Utrecht University

Geosciences

Judith A. Verstegen
(j.a.verstegen@uu.nl)

Multi-Objective Spatial Optimization for Sustainable Landscape Design

Background

Sustainability has a multitude of dimensions, reflected by the sustainable development goals. Designing sustainable landscapes thus implies accounting for multiple **objectives**, which may be compatible or may conflict with each other (Figure 1). For example, reaching zero hunger (SDG 2) in a certain area may conflict with maximizing life on land (SDG 15), through deforestation by cropland expansion.

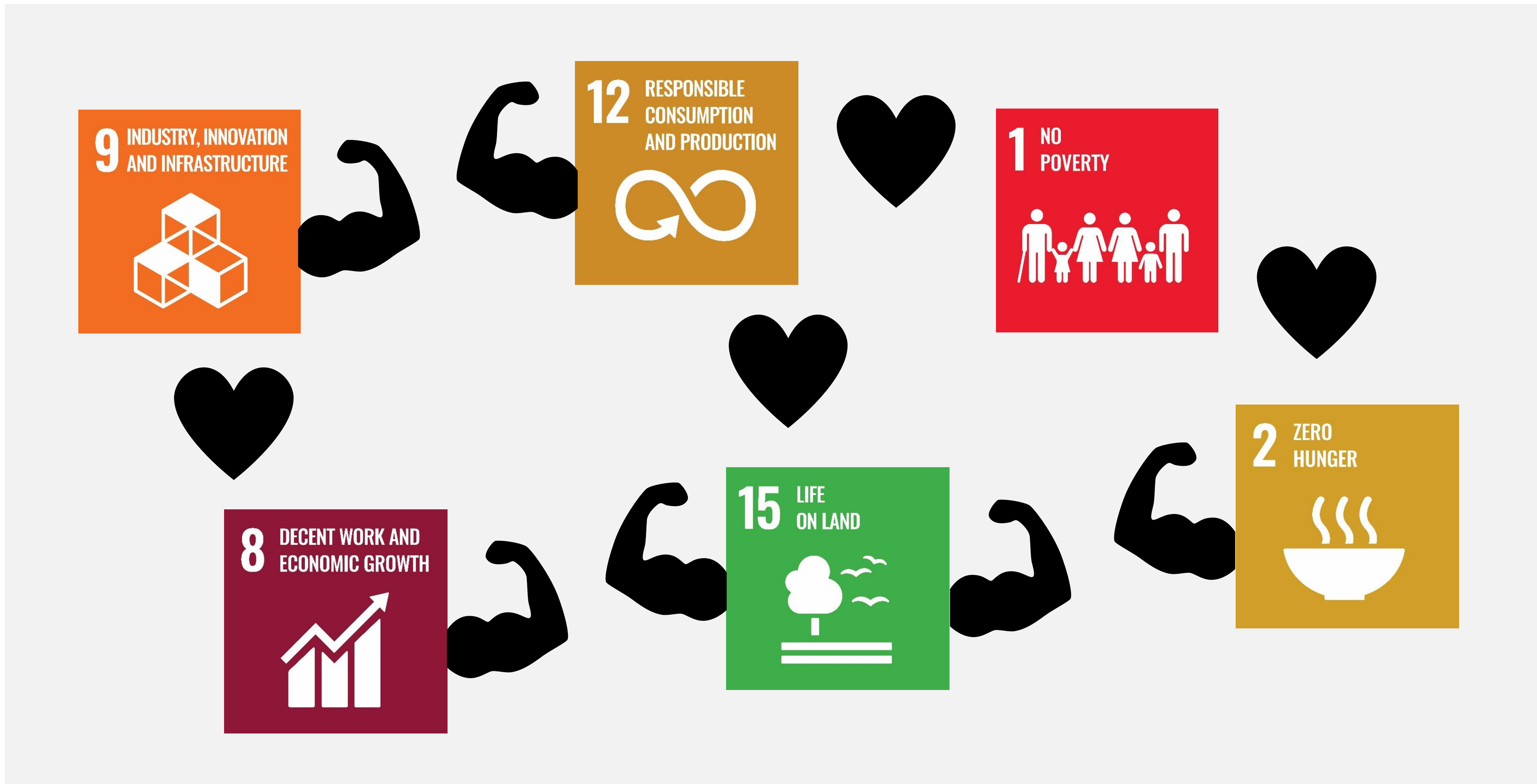

Figure 1. Some Sustainable Development Goals (SDGs) are compatible, while others conflict; simplified representation, as in reality synergies and trade-offs are place- and time-dependent.

Computational methods

Quantifying synergies and trade-offs between these objectives can serve the landscape-design process. **Multi-objective spatial optimization methods** offer this quantification. Our work is in 1) the **representation of space** in such methods, 2) the **consideration of uncertainty** in the spatial input data, and 3) the **integration of geosimulation and spatial optimization** methods.

