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Unraveling the spatial complexity of national energy system models: A systematic review

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A R T I C L E I N F O

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A B S T R A C T

The energy transition poses spatial planning challenges owing to reliance on renewable sources, featured by a decentralized nature and substantial space requirements. Developing national energy system models capable of integrating spatial details while being robust enough for coherent policy development remains challenging. This study aims to review and analyze necessary spatial modeling details at the national level and methodologies for integration into energy system models. We conduct a systematic literature review on integrating spatially dependent parameters in bottom-up energy system models. The essential role of spatial aspects is highlighted by introducing a classification system for comparing energy system models. We critically evaluate and explore various approaches for assessing spatially dependent parameters in energy systems (energy sources, demand, and infrastructure), spatial aggregation methods (clustering and regionalization), and linking techniques (soft-linking and hard-linking) for incorporating spatially dependent parameters into the energy system models. Results show that energy system models have some spatial capabilities, yet certain crucial elements, like energy infrastructure distribution, are highly aggregated or neglected. Clustering methods can effectively capture spatial variations, and soft-linking techniques can incorporate these spatial details into the energy system model. Here, we propose a novel framework to facilitate the integration of spatial elements into energy system model, a spatial converter to exchange information with the energy system model, a detailed energy system model, and a converter to exchange feedback to the spatial model. Additionally, we advocate for using a soft-linking method with a recursive procedure to exchange feedback between the energy system model and spatial model.

List of Abbreviations

ESM	Energy System Model
RE	Renewable Energy
RES	Renewable Energy Source
GHG	Greenhouse Gas Emissions
CCUS	Carbon Capture, Utilization, and Storage
CGE	Computable General Equilibrium
GMPV	Ground-Mounted Photovoltaic System
GDP	Gross Domestic Product
HVAC	High Voltage Alternating Current
HVDC	High Voltage Direct Current
TSO	Transmission System Operator
VRES	Variable Renewable Energy Source
PHS	Pumped Hydro Storage
GIS	Geographic Information System
OWPP	Offshore Wind Power Plant
LiDAR	Light Detection and Ranging
PV	Photovoltaic
HV	High Voltage
MV	Medium Voltage
LV	Low Voltage
DH	District Heating
LCOE	Levelized Cost of Electricity
NPV	Net Present Value
EU	European Union
LP	Linear Programming
MILP	Mixed-Integer Linear Programming
IWH	Industrial Waste Heat
NUTS	Nomenclature of Territorial Units for Statistics

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1. Introduction

Transition to a net-zero energy system poses spatial planning challenges due to increased reliance on renewable energy sources (RES) and corresponding infrastructure [1,2]. The decentralized nature of renewable energy (RE) and the uneven spatial and temporal distribution of energy demand and supply affect storage and logistics. Renewable technologies require more space aboveground and belowground for transportation, distribution, conversion, and storage compared to conventional systems [3,4], making energy infrastructure a primary land use nowadays [1]. The spatial configuration of an energy system affects its capacity as RE suitability varies across regions owing to location-specific factors, such as climate conditions, landscape, and local economic activities [5]. Climate change and environmental disasters pose further uncertainties to future energy system planning, especially for deploying RESs [6], which rely on weather conditions and are more susceptible to these changes [7]. The energy transition is challenging owing to the lock-in effect, path dependency due to high investments, and long construction times of energy infrastructure [8,9]. The visibility of many RE technologies, e.g., wind technology, can impact social acceptance, leading to opposition from affected actors [10]. In addition to technical significance, energy transition has potential socio-economic and health implications at the regional scale [11]. The deployment of RESs and its required infrastructure can contribute to promoting regional economic growth [12,13], increase new job opportunities [14], and reduce CO2 emissions [13]. Therefore, transitioning to a net-zero energy system requires a significant spatial reconfiguration [4], especially in densely populated regions with limited land availability [5]. Spatial planning facilitates energy transition, long-term land use change dynamics, potential spatial conflicts among multiple land uses, and considering stakeholders' perspectives [15,16]. To accelerate the energy transition, it is vital to grasp the space requirements for various energy system components, such as RE technologies, storage, pipelines, cables, and electrolyzers [17], as well as the impacts of spatial configurations on system performance and costs. For example, the potential of solar and wind fluctuates with varied weather conditions, highlighting the importance of efficient storage and transmission systems, which depend on spatial and temporal co-occurrence [18].

Energy System Models (ESMs) can be instrumental in providing solutions for specific policy questions [19], assessing energy-related policies' effects, and evaluating energy transition pathways [20,21]. ESMs incorporate the interactions of energy resources, demands, infrastructure, and storage [19]. ESMs are broadly classified as bottom-up or top-down [22]. Top-down models, like computable general equilibrium (CGE), focus on the macroeconomic system, considering policy and market impacts without detailed technological analysis [23,24]. However, bottom-up ESMs are partial equilibrium representations of energy sectors [25], structured as optimization problems to estimate cost-optimal solutions within technical and policy constraints [26]. Bottom-up ESMs provide future energy system pathways, boundary conditions for reducing greenhouse gas emissions (GHG) [22], detailed sector-specific insights [25], and solutions to balance between energy supply and demand [27]. Bottom-up models can be classified by temporal and spatial resolution, sector coupling, and their adopted modeling approaches [28].

Bottom-up ESMs integrated with spatially dependent parameters facilitate evaluating the feasibility and spatial requirements of deploying energy system components in real-world scenarios [29]. For example, this integration assists in identifying the location of energy demands, potential RES, and energy infrastructure, which can be unevenly distributed nationwide [30,31]. Spatial planning harmonizes land use regulations and policies that either restrict or promote the adoption of RE technologies [32]. Spatial analysis also supports the development of energy infrastructure to store, transport, and distribute the energy generated by RESs across the regions. Spatially explicit energy planning is crucial for evaluating land availability for RESs, assessing the spatial claims among land uses, and analyzing the compatibility of RE technologies in specific areas [16].

Choosing an optimal spatial resolution in ESMs is essential for balancing necessary details and managing computational loads [33–35], as it affects the model's ability to project system costs realistically [36]. Increasing spatial details in ESM poses a challenge owing to complexity, data-intensive computing, limited data availability, and diverse data structure [31]. Spatially explicit models aid in capturing transmission and distribution congestions [37] and estimating potential resources accurately, particularly in RE-dependent energy systems [37,38]. The results of ESMs are strongly influenced by spatially sensitive parameters, such as heat demand and RE potential, necessitating high-resolution spatial approaches [39]. Regarding spatial resolution, ESMs are classified into single-node or multi-node models [40]. Single-node models are assumed to be a perfect transmission system without internal bottlenecks or losses, while multi-node models incorporate grid bottlenecks and transmission constraints. However, spatially explicit models generate more realistic results but also increase the computational loads [22,31]. Spatial aggregation methods reduce data volume and simplify ESMs to address this challenge [36].

Future country-wide ESMs could enhance their flexibility to incorporate spatial details. Country-wide ESMs have some spatial capabilities, yet certain crucial elements are limited or overlooked. Firstly, explicitly addressing spatial resolution, particularly energy infrastructure, is essential, yet it is often limited in many ESMs. Despite its vital role in the cost of future energy systems, many ESMs have overlooked bottlenecks and aggregated networks into single nodes. For instance, unlike power networks, most ESMs often overlook heat, gas, hydrogen, methane, and CCUS [37–39] or represent these components in a single node. Secondly, incorporating inputs from spatial planning into ESM is beneficial for optimizing and designing future pathways. Climate change, biodiversity, and landscape protection significantly influence a country's spatial layout. ESMs can benefit from spatial planning that considers these factors alongside spatial dynamics such as population growth, urbanization, and industrial transformation. Notably, spatial planning is not often included in current country-wide ESMs, and land use assessment is overlooked [28,41] or limited to evaluating RES potential [42,43]. Thirdly, enhancing future ESMs with bidirectional data exchange with a spatial model could help identify potential bottlenecks, such as land availability or infrastructure capacity constraints [31]. Lastly, enabling scalability from the national to the regional level can enhance the model's adaptability.

Integrating country-wide ESMs and spatially dependent parameters is an emerging field, and the relevant literature on the topic needs to be more extensive. Martínez-Gordón et al. [31] conducted a holistic review of the importance of spatial resolution in ESMs. They proposed a spatially explicit framework for the North Sea region to integrate offshore energy by addressing spatial planning challenges. Aryanpor et al. [36] critically reviewed the spatial resolutions of various national energy system optimization models, highlighting their impacts on scenario insights and the trade-off between spatial resolution and computational feasibility. Camargo et al. [44] reviewed the state-of-the-art trends in spatiotemporal modeling for distributed energy system planning on local scales, emphasizing approaches to optimize renewable energy potential and energy demand estimations. While these studies have addressed various spatially dependent parameters and introduced methods to incorporate them into energy system optimization, there is a lack of comparison and evaluation of approaches to incorporate spatial planning and high-quality databases into these models, especially in country-wide ESMs. Utilizing high-quality validated databases, particularly those that provide spatially explicit inputs for energy supply, demand, and infrastructure, is essential. Therefore, our study contributes to the existing literature by highlighting the spatial characteristics of different bottom-up ESMs at the national level. We also explored methods for evaluating the spatially dependent parameters of energy system components (energy supply, demand, and infrastructure). Our study also emphasizes spatial aggregation methods for integrating these spatially dependent parameters into ESMs and evaluates linking methods for incorporating spatial models into ESMs.

Various bottom-up ESMs have been developed to assess, optimize, design, and project future energy systems but often overlook spatially dependent parameters. The challenge lies in developing a national ESM that incorporates spatially dependent inputs while ensuring robustness for coherent policy development. The critical question is: What spatial details and methodologies are needed for national ESMs to evaluate spatial configuration, system performance, and the cost of a net-zero energy system? Therefore, this study aims to systematically review and synthesize spatially dependent parameters and methods for integrating spatial details into national-scale ESMs while considering the spatial feasibility of ESMs' solutions and managing the computational load. The following questions are answered by reviewing the literature to obtain insights and address research gaps.

- Which national-scale ESMs explicitly integrate spatially resolved representations of energy supply, demand, and infrastructure for long-term energy planning, and how do they address key spatial interconnections?
- What spatially dependent parameters and methods are employed in bottom-up ESMs to assess energy supply, demand, and infrastructure?
- What methods are used to aggregate spatially dependent parameters into ESMs?
- What are the techniques for linking spatial models and ESMs?

2. Review methodology

The methodology of this study was conducted in five steps. Firstly, the research scope was determined to establish the research boundary, which is the basis for the next step. Secondly, an identification step was carried out based on the research scope to select relevant literature for review. This step was conducted in four stages: inclusion criteria, exclusion criteria, abstract screening, and in-depth screening of the full text. Thirdly, a classification scheme was established to compare and evaluate the functionality of ESMs using criteria such as mathematical features, modeling resolution, and spatial methods. Fourthly, an overview was conducted to assess the spatially dependent parameters of energy system components (energy supply, demand, and infrastructure), different spatial aggregation methods, and existing linking methods to incorporate spatial inputs into ESMs. Lastly, given the results from previous steps, a holistic framework was proposed to integrate spatially dependent inputs into future national ESMs.

2.1. Defining research scope

We identified the research boundaries by focusing on bottom-up ESMs that assist in analyzing energy policies and technological details of energy systems. Spatially, ESMs that employed multi-node spatial analysis at national and regional levels were selected, as policies are often formulated at these levels. Temporally, the focus is on hourly resolution to effectively tackle the intermittency of variable renewable energy sources (VRESs). Additionally, we consider ESMs that reduce temporal resolution by using hourly time slices, which helps to mitigate computational load. While short-term temporal extent is considered, the main focus is on the long-term temporal extent that aligns with national policies and ambitions such as net-zero emissions by 2050. This study focuses on technologically rich ESMs with diverse RESs, storage, and energy carriers because they can capture energy system complexities and facilitate the exploration of cost and emission optimization options.

2.2. Systematic literature review

This study employed a systematic review of integrating spatially dependent parameters into ESMs in four stages. Fig. A- 1 shows the document selection and literature review process, conducted in multiple stages to determine whether a document meets inclusion criteria. Scopus© was chosen to retrieve literature on October 1, 2023. This systematic search included several studies that used spatially dependent parameters in ESMs. A meta-analysis was also conducted to explore the classification scheme used in relevant review papers.

Defining search criteria: Three keyword categories were defined to filter search results. Table 1 presents the search terms used to collect relevant documents within the study's scope, resulting in 750 papers and 42 paper reviews. Keywords should appear in the papers' titles, abstracts, or keywords. The AND operation was used in the search query between primary, secondary, and tertiary terms and between two primary keywords to ensure the inclusion of papers using a model or modeling of the "energy system." This approach also helps to identify documents that separately mention the terms "energy system" and "model."

Applying exclusion criteria: We applied exclusion criteria to focus on English-language journal articles, resulting in 480 journal articles and 39 review papers. Given the significant increase in spatial-based ESMs publications after 2012, the search was limited to articles released between 2012 and October 2023, as shown in Fig. A- 2.

Screening based on title and abstract: The remaining articles were screened based on title, abstract, and keywords. This step excluded 357 articles out of 474 journal papers that focused on climate [45], food [46], water [47], air pollution [48], radiation models [49], specific sectors or technologies [50], or local-scale ESMs [51]. Next, 117 articles were excluded as their content did not meet the research scope based on the following requirements.

- Clearly describe using a bottom-up ESMs in the methodology.
- Implement multi-node ESMs at a national level.
- Complete articles should be accessible online (for some, just the abstract is available).

Full text review and study selection: The full text of the papers was reviewed to confirm the use of spatially explicit ESMs at a national scale. This detailed screening identified 38 journal papers. Then, the selection criteria prioritized studies that used unique ESMs. For models that were repeated across studies, the selection was limited to a maximum of two studies per model, as long as they used different spatial inputs, spatial methods, or ESM configurations. Based on these criteria, 20 models were chosen for in-depth analysis. Additionally, 11 review papers that met the requirements of previous stages were selected and used to create the classification scheme.

2.3. Classification of energy system models

A classification scheme was developed to facilitate ESM comparisons, highlight their capabilities, and identify those suitable to meet our objective of reviewing and evaluating spatial details and methods integrated within national ESMs. To create a comprehensive scheme, several review papers were identified in the first step (see Fig. A- 1) to determine the criteria and sub-criteria for comparing ESMs. Thus, existing schemes, as shown in Table A- 1, were adapted by adding spatial-related sub-criteria to align with our research scope. We used this scheme to

Table 1
Search terms for finding relevant literature in Scopus.

Primary terms	Secondary terms	Tertiary terms
energy system*	GIS geographic information system	nation*
model*	geospatial	region*
	spatio*	countr*
	spatial	state
		node*

compare 15 specific ESMs across 20 documents selected in the second step.

2.4. Assessment of spatial parameters and linking techniques

The snowballing technique is used to review a broader range of literature beyond the documents filtered in the second step. We identified the spatially sensitive parameters of energy system (energy supply, demand, and infrastructure), their relation to land use, and the approaches for evaluating these parameters in the literature and the reviewed ESMs. This review was conducted to identify and analyze the existing spatial aggregation methods to integrate spatially dependent parameters into ESMs and explored linking methods to integrate spatial models with ESMs.

2.5. Spatially integrated framework

We proposed a framework that incorporates the essential details of energy system components (energy supply, demand, infrastructure), as identified in the previous steps. Additionally, we outlined methods to aggregate these spatial details to incorporate them into ESMs. This framework also integrated a spatial model with ESMs for land use allocation.

3. Results and discussion

3.1. Classification and evaluation of ESMs

A classification scheme of ESM gives insight into whether to include new criteria or exclude ones not aligned with the study's scope. Hall et al. [52] proposed a classification scheme with four criteria and 14 sub-criteria divided into purpose and structure (model structure, spatial, sectoral, and time resolution), technological details (renewable and storage technology inclusion, energy demand, cost), and mathematical description (mathematical approach and data requirement). Plazas-Niño et al. [53] suggested a categorization scheme comprising 23 sub-criteria classified into three groups: a modeling approach, modeling resolution, and technological details. Similarly, Savvidis et al. [54] proposed a framework with 28 sub-criteria, including four categories: model-theory specifications, modeling details, market representation, and general information. Table A- 1 highlights key factors in comparing ESMs, such as analytical approach, availability, methodology, algorithm, and spatiotemporal resolutions.

Due to our focus on spatial-based ESMs, spatial methods criterion, and its relevant sub-criteria were incorporated into the existing classification schemes. Therefore, we proposed a classification scheme with five criteria and 31 sub-criteria, as shown in Fig. 1. The spatial methods category covers the approaches used for assessing spatially dependent parameters (e.g., the spatial distribution of energy demand, supply, and infrastructure), spatial data utilization, spatial aggregation methods (e.g., clustering), and linking techniques (e.g., soft-linking).

3.2. Spatially explicit ESMs

This section compares spatially explicit ESMs for analyzing and assessing their capabilities. This comparison shows a tradeoff between spatial and temporal resolution with their spatial extent. While most ESMs have high temporal resolution, few achieve high spatial resolution. Additionally, many ESMs can be applied across different spatial extents, from local to international scales. There is also diversity in technical, mathematical, and general characteristics of ESMs. Table 2 summarizes the general information about ESMs, including case study, model purpose, availability, and documentation. It shows that model purposes vary, including cost optimization, GHG reduction, and support for the energy transition. Additionally, most ESMs are open source, but their documentation still needs improvement to clearly describe the methodology and data used.

