# Locating the position of a scenario projection in solution space


Judith A. Verstegen
University of Münster,
Institute for Geoinformatics
Heisenbergstraße 2
Münster, Germany
j.a.verstegen@uni-muenster.de

Floor van der Hilst
Utrecht University,
Copernicus Institute
Heidelberglaan 2
Utrecht, The Netherlands
f.vanderHilst@uu.nl

Derek Karssenberg
Utrecht University,
Department of Physical Geography
Heidelberglaan 2
Utrecht, The Netherlands
d.karssenberg@uu.nl



**Abstract**

Geosimulation models are used in various domains to make projections for a set of scenarios, characterizing different future story lines. An impact assessment is applied on the results hereof to compare scenario outcomes with respect to given indicators. The impact assessment, however, does not represent the complete solution space of indicator values, meaning that it is unclear how optimal the best-performing scenario is. In this paper, we explain how the addition of an optimization approach to a scenario projection impact assessment can reduce solution-space uncertainty. This helps policy makers to place scenario results in context, by providing them with information about the relative performance and improvement potential in terms of impact indicator values. This idea is illustrated by a case study of land expansion for ethanol production in the state Goiás, Brazil, for 2030. Impact indicators production costs and greenhouse gas (GHG) emissions are first calculated for a Business as Usual scenario projection from a land use change model. Next, optimal values for these indicators are determined through optimization of the land use configuration. Projected production costs are 729 $US\$_{2014}$ / $m^3$ ethanol, with GHG emissions of 40 kg $CO_2$-eq / $m^3$ ethanol. Locating the position of this point in solution space yields two findings. The scenario's relative performance is particularly good in terms of emissions, given that the scenario assumes no added emission strategies. The improvement potential is 50 $US\$_{2014}$ / $m^3$ ethanol, when keeping emissions fixed, or 250 kg $CO_2$-eq / $m^3$ ethanol, when keeping costs fixed.



*Keywords*: geosimulation, optimization, Pareto frontier, land use change, scenarios, Brazil

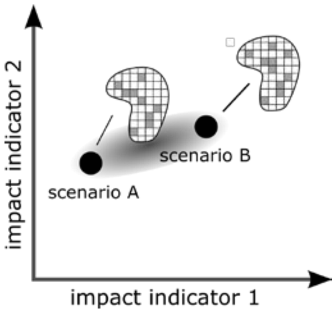

## 1 Introduction

Geosimulation models of human-environment interaction processes are in use for a wide range of application domains, including water demand management (e.g. Galán, López-Paredes and del Olmo, 2009) and land use change (e.g. Verstegen *et al.,* 2016). In most studies, the model is run for a range of scenarios, characterizing the system's drivers for different future story lines. Each scenario results in a, slightly or very, different future system state. Such scenario projections can be combined with impact assessments to compare the values of the different story lines with respect to given indicators.

Well-known examples of scenario projection impact assessment studies are the IPCC assessment reports (e.g. IPCC, 2014). In these reports, the IPPC shows the expected global-mean temperature increase (impact indicator) for different greenhouse gas (GHG) emission pathways (scenarios), using a climate model (geosimulation model).

Yet, the typical results of such studies do not depict the full context (Figure 1). Namely, the scenarios describe a specific set of future story lines, resulting in a specific set of projected system state changes and related impacts. Thereby, scenario projection impact assessment studies give no information on how this specific set of impact indicator values relates to the complete set of potential impact indicator values for the case study area (Seppelt, Lautenbach and Volk, 2013). This imperfect information can lead to imperfect decisions.

Figure 1: Hypothetical results of a scenario projection for two scenarios, A and B. The spatial configurations represent the system states projected for these scenarios by a geosimulation model. The black dots in the plot give the impact assessment results for two indicators, 1 and 2, aimed to be minimized. The grey area is the solution space, fading out in all directions, as the boundaries are unknown.




To illustrate this: when the impacts of two scenario projections are compared (Figure 1), one scenario (scenario A in Figure 1) results in a lower impact than the other one for one or more indicators. But this does not ascertain that this lower impact is the lowest attainable impact, i.e. the optimum. The distance between the low impact and the optimum, marks the theoretic improvement potential. Even if the improvement is not reachable given the available policy instruments, it does provide information on the relative performance of the scenario, thereby putting it in context.

In this paper, the total combined range of values impact indicators can have in a study, is called the solution space. In Figure 1, with two indicators, the solution space is a polygon, encompassing at least the two scenarios, but its shape and extent are unknown. This indistinctness of the set of potential futures, is defined as solution-space uncertainty. All solutions for which it is impossible to improve one indicator, without impairing another, can be expressed quantitatively by a Pareto-optimal set, or Pareto frontier (Baños *et al.,* 2011). This Pareto frontier is one boundary of the solution space, the optima, where the optimality depends on the weighting of the indicators. It is the most relevant boundary of the solution space, as it shows the improvement potentials of the scenarios.

