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# A review of the role of spatial resolution in energy systems modelling: Lessons learned and applicability to the North Sea region

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ABSTRACT

The importance of spatial resolution for energy modelling has increased in the last years. Incorporating more spatial resolution in energy models presents wide benefits, but it is not straightforward, as it might compromise their computational performance. This paper aims to provide a comprehensive review of spatial resolution in energy models, including benefits, challenges and future research avenues. The paper is divided in four parts: first, it reviews and analyses the applications of geographic information systems (GIS) for energy modelling in the literature. GIS analyses are found to be relevant to analyse how meteorology affects renewable production, to assess infrastructure needs, design and routing, and to analyse resource allocation, among others. Second, it analyses a selection of large scale energy modelling tools, in terms of how they can include spatial data, which resolution they have and to what extent this resolution can be modified. Out of the 34 energy models reviewed, 16 permit to include regional coverage, while 13 of them permit to include a tailor-made spatial resolution, showing that current available modelling tools permit regional analysis in large scale frameworks. The third part presents a collection of practices used in the literature to include spatial resolution in energy models, ranging from aggregated methods where the spatial granularity is non-existent to sophisticated clustering methods. Out of the spatial data clustering methods available in the literature, k-means and max-p have been successfully used in energy related applications showing promising results. K-means permits to cluster large amounts of spatial data at a low computational cost, while max-p ensures contiguity and homogeneity in the resulting clusters. The fourth part aims to apply the findings and lessons learned throughout the paper to the North Sea region. This region combines large amounts of planned deployment of variable renewable energy sources with multiple spatial claims and geographical constraints, and therefore it is ideal as a case study. We propose a complete modelling framework for the region in order to fill two knowledge gaps identified in the literature: the lack of offshore integrated system modelling, and the lack of spatial analysis while defining the offshore regions of the modelling framework.

## 1. Introduction

Efforts to reduce greenhouse gas (GHG) emissions are taking place worldwide. On the global scale, the Paris Agreement was signed by 195 nations in 2016, aiming to ''*Hold the increase in the global average temperature to well below 2°C above pre-industrial levels and pursuing efforts to limit the temperature increase to 1.5°C above pre-industrial levels, recognizing that this would significantly reduce the risks and impacts of climate change*'' [1]. On the European scale, the European Commission has also set different goals and milestones, for example the European Green Deal, presented in 2020, which outlines the necessity to eliminate emissions of greenhouse gases by 2050 [2], or the 'Clean energy for all Europeans strategy', updated in 2019 and targeting different areas such as energy efficiency, renewable energy or electricity market design [3].

*Abbreviations:* CCS, Carbon Capture and Storage; ESM, Energy System Model; GDP, Gross Domestic Product; GHG, Greenhouse Gas; GIS, Geographic Information System; HVAC, High Voltage Alternating Current; HVDC, High Voltage Direct Current; LP, Linear Programming; MILP, Mixed Integer Linear Programming; MIP, Mixed Integer Programming; MIQCP, Mixed Integer Quadratically Constrained Programming; NLP, Non Linear Programming; NSR, North Sea Region; O&G, Oil and Gas; PRISMA, Preferred Reporting Items for Systematic Reviews and Meta-Analyses; PtG, Power to Gas; VRE, Variable Renewable Energy; WEO, World Energy Outlook.

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According to the World Energy Outlook (WEO) 2018 [4], in 2017 the power, transport and industry sectors represented 85% of the total energy-related $CO_2$ emissions (42%, 24% and 19% respectively). The importance of the power sector in this contribution is expected to increase in the following decades, due to the electrification of other energy sectors, mainly heat and transport. Thus, in order to reduce the emissions related to the power sector, large deployments of low-carbon energy sources are required in short, medium and long term. Indeed, according to the ambitious 'sustainable development scenario' of the WEO 2018, the contribution of wind to the electricity generation will increase from 1085 TWh in 2017 to 7730 TWh in 2040, and the contribution of solar PV will increase from 435 TWh to 6409 TWh. Even in more conservative scenarios, for example the 'current policies', the increase of Variable Renewable Energy (VRE) is considerable (3679 TWh of wind and 2956 TWh of solar in 2040) [4]. This expected increase of the penetration of VRE sources poses a major challenge to the analysis, design and implementation of energy systems. The global energy production system has traditionally been highly centralized and (almost) deterministic, with large power plants supplying energy with low levels of uncertainty. However, future energy systems dominated by wind and solar will be intermittent, meteorologically and spatially dependent, and will have high levels of uncertainty associated. As a consequence, large deployments of flexibility resources are expected in order to properly balance supply and demand. System integration (i.e. power to gas, power to liquids, power to heat, gas to power, electric vehicles) [5,6], seasonal storage [7] and the use of flexible generators with Carbon Capture and Storage (CCS) [8] have been analysed as promising technologies to provide this flexibility in low-carbon systems.

As a consequence of this turnaround, the importance of spatial granularity for energy planning, modelling and analysis has increased in the last years and it is expected to play a major role in the future. As an example, Fig. 1 shows the search results in the Scopus database using the keyword 'Renewable Energy' combined with either 'Spatial resolution' or 'GIS' (Geographic Information System) in the last two decades. Integrating these spatial aspects in energy system models (ESMs) is not a straightforward issue. Traditionally, the main trade-off in ESMs was between temporal resolution and technological resolution. Hence, ESMs focused on a single energy sector tend to have higher temporal resolution (i.e. power system models with hourly resolution such as PLEXOS), while integrated ESMs tend to include more energy sectors using time-slicing methods (i.e. the approach used in most TIMES models). When adding the spatial resolution to the mix, the trade-off between these three dimensions (spatial, temporal and technological resolution) becomes less obvious, and to balance them in order to improve the quality of the modelling framework becomes a huge challenge.

In this context, the North Sea region (NSR), shown in Fig. 2, emerges as a perfect example of a region where the spatial component influences the energy planning, model and analysis, as it combines a large amount of planned deployments of VRE; and multiple aspects in which spatial resolution can affect modelling results: meteorological data used, infrastructure costs including power and gas networks, allocation of supply and demand and spatial planning of different offshore activities (for example fisheries, maritime transport or sand extraction).

In terms of population, the NSR area contains around 200 million inhabitants, representing around a 40% of the total population of the European Union [9]. The aggregated GDP of the countries around the NSR adds up to 9.6 billion of euros, representing 60% of the GDP of the EU [9]. In contrast, in terms of land this region represents only 15% of the surface of the EU. In terms of energy, since the late 19th and early 20th century the North Sea has been a key player in terms of Oil and Gas (O&G) extraction. As of today, more than 300 O&G fields, 5000 wells, 500 platforms and a network of around 10,000 km of pipelines can be found offshore [10]. As a result of this long exploitation, the current mapping of the North Sea available in the literature (including spatial and geophysical information) is pretty comprehensive. As an example, in Ref. [10] a compilation of oil and gas fields, pipelines (both existing and proposed) and terminals can be found with a resolution of around 20 km.

Moreover, current trends, in line with European and worldwide policies, point out that in the following years the NSR will play a crucial role in the decarbonisation of the energy sector, due to the large deployment of offshore renewable energy sources. Offshore and onshore wind energy, wave energy, micro algae production, ocean thermal energy conversion or tidal energy are examples of sources planned to be relevant in the future in the NSR [11].

Additionally, the coexistence of large deployments of renewables and O&G infrastructure in the last step of its life cycle brings an opportunity to analyse and investigate synergies between activities. Decommission scenarios are widely analysed in the literature (see Ref. [12] and references therein). Interactions between activities have been also widely investigated, including electrification of gas platforms, power to gas conversion (PtG) in offshore platforms, carbon capture and

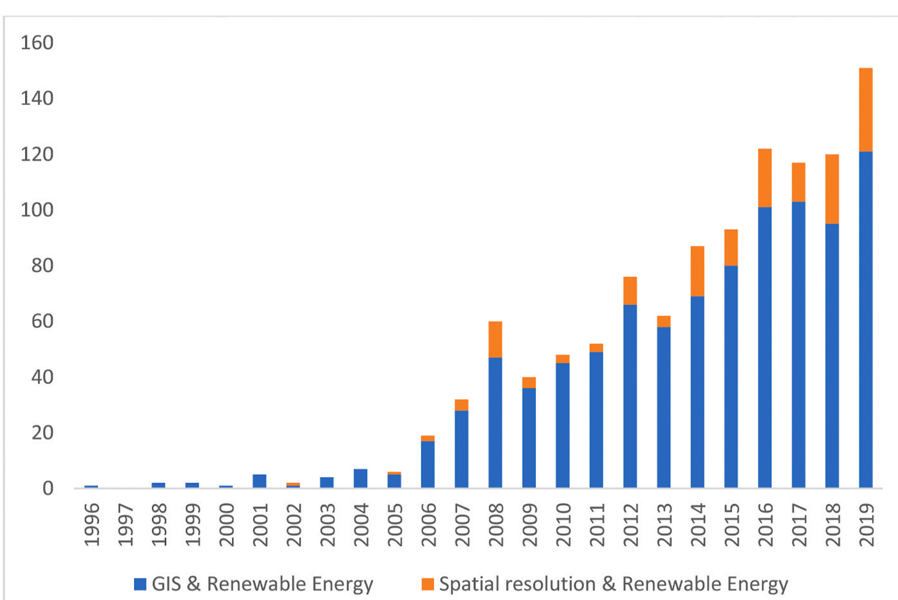


**Fig. 1.** Evolution of search results in Scopus with the keywords GIS, spatial resolution and renewable energy in title, abstract or keywords.


**Fig. 2.** North Sea map with regions, adapted from Wikimedia Commons [17].

storage (CCS) in offshore fields and caverns and energy storage [12]. More recently, a large number of studies have discussed how offshore VRE could be connected to shore, including case studies about different offshore grids [13].

Regarding spatial claims, there are multiple coexisting activities competing for space. The energy sector related activities are predominant, including O&G extraction and infrastructure, offshore deployments of renewables, and pipelines and power cables to connect these activities to mainland. But aside of that, the NSR harbours a wide variety of activities that are spatially demanding. Maritime transport is one of the main activities, being the NSR one of the busiest areas in the world, and including three of the most important seaports in the world (Rotterdam, Hamburg and Antwerp). Fishing areas are also predominant in the NS, being protected and coordinated by the European Commission. Some countries around the NS also allocate part of their shelves for military purposes. Finally, recreation and sand extraction areas also demand space.

The literature regarding spatial resolution and energy system models is relatively recent and scarce. Previous studies, like [14] or [15], presented some challenges and opportunities of the integration of spatial resolution and energy models, and analysed relevant literature, but focusing mainly on GIS applications. Other studies, like [16] tried to quantify the trade-off between spatial data aggregation and precision of results.

This paper aims to, first, analyse what is the role of spatial resolution when modelling energy systems, and second, from the findings and lessons learned from the literature review, analyse the NSR from a spatial perspective and propose a complete modelling framework that can capture this spatial component. The paper is divided in four main sections, which cover aspects related to spatial resolution from different perspectives:

- First, we review studies where Geographic Information Systems (GIS) have been used in an energy system analysis, or where GIS has been applied to energy models. Those include assessment of meteorological conditions, deployment and expansion of energy infrastructure or land availability. In the paper this corresponds to section 3.

- Second, a literature review and an assessment of a selection of ESMs is done, in order to understand how different ESMs permit to include spatial resolution and to what extent this resolution can be modified. This analysis includes other features such as the mathematical method used in each model, or the level of sector integration, in order to find correlations (if any) between the level of spatial detail and these features. In the paper this corresponds to section 4.
- Third, a summary of techniques and practices found in the literature to account for spatial data in large scale energy systems is performed, including mathematical methods for spatial data clustering that have been applied in ESMs. In the paper this corresponds to section 5.
- Last, the analysis of the NSR as a case study is developed including: 1) a literature review of previous modelling efforts in the NSR, with a special focus on the spatial resolution used, 2) a definition of a new case study which complements the ones available in the literature, 3) a proposal of a modelling framework to address this case study and 4) an assessment of which of the modelling tools available in the literature could be successfully used to analyse the proposed case study. In the paper this corresponds to section 6.

