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Ruth Delzeit, Karin Holm-Müller, Wolfgang Britz

Abstract

The location of first generation processing plants for biogas using bulky inputs is a prominent example of locational decisions of plants that face high per unit transport costs of feedstock and simultaneously depend to a large extent on feedstock availability. Modelling the resulting regional feedstock markets then requires a spatially explicit representation of demand. With production capacities of plants small in comparison to market size, large numbers of possible type-location combinations need to be considered, requiring considerable computation time under existing integer programming-based approaches. Therefore, in this paper we aim to present an alternative, faster and more flexible iterative solution approach to simulate location decisions for processing plants. And with greater flexibility, this approach is able to take into account spatially heterogeneous transport costs depending on total demand. The approach is implemented in a modelling framework for biogas production from green maize in Germany, which currently accounts for ca. five percent of Germany's agricultural area. By modifying green maize prices, demand functions are derived and intersected with regional supply functions from an agricultural model to simulate market clearing prices and quantities. The application illustrates that our approach efficiently simulates markets characterised by small-scale demand units and high, spatially heterogeneous transport costs.

Keywords: Competitive facility location, transport costs, modelling, biogas, biomass transportation
JEL-classification: Q16, C31, C63.

1 Introduction

The agricultural sector is rapidly being integrated into energy markets. Feedstock demand of first generation biofuels relies on existing market channels for cash crops such as cereals or oilseeds, and can therefore be integrated into existing economic simulation models for agriculture to assess social, economic and environmental impacts arising from changes in policies or markets (see. e.g. BANSE et al. 2008, LAMPE 2007, HERTEL et al. 2008). Second generation biofuel production or first generation biogas production from agricultural biomass is however mainly based on bulky raw products with much higher per unit transport costs and small scale, localised demand. The latter stems from location decisions for numerous bioenergy processing plants which are driven to a large degree by regional differences in transport and production costs of feedstock, especially if there is little spatial variance in other important factors such as output prices, investment costs and other operational costs. These location decisions in turn will drive regional markets for bioenergy feedstocks and interact with the market for cash crops, which calls for an integrated assessment of both types of markets.

In Germany, first generation biogas production from green maize and manure provides a prominent example for this type of problems The so-called German Renewable Energy Act (EEG) supports the erection of biogas plants by implementing attractive feed-in tariffs for electricity produced by this type of source, guaranteed for 20 year and adjusted depending on manure shares, plant size and plant technology. The EEG, created in 1991 and reformed in 2004 and 2008 (BGBL, 2004), led to a sharp increase in electricity production from biogas and an increase in average plant sizes. It is estimated that by 2009, 530,000 ha of German land have already been used to provide inputs for biogas production (FNR, 2009), accounting for about five percent of total agricultural land in Germany, or about 1/4 of what the EU subsidises as renewable energy areas across the entire EU.

To the authors' knowledge, there is currently no tool available to simulate changes in feedstock demand and supply arising from this legislation or variants thereof. This paper therefore proposes a numerically feasible and efficient methodology to determine regional demand curves for agricultural bioenergy feedstock, which can then be integrated into existing impact assessment tools. It uses an iterative approach to determine maize and manure input demand for the most profitable plant at the most profitable locations first. Then, based on the remaining feedstock, demand for the next profitable plant is calculated, and so on. As a result, our approach does not imitate a social planer but rather replicates decentralised decisions under the assumption that the most profitable plants are opened first.[1] The approach is able to derive the number, locations and types of processing plants even if several thousands of possible combinations are under investigation for a region. Building on given regional supply curves for the feedstock, the methodology is applied to determine market clearing prices and quantities for biogas production from green maize and manure in Germany, based on the newly developed simulation tool ReSI-M (Regionalised Location Information System – Maize). Besides showing exemplary results for demand functions and regional market clearing quantities and prices, we provide detailed motivation for the cho-

[1] This approach allows for flexibility regarding the decision rule which plant (characterised by type and location) to realise in each iteration. Besides different definitions of "most profitable" (i.e. based on absolute profits, profits per unit of investment, or introducing side conditions such as collateral necessary), stochastic rules, such as randomly choosing plants exceeding profitability thresholds, could also be used.

sen methodology, discuss underlying data and parameters and derive regional averages based on a sensitivity analysis for the key parameter “energy efficiency“.

The paper is structured as follows: section 2 provides the problem setting and relates it to relevant studies, motivating our choice of methodology. Section 3 provides the detailed methodology of ReSI-M. This is followed by section 4 on the underlying data and its parameterisation. In section 5, we discuss our approach with respect to the performance of the model, and finally, draw conclusion for the use of location models in the case of agricultural products with high transportation costs.

2 Problem setting, relevant studies and choice of methodology

Our objective is to determine the total feedstock demand d for regions r at given feedstock demand prices w. Total regional demand d equals the sum of plant type t specific feedstock demand x times their location-specific number n:

$$d_r(w) = \sum_t n_{r,t}(w) x_t \tag{1}$$

The plant types are characterised by the given size and feedstock mix. The number of plants *n* of a specific type *t* erected at location *r* depends on their operational profits η which are defined as the difference between revenues - output *y* times price *p* -, operational costs *oc* net of feedstock, and feedstock costs. The latter are equal to the given input demand *x* multiplied by the sum of per unit transport costs *tc* and feedstock price *w*.

$$\pi_{r,t} = y_t p_t - oc_t - x_{r,t}(tc_{r,t} + w) \tag{2}$$

Per unit transport costs *tc* depend on the regional availability of feedstock, which is determined by regionally differing “location factors”. These are feedstock yields as well as the share of arable land on total land, the spatial distribution of this share and the amount of feedstock that is already used. This spatial distribution determines the homogeneity of a region.

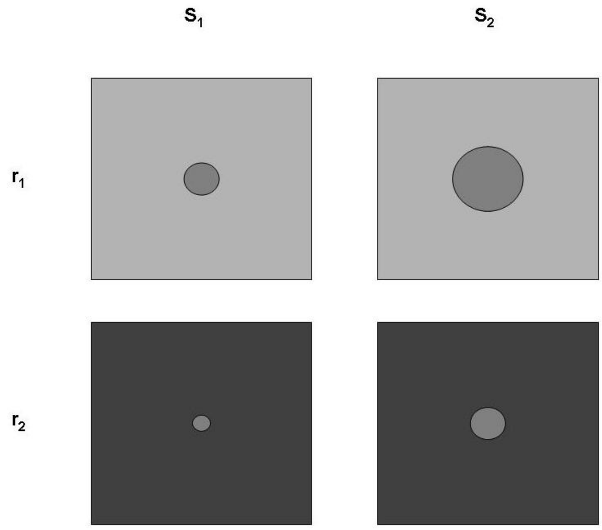


Figure 1: Feedstock availability and related harvesting area

In order to illustrate how location factors impact optimal plant size, Figure 1 shows a hypothetical example with plants of two size classes s_1 and s_2 shown in the columns and two regions r_1 and r_2 in the rows. The intensity of the background colour relates to average feedstock availability of the regions, whereas the circles indicate the necessary harvest areas to feed the plants. Clearly, transport costs *tc* per unit of feedstock demand are higher in r_2 and for plant s_2. Accordingly, profits by plant size may be ranked differently in regions depending on feedstock availability. Equally, differences in regional feedstock prices may have an impact on the ranking.

