Implementing the Green Deal in EU agriculture: metamodeling the CAPRI model to derive optimal policies

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Abstract

The European Green Deal has been designed to transform the European economy to become climate neutral, modern and resource-efficient. To reach the goals in the agricultural sector, the Farm To Fork Strategy has been proposed in May 2020 and is still heavily disputed. As previous research has shown, if implemented as proposed, the Farm To Fork Strategy in connection with the Biodiversity Strategy will have far reaching impacts on the economy and environment not only in Europe but worldwide. Consequently, we aim to fill the research gap in finding alternative, optimal policies that reach the same goals more efficiently than the Farm To Fork Strategy. The results show that the optimal policy set differs from the Farm To Fork Strategy not only in scope but also in the choice of the policy measures. Further, a compromise among EU member states could be realized fairly easily as member states specific optimal policy sets are akin.

1 Introduction

The Green Deal is Europe's new growth strategy to become the first climate-neutral continent by 2050. The overall goal is to transform the European economy to become modern, resource-efficient and competitive. An effective implementation of the European Green Deal appears to be heavily disputed between societal groups within and across EU-member states. A good case in point is the Farm To Fork Strategy (F2F), suggested by the EU-commission in May 2020, to achieve the goals of the Green Deal in agriculture. The Farm To Fork Strategy (F2F), together with the Biodiversity Strategy, initially focuses on the implementation of the goals of the Green Deal in agriculture, which are defined as the following technical production restrictions and target values (European Commission, 2020):

- Reduction of mineral fertilizer use by 20% [fertilizer]
- Reduction of pesticide use by 50% [pesticide]
- Reduction of the Nitrogen-balance surplus by 50% [nsurplus]
- Share of high diversity landscape features/set-aside of at least 10% [national/set-aside]
- Share of organic farming of at least 25% [organic]

Several studies have assessed and quantified the ecologic and economic effects of the Green Deal and the Farm To Fork Strategy (see Beckman et al. (2020); Barreiro-Hurle et al. (2021); Bremmer et al. (2021); Henning et al. (2021); Jongeneel et al. (2021)). The studies differ methodologically: both Barreiro-Hurle et al. (2021) and Henning et al. (2021) use the partial equilibrium model CAPRI, Beckman et al. (2020) use the general equilibrium model GTAP while Bremmer et al. (2021) use the partial equilibrium model AGMEMOD and case studies while Jongeneel et al. (2021) beside others perform a literature analysis and case studies. In short, the findings are similar in that the Green Deal leads to a reduction of agricultural output while farm income increases and consumer welfare decreases.

Yet, as the Farm To Fork Strategy is no concrete policy, the question remains whether this proposed strategy will eventually be implemented. Moreover, as it is not public how the policies of the F2F Strategy were decided upon and appear to be at best guessed, there might be alternative policy sets which achieve the goals of the Green Deal more efficiently.

Therefore, the objective of this paper is to explore the possibility of apply the metamodeling approach on the CAPRI model to derive optimal political positions with respect to the Farm To Fork Strategy which are both efficient and effective in achieving the Green Deal goals. Further, the optimal policies are derived for each member state to reproduce the European Union decision making process. In addition to the policy measures of the Farm To Fork Strategy, a price for CO2eq emissions is included in the optimization model to determine what impacts expanding the CO2 price, currently established in i.a. the energy and industry sector, by agriculture would imply.

The paper is organized as follows. Data and methods are presented in section 2. Subsequently, optimal policies on member state and EU level are presented in section 3. Finally, the paper concludes with a discussion in section 4.

