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Energy-Landscape Optimization for Land Use Planning. Application in the Barcelona Metropolitan Area

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ABSTRACT

Rapid population growth and urban expansion in metropolitan areas have led to a dramatic increase in food demand. In most cases, urban sprawl occurs in unplanned ways, forcing peri-urban agriculture to adopt detrimental practices for biodiversity conservation and metabolic efficiency (i.e. landscape homogenization and dependence on non-renewable external inputs), facing the food-biodiversity dilemma. In order to ameliorate these negative effects over the metropolitan socioecological system, researchers have focused on developing comprehensive indicators to support sustainable urban expansion in metropolitan areas. In this paper, we use these indicators to develop an Energy-Landscape Optimization (E-LO), a nonlinear model designed for land use planning by means of considering biophysical constraints. Then, we test the model in a representative Mediterranean bio-cultural landscape in the Barcelona metropolitan area (Spain). The E-LO results allow us to propose different land use configurations for both conventional and organic agriculture, taking into account the associated socio-metabolic balances and the related landscape functional structures, with the aim to meet different societal objectives. We have fruitfully tested three settings: i) to increase conditions to host farm associated biodiversity, ii) to increase agricultural production, and iii) to minimize dependence on non-renewable external inputs. According to these socioecological objectives, we have obtained the best landscape-metabolism integration, which is a useful methodology for sustainable land use policy. This socioecological perspective is necessary for the new paradigm on agroecosystem management and landscape planning, and can help advancing towards functional green infrastructures in metropolitan areas, especially in the climate change and agroecological transition global context.

1. Introduction

Global human-driven Land Use and Cover Change (LUCC) have spread the so-called ‘anthropogenic habitats’ in many regions of the world thus determining biodiversity and ecosystem functioning in human-transformed landscapes for centuries, as in the Mediterranean (Grove and Rackham, 2001). However, increasing landscape transformation linked to fuel energy consumption (Giampietro et al., 2013) have driven to unprecedented levels of affectation of ecosystem functioning at landscape and regional scales (Sterling and Ducharne, 2008; Ellis et al., 2008). The past century was witness to particularly severe LUCC, which affected habitat and biodiversity conservation (Newbold et al., 2015; UN-IPBES, 2019). These effects lead to biotic homogenization in most-human transformed regions like metropolitan areas (McKinney, 2006). In any case, human-transformed landscapes are the outcome of a shifting interplay between spatial patterns of land-use types, their associated ecological processes and their socio-metabolic energy flows driven by human activity (Haberl, 2001; Wrbka et al., 2004). The human population has continued growing in the last decades, and the huge increase in global food production through increasingly industrialized and globalized production systems has provoked many serious socio-ecological impacts and conflicts (Tilman et al., 2002; Mayer et al., 2015).

The dilemma that land-use planners and agroecosystem managers are facing today is between increasing the “efficiency” of land trying to provide the demanded food and products at the cost of losing important features of landscape, and trying to keep the sustainability of the agroecosystem, which means limiting the production per unit area of land (Nair, 2014). The main strategies to respond to the growing food demand are: i) to increase production per unit area of land; ii) to increase the land used for food production. One of the most common ways used in industrialized agriculture to increase the production per unit area of land or increasing the “efficiency” of the land, is using fertilizers, pesticides and other non-renewable inputs. Although in the

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short run, these options seem desirable, the long-term effects are disastrous due to the loss in biodiversity, soil nutrition and other reproductive characteristics of agroecosystems that we call “funds” (Giampietro, 1997).

Hence, there is an urgent need for tools that support the designing of sustainable agroecosystems, where socioecological goals (i.e. food production, biodiversity conservation, ecosystem service provisioning) are optimized, while they operate within a framework of constrained reproductive imperatives (Padró et al., 2019a). To solve this food-biodiversity dilemma (Cardinale et al., 2012) a deeper research on how landscape ecological functionality is kept in different land use patterns is required, according to the quantity and quality of the human disturbance that farmers carry out across the landscape (Marull et al., 2018). The aim of this research is to find optimal scenarios for land use management in the Barcelona Metropolitan Area (BMA) that maximize key reproductive characteristics of agroecosystems (Padró et al., 2019) such are metabolic efficiency, landscape ecological functionality, biodiversity and associated ecosystem services, and also climate change mitigation and adaptation (Marull et al., 2020; Padró et al., forthcoming). To that aim, the objective of this paper is to develop an Energy-Landscape Optimization (E-LO) nonlinear modelling based on the Energy-Landscape Integrated Analysis (ELIA) (Marull et al., 2016) to find the optimal land uses that lead to a sustainable agroecosystem. Then, we test the E-LO model by applying three optimization scenarios in a Mediterranean bio-cultural landscape of the BMA, considering different LUCC under both conventional and organic agricultural practices. The E-LO is designed to help land-use policy-makers and agroecosystem managers to advance towards a socioecological transition taking into account societal priorities and environmental constrains in a human-transformed landscape.

2. Material and methods

The methodology considered for the E-LO model is based on applying an optimization procedure to the ELIA (Marull et al., 2016). The latter is a socio-metabolic and landscape ecology methodology that brings together landscape patterns and processes and describes how agrarian flows (such as energy, fertilizers or production) are distributed amongst the landscape. This tool is particularly useful to represent complex performances of cultural landscapes as human-nature co-evolutionary systems.

2.1. Energy-Landscape integrated analysis (ELIA)

2.1.1. Agroecosystem energy flows from a landscape ecology standpoint

ELIA summarizes human coproduction with nature (Marull et al., 2016) through the connection between energy flows (Fig. 1) coming from solar radiation through the photosynthesis (vertical axis) and coming from outside the landscape (left side of the horizontal axis). Both energy flows interact across a landscape functional structure to give rise to a final product extracted from it (right side of the horizontal axis). The ELIA graph expresses this network of energy flows across the agroecosystem, which are partially recirculating internally (to keep its own reproduction) and partially open externally (to sustain the agri-food chains of human society). β_i's are the incoming-outgoing energy flows coefficients.

The phytomass obtained from solar radiation through autotrophic production by plants is the *actual Net Primary Production* (NPP_{act}) (Vitousek et al., 1986). The biomass included in NPP_{act} that becomes available for heterotrophic species splits into *Unharvested Biomass* (*UB*) and the share of *Net Primary Production harvested* by farmers (NPP_h). *UB* generally remains in the same place where it has been originally growing and can feed farm-associated biodiversity. It becomes a source of *Agroecosystem Total Turnover* (*ATT*), which closes the cycle of the ‘natural’ subsystem (Fig. 1).

This ‘natural’ subsystem allows maintaining the farm-associated biodiversity and, in turn, the NPP_{act}, again through the trophic net of non-domesticated species either aboveground or in the soil (such as decomposer organisms). NPP_h splits into *Biomass Reused* (*BR*) inside the agroecosystem and *Farmland Final Produce* (*FFP*) that goes outside. *BR* is an important flow that remains within the agroecosystem as the farmers’ investment directly or indirectly addressed to maintain two basic fund elements: livestock and soil fertility. Hence, *BR* closes the ‘farmland’ subsystem (Fig. 1).

Then *BR* splits into the ‘livestock’ subsystem (Fig. 1) that goes to feed and bed the domesticated animals as *Livestock Biomass Reused* (*LBR*), which is added to the *Livestock Total Inputs* (*LTI*), and *Farmland Biomass Reused* (*FBR*). In turn, these flows add up to *Farmland Total Inputs* (*FTI*) as seeds, green manure and other vegetal fertilizers. These energy linkages in the ELIA graph enable us to see to what extent the land use management is integrated or not within the surrounding agroecosystem. Afterwards, domestic animals perform bioconversions and then the *LTI* is converted into *Livestock Final Produce* (*LFP*) and internal *Livestock Services* (*LS*). *LFP* includes a wide range of food and fibre products, and *LS* services include manure. Together they make up *Livestock Produce and Services* (*LPS*).