However, as long as some feedstock is left, adding more plants would not change profitability for the different sizes, as the harvest area for each region, size and therefore transport costs are fixed. Total feedstock demand could simply be derived by first determining the most profitable plant size and then calculating the maximal number for that size possible from feedstock supply *s* at given feedstock price *w*. Unused regional feedstock quantities could then be eventually used for smaller sized plants with a lower profit.

For the problem at hand, feedstock demand per plant is small compared to maximal feedstock supply quantities s_r, so that a large number of potential plants must be investigated. Moreover, data suggests that feedstock availability within the regions differs considerably, as shown by the grey gradient in Figure 2. Accordingly, harvest areas vary within regions depending on feedstock density. Investors will now start to erect plants at such locations where feedstock availability is high and consequently transport costs low. Transport costs *tc* become a function of plants already erected. Our final problem setting adds complexity to figure 2 in that several regions are optimised together while allowing plants to acquire feedstock from any of them.

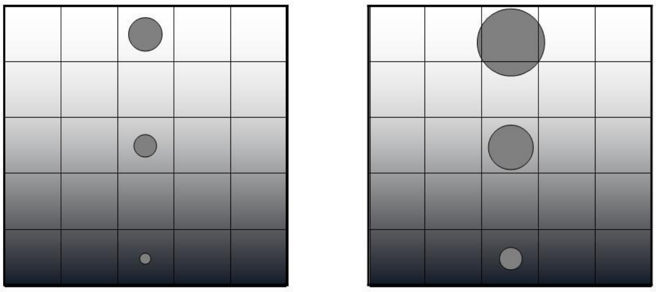


Figure 2: Influence on harvesting area of intraregional feedstock availability

Existing literature (for an overview of methods used in location optimisation, see e.g.: KLOSE, 2001, DREZNER and HAMACHER, 2002, KLOSE and DREXL, 2005) does not directly offer a methodology to solve our problem setting efficiently. Classical solutions to combined location and capacity problems (cp. AARDAL, 1998, NAGEL, 2000, MELKOTE and DESKIN, 2001) work with a distinct, predefined number of locations in space, and are solved as Mixed-Integer Linear Programming Problems in which per unit transport costs are given. Recent literature focusing on second generation biofuel plants stems from LEDUC (2008) and (2010), and KERDONCUFF (2008) applies a Ware-House Location Problem with scenarios with given demands for bioenergy to determine an optimal location and size of biogas to liquid plants. Depending on the assumed demand and regional case study, resulting plant numbers are one to two in case of LEDUC (2008, 2010) and KERDONCUFF (2008) determines ten optimal locations for a decentral design in his study. BOYSEN and SCHROEDER (2006) provide a typical example of determining simultaneously optimal sizes and locations of dairies for ~350 regions covering Germany, taking regional milk supply as given. The model is formulated as a Mixed-Integer Linear Programming Problem and solved by combining Genetic Algorithms with Tabu Search. These problems are classified as NP-hard (non-deterministic polynominal time-hard) problems, indicating that the computational efforts increase exponentially with the size of the problem (DOMSCHKE and DEXEL, 2005, p. 125). MAHLER (1992) provides an analysis for German sugar beet and raw sugar production, simultaneously minimising production costs of sugar beet and sugar for fixed total German sugar output, analysing simultaneously 157 potential locations, different plant sizes and lengths of the harvesting and processing period for the sugar beet.

For our problem these approaches are unsuitable without further modification and extension as they first of all do not deal with a continuous spatial distribution of feedstock availability and its consequences on transport costs, and secondly take either feedstock supply or output demand as given.

Approaches which define an optimal location in a continuous space typically only look at a single or a rather limited amount of potential plants. In his pioneering work in 1963, out of seven potential pear packing plants, STOLLSTEIMER (1963) simultaneously determined which of those plants, characterised by size and location, would be chosen. Extensions of that approach are found in supply chain optimisation, where locations are optimised along the chain, either minimising total chain costs or maximising chain profits (see e.g. ALLEN, et al. 1998, GRONALT and RAUCH, 2007, HIGGINS and DAVIES, 2005 and SEARCY et al., 2007). These approaches assume a central planning instance to determine an overall optimal industry structure and are therefore not applicable for our example, which deals with many small-scale, private, uncoordinated investment decisions. In addition, these frameworks most likely cannot be solved numerically for the number of possible combinations in our analysis.

In summary, our problem calls for an algorithm that (1) is efficient for a high number of potential plant type-location combinations, i.e. is not NP-hard, (2) does not set the quantities of supply and demand of inputs or of output as given, (3) considers intra-regional distribution of input availability and (4) does not assume a central planner. None of the algorithms used in the aforementioned studies fulfils already conditions (1) – (3), with (4) introducing a different behavioural model.

Therefore, we propose a relatively simple, but efficient solution algorithm to the problem of determining the number and locations of plants at given feedstock prices and maximal feedstock supply, described by the following iteratively repeated steps:

1. Determine minimum harvest areas for each plant type at given feedstock density to derive type-specific per unit transport costs.
2. Determine the profits of each plant type and sub-regional location at given per unit transport costs for feedstock. As will be motivated later, this involves solving a transport cost minimisation problem for each plant type-location combination, as we are dealing with different feedstocks and sub-regions in the analysis.
3. Determine the plant type-location combination with the highest return on investment (ROI).
4. Reduce regional feedstock supply according to the selected type and location and determine from this point the current feedstock density.
5. Repeat this procedure from step 1 until ROI determined in step 3 falls below a predefined interest rate.

Step 2 above is equivalent to a very simple location model: for each plant type, select the sub-region inside the region under investigation where transport costs are minimal, feedstock demand is satisfied and transports do not exceed feedstock supply. The decision rule in (3) could be replaced by alternatives, as discussed above.

The following section describes our solution in more detail.

