# Uncertainty analysis of cattle-based product LCA related to model variables: case study of milk production in Belgium

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**ABSTRACT**

Uncertainties in environmental impacts of milk production related to model variables were investigated with Monte-Carlo simulation in a case study. Per kg of fat-and-protein-corrected milk produced, the 95% confidence interval of impacts was 6.2-10.4 g $PO_4$eq, 10.1-25.6 g $SO_2$eq, 1.1-1.9 kg $CO_2$eq, -7.6-19.2 CTUe, 4.3-4.9 MJ and 1.11-1.28 m²yr for eutrophication, acidification, climate change, ecotoxicity, CED and land occupation respectively. Expressed as coefficients of variation, uncertainties ranged from 3% to 2097% as a function of the impact category. The most influential variables changed with impact category, except those related to the functional unit. Monte-Carlo simulation and sensitivity analysis help to identify variables requiring more accuracy and detect errors implementing multiple-variables models in calculation tools.

Keywords: distribution, Monte-Carlo simulation, life cycle assessment, IPCC

## 1. Introduction

Uncertainty assessment in life cycle assessment (LCA; ISO 2006) of agricultural products, milk in particular, is a major concern, and relatively few studies have considered it (Yan et al. 2011). Flysjö et al. (2011) showed the importance of uncertainty in some emission factors, such as $N_2O$ from soil used in relatively simple models, on the uncertainty in the carbon footprint of milk production. The influence of emission factors on nitrogen (N) compound emissions at the farm level compared to calculation with the N balance has also been highlighted (Payraudeau et al. 2007). Since agricultural activities are involved in most major environmental problems in Wallonia (e.g. acidification, surface water pollution, greenhouse gas (GHG) emissions; KIEW 2013), Belgium, a multiple environmental impact approach is necessary for milk production. To this end, a tool called "Weden" based on van der Werf et al. (2009) was built that included the ability to explore uncertainty in environmental impacts. This study aimed to investigate uncertainties in environmental impacts of milk production related to model variables and identification of the most influencing variables with a Monte-Carlo simulation approach based on a case study.

## 2. Methods

### 2.1. Weden tool

LCA of milk production on a farm was performed with a tool called Weden, consisting of an Excel® spreadsheet, described in Mathot et al. (2014). Models used for the on-farm inventory were based mainly on element balances (N, P, K and trace metals) at the farm level. Methane ($CH_4$) and nitrous oxide ($N_2O$) emissions were modeled with IPCC (2006), mainly Tier 2. Ammonia ($NH_3$) and N oxide ($NO_2$ and $NO_x$) emissions were calculated according to EMEP/EEA (2009), mainly Tier 2, approaches. For these two models, causality chains for calculation of N and $CH_4$ emissions from cattle feed ingestion to manure spreading were fully implemented. Phosphorus emissions to water were estimated according to Nemecek and Kägi (2007), and inputs at the farm level were adapted mainly from Frischknecht et al. (2007) using SimaPro software (PRé Consultants 2007). System boundaries, compound targets in the inventory and environmental impacts considered are summarized in Fig. 1. In the model used it is considered that imported animals and manures had no environmental burden but they are included in nutrient balance calculation. However, in this case study no manure or animal was imported into the farm.

