COMBINING SENSITIVITY ANALYSIS AND NON-PARAMETRIC STATISTICS TO ASSESS FARM-LEVEL GHG EMISSION DRIVERS

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Abstract. Farm-level greenhouse gas (GHG) assessments and mitigation measures are becoming more crucial in effective, comprehensive climate change mitigation action. It is imperative that farmers are supported in their efforts to mitigate climate change. This support must take the form of decision support tools that are estimating GHG emissions and developing effective decarbonisation plans. Consequently, the DecarbFarm decision support tool was developed. In order to guarantee the tool's robustness, a sensitivity analysis utilising Morris sensitivity analysis methodology was conducted, and the most influential parameters were identified. These parameters should be prioritized in the development of decarbonisation plans. The aim of this study is to evaluate whether variations in input parameters classified as highly sensitive by Morris sensitivity analysis lead to statistically significant differences in modelled farm-level GHG emissions of these parameters. The study is performed by utilising randomised input datasets, consisting of 250 data points per parameter. The input data is used by the DecarbFarm decision support tool to calculate the respective GHG emissions. The statistical analysis to assess differences between GHG emission distributions is conducted using Kruskal-Wallis test. The results indicate that variations in highly sensitive input parameters result in statistically significant differences in modelled farm-level GHG emissions. This finding underscores the importance of prioritizing these parameters in decarbonisation planning to enhance the effectiveness of mitigation measures.

Keywords: GHG emissions, statistical testing, Kruskal-Wallis test.

Introduction

In 2015, the Paris Agreement was adopted, representing an important step in climate change action. To achieve the Paris Agreement goal in limiting global warming, comprehensive mitigation measures need to be implemented worldwide, including Baltics. The Paris Agreement sets a commitment to reduce global greenhouse gas (GHG) emissions in all countries. As 14.6% of Latvia's GHG emissions (excluding land use, land use change and forestry sector) in 2023 [1] stem from agriculture, integrated agricultural GHG emission mitigation measures on the farm-level become crucial. Latvia's National Energy and Climate Action Plan recognises agriculture decarbonisation as a contributor to national GHG emission reduction targets [2]. These targets apply to sectors outside the European Union Emissions Trading System. Achieving these targets requires changes in farm operations, including farm-level emission reduction. This increases the need for practical support in calculating and monitoring GHG emissions, and at the same time managing them to achieve GHG emission reduction. Given the increasing regulatory pressure and increasing expectations from stakeholders, farmers experience the need for reliable, data-driven decision support tools to ensure credible reporting of GHG emissions.

Digital decision support tools help farmers identify ways to reduce GHG emissions and assist with decarbonisation planning at the farm level. Such tools integrate farm activity data, local emission factors and underlying methodology utilised in the tool. Some, more advanced tools, allow tool users to explore different GHG mitigation scenarios, potentially finding the most suitable for the farm operations. Despite this, there is limited agriculture tool availability in Latvia aimed at supporting Latvian farmer decarbonisation. This gap highlights the need for a locally adaptable and methodologically robust tool that supports accurate and transparent emission estimation.

The DecarbFarm decision support tool was developed to provide support for farmers in computing farm GHG emissions and to define their decarbonisation plans within one solution. The tool provides wide application within crop, livestock or mixed crop and livestock farms in Latvia [3], covering majority of farm types in Latvia. As the farm level GHG emission data collection is at the beginning stages, farmer GHG data would become a lager interest of farm stakeholders, for example, financial institutions [4, 5]. The study also highlights the initial interest in decarbonisation plan elements, such as GHG reduction targets or internal governance for the target achievement [4]. In longer term, practical application of the DecarbFarm tool could support not only the Paris Agreement targets, but also contribute to actions defined within Latvia's National Energy and Climate Action Plan [2].