2 Data & Methods

2.1 CAPRI model

Since the CAPRI model is used for metamodeling, its essentials are described in the following. The Common Agricultural Policy Regionalised Impact (CAPRI) model is a regional partial equilibrium model focused on the agricultural sector including environmental and land-use effects induced by farm production. CAPRI combines detailed models of the agricultural supply in the EU regions with a global trading model to include trade flows and price effects. The model provides highly detailed results on NUTS2 level for a large number of production activities. In addition, CAPRI also provides detailed results of the environmental effects, e.g., CO2 emissions, nitrogen balance and an index to measure the level of biodiversity. Moreover, the impacts on consumer, producer and total welfare are captured. CAPRI has been used intensively in the past twenty years to analyze the impacts of policies and other exogenous shocks on agriculture, environment and trade[1]. In addition, it has lately been used to determine the impacts of the Farm To Fork Strategy on economy and ecology, see for example Henning et al. (2021); Barreiro-Hurle et al. (2021).

2.2 Naive approach

A naive approach to derive optimal policies works is described in the following. Let Γ be the set of policies, $\Gamma = \{\text{fertilizer, pesticides, organic, national, nsurplus, co2}\}$, see section 1. Each policy $\gamma \in \Gamma$ can take on values in a certain range I limited by lower and upper bounds, $I_\gamma = [l_\gamma, u_\gamma]$, where $l_\gamma < u_\gamma$ and $l_\gamma, u_\gamma \in \mathbb{R}$, e.g. a range from 0 to 100. As considering all possible values in the range I results in an infinite set of policy specifications, W_γ, we need to take a finite subset, $V_\gamma \subset W_\gamma$. For example, let $V_\gamma = \{x \in \mathbb{Z} | l_\gamma \leq x \leq u_\gamma\}$, so that the subset V consists of all whole numbers in the range I_γ. Then the set of all combinations of policy specifications is the Cartesian product of the sets of possible policy specifications V_γ and defined as $\mathbb{P} = \prod_{\gamma\in\Gamma} V_\gamma$. Next, the CAPRI model is solved for each policy specification set $p \in \mathbb{P}$ to determine the impacts on the model outputs, e.g. welfare, prices and environmental impacts. Finally, the policy specification set p^*, which achieves desired goals the best, is selected as the optimal policy set.

However, although this approach appears to be straight forward, this is not a trivial task. First of all, reducing the set of policy specifications from W_γ

[1] See `www.capri-model.org`

to V_γ eliminates an indefinite number of policy specifications and hence limits the solution space. Second, as each model run takes a considerable amount of time, $|V_\gamma|$ model runs take a cumbersome amount of time. Assume that $|V_\gamma| = 10$ for each $\gamma \in \Gamma$, i.e., each policy can take on 10 different values. Then the number of combinations of policy specifications $|\mathbb{P}| = 10^6 = 1.000.000$. Even though computing power has increased in the past years, it still takes a considerably amount of computing time to run all scenarios and is simple not realizable. On an average computer one model run of CAPRI takes about one hour to solve. Even if this could be reduced to one minute, 1.000.000 model runs would take 1.9 years to solve. Additionally, the issues of time to read/write data and providing the storage space for the data would have to be addressed. Thirdly, this approach only leads to implicit input-output relations and no analytical form, limiting the choice of methods in further analyses.

In conclusion, this approach is extremely costly in time and effort, and only approximates the optimal solution. Consequently, as the naive approach is not suited for the optimization problem, a smarter approach is required as shown in the following section.

2.3 Metamodeling approach

Metamodeling is widely used in research fields in engineering and natural sciences (Simpson et al., 1997; Barthelemy and Haftka, 1993; Sobieszczanski-Sobieski and Haftka, 1997; Razavi et al., 2012; Gong et al., 2015) and has in recent years also been applied in economics (Ruben and van Ruijven, 2001; Villa-Vialaneix et al., 2012; Yildizoglu et al., 2012). In general, the metamodeling technique generates a simpler model of the simulation model. As this surrogate model is smaller and hence computationally faster but still includes the main features of the original model, it may be used in further analyses. Moreover, metamodels are in an analytical form and can therefore easily be used for optimization. In general, metamodeling requires three parts: the choice of metamodel type, the Design of Experiments (DOE) and the model validation (Kleijnen and Sargent, 2000).