The ‘farmland’ and ‘livestock’ subsystems are partially closed within the agroecosystem, since they offer a *Final Produce* (*FP*) to be consumed outside—as well as receive *External Inputs* (*EI*). Therefore, *UB, BR* and *LS* regulate the internal flows that lead to a higher or lower internal circularity in the pattern of energy networks of the agroecosystem (Fig. 1). They constitute important flows of recirculating biomass that contribute to the maintenance of the agroecosystem funds: landscape processes and associated biodiversity, soil fertility and livestock (Marull et al., 2016).

The internal circularity of energy flows is kept within the agroecosystem because the outputs of one subsystem serve as inputs for the next subsystem, allowing the storage of energy carriers and information within its dissipative structure (Ho and Ulanowicz, 2005). There is an exception to this rule though, when some energy carriers circulating

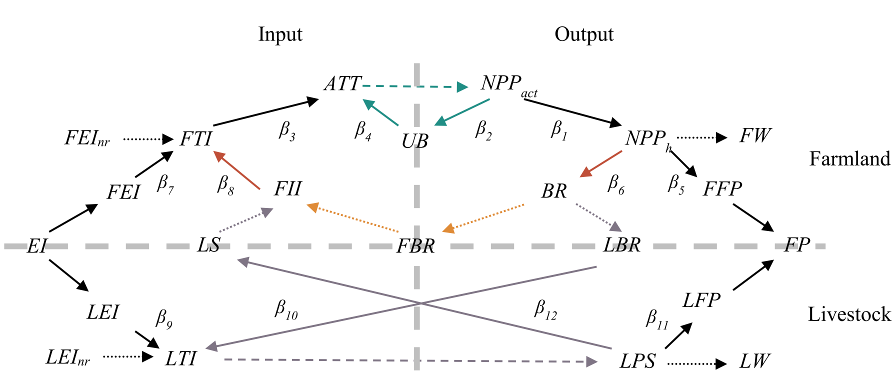


Fig. 1. Graph model of interlinked energy carriers flowing in a mixed-farming agroecosystem[1].
Variables: Actual Net Primary Production (NPP_{act}); Unharvested Biomass (*UB*); Harvested Net Primary Production (NPP_h); Biomass Reused (*BR*); Farmland Biomass Reused (*FBR*); Livestock Biomass Reused (*LBR*); Farmland Final Produce (*FFP*); External Input (*EI*); Farmland External Input (*FEI*); Livestock External Input (*LEI*); Livestock Total Input (*LTI*); Livestock Produce and Services (*LPS*); Livestock Final Produce (*LFP*); Livestock Services (*LS*); Final Produce (*FP*); Agroecosystem Total Turnover (*ATT*); Farmland Total Input (*FTI*); Farmland Internal Input (*FII*); Farmland Waste (*FW*): Livestock Waste (*LW*). *nr* means no-renewable. β_i's are the incoming-outgoing coefficients.

Relationships between variables: $NPP_{act} = UB + NPP_h$; $NPP_h = BR + FFP$; $BR = FBR + LBR$; $EI = FEI + LEI$; $LTI = LEI + LBR$; $LPS = LFP + LS$; $FP = FFP + LFP$; $ATT = FTI + UB$; $FTI = FII + FEI$; $FII = FBR + LS$.

Note: [1] The colours of the arrows represent the ‘natural’ (green), ‘farmland’ (red) or ‘livestock’ (purple) subsystems.

inside the agroecosystem imply losses as opportunity costs, because of farmers' mismanagement, into what Odum (1993) named a 'resource out of place'—i.e. a waste. We consider wastes as energy flows that cannot be integrated by farm systems, either because they exceed the carrying capacity, or they are not correctly disposed for the agroecosystem funds according to societal goals (Douglas, 1966).

Sometimes a fraction of NPP_{act} can be wasted, such as crop stubble or tree pruning that are burnt on the field instead of being used, as it often was in the past, for bedding (straw), home heating (branches), or animal feed (leaves). The same may happen with a fraction of the *LPS*, such as dung slurry coming from agro-industrial feedlots that is spread out in excess of cropland carrying capacity and finally contaminates the water table. If they exist, *Farmland Waste* (*FW*) and *Livestock Waste* (*LW*) do not contribute to the renewal of the agroecosystem's funds; they neither enhance its reproduction, nor meet human needs.

2.1.2. Agroecosystem energy flows and landscape ecology integration

ELIA combines three indicators: the energy storage performed through the internal cycles of agroecosystems –'energy reinvestment' (*E*), the information embedded in the energy network of flows –'energy redistribution' (*I*), and the landscape functional structure –'energy imprint' (*L*). The circularity of energy carriers driven by farmers through *UB, BR* and *LS* flows (Fig. 1) is a metric of *E* and *I*, which contributes to the energy potentially available for trophic chains existing in agroecosystems.

2.1.2.1. Measuring energy storage as reinvestment of energy cycles (E).

We understand agroecosystem complexity as the differentiation of dissipative structures (metabolic cycles) allowing for diverse potential ranges in their behaviour (Tainter, 1990). The more complex the space-time differentiation of these structures, the more energy is stored within a living system (Ho and Ulanowicz, 2005). Hence, higher mean values of even β_i's (Fig. 1) entail that agroecosystems are increasing in complexity because the different cycles are coupled to each other, and the residence time of the stored energy increases thanks to a greater number of interlinked energy transformations circulating inside. Accordingly, our way of calculating the *Energy Stored* (*E*) to keep the agroecosystem's funds functioning goes as follows (eq. (1)):

$$E = \frac{\beta_2+\beta_4}{2}k_1 + \frac{\beta_6+\beta_8}{2}k_2 + \frac{\beta_{10}+\beta_{12}}{2}k_3.$$
$$k_1 = \frac{UB}{UB+BR+LS},\ \ k_2 = \frac{BR}{UB+BR+LS},\ \ k_3 = \frac{LS}{UB+BR+LS}, \qquad (1)$$

Where the coefficients k_1, k_2, k_3 account for the share of reusing energy flows that are circulating through each of the three subsystems (Fig 1), which allows differentiating the agroecosystems' fund composition and making their energy patterns comparable. *E* remains within the range [0, 1]. *E* close to 0 implies low reuse of energy flows—usually associated with industrial farm systems, which are highly dissipative and dependant on external inputs. *E* close to 1 implies the existence of internal cycles only, usually translating into land abandonment (i.e. loss of cultural landscapes) or to a simple extractive use of the land (i.e. foraging or hunting).

E assesses the amount of all the energy flows that go back inside the agroecosystem. When we account for the three subsystems altogether (natural, farmland and livestock), we are adopting a landscape agroecology standpoint. This allows linking farming energy analysis with landscape ecology assessment.

2.1.2.2. Measuring information as complexity of energy flow patterns (I).

Agroecosystems have a quantity of information embedded in the network structure through which their reproduction takes place over time. This way of information accounting can be seen as a measure of uncertainty, or the degree of freedom for the system to behave and evolve (Prigogine, 1996). It is called 'information-message' and registers the likelihood of the occurrence of a pair of events (Passet, 1996; Ulanowicz, 2001). The *Energy Information* (*I*) is always site-specific, which becomes an important trait from a cultural standpoint (Barthel et al., 2013; Font et al., 2020). In general, when a balanced agroecosystem registers a decrease of *I*, some important parts of the agroecosystem functioning are then no longer controlled at the landscape level, but linked to increasingly globalised agri-food chains (McMichael, 2011; Tello and González de Molina, 2017). This work used a Shannon-Wiener Index adaptation over each pair of β_i's (Fig. 1), so that this indicator shows whether the β_i's pairs are evenly distributed or not. This measure of *I* accounts for the equi-proportionality of pairwise energy flows that exit from each node in every sub-process (eq. (2)).

$$I = -\frac{1}{6}\left(\sum_{i=1}^{12}\beta_i \log_2\beta_i\right)(\gamma_F+\gamma_L)(\alpha_F+\alpha_L),$$
$$\gamma_F = \frac{UB+NPP_h}{2(UB+NPP_h+FW)},\ \ \gamma_L = \frac{LS+LFP}{2(LS+LFP+LW)}$$
$$\alpha_F = \frac{FEIr}{2(FEIr+FEInr)},\ \ \alpha_L = \frac{LEIr}{2(LEIr+LEInr)} \qquad (2)$$

Base 2 logarithms are applied as the probability is dichotomous. The introduction of the information-loss coefficients γ_F, γ_L ensures that *I* remains lower than 1 when the agroecosystem presents farm and/or livestock waste. The coefficients α_F, α_L act as a penalization for the use of non-renewable external inputs, which entail an internal information loss given that the agroecosystem functioning is no longer self-reproductive. *I* values close to 1 are those with an equi-distribution of incoming and outgoing energy flows, where the 'information-message' embedded in the agroecosystem structure is high, whereas *I* values close to 0 mean patterns of probability far from equi-distribution which endow less information. These lower *I* values correspond to an industrialised farm system; or, by contrast, to an almost 'natural' turnover with no external inputs and no harvests. Conversely, agroecosystems with *I* equal to 1 are the ones with equi-distributed incoming and outgoing energy flows in each sub-process, that probably correspond to a mixed farming in which external inputs play a balanced role integrated with local energy recirculation (Tello et al., 2016).

