Original Article

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Assessing the impact of seasonality on bioenergy production from energy crops in Germany, considering just-in-time philosophy

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Abstract: The availability of biomass is strongly influenced by seasonality, which can affect the production of biofuels, biogas, and bio-based products in the downstream bioenergy supply chain. Rapeseed, maize silage, sugar beet, wheat, and grass from grassland are the most popular energy crops; they play a significant role in the German bioenergy strategy and are being discussed extensively in the current gas shortage context. Most models in the literature assume yearly temporal resolution for these energy crops, which can negatively impact the accuracy of results. This problem is increasingly relevant under weather conditions that are varying increasingly due to climate change; in this study we therefore employ the extended bioenergy optimization model (BENOPTex) to explore the impact of seasonality on the optimal deployment of biomass from energy crops in bioenergy production in the German heat, power, and transport sectors, which typically show high dependency on fossil fuels. First, we increased the model's temporal resolution using available datasets and documents. Next, the varying availability factors were embedded in the optimization model, considering the no-storage policy for energy crops in accordance with the just-in-time philosophy. Finally, the outcomes of the BENOPTex with annual resolution were contrasted with the results including the effects of seasonality, while considering various objective functions. We demonstrated a shift toward the consumption of woody biomass until 2045 due to its longer shelf life and improved storability. The energy demand stemming from summer leisure travel was also anticipated to exceed the bioenergy system's capacity. The insights provided here might be interesting for policymakers who design roadmaps for bioenergy development with a more resilient energy supply. © 2024 The Authors. *Biofuels, Bioproducts and Biorefining* published by Society of Industrial Chemistry and John Wiley & Sons Ltd.

Key words: bioenergy; seasonality; energy crops; sustainable agriculture; just-in-time

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Introduction

Efforts to mitigate climate change have encouraged the use of renewable resources to replace fossil counterparts. The Paris Agreement lays the foundation for accelerated action plans to rectify targets from previous pacts (e.g., the Kyoto protocol). For instance, it demands that at least 40% of new electricity supplies should be from renewable electricity by 2040. However, some countries have chosen higher proportions – as much as 63%. There are also debates regarding the viability of 100% renewable energy (RE).[1] As a leading actor, Germany has taken appropriate measures to transform its energy system so that the share of renewable electricity will be at least 80% by 2030[2,3] (beyond the 2030 target in the Paris Agreement), and is constantly reviewing and updating its targets. To meet the demand for clean energy, Germany relies primarily on hydroelectric power, wind turbines, solar photovoltaics, and bioenergy; however, the amount of energy produced by intermittent renewable sources can fluctuate over time due to their variable nature. Capturing the temporal aspect of these intermittent sources is an indispensable part of energy system modeling, providing insights regarding the synergy between these sources in order to enhance the flexibility of energy systems. As Germany transitions toward the use of higher proportions of intermittent renewables, it should therefore be prepared to cope with a multitude of problems in both supply and grid stability by 2050.[4]

Over the past decade, the consumption of renewable energy sources (RES) has been increasing worldwide, with biomass accounting for approximately 10% of total global primary energy demand.[5,6] In 2021, bioenergy production from organic waste, forestry, and agricultural feedstock accounted for approximately 59% of RE consumption in the EU.[7] According to the International Energy Agency, under the 2 °C scenario, bioenergy will account for 17% of the cumulative emissions savings until 2060.[8,9] To keep global warming below the target of a 1.5 °C increase in average global temperatures, the International Panel on Climate Change claims that primary bioenergy use should range from 40 to 310 EJ/year.[10] This underscores the importance of bioenergy as a key component of the global energy mix in the future. It is likely that the energy system of the future will rely heavily on RES, with biomass playing a critical role in niche applications. Biomass can be directly combusted to generate electricity and heat or serve as a feedstock for biorefineries to produce biofuels. An energy mix with a high reliance on intermittent sources needs storable energy, which biofuels can provide, to generate heat and power on demand.[11] Energy carriers in various states (i.e., liquid, solid, or gas) can be derived from biomass to cater for the requirements of different markets.

A multistage supply chain is involved in the generation of bioenergy, beginning with the collection of residues, byproducts, and wastes, and the cultivation of energy crops. Depending on local conditions and the desired final product, biomass is then mechanically processed, stored, transported, and converted into secondary energy carriers (e.g., biomethane and biofuels). A wide range of biomass resources can be used for energy purposes (e.g., forest wood, straw, cereals, liquid manure), most of which are affected directly by seasonality.[12] The availability of biomass, which can influence prices,[13] is highly dependent on the seasons and the region. Incorporating a high temporal–spatial resolution is therefore vital to capture the biomass allocation realistically. Considering a yearly time resolution in most transportation and energy system studies, there is a gap in the literature to investigate the impact of seasonality on bioenergy supply and demand. Assuming a yearly resolution ignores the seasonality of its production and implicitly means that biomass is always available on demand, which may involve perfect and free storage conditions.

Biomass, as feedstock, can be stored reliably for short and medium durations at a modest cost and requiring little technical knowledge, unlike gaseous fuels, which need proper infrastructure to store and transfer. However, as the bioenergy share in the energy mix increases, so does the need for long-term storage. Unfortunately, biomass storage for a long duration can result in its degradation, which can have multiple negative consequences, such as greenhouse gas (GHG) emissions, loss of feedstock and energy, and economic losses.[14] This degradation may occur due to various factors, such as microbial activity, moisture content, and exposure to oxygen, leading to the breakdown of the biomass into less valuable components. There are two major storage practices: dry storage and wet storage systems. Dry storage systems pose a higher risk of microbial degradation of biomass if they provide favorable conditions for enzymatic activity or microorganism growth.[15] Exceeding the moisture threshold in field-side storage of corn stover has been found to cause substantial losses in dry matter due to microbial degradation.[16]

Although wet storage systems are more efficient in long-term storage, they are more expensive than their dry counterparts. It is therefore crucial to exercise the just-in-time (JIT) management philosophy and lean manufacturing principles[17] to mitigate these adverse effects by removing the need for storage. The application of JIT in managing biomass supply chain has been discussed previously in the literature. For instance, using an optimization model, Sun

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et al.[18] compared the JIT and regular delivery options of sorghum biomass feedstock. The authors concluded that the nonensiling options are competitive when the biomass yield and equipment rate are stochastic. With the lean philosophy in mind, Brue[19] studied the technoeconomics of in-field harvest operations using data from a cellulosic ethanol biorefinery.

Lean manufacturing calls an action 'Waste' when no value that customers will be willing to pay for is added to the final product. There are seven wasteful manufacturing practices: Overproduction, waiting, transportation, inappropriate processing, excessive inventory, unnecessary motion, and defects. In this article, we concentrate on storage. Eliminating the need for long-term storage means that energy crops can be transformed immediately into final products when available, and should be consumed shortly after (i.e., a pull production system instead of a push system), which requires modeling at higher temporal resolution.