## 2. Methods

As mentioned above, this paper is divided in four sections, each of them analysing a particular aspect of spatial resolution and energy modelling. In order to compile the relevant literature for each section, we conduct four different literature reviews, as shown in Fig. 3.

The method combines systematic literature reviews, following partially the PRISMA statement and recommendations [18], and a complementary non-systematic review, targeting specific literature and documentation. In short, the steps followed are:

i) Identifying a primary list of journal articles through database search, using search strings dependent on the aim of the section.
ii) Screening the abstracts of the articles in order to filter the ones that meet a given criterion.
iii) Analyse the whole text of the screened articles in order to exclude the ones that do not fit within the scope of our review.
iv) Complement the selection of papers conducting a non-systematic review, targeting relevant literature that it is not included in i-ii and that can add meaningful insights.

### 2.1. Section 3

For Section 3 a two-step literature review is conducted, consisting of a systematic literature review, followed by a complementary non-systematic review. For the systematic review, the search of peer-reviewed articles is performed in Scopus, searching documents from 2016 until late 2020. This timespan permits to evaluate recent findings while maintaining a manageable number of publications to screen. The search string used can be found in Table 1 under the name S3.

The primary goal of Section 3 is to review studies were GIS is combined with energy system analysis, therefore the first search targets articles including "GIS", "energy" and '"modelling" in the title, abstract or keywords. The list of 540 articles is narrowed down to 48 articles using the criteria shown in Fig. 3. The subsequent non-systematic review aims to target articles related to the scope of Section 3 which are not indexed in Scopus or do not fall within the search criteria, but are considered relevant for the analysis. Six additional articles are added in this step.

### 2.2. Section 4

For Section 4 a two-step literature review is conducted, consisting of a systematic literature review, followed by a complementary non-systematic review. For the systematic review, the search of peer-reviewed articles is performed in Scopus, searching documents from 2018 until late 2020. There are several reasons to justify the choice of this short timespan. First, reviews of energy models are abundant in the literature, and therefore a wider timespan would entail a huge number of articles to screen. Second, recent reviews usually include an up-to-date list of models, and therefore recent model developments are included. Third, reviews from 2018 to 2020 probably include within their references reviews from previous periods. Thus, if needed, relevant documentation from previous years can be derived from them. The search string used can be found in Table 1 under the name S4.

As the literature required for Section 4 is formed mainly by reviews of energy system models, the first search targets articles including "review", "energy", "systems" and "models" in the title, abstract or keywords, within the category "review articles". The list of 470 articles is narrowed down to 6 articles using the criteria shown in Fig. 3. The subsequent non-systematic review aims to target the documentation and related publications of the models included in the analysis of Section 4, and relevant review documents referenced in the selected articles. Sixty-six additional documents are added in this step.

### 2.3. Sections 5 and 6

For Sections 5 and 6 only non-systematic literature reviews are conducted. In the case of Section 5, the goal is to identify clustering techniques applied in the literature to aggregate spatial data, and due to the fact that the literature is relatively scarce and there is a lack of standardized definitions, it is challenging to conduct a systematic review that produces relevant results. In the case of Section 6 the reason is similar: the literature prior to 2015 has already been reviewed in some journal articles (e.g. Ref. [19]), and the literature from 2016 to 2020 is relatively narrow and easy to manage with a non-systematic literature review.

## 3. Spatial resolution and GIS-based energy modelling in the literature

The objective of this section is to present a literature review of studies where GIS-based approaches have been applied to energy systems modelling. GIS-based modelling has been widely used during the last decades in multiple fields, such as urban planning, disaster management and mitigation or mapping. Previous analyses of GIS-based modelling for energy applications, such as [14,15], point out that, although the interaction between GIS and energy modelling is beneficial, it is still in a development stage and has to be strengthened. As one of the goals of this paper is to understand the impact of spatial resolution in energy models, and due to the fact that GIS is one of the most mature fields in terms of spatial data analysis, we consider convenient to include in this review a summary of relevant studies where this interaction is included.

Most of the previous applications of GIS to the energy field have been evaluated at local scale. Since local applications are out of the scope of this paper, one of the screening conditions for the systematic literature review is that at least regional coverage should be included.

As a result of the systematic and non-systematic literature review 54 journal articles are included in this analysis. We classify these articles according to two categories: the energy sector or specific energy application where they are applied, and the geographical coverage that they include. Results are summarized in Fig. 4 and Fig. 5, and a brief description of the selected literature can be found in Appendix A.

Results show that biomass (12 articles), solar (14 articles) and wind (11 articles) are the most common applications regarding GIS and energy modelling. Analysis of energy demand (6 articles) and power plant sitting (3 articles) are also present in the literature. Regarding geographical coverage, it can be concluded that regional and national analysis are so far the most usual resolutions included, whereas the contributions at multinational scale are extremely scarce.

**Systematic + non-systematic literature review**

| Steps | Section 3: Criteria | Section 3: Result | Section 4: Criteria | Section 4: Result |
|---|---|---|---|---|
| 1. Database search | Search in Scopus with the search string S3. | 540 journal articles. | Search in Scopus with the search string S4. | 470 journal articles. |
| 2. Screening | Screening of abstracts based on:<br>- Combine GIS and energy modelling. | 226 journal articles | Screening of abstracts based on:<br>- At least 5 different models reviewed.<br>- Part of the reviewed models should cover at least national scale | 6 journal articles |
| 3. Scoping and final selection | Eligibility of full articles. Exclusion based on:<br>- Same criteria as step 2.<br>-At least regional geographical coverage (exclusion of local analysis).<br>- Inclusion of detailed description of the methodology. | 48 journal articles | Eligibility of full articles. Exclusion based on:<br>- Same criteria as step 2.<br>- Inclusion of information about spatial resolution/geographical coverage in the reviewed models. | 6 journal articles |

**Non-systematic literature review** | **Non-systematic literature review**

| Steps | Criteria | Result | Criteria | Result |
|---|---|---|---|---|
| 4. Targeted search | Non systematic search focused on:<br>- Reviews of GIS used in energy systems.<br>- Relevant literature not indexed in Scopus under S2. | 6 journal articles | Non systematic searched focused on:<br>- Documentation of models included in the analysis.<br>- Reviews cited in the articles screened in the systematic review. | 62 documentations, 4 reviews cited |
| 5. Total | Total list of documents included after the systematic and non-systematic review. | 54 journal articles | Total list of documents included after the systematic and non-systematic review. | 72 files |

**Non-systematic literature review**

| Steps | Section 5: Criteria | Section 5: Result | Section 6: Criteria | Section 6: Result |
|---|---|---|---|---|
| 1. Targeted search | Non systematic search focused on:<br>- Reviews of clustering methods applied to spatial data in energy systems.<br>- Journal articles in which spatial clustering methods are used. | 14 journal articles | Non systematic search focused on:<br>- Journal articles in which energy modelling analyses have been performed in the North Sea region | 21 journal articles |
| 2. Total | Total list of documents included after the non-systematic review | 14 journal articles | Total list of documents included after the non-systematic review | 21 journal articles |

**Fig. 3.** Description of the methodology to search and filter the selected literature.

### 3.1. Biomass

The biomass studies screened are mainly focused on national scale. There are two different types of GIS studies applied to biomass: first, articles aiming to calculate or estimate the potential and availability of certain types of biomass [20–22], second, articles aiming to analyse optimal locations of biomass power plants based on proximity to biomass sources [23–31]. In the latter, due to the fact that the transport

**Table 1**
Search strings used in Scopus as input for the systematic review.

| Order | Search string |
|---|---|
| S3 | TITLE-ABS-KEY (gis AND energy AND modelling) AND (LIMIT-TO ( PUBYEAR, 2020) … OR LIMIT-TO (PUBYEAR, 2016) AND (LIMIT-TO ( LANGUAGE, "English") ) |
| S4 | TITLE-ABS-KEY (review AND energy AND system AND models) AND (LIMIT-TO ( DOCTYPE, "re") ) AND (LIMIT-TO ( SUBJAREA, "ENER") ) AND (LIMIT-TO ( PUBYEAR, 2020) … OR LIMIT-TO (PUBYEAR, 2018) ) AND (LIMIT-TO ( LANGUAGE, "English") ) |

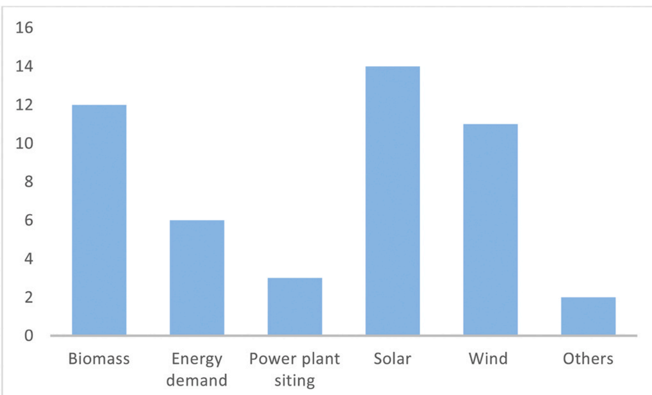


**Fig. 4.** Categorization of selected articles according to their energy application.

of biomass to the generation units entails a considerable cost, GIS approaches are used to consider distances in multiple technoeconomic assessments.

### 3.2. Energy demand

Studies related to energy demand have been found only in national and multinational scale. Two types of analysis are identified: GIS applied to buildings, in order to estimate heating or cooling demand [32–35], and GIS applied to estimate electricity consumption [36,37].

### 3.3. Power plant siting

Few studies analyse siting of different types of power plants, such as gas generators [38,39], in which GIS is generally used to geographically match supply and demand, or hydro plants [40] in which optimal areas based on geography are defined.

### 3.4. Solar and wind

GIS studies applied to solar and wind energy are probably the most popular and abundant in the literature. The studies included in this section can be divided in two categories, first, analyses in which the potentials of wind or solar across a certain area are evaluated ([41–43] in the case of solar and [44–48] in the case of wind), and second, studies where the best locations to deploy solar or wind installations are determined, considering not only meteorological conditions, but also other spatial components such as land availability, connectivity with existing infrastructure or correlation with existing energy demand ([49–59] for solar and [60–65] for wind).

### 3.5. Benefits and challenges of GIS and ESM integration

On top of the specific literature reviewed for this section, other studies analyse how GIS and ESM integration present multiple benefits to energy models, but also some challenges in order to implement them. Ref. [14] already pointed some challenges in GIS-based planning for renewable energy, such as the complexity of energy system models and geospatial models, which complicates their integration; the huge computational requirements of the resulting modelling framework; the limited availability of GIS data; or the variety of highly heterogeneous data structures, which again complicates GIS and ESM integration. Ref. [15]. also showed the benefits of GIS and ESM integration, also considering the temporal component, and analysing the impact of spatiotemporal modelling in VRE potentials and design of VRE plants. In different reviews of ESM, like [66], the role of spatial resolution and GIS-based approaches in ESMs is highlighted as one of the crucial features for modelling systems with high penetration of VRE, and it is considered an area with room for improvement in future model developments.

