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A novel uncertainty assessment protocol for integrated ecosystem services-life cycle assessments: A comparative case of nature-based solutions

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ABSTRACT

Integrating ecosystem services and life cycle assessment is gaining increasing attention for the analysis of environmental costs and benefits associated with human activities covering multiple geographical scales and life cycle stages. Such integration is particularly relevant for evaluating the sustainability of nature-based solutions. However, merging these methods introduces additional uncertainties. This paper introduces a novel protocol to assess uncertainties in combined ecosystem services-life cycle assessment, focusing on ecosystem services accounting, life cycle inventory of foreground systems, and life cycle impact assessment characterisation factors. Applied to a nature-based solution case study compared to no-action and energy-intensive scenarios, the uncertainties were analysed using multi-method global sensitivity analysis. The robustness of the analysis results was assessed through convergence plots and statistical tests. Findings reveal significant uncertainties, especially in life cycle impact assessment characterisation factors, with the extent varying by impact category. Uncertainties in foreground life cycle inventory, particularly in land use of nature-based solutions scenario, are also notable. Compared to these, uncertainties associated with indicators of impact on ecosystem services (uncertainty arising from input variability in ecosystem services accounting) are relatively lower. This study underscores the critical role of uncertainty assessment in enhancing the reliability of integrated assessments for nature-based solutions, providing a framework to identify and quantify key uncertainties, thereby supporting more informed decision-making.

Acronyms

AF	air filtration
CF	characterisation factor
CSS	carbon storage and sequestration
DM	delta method
eFAST	extended Fourier Amplitude Sensitivity Test
ES	ecosystem services
FE	freshwater eutrophication
FP	freshwater provisioning
FPMF	fine particulate matter formation
GR	groundwater recharge
GWP	global warming potential
KIA	key issue analysis
LCA	life cycle assessment
LCI	life cycle inventory
LCIA	life cycle impact assessment
LH	Latin hypercube
LU	land use
MC	MonteCarlo simulation
ME	marine eutrophication
MM	Method of Morris
MS	Morris sampling
NbS	nature-based solution

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PAWN	PAWN method
RBD	random balance design
RF	RBD-FAST
RS	random sampling
RUSLE	Revised Universal Soil Loss Equation
S1	Sobol's sensitivity first-order index
SCC	Spearman correlation coefficient
SR	sediment retention
SRC	standardised regression coefficient
SS	Sobol's sequence
SSI	Sobol's sensitivity indices (first-order and total-order)
ST	Sobol's sensitivity total-order index
UA	uncertainty assessment
WC	water consumption
WP_N	water purification (nitrogen)
WP_P	water purification (phosphorus)

1. Introduction

The advent of nature-based solution (NbS) systems heralds a promising approach to addressing environmental challenges while enhancing sustainability. NbS is defined by the International Union for Conservation of Nature (IUCN) as "actions to protect, sustainably manage and restore natural or modified ecosystems that address societal challenges effectively and adaptively, simultaneously providing human well-being and biodiversity benefits" (IUCN, 2020). The NbS applications range across many domains including sustainable stormwater management, wastewater treatment, urban agriculture, agroecological farming, coastline erosion prevention, and remediation of contaminated soil and groundwater (European Commission. Directorate General for Research and Innovation., 2020). To assess the sustainability of NbS several approaches have been used including cost-benefit analysis, life cycle assessment (LCA), ecosystem services (ES)-based approaches, multi-criteria decision analysis, or a combination of two or more approaches (Loiseau et al., 2016). LCA measures the environmental impacts over the life cycle of a system/service (Guinée et al., 2011; Rebitzer et al., 2004); while ES accounting is the process of quantifying and valuing the services provided by natural ecosystems to humans such as carbon sequestration (Schröter et al., 2015). The integration of ES and LCA is an increasingly used approach (Rugani et al., 2019), to provide a comprehensive assessment of the environmental impacts and benefits that a single approach could provide (Rugani et al., 2023) particularly in the sustainability assessment of NbS systems (Alshehri et al., 2023a). The integration of ES and LCA could be performed in several ways, such as post-analysis by qualitative interpretation of the ES and LCA results (e.g., ES and LCA are conducted independently, then the results are analysed qualitatively based on risk scale), through integration by the combination of the results (e.g., approaches are performed separately, then the results are combined by ranking method), or by complementing a driving primary method (e.g., ES results to the LCIA phase) (De Luca Peña et al., 2022).

Both ES and LCA are influenced by different sources of uncertainty (Lima et al., 2017; Barahmand and Eikeland, 2022). Given that ES modelling is essentially a spatial modelling exercise (Andrew et al., 2015), the quality of spatial data is a major source of uncertainty in ES modelling (Hamel and Bryant, 2017). Additionally, the structural uncertainties arising from simplified ES models are yet another significant source of uncertainty in ES modelling (Natural Capital Project, 2022).

In the LCA domain, the common sources of uncertainty are due to data variability and availability (e.g., foreground life cycle inventory (LCI), LCI; background LCI), methodological choices (e.g., definition of system boundary; functional unit; impact assessment method including relevant characterisation factors (CFs)), choice of normalisation and weighting, lack of knowledge of biogeochemical processes (epistemic uncertainty; e.g., land use change, ecosystem functions), and assumptions of linearity and fixed relationships (Bamber et al., 2020).

The integration of various assessment approaches, each carrying its own set of uncertainties, leads to compounded uncertainty (Hamel and Bryant, 2017). The sources of uncertainty in integrated modelling could arise from the context and framing of the system under study (i.e., the scope of the assessment), input uncertainty driven by external parameters (e.g., natural variability of climatic parameters), parameter uncertainty (i.e., pertaining the parameter value potentially arising from measurement errors), structural model uncertainty (simplified or incomplete description of the modelled system relative to reality), model technical uncertainty which are implementation related uncertainties (e.g., coding and software technical bugs) (Walker et al., 2003; Refsgaard et al., 2007). The total uncertainty of the model output (s) is attributed to various sources of uncertainties (Loucks et al., 2005). These uncertainties could undermine the credibility of integrated assessments if not treated properly (Baustert et al., 2018). Igos et al. (2019) identified several steps in the uncertainty treatment which are:

- uncertainty identification (determining sources of uncertainty),
- uncertainty characterisation (defining the range of variability in uncertainty sources),
- uncertainty analysis (i.e. simulation of possible representative scenarios using sampling methods for instance),
- sensitivity analysis (understanding the magnitude of contribution of the sources of uncertainty to the output uncertainty using either local sensitivity analysis or global sensitivity analysis approaches), and
- uncertainty communication (i.e., transparent dissemination of uncertainty assessment results)

While uncertainty assessment protocols have been proposed in individual domains, whether in ES accounting (Lima et al., 2017; Yang et al., 2019; Connor et al., 2022) or LCA modelling (Padey et al., 2013; Barahmand and Eikeland, 2022; Ravi et al., 2022), to our knowledge no uncertainty assessment protocol yet exists for integrated ES-LCA assessment. Section 2 of this paper offers further discussions of the state-of-the-art of uncertainty assessment in ES-LCA modelling. Consequently, there arises a critical need for a comprehensive and robust framework to quantify the uncertainties inherent to the integrated sustainability assessment of NbS systems.

1.1. Objectives and novelty

In response to this imperative, we propose a novel uncertainty assessment protocol for integrated ES-LCA assessments to quantify the effect of different sources of uncertainty. To test the applicability, uncertainty on several representative ES assessment factors (i.e. carbon sequestration, groundwater recharge, water purification, and air filtration) was considered, together with uncertainty affecting foreground LCI parameters, and CFs of life cycle impact assessment (LCIA). Specifically in this work, we aim to achieve the following objectives: the development of a novel quantitative uncertainty assessment of ES-LCA protocol; the application of multi-method global sensitivity analysis (GSA) to a NbS system; the assessment of the robustness of the multi-method GSA through visual inspection and statistical testing; and the study of the impacts of sampling strategy and the number of simulations on the GSA results. The novelty of this work lies in the development of the first quantitative uncertainty assessment protocol for an integrated ES-LCA assessment within the context of NbS systems sustainability assessment.

2. Uncertainty of ES-LCA integration: a brief literature review

The integration of ES-LCA is a developing research focus aimed at broadening LCA frameworks to include ES accounting (VanderWilde and Newell, 2021). Yet, the exploration of uncertainty and sensitivity in ES-LCA remains an emerging field, with limited studies to date (Rugani et al., 2023; Yao et al., 2024). The terms uncertainty and sensitivity analysis are frequently used interchangeably (Rosenbaum et al., 2018).

In this study, we use Saltelli's definition of sensitivity as "*The study of how uncertainty in the output of a model (numerical or otherwise) can be apportioned to different sources of uncertainty in the model input*" (Saltelli, 2004). Sensitivity methods can be classified as either local or global. Global sensitivity methods generally fall into distinct categories: derivative-based, distribution-based (also known as variance-based), variogram-based, and regression and correlation-based methods (Razavi et al., 2021). Interested readers are suggested to consult Iooss and Lemaître (2014) and Razavi et al. (2021) for comprehensive overviews of GSA methods, and Saltelli (2008) for a more in-depth exploration. Despite the increasing number of stand-alone ES accounting assessments, they are not often coupled with uncertainty assessments (Hamel and Bryant, 2017), which could potentially undermine the robustness and usefulness of such assessments (Bryant et al., 2018). The application of GSA to ES accounting is still a relatively unexplored topic demonstrated by the number of studies. Noting that there are several ES accounting models, a Scopus search with the terms "ES accounting AND global sensitivity analysis" returned a few results, some examples of which are presented in Table 1.

Sánchez-Canales et al. (2015) employed the method of Morris (MM) to investigate sediment retention ecosystem services in the Iberian Peninsula. They analysed input parameters like rainfall erosivity, soil erodibility, and land use/land change (LULC) related factors. The study focused on three model outputs: total exported sediments, improved water quality from retained sediment fraction, and reduced reservoir sedimentation due to retention. Huang et al. (2019) employed MM to study the impact of land conservation on climate change-induced degradation of ES in a semi-arid catchment in Idaho, USA, using InVEST's water yield and sediment retention models. Likewise, Yang et al. (2019) utilized MM to assess the precision of InVEST's water yield model in predicting water provisioning in South China (Yang et al., 2019), employing a Latin hypercube sampling (LHS) approach distinct from the Monte Carlo simulations used in the studies by Sánchez-Canales et al. (2015) and Huang et al. (2019). Wang et al. (2022) recently carried out a GSA implementation on an InVEST model (nutrient delivery retention), using the extended Fourier Amplitude Sensitivity Test (eFAST) to pinpoint the significant environmental management factor affecting the economic gains of excess nitrogen and phosphorus retention as an ecosystem service. In another context, Connor et al. (2022) used the MM to gauge the responsiveness of ES payments to both biophysical and economic factors, grounded in an urban forest regeneration initiative. This analysis encompassed carbon storage, sequestration, and freshwater provisioning as key ES benefits.