Since the 1970s, techno-economic energy system models have been employed extensively to study energy systems, using different spatial and temporal resolutions.[20] The MARKet ALlocatio (MARKAL) model[21] was designed to have fixed length time periods, whereas TIMES[22] benefits from flexible time slices. The flexible time slices enabled modelers to formulate flexible technologies. Using TIMES, Aliabadi *et al.*[23] modeled bioenergy in eight time slices, distinguishing day and night in each season for each year in Turkey; however, the biomass potential is set annually. Tuck *et al.*[24] studied the potential distribution for four groups of bioenergy crops in monthly time resolution under future climate conditions using a simple Fortran program, ignoring the downstream consumption pathways. TIMES-DK, a complete Danish energy system model covering the long-term investments required for technological development, was provided by Balyk *et al.*[25] Each year (from 2010 to 2050) consists of 32 non-sequential time slices, representing seasonal, weekly (working/non-working days), and daily (4 categories) variations. Using TIMBRA (The Integrated Market allocation Energy flow optimization System—BRAzil), Lap *et al.*[26] examined how the domestic final energy mix was affected by GHG emissions related to land use change, under the influence of Brazil's bioenergy demand. Even though the study spans a period between 2010 to 2050, it is divided into 5-year segments.

Millinger *et al.*[27] proposed the bioenergy optimization (BENOPT) model, which formulates processes from source to end-of-service, allowing a detailed life-cycle GHG and cost assessments for optimal biomass and hydrogen allocations across sectors. However, it is important to note that the BENOPT model is not spatially explicit and functions mostly on yearly basis.

In Musonda *et al.*,[28] a model of biomass crop cultivation, conversion processes, and sectoral demands was developed as part of a deterministic bottom-up linear optimization model. Biomass utilization through 2020 to 2050 was optimized based on GHG abatement and cost minimization in an annual time frame for bioenergy, biofuels, and biochemical technologies.[28] In Millinger *et al.*,[29] a study was conducted to formulate the competitiveness between conventional and advanced biofuels for road transport in Germany over the medium to long term. The results suggest that conventional bioethanol and biodiesel were the most cost-competitive biofuels throughout the study period. The main feedstock for bioethanol is sugar beet and rapeseed for biodiesel. These energy crops could remain important sources for the transportation market even though there is fierce competition between advanced and conventional biofuels. As a result, a higher time resolution will enhance the development of the model significantly by incorporating the impact of energy crops' seasonality on resource availability, land use, GHG abatement, and market barriers.

Using Irish TIMES, Yue *et al.*[30] probed optimal pathways toward 100% RE by 2050. While the Irish TIMES model considers 12 time slices in the power sector (i.e., four seasons, each comprised of day, night, and peak), the biomass potential has a yearly time resolution. In PRIMES,[31] the production of biomass feedstock for bioenergy is modeled via competing technologies with different cost-supply curves with annual time resolution.

Using a technology-rich optimization model, Jordan *et al.*[32] studied the role of cultivated biomass with annual resolution in the German energy system, with a special focus on the heat sectors. The authors show that the strategic decision to grow energy crops will influence directly future transformation strategy, especially for high-temperature industrial heat applications.

As scientists request that the temporal resolution of intermittent renewable sources be increased for better management of energy systems, the role of variability in the availability of biogenic materials is becoming increasingly important.[33] The annual resolution of biomass feedstock is a universal limitation of many energy system models because information regarding biomass potential is retrieved from the energy balances of the corresponding countries. Unfortunately, acquiring more refined data is not always straightforward, as there are laws (e.g., the EU General Data Protection Regulation[34]) in place to safeguard data at different levels. To cope with this issue, we take an alternative approach in this study. Recognizing that every plant undergoes distinct growth stages from seed to fruit at precise times within specific environmental conditions, we have adopted a unique approach based on the natural vegetation cycle to further dissect the yearly biomass availability into shorter, more refined time slices.

The vegetation period is the part of the year when plants actively grow and develop. It varies in length depending on the region and is affected by genotypic differences and climate changes. C3 and C4 plants have evolved different photosynthesis cycles to adapt to hot and dry environmental conditions. Both plant types are important biomass sources but C4 plants may provide higher annual biomass than C3 and other woody plants due to more efficient photosynthetic pathways.[35] Native European plants and grasses have been extensively studied for their potential as efficient bioenergy sources under different climate conditions. In this article we therefore evaluate the bioenergy production potential of the critical bioenergy plants based on data from their specific vegetation phases in different regions of Germany. We study the impact of seasonality on the downstream of the bioenergy supply chain when the storage is eliminated. To the best of the authors' knowledge, this study is the first of its kind to consider a refined temporal resolution in an optimization setting for investigating the effect of seasonality on biomass availability.

The remainder of the article is organized as follows. The next section describes our assumptions and the modeling approach. We then present the results and discuss the impact of seasonality on various feedstocks. Finally, we draw some conclusions from the study.

Material and methods

Energy systems can be analyzed either using top-down or bottom-up approaches.[36] Optimization and simulation models from the bottom-up approaches and equilibrium models from the top-down approaches are well known methods. Optimization models aim to determine the optimal mixture of technologies that can achieve a certain target with a minimum cost or emissions, respecting technical and political constraints. Historically, optimization models are preferred in the literature as they can take into account the evolution of technologies through time and provide straightforward recommendations to policymakers.

Equations (1) and (2) present the standard form of energy system optimization models (ESOMs), where the objective function, $f(\mathbf{x})$, and constraints, $g_j(\mathbf{x})$, can be nonlinear for a vector of decision variables $\mathbf{x}$; however, most ESOMs are formulated in a linear form[37] due to the complexity of the problem, which means that $f(x) = c.\mathbf{x}$ where c is a vector of cost coefficients, and $g(x) = A.\mathbf{x} - b$ where A is a matrix representing technical constraints, and b is a vector for the resource limitations:

$$\begin{aligned} min \quad & f(\mathbf{x}) \\ s.t. & \end{aligned} \tag{1}$$

$$g_j(\mathbf{x}) \geq 0 \ \ , \forall j \in J \tag{2}$$

To accomplish the techno-economic analysis considering seasonality, we employ the extended bioenergy optimization (BENOPTex) model.[38] The BENOPTex model is a perfect foresight optimization model that integrates detailed process and techno-economic-political factors, such as capital and operational expenditures, and GHG emissions across sectors with life cycle considerations in mind. The optimization model is mathematically formulated in GAMS and used in interaction with MATLAB for visualization and scenario generation. Given the available resources, such as the available land, the GHG abatement level, and energy crops, BENOPTex finds the cost-optimal solution.

The BENOPTex model optimizes the allocation of dispatchable renewable energy carriers across sectors in the energy system using two objective functions: maximizing the GHG abatement level and minimizing the total system cost across multiple decades from the base year (i.e., 2020) until 2050. First, the model finds the optimal solution that maximizes the GHG abatement level. Then, it uses a portion (~99.5%) of the first objective function as the GHG abatement level requirement while minimizing the total system cost. Doing so ensures that alternative solutions with exorbitant system costs are filtered out. To summarize, our approach consists of multiple stages: reading data from databases in MATLAB and generating c, A and b, running the optimization model in GAMS with the first objective function (i.e., maximizing the GHG abatement level), introducing a new constraint for the minimum acceptable level of the GHG abatement, run the model with the second objective function (i.e., minimizing total system cost), and finally collecting results and plotting them in MATLAB. Aliabadi *et al.*[39] discuss our approach to decreasing the runtime by accelerating each of the steps mentioned above.