Therefore, *E* measures the energy reinvested and temporarily stored in the agroecosystem and *I* assesses how the farmers redistribute this energy in the landscape. Needless to say, the more complex (i.e. internally differentiated and interlinked) an agroecosystem is, the greater the farming information required to manage it.

2.1.2.3. Measuring energy imprint as landscape structure (L).

In order to measure the *Energy Imprinted* (*L*) in the landscape, we introduce a land metric. We use *L* to account for landscape heterogeneity, which reveals the capacity of differentiated land cover mosaics to circulate the energy flows and offer a range of habitats that sustain biodiversity (Harper et al., 2005). The underlying assumption is that species richness associated with agricultural landscapes depends on both energy availability and landscape heterogeneity, measured at scales larger than the farm level (Loreau et al., 2003) (eq. (3)).

$$L = -\sum_{i=1}^{k} p_i \log_{k+1} p_i \qquad (3)$$

Where *k* is the number of different land covers (potential habitats), and there are *k + 1* possible land covers in each unit of analysis. We consider that the existence of urban land cover results in a loss of potential habitats. Thus, p_i is the proportion of land covers *i* into every unit of analysis. These *L* values can be seen as a proxy for the spatial insurance of farm-associated biodiversity, so that species whose populations are disturbed by agriculture can find safe haunts nearby by activating their own dispersal abilities (Tscharntke et al., 2012).

2.1.2.4. Measuring the energy-landscape integrated analysis (ELIA).

After having defined the three ELIA indicators (*E, I* and *L*), we are going to analyse their relationship. We surmise that the interplay between *E* and *I* jointly leads to complexity, understood as a balanced level of intermediate self-organisation (Gershenson and Fernández, 2012). We assume that the agroecosystems' complexity of energy flows ($E \cdot I$) are related to more heterogeneous landscapes where the ecological patterns and processes that sustain farm-associated biodiversity become stronger (Marull et al., 2016). Therefore, *ELIA* combines the agro-ecological landscape functional-structure with the complexity of the interlinking

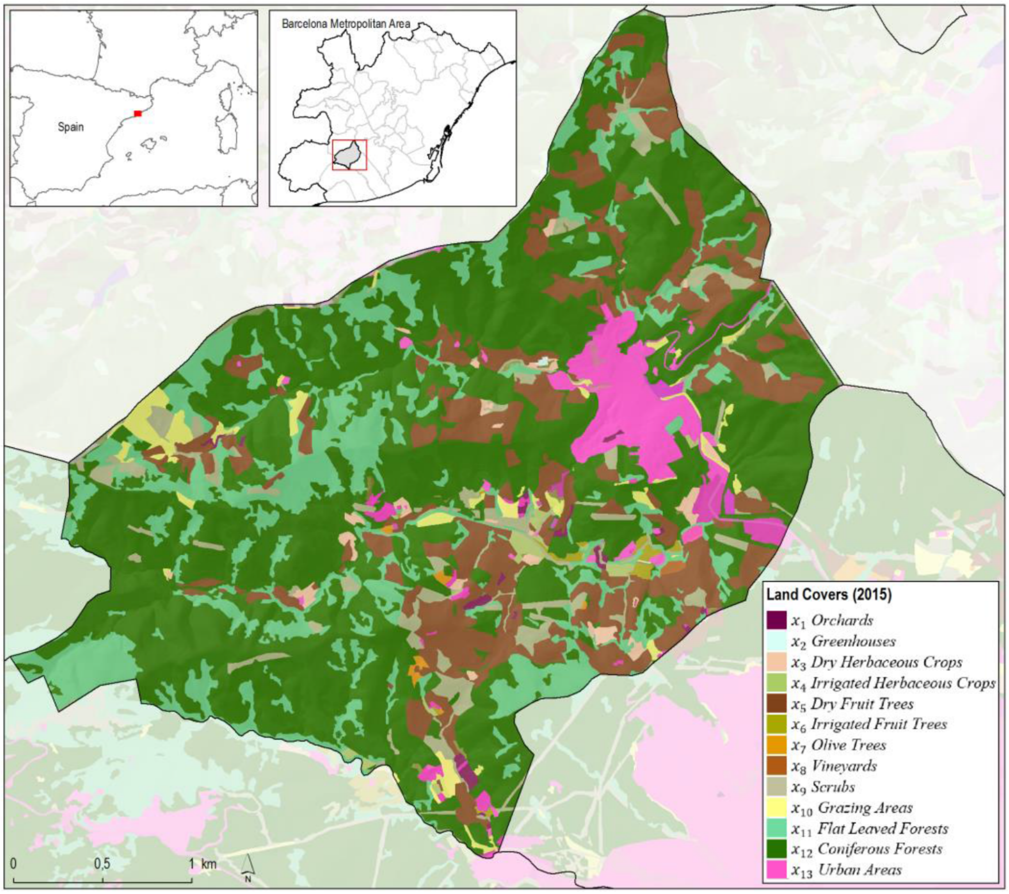


Fig. 2. Land covers in 'Sant Climent de Llobregat' municipality, Barcelona Metropolitan Area, Spain.
Source: Centre for Ecological Research and Forestry Applications (CREAF, https://www.creaf.uab.es/mcsc/).

pattern of energy flows, as a proxy for the agroecosystem's biodiversity (Marull et al., 2019) (eq. (4)).

$$ELIA = \left(\frac{(E \cdot I)\ L}{max\{EI\}a}\right)^{1/3} \tag{4}$$

Where E is the energy storage, I is the information carried by the network structure of energy flows and L is the heterogeneity of land covers seen as the energy imprint in the landscape structure. The equilibrated $max\{EI\}e = 0.6169$ $(k_i = \frac{1}{3})$ –implies subsystems equilibrium and no waste. When there is no such equilibrium, the absolute $max\{EI\}a = 0.7420$ $(k_i = 1)$ –even though this last combination is unlikely in an agroecosystem– it is possible in a theoretical mathematic case. Hence, *ELIA* theoretically ranges from 0 to 1 for any value of the parameters considered.

In order to understand the relationship between the stored energy (E), the information it contains (I) and its imprint on the landscape (L), we have to consider a three-dimensional model. ELIA can be interpreted in the sense that it is culture, which allows farmers to manage the energy entering the system to meet their needs and goals, while taking care of the agroecosystem funds' reproduction and biodiversity conservation (Marull et al., 2019). This calls for an integrated research of coupled human-natural systems aimed at revealing the functioning of complex structures and processes (Liu et al., 2007).

2.2. Energy-Landscape optimization (E-LO)

2.2.1. Case study databases

This work uses data of land covers and the associated energy flows of Sant Climent de Llobregat (Fig. 2), a rural municipality of the BMA. This municipality has been chosen because it consists of a complex land matrix (land use mosaic) that can be a good representative of the Mediterranean bio-cultural landscapes.

