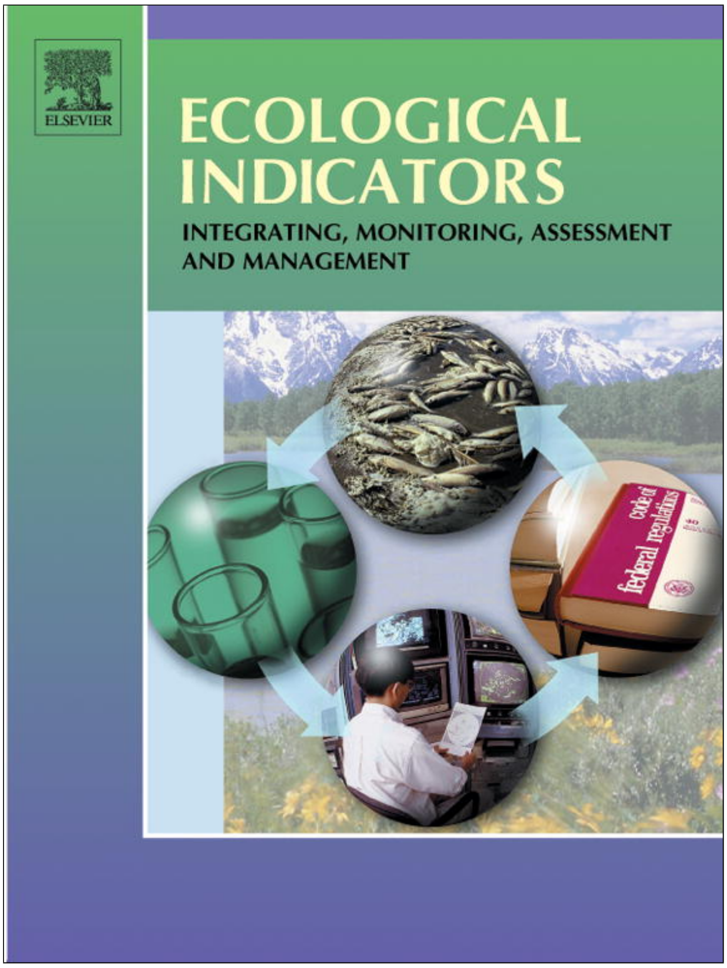
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Framework for the inter-comparison of ecological footprint of universities

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ABSTRACT

The ecological footprint (EF) method represents the suitability of a given population on the carrying capacity of the total system. It was developed in order to measure the relationship between nature and humans, being supported on the premise that each individual requires a surface area that provides goods and services essential to life. In this article only in EF for universities is studied, but most of the underlying concepts and methods are valid for any other human activity for which EF may be applied.

In this study an uncertainty analysis of EF of universities is made. This is, to the authors' knowledge, the first time such a study is published on the subject. The intention is to demonstrate the usefulness of uncertainty analysis in the evaluation of results, inter-comparability, and on communication of EF outcomes.

Results showed that EF model uncertainties have large impact on EF estimates, in particular in what regards the decision about accounting or not the contribution of key parameters. Inclusion or not of very sensitive parameters, for which there is also high uncertainty, in the estimation of EF may have a strong impact on the estimated values and also in the inter-comparability of EF estimates. This is the case of mobility.

Uncertainty analysis, by studying model uncertainty, parameter uncertainty and variability, can provide a robust framework for the inter-comparison of ecological footprints of universities. In fact, the method may prove useful for the assessment of ecological footprints of any kind.

1. Introduction

In the introductory paragraph of the Talloires Declaration for sustainability, university presidents, chancellors, and rectors state their commitment to environmental sustainability in higher education, and their concern about the unprecedented scale and speed of environmental pollution and degradation, and the depletion of natural resources. They agreed in promoting the creation of an equitable and sustainable future for all humankind, namely by increasing awareness of environmentally sustainable development, creating an institutional culture of sustainability, educate for environmentally responsible citizenship, fostering environmental literacy for all, and practice institutional ecology. Many of these objectives are well answered by the ecological footprint (EF).

Wackernagel and Rees (1996) proposed EF as a quantitative method to measure sustainable development and impact of human activities. According to the authors, EF is the 'load' imposed by a given population on nature, being an accounting tool that enables us to estimate the resource consumption and waste assimilation requirements of a defined human population or economy. It is accounted in terms of a corresponding productive land area, as the amount of nature mankind occupy in order to live (Wackernagel et al., 1999; Wackernagel and Rees, 1996). The method represents the suitability of a given population on the carrying capacity of the total system. In theory, EF is estimated by determining how much land area would be necessary to produce all the goods consumed, and to assimilate all the wastes generated by a human activity. Thus, it expresses the load on the environment caused by the system under study. It was developed in order to measure the relationship between nature and humans, being supported on the premise that each individual requires a surface area that provides goods and services essential to life. There has been a widespread interest in the methodology, which led to it being included in the European Commission's Common Indicator set for regional sustainability (ECIP). Along with this interest also the need for standardizing methodologies has grown in order to reduce discrepancies. This has ultimately resulted in the formation of the Global Footprint Network (GFN),

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which has so far concentrated on the standardization of methodologies for EF of nations, cities, and finance. Educational facilities have not been included yet. Probably, as a result of this lack of guidance, EF accountings for university facilities vary substantially, much due to methodological differences, in particular in how some key variables are accounted.

As yet, proposed EF methodologies have concentrated in making the process of calculation as simple as possible, but in doing so, large amounts of information are discarded. In particular, the variability in the data supporting the calculations and the uncertainty inherent to the methodologies has been largely overlooked. In contrast to the classic deterministic approach, probabilistic evaluation of the EF is here proposed, with which much more information can be retrieved from the supporting data and be transposed to easily interpretable outputs. We focus on EF of educational facilities, in particular universities, but the method may be applied to any other human activity.

