engineering proceedings

MDPI

Proceeding Paper

uqStudio: A Modular Framework for Uncertainty Quantification in Multidisciplinary Design †

Tawfiq Ahmed * and Marko Alder *

Institute of System Architectures in Aeronautics, German Aerospace Center (DLR), Hein-Saß-Weg 22, 21129 Hamburg, Germany

* Correspondence: tawfiq.ahmed@dlr.de (T.A.); marko.alder@dlr.de (M.A.)

† Presented at the 15th EASN International Conference, Madrid, Spain, 14–17 October 2025.

Abstract

Uncertainty quantification (UQ) is essential for the robust and competitive design of climate-friendly transportation systems, such as aircraft and space launch systems. However, supporting software applications for UQ are fragmented across numerous open-source libraries, often require in-depth knowledge of the mathematics underlying UQ, and commercial solutions often involve licensing costs. This can make it difficult for design experts to take uncertainties into account. To address this issue, we propose a modular, web-based framework that will guide practitioners through the most common UQ processes, such as statistical sampling, propagation through design workflows, and statistical analysis of the results. Adopting a modern client-server architecture, a backend service, called uqFramework, wraps relevant software libraries for each of the aforementioned steps. The current version focuses on probabilistic approaches, enabling the generation of Design-of-Experiment (DOE) inputs via Quasi-Monte Carlo, Latin Hypercube, and Low Discrepancy Sequence sampling methods. Furthermore, it enables the parallel execution of design and analysis workflows via DLR's Remote Component Environment (RCE) or Python scripts. Finally, uqFramework performs global sensitivity analyses using Sobol, FAST, or Morris techniques. An interactive front-end application called uqStudio connects to uqFramework through a Representational State Transfer (REST) interface. It guides users through the UQ process via an intuitive, step-by-step interface. Interactive visualizations enable detailed exploration of each step. The framework's capabilities are illustrated through two examples, the Ishigami function and a multidisciplinary UAV design study, verifying its precision, adaptability, and user-friendliness. We demonstrate that uqStudio enables researchers to conduct integrated UQ studies covering uncertainty specification, propagation, and sensitivity analysis without the difficulty of installing and properly using fragmented libraries. Future work includes extending visualization capabilities and integrating surrogate-modeling capabilities to enable faster workflow execution.

Keywords: uncertainty quantification; data sampling; workflow automation; global sensitivity analysis; multidisciplinary design

Check for updates

Academic Editors: Spiros Pantelakis, Andreas Strohmayer and Gustavo Alonso

Published: 7 May 2026

Copyright: © 2026 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license.

1. Introduction

Uncertainty Quantification (UQ) is vital for robust and climate-conscious conceptual design of aircraft and launch systems, where early decisions made under uncertain aerodynamic, structural, and mission parameters strongly affect performance and cost. Although Multidisciplinary Design Optimization (MDO) frameworks can address these

uncertainties, UQ is often applied inconsistently or too late, resulting in non-robust or overly conservative designs.

Existing UQ tools and libraries offer advanced probabilistic modeling, sampling, and sensitivity analysis capabilities. While several high-quality open-source solutions exist, practical deployment in multidisciplinary engineering environments often remains challenging. Many tools are script-based and require significant expertise in numerical methods and software integration. In addition, commercial UQ software typically involves licensing costs, and integrating either open-source or commercial tools into Model-Based Systems Engineering (MBSE) workflows often requires substantial engineering effort and maintenance [1–4].

This paper presents a modular, web-based framework designed to support probabilistic analysis within existing workflows. It comprises two main components: *uqFramework*, a RESTful backend for sampling, propagation, and sensitivity analysis; and *uqStudio*, a web-based frontend offering intuitive configuration and visualization. A unified data model (*uqDatamodel*) ensures consistent definition, storage, and reuse of all study elements.