Table 1
Brief literature review of global sensitivity analysis (GSA) approaches applied to ES accounting model(s)[a].

Reference	Modelled ES(s)	ES model (s)	Sampling methods	ES	LCA	ES-LCA
(Sánchez-Canales et al., 2015)	SR	InVEST	MS	MM	n.a.	no
(Huang et al., 2019)	FP, WP_P, WP_N	InVEST	MS	MM	n.a.	no
(Yang et al., 2019)	FP	InVEST	LH	MM	n.a.	no
(Estrada-Carmona et al., 2017)	SR	RUSLE	RS	SRC	n.a.	no
(Connor et al., 2022)	CSS, FP, WP_P	InVEST	MC	MM	n.a.	no
(Wang et al., 2022)	WP_P, WP_N	InVEST	eFAST	eFAST	n.a.	no

[a] CSS: carbon sequestration and storage, eFAST: extended Fourier Amplitude Sensitivity Test, FP: freshwater provisioning, LH: Latin hypercube sampling, MC: MonteCarlo sampling, MM: Method of Morris, MS: Morris sampling, RS: random sampling, SRC: Standardised regression coefficient, SR: sediment retention, WPN: retention of Nitrogen, WPP: retention of phosphorus.

Beyond InVEST models, Estrada-Carmona et al. (2017) employed Monte Carlo simulations and random forest techniques to reduce the model uncertainty of the Revised Universal Soil Loss Equation (RUSLE) model. They examined 18 distinct input parameters, utilizing random forest on six spatial datasets representing varying climatic and geographical conditions that affect sediment retention ES delivery.

While GSA is relatively more common in LCA than in ES accounting, widespread application remains limited (Mahmood et al., 2022). Table 2 presents key examples of GSA applied to LCA studies. The first GSA application to an LCA was reported by Padey et al. (2013). They employed first-order and total-order Sobol's sensitivity indices (SSIs) using Monte-Carlo (MC) simulation for a wind power electricity case study to determine uncertainty arising from foreground system parameters and global warming potential characterisation factors. In the notable work of Groen et al. (2017), six GSA methods were utilized, encompassing key issue analysis (KEI), SSIs (1st and total-order), random balanced design (RBD), and sampling-based techniques including standardised regression coefficient (SRC) and Spearman correlation coefficient (SCC). Two case studies were conducted: one involving a simple LCA of electricity production and another with a more sophisticated LCA model of fishery activities.

SSI emerged as the most frequently employed GSA method, as illustrated by Lacirignola et al. (2017), Paulillo et al. (2021) and Gkousis et al. (2022) in the context of geothermal energy production, and by Lin et al. (2022) in the recycling of delivery packages. SSI has also been used to assess the uncertainty of emerging technologies. For instance, Jouannais and Pizzol (2022) employed SSIs with MC and SS sampling strategies for a consequential ex-ante LCA of European production of emerging microalgal compounds. Additionally, Baaqel et al. (2023) applied SSI to assist in early-stage chemical production.

The method of Morris (MM), also known as the elementary effects test, stands as another commonly used, cost-effective variance-based GSA approach. It frequently serves as a screening step to identify non-influential parameters, thus reducing the computational expenses linked with resource-intensive methods like SSI. This utility is showcased in various instances, such as Elias et al.'s (2021) application to bioethanol production, the examination of Swiss food consumption (Kim et al., 2022a), and the study of rice farming (Xu et al., 2022).

Regression and correlation-based GSA methods have also been utilized in LCAs, albeit to a lesser extent. In the work of Groen et al. (2017), SRC and SCC were implemented using a random sampling strategy for the aforementioned case studies. It was observed that SRC exhibited superior performance when dealing with small variances (5 %) in both simple and complex LCA models. Conversely, SCC demonstrated greater robustness when confronted with larger variances (30 %) in the complex LCA model. Xiao et al. (2023) employed SRC to assess the impact of parameter uncertainty in a case study involving the recycling of secondary aluminium, encompassing variances ranging from 10 % to 50 % of the base values of input parameters.

Moment-independent GSA methods distinguish themselves from variance-based methods by encompassing the entire distribution of the model output, rather than focusing solely on its variance (Borgonovo, 2007). This characteristic makes them more suitable for models featuring non-normal output distributions (Liu and Homma, 2009). The delta moment-independent (DM) and PAWN methods exemplify moment-independent GSA approaches (Wei et al., 2013; Pianosi and Wagener, 2018). Within the LCA domain, Jaxa-Rozen et al. (2021a) employed both the DM and the PAWN method in a geothermal energy case study, whereas Kim et al. (2022a) employed DM in the context of Swiss food consumption. Additionally, Ravi et al. (2022) utilized DM to explore wastewater sludge recovery. While prior investigations primarily centred around foreground LCI, Cucurachi et al. (2022) extended the application of DM to assess the uncertainty of background LCI, using the ecoinvent database as an illustrative example.

While GSA methods are increasingly applied in LCA, their adoption

Table 2
Brief literature review of global sensitivity analysis (GSA) applications in the life cycle assessment (LCA) domain[a].

Reference	ES modelling	ES model(s)/sectors of LCA	Sampling method	ES	LCA	ES-LCA
(Padey et al., 2013)	n.a.	Wind power electricity	MC	n.a.	SSI	no
(Groen et al., 2017)	n.a.	Electricity production + Fishery production	MC, RBD	n.a.	KEI, SCC, SRC, SSI, RF	no
(Lacirignola et al., 2017)	n.a.	Geothermal energy	MC	n.a.	SSI	no
(Elias et al., 2021)	n.a.	Bioethanol production	MS	n.a.	MM, SSI	no
(Jaxa-Rozen et al., 2021a)	n.a.	Geothermal energy	LH, SS	n.a.	SSI, DM, PAWN	no
(Paulillo et al., 2021)	n.a.	Geothermal energy	SS	n.a.	SSI	no
(Zhao et al., 2021)	n.a.	Geothermal energy	LH, SS	n.a.	SSI, RF, PAWN	no
(Cucurachi et al., 2022)	n.a.	Photovoltaic system	MC	n.a.	DM	no
(García-Velásquez and Van Der Meer, 2022)	n.a.	Bio-based PET production	MC	n.a.	SCC	no
(Gkousis et al., 2022)	n.a.	Geothermal energy	MC	n.a.	SSI	no
(Jouannais and Pizzol, 2022)	n.a.	Microalgal production	MC, SS	n.a.	SSI	no
(Kim et al., 2022a) (screening)	n.a.	Food consumption	MC	n.a.	MM, SSI, DM	no
(Kim et al., 2022b) (background LCI)	n.a.	Food consumption	MC	n.a.	SSI, DM	no
(Lin et al., 2022)	n.a.	Delivery package recycling	MC	n.a.	SSI	no
(Paulillo et al., 2022)	n.a.	Geothermal energy	MC	n.a.	SSI	no
(Ravi et al., 2022)	n.a.	Struvite and wastewater sludge recovery	MC	n.a.	SSI, DM	no
(Xu et al., 2022)	n.a.	Rice farming	MS	n.a.	MM, SSI	no
(Xiao et al., 2023)	n.a.	Secondary aluminium recycling	MC	n.a.	SRC	no
(Baaqel et al., 2023)	n.a.	Early-stage chemical production	MS	n.a.	SSI	no
This study	CSS, GR, WP_N, WP_P, AF	Brownfield remediation	LH, SS	MM	SSI, RF, PAWN	SSI, RF, PAWN

[a] AF: air filtration, CSS: carbon sequestration and storage, GR: groundwater recharge, WPP: retention of phosphorus, WPN: retention of Nitrogen, MC: MonteCarlo sampling, LH: Latin hypercube sampling, RS: random sampling, MS: Morris sampling, eFAST: extended Fourier Amplitude Sensitivity Test, SCC: Spearman correlation coefficient, SRC: Standardised regression coefficient, PAWN: the PAWN method, DM: Delta moment-independent method. MM: Method of Morris, SSI: Sobol's sensitivity indices, RF: RBD-FAST, KEI: key issue analysis.