Due to the uncertainty, irreversibility and complexity that characterize global environmental problems, conservation messages are strengthened when people can use prior experience to assess new information, i.e., when inter-comparability is possible (Faucheux and Froger, 1995). Several authors have stated that in face of uncertainty, people increase the intertemporal flexibility of the decisional strategy, being more environmentally conservative (Borgonovo and Peccati, 2007; Vercelli, 1991), which plays in the same direction as the message conveyed by EF. Having these conclusions in mind, the following paragraphs will discuss how uncertainty analysis may contribute to strength EF message by explicitly quantifying the uncertainty about results and by providing a framework for inter-comparison of studies. Methods will be detailed for Monte Carlo simulations as the methodology here proposed does not require advanced statistical skills.

Our working question is: Is the ecological footprint of universities comparable? Or are the fundamental parameters in the model too different? In this article we state the hypothesis that uncertainty analysis can help in assessing the relevancy of parameters and in making the distinction between parameters. We test the hypothesis with a case-study similar to many others around the world, but we introduce in the analysis both epistemic and aleatory uncertainty and evaluate how these two sources of uncertainty can affect inter-comparison.

Uncertainty includes epistemic uncertainty and aleatory uncertainty. Though several other classifications have been proposed (Helton and Davis, 2003; Khuri and Mukhopadhyay, 2010; Myers, 1999; Saltelli and Marivoet, 1990; Shih et al., 2009), in general all agree about these two major divisions. Epistemic uncertainty is the scientific uncertainty about the model itself, namely on appropriateness to model a given problem, about the equation and its parameters, and about the modelling domain, boundary and initial conditions. All parameters are also subject to epistemic uncertainty as their measured values depend on decisions about data collection methods or data transformation. As a consequence, discussion about epistemic uncertainty relies on different perspectives of how the system should be represented and many times on what is it representing.

Epistemic uncertainty is related to model's strengths and weaknesses. Frequently mentioned strengths are (Rees, 2000): (i) it incorporates several defining qualities of ecological economics; (ii) is comparable to other measures of human impact, such as Ehrlich's and Holdren's (1971) definition of human impact on the environment, and human 'load' as defined by Catton (1980); and (iii) is conceptually simple and intuitive. The weaknesses of EF are Fiala (Fiala, 2008; Rees, 2000): (i) it does not capture the full range of ecologically significant impacts on the ecosphere; (ii) it over-simplifies nature and society, having little predictive value; (iii) is not dynamic modelling; and (iv) cannot be used for detailed forecasts; (v) cross-country comparisons of the ecological footprint rely on boundaries that are arbitrary, and thus potentially meaningless; (vi) arbitrariness of assuming both zero greenhouse gas emissions and national boundaries; and (vii) it is a measure of inequality as EF is strongly related to human development.

Some other problems have been referred due to incorrect implementation of EF, namely (Herendeen, 2000): (i) confounding sustainable and conventional (unsustainable) agriculture in calculating 'food land' – sustainable agriculture would require more land per unit of food, increasing EF; (ii) using the net CO_2 sequestering potential of an immature, successional forest as 'energy land', which can lead to both under and over-estimation of CO_2 uptake; (iii) considering only gross, not net, imports and impacts. This latter argument is particularly important when dealing with universities, which are activities inside a larger system (country), as it raises the problem of accountability: for instance, the atmospheric emissions made during the transport of staff, faculty and students between their place of residence and the university is a footprint of the university, or external to it? One may argue that emissions are an unavoidable consequence of its existence, in which case it should be accountable for. However, the decision about its location, transport network and residential park is usually a responsibility of the state, therefore a very significant share of the emissions is due to planning options over which the university has very little control. Then, should the university be made accountable for the emissions? Why not also account all emissions produced during the transport of other goods, such as food, paper, mail, from the energy needed to transport water, etc.? This also raises the problem of the arbitrariness of boundaries as referred by Fiala (2008): where is the system boundary? At the university walls/fence, or at some, to be defined, distance? One solution is to set the boundary at the fence and account in EF only what is effectively consumed internally. This is more in agreement with the concept of net EF as all impacts made between the production and transportation are attributed to the activity of third parties: the university accounts for EF of the production, irrespective of where it was produced. A more in depth discussion on the subject was made elsewhere (Frey, 1992).

The calculation of EF requires that a detailed mass and energy balance should be made for the activity, quantifying inputs and outputs that may have relevant impacts. The following consumption categories have been identified by authors for EF of universities (see references in Table 6): energy consumption for lighting and climatization, fuel for heating, consumption of water, paper, and food, emissions due to mobility (vehicle emissions), and built area. Production of wastewater has been either overlooked or treated together with the consumption of water (with many simplifications, namely by accounting only energy use, and not the emission of, e.g., methane and nitrous oxide). Wastewater treatment relative weight for the total EF has been indicated as equal to that of tap water production: Jenkin and Stentiford (2005) refer 0.004 ha/person for the first and 0.005 ha/person for the latter. Such a methodological simplification may be justified by the still very limited number of EF studies on the subject.

Aleatory uncertainty represents the diversity or heterogeneity in a well characterized population, refers to the natural variability of the process being evaluated, and unlike the epistemic uncertainty it cannot be reduced by further study or measurement. This is not to say that measurements are not necessary, quite on the contrary as the quantification of variability requires that a representative number of samples should be taken from the population.

Mathematical representations of both aleatory and epistemic uncertainties can be conceptualized as uncertain frequency distributions. With the proper methods one can propagate uncertainty through the model to estimate both aleatory and epistemic uncertainties in the output (Simon, 1999). Even though there are many alternative characterizations of uncertainty (e.g., possibility theory,

Table 1
Epistemic uncertainty in the calculation of EF for universities.