We perform metamodeling based on the CAPRI model described in section 2.1. First, as model type, we use a second-order polynomial model of the following form:

$$Y = \beta_0 + \sum_{h=1}^{k} \beta_h \gamma_h + \sum_{h=1}^{k} \sum_{g \geq k}^{k} \beta_{h,g} \gamma_h \gamma_g + \epsilon$$

where γ_1, ..., γ_k are the k independent policy variables, Y is the dependent variable and ϵ is the error term. As we are interested in the change of targets, the dependent variable Y is the percentage change of a certain model output compared to the baseline scenario (no policies). The coefficients β are commonly estimated using a least squares linear regression (Chen et al., 2006). The advantage of polynomial models is that they are easy to understand and manipulate, and the computational effort is low (Ziesmer et al., 2022).

Secondly, we draw a simulation sample by Design of Experiments (DOE) to estimate the corresponding coefficients of the metamodels. DOE is a statistical method to draw samples in computer experiments (Dey et al., 2017). The space-filling design Latin Hypercube is used to generate sample points as it is able to generate uniformly distributed sample points that cover the parameter space well (Sacks et al., 1989).

Thirdly, validation is required to determine whether the metamodels predict well (Villa-Vialaneix et al., 2012; Kleijnen, 2015). For this, two samples are necessary: the training sample and the test sample. While the training sample is used to fit the model parameters, the test sample is used to validated the model. Note that the test sample must not include data points that are part of the training sample. The test sample lets us determine whether the metamodels can be generalized and the simulation model can be replaced with the metamodels (Ziesmer et al., 2022). The model is validated using the common coefficient of determination R^2 and the Root Mean Squared Error (RMSE). While R^2 measures how close the data are to the fitted regression line, $RMSE$, indicates how close the model's predicted values are to the true values:

$$R^2 = 1 - \frac{\sum_{i=1}^{n} \left(Y_i - Y_i^0\right)^2}{\sum_{i=1}^{n} \left(Y_i - \overline{Y^o}\right)^2} \tag{1}$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^{n} \left(Y_i - Y_i^o\right)^2} \tag{2}$$

where Y_i and Y_i^o are the predicted values and true values for the test sample at sample point i, and $\overline{Y^o}$ is the mean of Y^o in the test sample. In addition, we use the Absolute Error Ration (AER), to compare the prediction performances of the dependent variables that have different scales. AER indicates how large the prediction errors are in comparison to the true simulated values on average (Ziesmer et al., 2022).

$$AER = \left| \frac{RMSE}{\overline{Y^o}} \right| = \left| \frac{\sqrt{\frac{1}{n} \sum_{i=1}^{n} \left(Y_i - Y_i^o\right)^2}}{\overline{Y^o}} \right| \tag{3}$$

2.4 Optimization

As the metamodeling technique results in an analytical form, optimization techniques may be used to derive optimal policy sets. To incorporate both economic and ecologic aspects into the optimization, the objective function was defined as the weighted sum of environmental and economic outcomes:

$$max_{\Gamma} \sum_{j \in J} w_j Y_j(\gamma)$$

where

- Γ set of policies

- J set of economic and ecologic indicators: CO2 emissions, Nitrogen surplus, biodiversity and total welfare
- w_j weight of outcome Y_j
- Y_j percentage change of outcome j to baseline

Weights are based on consumers' Willingness-To-Pay to reflect the relative importance of goals and set as follows: 70% total welfare, 30% ecosystem services, of which 80% CO2 reduction, 10% biodiversity increase and 10% nitrogen reduction.

3 Results

First, some general metamodeling results are presented. Then, the optimization results are shown on EU and member-state level.

At first, validation results for selected model outcomes on EU27 level are shown in table 1. The results are similar on member states level. As RMSE and AER are low and R^2 high for the central model outputs, the models may be considered highly valid.

