Can the European Green Deal be a game changer for sustainable food system transformation? A computational political economy approach

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Abstract

The urgency for a global and fundamental transformation of food systems is undeniable in these days. Agriculture, together with its associated land-use changes, significantly contributes to climate change and deforestation for agriculture and the intensification of agricultural landscapes are major contributors to biodiversity loss. Moreover, the current management of food systems leads to environmental damage that exacerbates various disruptions.

Ecological-economic models are the first choice to assess the impacts of policies but neglect the political process. What is needed are political economy modeling approaches which allow both the identification of optimal public policies as well as the assessment of their political feasibility. Hence, ideally political economy modeling integrates both an ecological-economic model to identify first best policies, and a quantitative political decision-making model that allows the assessment of the political feasibility of public policies.

Given the fact that for real world systems often a trade-off between ecological-economic efficiency and political feasibility can be observed, i.e. the probability that scientifically identified first best policies will be effectively implemented in real world political systems is rather low, while vice-versa policy choices resulting from real world policy processes lead to rather inefficient and less sustainable policy outcomes, it is especially important that integrated political economy modeling frameworks allow the

identification of second best policies, i.e. policies which are political feasible given specific features of real world political systems and which lead to policy outcomes which achieve efficiency levels that compare to first best policies.

In this context this paper suggests an innovative political economy approach combining quantitative economic-ecological modeling with a non-cooperative legislative bargaining model. In particular, public policies result as an equilibrium outcome of a multi-stakeholder process, where policy decisions are the outcome of legislative bargaining among involved legislative actors. Based on our theory, a mean voter theorem applies, i.e., final policy outcomes result as a weighted mean of legislators ideal points, where the weights of individual legislators depend on the constitutional decision-making rule. Legislators' policy preferences are derived from political communication processes among governmental and non-governmental stakeholders, where actors up-date their beliefs how specific polices impact on relevant policy outcomes.

To go into detail, we use the economic-ecological model CAPRI which has been used extensively to assess the impacts of policies mainly on the European agricultural sector. Further, we use metamodeling to derive an analytical form of policy impact functions which are used to derive endogenous policy preferences determining the non-cooperative legislative bargaining equilibrium.

We apply our innovative framework to the European Green Deal which 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 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.

However, we use our innovative framework to assess the following questions:

1. To what extend do first-best policies differ from the Farm To Fork Strategy in terms of efficiency and ecological effectiveness?
2. To what extend are first-best policies politically feasible?
3. What are second best policies and to what extend do they deliver results which compare to first-best policies?

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, suggested by the EU-commission in May 2020, to achieve the goals of the Green Deal in agriculture. The Farm To Fork Strategy, 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 meta-modeling 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 3. Subsequently, optimal policies on member state and EU level are presented in section 4. Finally, the paper concludes with a discussion in section 5.

2 Computational Political Economy Framework

2.1 Ideal policy choice of a social planner

Formally, let F denote a model, which implicitly determines outputs, z, as a function of a set of policies, γ, and a set of model parameters, ω:

$$F(z, \gamma, \omega) \equiv 0. \tag{1}$$

F is an I-dimensional vector-valued function, z an I-dimensional vector of endogenous output variables, γ is a J-dimensional vector of policy dimensions, and ω a K-dimensional vector of exogenous model parameters. Relevant outputs z might include economic growth measured by growth in income per capita, environmental protection, e.g., measured by reduction in CO_2 emissions, as well as poverty reduction, measured by the share of households below the poverty line. Policy dimensions include policies controlled by the government, e.g., taxes, subsidies, or tariffs, as well as government expenditure on specific policy programs like, for example, public investments in extension services, infrastructure, or education as well as provision of public services, e.g., health or social services. Model parameters can be further disaggregated into different subsets, e.g., behavioral parameters or exogenous variables. Exogenous variables include demographic or economic variables uncontrolled by the government, e.g., world market prices or population growth. Changes in the values of exogenous variables correspond to exogenous shocks, which induce changes in the endogenous variables. The latter corresponds to the response of the economic, ecological, and social systems to exogenous shocks. Behavioral parameters define the response of the system to these shocks. Hence, assuming behavioral parameters correspond to their true values implies that the model replicates the true response of the economy to exogenous shocks. F defines an intervention logic of transforming γ into z and could correspond to any scientific model. However, we focus in the following on Computable General Equilibrium (CGE) models. An advantage of CGEs is that one can simulate counterfactual scenarios, i.e., one can calculate the values of the endogenous variables that result from assuming parameter values that differ from their corresponding baseline values.

2.1.1 Policy Choice under Model Uncertainty

In a pure modeling framework, a benevolent social planner is assumed to choose policies γ that maximize an evaluation function (social welfare function) $S(z)$, i.e. policies are the choice variables controlled by a social planner, while evaluation of policy choices depend on specific output variables, z, that are determined by policy variables. Technically, the relation between policies, γ, and outputs, z, is determined by a model, F, as defined in 1. Hence, formally rational policy choices of a benevolent planner can be derived from the following social welfare maximization problem:

$$\begin{aligned} \max_{\gamma} \quad & S(z) \\ F(z, \gamma, \omega) \quad & \equiv 0. \end{aligned} \tag{2}$$

Standard CGE policy analysis is often focused on policies that can be directly integrated into a CGE model, e.g., taxes, subsidies, transfers, or tariffs. The latter are incorporated in the CGE model as exogenous parameters. In contrast, other policies can only be indirectly implemented applying the concept of policy impact functions. For example, the Maquette for MDG Simulations (MAMS) model defines Millennium Development Goals (MDGs) as a political production function of budget allocation across specific public services (Löfgren et al., 2002). Analogously, analyzing the impact of investment policies under the Comprehensive Africa Agriculture Development Programme (CAADP), the change in sectoral technical progress is defined as a function of budget allocation across different CAADP-policy programs (Henning et al., 2017). In order to analyze these policies within a CGE framework, their impact has to be transformed into corresponding policy shocks, which are integrated in the CGE model as exogenous parameters. Formally, this transformation corresponds to our concept of policy impact functions (PIFs). Accordingly, F is specified as a nested function:

$$F : (\gamma, \omega) \ \rightarrow \ z, \ T(z, \eta, \theta)) \equiv 0 \wedge H(\eta, \gamma, \xi) \equiv 0, \tag{3}$$

comprising of an economic-ecological model, $T(\eta, z, \theta)$ and a PIF, $H(\eta, \gamma, \xi)$, with $\omega = (\theta, \xi)$. The PIF transforms γ into policy shocks η. The outcomes z are an indirect effect of policies defined through policy shocks η induced by policies. For example, public investment policy programs might induce technical progress defined by the PIF, while technical progress, in turn, is modeled as an exogenous parameter, η, in the CGE implying a change in poverty or economic growth defined by the economic-ecological model. ξ denotes a vector of parameters determining the relationship between policies and induced shocks, e.g., the effectiveness of public investment in specific policy programs. The parameters defining the behavior of the economic-ecological model are denoted by θ.

To demonstrate how to derive optimal polices (γ^*) under model uncertainty, we define the following maximization problem:

$$\begin{array}{lcr} \max\limits_{\gamma} & S(z) & \textit{evaluation function} \\ \textbf{s.t} & & \\ T(z,\eta,\theta) & \equiv 0 & \textit{economic-ecological model} \\ H(\eta,\gamma,\xi) & \equiv 0 & \textit{policy impact function} \\ R(z,\eta,\theta,\gamma,\xi) & \equiv 0 & \textit{restrictions} \end{array} \tag{4}$$

The function R represents any further restrictions defined on policies, policy outputs, or model parameters that reflect exogenous framework conditions or correspond to restrictions implied by economic theory.