3 The simulation tool ReSI-M

3.1 *Overview*

The regionalised location model ReSI-M determines the optimal number of plants, their location in subregions and their type, characterised by size and feedstock mix at given feedstock prices, in a sequential process. This is done by iteratively maximising the ROI for biogas plants in NUTS 3 (Nomenclature of Territorial Units for Statistics)[2] regions inside each German NUTS 2 region, characterised by average sizes of ~900 km². Aggregated across plants, total feedstock at different prices for maize (21-53€/t) is determined for each NUTS 3 region, which by interpolation allows for regional feedstock demand curves to be derived.

The framework takes into account important regional factors and their interaction determining the optimal location and size of biogas plants: output prices according to current legislation, input availability and resulting transportation costs, processing costs, and utilisation possibilities for crude biogas and heat.

The number of plants erected *n* of a specific type *t* in a NUTS 3 region *r* are assumed to depend on plants' *ROIs* which are calculated from yearly operational profit η as defined above and total net present value of investment costs *I* divided by the length of the planning horizon *T*:

$$ROI_{r,t}(w) = \frac{\pi_{r,t}}{I_t / T} \tag{3}$$

Transport costs per unit *tc* are specific for a certain plant type, its NUTS 3 location r_1 and the NUTS 3 region from which its feedstock is taken, r_2, as well as feedstock demand of already erected plants. As seen in (4), *tc* depend on three terms. The first term α_t covers the costs of un- and uploading. The second term relates to the driving distance *m* from the location region r_1 of the plant to the procurement region r_2, times the transport costs per unit and km β_t. α_t, whereas β_t are type-specific as different sized trucks are used. The third and last term captures the intra-regional transport costs for transporting the feedstock from the fields either to the plant or the starting point of interregional transport. It is calculated by assuming that the plant/starting point is placed in the middle of a circle surrounded by plots covered partially with arable land, from which the feedstock

[2] For a description, see: http://ec.europa.eu/eurostat/ramon/nuts/basicnuts_regions_en.html

is collected, and partially with other land cover. The radius of the circle depends on three parameters: (1) the plant's given input demand for maize *x*, (2) the maize yield on arable land *e* and (3) the share of arable land on land cover *b*. The square root and the constant π stem from the formula to calculate the radius of a circle from its area.

$$tc_{r_1,r_2,t} = \alpha_t + m_{r_1,r_2}\beta_t + \sqrt{\frac{x_t}{\pi e_{r_2} b_{r_2,cur}}}\beta_t \qquad (4)$$

The share of arable land *b* varies in each region according to uniform distribution from a minimal share b_{min} to a maximal one b_{max}. Collection costs will be minimal where the share is highest, i.e. equal to b_{max}, defining the location inside the region where the first plants will be erected. The maximal share is reached when the maximal available feedstock d_{max} is used. Accordingly, the current share b_{cur} in an iteration can be derived from the already used feedstock d_{cur}, as seen in (5).

$$b_{r_2,cur} = b_{r_2,\max} - \frac{b_{r_2,\max} - b_{r_2,\min}}{d_{r_2,\max}} d_{r_2,cur} \qquad (5)$$

An overview on ReSI-M is provided in Figure 3, showing exogenous and endogenous factors as well as how the simulation tool iteratively solves the location problems (grey box). Exogenous parameters include yields, per unit transport costs, as well as other operational costs, output price for the electricity produced, and maize prices. The amount of feedstock which is transported to a biogas plants ($x_{r,s}$) is an endogenous variable. The main results are regional feedstock demands for green maize and manure.

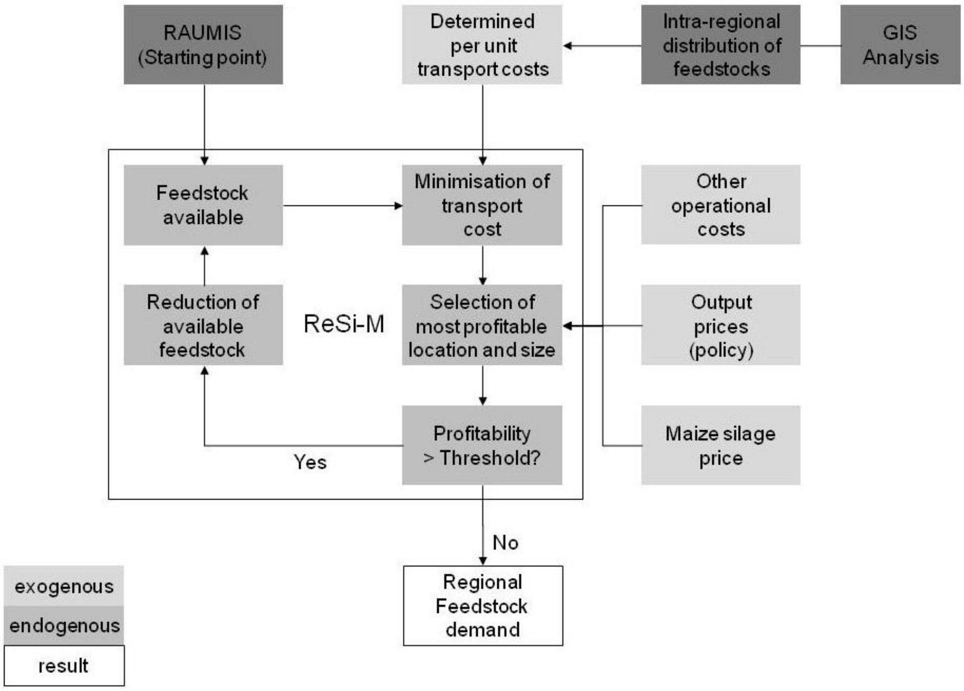


Figure 3: Overview of ReSI-M

3.2 *Assumptions*

Given that the EEG guarantees output prices for 20 years after constructing a plant, we take that period as the planning horizon and assume that investments in plants are ranked and realised according to their net present ROI. We distinguish four possible size classes operating with three different manure shares in about 350 administrative NUTS 3 regions inside German NUTS 2 regions. Distinction by size class and manure share is introduced to reflect differences in output prices according to the EEG. Depending on the size of the 35 German NUTS 2 regions and feedstock density, the ROI for several thousand type-location combinations are determined in each region under investigation.

We assume that transport costs for maize are paid fully by the biogas plant. For transport and storage, a 12% loss is assumed (KTBL, 2006). We take different shares of arable land on total land inside the NUTS 3 regions into account so that per unit transport costs increase with rising amounts of used feedstock by already realised plants during the iteration process. Details on the calculation are given in section 3.1.