There are multiple benefits of GIS and ESM integration in different applications. GIS has shown promising results to calculate weather potentials, especially for wind (both offshore and onshore) and solar energy. GIS-based approaches are useful to define the optimal location of VRE plants based on meteorological conditions, but also to analyse the variability of VRE potentials across a certain territory. Note that it has been proven in the previous literature that in the case of wind energy,

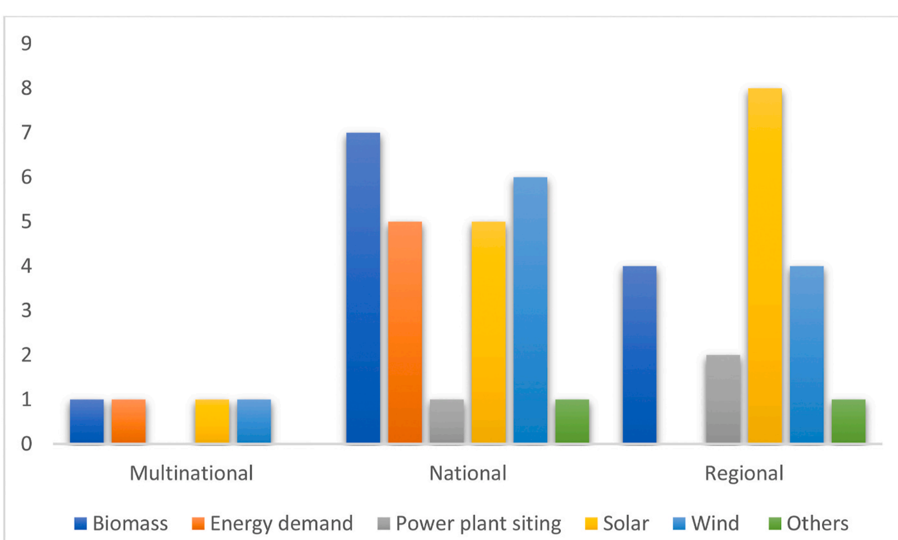


**Fig. 5.** Categorization of selected articles according to their geographical coverage.

with a proper combination of wind farm locations and considering enough interconnection between them, the energy output is more consistent than if the same locations were located in closer areas [67]. These studies proved that up to 47% of the yearly averaged wind power could be used as baseload power [68]. This shows that GIS-based analyses are important not only to increase the spatial resolution and get insights of very local parameters, but also to understand variations of certain parameters across a territory, even in national or international scales. As a consequence, a poor spatial analysis might end up underestimating this geographical variability as well as overestimating the uncertainty and flexibility requirements to balance supply and demand. GIS has also shown promising results in other areas, such as design of power, heat or gas infrastructure, for example through GIS-based routing of pipelines; interactions between biomass sources and biomass plants; and spatial interactions between supply and demand, due to the analysis of the spatial distribution of demand across a territory.

GIS-based approaches can also be beneficial to create spatial data clusters, in order to define the regions of ESMs. ESMs usually include regions which are defined according to political borders or geographical regions. Creating regions using GIS-based techniques might be a good alternative, due to the fact these resulting regions would be more balanced. For example, if we want to analyse VRE and we use political borders, some regions might have huge VRE potentials, while others might have a lower value. If we use a GIS-based approach we would define the regions based on the VRE potential data, and we will not have this problem of unbalance.

One of the shortcomings found in the integration of GIS and ESM in the literature is that most of the applications are in local scale, for example, using meteorological data to define which is the best location of a single VRE plant, or analysing the distribution of the energy demand across a city at building level. There are multiple reasons for this trend, like the huge computational requirements for GIS and ESM integration at large scale level or the lack of homogeneous data in large areas [14]. However, in the future, with improvements in computational capacities and more data availability, this knowledge gap should be covered.

It is also important to mention that the interaction of GIS and ESM is usually unidirectional, that is, the GIS analysis is used as an input for the ESM, in order to improve the quality of the results. One interesting future research avenue would be to make this interaction bidirectional, that is, to analyse the outputs of ESM using GIS analysis. For example, after running an ESM with spatial data at national level (i.e. one node per country) a GIS-based approach could be used to analyse the output of the ESM and identify different bottlenecks, such as land availability for VRE deployments or lack of transmission capacity. This information might be eventually sent back to the model in an iterative fashion.

## 4. Spatial resolution in energy system models

The objective of this section is to analyse how different energy modelling tools permit to include spatial resolution and to what extent this parameter is flexible.[1] This analysis will also include other features such as the mathematical method used in each model, or the level of sector integration, in order to find correlations (if any) between the level of spatial detail and these features. It is not the goal of this paper to analyse the general state of the art of energy systems modelling. For that purpose, the reader is forwarded to Refs. [66,69–71], where extra background on energy modelling history, classification, trends, challenges and future expectations are presented.

The systematic and not-systematic literature review presented in Section 2 permitted to collect a comprehensive set of review articles related to energy system models. Table 2 presents a summary of their goal and coverage. For the analysis pursued in this section we will use these studies and the references therein as a starting point.

Connolly et al. reviewed 37 different energy modelling tools analysing the integration of renewable energy into various energy-systems, analysing features such as the tool availability, the energy sectors considered, the geographical area and the time-step [72]. A similar review was carried out by Bhattacharyya et al. analysing and characterizing ten specific computer tools, but in this case with the aim to determine whether they were suitable for analysing energy policies in developing countries [69]. Foley et al. presented and reviewed 7 electricity system models, pointing out how their role has changed while moving towards liberalized electricity markets [73]. In Ref. [74], Després et al. proposed a new typology for long term energy models and electricity system models with a focus on future energy systems with large shares of VRE. More recently, Ringkjøb et al. reviewed 75 modelling tools in terms of their performance with large shares of variable renewable energy sources [76]. Similar studies have been carried out by Lopion et al. to analyse the future challenges of national energy models to properly account for the variability and intermittency of renewable energy sources [75]. Other publications have compared several models with a higher level of detail, for instance EnergyPLAN and H2RES [81], or NEMS and MARKAL-MACOR [82]. Also, Pfenninger et al. included future challenges such as the integration of human behaviour and social risks and opportunities [66]. Fattahi et al. [77] reviewed 19 national integrated energy system models, including also an analysis of capabilities and shortcomings of their use in low carbon energy systems. Maruf [78] included a review of 16 open source energy system models and assessed their capabilities in the context of a sector coupled scenario of the North Sea region. In Ref. [79] Prina et al. reviewed 22 energy system models with four main foci: resolution in space, in time, in techno-economic detail and in sector coupling. Finally, in Ref. [80] Groissbok et al. reviewed 31 open source energy modelling tools, in order to compare how mature are open source energy models compared to some widely used non open source models. It is important to mention that none of the previous reviews extensively analyses the trade-offs between temporal, spatial and technological resolution, and the analysis of the spatial resolution is usually reduced to investigate what is the number of regions included in the model, and how many nodes are included in each of them.

Considering only the selection of reviews proposed in Table 2, it is possible to find detailed information of more than 100 models. As the intention of this section is to analyse up to date tools which can be used in large scale applications (analysing the role of spatial resolution in tools with a local focus is to some extent contradictory) we decided to filter those models. The selection criteria are that the models should have been used after 2010, and they should have been applied at least at

**Table 2**
Selected papers analysing energy modelling tools.

| Reference | Goal | Coverage |
|---|---|---|
| Connolly el al. [72] | Renewable integration in energy models | 37 energy modelling tools |
| Foley et al. [73] | Strategic review of electricity models | 7 power system models |
| Bhattacharyya et al. [69] | Comparison and classification of energy models | 10 energy modelling tools |
| Després et al. [74] | New typology for models proposed | 35 energy modelling tools and 5 power system models |
| Lopion et al. [75] | Comparison and classification of energy models | 24 energy modelling tools |
| Ringkjøb et al. [76] | Analysis of energy models | 75 energy modelling tools |
| Fattahi et al. [77] | Analysis of energy models | 19 energy system models |
| Maruf et al. [78] | Analysis of energy models | 16 energy system models |
| Prina et al. [79] | Analysis of energy models | 22 energy system models |
| Groissbok et al. [80] | Analysis of open source energy models | 31 energy system models |

[1] In this context, we consider that the spatial resolution of a model is ‘flexible’ when it can be easily modified, that is, the number of regions/nodes and the resolution of the data can be increased/decreased.

national scale. After this filter, the number of models is reduced to 34. For the categorization of the selected models we define 6 different parameters, which are shown in Table 3.

In Table 4 the models are described according to the aforementioned parameters.

### *4.1. Methodology and mathematical approach*

The most common methodology used in the selected models is optimization. In fact, 23 out of 34 models (68%) include optimization as a methodology, while 15 (44%) include simulation. Note that 4 of the selected models include both optimization and simulation within their frameworks.

Regarding the mathematical approach, it is interesting to see that linear programming (LP) is the favourite approach, being part of 18 of the 23 optimization models (78%). This choice is reasonable taking into account that the selected models are applied at least in national scale (according to our selection criteria). Optimization problems written as LPs can be solved relatively fast, and their computational performance is much better (in terms of running time) than other approaches such as MIP or non-linear programming (NLP). Thus, when considering large scale energy systems, which means large amounts of data, it is a usual practice to use a LP approach in order to keep a reasonable computational burden. The same principle applies when multiple energy sectors are included in a model, or when a higher temporal resolution is required.

### *4.2. Geographical area and spatial resolution flexibility*

Out of the 34 selected models, 7 can be applied to the whole world (20%), while 27 can be used to analyse international scenarios (80%). These figures solely indicate the area covered by the model, but give no information about the level of spatial flexibility or how the models account for spatial data (for example, GEM-E3 [83] has a global coverage, but its resolution is fixed to 38 regions, so the level of spatial data is highly aggregated and the spatial resolution is relatively low). That is the reason why the spatial resolution flexibility parameter can provide some extra insights on this matter.

However, estimating how flexible is the spatial resolution of a model is not straightforward. From a purely theoretical perspective, most energy models are a set of mathematical equations written in a certain software. Therefore, in theory it should be possible to modify some of the parameters or equations in order to have a different spatial resolution. In reality this is not entirely true: some models do not permit to change their structure at all; others do permit it, but they are calibrated and tailor-made for a specific region, and broadening the regional scope might entail infeasibilities or computational problems.

There are two main aspects that can affect and limit the spatial resolution that an energy model can reach. The first one is the data availability. Naturally, if the resolution of a model wants to be increased but there is no data available at that precise resolution, the enhancement of the model will be imprecise or even impossible. As an example, if a model has national level resolution and is modified to account for subnational regions, but the data remains aggregated at national level, the model will fail to provide meaningful results. Data availability has indeed been pointed out as one of the main challenges in order to increase spatial resolution in energy models [14].

The second one is related to the specific formulation of each model. Some energy models are released as "black boxes", and the user is not allowed to modify the internal configuration, and therefore the spatial resolution is limited to the predefined options that the tool developer included. Other models are released under open source licenses, allowing the user to access the codes and formulations, and therefore to modify them. However, this is not a guarantee that the spatial resolution can be increased as much as possible, as at some point computational limitations might appear.

Measuring the trade-off between spatial resolution and computational performance is extremely complex, as there are multiple variables that can affect it. First, the specifications of the computer used are decisive, and a model might be successfully solved by a powerful desktop but not by a standard laptop. Second, models are usually simplified when covering larger areas in order to reduce their complexity, and therefore the comparison of the running times of the same tool with different resolutions is not valid. As an example, PyPSA has been used in case studies ranging from regional scale to international scale, with running times ranging from few minutes to multiple hours. However, each case study has a different level of technological resolution, which naturally affect the computational performance as well. Other models, like the TIMES family models, tend to use timeslicing techniques in order to reduce the temporal complexity of the problem. As a consequence, it might happen that a model with certain spatial resolution faces computational problems when solved using hourly resolution, but can be solved using multiple timeslices per year. Finally, the development of new optimization solvers, or the improvement of the mathematical formulations can also reduce the running time and permit some models to be solved.

In short, there is no generic rule to calculate or measure which is the exact spatial resolution that a model can solve in practice. In this paper, in order to set a reference point, we thoroughly review the documentation and related publications of the selected models in order to assess if they permit to modify the spatial resolution, and what different geographic coverages they have included. We consider that a model has spatial flexibility if it fulfils one of the following requirements: 1) it has been used in the literature in different areas/with different resolutions. 2) previous literature reviews on energy modelling have been pointed out that the geographical scope is variable, or that the model can cover different geographical scales. 3) the documentation of the model explicitly explains that the spatial resolution can be defined by the user.

Sixteen of the selected models (47%) permit to increase/decrease their spatial resolution. That means that the geographical coverage can be extended/reduced, and also that the resolution within each region of the system can be increases/decreased as well. As an example, the Oemof framework [84] could be extended from Germany to surrounding countries, and also the resolution of each of the countries could be increased to represent different regions.