Given a specification for T, H and R one is able to solve 4 and obtain the corresponding optimal policy. However, the solution of 4 is driven by a lot of model assumptions, e.g., functional forms, parameter values, model structure, which are highly uncertain. In particular, fundamental model uncertainty can be separated into parametric and non-parametric uncertainty (Marinacci, 2015). Non-parametric uncertainty corresponds to different model structures and different functional forms within the same model structure. In contrast, parametric uncertainty corresponds to different parameter specifications within the same model structure and the same functional forms.

Formally, let M denote a set of model structures, and $m \in M$ a specific model, i.e. corresponding to a specific $T_m()$ and a specific $H_m()$ with specific parameters, θ_m and ξ_m, respectively. Then the solution of 4 implies: $F_m(z^*_m, \omega_m, \gamma^*_m) \equiv 0$, where F_m corresponds to a specific intervention logic defined by the model m.

Further, let $Pr(m)$ denote the probability that the structural model m corresponds to the true data generating process, while $Pr(\omega_m \mid m)$ denote the conditional probability distribution of the model parameters $\omega_m = (\theta_m, \xi_m)$ given the structural model m. Assuming a rational, risk-averse actor, we can define the expected evaluation as follows:

$$E(S(z)) = \sum_m Pr(m) \int_\Omega S(F_m(z, \omega_m, \gamma)) Pr(\omega_m \mid m) \, d\omega \tag{5}$$

Solving the policy choice problem involves the solution of the integrand. However, the integrand may be difficult or impossible to evaluate analytically. Accordingly, in most cases, one is forced to evaluate the integral numerically. In general, numerical approximations of the integral take the form:

$$\int_{\Omega} S(F_m(z, \omega_m, \gamma))Pr(\omega_m \mid m)\, d\omega \approx \sum_{J} g_j S(F_m(\omega_{m,j}, \gamma))Pr(\omega_{m,j} \mid m), \tag{6}$$

where J represents the total number of evaluations of $S(F_m()$ and g_j represents the weight associated with each evaluation j (Haber, 1970). The Monte Carlo approach represents a special case where one generates L pseudo-random numbers from the distribution $Pr(\omega_m \mid m)$, evaluates the integrand L times, and attaches a weight of $1/L$ to the result from each evaluation, i.e., drawing L random samples $\omega_{m,l}$ from the distribution $Pr(\omega \mid m)$, we can approximate the integrand by:

$$\frac{1}{L}\sum_{l=1}^{L} S(F_m(\omega_{m,l}, \gamma)) \tag{7}$$

If L is sufficiently large, the approximation will be good under extremely mild conditions on the integrand. Alternatively, one might use Gaussian Quadrature methods to keep the number of evaluations of the integrand, L, small (Arndt and Pearson, 1998; Villoria and Preckel, 2017).

Beyond a numerical solution of the integral, solving the policy choice problem still includes the evaluation of the function F_m, which is usually only implicitly defined and not in an explicit analytical form (e.g., T_m is defined by a recursive-dynamic CGE). Accordingly, it might be rather tedious to differentiate F_m applying the implicit function theorem and solving the corresponding first order conditions (FOCs) numerically for the optimal policy. In general, the optimization problem might still be solved by applying simulation optimization techniques (Amaran et al., 2015). However, applying these techniques might become tedious if a large and complex CGE with a large set of policies is used.

In this regard we suggest to apply metamodeling (see **??** for a comprehensive introduction) to derive an explicit function $z_m = f_m(\omega_m, \gamma)$ approximating the implicit function F_m. In contrast to other simulation optimization techniques, this approximation implies that the FOCs can be explicitly formulated and hence easily solved applying standard numerical solution algorithms. Hence, combining the numerical approximation of the integrand with metamodeling, we derive a numerically tractable optimization problem for the policy choice problem under model uncertainty:

$$
\begin{aligned}
&\max_{\gamma} && E(S(z)) = \sum_{m} Pr(m) \frac{1}{L} \sum_{l=1}^{L} S(z_{m,l}) \\
&\textbf{s.t} && \\
&z_{m,l} && = f_m(\omega_{m,l}, \gamma) \\
&R(z, \eta, \gamma, \omega_{m,l}) && \equiv 0
\end{aligned}
\tag{8}
$$

2.2 Real World Policy Choices

Thus far, we have looked at policy choice as a complex but purely technical task assuming a benevolent social planner undertakes the final choice. In reality, however, individual society members evaluate outcomes differently and need to agree on a common policy. Therefore, the policy choice is a collective choice, where heterogeneous policy preferences of individual society members are aggregated to a joint political decision based on specific constitutional decision-making rules.

Comprehensive policy analysis includes both the analysis of the technical transformation of policies into relevant outcomes, as well as the political process in which an actual policy is collectively selected. In representative democracies, preference aggregation is subdivided into two steps. First, heterogeneous voter preferences are transformed into the corresponding preferences of a subset of political representatives via democratic elections. Second, the heterogeneous preferences of political representatives are aggregated into a final political decision via legislative voting procedures. Based on their policy beliefs, political actors derive their individual policy preferences.

2.2.1 Legislative Bargaining

At a methodological level collective policy choices result from legislative bargaining, where a set of political agents $g \in G$ select a policy γ according to given constitutional rules ξ. Each legislator has a spatial policy preference, $U_g(\gamma, \hat{\gamma}_g)$, where $\hat{\gamma}$ denotes legislators' ideal point, the policy she prefers to all other policies. A legislative bargaining model Ξ transforms given policy preferences of legislators, u^G, and given constitutional rules φ, into a legislative decision γ^*:

$$\gamma^* = \Xi(u^G, \varphi). \tag{9}$$

Policy preferences of legislators are derived from political support maximization:

$$U_g(\gamma) \quad = E(S^g(z(\gamma))) = \sum_{m} \tilde{P}r^g(m) \frac{1}{L} \sum_{l=1}^{L} S^g(f_m(\omega_{m,l}, \gamma)) \tag{10}$$

$\tilde{P}r^g(m)$ denotes the subjective policy beliefs of a legislator g and $S^g(z)$ denotes the individual support function. In democratic systems, agents' polictical support functions result from electoral competition including lobbying activites (see for example Grossman and Helpman (1996))[1]

In this regard Braack et al. (2023) suggest an innovative non-cooperative legislative bargaining game and proof a mean voter theorem that implies that the equilibrium bargaining outcome correpsonds to a lottery of legislators' proposals with following expected outcome:

$$E(\gamma^*) = \sum_g C_g \tilde{\gamma}_g \tag{12}$$

$C_g = \sum_h Q_h \alpha_{hg}$ denotes the political control of legislator g and is determined in the equilibrium of the game as a function of the propability that legislator h's proposal will be the final outcome of the game, Q_h, and relative weight of legislator g's idealpoint determining legislator h's proposal, $x_h = \sum_g \alpha_{hg}\gamma_g.x_h$ denotes the proposal of h and γ_g denotes g's idealpoint (for further details see (Braack et al., 2023)).

2.2.2 Evaluation Measures

Policy analysis includes the identification of an optimal policy, γ^{opt}, as well as the evaluation of empirically observed policy outcomes, γ^*. For the latter, an appropriate evaluation measure is required. An obvious candidate for an appropriate evaluation measure would be the expected welfare $E(S(z))$. In particular, one could compare the expected welfare derived under an observed policy, γ^o, with the expected welfare derived under the optimal policy. However, to derive a consistent measure of political performance which is also straightforward to interpret, we suggest the concept of a political loss function. In particular, we define $B(\gamma)$ as the economic welfare loss of a policy measured in money metric, e.g. the Hicksian equivalent variation implied by a policy.