The market for manure as feedstock operates differently in regions with low and high animal densities. In some German regions with high stocking densities, farmers are facing costs for manure removal due to the maximum organic fertilising doses. They either have to rent additional land or enter a contract with another farmer to spread their manure. In these regions, we assume that farmers will pay transport costs of manure to the biogas plants. As using manure in certain shares will drive up the guaranteed feed-in price, biogas operators will try to reach those shares. We therefore assume that in regions with low stocking densities, transport costs will be fully paid by the biogas plant. As with maize, intra-regional differences in manure availability render per unit transport costs of manure as a function of the amount of manure already used as feedstock for every NUTS 3 region.

The crude biogas produced can be used in different ways. The EEG 2004 favours two pathways of usage. The main technology used is based on so-called heat-electricity plants (BHPPs), where electricity is produced with the heat emitted from the engine used locally as a by-product. We presume that plants with sizes of 150 and 500 kW_{el} apply this technology. Another pathway is to upgrade crude biogas and induct it into gas pipelines. This allows for production of electricity and heat in a BHPP at another location along the pipeline where heat can be efficiently used. This pathway is only profitable for large-scale plants, which we assume apply this technology. The exact implementation of the different pathways is based on pre-calculations, which determine the most profitable option depending on the plant size and regional availability of gas pipelines and demand for heat for housing.

As we use the year 2004 for our baseline scenario, our calculations are also based on input and output prices prevailing in 2004. We also incorporated the political framework with revenues from the EEG 2004 and can thus compare our results with the current plant structure in Germany (see section 4.1).

3.3 *Data sources and processing*

Some data input for the simulation tool are taken from literature, and some are obtained based on a GIS-analysis.

NUTS 3 regions are classified according to their selling opportunities for heat produced by biogas plants and the possibility of inducting gas into a natural gas pipeline. A GIS-analysis excludes urbanised NUTS 3 regions as possible locations for biogas plants, assuming that zoning laws and low feedstock availability prevent installation of those plants in urbanised areas. For the remaining NUTS 3 regions, variances and mean shares of agricultural land are calculated from data provided by LEIP et al. (2008), who calibrated data from the European CORINE land cover (CLC) database to national and regional agricultural statistics. Data are available for so-called “Homogenous Spatial Mapping Units” (HSMU) with a resolution of 1x1 km^2 which consider soil, slope, land cover and administrative boundaries as delineation features. Variance and mean for the share of arable land for each NUTS 3 region was derived from that data set to determine the parameters for the Uniform Probability Density Function used in equation (5). Typical data are found in the following table 1 for the NUTS 3 regions within the NUTS 2 region “Arnsberg”. Their influence on driving distances is discussed in section 5.1.

Table 1: Exemplary data on land use data; * from RAUMIS (Regional Agricultural Environmental Information System)

NUTS 3 regions in Arnsberg	Yields (t/ha)*	Mean of share of arable land on total land (%)	Variance of share of arable land on total land
ENQ	61	6	15.1
HSK	63	5.8	4.6
MK	61	4.8	13.8
OE	41	0.9	39.4
SI	65	1.3	0.4
SO	64	34.9	248.2
UNQ	64	28.2	50.4

Exogenous data to determine profits π (used in equation (2) and (3)) are taken from literature. Data on revenues are derived from electricity prices according to the EEG, 2004, augmented by heat sales depending on the plant size and degree of combined heat generation (BGBL, 2004). Production and processing costs for three plant sizes are taken from URBAN et al. (2008). Underlying assumptions for these costs are described in detail in URBAN et al. (2008, p. 84ff). Missing data for the size of 150kW_{el} are based on KTBL (2005, p. 942-944). Assumptions on mean energy efficiency and maximum operating hours were also adopted from URBAN et al. (2008). The Federal Office for Building and Regional Planning (BBR) provided data on population density (BBR, 2005).
Per unit transportation costs per km for maize (α_t and β_t, see equations (4) and (5)) are extracted from TOEWS and KUHLMANN (2007), while KELLNER (2008) provided these for manure.

Available manure for biogas production is calculated by converting data on animal stocks from the Regional Statistics of Germany “Regionaldatenbank Deutschland” (STATISTISCHE ÄMTER DES BUNDES UND DER LÄNDER, 2009). The amount and type of livestock can be used to derive the amount of manure they produce. To convert animal stocks into manure production, a conversion index was taken from the STATISTISCHES BUNDESAMT (1991) and NIEDERSÄCHSISCHES MINISTERIUM FÜR DEN LÄNDLICHEN RAUM, ERNÄHRUNG, LANDWIRTSCHAFT UND VERBRAUCHERSCHUTZ (2006). This calculation resulted in the total available manure. As we assume that only fluid manure is fed to the plants, fluid manure shares are taken from RAUMIS to derive total available fluid manure. RAUMIS also provides maize yields at the NUTS 3 level.

3.4 *The solution algorithm*

The research area of Germany is subdivided into NUTS 2 level regions to which the algorithm is applied. Each NUTS 2 level region encompasses a set of NUTS 3 regions. The breakdown to NUTS 3 matches the regional resolution of RAUMIS. Accordingly, yields and feedstock availability at given prices can be taken directly from RAUMIS, and market clearing prices and quantities for each NUTS 3 region can be calculated by intersecting maize supply curves from RAUMIS with maize demand curves from ReSI-M.

To find the optimal number of plants at a certain size and location, we apply an iterative approach (see Figure 3 as discussed above. During iterations, minimal total transport costs for each location-plant type combination is determined based on solving a simple transport cost minimisation model at the given regional maize and manure availability (see equations (3), (4) and (5)). Assuming a green maize price at the field level, the transport costs along with other given data then allow us to define the ROI for each location-type combination.

From all possible locations and plant types, the combination with the highest ROI is chosen in any iteration. The iteration process continues as long as a type-location combination exists whose ROI exceeds an assumed minimum interest rate. Given the simulation tool's structure, it would also be possible to define other threshold criteria such as absolute profits to stop the iteration process.

Another advantage stems from the design of the iteration procedure: It forces profits to decrease over iterations as feedstock availability decreases and consequently per unit transport costs increase. Accordingly, any location size class combination with a ROI below the threshold in a given iteration will never be realised in any follow-up iteration. That allows for a rapid reduction of many type-location combinations during iterations, speeding up the process further.

NUTS 2 administrative units are solved independently of each other in parallel in a computing grid, each problem simultaneously optimising all NUTS 3 regions in the respective NUTS 2 unit. The speed increase by solving for blocks of NUTS 3 regions instead of simultaneously solving for all of Germany does however come along with a loss of accuracy as transport flows across NUTS 2 regions are excluded by this approach.