The framework's functionality is demonstrated through two benchmarks: the Ishigami function and a multidisciplinary UAV design study, confirming its accuracy, flexibility, and ease of use. The remainder of this paper reviews related tools (Section 2), outlines the framework architecture (Section 3), presents validation results (Section 4), and concludes with future directions (Section 5).

2. Background and Related Work

2.1. Probabilistic Uncertainty Quantification

Uncertainty Quantification (UQ) systematically assesses how input variability affects model outputs. In probabilistic analysis, inputs are modeled as random variables with defined distributions, and sampling-based approaches such as Monte Carlo, Latin Hypercube Sampling (LHS), and sensitivity-driven schemes (Sobol, FAST, Morris) are widely used for nonlinear and multidisciplinary systems [5,6]. The resulting ensembles enable statistical characterization of performance metrics and design robustness. Global Sensitivity Analysis (GSA) quantifies each variable's influence on output variance through methods such as Sobol indices [7], FAST [8,9], and Morris screening [10], supporting variable ranking and model simplification in multidisciplinary design optimization (MDO).

2.2. Existing Tools and Limitations

Existing UQ tools, such as *SALib* [11,12], *OpenTURNS* [1], *UQLab* [3], *Dakota* [2], and commercial software such as *SmartUQ* [4], offer robust algorithms for sampling, surrogates, and analysis but are often fragmented and script-heavy, requiring advanced numerical expertise. Integration within multidisciplinary environments like DLR's *Remote Component Environment* (RCE) [13] demands manual interfacing and reduces reproducibility. Commercial licensing further limits accessibility. These challenges motivate a unified, modular, and web-accessible framework that combines trusted UQ libraries with an intuitive interface, enabling consistent sampling, propagation, and sensitivity analyses directly within RCE or Python-based workflows.

3. Methods

3.1. Design Objectives

The framework presented in this paper intends to enable efficient, accessible, and reproducible Uncertainty Quantification (UQ) in early-stage engineering design, with four core objectives: providing end-to-end UQ capabilities (sampling, propagation, and sensitivity analysis) within a unified environment; adopting a modular and extensible

https://doi.org/10.3390/engproc2026133087

architecture for easy integration of new methods; ensuring non-intrusive compatibility with existing workflows such as RCE or Python-based studies; and offering a web-based, intuitive interface to make advanced UQ methods accessible to a wider range of users.

3.2. Architecture Overview

The overall system adopts a modern client–server architecture (Figure 1) consisting of a backend service, called *uqFramework*, and an interactive frontend, called *uqStudio*. Communication between both components occurs via a Representational State Transfer (REST) interface, ensuring full decoupling between computation and visualization layers.

The backend provides the computational logic for sampling, propagation, and sensitivity analysis, whereas the frontend offers the user interface, interactive visualizations, and process guidance. This architecture allows deployment on local servers or cloud infrastructure.