Land covers are classified into 13 categories, namely *Orchards, Greenhouses, Dry herbaceous Crops, Irrigated Herbaceous Crops, Dry Fruit Trees, Irrigated Fruit Trees, Dry Olive Trees, Vineyards, Scrubs, Grazing Areas, Flat-leaved Forests, Coniferous Forests* and *Urban Areas*. The land cover thematic map (2015) used in this study have been provided by CREAF (https://www.creaf.uab.es/mcsc/). For each current land cover, the surface in hectares covered by each category is given. We call this parameter x_i *CurrentCover*, which is an array of size $i = 13$ and defines the input land use pattern to be modified. For each land cover there is a set of energy flows coming from the socio-metabolic pattern of the municipality (Marull et al., 2020).

Metabolic flows are calculated from land cover and farming databases on agriculture, livestock, forestry and trade following the procedure described in Marco et al., (2017). Land surfaces are taken from DARPA (http://agricultura.gencat.cat/ca/inici), together with production and yields from DUN (http://agricultura.gencat.cat/ca/ambits/desenvolupament-rural/declaracio-unica-agraria/) and SIGPAC (https://www.mapa.gob.es/es/agricultura/temas/sistema-de-informacion-geografica-de-parcelas-agricolas-sigpac-/default.aspx) databases. From MAPAMA (https://www.mapama.gob.es/) we have taken provincial data from livestock surveys, statistics on dairy and eggs production, and wool, yearbook of annual statistics on crops, fertilizers, farm implements, and statistics on phytosanitary products consumed, as well as forestry statistics and annual management balances of cereals, and statistical data on fisheries. From IDESCAT (https://www.idescat.cat/?lang=es) data on agricultural machinery according to their ownership have been used. To simulate organic agriculture scenarios we have followed the CCPAE recommendations (http://www.ccpae.org/index.php?option=com_frontpage&Itemid=1&lang=en; see Table 1).

Table 1
Conditions and assumptions for the modeling of conventional and organic scenarios
Source: Our own

Dimension	Theme	Conventional	Organic
General definition		Current agricultural management in the MAB defined from land uses, comarcal agricultural production. It relies on chemical intervention to fight pests and weeds and provide plant nutrition and animal feed imports.	Hypothetical scenarios that restrict the use of external agrochemical inputs and animal feeds. Aims to close nutrient cycles whenever it is possible by adjusting the livestock load to the area's resources.
Land use distribution		Land covers based on CREAF 2015 4 Scenarios of land use given by PDU 2019.	Same as in conventional.
Agriculture	Yields	Current crop yields (DARPA 2015).	Yields per hectare decrease up to 30% (Seufert et al. 2011, De Ponti et al. 2012, CCPAE, 2017).
	By-product management Net primary production and waste management	Olive and vine pomace are considered waste. Fruit woodcuts and branches are burn.	Used for animal feeding (olive and vine leaves and pomace) Fruit woodcuts and branches are not burned but considered Final Product. Woodcuts are buried and used as compost. Associated biodiversity increases (Guzmán et al., 2014).
	Crop losses due to herbivory	Conventional management factors (Oerke et al. 1994).	Higher than in conventional Factors adjusted to Organic management records (Oerke et al. 1994).
	Fertilization	Chemical fertilization is allowed and unrestricted. (Data sources: MAGRAMA 2015, MAPMA 2015).	The use of synthetic and industrial fertilizers is prohibited The use of synthetic nitrogen fertilizers is prohibited External mineral inputs are only applied when necessary (i.e. In extreme cases of mineral deficiencies) and must proceed from natural sources and authorized products by the CCCPAE. Organic in-bound fertilization: use of unharvested biomass as compost (i.e. woodcuts) and local manure.
	Pesticides and herbicides	Chemical management is allowed and unrestricted (data sources: MAGRAMA 2015, MAPMA 2015).	Chemical management is restricted. The model assumes zero input of chemical inputs.
	Seed source	Local and imported seeds.	Reused from local production. No imports.
Husbandry	Size (number of animals)	Actual livestock units as given by the DARPA (2015) at municipal, comarcal and provincial scale. In addition, the agrarian census 2009.	Adjustment of the livestock cabin with regard local food availability (see diet conditions below).
	Diets	Used of type- diet for each species (Flores and Roriguez-Ventur 2014) adjusted for ovine and caprine grazing.	Minimum 60% of the animal diet should come from local production. Minimum daily ration of common forages (Animal feed consumption limit): Herbivores: 60% (40%) Poultry and pigs: 20% (60%) Grazing adjusted by minimum advised outdoor (grazing) time (CCCPAE 2017).
	Manure management		Surplus use optimized according to agricultural nutrient requirements of local and organic production.
	Animal life cycles and productivity		Longer life cycles Meet, milk and eggs production was adjusted to life cycles of each species under Organic management.
Labor	Human labor	Base data from the 2009 Agrarian census.	Overall increase of human labor (up to 20%) (Departamento de Agricultura, Alimentación y Acción Rural – Generalitat de Catalunya, 2007).

2.2.2. *Energy flows definition*

The energy flows are essentially the nodes of the ELIA graph previously seen in Fig. 1. In fact, we have the values for 12 of the primary flows, while the values of the other 10 flows are calculated using the ELIA graph. For this reason, two sets of variables are considered for these flows; namely e_j^1 for the so-called primary flows and e_k^2 for secondary flows with $j = 1, \ldots, 13$ and $k = 1, \ldots, 10$. It could be confusing to see that j is ranging from 1 to 13 instead of 12. The reason is that in the data, there are two variables considered for *Livestock Biomass Reused: LBR1* and *LBR2*. The former is the biomass that 'farmland' subsystem makes available to be used in the 'livestock' subsystem (seen from the farmland standpoint as the share of *NPPh* devoted to livestock), while the latter is the biomass that is required for the 'livestock' subsystem (seen from the livestock standpoint as the share of total requirements coming from the agroecosystem). In this sense, it is useful to consider them separately, and as one of the possible constraints, make them have equal values, so that the amount of *Biomass Reused* (*BR*) requirements of livestock match with the production of farmland for this purpose.

From this socio-metabolic pattern, we calculate the metabolic flows (j) for each land use (i). This parameter is called $d_{i,\,j}$. Using this parameter, the variables e_j^1 can be obtained as $e_j^1 = \sum_{i=1}^{15} x_i\ d_{i,j}$. Also e_k^2 can be obtained using the relations seen in the ELIA graph (Fig. 1) from e_j^1. The summary of variables used in the model is as follows:

x_i Land covers	e_j^1 Primary flows	e_k^2 Secondary flows
x_1 *Orchards*	e_1^1 *FFP*	e_1^2 *EI*
x_2 *Greenhouses*	e_2^1 *LFP*	e_2^2 *FTI*
x_3 *Dry Herbaceous Crops*	e_3^1 *LBR1*	e_3^2 *LTI*
x_4 *Irrigated Herbaceous Crops*	e_4^1 *LBR2*	e_4^2 *ATT*
x_5 *Dry Fruit Trees*	e_5^1 *FEI*	e_5^2 *FII*
x_6 *Irrigated Fruit Trees*	e_6^1 *FEInr*	e_6^2 *NPPact*
x_7 *Olive Trees*	e_7^1 *LEI*	e_7^2 *BR*
x_8 *Vineyards*	e_8^1 *LEInr*	e_8^2 *NPPh*
x_9 *Scrubs*	e_9^1 *FFP*	e_9^2 *LPS*
x_{10} *Grazing Areas*	e_{10}^1 *FW*	e_{10}^2 *FP*
x_{11} *Flat Leaved Forests*	e_{11}^1 *LW*	
x_{12} *Coniferous Forests*	e_{12}^1 *LS*	
x_{13} *Urban Areas*	e_{13}^1 *UB*	

The last set of variables we consider in our modelling are the constant values that measure the system (or subsystems) in one way or another, and in the end they all contribute to one of our main indicators. These variables include the coefficients β_l (l = 1, 2 … 13), k_1, k_2, k_3, γ_F, γ_L, α_F, α_L, the indicators *E, I, L* and finally *ELIA*.

