Applied Energy 426 (2026) 128628

Contents lists available at ScienceDirect

Applied Energy

journal homepage: www.elsevier.com/locate/apenergy

Agrivoltaics could increase global land use efficiency compared to bioenergy

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HIGHLIGHTS

- Global land use model simulates agrivoltaics, PV, and bioenergy under Net Zero.
- Agrivoltaics require 30× less land than bioenergy for equivalent electricity output.
- Replacing bioenergy saves 106 Mha natural land and 52 Mt. fertiliser by 2060.
- Agrivoltaics show 32% higher land efficiency than separate solar and crop systems.
- Solar energy policies can reduce food-energy-nature land use trade-offs globally.

ARTICLE INFO

Keywords:
Agrivoltaics
Photovoltaics
Bioenergy
Land use

ABSTRACT

Climate change mitigation scenarios often include a substantial bioenergy component, raising concerns about the land use impacts of large-scale energy crop production. However, agrivoltaic systems have the potential to generate electricity with a higher land use efficiency than bioenergy by integrating photovoltaic panels into agricultural land. Here, we model the global land system to explore the land use impacts of energy crops, agrivoltaics, and photovoltaics under a 1.5 °C climate change mitigation scenario. Bioenergy demand in the bioenergy scenario increases almost six-fold from 2020 to 2060. Replacing all bioenergy with agrivoltaics requires 30 times less land, leading to 106 Mha more natural land cover, 52 Mt. less nitrogen fertiliser applied, and 305 km^3 less irrigation water withdrawn per year by 2060. Similar but smaller reductions in land use are achieved with standard photovoltaic systems. Our findings suggest that future net cropland expansion can be avoided by prioritising agrivoltaic and photovoltaic systems over bioenergy. Policies that incentivise the adoption of agrivoltaics could increase global land use efficiency, reducing the trade-offs between energy supply, food production, and nature protection.

1. Introduction

Global primary energy consumption is projected to increase 30% by 2050, driven primarily by population growth and industrialisation in emerging economies [1,2]. Achieving the Paris Agreement target to limit warming below 2 °C will require rapid decarbonisation of the world's energy supply [1,3], reaching net zero emissions where anthropogenic greenhouse gas (GHG) emissions are balanced by GHG removals [3]. However, current actions are insufficient to meet this target, with a projected warming of 2.3–2.5 °C if all Nationally Determined Contributions (NDCs) are implemented and 2.8 °C under current policies [4]. Mitigation of carbon emissions requires a shift from fossil fuels to a combination of renewable energy technologies, particularly wind, solar, and bioenergy [3]. Meeting the world's growing energy demand while reducing GHG emissions will require careful policies which consider the trade-offs and benefits of different energy sources to

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https://doi.org/10.1016/j.apenergy.2026.128628
Received 30 March 2026; Received in revised form 26 June 2026; Accepted 2 August 2026
Available online 7 August 2026

minimise environmental impacts such as land use change, water consumption, and biodiversity loss [3].

Bioenergy has long been a critical component in climate change mitigation scenarios [5–8]. First-generation energy crops such as sugarcane, maize and oil crops already make a significant contribution to the energy supply in some countries [9]. In Brazil, vehicle fuel is required to contain at least 27% ethanol [10]. In the US, 40% of maize is used for the production of ethanol, and the EU has specific policies to increase the share of biodiesel in transportation [11,12]. There is now a growing focus on second-generation biofuels, which are produced from lignocellulosic biomass rather than edible carbohydrate or oil feedstock [13,14]. Second-generation energy crops such as *Miscanthus* can be grown on less productive land, potentially reducing competition with food production [15,16].

The relative ease of substituting fossil fuels with biofuels and the potential to sequester carbon through carbon capture and storage (BECCS) make bioenergy an attractive GHG mitigation option [17,18]. However, competition for land between energy crop cultivation and food production could affect food security by potentially limiting food production and inflating food prices [19–22]. The cultivation of energy crops could lead to additional pressure on water resources and increase the rate of soil degradation in existing agricultural areas [23]. There are also concerns that bioenergy may not be as carbon neutral as initially believed, due to factors such as delayed carbon reabsorption, emissions from cultivation, processing, and land use change [24,25]. Fossil fuel usage in the manufacture of fertilisers, agricultural machinery and transport of energy crops could lead to additional GHG emissions, which partly negate the mitigation benefits of bioenergy [23,24]. Large-scale energy crop production could also lead to unprecedented cropland expansion, leading to the destruction and degradation of carbon-rich and biodiverse ecosystems [12,26,27].

A shift away from bioenergy may be needed to avoid the negative environmental impacts of energy crop cultivation. Photovoltaics are a clear alternative, given the maturity of the technology, growing cost competitiveness, and already prominent role in the energy sector [9,28]. The solar energy capture efficiency of photovoltaic panels is significantly greater than that of photosynthesis, and therefore, the same amount of primary energy can be captured with less land [29]. Comparing the efficiency of final energy generation (e.g. electricity and liquid fuels) between photovoltaic and crop-based approaches is more complex since photovoltaics are used exclusively for electricity generation, whereas energy crops are usually converted to liquid fuels or combusted directly. However, for an equivalent amount of electricity generation, photovoltaics are more efficient since the conversion of energy crops to electricity involves significant energy losses through combustion or fuel cell technologies [30]. Given the rapidly growing electricity demand from the electrification of industry and transport, a focus on electricity generation is both timely and warranted.

Dual production of crops and solar energy, termed agrivoltaics (alternatively: agrophotovoltaics or aglectric farming), offers a potential way to further reduce land competition between food and energy production [31–34]. In agrivoltaic systems, crops use the space between or underneath photovoltaic arrays, thus potentially leading to higher land use efficiency. While shading from photovoltaic panels reduces the amount of solar radiation reaching the crops, the effect on yields is not necessarily negative [35–37]. The relationship between shading and yield reduction is often non-linear, and experimental evidence suggests that crops broadly fall into three categories: shade-benefiting, shade-tolerant, and shade-susceptible [36]. Shading potentially protects crops from extreme weather, such as intense heat, and the physical protection offered by photovoltaic panels could reduce the impact of hailstorms, rainstorms and extreme wind [35,38,39]. By trapping moisture and heat, photovoltaic panels create a micro-climate which may positively affect yields [40]. The degree of shading from a photovoltaic panel array is influenced by panel spacing, orientation, tilt and height, as well as the solar azimuth angle, which varies with season, latitude, and time of day [32].

Global electricity generation from solar energy has increased at an unprecedented rate over the last decade, from 132 TWh in 2013 to 1632 TWh in 2023 [41]. Although rooftop photovoltaics have a global technical potential to generate 27,000 TWh yr^{-1} [42], this falls short of the approximately 100,000 TWh yr^{-1} required in a Net Zero by 2050 scenario [43]. While ground-based solar installations are expanding rapidly and bioenergy is being positioned as a key component of future energy strategies, both are competing for arable land. There remains a significant research gap in understanding how the land use impacts of these two energy sources interact – and potentially conflict – with each other, and with food production. Previous studies have assessed the land requirements of photovoltaics, ranging from 0.5% to 5% of land area depending on the region [44,45]. However, global assessments of the land use implications of substituting energy crops with photovoltaic systems are limited [29]. Additionally, no previous global-scale study has explored how the integration of agrivoltaics could further improve global land use efficiency by co-producing electricity and crops, potentially reducing the need for cropland expansion. This research gap is particularly important given the increasing pressures on land from food and energy production and the need to conserve natural ecosystems.