We define a political loss function, $L(\gamma^o)$, related with a specific policy, γ^o:

[1] Following Grossman and Helpman (1996) or Henning et al. (2018)) political support function can be derived a weighted social welfare function:

$$S_g(z,\gamma) = \sum_v \phi_v^g \left(\delta_v^g U_v(\gamma,\hat{\gamma}_v) + (1-\delta_v^g) S_v(z)\right) + (1 - \sum_v \phi_v^g) \sum_i \phi_i^g U_i(\gamma,\tilde{\gamma}_i) \tag{11}$$

v is an index denoting different social voter groups, and i is an index denoting different lobbying groups. ϕ_v^g, δ_v^g are weighting parameters determined by the voting behavior, while ϕ_i^g is the relative political weight of a lobbying group i depending on the relative access to political agents g.

$$\begin{aligned}
\mathcal{L}(\gamma^o) \quad &= \max_{\gamma} \quad dB \\
&\textbf{s.t} \\
&E(S(z_{m,l})) \geq E(S(z^o_{m,l})) \\
&z_{m,l} = f_m(\gamma, \omega_{m,l}) \quad \text{and} \quad z^o_{m,l} = f_m(\gamma^o, \omega_{m,l}) \\
&R(z, \eta, \gamma, \omega_{m,l}) \equiv 0 \\
&B(\gamma) - B(\gamma^o) \geq dB
\end{aligned} \tag{13}$$

dB correspond to the maximal economic welfare gain that could be realized if an optimal policy is implemented to reach at least the expected welfare $E(S(z^o_{m,l}))$ achieved by the policy γ^o inducing the economic welfare $B(\gamma^o)$. Obviously, the maximal gain will be zero if γ^o corresponds to the overall optimal policy. The political loss can also be normalized expressing the relative loss compared to a benchmark economic welfare, $\bar{B}$, i.e., $\frac{dB}{\bar{B}}$. However, evaluating legislative bargaining outcomes implies that one assess the expected loss:

$$E(\mathcal{L}) = \sum_g Q_g \mathcal{L}(x^*_g), \quad x^*_g = \sum_h \alpha_{gh}\gamma_h$$

Overall, political economy of real world policy choices includes two aspects of inefficiency. First, inefficient policy choices correspond to biased political incentives of elected politicians to represent society interests. Technically, incentive bias implies that agents' political support functions, $S^g()$, do not correspond to society's social welfare, $S()$. [2] Secondly, inefficient policy choices result from biased policy beliefs, i.e. prior probabilties $Pr^g(m)$ do not prefectly reflect available political knowledge. Let $Pr(m), \quad m \in M$ denote the priors based on all available scientifc knowledge. Then, we can calculate two counterfactual policy outcomes, γ^{know} and γ^{soc}. The former corresponds to the equilibrium outcome of the legislative bargaining assuming all legislators individual support functions equal exactly society's spcial wefare function, i.e. $S^g(z) = S(z), \quad \forall g$. The second counterfactual correpsonds to the legislative bargaining equilibrium assuming policy beliefs of all legislators correpsond exactly to available scientific knowledge, i.e. $Pr^g(m) = Pr(m), \forall g$.

Let $L^{know} = E(\mathcal{L}(\gamma^{know}))$ denote the expected loss for the policy outcome γ^{know} , while $L^{soc} = E(\mathcal{L}(\gamma^{soc}))$ denotes the expected loss for the legislative equilibrium outcome γ^{soc}. Then we can disentangle the total political performance gap, defined as $L^{tot} = E(\mathcal{L}(\gamma^*))$, i.e. the expected policy loss resulting from the legislative bargaining outcome derived for the real world political system under consideration, into a knowledge gap, L^{know}, i.e. the

[2]Biased incentives of elected politicians correspond to biased political weights, and result from asymmetric lobbying activities (Grossman and Helpman, 1994) or biased voter behavior (Bardhan and Mookherjee, 2002). More recently, Persson and Tabellini (2000) highlight the role of formal constitutional rules as determinants of politicians' incentives to misrepresent society's interests and choose inefficient policies.

policy loss resulting from biased policy beliefs and an incentive gap, ; L^{soc}, i.e. the policy loss resulting from biased political support functions .

2.2.3 Political feasibility and second-best policies

Furthermore, it is interesting to assess political feasibilty of first best policy choices derived from a social welfare maximization as well as to identify second best policies, i.e. policies which are politically feasible and approximate social welfare derived from first best policies.

Within the CGPE approach political feasibility of a policy can be measured via the following feasibility index, $FS(\gamma)$:

$$FS(\gamma) = Prob(\gamma, (Q^*, x^*))$$

$Prob(\gamma, (Q^*, x^*)$ corresponds to the probability that a winning coalition will form that would accept the exogneous policy proposal, γ, given that the continuation value of the legislative bargaing game just corresponds to the equlibrium outcome, i.e. the lottery (Q^*, x^*) (see Braack et al. (2023)).

Hence, second best policies can be derived from the following maximization problem:

$$\begin{aligned} \gamma^{**} \quad &= arg \max_{\gamma} \quad [E(S(z_{m,l}))FS(\gamma)] \\ &\mathbf{s.t} \\ &FS(\gamma) = Prob(\gamma, (Q^*, x^*)) \\ &z_{m,l} = f_m(\gamma, \omega_{m,l}) \\ &R(z, \eta, \gamma, \omega_{m,l}) \equiv 0 \end{aligned} \tag{14}$$

Formally, political economy approaches should take both aspects into account. However, existing approaches rather focused on biased political incentives, while biased political beliefs have not yet been talen into account [3]. An exemption is the computational general political economy equilibrium approach (CGPE) suggested by Henning et al. (2018)).

In this paper we focus on both aspects applying a CGPE-modeling approach to analyze policy gaps realized in the EU-system regarding the Green Deal implementation in EU agriculture. In particular, we disentangled total performance gaps into incentive-induced and knowledge-based gaps. Furthermore, we derive second-best policies.

[3]Interestingly, some authors have recently highlighted the role of biased voter beliefs as the primary determinant of inefficient policy choices (Beilhartz and Gersbach, 2004; Bischoff and Siemers, 2011; Caplan, 2007). In particular, the work by Caplan (2007) has been highly recognized in public choice literature, as he has collected an impressive amount of evidence showing persistently biased voter beliefs.

3 Empirical application of a CGPE approach to the Green Deal implementation in EU agriculture

3.1 The Green Deal and EU-agriculture

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, suggested by the EU-commission in May 2020, to achieve the goals of the Green Deal in agriculture. The Farm To Fork Strategy, 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]
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- Share of high diversity landscape features/set-aside of at least 10% [national/set-aside]
- Share of organic farming of at least 25% [organic]

Although scientific studies commonly agree that increasing ecosystem services potentially creates a win-win situation, where all European social groups including farmers and consumers could benefit, political debates are nowadays highly conflictual and emotional. While all social groups seem to agree in fundamental goals, e.g. to achieve a sustainable agricultural production guaranteeing a healthy nutrition at reasonable prices for all people in the EU and contributing to the reduction of hunger in the world, they have different opinions on how to best achieve these commonly shared goals politically. Obviously, political conflicts result from different narratives on how specific policies impact the state of the world.

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

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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 meta-modeling 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.