Our database contains annual information regarding the available residues and wastes in Germany.[40,41] The available land to plant energy crops is assumed to decrease from 2.40 million hectares (Mha) in 2020 to 2.16 Mha in 2050. The optimization model endogenously decides the appropriate quantities of energy crops to be grown on the designated lands, given the energy demand requirements of each year. In Germany, wheat is considered the most common crop;[42] thus, the final price of other energy crops is calculated such that their profit margins are on par with the wheat profit margin as the benchmark.[43] The electricity price has been calculated in the Renewable Energy Mix (REMix) model,[44] as described in Aliabadi *et al.*[45] REMix approximates day-ahead electricity prices using the merit order of thermal power plants' dispatch,[46] ignoring the strategic bidding behavior of power-generation companies.[47,48] BENOPTex adds tariffs and levies on top of the market-cleared price, considering sectors (e.g., residential or industry).

We further improved the temporal resolution of energy crops using harvesting time windows and amounts as described in Fig. 1. The monthly harvest data and yields for different energy crops, including rapeseed,[49] maize silage, and wheat,[50,51] field grass from arable land,[52] grassland,[53] miscanthus,[54,55] and sugar beet,[56,57] are extracted and normalized to a yearly total of 100%. Poplar is harvested from January, and is commercially available until mid-October;[58] one can therefore assume that the poplar wood quality and properties are less affected by storage time in comparison with other biomass types. We also differentiate field grass from grassland in our model, as the harvested biogas substrate from the permanent grassland can have a different harvest pattern from the arable land field grass (see https://www.effizientduengen.de/gruenland/). Finally, the techno-economic parameters of each energy crop are derived from Belau.[59]

We modified the mathematical constraints and introduced new four-dimensional decision variables in BENOPTex to take seasonality into account. Equation (3) sets an upper bound on the availability of each energy crop based on harvest time and annual potential ($\dot{m}_{tifc}$). Equation (4) imposes the condition that the total consumption over time slices be equal to the annual use of the respective energy crop over entire cost categories ($c \in \{\text{cheap, average, premium}\}$):

$$\sum_i \dot{m}_{dtif} \leq M_{df} \times \sum_{i,c} \dot{m}_{tifc} \qquad \forall t, f \in E, d \tag{3}$$

$$\sum_d \dot{m}_{dtif} = \sum_c \dot{m}_{tifc} \qquad \forall t, i, f \in E \tag{4}$$

E is the set of energy crops in our model. $\dot{m}_{dtif}$ is a temporally resolved decision variable showing the total amount of energy crop $f \in E$ used by technology i at time slice d of year t in petajoules (PJ). M_{df} is a parameter that describes the availability of energy crop f at time slice d as a percentage. This percentage has been interpolated based

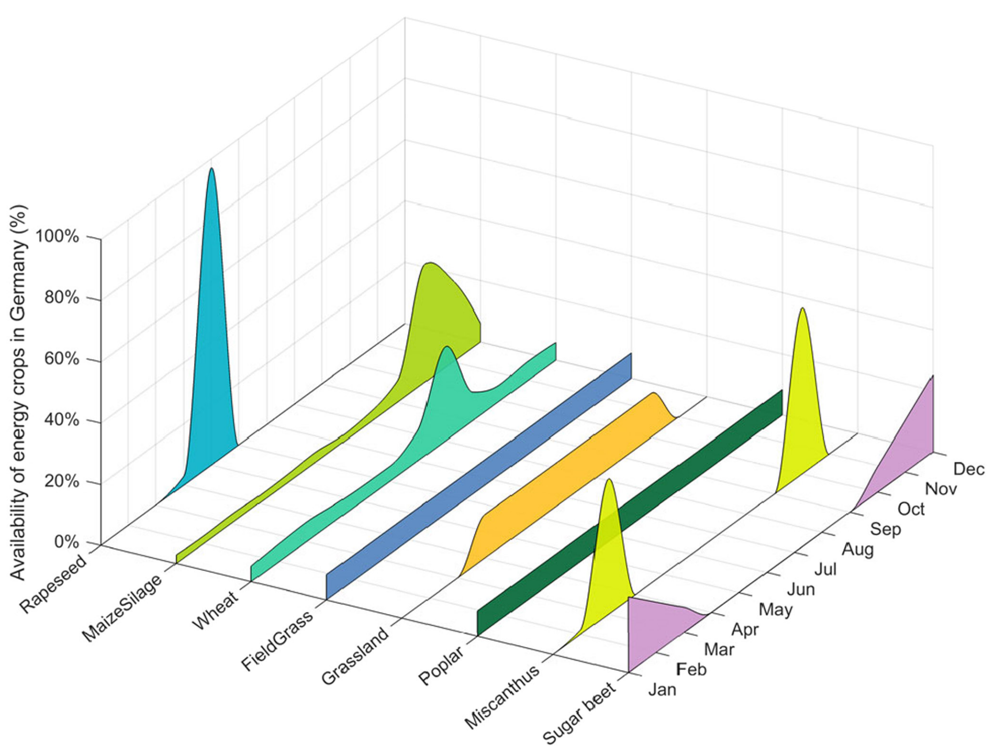

Figure 1. Percentage of energy crops available in Germany on a monthly basis.

on the monthly production of energy crops in Fig. 1. As is evident, $\dot{m}_{dtif}$ increases the number of decision variables significantly.

Equation (5) links the consumed feedstock in each time slice to the final product π_{dtis} considering the efficiency of technologies:

$$\sum_{s}\pi_{dtis} = \sum_{f\in\{E\cup\mathscr{E}\}} \dot{m}_{dtif}\times\eta_{tfi} + \frac{\sum_{f\in R,c}\dot{m}_{tifc}}{|D|}\times\eta_{tfi} + \frac{\sum_{f}\tilde{m}_{tif}}{|D|}\times\eta_{tfi} + \hat{m}_{dti}\times\eta_{ti} \quad \forall d,t,i \tag{5}$$

R and $\mathscr{E}$ are sets for the residues and electricity, respectively. η_{tfi} is a parameter describing the efficiency of technology i at year t in converting feedstock f to the final product. D is the set of time slices; hence, $|D|$ is the number of time slices in a year. $\tilde{m}_{tif}$ represents the imported feedstock f at year t for technology i. $\hat{m}_{dti}$ denotes consumed fossil fuel in time slice d of year t by technology i. Equation (5) implicitly assumes that residues and imported feedstock are available uniformly throughout the year.

