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A numerical method to account for distance in a farmer's willingness to pay for land

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ABSTRACT

Land transactions between farmers are responsible for landscape changes in rural areas. The price a farmer is willing to pay (WTP) for vacant land depends on the distance of the parcel to the farmstead. Detailed quantitative knowledge of this WTP– distance relationship is of utmost importance for accurate modelling of land markets, and for the design and implementation of effective and robust land consolidation schemes. Practical experience suggests, however that it is not particularly easy to back out the WTP–distance relationship from empirical transaction data. Here, we present a novel statistical framework to help quantify the relationship between a farmer's WTP and the distance of his/her farmstead to the vacant parcel. We describe a land market with a simple statistical model and simulate an artificial archive of land transactions via Monte Carlo sampling. The parameters of our virtual market are estimated from a historical archive of land transactions in the Province of Gelderland The Netherlands, using minimization of the divergence (relative entropy) between the observed and simulated joint distributions of distance and transaction price. A reasonable agreement was observed between the observed and simulated bivariate distributions of distance and transaction price. Our results demonstrate that for short distances (500–1000m) any additional metre distance reduces the WTP by about 60 € ha^{-1}. The

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impact of distance on WTP gradually levels off with larger distance: beyond 5 km the effect has reduced to less than 0.5 € ha^{-1}

1. Introduction

Landscape change in rural areas is to an important extent brought about by land transactions between buyers and sellers of land (Filatova et al., 2011; Sun et al., 2014). Not only urbanization, but also changes in agricultural land use (e.g. from crop cultivation to livestock breeding) are largely caused by land exchange between land owners (Bakker et al., 2014). This exchange may take the form of a lease, but the most common form is through land sale. Drivers of land exchange can be changes in agricultural prices, allowing farmers of profitable crops to expand at the expense of those growing less profitable crops; demographic change, whereby young farmers buy land from retiring farmers; or the implementation of voluntary land consolidation schemes, aimed at creating more efficient farm layouts or the connection and enlargement of nature reserves (Bakker et al., 2015).

To understand, simulate and predict land transactions, one needs to know the factors that determine the willingness to pay (WTP) for a specific parcel by potential buyers and the willingness to accept (WTA) a bid by potential sellers. Hedonic price analysis is a common method used by economists to help identify such factors, using multiple linear regression techniques on observed transactions to estimate the relationship between a buyer's WTP for a certain asset and the respective properties of this asset (Lancaster, 1966; Rosen, 1974). In this way it has been demonstrated, for example, that, for each kilometre closer to the city centre, people in Zurich, Switzerland, are willing to pay an extra 2% for an apartment, and that an extra room increases the WTP by 10% (Banfi et al., 2007). Using the so obtained WTP and WTA values, residential property markets have been successfully modelled and simulated (Gauvin et al., 2013; Osullivan, 2009).

Rural land transactions, however, differ principally from residential property transactions in that both buyer and parcel have a fixed location (barring the few occasions in which entire farms are moved), whereas in residential-property transactions the buyer – if (s)he is also the prospective resident – in most cases moves to the property (s)he bought. In rural land transactions, the farmer will continue living where (s)he was, and so the new parcel's proximity to the farmstead of the buyer plays an important role in determining the WTP (Feinerman and Peerlings, 2005; Raup, 2003). Although hedonic price analyses have been performed for agricultural land markets as well (revealing, for instance, that farmers attach value to parcel properties such as parcel size, soil productivity, and remoteness from marshlands, and that younger farmers or farmers with children are willing to pay more than older farmers without a successor (Cotteleer et al., 2008; Huang et al., 2006)), such analyses have not properly included assessing the effect of distance between parcel and farmstead on an individual buyer's WTP.

Assessment of the effect of distance between parcel and farmstead is not possible with hedonic price analysis, because distance (from buyer) is neither a parcel characteristic, nor a buyer's characteristic, but a characteristic of a specific buyer-parcel combination. Moreover, transactions are generally only successful for short distances between buyers and parcels, as farmers in close vicinity to a parcel are willing to pay more than those far away. In other words, the actual transactions (on which the hedonic models are calibrated) are biased towards short distances. This may explain why Cotteleer et al. (2008) did not find 'distance between farmstead and parcel' to be an important factor in their hedonic price analysis, even though their dataset indicated that 90% of the agricultural buyers are located within 6.7 km of the parcels they bought.

The goal of this paper is to propose an alternative method for assessing the relationship between the WTP for vacant land and the distance of this parcel to the buyer's farmstead. We present a simple numerical model of a land market and simulate a large number of parcel transactions using Monte Carlo sampling. The parameters of this numerical model are estimated from a historical archive of land transactions in the Province of Gelderland, the Netherlands, using minimization of the divergence (relative entropy) between the observed and simulated joint distributions of distance and transaction price.