3.2 Methodology and data

To apply our CGPE-approach to analyze the F2F-strategy implenting the Green Deal in EU-agriculture we proceed as follows:

- First, we define a set of relevant policy instruments, $\Gamma = [0,1]^k$, where k denotes the number of relevant policy measures and $\gamma_k \in (0,1)$ denotes the policy for the kth measure. In partilcuar, we consider the five policy measuers of the F2F-strategy as suggested by the EU Commission as relevant policies. Furthermore, we conider the pricing of GHG emissions as an addtional sixth policy instrument. To normalize policy measures to the (0,1) interval we proceed as follows. Let γ^0 denote the levels suggested for each policy in the F2F-strategy. The we define $\gamma_k^{min} = 0$ as the minimum level and $\gamma_k^{max} = 1.5\gamma^0$ as the maximum level for each policy. Hence, we transform policies into the (0,1) interval via:

$$\gamma_k = \frac{(\gamma_k - \gamma_k^{min})}{(\gamma_k^{max} - \gamma_k^{min})}$$

- We define the set of legislators, N. Nowadays the co-decision became the main legislative procedure applied for the CAP. Technically, the co-decision procedure potentially involves up to three readings of proposed legislation by the European Parliament (EP) and the Council of Ministry (CM). It is initiated by a policy proposal of the European Commission (EC). The EC proposal is submitted to the EP and the CM [4]. First, the EP can in its first reading approve the EC proposal or replace it with an amended version. Then, the CM either approves the EP proposal or initiates a second stage of decision making by making amendments. In the latter case the new CM proposal is either approved by the EP in a second reading or again amended. If in the later case the CM does not accept the new EP proposal, the Conciliation Committee (CC) represents the final stage of decision-making. The Conciliation Committee comprises of all national members of the CM (currently 27) and a delegation of the EP of the same size; it is co-chaired by an EP Vice-President and the national Minister of the member state holding the Council Presidency without fixed negotiation protocol. Furthermore, representatives of the EC are members of the CC. However, the latter have only an informal supporting role. If the CM and EP agree on a compromise it is submitted to the EP and CM for acceptance in a third reading in which CM and EP use their typical qualified and simple majority rules, respectively. Assuming that all involved players have no time preferences for agreeing on a legislature implies that codecision outcome can be identified with the policy which CM and EP expect to agree on in the CC. Thus, analysis of the Codecision procedure focus on the analysis of legislative bargaining in the CC. In particular, final bargaining outcome has to be accepted by a winning coalition corresponding to a majority in the EP and a qualified majority in the CM. Accordingly, we consider all 27 national council members, i.e. the national Ministries of Agriculture, the Directory Agriculture of the EC as well as all relevant EP-groups as indiviudal legislators involved in the legislative bargaining on the CAP under the co-decision procedure.

- Definition of political support functions, $S^g(z)$ and social welfare function, $S(z)$. Based on the Green Deal we consider the ecosystem services (1) reduction of GHG-emissions (Z_{GHG}), (2) reduction of nitrogen pollution (Z_N) as well as (3) biodiversity (Z_{BIO}) as relevant policy goals. Furthermore, we consider the total economic welfare, Z_{Econ}, i.e. the sum of the economic welfare of consumers, agriculural producers and agribuisness, as an additional relevant policy goal. Political support functions correspond to linear functions of growth rates in goal achievements: $S^g(z) = \phi^g w$, where $\phi^g = (\phi^g_k), k \in \{ghg, n, bio, econ\}$ denotes the vector of relative weights of a policy goal. $w = \{W_k\}, k \in \{ghg, n, bio, econ\}$ denotes vector of growth rates in the goal achievement realized for policy goals.

[4]For further details see The co-decision Guide, available from the European Parliament (http://..)

- To model policy impact on policy goals we apply the CAPRI model described in detail in the next section. In particcluar, we describe applied metamodeling techniques to derive correpsonding policy impact functions $f^m(\gamma)$ for the CAPRI-model.

- To model legislative bargaining we apply the innovative non-cooperative legislative bargaining model of Braack et al. (2023). The model will be decribed in more detail in the subsection below. In particular, we will also describe how we estimated policy beliefs, $\hat{f}_m(\gamma)$ and derived legislators' individual spatial policy preferences.

3.3 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[5]. 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).

3.4 Metamodeling CAPRI

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.

To explain the metamodeling technique intuitively, let $(\mathbf{x}, \mathbf{y})$ represent the dataset[6] that

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

[6] The dataset is also called the training sample.

contains n pairs of (x_i, y_i) where $x_i = (x_i^1, \ldots, x_i^k)$ are the exogenous parameters and y_i are the endogenous responses. Thus, the simulation model is referred to as:

$$F^{SIM}(y_i, x_i) \equiv 0 \qquad i = 1, ..., n. \tag{15}$$

Furthermore, with x_i and y_i, we can fit a metamodel which can be formulated as:

$$\hat{y}_i = f^{meta}(x_i) \qquad i = 1, ..., n, \tag{16}$$

where f^{meta} represents the metamodel that we utilize to approximate the relationships of the underlying simulation model and $\hat{y}_i$ is the predicted values of the outputs using x_i.

In the following we briefly describe how metamodels can be derived from complex scientific models. Basically, this derivation entails three steps: selection of metamodel types, Design of Experiments (DoE), and model validation (Kleijnen and Sargent, 2000).

We perform metamodeling based on the CAPRI model described in section 3.3.

3.4.1 Selection of metamodel type

Metamodels are classified into parametric and non-parametric models (Rango et al., 2013). Parametric models, such as polynomial models (Forrester et al., 2008; Myers et al., 2016), have explicit structure and specification. Examples of non-parametric models include of Kriging models (Cressie, 1993; Yildizoglu et al., 2012; Kleijnen, 2015), support vector regression models (Vapnik, 2013), random forest regression models (Breiman, 2001), artificial neural networks (Smith, 1993), and multivariate adaptive regression splines (Friedman et al., 1991).

In this paper, we focus on the use of polynomial models in our policy optimization framework, where we use a second-order polynomial model of the following form:

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

where γ_1, ..., γ_k are the k independent policy variables, Z is the dependent variable and ϵ is the error term. As we are interested in the change of targets, the dependent variable Z 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).

3.4.2 Design of Experiments

To utilize metamodels, we need to estimate the corresponding coefficients. We generate the simulation sample by DoE, which is a statistical method of drawing samples in computer experiments (Dey et al., 2017) and perform the estimation by entering the simulation sample into the simulation model. DoE could be set-up in two ways: the classical experimental design and the space-filling experimental design (see Figure 1). The former places the sample points at the boundaries and the centre of the parameter space to minimize the influence of the random errors from the stochastic simulation models. However, Sacks et al. (1989) have argued that this is not the case for deterministic simulation models where systematic errors prevail. Therefore, the space-filling experimental designs should be employed to replace the classical ones. Among popular space-filling designs, Latin Hypercube design enjoys great popularity due to its ability to generate uniformly distributed sample points with ideal coverage of the parameter space as well as the flexibility with the number of the sample points (Sacks et al., 1989).

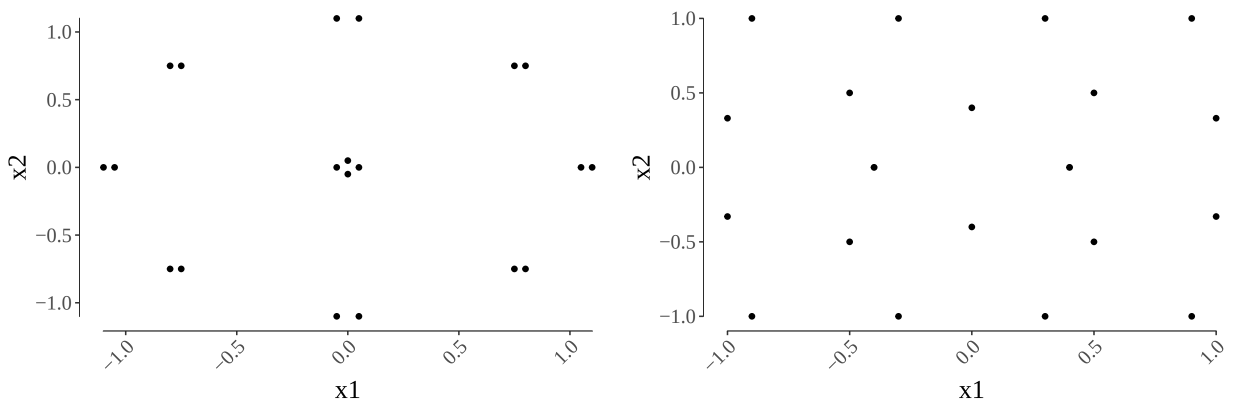

Figure 1: Classical and Space-filling Design.(adapted from Simpson et al. (2001))