3.5 *IT aspects*

In our application, the algorithm was implemented in GAMS (ROSENTHAL, 2010) with CONPT (DRUD, 1992) used as the LP solver. Given the very small size of the LPs to solve – each one minimises for one given plant and location transport costs for two feedstocks from a handful of regions – most likely any other LP solvers might be used instead. Equally, given the simplicity of the sequential algorithm, alternative implementation in other programming languages should be easily feasible.

Each transport cost minimisation problem, calculation of ROI per type-location combination and selection of the most profitable location-size class requires very little computing power in the range of milliseconds. Additionally, the transport cost models for different location and types can be solved in parallel during each iteration. That explains why the sequential process is by far faster even for moderately sized problems compared to a simultaneous solution. Total processing time can be taken as a solid indication of the performance of the algorithm: To solve the 35 NUTS 2 regions for Germany for nine different price levels, the algorithm require about 4 hours on an 8 core machine, simulating in total approximately 100,000 erected plants, requiring an analysis of many more possible type-location combinations. As mentioned above, the NUTS 2 regions are solved in parallel and not simultaneously.

The sequential process allows for some flexibility in that, for example, different decision rules about the most desirable type-location combination in each iteration can be implemented and tested. In our applications, we also use the possibility to change parameters, specifically the share of arable land impacting collection costs and made them depend on previous iterations as the solution processes continued. Such a change would introduce nonlinearities into a simultaneous solution process, which would increase solution time further, as it would require solving large-scale mixed integer NLP problems.

3.6 *Incorporation of uncertainties about energy efficiency*

Data from existing plants suggests that energy efficiency can differ substantially from the mean energy efficiency levels reported in literature (see section 3.3). Energy efficiency is directly linked to feedstock costs per unit of output and is therefore a main driver for the ROI of plants. ROI in turn is the main driver for regional demand: at given feedstock prices, ROI stems from the number, type and location of plants which have an ROI above the assumed break-even interest rate. Therefore, demand is crucially dependent on assumptions about energy efficiency. Even small changes in energy efficiency could have a major impact on derived demand curves and simulated market equilibrium. To deal with the uncertainty of mean energy efficiency we calculate three demand functions, one for the mean efficiency level from literature and two for efficiency levels that are calculated by either reducing or increasing mean energy efficiency by 10%.

As we do not know the exact efficiency level, for every given price we compute demand as the average of the resulting three demand functions (see Figure 4). Assuming a higher efficiency level (+10%, solid black line) increases demand for all analysed price levels until feedstock is exhausted, while lowering the number of plants necessary and thereby also total costs. A lower efficiency level (-10%, light grey line) has the opposite effect.

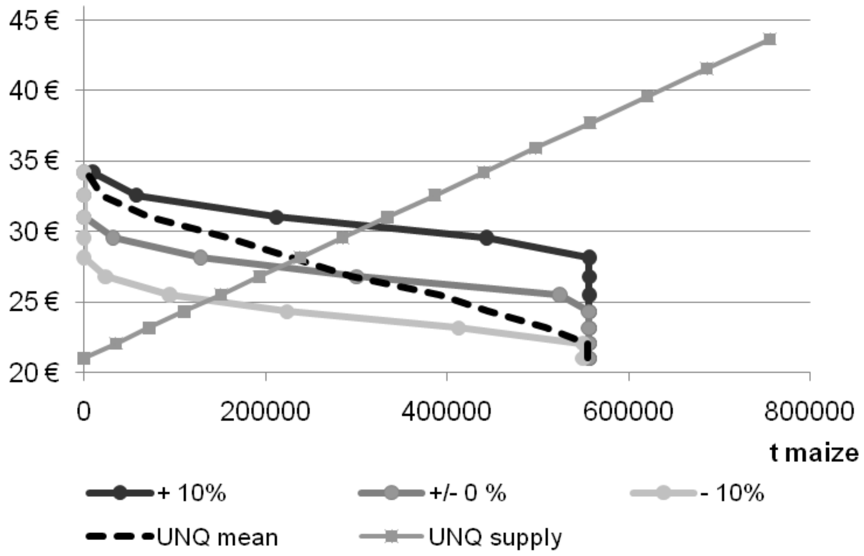


Figure 4: Example of a sensitivity analysis of energy efficiency

The reader should note how steep the curve behaves at the lower and upper end, indicating a highly nonlinear response to changes in efficiency at the tail of each relevant price change. These nonlinearities explain why the dotted line, which represents the average quantity demanded at each price from the three demand functions, differs considerably from the dark grey line showing the demand at mean efficiency. We took this average demand function to derive market clearing quantities and prices as we consider it not very likely that all investors assume the same mean efficiency, leading to almost rectangular demand curves at certain price levels. Accordingly, using the averaged demand curve should provide a more realistic picture.

3.7 *Simulating Market clearing*

In order to perform an impact analysis, market clearing prices and quantities are derived by intersecting the regional demand functions from ReSI-M with supply functions for green maize from RAUMIS. RAUMIS consists of independent regional Quadratic Programming Models for German NUTS 3 regions, which simulate the supply of agricultural products at given prices for agricultural inputs and outputs, production technologies for the different agricultural production processes and agricultural resource endowment. Each NUTS 3 region is treated as a fictitious "region-farm" that maximises agricultural income. Overspecialisation resulting from aggregation bias is reduced by a quadratic cost function depending on the production mix (for details on RAUMIS see HENRICHSMEYER et al., 1996, GÖMANN et al., 2007). Simulations using RAUMIS provided supply of green maize (net of regional feed use) for prices ranging from €20 to €53, providing a secure range around the typical average green maize prices of 30 €/t including transports used in other studies (cp. URBAN et al., 2008, HOFMANN et al., 2005). Prices of all other inputs and outputs and the agricultural policy framework were taken from the 2004 baseline of RAUMIS (GÖMANN et al., 2007). In RAUMIS, green maize competes for land with other crops, acts as a substitute for other animal feedstocks and, when sold, provides residues from biogas production as an organic fertiliser. Accordingly, the supply curves for green maize derived from RAUMIS take into account production and opportunity costs, relating for example to competition for land between the different crop activities, as well as feeding and fertiliser substitution values.