Representation of space

Genetic algorithms are the most commonly used multi-objective optimization methods. To apply them to *spatial* optimization problems, spatial arrangements (phenotype) need to be denoted by chromosomes (genotype). This brings about challenges to keep **spatial relations** intact in optimization processes, when cross-over and mutation alter the chromosomes (Figure 2).

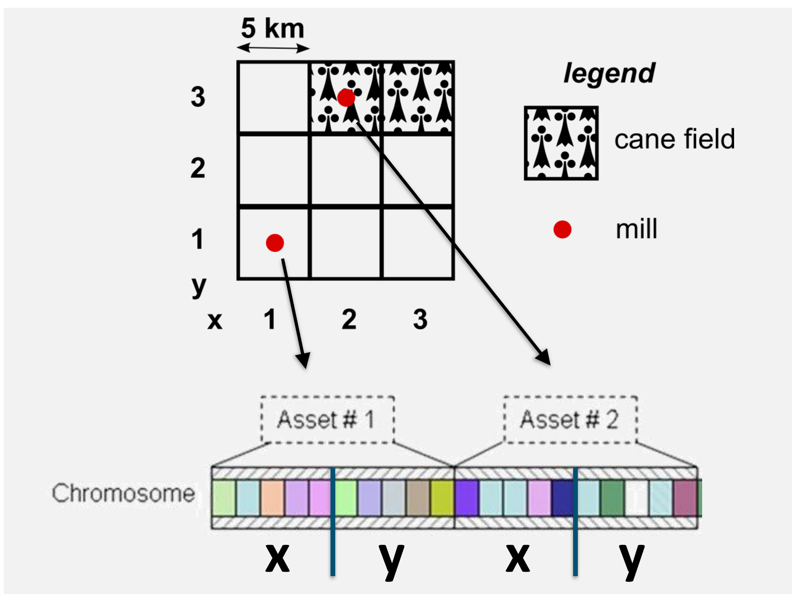

Figure 2. Translation from the spatial arrangement of assets (here sugar cane mills) to chromosomes, still allowing small and large jumps to avoid local minima.

Consideration of uncertainty

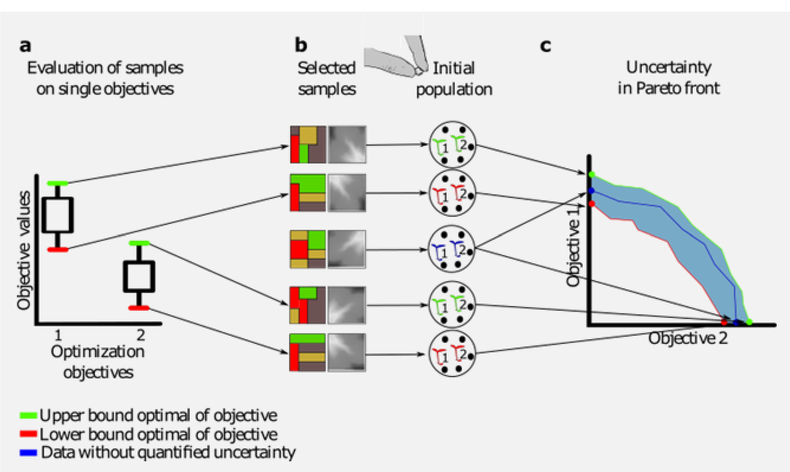

Figure 3. Approximation of Pareto interval: a) sample spatial data, compute objectives, b) Seed extremes into genetic algorithm, c) Run GA 5x (Hildemann & Verstegen, 2021).

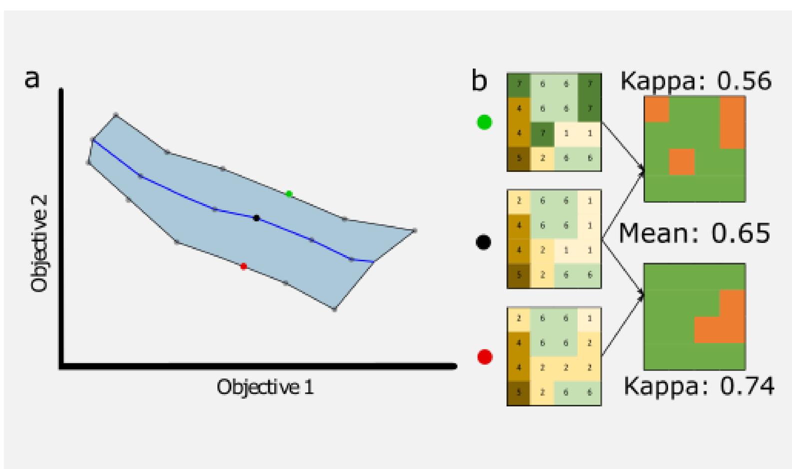

Figure 4. a) A Pareto interval between two objectives and b) spatial similarity (Kappa) of solutions in this interval (Hildemann & Verstegen, 2021).

