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Comparative Energy-Landscape Integrated Analysis (ELIA) of past and present agroecosystems in North America and Europe from the 1830s to the 2010s

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Abstract

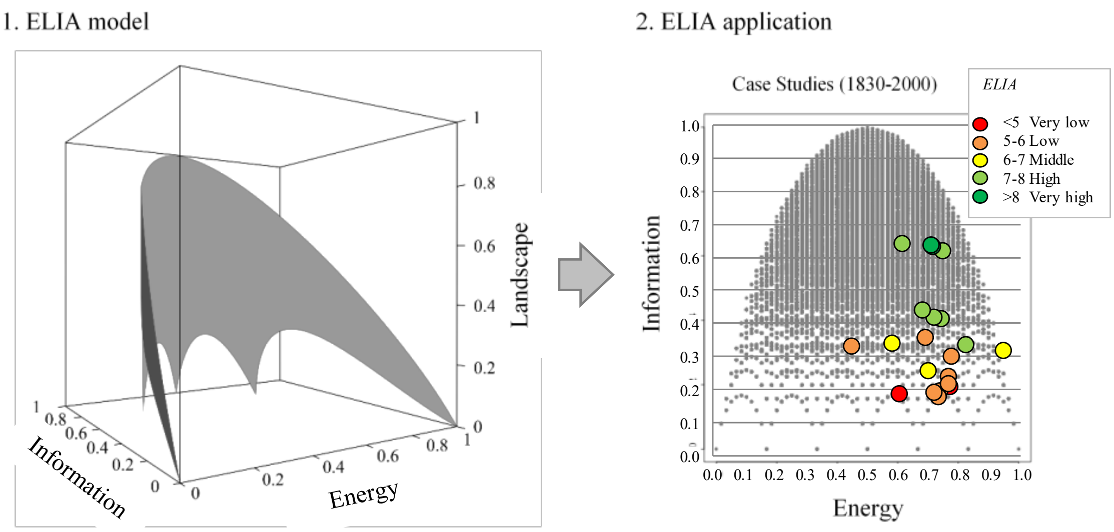
Along the last century there has been an unprecedented growth in both global food production and related socioecological impacts. The objective of this paper is to analyse the effects of long-term metabolic patterns of agrarian systems on land use and cover changes (LUCC). We have developed an Energy-Landscape Integrated Analysis (*ELIA*) of agroecosystems to measure the energy storage (*E*) and the information (*I*) represented by the complexity of internal energy cycles, in order to correlate both with the energy imprint in the landscape functional-structure (*L*) that sustains biodiversity. *ELIA* values are used to assess the agro-ecological landscape transitions in different case studies analysed in North America (Canada and USA) and Europe (Austria and Spain), demonstrating their sensitivity and robustness for case study comparisons on farm-driven environmental change. The results show two stages of the socio-metabolic transition: a first period (from 1830 to 1956) characterized by a non-significant decrease in energy reinvestment (*E*) and a decrease in energy redistribution (*I*); and a second period (from 1956 to 2000) with a significant loss of $E{\cdot}I$ optimal values and associated landscape patterns (*L*). To overcome the socioecological degradation that these trends implied requires a low external input strategy based on an innovative enhancement of cultural knowledge kept by rural populations, which may help to empower farm communities in the markets and in the public arena. Further research could help to reveal how and why different strategies of agroecosystem management lead to key turning points in the relationship between energy flows, landscape functioning and biodiversity. This research will be very useful for public policies aimed to promote more climate and socioecological resilience of agricultural landscapes and food systems worldwide.

Keywords

Long-term socioecological metabolism; Agroecosystem complexity; Energy return on investment; Low external input strategy; Landscape agroecology; Sustainable farm systems.

Graphical Abstract

The Energy–Landscape Integrated Analysis



Highlights

- An Energy-Landscape Integrated Analysis (ELIA) of agroecosystems is proposed.
- ELIA relies on the complexity of internal energy cycles and land-use heterogeneity.
- ELIA measures the energy reinvested, redistributed and imprinted in the landscape.
- ELIA is used to assess long-term socioecological transitions in western agriculture.
- Results recommend a low external inputs strategy for agroecosystems.

Manuscript

1. Introduction

During the last century, there has been an unprecedented growth in global food production that allowed farmers to feed billions of people and put an end to famines in western agriculture, at a cost of a set of socio-environmental problems stemming from increasingly industrialized and globalized agricultures (Mayer et al., 2015). As a result, farm systems are facing global challenges amidst a socio-metabolic transition (Schaffartzik et al., 2014) that places them in a dilemma between intensifying land use to meet the growing demand of food, feed, fibres and fuels (Godfray et al., 2010), and attempting to avoid a dangerous loss in biodiversity and associated ecosystem services (Cardinale et al., 2012). The industrialization of agriculture through the 'green revolution' approach, which spread from the 1960s onwards, has been a major cause of this loss (Matson et al., 1997; Tilman et al., 2002).

Farm systems can be seen as the historically changing outcome of the interplay between socio-metabolic flows (Haberl, 2001), land use patterns created by farmers, and the ecological functionality of agroecosystems (Wrbka et al., 2004). Despite the long work carried out on energy analysis of agriculture, which revealed a substantial decline in the energy returns of agro-industrial management brought about by the massive consumption of cheap fossil fuels until recently (Giampietro et al., 2013), the role of socio-metabolic energy flows as drivers of contemporary land use and cover change (LUCC) is not yet well-understood (Peterseil et al., 2004). More research is required to study how the agroecosystem disturbances caused by anthropogenic energy flows interact with landscape patterns, ecosystem services and climate change.

We assume as a hypothesis that the best improvement farm systems can make to become more sustainable is to reduce their current dependence on external inputs (Tello et al., 2016). By replacing the consumption of inputs with large carbon imprint with internal reuses of biomass flows energy efficiency can be improved, greenhouse gas emissions reduced, climate change mitigation enhanced, soil fertility increased, and water pollution prevented mainly through increasing the diversity, complexity and circularity of agroecosystems (Gonzalez de Molina and Guzmán, 2017).

The Energy Landscape-Integrated Analysis (*ELIA*) of farm systems (Marull et al., 2016) allows examining to what extent this hypothesis may actually enhance landscape functional structure and the biodiversity-related ecosystem services that these landscapes can provide (Marull et al., 2018a, 2019). *ELIA* intends to link the agro-ecological energy flow accounting and the study of LUCC from a landscape ecology standpoint. It assesses, through the complexity of energy cycles, the energy internally stored to keep the agroecosystem funds and functions, and the information (energy redistribution patterns) held in the whole network of socio-metabolic flows. The result allows to correlate this energy-information interplay with the ensuing LUCC impact on landscape patterns and processes in order to help develop better public policies, and take private decisions as producers and consumers, aimed to develop more sustainable agri-food systems worldwide.

The main objective of this paper is to test whether the relevance of internal cycles of renewable energy flows moved by farming has played a role to improve or lessen landscape agro-ecological functionality in western agriculture. It does so by presenting an integrated methodology to deal with the long-term socio-metabolic balances and LUCC in past and present agroecosystems of Europe and North America from the 1830s to the 2010s.

2. Material and methods

2.1. Western Agroecosystems studied

We use a set of seven representative case studies in North America and Europe from the 1830s to the 2010s. They have been researched within the Sustainable Farm Systems (SFS) project, dealing with energy and land-use transitions in agroecosystems (Gingrich et al., 2018c). The cases are from Central European lowland and prealpine agriculture (St. Florian and Grünburg, Austria) (Gingrich et al., 2018b), Western Mediterranean agriculture focusing on vineyards (Vallés, Catalonia, Spain) (Marco et al., 2018) and irrigated crops (Santa Fe, Andalusia, Spain) (Guzmán and González de Molina, 2015), maritime frontier agriculture (Queens, Prince Edward Island, Canada) (Mac Fayden and Watson, 2018), and grassland frontier agriculture (Nemaha and Decatur, Kansas, USA) (Cunfer et al., 2018) (Figure 1).

The database used (Figure 2) builds on the energy flow calculations used in each of these case studies and follows the same methodological procedure (Tello et al., 2016). The cases represent various types of agricultural systems under different climatic conditions, and they vary in terms of administrative organization –In North America they are counties, in Europe they are municipalities— as well as in area extent. All the data (see Appendices A-G) has been obtained following a harmonization process and the variables have been relativized (GJ/ha) to be comparable (Table 1 and Table 2). For all case studies, the data sources include region-specific agricultural censuses and cadastral records providing information on land use, population and livestock, crop yields, agricultural labour force, farming machinery, fertilizers and agrochemicals. National or regional data has been used and downscaled to the respective regions in order to fill data gaps.

2.2. Agroecosystem Energy Flows from a Landscape Ecology Standpoint

The *ELIA* starting point is considering that farming is a coproduction with nature. Through their labour and knowledge, farmers invest on the land a purposely-oriented set of external energy flows that transform the existing ecosystem into an agroecosystem. Nature keeps on functioning in these agroecosystems, through the metabolic flows driven by the photosynthesis and genetic information of all the species involved, but they are no longer self-reproductive as such without the external energy and information driven by farmers. *ELIA* summarizes the agricultural coproduction with nature (Figure 2) through the junction between the matter-energy flows coming from solar radiation through the photosynthesis (vertical axis) and the matter-energy flows coming from outside (left of the horizontal axis). Both interact across the agroecosystem functioning to give rise to a final useful product extracted from it (right side of the horizontal axis). *ELIA* graph expresses this socio-metabolic biophysical interaction.

As natural structures driven by genetically ruled trophic chains that stem from photosynthesis, agroecosystems create a circular network of matter-energy flows closed in them. As nature transformed by human labour and knowledge to give way to a final output useful to meet societal needs, agroecosystems are open to the incoming matter-energy flows as well as to the outgoing produce. The *ELIA* graph (Figure 2) expresses this network of matter-energy flowing across the agroecosystems that is partially closed internally (something crucial to keep its own reproduction as natural system) and partially open externally (something crucial to perform its role to sustain the agri-food chains of human society). Accordingly, the flows of energy carriers coming from the solar radiation photosynthetically converted into biomass (i.e. the itinerary of the photosynthetic Net Primary Production –NPP- along the vertical axis) interact with the ones invested by farmers' labour (i.e. the itinerary of the external energy carriers moving along the horizontal axis). All matter-energy flows that arrive to a node are split later into two, one incoming flow recirculates within the agroecosystem, and another outgoing flow ends up into the agri-food basket of consumable products delivered to society.

The *ELIA* graph (Figure 2) resulting from this pairwise distribution of flows distinguishes among three main internal loops that characterize the agroecosystem functioning: 1) the more 'natural' cycles (e.g. forestry and livestock grazing of natural pastures), which merely extract some amount from the NPP, leaving the rest to internal recirculation without directly interfering with the reproductive natural cycling of these flows that end up decomposed as organic matter that temporarily accumulates energy in the fertile soils where ecological turnover is restarted; 2) the 'cropland' cycles, which require a direct intervention of farmers' labour in ploughing, seeding, weeding, harvesting and fertilizing the soils where NPP is reinitiated again on arable land; and 3) the livestock rising cycle, by means of which part of the previous biomass flows that circulate in loops 1 to 2 are diverted to feed farmers' herds that, in turn, recirculate manure into cropland and pastureland while provisioning livestock produce to the agri-food chains. The more coupled the flows of matter and energy that move through these three cycles, the more complex the agroecosystem is.

The phytomass obtained from solar radiation through the autotrophic production by plants is the *actual Net Primary Production* (NPP_{act}), i.e. the energy source for heterotrophs living there (Vitousek et al., 1986). The biomass included in NPP_{act} that becomes available for all heterotrophic species splits into *Unharvested Biomass* (*UB*) and the share of *Net Primary Production harvested* by farmers (NPP_h) (Figure 2). *UB* generally remains in the same place where it has been originally grown and can feed the farm-associated biodiversity. It becomes a source of the *Agroecosystem Total Turnover* (*ATT*), which closes the cycle of the 'natural' subsystem. This subsystem allows maintaining the farm-associated biodiversity and, in turn, the production of NPP_{act}, again through the trophic net of non-domesticated species either aboveground or in the edaphic decay processes of the soil. 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 funds: livestock and soil fertility. Hence, *BR* closes the 'farmland' subsystem circle.

