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Socially preferable and technically feasible: European citizens choose solar power and import independence over lower costs

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ABSTRACT

Citizen's preferences about decarbonised electricity supply are crucial for a successful energy transition, both regarding the direction and the speed at which it can unfold. While preferences about single aspects, like prices and technology, have been assessed before, these preferences cannot be directly translated to preferred energy supply on the system level, for two reasons: First, the individual aspects interact and cannot be assessed in isolation. Varying the technology mix, for example, affects many other aspects of the electricity system such as prices. Second, many aspects have both local and global impacts and cannot be assessed for just a single region. Constraining imports in one region, for example, affects the technology mix in other regions. Therefore, preferences can only be meaningfully analysed within consistent scenarios that incorporate multiple aspects including their interactions, are able to represent the local context, and have a broad spatial scope. Such scenarios are out of scope of pure preference studies. Here, we overcome these limitations by combining preference data with detailed techno-economic scenarios on the national and subnational scale. Building on random utility theory, we fit a discrete choice model to data from a choice experiment conducted in four European countries and use it to predict choices of scenarios. We find that citizens would choose scenarios with high shares of local self-sufficiency and solar power over trade- and wind-power-centered least-cost scenarios, although they are more expensive. Our approach allows to evaluate energy plans not only by technical and economic aspects, but also by citizen preferences.

1. Introduction

The energy transition has accelerated significantly in recent years [1], although the pace must increase to meet the Paris Agreement and national climate targets. Over the last decade, technologies have matured, and in most countries, renewable energy is today the cheapest source of electricity ever available [2]. This offers hope that the decarbonisation can proceed fast enough to avoid the worst impacts of climate change.

However, as technologies mature and grow, new problems grow with them: going from 15 % to 40 % renewable power, as the EU did 2005–2024, is a different challenge than going from 75 % to approaching 100 %, which it will have to do in the 2030s. To explore and identify feasible and low-cost system designs, the field of energy system modelling has taken vast methodological strides over the last 20 years. Today, we know that there are many different ways to design a fully renewable power system, relying mainly on solar or on wind (or both), and that balancing such systems is possible through combinations of grid expansion, demand flexibility, and storage [3–5]. Through the rise of systems modelling, there is truly no dearth of concepts and solutions to address the technical challenges of the energy transition.

The well-established policy frameworks in many countries contribute to the continuous expansion of renewable energy and accompanying infrastructure. But with this expansion comes an increase in land-use, leading to rising public opposition. These local conflicts often slow down implementation and, in some cases, bring projects to a complete halt.

The growing importance of such non-technical transition obstacles has been accompanied by a growing social scientific body of research, focusing on acceptance and opposition, and citizen preferences for the transition in general. In numerous studies, perceptions, attitudes, and preferences have been assessed through a variety of quantitative and qualitative methods, considering, e.g. aspects such as preferences on technologies for supply [6] and demand [7], but also preferences at the system level where individual aspects interact [8,9]. These studies reveal the complexity of interacting factors influencing citizens' views on how to build the future energy system, driven by concerns not only over costs, but also questions of procedural and distributive justice [10–13], or over trade-offs between climate and biodiversity demands [14,15].

There is much knowledge about how to bring the transition to a successful end, both from a technical and a social perspective, but the

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two research fields exist largely separately from each other. Energy system models grow ever more sophisticated and detailed, showing how to build working and low-cost renewable energy systems, and yet risk generating irrelevant results as they ignore the social factors that constrain and drive on-the-ground developments. Social scientific studies show how acceptance and opposition develop and identify the factors driving and mitigating them, but ignore whether the sum of all measures to accommodate societal wishes and needs may render the resulting system technically or techno-economically infeasible.

Increasingly, calls to respond to this problem by integrating social and political issues into energy system modelling have been made [9,16,17], and several studies attempting this have been published. For example, scenarios with high shares of self-sufficiency have been assessed [3,18], based on the observation that electricity imports are often rejected by the public, whereas the possibility for self-sufficiency has been a driver of renewable energy uptake. Other studies have assessed the impact of minimising infrastructure build-up in scenic landscapes to minimise opposition [19], of generally minimising all land requirements [20], and of distributing the infrastructure fairly across subnational regions [21]. Such scenarios are useful steps ahead from the purely techno-economic models that still dominate the field, but remain insufficient in several aspects.

First, they test sensitivity to opposition by limiting single simulated "opposition factors", such as randomly halting the construction of all or single new power lines in the model [22]. Such scenarios are informative, showing potential cost impacts of not overcoming opposition, but are also negative and reactive in nature, revealing the impact of the problem but often not solutions to it. An alternative to scenarios removing what citizens may dislike could be exploring technical scenarios based on what citizens prefer and seeking most-desired system designs rather than least-rejected ones.

Second, such models and scenarios do not capture trade-offs with social and political factors [23], and they do not consider the interconnectedness between factors. For example, wind power is typically less preferred than solar power [24], so a scenario may explore impacts of limiting or removing wind power, as a way to increase acceptance and societal feasibility. But wind power is often the cheapest technology, and citizens may have an even stronger preference for low costs [9]. A scenario considering preferences for both low cost and wind power, with an explicit systemic link between the two, may show that scenarios accommodating a "low wind share" wish are likely more expensive, so that it is, in sum, less preferred than scenarios with higher shares of wind power.

In this paper, we respond to these challenges and take first methodological steps for explicitly integrating citizen preferences into energy system modelling and creating robust, preference-guided scenarios. We ask the research question: If citizens could decide between decarbonised electricity scenarios, which future electricity system would they choose? We do this by combining data from three previous studies: one study that conducted a choice experiment in four European countries to identify preferences on electricity system designs, and two studies that used energy system models to identify robust and technically feasible energy scenarios for all of Europe. Using the choice data, we derive citizen preference functions for all European countries through validated extrapolation and apply the functions to the scenarios.

Our work results in two main contributions. Methodologically, we demonstrate that integrating citizen preference functions with detailed energy scenarios is feasible and meaningful. Empirically, we show that the most preferred energy scenarios in Europe are not the least-cost ones but those with moderately high regional self-sufficiency and solar power. As solar-powered self-sufficiency increases across scenarios, the resulting higher cost eventually reduces scenario desirability, so that wind power and electricity trade remain important options, even in preference-based scenarios.

2. Literature review

To the largest extent, energy system modelling and social acceptance research are two different fields, with little interaction. Increasingly, approaches to merge social scientific variables and data into models have arisen, but this field is still in its infancy: there are several promising approaches, each with specific problems and each being closer or further away from the intended "integration of societal factors" into energy models.