The remainder of this paper is organized as follows. Section 2 introduces the study area and available data set. In Section 3, we discuss the rationale and different building blocks of the numerical model that is used to simulate virtual land transactions and introduce the Bayesian methodology that is used to estimate the parameter values of the land market in Gelderland. This is followed in Section 4 with a detailed analysis of our results. Here, we are especially concerned with an interpretation of the inferred parameter values and the WTP–distance relationship. The penultimate section of this paper discusses model applicability, limitations and potential improvements. We conclude in Section 6 with a summary of our main findings.

2. Case study area and data

Our historical archive of land transactions originates from the province of Gelderland, which is the Netherlands' largest province and situated in the centre-east of the country. According to the Dutch Agricultural Census, the province comprises about 12,500 farms and 260,000 hectares of agricultural land. Most of the farming is pasture-based (primarily dairying), but arable farmers, pig- and poultry farmers, and market gardeners are also active in the area. As in most western countries, the rural population is ageing and remaining farmers are forced to reap economies of scale in order to maintain their income. Hence, land transactions are generally driven by old farmers who sell land as a source of income, and young farmers that both sell and buy land to enlarge their farms and optimize its spatial layout.

We had access to a digital archive in which all land transactions that took place in the Dutch rural area are recorded from the year 1998 onwards (DLG, 2012). From this archive, we took a subset of (a) the province of Gelderland; (b) the years 2008 and 2009 (these years had the largest number of complete records in the archive, while the overall land prices were rather stable during this period); (c) parcels without buildings, and (d) transactions between farmers registered in the agricultural census (therewith excluding transactions involving municipalities, property developers, the province, and nature organizations). Furthermore, we discarded some of the largest transaction prices (i.e., around 500,000 € ha^{-1}), as we assume that these are due to aberrations (e.g. parcels sold to a property developer who is also registered as a farmer). The final data set comprised 1279 transactions, with transaction prices ranging from 8350 € ha^{-1} to 150,462 € ha^{-1}. Fig. 1 presents a scatter plot of the final data set using a linear (left-hand side) and log–log scale (right-hand side) of the distance between parcel and buyer and corresponding transaction price. The scatter plots demonstrate why linear, homoscedastic regression methods (and therefore hedonic price analysis) are less suitable for assessing a relationship between WTP and distance. We refer to Section 3.2 for a more detailed discussion of the joint distribution of WTP and distance.

3. Methods

3.1. Concepts

Before we present our conceptual model, we first discuss briefly the following key concepts: agricultural production value, subjective appreciation, distance, and WTP.

Agricultural production value: This covers properties that determine the agricultural productivity of the parcel, such as water-retention capacity of the soil, how well excess water can be drained, parcel shape and size (affecting effectiveness of agricultural machinery), and restrictions on use, e.g. due to vicinity of nature reserves. In this paper we assume each parcel to have a given production value, without specifying the properties that determine it. Furthermore, we assume the production value to be a parcel property; any subjective element about the agricultural production value is captured in the next concept, the subjective appreciation.

Subjective appreciation: Although properties constituting agricultural production value are important, each farmer will value a parcel differently. Subjective appreciation may be determined by the intended use of the buyer, as each agricultural use has somewhat different requirements. The subjective value of a parcel also depends on the size, capital and available labour of the purchasing/owning farm (Schmitz and Just, 2003). Lastly, the assessment of production value differs between buyer and

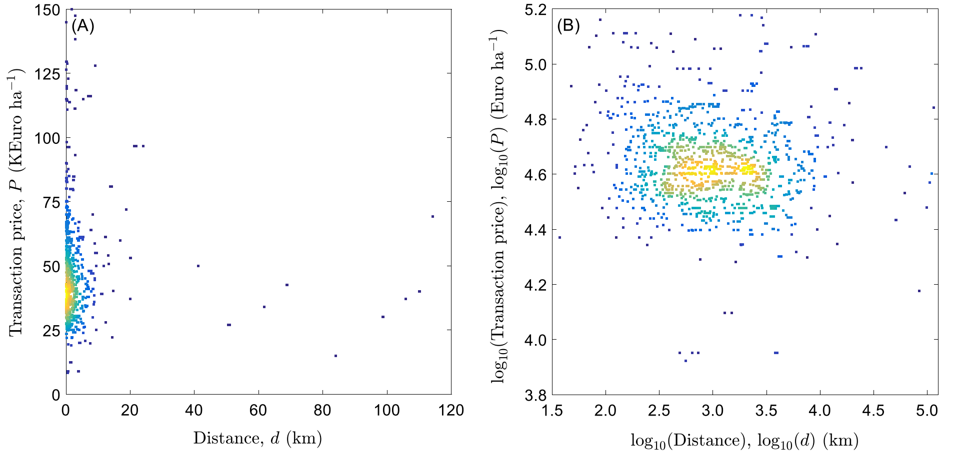

Fig. 1. Scatter plots of transaction price against distance between parcel and buyer on linear (A) and log–log scale (B; base 10) for agricultural transactions within the Province of Gelderland in 2008 and 2009. Colour coding is used to characterize the density of the data (lighter means higher).

seller due to incomplete information about the parcel's characteristics, especially from the buyer's side, as (s)he does not know the parcel as well as the current owner. Distance is another subjective factor, which we treat separately, as it is the specific object of interest in this study.