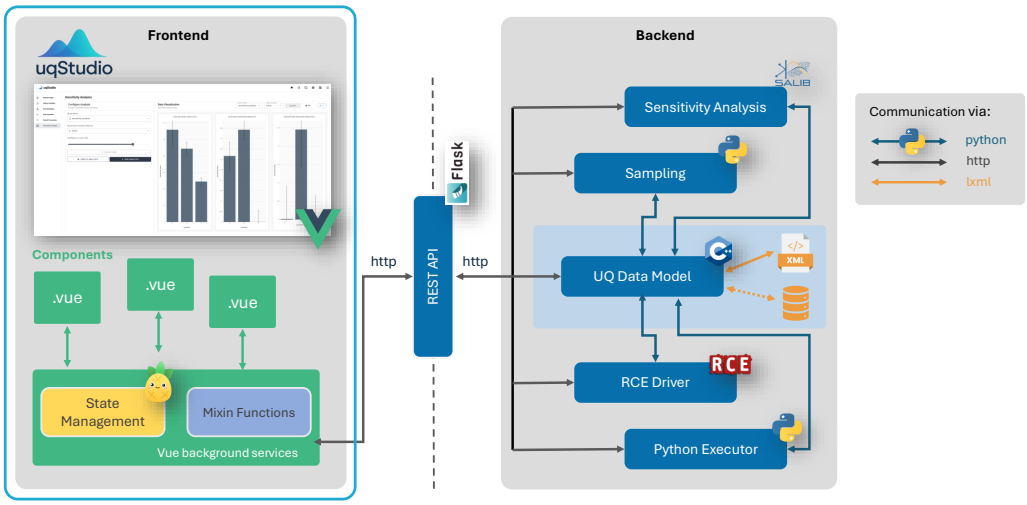


Figure 1. Architecture of *uqFramework* and *uqStudio*. The figure illustrates the layout and flow of the architecture rather than individual dashboard visualization.

3.3. Backend: uqFramework

The *uqFramework* acts as the computational core, providing a RESTful backend for sampling, propagation, and sensitivity analysis using established open-source libraries, especially *SALib*, a widely known Python library for uncertainty quantification [11,12]. By re-using *SALib*'s well-tested routines, the correctness of the mathematical implementation in *uqFramework* can be verified. *uqFramework* includes a sampling engine supporting random sampling, LHS, and sensitivity-driven methods (Saltelli, FAST, Morris).

Workflow execution is automated via parallel RCE executions. In addition to the RCE-based workflow demonstrated in this paper, uqFramework also supports standalone Python-based workflows. In this mode, the framework automatically generates input samples, executes user-provided Python scripts, and collects the resulting outputs for subsequent analysis. The RCE-based workflow was selected for demonstration because it represents a typical multidisciplinary integration environment at DLR.

Post-processing computes global sensitivity metrics (Sobol', FAST, Morris) validated against Ishigami and UAV benchmarks. All data are managed through the standardized *uqDatamodel*, an XML-based structure with C++/Python 3.10+ bindings ensuring consistent handling of probabilistic inputs, samples, and results across studies [14].

3.4. Frontend: uqStudio

The *uqStudio* frontend provides a web-based graphical user interface that guides users through the full UQ process. It is implemented as a single-page application (SPA) connected

to the *uqFramework* backend via REST APIs. All plots and visualizations are interactive, built with the Plotly library, and can be customized or exported in multiple formats. Because the interface runs entirely in a browser, no local installation of UQ libraries or dependencies is required.

The user workflow in *uqStudio* follows a structured, stepwise interaction:

1. **Project definition:** Create a new project and specify metadata such as project name, domain XML path, and version.
2. **Input definition:** Define uncertain inputs via their statistical moments based on given knowledge (e.g., from literature, expert judgment, etc.), and references to the design variables in the domain file.
3. **Study definition:** Each project can host multiple studies, each representing a distinct UQ setup linking selected inputs and outputs.
4. **Sampling:** Choose a study and configure a sampling strategy (e.g., LHS, Sobol, or Quasi–Monte Carlo) to generate the DOE.
5. **Run execution:** Execute the study using the selected workflow engine (RCE or Python). This corresponds to uncertainty propagation. All simulation outputs are automatically stored in the study directory.
6. **Result processing:** Post-process the simulation outputs with statistical summaries and visualizations such as histograms, scatter plots, and cumulative distributions.
7. **Sensitivity analysis:** Select the desired method (Sobol, FAST, or Morris) to compute and visualize sensitivity indices. Interactive plots assist in interpreting the most influential parameters.

The interface provides visual validation feedback, exception handling, and progress monitoring throughout each stage, making the UQ process accessible even to non-experts. To manage visualization load for large datasets, *uqStudio* shows downsampled data in plots, while the backend always operates on the full dataset; users may also download the complete sample set for external analysis. All results and configuration data can be exported locally in the XML-based uqDataModel format, enabling users to reload, edit, or continue their projects in *uqStudio* at any time.