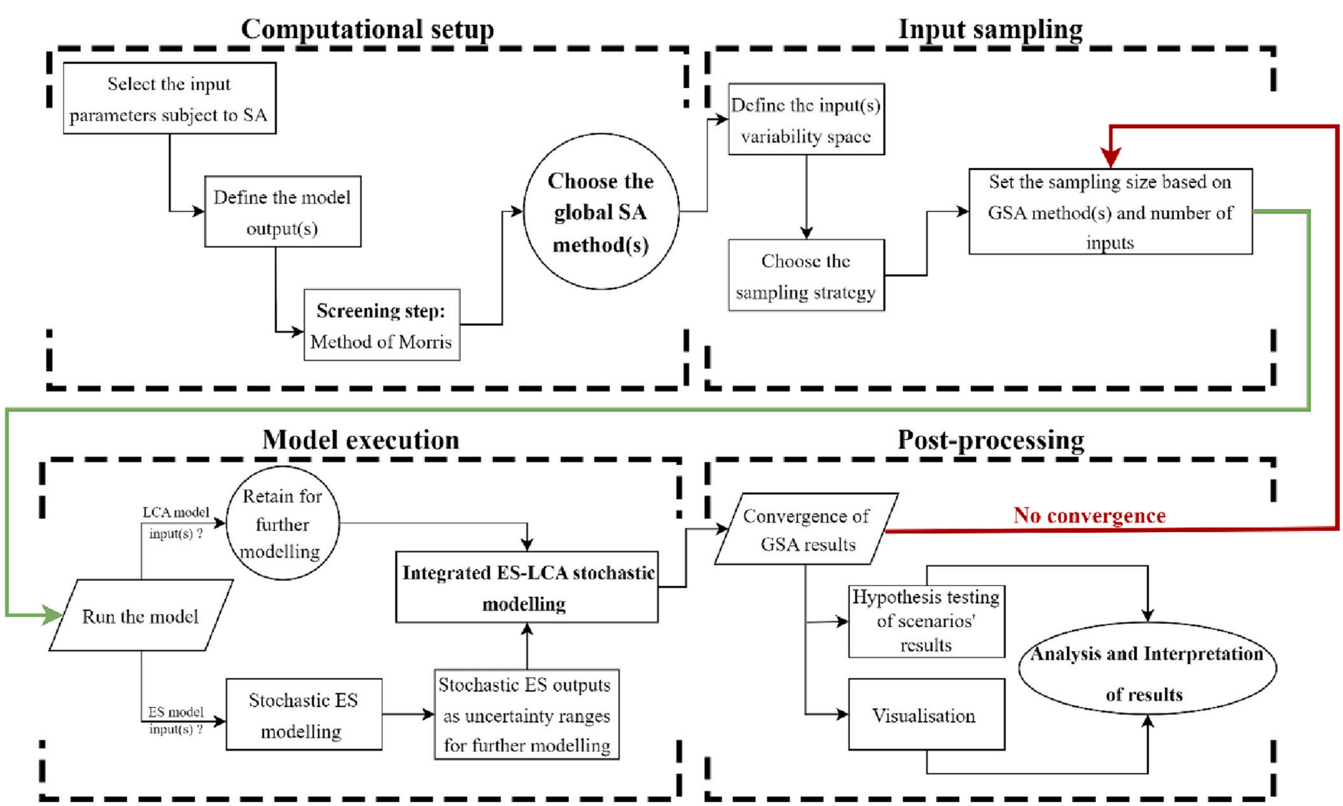

Fig. 1. The proposed uncertainty assessment (UA) protocol of the ES-LCA assessment (ES: ecosystem services, GSA: global sensitivity analysis, LCA: life cycle assessment, SA: sensitivity analysis).

in the ES domain is still limited. To our knowledge, no uncertainty assessment framework for integrated ES-LCA exists. Introducing GSA to the ES-LCA context could significantly improve sustainability assessments and decision-making for NbS. Reducing uncertainty in NbS modelling is vital for land planners, potentially lowering design and implementation costs while boosting ES in human-altered landscapes.

3. Methods

3.1. Uncertainty assessment protocol

A comprehensive multi-method uncertainty assessment (UA) protocol was devised to assess the uncertainty of the ES-LCA integration across the foreground LCI, LCIA's CFs and ES assessment factors. We excluded the uncertainty of background LCI flows from our analysis due to large number (hundreds of thousands) of sources that would require consideration (Wernet et al., 2016). Including these flows would significantly increase the complexity of the analysis (Kim et al., 2022b) and impose unmanageable operational limitations on computational resources (Cucurachi et al., 2022) necessary for the scope of this work. Moreover, while ecoinvent includes uncertainty details for background LCI, this aspect is notably absent in other background LCI databases (Ciroth et al., 2016). Fig. 1 shows the structure of the proposed UA protocol follow the structure of n Pianosi et al. (2016)'s workflow consisting of 4 general steps: computational setup, input sampling, model execution, and post processing. We have adapted Pianosi et al.'s broad recommendations into specific strategies, including sampling techniques, GSA methods, and tailored post-processing approaches for ES-LCA assessments.

3.1.1. Computational setup

The input parameters considered fall under one of the three groups including foreground LCI, ES-LCA's CFs, and corresponding ReCiPe's CFs. Those parameters are fully reported in Tables A.1–A.4 of the supplementary material (SM). The well-known data quality "pedigree" matrix concept developed to include uncertainty parameters in life cycle inventories (Weidema and Wesnæs, 1996) was applied to the foreground LCI base values. This resulted in the definition of semi-quantitative data quality indicators (DQIs).

Those data quality indicators were then transformed into probability distribution functions (PDFs) using Muller et al. (2016)'s approach. Two independent DQI assessments were performed to limit the potential subjectivity of the DQI results. The lower and upper bounds for PDFs of ES-LCA's CFs were obtained through as the minimum and maximum stochastic values of spatial ES modelling biophysical parameters as highlighted in Table A.1 included in the SM. Santos et al. (2022)'s approach was applied to obtain the PDFs of standard LCIA's CFs which implied varying the CF value by a certain ±% based on the perceived uncertainty in the impact category methodology, the common elementary flows from the modelled with the largest contributions (≥99 %) to LCIA scores were selected to assign uncertainty ranges to ReCiPe's CFs (refer to Table A.2-A.3 in the SM).

The selected GSA methods in the UA strategy were Sobol's sensitivity indices (Saltelli et al., 2010), PAWN (Pianosi and Wagener, 2015), and the Random Balance Designs-Fourier Amplitude Sensitivity Test (RBD-FAST) (Tarantola et al., 2006).

The use of several GSA methods is recommended to cross-check the GSA results (European Commission. Joint Research Centre, 2020). We implemented the Sobol's sensitivity index, a variance-based method which is considered the gold standard of GSA (Iooss and Prieur, 2019). Due to its wide applicability across models such as ES and LCA, and its ability to discern interaction effects of input parameters on output uncertainty (Saltelli, 2008)., Yet the high computational cost and dependence on specific input sampling strategy remained major drawbacks (Iooss and Prieur, 2019). Therefore we used a distribution-based GSA method such as PAWN, which is becoming popular as sampling strategy-agnostic and computationally-efficient alternative/complementary tool to the variance-based method (Pianosi and Wagener, 2018). Additionally, we used the improved RBD-FAST which requires significantly less computational costs and works with several input sampling strategies (Tissot and Prieur, 2012). Hence, we were able to obtain multi-method GSA results using a single input sampling strategy with no additional computational costs.

A screening step using the method of Morris (1991) was implemented to filter the less influential parameters to reduce the computational cost of the more sophisticated GSA method. The method of Morris, also known as the elementary effects test, is a widely used computationally inexpensive screening method that determines the influence of input parameters on the model's uncertainty (Saltelli, 2008).

3.1.2. Input sampling

The Morris (1991)'s sampling for elementary effects with Campolongo et al. (2007)'s optimal trajectory improvements, which pertains to the required model simulations per input parameter, was used to sample the inputs for the screening step. We assumed 200 optimal trajectories as suggested by Garcia et al. (2019), who found that the Morris method converges at 200 trajectories for complex models.

For the multi-method GSA step, we implemented the Sobol Sequence (SS) required by the Sobol's sensitivity index is a well-known quasi-random low-discrepancy sequence used to produce uniform samples of input parameter space (Sobol, 2001). We assumed $N = 1000$ simulations per parameter for the multi-global sensitivity analysis step. To understand the impacts of sampling strategy on multi-method GSA results, We applied the Latin hypercube (LH) sampling technique that samples the input variable into distinct strata to ensure equal representation of every input variable in the sample (Mckay et al., 2000).

3.1.3. Model execution

In this step, we first model ES stochastically based on literature uncertainty ranges of the biophysical inputs of the InVEST models (refer to Table A.1), to assess the changes on ES delivery for each modelled scenario. Then the minimum and maximum stochastic values are assumed to be the lower and upper bounds of the novel CFs of ES-LCA (refer to Alshehri et al. (2023b)) for more details about the ES-LCA framework). Pianosi and colleagues recommend evaluating the robustness and convergence of sampling-based Sensitivity analysis(SA) techniques (Pianosi et al., 2016). Convergence of SA results indicates that the sensitivity indices are no longer influenced by the sample size (by plotting the sensitivity index value vs the sample size as line graph), indicating that the number of samples meets the requirements for GSA methods (Wainwright et al., 2014). Additionally, the model behaviour was assessed and compared to the deterministic ES-LCA results reported in Alshehri et al. (2023b).

3.1.4. Post-processing

In this step, we assessed the robustness of GSA results by plotting heatmaps of the selected GSA sensitivity indices. We also applied the Kruskal-Wallis (KW) test and Dunn's post-hoc pairwise comparison test to determine if there was a statistically significant difference in the stochastic ES-LCA results of the modelled scenarios. The statistical significance is determined by comparing p-values of the employed tests against a predefined alpha level ($\alpha = 0.05$), if the p-value is less than a it indicates the differences among between is not due to chance (Hollander et al., 2014).

3.2. Illustrative case study

We employed the London Olympic Park case study which is a mega brownfield redevelopment project (200 ha) undertaken to host the London 2012 Summer Olympics, formerly described at length in Alshehri et al. (2023b). To this end, we explored three modelled scenarios reflecting different remediation strategies including conventional

Table 3
Modelled scenarios.

Scenario	Description
London Olympic Park (LOP)	This scenario represents the soil remediation activities preceding the construction of LOP, including soil washing, chemical and geotechnical stabilisation, bioremediation, and material sorting, with a duration of 3 years.
Nature-based solution (NbS)	A simulated large-scale hybrid poplar phytoremediation scenario with 5000 trees/ha over 12 years, 30 % die-out, and anaerobic digestion of phyto-biomass post-remediation.
No action (NA)	A no-action scenario involving monitored natural attenuation with a total of 27 monitoring wells over 30 years assuming the 2000 land cover map (LCM) as reference and no land use change of the LCM2007

remediation technologies, a NbS remediation system, and no-action scenario each of which is outlined in Table 3:

3.3. Computational implementation

We adapted the sensitivity analysis computational workflow developed by Jaxa-Rozen et al. (2021b), which was based on the openLCA IPC python wrapper. The Morris and Sobol input sampling, as well as the implementation of global sensitivity methods, were performed using SALib, a well-known sensitivity analysis python library (Usher et al., 2016; Herman and Usher, 2017). The input sampling for stochastic ES modelling was achieved by uniform sampling function from Numpy (Harris et al., 2020), while the stochastic ES modelling was implemented using the InVEST API python (Natural Capital Project, 2022), the modelling approach for each ES is detailed in the InVEST user guide for interested readers (InVEST® User Guide — InVEST® Documentation, 2024). However, for air filtration (AF) ES modelling, a different approach was used because the InVEST suite does not have module of AF modelling, as highlighted in Alshehri et al. (2023b). The KW test was implemented using the relevant Scipy function (Virtanen et al., 2020), whereas the Dunn's test for pairwise comparison was applied using the scikit-posthocs python package (Terpilowski, 2019).