The annual energy consumption in the aviation sector is adjusted in conformity with the business-as-usual scenario considering the impact of the pandemic from 4D-Race,[60] a calculation model that produces air traffic emission inventories. For road transportation, we relied on the Vector21 model's output, which simulates and assesses various transport technologies within the context of light and heavy-duty vehicle fleets.[61] Due to the impact of seasonality on the consumption pattern of gasoline and kerosene, we included constraints (6) and (7) based on the periodic pattern in Dembińska *et al.*[62] The authors show that gasoline and kerosene consumption in Europe reach their zenith during summer; however, this particular consumption pattern is not observed in the case of diesel fuel. This disparity is understandable considering that diesel finds application in other sectors like agriculture and heavy-duty trucks, whereas gasoline and kerosene are more correlated to leisure travel. Furthermore, for the same reason, the consumption pattern for gasoline and kerosene in Europe is at a minimum in February.

$$\left(\sum_{d,i\in I^{EtOH}}\pi_{dtis}\right)\times M_{d}^{EtOH} = \sum_{i\in I^{EtOH}}\pi_{dtis} \qquad \forall dt, s\in S^{LDVs} \tag{6}$$

Equation (6) shapes the temporally resolved bioethanol production, π_{dtis}, based on the consumption pattern of gasoline. In Eqn (6), M_{d}^{EtOH} is an interpolated parameter describing gasoline consumption level at time slice d in passenger vehicles $\left(s\in S^{LDV}\right)$.

$$\delta_{ts}\times M_{d}^{A} = \sum_{i\in I^{KER}}\left(w_{tis}\times\pi_{dtis}\right) + \frac{w'_{ts}\times\pi_{ts}^{Imp}}{|D|}\forall dt, s\in S^{A} \tag{7}$$

Equation (7) ensures that the supply-and-demand balance is held for aviation fuel in each time slice. In this equation, i represents technologies that can provide sustainable aviation fuels and synthetic fuels similar to kerosene. M_{d}^{A} is a parameter determining the kerosene consumption pattern for each time slice. δ_{ts} denotes the annual energy demand in the aviation sector ($s\in S^{A}$) in PJ. w_{tis} represents the relative fuel economy of fuel produced by technology i at year t for sector s, and w'_{ts} denotes the fuel economy of imported synthetic fuel $\left(\pi_{ts}^{Imp}\right)$.

To keep this discussion straightforward, we confined ourselves to explaining equations that are directly related to our contribution to the current study. However, readers should bear in mind that the BENOPTex model has multiple objective functions and technical constraints, similar to any other optimization model. The general description of terms in the objective functions has been presented in Appendix A; however, the interested modelers are invited to read Aliabadi *et al.*[63] and Millinger *et al.*[27]

Results and discussion

Numerical results

For this study, we adjusted all time-related parameters and decision variables to a daily resolution. Nonetheless, our methodology is generic and can be accommodated to higher temporal resolutions. The introduction of four-dimensional decision variables has extended the computation time. For a daily resolution ($d = 365$), $\dot{m}_{dtif}$ and π_{dtis} increase the number of decision variables in the model by 4.63 million and 6.03 million, respectively. While GAMS solved the problem with yearly resolution in 640 s, the runtime of the daily model was above 16 069 s.

Improving the temporal resolution of the model increased the system cost of the optimal solution by 0.19%, while also resulting in a 0.12% reduction in the optimal GHG abatement level. This highlights a crucial point: models that have inadequate temporal resolution may overestimate emission reduction capabilities while underestimating logistic- and storage-related costs.

Figure 2 shows the annual distribution of various alternative fuels from 2020 to 2050 in the transport sector for two settings in the presence or absence of daily resolution. The demand for energy in the transportation sector exhibits a decreasing trend after 2026, attributed to the increased efficiency of battery electric and fuel-cell vehicles compared to vehicles with internal combustion engines. We can see that the production of bioethanol from energy crops is affected negatively when the temporal resolution is increased. The reduction in bioethanol production from energy crops might be attributed to the abundance of these crops in a short period, resulting in processing facilities with limited capacities struggling to consume them during these brief intervals. The right-hand bottom corner magnifies two boxes in each plot in order to better exhibit the differences between these two settings.