On the social scientific side, research on acceptance of renewables and infrastructure has grown very fast over the last two decades, reflecting the fact that the realisation of future electricity systems ultimately depends on political decisions that require legitimacy and public support. Indeed, societal discontent and conflicts over infrastructure siting have further driven social acceptance research towards becoming one of the most policy-relevant social science concepts [25,26], reaching much beyond earlier views of public opposition to energy generation and infrastructure being mainly a Not-In-My-Backyard syndrome [27–29]. In the last decades, the 'triangle of social acceptance' (socio-political, market, and community acceptance) has served as an analytical lens in the field [30], referring to the set of processes of decision-making "on issues concerning the promotion of – or counteraction against – new phenomena and new elements in the transformation of current energy systems" [31]. This understanding has further evolved and become more differentiated, highlighting, e.g. ambiguities in the use of (passive) acceptance versus (active) support [32], and warnings not to conflate the ex-post acceptance with ex-ante acceptability [10,11,33]. Especially, this latter point is crucial for designing and preparing activities prior to implementation to ensure they are acceptable from the outset. It also helps explain why a large majority of citizens support the energy transition in general, and yet protests delay or stop projects in their neighbourhoods [6]. As a multifactorial phenomenon, other studies highlight place identity and place attachment as key factors influencing local responses to infrastructure siting, as they are closely tied to social values and the ways communities ascribe meaning to their surroundings [25,34–38]. How distributive and procedural justice elements are considered also shapes local reactions [39]. Ultimately, the focus is on social and ethical desirability aspects of technology implementation, indicating a citizen's willingness and readiness towards a new technology [40].

Overall, acceptance denotes "a favourable or positive response (…) relating to a proposed or in situ technology or socio-technical system, by members of a given social unit" [41], while "preferences regarding energy technologies [are formed] by making trade-offs between the various attributes of those technologies" [41]. Asking for individuals' preferences is often used to understand community acceptance for a project sited nearby, while considerations for the overarching system designs and respective policies are associated with the socio-technical acceptance dimension [30]. Although numerous studies have examined preferences within either of these dimensions [42–44], empirical investigations into localised manifestations of socio-political acceptance remain limited [45].

In addition, technical aspects of electricity system interactions and the ultimate feasibility of certain citizen preferences are often overlooked, despite their crucial role in determining whether proposed energy pathways can be realistically implemented. For example, whereas many studies find that citizens tend to reject wind power [38,46,47], it is not always certain that they prefer some other technology more – and especially not when the systemic, including economic, effects of limiting an undesired technology are included [48].

This is, in turn, the realm of energy system models, which have become a core element in energy policy processes [49]. Driven by the observation that techno-economic optimisation models are very sensitive to changes in relative technology costs, several research groups have started developing models for near-optimal scenarios (modelling to generate alternatives; e.g. [50–52]). Within this type of approach, some groups work to improve the relevance of their models by allowing for inclusion of actor preferences, generally ex post, based on cost-driven scenario results. For example, Pickering, Lombardi and others developed the SPORES approach ("Spatially and technologically distinctive alternatives") not only to better account for uncertainties in assumptions, but also to identify solution spaces and enable discussion of future options with decision-makers. The approach helps decision-makers to set politically attractive and technically feasible futures as goals and implement corresponding policies [53].

These models, however, do not include the main driver of the energy transition – policy – or one of its present main challenges – public opinion. It is reasonable to question the usefulness of a model that portrays potential futures but excludes the primary variables that determine them. So correspondingly, calls for better integrating social and political aspects in energy system modelling become louder, as models otherwise miss real developments [23], and barely reflect actual transformation processes [54]. The energy system modelling community has responded to this challenge, in many different ways but often with incremental additions rather than deep model changes. For example, 13 of the 23 models developed in the EU projects SENTINEL and Open-ENTRANCE state that they cover social or political variables, in particular acceptance/resistance and behaviour/lifestyle. However, in most instances, this is only done in a rudimentary way, usually without an empirical basis and only through exogenous, rigid assumptions. Such modelling will provide insight into the possible effects of severe opposition, for example, but is hardly useful to show ways ahead, or possibilities for solving or going around opposition problems.

Evidence for this shortcoming is presented by a large-scale study [8]. It shows that although energy models generate many different scenarios, these correlate poorly with citizens' preferences. For example, the models mainly show wind power-based futures, as these are cost-optimised, but citizens tend to prefer solar power; citizens also see nuclear power as a less preferable option than the majority of energy system models suggest, while the continued operation of fossil fuel power plants with carbon capture and storage is viewed more positively. To remedy this, other studies use scenario results that have already been generated and reinterpret these ex-post in order to describe specific social impacts, such as distribution effects, that can be easily derived from cost optimisations and allow statements on distributive justice [55].

In other cases, the effect of opposition is modelled, for example as "unacceptance scenarios" [22], which are limited by an exogenously imposed maximum expansion of certain technologies: this describes the system effects if a technology is only available to a limited extent, but not the effects of protest or resistance on transformation processes [23]. Such scenarios can show effects of severe protests, but it remains reactive and negative, and not showing ways out or failing to address the root cause of the protests.

There are efforts with deeper model changes as well, for example, to depict the feasibility of policies or targets in the model. For example, [56] includes "political capital" in her model, and letting this determine the ability of a government to set new targets (low political capital cost) and implement measures to reach that target (high cost). This then endogenises political ability for ambitious policy, but does so via an artificial metric: how political capital grows or how much is consumed remain vague. Others rely on empirical observation of how fast technological change has been in the past, and use such estimates to constrain model runs into a "feasibility space" [57,58] of how fast future change may reasonably be. This then makes models more realistic from the socio-technical perspective, although it only implicitly deals with political and societal constraints to change.

A rising field is participatory modelling, in which stakeholders, from policymakers to industry and citizens, are included in the modelling process. Such participation can take many shapes, from co-creative processes with stakeholders involved in defining the research questions to evaluating the results. More often, the participation is more modest, with the role of stakeholders limited to providing their views on desirable futures, input data for the model, and reflections on interim and final scenarios [59–61].

A further way to bring in citizen preferences for energy system design is to generate, for example through choice experiments, preference data that can be integrated into energy models, either as variables of the modelling or ex-post for quantitative, empirically grounded analysis of how scenarios fare not only in terms of techno-economics but also how they match citizens' views. For example, in a study for four European countries [9], the authors carried out a choice experiment to assess citizens' stated preferences of future, zero-carbon electricity systems in Europe. They showed that citizens find low costs important, but they also prefer a decentralised energy future with less wind power, more solar energy, and fewer imports. An important innovation of the study [9] is that it does not determine preferences of isolated aspects (as do Likert scale surveys, for example), but identifies citizen preferences as preference functions of entire electricity systems. Such functions can be used for energy modelling based on citizen preferences, instead of energy system costs, as the optimisation function thus incorporates the social aspects directly and explicitly into energy system modelling. The data generated by the study do not yet allow for this – a choice experiment that better matches the variables representable in system modelling would be necessary – but they do allow for an empirical ex-post assessment of preferability of modelled scenarios, showing how different futures would fare when exposed to citizens and citizens' preferences.

We seek to close the gap between the two research streams with our approach by mapping preferences onto existing (cost-optimised) energy scenarios and illustrating how the combination of energy scenarios and citizen preferences can be joined for a more holistic analysis. Unlike case studies that explain the success or failure of specific projects, our study explores general preference patterns across different electricity scenario designs – as possible future visions for a regional electricity system. Hence our findings relate to the concept of local acceptance, understood as a more general form of socio-political acceptance – not asking under which conditions citizens would accept a concrete wind or solar farm, but asking under which conditions citizens would accept a local energy plan. In doing so, we follow calls for more comparative approaches in energy research [62] and contribute to identifying "feasibility spaces" [63] from a social acceptance and technical perspective for doable and desirable energy modelling outputs, consequently informing future policy strategies. Since energy policy strategies are often dominated by incumbent actors [64], our approach can help to broaden the range of input by more systematically incorporating citizen perspectives in energy modelling, thereby addressing concerns related to justice, legitimacy, and equitable participation in decision-making processes.