Then *BR* splits into the share 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 (Figure 2). These energy linkages in the graph model enable us to see to what extent land-use management is integrated or not within the surrounding agroecosystem. Afterwards, domestic animals perform bioconversion and then the *LBR* flow splits into *Livestock Final Produce* (*LFP*) and internal *Livestock Services* (*LS*). *LFP* includes a wide range of food and fibre products, and *LS* services include draft power and manure. Together they make up *Livestock Produce and Services* (*LPS*).

The 'farmland' and 'livestock' subsystems are partially closed within agroecosystems, while offering a *Final Produce* (*FP*) to be consumed outside—as well as receiving *External Inputs* (*EI*). Therefore, *UB*, *BR* and *LS* regulate the internal flows that lead to a higher or lower circularity in the pattern of energy networks of agroecosystems (Figure 2); they constitute important flows of recirculating biomass that contribute to the maintenance of the agroecosystem funds: associated biodiversity, soil fertility and livestock (Marull et al., 2016). Conversely, their weakening denotes an increase in the linearity and external dependence of an agroecosystem.

The circularity of matter-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 inside the agroecosystem are turned, because of farmers' mismanagement, into what Odum (1993) named a 'resource out of place'—i.e. a waste. We consider waste an energy flow that cannot be integrated by farm systems, either because it exceeds the carrying capacity, or is not correctly disposed of in a way that makes it useful for the agroecosystem funds according to the prevailing societal goals (Douglas, 1966). In some cases the cost of certain biomass flows are larger than the benefits they generate, leading to misuse. The result is a waste flow.

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 (a resource out of place). 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 internal complexity, nor meet human needs.

In Figure 2 we distinguish three types of arrows. Solid arrows show the energy flows that represent the internal and external exchange of energy carriers. Dashed arrows indicate flows that require biological energy conversion (photosynthesis and animal metabolism). Finally, point-line arrows show energy carriers which are not diverted inside or outside but remain as 'resources out of place' (waste).

2.3. Agroecosystem Energy Flows and Landscape Ecology Integration

ELIA combines the following three indicators: the energy storage performed through the internal cycles of agroecosystems (*E*); the information embedded in the energy network of flows (*I*); and the landscape functional-structure (*L*). The circularity of energy carriers driven by farmers through *UB*, *BR* and *LS* flows (Figure 2), calculated using the Energy Return On Investment (EROI) methodology (Gingrich et al., 2018a), is a measure of *E*, that contributes to the energy potentially available for the trophic chains existing in the agroecosystems.

Measuring Energy Storage as a Reinvestment of Energy Cycles (E)

We understand agroecosystem complexity as the differentiation of dissipative structures (e.g. metabolic cycles) that allows 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 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 circling inside. Accordingly, our way of calculating the energy stored to keep the agroecosystem's funds functioning is as follows (Eq. 1):

Eq.1

$$E = \frac{\beta_2 + \beta_4}{2} k_1 + \frac{\beta_6 + \beta_8}{2} k_2 + \frac{\beta_{10} + \beta_{12}}{2} k_3.$$

$$k_1 = \frac{UB}{UB + BR + LS}, k_2 = \frac{BR}{UB + BR + LS}, k_3 = \frac{LS}{UB + BR + LS},$$

Where the coefficients k_1, k_2, k_3 account for the share of reusing energy flows that are circling through each of the three subsystems (Figure 2), 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 agroecosystems, which are highly dissipative and dependent on external inputs. *E* close to 1 implies the existence of internal cycles only, meaning land abandonment (which is associated to the 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, relative to the total amount of energy flowing across each one of the three subsystems. When we account for the three subsystems altogether, we are adopting a landscape agroecology standpoint focused on what happens with the energy carriers flowing across different land units driven by farmers. This allows linking farming energy analysis with landscape ecology assessment.

Measuring Information as the Complexity of Energy Flow Patterns (I)

There is no structure without information. This means that agroecosystems have a quantity of information embedded in the network structure through which their reproduction takes place over time. It can be assessed through their graph complexity—i.e. the degree to which energy is flowing equidistributed across all edges and nodes of the graph or, conversely, is concentrated only on some of them. According to Information Theory, the equidistribution of the energy flowing across the edges that link the nodes of a graph (Figure 2) means that the information carried cannot be known beforehand. Therefore, the information given by each event is the highest that can be transmitted by the channel considered. 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 (Ulanowicz, 2001).

Energy Information (I) is always site-specific, which becomes an important trait from a cultural standpoint (Barthel et al., 2013). In general, when a balanced agroecosystem registers a decrease of I, the information has been lost or transferred from the site-specific traditional agro-ecological knowledge of farmers located at landscape level towards higher hierarchical scales. 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).

We use a Shannon-Wiener Index, adapted to be applied over each pair of β_i's, 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):

Eq. 2

$$I = -\frac{1}{6}\left(\sum_{i=1}^{12} \beta_i \log_2 \beta_i\right)(\gamma_F + \gamma_L)(\alpha_F + \alpha_L),$$

$$\gamma_F = \frac{UB + NPP_h}{2(UB + NPP_h + FW)}, \gamma_L = \frac{LS + LFP}{2(LS + LFP + LW)}$$

$$\alpha_F = \frac{FEIr}{2(FEIr + FEInr)}, \alpha_L = \frac{LS + LFP}{2(LEIr + LEInr)}$$

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. We have also introduced the coefficients α_F, α_L 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 equidistribution 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 equidistribution which endow less information. These lower I values correspond to disintegrated agroecosystems with either low site-specific information, which may be related 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 equidistributed 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 land-matrix. Needless to say, the more complex (i.e. internally differentiated and interlinked) an agroecosystem is, the greater the farming information required to manage it.

Measuring Energy Imprint as the Landscape Structure (L)

In order to measure the energy imprinted in the landscape, we introduce a land metric. We use L to account for landscape heterogeneity, which reveals the capacity of differentiated landscape mosaics to 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 the landscape heterogeneity of land covers measured at scales larger than farm level (Loreau et al., 2003) (Eq. 3).

Eq. 3

$$L = -\sum_{i=1}^{k} p_i \log_{k+1} p_i$$

Where k is the number of different land covers (potential habitats) in each case, 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. The more spatially heterogeneous the vegetated land covers of an agro-ecological landscape are, the more likely will be their capacity to withstand discontinuous disturbances through dispersion towards less disturbed or undisturbed spaces in the landscape (Tscharntke et al., 2012).

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 pattern of energy flows, as a proxy for the agroecosystem's biodiversity (Eq. 4):

Eq. 4

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

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 impression on the landscape (L), we have to consider a three-dimensional model that can be interpreted in the sense that it is culture (the site-specific knowledge passed down from generation to generation combined with knowledge of opportunities external to the farm system), which allows farmers to manage the energy entering the system to meet their needs and goals while taking care of the agroecosystem funds' reproduction. 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).

3. Results and discussion

3.1. Long-term Energy-Landscape Integrated Analysis in Western Agriculture

Figure 3 shows the transition paths experienced for all case studies: i) from 'past organic agriculture' (T1: 1830-1904), usually based on high levels of E and I within the farm system (except in the colonizing North American case studies, with lower levels of I due to the adaptation of European settlers to the new land and labour conditions; see Cunfer and Krausmann, 2015; Cunfer et al., 2018); ii) to 'intermediate organic-industrial agriculture' (T2: 1934-1956), in general based on high levels of E, both of biotic-renewable character and mineral-industrial origin, but a considerable loss of I, that still allowed maintaining good levels of L; and iii) a 'fully-industrial agriculture' (T3: 1996-2010), based on amounts of non-renewable external inputs larger than ever before, with the lowest levels of local information (I). The whole socioecological transition (from 1830 to 2010) reflects an overall decrease in *ELIA* values in all European and North American case studies.

Figure 3 clearly reflects the industrialization of western agriculture (T3), with internal reuses decreasing with respect to an increasing dependence on external inputs (often of fossil origin), and the loss of landscape functional-structure (L; except in some specific cases) created by organic mixed-farming (T1). *ELIA* scores tend to decrease as a reduction in the complexity of the interlinking pattern of energy carriers ($E \cdot I$) flowing across the land-matrix. This pattern is driven by the trend that I value adopts overtime. As soon as there appear some waste and non-renewable inputs (both measured as a loss of information) *ELIA* values decrease. This implies that there are β*'s* values well balanced in T1, a typical feature of 'past organic agriculture', mainly based on circling internal inputs, together with high levels of energy complexity ($E \cdot I$), which allow maintaining agricultural landscape complexity (L).

Then, in T2 the functioning of farm systems was not sustained endogenously anymore (Figure 3)—i.e, based on local natural resource endowments and internal biomass cycling (like in T1), but rather increasingly dependent on external inputs. However, in this period an intermediate industrial-organic farming still combined greater but limited amounts of external input β*'s* with significant although proportionately lower amounts of internal recycling β*'s* not as well balanced as before, a shift accompanied with lower L values). Finally, we found the *ELIA* values of almost totally open farm systems of current agro-industrial times (T3), in which dependence on fossil-fuelled input energy flows have increased to the point that the values of $\beta 7$, $\beta 9$ as well as $\beta 5$ and $\beta 11$ flows are disproportionately large (Figure 2) in a way that collapses the overall I, E and L values.

Therefore, 'past organic agriculture' (T1) can be seen as 'locally-based' mixed farm systems sustained by many internal biomass flows (higher E) and, in European case studies, high local energy information (I). Current 'industrial agriculture' (T3) can be seen instead as 'globally-open', fundamentally dependant on external non-renewable and fossil-fuelled energy flows (lower E). The I indicator captures the loss of self-reproducibility and sustainability entailed by the increasing dependence on these external energy flows, as if they are of fossil origin and disproportionately large in replacing biomass reinvestments into the soil (such as chemical fertilizers in T2) they contribute to a lesser I value.

Towards the beginning of agricultural industrialization, farmers counted on a combination of traditional organic farming techniques and started to adopt industrial inputs, which could partially supplement traditional farming methods and overcome shortfalls. This may also entail a legacy of past management resulting in high soil organic matter and other ecosystem services that lasted over time. Indeed, I values show that 'intermediate organic-industrial' farm systems (that is, open to a certain amount of external energy flows, as current organic farmers usually do) kept some information without considering their faraway ecological imprints through the global mining and trade of guano, as well as phosphates and potash mineral deposits from the 1870s up to the WWII (Cushman, 2013).

3.2. Socioecological Transitions in North American and European Case Studies

From the 1830s to the 1950s I values go quickly down and then, towards 2000, continue decreasing in all North American and European case studies (Figure 3). However, beyond this general trend regional levels differ. In T1, I was above 0.6 in Austrian and Spanish case studies and only around

0.4 in the first data point in the Canadian and 0.3 in the US case studies. In T2, farmers started to adopt some amounts of industrial inputs (such as mechanization, synthetic and mineral industrial fertilizers or high-yielding seed varieties), that mainly complemented without supressing traditional (and labour expensive) farming methods.

Towards T3, *I* decreased in all cases to a lower value than in T1 and T2 (Figure 3). This is due to two main reasons: *i*) because waste flows are increasingly present in farmland and livestock sub-systems and therefore penalize *I*; and *ii*) because external inputs considerably added to biomass recirculating within the agroecosystem, and therefore the relative importance of recirculated biomass declined despite the larger flows of grains devoted to an increasingly linear feed-meat bioconversion in feedlots. Although biomass recirculation use to be higher than in the past with respect to the correspondent incoming or outgoing flows, due to dietary transition towards larger, unhealthy amounts of meat intake (Tilman and Clark, 2014), its size is proportionally less important relative to external inputs. In summary, while in the organic past (T1) *I* was skewed towards slightly closed-circularity, it is skewed towards open-linearity at present (T3).