3.4.3 Model Validation

Validation refers to assessing whether the prediction performances of the metamodels hold an acceptable level of quality (Kleijnen, 2015; Villa-Vialaneix et al., 2012; Dey et al., 2017). Normally, two samples are needed to assess the quality of a derived metamodel: the training sample and the test sample. The training sample is used to fit the parameters of the metamodel, whereas the test sample is used to validate the trained metamodel, and the test sample must include data points that are not part of the training sample. It is important that the metamodels have good predictions while maintaining generality. For this reason, a test sample is essential because it helps us evaluate if the metamodels can be generalized and whether the simulation model can be replaced with them.

$$\begin{aligned} R^2 &= 1 - \frac{\sum_{i=1}^{n}(y_i-\hat{y}_i)^2}{\sum_{i=1}^{n}(y_i-\bar{y})^2} \\ RMSE &= \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i-\hat{y}_i)^2}, \end{aligned} \tag{17}$$

where y_i are the model responses in the test sample and $\hat{y}_i$ the predicted values of the metamodel on the test sample and $\bar{y}$ is the mean of all y_i in the test sample. The Root Mean Squared Error (RMSE) is a frequently used measure of a model's predictive accuracy and R^2 represents the correlation determination. In addition, to compare the prediction performances for dependent variables that have different scales, we introduce the Average Error Ratio (AER), which is calculated by taking the absolute value of RMSE divided by the corresponding mean:

$$\text{AER} = \left|\frac{RMSE}{\bar{y}}\right|. \tag{18}$$

The metric gives us an idea of how large the prediction errors are in comparison to the true simulated values on average, i.e., the lower the AER values, the better the prediction performances. As we want to use the metamodels replacing the CGE in our policy optimization framework it is particularly important that metamodels have a global prediction accuracy, e.g. predict quite well relevant policy outcomes over a compact subset of policies.

3.5 Modelling legislative bargaining

In this section we derive a political bargaining approach to model the collective choice of F2F-policies under the EU co-decsion procedure. In particular, we apply an innovative non-cooperative legislative bargaining model suggested by Braack et al. (2023). For notational convenience let $x \in X$ denote the policy, while $U_g(x)$ correspond the spatial utility function representing the policy preferences of legislator $g \in N$. Corresponding to the legislative bargaining model of Braack et al. (2023) we define a legislative bargaining. Let $X \subset \mathbb{R}^m$ denote a non-empty, compact, convex set of F2F policy alternatives, with $m \in \mathbb{N}$. Let $N = \{1, ..., n\}$ denote the set of legislators involved in legislative bargaining on the CAP under the co-decision procedure. Each legislator $g \in N$ has preferences described by a von Neumann-Morgenstern utility function $U_g : X \to \mathbb{R}$. (Braack et al., 2023) assume that U_g is continuously differentiable and concave. Legislators have to collectively select an alternative $x \in X$, where the collective decision is made according to an exogenously given voting rule

[7]. The timing of interaction of our legislative bargaining is defined as follows:

a. At each period $t = 1, 2, \dots$ legislator $g \in N$ is recognized with probability q_g, where $q = (q_1, q_2, \dots, q_n) \in \Delta$, the unit simplex in $\mathbb{R}^n$.

b. When recognized, legislator i selects a policy $x_i \in X$ and formulate a proposal and submits it to legislature.

c. When a proposal has been submitted to the legislature, all legislators $h \in N$ simultaneously vote under a given voting rule to either accept or reject the proposal;

d. If the proposal x_g is accepted, the game ends.

e. Otherwise, there are two alternatives.

   e1: With probability $q_0 \in [0, 1]$ the status quo $x_0 \in X$ is selected and the game ends.

   e2: The game continues with probability $1 - q_0$, i.e., the process moves to period $t + 1$ and is repeated (step a.).

The probability that legislator g is chosen to make his proposal is denoted by $q_g \in (0, 1]$. We have the relation $\sum_{g=1}^{n} q_g = 1$. Furthermore, the conditional probability that the game ends with the selection of the status quo after each round in which a proposal has been rejected is given by $q_0 \in [0, 1]$.

Braack et al. (2023) study the infinite horizon game, with no discounting. Following Baron and Ferejohn (1989) as well as Banks and Duggan (2000), the solution concept used is stationary equilibrium. Strategies under this concept are stationary, and thus each player uses history-independent strategies at all proposal-making stages. Avoiding unneeded generality, a formal definition is only provided for stationary strategies. A pure stationary strategy for $g \in N$ consist of a proposal $x_g \in X$ offered anytime g is recognized and a voting rule.

So far our set-up of Braack et al. (2023) basically follows Banks and Duggan (2000). However, in contrast to most existing bargaining models including the legislative bargaining model of Banks and Duggan (2000) as well as Baron and Ferejohn (1989) Braack et al. (2023) do not assume that legislators who have been selected to formulate a proposal can exactly predict if other legislators will accept or reject her suggested proposal. In contrast, they follow a common observation in political practice that legislators are often unable to predict future behavior with perfect certainty, but voting behavior of legislators appears rather probabilistic (Burden and Frisby, 2004; Burden, 2007; Carey, 2008). Hence, overall

[7]We follow the standard approach used in the literature on legislative bargaining, decision theory and social choice theory and interpret X as a multidimensional policy space, where each dimension corresponds to a specific policy issue. Accordingly, legislators have spatial preferences.

acceptance of submitted proposals becomes also stochastic at the approval stage c. Accordingly, in our game a stationary pure strategy for a legislator $g \in N$ consists of a proposal $x_g \in X$ suggested anytime g is recognized and a measurable decision rule or equivalently an acceptance set. Let $\pi_{gh} : \mathbb{R} \to [0, 1]$ denote individual probabilistic decision rules. Let $\sigma_g = (x_g, \pi_g)$ denote a stationary strategy of legislator g, while $\sigma = (\sigma_1, .., \sigma_g, ..., \sigma_n)$ denotes a profile of stationary strategies.

Informally, a profile σ constitutes a stationary equilibrium if, for every legislator $g \in N$, the proposal strategy x_g is optimal given the probabilistic acceptance rules $(\pi_1, ..., \pi_n)$ of the other legislators, and individual probabilistic acceptance rule $\pi_g(x_g, x)$, is optimal given that σ describes what would happen if the current proposal were rejected.

Braack et al. (2023) could prove the existence of global stationary subgame Nash equilibria under very general conditions. Moreover, they could prove a Mean Voter Theorem, i.e. assuming separable spatial preferences, the equilibrium outcome of the legislative bargaining game corresponds to a lottery of legislators' proposals, (x, Q), where each individual proposal corresponds to the weighted mean of legislators' ideal points (y). Accordingly, the expected decision outcome of legislative bargaining corresponds to the weighted mean: $E(x) = \sum\limits_{g \in N} \omega_g y_i$, while in equilibrium probabilistic acceptance rules correspond to the following logistic function:

$$\pi_{gh}(u) \;:=\; \pi_h(u) = \frac{1}{1 + e^{\alpha_h (V_h - u)}} \quad g \neq h.$$

$$\pi_{gg}(u) := 1 \quad \forall g \in N$$

V_h denotes the continuation value of the game for legislator h. α_h is a scaling parameter which plays a crucial rule in determining the shape and steepness of the probability distribution over a range of possible utilities, thus influencing the likelihood of different choices [8].

Further, Braack et al. (2023) could prove differnt special cases of their mean voter theorem. In particluar, assuming a sufficiently low voting response (α) expected equilibrium decision outcomes correspond to a lottery over legislator's ideal points, where individual probabilities (Q) that the bargaining outcome corresponds to legislator' idealpoint correspond to an affine transformation of their corresponding Banzhaf decision-power value (Banzhaf, 1965) derived for the co-decision procedure.Interestingly, in contrast to existing game-theoretical analysis based on our non-cooperative bargaining theory the commission has some decsion-making power, i.e. in equilibiurm results a non-zero probability that the outcome will be the

[8] As Braack et al. (2023) show the level of scaling parameters has also an important impact on existence of Nash equilibrium and equilibrium outcomes.

idealpoint of the commission (Napel, 2006).