Table 3 overviews the components, such as renewable and storage technologies, energy carriers, and demand sectors. Most ESMs include different types of RE and storage technologies. Additionally, they incorporate various types of energy carriers, including heat, electricity, and hydrogen. For the energy demand sectors, several ESMs either exclude some sectors or aggregate all sectors together, while only a few ESMs include all energy demand sectors separately. For emissions, they mostly consider CO_2, and few ESMs include all GHG emissions. They also include multiple cost factors to improve their comprehensiveness in

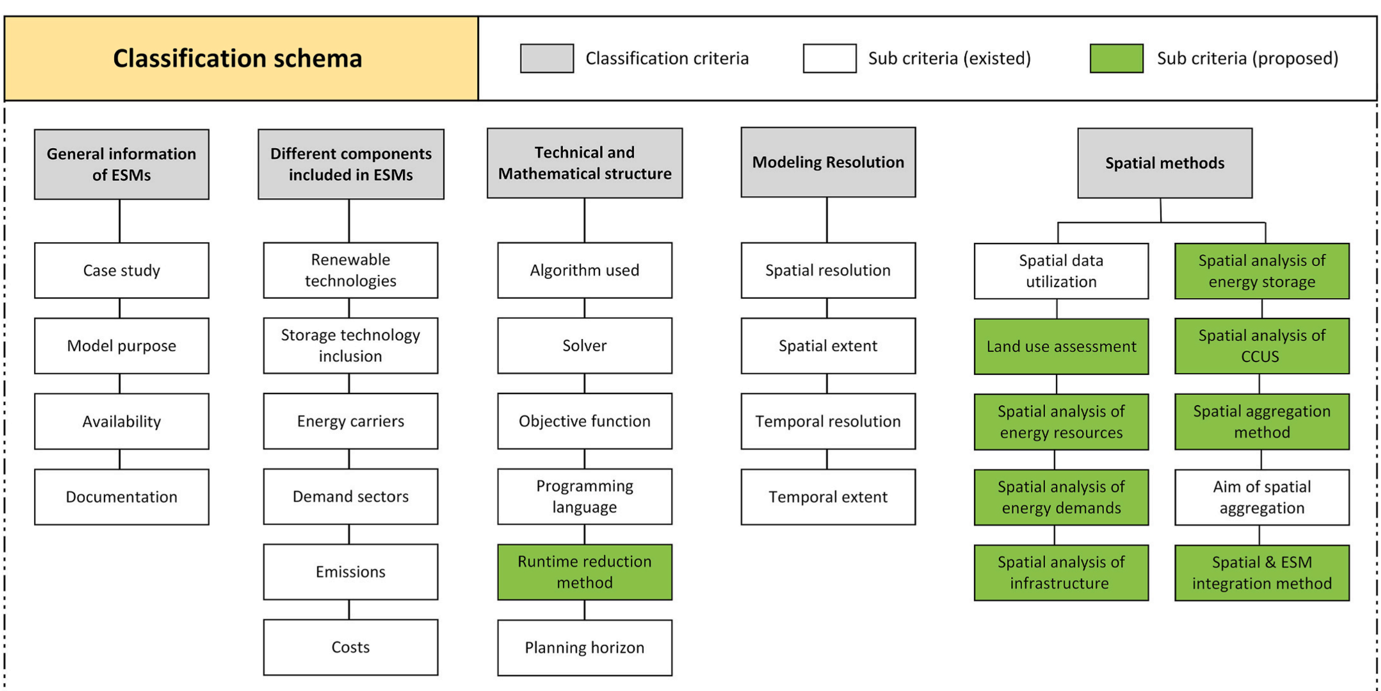


Fig. 1. The proposed classification scheme for analyzing and comparing ESMs.

Table 2
General information on *ESMs*.

Model	Case study[a]	Model purpose	Availability	Documentation	Ref
OMNI-ES	Italy	Optimization of network-integrated energy system	Not OS[b]	https://doi.org/10.1016/j.enconman.2023.117168	[40]
Balmorel	Denmark	Investigating the decarbonization pathways of sector-coupled energy systems	OS	https://github.com/balmorelcommunity/Balmorel	[55] [56]
OPERA	North of the Netherlands Groningen province in the Netherlands	Optimize energy decarbonization and sector integration for a low-carbon future	Not OS	https://doi.org/10.1007/s10666-020-09741-7	[30] [39]
IESA-NS	North Sea region	Optimize decarbonization of energy system	OS	https://github.com/IESA-Opt	[29, 31]
urbs	European union (EU) −28 countries	Optimization of capacity expansion planning and unit commitment for distributed energy system	OS	https://github.com/tum-ens/urbs	[42]
LUT-ESTM LUT	Japan Egypt	Analyzing cost-optimal energy system pathways with high RE shares	Not OS	https://doi.org/10.1016/j.energy.2023.127213/	[57] [41]
BeWhere	Malaysia	Optimizing the allocation of RESs	OS	https://pure.iiasa.ac.at/id/eprint/17549/	[58]
MyPyPSA-Ger	Germany	Simulating and optimizing modern power and energy system	OS	https://github.com/PyPSA/PyPSA	[59]
PyPSA-EU	Germany				[60]
Oemof-moea	Italy A County in Germany	Analyzing multi-objective models and spatiotemporal resolution effects	OS	https://github.com/matpri/oemof-moea	[28] [61]
TIMES	North of India	Exploring possible energy futures based on contrasted scenarios	Commercial	https://iea-etsap.org/index.php/etsap-tools/model-generators/times	[62]
AnyMOD	Germany	Modeling system with high RE shares and cross-sectoral integration	OS	https://github.com/leonardgoeke/AnyMOD.jl	[43] [63]
REMix	Germany	Assessing techno-economic of possible future energy system designs	OS	https://dlr-ve.gitlab.io/esy/remix/framework/dev/index.html	[64]
Calliope	Italy	Analyze energy systems with high RE shares with flexible spatial-temporal resolution	OS	https://github.com/calliope-project/calliope	[65]

[a] Study-based characteristics of the model, not necessarily the model's specifications.
[b] Open source.

Table 3
Different components included in the models.

Model used	Renewable tech[a]	Storage tech inclusion[a]	Energy carriers[a]	Demand sectors[a]	Emission	Cost[a]	Ref
OMNI-ES	Solar, wind, geothermal, biomass, hydro	Battery, Hydrogen, pumped hydro storage (PHS)	Electricity, gas, heat, hydrogen	Residential, services, industry, transportation	CO2	Annualized capital cost, operational costs	[40]
Balmorel	Solar, wind, hydropower, wave power	Hydrogen, heat storage	Electricity, hydrogen, gas	Residential, services, industry, transportation	CO_2, SO_2, NO_X	Investment, operational, fuel, and carbon costs	[55, 56]
OPERA	Solar, wind, geothermal, biomass	Battery, Hydrogen	Electricity, gas, heat, hydrogen	Residential, services, industry, transportation, agriculture	GHG emissions	Investment, variable, and operational costs	[30, 39]
IESA-NS	Solar, wind	Hydrogen storage	Electricity, hydrogen, gas	Residential, services, industry, transportation, agriculture	CO2	Investment, retrofitting, decommissioning, and operation costs	[29, 31]
urbs	Solar, wind, hydro, biomass	Battery, heat storage	Electricity, heat	Aggregated demand	CO2	Investment, fixed, total variable, fuel, and environmental pollution costs	[42]
LUT-ESTM LUT	Solar, wind, geothermal hydro, wave power	Battery, PHS, compressed air energy storage	Electricity, heat, methane, synthetic fuels	Residential, services, industry, transportation	GHG emissions	Annualized capital, operational, fuel, and CO2 costs	[57] [41]
BeWhere	Bioenergy	N/A[b]	Electricity, heat	Aggregated	CO2	Technology and transport cost	[58]
MyPyPSA-Ger	Solar, wind, biomass, hydropower	PHS, hydro reservoirs	Electricity	Residential, industry, services, transportation	CO2	Capital costs	[59]
PyPSA-EU		Battery				Technology, fuel, CO2 costs	[60]
Oemof-moea	Solar, wind, biomass, geothermal, hydro	Battery, PHS, hydro reservoirs	Electricity, heat, hydrogen	Residential, services, industry, transportation	CO2	Investment, operational, maintenance, and fuel costs	[28]
	Solar, wind, biomass	Hydrogen storage	Electricity, heat, hydrogen				[61]
TIMES	Solar, wind, biomass, hydro	Battery, PHS	Electricity	Aggregated	GHG emissions	–	[62]
AnyMOD	Solar, wind, Hydrogen, biomass	Battery, Hydrogen storage, gas	Electricity, heat, hydrogen, methane	Buildings, industry, transportation	N/A	Investment and variable costs	[43, 63]
REMix	Solar, wind, hydro, biomass, Hydrogen	Battery, PHS, Hydrogen, heat storage	Electricity, heat, hydrogen	Aggregated	CO2	Operational, fuel, and CO2 costs	[64]
Calliope	Solar, wind, geothermal, hydro, biomass	Battery, PHS, gas, hydro reservoir	Electricity, hydrogen, gas	Residential, industry, and transportation in an aggregated way	GHG emissions	Investment, operational, and maintenance costs	[65]

[a] Study-based characteristics of the model, not necessarily the model's specifications.
[b] Not clearly mentioned.

energy planning.

Table 4 illustrates the technical and mathematical features of ESMs, such as the algorithm used, solver, programming language, and planning horizon. Linear programming (LP) is the prevalent algorithm used in most ESMs. A few models use mixed-integer linear programming (MILP) or a combination of LP and MILP, which adds complexity to the model. These ESMs use solvers such as Gurobi, CBC, and CPLEX, as well as different programming languages like AIMMS, GAMS, and Python, to optimize solutions. We evaluated the feasibility of these models for long planning horizons and considered different runtime reduction methods they used to mitigate computational load.

Table 5 outlines the models' temporal and spatial resolution, as well as their spatial and temporal extent. It shows a significant variation in spatial resolution from a few nodes to hundreds, resulting in a wide range of spatial granularity. Temporal resolution varies from hourly time slices to broader time slices using representative days. The temporal extent also varies, from snapshots of specific years to evolutionary extents covering multiple time intervals. Fig. 2 compares temporal and spatial resolution with the spatial extent of ESMs. We assumed a model with 30 nodes and 300 hourly slots has a medium spatial and temporal resolution, respectively. This figure shows that while most ESMs have a high temporal resolution, such as OMNI-ES, Calliope, IESA-NS, and LUT models, only a few models have a high spatial resolution, such as PyPSA, OPERA, and Balmorel. Some ESMs, like TIMES, can be implemented at various resolutions and scales. It is worth noting that these characteristics are specific to the selected papers reviewed in this study and do not represent the overall scope of the model. For instance, while the Calliope model is represented with 6 nodes [65], the Euro-Calliope configuration operated in higher spatial resolution, covering 98 regions [66].

3.3. Spatial aspects of energy systems

The energy supply chain significantly affects land use depending on where it is extracted, generated, transported, distributed, and used [67]. The spatial requirement of energy production depends on the energy source density and land use compatibility [68,69]. RE technologies are land intensive due to low energy density compared to fossil fuels, which highly affects land use [32]. The expansion of RESs has spatial

Table 5
Modeling resolutions and extents.

Model used	Spatial resolution[a]	Spatial extent	Temporal resolution[a]	Temporal extent[a]	Ref
OMNI-ES	20 nodes	Regional-National	Hourly	Snapshot (2050)	[40]
Balmorel	15 regions	Regional-International	96-time slices	Evolutionary (10 years)	[55]
	98 regions		672- time slices	Snapshot (2050)	[56]
OPERA	5 nodes	Regional-National	(32–432) time slices	Snapshot (2030–2050)	[30]
	96 nodes				[39]
IESA-NS	8 nodes	Regional-International	Hourly	Snapshot (2050)	[29, 31]
urbs	28 regions	Local-International	96-time slices	Snapshot (2015–2050)	[42]
LUT-ESTM	9 regions	Local-International	Hourly	Evolutionary (2020–2050 every five years)	[57]
LUT	7 regions				[41]
BeWhere	560 equal regions	National	Two-month sub-annual time intervals.	Evolutionary (2020–2050 every five years)	[58]
MyPyPSA-Ger	Up to 317 nodes	Local-International	3-Hourly interval	Snapshot (2050)	[59]
PyPSA-EU	37/1024 nodes		Hourly		[60]
Oemof-moea	6 nodes	Regional-National	Hourly	Snapshot (2050)	[28]
	5 nodes				[61]
TIMES	9 regions	Local-International	288- time slices	Annual Evolutionary (2012–2050)	[62]
AnyMOD	29 regions	Local-International	Hourly	Snapshot (2030)	[43]
	38 regions				[63]
REMix	18 nodes	Regional-National	Hourly	Annual Evolutionary (2020–2050)	[64]
Calliope	6 regions	Local-International	Hourly	2050	[65]

[a] Study-based characteristics of the model, not necessarily the model's specifications.

Table 4
Technical and mathematical structures of models.

Model used	Algorithm used	Solver reported[a]	Objective function	Programming language	Runtime reduction method[a]	Planning horizon	Ref
OMNI-ES	LP	Gurobi	Cost minimization	MATLAB®	N/A[b]	Perfect foresight	[40]
Balmorel	LP	N/A	Cost minimization	GAMS	Time slice	Perfect foresight- Myopic	[55, 56]
OPERA	LP	Gurobi	Cost minimization	AIMMS	Time slice	Perfect foresight	[30, 39]
IESA-NS	LP	Gurobi	Cost minimization	AIMMS	Clustering method to simplify spatial details	Perfect foresight	[29, 31]
urbs	LP	Gurobi	Cost or CO2 minimization	Python	Time slice and three steps clustering	Perfect foresight	[42]
LUT-ESTM	LP	MOSEK	Total annual system cost	MATLAB®	Hierarchical simulations for regional disaggregation	Myopic- perfect foresight	[57]
LUT					N/A		[41]
BeWhere	MILP	CPLEX	Cost minimization	GAMS	Using cells to aggregate variables	Perfect foresight	[58]
MyPyPSA-Ger	LP	Gurobi	Cost minimization	Python	Aggregating data across nodes	Myopic (Perfect foresight in recent versions)	[59]
PyPSA-EU							[60]
Oemof-moea	LP	Gurobi	Cost or CO2 minimization	Python	Aggregating data across nodes	Myopic	[28]
					Clustering data		[61]
TIMES	LP	N/A	Cost minimization	GAMS	Time slice	Perfect foresight	[62]
AnyMOD	LP	Gurobi	Cost minimization	Julia	Aggregating data across nodes	Myopic	[43, 63]
REMix	LP, MILP	CPLEX	Cost minimization	GAMS	Aggregating data across nodes	Myopic	[64]
Calliope	LP, MILP	CBC or Gurobi	Cost minimization	Python	Aggregating data across nodes	N/A	[65]

[a] Study-based characteristics of the model, not necessarily the model's specifications.
[b] Not clearly mentioned.

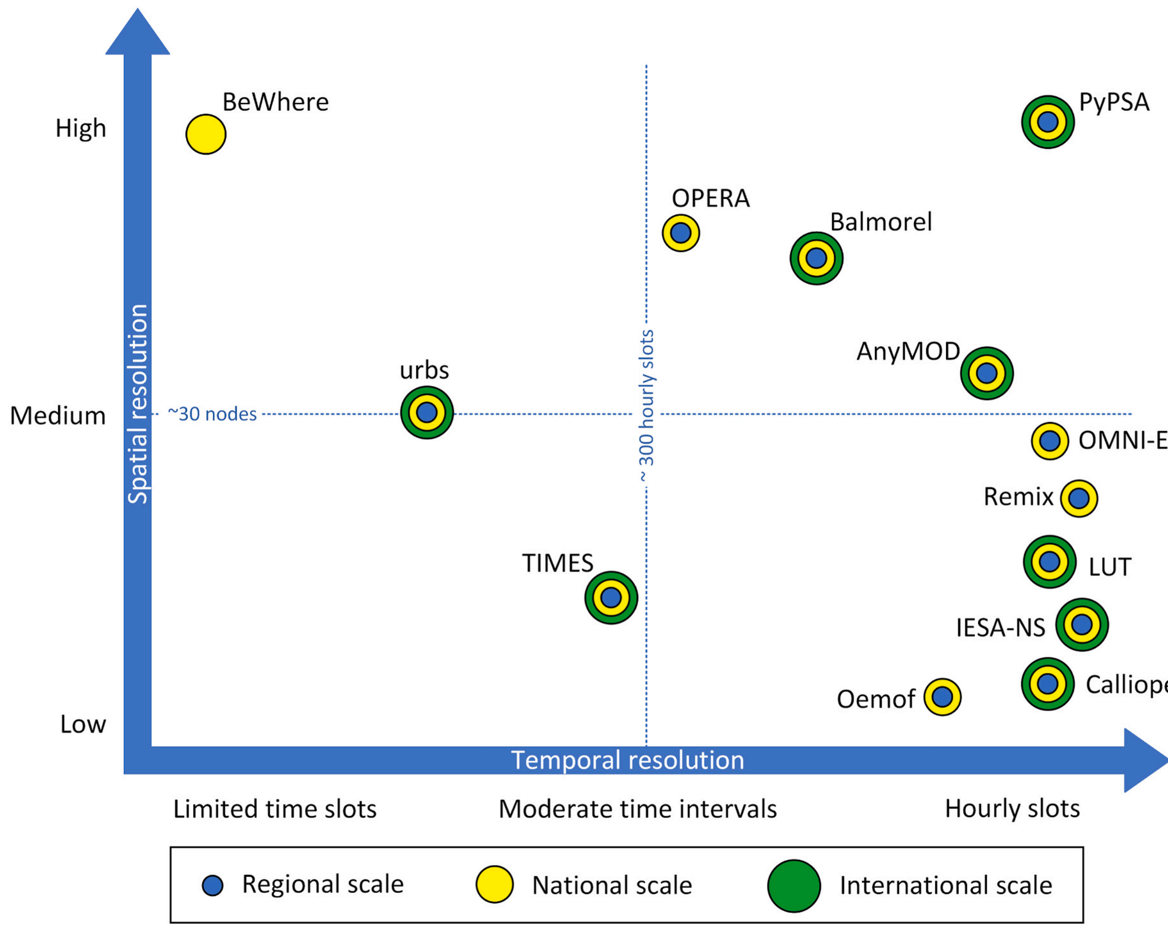


Fig. 2. Temporal and spatial resolution and spatial extent of the reviewed ESMs of the selected studies.

implications on landscapes, such as competition for land and the potential declines in environmental quality [70]. Given that RESs are localized and site-specific, shifting to a more decentralized and diversified energy system necessitates a closer spatial correlation between where the energy is produced, transported, and consumed [71]. Energy infrastructure such as pipelines, grids, and roads affect neighboring land use patterns [67]. The energy system has three main components: supply, demand, and infrastructure. Various methods were used in the literature to evaluate spatially dependent parameters for estimating RES potential. Land use was inherently considered within energy system components, recognizing their significant overlaps, see Fig. 3. Additionally, the full overview of geospatial aspects and linking methods to integrate spatially dependent parameters into ESMs is depicted in Table 6.