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To ensure most effective application of the tool, specifically the functionality of GHG emission reduction plan definition, a robust validation of the tool is required. The previous study by the authors has explored the sensitivity between the input and output parameters of the developed tool [6] utilising Sobol and Morris sensitivity analysis methods. The study identified in total 25 sensitive parameters out of 75 tested, while specifically Morris method yielded 16 sensitive parameters [6]. These parameters were identified as the priority for which decarbonisation measures should be defined and included in the DecarbFarm tool. Although the most sensitive parameters identified in the study should be prioritized for the GHG mitigation measure definition, the identified most sensitive parameters do not contribute equally to the final farm GHG emissions. Sensitivity analysis alone does not show whether the emission responses generated by these parameters are statistically distinguishable from one another. As a result, additional statistical evaluation is needed to determine whether the most sensitive parameters also differ in their practical importance for further mitigation planning. To further identify which parameters prioritize definition of mitigation actions, additional evaluation is necessary. While in literature there have been several studies evaluating different GHG emission accounting tools in agriculture, proving variabilities in GHG estimates among different tested tools [7; 8], there has been limited research on determining the statistical differences between the most sensitive parameters within one GHG accounting tool. Such validation proves that recommended mitigation measures are not only theoretically justified, but also practically meaningful and proportionate to the actual impact on farm GHG emissions.

This study aims to evaluate whether variations in input parameters classified as highly sensitive by Morris sensitivity analysis lead to statistically significant differences in modelled GHG emissions. Such analysis is essential for determining whether sensitivity-based prioritisation can be further refined using statistical comparison of model outputs. The study therefore proposes an additional statistical evaluation step to support more precise prioritisation of farm-level mitigation measures within the DecarbFarm tool. By improving the precision of parameter prioritisation, the study directly contributes to enhancing the practical usability of the tool for farmers, enabling more effective and more targeted decarbonisation strategies.

Materials and methods

The statistical analysis is performed on the parameters deemed most sensitive from Morris sensitivity analysis on the DecarbFarm tool as published in Muizniece et.al. study [6]. The most sensitive parameters from the Morris analysis further analysed in this study are provided in Table 1. Morris sensitivity level for all data is high.

Table 1

Parameters of the DecarbFarm tool used in the study

Input data page	Parameter	
	Abbreviation	**Full name**
Scope 1	LNG	Liquefied natural gas
	TLPG	Liquefied petrol gas for transport
	CNG	Compressed natural gas
Arable land - fertilizers	NH_4NO_3	Ammonium nitrate
	$(NH_4)_2SO_4$	Ammonium sulphate
	$(NH_4)_2HPO_4$	Diammonium phosphate
	CAN	Calcium ammonium nitrate
	$Ca(NO_3)_2$	Calcium nitrate
	KAS	Urea and ammonium nitrate solution
	$(NH_4)(H_2PO_4)$	Ammonium dihydrogen phosphate
	NPK	NPK complex

For each parameter a randomized input data list of 250 input data points between 10 and 1000 is generated. The wide input range was intentionally selected to explore the model's response behaviour across a broad spectrum of possible parameter values rather than to represent realistic farm management conditions. All input data were generated synthetically, not taken from real farm datasets or external sources. The DecarbFarm tool calculated GHG emissions from the generated input values.

In the simulation procedure, each parameter was varied independently while all remaining model inputs were kept constant at their baseline values. This one-factor-at-a-time approach allowed the individual influence of each parameter on the modelled farm-level GHG emissions to be evaluated without interactions from other variables. For every generated input value, the DecarbFarm model was executed and the resulting total farm-level greenhouse gas emissions were recorded for further statistical analysis. The chosen range does not accurately represent the usual input variability observed in farm-level activities. This methodology is primarily employed to assess the conceptual framework of the DecarbFarm tool. This data list is fed into the DecarbFarm tool to calculate the respective GHG emissions.

All the data used in this study has been checked to ensure that it meets the requirements for parametric analysis, applying normality and homogeneity of variance tests. If data meets the parametric analysis requirements, then parametric analysis is used. Otherwise, a nonparametric Kruskal-Wallis test [9] is used. The Kruskal–Wallis test was therefore selected because it allows comparison of multiple independent groups without requiring normally distributed data.