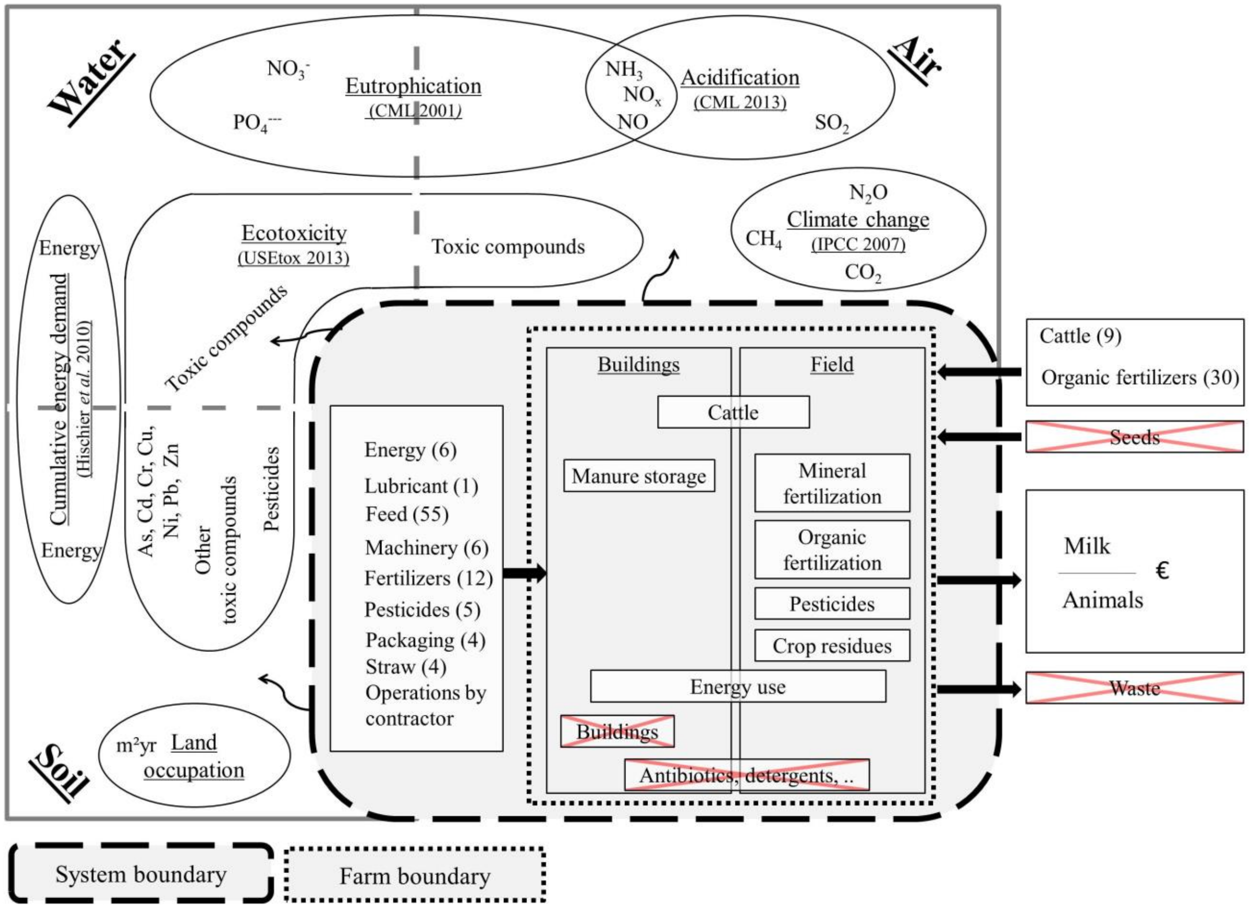


Figure 1. System description, impact categories and related damaging compounds and resources considered. Numbers in parentheses indicate the number of items considered in the inventory after aggregation (e.g., 63 machinery alternatives recorded on farms were aggregated into 6 groups).