Distance: Larger distances between parcel and farmstead mean higher costs, as farmers have to travel to and from the parcel for transporting livestock, agricultural inputs, and farm produce, as well as for working the land. Transport costs increase linearly with distance, suggesting a linear relationship. However, as parcels can be used for different purposes, the distance–value relationship is composed of multiple linear functions (Fig. 2). For example, parcels used for grazing by dairy cattle are preferably close to and contiguous with the stable where the cattle is milked. Parcels used for crop or fodder production can be further away without incurring high extra costs, and hence additional distance will decrease the WTP but not as steeply as in the case of pasture. Lastly, parcels not actively used but kept for other reasons (e.g. for speculation or in order to satisfy manure regulations) may be quite remote, and additional distance will hardly affect the WTP. The combination of several of such parcel–farmer relationships leads to a convexly shaped function, as illustrated in Fig. 2.

WTP: The agricultural production value, in combination with the subjective appreciation and the effect of distance is reflected in the willingness to pay (WTP). The willingness to pay is the maximum price a farmer will pay for land, with given properties, at a given distance from his/her farm. Transaction prices will never exceed the buyer's WTP (and, for that matter, will never be smaller than the seller's willingness to accept (WTA)).

3.2. Conceptual model

The conceptual model is illustrated in Fig. 3 for a range of distances between parcel and buyer. The buyer's WTP for a parcel is presented by the black line. The convex function, as described in Section 3.1, is approximated by a one-over-distance relationship. This is a crude approximation, but assessing the individual linear functions would lead to a situation with too many parameters to be estimated by the proposed method. From a seller's point of view, the price (s)he is willing to accept for the parcel (WTA) is, of course, not affected by the distance to the buyer, but only by the agricultural production value, the subjective appreciation, and the distance to his/her own farmstead (which is independent from the distance between parcel and buyer). This is indicated by the horizontal, grey line in Fig. 3. A transaction between buyer and seller is possible when the buyer's WTP is equal to or larger than the seller's WTA. In this illustration, this is the case when the distance between buyer and parcel is

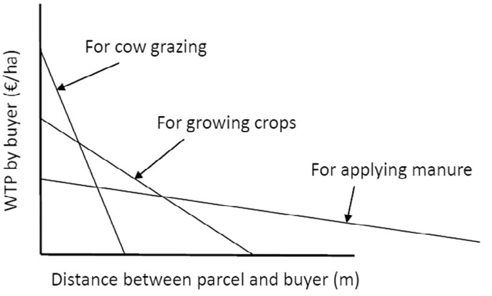

Fig. 2. Multiple linear distance–value functions for different parcel use together shape the relationship (dashed line) between WTP and distance between farmstead and parcel (example for dairy farms).

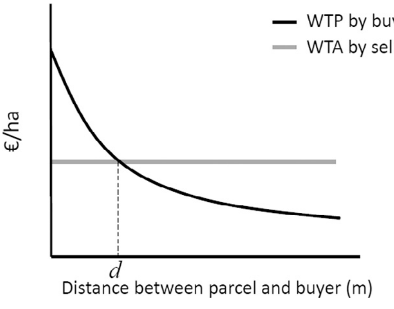

Fig. 3. Theoretical relationship between WTP by buyer and distance between buyer and parcel. The WTA by seller does not depend on distance between buyer and parcel. A transaction can occur when the WTP is equal to or exceeds the WTA, i.e., up to distance *d*.

equal to or smaller than *d*. Whenever a transaction occurs, the transaction price will lie in between the buyer's WTP and the seller's WTA.

Just as with hedonic price analysis, the parameters of the WTP–distance function can be estimated using real-world transaction data comprising a range of distances and transaction prices. When considering many parcels and many buyers and sellers, we must take into account variations among parcels, buyers, and sellers. In Fig. 4, the hatched area represents the zone of successful transactions under varying agricultural production values and subjective appreciations by buyers and sellers. If the conceptual model is to be populated with real transactions, these will occur within the hatched area, with the highest density in the area where the WTP function is substantially higher than the WTA function. However, the number of parcels a buyer can choose from is smaller at smaller distances, because the amount of available land increases proportionally with the square of the distance. The combined effect of a decreasing hatched zone with increasing distance and an increasing number of parcels for sale with increasing distance will result in a positively-skewed marginal distribution of transactions with distance (see bottom part of Fig. 4). These complicating factors explain the typical distribution shown in Fig. 1 and elucidate why linear regression of parcel price against distance may produce poor results. Instead, a tailored model needs to be developed, the parameters of which can be derived from a dataset of actual land transaction prices.