Model epistemic uncertainty (MUN)		Parameters epistemic uncertainty (PUN)	
Origin	Description	Origin	Description
Completeness	Does the model account for all the variables which can significantly affect the results?	Origin of the uncertainty	Is the relevant source of uncertainty being considered, i.e., what parameters are uncertain?
Indefiniteness in the model's characterization	Does the model account for all the relations and descriptions?	Characterization of parameter uncertainty	How is the statistical distribution obtained?
⇓		⇓	
Tested models (see legend)	A1: {B, W, E, M, F, P, WS} A2: {B, W, E, M, F, P, WS, WW} A3: {B, W, E,· · ·, F, P, WS} A4: {B, W, E,· · ·, F, P, WS, WW}	Uncertainty parameters	Mobility; Population; Food

B: built area; W: water consumption; E: energy consumption; M: mobility; F: food consumption at the canteen and cafeteria; P: paper consumption; WS: production of wastes; WW: production of wastewater.

fuzzy set theory, evidence theory, interval analysis) we consider here only probabilistic characterization. For short, we will designate aleatory uncertainty as "variability" and epistemic uncertainty as "uncertainty".

In this study an uncertainty analysis for EF applied to universities is made. This is, to the authors' knowledge, the first time such a study is published on the subject. The intention is to demonstrate its usefulness in the evaluation of results, inter-comparability, and on communication of model outcomes.

2. Methods

2.1. Variability and uncertainty propagation through the model

Variability and uncertainty, in one or more of the model inputs, in a probabilistic assessment may be introduced by second-order random variables. First-order variables represent variability, i.e., the heterogeneity or diversity in a well-characterized population, while second-order random variables also include uncertainty, i.e., partial ignorance or lack of perfect knowledge about a poorly characterized phenomenon which may be reducible through further study (Hart et al., 2003). Second-order (also known as "two-dimensional") Monte Carlo simulation (2D-MCS) has been extensively used to separately propagate uncertainty and variability (Hoffman and Hammonds, 1994). 2D-MCS involves a double nested looping procedure consisting of multiple realizations of model parameters and iterations of input variables. The outcome is a set of cumulative distribution functions simultaneously displaying uncertainty and variability in the results. Several other methods exist for uncertainty propagation, each with some advantages and disadvantages (Pouillot and Delignette-Muller, 2010). These methods include differential analysis (Helton and Davis, 2003; Shih et al., 2009), response surface methodology (Khuri and Mukhopadhyay, 2010; Myers, 1999), Monte Carlo simulations (MCS) (Helton, 2008; Öberg and Bergbäck, 2005; Saltelli and Marivoet, 1990), and variance decomposition procedures (Borgonovo and Peccati, 2007; Li et al., 2001). There has been very limited analysis on uncertainty propagation through the EF model, being the exceptions focused only on the propagation of aleatory uncertainty with probabilistic assessment methods (Li et al., 2001), with fuzzy set theory (Borgonovo and Peccati, 2007), and MCS to evaluate the effect of climate change (Klein-Banai and Theis, 2011). Given the large epistemic uncertainties associated to the models and to the parameters, more frequent complete uncertainty analysis would be desirable.

Consider that results of ecological footprint, $\mathbf{EF}(\mathbf{x}) = [\mathrm{EF}_1(x), \mathrm{EF}_2(x), \ldots, \mathrm{EF}_{nY}(x)]$ are functions of uncertain analysis input parameters $\mathbf{x} = [x_1, x_2, \ldots, x_{nX}]$. Uncertainty in $\mathbf{x}$ will have as a consequence an uncertainty in $\mathbf{EF}(\mathbf{x})$. Two questions are usually put (Helton, 2008): (1) What is the uncertainty in $\mathbf{EF}(\mathbf{x})$ given the uncertainty in $\mathbf{x}$?, and (2) How important are the individual elements of $\mathbf{x}$ with respect to the uncertainty in $\mathbf{EF}(\mathbf{x})$? Uncertainty analysis answers the first question, while sensitivity analysis answers the second.

The second-order random variable, EF, can be approximated using Monte Carlo or Latin Hypercube sampling in nested loops to maintain the isolation between variability and uncertainty as given by the following pseudo-code (Burmaster and Wilson, 1996; Frey, 1992):

```
Begin outer loop for Uncertainty (repeat N_outer times)
  Pick one set of point values from each distribution representing Uncertainty
  Begin inner loop for Variability (repeat N_inner times)
    Compute this one simulation
    Store desired information
  End inner loop
End outer loop
```

Algorithm routine counters N_{outer} and N_{inter} assume usually large numbers, in the order of a few thousand to guarantee the required minimum level of accuracy for the statistics that one is interested in from model outputs (e.g., the mean, and percentiles) – see, e.g., (Thompson, 1992) for methods to determine the exact number. As a rule of thumb, about 3000 runs should be enough for most applications (Vose, 2012).

Table 1 shows the main epistemic sources of uncertainty: model epistemic uncertainty (MUN), and parameters epistemic uncertainty (PUN), i.e., uncertainty in the number and properties of input parameters $\mathbf{x}$. The option here was to separate uncertainty sources as it helps differentiating the component of uncertainty propagation which results from modelling assumptions (i.e., which parameters to include in the model, and mathematical expressions describing the model), from the component due to parameters uncertainty (i.e., the quantification of modeller's uncertainty about their true values) which is handled by the techniques of uncertainty propagation described above.

MUN is only dependent of decisions about what equations to use and what parameters to include. This uncertainty is quantified by testing alternative models and parameters, in a loop external to the outer loop in the pseudo-code presented above, and comparing their results. We tested four models for the quantification of EF, where the only differences were the inclusion or removal of one or two parameters. Model A1 represents the most common description found in literature, being a function of seven major parameters, usually designated consumption categories (Table 1). Model A2 is similar to A1, but the production of wastewater from all activities in the campus is also considered, which is accomplished by adding a second term equal to the consumption of water, multiplied by a coefficient to account for leaks, equal to 0.9. Model A3 includes all parameters of A1, except mobility, hence accounting exclusively for direct impacts. Finally, Model A4 is similar to A2, but excludes mobility.