In this paper we will apply the special case of the mean voter theorem derived for low voting response to calculate decision making outcomes for the CAP. Hence, the expected outcome correpsonds to the weighted mean of legislators' idealpoints, where the weights just equal to the Banzhaf values of indvidual legislators derived for the co-decsion procedure. Furthermore, the latter corresponds to the probability that the final bargaining outcome equals to legislators' idealpoint **?**.

3.6 Estimating policy beliefs

To estimate policy beliefs, $\hat{\beta}^g$ of individual legislators $g \in N$ we proceed in two steps. First, we identified a set of political expert, E, where $e \in E$ denotes the index of a specific expert $e = 1, ..., n_e$. Political experts are relevant stakeholder and governmental organizations operating in the policy domain of CAP consideration. In undertaken expert surveys (Henning, 2022) political experts are asked to assess optimal future developments of relevant policy goals, z_e^o, i.e. experts estimates the gain in goal achievement, w_e, for each relevant policy goal, which their organization desires to achieve realistically within the next T years, i.e. $z_e = (1 + w_e) z_{t_0}$. Moreover, experts are asked to indicate how they would choose relevant F2F-policy instrument, $\gamma \in \Gamma$, to most efficiently achieve their desired policy goals, z_e. In particular, γ_e denotes the F2F-policy set-up preferred by expert e. Under these assumption expert judgements (z^o, γ_e) are informative regarding the metamodels, $z = f(\gamma, \beta)$.

Following Ziesmer et al. (2022) we apply a Bayesian estimation framework to estimate metamodels based on expert data, where we used the metamodels estimated via CAPRI-simulations as priors $(\bar{\beta}_e)$:

$$\begin{aligned} \beta_e^* &= \arg\min_{\beta_e} (\beta_e - \bar{\beta}_e)' \Sigma^{-1} (\beta_e - \bar{\beta}_e) + \epsilon' \Sigma_\epsilon^{-1} \epsilon \\ \epsilon &= z^o - z_e \\ z_e &= f(\beta_e, \gamma) \\ 0 &\equiv R(z_e, \eta_e, \gamma, \beta_e) \end{aligned} \tag{19}$$

To identify different metamodels expert policy positions are clustered to identify specific macro policy position. For each identified policy cluster we conducted separately the Bayesian estimation 19.

In a second step we used data on legislators policy preferences and desired policy achievements. Data has been collected in policy network survey (Henning, 2009). In particular, we asked all legislators to assess the relative importance of different policy goals, e.g. the vector $\phi^g = (\phi^g_{ghg}, \phi^g_n, \phi^g_{bio}, \phi^g_{econ})$. Moreover, we asked legislators to reveal their specific achievement levels they want to realistically realize within the next 10 years reagridng the different policy goals, where $w^g = \{W_{gk}\}$ denotes the vector of policy growth rates legislator g wants to achieve compared to a base year level z^0: $W_{gk} = \frac{(Z_k - Z_k^0)}{Z_k^0}$.

Further, we define identified parameter sets, β_c, for the different expert clusters as different structural metamodels of the set M, i.e. we set $M = \{1, .., c, ..m_c\}$ $\beta_m = \beta_c$ and use collected data from legislators (w^g, γ^g) to estimate individual probabilities that a specific metamodel is the true data generating process regading the impact of F2F-measures.

In particicluar, following the logic of Bayesian model averaging the aposteriori probability derived from the data D^g of an individual legislator g can be derived as the integrated likelihood $pr(m \mid D^g)$ **?**. The latter can be approximated using the BIC measure (Schwarz, 1978; Raftery, 1995; Handcock and Raftery, 2007) :

$$pr(m \mid D^g) = \frac{e^{-BIC_m^g}\, pr(m)}{\sum\limits_{m' \in M} e^{-BIC_{m'}^g}\, pr(m')}$$

, where BIC_m^g is the BIC value derived for model m for the following likelihood function:

$$\begin{aligned}
&\Pr(\mu_g)\Pr(\epsilon_g) \\
&s.t. \\
&z^g = (1 + w_g)z^0 \\
&z^g = f(\gamma^g, \beta^m) + \epsilon_g \\
&\nabla S^g \nabla f + \mu_g \leq 0 \perp \gamma^g \geq \gamma^{min} \\
&\nabla S^g \nabla f + \mu_g \geq 0 \perp \gamma^g \leq \gamma^{max}
\end{aligned} \tag{20}$$

3.7 Derivation of spatial policy prferences

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.

3.8 Implementation of the framework

In order to apply our framework, six main steps are necessary, which are summarized in Algorithm 1. We implemented the individual steps in a mix of R (R Core Team, 2022) and General Algebraic Modeling System (GAMS) (GAMS Development Corporation, 2022). Solving the different optimization models in GAMS is mostly single-threaded, therefore we structured our code to allow the usage of multiple CPU cores and high-performance computing resources. This is possible due to the independence of the individual simulations in step two, for example. Please also note, that one needs to generate two samples: The first for the derivation of the metamodels (steps one to three), and the second for the actual policy analysis (steps four to six).

Algorithm 1 Steps

1) DoE: Sample generation for metamodel derivation
2) Computing simulations
3) Estimating and validating metamodels
4) DoE: Sample generation for policy analysis
5) Identify optimal policies applying Bayesian model averaging and model selection techniques $\Rightarrow \gamma_l^*$
6) Solving legislative bargaining model and various scenarios and calculating political performance gaps, $L(\gamma_l^*)$

4 Results

4.1 Validation of metamodeling

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.

To get a first impression of the results, figure 2 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