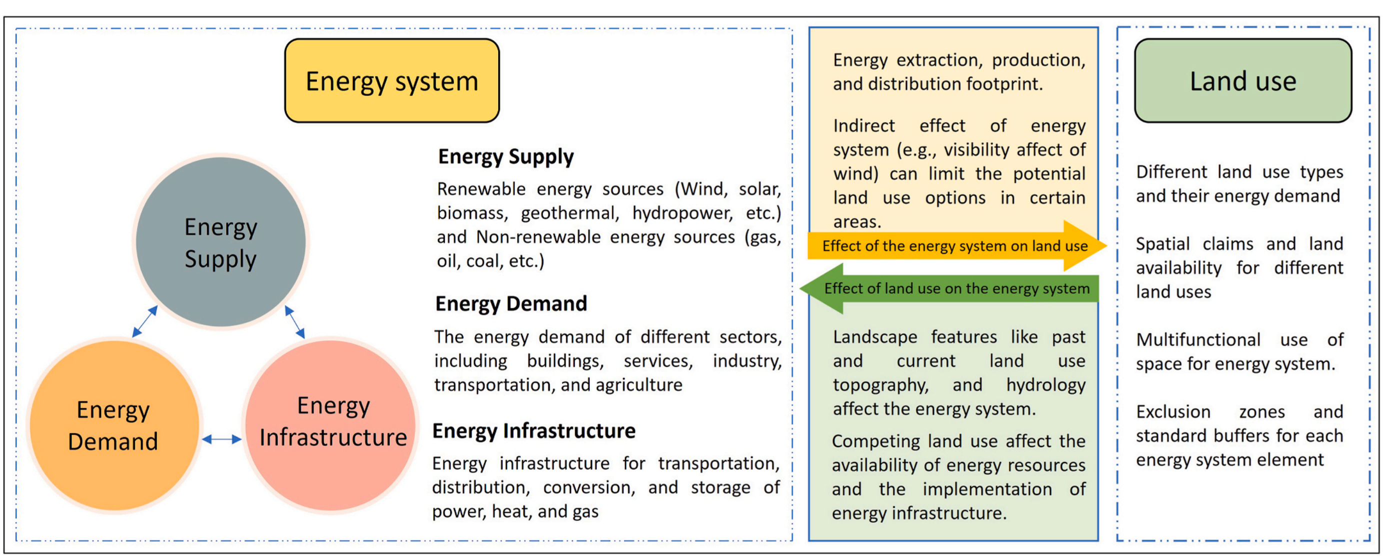


Fig. 3. The interconnection between the energy system and land use.

Table 6
Summary of spatial methods to incorporate spatial components, aggregate these details, and integrate them into ESMs.

ESM	Spatial data utilization	Land use assessment	Spatial approaches to evaluate the distribution of energy system components					Spatial aggregation method	Aim of spatial aggregation	Ref
			Energy resources	Energy demands	Infrastructure	Storage	CCUS			
OMNI-ES	Exogenous spatial databases	Land use potential for RESs	Using land limit percentages and weather data	Allocate demand from a database to regions.	Allocating infrastructure capacity of bidding zones between regions	Using a database to define PHS regionally	Aggregated in one node	Regionalization (sub-national)	Tracking energy vector flows to identify infrastructural needs	[40]
Balmorel	Exogenous spatial databases	–	Solar and wind capacity	Heat demand for regions	Large, medium, and small district heating networks for regions	Short-term and seasonal storage for heat and electricity	–	Regionalization (sub-national)	N/A[a]	[55]
Balmorel-OptiFlow	Exogenous spatial databases	–	Using a database to allocate biomass potential across areas	Obtained exogenously from TIMES-DK	Euclidean distance of regions' centers	Short-term and seasonal storage for heat and electricity	–	Regionalization (sub-provincial)	The importance of the local distribution of energy resources	[56]
OPERA	GIS[b] analysis	Assessing spatial claims	GIS analysis and external database	Using GIS analysis	Using an actual physical electricity network	N/A	Aggregated in one node	Regionalization (sub-national & provincial)	To show the impacts of energy system components regionally	[30, 39]
IESA-NS	GIS analysis	Assessing spatial claims	Wind potential, considering the available area	Database for demand allocation	It is considered, as noted in Appendix B	Using a database to allocate hydrogen storage	–	Clustering (k-means)	Model simplification for finding the best offshore hubs	[29, 31]
urbs	GIS analysis	Land use potential for RESs	Using available lands and weather data	Using land use map	Allocating transmission lines between regions using a database	N/A	–	Clustering (k-means++ & max-p)	Generate cohesive clusters with maximum data similarity	[42]
LUT-ESTM	Exogenous spatial databases	–	Using land limit percentages and weather data	Using a database, a general assumption for 2050	Power transmission capacity of regions and their annual trading	Regional battery capacity	–	Regionalization (sub-provincial)	Reduce simulation time in spatially low-resolution with high-quality results.	[57]
LUT				Different criteria for obtaining each demand type		Regional electricity, heat, and gas storage	–	Regionalization (sub-national)	Spatially dissolving data in energy demand zones	[41]
BeWhere	GIS analysis	Considering protected area	It is considered, as noted in Appendix B	Power, heat, and transport demand for areas	Transportation network (road and sea), pipeline, power grid transmission	N/A	–	Regionalization (equally-sized regions)	Spatially dissolving in equal cells	[58]
MyPyPSA-Ger	Exogenous spatial databases	–	Using a database for RESs	Linear regression for power demand	Using the power network	Energy storage for each node	–	Clustering (k-means)	Aggregating information and simplifying the analysis process	[59]
PyPSA-EU			Using a database to allocate RESs	It is considered, as noted in Appendix B.					Dissolving data in different spatial levels.	[60]
Oemof-moea	Exogenous spatial databases	–	Population factor for PV[c] and using a database for wind	Heat and power demand for each node	Power transmission capacity and bottlenecks between bidding zones	Regional capacity for PHS	–	Regionalization (sub-national)	Spatially dissolving in regions	[28]
		–	Using a database for RES capacity	Database for electricity, heat, and hydrogen demand	Not clearly mentioned	N/A	–	Clustering (hierarchical agglomerative)	Spatially explicit data for decentralizing municipal energy systems	[61]
TIMES	GIS analysis	Assessing spatial claims	PV/wind potential and considering land claims	Regression method	The power transmission network between regions	N/A	–	Regionalization (sub-national)	Spatially dissolving in regions	[62]
AnyMOD	Exogenous spatial databases	It is considered, as noted in Appendix B	Allocate potential from a database to regions considering land availability.	Database for demand allocation	Transmission networks and their capacity between regions	Battery and hydrogen storage	–	Regionalization (sub-provincial)	Spatially dissolving in regions	[43, 63]
REMix	Exogenous spatial databases	–	Using the European model's results for RE potential	Database for demand allocation	Using the power network	Aggregating storage for each node	–	Regionalization (sub-provincial)	Spatially dissolving in regions	[64]
Calliope	Exogenous spatial databases	–	Using a database for a maximum capacity of RESs	Using bidding zone and demand profile of sectors	Transmission between central nodes and VRESs with their linked nodes	Aggregated regional storage capacity	–	Regionalization (sub-national)	Spatially dissolving in regions	[65]

All variables in this table are related to the studies that used ESMs, not necessarily the model's specifications.
[a] Not clearly mentioned.
[b] Geographic information system.
[c] Photovoltaic.

3.3.1. *Spatial aspects of energy supply*

Distinguishing between different levels of potential for evaluating RE capacity is crucial. These levels are classified into four key groups. Theoretical potential is the highest resource capacity based on natural and climatic factors [72,73]. Technical potential considers geographical and system limitations, including land use, infrastructure constraints, and technically feasible technologies [73,74]. Economic potential refers to cost-effectiveness, where RE's revenue covers its cost [74]. Market potential indicates the amount of RE that can be implemented, considering regulatory limits, policies, and competition with other technologies [73]. Our review shows that most selected papers focused on the theoretical potential, often simplifying the technical and economic potential and overlooking the market potential, see Appendix B.

The systematic approach to identifying high-potential areas for RESs considers environmental and legal constraints, land use claims, suitability analysis, spatial competition of RE technologies, and these technologies' technical and economic feasibility, as illustrated in Fig. 4. This procedure can be applied for each specific RE technology to estimate the land availability of different technologies. Our review shows that some studies simplified calculations for RES's theoretical and technical potentials using low-resolution renewable capacity factor maps [63,65], generalized approaches to estimate available land, or highly aggregated methods for allocating solar potential regionally. For solar energy, these methods included equal distribution of solar potential between regions by using a weighted average approach [57] or selecting a representative site for each region [75,76]. Additionally, only a few studies have examined the explicit technical potential of RESs by considering land use restrictions and claims [29,30]. Table 7 provides an overview of proposed indicators to assess RE production in the literature and those used in the reviewed papers. The methods of how the spatially dependent parameters of energy resources are used in ESMs are summarized in Table 6 and detailed in Appendix B.

3.3.2. *Spatial aspects of energy demand*

Aggregation and disaggregation represent the literature's common methods for the spatial distribution of energy demand among regions. The aggregation approach helps summarize data such as energy profiles of buildings and vehicles and the energy consumption of different building types. In contrast, the disaggregation technique uses statistical approaches to allocate energy demand across smaller regions [86]. Studies either used specific indicators for each energy sector [39,60] or utilized indicators applicable to combined energy sectors [41,58]. For instance, in OPERA, the energy demand inputs were obtained by estimating the energy demands of different energy sectors, including residential buildings, services, industry, and agriculture. Building information such as building use, type, energy label, construction year, and population is used to estimate the energy consumption of the built environment. For transportation, demand information is obtained using the population factor. REMix used population distribution to estimate building energy demand and the number of vehicles needed for transportation energy demand. LUT, Urbs, and BeWehre utilized indicators for energy demand estimation for combined energy sectors. Therefore, a comprehensive methodology is required to obtain a detailed analysis of energy demand for different energy sectors. Table 8 summarizes critical indicators to evaluate energy demand in the literature and those applied in the reviewed ESMs. The methods used to assess spatially dependent parameters of energy demand in ESMs are summarized in Table 6 and explained in detail in Appendix B.

3.3.3. *Spatial aspects of energy infrastructure and storage*

Energy infrastructure, comprising energy grids, conversion technologies, and storage options should be integrated into ESMs to evaluate balance constraints in energy flow. Some ESMs represent the energy infrastructure as a copper plate, neglecting transportation distances and related losses in balancing energy supply and demand [63]. However, some models, such as PyPSA, IESA-NS, OPERA, and OMNI-ES, use holistic approaches to incorporate spatially dependent parameters of energy infrastructure. For example, PyPSA uses a structured methodology that effectively captures the interaction of spatially dependent parameters within energy systems. It aggregates energy supply and demand in the same nodes and links multiple nodes through energy infrastructure. This model uses power substations to define the nodes, and these nodes represent various components such as generators, consumers, storage capacity, and transmission lines [94]. PyPSA-Eur's network typology is designed based on a power transmission grid map, including high voltage alternating current (HVAC) and high voltage direct current (HVDC) power lines. In addition, countries are split into Voronoi cells as catchment areas and connected to substations through low-voltage (LV) networks. These cells include power plant capacities, RE potential, and the share of demand that can be met at each substation [95].

Following a similar approach, most ESMs aggregated the capacity of one or multiple energy networks (power, heat, and gas) and storage options at their closest node. For instance, PyPSA-Eur-Sec [96] and OMNI-ES [40] developed a detailed methodology to incorporate various

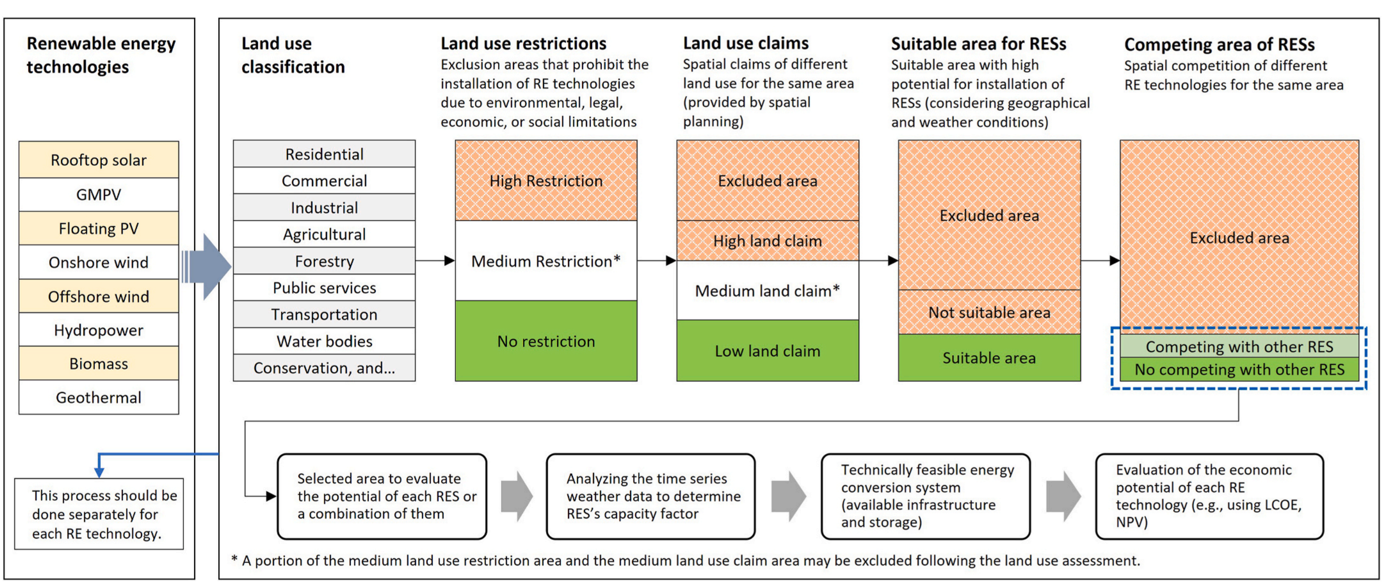


Fig. 4. The procedure of determining the technical and economic potential for each specific RE technology adopted from [77,78].

Table 7

RE potential factors	Proposed inputs and indicators to evaluate and estimate energy potential (from literature)	Inputs and indicators used in selected ESMs
Land use restrictions	Environmental and legal restrictions	**OPERA**: land limit assumptions for solar and wind **LUT** [41]: land limit assumptions for solar and wind **AnyMOD**: site quality of land uses for PV and wind **IESA-NS**: protected areas and exclusion zones
	Social acceptance	**IESA-NS**: sensitivity analysis for onshore wind acceptance levels
Land use claims	Spatial planning	**OPERA**: spatial planning as scenarios **IESA-NS**: sea use claims and multi-use of sea spaces
Suitability analysis	**GMPV[a]:** solar radiation, slope, aspect [79], onshore water body)	**OPERA**: agricultural land, onshore water body **LUT** [41]: solar radiation, solar power density **AnyMOD**: capacity factor of PV
	Rooftop PV: solar radiation, building data, rooftop area constraint, shading factor, future building growth rate [80])	**OPERA**: building footprint for agriculture, industry, roadside, and ground-based **AnyMOD**: capacity factor of PV
	Wind: wind speed, slope, aspect, roughness length, longitudinal, plan, and transverse curvature [79])	**OPERA:** annual wind speed profile **LUT** [41]: wind speed, wind power density **AnyMOD**: capacity factor of wind **IESA-NS**: wind power density, water depth
	Geothermal: surface ambient temperature, heat flow [75, 81])	**LUT** [41, 75]: surface ambient temperature, heat flow
	Biomass (Energy crops): altitude constraint, slope, soil characteristics, geotechnical characteristics, precipitation, temperature [82];	**OPERA**: region-based residue potential **Balmorel** [56]: geographical distribution of residue potential
	Biomass (Residue potential): livestock manure, straw potential, forestry residue, urban greenery residue, food waste [83]	**LUT** [41]: region-based residue potential **Bewhere**: palm oil mill's locations and capacities, palm plantation, locations and capacities of rice miles, paddy plantation, livestock population
	Hydropower: slope, elevation, precipitation, temperature, soil classification, runoff, land cover, river discharge [84, 85]	**LUT** [41]: real weather data
Competing technologies	Suitability map of RE technologies, land use, spatial planning scenarios	Not considered
Combination of RE technologies		Not considered

[a] Ground-mounted PV systems.

energy networks such as power, heat, gas, CCUS, and related components. OPERA used a spatially explicit approach for the heat network to integrate heat supply sources and the DH network at the regional scale. This model combines the district heating (DH) transmission and distribution network across industry clusters, geothermal source locations, city centers, and city outskirts [39]. Moreover, existing energy infrastructure is vital in developing economically feasible and efficient plans. For example, onshore wind and ground-mounted PV installations near their corresponding energy infrastructure are more financially desirable

Table 8
Methods and indicators employed for estimating spatially sensitive parameters of energy demand.

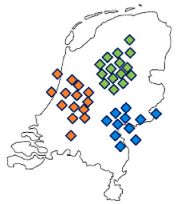
Demand sector	Proposed indicators to calculate energy demand (from literature)	Indicators used in selected ESMs
Residential buildings	Household numbers, building type, energy label, building size, building age, climate condition [30,86,87]	**OPERA**: building use, building types, construction year, household numbers, energy label **PyPSA-EU**: (future) population, living space (for heating) **REMix**: population distribution
Non-residential buildings (services)	Operating hours, occupancy rate, building function, building type, energy label, building size, building age, climate condition [30,86–89]	**OPERA**: building use, building types, construction year, energy label **PyPSA-EU**: current and future population, employment rate
Industry	Industrial activity type, production volume, plant size, climate condition [30]	**OPERA**: final industrial product unit **PyPSA-EU**: current and future population, employment rate
Transportation	Network density, vehicle kilometers traveled, population density and distribution, public transport infrastructure, freight and passenger movement [86, 90–92]	**OPERA**: population distribution **PyPSA-EU**: population, e-mobility penetration **REMix**: number of vehicles
Agriculture	Agriculture area, crop types, and livestock, irrigation needs, machinery usage, climate condition [93]	**OPERA**: heat, electricity, machinery demand
Combined sectors	–	**BeWhere**: power substation map for electricity, natural gas map for heat demand, population map for transport fuel demand **Urbs**: hourly load profile **LUT**: air conditioning, tourism contribution, and local and seasonal temperatures **TIMES** & **MyPyPSA-Ger**: population, gross domestic product (GDP), historical trend of power consumption

[97]. In IESA-NS, the capacity and size of power cables and gas pipelines are estimated for reuse for energy transportation. Considering these challenges, a holistic methodology is needed to measure the current and potential capacities, transportation constraints, and capacity limitations of different energy networks (power, heat, gas, and CCUS), and energy storage [29]. The methods used to assess the spatially dependent parameters of energy infrastructure, storage options, and CCUS are summarized in Table 6 and explained in detail in Appendix B.