Something similar occurs with *E* (Figure 3). The lowest value is usually in T3 (except in Vallès and Queens case studies, again due to greater share of cropland produce allocated to animal feeding combined with forestland expansion and abandonment; Marco et al., 2018; MacFadyen and Watson, 2018; Appendix E and C), while T1 and T2 show higher values–in some cases slightly declining and in others slightly increasing, depending on the site-specific fund composition of agroecosystems. The *E* decrease over time is due to a transition from highly endogenously sustained farm systems to more linear ones, based on a high dependence on external inputs. Vallès is an extreme case because the value of *E* is associated to a high energy reinvestment in woodland due to pastureland and cropland abandonment, which highlights that forest transition driven by rural abandonment involves a greater risk of wildfires that offsets the afforestation contribution to Carbon sequestration (Rudel et al., 2005; Bowman et al., 2011; Pausas and Fernández-Muñoz, 2012). Meanwhile, *E* for the rest of the Vallès land is lower too, as expected in a linear input-output system mainly oriented to a feed-meat bioconversion (Padró et al., 2017; Marco et al., 2018; Appendix E). As a result, Vallès is a case study where spatial polarization of land uses and human intervention is maximum (Marull et al., 2010, 2016).

While the energy-related metrics show some common trends along North American and European case studies (except in T1 for *I* values, due to the contrast between old European historical landscapes *vs* recent North American agricultural colonization of the Great Plains), the landscape metric (*L*) reveals different trends (Figure 3). In 'past organic agriculture' (T1), European land uses were dominated by cropland (40%-65%) and *L* values were quite high revealing that complex agro-silvo-pastoral mosaics kept by mixed farming were still in place (Gingrich et al., 2018b; Gingrich and Krausmann, 2018; Marco et al., 2018; Guzmán et al., 2018). Around T2 cropland was less dominant (as work animals decreased and started to be replaced by tractors) partially contributing to higher *L* values. Towards T3, *L* dropped significantly mainly because the loss of landscape mosaics as a result of the spread of monocultures, feedlots and urban sprawl. Santa Fe is the exception because since 1904 cropland use was predominant and still is (>75%; Guzmán and González de Molina, 2015; Appendix D).

In the US Great Plains, Decatur shows a case of agricultural colonization, initially dominated by pasture with a low *L* value, and later on, as cropland increased, *L* also improved and then stabilized. In Nemaha *L* values have slightly decreased and then stabilized, because being earlier colonized, cropland was already large in T1 and towards T2 it grew above 50%. Queens always showed high *L* values due to the balanced mix of land uses, only decreasing in T3 due to the near disappearance of pastureland. In general, spatial heterogeneity expresses in Europe the functional integration of agricultural landscape, its mosaic disposition in the territory and a high level of closure of the biophysical cycles. In Nemaha, however, the closing of these matter-energy cycles is done with a more homogeneous landscape in terms of land use interactions. This contrast raises the question whether the cultural landscapes are able or not to close their biophysical cycles that ensure an autonomous self-reproduction of the agroecosystem (Cunfer and Krausmann, 2015; Cunfer et al., 2018; Appendix F and G).

What we observe in Europe is a decrease in *E* values from T1 to T3 in almost all case studies (Grünburg, St. Florian, and Santa Fe –except Vallès, again mainly due to the local relevance of forest abandonment combined with grain growing diverted towards livestock feeding; Appendix E), but with certain increase in T2, probably to compensate the important *I* values decrease in all cases from T1 to T2 (Figure 3). *L* values decrease slowly in Grünburg and Vallès, while *L* first increases and then dramatically decreases in St. Florian due to different local paths taken in agricultural specialisation (Gingrich et al., 2018a, 2018b; Marco et al., 2018; Appendix A, B and E). Only in Santa Fe does *L* increase due to woodland increase mainly at the expense of cropland (Guzmán and González de Molina, 2015; Appendix D). *E* values show that the part of energy reinvestment which depends on human labour is much lower at present than in the past. This implies less effort in recycling biomass (*BR*) into the soil either indirectly through livestock (manure) or directly by farmers (green manure), with respect to the share of biomass that without human intervention returns to the agroecosystems in the form of unharvested biomass (*UB*). Hence, energy storage within the agroecosystem loses an important component (organic matter replenishment in cropland soils) with relevant consequences in agro-ecological performance. In all cases *ELIA* values dramatically decrease from T1 to T3, which likely implies less capability of farm systems to provide associated biodiversity and related ecosystem services (Marull et al., 2018a, 2019).

Finally, the North American case studies analysed show a decrease in *E* values (except in Queens due to the woodland expansion at the expense of pastureland and cropland; MacFadyen and Watson, 2018; Appendix C). At the same time *I* strongly decreased in all cases. In the meantime, *L* has changed a bit erratically over time because land uses have evolved, generally with an increase in cropland area and a decrease in pasture or non-colonized land countered by the impact of the Dust Bowl and the Great Depression in the 1930s followed by the set-aside public policies for soil and nature conservation until today. Woodland area has also been maintained (in the Great Plains at almost insignificant levels). We note that while in Decatur *L* shows an increase, in Nemaha and Queens it decreases. For Decatur the increase is due to the late colonization and the transformation of grassland into cropland. Since part of this colonization has occurred not through organic agriculture, but in an era of high external industrial inputs (fertilizers, fuels, and machinery) we cannot observe that peaks in *L* were associated to *I*. In the three cases, *ELIA* decreases from T1 to T3, probably with important effects in landscape agro-ecological functioning (Cunfer and Krausmann, 2015; Cunfer et al., 2018; Marull et al., 2018b).

3.3. Summary of the Comparative Energy-Landscape Integrated Analysis

ELIA reveals the changing of energy-information-landscape patterns along the socioecological transitions experienced by the different agroecosystems analysed in North America and Europe (Figure 4a) in a way that helps to disentangle their main farming drivers and impacts on the ongoing global environmental change. While 'past organic agriculture' (T1) was based on higher energy reinvestment (E), and in the European case studies also exhibited in an important energy redistribution (*I*), taking advantage of a clear balanced relation between E and I (close to $max\{EI\}e = 0.6$), an 'intermediate organic-industrial agriculture' (T2) was based on less local energy information (*I*) while keeping a remarkable energy storage (*E*). Current 'fully-industrial agriculture' (T3) shows a more polarized energy and land use pattern because of the massive use of external inputs in cropland, sometimes combined with forest and pastureland abandonment. This has involved strong dependence on non-renewable energy fluxes, and a loss of complexity both aboveground in the land covers and into the soil, which are the most important energy accumulators of agroecosystems together with seeds, livestock, cultivated trees, woods and non-domesticated species (Ulanowicz, 2003; Ho and Ulanowicz, 2005; Ho, 2013).

These diverse agricultural patterns and management strategies denote contrasting energy-landscape properties (Figure 4b), providing different amounts of energy carriers potentially available for non-colonized trophic chains to maintain biodiversity—either belowground (in the soil biotic activity), and aboveground (in land cover heterogeneity, habitat differentiation and farm-associated species richness). The results show very high values of *ELIA* (>8) close to the $max\{EI\}e = 0.6169$ ($k_i = \frac{1}{3}$), that implies subsystems equilibrium and no waste in European 'past organic agricultures' (T1), and low or very low values of *ELIA* (<5) in all 'fully-industrial agricultures' (T3). On the other hand, 'intermediate organic-industrial agricultures' (T2) allowed medium to high values of *ELIA* (5-8). We infer that a 'balanced' agroecosystem with minimum or none application of chemical fertilizers and pesticides, as 'past organic agriculture' did, might be the way towards more sustainable farm systems to lower the current dependence on fossil-fuelled external inputs and enhance all types of ecosystem services provided by farm-associated biodiversity.

ELIA values show similar decreasing trends in each case study (Figure 3), and may be adjusted to a linear regression in the period of analysis (R^2=0.72; Figure 5). The results suggest two stages of the socio-metabolic transition: a first period (T1-T2) characterized by a non-significant decrease in energy reinvestment (*E*), and an important decrease in energy redistribution (*I*); and a second period (T2-T3) with a significant loss of the *E-I* values and agro-ecological landscape functionality (*L*).

The sensitivity method used for the historical analysis (Kruskal-Walis Test), demonstrates significant *ELIA* differences between time-periods (coefficient = 0.001), and non-significant *ELIA* behaviour differences among case studies (coefficient = 0.577), which means method robustness for long-term case study comparison (Figure 5). These results are contrasted by two complementary statistical analyses (t-Student Test). On the one hand, Table 1 shows *ELIA* as the better indicator (together with *FEInr*, the amount of non-renewable *Farmland External Inputs*) to monitor the historical socioecological transition of agroecosystems. Results also indicate that all the periods of analysis are statistically different, taking into account all the case studies and variables used in the model—i.e. primary and secondary energy variables, Energy Return of Investment (EROI) metrics, and *E*, *I*, *L* components. Furthermore, Table 2 shows no-different *ELIA* behaviour between European and North American case studies, expressed by the primary and secondary energy variables used in the graph model of interlinked energy carriers flowing in the agroecosystem (Figure 2).

Interestingly, although *ELIA* is built upon the energy balances of farm systems that were accounted to evaluate their energy efficiency from the farmers' standpoint, the EROI values are not statistically significant to explain the joint socioecological transition of the case studies evaluated (Table 1). This shows that energy analysis is needed to understand the global environmental changes driven by farming, but it is not enough to assess how these farming energy fluxes give rise to different agricultural landscapes that provide different ecosystem services to society. This highlights the usefulness of *ELIA* model to tackle global trends from a landscape agroecology standpoint.

Finally, a panel statistical analysis (Hausman Test) including all primary and secondary energy variables (Figure 2) and *ELIA* components (*E*, *I*, *L*) has been done, for all the case studies and periods (T1, T2, T3), to analyse their contribution to *ELIA*, as dependent variable. The results show three complementary statistical linear models (Table 3) for components (Model 1), primary (Model 2) and secondary (Model 3) variables to understand their influence in the *ELIA* expression, with better estimations using stochastic effects:

- Model 1 takes into account the three components of *ELIA* (r^2 = 0.989), and founds highly statistically significant the energy information (*I*; coefficient = 0.583), the landscape complexity (*L*; coefficient = 0.327) and the energy storage (*E*; coefficient = 0.289).
- Model 2 takes into account the primary energy variables (r^2 = 0.680), and founds that *Livestock Services* (*LS*, i.e. manure and animal traction) increase is positively related with *ELIA*, while an increase in *Livestock Waste* (*LW*) has the opposite effect.
- Model 3 takes into account the secondary energy variables (r^2 = 0.816), and founds that increases in *Farmland Total Input* (*FTI*) and *Livestock Total Input* (*LTI*) are positively related with *ELIA*, while the increase in non-renewable *Farmland External Inputs* (*FEInr*) has a negative impact.

Consequently, the variables that more negatively affect *ELIA* are wastes (*LW*) and dependence on fossil-fuelled external inputs (*FEInr*). Conversely, manure and animal traction (*LS*), cropland energy investment (*FTI*) and biomass reinvestment in animal feeding (*LTI*) are the more important variables to maintain high levels of *ELIA* due to their crucial role as biomass reuses of renewable inputs that clearly increase the agroecosystem complexity and its energy storage capacity (Table 3). All these results make sense in terms of landscape agroecology functioning (Wojtkowski, 2003), and provide good lessons to devise and plan more sustainable farm systems in the future.

3.4. Discussion and Limitations of the Energy-Landscape Integrated Analysis

ELIA values are used to assess the agro-ecological landscape transitions in different case studies analysed in North America (Canada and USA) and Europe (Austria and Spain). Our results show that 'past organic agriculture', with a solar-based metabolism, and the intermediate organic-industrial agriculture of mid-20th century, tended to organise their land usages according to different gradients of energy intensity, keeping an integrated land use management (e.g. the metabolic integration of crops, livestock and forestry activities can improve the resilience and ecosystem services provision of agriculture), mainly because the whole subsistence of the peasants and rural societies that created them depended on the landscape functional structure (Font et al., 2019).

