equals the four numbers of the postal code of house i. In other words, we relate houses which have the same postal code, up to the four numbers in the postal code. After constructing the weight matrix, it is row-standardized such that the elements of each row sum up to one, which is standard practice (Anselin, 1988).

Fixed Effects Model

The last method we consider is the use of neighbourhood fixed effects, together with some neighbourhood characteristics. The model is defined as follows

$$\ln (AV) = X\beta + N\gamma + f_z + \varepsilon, \tag{10}$$

where f_z is a vector of neighbourhood characteristics, together with group fixed effect of neighbourhood z defined on the PC4 level. The fixed effects try to capture the omitted or unobserved neighbourhood effects.

The main parameter of interest is γ, which captures the marginal effect of nature proximity on the price of houses, and is thus the vector of average treatment effects. In order to correctly identify this parameter, it is important that there are no omitted variables correlated with the nature proximity variable N. Controlling for these possible omitted variables is done through the spatial lag, spatial error, spatial difference or spatial fixed effect. The main assumption for these models to correctly identify the parameter of interest, is that the scale of spatial correction is well defined. The spatial scale should not be too large, as then local effects are averaged out too much. On the other hand, the scale should not be too small, as variation within spatial units will be to little, and the marginal effect of nature proximity will get absorbed in the spatial correction. Therefore, the scale is chosen to be at PC4 level, which is common in comparable studies (Bouwknegt & Schilder, 2023; Daams et al., 2016), and even shown to be optimal in Daams, Proietti, and Veneri (2019).

In order to decide which of the models is preferred, we look at the adjusted R^2, defined as $1-\frac{n-1}{n-k}\left(1-R^2\right)$. Here n is the number of observations, and k the amount of variables included in the model. Difficulty in the cross model comparison comes from the spatial difference model as described in Equation (5). The dependent variable for observation i is not equal to the ones in the other model specification, in addition to losing the reference observations. To be able to compare them using the adjusted R^2, we have to transform the fitted values of Equation (5) by adding back the value of $\ln\left(AV_{jz}\right)$ to the fitted value, and then manually computing the adjusted R^2. Note that this procedure means that all reference observations are lost, as we do not get fitted values for these observations. Furthermore, due to the transformation as shown in Equations (7) and (8), we can not compare the R^2 values of these models with those of other models, as they have different interpretations for the spatial lag and spatial error model.

4.3 Valuating the Ecosystem Service

Once a preferred model is chosen, the percentage of the value of a house explained by its proximity to nature can be calculated. In the models with dummies for discrete distance intervals, the estimated fraction $\hat{p}$ of a property's value explained by nature proximity dummies is calculated by applying the transformation $\hat{p} = e^{\hat{\gamma}} - 1$, where $\hat{\gamma}$ is the estimate of γ in Equation (4), (6), (8), (5), or (10). Note that all these operations are element wise. Important to note is that this transformation is biased, but consistent. Given the size of our dataset, this simple transformation is justified, and a bias correction is not necessary (Kennedy, 1981). In the model using the nature density score, $\hat{p}$ is simply given by $\hat{p} = \hat{\gamma}$. The value of a house which is generated by nearby nature is then calculated as $AV_i \cdot N_i\hat{p}$.

Once these values are added together for each house, it results in the total amenity value of ecosystem asset in the Netherlands. However, this number is a stock value, as it represents the amenity value of the ecosystem over its entire lifespan. Since we are interested in the value of the ecosystem amenity service for the year 2021, which is a flow variable, we have to convert from stock to flow. To this end, we make use of the Net Present Value method as described in the Natural Capital Accounting in the

Netherlands - Technical Report by Statistics Netherlands and WUR (2022). The value of an ecosystem asset is calculated as

$$K_0 = \sum_{t=1}^{T} \frac{d_t}{(1+r)^t}, \tag{11}$$

where K_0 is the value of the asset, d_t is the flow in year t, r is the discount rate, and T is the asset life in years. We assume a lifespan of $T = 100$, and a discount rate of $r = 0.02$ for the first 30 years, $r = 0.015$ for the following 45 years, and $r = 0.01$ for the rest of the lifespan. Additionally, we assume that the flow d_t is the same for all $t = 1, \ldots, T$. The value of the ecosystem service can then be calculated by dividing the value of the ecosystem asset, which is estimated by the regression model, by approximately 54. The assumptions come from the Principles of Capital Accounting by Philips (2017), which are the principles used by the Office for National Statistics.

5 Main Findings

The regression results for models (4), (6), (8), (5), and (10) are presented in Table IV. An important first note is the running time and computational feasibility of the models. Whereas the regular linear regression and the spatial difference model run relatively quickly, issues arise mainly in the spatial lag and spatial error model, where the weight matrix as defined in Equation (9) is needed. This matrix is of dimension $n \times n$, and given the size of the data ($n = 7,317,288$) this leads to a matrix too large to fit in memory of statistical software. Similar issues arise for the fixed effects model, although to lesser extent.

Consequently, the spatial lag and spatial error model were estimated on a subset which is close to the largest dataset the implementation of this method in statistical software is able to handle ($n = 14,634$). However, even on this relatively small subset, both the spatial lag and spatial error model need about ten hours to converge to an optimal solution. Therefore, it is not feasible to estimate these models on the full dataset by means of model averaging, as this would take about 200 days per model. These models were thus estimated on a single subset. As mentioned before, the spatial lag and spatial error model can not be compared to the other models by adjusted R^2. However, they can be compared to the other models by means of the AIC.

For the fixed effect model, the dataset was first split in 500 subsets, and the model was estimated on each subset, after which the results were averaged. However, the model showed curious results for some of the subsets, leading to estimates of the intercept to become arbitrarily large or small at times. A similar result occurred when the model was estimated on a larger dataset (500,000 observations). Therefore, this model was estimated using the same subset on which the spatial lag and spatial error model were estimated.

TABLE IV. Regression results for the five model specifications

	Base model	Spatial difference	Fixed effects	Spatial lag	Spatial error
Discrete Distance Measures					
Dist. to ONA					
0-50 m	0.035***(0.001)	0.037***(0.001)	0.034***(0.010)	0.035**(0.017)	0.038***(0.011)
50-100 m	0.027***(0.001)	0.020***(0.001)	0.006(0.008)	-0.001(0.012)	0.014*(0.008)
100-150 m	0.012***(0.000)	0.007***(0.001)	0.008(0.007)	0.009(0.011)	0.013*(0.007)
150-200 m	0.006***(0.000)	0.003***(0.001)	0.009(0.007)	-0.007(0.011)	0.011(0.007)
200-250 m	0.002***(0.000)	0.002**(0.001)	0.005(0.007)	0.001(0.010)	0.009(0.007)
250-300 m	0.002***(0.000)	0.000(0.0001)	-0.002(0.007)	-0.004(0.011)	0.004(0.007)
300-350 m	-0.001(0.000)	0.000(0.0001)	0.001(0.007)	0.013(0.011)	0.007(0.007)
350-400 m	-0.004***(0.001)	-0.000*(0.0001)	-0.008(0.007)	-0.006(0.012)	-0.009(0.008)
400-450 m	-0.001**(0.001)	0.000(0.001)	0.007(0.007)	-0.004(0.012)	0.007(0.008)
450-500 m	-0.004***(0.001)	-0.002**(0.001)	0.003(0.008)	-0.012(0.013)	0.002(0.008)
Dist. to CANA					
0-500 m	0.364***(0.001)	0.069***(0.003)	0.032(0.030)	0.372***(0.013)	0.288***(0.016)
500-1,000 m	0.320***(0.001)	0.040***(0.003)	0.011(0.028)	0.307***(0.012)	0.263***(0.015)
1,000-2,000 m	0.253***(0.000)	0.020***(0.003)	0.001(0.027)	0.244***(0.010)	0.237***(0.013)
2,000-3,000 m	0.189***(0.000)	0.013***(0.003)	-0.011(0.027)	0.192***(0.010)	0.202***(0.013)
3,000-4,000 m	0.146***(0.000)	0.011***(0.002)	-0.015(0.025)	0.148***(0.011)	0.162***(0.014)
4,000-5,000 m	0.121***(0.001)	0.000(0.002)	-0.041*(0.024)	0.120***(0.010)	0.105***(0.014)
5,000-6,000 m	0.122***(0.001)	0.006***(0.002)	-0.030(0.022)	0.118***(0.012)	0.091***(0.014)
6,000-7,000 m	0.102***(0.001)	-0.001(0.002)	-0.024(0.019)	0.112***(0.013)	0.058***(0.014)
7,000-8,000 m	0.052***(0.001)	-0.006***(0.002)	-0.029*(0.015)	0.040***(0.014)	0.019(0.013)
Spatial parameter	-	-	-	$\rho = 0.021$	$\lambda = 0.715$
Adjusted R^2	0.5673	0.8902	0.8749	-	-
AIC	9078.30	-11271.04	-6494.39	8756.00	-402.75
Nature Density Measures					
	Base model	Spatial difference	Fixed effects	Spatial lag	Spatial error
ONA density	0.00001***(0.000)	0.00001***(0.000)	0.00001***(0.000)	0.00001***(0.000)	0.00002***(0.000)
CANA density	0.00006***(0.000)	0.00003***(0.000)	0.00003***(0.000)	0.00007***(0.000)	0.00007***(0.000)
Spatial parameter	-	-	-	$\rho = 0.007$	$\lambda = 0.900$
Adjusted R^2	0.5336	0.8901	0.8751	-	-
AIC	10121.00	-11307.24	-6528.00	9968.10	-24.17
Observations	7,317,288	7,313,249	14,634	14,634	14,634

Note. The dependent variable is the natural logarithm of assessed value. Reference categories include Freehold, Detached, constructed before 1905, distance to ONA > 500 m, and distance to CANA > 8000 m. Each model includes a constant and property characteristics. Standard errors are in parentheses. For the spatial difference model, standard errors are clustered. AIC is based on estimation in a subset of the data. *** p<0.01, ** p<0.05, * p<0.1.