Shapiro-Wilk normality test is performed in RStudio statistics software (version 2026.01.0 + 392) for all data used in this study. The data with a p-value above 0.05 meets the normal distribution requirements. The Bartlett test is performed as homogeneity of variance test in RStudio statistics software version 2026.01.0 + 392 for all data used in this study. If the test p-value is greater than 0.05 then the homogeneity of variance criteria is met.

Kruskal-Wallis chi-squared test is used to determine, if there is a significant difference between the sensitive parameters. Using RStudio statistics software version 2026.01.0 + 392, the Kruskal–Wallis test was performed to evaluate whether GHG emission outcomes differed significantly across the identified sensitive parameter, assessing the p-value = 0.05 significance threshold to determine whether the null hypothesis equal underlying distributions across groups could be rejected. This analysis enabled the identification of parameter changes that produce statistically distinguishable GHG emission patterns, supporting the sensitivity insights obtained from the Morris method.

To assess differences among the most sensitive model parameters, Kruskal–Wallis pairwise post-hoc comparisons were conducted. The analysis was performed using RStudio statistics software version 2026.01.0 + 392. This approach facilitates the identification of parameter groups that differ significantly from one another at a p-value = 0.05.

Results and discussion

Shapiro–Wilk normality test was applied to the residuals of the obtained GHG emission data from the DST model. As presented in Figure 1, the test indicated significant deviation from the normal distribution ($W = 0.856$, $p < 0.05$) with a 95% confidence. For this reason, the normality requirement for parametric statistical analysis is not met, therefore non-parametric analysis is applied in subsequent analysis.

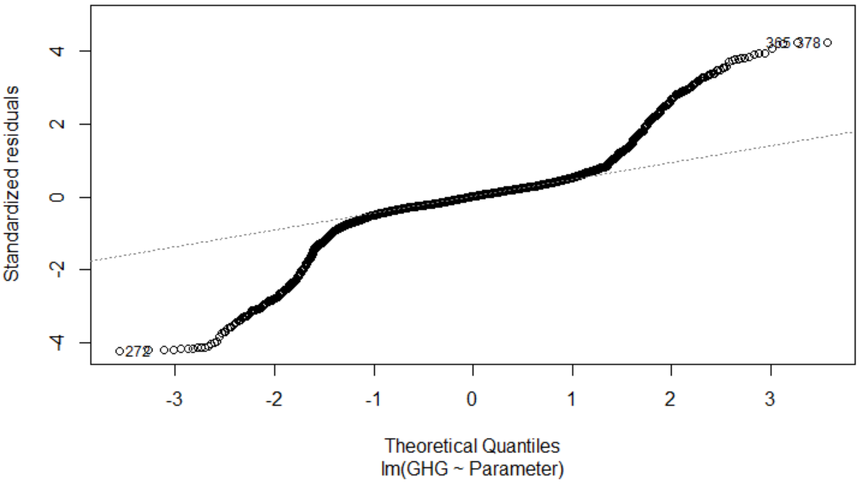


Fig. 1. **Shapiro-Wilk normality test result visualisation**

Bartlett test for homogeneity for residual results indicate a significant violation of the homogeneity of variance assumption (Bartlett's $K^2 = 4096.3$, $df = 10$, $p < 0.05$) with a 95% confidence, demonstrating that variances differed significantly between groups (see Figure 2). As the homogeneity requirement is not met, non-parametric statistical methods are applied in subsequent analysis.