4. Results

4.1. Screening step

In this section, we present the results of the screening step in the experimental setup of the proposed protocol. There are 58, 59, and 53 input parameters in the initial lists for the LOP, NbS, and NA modelled scenarios respectively (see the SM, Tables A.5–A.7 for detailed description of the input parameters). The screening step aims to retain the 33 most influential input parameters for further GSA analysis. Fig. 3 shows a scatterplot of the method of Morris results, with the y-axis representing the standard deviation of the elementary effects (EEs) and the x-axis showing the mean of EEs. As input parameter markers move to the top-right corner of the plot, they indicate higher contributions to output variance, signifying greater relevance in terms of uncertainty (Pianosi et al., 2016).

In the LOP scenario (refer to Fig. B.1 in the SM), the uncertainty of the global warming potential (GWP) category was mainly dominated by CF's uncertainty, except for the foreground LCI of CHEM (chemical stabilisation). The uncertainty of the water consumption (WC) category was primarily controlled by foreground LCIs of remediation technologies, notably chemical and geotechnical remediation. For the fine particulate matter formation (FMPF), freshwater eutrophication (FE), and marine eutrophication (ME) categories, contributions to model uncertainty came mainly from CFs and the LCI of CHEM and bioremediation. In the land use (LU) category, the CF's contribution to the output variance was significantly higher than the foreground LCI aside from CHEM.

Regarding the NbS scenario (see Fig. B.2), a prominent contribution to uncertainty is observed from the foreground land use LCI (LU-LCI) of the NbS remediation across various impact categories. In both the GWP and FMPF categories, the primary contributors to output variance are the foreground LU-LCI and diesel consumption in agricultural activities within the NbS system. Within the ME, FE, and LU categories, the CFs are a significant contributor to uncertainty, ranking second only to the LU-LCI. It is worth noting that the foreground LCI of the NbS_D11 parameter (which represent diesel consumed in harvesting activities) consistently appears in close proximity to the LU-LCI, suggesting a positive correlation.

In the context of the NA scenario (refer to Fig. B.3), a parallel pattern of LU-LCI dominance in terms of contribution to uncertainty becomes evident. In the GWP, WC, and FMPF categories, the foreground LCI associated with collecting samples from monitoring well samples closely follows the LU-LCI. This noteworthy contribution could be attributed to the sampling frequency (4 times a year) which is reflected in the total distance travelled to testing facilities (Table A.2). For the FE and LU categories, it is observed that the corresponding CFs closely trail the LU-LCI in terms of their contribution to the variance of the output. In the ME category, it is apparent that the contribution to uncertainty is exclusively dominated by foreground LCIs.

4.2. Comparison of deterministic and stochastic ES-LCA results

In this section, we compare the stochastic ES-LCA results of the modelled scenarios in with the deterministic figures presented in Alshehri et al. (2023b). Fig. 2 represents the GWP results, while the remaining impact categories are detailed in Fig. B4–6 in the SM. Upon visual inspection of the results, it becomes evident that the deterministic value closely aligns with the mean value across the six impact categories under investigation, specifically for the LOP.

In contrast, for the NbS and NA scenarios, the deterministic values consistently fall below the mean value, exhibiting varying margins across the impact categories. Notably, the WC category stands out as an exception, where the two values are approximately equivalent. With the exception of the LU and WC categories, the dispersion of the ES-LCA outcomes remains minimal, as evidenced by a standard deviation (SD) of 0.However, a substantial degree of variability becomes apparent in the WC category, with SDs ranging from 27 to 200 times the mean. The LU results display a comparatively more moderate level of variance.

A direct comparison between deterministic results reported in Alshehri et al. (2023b) and stochastic ES results of this study is not feasible because a different modelling approach has been used for the NA scenario to obtain values for CSS, ME, FE, and GR by using land cover map (LCM) 2000 as a reference point (refer to Section 6 for further discussions). The stochastic ES results are presented in Fig. B.7–9.

4.3. Results of GSA methods

In this section, we present the outcomes of the multi-method GSA applied to the filtered input parameters of the modelled scenarios. We emphasize the significant trends observed in the GSA results of foreground LCIs and CFs across these scenarios. Fig. 5, Fig. B.10a, and Fig. B.10b display the normalised GSA results for the LOP, NbS, and NA scenarios, respectively. These normalised results are scaled from zero (indicating the least importance) to one (representing the highest importance), enabling a straightforward comparison among the selected GSA methods.

In the LOP scenario, the CHEM (Chemical stabilisation of soil contaminant) parameter appears to be the most influential foreground parameter within the FMPF, ME, and LU impact categories given CHEM's high DQI score which is translated in higher variability of the input value. However, the uncertainty of CFs varies in its impact across the categories, as indicated in Fig. 5. Generally, the GSA methods yield consistent results, particularly in identifying the most influential parameter. Nevertheless, this observation appears to diminish as the

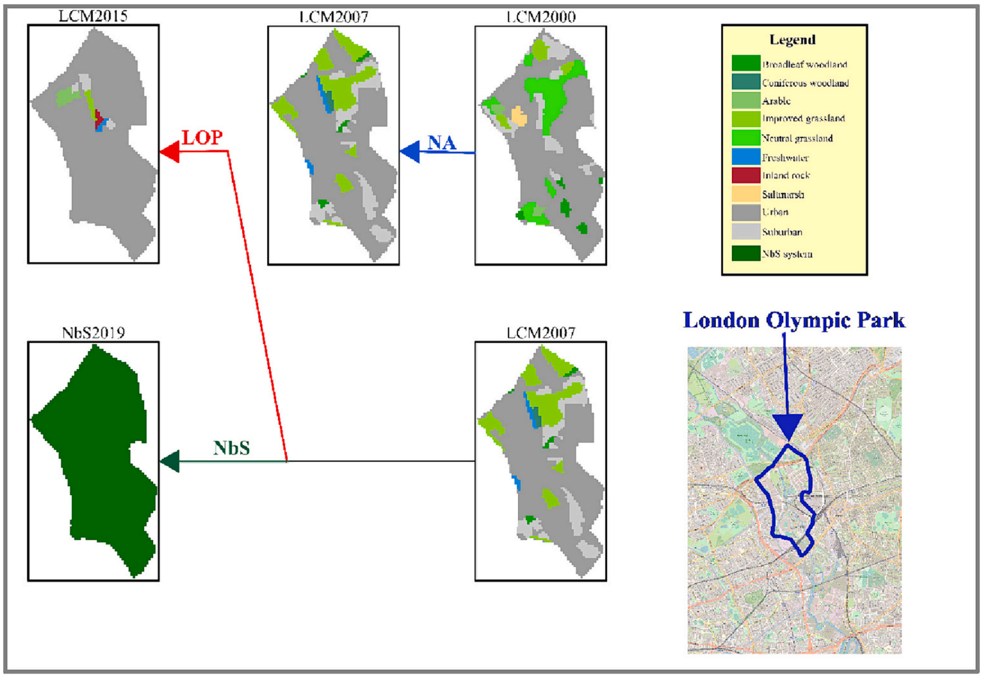

Fig. 2. Case study map and modelled scenarios (LCM: land cover map, LOP: London Olympic park, NA: no action scenario, NbS: nature-based solution scenario).

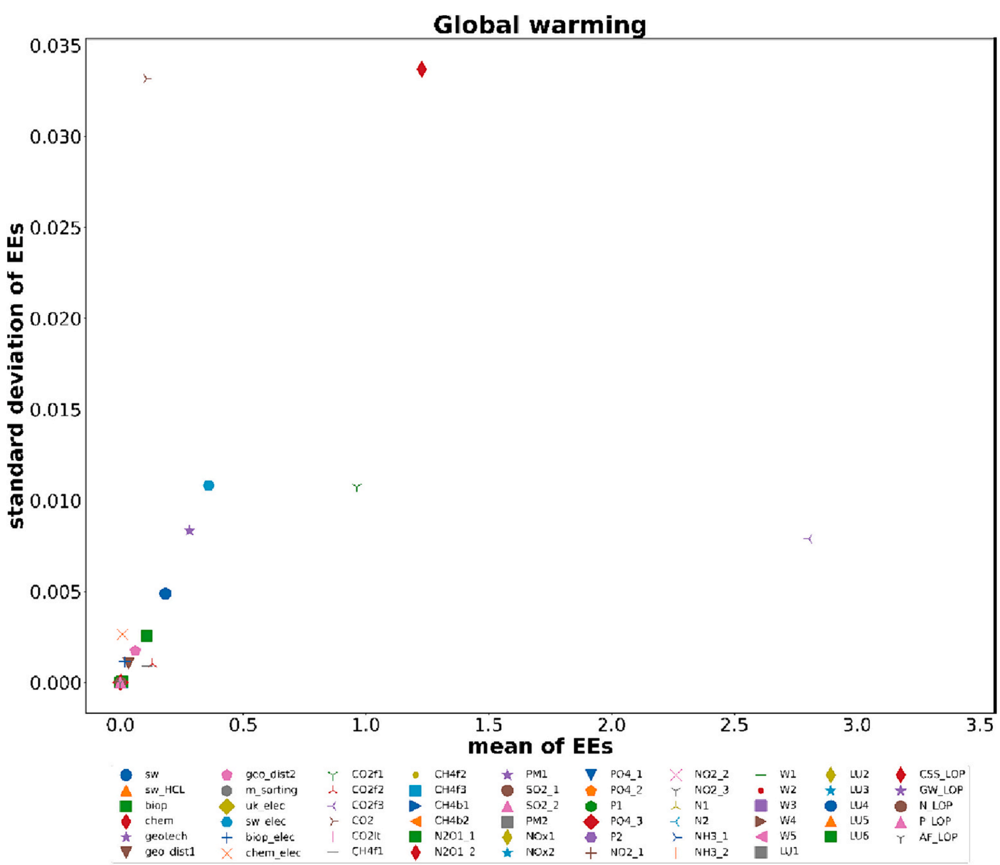

Fig. 3. Screening step results of global warming potential (GWP) results of the LOP scenario; (EEs: Elementary Effects, Tables B.1–B3 present full description of the investigated input parameter).

importance value approaches zero. Notably, the PAWN method appears to produce false positive values, evident in the PAWN index values of CFs displaying sensitivity beyond their respective categories corroborating Puy et al. (2020)'s findings. There seems to be minimal impact from the interaction between model parameters, as indicated by the near-zero values of the Sobol's total-order index (ST). Finally, Sobol's