3.4. Spatial aggregation methods

The literature review highlights clustering and regionalization as primary spatial aggregation methods for defining regions or nodes in ESMs. K-means, max-p, k-means++ & max-p are the standard clustering methods in ESMs. Regionalization can be classified into market-bidding zones, subnational, sub-provincial, and equally-sized regions. Table 9 provides a checklist to evaluate these approaches and their pros and cons based on four criteria and their corresponding sub-criteria: policy (policy alignment and understandability by policymakers), flexibility (to accommodate inputs and sensitivity to variation), spatial capabilities and features, and knowledgebase (including available literature and

Table 9

Aggregation methods	Schematic design	Ref	Policy		Flexibility		Spatial capabilities					Knowledgebase/Databases	
			Policy alignment	Easily understandable by policymakers	Allows customization of spatial resolution	No sensitivity to input variations	Homogeneity of results	contiguity of results	Flexibility in capturing spatial variation	Identifies distinct spatial patterns	Better reflects socioeconomic patterns	Corresponds to the available data	Supported by extensive literature and algorithms
K-means		[29]	–	–	✓	–	✓	–	✓	✓	–	–	✓
Max-p		[27]	–	–	–	–	–	✓	–	✓	–	–	–
K-means++ & max p		[42]	–	–	✓	–	✓	✓	✓	✓	–	–	–
K-means using power nodes		[59, 60]	✓	–	✓	–	✓	–	✓	✓	–	✓	✓
Market bidding zones		[55, 57, 64, 65]	✓	✓	–	✓	–	–	–	–	–	✓	✓
Sub-national (Provincial level)		[28, 40, 41, 62, 75, 81, 108]	✓	✓	–	✓	–	–	–	–	✓	✓	✓
Sub-provincial (municipality level)		[30, 39, 43, 56, 63]	✓	✓	–	✓	–	–	–	–	✓	–	✓
Equally sized regions		[58, 109]	–	–	✓	✓	–	–	–	–	–	–	–

data). This assessment compares the capabilities and limitations of clustering and regionalization methods in ESMs.

Most ESMs use input data that is available in administrative units. However, there is often a lack of alignment between the administrative divisions and spatial distribution of energy supply (due to differences in factors such as wind speed and solar radiation) and power and heat demand [42]. Because policies are primarily formulated at national or regional levels, regionalization aligns better with policy assessment and is more accessible to policymakers and stakeholders. While clustering provides flexibility to customize the number of nodes, regionalization is less adaptable. This flexibility helps scale down or up by changing the number of regions or nodes exogenously. Clustering methods can adjust node distribution based on input data, unlike regionalization, where input variations do not impact region numbers. In the max-p clustering method, node numbers are fixed and cannot be adjusted exogenously to ensure the spatial contiguity [31]. K-means clustering prioritizes homogeneity when clustering nodes, demonstrating similarity and consistency in energy-related attributes such as demand, supply, and storage. Meanwhile, max-p clustering offers contiguity of results as regions and nodes are clustered through spatial proximity [27,31,98], ensuring each area shares at least one border with adjacent areas in the same region [27].

Both regionalization and clustering are spatially explicit approaches, but regionalization, defined by fixed administrative units like provinces, may only partially capture the spatial distribution of energy supply, demand, and infrastructure. For instance, while regionalization assigns one node to each province or municipality, k-means clustering flexibly adjusts the node numbers according to the spatial distribution of energy system components. Thus, using administrative units such as provinces may lead to an inadequate representation of resource variation [99]. Clustering methods can better handle spatial variations by tracking distinct spatial patterns, e.g., the spatial pattern of demand distribution, supply, or industry locations. Spatial aggregation using administrative units benefits from greater data availability and aligns better with socioeconomic patterns [100]. Additionally, extensive knowledge bases and relevant algorithms support k-means clustering, power zone clustering, and administrative unit approaches.

Regionalization based on administrative units is also a common approach to aggregate spatial variations. Sahoo et al. [30] conducted an ESM analysis to regionalize a national ESM in the Netherlands at multiple administrative levels. They studied the municipality of Groningen with high spatial detail, the northern part of the Netherlands at a provincial level, and the remaining part of the country as a single region. In another study, Sahoo et al. [39] used multiple nodes with distinct types, e.g., demand, supply, and energy infrastructure, by considering 24 Dutch regions corresponding to energy demand and supply. To represent the energy infrastructure, they incorporated 67 nodes, including industries, geothermal, district heating, and power nodes.

Clustering is a practical approach for aggregating spatial data. Martínez et al. [29] used k-means clustering to identify suitable offshore hubs in the North Sea. Their approach connected offshore wind power plants (OWPP) to the nearest hub and deployed the fewest hubs possible to accommodate the maximum number of OWPPs. Due to the significance of geographical distance between OWPPs and hubs, k-means clustering is an effective method to find the optimal offshore hubs. They assessed potential conflicts between various space uses to identify suitable areas for offshore wind deployment, which were used as input for the clustering. Jarosch et al. [61] employed clustering analysis to characterize distinct clusters with internal homogeneity and similarities within each cluster, while external heterogeneity and differences between clusters. They used various indicators to determine clusters, including population, power demand, and installed capacity of RE technologies. In PyPSA, power substations are clustered through the k-means technique to group geo-located buses of the power networks [95,101]. This approach can help to capture, manage, and represent spatially explicit data.

Clustering methods aim to aggregate data according to similarities or dissimilarities criteria while minimizing information loss. For instance, high-potential areas for RESs can be identified using clustering, unlike regionalization methods [102]. Clustering techniques, like k-means, use input data to identify regions based on similarities in their attributes (e.g., energy demand and supply). This flexibility allows clustering to define regions that align more with energy system inputs, unlike regionalization methods that rely on fixed administrative units. However, clustering techniques have limitations, as they are highly sensitive to input data and parameters like the initial number of node selected [103,104]. K-means is particularly sensitive to the initial centroid selection, as well as to outliers and noise, which can distort the cluster shapes [105,106]. Moreover, if the spatial variations are highly scattered, clustering may fail to capture the complexity of spatial variation due to its reliance on specific parameters to define clusters [103,107]. Therefore, parameters (e.g., initial centroids and cluster numbers) and input data should be carefully selected to ensure that the clusters accurately represent the spatial distribution of relevant features.

3.5. Linking methods of ESM and spatial model

Researchers have classified linking methods for integrating ESMs with other models differently. Wene [110] identified hard link and soft link approaches in ESMs, shown in Fig. C- 1 (a), while Helgesen et al. [111] added an integrated approach, where models combine into a single model. Linking methods are crucial for balancing granularity and complexity while ensuring system adaptability. The selection of the linking method depends on model types, purpose, and capabilities. Fattahi et al. [19] proposed hard link ESMs with regional and energy market models and soft-linking with the macroeconomic model. A soft link method is recommended to integrate ESM and spatial models to encompass higher spatial granularity, land use assessment, and infrastructure analysis in ESMs.

In the hard link approach, models are connected to transfer data automatically without user intervention [41], with one model as the master and others as complementary models, all running simultaneously [19]. Durand-Lasserve et al. [112] defined hard links as a fully integrated method, and soft links as a partial linking method for a few variables. This linkage can be intensified when the objective function of various methods is translated into a single equation [113]. Wene [110] highlighted the advantages of hard link methods, such as productivity, uniqueness, and control. However, it has limited computational efficiency and data resolution compared to the soft link process [114]. Helgesen et al. [111] indicated that soft linking can improve model capabilities, but it can pose challenges like convergence issues and identifying connection points [19]. Hard-link method yields consistent and efficient outcomes by incorporating all constraints within a single model but it can lead to complex optimization problems [114]. For instance, Bramstoft et al. [56] proposed a methodology to assess possible solutions for ESM biomass distribution (see Fig. C- 1 (b). They co-simulated OptiFlow with Balmorel, a hard-link approach to exchange data. Additionally, the TIMES-DK model optimizes energy demand as an exogenous input for OptiFlow-Balmorel.

In the soft-link approach, multiple models operate separately, transferring information iteratively and sequentially [114]. In this approach, one model generates a result as an input for another and can be structured as a feedback loop between models [37]. The soft-link method attracts more attention as it leverages the high resolution of each model involved in the linking process [114] and provides better system complexity management than hard-linking [115]. However, combining models using soft-link techniques might reach a different level of accuracy than the hard-linked linking model [114]. Identifying the connection points is essential, as one model's endogenous variable becomes the other's exogenous variable [24]. Soft-linking provides practicality, transparency, and learning advantages [110], but does not guarantee model convergence to optimal outcomes. It may also cause substantial problems in obtaining consistency owing to differences in model structure and methodologies [23]. Unlike hard-linking, which limits technological resolution, soft-linking divides problems into sub-problems, allowing for higher technological resolutions [114].

Soft link methods are classified as bidirectional and unidirectional approaches. The data flow between models occurs iteratively in the bidirectional method, leading to more reliable results [29]. Each model can modify the other iteratively until convergence criteria are met. This technique was designed to improve the quality of results in both models [116]. However, this method demands higher computation loads and deals with challenges in reaching convergence. In contrast, in the unidirectional method, the output of one model feeds into the second model without iteration [29]. For instance, Sahoo et al. [30] used a unidirectional method to soft-linked the pan-European power model, COMPETES, to consider the power exchange beyond the country, as shown in Fig. C- 1 (c). On the other hand, Pina et al. [117] used a bidirectional soft-link technique to integrate TIMES, a long-term model for optimizing electricity generation investments, and EnergyPLAN, a short-term model for optimizing system operation. The results of installed capacity from TIMES are used as inputs in EnergyPLAN to calculate the maximum production potential for each generator. The convergence criteria ensure that installed RE technologies can generate at least 90 % of the expected annual output. If the requirements are not met, a new yearly capacity limit is defined to update the previous constraints of all sources in TIMES [117]. Similarly, Seljom et al. [116] developed an iterative soft-link method by integrating TIMES-Norway into the EMPS operational power market model to enhance the decision support provided by both models. All European countries are included in EMPS, while only Norway is covered in TIMES-Norway. The income generated by hydropower from both models is used as a convergence criterion to determine generation and electricity prices.

4. Synthesis and perspective

Given the insights drawn from the analysis and results, this section outlines a methodological proposal for ESM design by linking a spatial model with an ESM. This proposal specifically focuses on national energy planning by incorporating spatial dynamics and constraints at a high spatial resolution. The key recommendation is to integrate various spatially dependent parameters into an ESM (see Fig. 5). We propose linking the ESM to a spatial model for optimizing land use allocation, recognizing that various competing land use claims should be considered to assess the feasibility of ESM solutions in terms of spatial feasibility.

Regarding the aggregation approach, while clustering techniques can allow for adaptability in representing the spatial variation of energy supply and demand, their suitability is context-dependent. For instance, if policy advice is targeted at specific administrative units, e.g., provinces or municipalities, aligning the analysis with administrative units may provide more policy-relevant results due to data availability and alignment with policy goals. However, for a spatially explicit ESM at the national level we propose using clustering methods (e.g., k-means or k-means++ & max-p). Unlike regionalization methods that are limited by administrative boundaries, clustering provides more flexibility to capture spatial variability in energy supply, demand, and infrastructure. It minimizes information loss and defines regions based on shared characteristics rather than predefined boundaries. It also enhances scalability in adjusting the spatial resolution. However their limitations such as sensitivity to input data, initial centroid selection, and challenges in determining the number of clusters should be carefully managed (see section 3.4).

To link the spatial model with ESM, we propose a bidirectional soft-linking technique. As discussed in section 3.5, this approach enables the inclusion of higher resolution data from each model involved in the linking process, leading to better management of system complexity. Although soft-linking possess challenges, such as potential convergence validation issues, managing two distinct models, and ensuring consistency between models, its advantages outweigh these disadvantages, particularly for managing high-resolution data and reducing computational demand. Moreover, we propose using a recursive soft-linking technique that offers another layer of robustness by providing recursive feedback exchanges between two models. While this approach

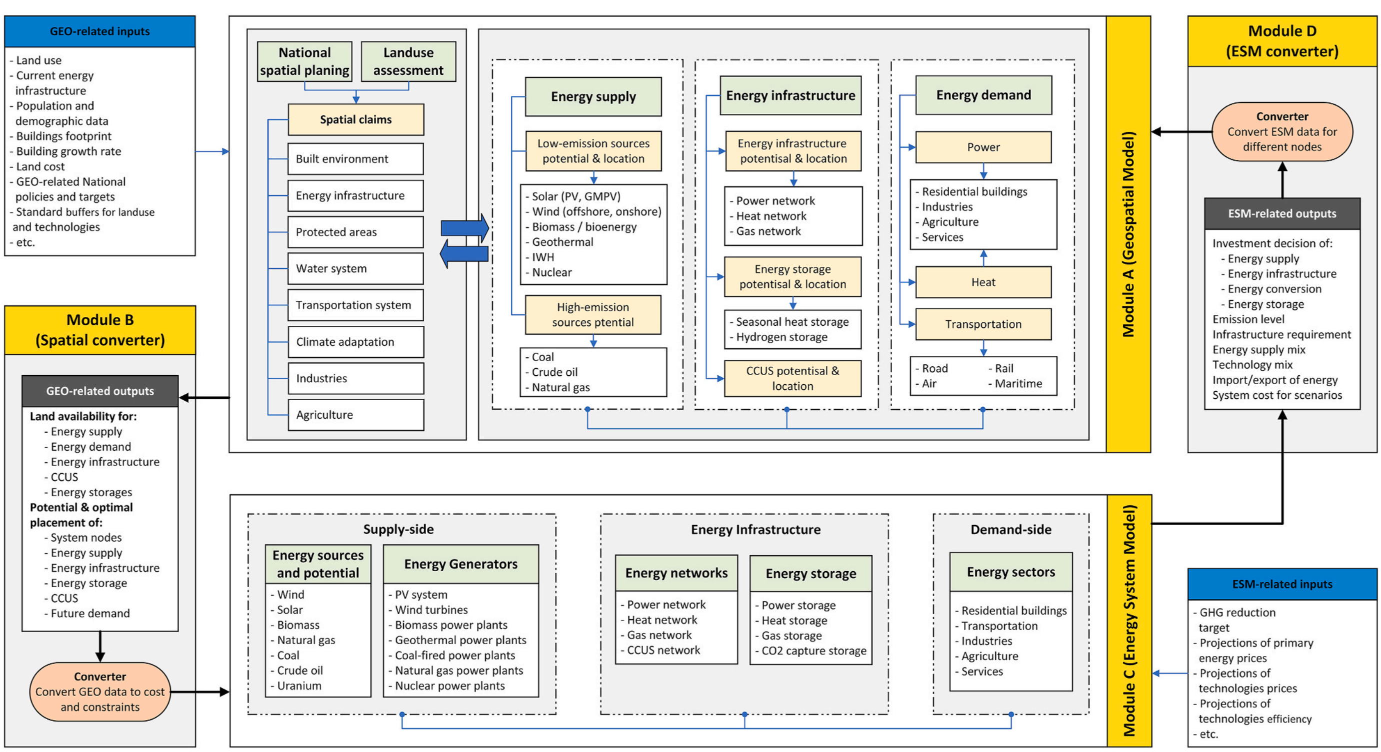


Fig. 5. A conceptual schematic of linking a spatial model with an ESM.

requires higher computational loads and tackles challenges in reaching convergence, it enhances the reliability of results by enabling iterative adjustments between models.

4.1. A modular framework for integrating spatial aspects into ESM

4.1.1. Module A: A detailed spatial model

Developing a spatially explicit ESM is essential for obtaining reliable outcomes and addressing challenges like the varied distribution of RESs. A detailed spatial model ensures that key spatial dynamics, such as land use competition and regional variation in energy supply and demand are included. This module emphasizes two main components: a spatial model to allocate land use based on spatial planning scenarios, and the incorporation of spatially dependent parameters for energy demand, sources, and infrastructure.

For the first component, we recommend considering national spatial planning to include economic growth, land use management, environmental conservation, social coherence, and disaster risk management. For example, Spatial Outlook 2023 presents four scenarios for spatial decision-making in the Netherlands for 2050, each prioritizing either economic growth, nature-based solutions, technology, or community-led development [118]. Incorporating such national spatial planning scenarios and land use assessments into an ESM allows for considering different dynamics influencing future energy systems. This combination leads to spatial coherence (determining what fits where) and choices of optimal use of space, which is crucial, especially in densely populated countries.

However, there is a lack of studies that directly incorporate a spatial model into an ESM to optimize land allocation for energy supplies and infrastructure. Most ESMs (e.g., OPERA, PyPSA, and Calliope) use GIS input data or preprocess these data to include only spatially dependent parameters into ESM. In contrast, we propose incorporating a spatial model that goes beyond this preprocessing step, facilitating land allocation for energy supply, storage, and infrastructure while considering competing land uses such as residential areas, green spaces, agriculture, transportation networks, and protected areas. This model integrates spatial planning inputs such as future land use scenarios with ESM results, which provide cost-optimized energy supply and infrastructure. The spatial model allocates the energy system's land use requirements across different regions while balancing competing land uses. An example of such a spatial model is RuimteScanner 2.0, which allocates regional land demand to specific grid cells based on land availability, suitability, and supporting long-term planning by simulating land use changes, as described in Ref. [119]. Another example is a spatially explicit energy location model, ADVENT-NEV, which optimizes the location of solar farms, wind farms, bioenergy power stations, and their associated bioenergy crops [120].