## 2.2. Uncertainty calculation

Uncertainty analysis was performed with Monte-Carlo simulations and sensitivity analysis using three types of distribution: triangular, lognormal (with geometric mean) and normal (Weidema et al., 2013). Input variables supplied by farmer (Table 1) were excluded while model variables (e.g. mean cattle weight, $N_2O$ emission factors, manure composition, feed N concentration) were varied in the uncertainty analysis. For each variable, a distribution was chosen based on characterization from available databases or literature data and a realistic range (e.g. nutrient concentration in slurry). When a variable's distribution was unknown, it was subjectively defined as normal with a coefficient of variation of 5% around the mean. Uncertainty in impact characterization factors was estimated only for ecotoxicity factors missing in USEtox (2013). Values for active ingredients used as plant protection products (PPPs) were considered to be lognormally distributed based on the geometric mean and standard deviation (SD) of the other PPPs in USEtox (2013) used. For some variables, Monte-Carlo simulation with not-well-characterized uncertainty parameters, as found in the literature, may lead to unrealistic variable values. For example, for dry matter content in certain manures, uncertainty parameters were arithmetic means and SDs, suggesting a normal distribution of the content. However, during Monte-Carlo simulation, it was possible to obtain negative values. If that occurred, the distribution was not changed; instead, the simulation was looped to consider only realistic minimum and maximum values. Monte-Carlo simulation was iterated 1000 times. A sensitivity analysis was also performed to investigate influence of variables with default uncertainty parameters and to identify major influencing variables. This operation consisted of recording changes in all impacts associated with a change in a single variable equal to the 75th percentile of its distribution. Two results were recorded: relative change in the impact, calculated as $Var=(Y_{0.75}-Y_{0,5})/Y_{0,5}$, and relative change in the impact divided by relative change in the variable, $Sen=Var/((X_{0.75}-X_{0,5})/X_{0,5}))$, where Y is the impact value and X is the variable value. Indices indicate the percentile in the distribution corresponding to the value used.

Var indicates the proportion of change in the impact according to the change in the variable at its 75th-percentile value. It allows ranking variables according to their influence on results but relies strongly on the uncertainty parameters chosen for a given variable; therefore, it is not completely suitable for variables with default uncertainty parameters. Indeed, for these variables, strong underestimation or overestimation can be suspected. Sen indicates the relative sensitivity of the impact to the change in the variable. It is useful for identifying variables with default parameters whose precision has to be increased due to their potentially large influence on impacts.

Table 1: Input variables not considered in the uncertainty analysis.

| Domain | Input variable |
|---|---|
| Cattle management | Head of cattle (in, out, losses, change in stock); milk production, consumption of veal, protein and fat concentrations; proportion of pregnant cows; lactation and non-lactation duration; distribution of calving period; grazing duration; diet composition |
| Crop management | Surface areas; amount and type of mineral and organic fertilizations; plant protection product amount and type used |
| Manure management | Amount produced and exchanged (in and out); type; treatment; application system |
| Revenue | From milk, from meat, from crops |
| Input | Amount of feed, straw, fertilizers, plant protection products, energy, plastics |
| Machinery | Type; amount and use |
| Operations by contractors | Type; amount |

### 2.3. The case study

One of the farms analyzed by Mathot et al. (2014) was chosen as case study because of the supposed reliability of its input variables. This farm contained 77 dairy cows, for a total dairy herd of 168 head of cattle. Usable agricultural area was 67.4 ha, with 80% covered by grasslands, 12% by silage maize and 7% by other crops. Total milk produced in the year investigated, 2012, was 669.5 $10^3$ liters of milk, with a mean concentration of 42.4 g of fat and 33.5 g of protein per kg of milk produced. Inputs through feed and fertilization were 63.7 g N/m² and 1.43 g P/m². Of total revenue, 93.7% came from milk, and 6.3% came from meat.

## 3. Results

### 3.1. Distribution

According to the Shapiro normality test (R Development Core Team 2011) only the predicted values for CED were normally distributed. Per kg of fat-and-protein-corrected milk (FPCM) produced, impacts (95% confidence intervals) were 6.2-10.4 g $PO_4$eq, 10.1-25.6 g $SO_2$eq, 1.1-1.9 kg $CO_2$eq, -7.6-19.2 CTUe, 4.3-4.9 MJ and 1.11-1.28 m²yr for eutrophication, acidification, climate change, ecotoxicity, cumulative energy demand (CED) and land occupation respectively. Impact means (and CV) were, respectively, 8.2 g $PO_4$eq (13%), 16.3 (25%) g $SO_2$eq, 1.4 (14%) kg $CO_2$eq, 10.0 (2097%) CTUe, 4.6 (3%) MJ and 1.2 m²yr (3%) (Fig. 2).