5.1 Spatial Extent

The spatial extent to which the positive effect of nature on house values reaches, is defined by the positive, significant coefficients. The first remarkable result is the significance in the basic linear model. All but one of the coefficients for amenity variables are significant at the 1% level. This is to be expected, as ignoring spatial dependence leads to an overestimation of the coefficient estimates (Anselin, 2009).

Also notable is the significance of coefficients in the fixed effects model. Contrarily to the basic linear regression, this model barely shows any significance in the parameter estimates of the discrete amenity variables. It is important to realize that, in general, standard errors are larger in smaller samples. Given that the sample for the fixed effect model, as well as the spatial lag and spatial error model, is significantly smaller than for the other models, this is a possible reason for the low number of significant parameters. However, for the spatial regression models, the dummies for distance to CANA do show high significance. Interestingly, for all models, the density parameters all show significance at the 1% level.

Besides statistical significance, the notion of practical significance is also of importance. For the calculation of the value of the amenity service, only the coefficients which are statistically significant and positive are used. Therefore, in Section 5.3 and 5.4, only those coefficients which are positive and statistically significant are considered.

5.2 Model Fit

Comparing the adjusted R^2 of the basic linear model to those of the other models, it clearly has the worst in-sample fit, both in the discrete and the density specification. Similarly, the AIC is the highest for the basic linear model, also confirming that this basic model is misspecified. Additionally, as can be seen in Appendix C, the other coefficients also show some curious results, like the basic model estimating a positive coefficient for the variable Multifamily home, indicating that an apartment is, ceteris paribus, more expensive than a detached house.

For the spatial lag and error model, we can not compare them to other models by means of the adjusted R^2, so we therefore turn to the AIC. Although the AIC value is slightly lower, the spatial lag model does not seem to increase model fit that much compared to the basic linear regression for both nature specifications. The spatial error model on the other hand does show sizable improvement. However, both models have a higher AIC than the fixed effects model.

Next we look at the spatial difference model. First, note that the spatial difference model has a different dependent variable than the other models. Therefore, in order to compare this model to the others, we transform the fitted values of this model back to a prediction of the log assessed value, instead of the difference in log assessed values. Based on these transformed fitted values, the adjusted R^2 and AIC are calculated. This model shows the least curious pattern of significance. Both for ONA and CANA distance, the short distances are positively significant, slowly decaying to zero coefficients, and ending with negative significance. Furthermore, this model has the highest adjusted R^2 value of the three regular regression methods, both for the discrete distance specification as the density specification. Additionally, it has the lowest AIC by far for both nature specifications. Therefore, the spatial difference model is the preferred model, followed by the fixed effects model.

Moreover, we wish to decide on a preferred nature specification. On first glance, both models appear to fit similarly well. The adjusted R^2 in the spatial difference model is slightly higher in the discrete distance specification, although only by 0.0001. The AIC calculated on the subset shows a preference for the density specification. We also calculate the AIC for the spatial difference model estimated on the full dataset, and internally compare the two nature specifications by means of this criterion. In the full sample, the discrete nature specification attains an AIC of 762126.62, whereas the density specification has an AIC of 769763.11, meaning the discrete specification is preferred in this case. Interesting enough, we see the reverse results for the fixed effects model. The adjusted R^2 is slightly higher in the density specification, and similarly the AIC is lower in the density specification than the discrete one. This means that, based on these criteria, there is no clear cut preferred model.

However, which specification is preferred does not only depend on model fit. Another important aspect is interpretability, especially since the results of the estimation are important in the domain of public decision making. In terms of interpretability, the discrete specification is preferred to the density specification. For instance, the coefficient for *Dist. to ONA 0-50 m* in model (2), which equals 0.037, can be interpreted after applying the transformation $e^{0.037} - 1 \approx 0.037$ as follows. Whenever a dwelling lies within 50 meters of an ONA, the price is on average 3.7% higher than a dwelling which is more than 500 meters away from an ONA.

On the other hand, interpretation in the density specification is not as straightforward. It is not directly clear what a one point increase in nature density means when the corresponding coefficient equals 0.00001, especially since the variable is not directly proportional to distance. Furthermore, the density score of a dwelling does not depend on one piece of nature, like the discrete measure, but depends on all nature cells within the search radius as defined in Section 4.1. Therefore, in terms of interpretability, the discrete nature specification is preferred to the density specification.

5.3 Effect of Nature on Housing Value

We now turn to the interpretation of the coefficients. Beforehand, it is expected that when the distance to ONA/CANA increases, the coefficients corresponding to the distance gradually decrease towards zero. We see this happen in most models, up until a certain distance. For instance, the coefficients corresponding to distance to ONA follow this pattern, although the coefficient is slightly negative for distance between 450 and 500 meters. Similarly in this model, the coefficients for distance to CANA gradually decrease towards zero, but jump back up a bit for 5,000-6,000 meters. The gradual decay of percentage of housing value explained by nature distance is shown in Figure III.

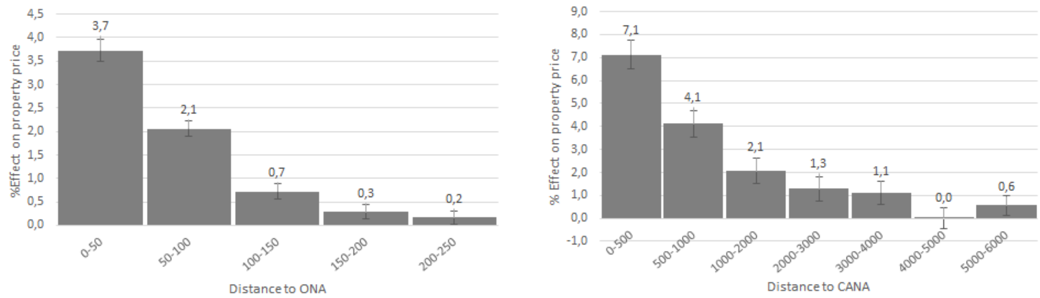

FIGURE III. Effects on property prices with 95% confidence intervals as estimated by the spatial difference model for ONA (left) and CANA (right) using a discrete nature proximity specification.

We also take a look at the coefficients of the other models, to see if patterns somewhat match. First, as mentioned earlier, we see that the coefficients of the basic linear regression appear to be heavily overestimated, as an increase in house prices of 43.9% when living within 500 meters of CANA compared to living over 8,000 meters away is highly unrealistic. In the fixed effects model, there are close to no significant coefficients for the discrete distance variables. In the spatial lag model, again there is only one significant ONA coefficient. The CANA coefficients are all highly significant, but again seem to be overestimated similarly to the basic linear regression. The same holds for the spatial error model, although to a lesser extent.

We compare the estimation results to those of a previous study conducted by Statistics Netherlands, estimated on data from 2013 [1]. The model used was a spatial difference model, with similar controls. In the 2013 study, the coefficients were found to be significant up until a distance of 350 meters to ONA, and 7000 meters to CANA, which is close to what was found in the current study, where significance was found up to and including 250 meters to ONA, and 6000 meters to CANA. However, the percent effect

[1] This is an internal study, and therefore not public.

on property prices is found to be different between studies. Whereas the effect of living within 50 meters of ONA was estimated to be 4.9% in 2013, we now find an effect of only 3.7%. All subsequent coefficients are also lower than in 2013. However, the effect of living within 500 meters of CANA was estimated to be 6.7% for the 2013 data, whereas an effect of 7.1% was found in our study. All subsequent estimated effects were also lower, except for the distance lying between 5000 and 6000 meters. In the 2013 study, a 0.4% effect was found, whereas in this study, an effect of 0.6% was estimated.

In order to interpret the results for the nature density specification, we do the following. For each of the discrete intervals used in this study, we calculate the mean percent added value to the assessed value, based on the estimated nature density coefficient. The results are shown in Figure IV.

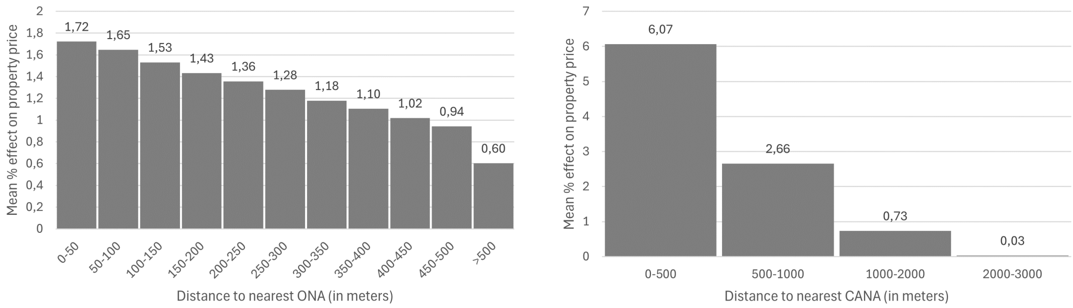

FIGURE IV. Effects on property prices as estimated by the spatial difference model for ONA (left) and CANA (right) using a nature density specification.

We see that, contrarily to the results for the discrete specification, the effect of ONA reaches way further in space, whereas the effect of CANA already stops after 3000 meters. This is the result of the search radius as calculated in Algorithm 1. The search radius for ONA (approximately 2156 meters) is significantly larger than the maximum distance considered in the discrete specification. On the other hand, the search radius for CANA is only about 2795 meters, which is a lot smaller than the maximum distance considered earlier. As a robustness check the density specification is also estimated whith a CANA search radius of 8000 meters. The adjusted R^2 of the model decreases slightly (R^2 = 0.8900), but the reach of the effect does not increase. After 3000 meters, the nature density score of dwellings is negligible. The only difference is that the percentages shown in the right panel of Figure IV increase to 9.38, 4.11, 1.14 and 0.04, respectively. Given that in the discrete specification the CANA effect reaches until 6000 meters, one might wonder if this density specification is desirable.