The definition of the statistical distributions characterizing PUN in the components of **x** is the most important part of the method as these distributions determine both the uncertainty in EF and the sensitivity of the elements of EF to the elements of **x** (Helton, 2008). They are typically defined with the help of experts (Ayyub, 2001), being a costly part of the process. Uncertainty characterization effort should be concentrated on the parameters considered by the analyst as having more PUN. In our case uncertainty was introduced in the parameters population (P), mobility (M), and food (F), as these parameters are less well characterized and the uncertainty about their true value is the highest.

Variability is discussed when presenting the case-study, as it reflects properties of specific parameters.

2.2. Data collection

Different methods were used to collect the data required depending on their availability. Data concerning built land, consumption of materials and energy, and population (students, staff and faculty) were obtained directly from the central offices of the University of Algarve. As data concerning the means of transportation used by the population was not available a specific survey was put in place, as described below. Student's residence halls are outside the university premises and were not accounted.

2.2.1. Food

Food variables were divided into the following categories: meat, fish and shellfish, vegetables, and fruit. Very detailed data on the amount (weight) of each category was provided by the university services, discriminating several sub-categories in each, on a yearly basis.

2.2.2. Electricity and water consumptions

Detailed monthly records were provided by the central services of the university for electricity (kWh/month) and water consumptions (m^3/month).

2.2.3. Paper consumption

Paper consumption per size (A5, A4, A3) was obtained from: (i) data provided by central services; (ii) inquiries made independent reprographies inside the institution. Three types of paper formats were considered: from A5 to A3 and test paper (equivalent to two A4 sheets). Conversion of paper sheets to tones was made by applying a conversion factor of 210,000 sheets/t, as obtained from weighting experiments.

2.2.4. Waste production

The amount of recyclable and general domestic equivalent wastes were estimated considering the deposition capacity (m^3), determined by the number of containers multiplied by their capacity and filling fraction, f_c at the time of collection. Data was obtained by surveys made to personnel responsible for the deposition of wastes. Mass of wastes (t) was obtained by multiplying waste volume (m^3) by the random variable specific weight, ρ_w (t/m^3). Emissions from the trucks used in the collection of the wastes were calculated as for mobility.

2.2.5. Mobility

Emissions from vehicles are an important source of gases into the atmosphere being, in some universities, responsible for the largest footprint (Table 6). There are two main methodologies to quantify these emissions: by measuring at a representative number of vehicles, or by estimation using emission factors. The first method, though much more accurate, takes longer to implement and is a very costly option (both economically and in its footprint). The later requires some base data on the categories of vehicles, travelled distances, and use frequency. This latter option was the one chosen. Data was obtained by surveying the population for the following information: (i) position in the institution; (ii) transport used in the trips to and from the university (passenger car, motorcycle, bus, on foot or bicycle, car sharing); (iii) travelled distance, each way; (iv) type of engine of the vehicle (gasoline, diesel, liquefied petrol gas, other); (v) engine volume; (vi) average velocity used during the trip.

Emissions of carbon monoxide, methane and nitrogen oxides were estimated by multiplying the travelled distance, per engine type and volume, by the corresponding emission factor. These latter were calculated using equations provided in COPERT III – Computer program to calculate emissions from road transport in Europe (Ntziachristos and Samaras, 2000), which uses velocity as the independent variable. Emissions from public transports were weighted by the fraction of BUS passengers that attend the university. Total emission per substance was obtained by adding individual emissions for all vehicle types.

2.3. Ecological footprint

EF was determined by a component-based method, reflecting the four main categories of final consumption: energy, which accounts the area needed to absorb emissions of carbon dioxide, corresponding to electrical energy and fuels; food, corresponding to the area required to produce it; materials, corresponding to the area required to produce primary materials, such as tap water, metals, plastics, paper; and built land, corresponding to areas that became unproductive due to the construction of buildings and other facilities. *Total EF* (total gha) was determined by a weighted sum of the final consumption categories, c_i (t/year), where the weights are the equivalence factors, ef_i (global ha/category ha), divided by the land productivity, p_i (category ha/t/year) (Chambers et al., 2001); *EF* (gha) per person is obtained by dividing the former by the *population*:

$$\text{Total} \quad \text{EF} = \sum_i \frac{c_i \cdot ef_i}{pi} \tag{1}$$

$$\text{EF} = \frac{\text{total} \quad \text{EF}}{\text{population}} \tag{2}$$

Land productivity and equivalence factors are presented in Table 2. Probabilistic EF estimation was made through application of Monte Carlo simulation (MCS) considering the probability density functions for the former parameters as indicated in Table 2. Simulations were performed with Crystal Ball® (Oracle, 2010). To better reproduce the probability density functions and increase the accuracy of the estimates, Latin hypercube sampling was used. With the advent of commercial software products for probabilistic assessment, the calculations involved in uncertainty analysis became easy to learn, implement, and fast even for non-specialist.

3. Case-study

The case-study we use to demonstrate the application of the method is the University of Algarve campus at Gambelas (CGUA), located in the south of Portugal. It is about 10 km from the centre of Faro, the district capital, inside a natural area, and only a couple of kilometres from the Ria Formosa Lagoon Reserve. The total population (staff and students) attending the facilities is of about 4950 people. Small oscillation around this value is considered due to the many different academic and scientific activities taking at the campus. The campus has a total area of 20 ha and the buildings occupy a land surface of 6.9 ha. Due to the distance from the city centre, individuals make the travel using several alternative means of locomotion (personal car, motorbike, bicycle, or bus).

Table 2
Constants used in the calculation of EF.