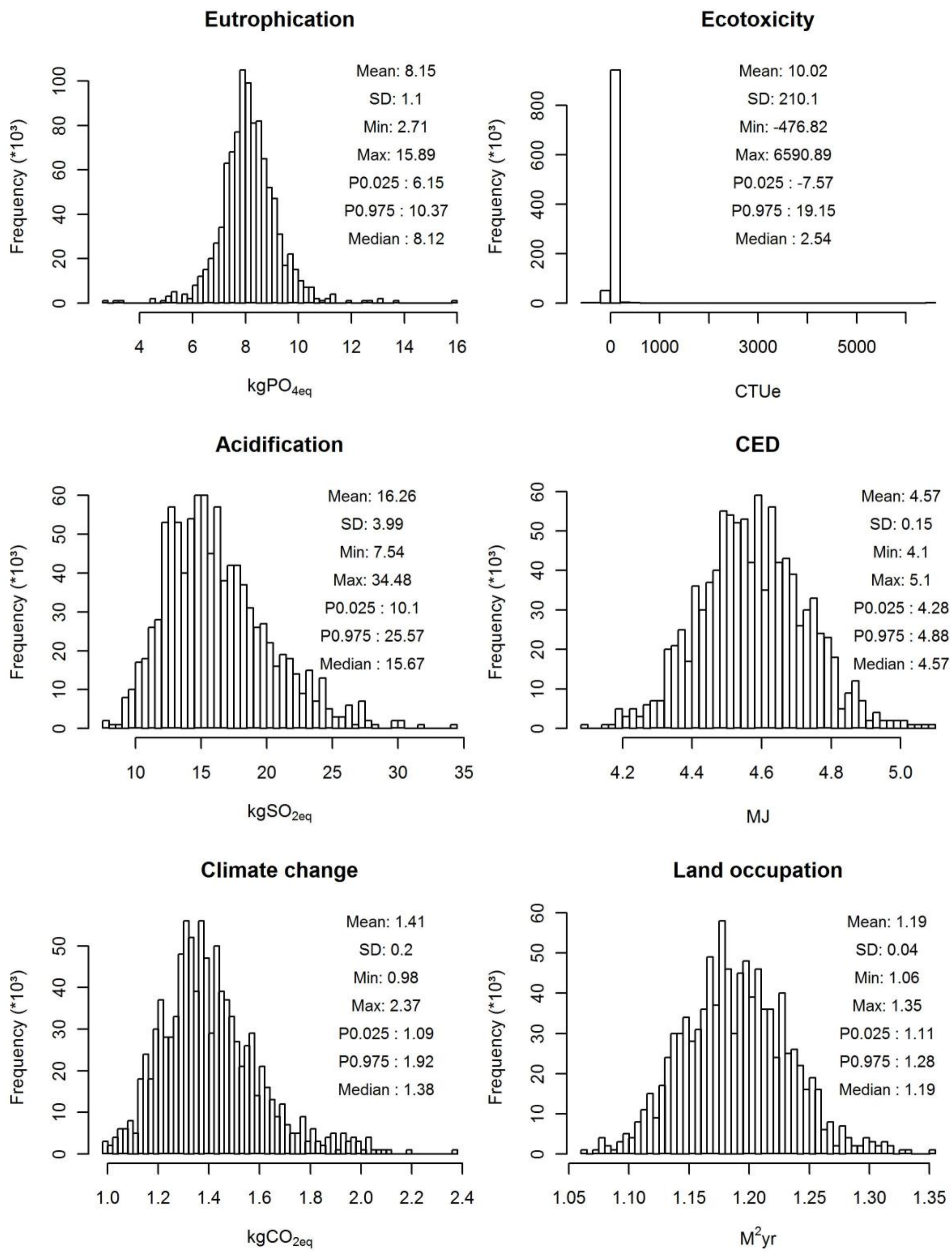

Figure 2. Distribution of values recorded in 1000 Monte-Carlo simulations and main statistics.