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

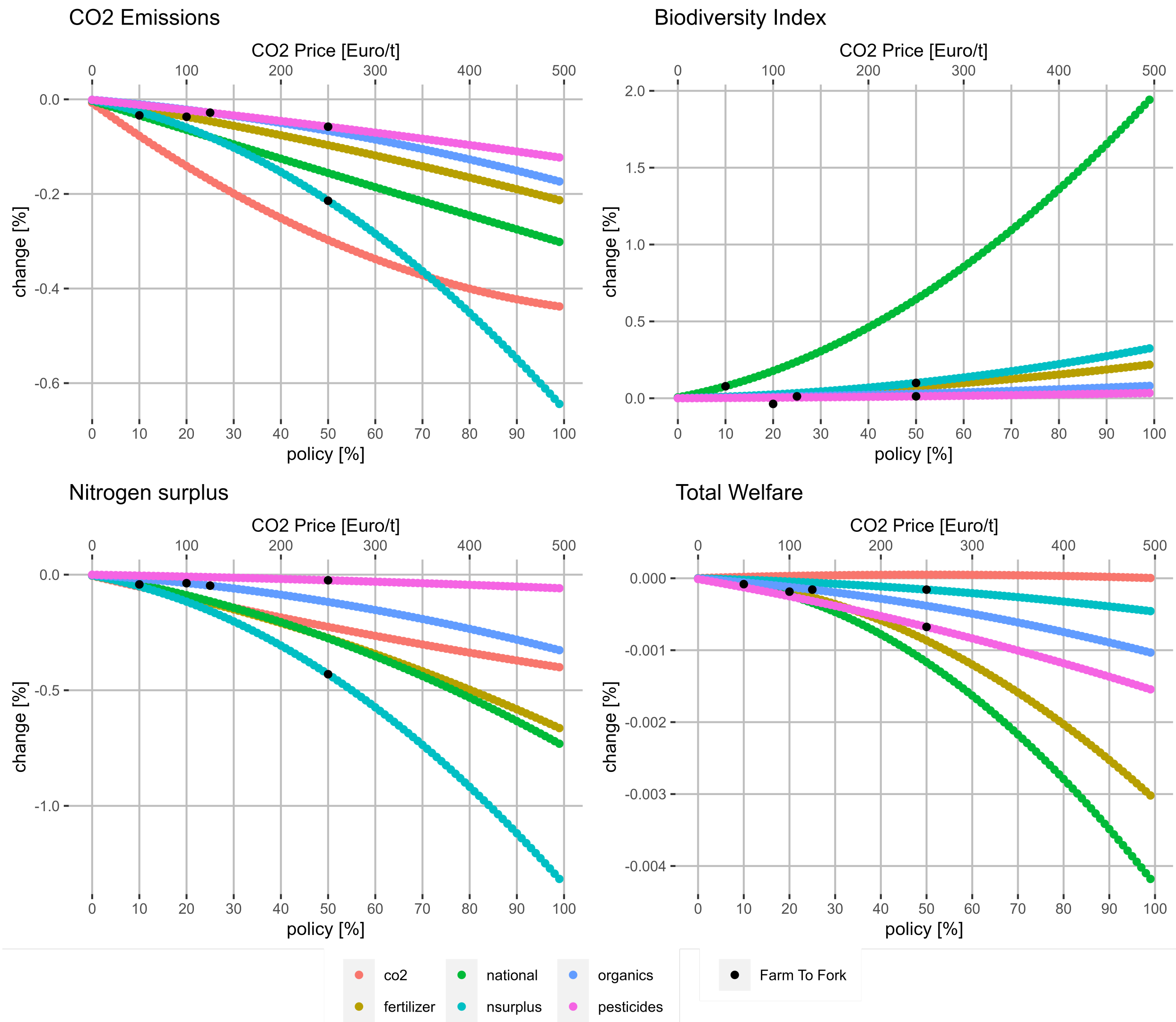

Figure 2: Separate impacts of F2F policies on selected goals

policy values 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 2, 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.

4.2 Policy Choices and induced outcomes

In table 1 the policy choices derived as the outcome of the legislative bargaining model for three different policy scenarios:

- sc1 $social\_true$: Assuming legisators policy support function correspond to EU-society social welfare function and all legislators hold policy beliefs corresponding to the metamodels derived from CAPI model.
- sc2 $social\_belief$: Assuming legisators policy support function correspond to EU-society social welfare function, but legislators hold their individual policy beliefs which differ from metamodels derived from CAPI model.
- sc3 $support\_true$: Deriving legisators individual policy support function from their stated policy preferences, while it is assumed that all legislators hold policy beliefs corresponding to the metamodels derived from CAPI model.
- sc4 $support\_belief$: Deriving legisators individual policy support function from their stated policy preferences, and assuming legislators hold their individual policy beliefs which differ from metamodels derived from CAPI model.

Scenario sc1 comes close to the ideal political process. However, national legislators are still facing their specific national policy impacts encapsulated in the nation specific metamodels regarding the policy goals: economic welfare, biodiversity and N-balance, while GHG-emission is considered as a global environmental good applying the same metamodel for all EU-meber states.

In tabel A1 in the appendix the ideal positions for all legislators are reported for the different policy scenarios. As can be seen if one assumes that all legislators have the perfect knowledge e.g. apply the science-based policy impacts and maximize social welfare of total EU population, legislators almost have the same ideal points, wich also corresponds to the optimal policy derived from social welfare maximization. As can be seen from table 1 the optimal policy focus on the measures with a rather high CO2-Pricing of 275 Euro per t CO2.eq, a maximal set-aside of 15%, a maximal reduction of pesticides and nitrogen balance by 75% , while neither ecological farming nor reduction of mineral fertilizer is executed under an optimal F2F-strategy. Interstingly, assuming all legislators have perfect knwoledge and are social-welfare maximizers implies that policy preferences are rather homogeneous and legislative bargaining outcomes correspond to the optimal policy. Only reagrding set-aside national member states disagree, where basically to coalition form, one prefering maximal set-aside of 15% and a second prefering no set-aside (see **??**).

		Policy Scenario				
Policy	Unit	social_true	social_belief	support _true	support_ belief	optimal
co2	€ t Co2.eq	285	46	140	12	274
fertilizer	in %		18	10	20	
set-aside	in %	8	11	7	11	15
nsurplus	in %	75	31	21	20	75
organics	in %		22	14	25	
pesticides	in %	75	68	4	54	75

Figure 3: Table 1: Optimal and real World Policy Choices

Interestingly, none of the member states would prefer to implement ecological farming or regulation of mineral fertilizer use. Given the fact that current political discussions put a high emphasis especially on these two measures thsi result appears surprising. However, given the fact that based on CAPRI-modle simulation it results that especially ecological farming is a rather ineffective and inefficent measures which neither has a significant positive impact on reduction of GHG-emissions nor on the reduction of nitrogen pollution, this result appears as a logical consequence of technological facts (see also figure 1).

Interestingly, relevant legislators have biased policy beliefs regarding the impact of ecological farming as well as mineral fertilizer regulation when compared to other F2F-measures. In particuar, biased beliefs seem to be mainly determined by the two narrative ecological regulation and market driven innovation. The former focus on the measures ecological farming, regulation of chemical inputs, i.e. mineral fertilizer and pesticides, and set-aside, while Co2-pricing plays no major role in this narratives. Vice-versa the narrative market-driven bio-technological innovation does not focus on specific measures, but rather suggests a rather low intensity of all F2F-measures, while both narratives have in common that Co2-pricing plays no promiment role. Accordingly, legislative bargaining outcomes correspond to a compromise between these two narratives, where ecological farming, set-aside and mineral fertilizer is more determined towards the ecological farming narrative, while especially the nitrogen balance would only be moderatly regulated at a level below 20%.

Comparing relevant outcomes induced by the optimal and the real-world policy choices reveals first of all that the Green Deal could be a win-win situation for both farmers and consumers. As can be seen from table 4 under an optimal implementation strategy eco-system services would be significantly increase, i.e. GHG-emissions would be reduced by almost -70% from roughly 2.4 t/ha today to less than 1 t/ha in 2030. Furthermore, nitrogen pollution would be reduced by almost 80% from currently 68 kg/ha to less than 15kg/ha, while biodiversity will be increased by 22%. Interestingly, implementing the Green Deal by the optimal policy strategy would only imply moderate adaption costs amounting to less than -0.15% of total per-capita income or 46 Euro per capita, where the cost are completely beared by the consumers realizing a reduction of per capita income amounting 105 Euro per capita, while farmers will even realize significantly higher profits by over 150%.

Summarizing total costs and benefits via evaluating ecosystem services with corresponding willingness-to-pay measures (WTP[9]) an overall net-benefit of 350 Euro per capita. Farmers would even realize a net-profit gain of 6650 per capita.

[9]Based on existing survey estimates in the literature we assumed WTPs of 11 Euro per kg/ha nitrogen pollution, 288 Euro per t CO2.eq/ha emission and 663 Euro per ha for achieving a maximal biodiversity index for the total UAA of the EU.