3. Methods

We use existing choice experiment and energy scenario data in order to predict preferences of scenarios: assuming citizens had the choice between these scenarios, which one would they choose?

We predict choices of energy scenarios in three analytical steps. First, we build a choice model based on random utility theory, which we fit to the experimental data. Second, we map energy scenario variables to the scale and domain of the variables in the experimental data. Third, we use the mapped scenario variables as predictors of the choice model to predict choices.

In the following, we describe the choice data and model, the energy scenarios, how we map energy scenario variables to choice data variables, how we predict choices of scenarios, and how we quantify the sensitivity of this approach to changes in individual variables.

3.1. Choice data and model

We use data from a choice experiment conducted in 2022 [9] in which about 4000 respondents from Denmark, Germany, Poland, and Portugal stated their preferences with regard to attributes of the electricity supply in their home region. There were six attributes that described the regional electricity supply: the dominant supply technology, land requirements of the necessary infrastructure, necessary transmission capacity, share of imported electricity, household electricity price changes, and ownership of the assets (see Supplemental Table S1 for attribute levels and [9] for detailed information). The attributes were combined in a conjoint design, and respondents were asked to choose the supply they preferred among two randomly created options consisting of combinations for these attributes.

We choose this choice dataset for its scope and regional resolution. First, its options represent the total electricity system, covering aspects of the system that can be assumed to be most important to the public. Other choice data typically include individual technologies or projects and would not be useful for integration in energy system models. Second, the options represent the electricity system of each respondent's region. This allows for integration into energy system models with high spatial resolution and for representing the local context.

We analyse the data using discrete choice models based on random utility theory (Eq. 1). Random utility theory assumes that each option has a certain utility for each person and that people choose the option with higher utility. In the case of this choice experiment, respondents had to choose among two options, one of which was shown on the left-hand side, and one of which was shown on the right-hand side. Utility is modelled as a sum of a deterministic term which is a function of the attributes (e.g. electricity prices) and a random term that covers aspects out of control of the experimenter. The deterministic term of utility (U_{left} and U_{right}) comprises the linear combination with unknown weights ($\beta_{\text{attribute}}$) of all attribute levels that are included in the option. We model the unknown weights as the sum of an international average ($\alpha_{\text{attribute}}$) and a varying effect on the national level ($\gamma_{\text{attribute,country}}$) as part of a multi-level model. Additionally, we add interaction effects which we model as non-varying across countries.

$$
\begin{aligned}
\text{choice}_{\text{left}} &\sim \text{Bern}\left(p_{\text{left}}\right) \\
p_{\text{left}} &= \frac{\exp\left(U_{\text{left}}\right)}{\exp\left(U_{\text{left}}\right) + \exp\left(U_{\text{right}}\right)} \\
U_{\text{left}} &= \alpha_{\text{left,respondent}} + \sum_{\text{attribute}} x_{\text{attribute}} \cdot \beta_{\text{attribute,country}} \\
&\quad + \sum_{\text{interaction}} x_{\text{attribute1}} \cdot x_{\text{attribute2}} \cdot \beta_{\text{interaction}} \\
U_{\text{right}} &= \sum_{\text{attribute}} x_{\text{attribute}} \cdot \beta_{\text{attribute,country}} \\
&\quad + \sum_{\text{interaction}} x_{\text{attribute1}} \cdot x_{\text{attribute2}} \cdot \beta_{\text{interaction}} \\
\beta_{\text{attribute,country}} &= \alpha_{\text{attribute}} + \gamma_{\text{attribute,country}}
\end{aligned}
\tag{1}
$$

The multi-level nature of the models allows us to derive estimates for countries not included in the sample as it yields estimates both on the level of sampled countries ($\alpha_{\text{attribute}} + \gamma_{\text{attribute,country}}$) and on the European level ($\alpha_{\text{attribute}}$). Within such models, the uncertainty of estimations for countries not included in the sample is larger than for sampled countries and depends on the observed variability across sampled countries. For example, if preferences across the four sampled countries barely varied, strong deviations of other countries would be less probable. However, if preferences varied strongly across the four sampled countries, preferences in unobserved countries could vary strongly as well.

Of the six attributes in the choice data, we exclude the one that describes ownership of generation assets as this is not represented in the energy scenarios. Among the remaining five attributes, we model one attribute as a categorical variable (dominant technology) and the other attributes as continuous variables (land requirements of the necessary infrastructure, necessary transmission capacity, share of imported electricity, and household electricity price changes).

The models include six main parameters per level (one for each of the four continuous variables, two for the categorical variable) and six levels (European level, four sampled and one not-sampled countries), resulting in 36 main parameters. In addition, we add up to fifteen interaction effects. The models also include one parameter per respondent that models the respondent's probability to choose the left option irrespective of the shown attributes ($\alpha_{\text{left,respondent}}$ in Eq. 1), resulting in another ~4000 parameters.

We use a Bayesian approach that includes weakly informative priors for these parameters (Eq. 2). All priors are centred at zero to not assume the existence of any effects a priori. The measures of dispersion of these priors are chosen such that their values are most likely in the range of −4 to 4 – a range that we consider weakly informative. This design choice is based on a specificity of the multinomial logit choice model (Eq. 1): the choice probability reaches nearly 100 % when the utility difference between two options approaches an absolute value of 4, making absolute utility values much larger than 4 less likely. We also perform a sensitivity analysis of the choice of priors (Supplemental Note S1).

$$
\begin{aligned}
\alpha_{\text{attribute}} &\sim \text{N}(0, 4) \\
\beta_{\text{interaction}} &\sim \text{N}(0, 1) \\
\gamma_{\text{attribute,country}} &\sim \text{N}\left(0, \sigma_{\text{attribute,country}}\right) \\
\sigma_{\text{attribute,country}} &\sim \text{Exp}(4) \\
\alpha_{\text{left,respondent}} &\sim \text{N}\left(\mu_{\text{left}}, \sigma_{\text{left}}\right) \\
\mu_{\text{left}} &\sim \text{N}(0, 0.25) \\
\sigma_{\text{left}} &\sim \text{Exp}(3)
\end{aligned}
\tag{2}
$$

We estimate the parameters of the models using the Hamiltonian Monte Carlo method; an algorithm based on Markov chain Monte Carlo. We sample 1000 times from four chains each, with each chain being tuned up-front using another 1000 samples. The chains converge (Supplemental Figs. S1 and S2) with a ratio of inter-chain to intra-chain variances (R-hat) below 1.01 for all main parameters (Supplemental Table S2).

We compare the predictive fit of models with different sets of interaction effects ranging from no interactions between choice experiment attributes to all fifteen possible interactions (Supplemental Table S3). We find the best predictive fit in a model with interaction effects that are selected a priori (Supplemental Table S4), but the differences between models are minor (Supplemental Table S4). In fact, only the difference between the worst performing model ("base", no interaction effects) and the best performing model ("selection") can be shown to be different from 0, and the difference is small even for this pair. We continue our analysis with the best performing model based on an a priori selection of interaction effects.