Consumption categories (ha/t/year, unless otherwise stated)	Land productivity (p_i)	Equivalent factors (ef_i) (Wackernagel et al., 2005)
Paper (forest land)	0.9 (Chambers et al., 2001)	1.37
Water (forest land)	2.06×10^{-7} (Chambers et al., 2001)	1.37
Waste (landfill area)	1.65×10^{-6} (this study)	0.48
CO_2 emissions (forest land)	0.56 (Chambers et al., 2001)	1.37
CH_4 emissions (pasture land)	454.5 (Walsh et al., 2009)	0.48
NO_2 emissions (pasture land)	181.8 (Bontemps et al., 2011)	0.48
Energy (earth power or forest land) (ha/kWh/year)	2.11×10^{-3}[a] (Chambers et al., 2001)	1.37
Food meat	0.19 (FAO, 2000)	0.48
Vegetables	22.50 (FAO, 2000)	1.8
Fruit (orange)	30 (FAO, 2000)	1.8
Fish and shellfish	0.033 (FAO, 2000)	0.36

[a] Considering CO_2 emission factor for Portugal (EDP, 2012).

Faro has a moderate Mediterranean climate. Summers are warm to hot with average daytime temperatures of 27–35 °C. In the autumn and winter months, temperatures are around 8–17 °C. Annual average temperature is around 17 °C. Air conditioning is, therefore, used more intensively during summer and winter months to produce cold and hot air, respectively.

There is one central cantina and several small bars where most of the staff, faculty and students have their meals. Wastes produced by these and other services are deposited in two types of containers: domestic containers with a total deposition capacity of 11.66 m^3; and containers for recyclables (paper, glass, packages, batteries), with a total deposition capacity of 30 m^3. Domestic wastes (non-recyclables) are collected daily by the municipality; recyclables are collected twice per week by a private company. Total waste production was estimated considering a random variable filling percentage, f_c. More details on the statistical distribution fitted to all the parameters are presented in Table 3. Annual water and electricity consumption are, respectively, of about 49,000 m^3 and 2.4 GWh. Consumption of paper was estimated from results of the inquiry as about 2.01 million A4 sheets (after conversion from other sizes), i.e., about 9.9 t.

Inline with the arguments presented in the Introduction about accountability of mobility we introduce it here as one of the uncertain parameters. The other is food consumption as the menu can change substantially, and population due to uncertainties in the quantification of the number of people effectively utilizing the campus in a given period.

4. Results and discussion

Numerical stability was achieved after counter N_{inner} = 3000 trials, as indicated by a difference lower than 1% on the calculated EF values of the 50th and 95th percentiles. N_{outer} was set at 100 trials after verifying that the variance of the estimated percentiles did not change for higher values. A total of 300,000 model outcomes were thus obtained and are analysed in the following paragraphs.

4.1. Sensitivity analysis

The parameters that most contribute for EF total variance are those related to mobility, namely the velocity of gasoline personal automobiles, energy consumption, food (in particular, the amount of meat, fruit and fish), population utilizing the campus, and water use (which for models A2 and A4 also include wastewater) (Table 1). When mobility is included in the computation of EF they are the parameter for which the model is more sensitive, with contributions to variance (CV) between 44.4% and 42.9% obtained for models A1 and A2, respectively (Table 4). Energy consumption is the second most important parameter with CV between 25.3% and 25.4%, becoming the most important parameter if mobility is not considered (models A3 and A4), with CV varying between 42.8% for the first and 41.9% for the latter. Food ranks third, in particular due to the contribution of consumption of meat, fruit and fish (CV ranging between 6.7% and 7.4% for A1 and A2; and between 10.3% and 11.4% for A3 and A4, Table 4). Population size and water consumption are only relevant for models A3 and A4 (CV > 5.0%), i.e., when mobility is not considered. The inclusion of wastewater in the model (A2 and A4) has a small impact with CV < 5.0% when mobility is considered; but becomes relevant when they are not (CV between 6.8% and 8.0% respectively for models A3 and A4, Table 4).

Mobility is a key parameter in the model, both in terms of CV (Table 4) and relative contributions of parameters to the EF (Table 5). They account to over 41% of EF (models A1 and A2), being only surpassed by energy consumption (CV > 51%) – see Table 5. High weights for transport have been reported in other universities, namely at the Universities of Redlands (Venetoulis, 2001), Ohio (Janis, 2007) and Willamette University (Torregrosa-López et al., 2011) in the USA, Kwantlen (Burgess and Lai, 2006) in Canada, Newcastle (Flint, 2001) in Australia, La Coruña (Álvarez, 2008) in Spain (Table 6).

Table 5 also shows that energy has a high contribution to the EF, with or without mobility, being the most relevant consumption category in the models where mobility is not considered (models A3 and A4).

4.2. Uncertainty in ecological footprint estimates

The ecological footprint of is presented in Table 7 for the studied models. Uncertainty analysis indicates that the choice of model parameters (MUN) may make the estimated EF to change by a factor of five (Table 7): from a maximum of 2.49 ± 0.17 gha in model A2 to a minimum of 0.55 ± 0.04 gha in model A3. This is due to two modelling options: (i) inclusion of wastewater production; (ii) inclusion of mobility. The impact of the first parameter is very small, as reflected in the statistics of models A1 against A2 and A3 against A4 (Table 7). The impact on EF mean value is only of about 2.5% and 2.0%, respectively. Quite on the contrary, the impact of mobility in the outcome is high, as reflected in disparate estimated EF values for models A1 against A3 and A2 against A4 (Table 7). In the former a 93.1% increase was obtained when comparing models with and without mobility; in the latter the increase was even larger, attaining 94.2%.

In addition, the weights of each parameter on the total EF, reported for different universities (Tables 6 and 7) can vary substantially. Such that no statistically significant linear correlation was found between parameters (Pearson r < 0.75), nor was it possible to discriminate any meaningful clustering using principal component analysis, linear discriminant analysis, and cluster analysis (results not shown here), which are three commonly used exploratory data analysis. Still, for most of the cases, energy consumption, mobility and food consumption ranked among the most relevant. Three main reasons may have lead to the observed lack of similarity:

Table 3
Properties of random variables used in the calculation of EF.