Here, we explore the land use implications of energy crop cultivation, agrivoltaics, and ground-based photovoltaics under a Net Zero by 2050 scenario. Using the Land System Modular Model (LandSyMM; https://landsymm.earth), we compare three scenario variants: a reference scenario with a mix of bioenergy and photovoltaics (BE), a scenario where all bioenergy is replaced with agrivoltaics (AV), and finally a scenario where all bioenergy is replaced with photovoltaics (PV). We quantified potential land, fertiliser and irrigation savings from substituting bioenergy with agrivoltaics and photovoltaic systems from 2020 to 2100.

2. Methods

2.1. Land use modelling framework

The Land System Modular Model (LandSyMM; https://landsymm.earth) is a spatially explicit model of the global land system that couples a dynamic global vegetation model (LPJ-GUESS) and a land use model (PLUM) (Fig. 1). Here, LandSyMM operates on a 0.5-degree spatial resolution, with a sub-daily time step for crop simulations and an annual time step for land use decisions. LPJ-GUESS simulates ecosystem processes, including vegetation and soil carbon dynamics, the nitrogen cycle, and plant responses to climate change, CO_2 levels and land management [46–49]. Here, we used LPJ-GUESS to generate potential yield responses for crops and pasture under different climate, nitrogen fertilisation, and irrigation regimes. PLUM incorporates these crop yields, pasture yields, and water run-off to simulate land use changes driven by demand for food, feed and bioenergy [50,51]. PLUM uses least-cost optimisation to determine land use factors such as cropland area, fertiliser input, and irrigation. Food demand is projected using a price-elastic demand system which models dietary changes based on countries' incomes [52]. Shortfalls and excess in domestic production are traded through an international market, with prices adjusted annually based on global trade balances. Protected areas [53], barren land, and terrain too steep for agriculture are not included in the land use optimisation.

2.2. Scenarios

Scenario variants were based on the “Net Zero by 2050” (NZ2050) scenario from the Network for Greening the Financial Sector (NGFS) database [43]. We used outputs from the REMIND-MAgPIE-3.2-4.6 Integrated Assessment Model. The NZ2050 scenario incorporates a global energy mix consistent with limiting global warming to 1.5 °C and

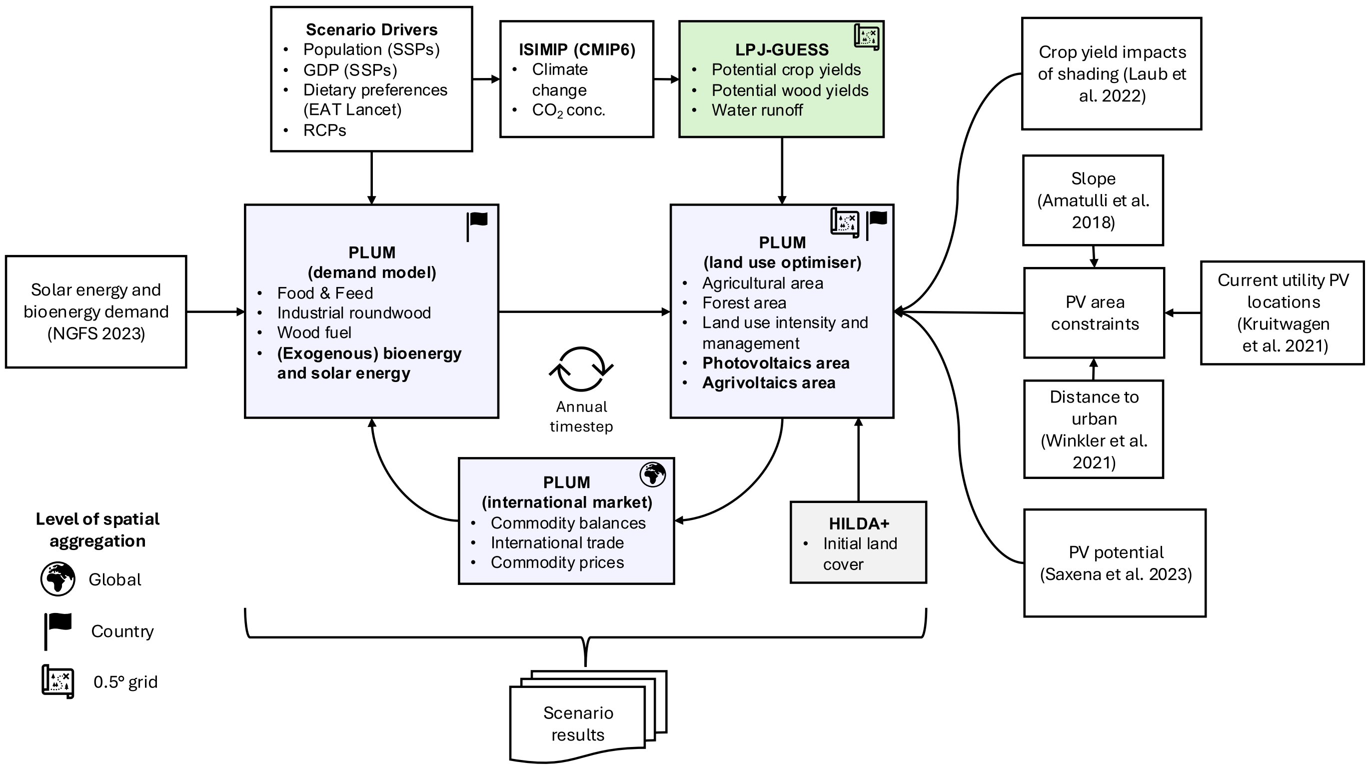

Fig. 1. Schematic of LandSyMM framework and additional data sources used for the implementation of agrivoltaics and photovoltaics.

includes a mixture of solar energy, bioenergy, and other renewables. Socioeconomic development follows the Shared Socioeconomic Pathway 2 (SSP2) scenario, representing business-as-usual economic and population growth [54]. Consistent with net zero emissions by 2050, we use crop yield projections (from LPJ-GUESS) based on the Representative Concentration Pathway 2.6 (RCP2.6) climate scenario, using outputs from the MRI-ESM2.0 Earth System Model [55]. Here, we refer to the reference scenario as BE. From this reference scenario, we constructed two further scenario variants. In the photovoltaics (PV) scenario, all bioenergy generation is substituted with photovoltaic generation. In the agrivoltaics (AV) scenario, all bioenergy generation is substituted with agrivoltaic generation. All three scenarios include a base photovoltaic demand but differ in whether additional energy generation comes from bioenergy (BE), photovoltaic systems (PV) or agrivoltaics systems (AV). To avoid sudden demand shocks, demand for bioenergy in scenarios AV and PV is gradually replaced between 2020 and 2030 by demand for energy from photovoltaic and agrivoltaic systems, respectively. After 2030, all energy that energy crops would have supplied is instead shifted to photovoltaic or agrivoltaic systems.