## 3.2. Variation and sensitivity

In total, 1084 variables influenced the results, all impact categories included. For 85% of the variables, the uncertainty in parameters was taken from literature, calculated or estimated. For the remaining 15%, uncertainty parameters were default values.

Table 2. Number (n) of variables influencing environmental impacts. The variable n indicates the number of variables influencing Var and Sen at more than |±1%| and |±10%|, respectively. Min and max are the values of the minimum and maximum influences observed. Moy<0 and Moy>0 are the means of negative and positive influences, respectively.

| | | Var | | | | | | Sen | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | N | | Value | | | | n | | Value | | | |
| Impact | n | +1% | -1% | Min | Moy <0 | Max | Moy >0 | +10% | -10% | Min | Moy <0 | Max | Moy >0 |
| Eutro. | 314 | 3 | 1 | -0.038 | -0.001 | 0.048 | 0.001 | 5 | 7 | -0.496 | -0.024 | 0.402 | 0.011 |
| Acidif. | 221 | 8 | 10 | -0.064 | -0.006 | 0.088 | 0.003 | 14 | 23 | -1.908 | -0.175 | 2.528 | 0.060 |
| Climate ch. | 278 | 6 | 8 | -0.041 | -0.003 | 0.055 | 0.001 | 13 | 16 | -1.222 | -0.092 | 1.631 | 0.029 |
| Ecotoxicity | 141 | 2 | 7 | -0.031 | -0.004 | 0.042 | 0.002 | 4 | 3 | -0.496 | -0.070 | 0.268 | 0.009 |
| CED | 59 | 1 | 0 | -0.017 | -0.008 | 0.005 | 0.001 | 4 | 5 | -0.496 | -0.310 | 0.244 | 0.026 |
| Land occ. | 48 | 1 | 0 | -0.017 | -0.008 | 0.009 | 0.001 | 4 | 0 | -0.496 | -0.310 | 0.063 | 0.004 |

Table 3. Classification (number) of variables influencing the impacts more than |±1%| for Var and more than |±10%| for Sen. "Default parameters" is the number of variables using default parameters

| | Eutrophication | | Acidification | | Climate change | | Ecotoxicity | | CED | | Land occupation | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Variable | Var | Sen | Var | Sen | Var | Sen | Var | Sen | Var | Sen | Var | Sen |
| Feed and manure composition | 0 | 0 | 4 | 11 | 2 | 5 | 1 | 0 | 0 | 0 | 0 | 0 |
| Other input characteristics | 1 | 1 | 0 | 0 | 0 | 0 | 3 | 0 | 0 | 4 | 0 | 0 |
| Output characteristics | 0 | 0 | 0 | 0 | 0 | 0 | 3 | 0 | 0 | 0 | 0 | 0 |
| Fat-and-protein-corrected milk | 1 | 3 | 1 | 3 | 1 | 3 | 1 | 3 | 1 | 3 | 1 | 3 |
| Animal diet requirement | 0 | 2 | 7 | 17 | 5 | 12 | 0 | 0 | 0 | 0 | 0 | 0 |
| Emission factor | 2 | 0 | 4 | 1 | 4 | 2 | 1 | 3 | 0 | 0 | 0 | 0 |
| Other modeling | 0 | 2 | 0 | 1 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 |
| Conversion factor | 0 | 4 | 2 | 4 | 2 | 6 | 0 | 1 | 0 | 2 | 0 | 1 |
| Default parameters | 1 | 8 | 14 | 33 | 10 | 26 | 1 | 3 | 1 | 3 | 1 | 3 |

### 3.2.1. Relative changes in impacts

CED and land occupation were influenced by relatively few variables (<60) while others were influenced by many more (141-341; Table 2). Eutrophication, acidification, climate change and ecotoxicity were subject to larger changes (greater than |±2%|) from the most influential variables than CED or land occupation (less than |±2%|). Regardless of the impact category, less than 10% of the variables changed the impact more than |±1%|.