During T1, in order to offset the energy lost in animal bioconverters, on which they had to depend to obtain the internal farm services of traction and manure (Guzmán and González de Molina, 2015), traditional farmers kept livestock breeding carefully integrated with cropland, pasture and forest spaces (Krausmann, 2004). On the other hand, the introduction of external industrial inputs in T2 reduced the information indicator (*I*) in all cases, meaning that their arrival started to reduce the endogenous self-reproduction of agroecosystems, resulting in a loss of farmers' know-how and information. Between T1 and T2, *E* showed little variations, but with an overall decrease trend from T1 to T3 (except Vallés, an outlier affected by specialization in livestock feedlots and afforestation of abandoned land; (Marull et al., 2016). High values of *E* are associated to farm systems with large non-colonized or abandoned portions of land, as for Great Plains case studies in T1 or Vallés in T3.

Finally, *L* in some cases increased in value, and in others decreased, although remaining at relatively high levels overall. The most prominent decreases of *L* have occurred towards T3 in Europe, because of the joint effect of urbanization and of regional agro-industrial specialization in certain agricultural systems (Gingrich et al., 2018b). The traditional 'organic agriculture' management based on closing energy cycles within agroecosystems, and the intermediate 'organic-industrial' system, have kept high levels of landscape heterogeneity which allowed a land-sharing strategy for biological conservation (Tscharntke et al., 2012).

It is likely that the intermediate organic-industrial farm systems (T2) have quite good results also because it received a subsidy of nutrients, organic matter, and other ecosystem services from the previous organic management (T1)—a legacy hypothesis that deserves further research. In short, the most prominent changes are visible in the socioecological transition to 'fully-industrial agriculture' in T3 that depends on large amounts of external fossil inputs. This has enabled society to overcome the age-old energy dependency on live bioconverters (Schaffartzik et al., 2014) while at the same time losing the environmental advantages of mixed farming integrated with more complex agro-ecological landscapes. As a result, in almost all cases *E*, *I* and *L* values have decreased towards T3 and in some cases they even collapsed. Since an integrated land-use management was no longer necessary, overcoming that former necessity has led to the loss of agro-ecological functionality of farm systems and their landscapes.

The environmental damage caused worldwide by this lack of integrated management between energy flows and land uses urges societies to recover the former 'landscape efficiency' (i.e., the socio-economic satisfaction of human needs while maintaining the landscape agro-ecological functionality; Marull et al., 2010). We now know that depending on the level of reinversion and redistribution of energy flows in farm systems (*E* and *I*), and on how these energy flows are imprinted in the landscape (*L*), agroecosystems may either enhance or decrease biodiversity (Marull et al., 2019). Since the lack of an integrated management of socio-metabolic flows and land uses is part of the current global ecological crisis, its recovery becomes crucial for more agro-ecologically balanced, circular and sustainable farm systems.

*ELI*A has shown its capability to assess the long-term agro-ecological landscape performance throughout the socio-ecological transitions in the seven case studies analysed in western agriculture. It has also demonstrated its sensitivity for environmental history analysis, and its robustness for case study comparison. Considering renewables *vs* non-renewables in external inputs has improved our sustainability assessment of farm systems. Including a GIS account of *ELIA* values into digital land cover maps of agroecosystems would largely improve our results by widening the landscape metrics used and the energy accounting datasets for statistical analysis (Marull et al., 2016).

This line of research involves a novel and more complex approach to agroecosystems' energy efficiency. It requires not only accounting for a single input-output ratio between the final product and the external energy applied, but also looking at the harnessing of energy flows that cycle within. The circled nature of these flows is important in order to grasp the emergent complexity held in the agroecosystem, given that they involve an internal maximisation of less-dissipative energy cycles. The temporary energy storage that these cycles allow becomes a foundation for all sustainable systems (Ho, 2013).

4. Conclusion

This paper has analysed the long-term change in the energy metabolic patterns of agrarian systems and their land use and cover changes in an integrated manner. To that aim, the usual methodology of energy flow analysis of farm systems has been adapted and enlarged in order to account for the complex internal processes of agroecosystems and their imprint in agricultural landscapes (Guzmán and González de Molina, 2015; Tello et al., 2016). Following this research strategy, we have developed an Energy-Landscape Integrated Analysis (*ELIA*) of agroecosystems that allows measuring the matter-energy temporarily stored through internal energy cycles, and the information held in the complexity of the whole network of socio-metabolic energy flows. Both are correlated with the energy imprint in the landscape functional structure that potentially sustain ecological processes and ecosystem services in agricultural mosaics of heterogeneous land cover patterns.

The results obtained with this *ELIA* model have confirmed the hypothesis that a major improvement farm systems can make worldwide to become more sustainable is to reduce their current dependence on external inputs. This means relying more on internal reuses of renewable biomass flows in a way that can improve energy efficiency and, in turn, enhance soil fertility through a more circular biophysical set of flows that increases the internal complexity of agroecosystems. The *ELIA* results help better understand that a decrease in landscape efficiency has been related to a misplacing of information held by the interlinked pattern of energy flows and its mutual interplay with energy circularity and complexity.

Our results also imply that the long-term decrease of energy efficiency is closely related with the impacts of industrialized and globalized agricultural systems that are currently deteriorating the farm-associated biodiversity and related ecosystem services (Marull et al., 2019, Sanchez-Bayo and Wyckhuys, 2019). Confirming or rejecting this interpretation requires further research applying *ELIA* to different biomes and time-periods, and using larger farm energy accounts and biodiversity datasets in order to find out where the critical thresholds in energy throughputs and the information-complexity interplay are located. There is no doubt that this landscape agroecology research would be very useful for improving the circularity and resilience of agri-food systems in the future, as well as their contribution to climate change mitigation and biodiversity conservation. This would also require innovative ways to enhance the cultural knowledge and agricultural heritage kept by rural populations, which may help to empower farm communities in the economic markets and in the public sphere as well.

References

Barthel, S., Crumley, C., Svedin, U., 2013. Bio-cultural refugia—Safeguarding diversity of practices for food security and biodiversity. Global Environ Chang 23(5):1142-1152. https://doi.org/10.1016/j.gloenvcha.2013.05.001

Bowman, D.M.J.S., Balch, J., Artaxo, P. et al., 2011. The human dimension of fire regimes on Earth. J Biogeogr 38:2223–2236. https://doi.org/10.1111/j.1365-2699.2011.02595.x

Cardinale, B.J., Duffy, J.E., Gonzalez, A., et al., 2012. Biodiversity loss and its impact on humanity. Nature 486:59-67. https://doi.org/10.1038/nature11148

Cunfer, G., Krausmann, F., 2015. Adaptation on an Agricultural Frontier: Socio-Ecological Profiles of Great Plains Settlement, 1870–1940. J Iinterdiscipl Hist 46(3): 355-392. https://doi.org/10.1162/JINH_a_00868

Cunfer, G.,Watson, A., MacFadyen, J., 2018. Energy profiles of an agricultural frontier: the American Great Plains, 1860–2000. Reg Environ Change 18(4):1021-1032. https://doi.org/10.1007/s10113-017-1157-x

Cushman, G.T., 2013. Guano and the Opening of the Pacific World: A Global Ecological History. Cambridge University Press, Cambridge

Douglas, M., 1966. Purity and Danger: An Analysis of Concepts of Pollution and Taboo. Routledge, Oxon

Font, C., Padró, R., Cattaneo, C., et al., 2019. How farmers shape cultural landscapes. Dealing with information in farm systems (Vallès County, Catalonia, 1860). Ecol Ind, in process

Gershenson, C., Fernández, N., 2012. Complexity and information: measuring emergence, self-organization, and homeostasis on multiple scales. Complexity 18(2):29-44. https://doi.org/10.1002/cplx.21424

Giampietro, M., Mayumi, K., Sorman, A.H., 2013. Energy Analysis for Sustainable Future: Multi-Scale Integrated Analysis of Societal and Ecosystem Metabolism. Routledge, Oxon

Gingrich, S., Marco, I., Aguilera, E., et al., 2018a. Agroecosystem energy transitions in the old and new worlds: trajectories and determinants at the regional scale. Reg Environ Change 18(4):1089-1101. https://doi.org/10.1007/s10113-017-1261-y

Gingrich, S., Theurl, M.C., Erb, K., et al., 2018b. Regional specialization and market integration: agroecosystem energy transitions in Upper Austria. Reg Environ Change 18(4):937-950. https://doi.org/10.1007/s10113-017-1145-1

Gingrich, S., Cunfer, G. Aguilera, E., 2018c. Agroecosystem energy transitions: exploring the energy-land nexus in the course of industrialization. Reg Environ Change 18(4):929-936. https://doi.org/10.1007/s10113-018-1322-x

Gingrich, S., Krausmann, F., 2018. At the core of the socio-ecological transition: Agroecosystem energy fluxes in Austria 1830–2010. Science of The Total Environment 645(15):119-129. https://doi.org/10.1016/j.scitotenv.2018.07.074

Godfray, H.C.J,. Beddington, J.R., Crute, I.R., et al., 2010. Food Security: The Challenge of Feeding 9 Billion People. Science 327:812-818. https://doi.org/10.1126/science.1185383

González de Molina, M., Guzmán Casado, G.I., 2017. Agroecology and Ecological Intensification. A Discussion from a Metabolic Point of View. Sustainability 9(1):1-19. https://doi.org/10.3390/su9010086

Guzmán Casado, G.I., González de Molina, M., 2015. Energy efficiency in agrarian systems from an agro-ecological perspective. Agroecology and Sustainable Food Systems 39:924-952. https://doi.org/10.1080/21683565.2015.1053587

Guzmán, G. I., González de Molina, M., Soto, D., et al., 2018. Spanish agriculture from 1900 to 2008: a long-term perspective on agroecosystem energy from an agroecological approach. Reg Environ Change 18(4):995–1008. https://doi.org/10.1007/s10113-017-1136-2

Haberl, H., 2001. The Energetic Metabolism of Societies. Part I: Accounting Concepts. J Ind Ecol 5:107-136. https://doi.org/10.1162/108819801753358481

Harper, K.A., MacDonald, S.E., Burton, P.J., et al., 2005. Edge Influence on Forest Structure and Composition in Fragmented Landscapes. Conserv Biol 19:768-82. https://doi.org/10.1111/j.1523-1739.2005.00045.x

Ho, M-W., Ulanowicz, R., 2005. Sustainable systems as organisms? BioSystems 82(1):39-51. https://doi.org/10.1016/j.biosystems.2005.05.009

Ho, M-W., 2013. Circular Thermodynamics of Organisms and Sustainable Systems. Systems 1(3):30-49. https://doi.org/10.3390/systems1030030

Krausmann, F., 2004. Milk, Manure, and Muscle Power. Livestock and the Transformation of Preindustrial Agriculture in Central Europe. Hum Ecol 32(6):735-772. https://doi.org/10.1007/s10745-004-6834-y

Liu, J., Dietz, T., Carpenter, S.R., et al., 2007. Complexity of Coupled Human and Natural Systems. Science 317(5844):1513-1516. https://doi.org/10.1126/science.1144004

Loreau, M., Mouquet, N., Gonzalez, A., 2003. Biodiversity as spatial insurance in heterogeneous landscapes. P Natl Acad Sci USA 100(22):12765-12770. https://doi.org/10.1073/pnas.2235465100

MacFadyen, J., Watson, A., 2018. Energy in a woodland-livestock agroecosystem: Prince Edward Island, Canada, 1870–2010. Regional Environmental Change 18: 1033-1045. https://doi.org/10.1007/s10113-018-1315-9

Marco, I., Padró, R., Cattaneo, C., et al., 2018. From vineyards to feedlots: a fund-flow scanning of sociometabolic transition in the Vallès County (Catalonia) 1860–1956–1999. Reg Environ Chang 18(4):981-993. https://doi.org/10.1007/s10113-017-1172-y

Marull, J., Pino, J., Tello, E., et al., 2010. Social metabolism, landscape change and land use planning in the Barcelona Metropolitan Region. Land Use Policy 27(2):497-510. https://doi.org/10.1016/j.landusepol.2009.07.004