3.3. Statistical simulation model

To simulate the distribution of the distance between parcel and buyer we imagine that potential buyers randomly queue in line and make a bid equalling their WTP when it is their turn. The parcel goes to the first buyer in line whose bid exceeds the WTA of the seller. This approach is a simplification

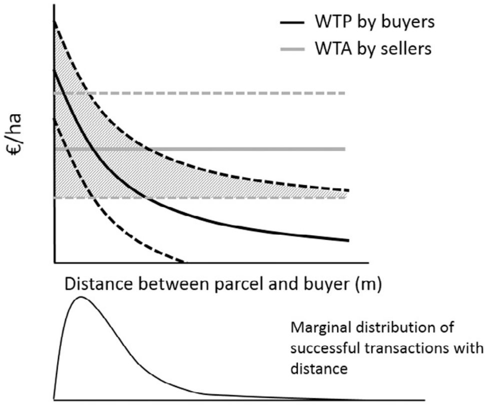

Fig. 4. Expected occurrence of land transactions. Variability in production value and subjective appreciation induce a spread around the WTP and WTA, illustrated by the dashed lines that indicate lower and upper boundaries of this spread. Transactions will occur within the hatched area. The density of transactions within the hatched area increases with increasing distance because the number of parcels for sale increases quadratically with distance, but the hatched area itself becomes smaller as distance increases. As a result, the marginal distribution of transaction price with distance is small at first, then increases to a maximum and finally decreases gradually as the distance between buyer and parcel becomes large.

of known auction models (McAfee and McMillan, 1987), but is in agreement with decision-making theory, which states that, in the absence of full information, people tend to accept the first good offer (Todd, 1997).

Let V (€ ha^{-1}) be the agricultural production value of a parcel that enters the market, which is assumed normally distributed (because value-determining properties such as the water-retention capacity are typically normally distributed for agricultural parcels) with mean μ (€ ha^{-1}) and standard deviation σ (€ ha^{-1}), i.e., $V \sim \mathfrak{N}(\mu, \sigma^2)$. The non-zero standard deviation is caused by differences in parcel properties, such as parcel shape and soil quality. The seller's WTA (€ ha^{-1}) is thus given by:

$$WTA = V + \varepsilon_S \tag{1}$$

where ε_S (€ ha^{-1}) is normally distributed with zero mean and standard deviation τ_S (€ ha^{-1}), and represents subjective judgements of the selling party (e.g. use-specific production value, distance to own farmstead).

The locations of potential buyers are simulated from a uniform distribution within a circular area surrounding the parcel. We set the radius of this circle equal to 20 km, as 98% of the observed transactions took place within this distance. The prospective buyer's WTP is a function of distance d (m), and is given by:

$$WTP = V + 1/(\alpha d + \beta) - \gamma + \varepsilon_B \tag{2}$$

where the term $1/(\alpha d + \beta)$ (€ ha^{-1}) measures the effect of distance d on the buyer's WTP. The coefficients α (ha €$^{-1}$m^{-1}) and β (ha €$^{-1}$) are both positive and lead to a WTP that on average decreases with distance. The relative position of the WTP function to the WTA function is specified by γ (€ ha^{-1}), which can be interpreted as a measure of how dynamic the land market is. If the WTP function is high relative to the WTA function ($\gamma < 0$), the hatched area in Fig. 4 will be large and many transactions will occur. Lastly, ε_B (€ ha^{-1}) signifies the buyer's subjective parcel appraisal and is taken to be normally distributed with zero mean and standard deviation τ_B (€ ha^{-1}). We conveniently assume here that ε_S and ε_B are independent and $\tau_S = \tau_B = \tau$, although this assumption could easily be relaxed.

In case of a successful transaction, the transaction price P (€ ha^{-1}) is taken to be the average of the WTP and WTA, therewith simulating a situation in which buyer and seller have equal bargaining power:

$$P = (WTP + WTA)/2 \tag{3}$$

When a transaction is realized (i.e., when $WTA < WTP$), the distance, d, between parcel and buyer and corresponding transaction price, P, are stored and the process is repeated. That is, a next parcel is drawn at random and a queue of potential buyers simulated. If we repeat this Monte Carlo simulation N times, with N set large, say $N = 1000{,}000$, then the frequency distributions of simulated distances and simulated transaction prices should closely approximate their theoretical distribution.

Note that WTP and WTA are theoretical constructs, of which the distribution and functional form can only be indirectly inferred from the observed joint density of transaction price, P, and distance, d. As pointed out in the introduction, transaction price and distance are only recorded for successful transactions, while WTA and WTP exist for any possible combination of parcel and seller/buyer.

3.4. Parameter estimation

The simulation model has six parameters, $\boldsymbol{\theta} = \{\alpha, \beta, \gamma, \tau, \mu, \sigma\}$, whose values needed to be specified a-priori before transactions can be simulated as described above. In this way the probability distribution of the distance d between parcel and buyer is derived numerically, and similarly the joint distribution of simulated distance, d, and corresponding transaction price P.