4. Demonstration and Discussion

4.1. Application Case 1: Ishigami Function

The first application case employs the Ishigami function [15] as a nonlinear model for testing global sensitivity analysis. It is defined as

$$f(X_1, X_2, X_3) = \sin(X_1) + a \sin^2(X_2) + b X_3^4 \sin(X_1), \tag{1}$$

where $a = 7$ and $b = 0.1$.

4.1.1. Problem Setup

For this demonstration case, each input variable X_i is uniformly distributed over $[-\pi, \pi]$. The goal here is to verify the correct implementation of GSA methods in *uqFramework* and its linkage to *uqStudio* by comparing numerical Sobol' sensitivity indices with analytical reference values.

4.1.2. Implementation in uqStudio

The Ishigami test case was configured in uqStudio using a simple Python workflow coupled with a domain XML file that defines the input and output parameters. This approach is described in detail by Koch et al. [14].

https://doi.org/10.3390/engproc2026133087

Uniform input distributions were specified in the *Project definition* interface, and Sobol' sensitivity analysis was selected in *Sensitivity analysis* (see Section 3.4). Sampling was performed using the 2nd order Saltelli scheme with a total of 1024 base samples ($N = 1024$), resulting in $N(2d + 2) = 8192$ model evaluations for the three-dimensional Ishigami function.

4.1.3. Results

Based on the *uqStudio* problem setup, *uqFramework* computes both first-order (S_i) and total-order (S_{Ti}) Sobol' indices, which were compared to analytical results (see Table 1). The computed indices closely match the analytical references, with differences below 1%, confirming the numerical correctness of the implementation.

Table 1. Summary of analytical and uqStudio sensitivity indices for the Ishigami function.

Index	Analytical	uqStudio
First-order indices (S_i)		
S_1	0.318	0.316
S_2	0.444	0.442
S_3	0.003	0.001
Total-order indices (S_{T_i})		
S_{T1}	0.558	0.558
S_{T2}	0.442	0.443
S_{T3}	0.247	0.244
Second-order interactions (S_{ij})		
S_{12}	0.009	0.001
S_{13}	0.238	0.245
S_{23}	0.005	0.001

The results confirm that the computed indices reproduce the analytical solution with negligible deviation, verifying the correct implementation of the framework's sampling and analysis modules. Computational time for this benchmark remained within minutes on a standard laptop using parallel execution.

4.2. Application Case 2: Multidisciplinary Aircraft Design

The second benchmark evaluates the capability of the framework to handle multidisciplinary engineering workflows. The study adopts a nonlinear UAV design case originally introduced by Jiang et al. [16].

4.2.1. Workflow Description

The design process consists of four interconnected disciplines: payload, propulsion, airframe performance, and cost estimation (Figure 2). The objective is to quantify how uncertainties in input parameters affect the predicted vehicle acquisition cost.

4.2.2. Uncertain Inputs and Sampling

Nine uncertain input factors were defined according to [16]. Their probability distributions and physical ranges are summarized in Table 2. Sampling was performed using Saltelli sampling with 1024 samples per input parameter to propagate uncertainties through the UAV workflow (Figure 3).

The workflow produced two key output quantities: (i) the vehicle acquisition cost, C_{acq}, and (ii) the ground area imaged by the onboard sensor, S_{sensor}.