Population, GDP, and all model parameters (consistent with SSP2-RCP2.6) were kept the same in each scenario to ensure a like-for-like comparison. To simulate uncertainty in scenario outcomes, we used a Monte-Carlo approach to sample model parameters from distributions consistent with the scenario (Supplementary Table 1). A total of 30 ensemble members were simulated for each scenario. Energy demand in each scenario was adjusted for conversion efficiencies, ensuring that the final energy output remains consistent. We used data from Laub et al. [36] to estimate the yield reduction from shading for each modelled crop type. Projected solar energy potentials were taken from Saxena et al. [56] and used to model electricity generation from fixed-tilt photovoltaics. These scenarios are intended as stylised representations to isolate the land-system consequences of substituting dedicated bioenergy with solar alternatives, rather than as policy prescriptions or complete energy-system pathways.

2.3. Bioenergy demand

While the NGFS database includes down-scaled country-level primary energy supply from biomass, it does not differentiate between first and second-generation bioenergy, which is only provided on a regional level. In PLUM, initial country demand for first-generation energy crops is calculated from the Food and Agriculture Organization Statistical Database (FAOSTAT) [57]. Given that demand for first-generation energy crops is constant in the NGFS NZ2050 scenario, down-scaling of first-generation bioenergy demand was not necessary. Instead, we assume that demand for first-generation energy crops remains fixed at 2020 levels. For second-generation bioenergy, demand was downscaled from region to country by assuming that a country's share of the regional second-generation bioenergy demand is equal to the country's share of the total bioenergy demand. The downscaling was calculated separately for each year. Given that the current global production of second-generation energy crops is negligible, demand for second-generation energy crops was rebased to 1% of the modelled demand in 2020 and then interpolated linearly to match the modelled demand by 2030.

Energy crop demand was converted from mass units to energy units using energy content values from Slattery and Ort [58]. Energy content was also adjusted for primary to final energy conversion efficiency. We assumed a conversion efficiency of 42%, consistent with electricity generation from biomass in an integrated gasification combined cycle (IGCC) system [59]. This approach is the inverse of the substitution method commonly used to compare primary energy from renewable sources (usually in terms of electricity generation) and that of fossil fuels and biomass (usually in terms of the thermal energy content of the fuel).

2.4. Solar energy demand

We assumed that all solar energy is produced using photovoltaic panels and that the contribution of concentrated solar power (CSP) is negligible. Modelled demand for solar energy was rebased to 2020 using reported annual electricity generation data from Ember [41] and linearly interpolated to 2030 to match modelled data. The data from REMIND-MAgPIE does not distinguish between rooftop and ground solar energy, therefore requiring some assumptions about the rooftop share of solar energy. We used data from the IEA [60] to calculate the ground share of solar energy in 2020. The mean global rooftop share was used for countries where data was unavailable. Then, following Malik et al. [61], we assumed that the rooftop share is 30% in 2030 in all countries except Japan and India where it is 40% (due to low land availability). Rooftop share was linearly interpolated between 2020 and 2030 and afterwards held constant. Rooftop solar energy generation is not modelled in LandSyMM and only demand for ground-based solar is used. The additional demand for solar energy from the substitution of bioenergy was added to the base photovoltaic demand in scenario PV and taken as a separate demand for agrivoltaics in scenario AV.

2.5. Implementation of photovoltaics

In PLUM, the demand for solar energy can be met by allocating land to photovoltaics or agrivoltaics. A constraint requires each country to produce sufficient solar energy to meet demand. To avoid solution failure when this is not possible, energy import was permitted at a high cost. Although the generation of imported energy was not modelled, imports were negligible in all scenarios. We used photovoltaic potentials produced by Saxena et al. [56] which include the impact of climate change on solar irradiance and photovoltaic panel efficiency. During a model run, photovoltaic potentials were updated every ten years. We used a starting photovoltaic efficiency of 20.9% as per Fraunhofer ISE [62]. The photovoltaic efficiency was increased on average by 0.10 percentage points (95% CI: 0.08–0.12) per year based on historical trends [63]. The ground coverage ratio (GCR; the ratio of photovoltaic panel area to ground area) was calculated for each latitude using a relationship between the latitude and optimal GCR from Tonita et al. [64], assuming fixed-tilt systems. Additionally, we accounted for the space required for electrical and access infrastructure using a constant generator-to-system ratio (GSR) of 0.75 based on existing solar installations [44]. Therefore, the electricity generation density from photovoltaics was calculated as follows:

$$\mathrm{P}_{i,t} = \mathrm{E}_t \cdot \mathrm{GCR}_i \cdot \mathrm{GSR} \cdot \mathrm{Q}_{i,t}^{\max}, \tag{1}$$

where $P_{i,t}$ is the electricity generation density (MWh ha^{-1} yr^{-1}) at location i at time t, E_t is photovoltaic efficiency, GCR_i is the ground coverage ratio, GSR is the generator-to-system ratio, and $Q_{i,t}^{max}$ is the solar energy potential.

System installation and maintenance costs were obtained from IRENA [28]. Costs were annualised over the expected lifespan of the system, taken to be 25 years [28] (Eq. (2.1)).

$$\mathrm{C}_{i,t}^{ann} = \mathrm{K}_{i,t}\left(\mathrm{C}^{main} + \frac{\mathrm{C}^{inst}}{25}\right); \tag{2.1}$$

$$\mathrm{K}_{i,t} = \mathrm{E}_t \cdot \mathrm{GCR}_i \cdot \mathrm{GSR}, \tag{2.2}$$

where $C_{i,t}^{ann}$ is the annualised cost (\$ m^{-2} yr^{-1}) at location i at time t, C^{main} is the annual maintenance cost (\$ kW^{-1} yr^{-1}), C^{inst} is the installation cost (\$ kW^{-1}), and $K_{i,t}$ is the system capacity (kW m^{-2}). The values for C^{main} and C^{inst} are \$876 per kW and \$13.2 per kW per year, respectively. A capacity factor $K_{i,t}$ is calculated for each location to convert cost per unit of capacity to cost per unit area (Supplementary Fig. 6).

2.6. Implementation of agrivoltaics

For agrivoltaics, we used the same photovoltaic potentials and cost assumptions as described previously but with an additional 30% cost to account for additional installation and maintenance costs [38]. While the GCR for photovoltaics was calculated solely to maximise energy generation, the optimal GCR for agrivoltaic systems depends on the trade-offs between electricity generation and crop production [32,65]. This requires a detailed simulation of the effect of photovoltaic panel array geometry on power generation and crop yields, which is beyond the scope of this study. Therefore, a constant GCR of 0.25 was chosen based on reported values in existing agrivoltaic systems [65]. Following Dupraz [65], we assumed that the relative reduction due to shading equals GCR + 0.05.

We used data from Laub et al. [36] to estimate the impact of shading on crop yields (Supplementary Fig. 7). Crops were mapped to PLUM crop types as shown in Supplementary Table 2. A proxy crop was used where no data was available (rice, other oil crops, and *Miscanthus*). We used ordinary least squares (OLS) regression to estimate the yield reduction from shading (Eq. (3)).

$$\ln\left(\mathrm{Y}_{c,i}\right) = \beta_1 \mathrm{S}_{c,i} + \beta_2 \mathrm{S}_{c,i}^2 + \beta_{3,c} \mathrm{S}_{c,i} + \epsilon_{c,i}, \tag{3}$$

where $Y_{c,i}$ is the yield of shaded crops relative to unshaded crops for crop type c, $S_{c,i}$ is the relative shading, β_1, β_2 and $\beta_{3,c}$ are fitted parameters, and $\epsilon_{c,i}$ is the error term. $Y_{c,i}$ was log-transformed to ensure that predicted values are positive.