If we denote with M and $S(\boldsymbol{\theta})$ the Measured and Simulated bivariate distributions of distance and transaction price, respectively, then we can measure their similarity with the Kullback–Leibler (KL) divergence (Kullback and Leibler, 1951), which, for discrete distributions, can be written as

$$D_{KL}\left(M \,\|S\left(\boldsymbol{\theta}\right)\right) = -\sum_{i=1}^{n} M\left(i\right) log\left\{\frac{M\left(i\right)}{S\left(i, \boldsymbol{\theta}\right)}\right\}, \tag{4}$$

where n signifies the number of rectangular grid points of distance and transaction price used to characterize both bivariate pdfs. This metric, also-referred to as relative entropy, is nonnegative. A value of $D_{\mathrm{KL}}\left(M \,\|S\left(\boldsymbol{\theta}\right)\right) = 0$ indicates that S and M are in perfect agreement. This agreement deteriorates with increasing value of $D_{\mathrm{KL}}\left(M \,\|S\left(\boldsymbol{\theta}\right)\right)$. We adopted a Bayesian approach and infer the statistical (=posterior) distribution, $p(\boldsymbol{\theta}|M)$, of the model parameters, $\boldsymbol{\theta}$, using a uniform (non-informative) prior distribution, $p(\boldsymbol{\theta})$, with parameter ranges listed in Table 1, and likelihood function, $L(\boldsymbol{\theta}|M)$, commensurate with Eq. (4) (see e.g. Greenwood and Wefelmeyer (1997)), or

$$p(\boldsymbol{\theta}|M) \propto p(\boldsymbol{\theta})L(\boldsymbol{\theta}|M), \tag{5}$$

which, with a (multivariate) uniform prior distribution, equates to $p(\boldsymbol{\theta}|M) \propto L(\boldsymbol{\theta}|M)$. Thus, the model parameters that maximize the a-posteriori density, are equivalent to the maximum likelihood (ML) solution. Note that we used a uniform prior on the logarithmic (base 10) values of μ and σ. This is equivalent to a Jeffrey's prior (Jeffreys, 1939).

For our land market model, the posterior distribution is hard or even impossible to derive by analytical means nor by analytical approximation, and Monte Carlo sampling methods are required to approximate $p\left(\mathbf{x}|M\right)$. Of these, Markov chain Monte Carlo (MCMC) simulation methods are particularly powerful. Such methods generate a random walk through the parameter space and, under certain regularity conditions, will successively visit solutions with frequency proportional to the underlying target density, $p(\boldsymbol{\theta}|M)$ (Metropolis et al., 1953; Robert and Casella, 2004).

In this paper, MCMC simulation is performed using the DREAM algorithm (Vrugt, 2016; Vrugt et al., 2009). This multi-chain MCMC simulation algorithm automatically tunes the scale and orientation of the proposal distribution in pursuit of the target distribution. Many published studies have shown that DREAM exhibits an excellent performance on complex, high-dimensional, and multi-modal target distributions. The use of multiple chains protects against premature convergence and opens-up a wide arsenal of statistical tests to determine when the chains have reached the stationary distribution. After a burn-in period, the Markov chains have become independent of their initial value and convergence is monitored with the univariate $\hat{R}$-convergence diagnostic of Gelman and Rubin (1992). A full description of the DREAM algorithm can be found in Vrugt et al. (2009) and Vrugt (2016).

Table 1
Parameter ranges, posterior estimates, and units.

Parameter	Minimum	Maximum	ML	Std.	Units
α	-12	3	-7.48	1.658	$\log_{10}(€\ \text{ha}^{-1})$
β	-12	3	-7.79	0.062	$\log_{10}(€\ \text{ha}^{-1})$
γ	0	5	4.53	0.039	$\log_{10}(€\ \text{ha}^{-1})$
τ	0	5	3.72	1.005	$\log_{10}(€\ \text{ha}^{-1})$
μ	2.0	6.0	4.56	0.02	$\log_{10}(€\ \text{ha}^{-1})$
σ	2.0	6.0	3.69	0.511	$\log_{10}(€\ \text{ha}^{-1})$

Minimum and maximum show the range of the priors; the posterior parameter values are shown in column ML (Maximum likelihood), together with their standard deviation (Std.).

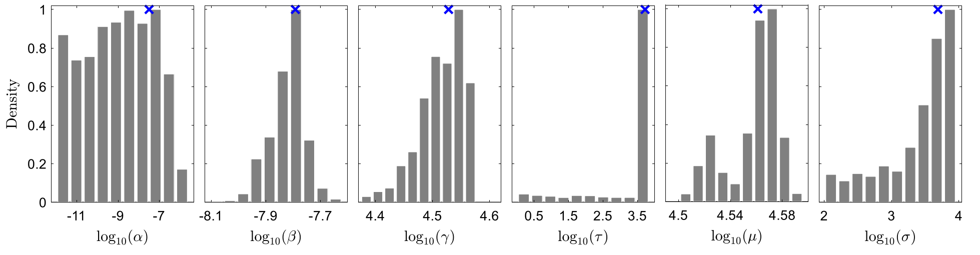

Fig. 5. Marginal posterior distributions of the model parameters derived using the DREAM algorithm. The crosses in each plot indicate the maximum likelihood value of each parameter.