The best-performing model has an in-sample prediction accuracy of 66.8 %, i.e. it predicts choices of respondents in the choice data correctly in ~67 out of 100 times. Here, we predict binary choices by choosing the option with higher expected posterior choice probability. The accuracy of the model is lower than that of the one applied in the original study of Mey et al. (87 %), because of a large variability across respondents [9] which is irrelevant for our study and which we therefore ignore. Here, we are interested in national averages, rather than individual-level preferences. As a consequence, the model has lower power to predict choices of individuals.

The multi-level approach of the model allows us to extrapolate choices to countries that have not been sampled. We validate this approach using leave-one-out cross-validation on the level of countries. As there are four countries in the choice data, this leads to a total of four model runs in which we leave out the choice data of one of the four sampled countries each. On average, this leads to a prediction accuracy of 65.0 % in-sample and 64.7 % out-of-sample. This shows that prediction accuracy is only slightly lower for countries not used for fitting the model and that the model is therefore able to make valid predictions for countries not included in the sample.

We derive mapping functions for each attribute of the choice experiment. Linear regression functions for the four interval-based attributes are steeper for attributes with higher impact on utility, namely household electricity prices and share of imports (Supplemental Fig. S3). The uncertainty of mapping functions for countries not sampled is much larger than for sampled countries and depends on the variance across sampled countries (Supplemental Fig. S3).

The choice experiment whose data we use [9] has been designed in a way that each option, each regional electricity supply, is plausible, but without considering the technical feasibility of preferred scenarios (i.e. combinations of preferred attribute levels) and the potential interactions within the technical system. For example, both in reality and the choice experiment it is possible for each region to import electricity, but in reality, it is not possible for *every* region to import electricity, as at least one region must also export that electricity. These interactions between regions can only be simulated and validated using technical energy system models.

3.2. Energy scenarios

In this study, we use pre-existing European energy scenarios developed in previous studies [3,20]. All scenarios supply the European Union, Western Balkans, Norway, Switzerland, and the UK with 100 % renewable electricity, mostly from wind and solar power, at today's demand level.

The first set of scenarios assesses the impact of **self-sufficiency** [3]. It comprises scenarios with self-sufficiency on different spatial and administrative levels (Table 1). The least-constrained and therefore least-cost option is a scenario in which countries and regions can freely trade, with no restrictions on imports. In addition, there are two scenarios each in which either all countries or all subnational regions are self-sufficient. Countries and regions are either fully self-sufficient, without any connections to neighbours, or they are net self-sufficient, in which case they generate the annually required electricity themselves but trade inter-annually to deal with fluctuations in their supplies. For example, net self-sufficient countries could decide to install only solar power, leading to a summer excess and a winter deficit. While the original study [3] assessed further scenarios, we limit our analysis here to these five scenarios.

The second set of scenarios assesses the impact of **supply technology mix** [20]. It comprises scenarios in which varying shares of utility-scale solar power and onshore wind supply each country (Table 2). Shares are based on installed capacity and are enforced in each country, with each country being net self-sufficient. Shares of both technologies are varied in 10 % steps, leading to a total of eleven scenarios of which we select six – for example, a scenario with 10 % solar power and 90 % wind power. The original study [20] assessed a total of 286 scenarios, most of which we ignore here for the sake of comprehensibility.

3.3. Mapping energy scenario variables to choice data variables

To be able to use energy scenario variables as predictors in the discrete choice model, we map the variables to the domain and scale of the five variables in the choice data (Table 3).

Table 1
List of energy scenarios within the first set of scenarios. Scenarios vary with respect to electricity and trade patterns.

Scenario	Self-sufficient regions	Self- sufficiency
Least-cost	–	–
Net national self-sufficiency	Countries	Net
Full national self-sufficiency	Countries	Full
Net regional self-sufficiency	Sub-national regions	Net
Full regional self-sufficiency	Sub-national regions	Full

Table 2
List of energy scenarios within the second set of scenarios. Scenarios vary with respect to the technology mix within countries.

Scenario	Capacity share onshore wind	Capacity share solar power
Least-cost	70 %	30 %
50 % solar, 50 % wind	50 %	50 %
70 % solar, 30 % wind	30 %	70 %
90 % solar, 10 % wind	10 %	90 %
100 % solar	0 %	100 %
100 % wind	100 %	0 %

Table 3
Variables of the choice experiment and corresponding energy scenario variables. To map energy scenario variables to choice experiment variables, we use additional data in some cases.

Energy scenario	Additional data	Choice experiment
Technology mix	–	Dominant technology (categorical)
Generation and demand	–	Import level
Generation capacity	Power density	Land requirements
Transmission capacity	Today's transmission capacity	Change in transmission capacity
System cost	Today's price breakdown	Change in household prices

The choice experiment assessed preferences regarding the **dominant technology** of the electricity supply within each region: rooftop solar power, open-field solar power, or onshore wind turbines. The energy scenarios contain technology mixes for all regions in Europe on a continuous scale. To map to the experimental variables, we define the technology with the largest share as being dominant in the region and use this categorical variable as a predictor in the choice model.

Regarding **electricity imports** into the region, the choice experiment assessed preferences for four levels of imports: 0 %, 10 %, 50 %, and 90 % of the total consumed electricity. Within the energy scenarios, we define imports as the difference between annual generation and annual electricity demand per region, yielding a measure on the 0–100 % scale. We use this variable as a predictor in the choice model.

Regarding **land requirements** of generation infrastructure, the choice experiment assessed preferences for five levels: 0 %, 1 %, 2 %, 4 %, and 8 % of total land. To derive land requirements in the energy scenarios, we use installed capacities per region multiplied by technology-specific capacity densities: 8 MW/km^2 for onshore wind turbines [65] and 80 MW/km^2 for utility-scale photovoltaics [66,67]. We divide absolute land requirements by the total land area per region [68,69] to derive relative land requirements as given in the choice experiment.

Regarding **overhead transmission capacity**, the preference study assessed preferences on five levels: −25 %, 0 %, 25 %, 50 %, and 75 % overhead transmission capacity increase compared with 2022's levels. We derive today's levels from a dataset included in the PyPSA optimisation model [70]. We overlay the dataset on the regions used in this study to link transmission lines to our regions. We assume the line length does either not change between our scenarios or it changes proportionally with transmission capacity and we therefore ignore line lengths. Because the energy scenarios do not include transmission capacities within regions, we quantify transmission capacities between regions only.

For 92 (∼19 %) subnational regions, we cannot determine today's transmission line capacity, mostly due to insufficient resolution of the data. Often, these are small regions with small populations such as Lääne County in Estonia, the Swiss canton of Nidwalden, or the canton of Diekirch in Luxembourg. For these regions, we assume no change of transmission capacity across scenarios. While this adds a bias to choice estimations for these regions, the impact on European estimates is small, given that the total population of these regions is below 17 million, which is about ~3 % of the total European population.