To account for the area taken up by photovoltaic infrastructure (e.g. panel supports) in agrivoltaic systems, we included an additional 10% reduction in yields and a corresponding 10% reduction in per unit area production cost given the smaller area available for cultivation. We furthermore imposed a lower limit on crop management intensity (equivalent to 50% of maximum yield potential), firstly by assuming that agrivoltaic farming occurs at high agricultural intensities and secondly to avoid cases where management intensity and, therefore, crop yields are zero (which would be equivalent to a standard photovoltaic system).

2.7. Area constraints

The allocation of land to photovoltaics and agrivoltaics was constrained using a suitability map based on terrain slope and proximity to urban areas. We used global slope data from Amatulli et al. [66] and calculated the distance to the nearest urban area using 2020 land cover data from HILDA+ [67]. Placement of photovoltaic panels was limited to slopes of less than 10 degrees and within 35 km of the nearest urban area (Supplementary Fig. 8). The distance to urban area constraint was based on the location of existing solar energy installations from Kruitwagen et al. [68] and land cover data from HILDA+ [67]. We also used data from Kruitwagen et al. [68] to initialise the modelled photovoltaic areas in 2020. Distance to urban areas and land slope do not alone fully reflect the constraining factors for photovoltaic installations such as grid capacity, distance to transmission lines, and distribution of electricity demand. While our approach is sufficient for global scale modelling, future work could improve this aspect using detailed energy system models.

3. Results

3.1. Land use and land cover

The following results focus on 2060 when bioenergy demand and its impact on the global land system are found to be greatest by this study. The complete time series of global land use under each scenario can be found in Supplementary Fig. 1. Global electricity demand was not modelled here and, therefore, the different demand scenarios (BE, AV and PV) were based on a Net Zero by 2050 scenario from NGFS [43]. In scenario BE, the global annual electricity generation from bioenergy increases from 1576 TWh to 8963 TWh between 2020 and 2060 (Fig. 2a). Conversely, in scenarios PV and AV, bioenergy declines after 2020 and is fully phased out by 2030. Electricity generation from

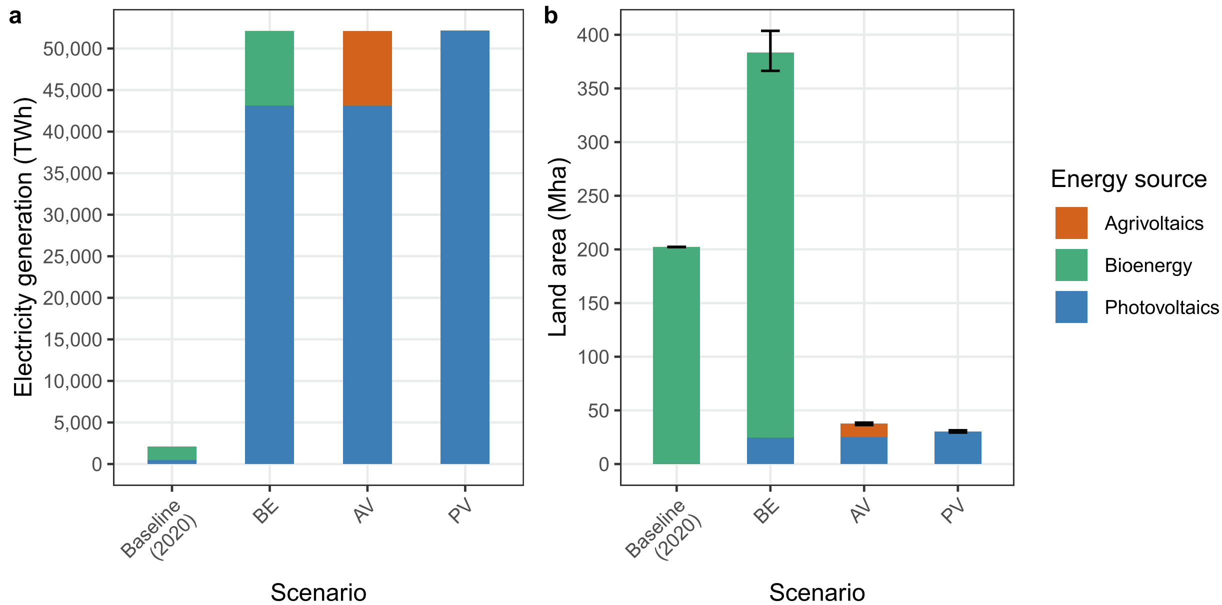

Fig. 2. (a) Global annual electricity generation in 2060 from agrivoltaics, photovoltaics, and bioenergy. (b) Global land area in 2060 required for electricity generation (photovoltaics and agrivoltaics) or energy crop cultivation (bioenergy). Baseline modelled values in 2020 are shown for reference. Bars show the median estimates and error bars show the 90% CIs ($n = 30$).

photovoltaics increases from 510 TWh to 43,160 TWh in scenarios BE and AV, and to 52,123 TWh in PV. In scenario AV, electricity generation from agrivoltaics reaches 8963 TWh, mirroring the increase in bioenergy in scenario BE.

Each year, LandSyMM allocates land for energy crops, photovoltaics, and agrivoltaics to satisfy demand for energy from each of these sources. Land is also allocated for food and feed production. In each grid cell, crop yields are modelled as a function of nitrogen fertiliser application, irrigation water withdrawal, and management intensity (representing factors such as pesticide use and mechanisation). We estimate that 202 Mha of land was used for the cultivation of first- and second-generation energy crops in 2020 (Fig. 2b). In scenario BE, this increases to 359 Mha (90% CI: 342–380) by 2060 – an area greater than India. Over the same period, the land area used for photovoltaics increases from 0.3 Mha to 24.7 Mha (23.9–25.5) in BE, 24.9 Mha (24.2–25.8) in AV, and 30.0 Mha (29.1–31.0) in PV. Finally, the land area for agrivoltaics increases to 12.3 Mha (11.9–12.7) in AV. In total, to generate 52,123 TWh of electricity, 384 Mha (366–404) of land is required in BE, compared to 37.5 Mha (36.3–38.6) in AV and 30.4 Mha (29.3–31.4) in PV.