4. Results

Fig. 5 shows histograms of the marginal posterior distributions of the six model parameters α, β, γ, τ, μ and σ. The maximum likelihood values are separately indicated in each panel with a cross symbol and listed in Table 1, under ML (Maximum likelihood) and Std. The results can be interpreted as follows. The average agricultural production value (also reflecting the average seller's WTA) is around 36,300 € ha^{-1} (i.e., $10^{4.56}$). The price a farmer is willing to pay for a parcel near his/her farmstead (say $d = 200$ m) is on average € 153,000 € ha^{-1} (i.e., $10^{4.56}+1/(10^{-7.79}*200+10^{-7.48})-10^{4.53}$). Depending on parcel properties, this price may in- or decrease by about € 9800 € ha^{-1} (i.e., two times $10^{3.69}$). The subjective appreciation by buyers due to variations in intended use or farm structure and/or an over- or under-appreciation of the parcel value leads to average deviations of 3720 € ha^{-1} (i.e., $10^{3.72}$) in the WTP.

The model parameters appear to be well defined with posterior ranges that are confined to a small region interior to the multivariate uniform prior distribution. Most histograms deviate substantially from normality and exhibit multiple peaks. This finding, together with the relatively low acceptance rate (2%–4%) of candidate points in the Markov chains, provides evidence of a rather difficult response surface with local minima and pits. This introduces small artefacts in the marginal distributions and makes it difficult for the Markov chains to explore efficiently the parameter space in pursuit of the target distribution.

The simulated joint distribution of distance and transaction price of the ML parameter estimates using 1 million Monte Carlo samples is shown in Fig. 6. At the left-hand-side the bivariate distribution derived from our data set is shown for comparison. The simulated and observed bivariate densities were characterized using $n = 256$ points (see Eq. (4)) on a 16×16 equidistant rectangular grid. The most important results are as follows. First, the simulated distribution is constricted to a maximum distance of 20,000 m between the parcel and the buyer, and appears to be less peaky than the observed distribution. Second, the simulated distribution is much smoother because of the use of a much larger "data set" of 1-million Monte Carlo samples. Third, the simulated distribution does not capture adequately the short-distance transactions. These discrepancies may be explained in part by the small number of observed short-distance transactions (i.e. within 200 m), and in part by inadequate assumptions in our market model, which are further discussed in the Discussion.

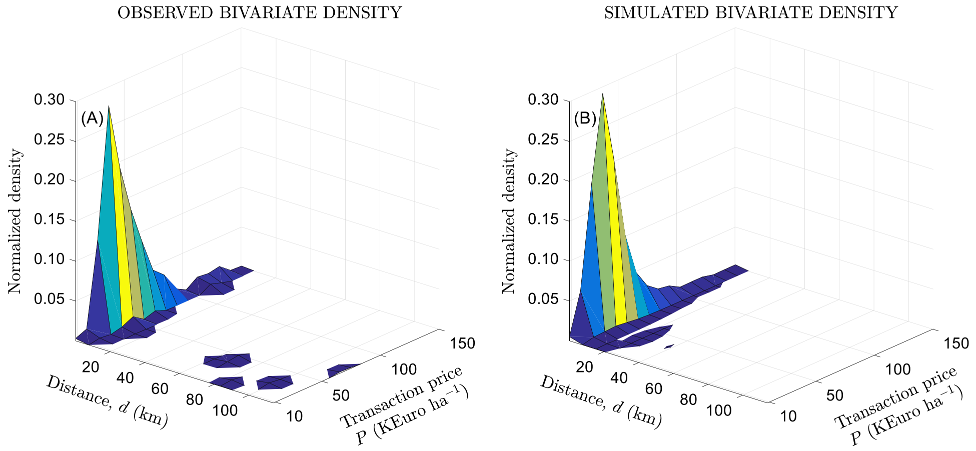

Fig. 6. Observed and fitted joint distributions of distance and transaction price.

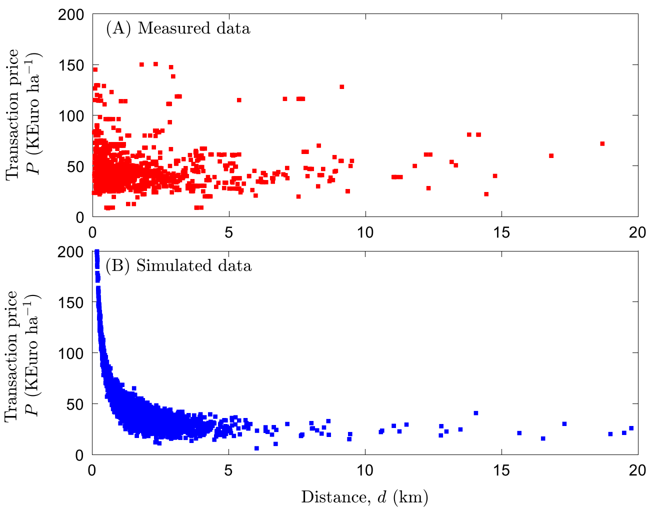

Fig. 7. Observed and fitted marginal cumulative distributions of distance and transaction price.