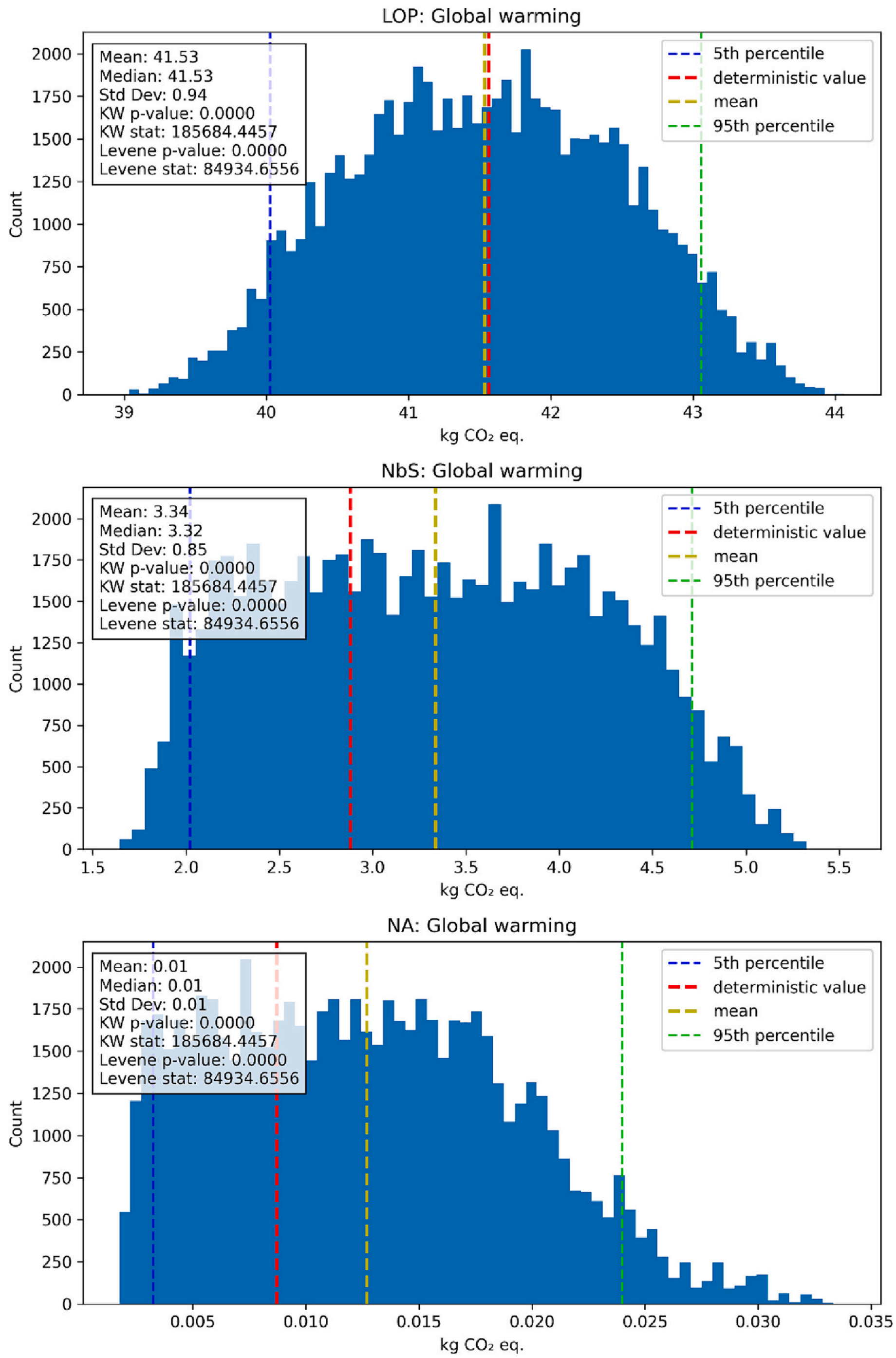

Fig. 4. Comparison of the stochastic global warming potential (GWP) results for the three scenarios relative to the deterministic values; (KW: Kruskal-Wallis test, LOP: London Olympic park, NA: no action scenario, NbS: nature-based solution scenario, Std Dev: standard deviation).

first-order index (S1) and RBD-FAST S1 demonstrate better agreement compared to the results of other indicators.

In parallel with the LOP scenario, a consistent pattern emerges among the agreement of GSA results of the NbS and NA scenarios, extending to less influential parameters in terms of the output uncertainty. Moreover, the PAWN results exhibit greater consistency when compared to the LOP results. In contrast to the GSA findings of the LOP scenario, both the NbS and NA GSA indices point to the foreground land use (LU)-LCI flow as the most significant parameter across the impact categories. This occurs with exception for the WC category, where CFs take dominance, mirroring the LOP scenario results shown in Fig. B.10a, and Fig. B.10b.

In the FE and LU GSA results of the NbS scenario, the second most important parameters are the CFs from the respective impact categories, and a similar trend is observed in the NA's LU indices. Finally, the substantial contribution of the LU-LCI to uncertainty could be attributed to its higher correlation with other parameters, as indicated by the ST results.

4.4. *Post processing*

4.4.1. *Convergence analysis: impact of the sample size*

In this section, we assess the robustness of GSA results based on Sobol's sequence sampling by analysing the convergence of sensitivity.

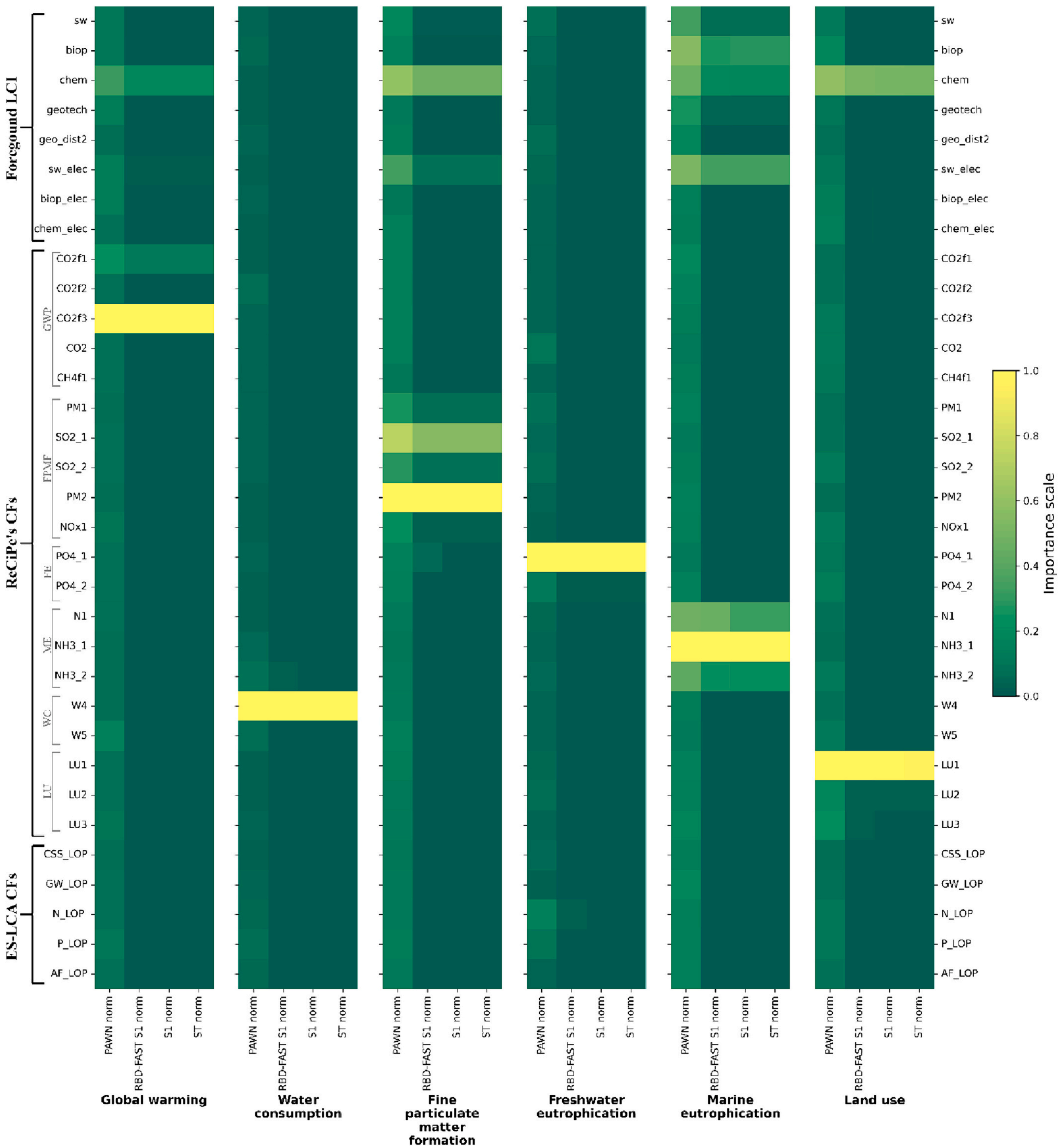

Fig. 5. GSA results of the LOP scenario; (Tables B.1–B3 present full description of the investigated input parameter, FE: freshwater eutrophication, FPMF: fine particulate matter formation, GWP: global warming potential, LU: Land Use, ME: Marine Eutrophication, PAWN norm: normalised PAWN indicator, RBD-FAST S1 norm: normalised 1st order indicator of random balance designs Fourier amplitude sensitivity test, S1 norm: normalised 1st order Sobol's index, ST norm: normalised total order Sobol's index, WC: water consumption).

Convergence of sensitivity indices occurs when the values of sensitivity indices stabilize at a certain sample size. Fig. 6, along with Fig. B.15, and Fig. B.19, illustrates S1 value in relation to the sample size. S1 measures the contribution of parameters to the model's variance.

Upon inspecting Fig. 6, Fig. B.15, and Fig. B.19 for the LOP, NbS, and NA scenarios, we observe that in the LOP scenario, S1 values converge at a sample size of 8704 for the WC and FPMF categories, while they reached stability at a sample size of 17,408 for the remaining categories. In the NbS scenario, S1 convergence for the GW and FMPF categories occurred at a sample size of 8704, and at 17408 for the remaining categories. In the NA scenario, S1 convergence for the GW and WC categories took place at a sample size of 8704, while for the rest of the categories, the sensitivity results converged at 17408 sample size.