2.2.3. Formulation

Departing from the variables x_i (land covers; i = 1, 2… 13), e_j^1 (primary energy flows; j = 1, 2… 13), e_k^2 (secondary energy flows; k = 1, 2… 10), β_l (incoming-outgoing coefficients; l = 1, 2 … 12), k_1, k_2, k_3 (reusing energy flows coefficients), γ_F, γ_L (information-loss coefficients) and α_F, α_L (non-renewable external input coefficients), we can describe, as a summary, the following E-LO equations:

$$\begin{aligned}
&e_1^2 = e_6^1 + e_8^1\ ;\ e_2^2 = e_7^1 + e_6^1 + e_5^2\ ;\ e_3^2 = e_9^1 + e_8^1 + e_4^1\ ;\\
&e_4^2 = e_{13}^1 + e_2^2\ ;\ e_5^2 = e_{12}^1 + e_3^1\\
&e_6^2 = e_{13}^1 + e_8^2;\ \ e_7^2 = e_3^1 + e_4^1;\ \ e_8^2 = e_7^2 + e_1^1 + e_{10}^1;\ \ e_9^2 = e_{12}^1 + e_2^1 + e_{11}^1;\\
&e_{10}^2 = e_1^1 + e_2^1\\
&\beta_1 = \frac{e_8^2}{e_6^2};\ \beta_2 = \frac{e_{13}^1}{e_6^2};\ \beta_3 = \frac{e_2^2}{e_4^2};\ \beta_4 = \frac{e_{13}^1}{e_4^2};\ \beta_5 = \frac{e_1^1}{e_8^2};\ \beta_6 = \frac{e_7^2}{e_8^2}\\
&\beta_7 = \frac{e_6^1}{e_2^2};\ \beta_8 = \frac{e_5^2}{e_2^2};\ \beta_9 = \frac{e_8^1}{e_3^2};\ \beta_{10} = \frac{e_4^1}{e_3^2};\ \beta_{11} = \frac{e_2^1}{e_9^2};\ \beta_{12} = \frac{e_{12}^1}{e_9^2}\\
&k_1 = \frac{e_{13}^1}{e_{13}^1 + e_7^2 + e_{12}^1};\ k_2 = \frac{e_7^2}{e_{13}^1 + e_7^2 + e_{12}^1};\ k_3 = \frac{e_{12}^1}{e_{13}^1 + e_7^2 + e_{12}^1}\\
&\gamma_F = \frac{e_{13}^1 + e_8^2}{e_{13}^1 + e_8^2 + e_{10}^1};\ \gamma_L = \frac{e_{12}^1 + e_2^1}{e_{12}^1 + e_2^1 + e_{11}^1}\\
&\alpha_F = \frac{e_6^1 - e_7^1}{2e_6^1};\ \alpha_L = \frac{e_{12}^1 - e_2^1}{2e_8^1}\\
&E = \frac{\beta_2 + \beta_4}{2}k_1 + \frac{\beta_6 + \beta_8}{2}k_2 + \frac{\beta_{10} + \beta_{12}}{2}k_3\\
&I = -\tfrac{1}{6}\left(\textstyle\sum_{i=1}^{12} \beta_i \log_2 \beta_i\right)(\gamma_F + \gamma_L)(\alpha_F + \alpha_L)\\
&L = -\textstyle\sum_{i=1}^{k} p_i \log_{k+1} p_i\\
&ELIA = \left(\frac{(E\cdot I)\ L}{max\{EI\}a}\right)^{1/3}
\end{aligned} \tag{5}$$

For the nonlinear models, there are boundary constraints considered in the implementations. The general form for these constraints are $LowerBound_i \leq x_i \leq UpperBound_i$. In principle, these bounds can have any value, according to the unique situations of land cover i (x_i), and if detailed studies are done in this regard, exact values can be used. We assume that each x_i with the specific characteristics that they have ($\sum_{i=1}^{15} x_i = \sum_{i=1}^{15} CurrentCover_i$) can be changed to a certain range with respect to the $CurrentCover_i$. Thus, we have considered these bounds to be of the form: $LowerBound_i = (1 - LandChange_i)CurrentCover_i$; $UpperBound_i = (1 + LandChange_i)CurrentCover_i$.

In addition, $LandChange_i$ can be specified according to the properties of x_i, but with the available data these $LandChange_i$ values are considered. Later on, a parametric analysis is conducted, in which we change $LandChange_i$ (except x_{13} *Urban Areas*) to analyse the way they might affect the optimization solution. Different objective functions that we consider for non-linear models are *ELIA* (First Setting), *FP* (Second Setting) and *EInr* (Third Setting). Then we implement the settings for both conventional and organic agriculture, which are characterized by different patterns of energy flows for each land use ($d_{i,\ j}$).

2.2.4. Implementation

Different optimization tools are tested to implement the model using data from the Sant Climent de Llobregat case study (Torabi, 2019): We have used the algorithms from the General Algebraic Modelling System (GAMS; https://www.gams.com/), Constrained Optimization BY Linear Approximation (COBYLA) (Powell, 2007) and Improved Stochastic Ranking Evolution Strategy (ISRES) (Runarsson and Yao, 2005), the last two through its implementation in the open-source C library of non-linear programming algorithms NLopt (https://nlopt.readthedocs.io).

The CONOPT procedure in GAMS is essentially based in the Generalized Reduced Gradient method (Abadie and Carpentier 1969; Fletcher, 1987), with some pre-processing that helps reducing the dimension of the model. COBYLA relies on linear approximations of objective function and constrains, combined with a trust region kind of step choice. Finally, ISRES is an evolutionary population-based heuristic algorithm.

We consider three different settings for objective functions and constraints, each one following a specific goal, while trying to consider other restrictions, in order to keep the balance between variables. To compare the results obtained from the different optimization tools, we observe the following for each setting:

First Setting: maximize ELIA, while maintaining at least a certain percentage of the current Final Produce, $e_{10}^2 \geq$ FPchange $e_{10,\ current}^2$. COBYLA algorithm results in a solution with the highest value for the objective function, as well as being feasible. However, the values for all the related variables in the best solution obtained by COBYLA are very close to the solution obtained by GAMS. Considering the fact that GAMS is faster than running the C program using COBYLA, we can say the results obtained by GAMS are acceptable.

Second Setting: maximize Final Produce (e_{10}^2), while the indicators *E* and *I* do not decrease more than a certain percentage of the current amount, $E \geq$ Echange $E_{current}$, and $I \geq$ Ichange $I_{current}$. Contrary to the previous case, none of the methods have resulted in a superior solution in all aspects. On one side, in the sense of obtaining the most significant value for the objective function, it seems that ISRES produces best results. However, first and second constraints are not met in this solution, making it infeasible. On the contrary, the results obtained from COBYLA and GAMS are very close and are feasible.

Third Setting: minimize non-Renewable External Inputs ($e_6^1 + e_8^1$), while the indicator *L* is maintained at least to a certain percentage of the current value, $L \geq$ Lchange $L_{current}$. The best solutions are given by COBYLA algorithm with the least value for objective function as well as being a feasible solution. The explanations given for the previous case about the differences between COBYLA and GAMS results hold here too.

Considering this preliminary analysis, the CONOPT algorithm implemented in GAMS is used in the research (Torabi, 2019), because it was found that the supplying different initial point to COBYLA may lead to different final points, the difference between COBYLA and GAMS in the optimal values found is very small, and the execution of GAMS is faster than the C program using the COBYLA implementation of the NLopt library.

In this paper, we aim at analysing the effects that changing the parameters, specifically $LandChange_i$, may have on the results of each setting. The values of $LandChange_i$ were considered to be 10%, 20%, 30%, 40% and 50% of land cover change for both conventional and organic agriculture typologies. In Annex C we present an example of the model syntax (Table 4C).