In the remainder of this paper, the spatial difference model is the preferred model, and all further analysis will be done using this specification. Since there is no clear preference based on in-sample fit between the discrete distance and density specification, analysis will be done with using both specifications.

5.4 Ecosystem Valuation

It now rests to estimate the total value of the amenity asset and service in the Netherlands. Using the methodology described in 4.3, we get the valuation of the amenity asset as shown in Table V.

TABLE V. Valuation of the amenity asset in billions of euros as estimated by the spatial difference model.

	Density	Discrete Distance (2021)	Discrete Distance (2013)
ONA	25.2	8.5	18.4
CANA	18.7	35.4	52.1
Total	43.9	43.9	70.5

Although both specifications give a similar estimate of the total asset value, the composition of these estimates is completely different. However, given the results shown in Figure III and IV, a different composition is to be expected. The discrete distance specification showed more and higher significant percentages for the CANA distances, whereas the reverse is true for the density specification. The amenity service can now be valuated using the procedure described in Section 4.3, leading to a final estimate of 818.2 million euro using the discrete specification, and 817.2 million euro for the density specification. We compare these results to those of the earlier study by Statistics Netherlands (Statistics Netherlands & WUR, 2022). Using the estimated coefficients of that study and our dataset, we find the estimates as presented in the last column of Figure V. The estimated values using the newly estimated coefficients are about 33% lower, which is a considerable decrease. The estimated value of the amenity service using the old coefficients equals 1,216.8 million euro. A possible reason for this decrease in value could be the growing scarcity of houses. When housing is scarce, the importance of factors like nature proximity might decrease. Alternatively, the scarcity of nature could play a role. In 2021, the average distance to ONA and CANA were 396 and 4,459 meters, respectively. However, in 2013 these average distances were 392 and 4,906 meters, meaning the mean distance to nature has decreased over time. This means living close to nature has become "less special", which could lead to a lower valuation.

5.5 Outlier robustness

In Section 3.3 it was described how outliers were handled. As a robustness check, the preferred model, namely the spatial difference model, is also estimated using the full, likely contaminated data set. This is done both by regular OLS, as well as a robust MM-estimator. Details and results of this estimation are shown in Appendix D. The results show that removing the outliers manually does not lead to estimates that are too different from the use of the full dataset. However, the use of a robust estimator does lead to several significantly different estimates, advocating for the use of robust estimation in future research.

6 Heterogeneity in Urbanization Degree

All models until now have been estimated under the assumption that all home owners value housing characteristics and nature amenities in the same way. However, it is highly unlikely that this assumption is satisfied. Specifically, we hypothesize that the effect of nearby nature on house prices depends on the scarcity of nature, and thus on the degree of urbanization of an area (Brander & Koetse, 2011). Therefore, we also estimate a model which allows for heterogeneous responses across the degree of urbanization. To define the degree of urbanization, first define the address density AD_i for a house i as

$$AD_i = \frac{\sum_{j=1}^{n} \mathbb{1}\left\{d_{ij} < d_{max}\right\}}{\pi d_{max}^2}. \tag{12}$$

Here, d_{ij} is the distance between house i and house j, d_{max} is the search radius, and $\mathbb{1}(\cdot)$ is the indicator function, being equal to 1 if the expression inside the brackets is correct, and 0 otherwise. The value of d_{max} is 1 kilometer. The following step is to give each house a degree of urbanization. It is common practice to average the address density of all houses in the same municipality, such that all houses within the same municipality have the same degree of urbanization (Den Dulk, Van De Stadt, & Vliegen, 1992). However, we hypothesize that inhabitants of neighbourhoods in the city center will have different preferences than those located on the border of a city. Therefore, averaging is both done per municipality, as well as per PC4 area. The degree of urbanization U_i of house located in a PC4 area or municipality c is then defined as

$$UD_c = \begin{cases} 1 & \text{if } AD_c \geq 2500 \\ 2 & \text{if } 1500 \leq AD_c < 2500 \\ 3 & \text{if } 1000 \leq AD_c < 1500 \\ 4 & \text{if } 500 \leq AD_c < 1000 \\ 5 & \text{if } AD_c < 500 \end{cases} . \tag{13}$$

These thresholds are in line with the definition used by Statistics Netherlands (Den Dulk et al., 1992). After calculating the urbanization degree for all dwellings, we estimate a single model, with a dummy variable for the degree of urbanization. Pooling all urbanization degrees instead of estimating five separate models preserves degrees of freedom, and allows for direct comparison of coefficients.

Since we concluded in Section 5 that the spatial difference model is the preferred specification, this is the model we use for this analysis. This leads to the following model specification.

$$\ln(AV_{iz}) - \ln(AV_{jz}) = \sum_{u=1}^{5} \left(\mathbb{1}\{UD_c = u\}\left[(X_{iz} - X_{jz})\beta_u + (N_{iz} - N_{jz})\gamma_u\right)\right] + \varepsilon_{ijz}. \tag{14}$$

Here, $\ln(AV)$ denotes the natural logarithm of assessed value, X is a matrix of property characteristics as described in Section 3.2 and also includes the regression constant, N contains the variables related to nature proximity, and ε is the i.i.d. error term. Furthermore, i and j are indices of houses both located in neighbourhood z, and u indicates the urbanization degree category. Further, β_u and γ_u, $u = 1, \ldots, 5$, are parameters to be estimated. UD_c is the urbanization degree of the spatial unit (either municipality or PC4 area) c in which house i and j reside. Note that when urbanization degree is defined per PC4 area, c and z coincide.

6.1 Results

The parameter estimates of the nature proximity variables for the model with urbanization defined per PC4 area are given in Table VI.

TABLE VI. Regression results for the spatial difference model with heterogeneity in urbanization degree per PC4 area.

	Discrete Distance Measures				
	UD = 1	UD = 2	UD = 3	UD = 4	UD = 5
Dist. to ONA					
0-50 m	0.026***(0.004)	0.033***(0.002)	0.031***(0.002)	0.049***(0.002)	0.059***(0.002)
50-100 m	0.018***(0.003)	0.020***(0.001)	0.014***(0.001)	0.026***(0.002)	0.034***(0.002)
100-150 m	-0.000(0.003)	0.009***(0.001)	0.005***(0.001)	0.013***(0.001)	0.012***(0.001)
150-200 m	-0.005*(0.002)	0.006***(0.001)	-0.001(0.001)	0.010***(0.001)	0.005***(0.001)
200-250 m	-0.003(0.002)	0.005***(0.001)	-0.004***(0.001)	0.007***(0.001)	-0.001(0.001)
250-300 m	-0.004*(0.002)	0.003***(0.001)	-0.004***(0.001)	0.006***(0.001)	-0.002**(0.001)
300-350 m	-0.001(0.002)	0.002**(0.001)	-0.005***(0.001)	0.002*(0.001)	-0.000(0.001)
350-400 m	0.001(0.002)	-0.001(0.001)	-0.007***(0.001)	-0.002(0.001)	-0.002**(0.001)
400-450 m	0.004**(0.002)	-0.000(0.001)	-0.008***(0.001)	0.005***(0.001)	-0.002(0.001)
450-500 m	-0.002(0.002)	-0.001(0.001)	-0.005***(0.001)	-0.000(0.001)	-0.001(0.001)
Dist. to CANA					
0-500 m	0.114***(0.010)	0.058***(0.006)	0.090***(0.010)	0.055***(0.006)	0.008(0.005)
500-1,000 m	0.074***(0.010)	0.044***(0.005)	0.067***(0.009)	0.029***(0.005)	-0.014***(0.005)
1,000-2,000 m	0.050***(0.010)	0.026***(0.005)	0.042***(0.008)	0.006(0.005)	-0.017***(0.004)
2,000-3,000 m	0.036***(0.010)	0.024***(0.005)	0.036***(0.008)	-0.000(0.005)	-0.015***(0.004)
3,000-4,000 m	0.032***(0.009)	0.030***(0.004)	0.021***(0.007)	-0.008*(0.005)	-0.007*(0.004)
4,000-5,000 m	0.004(0.009)	0.013***(0.004)	0.008(0.006)	0.001(0.004)	-0.014***(0.004)
5,000-6,000 m	0.019**(0.009)	0.019***(0.004)	0.010*(0.005)	0.003(0.004)	-0.011***(0.003)
6,000-7,000 m	0.019***(0.007)	-0.004(0.003)	0.013***(0.004)	-0.008**(0.003)	0.001(0.003)
7,000-8,000 m	0.002(0.006)	-0.008***(0.002)	0.006**(0.003)	-0.008***(0.002)	-0.004(0.002)
Adjusted R^2	0.8922				
	Nature Density Measures				
	UD=1	UD=2	UD=3	UD=4	UD=5
ONA density	-0.00003***(0.000)	0.00001***(0.000)	0.00002***(0.000)	0.00002***(0.000)	0.00002***(0.000)
CANA density	0.00005***(0.000)	0.00002***(0.000)	0.00004***(0.000)	0.00003***(0.000)	0.00004***(0.000)
Adjusted R^2	0.8923				
Observations	1,871,680	2,078,638	1,290,006	1,146,932	930,032

Note. The dependent variable is the natural logarithm of assessed value relative to a reference home within the same PC4 area. Reference categories include Freehold, Detached, constructed before 1905, distance to ONA $>$ 500 m, and distance to CANA $>$ 8000 m. All models contain an intercept and property characteristics. Adjusted R^2 is calculated based on predictions of the natural logarithm of assessed value, and not for the relative value. Clustered standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

From these estimates, it is immediately clear that there is indeed response heterogeneity across the different degrees of urbanization. Remember that category $UD = 1$ corresponds to the most urbanized areas, and $UD = 5$ the least urbanized areas. Looking at the coefficient estimates for ONA distance, we see that the higher the urbanization, the less important living very close to ONA becomes. For the highest urbanization degree, being within 50 meters of ONA only leads to a 2.8% increase of housing prices, whereas for the lowest urbanization degree, this increase is 6.1%. Furthermore, we see that for urbanization degree 1, the coefficients fall below zero after 100 meters. However, weirdly enough, the coefficients again turn positive between 350 and 450 meters. The positive significance reaches way further for urbanization degrees 2 and 4, namely to 350 meters, whereas for degree 3 and 5 it only reaches to 150 and 200 meters respectively.