We calculated pairwise differences in global land use between

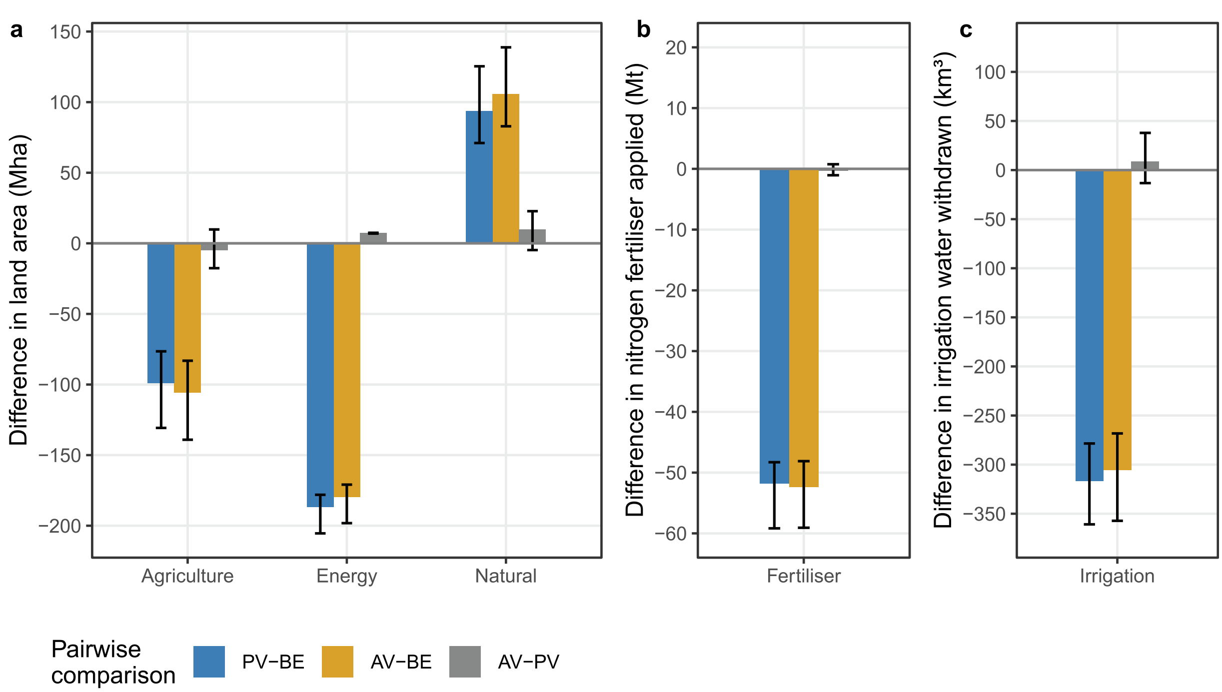

Fig. 3. Pairwise differences (PV-BE, AV-BE, and AV-PV) in (a) land area for agriculture, energy and natural areas, (b) nitrogen fertiliser applied, and (c) irrigation water withdrawn between scenarios in 2060. Median values are shown by bars, and 90% CIs are shown by ranges. Agriculture includes cropland, pasture, and agrivoltaics. Land for energy includes energy crops, photovoltaics, and agrivoltaics. Natural land cover includes unmanaged forests and other natural areas.

corresponding ensemble members from each scenario. Replacing bioenergy with solar energy results in a reduction in the global agricultural area by 2060 compared to scenario BE, with a difference of −105.7 Mha (90% CI: −139.1 to −83.1) in scenario AV and −98.9 Mha (−130.7 to −76.5) in scenario PV (Fig. 3a). There is also a slight reduction in agricultural areas in AV compared to PV of −4.6 Mha (−17.6 to 9.3). Larger reductions in land use are seen when looking at the land area used for energy, including bioenergy, agrivoltaics and photovoltaics. Results show a difference in the land area for energy of −179.7 Mha (−198.2 to −170.9) in AV and −186.5 Mha (−205.4 to −178.1) in PV, when compared to BE. Comparing AV to PV shows an increase in land area for energy generation of 7.1 Mha (6.9–7.5). Altogether, we find 105.5 Mha (82.9–138.8) more natural land cover in AV and 93.7 Mha (71.0–125.4) in PV compared to BE (Fig. 3a). Comparing AV to PV, we find 9.6 Mha (−4.8 to 22.8) more natural land cover.

We find large reductions in land use intensity in scenarios AV and PV, including fertiliser and irrigation usage. Compared to scenario BE, nitrogen fertiliser application shows a difference of −52.4 Mt. (−59.1 to −48.1) in AV, and −51.8 Mt. (−59.2 to −48.3) in PV (Fig. 3b). Furthermore, comparing AV and PV, we find a negligible difference of −0.3 Mt. (−1.1 to 0.8). For irrigation water withdrawal, we find a difference of −305.4 km^3 (−375.2 to −268.2) in AV, and −317.0 km^3

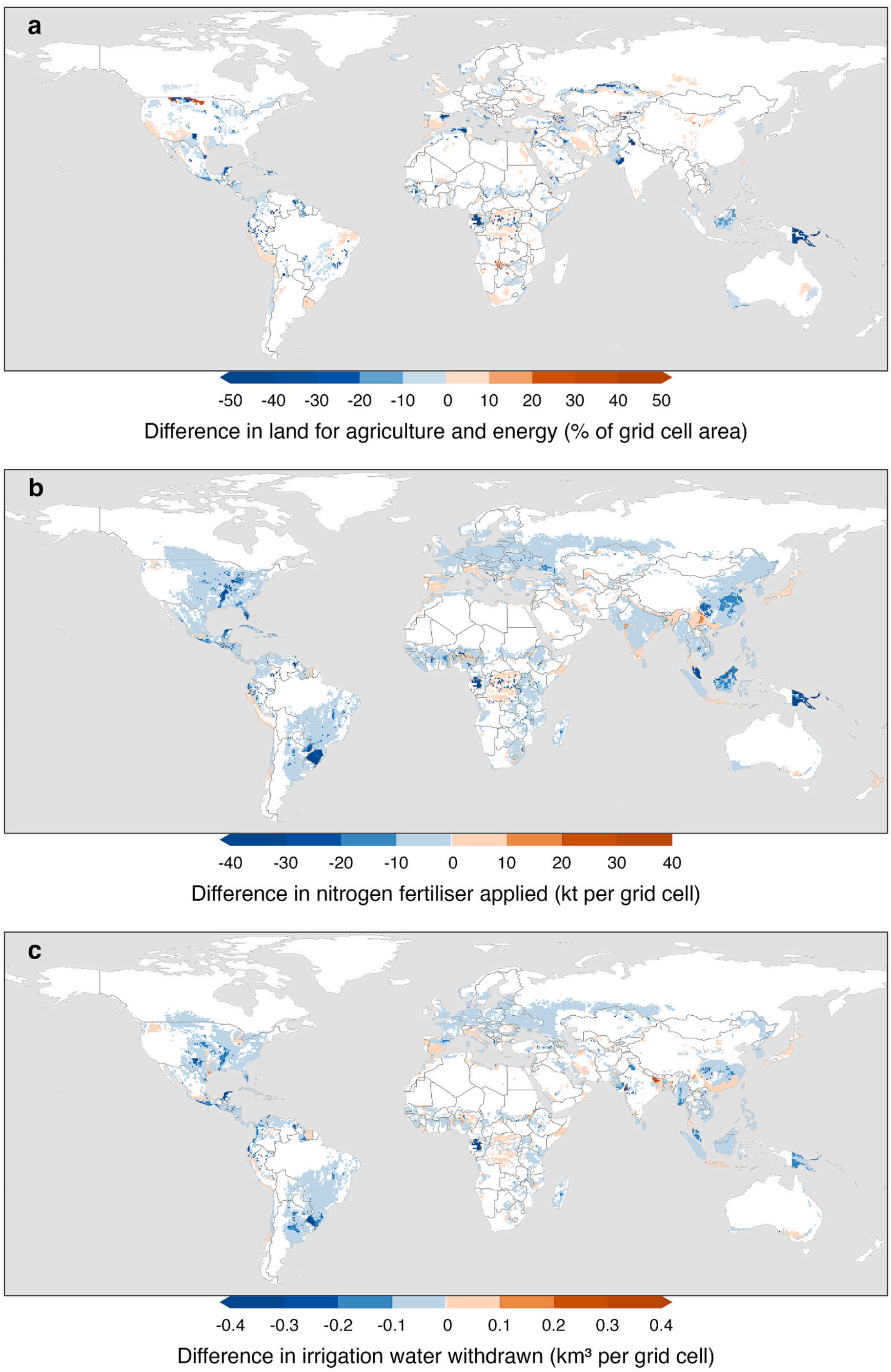

Fig. 4. Median difference in (a) land area used for agriculture and energy generation, (b) nitrogen fertiliser application, and (c) irrigation water withdrawal between scenario AV and BE in 2060.