Consumption categories	Parameters	Variability/uncertainty	Statistical distribution[a]	Data source
Paper consumption (t/year)		Variability	Triangular (9.107, 9.586, 10.065)	Central services – invoices
Water consumption (t/year)[b]		Variability	Normal (48,775.6, 9280.8)	Central services – invoices
Wastewater production (t/year)[b]		Variability	Normal (43,898.1, 8352.7)	Estimated from water consumption
Waste production	f_c	Variability	Triangular (0.4, 0.6, 0.75)	Estimated from deposition capacity and filling fraction
	ρ_w (t/m^3)	Variability	Triangular (0.15, 0.20, 0.25)	From bibliography
	Truck velocity (km/h)	Variability	Normal (35.0, 4.5)	Detailed survey
	Truck travelled distance (km)	Constant	24.0	From road map
Energy consumption (MWh/year)		Variability	Normal (2440.9, 331.8)	Central services – invoices
Built area (ha)		Constant	6.931	Central services
Food consumption (t/year)	Meat	Uncertainty	Triangular (38.4, 42.7, 46.99)	Central services – invoices
	Vegetables	Uncertainty	Triangular (93.5, 103.9, 114.3)	Central services – invoices
	Fruit (orange)	Uncertainty	Triangular (32.9, 36.5, 40.2)	Central services – invoices
	Fish and shellfish	Uncertainty	Triangular (16.3, 18.0, 19.9)	Central services – invoices
Mobility (velocity in km/h; distance in km – one way)	Gasoline passenger car (velocity)	Uncertainty	Normal (73.9, 18.4)	Detailed survey
	Gasoline passenger car (distance)	Uncertainty	Normal (14.1, 10.8)	Detailed survey
	Diesel passenger car (velocity)	Uncertainty	Normal (65.5, 15.0)	Detailed survey
	Diesel passenger car (distance)	Uncertainty	Normal (26.3, 22.0)	Detailed survey
	Motorcycle (velocity)	Constant	80.0	Detailed survey
	Motorcycle (distance)	Constant	42.0	Detailed survey
	Bus (velocity)	Uncertainty	Normal (35.0, 4.5)	Detailed survey
	Bus (distance)	Constant	13.0	From road map
Population		Uncertainty	Triangular (4700, 4948, 5195)	Central services

[a] Triangular (min, most probable, max); normal(average, standard deviation).
[b] Assuming that 1000 L = 1 tonne (t).

Table 4
Sensitivity analysis – contribution to variance (CV) (%).

Consumption categories	Model			
	A1: {B, W, E, M, F, P, WS}	A2: {B, W, E, M, F, P, WS, WW}	A3: {B, W, E,···, F, P, WS}	A4: {B, W, E,···, F, P, WS, WW}
Mobility[a] (M)	44.4	42.9	–	–
Energy (E)	25.3	25.4	42.8	41.9
Meat (F)	7.4	7.4	11.4	11.2
Fruit (F)	6.9	6.9	11.4	11.2
Fish (F)	6.7	6.8	10.5	10.3
Population (P)	<5.0	<5.0	10.4	10.7
Water (W) + wastewater (WW)	<5.0	<5.0	6.8	8.0
Wastes production (WS)	<5.0	<5.0	<5.0	<5.0
Build area (B)	<5.0	<5.0	<5.0	<5.0

[a] Velocity of gasoline cars.

Table 5
Model results: relative contribution of parameters (%) to the EF.

Consumption categories	Model			
	A1: {B, W, E, M, F, P, WS}	A2: {B, W, E, M, F, P, WS, WW}	A3: {B, W, E,···, F, P, WS}	A4: {B, W, E,···, F, P, WS, WW}
Mobility (M)	41.9	41.0	–	–
Energy (E)	52.1	51.0	89.6	86.7
Food (F)	3.3	3.3	5.9	5.6
Paper (P)	0.29	0.29	0.48	0.49
Water (W)	2.2	2.1	3.7	3.6
Wastewater (WW)	–	2.1	–	3.2
Wastes (WS)	0.14	0.14	0.25	0.27
Built area (B)	0.07	0.07	0.072	0.14
EF total	100	100	100	100

Table 6
Ecological footprint of universities.

University	University of Redlands (USA)	University of Toronto at Mississauga (USA)	Ohio State University (Columbus, USA)	Colorado College (USA)	University of Illinois at Chicago (USA)	Willamette University (USA)	Kwantlen University College (Canada)	University of Newcastle (Australia)
Ref.	Venetoulis (2001)	Conway et al. (2008)	Janis (2007)	Wright (2002)	Klein-Banai and Theis (2011)	Torregrosa-López et al. (2011)	Burgess and Lai (2006)	Flint (2001)
Year	1998	2005	2006	2006	2008	2007/2008	2005	1999
Population	2727	12,770	77,120	2500	36,640	3393	17,734	35,500
Area (ha)	57	91	711	36	97	28	62	140
Location	City	City	City	City	City	City	City	City
Total EF (total gha)	2300	8744	6,50,666	5603	97,601	7804	3039	3592
Total EF/Area	40	97	916	154	1 005	279	81	26
EF (gha)	0.9	1.1	8.7	2.2	2.7	2.3	0.33	0.19
EF/m [c]	0.6	0.9	2.4	2.2	2.4	1.3	0.16	0.10
Energy (%)	50.1	69.4	23.3	87.6	72.7	30	28.9	47.0
Mobility (%)	32.5	16.0	72.2	1.4	12.6	43	53.0	46.0
Wastes (%)	12.4	4.0	4.5	na	11.8	na	na	2.0
Paper (%)	na	na	na	na	na	na	7.2	na
Food (%)	na	9.2	na	10.0	2.6	25	9.6	2.0
Built land (%)	na	1.2	[a]	na	0.17	na	1.1	2.0
Water (%)	5.0	0.20	na	1.0	0.13	na	0.20	1.0
GDP × 10^{12} USD			14.5				1.6	1.2