Marull, J., Font, C., Padró, R., et al., 2016. Energy-Landscape Integrated Analysis: A proposal for measuring complexity in internal agroecosystem processes (Barcelona Metropolitan Region, 1860-2000). Ecol Ind 66:30-46. https://doi.org/10.1016/j.ecolind.2016.01.015

Marull, J., Font, C., 2017. The Energy-Landscape Integrated Analysis (ELIA) of Agroecosystems. In: Fraňková, E, Haas, W, Singh, SJ (eds) Sociometabolic Perspectives on Sustainability of Local Food Systems. Springer, New York

Marull, J., Tello, E., Bagaria, G., et al., 2018a. Exploring the links between social metabolism and biodiversity distribution across landscape gradients: A regional-scale contribution to the land-sharing versus land-sparing debate. Sci Total Environ 619:1272-1285. https://doi.org/10.1016/j.scitotenv.2017.11.196

Marull, J., Cunfer, G., Sylvester, K. et al., 2018b. A landscape ecology assessment of land-use change on the Great Plains-Denver (CO, USA) metropolitan edgeReg Environ Change (2018) 18: 1765. https://doi.org/10.1007/s10113-018-1284-z

Marull, J., Herrando, S., Brotons, Ll., et al., 2019. Building on Margalef: Testing the links between landscape structure, energy and information flows driven by farming and biodiversity. Sci Total Environ 674:603-615. https://doi.org/10.1016/j.scitotenv.2019.04.129

Matson, P.A., Parton, W.J., Power, A.G., et al., 1997. Agricultural Intensification and Ecosystem Properties. Science 277:504-509. https://doi.org/10.1126/science.277.5325.504

Mayer, A., Schaffartzik, A., Haas, W., et al., 2015. Patterns of global biomass trade and the implications for food sovereignty and socio-environmental conflict. EJOLT Report No. 20, 106 p

McMichael, Ph., 2011. Food system sustainability: Questions of environmental governance in the new world (dis)order. Global Environ. Chang 21(3):804-812. https://doi.org/10.1016/j.gloenvcha.2011.03.016

Odum, EP., 1993. Ecology and our Endangered Life-Support Systems. Sinauer Associates, Massachusetts

Padró R., Marco I., Cattaneo C., et al., 2017. Does Your Landscape Mirror What You Eat? A Long-Term Socio-metabolic Analysis of a Local Food System in Vallès County (Spain, 1860–1956–1999). In: Fraňková E., Haas W., Singh S. (eds) Socio-Metabolic Perspectives on the Sustainability of Local

Food Systems. Human-Environment Interactions, vol 7. Springer, Cham. https://doi.org/10.1007/978-3-319-69236-4_5

Pausas, J.G. and Fernández-Muñoz, S., 2012. Fire regime changes in the Western Mediterranean Basin: from fuel-limited to drought-driven fire regime. Climatic Change, 110(1-2) :215-226. https://doi.org/10.1007/s10584-011-0060-6

Peterseil, J., Wrbka, T., Plutzar, C., et al., 2004. Evaluating the ecological sustainability of Austrian agricultural landscapes—the SINUS approach. Land Use Policy 21(3):307-320. https://doi.org/10.1016/j.landusepol.2003.10.011

Prigogine, I., 1996. The end of certainty. Time, chaos and the new laws of nature. The Free Press, New York

Rudel, T.K., Coomes, O.T., Moran, E. et al., 2005. Forest transitions: towards a global understanding of land use change. Global Environ Chang 15:23-31. https://doi.org/10.1016/j.gloenvcha.2004.11.001

Schaffartzik, A., Mayer, A., Gingrich, S., et al., 2014. The global metabolic transition: Regional patterns and trends of global material flows, 1950–2010. Global Environ Chang 26:87-97. https://doi.org/10.1016/j.gloenvcha.2014.03.013

Tainter, J., 1990. The Collapse of Complex Societies. Cambridge University Press, Cambridge

Tello, E., Galán, E., Sacristán, V., et al., 2016. Opening the black box of energy throughputs in agroecosystems: a decomposition analysis of final EROI into its internal and external returns (the Vallès County, Catalonia, c.1860 and 1999). Ecol Econ 121:160-174. https://doi.org/10.1016/j.ecolecon.2015.11.012

Tello, E., González de Molina, M., 2017. Methodological Challenges and General Criteria for Assessing and Designing Local Sustainable Agri-Food Systems: A Socio-Ecological Approach at Landscape Level. In: Fraňková E, Haas W, Singh SJ eds. Socio-Metabolic Perspectives on Sustainability of Local Food Systems. Springer, New York

Tilman, D., Cassman, K.G., Matson, P.A., et al., 2002. Agricultural sustainability and intensive production practices. Nature 418:671-677. https://doi.org/10.1038/nature01014

Tilman, D., Clark, M., 2014. Global diets link environmental sustainability and human health. Nature 515:518–522. https://www.nature.com/articles/nature13959

Tscharntke, T., Clough, Y., Wanger, T.C., et al., 2012. Global food security, biodiversity conservation and the future of agricultural intensification. Biol Conserv 151:53-59. https://doi.org/10.1016/j.biocon.2012.01.068

Ulanowicz, R.E., 2001. Information theory in ecology. Comput Chem 25, 393–399. https://doi.org/10.1016/S0097-8485(01)00073-0

Ulanowicz, R.E., 2003. Some steps toward a central theory of ecosystem dynamics. Comput Biol Chem 27(6):523-530. https://doi.org/doi:10.1016/S1476-9271(03)00050-1

Vitousek, P.M., Ehrlich, P.R., Ehrlich, A.H., et al., 1986. Human Appropriation of the Products of Photosynthesis. BioScience 36(6):363-373. http://www.jstor.org/stable/1310258

Wojtkowski, P., 2003. Landscape Agroecology. CRC Press, Boca Raton.

Wrbka, T., Erb, K-H., Schulz, N.B., et al., 2004. Linking pattern and process in cultural landscapes. An empirical study based on spatially explicit indicators. Land Use Policy 21(3):289-306. https://doi.org/10.1016/j.landusepol.2003.10.012

Table 1. Long-term Energy-Landscape Integrated Analysis (*ELIA*) of seven case studies in Austria, Canada, Spain, and USA, from the 1830s to the 2000s. Statistical differencces between time periods

Variables		Time Period		
		T1	T2	T3
		(A)	(B)	(C)
Primary Variables (GJ/ha)	*FEI*	0.74	0.32	0.53
	UB	38.15	35.10	43.25
	FW	0.00	0.00	1.00
	FBR	3.27	1.44	4.97
	LBR	17.04	24.27	26.38
	FFP	15.15	16.02	36.71
	LEI	1.21	2.13	22.94
	LW	0.00	0.00	4.30
	LS	5.03 **C**	3.12	0.65
	LFP	0.67	1.06	5.77
Secondary Variables (GJ/ha)	*NPPact*	73.60	76.83	112.30
	NPPh	35.46	41.73	68.05
	ATT	47.19	39.97	49.40
	LTI	18.25	26.41	49.31
	LPS	5.70	4.18	10.72
	FTI	9.04	4.87	6.15
	FII	8.30	4.56	5.62
	FEInr	0.21	3.28	12.42 **AB**
	LEInr	0.00	0.01	2.73
EROIs	*F-EROI*	0.65	0.69	0.93
	NPP-EROI	4.81	3.02	2.72
	IF-EROI	0.71	0.75	1.44
	EF-EROI	9.50	16.70	8.02
	AE-FEROI	0.26	0.28	0.46
Indicators	*E*	0.75	0.74	0.66
	I	0.52 **BC**	0.32	0.23
	L	0.73	0.71	0.62
	E·I	0.38 **BC**	0.23	0.15
	ELIA	0.76 **BC**	0.63 **C**	0.52

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*); *nr* (no-renewable). Energy Returns on Energy Inputs (*EROI*): *F-EROI = FP / (EI + BR)*; *NPP-EROI = NPPact / (FEI + LEI + FBR + LBR); IF-EROI = FP / BR*; *EF-EROI = FP / EI*; *AE-EROI = FP / EI + BR*. Indicators: Energy Storage (*E*); Energy Information (*I*); Landscape Complexity (*L*). Results are based on two-tailed tests assuming equal variances with a significance level of 0.05. For each significant pair, the key under the category (A, B, C, D) shows up beneath the category with a major average value. Using Bonferroni adjustment, tests have been adjusted for all pairwise comparisons.

Table 2. Long-term Energy-Landscape Integrated Analysis (*ELIA*) of seven case studies in Europe and North America (from the 1830s to the 2000s). Statistical differences between case studies

Variables		Case Studies						
		Europe				North America		
		Vallès	Sta. Fe	Grünburg	St. Florian	Decatur	Nemaha	Queens
		(A)	(B)	(C)	(D)	(E)	(F)	(G)
Primary Variables (GJ/ha)	*FEI*	0.46	1.25	0.60	1.25	0.01	0.02	0.12
	UB	42.90	77.16 **ACDEG**	23.15	27.03	24.75	47.97	28.85
	FW	0.39	1.93	0.00	0.00	0.00	0.00	0.00
	FBR	5.81	8.45	1.19 **AE**	2.50 **AE**	1.12	2.19	1.32
	LBR	12.67	25.02	36.42	33.91	8.72	20.51	20.69
	FFP	20.56	38.42	16.64	38.96	7.24	15.54	21.02
	LEI	34.71	1.83	11.89	7.59	1.13	2.56	1.61
	LW	9.01	1.03	0.00	0.00	0.00	0.00	0.00
	LS	3.35	3.75	4.30	5.67	0.25	1.32	1.89
	LFP	8.75	2.27	2.92	2.08	0.20	0.65	0.62
Secondary Variables (GJ/ha)	*NPPact*	82.34	150.99 **EG**	77.39	102.40	41.82	86.21	71.89
	NPPh	39.05	71.89	54.24	75.37	17.08	38.24	43.04
	ATT	52.53	90.61 **ACDEFG**	29.23	36.46	26.13	51.50	32.19
	LTI	47.38	26.85	48.31	41.50	9.85	23.07	22.30
	LPS	21.12	7.04	7.21	7.75	0.45	1.97	2.51
	FTI	9.63	13.45	6.08	9.43	1.39	3.53	3.33
	FII	9.16	12.20	5.48	8.18	1.38	3.51	3.21
	FEInr	9.28	9.97	4.99	4.77	1.76	4.12	2.20
	LEInr	3.98	0.77	0.00	1.14	0.11	0.19	0.19
EROIs	*F-EROI*	0.94	1.06	0.42	0.85	0.52	0.60	0.91
	NPP-EROI	2.83	4.50	1.82	2.25	6.82	3.36	3.02
	IF-EROI	1.71	1.17	0.52	1.17	0.58	0.65	0.98
	EF-EROI	12.39	31.19	5.22	4.97	5.11	7.80	13.19
	AE-EROI	0.38	0.35	0.26	0.54	0.17	0.21	0.42
Indicators	*E*	0.69	0.71	0.68	0.63	0.81	0.77	0.70
	I	0.40	0.37	0.46	0.46	0.25	0.24	0.30
	L	0.53	0.50	0.84 **B**	0.70	0.60	0.73	0.90 **AB**
	E·I	0.27	0.27	0.32	0.30	0.21	0.19	0.21
	ELIA	0.61	0.58	0.75	0.69	0.58	0.60	0.66