Table 1: Validation results, EU27

Variable	RMSE	Mean	AER	R^2
Consumer welfare	0.0001	-0.0027	0.0395	0.9850
Producer welfare	0.0295	0.2450	0.1205	0.9839
Total Welfare	0.0001	-0.0020	0.0584	0.9824
Agric. global warming potential	0.0157	-0.2952	0.0532	0.9541
N surplus total	0.0173	-0.3177	0.0543	0.9460
Biodiversity Index	0.0040	0.1131	0.0353	0.9710

To get a first impression of the results, figure 1 shows how the policies affect selected model outputs separately. Note that all policies are measured in percentage except for the CO2 price which is measured in Euro/t CO2eq. Also note that while the x-axis has a range from 0 to 80%, a realistic policy could be substantially lower. The black dots highlight the policy values

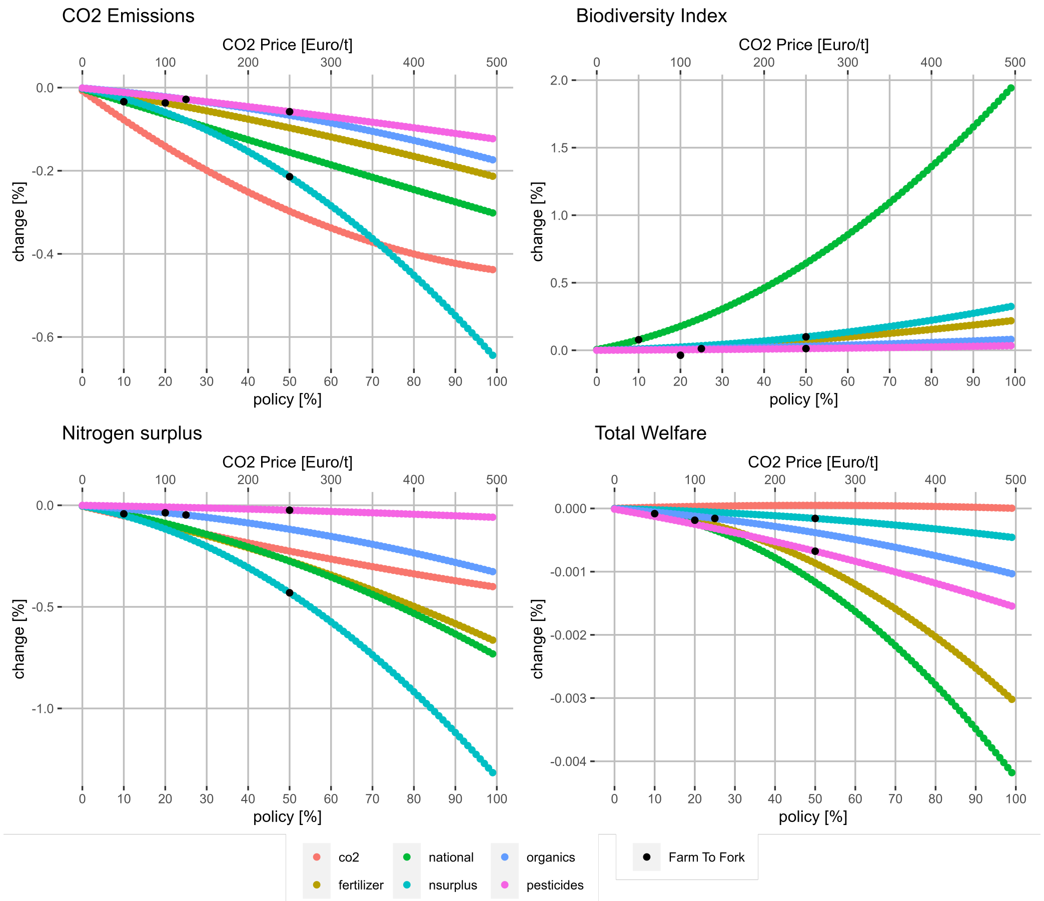

Figure 1: Separate impacts of F2F policies on selected goals

specified in the proposed Farm To Fork Strategy for reference purpose. It is shown how the main outcomes (CO2 emissions, nitrogen surplus, biodiversity and total welfare) change compared to the baseline (no policy) in response to an increase in the policy values if only this single policy would be introduced.