University	Holme Lacy College (UK)	University of East Anglia (UK)	Northeastern University (China)	Campus de Vegazana University León (Spain)	University of Valencia (tree campus) (Spain)	University Santiago Compostela (Spain)	University Coruña (Spain)	University of Algarve
Ref.	Dawe et al. (2004)	Wright et al. (2009)	Li et al. (2008)	Hernández et al. (2009)	López et al. (2010)	Álvarez (2008)	Álvarez (2008)	This study
Year	2001	–	2003	2006	2009	2007	2013	2013
Population	7500	3213	23,345	14,000	48,660	32,246	23,167	4950
Area (ha)	257	129	110	42	72	130	–	20
Location	Rural	City	City	City centre	City	City	City	Rural
Total EF (total gha)	296	23,455	24,787	6300	39,853	5159	3475	5049–9999
Total EF/Area	1.2	182	50	150	554	40	-	252–500
EF (gha)	0.57	7.3	1.1	0.45	0.81	0.16	0.15	1.02–2.02
EF/m [c]	0.44	6.9	1.1	0.45	0.66	0.13	0.07	–
Energy (%)	19.0	21.6	68.0	62.0	15	63	25.4	51.0–89.6
Mobility (%)	23.0	5.4	0.08	19.2	19	18	56.1	41.0–41.9
Wastes (%)	32.0	72.3	5.7	na	0	1	1	0.14–0.25
Paper (%)	na	na	2.0	2.8	0	1	1.3	0.29–0.49
Food (%)	25.0	na	21.8	na	11	na	na	3.3–5.9
Built land (%)	1.0	0.5	0.42	15.9	55	16	2	0.07–0.14
Water (%)	[b]	0.1	2.0	0.03	0	1	0.2	2.1–3.7
GDP × 10^{12} USD	2.3		5.9	1.5				0.22

[a] With mobility.
[b] With built land.
[c] EF per person without accounting for mobility.

(i) case-studies are intrinsically different; (ii) the methodologies used to quantify the many parameters are not consistent (different methods); and (iii) the "ignorance" about the true value of some parameters leads to biased estimates (uncertainty). In the case of mobility important differences are expectable between universities where students reside onsite in residence halls (e.g., Colorado University, USA and Northeastern University, China) from those where they do not (e.g., La Coruña, Spain and University of Algarve, Portugal). However, this cannot alone fully justify the difference, as some universities with large accommodation facilities have reported large EF for mobility (e.g., Ohio State University, USA). Methodological options and parameter uncertainty may be in the origin of most of the differences found.

Also, can methodological differences and uncertainties have a relevant impact on the objective of the EF? Namely, can they substantially alter the results of inter-comparison? Fig. 1 may help

Table 7
EF estimates (gha) for University of Algarve (mean ± standard deviation).

Statistical parameter	Model			
	A1: {B, W, E, M, F, P, WS}	A2: {B, W, E, M, F, P, WS, WW}	A3: {B, W, E,· · ·, F, P, WS}	A4: {B, W, E,· · ·, F, P, WS, WW}
Mean	1.97 ± 0.13	2.02 ± 0.16	1.02 ± 0.02	1.04 ± 0.02
Median	1.97 ± 0.13	2.02 ± 0.16	1.02 ± 0.02	1.04 ± 0.02
Standard deviation	0.13 ± 0.003	0.13 ± 0.003	0.13 ± 0.002	0.13 ± 0.003
Skewness	-0.0003 ± 0.0086	-0.0004 ± 0.0087	-0.0010 ± 0.0083	-0.0013 ± 0.0091
Kurtosis	2.99 ± 0.03	2.99 ± 0.04	3.00 ± 0.03	2.99 ± 0.03
Minimum	1.51 ± 0.14	1.54 ± 0.17	0.55 ± 0.04	0.57 ± 0.04
Maximum	2.44 ± 0.14	2.49 ± 0.17	1.48 ± 0.05	1.51 ± 0.05