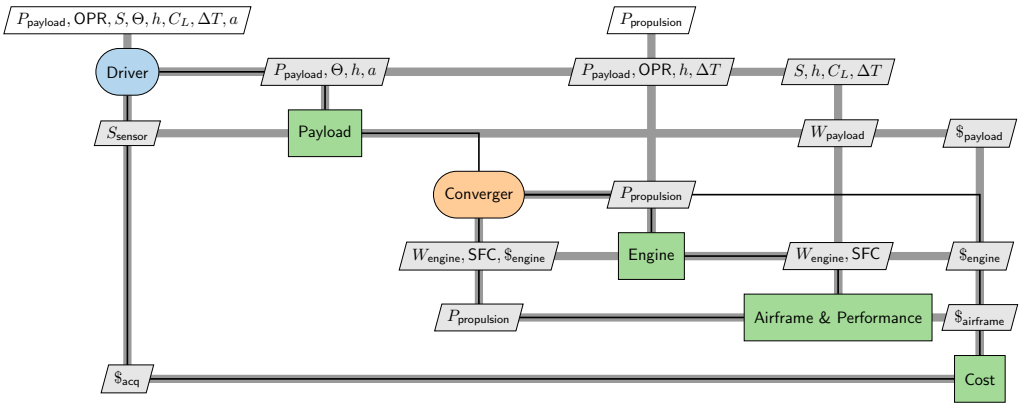


Figure 2. Multidisciplinary UAV design workflow adapted from Jiang et al., showing coupling between payload, engine, airframe, and cost modules. Green nodes are tool nodes, orange is the converger, and blue node is for drivers.

Table 2. Input parameters and their probability distributions for the UAV design benchmark [16].

Input	Description	Distribution	Marginals	Unit
ΔT	Temperature offset	Normal	$\mathcal{N}(0, 100)$	°F
a	Atmospheric attenuation factor	Normal	$\mathcal{N}(0, 0.05^2)$	-
P_{payload}	Payload power	Uniform	$\mathcal{U}[20, 50]$	hp
OPR	Overall pressure ratio	Uniform	$\mathcal{U}[8, 15]$	-
S	Wing surface area	Uniform	$\mathcal{U}[250, 350]$	m^2
Θ	Sensor aperture angle	Uniform	$\mathcal{U}[15, 30]$	deg
h	Altitude	Uniform	$\mathcal{U}[22500, 27500]$	ft
C_L	Lift coefficient	Uniform	$\mathcal{U}[0.7, 0.9]$	-

All parameters are treated as independent random variables with the given marginal distributions.

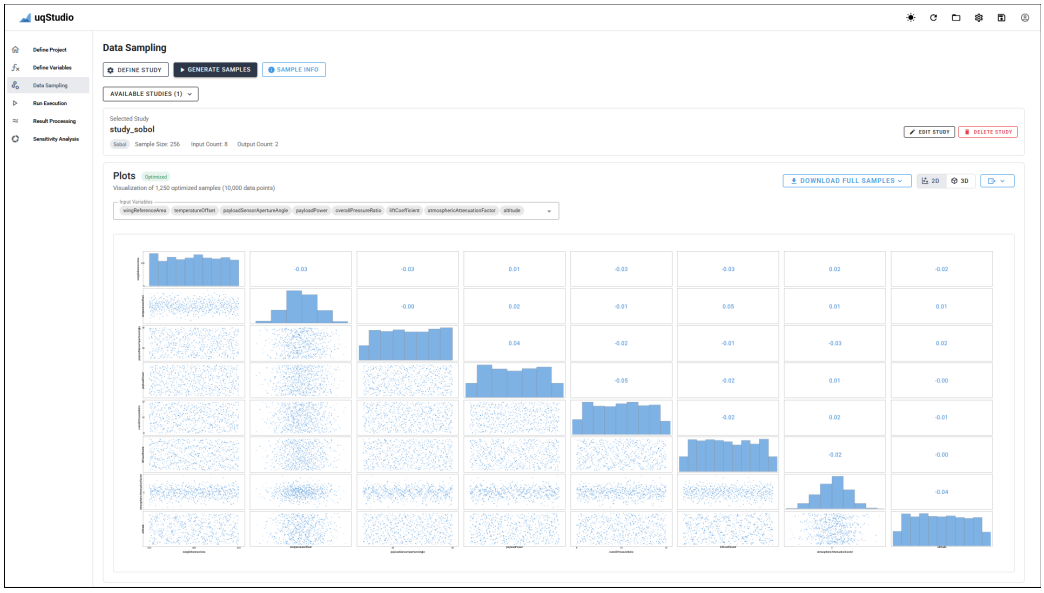


Figure 3. Overview of the data-sampling interface in *uqStudio*, showing the scatter-plot matrix and histogram visualization components. The figure illustrates the layout and interactive visualization capabilities of the user interface rather than individual data values.