The need of more spatial flexibility in energy models has been extensively discussed in the literature [14], and it has also been proved that recent model developments are moving towards more flexible and user-defined specifications, in both spatial and temporal resolution [84]. This trend is supposed to grow even more in the future, with expected larger penetrations of decentralized VRE.

It is important to be sceptical about how feasible it is to implement this flexibility in real case studies. From a purely theoretical point of view some models presented in Table 4 permit to increase their spatial resolution as long as there is enough data for the new regions. But in reality there are computational limitations that limit the levels of resolution in order to keep running times below a certain threshold. In the

**Table 3**
Rationale and categories used for the energy model analysis.

| Rationale | Categories |
|---|---|
| Underlying methodology | Optimization models, simulation models, econometric models, macro-economic models, economic equilibrium models, back-casting models, multi-criteria models and accounting models |
| Mathematical method | Linear Programming, Mixed Integer (linear) Programming, Mixed Integer Quadratically Constrained Programming |
| Geographical coverage | Regional, national, international, user defined |
| Inclusion of a GIS-based tool | Yes/No |
| Spatial resolution flexibility | Yes/No |
| Sectoral coverage | Electricity, heat, hydrogen, transport |

**Table 4**
Characterization of the models selected for the assessment. Abbreviations: S – Simulation; Op – Optimization; LP – Linear Programming; MIP – Mixed Integer Programming; MILP – Mixed Integer Linear Programming; MIQCP – Mixed Integer Quadratically Constrained Programming.

| Model name | Underlying methodology | Mathematical approach[a] | Geographical area | Includes a GIS-based tool | Spatial resolution flexibility | Sectoral coverage | Reference |
|---|---|---|---|---|---|---|---|
| AURORAxmp | Op&S | LP, MIP | Regional to international (used in USA and EU) | | ✓ | Electricity | [76,101–103] |
| BALMOREL | Op | LP/MIP | Regional to international | | ✓ | Electricity, district heating | [75,79,104,105] |
| Calliope | Op | LP/MILP | User defined | | ✓ | Electricity, heat, hydrogen | [75,76,79,106] |
| COMPETES | Op | LP/MIP | International, applied to the EU | | ✓ | Electricity, heat | [88] |
| DESSTinEE | S | – | 40 countries in EU and north Africa | | | Electricity | [105,107,108] |
| EMMA | Op | LP | Northwest Europe | | | Electricity | [105,109–112] |
| EMPIRE | Op | LP | 31 European countries | | | Electricity | [76,113] |
| EMPS | Op | LP | User defined | | ✓ | Electricity | [114,115] |
| EnergyPLAN | S | – | Regional to international | | | Electricity, heat, hydrogen, transport | [75,76,79,80,116,117] |
| ENTIGRIS | Op | LP | Regional to international, applied in Europe and north Africa | ✓ | ✓ | Electricity | [76,118] |
| ETM | S | – | User defined | | ✓ | Electricity, heat, hydrogen, transport | [76,119] |
| ETSAP-TIAM | Op | LP | Global, 15 regions considered | | | Electricity, heat, hydrogen, transport | [120–122] |
| EUCAD | Op | MIQCP | 24 European countries | | | Electricity | [123,124] |
| EUPower-Dispatch | Op | MIP | 32 European nodes | | | Electricity | [76,125] |
| GEM-E3 | S | – | Global, 38 regions considered | | | Electricity, heat, hydrogen, transport | [76,126,127] |
| LIBEMOD | S | – | 27 European countries | | | Electricity, heat, transport | [128–130] |
| LIMES-EU | Op&S | LP | 26 European countries | | ✓ | Electricity | [131–134] |
| MESSAGE | Op&S | LP/MIP | Global, 11 macro regions considered | | | Electricity, heat, hydrogen, transport | [79,135,136] |
| NEMS | S | – | Regional to national, applied in the United States | | | Electricity, heat, transport | [76,137] |
| Oemof | Op&S | LP/MILP | User defined | √[b] | ✓ | Electricity, heat, hydrogen, transport | [78–80,138,139] |
| OSeMOSYS | Op | LP | Regional to international | | ✓ | Electricity, heat, hydrogen, transport | [79,80,140,141] |
| PLEXOS | Op | LP/MIP/NLP | Regional to international | | ✓ | Electricity, heat | [76,79,87] |
| POLES | S | – | Global, 66 regions included | | | Electricity, heat, hydrogen, transport | [76,127,142] |
| PRIMES | S | – | Europe, recently calibrated to 11 north African countries | | | Electricity, heat, hydrogen, transport | [75,143] |
| PyPSA | Op | LP/MIP | Regional to International | ✓ | ✓ | Electricity, heat, hydrogen, transport | [79,80,105,144–146] |
| ReMIND | Op | NLP | Global, 11 regions considered | | | Electricity, heat, hydrogen, transport | [147–149] |
| REMix | Op | LP | Regional to international | ✓ | ✓ | Electricity, heat hydrogen | [79,80,150] |
| RETScreen | S | – | Regional to global | | | Electricity, heat, hydrogen | [80,151,152] |
| stELMOD | Op | MIP | Europe, with a particular focus on Germany | | | Electricity, heat | [76,105,153,154] |
| SWITCH | Op | MIP | Regional to international | | ✓ | Electricity | [80,105,155–157] |
| Temoa | Op | LP | United States (single region) | | | Electricity, heat, transport | [75,79,80,105,158,159] |
| TIMES | Op | LP | Local to global | | ✓ | Electricity, heat, hydrogen, transport | [160,161] |
| WEM | S | – | Global, including 25 regions | | | Electricity, heat, hydrogen, transport | [76,162] |
| WITCH | S | – | Global, including 13 regions | | ✓ | Electricity, heat, transport, hydrogen | [76,127,163,164] |

[a] Optimization models are divided into Linear Programming (LP), Mixed integer programming (MIP), Mixed Integer Quadratically Constrained Programming (MIQCP) or Non Linear Programming (NLP). Simulation models are not classified in terms of mathematical approach.
[b] The oemof framework includes applications like renpass-gis with high spatial resolution GIS data.

literature there has been continuous research about how temporal simplifications (timeslicing) can affect the performance of the models and the accuracy of the results [85]. However, as of our knowledge, analysing how different granularities affect the performance of energy models is a big knowledge gap.

### 4.3. Sectors modelled

Sector integration has been extensively discussed as a key element in future energy systems, in order to provide extra flexibility to the system and help to integrate larger amounts of VRE [86]. The importance of including interrelated sectors in energy models has also been defined as a key element for future energy models [5], and trends show that current tools are becoming more and more integrated [76]. Indeed, out of the selected models for this analysis, 24 (71%) include at least two different energy sectors. Even power system models, such as PLEXOS [87] or COMPETES [88], which describe in detail the electricity sector, include to some extent interactions with other energy sectors such as heat or transport. This interaction is extremely crucial to have realistic results that estimate correctly the flexibility that sector integration can provide to the system.

### 4.4. Trade-offs between features

As mentioned throughout different sections of this paper, the computational power and the state of the art of optimization solvers pose a limit to the level of detail that energy models can include. Ideally, in order to represent a realistic system, the temporal resolution should be as high as possible, the spatial granularity should be high enough to include enough spatial data, all energy sectors should be represented and nonlinearities should be included in the mathematical equations. However, it is naïve to expect all these features in an energy model as of today.

Different studies have tried to analyse how different levels of detail in those parameters can affect the performance of the model. In Ref. [89], Poncelet et al. used a TIMES model with different timeslicing methods in order to compare how different the solutions were in different long term scenarios. Similarly, in Ref. [90] also TIMES was used with a timeslicing strategy comparing the results of a deterministic scenario with multiple stochastic scenarios, pointing out that aggressive timeslicing barely captures the intermittency of VRE. In Ref. [91] multiple timeslicing strategies were compared to assess to what extent simple timeslicing methods can capture renewable intermittency. Regarding spatial resolution, in Ref. [16] different spatial resolutions were used in the same case study to compare how different granularities can affect the result in the power sector, finding out that with an appropriate clustering method different spatial resolutions could provide similar results. Finally, with sector integration, in Ref. [7] it was concluded that storage needs in energy systems are reduced if more sectors are considered in the analysis, that is, if the flexibility provided by sector integration is not taken into account models tend to overestimate the energy storage requirements. However, all these analyses evaluate how the performance of different models changes when varying only one of the parameters.

### 4.5. Models including GIS/models used in the literature with external GIS tools

The literature shows that the use of GIS in energy models has been growing during the last years. However, there is a lack of models integrating endogenously GIS tools, there is not a clear consensus on how to properly link GIS and energy tools, and in general there are many different challenges that have been discussed in the literature, such as the need of unified (spatial) data models.

The lack of endogenous integration of GIS in energy models can be exemplified attending to the selected models of Table 4. Out of them, only ReMIX, oemof, ENTIGRIS and PyPSA have an internal GIS related function. In ReMIX, this function is internally included in order to reduce processing times [92], but it only allows to calculate VRE potentials based on weather data depending on the resolution chosen (which in ReMIX, as pointed out, is flexible). In Ref. [93] it was used to analyse the Hashemite region in 2020, using GIS data of CSP, PV and wind power. In Ref. [94] it was used to analyse the potential of hydrogen storage in salt caverns in the North of Germany, but again the GIS data used was only for VRE potentials and feed-in time series with a resolution of 10 × 10 km. Another example with ReMIX is [95], where heat from biomass potential in Germany was analysed.

Other models displayed in Table 4 have been effectively used linked with different GIS-tools. In Ref. [96], EnergyPLAN was linked with a GIS tool to analyse a 100% RES scenario, but it was applied only in local scale in the city of Pompeii. In Ref. [97]. Balmorel is used to analyse the role of hydrogen in Germany in 2030, linking it with an external GIS tool to calculate infrastructure costs. In Ref. [98] RETScreen was used to investigate the potential of solar hot water system (SHW) in China at a national scale, linking it to a GIS tool at a local scale (applied to 31 capitals of China). PLEXOS has also been successfully linked with a GIS tool at a European scale [99]. Finally, TIMES family models have also been linked to GIS tools in previous reports [100].

Finally, in Ref. [80] a group of 31 energy models was reviewed, with the aim to compare the performance of open source models versus non open source models. The interesting output is that one of the parameters that they examined was the presence of a GIS related function in each one of those models. Out of the models analysed, only 7 (22%) presented an internal GIS tool, which in most cases only provided weather data for VRE potentials.

## 5. Practices found in the literature to account for spatial data in large scale energy system models

The goal of this section is to review some common practices used in the literature to include spatial resolution in energy models, ranging from aggregated methods where the spatial granularity is almost non-existent to sophisticated clustering methods. We focus on large scale systems, and therefore we only consider studies analysing at least national level.

### 5.1. No data aggregation

Although it is not a usual practice due to the high computational cost, in some previous large scale studies spatial data has been used without any type of clustering or aggregation technique. There are some reasons that can justify this choice. In some case studies local data can highly affect the results, and therefore it can be required to sacrifice other features of the model (i.e. temporal resolution or sector integration) to include spatial data without any kind of aggregation. In other cases, for instance when analysing particular scenarios of the power sector, it is required to have a detailed representation of the power network at local level. In those cases, feeding the energy model with raw spatial data may be required.

There are some examples in the literature where hardly or no spatial aggregation is used. In Ref. [99] PLEXOS is used to model the European power system with a high resolution spatial grid, of dimensions $0.75^\circ \times 0.75^\circ$. The spatial data fed to the model includes national boundaries, protected conservation areas, offshore areas with a depth up to 50 m, and weather data from the Corine dataset, with data for wind and PV generation. As a consequence of this high resolution the analysis is constrained only to the power sector, lacking the interaction of electricity with other sectors. Moreover, the temporal scale was also simplified in this case using 12 time-slices per year. A similar approach of low data aggregation is used in Ref. [165], where the grid resolution is $4^\circ \times 5^\circ$, and includes weather and power network data. Again, this level of detail requires huge simplifications. In this case, only the power sector of the US is included, and the model provides only one feasible solution, which is not guaranteed to be the optimal one.