As for the coefficients corresponding to the CANA distances, we find that significance persists for a long distance for the urbanization degrees 1, 2, and 3. In category 4, coefficients are positively significant until 1000 meters, whereas for category 5 no significant effects are found at all. Interestingly enough, the estimate for CANA density is higher in category 5 than in category 2 and 4, although these had higher and more significant CANA coefficient estimates in the discrete specification.

In order to find a possible explanation for these results, we look at the average distance to ONA and CANA per urbanization degree, as scarcity is likely a factor in the valuation of nature. See Table VII for the average distances to ONA and CANA for the different urbanization degrees.

TABLE VII. Average distance to ONA and CANA in meters per urbanization degree.

	UD=1	UD=2	UD=3	UD=4	UD=5
	Urbanization per PC4 area				
Average distance to ONA	410	333	380	418	501
Average distance to CANA	2,872	4,304	4,959	5,400	6,146
	Urbanization per Municipality				
Average distance to ONA	386	339	423	441	501
Average distance to CANA	2,932	4,520	4,223	5,792	6,811

We see that for the lower degrees of urbanization, the mean distance to both ONA and CANA is the largest. However, since urban green like public parks and hedgerows are also considered as nature in the context of this study, this likely also causes a decrease of distance to nature for urban areas. Additionally, this does not fully come as a surprise for the CANA, since the survey to obtain hotspot markers for attractive nature was answered mostly by respondents living in larger cities. This result could be a possible explanation as to why the number of positive significant coefficients is so low for the least urbanized category, as there is a relatively low amount of observations in the short distance categories. Further, in lesser urban areas, there is relatively more agricultural land than natural land (CBS, PBL, RIVM, WUR, 2023). Therefore, we do see that the coefficients that are positive and significant for the ONA distance are high in the lesser urbanized areas compared to those of other categories. On the other hand, in the highest urbanization category, the mean distance to CANA is the lowest by quite a margin. We also see the most significant positive coefficients in this category, as well as the highest coefficient estimates. For the ONA coefficients, these are only significant and positive until 100 meters for the highest urbanization degree, which is to be expected as the mean distance to ONA is higher than those of categories 2 and 3. Interestingly, category 4 has quite a lot of significant positive estimates for the ONA coefficients, although the mean distance is a slight bit higher than for category 1. They are also higher than those for category 1.

Obviously, mean distance is not the only explanatory factor for the results. When people live in a densely populated area, being able to easily get to a natural area might be a relief from the noise and masses of people. Therefore, it is to be expected that people who live in highly urbanized areas value nearby nature more. We see this in the estimates, as the coefficient estimates for CANA in category 1 are the highest by a decent margin, and the lowest in category 5. However, the contrary is true for the ONA coefficients, where the estimates are the lowest in category 1, and the highest in category 5. Similar patterns can be seen for the estimated density coefficients. The CANA coefficient in category 1 is the highest, and the ONA coefficients is the lowest in this category. However, given the estimates for the distances in category 2, the density estimate is expected to also be high, but it is in fact the lowest among all urbanization degrees. The ONA estimates are quite close for category 3, 4, and 5, and a bit lower for category 2. For category 1, it is even estimated to be negative. However, given the estimates for the discrete distance measures, this does not fully come as a surprise, given the low amount of positive estimates, and the positive estimates are also the lowest among all degrees of urbanization.

Next, we look at the results for the second heterogeneity specification, with urbanization defined per municipality. The estimation results are in Table VIII.

TABLE VIII. Regression results for the spatial difference model with heterogeneity in urbanization degree per municipality.

	Discrete Distance Measures				
	UD = 1	UD = 2	UD = 3	UD = 4	UD = 5
Dist. to ONA					
0-50 m	0.021***(0.003)	0.034***(0.002)	0.045***(0.002)	0.053***(0.002)	0.050***(0.003)
50-100 m	0.011***(0.002)	0.021***(0.001)	0.023***(0.002)	0.030***(0.001)	0.027***(0.002)
100-150 m	-0.003(0.002)	0.011***(0.001)	0.010***(0.001)	0.013***(0.001)	0.010***(0.002)
150-200 m	-0.008***(0.002)	0.007***(0.001)	0.007***(0.001)	0.008***(0.001)	-0.004**(0.002)
200-250 m	-0.008***(0.002)	0.005***(0.001)	0.008***(0.001)	0.001(0.001)	0.001(0.002)
250-300 m	-0.008***(0.001)	0.004***(0.001)	0.008***(0.001)	-0.001(0.001)	-0.003*(0.001)
300-350 m	-0.005***(0.002)	0.003***(0.001)	0.004***(0.001)	-0.002*(0.001)	-0.001(0.002)
350-400 m	-0.004**(0.002)	0.001(0.001)	-0.002(0.001)	-0.003***(0.001)	-0.004**(0.002)
400-450 m	-0.002(0.002)	0.000(0.002)	0.003**(0.001)	0.002*(0.001)	-0.003*(0.001)
450-500 m	-0.006***(0.002)	-0.001(0.001)	-0.001(0.001)	-0.000(0.001)	-0.004**(0.002)
Dist. to CANA					
0-500 m	0.120***(0.011)	0.085***(0.006)	0.069***(0.006)	0.035***(0.004)	-0.004(0.007)
500-1,000 m	0.091***(0.010)	0.057***(0.005)	0.038***(0.006)	0.010**(0.004)	-0.028***(0.007)
1,000-2,000 m	0.069***(0.010)	0.040***(0.005)	0.010*(0.006)	-0.008**(0.004)	-0.024***(0.006)
2,000-3,000 m	0.052***(0.010)	0.035***(0.005)	0.012**(0.005)	-0.008**(0.004)	-0.032***(0.006)
3,000-4,000 m	0.049***(0.009)	0.021***(0.005)	0.016***(0.005)	-0.003(0.003)	-0.026(0.006)
4,000-5,000 m	0.010(0.008)	0.014***(0.005)	0.013***(0.005)	-0.009***(0.003)	-0.030***(0.005)
5,000-6,000 m	0.018***(0.007)	0.018***(0.004)	0.018***(0.004)	-0.005*(0.003)	-0.031***(0.005)
6,000-7,000 m	-0.004(0.006)	0.008**(0.004)	0.022***(0.004)	-0.010***(0.003)	-0.013***(0.004)
7,000-8,000 m	-0.005(0.004)	-0.004(0.003)	0.009***(0.003)	-0.004**(0.002)	-0.003(0.003)
Adjusted R^2	0.8925				
	Nature Density Measures				
	UD = 1	UD = 2	UD = 3	UD = 4	UD = 5
ONA density	-0.00001***(0.000)	0.00001***(0.000)	0.00002***(0.000)	0.00002***(0.000)	0.00002***(0.000)
CANA density	0.00001***(0.000)	0.00005***(0.000)	0.00004***(0.000)	0.00003***(0.000)	0.00004***(0.000)
Adjusted R^2	0.8924				
Observations	1,991,915	2,271,544	1,063,561	1,498,176	492,092

Note. The dependent variable is the natural logarithm of assessed value relative to a reference home within the same PC4 area. Reference categories include Freehold, Detached, constructed before 1905, distance to ONA > 500 m, and distance to CANA > 8000 m. All models contain an intercept and property characteristics. Adjusted R^2 is calculated based on predictions of the natural logarithm of assessed value, and not for the relative value. Clustered standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

For this specification, we see similar patterns in significance and size of coefficients as for the PC4 specification, although there are some slight differences, mainly for category 3. In the PC4 specification, category 3 showed higher CANA estimates than in the municipality specification, whereas the opposite is true for the ONA estimates. If we look at Table VII, we see that the mean distance to ONA in category 4 is higher in the municipality specification, whereas the mean distance to CANA is quite a bit lower.

When taking this form of scarcity into account, the change in coefficient estimates is to be expected. All other estimates tend to follow similar patterns as in the previous specification.

In terms of density estimates, we see some curious results, especially for the CANA density. Although the estimates for the discrete case show that category 1 clearly displays the highest valuation of CANA, the density estimate does not reflect this, having by far the lowest estimate of all categories. However, density is not only based on distance to nature, but also the total amount of nature. Therefore, the low coefficient could also imply that in this category, the total amount of CANA nearby is not as important to buyers. However, given the high CANA density estimate in the PC4 specification, this result is still quite unexpected.

In terms of model fit, both specifications show an increase in adjusted R^2 compares to the spatial difference model estimated on the full data set. Furthermore, the heterogeneity specification on municipality level has a higher R^2 value than the PC4 specification for both the discrete distance and density specification, although by a slight amount.

7 Transactions Versus Assessed Value

The proposed methods so far made use of the assessed value in order to define the value of a dwelling, whereas most other hedonic studies use real transaction data (Bouwknegt & Schilder, 2023; Daams et al., 2016; van Ruijven & Tijm, 2022). Both of these valuations have their merits. The use of assessed value allows to cover the entire housing market, whereas this is not the case for transaction data, as not all houses are sold each year. Consequently, using transactional data drastically reduces the sample size. Furthermore, using transaction data means that there are no rental properties used in the estimation. However, transactional data more accurately reflects market behaviour, and thus is a better measure of revealed preferences, whereas the assessed value is only an approximation. This approximation, however, is largely based on actual market transactions (Waarderingskamer, 2024), meaning the values should in theory not drastically differ.