Regarding **household electricity prices**, the choice experiment assessed preferences on five levels: 0 %, 15 %, 30 %, 45 %, and 60 % price increase compared with 2022's levels. The energy scenarios do not include prices but only system cost based on 2050 technology cost projections. We map from system cost to household prices using data on taxes and levies given in [71]. From this dataset, we derive taxes and levies for the second half of 2022 (2022-S2) for the largest household consumers (KWH_HE15000) in purchasing power standard in each country. For the UK, we use data from 2020, the latest available data in the dataset. For Switzerland, we use data from Germany. To derive simulated prices, we add an assumed 10 % revenue margin and 2022 taxes and levies onto simulated system cost. We compare simulated and observed prices per region to derive price differences as assessed in the choice experiment.

3.4. Predicting scenario choices

We use the mapped scenario variables as predictors in the choice model (Eq. 1), which allows us to derive predicted utility values per effect (6 main and 5 interaction effects), region (497 subnational / 33 national), and scenario (5/6) and eventually predicted choices between scenarios. For countries included in the choice data, we use effects explicitly inferred from the data. For countries not included in the choice data, we use effects inferred from the average and variability across sampled countries (see Choice data and model).

Across scenarios in both studies, the maximal differences of predicted utility values per effect are below 2 almost all the time and below 1 most of the time (Supplemental Figs. S4 and S5). Such values are plausible as utility differences of magnitude 2 represent a fairly strong opinion, leading to a choice probability of ~88 %.

Across self-sufficiency scenarios, utility values of electricity imports show the largest median difference, with household electricity prices and wind power following along (Supplemental Fig. S4). Apart from the pair of wind power and electricity imports, interaction effects play only a minor role. Land requirements, household electricity prices, and transmission capacity show a large range of values, indicating that regions are very differently impacted. Across technology mix scenarios, the ranking of attributes is similar, apart from the import attribute which does not vary (Supplemental Fig. S5).

The predicted utilities per region allow us to derive predicted choices per region using the discrete choice model. For estimating choices on the entire continent, we form the population-weighted average across regions so that the voice of each person in Europe has the same weight. We use data from JRC's Global Human Settlement Layer [72] to determine the population in each subnational region and each country as weights. While we deem this step to be important, it has only a minor impact on the results: the population adjustment never changes the unadjusted average by more than 3 (4) percentage points for the self-sufficiency (technology mix) scenarios.

3.5. Sensitivity analysis

Like other online choice experiments, the ecological validity of this experiment is limited: the stated preferences derived in this study may not materialise the exact same way in the real world when people make real decisions. In addition, while preferences are likely to be dynamically stable over short and medium periods of time, they are also affected by trends and events, such as the Russian invasion of Ukraine and the corresponding energy crisis in Europe. To better understand the sensitivity of our main results to any such changes, we perform a local sensitivity analysis.

In the local sensitivity analysis, we vary the importance of attributes individually and assess the impact on scenario preference. To do so, we rank all scenarios based on their total European utility, such that scenarios with the highest utility and preference receive the highest rank. In a range of sensitivity cases, we then either increase or decrease the partworth utility of each attribute by 75 % and reassess scenario rankings. We find that changes to each individual attribute have only limited impact on the results and that scenario rankings are largely robust towards these sensitivity cases (Supplemental Figs. S6 and S7). Varying partworth utility of land requirements has no impact on rankings. Changes in household prices, share of electricity imports, and transmission requirements affect results in a few cases but do not change scenario rankings substantially. This means that there is no attribute that dominates our results and if any one attribute were to change individually in the European population, one could not expect a large deviation from our main results.

4. Results

4.1. Citizens prefer self-sufficiency over least cost

Citizens would choose a scenario with regional net self-sufficiency over a least-cost scenario in most regions of Europe, despite not only higher electricity prices but also higher local land requirements on average (blue regions in Fig. 1 A). This preference is strong and leads to a European choice probability of 60 % (46–71 %) for the self-sufficiency scenario. Some regions reject the least-cost scenario strongly, with choice probabilities of self-sufficiency close to 100 % (dark blue regions in Fig. 1 A). In most cases, these regions are disadvantaged in the least-cost scenario, either by high amounts of generation capacities due to their beneficial resources (e.g. Ireland, Denmark, Romania) or by transmission lines that connect these generation centres with demand centres (e.g. England, Hungary), or both.

Some regions prefer the least-cost scenario (orange regions in Fig. 1 A). Often, these are regions that are self-sufficient already in the least-cost scenario due to their beneficial resources allowing for low-cost local electricity, for example in Norway, Sweden, and Scotland. As we model a Europe-wide, perfect electricity market, the electricity price in all of Europe increases when other regions switch to net self-sufficiency. This comes without noticeable benefit for regions in the mentioned countries and therefore leads to lower approval. Consequently, we see the strongest preference for the least-cost scenario in Oslo with an expected choice probability of 19 % (0–41 %) as Oslo not only experiences higher prices but also large relative land requirements in the self-sufficiency scenario.

Oslo also sees one of the highest uncertainty ranges within our samples (compare Fig. 1 B and Fig. 1 C) and showcases how the scope of the choice data is driving uncertainty. Its uncertainty range based on the 96 % highest density interval is around two times larger than the average. This is due to two limitations of the choice data. First, Norway is a country not sampled in the choice data, and while our method allows for valid extrapolations to countries not sampled (see Methods), their choices are less certain. Estimations for countries within the sample are much more certain (see Germany in Fig. 1 and Supplemental Fig. S10). Second, Oslo sees relative land requirements that go far beyond what is included in the choice data. This extrapolation leads to higher uncertainty of Oslo's choices. Despite this uncertainty, Oslo and most regions lean strongly towards either one of the two scenarios (Supplemental Fig. S10), and estimated prediction accuracy out-of-sample is high (see Choice data and model).

Not only is regional net self-sufficiency preferred over the least-cost scenario, but in fact, all self-sufficiency scenarios are preferred over the least-cost scenario (Fig. 2), even if the effect is not as strong. Net regional self-sufficiency has the highest population-weighted European choice probability of 60 % (46–71 %). However, forms of national self-sufficiency are preferred as well, with up to 53 % (43–62 %) choice probability when contrasted with the least-cost scenario.