As shown in the upper left plot of figure 1, for all Farm To Fork Strategy policies but *nurplus*, an implementation of the F2F Strategy results in a decrease of CO2 emissions by less than 10%. Only the reduction of nitrogen surplus (*nsurplus*) results in a decrease of more than 20%. What is even more, as the dotted lines indicate, even a further increase in the policies *fertilizer*, *national*, *organics* and *pesticides* results in a lower reduction of CO2 emissions than *nsurplus*. Besides the Farm To Fork Strategy measures, the introduction of a CO2 price also clearly decreases CO2 emissions.

As one would expect, biodiversity is strongly affected by increasing the set-aside area as shown in the upper right plot. Yet, as realistic policy values are much lower, other policies also impact biodiversity, e.g. *nsurplus*. In the lower left plot, the impacts on the nitrogen surplus is shown. Clearly, introducing a policy, which reduces the nitrogen surplus, actually reduces the nitrogen surplus effectively. Other policies such as organic farming are less successful. Finally, the lower right plot shows the impact on total welfare. The change in total welfare is below 0.002% for most realistic policies. Even a CO2 price of 500 Euro/t decreases the total welfare hardly at all.

3.1 Optimization on EU-level

In table 2, the results of the optimization for the EU is shown if decisions in the EU were made by a benevolent dictator to get a first impression. For reference purpose, the Farm To Fork Strategy is shown in addition to the optimization result. To ensure feasibility in the optimization, bounds had to be set. The minimum value for each policy was set to 0 and the maximum value to 1.5 times that of the Farm To Fork Strategy. The upper limit for the CO2 price was set at 400 Euro/t which is currently at ca. 80 Euro/t CO2eq (The World Bank, 2022).

Table 2: Optimization results for EU27

	Farm To Fork	Optimization	Upper limit
fertilizer [%]	20	0	30
pesticide [%]	50	75	75
nutrient loss [%]	50	75	75
organic [%]	25	0	37.5
national [%]	10	15	15
CO2eq price [Euro/t]	-	274	400

In table 3 the relation between the percentage change of the ecosystem services and the percentage change of total welfare is shown to put the benefits and costs of the policies into relation. The optimization leads to more efficient relations for a reduction of CO2 and N emissions. A decrease in total welfare by 0.1% implies a decrease of CO2 emissions by 31.5% for Farm To Fork Strategy and 45.2 for the optimal. For N-reduction the effect is similar as nitrogen surplus is decreased by 50% and 56%, respectively. Only for the biodiversity index, the benefit-cost-relation for the F2F is lower. Yet the difference between the F2F Strategy and the optimal for the biodiversity index is smaller than for N and CO2 reduction with -179 and -162 respectively. However, biodiversity is difficult to measure and there are no ideal indicators in the literature yet. Hence, the biodiversity index also is not capable of measuring biodiversity precisely.

Table 3: Relation ecosystem service to cost
[% change ecosystem service/% change total welfare]

Ecosystem Service	Farm To Fork	Optimal policy
Biodiversity Index	-179.76	-162.41
Global warming potential	315.92	452.77
N Surplus total	500.30	567.42

3.2 Optimization on EU member-states level

Yet, decisions in the European Union are not based on what would be best for the European Union as a whole but takes the member states individual interests into account. Hence, in the following, the optimization results for each member state are stated. The optimization was performed similar to the EU level, but as CO2eq emissions are not locally restricted but affect globally, the CO2 emissions on EU level are considered by each member state in finding optimal policies instead of just their own emissions.

In figure 2 the optimization results from the point of view of each EU member states as well as for the EU as a whole for reference purpose is shown.

Figure 2: Optimization results for each member state

The only relevant policies are CO2 price, set-aside area, reduction of nitrogen surplus and reduction of pesticide use. Thus, organic farming and fertilizer reduction are not included in any optimal policy mix. To be precise, the *nsurplus* and *pesticides* policies should be at 75% for each member state. Hence, the only differences occur in the optimal CO2 price and the set-aside area which is shown in figure 3. If a CO2 price would be introduced in addition to the other policies, it would lie between 275 and 300 Euro/t CO2. The only dispute could be about the percentage of the set-aside as some member states favor 0% and others 15%.