Fig. B.12, Fig. B.17, and Fig. B.21 depict convergence plots of the

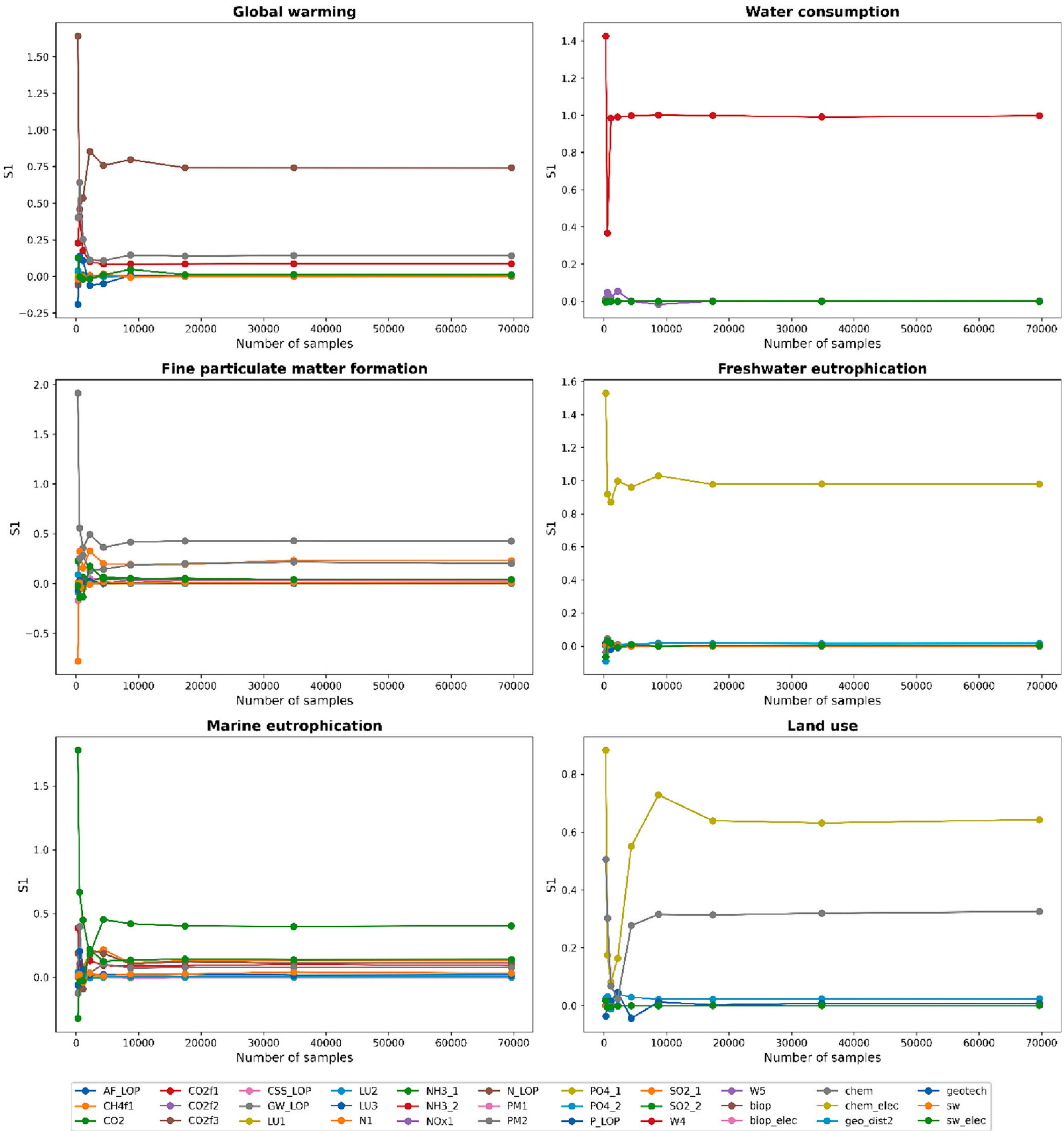

Fig. 6. Convergence analysis of S1 index of the LOP scenario; (Tables B.1–B3 present full description of the investigated input parameter).

total-order Sobol's sensitivity indices (ST), which assess the impact of interactions on the model's output variance. In both the LOP and NbS scenarios, ST converged at a sample size of 17,408, while for the NA scenario, the results stabilized at a sample size of 34,816.

The convergence analysis of PAWN indices is depicted in Fig. B.13, Fig. B.17, and Fig. B.21 while the RBD-FAST S1 indices are shown in Fig. B.14, Fig. B.18, and Fig. B.20 for the LOP, NbS, and NA scenarios respectively. Both indices exclusively assess the first-order impacts of the parameters and do not account for parameter interactions. The convergence of both the RBD-FAST S1 and PAWN indices was observed at a sample size of 17,408 across all impact categories in the modelled scenarios.

4.4.2. Convergence analysis: impact of the sampling strategy

In this section, we consider the impact of the sampling strategy on the robustness of sampling-agnostic GSA methods employed in this study, specifically the PAWN and RBD-FAST methods. We utilized SS sampling and LH sampling strategies. Our analysis unfolds in two steps. Firstly, we examine descriptive statistics through the analysis of box-plots for model outputs (refer to Fig. 7 for the NbS scenarios, Fig. B.23 for the LOP, and Fig. B.25 for NA scenarios). Secondly, we conduct convergence analyses of PAWN and RBD-FAST results, as presented in Fig. 8 for the NbS scenario GWP's PAWN results (the remaining NbS results are in Fig. B.38–49), and Figs. B.23–34 for the LOP scenario, and Figs. B.50–61 for the NA scenario.

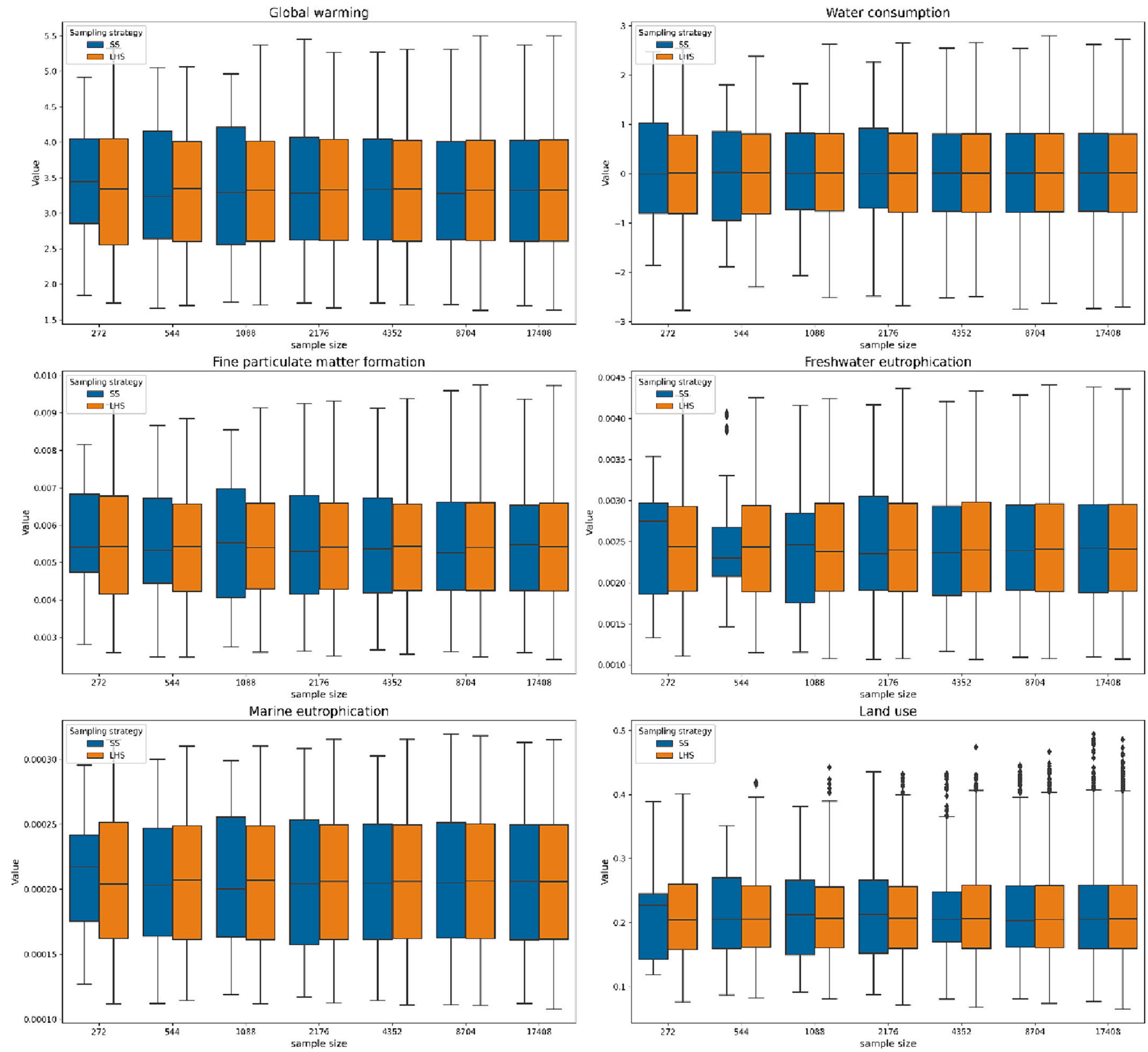

Fig. 7. Stochastic results of the NbS scenario based on the sampling strategy; (LHS: Latin hypercube sampling, SS: Sobol's sampling).

Upon analysing the boxplots, several observations emerge. Firstly, the means of the output groups tend to be approximately equal for both SS and LH samplings at sample sizes of 2176 and 4353, across all the modelled scenarios, except for the FMP and FE results in the LOP scenario, where equality of means was achieved at a sample size of 8704 (refer to Fig. B.23 The second observation pertains to the data spread of the output, as indicated by the 25th and 75th percentiles. The output distributions were fairly similar at a sample size of 2076, suggesting that lower sample sizes are insufficient to ensure result robustness.

The third observation relates to the presence of outliers, as indicated by the length of the boxplot whiskers and data points located farthest from the whiskers. Generally, LH sampling produced more outliers compared to SS sampling. This result is anticipated due to the way LH sampling is designed to fill the sample space in equal intervals, regardless of the density (Mckay et al., 2000).