Furthermore, over the past four years, on average only 2.4% of home-owners protested against the assessed value of their house, usually because they find the estimation to high. In less than 40% of these cases the assessed value is actually adjusted, implying that the assessed values quite accurately reflect the value of a dwelling (Netherlands Council for Real Estate Assessment, 2022). Trivially, there has not been a transaction for all dwellings in the Netherlands during the year 2021. In order to get a sizable dataset, transactions that took place in the period from January 2020 up to and including June

2024 are included in the analysis. Important to note is that some shortcuts were made for the data used in these estimations. The structural data on houses, as well as the distance to nature, were all measured on 2021 data, due to limited data availability.

As a preliminary check, we assess if the difference between the assessed value and market price of a property is significant. A paired t-test indeed confirms a significant difference between the two prices ($p < 0.01$), although they are highly correlated (correlation $= 0.931$, $p < 0.01$). Therefore, Model (5) is re-estimated on transaction data received from the Dutch cadastre.

As prices tend to change over time due to inflation, it is customary to include time period dummies in the hedonic regression equation (Eurostat, 2013). Therefore, Equation (5) is modified as follows

$$\ln(AV_{iz}) - \ln(AV_{jz}) = (X_{iz} - X_{jz})\beta + (N_{iz} - N_{jz})\gamma + (T_{iz} - T_{jz})\,\delta + \varepsilon_{ijz}. \tag{15}$$

Here, $\ln(AV)$ denotes the natural logarithm of assessed value, X is a matrix of property characteristics as described in Section 3.2 and also includes the regression constant. N contains the variables related to nature proximity, T is a matrix of time dummies, and ε is the i.i.d. error term. Furthermore, i and j are indices of houses both located in neighbourhood z. β, γ, and δ are parameters to be estimated. The estimation results are shown in Table IX.

TABLE IX. Regression results for the spatial difference model, estimated on sales prices for transactions from 2020 until 2024, and the corresponding assessed values

Discrete Distance Measures		
	Transaction Values	Assessed Values
Dist. to ONA 0-50 m	0.053***(0.002)	0.047***(0.002)
Dist. to ONA 50-100 m	0.031***(0.001)	0.028***(0.001)
Dist. to ONA 100-150 m	0.016***(0.001)	0.015***(0.001)
Dist. to ONA 150-200 m	0.007***(0.001)	0.008***(0.001)
Dist. to ONA 200-250 m	0.007***(0.001)	0.007***(0.001)
Dist. to ONA 250-300 m	0.004***(0.001)	0.004***(0.001)
Dist. to ONA 300-350 m	0.003***(0.001)	0.004***(0.001)
Dist. to ONA 350-400 m	0.001(0.001)	0.002**(0.001)
Dist. to ONA 400-450 m	-0.001(0.001)	0.001(0.001)
Dist. to ONA 450-500 m	-0.002**(0.001)	-0.001(0.001)
Dist. to CANA 0-500 m	0.068***(0.006)	0.076***(0.005)
Dist. to CANA 500-1,000 m	0.033***(0.006)	0.042***(0.005)
Dist. to CANA 1,000-2,000 m	0.008**(0.005)	0.017***(0.004)
Dist. to CANA 2,000-3,000 m	0.004(0.005)	0.014***(0.004)
Dist. to CANA 3,000-4,000 m	-0.001(0.005)	0.012***(0.004)
Dist. to CANA 4,000-5,000 m	-0.010**(0.004)	0.004(0.004)
Dist. to CANA 5,000-6,000 m	-0.009**(0.004)	0.004(0.003)
Dist. to CANA 6,000-7,000 m	-0.004(0.003)	0.003(0.003)
Dist. to CANA 7,000-8,000 m	-0.007***(0.002)	-0.007***(0.002)
Nature Density Measures		
	Transaction Values	Assessed Values
ONA density	0.00002***(0.000)	0.00002***(0.000)
CANA density	0.00005***(0.000)	0.00005***(0.000)
Observations	768,667	768,667

Note. The dependent variable is the natural logarithm of assessed value relative to a reference home within the same PC4 area. Reference categories include Freehold, Detached, constructed before 1905, distance to CANA $>$ 8000 m, and distance to ONA $>$ 500 m. All models contain an intercept and property characteristics. Clustered standard errors are in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Comparing the results for both models, we see a few differences. Although direct comparison of coefficients is difficult, we use a rule of thumb of coefficients being "equal" if they are within two standard errors of each other. Using this rule, we see that for ONA distance, the coefficients for 0-50 meters and 50-100 meters differ significantly, with the estimates in the transaction model being higher. As for the distance to CANA, the coefficients for 3,000-4,000 up to and including 6,000-7,000 are significantly different.

For the density specification, the ONA and CANA coefficients do not differ significantly. In general, the coefficients which differ significantly are higher when estimated on the assessed value. Possibly, valuation offices value the proximity of nature more than actual property buyers. Alternatively, there might be a difference in the nature of the sample, since the sample with transactions obviously does not contain any rental properties, which were included in the original dataset with assessed values.

We compare the estimates in the transaction sample to those in Daams et al. (2016), who also used transaction data. In that paper, only the effect of CANA (called PA space in the paper) was measured. In that study, an effect of approximately 15% was found for houses residing within 500 meters of CANA, decaying to 0.2% for houses within 7,000-8,000 meters of CANA, which are significantly higher estimates than found in this study. A possible explanation for this is the spatial control, since in the 2016 study, the scale of spatial control were sub-markets, of which 76 exist within the Netherlands. The current study uses PC4 areas as spatial scale, which are considerably smaller, since 4,045 exist within the Netherlands. Another possible explanation is that in the 2016 study, apartments were excluded from the analysis, whereas they are included in the analysis of this paper.

The results show that the use of assessed value in the analysis of added value of nature proximity to house prices does not fully reflect the effects measured in the market, although differences are limited. However, the importance of measuring the entire population should not be understated, pleading for the use of assessed values. This especially true when the total value of the ecosystem amenity asset is to be calculated.

8 Conclusion and Discussion

This study investigated the economic valuation of nature in the Netherlands by comparing five hedonic model specifications, combined with two ways of measuring nature proximity. Furthermore, a distinction is made between nature which is perceived as attractive, and other nature. It is found that a spatial difference model leads to the best model fit, followed by a neighbourhood fixed effects model. The more traditional spatial lag model and spatial error model fail to compete with the aforementioned specifications. The OLS model with no spatial control at all has the worst in-sample fit. Furthermore, it was found that the use of discrete variables for the distance to the closest piece of nature led to similar model fit as the use of density of nature around a dwelling.

Besides a comparison on model fit, a comparison on computational feasibility as well as interpretability is made. In terms of computational feasibility, the spatial lag and spatial error model leave a lot to be desired. For a dataset of the size used in this study, constructing a weight matrix is infeasible for most software. Furthermore, even for a dataset $\frac{1}{500}$th of the original size, estimation of these models takes 20 hours, making it infeasible to run these models on the full data and using model averaging. A similar issue arises for the fixed effects model, as adding dummy variables for each PC4 area leads to a dataset too large for most software. However, model averaging for this method would be slightly more feasible time wise, as it makes use of OLS instead of numerical optimization methods, like the spatial lag and spatial error model. However, subsamples need to be made with caution, as subsetting sometimes leads to curious regression results. The spatial difference and model without spatial control lead to no computational complications.

Further, it was found that there was no sizable difference in model fit between the discrete nature specification and the nature density specification. This results is somewhat surprising, as we hypothesized that the area of nearby nature is also relevant for the value of nearby nature, and thus including area is expected to improve model fit. However, it was found that the effect of nature on house prices reaches further for the density specification when considering ONA, but less far for CANA nature, although, this is more a consequence of the density estimation than of model significance. Since in the discrete distance specification, most value comes from CANA, this shorter effect reach could decrease model fit again, cancelling out the added fit from including area in the model.

As for the interpretability of the nature proximity specifications, the discrete distance measure has the edge over the density. Whereas both the covariates and the coefficients of the discrete distance variables are easy to interpret, this is not true for the density measures. For the discrete specification, a coefficient of, for instance, 0.034 for the variable *Dist. to ONA 0-50 m* implies that, if a dwelling lies within 50 meters of an ONA, the price of that dwelling increases by approximately $100 \times \left(e^{0.034} - 1\right) = 3.5\%$ compared to a house which lies more than 500 meters from an ONA. However, such interpretation is a lot less straightforward for the density. Since density is not linear in distance, a one point increase in density does not always have the same meaning. On top of this, density relies on all pieces of nature within the search radius, whereas the discrete distance measure depends only on the closest piece of nature. Therefore, although the discrete distance specification and the density specification result in similar in-sample fit, the discrete distance specification is the preferred model in terms of interpretability.

This study finds that the effect of nature on housing value decreases gradually across space, both for CANA and ONA. It was also found that the estimated percent effect of nature proximity on housing value is lower for the model estimated on 2021 data compared to those estimated by Statistics Netherlands on 2013 data (Statistics Netherlands

& WUR, 2022). A possible explanation for this decreased effect is the scarcity in the housing market. Alternatively, when comparing the distance to nature in 2013 to the distances of 2021, we see that on average dwellings lie closer to nature in 2021 than in 2013, implying that nature proximity has become less scarce. Furthermore, it was found that the effect of nature on house prices reaches further for the density specification when considering ONA, but less far for CANA nature. However, this is more a consequence of the density estimation than of model significance.