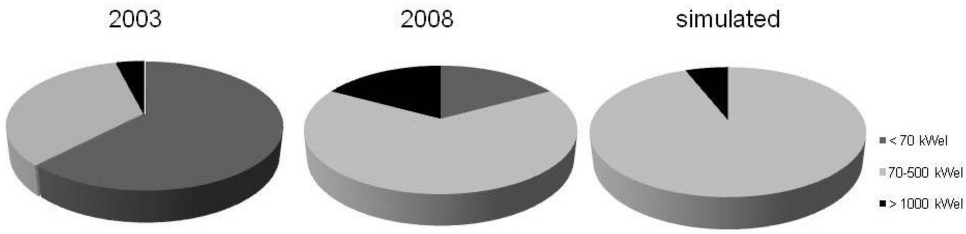
The simulated price/quantity combinations over the relevant price range suggest linear marginal cost curves, which can be explained by the combination of linear constraints and a quadratic cost function (see HECKELEI, 2002). The points on the regional demand curve from ReSI-M suggest a far more non-linear behaviour, which prompted us to use a second order point approximation to find its intersection with the supply curve. This point defines market clearing prices and quantities.

4 Results and Discussion

In this section we discuss selected results to present major findings both from data processing and simulations. We first compare the resulting plant structure with the plant structure in Germany in 2008. Then, we illustrate how regional feedstock availability impacts transport distances, and in turn how it affects the optimal number and types of plants. Next, we compare regional demand curves resulting from the location optimisation and finally link them with supply from RAUMIS to derive market clearing prices and quantities.

4.1 *Comparison of simulated future plant structure and location of regional distribution with current plant structure in Germany*

The modelling results simulate the number and sizes of plants which are constructed under the EEG 2004. Mainly medium-sized 500kW$_{el}$ plants are constructed with some share of large-scale plants (6%). Data on the current plant structure in Germany is not very detailed, but allows for a rough comparison with the modelling results. Within an evaluation of the EEG, TRÄHN et al. (2009) collected information on plant numbers for a range of plant sizes. Namely, plants smaller than 70 kW$_{el}$ make up 17%, plants with a capacity of 70-500kW$_{el}$ had a share of 65%, and plants larger than 500 kW$_{el}$ contribute to the total number of plants with 17%. An interesting feature is seen in the growth rates compared to 2003, when the EEG 2004 had not yet taken effect. The number of plants smaller than 70kW$_{el}$ decreased by 36%, whereas number of plants with capacities of 70-500 kW$_{el}$ more than quadrupled and, starting from a lower base, plants larger than 500 kW$_{el}$ increase tenfold (cp. Figure 5). Therefore, our modelling results seem to capture the development under the 2004 EEG quite well.



Source: Trähn et al. 2009, Schlowin et al. 2007, own simulations

Figure 5: Plant sizes in 2003, 2008 and simulations

Besides the plant structure, the distribution of plants within Germany is important to evaluate the performance of the simulation tool. In Figure 6 we compare the reported shares of energy production (see TRÄHN et al., 2009, p. 20) across 13 German states (city-states Hamburg, Bremen and Berlin are excluded) with the simulated shares in the modelling exercise. The shares of the modelling exercise comprise shares of existing plants, whose input demand has been subtracted from the available inputs for the simulated plants.

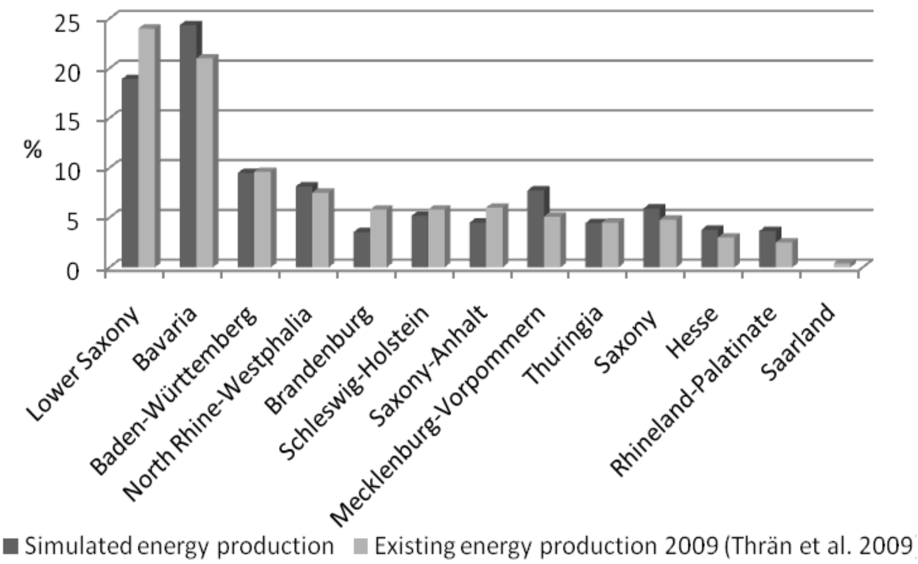


Figure 6: Distribution of existing and simulated energy production by state in Germany

4.2 *Influence of necessary feedstock harvesting areas on location choice and maize demand*

To explain how regional differences impact the number and type of plants simulated, we compare three German NUTS 3 regions differing in feedstock availability characteristics. Siegen (SI) is characterised by both moderate maize yields and a low mean and variance for the share of arable on total land (see Table 2), which implies low feedstock availability and rather homogenous conditions for biogas locations. Soest (SO) and Unna (UNQ) show comparatively high yields combined with a high share of arable land, thereby high mean feedstock availability. However, the variance of arable land shares in SO is almost five times higher than in UNQ.

We first take a look at harvesting areas necessary for different plant sizes at those locations in each region where the arable crop land share is highest (see Table 2), namely at the minimum of the uniform distribution (see section 3.1). The four plant sizes have a predefined feedstock demand, and besides the maximal feedstock density, the necessary harvesting radii around a plant depend on the square root of demand (cp. equation (4) and Table 2). It can easily be seen that the lower feedstock availability in SI results in much higher harvesting radii. The differences between SO and UNQ reflect the fact that SO has slightly higher yields and shows a less homogenous distribution of the arable land crop share, so that the arable land share and thus the feedstock density in the starting point is higher. We can also see that with the growth of plant size, the increase in the necessary area is much higher in SI than in the other two regions. This means that transport costs rise steeply with greater plant size in SI even for the best available location. We find the lowest increase in harvesting area for SO.

Table 2: harvesting radii (in km) in different NUTS 3 regions

	150 kW_{el}	**500 kW_{el}**	**1000 kW_{el}**	**2000 kW_{el}**
SI	3.45	6.3	8.91	12.56
SO	0.67	1.23	1.74	2.46
UNQ	0.75	1.37	1.94	2.74

As has been explained in section 3.1, radii increase with the amount of feedstock used by already erected plants (see equation (4)), as we assume that the most advantageous areas will be used first. The resulting plant structure is therefore a result of initial transport cost – at the maximum density - and its changes from iteration to iteration, which depends on how fast the density changes as a function of demand (see equation (5)).