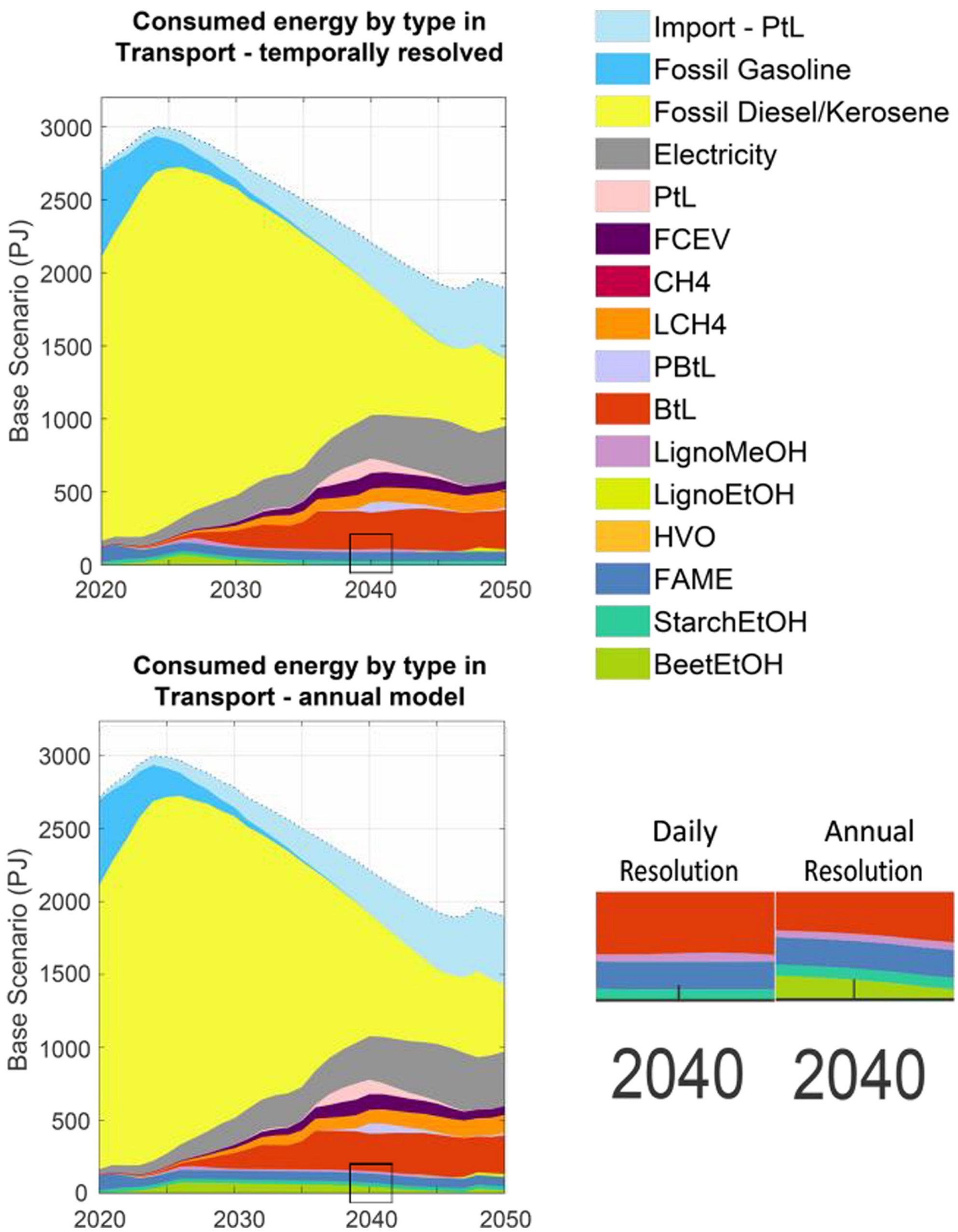

Figure 2. The distribution of alternative fuels in PJ in all transport sectors with and without daily time slices. PtL, power-to-liquid; FCEV, fuel cell electric vehicle; LCH4, liquefied methane (including biomethane); BtL, biomass to liquids via Fischer–Tropsch; PBtL, power-to-hydrogen + BtL; LignoMeOH, lignocellulose-based methanol; LignoEtOH, lignocellulose-based ethanol; HVO, hydrotreated vegetable oil; FAME, fatty-acid methyl ester; StarchEtOH, starch-based ethanol; and BeetEtOH, sugar beet-based ethanol. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Figure 3 depicts the daily fuel production of various technologies for gasoline and kerosene in 2020, 2030, 2040, and 2050. It shows that seasonal energy crops (e.g., sugar beet) will have a significant role in gasoline production until 2030; however, the energy crops that are used in conventional biofuels will be replaced by advanced technologies that convert lignocellulose to ethanol or methanol. In the aviation sector, sustainable aviation fuel produced using biomass by BtL and PBtL will gradually replace fossil kerosene. Nonetheless, fossil-based kerosene will be still needed in the summertime when air travel is at its peak. Thus, policymakers could advocate for measures that aid in leveling the consumption pattern by distributing travel across the entire year. Similar policy measures have been implemented in the past to tackle the climate/energy crisis in Tehran.[64]

Figure 4(a) depicts the production of heat in big industries, small-scale industries, trade and services, and households, and byproduct heat in the power sector. In the early years, the heat production variability is higher with heat being a byproduct of the Biogas technology, which consumes maize silage as feedstock to produce and combust biogas to produce electricity. The variability decreases between 2035 and 2045 as most technologies in this interval consume woody biomass and forest residues. However, after 2045, the need for biomethane will push the model to employ *BioCH4*, which again uses maize silage as feedstock to produce biomethane for heat in small and big industries.

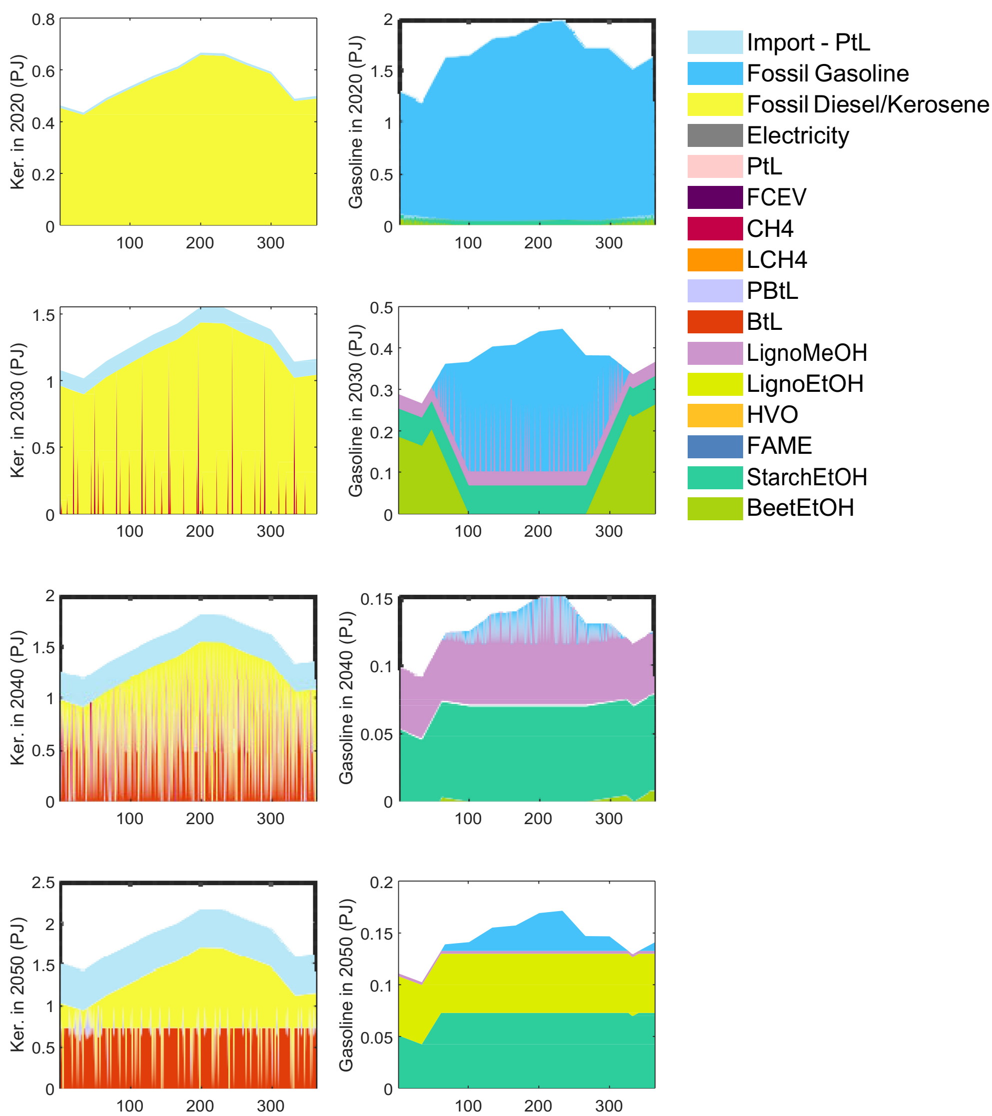

Figure 3. The distribution of alternative fuels for kerosene and gasoline in PJ. The horizontal axes display the day number within the specified year.

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Figure 4(b) shows the power production from dispatchable and nondispatchable sources. As we move into the future, the share of the electricity demand that should be satisfied by dispatchable sources will decrease as the solar and wind power will satisfy most demands in the shoulder hours and dispatchable power will only be needed to fulfill demand in peak periods. In 2050, gas and steam turbine peaking power plants (*GUD*) will be the dominant dispatchable option to produce electricity, which still uses more than 78% natural gas.

Figure 5 illustrates the daily consumption of energy crops in Germany from 2020 onward. It presents a clear depiction of the transition from conventional energy crops (rapeseed and sugar beet) to advanced bioenergy, with a shift toward woody biomass (i.e, poplar) as the primary feedstock until 2045. This transition is driven by the benefits of woody biomass, including its longer shelf life and improved storability compared with conventional energy crops. However, the interest toward woody biomass will be replaced by maize silage until 2050. In addition to the overarching trend, a discernible periodic pattern emerges within each calendar year. Three years (2025, 2035, and 2045) are shown as examples in Fig. 5. This cyclic pattern is caused by the availability of the required energy crops within each year based on the daily demand pattern of the specific fuel type (see Fig. 3).