### 5.2. Aggregated data in nodes

As mentioned and justified throughout the paper, aggregating spatial data in nodes is a usual technique in energy modelling. The main reason of the aggregation is to reduce the computational power required to run the model, but there are other reasons that may influence that choice. For example, in Europe day ahead electricity markets are cleared per zone, so every zone has a single price. Therefore, when defining the merit order curve and the equilibrium price, the underlying grid of each zone is in theory not taken into account, and generation and consumption data are aggregated per zone no matter where they are located.

There is not in the literature a description about how to aggregate spatial data. Here we suggest two different types depending on how the aggregation is done: non-optimal clustering and optimal clustering.

#### 5.2.1. Non-optimal clustering

We define non-optimal clustering as a simple method for aggregation in which only purely geographical parameters are taken into account (i.e. aggregating per country, per district, etc.). Pros of this method are that a good balance between spatial resolution and running times can be found if the number of nodes is selected carefully, and if data is available the definition of nodes is straightforward. On the other hand, the main drawback is that if no algorithm is used the resulting nodal configuration can be different than the optimal one.

This methodology has been widely used in the literature as it is the simplest and less computational demanding one. Most models without spatial flexibility (check Table 4) use this approach, as their spatial resolution is static and usually defined according to geographical regions.

#### 5.2.2. Optimal clustering

In the energy field clustering algorithms have been applied, especially over the last two decades with the increasing trend of machine learning and big data applications. Clustering has been mainly applied to the temporal scale of energy models. In Ref. [166], for example, Hoffmann et al. reviews multiple time series aggregation methods applied to energy models.

Using clustering algorithms to aggregate spatially-explicit data related to energy systems is scarce in the literature. Some GIS tools (e.g. ArcGIS) allow to create spatially constrained multivariate clusters [167]. This GIS-based clustering has been applied in multiple fields, such as demography, agriculture or urban planning. In the energy field most of the GIS-based clustering methods have been applied in local scale. For example, in Ref. [168] optimization based clustering is used to integrate district heating at city level. In Ref. [169] a GIS-based framework is used to analyse energy demand patterns in Greece.

Among the optimal clustering algorithms in the literature, there are two that have been successfully applied to large scale energy systems and show promising results. These are the k-means algorithm and the max-p regions method.

*5.2.2.1. K-means.* K-means is a very popular algorithm in data science. It was first introduced in Ref. [170], and in the last decades multiple variations and improvements have been built on top of it. Formally, the traditional k-means method can be described as a minimization problem, as described in Eq. (1).

$$\min_{S} \sum_{i=1}^{k} \sum_{x \in S_i} |x - \mu_i|^2 \tag{1}$$

Being $k$ the (desired) number of clusters, $S_i$ each cluster, $x \in S_i$ each observation $x$ included in a cluster $S$ and $\mu_i$ the mean of the observations in $S_i$.

The main benefit of k-means is that, although it is considered a computationally difficult problem (NP-hard), it can manage large amounts of data and converge relatively quickly, due to the fact that multiple algorithms to solve it have been developed in the past. Another advantage is that it has been used extensively and there is a large literature about it, and therefore it can be considered a reliable method.

As k-means is not an algorithm designed explicitly for spatial clustering, there are different shortcomings when defining regions using it. The most relevant one is that the regions delivered from the standard k-means (i.e. Eq. (1)) do not ensure contiguity. For example, if k-means is used with a dataset of solar potentials across Europe, it will group together the data values that are more similar to each other, in order to have homogeneous clusters (that is, in Eq. (1), every solar potential $x$ will be included in a cluster where the mean of solar potential data $\mu_i$ is as similar as possible). One alternative to ensure contiguity between regions using k-means is the one applied in Ref. [16], where the data used for the clustering stage is purely geographical. In Ref. [16] Brown et al. clustered a European power network dataset (including 5586 HVAC lines, 26 HVDC lines and 4653 substations) using the geographical coordinate of each data point. As a consequence, it is ensured that every point will belong to the nearest cluster. The drawback of this approach is that the resulting clusters only consider geographical data, so other features of the dataset are not taken into account, and therefore the homogeneity of the resulting clusters is not considered.

Another alternative to ensure contiguity with k-means is to include a contiguity constraint in the minimization problem (for instance penalizing distance in the objective function). In this case, clusters are defined according to a certain parameter (for instance, solar potential, as mentioned before) while ensuring spatial contiguity. However, the fact of enforcing this spatial contiguity might lessen the homogeneity of each cluster (in other words, the penalty in the objective function would affect more than the parameter itself), and it is in general not recommended [171].

Another problem with k-means is that, due to the fact that It is a NP-hard problem and convergence to the global optimum is never guaranteed, it might provide results that are arbitrarily bad compared to the optimal clustering. In order to improve that, Arthur et al. [172] proposed a variation, named k-means++, in which the initial values for the iteration are chosen following a methodology.

*5.2.2.2. Max-p.* The max-p regions problem was introduced by Duque et al. in Ref. [173]. According to the authors, the max-p problem entails the aggregation of a number of areas into a certain number of homogeneous regions, ensuring that each of the resulting regions satisfies a minimum threshold value, like for instance the energy demand per region. In this method, the resulting number of regions (clusters) is not defined by the user. The max-p problem is presented in Ref. [173] as a minimization problem. The objective function is shown in Eq. (2).

$$\min \quad Z = \left( -\sum_{k=1}^{n} \sum_{i=1}^{n} x_i^{k0} \right) \times 10^h + \sum_i \sum_{j|j>i} d_{ij} t_{ij} \tag{2}$$

where $k$ is the index of potential regions, $i$ is the index of areas, $x$ and $t$ are decision variables, $d$ is a dissimilarity relationship between areas and $h$ is a parameter calculated from $d$. The max-p problem is completed with a set of 7 constraints, more information and details of the formulation, parameters, variables and heuristics to solve it can be found in Ref. [173].

One of the problems of the max-p algorithm is that the number of resultant regions is not defined by the user, as it is delivered by the algorithm. However, the number of regions is highly correlated with the minimum threshold, and this threshold is an input to the model. Therefore, a wise choice of the threshold values can permit to constrain and estimate the number of regions that the algorithm will deliver. Another drawback is that max-p cannot handle large amounts of data. As described in Ref. [173] the formulation of max-p is a mixed integer problem (MIP) with $3n + (n-1)n^2 + n\frac{n^2-n}{2}$ constraints and $(n-1)n^2 + \frac{n^2-n}{2}$ variables, and therefore when the number of areas $n$ increases the problem becomes computationally intractable.

The max-p algorithm is very effective when clustering data that is geographically distributed across a territory. For example, in Ref. [174]

Fleischer applied the max-p method to cluster European regions considering population data, solar and wind resource potential and pumped-hydro storage capacity. In Ref. [175] Getman et al. compared the performance of k-means and max-p when clustering a large spatio-temporal dataset of solar resource data in Colorado. The dataset had a resolution of 10 × 10 $km^2$. The clusters provided by both approaches where assessed calculating two measures of consistency: sum of squares within (SSW), and $R^2$. According to these metrics max-p performed better than k-means. The reason is that k-means considered only the geographical coordinates of each data point, and therefore resulting clusters did not take into account the homogeneity of the solar resource within the cluster. Additionally, due to the fact that contiguity was not hardly imposed, some clusters included disconnected data points. The main conclusion that can be inferred from this study is that, with datasets that are spatially continuous, like solar or wind potentials, max-p is preferable over k-means if the computational complexity of the problem is tractable. K-means is therefore more suitable for discrete datasets, where there is no continuity and where geographical distances are more important than data homogeneity within the cluster[2].

*5.2.2.3. Combination of k-means and max-p.* As mentioned before, both k-means and max-p have been successfully applied for spatial clustering, but they have different strengths and weaknesses. In Ref. [171] Siala et al. propose a methodology in which both of them are combined, so their strengths are combined and their weaknesses are diluted.

The methodology is designed for cases in which contiguity between clusters and homogeneity within clusters is required, and the input dataset is too large, so that p-max cannot handle it. Therefore, what is proposed is to apply k-means++ and max-p sequentially. The complete methodology is fully described in Ref. [171], and the open source implementation can be found in Ref. [176]. In a simple way, the methodology first divides the input data in smaller cells, then applies the k-means++ algorithm to every cell to finally apply the max-p method. After that, the resulting clusters of every cell are put together, and if necessary another max-p clustering can be applied to the whole map in order to get a more reduced number of clusters.

*5.2.2.4. Others.* The literature of spatial clustering methods is extensive, and it is not the intention of this paper to review every single methodology in detail. For a more detailed review the reader is forwarded to Ref. [177] where 26 spatial data clustering methods are described.

Out of the methods not covered in this section, there are two that deserve a highlight: Skater, which stands for Spatial 'K'luster Analysis by Tree Edge Removal, and it was presented by Assunção et al. in Ref. [178], and Redcap, which stands for REgionalization with Dynamically Constrained Agglomerative Clustering And Partitioning, and was presented by Guo in Ref. [179].

### *5.3. Summary*

As a recapitulation, Table 5 provides a summary of the clustering methods evaluated in this section, including contiguity achieved, definition of the number of nodes, data tractability and extra comments.

**Table 5**
Summary of clustering methods covered in the article.

| Clustering method | Contiguity | Number of nodes | Data tractability | Comments and additional information |
|---|---|---|---|---|
| K-means | Not ensured | User defined | High | There are multiple heuristics to solve it, and it is overall pretty reliable and fast. However, resulting regions are not ensured to be contiguous. |
| Spatially constrained k-means | Ensured | User defined | High | If the contiguity constraint is very hard the homogeneity does not participate in the cluster definition, and therefore clusters are purely geographical. |
| Max-p | Ensured | Algorithm defined | Medium | It ensures contiguity and data homogeneity, but with large datasets the problem becomes intractable. |
| K-means++ with max-p | Ensured | Algorithm defined | High | It needs multiple steps and links between k-means++ and max-p, and it is challenging to automatize it. |

## 6. Spatial resolution and energy modelling in the North Sea region

As explained in the Introduction, there are multiple reasons to justify why the NSR is a relevant case study for analysing spatial aspects of the energy transition. Sections 2-5 of this paper provided insights about the interaction between spatial resolution and energy modelling. In this section we aim to focus on the NSR, in order to analyse previous modelling efforts and, with the findings and lessons learned throughout the paper, propose a methodology which permits to model the NSR while capturing relevant spatial interactions.

### *6.1. Offshore modelling in the NS region: previous studies*

Several studies have modelled and analysed the NS region from different perspectives. The majority of these studies are related to the analysis of the "North Sea offshore grid", which can be understood as the combination of offshore power generation, offshore loads and offshore interconnections. The offshore grid concept has been part of different projects during this decade, such as the North Seas Transnational Grid or the North Seas Countries' Offshore Grid Initiative.

Offshore grid projects in the literature are mainly focused on the power sector, hence paying special attention to investment and operation of power infrastructure. Studies covering other energy sectors are scarce, and they are reduced to the analysis of the role of CCS in offshore sinks. Recently some reports have emphasized the potential benefits of the interaction of offshore power and gas (i.e. power and offshore hydrogen and/or CCS), but these analyses have so far only been applied at regional scale. A global analysis (covering the whole NSR) of the offshore infrastructure including operation and investment in power and gas infrastructure is a missing piece of the puzzle, and a knowledge gap in the literature.