4.2.3. Propagation and Output Analysis

Each generated sample was executed through the coupled UAV workflow from Jiang et al. [16] within RCE. All results were stored and visualized through *uqStudio*, where histograms and scatter plots were generated for cost and sensor area outputs. The

resulting acquisition cost distribution exhibited a near-Gaussian trend, consistent with the nonlinear but smooth response surface defined by the workflow.

4.2.4. Global Sensitivity Analysis

Sobol' total and first-order indices were computed to identify the most influential design parameters. Results (Table 3) show that wing surface area dominates the output variance, followed by payload power and atmospheric temperature offset that is fully consistent with the reference results of Jiang et al.

Table 3. Total sensitivity indices (S_{T_i}) for the UAV design benchmark.

Input Factor	Influence [%]
Wing Area	91.4
Payload Power	3.84
Atmospheric Temperature Offset	3.61

The close match between the obtained and reference sensitivities validates both the accuracy and robustness of the framework for handling realistic multidisciplinary workflows.

5. Conclusions and Future Work

This work presented a modular, web-based uncertainty quantification environment composed of the *uqFramework* (backend) and *uqStudio* (frontend). The integrated system enables researchers to perform uncertainty propagation and sensitivity analysis within a unified interface.

The framework was successfully validated on the Ishigami benchmark and a multidisciplinary aircraft design study, demonstrating its flexibility and robustness across both analytical and high-fidelity engineering workflows. By combining a low-code graphical user interface with a standardized *uqDataModel*, the framework significantly lowers the barrier for conducting rigorous UQ studies while maintaining reproducibility and scalability. Typical application cases can be configured and executed within short setup times, and all analyses can be exported as a reusable *uqDataModel* for later extension or collaborative work.

In its current implementation, the probability distributions used to characterize input uncertainties are selected from a set of standardized distributions (e.g., normal, beta, and uniform) and are typically derived from external sources such as literature values or expert judgment. The framework assumes that uncertainty characterization is performed prior to the UQ study and focuses on providing a consistent environment for specifying, propagating, and analyzing these uncertainties. Future extensions will include statistical inference methods to support data-driven estimation of input distributions, including non-standard distributions, directly within the framework.

Although the framework is designed to support multiple workflow environments, including standalone Python-based workflows, this paper focused on demonstrating integration with RCE as a representative multidisciplinary environment. Future work will include systematic demonstrations with additional workflow tools and environments to further validate the framework's modularity and interoperability.

Methodologically, future developments will focus on integrating surrogate modeling methods, such as Gaussian Process models and Polynomial Chaos Expansion, and extending the framework to support epistemic and mixed uncertainties.

Author Contributions: Conceptualization, T.A. and M.A.; methodology, T.A. and M.A.; software, T.A. and M.A.; validation, T.A. and M.A.; writing—original draft, T.A.; writing—review and editing,

T.A. and M.A.; supervision, M.A. All authors have read and agreed to the published version of the manuscript.