The growing trend in the consumption of maize silage after 2045 is linked to the Renewable Energy Directive (RED) and high biomethane demand for heat, which mandate the total utilization of the bioenergy capacity in order to reach at least 80% of the GHG quota in the road and rail transport by 2050. The GHG quota trend is depicted in Fig. 6. As shown, the gap between the perceived RED requirements and the GHG quota of the optimal solution is narrowing down in two sections, corresponding to the technological and managerial obstacles in the near future and the distant future.[63] The pressure on the bioenergy supply chain caused by RED requirements will indirectly increase the consumption of maize silage for heating purposes in industry, trade, commerce, and services. As illustrated in Figure 1 of Aliabadi *et al.*[63] the utilization of energy crops for biogas/biomethane production for non-transport-related applications is governed outside RED, allowing suitable energy crops to be available for biofuel production for the transport sector.

Avoided storage emissions

To model different storage strategies, an additional set of decision variables is needed in order to take into account the delay between the harvest and the processing time. This means having another $|E|/4\times\left(|D|^2\times|T|^2-|T|^2\times|D|-|T|\times|D|^2+|T|\times|D|\right)$

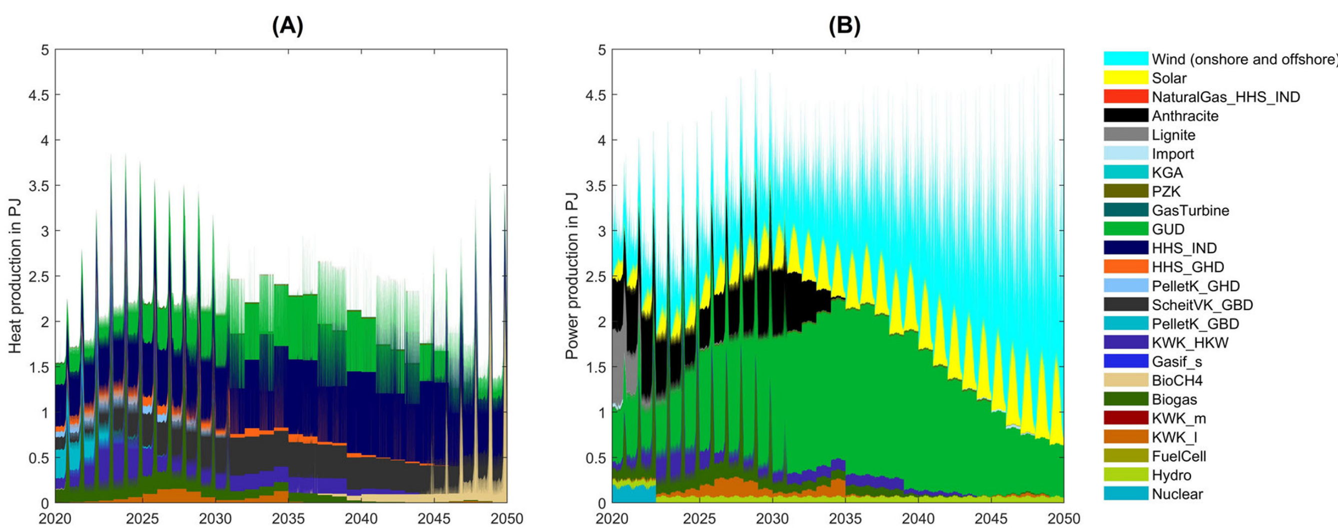

Figure 4. The daily mixture of technologies that produce heat as the main product (in big industries, commerce and trade, and residential sectors) and as a byproduct in the power sector in plot (a) and technologies that produce electricity in plot (b). KWK_l, large-scale combined heat and power (CHP) using wood; KWK_m, medium-scale CHP using rapeseed; Biogas, biogas combustion for electricity production using maize silage; BioCH4, biomethane production for heat production from maize silage; Gasif_s, wood gasification plant; KWK_HKW, wood-fired power plant with steam turbine; PelletK_GBD, pellet boiler for the residential sector; ScheitVK, log-gasification boiler; PelletK_GHD, pellet boilers for commerce trade service; HHS_GHD, wood-chip boiler for commerce and trade services; HHS_IND, wood-chip boiler for industries; GUD, gas-and-steam turbine power plant; PZK, paper and pulp + CHP; and KGA, sewage sludge digestion + CHP.

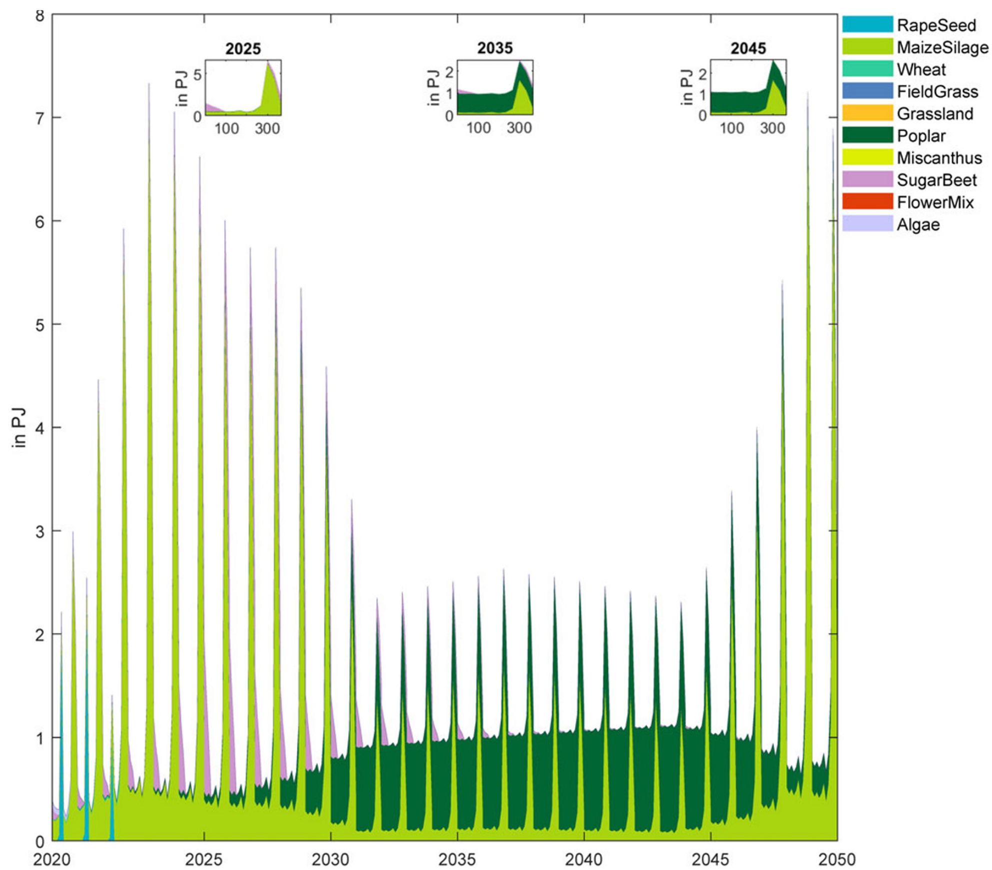

Figure 5. The daily energy consumption of crops until 2050 (in PJ).

decision variables, where $|E|$ is the number of energy crops, $|D|$ is the number of time slices within a year, and $|T|$ is the number of years; however, employing the lean philosophy (removing storage) not only simplifies the production processes but it also streamlines the modeling by removing the need for storage.