### 3.2.2. Relative sensitivity of impacts

Climate change and acidification impacts were highly sensitive to certain variables. For more than 10 variables, the sensitivity was higher than |±10%|. Furthermore, these two impacts were highly sensitive to some variables (>|±100%|).

### 3.2.3. Influential variables

The most influential variables (>|±1%| for Var and |>±10%| for Sen) were identified and classified in 8 categories: Feed and manure composition; Other input characteristics (e.g. fuel $CO_2$ emissions on combustion); Output characteristics (e.g. protein content in animal live weight sold); FCPM (equation for calculation of functional unit); Animal diet requirement (model for estimation of cattle requirement and manure production), Emission factors (e.g.: $N_2O$ emission from fertilization applied to soil); Other modeling (e.g., estimation of N fixation by plants) and Conversion factors (e.g., protein:N ratio of milk). For Var and Sen, the numbers of major (>|±1%| for Var and |±10%| for Sen) influencing variables were 4 and 12 for eutrophication, 18 and 37 for acidification, 14 and 29 for climate change, 9 and 7 for ecotoxicity, 1 and 9 for CED and 1 and 4 for land occupation, respectively (Tables 2 and 3). Among them, 1 and 8 for eutrophication, 14 and 33 for acidification, 10 and 35 for climate change, 1 and 3 for ecotoxicity, 1 and 3 for CED and 1 and 3 for land occupation were characterized with default parameters for Var and Sen, respectively. As expected, for all impact categories, conversion of milk production to FPCM influences the results, with the standardization of milk fat content as main contributor. Typically, results are sensitive to conversion factors but do not vary much because of them due to their low uncertainties, except for dry-matter-to-energy conversion and protein-to-N conversion, for which default parameters of distribution were attributed. Feed and manure composition and animal diet requirement variables influenced acidification and climate change impacts, while eutrophication impact was mainly influenced by emission factors in the model of N fixation by legumes. Ecotoxicity and CED were mainly influenced by other input characteristics and emission factors.

## 4. Discussion

Uncertainties in multiple environmental impacts of milk production were explored by considering mainly inventory model variables. Uncertainties, expressed as coefficients of variation, ranged from 3-2097% as a function of the impact category. The most influential variables changed with the impact category, except those used to calculate the functional unit. For this calculation, the most influential variable was milk fat content, which implies that accurate knowledge of milk fat content is necessary. Acidification and climate change impacts were influenced by many variables related to cattle requirements and feed composition. This reflects the impact of using IPCC and EMEP models, which consider the causal chain from feed ingestion to manure application and its input data through diet characteristics (digestible energy and protein content). When using these models, it is important to have good knowledge of diet composition. The influence of emission factors emphasizes the effect of a few generic values (e.g. $N_2O$ emissions from soils). CED and ecotoxicity impacts were calculated with balance models; consequently, they were mainly influenced by input-output characteristics or emission factors attributed to input production. This is also partially the case for eutrophication, which is based on balance equations for some compounds, such as on-farm nitrate emission, but also on emission models, such as on-farm phosphate emission.

In this study, the influence of uncertainty in input variables was not included but would certainly add large uncertainty to the results. This work highlights the influence that different variables have on different impact categories, showing that impact can be sensitive to variables whose uncertainty is high or not well characterized. The procedure used to calculate uncertainty has some limits, however, such as not taking into account covariance between the variables of the same model. A global model approach would be interesting to improve the understanding of uncertainty. In the future, uncertainty related to the complexity of estimating emissions of damaging compounds should also be considered using model comparison and validation. Ultimately, performing Monte-Carlo simulations, as in this study, may help identify errors in implementation of models in calculation tools.

## 5. Conclusion

This approach helps to bound uncertainties related to model variables, which can be quite high, in environmental impacts of milk production. In the future, the identification of the most influential variables in emission models should help in decreasing uncertainties by improvement of their accuracy. Finally research is required to investigate influence of input variables.

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