Spatial data contain uncertainty, which propagates to the Pareto front. We quantify uncertainty in a Pareto front by finding the extreme lower and upper bound of optimal values in the objective space: a **Pareto interval** (Figure 3). Spatial similarity between solutions in the interval shows the resulting landscape design uncertainty (Figure 4).

Integration of geosimulation and spatial optimization

Geosimulation modelling simulates the **future state** of a system under predefined (feasible) scenarios. An impact assessment can be applied to compute the sustainability of these states. However, the rest of the solution space remains unknown (Figure 5). In contrast, multi-objective spatial optimization finds states with minimal impact. Yet, it does not tell whether these states are feasible to reach. Integrating both approaches resolves these weaknesses.

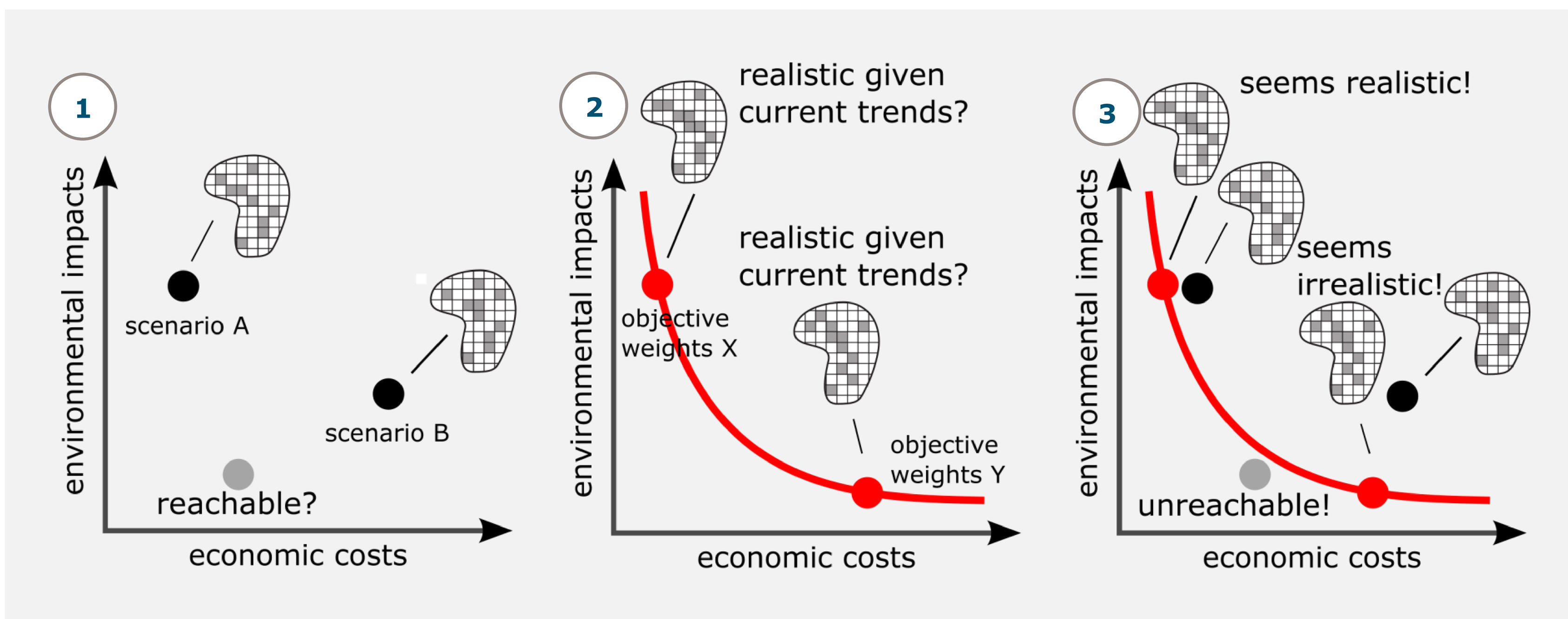

Figure 5. Schematic representation of a land use change impact assessment for two sustainability dimensions, economic costs and environmental impacts, with 1) two scenarios A and B from a geosimulation model, 2) the Pareto front resulting from spatial optimization, and 3) the integration of geosimulation and spatial optimization (Verstegen et al., 2017).

References

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Judith A. Verstegen, Assistant Professor
Utrecht University, Human Geography and Spatial Planning
Contact: j.a.verstegen@uu.nl