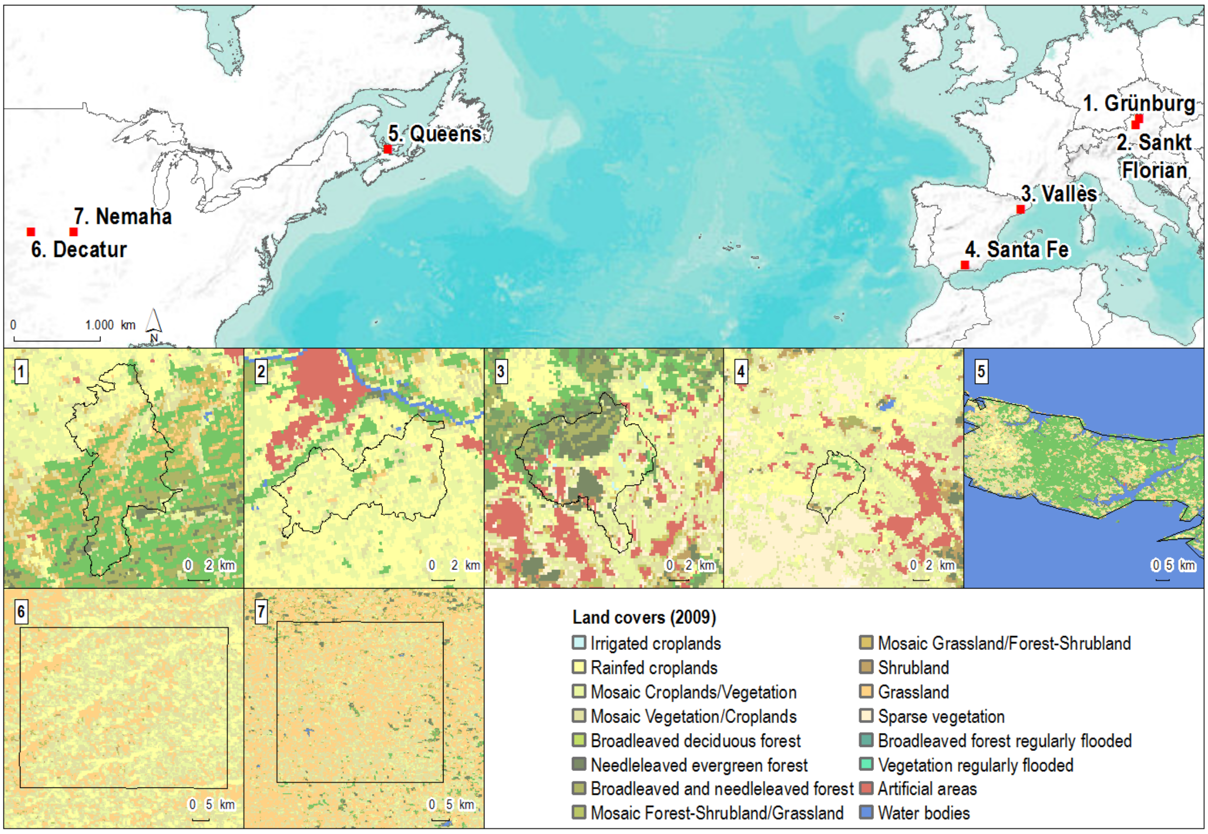
Variables: Actual Net Primary Production (NPP_{act}); Unharvested Biomass (*UB*); Harvested Net Primary Production (NPP_h); Biomass Reused (*BR*); Farmland Biomass Reused (*FBR*); Livestock Biomass Reused (*LBR*); Farmland Final Produce (*FFP*); External Input (*EI*); Farmland External Input (*FEI*); 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*) ; *nr* (no-renewable). Energy Returns on Energy Inputs (*EROI*): *F-EROI = FP / (EI + BR)*; *NPP-EROI = NPPact / (FEI + LEI + FBR + LBR)*; *IF-EROI = FP / BR*; *EF-EROI = FP / EI*; *AE-EROI = FP / EI + BR*. Indicators: Energy Storage (*E*); Energy Information (*I*); Landscape Complexity (*L*). Results are based on two-tailed tests assuming equal variances with a significance level of 0.05. For each significant pair, the key under the category (A, B, C, D) shows up beneath the category with a major average value. Using Bonferroni adjustment, tests have been adjusted for all pairwise comparisons.

Table 3. Energy-Landscape Integrated Analysis (*ELIA*) statistical models using Hausman Test, taking into account all case studies (Austria, Canada, Spain, USA) and time periods (from the 1830s to the 2000s). Only significative variables (Figure 2) and indicators are represented

Variable			Model 1	Model 2	Model 3
Indicators	*E*	Coef.	**0.289**	-	-
		t Student	15.78	-	-
	I	Coef.	**0.583**	-	-
		t Student	21.63	-	-
	L	Coef.	**0.327**	-	-
		t Student	19.85	-	-
Primary variables	*LS*	Coef.	-	**0.301**	-
		t Student	-	13.69	-
	LW	Coef.	-	**-0.009**	-
		t Student	-	-23.83	-
Secondary variables	*FTI*	Coef.	-	-	**0.103**
		t Student	-	-	4.33
	LTI	Coef.	-	-	**0.002**
		t Student	-	-	2.52
	FEInr	Coef.	-	-	**-0.019**
		t Student	-	-	-8.29
Statistics	Cons.	Coef.	0.001	0.563	22.55
		t Student	0.07	32.92	4.04
	N		21	21	21
	r^2		0.989	0.680	0.816
	X^2		5,067.581	649.048	534.370

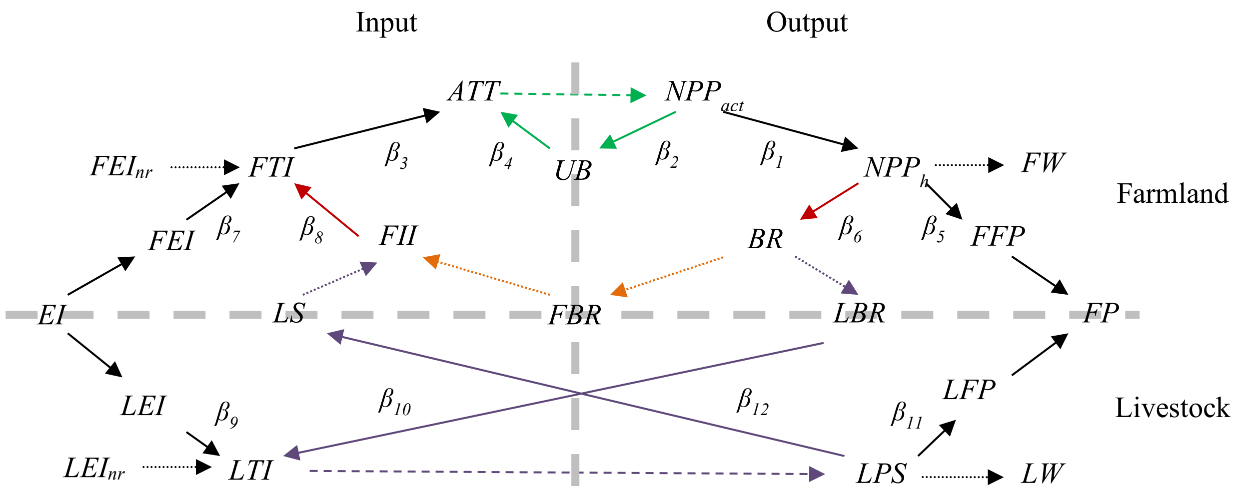
Indicators: Energy Storage (*E*), Energy Information (*I*), Landscape Complexity (*L*). Primary variables: Livestock Services (*LS*), Livestock External Input (*LEI*). Secondary variables: Farmland Internal Input (*FII*), Farmland Final Produce (*FFP*), Farmland Waste (*FW*). Secondary variables: Farmland Total Input (*FTI*), Livestock Total Input (*LTI*), Farmland External Input non-renewable (*FEInr*).

Figure 1. Map of the western agroecosystems' locations. Case studies in North America (Canada and USA) and Europe (Austria and Spain)



Source: Our own from GlobCover 2009 land cover map (European Space Agency)

Figure 2. Graph model of interlinked energy carriers flowing in a mixed-farming agroecosystem[1]

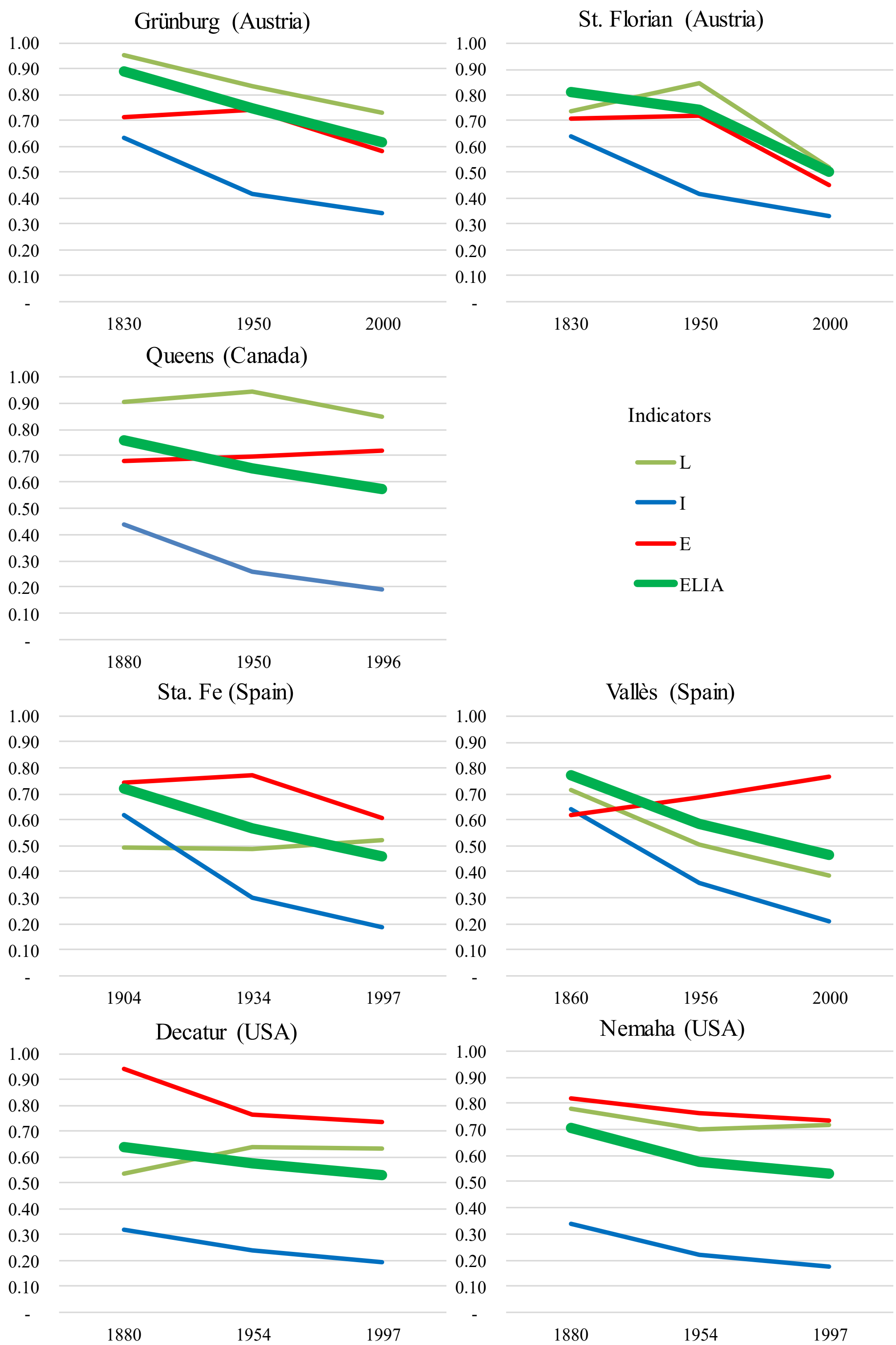


Variables: Actual Net Primary Production (NPP_{act}); Unharvested Biomass (*UB*); Harvested Net Primary Production (NPP_h); Biomass Reused (*BR*); Farmland Biomass Reused (*FBR*); Livestock Biomass Reused (*LBR*); Farmland Final Produce (*FFP*); External Input (*EI*); Farmland External Input (*FEI*); 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: $NPP_{act} = UB + NPP_h$; $NPP_h = BR + FFP$; $BR = FBR + LBR$; $EI = FEI + LEI$; $LTI = LEI + LBR$; $LPS = LFP + LS$; $FP = FFP + LFP$; $ATT = FTI + UB$; $FTI = FII + FEI$; $FII = FBR + LS$.