The aim of this paper is to show how solution-space uncertainty in a scenario projection impact assessment can be reduced by finding the Pareto frontier through spatial optimization. Optimization is an approach in which an optimal system state is designed, given one or multiple impact indicator(s) and a range of boundary conditions (Baños *et al.*, 2011). No simulation model is involved in the optimization, meaning that no system dynamics are imposed upon the realization of the optimal system state.

Although one group of researchers has pointed out that the combination of scenario projection and optimization can strengthen efficient decision making in the domain of sustainable land use (Seppelt, Lautenbach and Volk, 2013), there is, to our knowledge, no case study demonstrating this. Our paper presents such a case study. The key terms used in this introduction are summarized in Table 1.

Table 1: Definitions of key terms used in this paper.

| Term | Definition |
|---|---|
| Geosimulation model | A model simulating a system dominated by spatial processes over time |
| Scenario projection | Projection of a system state using a geosimulation model for a specific future storyline |
| Impact assessment | Evaluation of the effect of a projected system state on (an) indicator(s) of interest |
| Optimization | Method to optimize the system state based on (an) indicator(s) of interest |
| Pareto frontier | All system states for which no indicator can be improved without impairing another |
| Solution space | The total combined range of values indicators can cover for all possible system states |
| Solution-space uncertainty | The (shape and extent of the) solution space is completely or partly unknown |

# 2 Methods

## 2.1 Case study

An important current policy making issue that relies much on scenario projections, is the profitability and environmental sustainability of biofuels (Tempels and Van den Belt, 2016). A key player in the biofuel market is Brazil. The bulk of biofuel produced there, is ethanol from sugar cane. Whereas in previous decades sugar cane expansion in Brazil was concentrated in São Paulo state, recently Goiás has been experiencing a fast growth of sugar cane area (Adami *et al.,* 2012). Because this growth is expected to continue in the near future, Goiás was chosen as a case study area. Goiás is situated in central Brazil (Figure 2).

The production of ethanol from sugar cane has four phases: 1) Acquisition and preparation of land for the sugar cane plantation; 2) Sugar cane cultivation and harvest; 3) Transport of the harvested cane to the mill, the ethanol production facility; and 4) Processing of the sugar cane into ethanol.

## 2.2 Impact assessment

As described above, the biofuel debate involves two main issues: profitability and environmental sustainability. We have selected one impact indicator for each issue: production costs and GHG emissions. All four phases mentioned above involve both a production cost and a GHG emission component. Total production costs, $c$ (US$_{2014}$ / m$^3$ ethanol), are therefore:

$$c = c_l + c_c + c_t + c_p \qquad (1)$$

In equation 1, $c_l$ are the land costs (e.g. land rent), $c_c$ are the cultivation costs (e.g. fertilizers and machinery), $c_t$ are the transport costs, and $c_p$ are the processing costs that include revenues from selling produced electricity to the grid. All are in the unit US$_{2014}$ / m$^3$ ethanol. Correspondingly, total emissions $e$ (tonne $CO_2$-eq / m$^3$ ethanol) are:

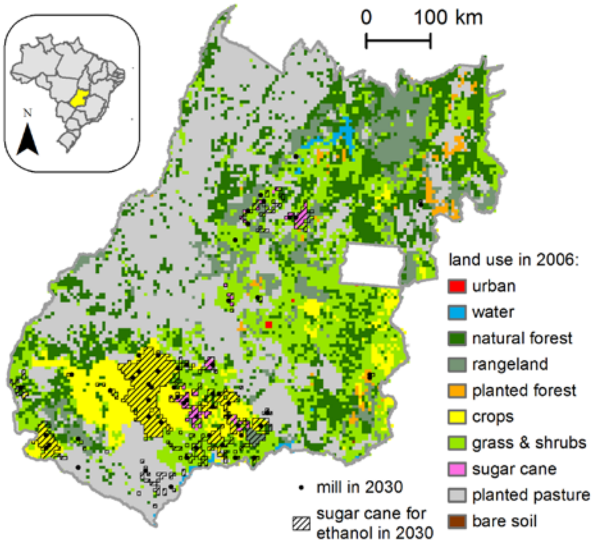
$$e = e_l + e_c + e_t + e_p \qquad (2)$$

In equation 2, $e_l$ are the land emissions (e.g. above ground carbon stock change), $e_c$ are the cultivation emissions (e.g. fertilizer emissions), $e_t$ are the transport emissions, and $e_p$ are the processing emissions that include abatements from the produced electricity. All are in the unit tonne $CO_2$-eq / m$^3$ ethanol. Note that we calculate costs and emissions at the 'factory gate', meaning that the revenues from selling the ethanol and the avoided emissions from the replacement of fossil fuel by the ethanol are not included. The cost and emission component calculations are based on two papers by Jonker *et al.* (2016, 2015).