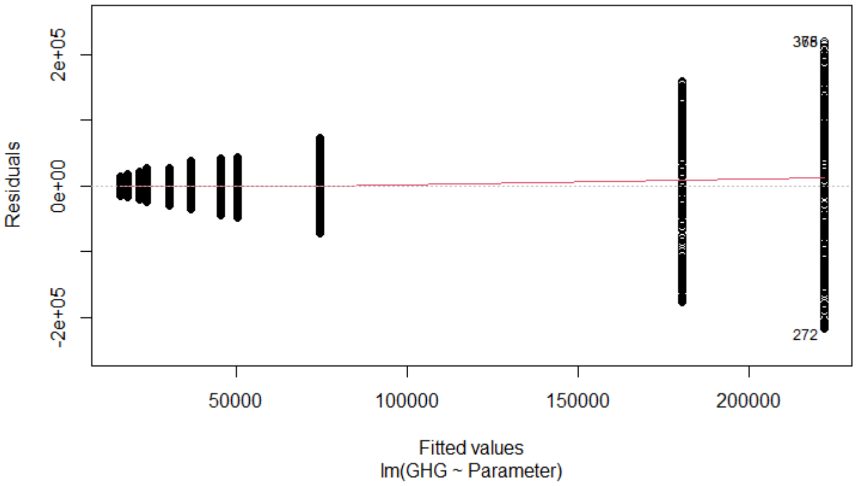


Fig. 2. **Bartlett normality test result visualization**

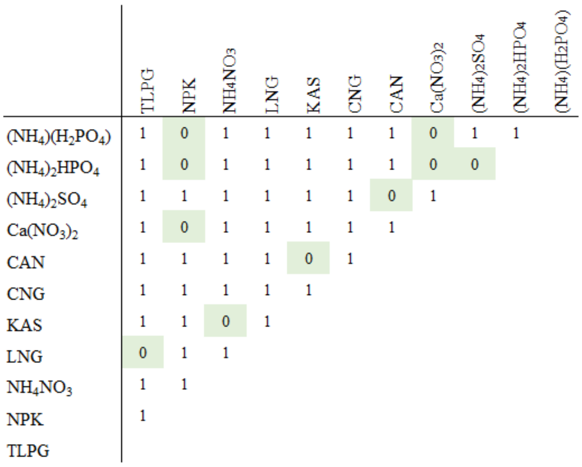
Differences in GHG emission distributions associated with variations in the analysed parameters were assessed using the Kruskal–Wallis rank-sum test. The test revealed a statistically significant difference between groups ($\chi^2 = 1377.3$, $df = 10$, $p < 0.001$) with a 95% confidence, indicating that GHG emission outcomes generated by varying different parameters do not originate from the same distribution. These results show that parameters identified as highly sensitive in the GHG emission accounting model can lead to statistically different distributions of GHG emissions for those parameters. This suggests that among the most sensitive parameters the additional prioritisation can be made when defining decarbonisation plans, leading to higher emission savings.

The post-hoc comparisons for parameters following Kruskal-Wallis test revealed numerous significant pairwise differences between the screened parameters. The magnitude of observed rank differences varied widely across parameter combinations, with several contrasts exceeding the critical threshold for statistical significance. To provide a comprehensive overview of these pairs, all comparisons are organized into a matrix visualization (see Figure 3). The heatmap highlights significant and non-significant pairs, enabling better understanding of prioritisation of parameters, to define additional decarbonisation measures. The pairwise comparison results indicate that several parameter groups produce statistically distinguishable emission outputs, while others show overlapping response distributions. This suggests that even among parameters identified as sensitive through Morris screening, their relative influence on the variability of farm-level GHG emissions may differ.

The results in Figure 3 indicate that there are no significant statistical differences between ten parameters pairs. This suggests that the calculated GHG emission responses between these parameter pairs are comparable, although the results do not imply exact equivalence. The heatmap (see Figure 3) provides an understanding, that the main priority should be given to liquefied natural gas, liquefied petrol gas for transport and compressed natural gas among energy-related parameters. Regarding the fertilizer application, priority should be assigned to NPK complex and ammonium nitrate. Compared to other parameters, these parameters have no or few non-significant comparisons, indicating their impacts to be more statistically distinct from other parameters.