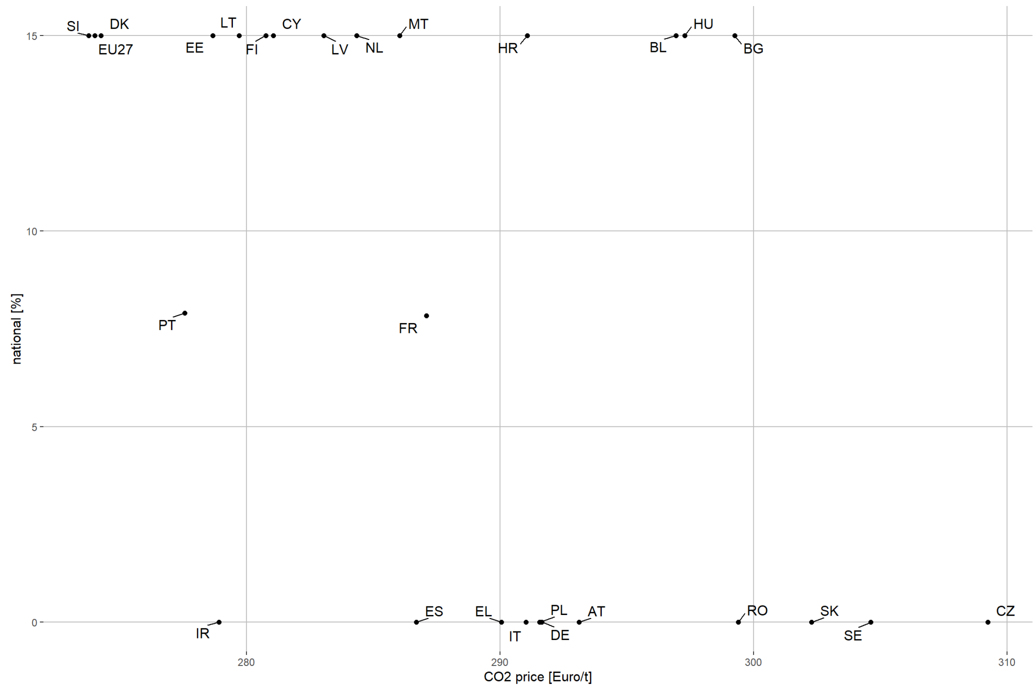

Figure 3: Optimization results for each member state, selected policies

4 Conclusion

The objective of this paper is to explore the possibility of applying the metamodeling technique on the CAPRI model with the goal of deriving alternative, optimal policies for the Farm To Fork Strategy to improve the implementation of the European Green Deal in agriculture. For that purpose, ideal policies for each member state of the European Union were derived using a metamodeling approach. This method was chosen as the naive approach of testing a large set of possible policy specifications and choosing the most desirable one out of hundred of thousands fails du to time and resource constraints. The metamodeling technique is widely used in engineering and natural sciences for optimization.

The results show that the approach of applying the metamodeling technique on the CAPRI model to derive optimal policies improving the Green

Deal is promising. First results show that a compromise on member state level could be achieved relatively easily as the optimal policy specifications are similar among member states. Additionally, it was shown that the derived optimal policies perform better than the proposed Farm To Fork Strategy in terms of economic and ecological goals. These findings are important, but there remain issues to consider. In general, future research could address model uncertainty regarding the CAPRI model as Computable General Equilibrium (CGE) models typically face the problem of specifying parameters facing unsupported assumptions and limited data. Yet, model uncertainty is widely neglected in policy analysis (Manski, 2018; Marinacci, 2015).

Furthermore, as the optimization is a weighted sum, the choice of weights also play a key role. Further research is therefore needed to determine, for example, member-state specific willingness-to-pay for environmental goods as those differ among EU member states.

In addition, future research could also include a proxy for world food security, e.g. agricultural commodity prices, to capture the global impacts of the European agricultural production.

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