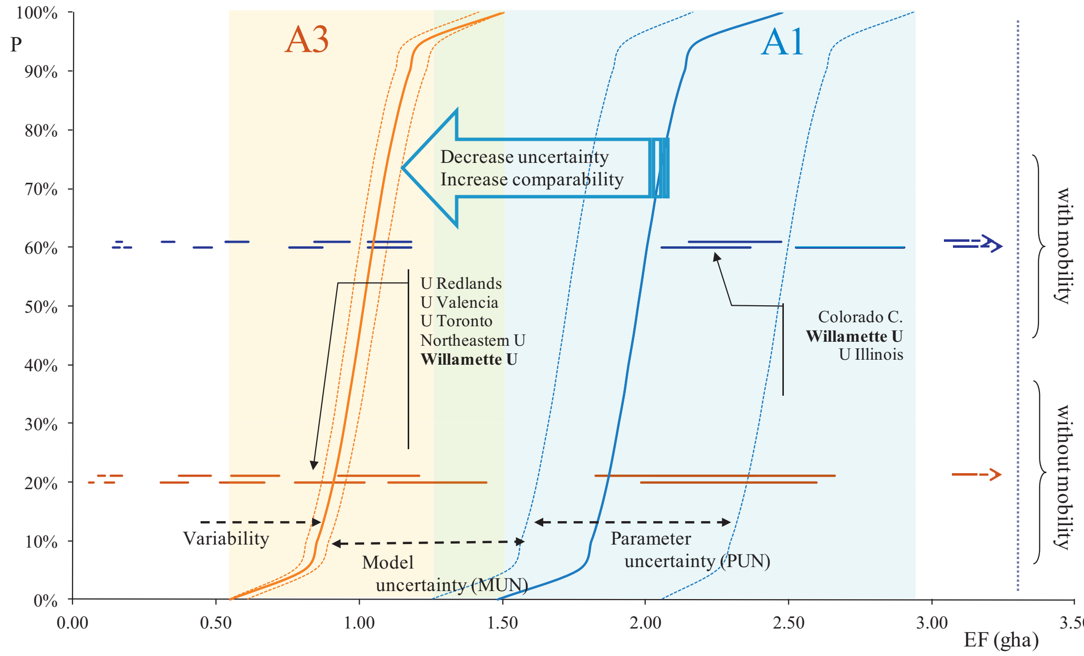

Fig. 1. Uncertainty analysis for the EF (gha): effect of considering mobility on the calculation of EF (models A1 and A3). Data with and without mobility from other universities was included for comparison.

answering this question. Both uncertainty (MUN and PUN) and variability are included, but for MUN, only the models for mobility are shown given the irrelevant variance introduced by wastewater. PUN is reflected in models A1 and A3; parameter uncertainty (PUN) is reflected by the uncertainty bands bracketing the central line, which is the cumulative distribution function for EF and is the quantification of variability. Results from the set of universities shown in Table 6 were included as horizontal lines, with the parameter mobility and also after subtracting it from EF ("without mobility"), hence allowing direct comparison with models A1 and A3. Model A1 EF estimates are similar to those of three other universities (Universities of Colorado, Willamette, and Illinois, all in the USA) as these are the only ones inside the interval of variation of EF, PUN considered. For model A3 five universities share similar footprints. By reducing the uncertainty brought into the model by mobility, similarity between universities increased, despite the fact that the range of variability decreased from a ΔEF (difference between the highest maximum and the lowest minimum) of 1.68–0.96 gha (i.e., 1.75 times). In conclusion, mobility biases the estimates and hinders comparability, mainly due to the fact that: (i) mobility patterns vary strongly between countries, even for equal population sizes, due to different traditions; (ii) within the same country, mobility patterns are affected by travel habits and transportation networks.

If cumulative distribution functions and uncertainty bands were available also for other published studies, then a much richer graphical and statistical analysis could have been made, leading, most probably to the conclusion that the majority of the universities shared the same EF, which is something impossible to evaluate when evaluating single EF values as those published so far. Strictly for demonstration purposes an uncertainty range was added to the results of all other universities assuming for them coefficients of variation equal to those of models A1 and A3 (Table 7). Note how variability increased from models A1 to A3, as indicated by a larger coefficient of variation for A3 (12.7%) than for A1 (6.6%) (Table 7). The more the range of EF for different universities superposes, the highest the probability that their EF is statistically equal. For instance, for model A1 the universities of Colorado, Willamette and Illinois could be considered as having an EF similar to that of the University of Algarve, but when uncertainty is excluded, the University of Illinois becomes significantly different from the other three. When mobility is excluded, as in model A3, a larger number of universities show EF similar to that of the University of Algarve, and also between themselves. Given the large weight of mobility on EF, and also its large PUN, it is, at the light of these results, the most relevant parameter affecting the estimates of EF of universities. This conclusion stills needs validated by futures studies. By filtering out uncertainty, the model reflects better the aleatory variability, a natural property of the system, non reducible by more studies and supplementary data, being, therefore much closer to the "true" value.

Moreover, by using probabilistic methods to estimate the EF, all available data, and expert opinion, may be integrated in the model through probability distributions, being the outcome a set of several hundred thousand model estimates, which contrast with the single value obtained by deterministic estimates, commonly published.

In what regards the proposed working question, these results indicate that the fundamental parameters in the EF model are essentially comparable between universities, as long as epistemic uncertainty is duly controlled. Also, uncertainty analysis has proven to be helpful in assessing the relevancy of parameters (sensitivity analysis) and in making the distinction between parameters (epistemic uncertainty analysis). Uncertainty analysis provides a robust framework for inter-comparison of universities and for the assessment of ecological footprint model uncertainties, uncertainty on the value of parameters and on their variability.

5. Conclusions

The usefulness of uncertainty analysis using Monte Carlo simulations for comparing the estimates of the ecological footprint of universities in different countries or locations was evaluated. The initial hypothesis was that uncertainty analysis can help in assessing the relevancy of parameters and in making the distinction between case-studies, allowing more robust inter-comparison.

Results showed, for a test case-study, that model uncertainties have the largest impact on the estimates, in particular in what regards the decision about accounting or not the contribution of mobility. When this parameter is excluded from the model, EF estimates for different universities converge to more similar values, indicating that it may be responsible for a non negligible bias. Wastewater production as also tested, but it showed an insignificant impact on the estimates.

Probabilistic uncertainty analysis, by studying model uncertainty, parameter uncertainty and variability provides a robust framework for the inter-comparison of ecological footprint of universities.

The method has some clear advantages over deterministic approaches: (i) all, or at least a great part of available base data can be incorporated in the final estimates; (ii) the weight of each parameter on the value of the estimate and its uncertainty can me measured, and in necessary, more data may be sought; (iii) modeller's uncertainty is directly accounted and estimated; (iv) estimates are "uncertain", which plays in favour of increasing stakeholders' intertemporal flexibility of decisional strategies and of more environmentally conservative decisions. It is not, however, without faults: (i) bad data will produce less accurate results – being the model more data intensive, it is more prone to biases due to incomplete and erroneous data; (ii) robust data quality assurance strategies are needed to control these errors (though not specific only to these models), which can take large amounts of time to do.

The method may prove useful for the assessment of ecological footprints of any kind; in particular, it may prove useful to incorporate regional variability into EF, which has been pointed out as one of the faults of EF (Fiala, 2008).

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