Table 6 summarizes the most relevant studies modelling the NS region with different spatial resolutions, including power sector, CCS and integrated setups. For a more comprehensive review of offshore power studies during the period 2010–2015, the reader is referred to Ref. [19], where Dedecca et al. analysed 26 studies from different angles. Here we aim to expand this analysis up to 2020 and with a special focus on the spatial resolution, paying special attention to the number of nodes/regions considered in each study, how these nodes/regions have been defined (i.e. defining them exogenously from the literature or defining them with a clustering method) and how many sectors are included in the assessment (i.e. only power or power/gas/CCS). Here, we also describe the interconnection typology, including radial interconnection (i.e. power generation connected to shore and countries connected via

**Table 6**
Selection of modelling studies analyzing the NS offshore network.

| Publication | Year | Description | Offshore nodes considered | Criteria for node definition | Sectoral coverage | Interconnection typologies | Model used |
|---|---|---|---|---|---|---|---|
| Dedecca et al. [182] | 2018 | Offshore power network design | 8 | Non-optimal. Based on ENTSO-E data | Offshore VRE and power interconnection | Radial and hybrid | PyPSA |
| Bermudez et al. [183] | 2019 | Offshore power network design | 15 | Non-optimal, based on NSON-DK data | Offshore VRE and power interconnection | Radial and hybrid | Balmorel |
| Strbac et al. [13] Konstantelos et al. [180] | 2014 2017 | Offshore power network design | 14 (32 in total, but not in NS) | Optimal, use of k-means algorithm | Offshore VRE and power interconnection | Radial and hybrid | DTIM |
| TenneT artificial island (conceptual) | 2018 | Offshore power network design | 1 | Non-optimal, using TenneT data | Offshore VRE and power interconnection | Radial | n/a |
| TenneT hub and spoke (conceptual) [184] | 2019 | Offshore power and gas design | 4 | Non-optimal, using TenneT data | Offshore VRE, power and gas interconnection | Radial and hybrid | n/a |
| OffshoreGrid [185] | 2011 | Offshore power network design | Case study dependent | Non-optimal | Offshore VRE, power interconnection | Radial and hybrid | Multiple models used |
| Konstantelos et al. [181] | 2017 | Offshore power network design | Case study dependent (2–6) | Non-optimal | Offshore VRE, power interconnection | Radial and hybrid | Pan-European grid model |
| Kristiansen et al. [186] | 2018 | Offshore power network design | 9 | Non-optimal | Offshore VRE, power interconnection | Radial and hybrid | Power expansion and planning model (PowerGIM) |
| Strachan et al. [187] | 2011 | Offshore CCS network design | 1 | Non-optimal, using GIS data | Offshore CCS | Radial | Combination of TIMES-MARKAL national models and TIMES pan-EU |
| Neele et al. [188] | 2011 | Offshore CCS network design | 8 | Non-optimal | Offshore CCS | Radial | PRIMES |

direct interconnectors), hub interconnection (i.e. power generation clustered in hubs which are connected to shore, and countries connected via direct interconnectors), and integrated or hybrid interconnection (i.e. power generation clustered and connected to shore, clusters connected to each other, and countries connected via direct interconnectors and via hubs connected to multiple countries). For a more detailed understanding of these typologies the reader is referred to Ref. [19], which presents a more standardized definition.

One conclusion that can be directly observed in Table 6 (see also Fig. 6) is that there is not a common trend regarding the number of nodes, their definition and the models used for the assessment. In Refs. [13,180] 14 offshore nodes are considered in the NSR. The nodes in this case are defined using the k-means method to cluster 532 offshore wind projects. Only offshore wind and investment in interconnections are considered in this analysis, and the model used is the Dynamic Transmission Investment Model (DTIM). In Ref. [181], Konstantelos et al. proposed 3 different case studies with 2, 3 and 6 offshore nodes, respectively. These case studies aimed to analyse costs and benefits of integrated interconnection versus radial interconnection, and how they are distributed between different countries. The nodes, in this case, were defined and fed into the model without using any clustering algorithm, using a tailor-made pan European power model.

In [186], Kristiansen et al. analysed the economic benefits of building an artificial power link island (PLI). For this case study, one node was defined for the PLI, and 8 more nodes were defined as offshore hubs. These 9 nodes were defined exogenously, without any clustering method. The model used was the Power expansion and planning model (PowerGIM), and the assessment included offshore wind generation and power interconnection. In Ref. [182], Dedecca et al. analysed the impact of governance in the planning of the NS offshore grid, and included 8 offshore nodes in their assessment. The nodes were taken directly from the ENTSO-E database, and therefore not using any clustering algorithm. The model used for the assessment was a MILP modification of PyPSA using a myopic approach. In Ref. [183], Gea et al. presented a similar study as in Ref. [182], but using an intertemporal approach with the Balmorel model. They included 15 offshore nodes which were taken from the NSON-DK energy system scenarios database, and assessed offshore power and investment in interconnections.

It is important to mention the two conceptual designs that TenneT (the Dutch and German Transmission System Operator) has proposed and that have inspired different studies. The first one, in 2018, suggested the creation of an artificial island in the Dogger Bank to host large deployments of wind power and to be connected to the surrounding NS countries. More recently, in 2019 the hub and spoke concept was presented [184], with a concept of multiple small hubs around the North Sea which could combine offshore generation of energy with offshore production of hydrogen, and an infrastructure consisting of both power cables and gas pipelines, the latter to transport the hydrogen to shore.

Offshore Carbon Capture and Storage (CCS) has also been analysed and modelled in the context of the NSR. In Ref. [187], Strachan et al. analysed the cost-effectiveness of $CO_2$ storage in the Utsira formation for Germany, Denmark, Netherlands, Norway and UK, using a combination of TIMES pan-EU and the TIMES model of each country, and considering different trunkline configurations, but all of them with only one offshore node (the Utsira formation). In Ref. [188], Neele et al. carried out a similar assessment, but including Central and North-west Europe, using the PRIMES model and evaluating 8 different offshore sinks in the NS, and therefore 8 nodes.

### *6.2. Proposed methodology: an integrated approach*

One of the main conclusions of the review of NSR modelling studies is that all offshore grid analyses consider exclusively the power sector, including offshore power generation and power interconnectors. CCS analyses consider different energy sectors onshore, but the offshore design is exclusively focused on gas pipelines to transport $CO_2$. The only efforts in the literature including synergies between different sectors such as power, hydrogen or CCS are either at a national level (see for instance The North Sea project [190]), or at a conceptual level, such as the Spoke and Hub proposal of TenneT. Moreover, the definition of nodes and regions for the energy models is usually non-optimal (i.e. not using clustering techniques), and the spatial analysis (e.g. land availability or synergies between activities) is low or inexistent.

In order to fill this knowledge gap, we propose a framework that includes, on the one hand, multiple sectors, so that the interactions of different offshore activities such as power, hydrogen or CCS can be

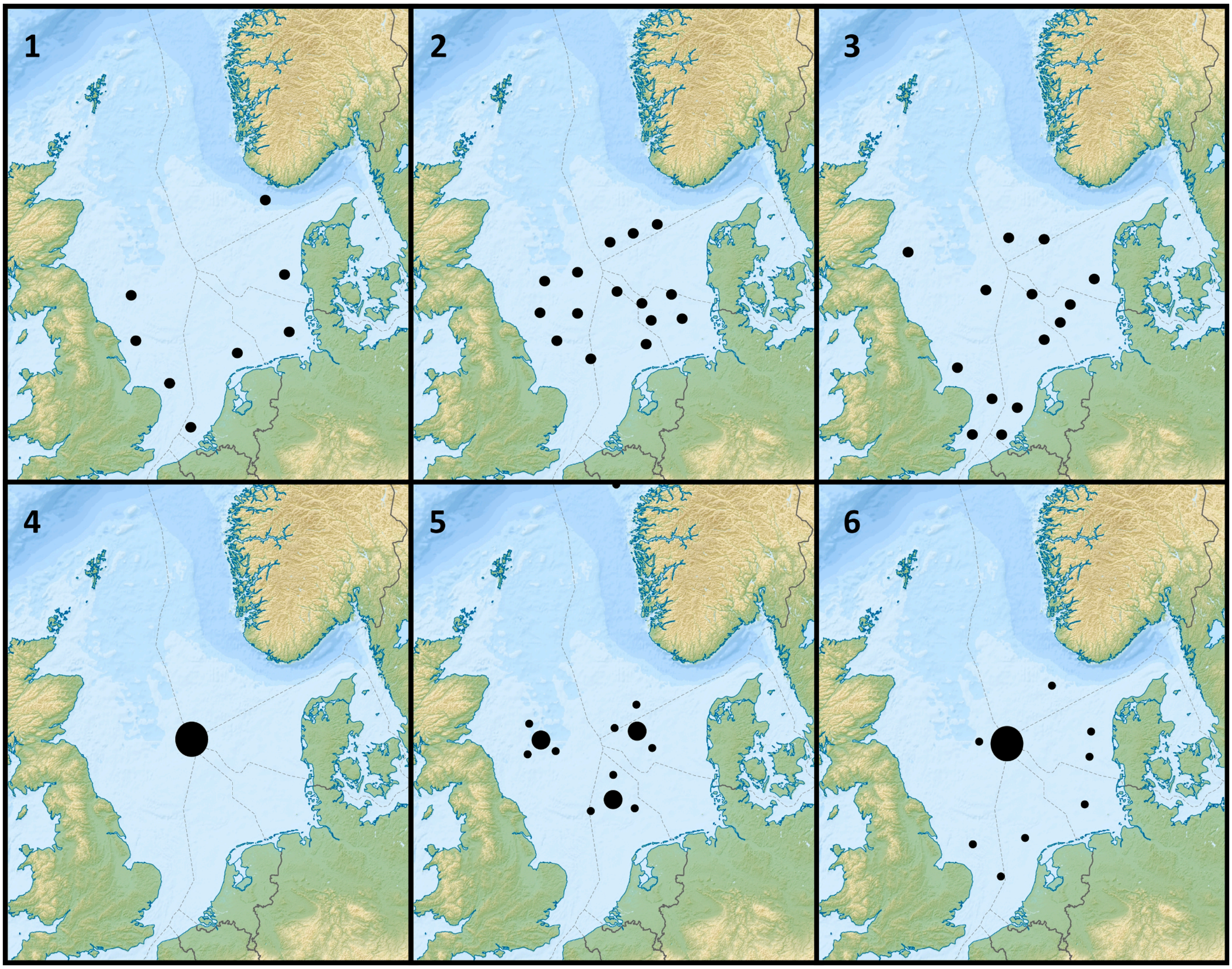


**Fig. 6.** *Sketch of the node definition of NS modelling studies. 1 corresponds to Dedecca* et al. [182]*, 2 corresponds to Bermudez* et al. [183]*, 3 corresponds to Strbac* et al. [13]*, 4 corresponds to the TenneT artificial island design, 5 corresponds to the TenneT spoke and hub concept design, 6 corresponds to Kristiansen* et al. [186]. *The NSR map is adapted from Wikimedia Commons* [189].

analysed; and on the other hand, an optimal definition of offshore nodes or regions through spatial data clustering algorithms.

For the spatial data clustering stage, we propose a variable number of nodes depending on the specific topic of the case study. The reason of proposing a variable number of nodes is because depending on the research question the node definition can have a high effect on the results. For example, it the main objective is to analyse the offshore power network, the main drivers to define the nodes will be the VRE potentials, planned offshore project locations and cable costs. If we also want to analyse offshore hydrogen production other variables should influence the node definition, such as suitable locations for electrolyser placement. If CCS is part of the analysis, $CO_2$ sinks, available pipelines and cost of new pipelines should also be part of the node definition. In short, a variable number of nodes allows that our methodology can be suitable for different analyses and case studies.

For the modelling framework the proposal is to include a power system model soft-linked with an integrated energy model. Soft-linking specific power system models with integrated energy system models is a usual approach in the literature, as it allows to combine the strong points of each of them: on the one hand, the high level of sectoral detail of the power system models, and on the other hand the broad sectoral coverage and high technological resolution of integrated energy system models. Furthermore:

1) Power system models usually have a high temporal resolution compared to integrated energy system models. This factor is crucial when analysing systems with a large penetration of intermittent renewable energy sources, due to the fact that large variations in power generation can happen in short periods of time. On the other hand, integrated energy system models usually work with lower resolutions (usually simplifying large periods into time-slices). This simplification has been proved to be sub-optimal and can lead to significant underestimations of the need for balancing resources.
2) Integrated energy system models include more energy sectors (usually at least electricity, gas and heat). Thus, outputs of these models capture interactions between different technologies/sectors and allows to understand energy systems from a global point of view. On the other hand, power system models are usually highly specified, focusing on the power sector only.