3. Results and discussion

In order to see the effect of $LandChange_i$ on the optimization scenarios, Fig. 3a and Fig. 4a can be used as a reference for conventional and organic agriculture, respectively, showing how land covers have changed with respect to the $CurrentCover_i$ in both agricultural typologies. These land cover changes and *L* can be seen in Tables A3 and B3. CS is the Current Scenario (conventional agriculture). S0 considers the same land cover structure than the Current Scenario but supposing a full organic agriculture transition (according to the CCPAE recommendations –Table 1). S1 corresponds to the First Setting (maximizing *ELIA* while maintaining at least 90% of *FP*). S2 is the Second Setting (maximizing *FP* while *E* and *I* do not decrease more than 10% of the current amount). S3 is the Third Setting (minimizing *EInr* while *L* is maintained at least to a 90% of the current value). For all settings, E-LO applies to 10%, 20%, 30%, 40% and 50% of land cover change for both agricultural typologies. Fig. 3b and Fig. 4b show the results of S1, S2 and S3 in terms of *ELIA, FP* and *EInr* in conventional and organic agriculture. Tables A1 and B1 show the energy flows and *E*, and Tables A2 and B2 show the energy coefficients and *I*.

3.1. Optimizing biodiversity conservation

The First Setting (S1) is designed to maximize the energy-landscape integration (*ELIA*), variable that has been related recently with biodiversity (birds and butterflies) and associated ecosystem services in

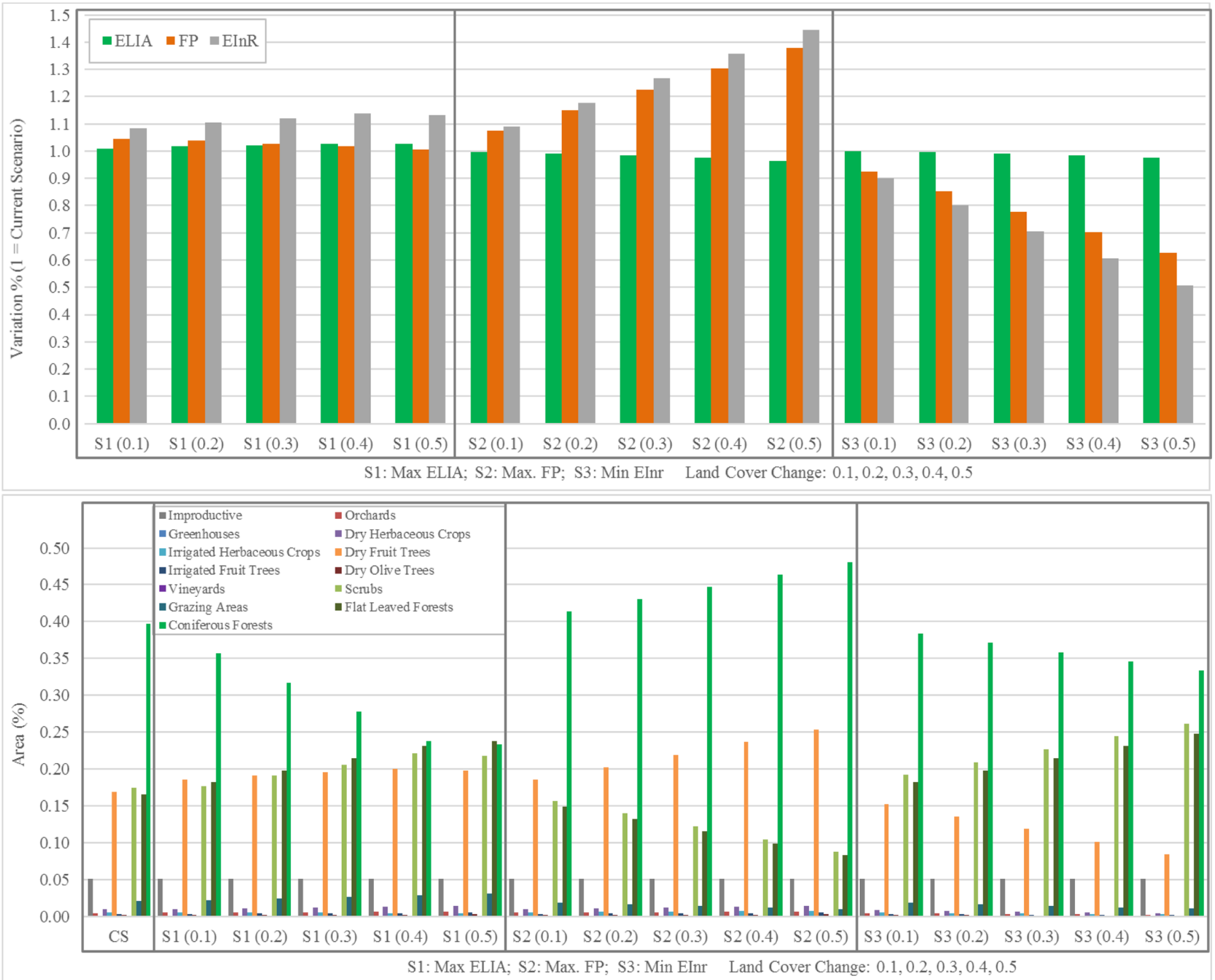


Fig. 3. Optimization scenarios for conventional agriculture in 'Sant Climent de Llobregat'municipality.
Note: CS is the Current Scenario; S1 is the First Setting (maximizing *ELIA* while maintaining at least 90% of *FP*); S2 is the Second Setting (maximizing *FP* while *E* and *I* do not decrease more than 10% of the current amount); S3 is the Third Setting (minimizing *EInr* while the indicator *L* is maintained at least to a 90% of the current value). For all settings, the optimization model applies 10%, 20%, 30%, 40% and 50% of land cover change.

Mediterranean bio-cultural landscapes (Marull et al., 2019). In conventional agriculture, S1 shows a slight increase on *ELIA* values (Fig. 3b), passing from 1.0% to 2.7%, for a land cover change of 10% and 50% respectively (Fig. 5). All land cover categories increase their area in percentage (Table A3), except *Coniferous Forests* (from 39.67% in CS to 23.35%) and, in less proportion, *Greenhouses* (from 0.03% in CS to 0.01%) and *Irrigated Herbaceous Crops* (from 0.51% in CS to 0.35%). The moderate increase in *ELIA* values first produces an increase and then a gradual reduction in *FP*, and a constant increase in *EInr*, when the model passes from 10% to 50% of land cover change (Fig. 3b).

This increase in *ELIA* values is higher in organic agriculture (Fig. 4b), passing from 2.4% to 5.3%, for a land cover change of 10% and 50% respectively (Fig. 5). Again, all land cover categories increase their area in percentage (Table A3), except *Coniferous Forests* (from 39.67% in CS to 20.58%) and, in less proportion, *Greenhouses* (from 0.03% in CS to 0.01%). The increase in *ELIA* values produces an increase in *FP* and *EInr*, when the model passes from 10% to 50% of land cover change (Fig. 3b).

The reason for the slight increase of *ELIA* values in S1 is because the 'Sant Climent de Llobregat' municipality represents a Mediterranean well-structured land cover mosaic (Fig. 2) and then there is a limited potential to improve landscape complexity. Compared to the average value for the whole BMA, St Climent de Llobregat doubles the ELIA value (Marull et al., forthcoming). However, the model prioritizes the balancing of land covers (mainly reducing the more abundant *Coniferous Forests* category), in order to increase *L* (Fig. 3b and 4b), rather than reducing *E* and *I* –see Tables A1, B1, A2 and B2-, and this is the reason that explains the increase of non-renewable external inputs (*EInr*). This agroecosystem dysfunction could be corrected including some constrains in the model (i.e. limiting the dependence on *EInr*). In this sense, it is interesting to note that organic agriculture practically doubles the increase of *ELIA* values of conventional agriculture in the different land cover change scenarios (Fig. 5), and therefore it underlines the importance of an agro-ecological transition for biodiversity conservation.