Scatterplots of simulated and observed Transaction price and Distance are shown in Fig. 7. Here, the failure to simulate short-distance transactions becomes even clearer, and also the spread of the observed distribution is less well reflected in the simulations. Nevertheless, the characteristic combination of a weak negative relationship between Transaction price and Distance and a clear decline in the number of observations with distance, is clearly reproduced.

Finally, we conclude this section with a plot of the relationship between distance between buyer and parcel and the corresponding WTP (Fig. 8). The WTP decreases rapidly with increasing distance between buyer and parcel. Within 900 m from the farmstead, buyers are willing to pay more than the agricultural production value (i.e., 36,300 € ha^{-1}). Transactions still occur at distances larger than 900 m, but only when the buyer has a subjective over-appreciation and/or the seller a subjective under-appreciation of the agricultural production value. The WTP decreases to about 4000 € ha^{-1} at a distance of 20 km, which is so low that only incidental transactions will occur. The relationship is

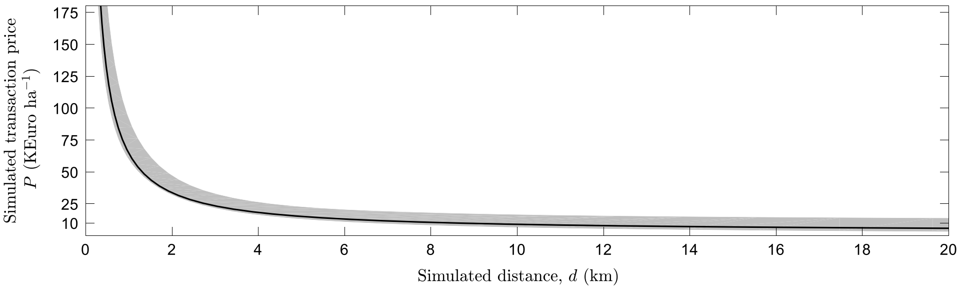

Fig. 8. Effect of distance on WTP. The WTP–distance relationship is given by $WTP\ (d) = \mu + 1/(\alpha d + \beta) - \gamma$, with ML values for μ, α, β and γ listed in Table 1.

non-linear, so that at short distances (500–1000 m) any additional metre distance reduces the WTP by about 60 € ha^{-1}, which for intermediate distances (100–3000 m) reduces to 10 € ha^{-1}, and for larger distances to less than 1 € ha^{-1}.

5. Discussion

We presented a novel statistical model for characterizing, via Monte Carlo simulation, the relationship between distance and WTP for land parcels. The six parameters in this model were estimated via Bayesian inference using a historical archive of land transactions in the Dutch province of Gelderland, and results appear to be in line with findings of Cotteleer et al. (2008) who found that 90% of the agricultural buyers are located within 6.7 km of the parcels they bought. The simulated land market matched empirical observations and appears useful for application in policy making. For example, the province of Gelderland is responsible for the implementation of an ecological network, and so it buys plots of agricultural land within a certain designated, but broad zone. Then, to consolidate nature areas, the province tries to trade these parcels with farmers for other parcels that are contiguous with the existing nature reserves. This process, however, appears to be ineffective, as farmers are often not interested in the parcels that are offered in exchange (Bakker et al., 2015). The method presented here allows the province to purchase and offer land more effectively. Furthermore, quantified relationships between distance and WTP are also needed by spatially-explicit agent-based models that simulate land transactions based on individual farmer decisions. Such models are increasingly used to simulate land markets (Alam et al., 2014; Bakker et al., 2014; Bert et al., 2010; Schouten et al., 2012), but all use crude assumptions on the relationship between WTP and distance between parcel and owner.

We believe that the presented method has a general applicability to agricultural land markets, provided that there is a situation with many farmers and many parcels, evenly spread throughout space. The functional form of the model, whereby WTP decreases with distance, is universal, while of course the actual parameter values, determining the shape and position of the function, will be different for each situation. The set of parameters we found is valid for the province of Gelderland, The Netherlands, where prices of agricultural land are high (thus high values for μ), as in other parts of the country. Land is scarce in this densely populated area, and agriculture is highly intensive, which enables farmers to pay a relatively high price for the land. In other countries these prices are likely to be lower. The premium paid for land near the farm buildings is related to the dominant position of the dairy sector in many parts of the Netherlands: parcels near the stable mean easy movement of cattle from milking-machine to pasture. This accounts for the rapid decline in WTP with increasing distance from the buyer's farm (thus high values for α and β). In areas where arable farming is more important (the province of Flevoland, for instance) that gradient would be less steep. The other characteristic of the graph, namely that the WTP hardly declines any further with distances beyond 5 km or so, relates to the fact that even distant land can be valuable to the farmer because it can be used to dump manure; this feature is relevant for dairy farmers, but also for pig farmers who have some arable land (thus, high values for α and γ). The number of parameters in our model allow for a flexible relation between

WTP and distance, ranging from functions that are virtually flat (i.e., when buyers do not care about the distance of the to-be-purchased parcel) to a very steep functional relationship that decreases rapidly to zero (e.g. when buyers are only interested in an adjacent parcel and nothing else). The degree of curviness is controlled by parameter α, also allowing for linear relationships between distance and WTP (which is probably more appropriate for arable farmers).