### 6.2.1. Models assessment

It is not the goal of this paper to choose a unique set of models for the analysis of the NSR, but to propose a framework that can be used with different tools to answer different research questions. In order to narrow down the tool selection, the list of 34 models analysed in Section 3 will be assessed in terms of the rationale shown in Table 7. Table 8 and

Table 9 classify the energy models of Section 4 (Table 4) according to the mentioned rationale.

*6.2.2. Node definition and soft-linked framework*

A graphical representation of the framework is presented in Fig. 7, including different stages and data inputs and outputs. The first part of the methodology includes the spatial data gathering, the GIS and analysis of these data, the optimal node definition using spatial data clustering algorithms, and the input of the defined nodes to the desired modelling framework.

The GIS and spatial analysis comprises 4 main categories. First, spatial claims, which comprise land reserved for military use, land reserved for energy uses, land for transportation, land for fisheries, land for recreation and sand extraction activities. From this analysis the land availability can be derived. Second, the $CO_2$ sink data, which includes the potential location and storage capacity of $CO_2$ sinks. Third, the $CO_2$ source data, which includes $CO_2$ emissions and locations around the NS region. From these two last categories, potential trunklines from sources to sinks can be obtained. Finally, infrastructure data, which comprises offshore gas pipelines and power lines.

In the node definition or clustering stage the clustering algorithm is applied to derive the distribution of nodes. The inputs to the algorithm are the existing infrastructure, the potential trunklines, the VRE potentials -which are a result of the combination of land availability and meteorological time series-, the planned offshore VRE projects and the desired number of nodes, which in general is a technical limit that the modelling framework imposes due to computational limitations.

Finally, the last stage comprises the input of the defined nodes to the modelling framework, which in other words means to modify the number regions considered within the models.

It is important to remark that this methodology can be applied for different case studies or modelling frameworks. For instance, if in a case study the $CO_2$ storage is going to be disregarded, the potential trunklines and existing gas infrastructure can be omitted into the clustering algorithm. If a case study wants to consider only planned VRE deployments, the VRE potentials can also be removed.

Finally, Table 10 shows a collection of up-to-date datasets that can be used as input for the proposed methodology, including offshore wind potentials, offshore VRE planned projects, available $CO_2$ sinks, offshore infrastructure and offshore land availability.

The last part of the framework comprises a soft link of the chosen energy system model and power system model. There are fundamentally two decisions that are extremely relevant when deciding how to soft-link a power system model and an energy system model. The first one is whether the data flow between the models is going to be iterative, or the output of one model is only going to be used as an input of the other without any iteration. The iterative fashion is in theory more accurate, but it has important drawbacks: it can be computationally demanding, as both models have to be run an undetermined number of times; finding the convergence between both models can be challenging, it might happen that the solutions do not converge; and the processing of data (i.e. aggregating/disaggregating data and timeslices) is multiplied as the number of iterations increase. As a consequence of these drawbacks, we decide for our framework to choose a one-direction soft-link, where one model feeds its output to the other model, and therefore only one run per model is required.

The second decision is defining which model is going to be run first, and which one is going to receive the input from the other. For our case we decide to have the energy system model as the first step, and the power system model as the final one. With this sequence, the energy system model can provide a comprehensive overview of all the energy sectors of the NSR, whereas the power system model can receive most of this information as an input (i.e. electricity demand, hydrogen demand, $CO_2$ emissions of multiple sectors, etc.).

It is out of the scope of this paper to define what are the exact data flows and interactions in the soft-linking part of the framework, as it is something that will depend on the models chosen, on the case study and on the data available. In Ref. [196], for example, a detailed description of a soft-linking methodology between TIMES and PLEXOS is explained in detail. This soft-linking methodology has also been implemented and further developed in Refs. [197,198], and can be used as a starting point

**Table 7**
Wish-list of features of the models included in the framework.

| | |
|---|---|
| Models included | Power system model and integrated energy model |
| Spatial coverage | At least NSR and surrounding countries |
| Spatial resolution flexibility | Both models should include spatial resolution flexibility |
| Temporal resolution | The power system model should have hourly resolution |
| Sectoral coverage | The integrated energy model should cover power, heat, hydrogen and CCS |
| Others | Choice of open-source models |

**Table 8**
Assessment of power system models.

| | Geographical coverage | Temporal resolution | Spatial resolution flexibility | Open source |
|---|---|---|---|---|
| Desired | NS and surroundings | Hourly | Yes | Yes |
| AURORAxmp | ✓ | ✓ | ✓ | |
| COMPETES | ✓ | ✓ | ✓ | |
| DESSTINEE | ✓ | ✓ | | ✓ |
| EMMA | ✓ | ✓ | | ✓ |
| EMPIRE | ✓ | | | |
| EMPS | ✓ | | ✓ | |
| ENTIGRIS | ✓ | ✓ | ✓ | |
| EUCAD | ✓ | ✓ | | |
| EU-Power Dispatch | ✓ | ✓ | | |
| LIMES-EU | ✓ | | ✓ | |
| PLEXOS | ✓ | ✓ | ✓ | |
| SWITCH | ✓ | ✓ | ✓ | ✓ |

**Table 9**
Assessment of energy system models. Models including an * have a global geographical coverage. Therefore, even though they include the NSR and surroundings, the level of aggregation is so high that they are not suitable for the analysis.

| | Geographical coverage | Sector integration | Spatial resolution flexibility | Open source |
|---|---|---|---|---|
| Desired | NSR and surroundings | Electricity, heat, hydrogen | Yes | Yes |
| Balmorel | ✓ | | ✓ | ✓ |
| Calliope | ✓ | ✓ | ✓ | ✓ |
| EnergyPLAN | ✓ | ✓ | | ✓ |
| ETM | ✓ | ✓ | ✓ | ✓ |
| ETSAM-TIAM | * | ✓ | | |
| GEM-E3 | * | ✓ | | |
| LIBEMOD | ✓ | | | |
| MESSAGE | * | ✓ | | |
| NEMS | | | | |
| Oemof | ✓ | ✓ | ✓ | ✓ |
| OSeMOSYS | ✓ | ✓ | ✓ | ✓ |
| POLES | * | ✓ | | |
| PRIMES | ✓ | ✓ | | |
| PyPSA | ✓ | ✓ | ✓ | ✓ |
| ReMIND | * | ✓ | | ✓ |
| REMIx | ✓ | ✓ | ✓ | |
| RETScreen | ✓ | ✓ | | ✓ |
| sTELMOD | | | | ✓ |
| Temoa | | | | ✓ |
| TIMES | ✓ | ✓ | ✓ | |
| WEM | * | ✓ | | |
| WITCH | * | ✓ | ✓ | |

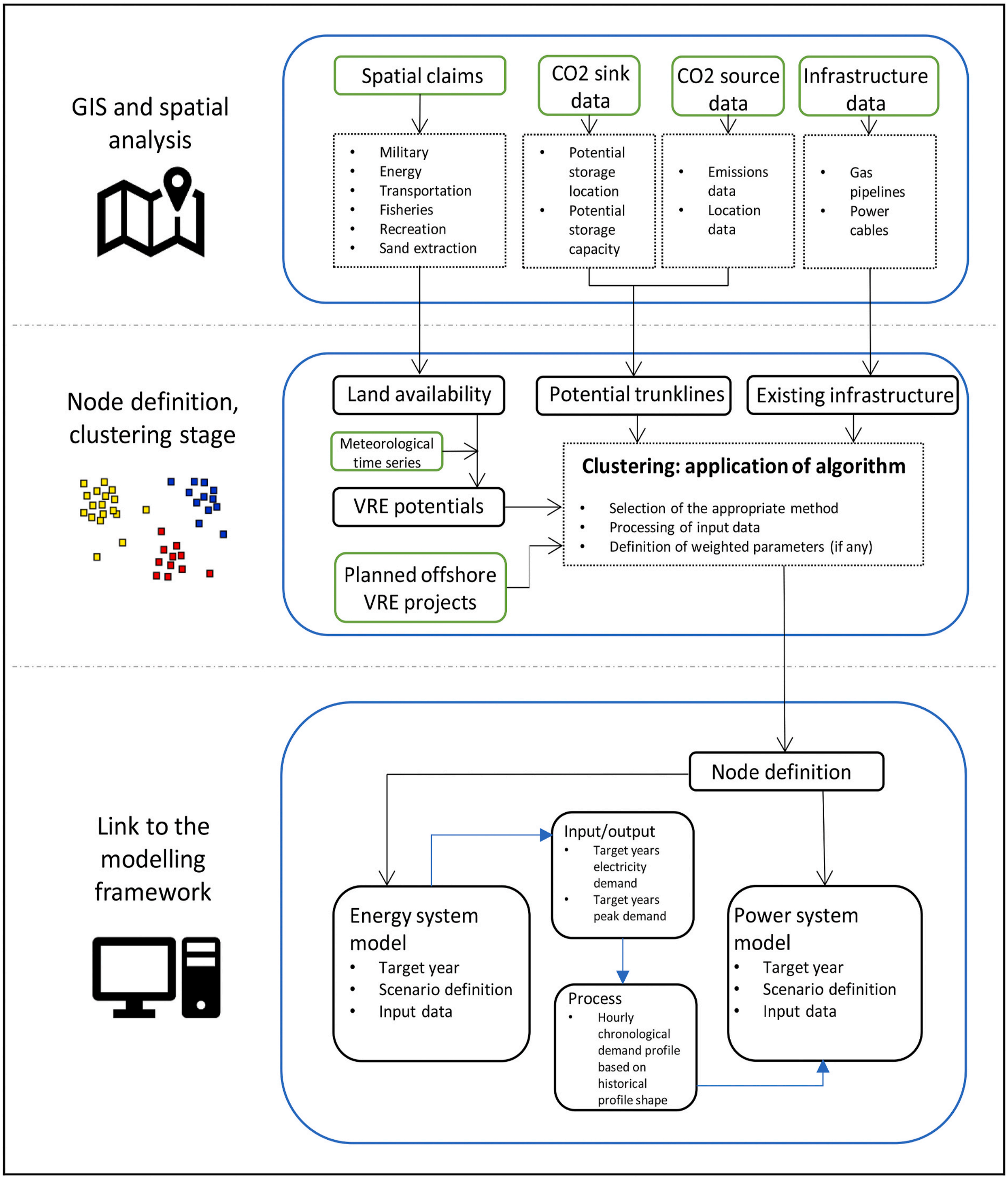


**Fig. 7.** Flowchart including the methodology to define the nodes of the case study and its application to the modelling framework.

in order to properly soft-link the selected models for the analysis.

## 7. Lessons learned, conclusions and future research avenues

In this paper we aimed to present a comprehensive review of the role of spatial resolution in energy planning, modelling and analysis, including how GIS and spatial resolution are applied in recent reports and publications, how different energy models tackle spatial resolution and GIS-based modelling and what are the most used techniques to aggregate spatial data into nodes in the literature. From this review, we aimed to apply the reviewed knowledge to the North Sea region.