Given the estimation results, the total value of the nature amenity asset in 2021 is estimated to be approximately 43.9 billion euro using both the density specification and the discrete distance specification. This again shows that results of both specification lie relatively close to each other. Compared to the coefficients estimated on the 2013 data, this value is approximately 38% lower. The estimated value of the nature amenity service in 2021 is estimated to be approximately 818.2 million euro using the discrete specification, and 817.2 million euro using the density specification.

Heterogeneity across urbanization degrees was also investigated, using two specifications of urbanization, one defining urbanization per PC4 area, and one defining it per municipality. It was found that there is indeed heterogeneity in the estimated coefficients across urbanization degrees for both specifications. Both specifications also lead to a higher adjusted R^2, with the specification on PC4 level attaining the highest adjusted R^2. In both models, it was found that property buyers in the highest urbanization degree tend to value CANA more than ONA, whereas the opposite is true for the lowest urbanization degree.

Furthermore, a comparison was made between the use of assessed values and market transactions. Based on estimation on transaction data ranging from 2020 until 2024, we find that estimated coefficients are generally lower when estimated on transactions than on assessed values for the discrete distance specification, when coefficients differed significantly. However, the gradual decay across space persists also in estimation on transactions, and the number of significantly different estimates are limited. The estimated coefficients for the ONA and CANA density do not differ significantly across models. As differences are limited, we conclude that the use of assessed value is a decent proxy. Further, the use of assessed values does allow us to observe the full housing stock, which is necessary for the valuation of the ecosystem amenity service. Important to note is that, in this study, the transaction values come from sales in the period of 2020 until 2024, but due to limited data availability, they were linked to housing characteristics observed in 2021. Therefore, there might be some slight mismatches between dependent and independent variable, although these cases should be limited.

Overall, the results from this study may be of value in the debate of nature conservation and renovation. Further, it informs in the debate of urban planning. The result that there is significant heterogeneity in nature valuation per urbanization degree gives insights in the construction plans per municipality or PC4 area. Given the finding that highly attractive nature provides most value in densely populated areas, but only little value in non-urban areas, preservation of CANA near urban areas should be prioritized over CANA near non-urban areas, as well as over ONA. Contrarily, ONA is valued more in the non-urban areas, and should thus be prioritized in preservation over CANA near non-urban areas.

9 Limitations and Future Research

The research conducted in this study comes with several limitations. First of all, the way CANA is defined leaves some questions. The current methodology of defining these areas of attractive nature sometimes leads to illogical clusters. It is unclear why only part of the Veluwe would be attractive, and there are seemingly arbitrary clusters of attractive nature in the middle of the IJssel lake. Different methods of defining the attractive clusters might lead to more logical results. A promising method of eliminating the seemingly random, small clusters is the use of a different clustering algorithm, namely DBSCAN. This method eliminates noisy points, but still leads to properly defined clusters. An example of the use of this method in a similar context can be found in (Daams, Sijtsma, & Veneri, 2019). Alternatively, the marked points from the Greenmapper survey could be overlapped with natural areas, and then some areas could be assigned the CANA status manually such that the clusters are more logical.

The second limitation comes from the treatment of outliers. Using a robust MM-estimator, it was found that the removal of outliers as described in Section 3.3 did not properly take care of outliers in the full covariate space, and therefore robust regression lead to different estimation results. Therefore, in future research, the use of robust estimation methods is recommended.

As for the main methodology, hedonic pricing models come with some limitations. In this study we impose a log-linear structure, whereas the relationship is likely non-linear (Rosen, 1974). Therefore, exploring different model specifications, either non-linear or non-parametric is recommended. However, non-parametric methods come with difficulties in the interpretation of the results. Furthermore, as extensively discussed, spatial correlation and omitted variable bias plays a big role in these models. Comparison of results from this hedonic study with a study in a controlled setting, like the contingent valuation method, could be used as either a validation or rebuttal of the results.

Further, the estimation methodology was highly limited by computational feasibility.

The spatial lag, spatial error, and fixed effects model can not be estimated on the full dataset, and model averaging over subsets takes a considerable amount of time. Constructing a reliable, representative subset of the data on which the models can be estimated, after which the results can be generalized to the full data, could lead to valuable insights and a more reliable comparison of model performance.

In terms of the valuation of the ecosystem amenity service, one could argue that adding together all separate values of houses attributable to nature proximity is not completely valid, given that the value of houses is correlated across dwellings. Therefore, further research as to how to properly aggregate the individual values attributable to nature is desirable. Furthermore, the use of the same estimated fractions for several years in a row, as currently done in Statistics Netherlands and WUR (2022), has some limitations. As is the case with all hedonic models, when prices increase by an external factor, like inflation, this increase in price is distributed among all features included in the model, proportional to their estimated contributions. However, assigning more value to the ecosystem amenity service when prices increase due to for instance economic activity is likely incorrect, as this would assume that the economic value of the amenity service grows proportional to house prices. Therefore, one should be careful when using the estimated fractions for several years, without correcting for inflation, or re-estimating the models.

An important final notion is that the valuation of nature in our study, and any study for that matter, is only an economic valuation based on statistical modelling. The intrinsic value of nature can not be overstated, and therefore can and should not be monetized, just like any life on earth.

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A Ecosystem Types

TABLE A1. Ecosystem types in the Netherlands. An * indicates that the ecosystem type is considered as nature in this study.

Category	Subcategory	Ecosystem type
Natural and Forest Area	Grassland	Tall Herbs*
		Floodplain*
		Semi-natural Grassland*
		Other natural Grassland*
	Forest Area	(Semi-)Natural Forest*
		Hedges and Treelines *
		Plantation Forest*
		Swamp Forest*
		Other Forest*
	Heathland and Driftsand	Heathland*
		Driftsand*
	Bogs and Fens	Bogs*
		Fens*
	Coastal and Dune Area	Coastal Dunes*
		Beach*
		Shoals*
		Salt Marshes*
Water	Streams and Rivers	Streams and Rivers*
	Lakes and Reservoirs	Lakes*
		Brackish*
		Other*
	Marine	Estaurium*
		Intertidal and Mud Flats*
		Wadden sea*
		North sea*
Agriculture	Cropland and Horticulture	Cropland, regular
		Cropland, extensive
		Biodiverse Cropland
		Perannuals, regular
		Perannuals, extensive
		Pasture, temporal
		Fallowland
		Arable Field Margins
		Nursery Container Fields
	Grassland	Pasture, permanent
		Pasture, extensive
		Other Agricultural Grassland
(Semi-)built-up land	Built-up Area	Greenhouse Horticulture
		Built-up (urban)
		Built-up (rural)
		Business Park
		Mining, Land Fills, etc.
		Infrastructural
		Infrastructural Green
		Marine, other
		Other Terrain
	Urban Green and Recreation	Public Park (large)*
		Public Park (small)*
		Public Green Space, other*
		Semi-public Green Space
		Sport Park
		Residential Recreation
		Landscape Garden

B Variable Distribution

In the figures below, the histograms of the skewed variables (Assessed Value, Living Area, and their ratio) are presented in the upper graphs. In the lower graphs, the distribution of their natural logarithm are shown. The first and last percentile of the dataset are trimmed of for the figures presented. After taking the natural logarithm, all these variables are close to normally distributed around the center, validating the use of normal distribution in the procedure in Subsection 3.3. The Jarque-Bera test statistics are approximately 43249, 14150, and 217129 for the logarithm of assessed value, logarithm of living area, and their ratio, respectively. Note that these all have a p-value of nearly zero, rejecting normality. However, in very large samples rejection is likely to happen even when a single observation does not fit the normal distribution.

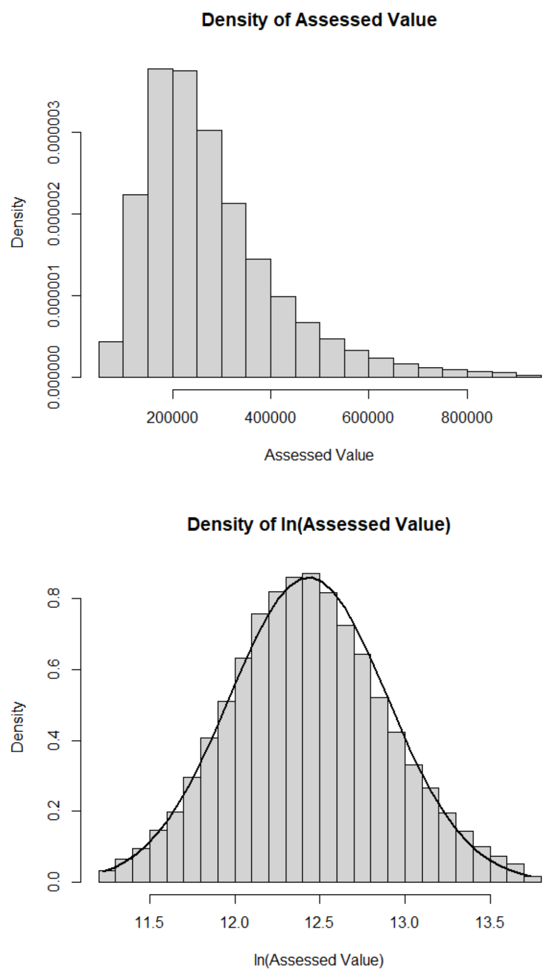

FIGURE A1. Distribution around the center of Assessed Value and the logarithm of Assessed value.