If deemed appropriate, model complexity can be further increased. For instance, the distance term in Eq. (2) can be raised to a power, and this power coefficient can be treated as unknown and inferred simultaneously with the other six parameters. Similarly, one could challenge the assumption that subjective appreciations of buyer and seller have the same spread, τ. On the one hand, one may argue that sellers have a wider spread in subjective appreciation as the distance to their farmstead is incorporated in their subjective appreciation. On the other hand, one can argue that buyers have a wider spread, as they know the properties of the to-be-purchased parcel(s) less well than the seller. Anyhow, it may be evident that the use of a common standard deviation, $\tau = \tau_S = \tau_B$, for ε_S and ε_B is inadequate as both these entities are determined by at least a few different variables. In principle, incorporating such additional parameters is easy to do, but we refrained from it because we already had some difficulty with model convergence due to local minima and pits. In other words, our data did not support additional model complexity.

The simulated bivariate distribution of distance and transaction price matched reasonably well its observed counterpart. We do see a mismatch in the observed occurrence of short-distance, low-price observations, which we were not able to simulate (Fig. 7). Apparently, in the real-world farmers sell land cheaply to farmers who should have a high WTP since they live near the for-sale parcel. There are several explanations. First, *willingness* to pay does not equal *ability* to pay. Especially among family farms, purchasing power is low due to declining margins in agriculture. Related to that, buyers and sellers in close-distance transactions are often neighbours or even relatives, so that the selling party may not wish to take advantage of the high WTP of the buyer. Third, in many cases the buyer may assume that the seller will not find an alternative buyer with an equally high WTP, and can therefore bargain a good price, despite his/her high WTP. Other processes that have been insufficiently captured in our conceptual model are concern the asymmetry of the distribution of market prices (Chang and Tang, 2015) and transaction costs. Regarding the asymmetry of market prices: The price of agricultural parcels is affected by (anticipated) changes in zoning policies, but the mechanism by which differs between designation types. When the designation changes towards a more profitable land use (e.g. residential), farmers are paid the *option value* of the land (what the land will be worth after the change in designation), while when the designation changes towards a less profitable land use (e.g. nature), farmers are paid the so-called *user value* (what the land is worth before the change in designation). This could be incorporated in the model by assuming a skew distribution for ε_S and ε_B rather than a normal distribution. Regarding the transaction costs, the transaction prices reflect what a seller receives, but costs of the transaction, which can easily amount to 10%–20% of the transaction price, are for the buyer. As we ignored these costs we structurally underestimated the buyer's WTP by about 10%–20%. This explains in part the relatively large (negative) value for γ, which makes the bid function relatively low compared to the ask function (Eqs. (1) and (2)). Thus, what we assessed in Fig. 8 is the WTP *excluding transaction costs*.

Regarding the optimization procedure some critical remarks can be made. Analysis of the sampled Markov chains (not shown) demonstrated relatively strong dependencies between some of the model parameters. This is particularly true for α, γ and τ which appeared to be highly correlated. Perhaps, this result is not surprising as these three parameters have an additive effect in Eq. (2). Nevertheless, all six model parameters appear relatively well defined with marginal posterior distributions in Fig. 5 that occupy only a small portion of the multivariate prior distribution. Future research should investigate in more detail model parameter uncertainty. This will help determine whether additional model components and/or parameters are warranted by the data.

6. Conclusions

The relationship between the distance between farmstead and parcel and the willingness to pay (WTP) for such a parcel is difficult to derive from land transaction data because the WTP is a latent variable, of which the observed transaction data are a biased manifestation (i.e., many high-price/small-distance observations and few low-price/large-distance observations). To address this issue, a statistical model was formulated that postulates an inverse-distance relationship between the distance between farmer and parcel and the WTP for such a parcel. By embedding this model in a Monte Carlo framework, we can simulate the land transaction market of buyers and sellers and make a quantitative assessment of the distance–WTP relationship. We used this model to analyse land transaction prices in the Dutch province of Gelderland. After Bayesian estimation of the parameters, we found that the proposed conceptual model predicts reasonably well the empirical bivariate distribution of transaction prices and distance from buyer to seller. The relationship found suggests that for short distances (−1000 m) any additional metre distance reduces the WTP by about 60 € ha^{-1}, which for intermediate distances (1000–3000 m) reduces to 10 € ha^{-1}, and for larger distances to less than 1 € ha^{-1}.

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