Medium-sized 500 kW_{el} plants with a 90% maize feedstock share dominate in all NUTS 3 regions, favoured by higher feed-in tariffs for small-scale plants with a minimum 10% manure share. Only in SO are some 2000 kW_{el} units with a 99% maize feedstock share constructed at low price levels for maize and after a high number of iterations, i.e. when the small-scale plants have used up most of the available manure.

Finding large-scale plants in SO is the outcome of somewhat lower harvesting radii in SO combined with a low variance in arable land shares, which cause transport costs to rise relatively slowly from one iteration to the next (see equation (5) in section 3.1. Figure 7 shows how different variances impact changes in transport costs per t of maize during the iterative solving process. Homogeneous land distribution (low variance, black line) lets per unit transport costs for maize rise moderately with demand quantities, whereas the increase of transport costs is strongest (light grey line) for the highest variance plotted. This implies that in regions with identical mean arable land shares but a more homogenous distribution of land, i.e. a lower variance, the first plants built in the solving process face higher per unit transport costs compared to regions with a higher variance, whereas lower transport costs increase during iterations.

Compared to small-scale plants, the ROI of large-scale biogas plants is less affected by transport costs. Large-scale plants show economies of scale, i.e. lower operational costs and a higher energy efficiency per investment cost and therefore lower feedstock demand per invested €, but also receive lower feed-in prices under the EEG. At a low sum of feedstock and per unit transport costs, i.e. the initial situation with no plants erected, the output price effect dominates. In other words, small-scale plants show a higher ROI and are erected first. If the collecting radius increases as locations with high feedstock availability are already occupied, the relative cost increase for small-scale plants is higher. First, they use smaller trucks so that per unit and km transport costs are higher compared to large-scale plants, and secondly, they require more feedstock per unit produced. As a result, after a large amount of feedstock is used by newly erected plants, the ROIs of 2000 kW_{el} plants exceed that of 500 kW_{el} plants.

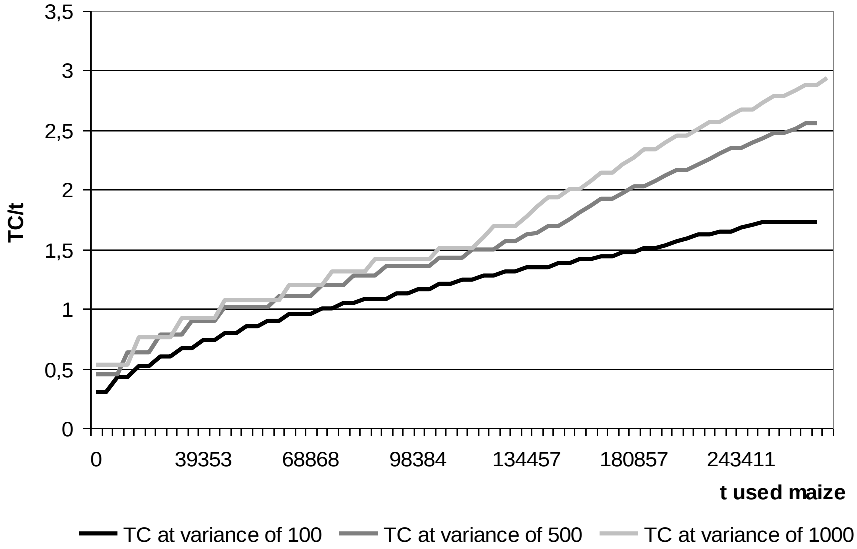


Figure 7: Influence of homogeneity on tc per t

4.3 *Market clearing prices and quantities*

Coupling maize demand at different prices from ReSI-M with maize supply curves from RAUMIS allows for a determination of market clearing prices and quantities (see section 3.7). First we will use the NUTS 3 regions introduced above to again illustrate the reasons for different regional outcomes and then we will show simulated shares of maize production on arable land for Germany. Figure 8 reports maize markets for SO and UNQ. As can be seen, both in SO and UNQ, the first plants, which are based on high manure shares and face low transport costs, are profitable even at rather high feedstock prices. For UNQ we simulate a higher market clearing price (at the intersection of the black lines), caused by a steeper supply curve, stemming from RAUMIS, and a demand curve lying above the SO curve for the relevant quantities stemming from ReSI-M.

Compared to UNQ the grey demand curve for SO drops faster until approximately 30€/ton, as the variance for the arable land share is higher. Thus, only few plants can be erected at locations with high feedstock availability in their vicinity and per unit transport costs will therefore increase rapidly as plants have to be erected at locations where feedstock availability is low. However, with the flatter grey supply curve for SO and therefore also greater maximal feedstock available, the demand curve extends further compared to the UNQ. Market clearing prices in SO – see the intersection of the grey supply and demand curves for SO - are thereby lower and quantities higher compared to the intersection of the black ones for UNQ.

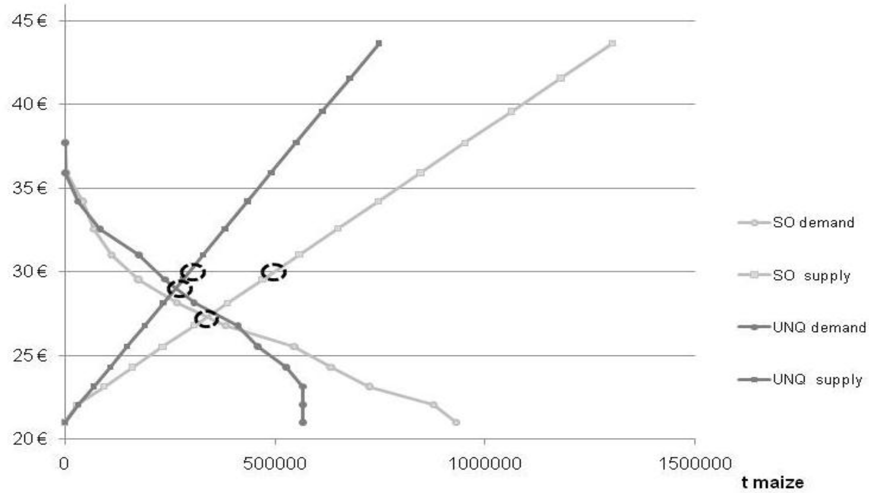


Figure 8: Maize markets in SO and UNQ

As previously mentioned, many studies assume a break-even price for maize of 30€/t for bio-gas plants (cp. URBAN et al., 2008, HOFMANN et al., 2005) and GÖMANN et al. (2007) determine feedstock supply from there. The two upper circles in Figure 8 illustrate maize supply at 30€ for the two NUTS 3 regions. Our analysis suggests considerably lower market clearing prices and quantities and consequently lower impacts of the legislation on farm income or the environment, for example. Indeed, for SO, our analysis suggests roughly half of the market size compared to the 30€/t assumption (see Figure 8).