Having the optimal solution for both scenarios enables us to evaluate the impact of lean manufacturing on the GHG emissions from a storage perspective. Figure 7 exhibits the difference between the production energy crops in the model with and without seasonality. In Fig. 7(a), we compare two settings (i.e., annual model and daily model) using $L_{d+1,t,f} = L_{d,t,f} + \sum_i \dot{m}_{dtif} - \sum_{i,c} \dot{m}_{tifc} / |D|$. In Fig. 7(b), we focus only on the temporally resolved daily model by ignoring the strategy differences, using $L_{d+1,t,f} = L_{d,t,f} + \sum_i \dot{m}_{dtif} - \sum_{i,d} \dot{m}_{dtif} / |D|$. Negative $L_{d,t,f}$ values mean that the uniform daily consumption of the annual harvest potential can exceed the availability of energy crops, indicating that the difference has to be met with storage (see Appendix B). The amplitude of oscillations is the result of the agricultural land size dedicated to that specific energy crop in each year. The more land we allocate to a specific crop, the greater the variation in the outcomes we can expect.

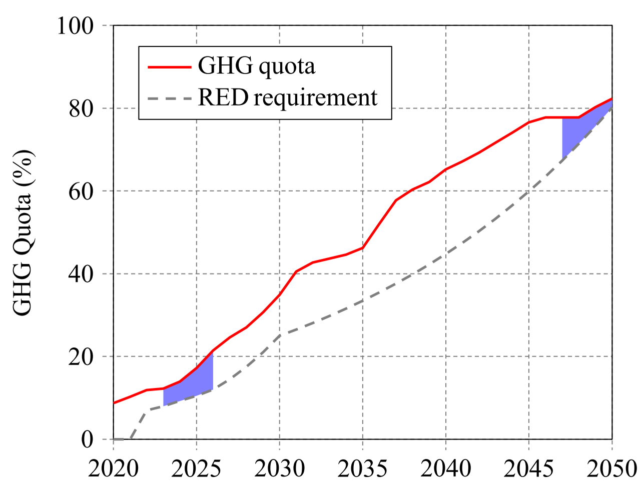

Figure 6. The GHG quota trend until 2050 for the temporally resolved model. The filled areas reveal the narrowing gaps between perceived RED requirements and the GHG quota of the optimal solution.

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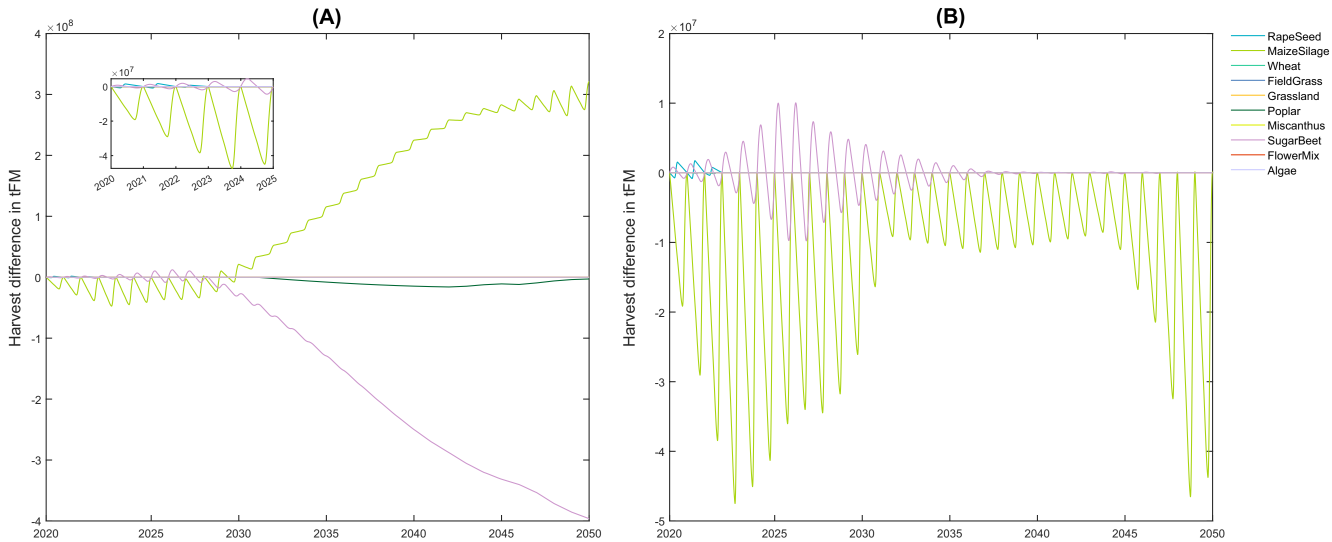

Figure 7. Energy crop availability differences in tonnes of fresh matters (a) between daily and annual models, and (b) in the daily resolved model with/without storage.

One can split Fig. 7(a) into two intervals: 2020–2025 and 2025–2050. In the first interval, which is displayed in the inset plot, a periodic behavior is witnessed, meaning that the optimal consumption patterns are similar between the daily and annual models, and the difference is driven by higher temporal resolution; however, beyond 2025, the temporally resolved daily model harvests more maize silage and less sugar beet. As the periodic behavior does not hold in this case, negative $L_{d,t,f}$ values cannot be utilized as proxies for the inventory. To retrieve the periodic behavior, we rely on the value of the daily model in Fig. 7(b). The stored energy crops in (B), which correspond to the area of the plot (B) below zero, are 5.971 million tonnes of fresh matter (MtFM) rapeseed, 704.153 MtFM maize silage, 0.324 MtFM wheat, and 142.430 MtFM sugar beet for a duration of a day. Employing the average daily emission factors for corn stover for a moisture content of 24% and an average temperature of 20°C [Table 6.7–8 in Emery[65]], the additional GHG emissions of 100 ± 90.5 $MtCO_2$ eq will be emitted from storage places in 30 years. This value is still far less than the emission gap between the annual model (with a perfect storage system) and the daily model (with no storage), which means that establishing a storage system will provide an opportunity to avoid consuming far more polluting energy sources in peak demand periods.

Conclusions

This study incorporated the natural vegetation cycle of plants in an optimization model to enhance the temporal resolution for energy crops as feedstock. By employing JIT philosophy, the long-term storage of perishable feedstocks is assumed to be prohibited. The improved model provides valuable insights to farmers and other stakeholders in managing available land, considering the downstream of the bioenergy supply chain. The enhanced optimization model also enables us to capture the effect of seasonality on the availability of processing facilities (e.g., in the sugar beet processing industry). The results show that excluding long-term storage by practicing the JIT philosophy might negatively impact the total system cost and emission reduction objectives. Thus, the development of new, affordable long-term storage techniques should be encouraged. The outcomes also reveal that conventional biofuels will be replaced with advanced lignin-based biofuels, which are more resistant to degradation, in the future. This finding has been corroborated by other studies that investigated the competition between conventional bioenergy and the food supply chain.[66] Finally, we demonstrated that, without storage, the high energy demand caused by summer leisure travel will surpass the bioenergy system's capacity.