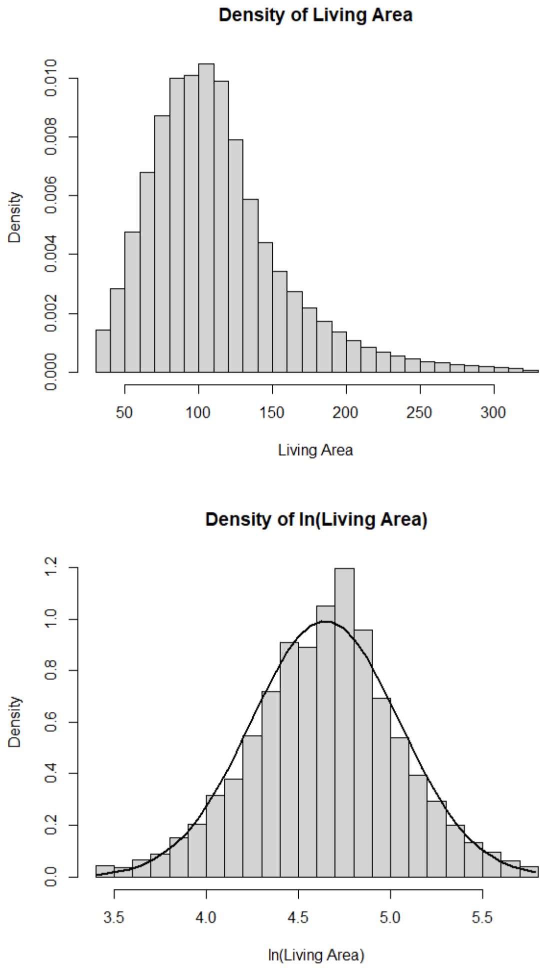

FIGURE A2. Distribution around the center of Living Area and the logarithm of Living Area.

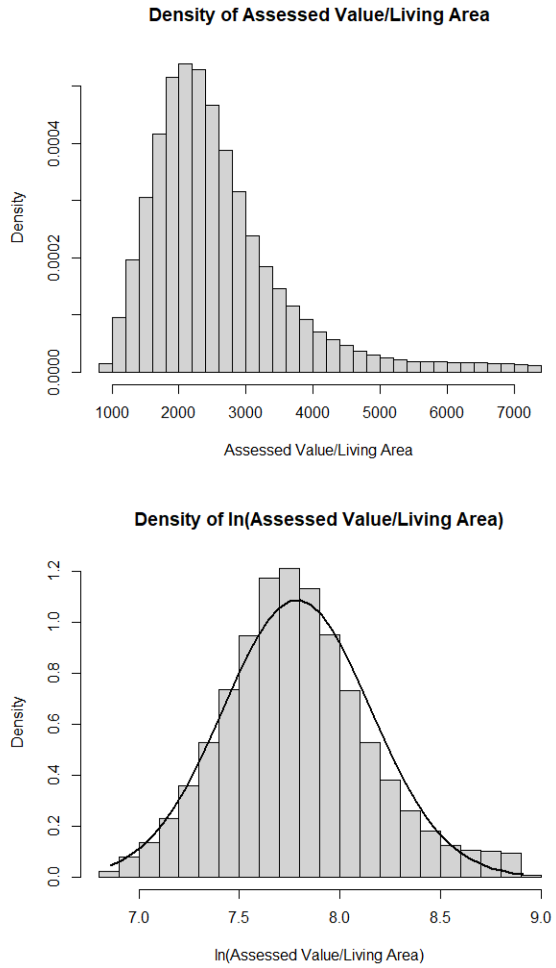

FIGURE A3. Distribution around the center of Assessed Value relative to Living Area and the logarithm of Assessed Value relative to Living Area.

C Full Regression Results

TABLE A2. Regression results for the 5 model specifications using discrete distance measures

	Base model	Spatial difference	Fixed effects	Spatial lag	Spatial error
Intercept	9.544***(0.002)	-0.000(0.003)	8.338***(0.764)	9.345***(0.050)	9.270***(0.034)
Living area (log)	0.652***(0.000)	0.680***(0.002)	0.706***(0.006)	0.671***(0.008)	0.689***(0.006)
Semidetached	-0.120***(0.001)	-0.149***(0.001)	-0.117***(0.008)	-0.132***(0.012)	-0.116***(0.008)
End-of-terrace	-0.098***(0.001)	-0.234***(0.001)	-0.222***(0.008)	-0.118***(0.012)	-0.193***(0.007)
Terraced	-0.111***(0.000)	-0.282***(0.001)	-0.263***(0.007)	-0.141***(0.011)	-0.227***(0.007)
Multi-family home	-0.052***(0.001)	-0.344***(0.001)	-0.312***(0.008)	-0.075***(0.012)	-0.258***(0.008)
Housing corporation	-0.215***(0.000)	-0.154***(0.001)	-0.154***(0.004)	-0.216***(0.007)	-0.166***(0.005)
Other leasehold	-0.109***(0.000)	-0.103***(0.001)	-0.102***(0.006)	-0.131***(0.010)	-0.107***(0.006)
Constructed					
1906-1930	-0.085***(0.001)	-0.010***(0.001)	-0.022*(0.011)	-0.139***(0.017)	-0.011(0.012)
1931-1944	-0.071***(0.001)	0.025***(0.001)	0.015(0.013)	-0.137***(0.020)	0.013(0.013)
1945-1959	-0.225***(0.001)	-0.023***(0.001)	-0.033***(0.012)	-0.276***(0.017)	-0.037***(0.012)
1960-1974	-0.282***(0.001)	-0.044***(0.001)	-0.063***(0.011)	-0.337***(0.015)	-0.075***(0.011)
1975-1989	-0.209***(0.001)	0.008***(0.001)	0.003(0.011)	-0.265***(0.016)	-0.011(0.011)
1989-2000	-0.086***(0.001)	0.112***(0.001)	0.103***(0.011)	-0.143***(0.016)	0.091***(0.011)
2001-2010	-0.014***(0.001)	0.178***(0.001)	0.160***(0.012)	-0.061***(0.017)	0.149***(0.012)
>2010	0.043***(0.001)	0.206***(0.002)	0.198***(0.012)	-0.004***(0.018)	0.189***(0.012)
Dist. to ONA					
0-50 m	0.035***(0.001)	0.037***(0.001)	0.034***(0.010)	0.035**(0.017)	0.038***(0.011)
50-100 m	0.027***(0.001)	0.020***(0.001)	0.006(0.008)	-0.001(0.012)	0.014*(0.008)
100-150 m	0.012***(0.000)	0.007***(0.001)	0.008(0.007)	0.009(0.011)	0.013*(0.007)
150-200 m	0.006***(0.000)	0.003***(0.001)	0.009(0.007)	-0.007(0.011)	0.011(0.007)
200-250 m	0.002***(0.000)	0.002**(0.001)	0.005(0.007)	0.001(0.010)	0.009(0.007)
250-300 m	0.002***(0.000)	0.000(0.0001)	-0.002(0.007)	-0.004(0.011)	0.004(0.007)
300-350 m	-0.001(0.000)	0.000(0.0001)	0.001(0.007)	0.013(0.011)	0.007(0.007)
350-400 m	-0.004***(0.001)	-0.000*(0.0001)	-0.008(0.007)	-0.006(0.012)	-0.009(0.008)
400-450 m	-0.001**(0.001)	0.000(0.001)	0.007(0.007)	-0.004(0.012)	0.007(0.008)
450-500 m	-0.004***(0.001)	-0.002**(0.001)	0.003(0.008)	-0.012(0.013)	0.002(0.008)
Dist. to CANA					
0-500 m	0.364***(0.001)	0.069***(0.003)	0.032(0.030)	0.372***(0.013)	0.288***(0.016)
500-1,000 m	0.320***(0.001)	0.040***(0.003)	0.011(0.028)	0.307***(0.012)	0.263***(0.015)
1,000-2,000 m	0.253***(0.000)	0.020***(0.003)	0.001(0.027)	0.244***(0.010)	0.237***(0.013)
2,000-3,000 m	0.189***(0.000)	0.013***(0.003)	-0.011(0.027)	0.192***(0.010)	0.202***(0.013)
3,000-4,000 m	0.146***(0.000)	0.011***(0.002)	-0.015(0.025)	0.148***(0.011)	0.162***(0.014)
4,000-5,000 m	0.121***(0.001)	0.000(0.002)	-0.041*(0.024)	0.120***(0.010)	0.105***(0.014)
5,000-6,000 m	0.122***(0.001)	0.006***(0.002)	-0.030(0.022)	0.118***(0.012)	0.091***(0.014)
6,000-7,000 m	0.102***(0.001)	-0.001(0.002)	-0.024(0.019)	0.112***(0.013)	0.058***(0.014)
7,000-8,000 m	0.052***(0.001)	-0.006***(0.002)	-0.029*(0.015)	0.040***(0.014)	0.019(0.013)
Spatial parameter	-	-	-	$\rho = 0.021$	$\lambda = 0.715$
Adjusted R^2	0.567	0.890	0.875	-	-
Observations	7,317,288	7,313,249	14,634	14,634	14,634

Note. The dependent variable is the natural logarithm of assessed value. Reference categories include Freehold, Detached, constructed before 1905, distance to CANA > 8000 m, and distance to ONA > 500 m. Clustered standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

TABLE A3. Regression results for the 5 model specifications using nature density measures