For the second component, several spatial approaches were defined to capture the spatially dependent parameters of energy supply, demand, and infrastructure, as explained in section 3.3. Sahoo et al. [30] and Martínez-Gordón et al. [29] included spatially explicit components in their model's framework. However, further improvement is needed to integrate energy systems' spatial dimensions, for example, spatially explicit gas, CCUS, methane, and hydrogen networks, into their approaches. Moreover, depending on data availability, we can employ either aggregation or disaggregation techniques to allocate values across nodes. For example, in the case of rooftop solar, a high-precision approach is illustrated in Fig. B- 1 in Appendix B to estimate potential using roof orientation, slope, and shading leveraging light detection and ranging (LiDAR) data. However, when data availability is limited, we suggest using either a representative area and extrapolating its potential to the targeted region [75,76] or solar energy density across available areas [95]. Such differentiated approaches exist for each RE technology, energy demand, and infrastructure.

4.1.2. Module B: spatial-converter

Module A provides spatially explicit outputs, including land availability and optimal placement of various energy system components aggregated within their respective nodes to feed into the ESM. Our analysis indicates that clustering methods offer more capabilities than regionalization methods to capture spatial variables (see Table 9). We recommend using either k-means or k-means++ & max-p clustering techniques among these clustering methods. Like PyPSA-Eur, a catchment area can be defined around each node to assign the available land and maximum capacity for energy supply, demand, infrastructure, storage, and CCUS. This catchment area defines boundaries for each node based on proximity, facilitating the allocation of different energy system variables to individual nodes [95]. Then, these components can be converted to costs or constraints and imported into ESMs.

4.1.3. Module C: A highly detailed ESM

ESMs are crucial for policymakers to evaluate energy-related policies' impacts and explore the most effective energy transition pathways. To address policy-related challenges, ESMs with high temporal, technological, and spatial resolutions are required for comprehensive decision-making support. Our findings indicate that PyPSA-EU, IESA-NS, MyPyPSA-Ger, AnyMOD, and Balmorel possess such detailed resolution (see Fig. 2). Furthermore, the ESM framework must incorporate highly detailed spatial features for energy demands, resources, infrastructure, and spatial claims. This capability is observed in REMix, Calliope, Opera, BeWhere, and TIMES. However, based on Table 6, these spatial capabilities are often highly aggregated or overlooked in current ESMs. For instance, many ESMs do not integrate national spatial planning to incorporate various spatial dynamics to address spatial conflicts among land uses.

We propose using an ESM that includes detailed spatial inputs. Our review in Table 6 reveals that most ESMs highly aggregate the spatial distribution of energy demand, supply, infrastructure, and storage. This aggregation reflects the limitation in data availability, lack of holistic perspective for spatially dependent parameters, or focus on high temporal and technological resolution, which restrict further improvement. Adding spatial details increases the complexity of the model and requires greater computational capacity, as a large amount of data is involved. Additionally, the capability of scaling up or down from an upper to a lower level is a practical feature to enhance the model's adaptability. This capability helps to change the resolution level based on policy needs. For example, PyPSA has this capability by using power system nodes and employing spatial clustering methods for node grouping.

4.1.4. Module D: ESM-converter

In this module, ESMs' outputs are integrated into the spatial model for further analysis. These outputs encompass investment decisions, emission levels, infrastructure requirements, and system costs for various scenarios. The ESM provides these results at individual nodes, which are then transferred to the spatial model through the ESM converter. This converter facilitates the implementation of a recursive procedure between the spatial model and the ESM. It helps to assess whether adjustments are needed for investments in ESMs to meet spatial model constraints. Additionally, it offers various benefits to support decisions, such as providing feedback on infrastructure requirements, identifying bottlenecks like insufficient transmission capacity, and optimizing the energy supply chain.

4.2. A recursive framework for ESM and spatial model

A recursive platform for exchanging feedback between the energy system and spatial models ensures consistent results. The spatial model can be soft-linked to the ESM through two-way connections. In this approach, the energy system and spatial models are linked iteratively using a recursive connection instead of a unidirectional linkage. For instance, the ESM may initially determine the placement of wind farms based on land availability and suitability criteria for wind energy at each node. However, if the spatial model cannot accommodate the required wind farm area in a specific region due to competing land use claims, it provides feedback to modify the ESM in subsequent iterations. The ESM can also provide feedback to the spatial model regarding the unmet energy demand in certain nodes, helping the spatial model to reconsider land allocation and potentially prioritize specific energy supplies over other land uses.

As illustrated in Fig. 6, the recursive soft link process involves several steps. The process begins with a preprocessing step, where spatial-based data (e.g., land use, suitability maps, exclusion areas) and energy data (e.g., energy demand profiles and fuel prices) are collected, analyzed, and stored in an integrated database. The spatial-based data are then transferred to the geo converter and spatial model. The geo converter is executed to cluster the input data into nodes and translate its outputs into cost parameters and constraints for the ESM. The ESM is executed, and its results are transferred through the ESM converter to the spatial model. The spatial model allocates the energy system's land requirement by optimizing land use while considering land use competitions and claims. Subsequently, feedback from the spatial model is used to update the ESM decisions. From the second iteration onward, convergence criteria are checked, and the process continues until these criteria are satisfied. One example of such a criterion is ensuring that the unmet energy demand across all nodes is below a certain threshold. Finally, the outputs of the ESM and spatial model are reported corresponding to the highest iteration index. Compared to unidirectional linking, this recursive approach provides more reliable results as it ensures the consistency of connected models.

4.3. Challenges in implementing spatially explicit ESM

Implementing a spatially explicit ESM at a national scale poses some challenges, particularly in balancing data availability, computation time, and accuracy. Various methods exist to reduce the computation time, such as aggregating temporal resolution, reducing the time extent, or lowering the technological resolution. Clustering time series can also effectively address the computation load [121]. Furthermore, increasing the number of generation nodes without expanding the energy system nodes can enhance model's accuracy and minimize runtime. For this purpose, Frysztacki et al. [99] compared different scenarios and concluded that increasing the spatial resolution of generation sites and aggregating them into energy system nodes, rather than increasing the number of system nodes, can be a practical approach to enhance the model's reliability when computational time is limited. Lombardi et al. [65] also structured a two-scale spatial configuration of the Italian power system in six bidding zones and 20 administrative-level regions using Calliope. They applied this two-scale resolution system to incorporate the variation of RESs and local political conditions in different areas. Bidding zones represent power demand profiles, transmission lines, and power storage plants. However, the regional administrative level helps to estimate renewable and PHS capacity. To reduce the model's complexity, this structure can incorporate variations at a lower scale and aggregate results at a higher scale.

Moreover, improving spatial details while maintaining maximum temporal, technological, and spatial resolution remains challenging. Incorporating additional spatial details impacts the resolution, as shown in PyPSA-Eur-Sec [96], which includes more detailed infrastructure for heat, methane, hydrogen, CCUS, and solid biomass compared to PyPSA-Eur [60]. Nevertheless, it decreases spatial resolution to one node per country, unlike PyPSA-Eur. Another challenge lies in the network typology for allocating supply and demand nodes, which can be structured through various methods. For example, clustering can be performed for supply nodes, followed by aggregation of demand nodes in these supply nodes, or vice versa. Alternatively, both energy demand and supply nodes can be clustered simultaneously. In addition, clustering can be separately performed for demand and supply nodes, subsequently aggregating them. Another challenge is selecting a method for the spatial aggregation of energy supply and demand in nodes. Different possibilities exist, such as connecting all energy demand points to the closest supply nodes or vice versa. The other possibility is to define a new node as a connector to link demand and supply nodes. These possibilities should be explored to find cost-effective configurations in future studies. The other challenge is the arrangement of nodes for

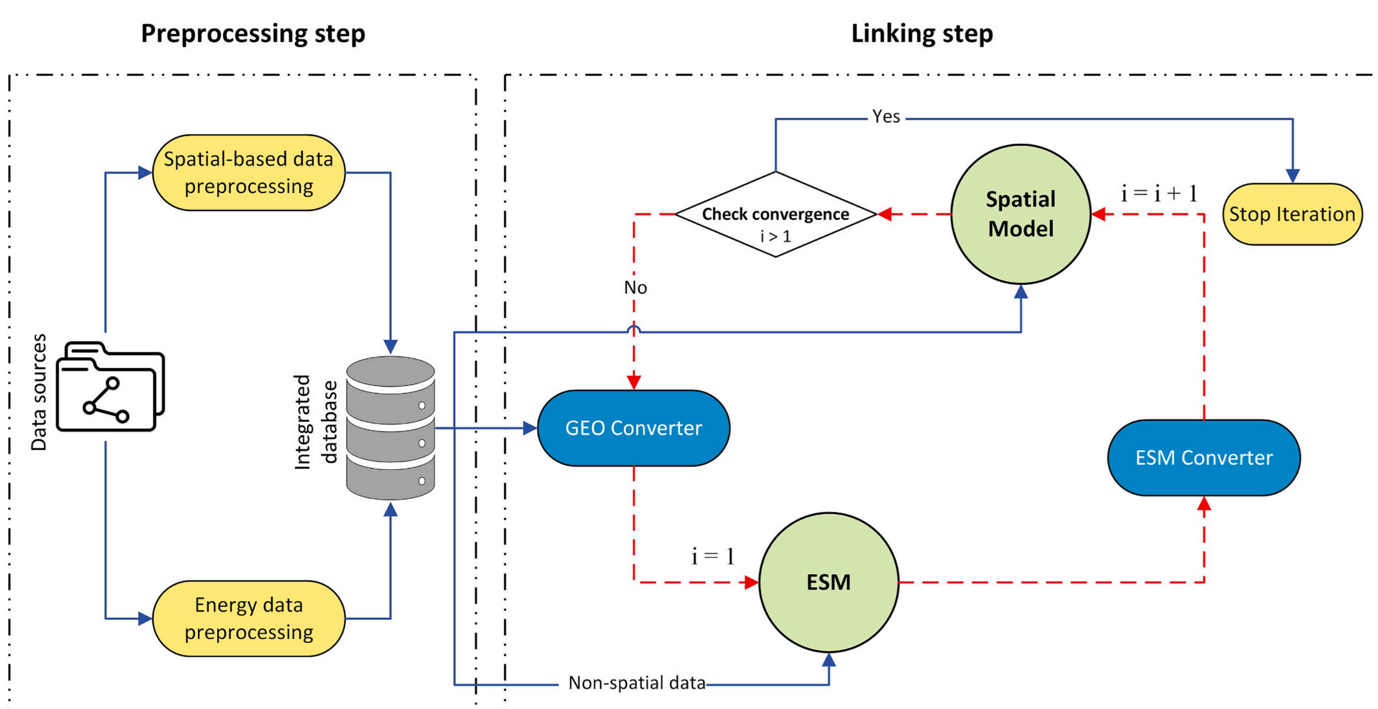


Fig. 6. The process flowchart of the proposed linking approach (i indicates the iteration number).

different energy commodities (power, heat, hydrogen, CCUS), as they have different characteristics and limitations and are grouped to match energy supply and demand.

5. Conclusion

ESMs can be instrumental in providing solutions and policy assessment but insufficiently incorporate spatial planning scenarios and high-quality spatially dependent parameters. This study evaluated the national ESMs that primarily focus on long-term energy planning models to provide energy transition pathways and infrastructure development over extended time horizons. It contributes to the existing literature by identifying and evaluating various spatially dependent parameters influencing energy supply distribution. It focuses, particularly on renewable energy potential, energy demand distribution, and the spatial arrangement of energy infrastructure. We reviewed the methods employed in existing literature to evaluate these spatially dependent parameters. Additionally, the importance of incorporating spatial planning into future ESMs was highlighted, as past and current spatial choices significantly impact the future energy system. Furthermore, we analyzed aggregation methods to integrate spatially dependent parameters into ESMs and explored linking methods to integrate spatial models with ESMs.

Our findings highlight that several ESMs such as PyPSA, IESA-NS, Calliope, OPERA, and Balmorel offer high spatial, temporal, and technological resolution. We also reviewed the approaches these ESMs use to incorporate energy infrastructure in their frameworks. The results show that clustering and regionalization are the main approaches to defining regions and nodes within the spatial domain. We suggest using clustering methods that provide greater flexibility in capturing spatial variations of spatially dependent parameters and adjusting spatial resolution for national ESMs. Regarding the linking methods, soft-linking and hard-linking are valid approaches in the literature to connect spatial models with ESMs. We recommend using the soft link method to link a spatial model with an ESM, as this approach allows for higher spatial resolution. We propose implementing a dynamic feedback loop to exchange data between ESMs and spatial models. This recursive soft-linking would provide continuous information exchange between two models, enhancing decision-making processes within energy systems such as resource allocation and infrastructure development.

We recommend a comprehensive framework including four modules to facilitate ESM and spatial model integration. In module A, a detailed spatial model evaluates spatial claims by integrating national spatial planning, policies, and land use assessments. It also includes spatially dependent parameters for energy demand, supply, and infrastructure as inputs for ESMs. Additionally, the spatially dependent parameters concerning energy demand, supply, and infrastructure are evaluated using the techniques overviewed in section 3.3. In module B, the output of the spatial model is aggregated to its respective nodes and regions using a clustering method, either k-means or k-means++ & max-p. A potential approach could involve using the supply areas as primary nodes and aggregating other elements like energy demand and storage with the closest nodes using a catchment area. A detailed ESM would offer a highly spatial, temporal, and technological resolution in module C. This ESM accommodates spatially explicit inputs and can scale up or down from an upper to a lower level. In module D, we proposed an ESM converter to employ a recursive procedure between the spatial model and ESM. It supports decisions regarding potential changes in investments in energy system components according to the constraints defined in the spatial model. Then, a recursive procedure is proposed to exchange information between ESM and spatial and define convergence criteria to obtain more reliable results. Minor adjustments based on data availability can adapt the methodology to any specific case study.

In future work, investigating a tradeoff analysis between data availability, accuracy, and computation time can provide clear insights to make informed decisions for spatial, temporal, and technological resolution of ESMs. Furthermore, future studies can investigate the role of climate change on the spatially dependent parameters that impact the energy system. Lastly, although we proposed using a bidirectional linking method to incorporate the spatial model and the ESM, we did not identify any studies implementing this approach to optimize land allocation for different land uses. Therefore, future studies can consider implementing such a recursive soft link platform between ESMs and spatial models.

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.

Acknowledgements

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Appendix A

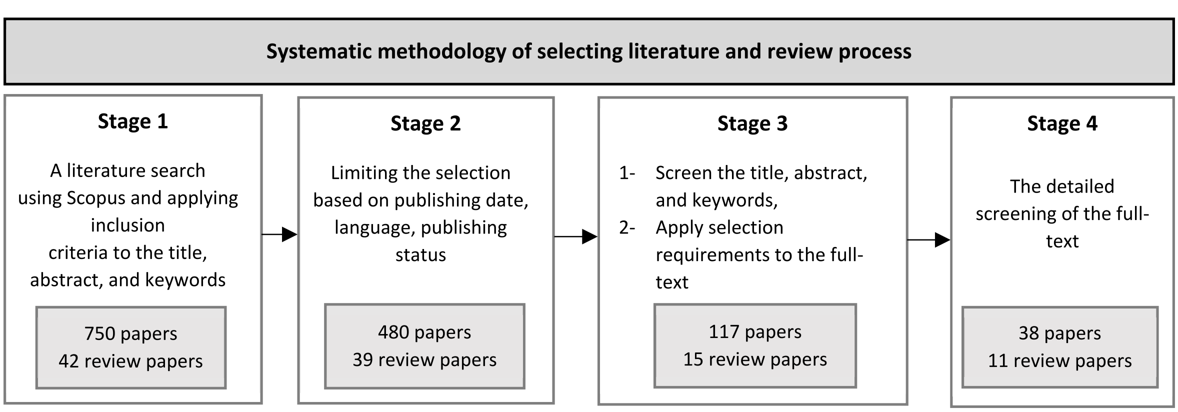

Fig. A- 1. Systematic process of literature review.

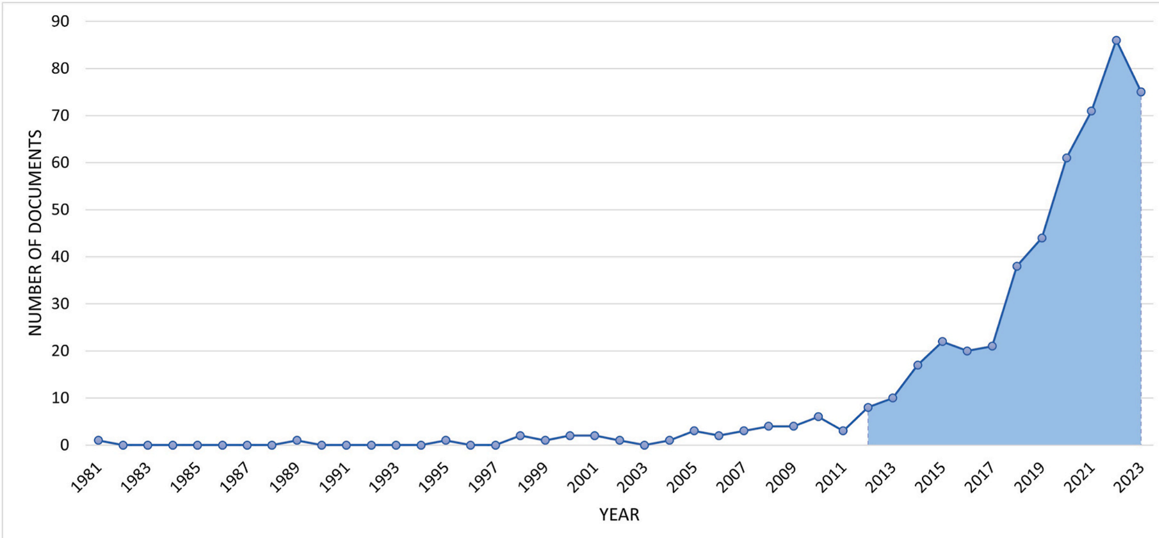

Fig. A- 2. The trend of published journal papers on spatial-based ESMs in the time frame of 1981–2023.