Despite the preferences for self-sufficiency, there can be too much of

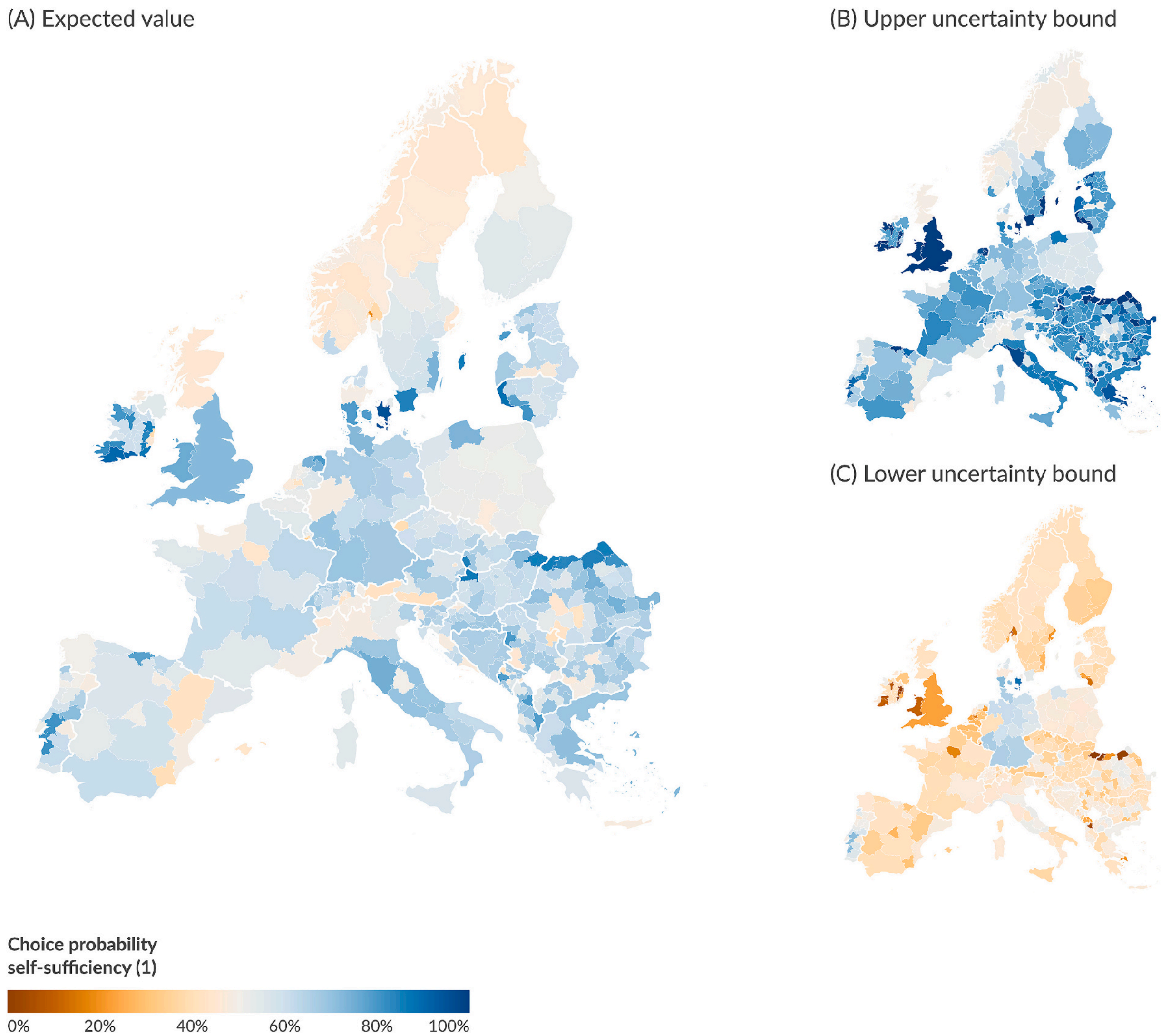

Fig. 1. Where citizens would choose a scenario based on net regional self-sufficiency over the least-cost scenario. Colours show choice probabilities for the regional net self-sufficiency scenario. Of the entire distribution of choice probabilities per region, we show (A) expected values on the large map, and the (B) upper and (C) lower bounds of the uncertainty range given by the 96 % highest density interval on smaller maps.

it. Given the choice between full and net regional self-sufficiency, citizens are slightly more likely to choose net self-sufficiency. This is based on the trade-off between prices and self-sufficiency: citizens are willing to pay for self-sufficiency, but there is a limit. Full self-sufficiency increases system cost by almost 70 %, and while citizens still prefer this scenario over the least-cost scenario, they prefer other scenarios with lower cost more.

4.2. *Citizens prefer solar power over least cost*

Citizens are more likely to choose higher shares of solar power over least cost in most countries of Europe (light-blue countries in Fig. 3 A). Increasing the solar power capacity share from 30 % given by the least-cost scenario to 90 % leads to a European choice probability of 56 % (48–64 %). Some countries deviate from this choice probability and have higher (Denmark, Germany) or lower (Norway, Bosnia and Herzegovina) choice probabilities. Mainly, this is based on the fact that they are advantaged or disadvantaged in either of the two scenarios. Denmark, for example, sees a six-fold expansion of its transmission capacities compared with today in the least-cost scenario, leading to its stronger rejection of this scenario. Such effects can only partly be attributed to the idea of least cost: likely, one could find scenarios with cost very close to least cost that would put less stress on Denmark by distributing the necessary transmission capacities more evenly.

More solar power leads to higher choice probabilities, but this probability decreases with very high shares as trade-offs start materialising. For example, a 90 % capacity share of solar power experiences the highest preference (Fig. 4), and both higher and lower shares are less preferred. When increasing the solar share to 100 %, the choice probability drops from 56 % to 48 % (40–61 %). This is a bad compromise: while it indeed removes wind power entirely, which is generally preferred by citizens, it increases household electricity prices and especially transmission capacities, and reduces overall preferability.

Solar power scenarios with high shares may in fact be more preferable than shown, because of a methodological shortcoming of our approach. As the technology variable of the choice data represents only the dominant technology as a category and not the exact share, an increase in solar power share when it is already dominant has no impact on preferences in the model. Correspondingly, the scenarios with high solar power shares may be more preferable than shown by our results.

Generally, choice probabilities are less pronounced for this set of scenarios compared with the set of self-sufficiency scenarios (compare colours in Figs. 1, 2 with Figs. 3, 4). In parts, this has to do with the different spatial resolutions of these energy scenarios: the higher

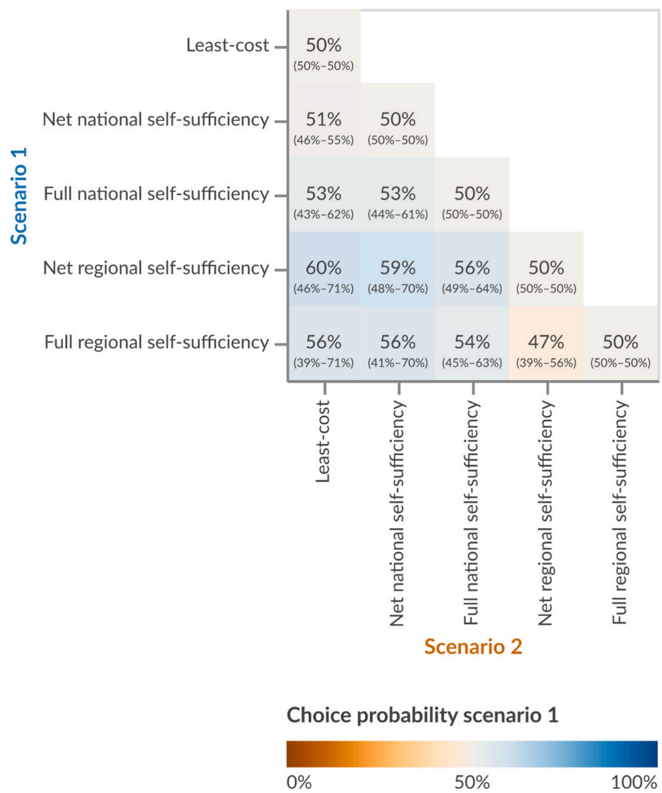

Fig. 2. How European citizens would decide among self-sufficiency scenarios. Values are European choice probabilities for the scenario on the vertical axis (scenario 1). Values in the upper triangular are complementary to the shown ones and not shown. Large text and colour show expected values, small text in brackets shows uncertainty range based on 96 % highest density interval. See Supplemental Fig. S8 for a visualisation of the full probability distributions.

resolution of the self-sufficiency scenarios leads to more pronounced effects as probabilities are not averaged across subnational regions as they are in Figs. 3, 4.