		Policy Scenario				
Policy Goal	Unit	social_true	social_belief	support_true	support_belief	optimal
Biodiversity Index	Euro per capita	-6,74	3,54	3,13	5,43	54,64
GHG-emission	Euro per capita	0	28,15	5,93	32,99	-150,93
Money Metric	Euro per capita	0,37	9,5	2,43	8,75	-105,04
Profit Farms	Euro per capita	0,3	-2,68	-1,05	-3,74	23,28
N-Balance	Euro per capita	-2,88	6,31	-3,74	3,29	-188,91
Economic Welfare	Euro per capita	1,64	2,8	-0,06	0,05	-43,55
Biodiversity Index	percentage	-2,8	1,47	1,3	2,25	22,67
GHG-emission	percentage	0	11,79	2,49	13,82	-63,2
Money Metric	percentage	0	0,03	0,01	0,03	-0,35
Profit Farms	percentage	1,92	-17,15	-6,74	-23,96	149,04
N-Balance	percentage	-1,21	2,65	-1,57	1,38	-79,21
Economic Welfare	percentage	0,01	0,01	0	0	-0,14
N-Balance	kg pro ha	-0,71	1,56	-0,92	0,81	-46,54
GHG-emission	t pro ha	0	0,27	0,06	0,32	-1,45

Figure 4: Table 2: Policy Outcomes and Performance Gaps

However, based on biased beliefs and political incentives real world legislative baragining implies far less efficient and effective outcomes. As can be seen from table 2 and 3 real world outcomes determined biased incentives and biased policy beliefs result in far less increase in ecosystem services. In particular, predicting real world bargaining outcomes with our legislative bargaining model implies a rather moderate decrease of GHG-emission of only 20%, while notrogen pollution is only reduced by less than 29% and biodiversity is increased by only 12%. In monetary terms total benefits from increased ecosystem services amount only 140 Euro per capita, while net-benits even reduce to only 114 Euro per capita. Farm profits even vanish under real world politics when compared to optimal F2F-policies. The latter reuslts from the fact real world politics puts much less restrictions on sustainable land use implying far less agricultural production reduction, which induce far less price increases which just compensate productions reductions leaving the average profit almost constant.

4.3 Assessing policy gaps

As described in the theoretical section real world policy fails for at least two reasons, biased political incentives or biased political beliefs. Following our CGPE-approach we assess both failures disentangeling total political performance gaps into knowledge and incentive gaps.

		Policy Scenario				
Policy Goal	Unit	social_true	social_belief	support_ true	support _belief	optimal
Biodiversity Index	Euro per capita	-4,87	-19,52	-31,44	-23,45	54,64
GHG-emission	Euro per capita	-0,02	-84,16	-96,31	-104,8	150,93
Money Metric	Euro per capita	0,06	-61	-73,39	-73,26	105,04
Profit Farms	Euro per capita	0,31	-20,43	-13,86	-22,98	23,28
N-Balance	Euro per capita	3,44	-106,47	-119,84	-125,7	188,91
Economic Welfare	Euro per capita	0,96	11,1	35,13	16,56	-43,55
Biodiversity Index	percentage	-8,9	-35,7	-57,5	-42,9	100,0
GHG-emission	percentage	0,0	-55,8	-63,8	-69,5	100,0
Money Metric	percentage	0,1	-58,1	-69,9	-69,7	100,0
Profit Farms	percentage	1,3	-87,8	-59,5	-98,7	100,0
N-Balance	percentage	1,8	-56,4	-63,4	-66,5	100,0
Economic Welfare	percentage	-2,2	-25,5	-80,7	-38,0	100,0
Total Gap	Euro per capita	-7,33	182,21	219,84	223,6	350,93
Total Gap	in %	0	51,9	62,6	63,7	

Figure 5: Table 3: Policy Outcomes and Performance Gaps

The former results comparing policy outcome derived under the counterfactual assumption that legislators drive their policy preferences from individual political support maximization, but know the true impacts of different policies. Hence, we derived individual policy preferences and simulated policy choices and induces policy outcomes with our CGPE-approach for the counterfactual scenario sc3 "*support_true*" and sc2 "*social_belief*" , respectively. In particular, we calculated net-benefits for this counterfactual scenarios and compared these to the optimal scenario. The realized difference for sc3 measures the knowledge gaps, i.e. the overall society welfare loss resulting from the fact that legislators have biased policy beliefs, while the realized difference for scenario sc2 indicates incentive gaps.

As can be seen from table 5 we identified significant incentive and knowledge gaps amounting to 57% and 61% , respectively, while the total performance gap amounts 68%. This underlines the inefficiency of current real world political processes within the EU-system.

4.4 Political feasibility and Second-best policies

Beyond the economic efficiency of real world politics it is further interesting to asses the political feasibility of first best policies and to identify second-best policies, i.e. policies with mimic the economic efficiency of first best politics and simultaneously are politically feasible in the real world political system.

	Feasibility-Index	
Policy-Scenario	first-best	second-best
social_true	1,0028	1,062
social_belief	0,0133	1,005
support_true	1,1434	1,523
support_belief	0,0018	0,87

Figure 6: Table 4: Political Feasibility

In table 6 we report the political feasibility of the optimal F2F-policy. As can be seen from table 6 political feasibilityis rather low wiht a Feasibility index (FS-index) of 0.0018, i.e. the probability that the optimal policy choice would be accepted by a majority coalition in the EU-system amounts only 0.18% of the average acceptance probability of the equilibrium proposals of all legislators. Interestingly, political feasibility of first best policy would significantly increase assuming legsilators would not have biased policy beliefs, i.e. the FS-index increases to over 1 assuming non biased beliefs (see table). However, interestingly assuming legislators would have no incentive baises would not increase political feasibility of first best policies.

Since changing political beliefs, i.e. policy learning is not easy to achieve it might be interesting to identify second-best policies. Following our methodology we calculated second-best policies for each scenario. The resulting second best policies are reported in table (5). As can be seen comparing second best with first best as well as with equilibrium policies reveals that second-best policies are compromises between real world policy and science-bases policy choices. Especially, the restriction of chemical inputs which is rather low for the real world politics could be significantly increased to the first best level reducing nitrogen balance and pesticides inputs by 75%. Further, organic farming could be significantly reduced from

		Policy Scenario				
Policy	Unit	social_true	social_belief	support _true	support_ belief	optimal
co2	€ t Co2.eq	285	59	173	26	274
fertilizer	in %	0	13	0	13	0
set-aside	in %	8	12	13	13	15
nsurplus	in %	75	75	75	75	75
organics	in %	0	13	0	4	0
pesticides	in %	75	75	75	75	75

Figure 7: Table 5: Second-best Policies

almost 25% to be expected under real world politics to only 12%. However, only the Co2 Price could only be increased to 26 Euro pro t Co2.eq, which is at least double the price resulting under real world politics. However, compared to the optimal price of 287 Euro this is still rather low. Nevertheless identified second-best policies almost mimic the efficiency of first best policies, i.e. a total performance gap of only 8% results for second best policy. Total net-benefit under second best policies would amount 320 Euro per capita compared to 350 Euro under a first best policy. However, main losses would result from less effective reduction of GHG-emissions which would be reduced by only 50% compared to 63% under first best policies.

5 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

		Policy Scenario				
Policy Goal	Unit	social_true	social_belief	support_ true	support _belief	optimal
Biodiversity Index	Euro per capita	-6,74	-3,54	-3,13	-5,43	54,64
GHG-emission	Euro per capita	0	-28,15	-5,93	-32,99	150,93
Money Metric	Euro per capita	-0,37	-9,5	-2,43	-8,75	105,04
Profit Farms	Euro per capita	0,3	-2,68	-1,05	-3,74	23,28
N-Balance	Euro per capita	2,88	-6,31	3,74	-3,29	188,91
Economic Welfare	Euro per capita	1,64	2,8	-0,06	0,05	-43,55
Biodiversity Index	percentage	-12,3	-6,5	-5,7	-9,9	100,0
GHG-emission	percentage	0,0	-18,7	-3,9	-21,9	100,0
Money Metric	percentage	-0,4	-9,0	-2,3	-8,3	100,0
Profit Farms	percentage	1,3	-11,5	-4,5	-16,1	100,0
N-Balance	percentage	1,5	-3,3	2,0	-1,7	100,0
Economic Welfare	percentage	-3,8	-6,4	0,1	-0,1	100,0
Total Gap	Euro per capita		33,72	-1	30,8	350,93
Total Gap	in %		9,6	-0,3	8,8	

Figure 8: Table 5: Policy Outcomes under second-best Policies

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 partial equilibrium 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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