Table A- 1
Classification scheme for ESM comparison from literature

Criteria	Sub-criteria	Details	References
Modeling Structure/ Components	Country/Institution	Country name, institute, or authors	[33,36,122]
	Analytical approach	Bottom-up, top-down, hybrid	[33,52,122–125]
	Purpose	• Investment decision support, operation decision support, scenario, power system analysis tool, analysis • General (forecasting, exploring, back casting); specific (energy demand, supply, environmental impacts, etc.)	[125] [52]
	Structure of the model	Degree of endogenization, description of non-energy sectors, end-uses, supply technologies, supply or demand analysis tool	[52]
	Transformation analysis	Myopic, Foresight, None	[22,33,53]
	Data requirements	Qualitative, quantitative, monetary, aggregated, disaggregated,	[52]
	Costs	Investment, operation maintenance, fuel,c arbon cost, taxes, balancing cost	[52,125]
	Emissions	CO_2, CH_4, No, NO_x, SO_2, SO_x, any pollutant	[125]
	Availability	• Commercial, open access • Commercial, free, open source, free academic version • Low, medium, and high	[31,33,53,123,124] [125] [22]
	Documentation	Link	[53,122–124]
Mathematical approach	Methodology	• Simulation, optimization, and hybrid • Simulation, dispatch optimization, single/multi-objective investment optimization • Simulation, scenario, equilibrium, operation/investment optimization	[31,33,123,125,126] [22,122] [124]
	Algorithm used	• Linear optimization, mixed integer linear programming, generic network, agent-based, etc. • Linear, nonlinear, dynamic, mixed-integer, heuristic, or other	[31,52,53,123,125] [22]
	Objective function	Levelized cost of electricity (LCOE), total cost, net present value (NPV), annualized system cost	[123]
	Programming language/ Software	GAMS, AIMMS, Python, Fortran, etc.	[33,53,125,126]
	Spatial aggregation method	Nonoptimal, optimal (k-means, GIS, etc.)	[31]
Modeling resolution	Spatial resolution	• Number of regions/nodes • Number of regions/nodes, region type (administrative, climate, etc.) • Single-node, multi-node	[31,33,125] [36] [22]
	Spatial resolution flexibility	Yes, No	[31,33,126]
	Spatial extent	Building local, regional, national, and global	[31,52,122–125]
	Temporal resolution	Sub-hourly to annual resolution	[22,33,36,52,122–126]
	Temporal flexibility	Yes, No	[33,52]
	Time Horizon	Short and long-term	[33,36,52,122,124,125]
	Time horizon flexibility	User-defined, no	[52,125]
	Time analysis	Snapshot, evolution	[53]
Technological details	Renewable technologies	Wind, solar, hydropower, geothermal, wave, and tidal power	[52,125]
	Storage technology inclusion	Pumped hydro storage, compressed air energy storage, batteries, hydrogen, and thermal energy storage	[52,125]

(continued on next page)

Table A- 1 (*continued*)

Criteria	Sub-criteria	Details	References
	Commodities	• Power, transport, heat	[123]
		• Power, transport, heat, fuels, hydrogen	[31,125]
	Demand sectors	• Building, electricity, transport, industry	[125]
		• Building, power, energy, heating, transport, hydrogen, biomass	[36]
		• Transport, residential, commercial, agriculture	[52]
		• Energy sector (electricity, heat, transport)	[124]
	Demand representation	Elastic, inelastic	[53,125]
Geospatial aspect	Incorporation of spatial details	Infrastructure planning, region-specific energy service demand, GIS, multi-scale modeling, region-specific reference energy system	[36]
	Aim of geographical disaggregation	Explanation	[36]
	Included GIS tool	Yes, No	[31,127]

Energy supply:

Several studies have simplified the assessment of RE generation using different approaches. Prina et al. [28] spatially disaggregated PV and onshore potential, battery storage, and power transmission capacity by multiplying the population by the average PV generation per person. ElSayed et al. [41] used various methods to estimate upper limits for RESs based on the renewables' current share and land availability. Regarding land availability, 6 % and 4 % restrictions are imposed for solar and wind installation after excluding protected and urban areas. In addition, global weather data was used to calculate the hourly solar and wind production. Another way to simplify the inputs is to evaluate a specific site as a representative node for a larger area. Solomon et al. [76] proposed assessing one site in each region as a representative indicator of the entire region's solar potential. Gulagi et al. [75] employed various approaches to extract the potential of RESs and subdivided the country's map with specified RE capacities. Because solar energy variation is negligible in Bangladesh, evaluating a specific site to represent the solar potential for the entire subregion is feasible. The biomass potential is obtained from existing research and is divided into sub-regions based on population factors. Additionally, geothermal energy potential is calculated based on the ambient surface temperature, heat flow, and extrapolation approach for areas without data. Furthermore, Lopez et al. [81] estimated geothermal potential using surface ambient temperature and heat flow for eight regions in Bolivia. Solar, wind, and hydro-energy potential is obtained from weather data. Biomass potential was also classified and estimated for solid biomass waste, residues, and biogas. As an illustration, Fig. B- 1 summarizes approaches for estimating solar rooftops and GMPV, considering spatial inputs, temporal resolution, spatial resolution, and constraints across three levels of accuracy, from highly precise to low-accurate approaches.

In addition to these methodologies, multiple investigations have used global or national databases and allocated data among targeted regions. For instance, they acquired solar and wind data at a spatial resolution of 50 km × 50 km from NASA's surface meteorology and solar energy database. They processed these data using the German Aerospace Centre database [41,57,76]. Göke et al. [63] obtained capacity factors of RESs and storage capacity from the Ninja website at the Nomenclature of Territorial Units for Statistics (NUTS) level. In addition, the capacity factors of PV and wind are allocated to regions at the NUTS2 level by considering urban and suburban areas for rooftop PV and agricultural and forest areas for wind and GMPV. Subsequently, the share of PV and wind for these land-use categories is determined based on assumptions from the literature to estimate the renewable potential for each region within the NUTS2 level. However, the total energy potential remains fixed for each NUTS level. Furthermore, Kendziorski et al. [43] used a database to extract data on solar (GMPV and rooftop PV) and onshore wind potential at the national level. The energy potential was allocated among 38 regions of Germany, considering forest and agriculture areas for onshore wind and GMPV and urban and sub-urban layers for rooftop PV. Furthermore, a geological map is used to assess the site quality for energy production. Hörsch et al. [95] estimated the maximum generation capacity of solar and wind by using a constant technical potential density for each RES and available area, considering land use claims and public acceptance. To this end, 30 % of available land is allocated to wind energy, and 1 % is designated for solar energy installations.

Some studies focus solely on investigating the availability of bioenergy in certain regions. Bramstoft et al. [56] extracted the geographical distribution of available bioenergy resources and straw across 98 municipalities of Denmark from available information. The biomass potential for different sources is considered at the municipality level, encompassing straw for energy and manure, deep litter, grass, and organic waste for biogas production. Mohd Idris et al. [58] disaggregated the availabile potential of bioenergy feedstock among 560 equally sized grids in Malaysia. Different criteria are used for each bioenergy type, including palm oil mills' locations and capacities for palm kernel shells, palm plantation maps for oil palm trunks, locations and capacities of rice mills for rice husks, paddy plantation maps for rice straw, and livestock population maps for manure.

In a comprehensive study in the Netherlands, the spatial claims are estimated for multiple land uses such as built environment, agriculture, forests, and nature. First, they distinguished rooftop PV and GMPV for their solar energy potential. For rooftop PV, they extracted building footprints using an intersection tool in GIS and estimated the PV potential for the case study. For GMPV, spatial claims were defined, including the built environment, forests and nature, national landscapes, and energy infrastructure. Additionally, this study determines standard buffer zones of the built environment, networks, and energy infrastructure in different scenarios as exclusion zones for 2030 and 2050. Furthermore, various fractions are used to determine the potential GMPV in agricultural land for progressive, intermediate, and conservative scenarios. For onshore wind, considering the scenarios mentioned, they used the layer of possible locations for GMPV, including transmission networks, and used a greater buffer zone to build the environment. Additionally, they utilized the exclusion zones to identify the geothermal potential areas and used a grid map (1 km × 1 km) to define their technical potential. For industrial waste heat (IWH), they used relevant databases to extract data from industries producing IWH. Finally, they classified biomass into six types for assesing biomass potential and assumed specific land availability for each type in 2030 and 2050 [30].

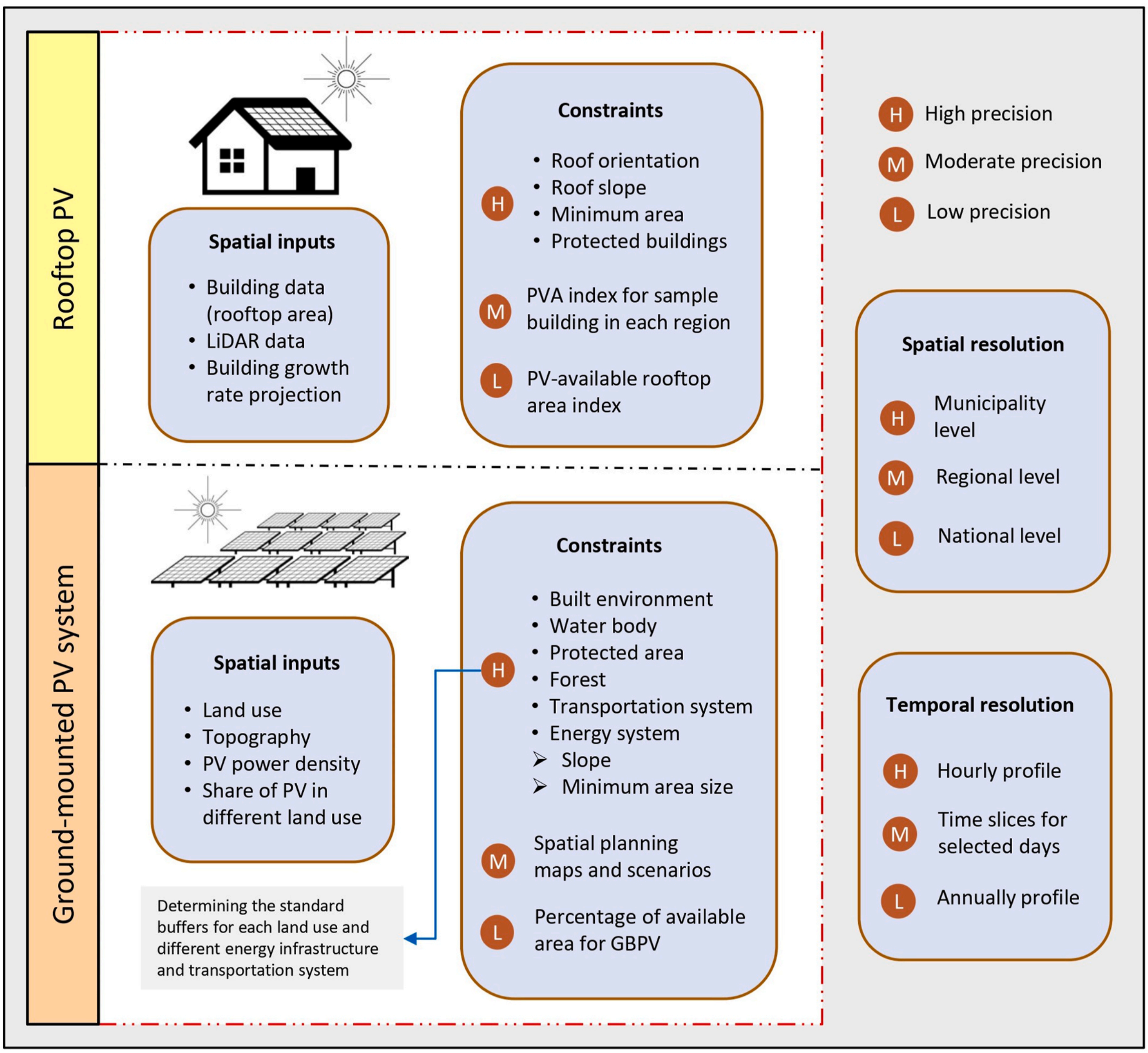

Fig. B- 1. Methods and components to estimate resource and technical potential of solar energy.

Appendix B

Energy demand:

As mentioned in section 3.3.2, studies use aggregation, disaggregation, or a combination of these approaches to obtain regional energy demand data. Using a disaggregation method, a study in Malaysia estimated power, heat, and transport energy demand between 2020 and 2050 for all 560 equally-sized grids. Various assumptions are made for the spatial disaggregation of energy demand, including the use of a power substation map for electricity, a natural gas map for heat demand, and a population map for transport fuel demand [58]. Henni et al. [60] used a hierarchical methodology to disaggregate heat and electricity consumption from national databases to state, district, and municipality levels across energy sectors. For the building sector, they used current and future population factors (at the state level), population for appliances, and population and living space for heat (at district and municipality levels). For industry and services, they used current and future population and employment rates (at the state level), energy consumption (at the district level), and the number of employees (at the municipality level). The transportation sector used current and future population, the rate of registered vehicles, and EVs for all administrative levels. Additionally, representative load profiles are used for each energy sector. Siala et al. [42] used an hourly load profile for each European country and disaggregated these data using a land use map for each demand sector. The same load profile was used for both 2015 and 2050.

ElSayed et al. [41] divided Egypt into seven sub-regions and obtained regional data from existing sources or by distributing national data using various methods. For example, the demand for space heating among regions is allocated using population data. As an assumption, a 3 % growth rate is considered for developing electricity demand by 2050. To obtain the hourly power demand profile, this study employed a methodology that involved different indicators such as air conditioning, tourism contribution, and local and seasonal temperatures. Colbertaldo et al. [40] used a transmission system operator (TSO) database to disaggregate energy load from the market zone to the regional level for the power, gas, and industry sectors. The demand is distributed among regions, considering the current shares of annual demand and the available areas defined by TSO. Similarly, hourly-resolved power demand profiles are provided for each bidding zone based on historical trends. Finally, the electric load is calculated by considering the contributions of residential, services, transportation, and industry sectors. One approach involved the extraction of power demand profiles and allocating them across regions using population distribution and the number of vehicles. Additionally, the hydrogen demand is estimated by analyzing the industry sector's heat demand and the share of cars. They also spatially disaggregated heat demand across the regions based on the plant distribution [64].

In contrast, by using an aggregation method, a study conducted in Chile derived demand data from an existing dataset, grouped these data by zone, and reclassified it by the energy sector (power, heat, transport, and desalination) and energy form (electricity, heat, and fuel). Then, the energy demand in each form is allocated among end-users or consumption sources, e.g., power demand is divided into residential, commercial, and industrial [128]. Sahoo et al. [30] proposed using the demand for the industry's final product unit instead of the energy demand of the industrial sector. The researchers used the projected dwellings as a suitable index instead of residential energy demand. Furthermore, a GIS database was used to collect building-related information, including building type, service type, energy label, and construction year. In another study, these researchers classified the energy demand sectors as the built environment, industries, agriculture, and transportation. For transportation, the information was allocated according to the population distribution at the regional level. The built environment is classified into three main categories: apartments, terraced houses, and other buildings, with their corresponding energy labels ranging from highly efficient to highly inefficient buildings. Additionally, services are classified into different types, including offices, educational institutions, hospitals, halls, and others with corresponding energy labels. The industry is considered in terms of its specific activities and current and future production projections. Finally, agriculture is considered in terms of its related heat, electricity, and machinery demand [39].

Population is a primary factor in allocating or calculating the energy demand in most studies. Two studies utilized a regression method by considering population, GDP, and the historical trend of power consumption to estimate the energy demand [59,62]. Furthermore, a different investigation used a current database to allocate energy demands among various regions based on population distribution and GDP. In addition, hourly demand profiles are calculated for residential, industry, and service sectors using standardized load profiles [43]. Bogdanov et al. [57] stated that the final electricity demand decreases due to population decline and advancements in technology and efficiency. It is assumed that residential and commercial energy consumption decreased by 20 %, industrial demand by 30 %, and cooling demand by 6 %. Transportation demand is based on the population decline factor and projected transportation volume for 2030, which is then extrapolated to 2050. However, another study derived power demand from an existing database for 2010 and 2016 and extrapolated it using a growth rate by 2050. The hourly load profile for each sub-region is calculated as a fraction of the total power demand, using data derived from the literature and weighted by the population of each sub-region [75]. In a study conducted in Bolivia, energy demand is extrapolated using an existing database for 2030. The growth rate for energy demand is estimated by considering the population and the increase in energy access. The power sector was classified into residential, commercial, and industrial demand categories. Heat demand was classified into space heating, domestic hot water, biomass, and industrial process heat. Additionally, the transport sector is categorized into road, rail, marine, and aviation, and the energy demand is estimated based on vehicle technology and specific vehicle energy demand [81].

Energy infrastructure:

Like most reviewed ESMs, OMNI-ES' energy infrastructure is designed as a network graph with nodes and edges. Spatial nodes depict energy system elements such as generators, energy demand, RESs, and storage, while edges represent energy networks. In this model, the power transport capacity is limited to seven bidding zones in Italy, based on the TSO's information. As each bidding zone includes several regions, these limits are set on the combined power flow between areas rather than separate limits for individual nodes. These values are determined according to current network capacity and planned upgrades by 2040. The same approach identifies power transfer limits at the country's import points. Furthermore, the gas network's transport capacity is estimated using existing natural gas pipelines' capacity to transfer the CH4-H2 blend. The transport capacity of all 20 nodes is determined by summing the capacity of pipelines that connect these regions in pairs. The hydrogen flow between nodes is calculated based on hydrogen capacity, which comprises production and import. Predefined limits on capacity and flow rates constrain hydrogen flow. For biofuel, the model consideres the constraint on biomass consumption. It also simplified all fuel types into a single category for each node. This study also simplified the CCUS process using an annual balance approach, without modeling the local storage, inter-nodal, and long-distance transportation [40].