5. Discussion and conclusion

We show that citizens would choose energy scenarios with higher shares of regional self-sufficiency and higher shares of solar power over least- and lower-cost scenarios, despite the higher electricity prices such shares are causing. Citizens would choose scenarios with higher levels of self-sufficiency, despite increased local land requirements for electricity assets. However, there is a limit to the amount of self-sufficiency and solar power that is preferred: ultimately, the trade-offs with increasing costs grow too high and reduce overall scenario preferability.

The high spatial resolution of our results reveals that both local and global contexts impact the choices citizens would make. For example, the least-cost scenario features electricity generation centres – regions with extraordinarily good resources that generate much more electricity than needed locally and transmit it to the places where it is consumed. The concentration of generation and transmission assets in these regions leads to low choice probability for the least-cost scenario in the regions hosting the generation and transmission assets. Instead, they prefer scenarios with higher shares of self-sufficiency, which would lower land use in their regions but increase the total European land use. As our approach explicitly considers trade-offs across disparate dimensions, it also, other than other approaches in the literature, supports the identification of solutions, not only of impacts of opposition problems.

Revealing such trade-offs can be an important contribution in often heated debates about how to design the future power system. Our findings highlight that factors beyond costs are important, and that distributive factors – including non-economic factors – are very important for overall preferability. Findings such as this highlight that the recent policy turn to consider acceptance is important and that finding ways for financial participation from local governments and citizens particularly affected by renewables or infrastructure siting could be one way to compensate regions for supplying energy to other regions and helping reduce total land use. Specifically, this includes identifying and addressing thresholds for community acceptance in generation centres which might experience increasing opposition towards the expansion of infrastructure siting leading to potential rifts between hosting and non-hosting regions. Limiting or entirely avoiding such generation centres, in the extreme case going for complete regional self-sufficiency, would address such distributive issues, but it would also require higher shares of land for local generation of electricity; which is why some regions actually prefer the least-cost scenario.

These contrasting preferences and trade-offs illustrate the complexity and ambiguity involved in accommodating diverse priorities. It also highlights the need for public debate at both EU and national levels, going beyond single factors of opposition and acknowledging the trade-offs between technical, environmental, and economic factors. In addition, the current series of geopolitical crises, such as the Russian invasion of Ukraine, have re-prioritised energy security as a dominant objective, shaping public narratives around European self-sufficiency. While these frames strengthen the case for accelerated rollouts of renewables as Europe's main domestic energy resource, this also risks downplaying other preferences or considerations – treating local contestation as a challenge to overcome rather than a signal of deeper values and regional concerns and so consequently risking further local opposition.

Methodologically, our study shows new ways in which energy modelling analysis can contribute to bridging the gap between techno-economics and social science, and that explicit integration of technological, economic, and social dimensions – here specifically public preferences – in energy system modelling is possible.

In contrast to existing approaches, our approach has two important features. First, it combines a large geographic scale with high geographic resolution. Only this combination allows for assessing local impacts of global decisions. Second, it is a *system* analysis throughout, including interactions and trade-offs between diverse aspects of the electricity system. It reveals trade-offs across very different dimensions and allows for much deeper analysis than, say, citizen surveys or energy system modelling alone. For example, we show that citizens choose solar power over wind despite its higher economic cost, and because of the solar/cost trade-off, there is a limit to how much solar citizens prefer before they would rather choose a future with more wind. Essentially, the approach is a multi-criteria decision analysis featuring technically rigorous trade-offs between energy scenario attributes like technology, cost, and land requirements, with the weights defined by citizens.

The approach can amend existing approaches in energy research. It builds on ideas of multi-criteria decision analysis, which is useful in situations where trade-offs across disparate dimensions and heterogeneous opinions exist. Multi-criteria decision analysis is typically performed on energy scenarios with low spatial scope, low spatial resolution, low temporal resolution, or a combination of these. We show that a high-resolution and broad-scope alternative is possible and useful. In addition, our approach can be combined with modelling to generate alternatives in order to assess preferences given a range of scenarios close to the cost-optimal point. Our results indicate, however, that the threshold of these analyses should be reconsidered: Often, modelling to generate alternative studies use a cost penalty of 10 % or even lower as a threshold, but we show that even a scenario with a cost penalty of 70 % is preferred over the least-cost scenario.

We also found that our approach is able to predict dichotomous choices in countries not included in the survey sample with roughly the same accuracy as countries included in the survey. This may seem surprising, considering the high choice probability uncertainty we