Regional market clearing quantities can be computed into the amount of land needed for maize cultivation (in ha). The amount of arable land differs considerably between regions in Germany. Therefore, to make the area used for maize production regionally comparable, we relate it to the total arable land in a region. The resulting regional shares are shown in Figure 9 for Germany. Regions with a high share of maize production on arable land are located in large parts of Hessen and Middle Franconia (dark shaded). In some regions in Upper Bavaria (south Germany), the area used for agricultural production is very small, and thus in relation the share of maize production is high. Regions with little livestock and dairy production delivering small amounts of manure as well as regions dominated by vegetable and crop production (especially Schleswig-Holstein in Northern Germany and Brandenburg in eastern Germany) show a low share of maize production for biogas (light regions).

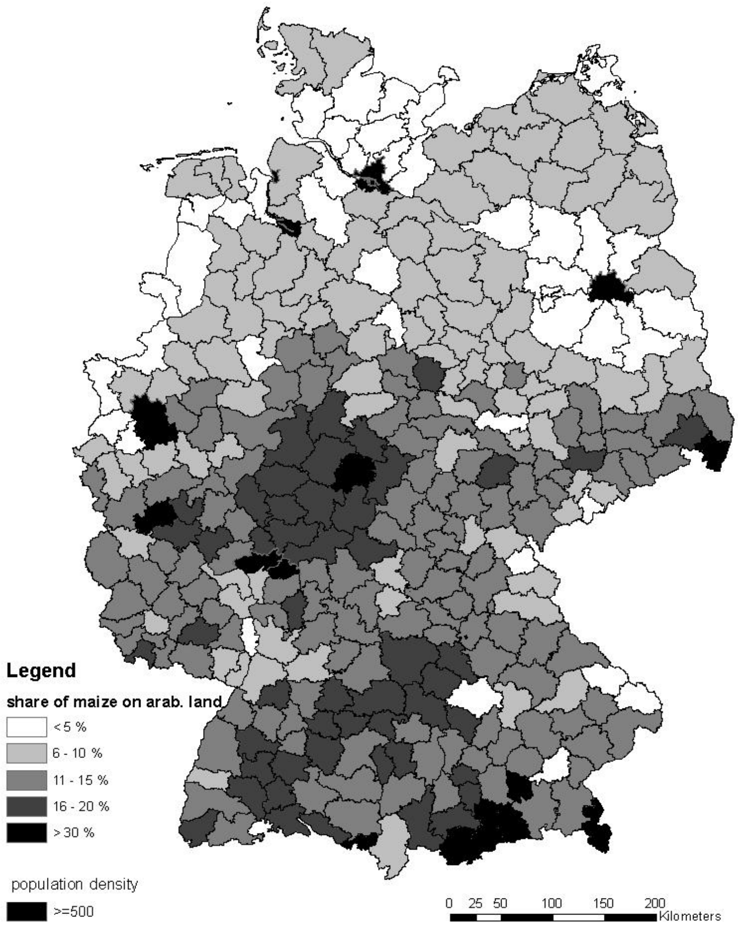


Figure 9: Share of maize on arable land in Germany's NUTS 3 regions

5 Summary and conclusions

The paper proposes a new methodology to simulate locations and sizes for processing plants when the number of possible combinations is very high. Compared to existing literature, the methodology allows for higher flexibility in decision rules to determine type-location combinations. It also allows us to treat both input and output quantities as endogenous. Furthermore, based on our iterative algorithm, parameter changes are possible based on results from previous iterations. In our application the latter allows for spatial heterogeneity to be taken into account, which lets per unit transport cost increase depending on the number of already erected plants. Finally, the iterative algorithm promises considerably reduced solution times for large-scale applications.

The methodology was successfully implemented into the ReSI-M framework, which simulates the number of biogas plants by size and sub-regional location for all ~350 NUTS 3 regions of Germany at different green maize prices and derives

regional demand curves from there. Adding supply curves from a regionalised economic model of German agriculture allows simulating market clearing prices and quantities for green maize.
ReSI-M is sourced, among others, by a detailed GIS analysis which calculates per unit transportation costs for feedstock based on high resolution land use maps.

The framework and method were tested on simulations relating to German legislation guaranteeing feed-in prices for electricity from biogas processing, adjusted by plant size and feedstock mix. The results under the current policy suggest the erection of mainly medium-size plants, which corresponds with what can be observed in reality. Compared to existing literature, ReSI-M adds regionally differentiated market clearing prices. Our results indicate that previous studies might have overestimated energy maize production in regions where feedstock availability is low. Further on, we have shown the importance of energy efficiency for market clearing quantities and prices and, to a lesser extent, for determining the most profitable plant types.

Generally, the framework shows that the proposed methodology can efficiently simulate markets characterised by small-scale demand units and high, spatially inhomogeneous transportation costs, as found for many promising inputs for bioenergy such as bulky raw materials for second generation biofuels.

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Appendix
GIS-analysis

Based on land use data “HSMUs” by LEIP et al. (2008), for each NUTS 3 regions, the overall share of arable land on total land area and also the variances of these shares are calculated using the ArcGIS tool box. The data is available for raster cells of one square kilometre, but as raster cells with equal attributes are merged in the database, they still show variations in size. Thus, the overall share per NUTS 3 region is weighted according to the size of each raster cell. Applying the analysis tool “statistics”, for each German NUTS 3 region, the respective mean arable land share of total land as well as their variances is calculated.

These values are used to set up a Probability Density Function (PDF) of a continuous uniform distribution. This function is defined as:

$$f\left(x\right)=\begin{cases}\dfrac{1}{b-a} & \text{for } a \le x \le b,\\ 0 & \text{for } x < a \text{ or } x > b,\end{cases} \tag{1}$$

where the parameter *a* and *b* are its maximum and minimum values.

Mean $\bar{x}$ of this function is

$$\bar{x}=\frac{1}{2}(a+b) \tag{2}$$

and variance of this function is

$$\sigma=\frac{1}{12}(b-a)^2 \tag{3}$$

The calculated arable land share of total land is equal to $\bar{x}$. As $\bar{x}$ and σ are gained from the GIS-analysis, we receive *a* and *b*. If we substitute them into the PDF we get the slope of transport costs (compare section 3.1).