Funding: This research has been funded by the German Aerospace Center (DLR), Germany.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Data and configuration files for the benchmark cases are available from the corresponding author on reasonable request.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. Baudin, M.; Dutfoy, A.; Iooss, B.; Popelin, A.L. OpenTURNS: An industrial software for uncertainty quantification in simulation. In *Handbook of Uncertainty Quantification*; Ghanem, R., Higdon, D., Owhadi, H., Eds.; Springer: Cham, Switzerland, 2017; pp. 2001–2038. [CrossRef]
2. Adams, B.M.; Bohnhoff, W.J.; Dalbey, K.R.; Eddy, J.P.; Eldred, M.S.; Hough, P.D.; Hu, K.T.; Jakeman, J.D.; Stephens, J.A.; Swiler, L.P.; et al. *Dakota, a Multilevel Parallel Object-Oriented Framework for Design Optimization, Parameter Estimation, Uncertainty Quantification, and Sensitivity Analysis: Version 6.12 User's Manual*; Sandia National Laboratories: Albuquerque, NM, USA, 2020.
3. Marelli, S.; Sudret, B. UQLab: A framework for uncertainty quantification in MATLAB. In *Proceedings of the 2nd International Conference on Vulnerability, Risk Analysis and Management (ICVRAM 2014), Liverpool, UK, 13–16 July 2014*; ASCE: Reston, VA, USA, 2014; pp. 2554–2563.
4. SmartUQ. *SmartUQ Software*, Version 10.0.0; SmartUQ: Madison, WI, USA, 2023. Available online: https://www.smartuq.com/ (accessed on 30 September 2024).
5. Saltelli, A.; Ratto, M.; Andres, T.; Campolongo, F.; Cariboni, J.; Gatelli, D.; Saisana, M.; Tarantola, S. *Global Sensitivity Analysis: The Primer*; John Wiley & Sons: Chichester, UK, 2008.
6. Sudret, B. Global sensitivity analysis using polynomial chaos expansions. *Reliab. Eng. Syst. Saf.* **2008**, *93*, 964–979. [CrossRef]
7. Sobol, I.M. Global sensitivity indices for nonlinear mathematical models and their Monte Carlo estimates. *Math. Comput. Simul.* **2001**, *55*, 271–280. [CrossRef]
8. Cukier, R.I.; Fortuin, C.M.; Shuler, K.E.; Petschek, A.G.; Schaibly, J.H. Study of the Sensitivity of Coupled Reaction Systems to Uncertainties in Rate Coefficients. I Theory. *J. Chem. Phys.* **1973**, *59*, 3873–3878. [CrossRef]
9. Cukier, R.I.; Levine, H.B.; Shuler, K.E. Nonlinear Sensitivity Analysis of multiparameter model systems. *J. Comput. Phys.* **1978**, *26*, 1–42. [CrossRef]
10. Morris, M.D. Factorial Sampling Plans for Preliminary Computational Experiments. *Technometrics* **1991**, *33*, 161–174. [CrossRef]
11. Iwanaga, T.; Usher, W.; Herman, J. Toward *SALib* 2.0: Advancing the accessibility and interpretability of global sensitivity analyses. *Socio-Environ. Syst. Model.* **2022**, *4*, 18155. [CrossRef]
12. Herman, J.; Usher, W. *SALib*: An open-source Python library for Sensitivity Analysis. *J. Open Source Softw.* **2017**, *2*, 97. [CrossRef]
13. Boden, B.; Flink, J.; Först, N.; Mischke, R.; Schaffert, K.; Weinert, A.; Wohlan, A.; Schreiber, A. RCE: An Integration Environment for Engineering and Science. *SoftwareX* **2021**, *15*, 100759. [CrossRef]
14. Koch, A.D.; Wilken, J.; Alder, M. Uncertainty quantification data model for the probabilistic design of the thermal protection system of a reusable launch vehicle stage. *CEAS Space J.* **2025**, *17*, 493–511. [CrossRef]
15. Ishigami, T.; Homma, T. An Importance Quantification Technique in Uncertainty Analysis for Computer Models. In *[1990] Proceedings. First International Symposium on Uncertainty Modeling and Analysis, College Park, MD, USA, 3–5 December 1990*; IEEE: Piscataway, NJ, USA, 1990; pp. 398–403. [CrossRef]
16. Jiang, Z.; Chen, W.; German, B.J. Multidisciplinary Statistical Sensitivity Analysis Considering Both Aleatory and Epistemic Uncertainties. *AIAA J.* **2016**, *54*, 1326–1338. [CrossRef]

Disclaimer/Publisher's Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.