PyPSA-Eur-Sec, an extension of PyPSA-Eur, offers a comprehensive ESM that integrates a spatially explicit approach to cluster power transmission nodes with RES. It includes details of the gas network, CCUS, and enhanced transportation and biomass components. The electricity network is modeled in nodal configuration, and its distribution network is designed as links representing the energy transfer between distribution and transmission levels. The model has two options for modeling solid biomass in one node or multiple nodes. The multi-node structure includes biomass potential (distributed based on each country's population density) and biomass transport between countries [129]. Biogas and solid biomass are assumed to be transported between countries without bottlenecks since each country has a surplus biomass supply compared to its demand. CCUS networks can be modeled as single node for Europe or disaggregated in nodal structures using CO2 transport pipelines. The transportation of CCUS is unconstrained among countries in the model. The Methene network can also be modeled in one node or multiple nodes. Notably, modeling methane in one node is logical as no bottlenecks are expected due to the future low demand, and it can be freely transported between countries. The liquid hydrocarbons are modeled as a single node due to a low transport cost and no bottlenecks in the future. The hydrogen network can be activated as the nodal configuration in the model. Two options for storing hydrogen include overground steel tanks and salt caverns, with a 50 km exclusion zone from the shore. Unlike the transmission grid, the distribution network is not included, and optimization focuses only on the capacity from the transmission grid to the LV level [96]. Therefore, PyPSA-Eur-Sec simplified the transportation of biomass, biofuels, and CCUS by assuming no regional bottlenecks. It also simplified the methene and liquid hydrocarbon infrastructure in one node. Compared to PyPSA-Eur [95], this model reduces the spatial resolution to one node per country to tackle computational limitation.

OPERA and IESA-NS are models that effectively integrate different spatial energy infrastructure components. OPERA is soft-linked by a pan-European power market model that considers the international electricity trade-off. They used GIS to calculate the high voltage (HV) power network distance between regions. Using the current power network plans, they have created some nodes and connected all municipalities with at least one HV line. They have also included the region-based medium voltage (MV) network in the ESMs and the network distance in the balance constraint of energy flow. They proposed MVs to connect cities, integrate RES with the grid, and link a sizeable industrial cluster. For the heating network, they incorporated new nodes to accommodate DH, an uncommon feature in the current ESMs. They have differentiated between the transmission and distribution of the heating network and connecting distant nodes through transmission networks. They used GIS to find the closest routes between industry clusters, city centers, city outskirts, and geothermal doublets. They included all possible routes between these nodes and optimized the results in OPERA [39]. The best offshore hubs are defined in IESA-NS by estimating the space available for single-use and multi-use activities of various clusters in the North Sea. They deduced unavailable areas due to different spatial claims within the defined groups. The study analyzed several spatial claims activities in the North Sea, including protected and vulnerable areas, fishing and shipping networks, sand extraction areas, and oil and gas networks. Furthermore, they calculated the physical distance between cluster centroids to measure the required HVDC and hydrogen pipeline length. In addition, they estimated the capacity and size of suitable infrastructure that could be reused for future energy system deployment, including power cables and natural gas pipelines. Moreover, a database is employed to calculate the potential of hydrogen storage within each node [29].

Three geographical dimension layers are defined in the Balmorel model that shapes its energy network structure. The first layer is countries, which help formulate policies and aims for them. The second layer consists of regions defined by power system transmission. This layer acts as copper plates regarding electricity generation and demand. The third layer includes areas that help determine VRES' capacity and investment options for energy generation and total load hours. The heat network is defined as a cooper plate in this layer [130]. AnyMOD follows a graph structure for modeling an energy system. Initially, the model is executed for Europe, and a single node defines each country. Subsequently, the investment decisions of all countries were fixed, and the model was executed for 38 regions in Germany. A simplified power transmission network is considered for exchanging power between regions. Synthetic methane can be transported through the existing pipeline network. For hydrogen, the current pipelines need to be upgraded [43]. Using the REMix model, Germany is divided into 18 regions, with aggregated power demand, power plants, and storage for each area. The transmission grid capacity, the electricity exchange, and the capacity of hydrogen electrolyzers and storage are obtained from European REMix results [64].

Energy transmission, storage, and CCUS are also synthesized in different ESMs. LUT-ESTM is designed to consider the HVAC and HDVC of power transmission between regions. The model calculates the optimal power transmission grid capacity, the capacity of AC/DC converters, the length of power lines, and their losses. The efficiency of HVDC grids is calculated using the grid length and converter's efficiency. Meanwhile, the efficiency of HVAC depends only on the transmission distance. The distance-related losses are calculated for both transmission lines [57,131]. Prina et al. [28] developed a framework based on dispatch/operational optimization to manage the surplus RE generation by storing it through pumped hydro or batteries or exporting it to another node to fulfill its demand or store it. Siala et al. [42] estimated regional pumped hydro storage capacities and divided an equal battery capacity between regions. Power constraints of transmission lines and their associated losses are also considered in the model. Transmission lines are allocated across regions based on their lengths and voltage levels. This transmission network is considered for connection between countries. Regarding the CCUS network, Mesfun et al. [132] identified the locations and potential of CO2 sources within the Alpine region using GIS. Considering the future projections, these databases include the CO2 emissions from power plants, CHPs and processes, other industrial processes, and air. However, they did not classify the industrial types as CO2 emitters in the model.

In many ESMs, the Euclidean distance approach is commonly used to estimate the transmission length and capacity. For instance, the OptiFlow model was employed to determine the location of biogas plants and refineries. The researchers applied the Euclidean distance by considering the geometric centroid of each municipality to transport the biomass across regions by trucks. Excess heat potential is distributed equally among Denmark's five main district heating networks [56]. The road and sea transportation network is established, including the distance between grids, grids and harbors, and harbors for optimization purposes in the model. In road transportation networks, trucks are used to transport products, while in sea transportation, ships are employed to move products from harbors to targeted grids. The required extension of power transmission lines is considered to connect agricultural mills to power substations. Additionally, the necessary extension of steam pipelines for transporting bioheat is considered for industrial demand centers [58]. Due to the lack of available data, Das et al. [62] utilized the Euclidian distance approach to calculate the length of HV power transmission lines between regions through the TIMES model. In another investigation, the same approach is used to estimate distances among grids and harbors to transport feedstock through roads, sea, and pipelines for all grids.

Appendix C

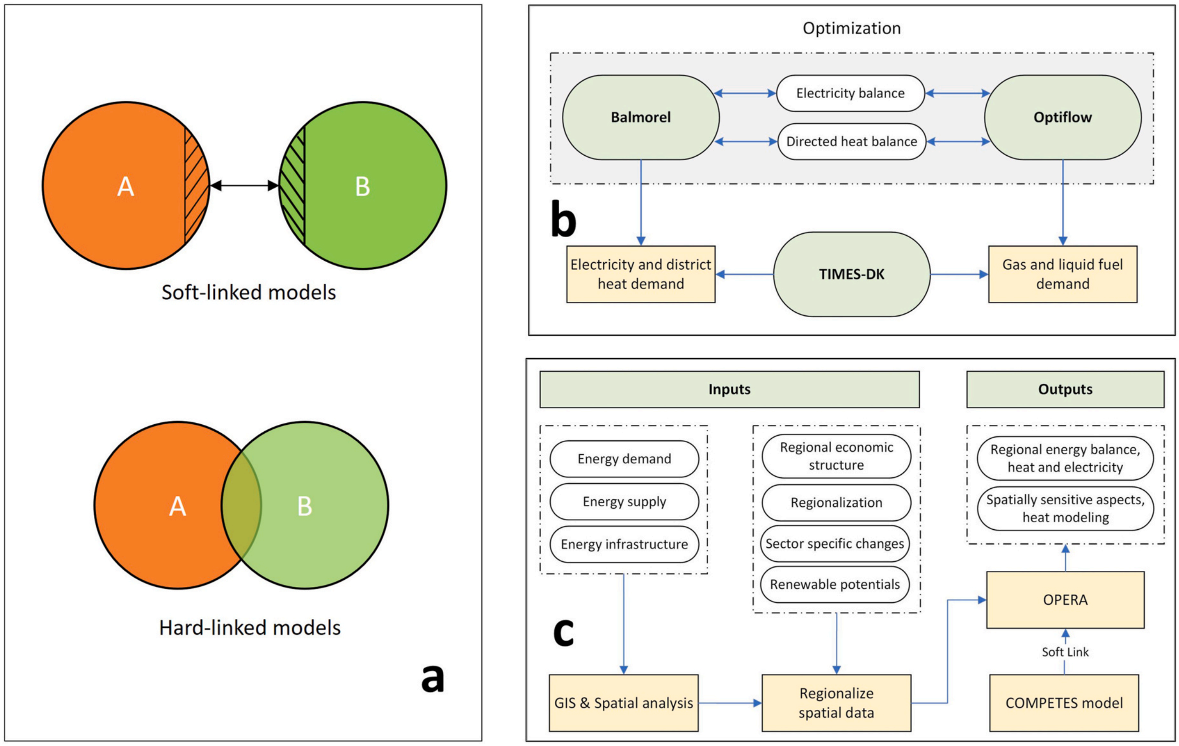

Fig. C- 1. (a) Linking approaches according to their linking degree taken from Ref. [111]; (b) The hard-linking of results between Balmorel, OptiFlow, and TIMES-DK taken from Ref. [56]; (c) Soft link method of spatial analysis, COMPETES, and OPERA model adopted from Ref. [30].

Data availability

No data was used for the research described in the article.

References

[1] Stremke S, van den Dobbelsteen A. Sustainable energy landscapes: designing, planning, and development. CRC Press; 2012.
[2] Bouckaert S, et al. Net zero by 2050: a roadmap for the global energy sector. 2021.
[3] Wang N, Verzijlbergh RA, Heijnen PW, Herder PM. A spatially explicit planning approach for power systems with a high share of renewable energy sources. Appl Energy 2020;260:114233. https://doi.org/10.1016/j.apenergy.2019.114233.
[4] De Laurentis C. Reshaping energy landscape: a regional approach to explore electricity infrastructure networks. Landsc Res 2023;48(2):224–38.
[5] de Boer J, Zuidema C. Towards an integrated energy landscape. Proceedings of the Institution of Civil Engineers-Urban Design and Planning 2015;168(5): 231–40.
[6] Solaun K, Cerdá E. Climate change impacts on renewable energy generation. A review of quantitative projections. Renewable and sustainable energy Reviews 2019;116:109415.
[7] Gernaat DE, de Boer HS, Daioglou V, Yalew SG, Müller C, van Vuuren DP. Climate change impacts on renewable energy supply. Nat Clim Change 2021;11(2): 119–25.
[8] Nordensvärd J, Urban F. The stuttering energy transition in Germany: wind energy policy and feed-in tariff lock-in. Energy Policy 2015;82:156–65.
[9] Gürsan C, de Gooyert V. The systemic impact of a transition fuel: does natural gas help or hinder the energy transition? Renew Sustain Energy Rev 2021;138: 110552.
[10] Oudes D, Stremke S. Spatial transition analysis: spatially explicit and evidence-based targets for sustainable energy transition at the local and regional scale. Landsc Urban Plann 2018;169:1–11.
[11] McKenna R, et al. System impacts of wind energy developments: key research challenges and opportunities. Joule 2025;9(1).
[12] Jenniches S, Worrell E. Regional economic and environmental impacts of renewable energy developments: solar PV in the Aachen Region. Energy for Sustainable Development 2019;48:11–24.
[13] Jenniches S. Assessing the regional economic impacts of renewable energy sources–A literature review. Renew Sustain Energy Rev 2018;93:35–51.
[14] Raupach-Sumiya J, Matsubara H, Prahl A, Aretz A, Salecki S. Regional economic effects of renewable energies-comparing Germany and Japan. Energy, Sustainability and Society 2015;5:1–17.
[15] Stoeglehner G, Neugebauer G, Erker S, Narodoslawsky M. Integrated spatial and energy planning: supporting climate protection and the energy turn with means of spatial planning. Springer; 2016.
[16] Calvert K, Mabee W. More solar farms or more bioenergy crops? Mapping and assessing potential land-use conflicts among renewable energy technologies in eastern Ontario, Canada. Appl Geogr 2015;56:209–21. https://doi.org/10.1016/j.apgeog.2014.11.028.
[17] Ontwerp-Programma Energiehoofdstructuur Ruimte voor een klimaatneutraal energiesysteem van nationaal belang. 2021. Rijksoverheid.
[18] Couto A, Estanqueiro A. Assessment of wind and solar PV local complementarity for the hybridization of the wind power plants installed in Portugal. J Clean Prod 2021;319:128728.
[19] Fattahi A, Sijm J, Faaij A. A systemic approach to analyze integrated energy system modeling tools: a review of national models. Renew Sustain Energy Rev 2020;133:110195.
[20] Fodstad M, et al. Next frontiers in energy system modelling: a review on challenges and the state of the art. Renew Sustain Energy Rev 2022;160:112246.
[21] Chang M, et al. Trends in tools and approaches for modelling the energy transition. Appl Energy 2021;290:116731.
[22] Prina MG, Manzolini G, Moser D, Nastasi B, Sparber W. Classification and challenges of bottom-up energy system models-A review. Renew Sustain Energy Rev 2020;129:109917.
[23] Böhringer C, Rutherford TF. Integrated assessment of energy policies: decomposing top-down and bottom-up. J Econ Dynam Control 2009;33(9): 1648–61. https://doi.org/10.1016/j.jedc.2008.12.007.
[24] Krook-Riekkola A, Berg C, Ahlgren EO, Söderholm P. Challenges in top-down and bottom-up soft-linking: lessons from linking a Swedish energy system model with a CGE model. Energy 2017;141:803–17.
[25] Pisciella P, van Beesten ER, Tomasgard A. Efficient coordination of top-down and bottom-up models for energy system design: an algorithmic approach. Energy 2023;284:129320.
[26] Böhringer C, Rutherford TF. Combining bottom-up and top-down. Energy Econ 2008;30(2):574–96.
[27] Fleischer CE. Minimising the effects of spatial scale reduction on power system models. Energy Strategy Rev 2020;32. https://doi.org/10.1016/j.esr.2020.100563. Art no. 100563.
[28] Prina MG, et al. Multi-objective investment optimization for energy system models in high temporal and spatial resolution. Appl Energy 2020;264:114728.