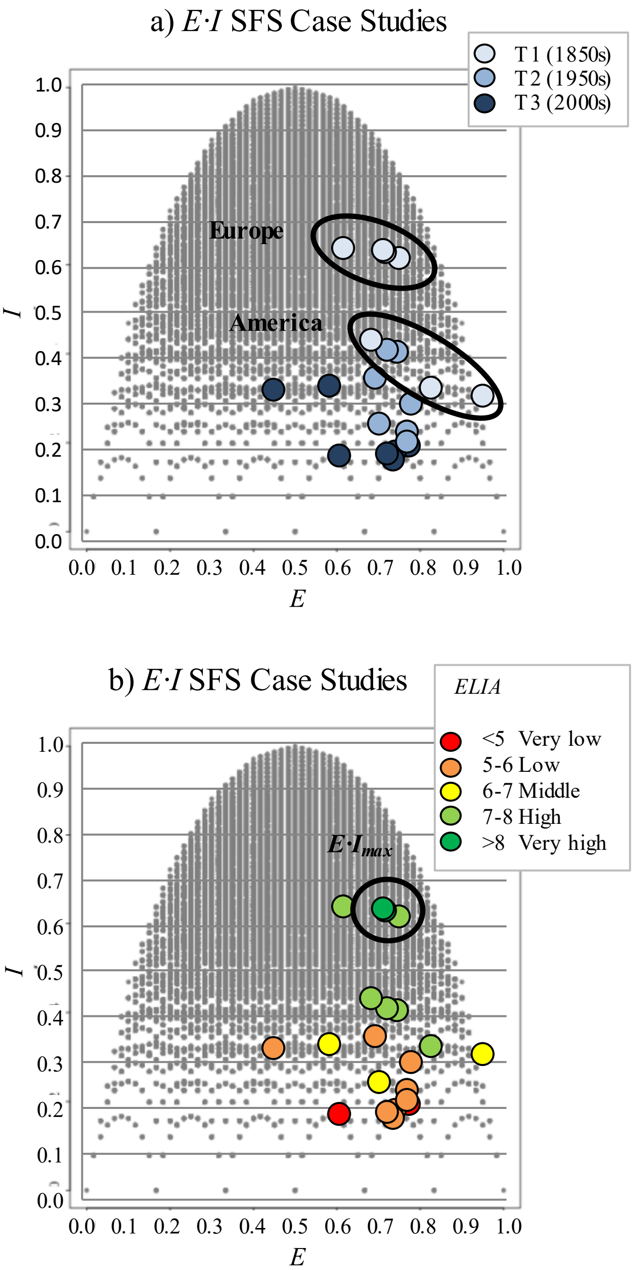
Note: [1] The colours of the arrows represent the 'natural' (green), 'farmland' (red) or 'livestock' (purple) subsystems.

Figure 3. Long-term Energy-Landscape Integrated Analysis (*ELIA*), and related indicators, applied to seven case studies (Austria, Canada, Spain, USA) and three historical periods (T1‘organic agriculture’: 1850’s; T2‘intermediate organic-industrial agriculture’: 1950’s; T3‘full-industrial agriculture’: 2000’s)



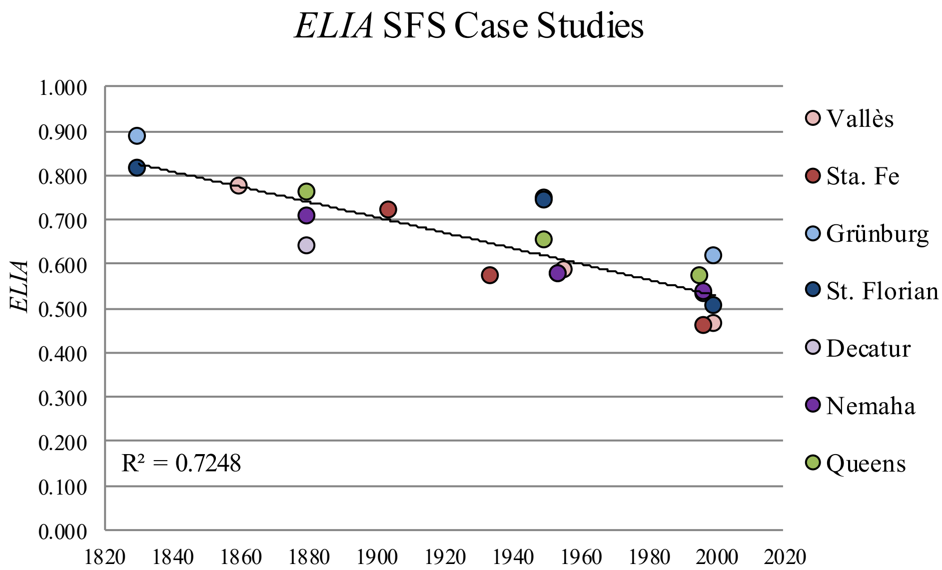
Indicators: Energy Storage (*E*); Energy Information (*I*); Landscape Complexity (*L*).

Figure 4. Theoretical (grey graph) and empirical (coloured dots) relationship between the complexity of internal energy cycles (E) and the information held in the network of energy flows (I) of seven case studies (Austria, Canada, Spain, USA) of the Sustainable Farm Systems (SFS) project, in three historical periods (a), including the Energy-Landscape Integrated Analysis (*ELIA*) (b)



Note: We have highligted T1 in European and Northamerican case studies (a), and the maximum theoretical value of $E{\cdot}I$ (b).

Figure 5. Long-term Energy-Landscape Integrated Analysis (*ELIA*) of seven case studies (Austria, Canada, Spain, USA) from the 1830s to the 2000s. Statistical differencces (Kruskal-Walis Test) between time periods (a) and case studies (b)



a) Kruskal-Wallis Test[1]

TP	*ELIA*
X^2	13.744
gl	2
Sig. Asin.	**0.001**

b) Kruskal-Wallis Test[2]

CS	*ELIA*
X^2	4.745
gl	6
Sig. Asin.	**0.577**

Note: [1] *ELIA* statistical differences between time periods (Table 1); [2] *ELIA* no statistical differences between case studies (Table 2).

Appendices

Appendix A. Energy-Landscape Integrated Analysis (ELIA) in Grünburg (Austria)

Energy flows (GJ)			
Flows	1830	1950	2000
FEI	3,942	7,292	5,903
UB	175,997	233,595	228,873
FW	0	0	0
FBR	10,249	15,362	6,079
LBR	135,028	424,011	566,661
FFP	80,340	126,314	290,908
LEI	4,435	25,371	369,697
LW	0	0	0
LS	44,053	65,122	0
LFP	5,411	19,167	69,964
NPP_{act}	401,614	799,282	1,092,521
NPP_h	225,617	565,687	863,648
ATT	234,240	321,371	240,855
LTI	139,463	449,381	936,359
LPS	49,464	84,289	69,964
FTI	58,243	87,776	11,983
FII	54,301	80,484	6,079
Fnren	0	22,270	147,247
Lnren	0	0	0
FEROI	0.558	0.308	0.381
NPP-EROI	2.614	1.693	1.152
IF-EROI	0.590	0.331	0.630
EF-EROI	10.237	4.454	0.961
AE-EROI	0.260	0.206	0.307
E	0.712	0.741	0.584

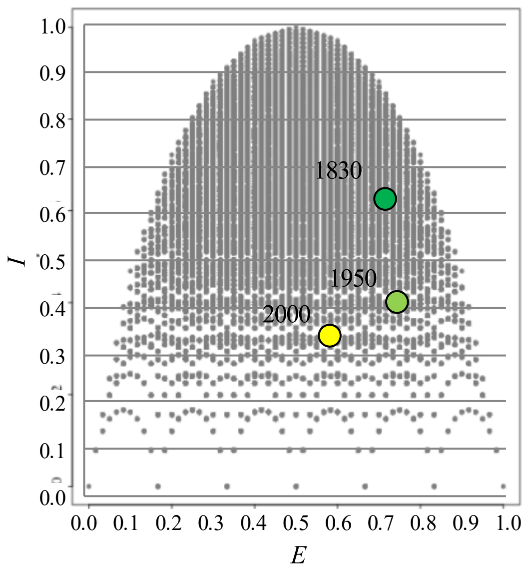
Energy of Internal Loops

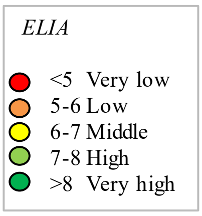
Coefficients			
Coef.	1830	1950	2000
β_1	0.562	0.708	0.791
β_2	0.438	0.292	0.209
β_3	0.249	0.273	0.050
β_4	0.751	0.727	0.950
β_5	0.356	0.223	0.337
β_6	0.644	0.777	0.663
β_7	0.068	0.083	0.493
β_8	0.932	0.917	0.507
β_9	0.032	0.056	0.395
β_{10}	0.968	0.944	0.605
β_{11}	0.109	0.227	1.000
β_{12}	0.891	0.773	0.000
α_1	0.500	0.123	0.019
α_2	0.500	0.500	0.500
γ_L	0.500	0.500	0.500
γ_B	0.500	0.500	0.500
k_1	0.482	0.316	0.286
k_2	0.398	0.595	0.714
k_3	0.121	0.088	0.000
I	0.633	0.414	0.339

Information of Energy Flows

Energy-Landscape Integrated Analysis			
Indicator	1830	1950	2000
E·I	0.450	0.307	0.198
ELIA	0.886	0.744	0.617

E·I Grünburg





Land Covers in each period of time						
Land Cover	Percentages			ha		
	1830	1950	2000	1830	1950	2000
Cropland area	38.7%	27.0%	24.4%	2,362	3,091	2,753
Woodland and scrub area	26.6%	19.7%	23.5%	1,625	2,259	2,655
Pastureland area	31.3%	41.1%	29.1%	1,912	4,714	3,292
Built-up and unproductive area	3.4%	12.2%	23.0%	207	1,404	2,596
L	0.95	0.83	0.73	6,107	11,468	11,296

Landscape Functional Structure

Appendix B. Energy-Landscape Integrated Analysis (ELIA) in St. Florian (Austria)

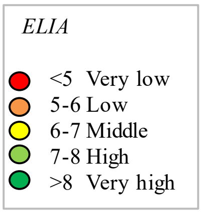
Energy flows (GJ)			
Flows	1830	1950	2000
FEI	4,093	5,881	19,083
UB	153,494	206,345	227,266
FW	0	0	0
FBR	15,244	18,648	19,807
LBR	152,472	339,808	268,970
FFP	82,861	143,689	705,097
LEI	8,261	52,942	125,263
LW	0	0	0
LS	50,150	62,018	0
LFP	5,171	14,930	29,157
NPP_{act}	404,071	708,491	1,221,140
NPP_{h}	250,577	502,146	993,874
ATT	222,981	292,892	266,156
LTI	160,732	392,750	394,233
LPS	55,322	76,947	29,157
FTI	69,487	86,547	38,890
FII	65,394	80,666	19,807
Fnren	0	27,252	93,159
Lnren	0	0	28,885
FEROI	0.489	0.380	1.695
NPP-EROI	2.244	1.698	2.819
IF-EROI	0.525	0.443	2.543
EF-EROI	7.126	2.697	5.087
AE-EROI	0.264	0.254	1.112
E	0.710	0.717	0.453