The first part of this paper presented a review of the literature publications in which GIS or spatial analyses have been used for studying energy systems, at local, national and international level. The review showed that this type of analysis is relevant to study how meteorological conditions can affect renewable energy production, to assess infrastructure investment needs and costs, including gas pipelines, transmission power grid or district heating network, and to consider allocation of resources, such as correlations between location of storage and energy production sites, correlations between $CO_2$ capture and $CO_2$ storage or correlations between generation plants and biomass sources. GIS-based modelling approaches show multiple benefits compared to non-spatially explicit energy modelling approaches. Regarding meteorological conditions, some GIS-based approaches

**Table 10**
List of data sets required for the clustering stage and data sources.

| Data input | Source | Reference |
|---|---|---|
| Offshore wind potentials | Renewables.ninja | [191] |
| Offshore wind planned projects | Emodnet, OSPAR and 4coffshore databases | [192–194] |
| Available offshore $CO_2$ sinks | Emodnet database | [192] |
| Available oil & gas infrastructure | Emodnet database | [192] |
| Exclusion areas/space availability | A spatial analysis of potentials for suitable clean energy infrastructure locations in the NSR | [195] |

permit to calculate VRE potentials (mainly wind and solar) with high accuracy, considering resolutions that can reach the order of magnitude of kilometres. GIS-based approaches also permit to identify best locations for VRE deployments, considering high resolution VRE potentials, land availability and other constraints that cannot be included in non-spatially explicit energy models. Regarding infrastructure, GIS approaches permit to define the cost-optimal routing of pipelines, cables and different networks, considering distances, infrastructure cost and areas where the infrastructure cannot be deployed. This also applies to $CO_2$ capture and storage, where GIS-based modelling can be used to identify possible links between $CO_2$ sinks and sources, considering distances between them. These multiple benefits could be used to improve the quality of energy modelling results, but this link between GIS-based approaches and large scale energy models is not straightforward, as it also presents certain challenges. On the one hand, GIS approaches normally use large amounts of spatial data, which can reach the order of magnitude of meters/kilometres. Incorporating this data to large scale energy models, even after processing or aggregating it (i.e. by means of clustering techniques) might result in intractable problems due to the huge computational requirements. On the other hand, the lack of homogeneous data structures poses a challenge to this integration between GIS and large scale energy models. In some cases GIS data is defined at a very local scale, and therefore the data might be structured and processed in a different way from one region to another. As a consequence, including this data in large scale energy models might require different harmonization steps in order to have an homogeneous database.

The second part presented a review of 34 energy modelling tools (including integrated energy models and power system models). This review included a description of the geographical area covered by each model, whether the spatial resolution of each model could be modified (the so called “spatial resolution flexibility”), and other modelling features such as technological detail, underlying methodology or mathematical approach. These features were used to try to understand if there is a trade-off between these features and the spatial resolution of the models concerned. The review showed that there are currently multiple models that permit to include tailor-made spatial resolution by increasing or decreasing the number of regions in the system. This trend is especially noticeable in open source models, due to the fact that open code eases the inclusion of modifications in the model structure. Out of the 34 models included in this assessment, 16 (47%) permit to include regional coverage, reaching at least NUTS2[2] level. Out of these 16 models, 13 (81%) include what we defined as spatial resolution flexibility. These numbers show that, with current computational capabilities, it is possible to incorporate regional analysis in available large scale energy models covering subnational levels. When it comes to higher levels of resolution of spatial data (e.g. NUTS 3 level or above, or local resolutions employed in typical GIS datasets) the integration is still a challenge and entails usually prohibitive running times.

The third part of the review focused on different practices found in the literature to account for spatial data in large scale energy systems. The practices found can be classified into no data aggregation, aggregation of data in geographical regions and aggregation of data through mathematical algorithms. This review showed that k-means and max-p are, as of today, the most popular clustering algorithms that have been used for spatial data analyses in the energy field. Spatial data clustering is heavily developed in other sectors, such as demography, urban planning or agriculture. Therefore, future research should try to export the lessons learned from these sectors to the energy field. K-means has been proved as a very powerful algorithm in terms of data tractability. Literature shows that k-means can be applied at continental scale with spatial data resolutions of under 1 km.[3] In the case of Europe, there are examples of k-means applied to datasets of up to $10^8$ data points. Considering typical resolutions of GIS and spatial data, it can be stated that, with current computational capabilities, k-means can be effectively used with any kind of spatial data resolution in large scale energy models. The shortcoming of k-means is that in general it does not ensure contiguity between the regions created, and therefore if it is applied to data that is not strictly geographical (i.e. coordinates) results might be misleading. Max-p is proved as an efficient algorithm to create regions that are contiguous and homogeneous, but it becomes intractable when the amount of input data reaches a certain threshold. GIS data falls within this threshold, and therefore max-p requires pre-processing and aggregation of high resolution data in order to provide meaningful results. In this regards, literature also pointed out the combination of k-means and max-p as a promising alternative for cluster creation when contiguity is required and the input datasets have very high resolutions.

In the last section the North Sea region was presented as a potential case study focusing on the spatial aspects of this region. Previous publications doing modelling exercises in the NS region were reviewed, including offshore grid projects and offshore CCS projects. First, we presented a case study which is innovative and contributes to the literature. We identified two knowledge gaps in the literature, which are the lack of offshore integrated energy modelling, due to the fact that most studies are focused only on one energy sector; and the lack of spatial analysis while defining the offshore regions of the modelling framework. We therefore proposed a case study including multiple energy sectors (i. e. power, hydrogen and CCS) and a regionalization based on spatial data analysis. Second, due to the particularities of the NSR, and based on the literature review, we proposed a modelling framework to analyse the defined case study. The framework, which was described in Fig. 7, includes GIS and spatial data analysis for the data input, a clustering stage, and a soft-link between a power system model and an energy system model. Finally, in order to understand which available energy models are a good match for our case study, we assessed the 34 large scale energy models reviewed in Section 3 according to a rationale. Our rationale required that both models cover at least the NSR and surrounding countries, that the power system model includes hourly resolution, that the energy system model covers at least power, heat, hydrogen and CCS, that both models include the so called “spatial resolution flexibility” and, if possible, that models are open source. After applying this rationale, 5 power system models (1 open source and 3 non open source) and 7 energy system models (5 open source and 2 non open source) fulfilled the minimum requirements.

In short, spatial resolution has been proved to be beneficial when analysing energy systems, especially when large deployments of VRE are considered. The role of spatial resolution is crucial to, for example, analyse bottlenecks in the transmission grid, assess VRE potentials based

[2] https://ec.europa.eu/eurostat/web/nuts/background.

[3] For example, a dataset of operating windfarms is not continuous, it is formed by discrete points with certain coordinates. When clustering, we most likely want to group wind farms that are close to each other rather than clustering wind farms that are far away but are similar in certain features.

on the location, understand geographical variations of energy demand or improve the design and routing of energy infrastructure (e.g. interconnectors or gas pipelines). Multiple energy models used as of today already permit to increase their spatial resolution, and the development and improvement of spatial data clustering algorithms permit that higher spatial resolutions can be incorporated to energy models at an affordable computational cost.

### 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

| Ref | Year | Short description | Category | Geographical coverage | |
|---|---|---|---|---|---|
| [199] | 2019 | Analysis of land suitability for hydrogen production from solar energy in Algeria | Others | National | 1 |
| [44] | 2020 | Use of satellite data to estimate potentials for wind power production in Sardinia | Wind | Regional | 2 |
| [41] | 2019 | GIS based model developed to estimate the large scale PV potential in China | Solar | National | 3 |
| [32] | 2019 | GIS based model developed to estimate global heating and cooling demand | Demand | Multinational | 4 |
| [33] | 2020 | Data driven GIS methodology to predict the energy performance of Irish houses | Demand | National | 5 |
| [40] | 2019 | GIS methodology to estimate the potential of PHES in Iran | Plant | National | 6 |
| [49] | 2019 | Optimal site selection of PV power plants in southern Morocco | Solar | Regional | 7 |
| [50] | 2020 | GIS based methodology to identify optimal locations of PV plants in Brazil | Solar | National | 8 |
| [200] | 2020 | Use of GIS and remote sensing to identify geothermal sites | Others | Regional | 9 |
| [38] | 2020 | Siting and sizing of biogas plants in Turkey | Plant | Regional | 10 |
| [52] | 2019 | GIS and MCDM tool to analyse feasible placements of solar PV in Mauritius | Solar | Regional | 11 |
| [53] | 2019 | GIS based analysis to determine optimal areas for installation of PV plants in Iran | Solar | National | 12 |
| [23] | 2020 | GIS based analysis of a 100% RES system in Australia with emphasis on biomass | Biomass | National | 13 |
| [24] | 2019 | GIS based framework to allocate biomass sources and facilities in Bolivia | Biomass | National | 14 |
| [60] | 2019 | GIS assessment of potential locations for wind power in Poland | Wind | National | 15 |
| [20] | 2020 | GIS based modelling of availability of residual biomass in Mexico | Biomass | National | 16 |
| [25] | 2020 | Techno-economics of a biomass based electricity generation facility in Bolivia | Biomass | National | 17 |
| [21] | 2020 | GIS based model to assess availability of biomass in Czech Republic | Biomass | National | 18 |
| [54] | 2020 | Use of a GIS based tool to analyse optimal placement of PV plants in West Bengal | Solar | Regional | 19 |
| [55] | 2020 | GIS, RS and MCDM use to define suitable locations for PV locations in North Egypt | Solar | Regional | 20 |
| [26] | 2020 | GIS approach to identify optimal location of biogas plant based on biomass availability | Biomass | Regional | 21 |
| [61] | 2020 | GIS and MCDM to analyse optimal siting of bottom fixed offshore wind in Aegan Sea | Wind | Regional | 22 |
| [62] | 2018 | GIS based model for wind farm site selection in Nigeria | Wind | National | 23 |
| [56] | 2019 | GIS based model combining legal and environmental aspects for wind siting in Valencia | Solar | Regional | 24 |
| [63] | 2016 | GIS based model to assess offshore wind economic feasibility in UK | Wind | National | 25 |
| [39] | 2019 | GIS and AHP based process to assess optimal plant siting of a gas unit in Esfahan (Iran) | Plant | Regional | 26 |
| [34] | 2020 | GIS approach combined with a building model to assess energy demand in Algeria | Demand | National | 27 |
| [42] | 2016 | Technical potential of solar generation in South East Asia using satellite radiation data | Solar | Multinational | 28 |
| [27] | 2020 | GIS method based on LISA to assess optimal location of bioenergy plants in Queensland | Biomass | Regional | 29 |
| [28] | 2018 | GIS based framework to match biomass resources and demand in co-fired plants in EU | Biomass | Multinational | 30 |
| [45] | 2020 | GIS based method to calculate wind potential and suitable placement in Saudi Arabia | Wind | National | 31 |
| [64] | 2017 | GIS combined with MCDM analysis to assess locations of wind energy in Saudi Arabia | Wind | National | 32 |
| [22] | 2020 | GIS based method to predict technical potential of biomass production in China | Biomass | National | 33 |
| [35] | 2016 | Bottom-up GIS based model to forecast energy consumption until 2040 in Algeria | Demand | National | 34 |
| [57] | 2020 | Geospatial approach used to identify suitable areas and potential of CSP in South Africa | Solar | National | 35 |
| [29] | 2018 | GIS based model used to identify favourable locations for biomass facilities | Biomass | Regional | 36 |
| [30] | 2018 | GIS and MCA used to identify optimal locations of biomass plants in Tasmania | Biomass | Regional | 37 |
| [58] | 2016 | GIS method to analyse PV potential considering existing grid infrastructure in Tibet | Solar | Regional | 38 |
| [31] | 2019 | GIS combined with mathematical programming to optimize biomass processing | Biomass | Mexico | 39 |
| [65] | 2018 | GIS tool used to select suitable sites for offshore wind in the coast of South Korea | Wind | Regional | 40 |
| [59] | 2017 | GIS and MCDM method to assess suitable locations for solar PV in Saudi Arabia | Solar | National | 41 |
| [36] | 2017 | GIS used to identify spatial patterns in energy demand in Greece | Demand | National | 42 |
| [51] | 2018 | GIS combined with fuzzy logic model to analyse site selection for PV in Markazi | Solar | Regional | 43 |
| [43] | 2020 | Spatiotemporal analysis using GIS tools to assess solar energy potential in Jubek | Solar | Regional | 44 |
| [37] | 2017 | Linear regression model to analyse electricity demand patterns in China | Demand | National | 45 |
| [46] | 2018 | GIS platform used to analyse technical potential of offshore wind along the China coast | Wind | Regional | 46 |
| [47] | 2018 | Use of a GIS based methodology to generate estimates of global wind potentials | Wind | Multinational | 47 |
| [48] | 2017 | GIS mapping and analysis of technical potential of wind generation in Thailand | Wind | National | 48 |

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