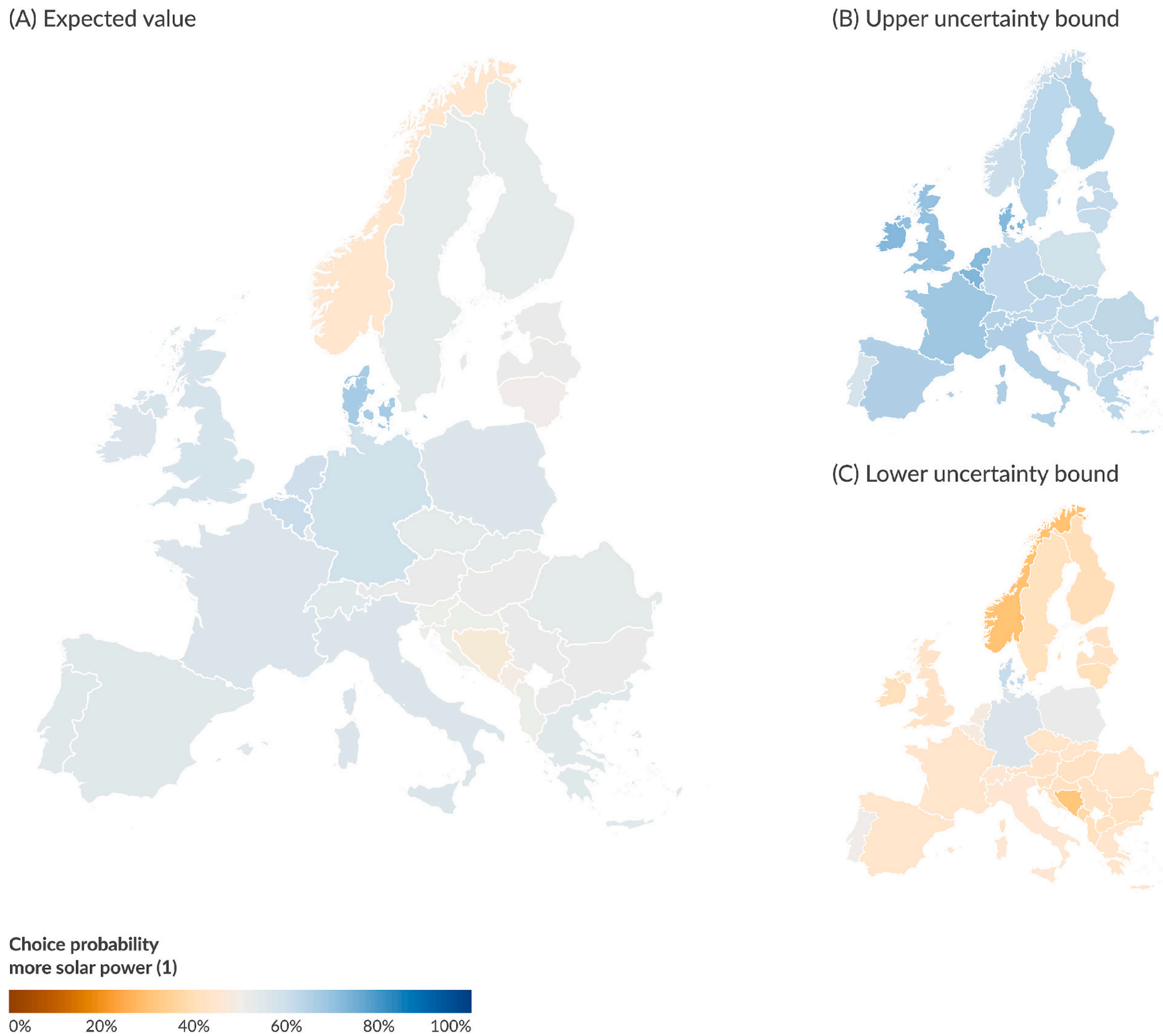

Fig. 3. Where citizens would choose a scenario with more solar power over the least-cost scenario. Colours show choice probabilities for the scenario with high solar power share of 70 %. Of the entire uncertainty distribution of choice probabilities per region, we show (A) expected values on the large map, and the (B) upper and (C) lower bounds of the uncertainty range given by the 96 % highest density interval on smaller maps.

identified (Figs. 1, 3 and Supplemental Figs. S3 and S10). This high accuracy of out-of-sample countries can be explained by the identified country differences: while they are large, they are not inverse, especially not for the important attributes household prices and share of imports (Supplemental Fig. S3). For example, based on the data, it is unlikely that people in countries not sampled would actually *prefer* higher electricity imports on average. As, ultimately, choices are dichotomous, it can be expected that people in all European countries would choose a scenario with lower imports, whether they reject high imports more like people in Germany or less like people in Poland (Supplemental Fig. S3).

Our approach has limitations and can be improved by further research. First, the mapping from preference data to energy scenarios can be improved, especially by tailoring preference elicitations to the concepts, data types, and data ranges used in the model. Preference data and energy scenarios should be aligned as much as possible so that the mapping becomes simpler and more precise. For example, the alignment of both the transmission and technology variables could be improved. Regarding transmission, the ranges of the variables in the choice experiment and the energy scenarios were not aligned, requiring substantial extrapolation. In the choice experiment, transmission expansion was always below a doubling of today's capacity while it could increase several-fold in the energy scenarios. Regarding technology, the choice data contains a categorical variable (dominant technology in the region) while the energy scenarios provided several variables modelling the electricity mix in much higher granularity. A better alignment to the energy scenarios would have allowed for more fine-grained predictions, possibly even including uncertainty stemming from these variables.

Second, choice data from more countries than the four we had within the sample would improve the accuracy of the results. It would substantially reduce the uncertainty of choice probability for this country which could, in turn, also reduce uncertainty on the European level. It would further increase accuracy of predictions for countries not sampled, as it would allow for better inferences of the international average and variability across countries. This does not mean that uncertainty necessarily will be reduced, though: if preferences of added countries were not in line with preferences of the countries we have sampled, variability across countries, and with it uncertainty of out-of-sample countries would increase. Adding choice data from more countries would increase the accuracy of the predictions no matter what.

Lastly, preferences should be considered when building the energy scenarios, not in hindsight. Here, we assessed preferences retrospectively to be able to use existing data and scenarios. Ideally, the statistical model of the preference data and the energy system model should be aligned so that they run simultaneously and scenarios can be optimised

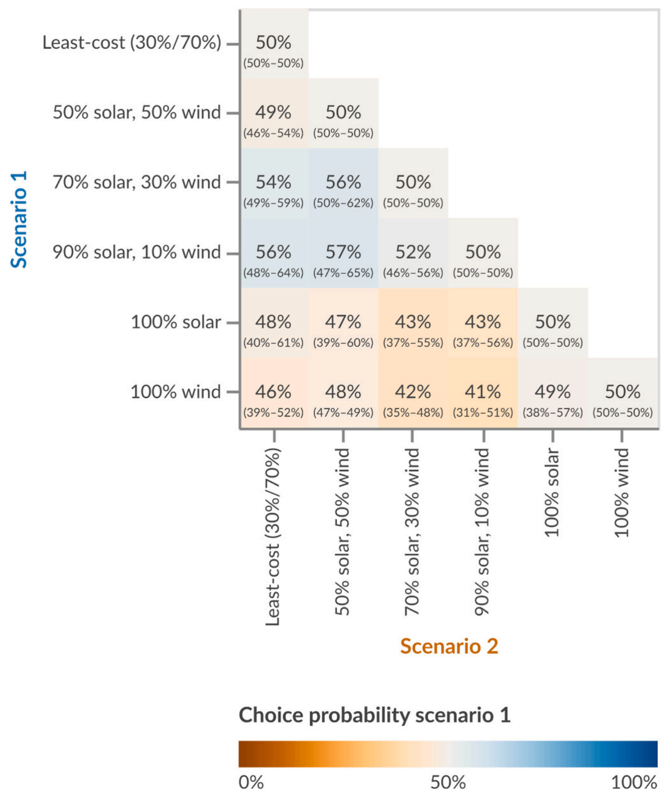

Fig. 4. How European citizens would decide among technology-mix scenarios. Values are European choice probabilities for the scenario on the vertical axis (scenario 1). Values in the upper triangular are complementary to the shown ones and not shown. Large text and colour show expected values, small text in brackets shows uncertainty range based on 96 % highest density interval. See Supplemental Fig. S9 for a visualisation of the full probability distributions.

for preferences.

We have demonstrated the feasibility of generating functions of public preferences and integrating them into energy system modelling. This shows that it is possible to explicitly derive such data for this purpose and redesign models to produce scenarios optimised according to stakeholder preferences. Our approach can help to improve policy decision-making with models that move beyond purely cost-based optimisation to include the non-economic factors that shape public preferences and acceptance. Our findings demonstrate how preference-informed modelling can systematically reveal societal trade-offs and help policymakers anticipate and navigate potential opposition. This approach enables more transparent, responsive, and legitimate decision-making by aligning energy strategies with the values and priorities of citizens.

Our study delivers evidence that least-cost scenarios are not preferred by the European population and that social acceptability research and energy system modelling can be combined more closely to identify preferred energy supplies and their implications.

CRediT authorship contribution statement

Tim Tröndle: Writing – original draft, Visualization, Software, Methodology, Investigation, Formal analysis, Conceptualization. **Franziska Mey:** Writing – review & editing. **Johan Lilliestam:** Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.erss.2025.104364.

Data availability

The datasets generated during this study are available on Zenodo with DOI https://doi.org/10.5281/zenodo.14501018.

The code to reproduce the results and all analysis steps are publicly available as a reproducible Snakemake [73] workflow on Zenodo with DOI https://doi.org/10.5281/zenodo.14501036.

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