(−360.8 to −278.5) in PV (Fig. 3c). Between AV and PV, we find a small difference of 8.8 km^3 (−13.2 to 37.9).

We find that reductions in the land area used for agriculture and energy in scenario AV occur in multiple hotspots (Fig. 4a). Notably, these include biodiverse, tropical regions such as Central Africa and South-East Asia. Some areas of increased land usage for agriculture and energy can also be seen, but these are less widespread. Similarly, many areas show large reductions in fertiliser application (Fig. 4b) and irrigation water withdrawals (Fig. 4c). These are typically concentrated in highly productive agricultural areas such as those found in China, the United States, and parts of South America. Areas with the largest differences between scenarios AV and BE also show the highest uncertainty across ensemble members (Supplementary Fig. 2), suggesting that the magnitude of local impacts is sensitive to model parameterisation.

3.2. Distribution of electricity generation

The shift from bioenergy to photovoltaics results in a substantial increase in photovoltaic generation in scenario PV (Fig. 5a; see Supplementary Fig. 3 for total photovoltaic generation in each scenario).

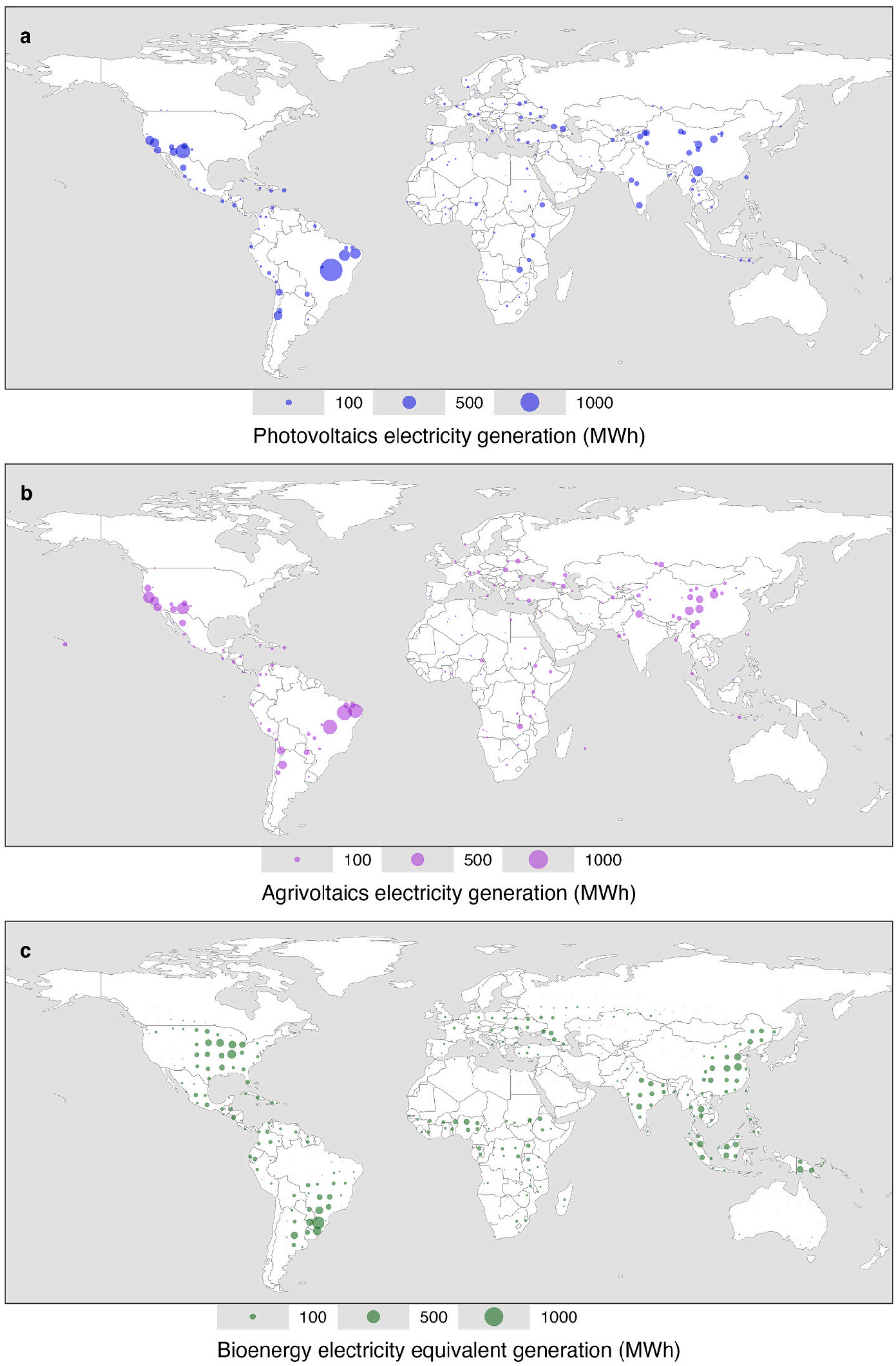

Fig. 5. (a) Additional photovoltaics generation required to replace bioenergy in scenario PV in 2060. (b) Agrivoltaics generation in scenario AV in 2060. (c) Bioenergy generation in scenario BE in 2060. Electricity equivalent generation from energy crops is based on an integrated gasification combined cycle (IGCC) system. The size of circles is proportional to the amount of electricity generated. Each circle corresponds to electricity generation within a 5-degree grid cell. Results are shown for a single, representative ensemble member.

Notably, this includes countries such as Brazil and the United States which rely heavily on bioenergy in scenario BE. In scenario AV, the replacement of bioenergy with agrivoltaics gives rise to three major hotspots of agrivoltaic systems which correlates with the largest photovoltaic generators: Brazil, China, and the United States (Fig. 5b). The distribution of agrivoltaics generally follows that of photovoltaics rather than corresponding to the cropland distribution. Fig. 5c shows the electricity equivalent generation from energy crops in scenario BE based on the location of energy crop cultivation.

3.3. Agrivoltaics crop mix

The allocation of different crop types and pasture in agrivoltaic systems is determined endogenously in PLUM, with no constraints on the crop mixture. In these simulations, we find that over 90% of the agrivoltaic area is used for pasture (Fig. 6). For crops other than pasture, the most common crop type in agrivoltaic systems is C3 cereals, accounting for 6% of the agrivoltaics area. Additionally, fruit and vegetables account for up to 38% of crop production in agrivoltaic systems despite representing 2% of the crop area. The simulated agrivoltaics crop mix is likely sensitive to modelled yield responses to shading which were based on a relatively small sample size from Laub et al. [36]. Crop types for which no data was available (rice, other oil crops, and *Miscanthus*) were substituted with proxy crops (Supplementary Table 2) and these should be interpreted with additional caution. While this makes the crop allocation uncertain, it has less impact on the total agrivoltaics area and the broader land use consequences.