The convergence analysis of LH and SS sampling's GSA results offers clearer trends about the GSA results of the PAWN and RBD-FAST results. For the PAWN method, while the input parameters influence ranking was similar for both sampling strategies, the LH sampling offered faster convergence at sample size of 2176 across all the modelled scenarios. In contrast, the SS sampling achieved a similar convergence at sample size of 8704 and 17,408. A second remark pertains to the fluctuation of the PAWN indices of the less influential parameters, we notice that LH sampling offer more consistent values while the SS values continue to fluctuate even at larger sample sizes of 34,816 and 69,032. Although this result might be model-specific, it indicates higher compatibility of LH sampling to the PAWN method.

Regarding the RBD-FAST S1 convergence, we noticed that LH sampling offered a superior performance relative to SS converging at sample sizes of 1088 and 2176 while the SS indices converged at samples sizes of 8704 and 17,408. A similar observation of the fluctuation of the RBD-FAST S1 values of the less influential parameters is noticed. Moreover, we notice that LH sampling offer more consistent values while the SS values continue to fluctuate even at larger sample sizes of 34,816 and 69,032.

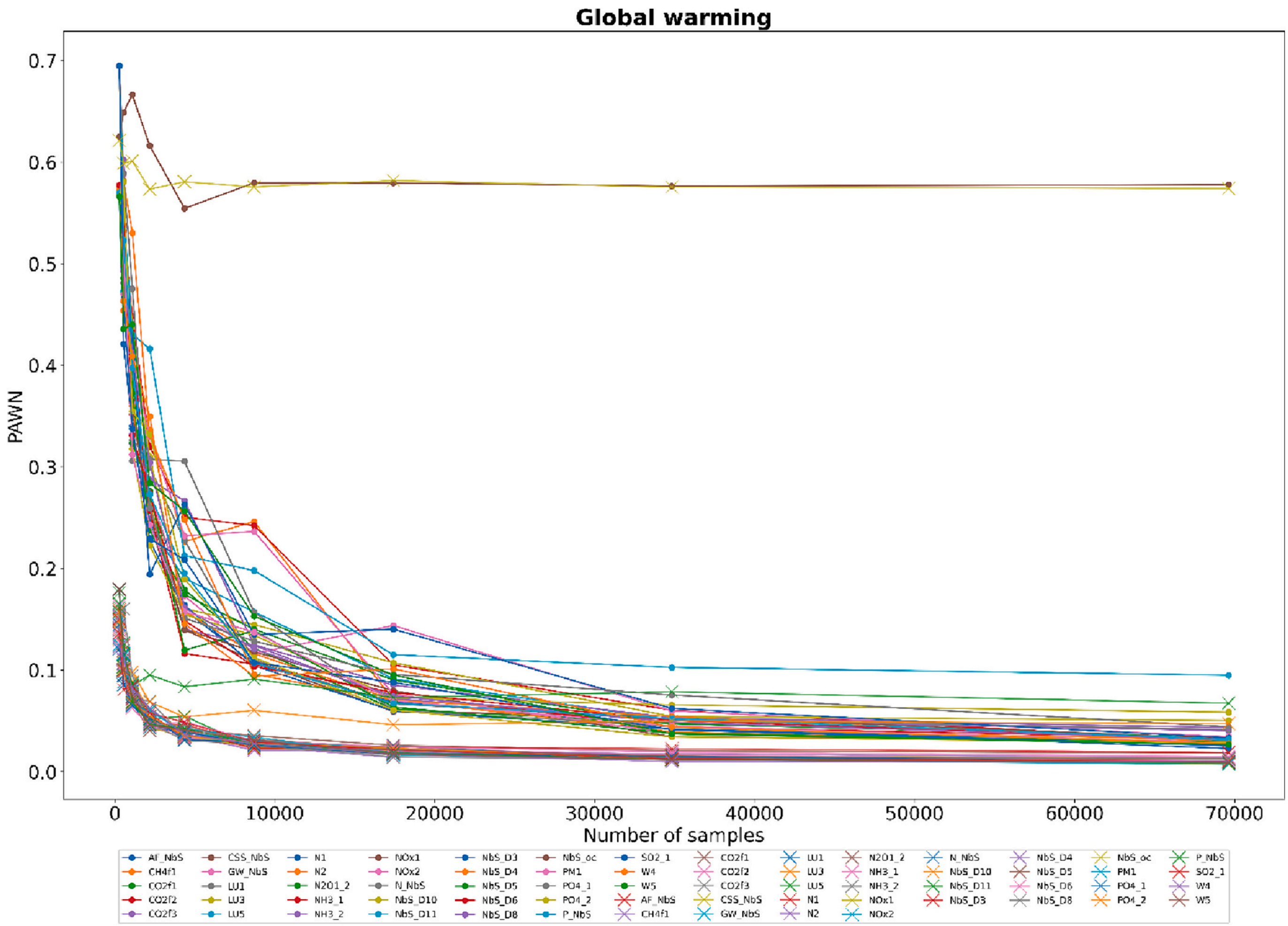

Fig. 8. Comparison of PAWN indices convergence of the NbS scenario's GWP results based on sampling strategy; (x-marker: latin hypercube sampling, dot-marker: Sobol's sampling, Tables B.1–B3 present full description of the investigated input parameter).

Table 4
Dunn's test results[a].

Impact	FE			WC			LU			ME		
Scenario	LOP	NbS	NA	LOP	NbS	NA	LOP	NbS	NA	LOP	NbS	NA
LOP	1	0	0	1	2.53E-07	2.48E-11	1	0	0	1	0	0
NbS	0	1	0	2.53E-07	1	0.032957	0	1	0	0	1	0
NA	0	0	1	2.48E-11	0.032957	1	0	0	1	0	0	1

Impact	GWP			FPMF			CSS			P retention		
Scenario	LOP	NbS	NA	LOP	NbS	NA	LOP	NbS	NA	LOP	NbS	NA
LOP	1	0	0	1	0	0	1	0	0	1	0	0
NbS	0	1	0	0	1	0	0	1	0	0	1	0
NA	0	0	1	0	0	1	0	0	1	0	0	1

Impact	AF			N retention			GR		
Scenario	LOP	NbS	NA	LOP	NbS	NA	LOP	NbS	NA
LOP	1	0	0	1	0	0	1	0	0
NbS	0	1	0	0	1	0	0	1	0
NA	0	0	1	0	0	1	0	0	1

[a] AF: air filtration, CSS: carbon storage and sequestration, FE: freshwater eutrophication, FPMF: fine particulate matter formation, GR: groundwater recharge, GWP: global warming potential, LU: Land Use, ME: Marine Eutrophication, WC: water consumption.

4.4.3. Hypothesis testing

In the post-processing phase of the proposed uncertainty protocol, we conducted the Levene's test on the impact categories of the modelled scenarios to ascertain the appropriate analysis of variance test. The results of the Levene's test are depicted in Fig. B4–6. Across all the modelled scenarios and impact categories, the p-values were found to be less than $\alpha = 0.05$. Consequently, we rejected the null hypothesis of the Levene's test, which posits that all the samples are drawn from populations with equal variances.

Given that the homogeneity of variances condition required for the ANOVA test was not met, we opted for the KW test, a non-parametric alternative to ANOVA. The results of the KW test are also presented in Fig. B4–6. In all cases, the p-values from the KW test were less than $\alpha = 0.05$, leading to the rejection of the KW test null hypothesis, which postulates that the medians of all groups are equal. While the rejection of the KW test null hypothesis suggests differences between the groups, it does not specify which group(s) differ(s).

Consequently, it becomes necessary to conduct a post-hoc test, such as Dunn's test, to determine the specific group(s) exhibiting differences. Dunn's test was employed to evaluate pairwise differences among multiple groups within the dataset, revealing statistically significant distinctions between specific group combinations ($p < 0.05$). Table 4 displays the results of the Dunn's test with the Bonferroni correction applied to both traditional LCIA and ES-LCA results. A p-value less than $\alpha = 0.05$ leads to the rejection of the Dunn's test null hypothesis which states that there is no significant difference between any of the pairwise group comparisons.

Analysing Table 4, we see significant differences across all impact categories among the scenarios. The very low p-values are due to the Bonferroni correction, which controls Type I error by adjusting the significance level for the number of comparisons (Armstrong, 2014). Larger sample sizes entail higher number of comparisons which improve detection power but demand a stricter significance threshold.

5. Discussion

5.1. Applicability of the proposed UA protocol

As discussed in Section 2, despite the increasing integration of ES-LCA assessments for NbS systems, they often lack adequate statistical treatment for managing multiple sources of uncertainty inherent in integrated assessments. Therefore, we have introduced a comprehensive uncertainty assessment protocol to support decision-making in NbS systems. This protocol has been demonstrated using an illustrative case study, showcasing its applicability to complex LCA models representing various scenarios.

As shown in Section 4.1, the screening step efficiently identifies influential input parameters at a low computational cost, facilitating early-stage design adjustments or the acquisition of higher-quality data. Section 4.2, with its visualization and descriptive statistics of stochastic outputs, aids in understanding the effects of input parameter uncertainty on ES-LCA outcomes. Additionally, the multi-method GSA results presented in Section 4.3 bolsters the robustness of integrated ES-LCA by comparing multiple GSA indices. The post-processing findings in Section 4.4 illustrate how we can evaluate the performance of the GSA methods used in the study. While the case study is specific to a particular domain, the proposed protocol has been designed to accommodate NbS systems across various sectors, including for instance green infrastructure and ecological farming systems.