3.2. Optimizing agrarian productivity

The Second Setting (S2) is designed to maximize the agrarian productivity (*FP*), parameter that could attain higher values in organic than in conventional agriculture in Europe, even in economic terms (van der Ploeg et al., 2019). In conventional agriculture, S2 shows an important increase on *FP* (Fig. 3b), passing from 7.6% to 37.8%, for a land cover change of 10% and 50% respectively (Fig. 5). All land cover categories increase their area in percentage (Table A3), except *Scrubs* (from 17.42% in CS to 8.70%), *Grazing Areas* (from 2.03% in CS to 1.01%) and *Flat Leaved Forests* (from 16.52% in CS to 8.25%) that are those more extensive areas. The major increase in area is produced in *Dry Fruit Trees* (from 16.88% in CS to 25.31%) and *Coniferous Forests* (from 39.67% in CS to 48.03%), the latter being just the opposite trend than in S1 (Table A3).

The increase in *FP* values is much higher in organic agriculture (Fig. 4b), passing from 95.1% to 157.0%, for a land cover change of

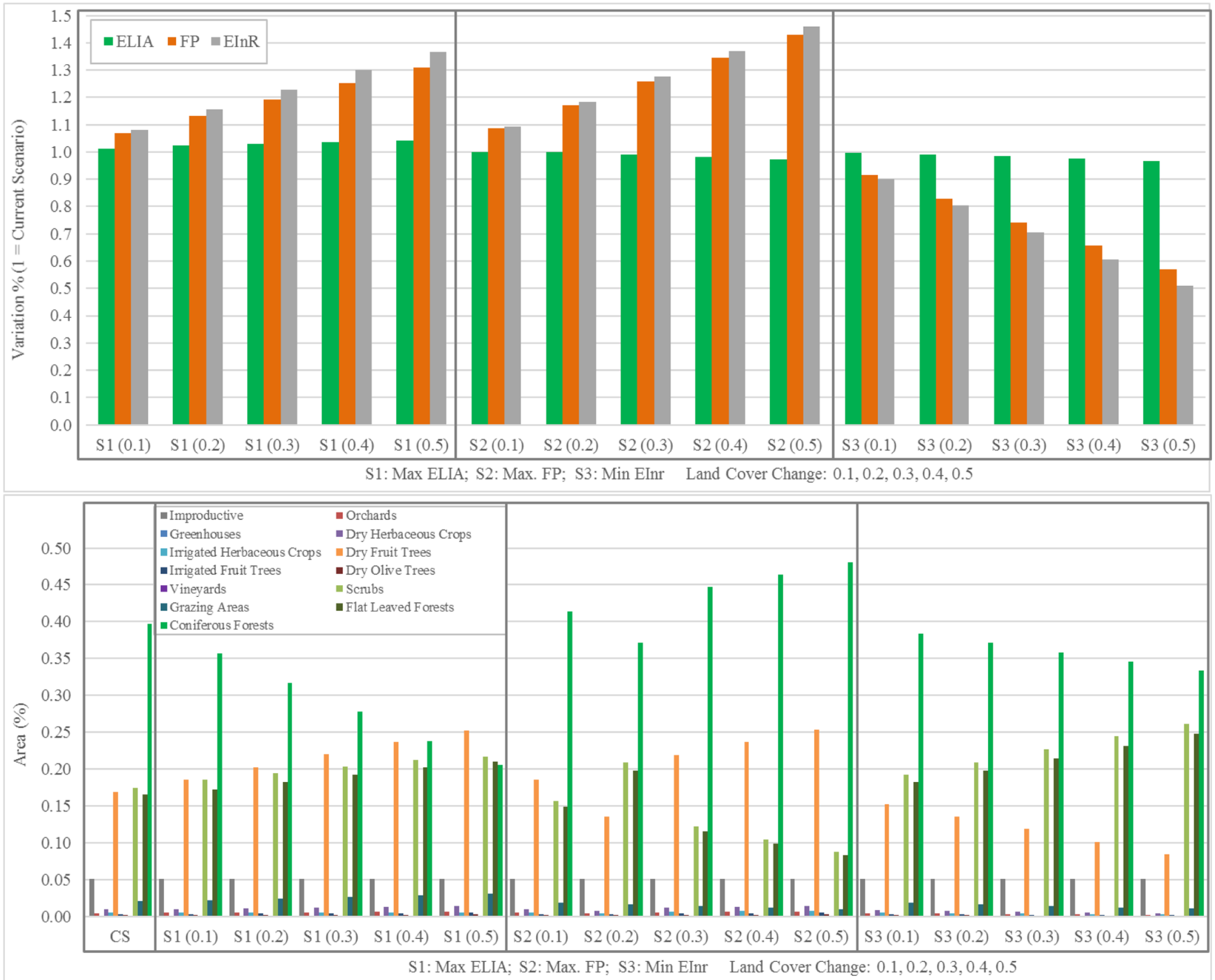


Fig. 4. Optimization scenarios for organic agriculture in 'Sant Climent de Llobregat'municipality.
Note: CS is the Current Scenario; S1 is the First Setting (maximizing *ELIA* while maintaining at least 90% of *FP*); S2 is the Second Setting (maximizing *FP* while *E* and *I* do not decrease more than 10% of the current amount); S3 is the Third Setting (minimizing *EInr* while the indicator *L* is maintained at least to a 90% of the current value). For all settings, the optimization model applies 10%, 20%, 30%, 40% and 50% of land cover change.

10% and 50% respectively (Fig. 5). All land cover categories increase their area in percentage (Table B3), except *Scrubs* (from 17.42% in CS to 8.70%), *Grazing Areas* (from 2.03% in CS to 1.01%) and *Flat Leaved Forests* (from 16.52% in CS to 8.25%), therefore behaving similarly to conventional agriculture. It is important to take into account that this increase in *FP* values is associated to the disappearing of waste (*FW*) in Fruit trees associated to the burning of pruning. Therefore, the greatest part of this change when it is compared to conventional scenarios is due to these woody by-products.

Probably the notable increase in *Dry Fruit Trees* guarantees the maximum *FP* in both conventional and organic agriculture, while *Coniferous Forests* contributes to maintain certain levels of energy reinvestment (*E*) and redistribution (*I*) (Tables A1, B1, A2 and B2). However, the *FP* increase in S2 is supported through an increase in non-renewable external inputs (*EInr*), which is not good news in terms of agrarian sustainability.

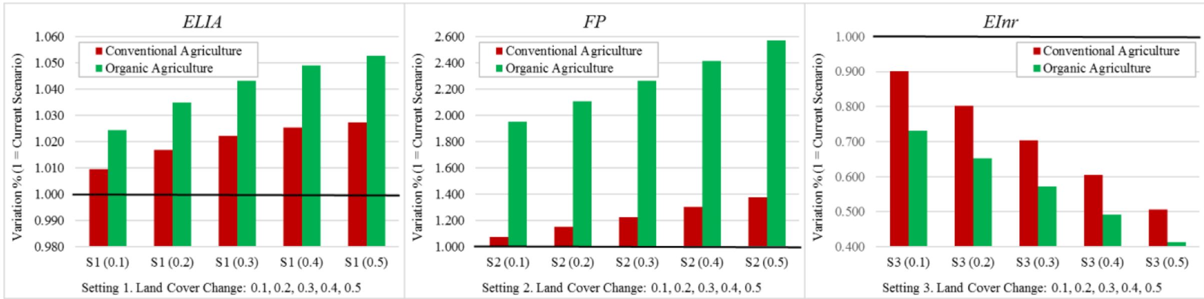
3.3. Optimizing climate change mitigation

The Third Setting (S3) is designed to minimize the dependence of non-renewable external inputs (*EInr*), parameter that is directly related with agrarian greenhouse gas emissions and then with climate change mitigation (Aguilera et al., 2015). In conventional agriculture, E1 shows an important decrease on *EInr* (Fig. 3b), passing from −9.9% to −49.3%, for a land cover change of 10% and 50% respectively (Fig. 5); all land cover categories decrease their area in percentage (Table A3), except *Scrubs* (from 17.42% in CS to 26.15%) and *Flat Leaved Forests* (from 16.52% in CS to 24.80%). For organic agriculture, the initial value for the current scenario (S0) is already 20%, being lower than for conventional. Then, the decrease in *EInr* values is higher in organic agriculture (Fig. 4b) passing from 26.9% to 58.8%, for a land cover change of 10% and 50% respectively (Fig. 5); all land cover categories increase their area in percentage (Table B3), except *Scrubs* and *Grazing Areas* in the same proportion than conventional agriculture.