3.4. Land equivalent ratio

We used the Land Equivalent Ratio (LER) to measure the land area savings from agrivoltaics compared to conventional agriculture and photovoltaics (Eq. (4)). The LER is calculated as the ratio of crop production in an agrivoltaic farm to a conventional farm plus the ratio of electricity generated in an agrivoltaic system to a standard photovoltaic system:

$$\mathrm{LER} = \frac{C_{av}}{C_{ref}} + \frac{E_{av}}{E_{ref}}, \tag{4}$$

where C_{av} and C_{ref} are crop production in an agrivoltaic and reference farm, and E_{av} and E_{ref} are the electricity generated in an agrivoltaic and reference photovoltaic system. A LER greater than one signifies more efficient use of land in an agrivoltaic farm compared to a reference farm and photovoltaic system. For these results, the global median LER is 1.323 (90% CI: 1.320–1.325) in 2060, suggesting a 32% higher land use efficiency when combining crop production and electricity generation (Supplementary Fig. 4). The LER for pasture is generally higher than that for non-pasture crops – 1.326 (1.326–1.328) compared to 1.192 (1.115–1.309), respectively.

3.5. Food prices

Including bioenergy in the energy mix in scenario BE resulted in higher food prices in all regions compared to scenarios PV and AV (Supplementary Fig. 5). However, the difference was relatively small with prices varying at most a few percent between the scenarios. By 2030, the global food price index is 101.3 (100.4–103.1) in scenario BE compared to 99.0 (98.1–100.7) in PV and 98.9 (97.9–100.6) in AV. After 2030, food prices fall in all regions except Africa and differences between the scenarios become narrower. After 2060, the food price index is virtually identical in each scenario. While food prices are initially higher in scenario BE when the growth in bioenergy demand is the greatest, the effect is small compared to the uncertainty range.

4. Discussion

Unprecedented transformation of the world's energy supply is needed to achieve rapid reductions in global GHG emissions [1,3]. There is currently a strong reliance on bioenergy in modelled climate change mitigation scenarios. However, our results support previous findings that energy crop cultivation is an inefficient use of the world's agricultural land and could lead to additional cropland expansion this century [12,23,24,26,27,29]. Replacing bioenergy with solar energy in a Net Zero by 2050 scenario avoids further cropland expansion and results in substantially lower nitrogen fertiliser and irrigation water use. This further avoids increases in food prices due to competition for land between bioenergy and food production, therefore increasing food

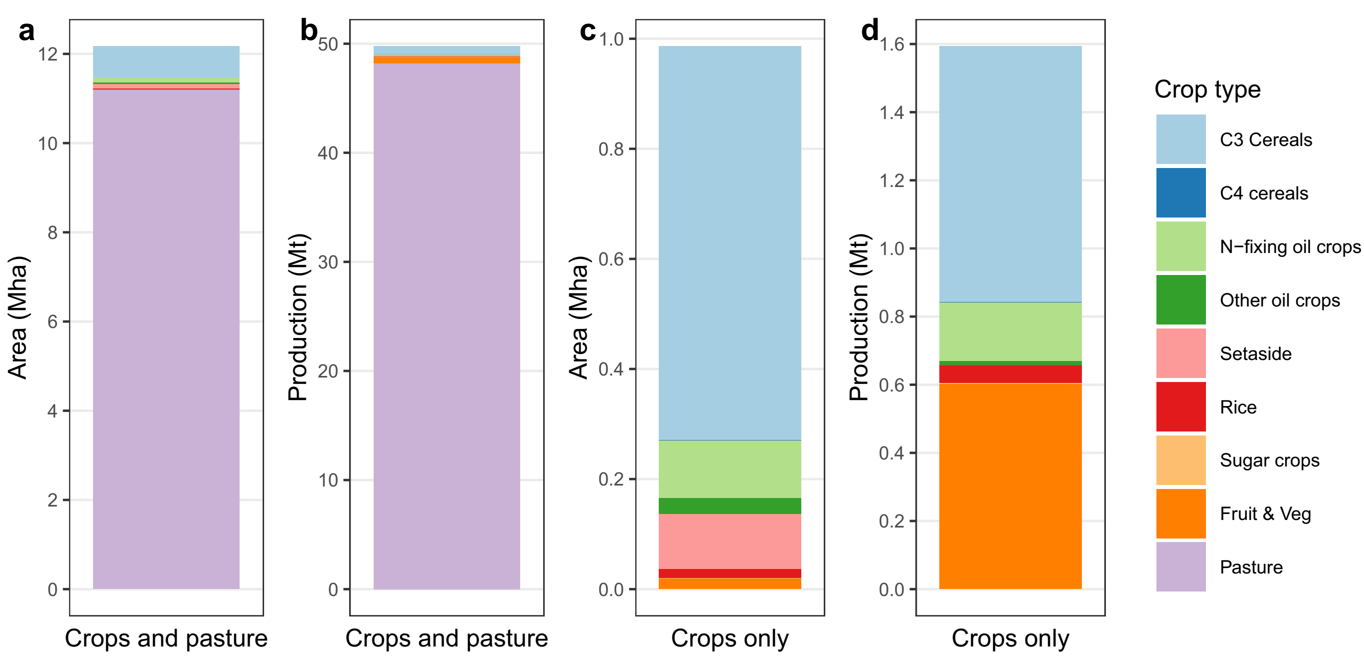

Fig. 6. Agrivoltaics land area in 2060 for (a) crops and pasture and (c) crops only. Production in 2060 from agrivoltaics systems for (b) crops and pasture and (d) crops only. Production is shown in dry-matter equivalent amount for pasture and wet-matter amount for other crop types.

security. Moreover, this study is the first to conduct a global assessment of the land use consequences of agrivoltaics using spatially explicit simulation of the land system. By combining electricity generation and crop production, we find that agrivoltaics can further improve land use efficiency compared to standalone photovoltaic systems.

The substantial land, water and fertiliser use required for large-scale energy crop production present strong environmental trade-offs [17,18,23,24,69]. The increase in the area used for energy crop cultivation (+156 Mha by 2060) greatly exceeds the net cropland expansion (+97 Mha) due to the overall intensification of agricultural production. In contrast, only an additional 12.3 Mha of agrivoltaics or 5.4 Mha of photovoltaics is required to replace all bioenergy. We estimate that the ratio of land area required for energy crops compared to agrivoltaics generating the same amount of electricity is approximately 29. For photovoltaics, the ratio is approximately 67. An analysis by Searchinger et al. [29] suggests a global average ratio of at least 100 when comparing photovoltaics and bioenergy. In contrast, our estimate is derived from a more realistic setup based on the simulated distribution of energy crops, photovoltaics, and realistic yield responses. Beyond resource efficiency, agrivoltaics could also provide co-benefits such as reduced crop drought stress and improved photovoltaic panel efficiency by reducing panel temperatures [35].

Furthermore, we find that the use of agrivoltaics in scenario AV results in an additional 9.6 Mha of natural land cover compared to scenario PV. While this difference is small relative to global land cover, it highlights the potential for agrivoltaics to make a marginal contribution to reducing the world's agricultural and energy land footprint. However, the adoption of agrivoltaics modelled here was very limited, corresponding to less than 0.5% of the global agricultural area. Higher rates of adoption could bring more substantial reductions in global land use. We also find that agrivoltaics have a negligible impact on aggregate global agricultural inputs, including fertiliser and irrigation, under the assumptions made in this study. This suggests that land savings from agrivoltaics are primarily due to redistribution of crop production and lower land competition with photovoltaics rather than agricultural intensification. However, aggregate differences can mask significant local impacts of agrivoltaics under specific conditions, such as improved water use efficiency in drylands [35].