5.2. Assigning uncertainty information to standard and ES-LCA CFs

Assigning reasonable probability distributions is a critical part of the uncertainty assessment exercise, but obtaining relevant uncertainty information in practice remains a challenge. Therefore, semi-quantitative data quality indicators such as the pedigree matrix have been extensively used in previous studies (Ciroth et al., 2016; Spreafico et al., 2023). Though in our work, the DQI has been assessed twice independently as discussed in Section 3.1.1 to reduce the potential risk of bias, we found that the variability of the output is sensitive to the choice of the DQI. Therefore, we recommend obtaining realistic uncertainty ranges where feasible. Assigning probability distribution to the CFs of ES-LCA was relatively straightforward given the availability of variability ranges of the biophysical inputs used in the ES modelling in addition to the relatively simple models used by the InVEST models (refer to Table A.1). That said, caution must be put in place when dealing with hydroclimatic factors such as annual rainfall because it could impact the groundwater recharge potential significantly (Moeck et al., 2020). Therefore it is suggested to consult multiple data source to ensure the robustness of the results (Redhead et al., 2018). The spatial scale and resolution of the spatial data is another uncertainty source that could impact the stochastic ES results thus affecting the uncertainty distribution of ES-related CFs. However, an extensive assessment of the impact of the quality of the spatial data is out of the scope in this work. The CFs of standard LCIA are the last part of the uncertainty triad in our protocol and was the most challenging component to find reasonable uncertainty probability distributions. On one hand, the perceived uncertainty of CF is relatively high as reported by Qin et al. (2020). On the other hand every impact category is essentially a separate model reflecting a different impact pathway and subject to different factors (Huijbregts et al., 2017). Additionally, the existing impact assessment methods still lack even semi-quantitative uncertainty information (Cucurachi et al., 2016; Qin et al., 2020). The GSA results of the LOP scenario (Fig. 6) indicate that the overall uncertainty is highly correlated with the variability of CFs while the NbS and NA paint a somewhat different image of dominant foreground-land use flow that is not always the case in all LCA models (see fig. B.10a & B.10b). While we acknowledge the work done by Santos et al. (2022), who proposed a semi-quantitative methodology for assigning uncertainty ranges to CFs of impact categories, we recommend future efforts to further develop stochastic analysis methodologies for assessing the quantitative uncertainty of CFs. This will enhance the robustness of LCAs by utilizing the numerous existing GSA tools.

5.3. Selection of the GSA methods

Results of this paper suggest that the selection of GSA methods is an important component of the uncertainty assessment exercise. The decision of GSA methods is driven by the scope of uncertainty assessment (a screening or ranking of input parameters) as well as the order of effect of interest (first, second, or total order). The availability of computational resources also controls the selection of GSA method, e.g., variance-based GSA methods are computationally expensive relative to distribution-based GSA methods. Additionally, the complexity of the LCA model is an important aspect since the number of parameters of interest often increases as the LCA model gets more complex. The choice of GSA method influences the sample size, sampling size, and compatibility with other GSA method; therefore, the GSA methods should be selected with care. In Section 4.3, we demonstrated the feasibility of a multi-method GSA approach at no additional computational cost using Sobol's sequence sampling strategy which is compatible with Sobol's sensitivity indices, RBD-FAST, and the distribution-based PAWN method.

The level of expertise of the LCA modeller might be another hindrance as the implementation of GSA in LCA is still absent from major LCA software aside from the AcitivityBrowser (Cucurachi et al., 2022). However, the advent of GSA tools and easy-to-use scripting interfaces of major LCA software is simplifying the GSA application to LCA as demonstrated in the present study as well as in Jaxa-Rozen et al. (2021a). Since NbS systems provide multiple ES benefits, the uncertainties of which are typically not assessed, we recommend applying GSA methods to the LCA of complex systems like NbS. This approach could yield valuable insights and enhance the decision-making process. We also recommend exploring additional GSA method such as the delta moment-independent method in tandem with other methods.

5.4. The number of simulations and sampling strategies

The results of the convergence analysis of sample size presented in Section 4.4.1 suggest that Sobol's indices converged at a smaller sample size than the assumed number of simulations per parameter ($N = 1000$). The convergence results suggest that a lower number of simulations per parameter ($N = 500$) could be sufficient. As for the PAWN and RBD-FAST S1 indices, the convergence took place by $N = 250$. We also observed the convergence speed depends on the complexity of the LCA model under study. Given the LCA models in this are fairly complex, we suggest a number of simulations per parameter between N = 250 and 500 as a starting point coupled with a convergence analysis plot to ensure the selected GSA method results are robust. A caveat here is that the appropriate sample size is still highly debated in the literature and depends on the used GSA method and the structure of the model under study. Therefore, additional investigation within the uncertainty of LCA and ES-LCA models, in particular, is required to draw universal conclusions about the appropriate sample size.

We also experimented with the impact of sampling strategy choice on the convergence of distribution-based GSA methods (refer to Section 4.4.2). We observed that choice of sampling strategy had a significant impact on convergence of the PAWN and RBD-FAST S1 methods, the LH sampling offered superior performance relative to the SS sampling strategy. Though using multiple sampling strategies might undermine the advantage of the no-additional computational costs of multi-method GSA, we found that conducting a distribution-based multi-method GSA before attempting the more resource-demanding Sobol's method provided useful insights which were often validated results of the Sobol's indices. Hence if the number of parameters is larger than 30, it might be useful to conduct PAWN as the second step of the two-stage screening phase while using the method of Morris in the first step to reduce the overall sample size required by Sobol's. Investigating the feasibility of random sampling-based multi-method GSA within the ES-LCA context is an interesting line of inquiry that could be explored in future efforts as random sampling functionality is already present in modern LCA software packages reducing the need to learn specialised statistical tools.

5.5. Selection of appropriate hypothesis testing

Hypothesis testing plays a crucial role in the post-processing phase, quantifying stochastic model outputs and facilitating comparisons between scenarios or systems (e.g., NbS systems vs. conventional active remediation). The choice of hypothesis testing depends on the shape of the model output probability distribution (normal or non-normal) and the number of scenarios or groups involved (two or more). These factors determine whether parametric or non-parametric tests are appropriate. Additionally, it is essential to verify that the assumptions of the hypothesis test are met, along with examining the null hypothesis to ensure the accuracy of the result interpretation.

In this study, we employed non-parametric KW and Dunn's tests, as we observed substantial skewness in several LCIA results, particularly for the NbS and NA scenarios (e.g., Fig. 4). It is worth noting that Dunn's test is known for its conservative nature, which means it may occasionally overlook differences between groups or scenarios. Depending on the scope of the uncertainty assessment, other powerful tests may be explored such as the Conover-Iman test (Conover, 1999), aligning with the context of the uncertainty analysis.

6. Conclusions

In this work, we presented a novel quantitative uncertainty assessment protocol for integrated ES-LCA to enable a thorough uncertainty characterisation and analysis of sensitive parameters and their impacts on the uncertainty of the ES-LCA results. Unlike previous studies which only focused on a single LCA phase (e.g., LCI), the uncertainty of several phases of the ES-LCA approach is assessed including foreground LCI, CFs of traditional LCIA, and CFs of ES accounting. We employed a multi-method GSA approach at no additional computational cost leveraging state-of-the-art uncertainty assessment tools. We also assessed the robustness of the multi-method GSA through convergence analysis visualisations as well as statistical hypothesis testing. Furthermore, we explored the influence of sampling strategy selection and the number of simulations on GSA results, comparing LH sampling with SS sampling and highlighting the significance of these choices in the context of uncertainty assessment. We also analysed the results of the proposed uncertainty protocol in the context of an illustrative NbS soil remediation case study highlighting the possibility of extending the protocol application to many other NbS contexts. Moreover, we discussed the results in terms of protocol applicability, uncertainty characterisation of the ES-LCA phases, selection of the GSA method, appropriate sampling size and strategy, and concluded with a discussion of the appropriate hypothesis testing for the proposed protocol.

The absence of uncertainty probability distributions for CFs in impact assessment methods posed a significant challenge when conducting stochastic simulations for the modelled scenarios. This challenge was especially pronounced when GSA results indicated that CF uncertainty played a central role in determining model outputs. As a result, we strongly recommend that developers of impact assessment methods incorporate suitable uncertainty assessment approaches to enhance the overall robustness of LCA analyses, including ES-LCA. In this case, special effort should be conveyed in determining spatial or other intrinsic uncertainties of the biophysical parameters associated with the functioning of ecosystems and the supply of ecosystem services.

Selecting a reference scenario, specifically the choice of the year for the land cover map, presented another challenge. Land Use/Land Cover (LULC) effectively serves as a proxy for ES modelling (Koellner et al., 2013). However, since the work on the case study began around 2007, it was challenging to select the reference scenario. Notably, the “no-action” scenario assumes no land use change occurs. If we had chosen LCM2007 as the reference scenario for the “no-action” scenario, we would not have been able to calculate changes in ES values (refer to Section 3 of Alshehri et al. (2023b) for further discussions). Consequently, we opted for LCM2000 as the reference scenario for the “no-action” scenario, while LCM2007 served as the reference for the LOP and NbS scenarios. Ideally, having a consistent reference scenario across all scenarios would be preferred. However, the static structure of InVEST models and the nature of the illustrative case study compelled us to select two reference scenarios. Lastly, the modelled ESs were limited by the availability of data and spatially-explicit ES accounting models.

Future efforts should consider dynamic ES modelling approaches capable of capturing the dynamism in ES delivery. These dynamic ES modelling results could then be integrated into a dynamic LCA approach. While such a modelling exercise would necessitate extensive data collection or an in-depth knowledge of the ecological mechanisms representative of the investigated ecosystems, it holds the potential for significant insights and advancements in this field. Automating the uncertainty assessment of ES-LCA approaches would streamline the application of GSA and eliminate technical hurdles. This automation can occur in two phases. The first phase involves automating deterministic ES-LCA assessments, initially in script form. Subsequently, a graphical user interface could be developed. Once the first phase is accomplished, the second phase would entail incorporating stochastic modelling into ES-LCA, which would be a relatively straightforward endeavour by comparison. Future work should also incorporate the uncertainty of background LCI and explore additional GSA methods and post-processing techniques. Furthermore, future efforts should aim to include additional ESs relevant to the NbS system under investigation, such as cultural services, as well as biodiversity. Lastly, integrating the economic uncertainties of NbS into the ES-LCA with an environmental life cycle costing approach (by accounting for the variability of economic inputs and outputs that generate costs and negative externalities) can facilitate a comprehensive triple-bottom-line sustainability assessment of the NbS system.

In conclusion, this study introduced a novel quantitative uncertainty assessment protocol tailored for integrated ES-LCA models, allowing for a thorough analysis of sensitive parameters across multiple ES-LCA phases. We utilized a multi-method GSA approach, assessed its robustness, examined the influence of sampling strategies, and applied the protocol to an illustrative NbS soil remediation case study. This demonstration illustrates its potential application in various NbS contexts. We also highlighted challenges encountered and offered suggestions for future research.

CRediT authorship contribution statement

Khaled Alshehri: Writing – review & editing, Writing – original draft, Visualization, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **I-Chun Chen:** Writing – review & editing, Methodology. **Benedetto Rugani:** Writing – review & editing, Validation, Formal analysis. **Devin Sapsford:** Writing – review & editing, Supervision, Methodology, Conceptualization. **Michael Harbottle:** Writing – review & editing, Supervision, Methodology, Conceptualization. **Peter Cleall:** Writing – review & editing, Supervision, Methodology, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

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