## 2.3 Scenario projection

We use an existing Business as Usual (BAU) scenario projection of land use change from Verstegen *et al.* (2016) for the 2030 configuration of sugar cane fields for ethanol. It is combined with results from Jonker *et al.* (2016) for the placement of the ethanol mills (Figure 2). We need the locations of the mills to compute the transportation costs and emissions, and the scale of the mills to compute the processing costs (variable through the economies of scale principle). With these, both impact indicator values, $c$ and $e$, can be calculated for the BAU scenario.

Figure 2: Land use in Goiás, Brazil, in 2006 and the projected locations of sugar cane fields and mills for ethanol in 2030. The inset shows the location of Goiás within Brazil.




Main sources: 2006 data: Globcover (Arino *et al.*, 2008) and Canasat (Rudorff *et al.*, 2010), 2030 data: Verstegen *et al.* (2016), and Jonker *et al.* (2016).

### 2.4 Optimization

To fairly compare the impact indicators of the scenario projection and optimization results, both should involve the same amount of ethanol (boundary condition). In the projection, 10.2 million $m^3$ ethanol is produced (calculated from Jonker *et al.*, 2016). So, the goal of our optimization is to allocate sugar cane fields and ethanol mills producing 10.2 million $m^3$ ethanol, in such a way that the combined value of the two impact indicators is minimal.

The two impact indicators, production costs and GHG emissions, can be combined into a single objective via a carbon price:

$$x = c + e \cdot p \tag{3}$$

In equation 3, $x$ (US$_{2014}$ / $m^3$ ethanol) are the aggregate costs (production costs plus GHG 'costs') that we aim to minimize and $p$ (US$_{2014}$ / tonne $CO_2$-eq) is the carbon price. The Pareto frontier between the production costs ($c$) and GHG emissions ($e$) of ethanol, i.e. one solution-space boundary, is found by minimizing the aggregate costs ($x$) for different carbon prices ($p$). The carbon price determines the weighting of the two indicators. Five different carbon prices are used: 0, 10, 100, 200 and 400 US$_{2014}$ / tonne $CO_2$-eq. In addition, we optimize once on emissions only, to get the minimum attainable emissions (minimum attainable costs are reached at a carbon price of 0 US$_{2014}$ / tonne $CO_2$-eq).

The optimization is performed with a genetic algorithm (GA), because this algorithm has proved to generate good results for optimization problems like ours (e.g. Stewart, Janssen and van Herwijnen, 2004). A GA mimics the process of natural selection in a population of solutions, called individuals (Baños *et al.*, 2011). The genes of the individuals encode the spatial configuration of sugar cane fields and mills. Through mutation and cross-over, the population evolves towards better solutions, i.e. lower aggregate costs, $x$. The best performing individual of the final evolved population is the optimal solution for the appointed carbon price, $p$. We use a population of 1000 individuals. The GA settings, such as the mutation rate, are determined by performance tests.

## 3 Results and discussion

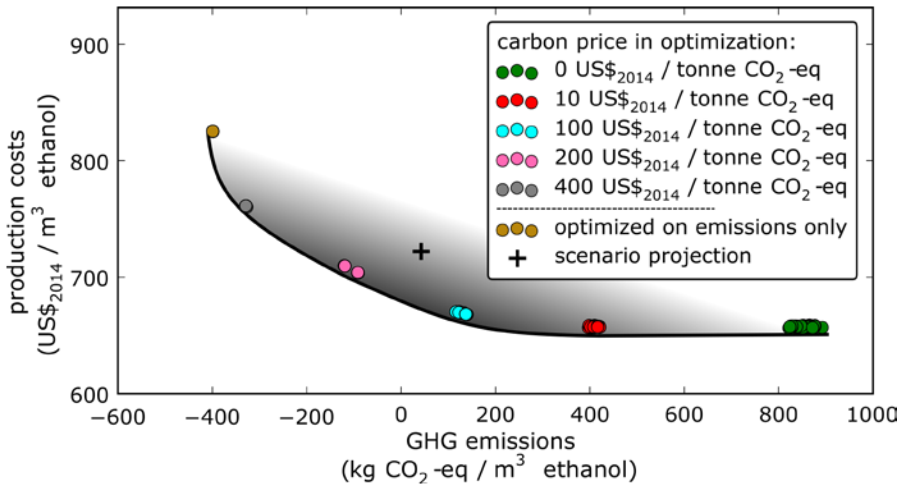
The impact assessment of the scenario projection yields production costs of 729 US$_{2014}$ / $m^3$ ethanol and GHG emissions of 40 kg $CO_2$-eq / $m^3$ ethanol (Figure 3). Without the results of the optimization, it would be unclear if this should be considered high or low, or good or bad, because the boundaries of the solution-space are unknown. One can compare the values with values reported in literature, but both indicators are very dependent on the study area location and on the total amount of ethanol produced. It is unlikely, that a comparative study for Goiás for the production of 10.2 million $m^3$ in 2030 can be found (except for the one we are using the results from).