This study can be extended in multiple directions. Forest residues are also affected by both seasonality and climate change. Therefore, one can soft-link vegetation models (e.g., FORMIND[67] and LPJmL[68]) with the BENOPTex model to provide insights for better forest management. Expanding the sectoral coverage can also be encouraged (e.g., chemical and pharmaceutical industries). Various storage techniques can also be studied with the model. Finally, increasing the spatial resolution of the optimization model can improve the quality of results by incorporating regional characteristics.[38]

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Conflict of interest

The authors declare that they have no competing interests.

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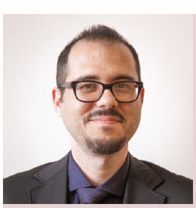

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Appendix A

Objective functions

As mentioned earlier, we use two objective functions consecutively. Equation (A1) presents a stylized representation of the first objective function that maximizes the GHG abatement level $\left(z^{GHG}\right)$:

$$\begin{aligned} \max z^{GHG} = & \overbrace{(\text{Avoide demissions})}^{z_1} - \overbrace{(\text{Energy crops emissions})}^{z_2} \\ & - \underbrace{(\text{Residues emissions})}_{z_3} - \underbrace{(\text{Emissions from electricity})}_{z_4} \\ & - \underbrace{(\text{Additional emissions from utilized } CO_2)}_{z_5} \\ & + \underbrace{(\text{Linearizing term})}_{z_6} \end{aligned} \tag{A1}$$

Equation (A1) consists of two positive and four negative terms. z_1 quantifies avoided emissions by producing 1 PJ energy (i.e., bioenergy and synthetic fuels) from various technologies through the time horizon from 2020 until 2050 for different sectors in ktCO$_2$eq/PJ. In z_2, emissions in different stages of the energy crops supply chain have been taken into account: emissions from cultivation- and transportation-related activities. On the other hand, for residues in z_3, only transport-related emissions are considered. In z_4, we consider the carbon intensity (in ktCO$_2$eq/PJ) of the utilized electricity from the grid. z_5 evaluates the additional CO_2 emissions from fossil fuels that are captured and used for the production of alternative fuels. $z_5 = 0$ as BENOPTex utilizes carbon from organic sources. Finally, z_6 is the linearization term to double count the use of advanced biofuels beyond 2.6% according to the renewable energy directives.

$$\begin{aligned} \min z^c = & \overbrace{\text{Production costs}}^{z_7} + \overbrace{\text{Investment costs}}^{z_8} \\ & + \underbrace{\text{Domesticfeed stock costs}}_{z_9} \\ & + \overbrace{\text{Imported feedstock/synthetic fuel}}^{z_{10}} \\ & - \underbrace{\text{Linearizing term}}_{z_{11}} \end{aligned} \tag{A.2}$$

The second objective function (z^c) minimizes the total system cost. z^c consists of five terms including the production (z_7), investment (z_8), consumed feedstock/fuel (including domestic z_9 and imported z_{10}), and penalty (z_{11}) costs. To be in line with REPowerEU,[69] we assume that imported synthetic fuel is more expensive than domestically produced fuel, considering external costs such as reliability and sustainability. z_{11} has a similar role as z_6 in the cost function. The detailed explanation for z_1 to z_{11} is presented in Appendix A of Esmaeili Aliabadi *et al.*[63]

Appendix B

Seasonality oscillation

To demonstrate the impact of seasonality on the optimization models, Fig. B1 concentrates on the oscillation of rapeseed in Fig. 7(b) in the first year. These oscillations resemble the economic production quantity (EPQ) models;[70] however, the rate of changes between two settings is a function of day in our case, giving smooth peaks and valleys.

In a continuous time space within each year, the blue area (S^-_{tf}) can be calculated by taking the integral of L_{dtf} function when its value is nonpositive (Eqn (B1)). The pink area (S^+_{tf}) can also be calculated similarly by integrating the L_{dtf} function when its value is non-negative (Eqn (B2)). These integrals can be approximated by summing all the L_{dtf} values over time slices, considering the duration of time slices (i.e., the Riemann method).

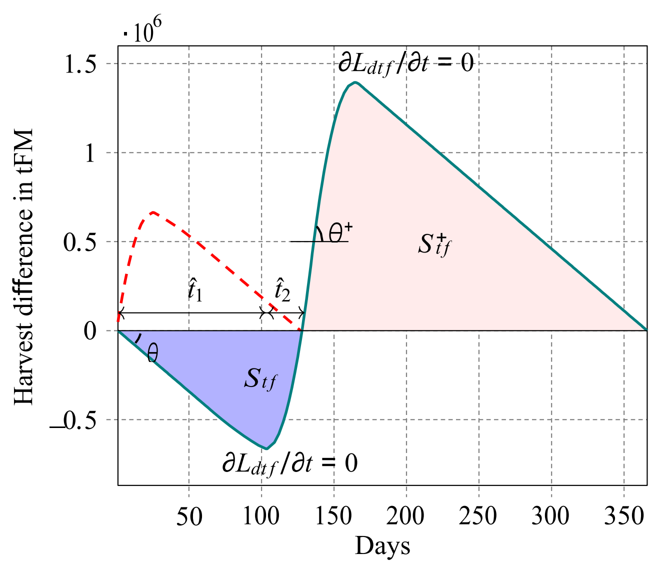

Figure B1. The harvest difference between the daily and annual temporal resolutions for rapeseed.

$$S_{tf}^{-} = -\int \left(1_{\{L_{dtf} \le 0\}} L_{dtf} \right) dt \approx \frac{-\sum_d \left(1_{\{L_{dtf} \le 0\}} L_{dtf} \right)}{|D|}, \forall tf \tag{B1}$$

$$S_{tf}^{+} = \int \left(1_{\{L_{dtf} \ge 0\}} L_{dtf} \right) dt \approx \frac{\sum_d \left(1_{\{L_{dtf} \ge 0\}} L_{dtf} \right)}{|D|}, \forall tf \tag{B2}$$

$S_{tf}^{-} \ge 0$ means that the constant harvest assumption overestimates the availability of energy crops in the respective period $(\hat{t}_1)$; however, the rapeseed harvest time in the daily formulation begins from April $(d = 100)$, turning the trend slope gradually from negative $(\theta^{-} = -\sum_{i,d} \dot{m}_{dtif} / |D|)$ to positive (i.e., θ^{+}). Assuming a smooth function, the trend is at minimum or maximum, when $\partial L_{dtf} / \partial t = 0 \Rightarrow \sum_i \dot{m}_{dtif} = \sum_{i,d} \dot{m}_{dtif} / |D|$.

Due to the low temporal resolution of the annual model, the availability of energy crops is overestimated in S_{tf}^{-} regions, having to be fulfilled from storage. The storage facility should be big enough to handle $\mathbf{I}_f^{\max} = 2S_{tf}^{-} / (\hat{t}_1 + \hat{t}_2)$ tFM for each energy crop for a short duration. The red dashed region in Fig. B1 depicts a system that takes into account the rapeseed storage with the amount of S_{tf}^{-}. Furthermore, $S_{tf}^{+} \ge 0$ means the possibility of storage; however, it depends on the daily consumption of harvested feedstock. All in all, this outcome affirms the inaccuracy of annual settings, which require the seasonality effect to be taken into account.

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