	Base model	Spatial difference	Fixed effects	Spatial lag	Spatial error
Intercept	9.679***(0.002)	-0.000(0.000)	8.313***(0.761)	9.645***(0.051)	9.323***(0.034)
Living area (log)	0.652***(0.000)	0.680***(0.001)	0.707***(0.006)	0.660***(0.009)	0.694***(0.006)
Semidetached	-0.109***(0.001)	-0.148***(0.001)	-0.117***(0.008)	-0.111***(0.013)	-0.110***(0.008)
End-of-terrace	-0.078***(0.001)	-0.233***(0.001)	-0.220***(0.008)	-0.083***(0.013)	-0.176***(0.008)
Terraced	-0.087***(0.000)	-0.281***(0.001)	-0.262***(0.007)	-0.100***(0.011)	-0.207***(0.007)
Multi-family home	0.005***(0.001)	-0.343***(0.001)	-0.311***(0.008)	-0.008(0.012)	-0.228***(0.009)
Housing corporation	-0.217***(0.000)	-0.154***(0.001)	-0.154***(0.004)	-0.217***(0.007)	-0.167***(0.005)
Other leasehold	-0.102***(0.000)	-0.103***(0.001)	-0.102***(0.006)	-0.119***(0.010)	-0.100***(0.006)
Constructed					
1906-1930	-0.087***(0.001)	-0.011***(0.001)	-0.022*(0.011)	-0.145***(0.018)	0.002(0.012)
1931-1944	-0.075***(0.001)	0.024***(0.001)	0.014(0.012)	-0.146***(0.019)	0.021(0.013)
1945-1959	-0.242***(0.001)	-0.024***(0.001)	-0.034***(0.012)	-0.287***(0.019)	-0.044***(0.012)
1960-1974	-0.318***(0.001)	-0.045***(0.001)	-0.064***(0.011)	-0.369***(0.016)	-0.079***(0.011)
1975-1989	-0.243***(0.001)	0.008***(0.001)	0.003(0.011)	-0.295***(0.017)	-0.013(0.011)
1989-2000	-0.119***(0.001)	0.111***(0.001)	0.102***(0.011)	-0.176***(0.019)	0.088***(0.012)
2001-2010	-0.057***(0.001)	0.178***(0.001)	0.159***(0.012)	-0.095***(0.017)	0.145***(0.012)
>2010	0.008***(0.001)	0.206***(0.002)	0.197***(0.012)	-0.044**(0.019)	0.195***(0.013)
ONA density	0.00001***(0.000)	0.00001***(0.000)	0.00001***(0.000)	0.00001***(0.000)	0.00002***(0.000)
CANA density	0.00006***(0.000)	0.00003***(0.000)	0.00003***(0.000)	0.00007***(0.000)	0.00006***(0.000)
Spatial parameter	-	-	-	$\rho = 0.007$	$\lambda = 0.900$
Adjusted R^2	0.534	0.890	0.875	-	-
Observations	7,317,288	7,313,249	14,634	14,634	14,634

Note. The dependent variable is the natural logarithm of assessed value. Reference categories include Freehold, Detached, constructed before 1905, distance to CANA > 8000 m, and distance to ONA > 500 m. Clustered standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

D Outlier Robustness

In the main analysis outliers were removed before model estimation. To verify that the treatment of outliers is necessary for the analysis, we estimate model (5) also on the data without any outlier treatment. Additionally, we also estimate this model using a robust regression method, namely an MM estimator. This is in order to compare regression results between manual outlier handling, and results when robust methods are applied. The general estimation of the MM estimator is as follows. For a regression model given by

$$y = X\beta + \varepsilon, \tag{16}$$

the MM estimate $\hat{\beta}_{MM}$ of β is given by

$$\hat{\beta}_{MM} = \arg\min_{b} \sum_{i=1}^{n} \rho_2 \left(\frac{y_i - x_i b}{\hat{\sigma}_s} \right), \tag{17}$$

where $\hat{\sigma}_s = \hat{\sigma}_M(\hat{\beta}_S)$ which is obtained from

$$\hat{\beta}_S = \arg\min_{b} \hat{\sigma}_M^2(b). \tag{18}$$

Here, $\hat{\sigma}_M(b)$ is the solution to the equation

$$\frac{1}{n} \sum_{i=1}^{n} \rho_1 \left(\frac{y_i - x_i' b}{\sigma_M(b)} \right) = \delta, \tag{19}$$

with $\delta = E_F[\rho_1 \left(\frac{X}{\sigma}\right)]$ ensuring Fisher consistency, and F the distribution function of X. The loss functions ρ_1 and ρ_2 are both the Tukey bi-square loss function given by

$$\rho(x) = \begin{cases} \frac{x^6}{6c^4} - \frac{x^4}{2c^2} + \frac{x^2}{2} & \text{if } |x| \leq c \\ \frac{c^2}{6} & \text{if } |x| > c \end{cases} \tag{20}$$

This estimation combines the highly robust S-estimator and the efficient M-estimator in order to retain both of these desirable properties. In order to attain the highest possible breakdown point of 50% the tuning constant is chosen to be $c = 1.547$ for ρ_1. When c in ρ_2 is chosen to be 4.685, the estimator has an asymptotic relative efficiency of 95% at the normal distribution (Yohai, 1987). Estimation is done using iteratively reweighted least squares (IRLS).

Table A4 presents the results of the OLS and MM estimation of Model (5) on the full, likely contaminated dataset.

TABLE A4. Regression results for OLS and MM estimation of the spatial difference model on the full (contaminated) dataset

Discrete Distance Measures		
	OLS	MM estimator
Dist. to ONA 0-50 m	0.037***(0.000)	0.033***(0.000)
Dist. to ONA 50-100 m	0.021***(0.000)	0.018***(0.000)
Dist. to ONA 100-150 m	0.008***(0.000)	0.007***(0.000)
Dist. to ONA 150-200 m	0.002***(0.000)	0.003***(0.000)
Dist. to ONA 200-250 m	0.002***(0.000)	0.002***(0.000)
Dist. to ONA 250-300 m	0.000(0.000)	-0.000(0.000)
Dist. to ONA 300-350 m	-0.000(0.000)	-0.000(0.000)
Dist. to ONA 350-400 m	-0.001**(0.000)	-0.001***(0.000)
Dist. to ONA 400-450 m	0.000(0.000)	-0.000(0.000)
Dist. to ONA 450-500 m	-0.002(0.000)	-0.002(0.000)
Dist. to CANA 0-500 m	0.069***(0.002)	0.062***(0.002)
Dist. to CANA 500-1,000 m	0.039***(0.002)	0.038***(0.002)
Dist. to CANA 1,000-2,000 m	0.019***(0.002)	0.021***(0.002)
Dist. to CANA 2,000-3,000 m	0.012***(0.002)	0.018***(0.002)
Dist. to CANA 3,000-4,000 m	0.011***(0.002)	0.014***(0.002)
Dist. to CANA 4,000-5,000 m	-0.001(0.001)	0.001(0.001)
Dist. to CANA 5,000-6,000 m	0.005***(0.001)	0.005***(0.001)
Dist. to CANA 6,000-7,000 m	-0.001(0.001)	-0.000(0.001)
Dist. to CANA 7,000-8,000 m	-0.008***(0.001)	-0.004***(0.001)
Nature Density Measures		
	OLS	MM estimator
ONA density	0.00001***(0.000)	0.00001***(0.000)
CANA density	0.00003***(0.000)	0.00003***(0.000)
Property Characteristics	Yes	Yes
Constant included	Yes	Yes
Observations	7,317,033	7,317,033

Note. The dependent variable is the natural logarithm of assessed value relative to a reference home within the same PC4 area. Reference categories include Freehold, Detached, constructed before 1905, distance to ONA > 500 m, and distance to CANA > 8000 m. All models contain an intercept and property characteristics. Clustered standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Looking at the parameter estimates for the OLS estimator and the MM estimator, we see that some of the parameter estimates differ quite a bit across estimation methods. This confirms the need of some outlier treatment, either using outlier removal or robust estimation methods. We also compare the estimates to those in Table IV. We find that the difference between the OLS estimation on the full dataset and the one on the filtered dataset do not differ by much, but the difference between the MM estimator and OLS on the filtered dataset differ quite a bit, suggesting the filtered dataset still contains contamination. In the MM estimator, approximately 58,000 observations receive a weight of (almost) 0, whereas in the outlier removal, only 3,784 observations were removed. However, in the outlier detection, only outliers in terms of the dependent variable (logarithm of assessed value) and the logarithm of living area (and their ratio) were examined, whereas the MM estimator takes care of outliers in the full covariate space.

Note that for the density specification, the coefficients do not differ to the 5th decimal. However, the OLS estimates are 0.0000120 and 0.0000341 for ONA and CANA density respectively, while the MM estimates equal 0.0000297 and 0.0000136. As the standard errors equal zero to the 6th decimal, these differences are quite substantial. This suggests the use of robust estimation would likely lead to more accurate model estimates. However, this leaves the question how those observations that are considered outliers by this method should be taken into account in estimating the final value of the amenity service.

E Code Description

Scripts

1. Natuur kaarten.py
2. Natuur afstanden.py
3. Data preparation.R
4. Summary statistics.R
5. Model estimation.R
6. Outlier robust estimation.R
7. Urbanization heterogeneity estimation.R
8. Transaction estimation.R
9. Error clustering.R
10. Value calculation.R

Important comment

In all scripts, the locations of of files, and file names, are empty and thus given by "". This is because of security reasons imposed by Statistics Netherlands. Furthermore, some python utility scripts which are needed to run the scripts is not provided, as these are proeprty of Statistics Netherlands and can not be shared.

Code content

Natuur kaarten.py is used to create a rasterized map of nature in the Netherlands. Results are needed for the calculation of distances from dwellings to nature.

Natuur afstanden.py calculates the distance from each dwelling to the closest piece of nature. Further, it calculates the nature density scores as described in Section 4.1 of the report.

Data preparation.R is used to merge all data sources, construct the necessary variables, and remove missing values and outliers.

Summary statistics is used to get summary statistics of the dataset before and after outlier removal.

Model estimation.R estimates all models as described in Section 4.2.

Outlier robust estimation.R is used to estimate the models in Appendix D.

Urbanization heterogeneity estimation.R is used to estimate the spatial difference model with heterogeneity, as described in Section 6.

Transaction estimation.R is used to estimate the spatial difference model on transaction data, as described in Section 7.

Error clustering.R is used to calculate the clustered standard errors for all spatial difference models.

Value calculation.R is used to calculate the value of the ecosystem amenity asset and service, given in Section 5.4.