In the AV scenario explored here, we allowed the model to allocate both crops and pasture to agrivoltaic systems. Results suggest that agrivoltaics are predominantly suited for pasture, representing 90% of the total agrivoltaics area. Although there could be potential for pasture cultivation under regular photovoltaic arrays, this is not modelled here. We acknowledge that the distinction between agrivoltaics and traditional photovoltaics becomes ambiguous in this case. However, not all photovoltaics systems are suitable for pasture cultivation as design accommodations need to be made to ensure accessibility to livestock and safety of electrical infrastructure. Additionally, agrivoltaics introduce a trade-off between pasture productivity and solar energy generation which is not considered in traditional photovoltaic systems, but which can significantly impact installation, maintenance costs and photovoltaic array design. The suitability of different crops for cultivation in agrivoltaic systems is strongly dependent on the crops' yield response to shading. Based on data from Laub et al. [36], we found pasture to be the most shade-tolerant crop type, explaining its predominance in the scenarios. However, limited sample sizes and a lack of global coverage in the data means that these results should be interpreted with a high level of uncertainty. Future work could improve this aspect of the study by supplementing empirical data using global simulations of crop responses to shading.

We find that the co-production of crops and solar energy is approximately 30% more efficient in terms of land area than separate production, with a global median LER of 1.32. While there is currently no global assessment of the LER of agrivoltaics, various local studies report similar observed and simulated values ranging from 1.1 to 1.8 [31,70,71]. In addition, the suitability of agrivoltaic deployment is likely to vary regionally depending on climatic conditions, solar radiation, and existing agricultural practices which warrants further regional analysis [56]. Our estimate of the global LER of agrivoltaics is dependent on the specific scenario assumptions made here and should not be interpreted as a universal global value. We find that the LER varies significantly through time (Supplementary Fig. 4) and further work is needed to explore the sensitivity of the LER to scenario drivers and assumptions.

One of the potential negative impacts of bioenergy is its inflationary effect on food prices [19,20,22]. Although food prices are initially higher in scenario BE compared to scenarios PV and AV, the effect is relatively small. By 2030, the global food price index is 2.3 percentage points higher in scenario BE compared to PV and 2.4 percentage points higher compared to AV. The initial spike in food prices in scenario BE corresponds to a rapid increase in energy crop supply. Differences in food prices between scenarios become negligible after 2060, suggesting that the food system has a high capacity to adapt to changing demand levels. Despite the higher cost of crop production in agrivoltaic systems, we find no difference in food prices between scenarios PV and AV. This may be because the additional production costs in agrivoltaic systems are balanced by reduced land competition with photovoltaics.

Despite the potential of agrivoltaics to improve land use efficiency, several challenges and barriers could hinder their adoption. Crop cultivation under photovoltaic panels requires significant changes to agricultural practices, potentially discouraging farmers from adopting this technology [72]. Crops such as fruit and vegetables are already produced under cover, for example, in tunnels or greenhouses, making integrating photovoltaic panels easier. However, wide-scale adoption of agrivoltaics may prove difficult for staple crops such as cereals. Upfront investment required for agrivoltaic installations may be prohibitive for many landowners, particularly if significant updates to energy infrastructure and grid systems are required [38]. Regulatory barriers and lack of social acceptance may also pose considerable hurdles to the adoption of agrivoltaics [73–75]. The scenarios presented here were intentionally designed to form extreme counterfactuals where rapid adoption of agrivoltaics and photovoltaics replaces all energy crop cultivation. In practice, full substitution of bioenergy is neither likely nor recommended due to potential trade-offs and benefits not explored here. For example, biofuels may be essential in replacing fossil fuels where electrification is not feasible. We also do not explore the potential of bioenergy from crop residues and organic waste.

These scenarios and modelling approach were based on a parsimonious set of assumptions about the energy and land use systems, which improves the interpretability of results but imposes some limitations. Firstly, we modelled a single global GCR for agrivoltaics consistent with known agrivoltaics installations [65]. Different GCR values, photovoltaic array geometries and tracking systems could produce significantly different microclimates and shading effects, leading to different yield responses. While the optimal GCR for agrivoltaics could vary significantly by location and crop type, representing this would require complex simulations of the impacts of photovoltaic panels on crop yields. Secondly, we assumed a one-for-one equivalence between bioenergy and solar energy (accounting for generation losses), whereas these energy sources have several differentiating properties. This includes the potential for bioenergy to remove carbon from the atmosphere through BECCS which is an important contributor to achieving net zero emissions in the reference scenario [43]. However, Direct Air Capture (DAC) powered by renewable energy such as solar energy could offer similar benefits to BECCS with significantly lower land use impacts [23,76,77]. Finally, we assumed globally uniform and constant photovoltaic system installation and maintenance costs, flat additional costs of agrivoltaics systems compared to standard photovoltaics, and no grid capacity limits. While more detailed parameterisation could result in different spatial patterns and additional uncertainty, the resulting contrast in land use between dedicated bioenergy and solar alternatives would be expected to be retained.

Decarbonisation of the energy system requires a radical transformation of the global energy supply. While bioenergy has been central to climate change mitigation scenarios, our findings suggest that its land, fertiliser, and water demands make it an inefficient choice compared to the potential of solar energy. By combining crop and energy production, agrivoltaics offer a potential alternative which can improve land use efficiency and reduce the environmental footprint compared to bioenergy and conventional photovoltaic systems. However, the wide-scale adoption of agrivoltaics presents several societal, economic, and regulatory barriers which could limit its timely contribution to decarbonisation. An improved understanding of the global potential of agrivoltaics, such as the modelling presented here, offers a way forward in tackling these barriers. Overcoming these barriers may require policy incentives such as subsidies for agrivoltaics infrastructure, adoption of feed-in tariffs, and farmer training programs to accelerate agrivoltaics adoption.

CRediT authorship contribution statement

Bartlomiej Arendarczyk: Writing – review & editing, Writing – original draft, Visualization, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Ankita Saxena:** Writing – review & editing, Methodology, Data curation, Conceptualization. **Almut Arneth:** Writing – review & editing, Supervision, Methodology, Conceptualization. **Mark Rounsevell:** Writing – review & editing, Supervision, Methodology, Conceptualization. **Peter Alexander:** Writing – review & editing, Supervision, Software, Resources, Methodology, Conceptualization.

Code availability

Model source code is available at https://git.ecdf.ed.ac.uk/lul/plumv2/-/tree/AgrivoltaicsPaper.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Bartlomiej Arendarczyk reports financial support was provided by UK Research and Innovation Natural Environment Research Council. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgement

Funding for this research was provided by NERC through an E4 DTP studentship (NE/S007407/1).

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.apenergy.2026.128628.

Data availability

Model output data can be found at https://doi.org/10.5281/zenodo.13994382. Model input data can be obtained from public sources including the FAO (https://www.fao.org/faostat), World Bank (https://data.worldbank.org), IIASA (https://tntcat.iiasa.ac.at/SspDb), and NGFS (https://www.ngfs.net/ngfs-scenarios-portal/data-resources).

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