The prioritisation of energy related inputs and nitrogen-based fertilisers is consistent with previous studies on agricultural GHG emission drivers. Abbas et.al. [10] in their study have also recognised the importance of fertilizer application and farm energy use in driving the GHG emission increase or reduction in farms. Pilvere et.al. [11] study recognizes the impact of increased GHG emissions from fertilizer use.

While the previous studies have more focused on statistical comparisons between different GHG accounting tools [8] or models [7], or used sensitivity analysis for identification of agriculture GHG emissions [10, 12], there is limited availability of studies that statistically evaluate emission outcome differences within a single tool application. This study addresses this gap by combining sensitivity analysis with non-parametric statistical testing. The study also shows the importance of analysing not only the sensitivity of the model parameters, but also evaluating, if there should be a further parameter prioritisation among the most sensitive parameters in the tool or the model.



	TLPG	NPK	NH_4NO_3	LNG	KAS	CNG	CAN	$Ca(NO_3)2$	$(NH_4)2SO_4$	$(NH_4)2HPO_4$	$(NH_4)(H_2PO_4)$
$(NH_4)(H_2PO_4)$	1	0	1	1	1	1	1	0	1	1	
$(NH_4)_2HPO_4$	1	0	1	1	1	1	1	0	0		
$(NH_4)_2SO_4$	1	1	1	1	1	1	0	1			
$Ca(NO_3)_2$	1	0	1	1	1	1	1				
CAN	1	1	1	1	0	1					
CNG	1	1	1	1	1						
KAS	1	1	0	1							
LNG	0	1	1								
NH_4NO_3	1	1									
NPK	1										
TLPG											

Fig. 3. **Post-hoc Kruskal-Wallis test pairwise parameter comparisons:** 1 – statistically significant difference between the parameters; 0 – statistically insignificant difference between the parameters; TLPG – Liquefied petrol gas for transport; NKP – NPK complex; NH_4NO_3 – Ammonium nitrate; LNG – Liquefied natural gas; KAS – Urea and ammonium nitrate solution; CNG – Compressed natural gas; CAN – Calcium ammonium nitrate; $Ca(NO_3)_2$ – Calcium nitrate; $(NH_4)2SO_4$ – Ammonium sulphate; $(NH_4)_2HPO_4$ – Diammonium phosphate; $(NH_4)(H_2PO_4)$ – Ammonium dihydrogen phosphate

The limitation of this study is the used simulated input datasets that do not reflect the potential real farm input data variability, rather than using empirical data obtained from farms. While application of real farm input data could yield differences in the calculated coefficients, the dominant parameters to evaluate would still emerge consistently [12]. From a practical perspective, parameters that produce clearly distinguishable emission distributions may represent stronger candidates for targeted mitigation strategies within farm-level decarbonisation planning.

One limitation of this study is that the parameter ranges used in the simulations were intentionally broad to explore model response behaviour, and therefore future research should evaluate the approach using parameter ranges derived from empirical farm datasets.

Conclusions

1. The Kruskal-Wallis test confirmed statistically significant differences between GHG emission distributions generated by the variations of the most sensitive DecarbFarm model parameters.
2. Energy related parameters and nitrogen-based fertilisers demonstrated the most statistically distinct GHG emission responses among the tested parameters, suggesting these parameters should be prioritised when developing GHG emission mitigation strategies.
3. Combining the sensitivity analysis with the non-parametric statistical testing improves the prioritisation of mitigation measure definition in the development of farm-level decarbonisation decision-support tools. In addition, the presented analysis focuses on model response behaviour under simulated parameter variation, and further research using realistic farm data ranges is required to confirm the practical prioritisation of mitigation measures.

Author contributions

Conceptualization, K.M., I.G. and J.P.U.; methodology, K.M., I.G. and J.P.U.; software, K.M..; validation, K.M., I.G. and J.P.U; formal analysis, K.M; investigation, K.M.; data curation, K.M.; writing – original draft preparation, K.M.; writing – review and editing, K.M., I.G. and J.P.U.; visualization, K.M.; project administration, I.G.. All authors have read and agreed to the published version of the manuscript.

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