The optimization generates the Pareto frontier, one boundary of the solution space (Figure 3). It ranges between 826 US$_{2014}$ / $m^3$ ethanol with -399 kg $CO_2$-eq / $m^3$ ethanol in the upper left of Figure 3, and 656 US$_{2014}$ / $m^3$ ethanol with 810 kg $CO_2$-eq / $m^3$ ethanol in the lower right of Figure 3, in a concave shape.

Knowing the lower-left boundary of the solution-space, leads to two findings. The first is the relative performance of the BAU scenario for both indicators. For example, the projected GHG emissions would be optimal for carbon prices between 100 and 200 US$_{2014}$ / tonne $CO_2$-eq. Given the fact that currently no carbon pricing system is installed in Brazil, one would expect results close to a carbon price of 0 US$_{2014}$ / tonne $CO_2$-eq. The relatively low emissions of the BAU scenario might be caused by other established conservation policies, such as national parks. Another reason is that some economic drivers automatically lead to relatively low emissions. An example is the preference for locations with high-yielding soils, often reducing not only costs but also emissions, e.g. because this requires less fertilizer per kg cane. Both dynamics were explicitly (a model rule) or implicitly (through calibration) captured in the geosimulation model structure, bringing about the observed projection results.

The second finding is the improvement potential. In theory, production costs could be lowered by about 50 US$_{2014}$ / $m^3$ ethanol compared to the projected costs, while keeping the projected GHG emissions (Figure 3, vertical distance to Pareto frontier from the +). Along the same lines, while keeping the projected production costs, GHG emissions could be lowered by about 250 kg $CO_2$-eq / $m^3$ ethanol, thereby reaching negative emissions (Figure 3, horizontal distance to Pareto frontier from the +). It should be noted that there can be costs and emissions related to changing the land use system in such a way that these optima are reached, such as the provision of subsidies to farmers to make them locate sugar cane plantations where they otherwise would not. These are not included in the calculations.

Figure 3: Pareto frontier (black solid line) between GHG emissions and production costs, constructed from optimization for different carbon prices (colored circles, one for each individual in the best 10% of the final GA population), the resulting solution space (grey area, fading out towards the upper right of the graph, as the boundary in that direction is unknown), and the position of the scenario projection within this solution space (black plus sign).




These two findings can assist policy-makers to decide if the best scenario performs good enough to implement it. If not, the system state belonging to the point on the Pareto frontier desired to be reached can be compared with the system state of the scenario results (Figure 1) to help designing better policy options than the ones in the original scenario. This spatial comparison is beyond the scope of the paper.

Our optimization only yields the minima, or minimal combinations, of the impact indicators. This means there is still solutions-space uncertainty left: the position of the upper-right boundary in Figure 3 is unknown. In our analysis this boundary is irrelevant, because we are interested in the improvement potential in the impact indicators. One could determine the second boundary by running the optimization with a reversed goal: maximizing the aggregate costs, *x*. Results hereof might be relevant when one is interested in the question “How much worse could it be?”. But most will be interested in the boundary of optima, the Pareto frontier.

## 4 Conclusion

In this paper, it is shown how solution-space uncertainty in a scenario projection impact assessment can be reduced by finding the Pareto frontier through spatial optimization. The reduced solution-space uncertainty allows policy-makers:

1. To see how a scenario performs in terms of impact indicators with respect to the optima (shown in this paper).
2. To improve scenario design by assessing the differences in impact indicator values (shown in this paper) and system states (not shown in this paper) between a scenario and the optima.

The approach is of particular use for studies in which the scenarios represent different policy options, management strategies or other conditions that can be influenced, such as in renewable energy planning (Baños *et al.*, 2011), or in spatial planning in general (Seppelt, Lautenbach and Volk, 2013).

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