The important decrease in *EInr* observed in S3 for conventional agriculture is comparable with the fall on *FP*, which means a non-desirable solution in socioeconomic terms and the claim for another model of agriculture. The good news is that for organic agriculture, the decrease in *EInr* is much more higher than in conventional agriculture, but with an interesting difference: while in conventional agriculture *FP* passes from a decrease of −7.4% to −37.2%, for a land cover change of 10% and 50% respectively (Fig. 5), in organic agriculture *FP* passes from an increase of 64.3% to 2.6%, for a land cover change of 10% and 50% respectively (Fig. 5). Consequently, there is room for an agro-ecological transition and climate change mitigation and adaptation without compromising the socio-economic viability of farm systems in metropolitan areas.

3.4. Limitation of the model

The main purpose of the E-LO model is to assess how the capacity of the agricultural landscapes to provide regulatory and cultural ecosystem services can be improved while, at the same time, maintaining o



			Settings														
Typology	Objectives	CS	S1 (0.1)	S1 (0.2)	S1 (0.3)	S1 (0.4)	S1 (0.5)	S2 (0.1)	S2 (0.2)	S2 (0.3)	S2 (0.4)	S2 (0.5)	S3 (0.1)	S3 (0.2)	S3 (0.3)	S3 (0.4)	S3 (0.5)
Conventional Agriculture	*ELIA*	1	1.010	1.017	1.022	1.025	1.027	0.997	0.992	0.985	0.976	0.965	0.999	0.996	0.992	0.985	0.975
	FP	1	1.045	1.039	1.027	1.016	1.007	1.076	1.151	1.227	1.302	1.378	0.926	0.851	0.777	0.702	0.628
	EInR	1	1.083	1.105	1.121	1.138	1.131	1.089	1.178	1.267	1.356	1.445	0.901	0.803	0.704	0.606	0.507
Organic Agriculture	*ELIA*	1	1.024	1.035	1.043	1.049	1.053	1.010	1.010	1.002	0.994	0.985	1.009	1.004	0.997	0.988	0.977
	FP	1	1.921	2.032	2.140	2.249	2.355	1.951	2.106	2.261	2.415	2.570	1.643	1.488	1.334	1.180	1.026
	EInR	1	0.877	0.937	0.995	1.054	1.109	0.886	0.960	1.035	1.110	1.185	0.731	0.652	0.572	0.492	0.412

Fig. 5. Summary of the Energy-Landscape Optimization (E-LO) results (expressed in relation to Current Scenario = 1) for both conventional and organic agriculture. The objectives of Settings S1, S2 and S3 are to increase Energy Landscape Integrated Analysis (*ELIA*), to increase Final Produce (*FP*) and to reduce Non-renewable External Inputs (*EInr*), respectively.
Note: CS is the Current Scenario; S1 is the First Setting (maximizing *ELIA* while maintaining at least 90% of *FP*); S2 is the Second Setting (maximizing *FP* while *E* and *I* do not decrease more than 10% of the current amount); S3 is the Third Setting (minimizing *EInr* inputs while the indicator *L* is maintained at least to a 90% of the current value). For all settings, the optimization model applies 10%, 20%, 30%, 40% and 50% of land cover change.

increasing local agri-food production (a provisioning ecosystem service) and reducing agricultural dependence on non-renewable external inputs. This is a very useful assessment for land use planners to make decisions.

However, in its current version, the model has certain limitations that should be taken into account in future research. If changes in land use were not only incremental but more substantial, giving rise to a completely different agroecosystem, the assumption made about maintaining the same set of energy flows per land cover that in the current situation would no longer be acceptable. The E-LO optimization is not taking into account whether the land use changes arising from its optimization are feasible or adequate considering other constrains (e.g. slopes, soil textures and capacities or being placed in flood zones). For the same reason, E-LO modelling is not fit to explore the synergies and trade-offs involved in changing the pattern of energy and material flows interlinking the agroecosystem funds involved, accounting them in the appropriate different units. It does not allow to connect land and livestock uses with dietary changes in the consumers' food baskets. All these limitations means that, while being a useful tool to help land use planes to make better decisions aimed at improving the landscape capacity to provide ecosystem services to metropolitan areas, E-LO cannot deliver yet scenarios of systemic changes such as scaling up organic farming into agroecological territories.

4. Conclusions

The Energy-Landscape Optimization (E-LO) nonlinear model for land use planning developed in this paper can be of great importance for an agro-ecological transition in the Barcelona metropolitan area and, by extension, to other metropolis of the world. The application of E-LO in specific land use policies combined with an agroecological transition can contribute to reduce the dependence on non-renewable resources and therefore to climate change mitigation, as well as promoting the conservation of complex landscapes, maintained through a more circular economy, which can promote the preservation of biodiversity and associated ecosystem services.

The results of the E-LO modelling presented in this paper allow us to propose different land use configurations taking into account the associated socio-metabolic balances and the related landscape functional structures, with the aim of accomplishing different societal objectives. We have tested fruitfully three different objectives: i) to increase biodiversity and ecosystem services (S1), ii) to increase agricultural production (S2), and iii) to minimize dependence in non-renewable external inputs (S3). According to these objectives, and introducing several constrains in the settings, we have obtained the best land use/metabolism combinations, which is a useful method for calculating sustainable LUCC scenarios. This integrated analysis is appropriate for assessing complex socioecological systems to advance towards the new 'green infrastructure' paradigm, promoting alternative agroecosystem management and a systemic landscape planning in metropolitan areas.

The results of the E-LO modelling show: i) in S1, organic agriculture practically doubles the increase of energy-landscape integration (*ELIA*), as a proxy of biodiversity, compared with conventional agriculture in different land cover change scenarios, and therefore underlines the importance of an agro-ecological transition for biodiversity conservation. However, it results as well in an increase of non-renewable external inputs (*EInr*). ii) In S2, the increase in agrarian production (*FP*) is also supported by an equivalent increase in *EInr*, which is not good news in terms of agrarian sustainability. iii) In S3, while the decrease in *EInr* for conventional agriculture is related with the fall on *FP*, in organic agriculture the decrease in *EInr* is much higher but with certain increase in *FP*. Consequently, there is room for an agro-ecological transition and climate change mitigation, without compromising the socio-economic viability.

The proposed methodology should be validated in the field and incorporate other constrains into the model, to be more site-specific and improve the model results, depending on the scope of study where it is intended to be applied (e.g. including slope, fertile areas for agriculture, protected natural spaces, or sectors with approved urban planning). In the parametric analysis, the scenarios could be considered in a more refined grid of values of land cover and metabolic changes, in order to see, for instance, in which point the direction of changes of some variables are altered taking into account the others. The transition costs of increasing land cover and metabolic changes should be considered to make more informative decisions about these parameters.

Finally, further research will improve the optimization model in a more geographical way, by means of the spatially implicit or explicit models (e.g. using cellular automata), in order to specify the best locations for land use change to maximize the closure of metabolic flows –circular economy. This research proposal would become a very important analytical advance, linking Ecological Economics (biophysical accounting) with Landscape Ecology (land use patterns and processes), in the design of metropolitan green infrastructures able to maintain biodiversity and provide ecosystem services to societies.

Credit author statement

J.M. and P.T. designed research; P.T., R.P. and A.A. analysed data; J.M., P.T., R.P., A.A., MJ.LR. and T.S. wrote the paper.

Declaration of Competing Interest

The work is all original research carried out by the authors.

All authors agree with the contents of the manuscript and its submission to the journal.

No part of the research has been published in any form elsewhere, unless it is fullyacknowledged in the manuscript.

The manuscript is not being considered for publication elsewhere while it is being consideredfor publication in this journal.

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Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.ecolmodel.2020.109182.

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