[29] Martínez-Gordón R, Gusatu L, Morales-España G, Sijm J, Faaij A. Benefits of an integrated power and hydrogen offshore grid in a net-zero North Sea energy system. Advances in Applied Energy 2022;7. https://doi.org/10.1016/j.adapen.2022.100097. Art no. 100097.
[30] Sahoo S, van Stralen JNP, Zuidema C, Sijm J, Yamu C, Faaij A. Regionalization of a national integrated energy system model: a case study of the northern Netherlands. Appl Energy 2022;306. https://doi.org/10.1016/j.apenergy.2021.118035. Art no. 118035.
[31] Martínez-Gordón R, Morales-España G, Sijm J, Faaij A. A review of the role of spatial resolution in energy systems modelling: lessons learned and applicability to the North Sea region. Renew Sustain Energy Rev 2021;141:110857.
[32] Kaza N, Curtis MP. The land use energy connection. J Plann Lit 2014;29(4):355–69. https://doi.org/10.1177/0885412214542049.
[33] Lopion P, Markewitz P, Robinius M, Stolten D. A review of current challenges and trends in energy systems modeling. Renewable and sustainable energy reviews 2018;96:156–66.
[34] Frew BA, Jacobson MZ. Temporal and spatial tradeoffs in power system modeling with assumptions about storage: an application of the POWER model. Energy 2016;117:198–213. https://doi.org/10.1016/j.energy.2016.10.074.
[35] Maclaurin G, et al. The renewable energy potential (rev) model: a geospatial platform for technical potential and supply curve modeling. Golden, CO (United States): National Renewable Energy Lab.(NREL); 2019.
[36] Aryanpur V, O'Gallachoir B, Dai H, Chen W, Glynn J. A review of spatial resolution and regionalisation in national-scale energy systems optimisation models. Energy Strategy Rev 2021;37. https://doi.org/10.1016/j.esr.2021.100702.
[37] Mimica M, Dominković DF, Kirinčić V, Krajačić G. Soft-linking of improved spatiotemporal capacity expansion model with a power flow analysis for increased integration of renewable energy sources into interconnected archipelago. Appl Energy 2022;305:117855.
[38] Reinert C, Nilges B, Baumgärtner N, Bardow A. This is SpArta: rigorous optimization of regionally resolved energy systems by spatial aggregation and decomposition. Appl Energy 2024;367. https://doi.org/10.1016/j.apenergy.2024.123323.
[39] Sahoo S, van Stralen JNP, Zuidema C, Sijm J, Faaij A. Regionally integrated energy system detailed spatial analysis: Groningen Province case study in the northern Netherlands. Energy Convers Manag 2023;277. https://doi.org/10.1016/j.enconman.2022.116599. Art no. 116599.
[40] Colbertaldo P, Parolin F, Campanari S. A comprehensive multi-node multi-vector multi-sector modelling framework to investigate integrated energy systems and assess decarbonisation needs. Energy Convers Manag 2023;291. https://doi.org/10.1016/j.enconman.2023.117168. Art no. 117168.
[41] ElSayed M, Aghahosseini A, Breyer C. High cost of slow energy transitions for emerging countries: on the case of Egypt's pathway options. Renew Energy 2023;210:107–26. https://doi.org/10.1016/j.renene.2023.04.036.
[42] Siala K, Mahfouz MY. Impact of the choice of regions on energy system models. Energy Strategy Rev 2019;25:75–85. https://doi.org/10.1016/j.esr.2019.100362.
[43] Kendziorski M, Göke L, von Hirschhausen C, Kemfert C, Zozmann E. Centralized and decentral approaches to succeed the 100% energiewende in Germany in the European context – a model-based analysis of generation, network, and storage investments. Energy Policy 2022;167:113039. https://doi.org/10.1016/j.enpol.2022.113039.
[44] Ramirez Camargo L, Stoeglehner G. Spatiotemporal modelling for integrated spatial and energy planning. Energy, Sustainability and Society 2018/10/16 2018;8(1):32. https://doi.org/10.1186/s13705-018-0174-z.
[45] Bhatti AR, et al. An improved approach to enhance training performance of ANN and the prediction of PV power for any time-span without the presence of real-time weather data. Sustainability 2021;13(21):11893.
[46] Tortorella MM, et al. A methodological integrated approach to analyse climate change effects in agri-food sector: the TIMES water-energy-food module. Int J Environ Res Publ Health 2020;17(21):7703.
[47] Mounir A, Guan X, Mascaro G. Investigating the value of spatiotemporal resolutions and feedback loops in water-energy nexus modeling. Environ Model Software 2021;145:105197.
[48] Ran L, Loughlin D, Yang D, Adelman Z, Baek B, Nolte C. ESP v2. 0: enhanced method for exploring emission impacts of future scenarios in the United States–addressing spatial allocation. Geosci Model Dev Discuss (GMDD) 2015;8(1):263–300.
[49] Chen J, He T, Jiang B, Liang S. Estimation of all-sky all-wave daily net radiation at high latitudes from MODIS data. Remote Sensing of Environment 2020;245. https://doi.org/10.1016/j.rse.2020.111842.
[50] Khan ZA, Hussain T, Baik SW. Dual stream network with attention mechanism for photovoltaic power forecasting. Appl Energy 2023;338:120916.
[51] Drożdż W, Bilan Y, Rabe M, Streimikiene D, Pilecki B. Optimizing biomass energy production at the municipal level to move to low-carbon energy. Sustain Cities Soc 2022;76:103417.
[52] Hall LM, Buckley AR. A review of energy systems models in the UK: prevalent usage and categorisation. Appl Energy 2016;169:607–28.
[53] Plazas-Niño F, Ortiz-Pimiento N, Montes-Páez E. National energy system optimization modelling for decarbonization pathways analysis: a systematic literature review. Renew Sustain Energy Rev 2022;162:112406.
[54] Savvidis G, et al. The gap between energy policy challenges and model capabilities. Energy Policy 2019;125:503–20.
[55] Sifnaios I, Sneum DM, Jensen AR, Fan J, Bramstoft R. The impact of large-scale thermal energy storage in the energy system. Appl Energy 2023;349. https://doi.org/10.1016/j.apenergy.2023.121663. Art no. 121663.
[56] Bramstoft R, Pizarro-Alonso A, Jensen IG, Ravn H, Münster M. Modelling of renewable gas and renewable liquid fuels in future integrated energy systems. Appl Energy 2020;268. https://doi.org/10.1016/j.apenergy.2020.114869. Art no. 114869.
[57] Bogdanov D, Oyewo AS, Breyer C. Hierarchical approach to energy system modelling: complexity reduction with minor changes in results. Energy 2023;273:127213. https://doi.org/10.1016/j.energy.2023.127213.
[58] Mohd Idris MN, Hashim H, Leduc S, Yowargana P, Kraxner F, Woon KS. Deploying bioenergy for decarbonizing Malaysian energy sectors and alleviating renewable energy poverty. Energy 2021;232. https://doi.org/10.1016/j.energy.2021.120967. Art no. 120967.
[59] Abuzayed A, Hartmann N. MyPyPSA-Ger: introducing CO2 taxes on a multi-regional myopic roadmap of the German electricity system towards achieving the 1.5 °C target by 2050. Appl Energy 2022;310:118576. https://doi.org/10.1016/j.apenergy.2022.118576.
[60] Henni S, Schäffer M, Fischer P, Weinhardt C, Staudt P. Bottom-up system modeling of battery storage requirements for integrated renewable energy systems. Appl Energy 2023;333. https://doi.org/10.1016/j.apenergy.2022.120531. Art no. 120531.
[61] Jarosch C, Jahnke P, Giehl J, Himmel J. Modelling decentralized hydrogen systems: lessons learned and challenges from German regions. Energies 2022;5(4). https://doi.org/10.3390/en15041322. Art no. 1322.
[62] Das P, Kanudia A, Bhakar R, Mathur J. Intra-regional renewable energy resource variability in long-term energy system planning. Energy 2022;245. https://doi.org/10.1016/j.energy.2022.123302. Art no. 123302.
[63] Göke L, Kendziorski M, Kemfert C, Hirschhausen CV. Accounting for spatiality of renewables and storage in transmission planning. Energy Econ 2022;113. https://doi.org/10.1016/j.eneco.2022.106190. Art no. 106190.
[64] Gils HC, Pregger T, Flachsbarth F, Jentsch M, Dierstein C. Comparison of spatially and temporally resolved energy system models with a focus on Germany's future power supply. Appl Energy 2019;255. https://doi.org/10.1016/j.apenergy.2019.113889. Art no. 113889.
[65] Lombardi F, Pickering B, Colombo E, Pfenninger S. Policy decision support for renewables deployment through spatially explicit practically optimal alternatives. Joule 2020;4(10):2185–207. https://doi.org/10.1016/j.joule.2020.08.002.
[66] Pickering B, Lombardi F, Pfenninger S. Diversity of options to eliminate fossil fuels and reach carbon neutrality across the entire European energy system. Joule 2022;6(6):1253–76.
[67] Dale VH, Efroymson RA, Kline KL. The land use–climate change–energy nexus. Landsc Ecol 2011;26:755–73. https://doi.org/10.1007/s10980-011-9606-2.
[68] Pasqualetti M, Stremke S. Energy landscapes in a crowded world: a first typology of origins and expressions. Energy Res Social Sci 2018;36:94–105. https://doi.org/10.1016/j.erss.2017.09.030.
[69] Lovering J, Swain M, Blomqvist L, Hernandez RR. Land-use intensity of electricity production and tomorrow's energy landscape. PLoS One 2022;17(7):e0270155.
[70] De Boer J, Zuidema C, Gugerell K. New interaction paths in the energy landscape: the role of local energy initiatives. Landsc Res 2018;43(4):489–502. 0.1080/01426397.2018.1444154.
[71] Calvert K, Simandan D. Energy, space, and society: a reassessment of the changing landscape of energy production, distribution, and use. Journal of Economics and Business Research 2010;16(1):13–37.
[72] Izadyar N, Ong HC, Chong W, Leong K. Resource assessment of the renewable energy potential for a remote area: a review. Renew Sustain Energy Rev 2016;62:908–23. https://doi.org/10.1016/j.rser.2016.05.005.
[73] Farooq MK, Kumar S. An assessment of renewable energy potential for electricity generation in Pakistan. Renew Sustain Energy Rev 2013;20:240–54. https://doi.org/10.1016/j.rser.2012.09.042.
[74] Brown A, et al. "Estimating renewable energy economic potential in the United States. Methodology and initial results. Golden, CO (United States): National Renewable Energy Lab.(NREL); 2016.
[75] Gulagi A, Ram M, Solomon AA, Khan M, Breyer C. Current energy policies and possible transition scenarios adopting renewable energy: a case study for Bangladesh. Renew Energy 2020;155:899–920. https://doi.org/10.1016/j.renene.2020.03.119.
[76] Solomon AA, Bogdanov D, Breyer C. Solar driven net zero emission electricity supply with negligible carbon cost: Israel as a case study for Sun Belt countries. Energy 2018;155:87–104. https://doi.org/10.1016/j.energy.2018.05.014.
[77] Obane H, Nagai Y, Asano K. Assessing land use and potential conflict in solar and onshore wind energy in Japan. Renew Energy 2020;160:842–51. https://doi.org/10.1016/j.renene.2020.06.018.
[78] Hu J, Harmsen R, Crijns-Graus W, Worrell E. Geographical optimization of variable renewable energy capacity in China using modern portfolio theory. Appl Energy 2019;253:113614. https://doi.org/10.1016/j.apenergy.2019.113614.
[79] Assouline D. Machine Learning and Geographic Information Systems for large-scale mapping of renewable energy potential. EPFL; 2019.
[80] Javanmardi K, Hernández P, Oregi X. From rooftops to roads: bilbao's geospatial solar and EV fusion. Sustain Cities Soc 2024;104:105290. https://doi.org/10.1016/j.scs.2024.105290.
[81] Lopez G, et al. Pathway to a fully sustainable energy system for Bolivia across power, heat, and transport sectors by 2050. J Clean Prod 2021;293:126195. https://doi.org/10.1016/j.jclepro.2021.126195.

[82] Fiorese G, Guariso G. A GIS-based approach to evaluate biomass potential from energy crops at regional scale. Environ Model Software 2010;25(6):702–11. https://doi.org/10.1016/j.envsoft.2009.11.008.
[83] Hamelin L, Borzęcka M, Kozak M, Pudełko R. A spatial approach to bioeconomy: quantifying the residual biomass potential in the EU-27. Renew Sustain Energy Rev 2019;100:127–42. https://doi.org/10.1016/j.rser.2018.10.017.
[84] Fasipe O, Izinyon O, Ehiorobo J. Hydropower potential assessment using spatial technology and hydrological modelling in Nigeria river basin. Renew Energy 2021;178:960–76. https://doi.org/10.1016/j.renene.2021.06.133.
[85] Guiamel IA, Lee HS. Potential hydropower estimation for the Mindanao River Basin in the Philippines based on watershed modelling using the soil and water assessment tool. Energy Rep 2020;6:1010–28. https://doi.org/10.1016/j.egyr.2020.04.025.
[86] McGookin C, Gallachóir BÓ, Byrne E. An innovative approach for estimating energy demand and supply to inform local energy transitions. Energy 2021;229:120731.
[87] Lin Q, Liu K, Hong B, Xu X, Chen J, Wang W. A data-driven framework for abnormally high building energy demand detection with weather and block morphology at community scale. J Clean Prod 2022;354:131602. https://doi.org/10.1016/j.jclepro.2022.131602.
[88] Happle G, Fonseca JA, Schlueter A. Impacts of diversity in commercial building occupancy profiles on district energy demand and supply. Appl Energy 2020;277:115594. https://doi.org/10.1016/j.apenergy.2020.115594.
[89] Afroz Z, Goldsworthy M, White SD. Energy flexibility of commercial buildings for demand response applications in Australia. Energy Build 2023;300:113533. https://doi.org/10.1016/j.enbuild.2023.113533.
[90] Chai J, Lu Q-Y, Wang S-Y, Lai KK. Analysis of road transportation energy consumption demand in China. Transport Res Transport Environ 2016;48:112–24. https://doi.org/10.1016/j.trd.2016.08.009.
[91] Sahraei MA, Duman H, Çodur MY, Eyduran E. Prediction of transportation energy demand: multivariate adaptive regression splines. Energy 2021;224:120090. https://doi.org/10.1016/j.energy.2021.120090.
[92] Maaouane M, et al. Using neural network modelling for estimation and forecasting of transport sector energy demand in developing countries. Energy Convers Manag 2022;258:115556. https://doi.org/10.1016/j.enconman.2022.115556.
[93] Zaman K, Khan MM, Ahmad M, Rustam R. The relationship between agricultural technology and energy demand in Pakistan. Energy Policy 2012;44:268–79. https://doi.org/10.1016/j.enpol.2012.01.050.
[94] Brown T, Hörsch J, Schlachtberger D. PyPSA: Python for power system analysis. J Open Res Software 2018;6:1–15. https://doi.org/10.5334/jors.188.
[95] Hörsch J, Hofmann F, Schlachtberger D, Brown T. PyPSA-Eur: an open optimisation model of the European transmission system. Energy Strategy Rev 2018;22:207–15. https://doi.org/10.1016/j.esr.2018.08.012.
[96] Victoria M, Zeyen E, Brown T. Speed of technological transformations required in Europe to achieve different climate goals. Joule 2022;6(5):1066–86.
[97] Sahoo S, Zuidema C, Van Stralen JN, Sijm J, Faaij A. Detailed spatial analysis of renewables' potential and heat: a study of Groningen Province in the northern Netherlands. Appl Energy 2022;318:119149.
[98] Anderski T, et al. European cluster model of the pan-European transmission grid: e-highway 2050: modular development plan of the pan-European transmission system 2050. Results/D2_2_European_cluster_model_of_the_Pan-European_transmission_grid_20072015. pdf 2015. https://doi.org/10.1109/ENERGYCON.2016.7513882.
[99] Frysztacki MM, Hörsch J, Hagenmeyer V, Brown T. The strong effect of network resolution on electricity system models with high shares of wind and solar. Appl Energy 2021;291. https://doi.org/10.1016/j.apenergy.2021.116726. Art no. 116726.
[100] Cole S, Dhaliwal I, Sautmann A, Vilhuber L. Handbook on using administrative data for research and evidence-based policy. 2020. admindatahandbook. mit. edu/book/v1. 0-rc5/index. html.
[101] Schwenk-Nebbe LJ. National-sectoral emission constraints in PyPSA-based open-source European energy system models. MethodsX 2023;10:102014.
[102] Cassetti LA, Fattori F, Dénarié A, Pozzi M, Spirito G, Motta M. Spatial clustering in energy system modelling: application to the case study of District heating. Energy Systems 2025:1–36.
[103] Xu D, Tian Y. A comprehensive survey of clustering algorithms. Annals of data science 2015;2:165–93.
[104] Mahdi MA, Hosny KM, Elhenawy I. Scalable clustering algorithms for big data: a review. IEEE Access 2021;9:80015–27.
[105] Saxena A, et al. A review of clustering techniques and developments. Neurocomputing 2017;267:664–81.
[106] Ezugwu AE, et al. A comprehensive survey of clustering algorithms: state-of-the-art machine learning applications, taxonomy, challenges, and future research prospects. Eng Appl Artif Intell 2022;110:104743.
[107] Liu Q, Deng M, Shi Y, Wang J. A density-based spatial clustering algorithm considering both spatial proximity and attribute similarity. Comput Geosci 2012;46:296–309.
[108] Jeon S, Roh M, Oh J, Kim S. Development of an integrated assessment model at provincial level: GCAM-Korea. Energies 2020;13(10). https://doi.org/10.3390/en13102565. Art no. 2565.
[109] Samsatli S, Samsatli NJ, Shah N. BVCM: a comprehensive and flexible toolkit for whole system biomass value chain analysis and optimisation–mathematical formulation. Appl Energy 2015;147:131–60.
[110] Wene C-O. Energy-economy analysis: linking the macroeconomic and systems engineering approaches. Energy 1996;21(9):809–24.
[111] Helgesen PI, Lind A, Ivanova O, Tomasgard A. Using a hybrid hard-linked model to analyze reduced climate gas emissions from transport. Energy 2018;156:196–212.
[112] Durand-Lasserve O, Almutairi H, Aljarboua A, Pierru A, Pradhan S, Murphy F. Hard-linking a top-down economic model with a bottom-up energy system for an oil-exporting country with price controls. Energy 2023;266:126450.
[113] Mustapha WF, Kirkerud JG, Bolkesjø TF, Trømborg E. Large-scale forest-based biofuels production: impacts on the Nordic energy sector. Energy Convers Manag 2019;187:93–102.
[114] Bauer N, Edenhofer O, Kypreos S. Linking energy system and macroeconomic growth models. Computat Manag Sci 2008;5:95–117.
[115] Krook-Riekkola A, Berg C, Ahlgren EO, Söderholm P. Challenges in soft-linking: the case of EMEC and TIMES-Sweden. Konjunkturinstitutet; 2013.
[116] Seljom P, Rosenberg E, Schäffer LE, Fodstad M. Bidirectional linkage between a long-term energy system and a short-term power market model. Energy 2020;198:117311.
[117] Pina A, Silva CA, Ferrão P. High-resolution modeling framework for planning electricity systems with high penetration of renewables. Appl Energy 2013;112:215–23.
[118] Hamers D, Kuiper R, van Dam F, Dammers E, Evenhuis E, van Gaalen F, Wolters H. Four scenarios for the development of the Netherlands in 2050: Spatial exploration 2023, Background report. Netherlands Environmental Assessment Agency (PBL); 2023. p. 5178.
[119] Claassens J, Koomen E, Rijken B. Actualisering landgebruiksimulatie Deltascenario's: achtergronddocument bij Ruimtescanner inzet. 2017.
[120] Delafield G, et al. Spatial context matters: assessing how future renewable energy pathways will impact nature and society. Renew Energy 2024;220:119385.
[121] Kotzur L, Markewitz P, Robinius M, Stolten D. Impact of different time series aggregation methods on optimal energy system design. Renew Energy 2018;117:474–87.
[122] Lv F, Wu Q, Ren H, Zhou W, Li Q. On the design and analysis of long-term low-carbon roadmaps: a review and evaluation of available energy-economy-environment models. Renew Sustain Energy Rev 2024;189:113899.
[123] Ma W, Xue X, Liu G. Techno-economic evaluation for hybrid renewable energy system: application and merits. Energy 2018;159:385–409.
[124] Connolly D, Lund H, Mathiesen BV, Leahy M. A review of computer tools for analysing the integration of renewable energy into various energy systems. Applied energy 2010;87(4):1059–82.
[125] Ringkjøb H-K, Haugan PM, Solbrekke IM. A review of modelling tools for energy and electricity systems with large shares of variable renewables. Renew Sustain Energy Rev 2018;96:440–59.
[126] Bottecchia L, Lubello P, Zambelli P, Carcasci C, Kranzl L. The potential of simulating energy systems: the multi energy systems simulator model. Energies 2021;14(18):5724.
[127] Groissböck M. Are open source energy system optimization tools mature enough for serious use? Renew Sustain Energy Rev 2019;102:234–48. https://doi.org/10.1016/j.rser.2018.11.020.
[128] Osorio-Aravena JC, et al. Synergies of electrical and sectoral integration: analysing geographical multi-node scenarios with sector coupling variations for a transition towards a fully renewables-based energy system. Energy 2023;279:128038. https://doi.org/10.1016/j.energy.2023.128038.
[129] PyPSA-Eur-Sec. "PyPSA-Eur-Sec: A Sector-Coupled Open Optimisation Model of the European Energy System." https://pypsa-eur-sec.readthedocs.io/en/latest/index.html (accessed.
[130] Wiese F, Bramstoft R, Koduvere H, Pizarro Alonso, Balyk O, Kirkerud JG, Tveten ÅG, Bolkesjø TF, Münster M, Ravn HV. Balmorel open source energy system model. Energy Strat Rev 2018;20:26–34. https://doi.org/10.1016/j.esr.2018.01.003.
[131] Bogdanov D, et al. Radical transformation pathway towards sustainable electricity via evolutionary steps. Nat Commun 2019;10(1):1–16.
[132] Mesfun S, et al. Power-to-gas and power-to-liquid for managing renewable electricity intermittency in the Alpine Region. Renew Energy 2017;107:361–72. https://doi.org/10.1016/j.renene.2017.02.020.