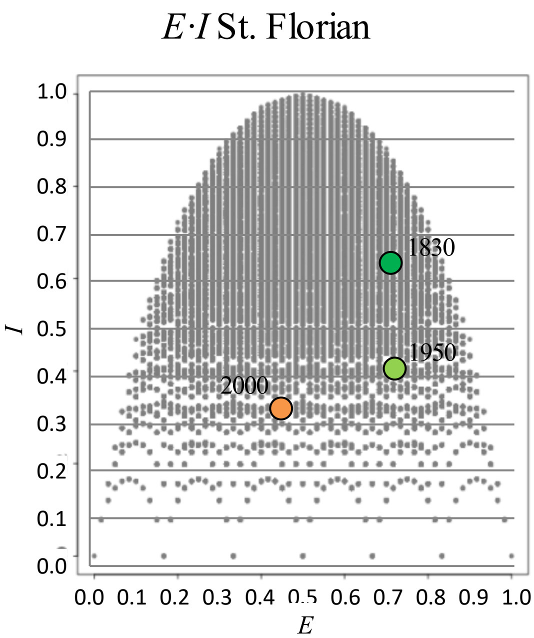
Energy of Internal Loops

Coefficients			
Coef.	1830	1950	2000
β_1	0.620	0.709	0.814
β_2	0.380	0.291	0.186
β_3	0.312	0.295	0.146
β_4	0.688	0.705	0.854
β_5	0.331	0.286	0.709
β_6	0.669	0.714	0.291
β_7	0.059	0.068	0.491
β_8	0.941	0.932	0.509
β_9	0.051	0.135	0.318
β_{10}	0.949	0.865	0.682
β_{11}	0.093	0.194	1.000
β_{12}	0.907	0.806	0.000
α_1	0.500	0.089	0.085
α_2	0.500	0.500	0.406
γ_L	0.500	0.500	0.500
γ_B	0.500	0.500	0.500
k_1	0.413	0.329	0.440
k_2	0.452	0.572	0.560
k_3	0.135	0.099	0.000
I	0.639	0.417	0.333

Information of Energy Flows

Energy-Landscape Integrated Analysis			
Indicator	1830	1950	2000
E·I	0.453	0.299	0.151
ELIA	0.814	0.743	0.502





Land Covers in each period of time						
Land Cover	Percentages			ha		
	1830	1950	2000	1830	1950	2000
Cropland area	64.5%	54.2%	61.4%	3,350	4,560	5,160
Woodland and scrub area	16.1%	17.3%	14.5%	836	1,454	1,221
Pastureland area	14.1%	23.6%	4.2%	731	1,986	352
Built-up and unproductive area	5.4%	4.9%	19.9%	279	410	1,677
L	0.73	0.85	0.52	5,197	8,410	8,410

Landscape Functional Structure

Appendix C. Energy-Landscape Integrated Analysis (ELIA) in Queens (Canada)

Energy flows (GJ)			
Flows	1880	1950	1995
FEI	52,069	16,746	2,826
UB	4,459,029	5,322,355	7,369,947
FW	0	0	0
FBR	119,410	259,714	407,883
LBR	3,932,850	4,106,583	4,260,067
FFP	4,000,186	3,947,291	4,547,257
LEI	180,475	333,904	444,170
LW	0	0	0
LS	1,122,458	0	0
LFP	24,867	72,481	273,709
NPP_{act}	12,511,474	13,635,943	16,585,153
NPP_h	8,052,445	8,313,588	9,215,206
ATT	5,752,966	5,598,815	7,780,656
LTI	4,113,324	4,440,487	4,704,237
LPS	1,147,325	72,481	273,709
FTI	1,293,937	276,460	410,709
FII	1,241,868	259,714	407,883
Fnren	35,168	303,686	970,584
Lnren	5,158	3,930	104,347
FEROI	0.939	0.852	0.943
NPP-EROI	2.920	2.891	3.242
IF-EROI	0.993	0.921	1.033
EF-EROI	17.309	11.464	10.785
AE-EROI	0.460	0.400	0.386
E	0.682	0.698	0.717

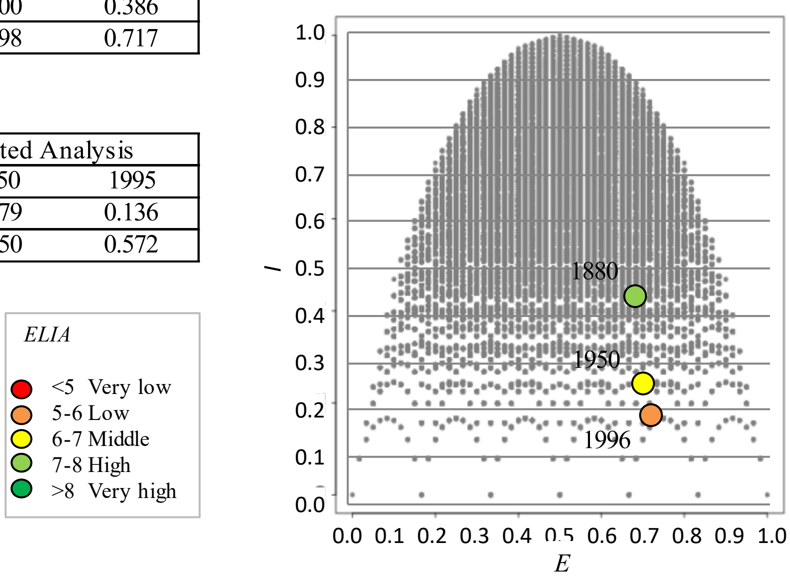
Energy of Internal Loops

Coefficients			
Coef.	1880	1950	1995
β_1	0.644	0.610	0.556
β_2	0.356	0.390	0.444
β_3	0.225	0.049	0.053
β_4	0.775	0.951	0.947
β_5	0.497	0.475	0.493
β_6	0.503	0.525	0.507
β_7	0.040	0.061	0.007
β_8	0.960	0.939	0.993
β_9	0.044	0.075	0.094
β_{10}	0.956	0.925	0.906
β_{11}	0.022	1.000	1.000
β_{12}	0.978	0.000	0.000
α_1	0.298	0.026	0.001
α_2	0.486	0.494	0.405
γ_L	0.500	0.500	0.500
γ_B	0.500	0.500	0.500
k_1	0.463	0.549	0.612
k_2	0.421	0.451	0.388
k_3	0.117	0.000	0.000
I	0.440	0.257	0.190

Information of Energy Flows

Energy-Landscape Integrated Analysis			
Indicator	1880	1950	1995
E·I	0.300	0.179	0.136
ELIA	0.761	0.650	0.572

E·I Queens



Land Covers in each period of time						
Land Cover	Percentages			ha		
	1880	1950	1995	1880	1950	1995
Cropland area	41.6%	34.9%	36.0%	82,364	69,193	71,359
Woodland and scrub area	30.0%	31.1%	39.7%	59,494	61,717	78,735
Pastureland area	14.3%	18.1%	7.3%	28,334	35,901	14,433
Unproductive area	13.0%	14.7%	14.7%	25,724	29,107	29,174
Built-up area	1.1%	1.1%	2.2%	2,217	2,217	4,433
L	0.91	0.94	0.85	198,134	198,134	198,134

Landscape Functional Structure

Appendix D. Energy-Landscape Integrated Analysis (ELIA) in Sta. Fe (Spain)

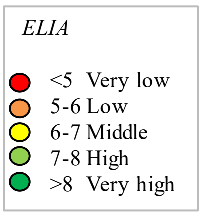
Energy flows (GJ)			
Flows	1904	1934	1997
FEI	10,971	1,042	2,419
UB	335,494	323,552	234,484
FW	0	0	22,394
FBR	6,004	6,537	85,328
LBR	75,501	98,163	116,073
FFP	94,230	85,265	265,436
LEI	2,150	236	18,808
LW	0	0	11,870
LS	17,555	23,232	2,638
LFP	7,227	7,836	11,187
NPP_{act}	511,228	513,516	723,715
NPP_h	175,735	189,964	466,837
ATT	370,023	354,363	324,868
LTI	77,651	98,399	134,881
LPS	24,782	31,068	25,695
FTI	34,529	30,811	90,385
FII	23,559	29,769	87,966
Fnren	4,296	16,820	94,318
Lnren	0	0	8,957
FEROI	1.072	0.878	1.243
NPP-EROI	5.403	4.846	3.251
IF-EROI	1.245	0.889	1.373
EF-EROI	7.733	72.818	13.032
AE-EROI	0.236	0.217	0.605
E	0.745	0.774	0.608

Energy of Internal Loops

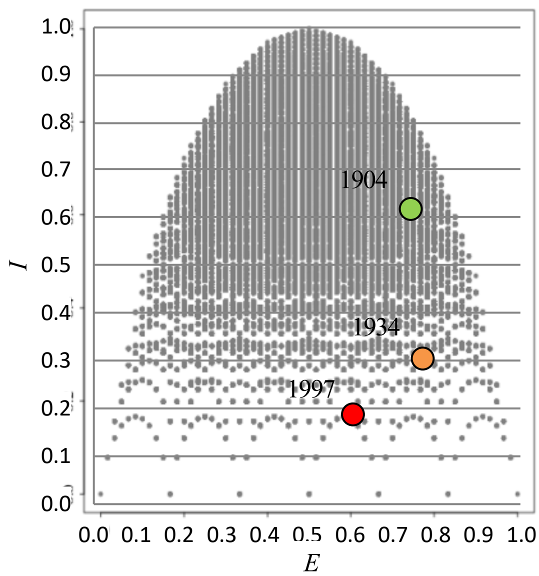
Coefficients			
Coef.	1904	1934	1997
β_1	0.344	0.370	0.666
β_2	0.656	0.630	0.334
β_3	0.093	0.087	0.278
β_4	0.907	0.913	0.722
β_5	0.536	0.449	0.569
β_6	0.464	0.551	0.431
β_7	0.318	0.034	0.027
β_8	0.682	0.966	0.973
β_9	0.028	0.002	0.139
β_{10}	0.972	0.998	0.861
β_{11}	0.292	0.252	0.809
β_{12}	0.708	0.748	0.191
α_1	0.359	0.029	0.013
α_2	0.500	0.500	0.339
γ_L	0.500	0.500	0.485
γ_B	0.500	0.500	0.269
k_1	0.772	0.717	0.535
k_2	0.188	0.232	0.459
k_3	0.040	0.051	0.006
I	0.620	0.302	0.186

Information of Energy Flows

Energy-Landscape Integrated Analysis			
Indicator	1904	1934	1997
E·I	0.462	0.234	0.113
ELIA	0.719	0.569	0.457



E·I Sta. Fe



Land Covers in each period of time						
Land Cover	Percentages			ha		
	1904	1934	1997	1904	1934	1997
Cropland area	78.7%	78.4%	75.6%	3,036	3,028	2,919
Woodland and scrub area	1.4%	5.8%	11.4%	53	223	440
Pastureland area	18.0%	9.1%	5.4%	693	350	210
Built-up and unproductive area	2.0%	6.7%	7.5%	78	259	291
L	0.50	0.49	0.52	3,860	3,860	3,860

Landscape Functional Structure

Appendix E. Energy-Landscape Integrated Analysis (ELIA) in Vallès (Spain)

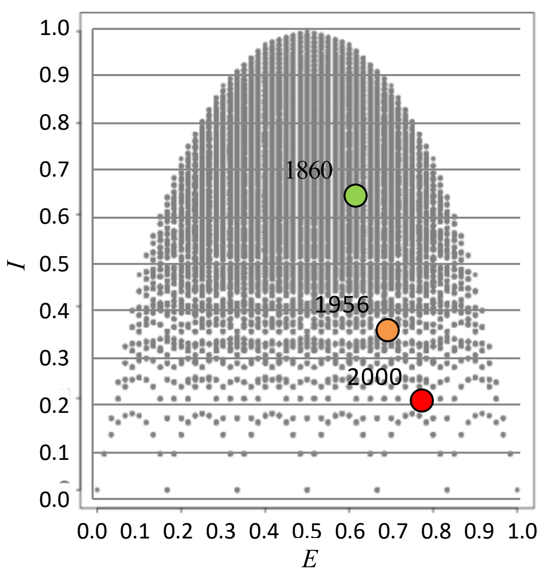
Energy flows (GJ)			
Flows	1860	1956	2000
FEI	5,553	4,833	2,847
UB	294,693	364,816	561,462
FW	0	0	11,150
FBR	146,555	9,405	9,323
LBR	96,308	134,604	129,766
FFP	259,972	227,680	97,615
LEI	6,656	10,542	970,522
LW	0	0	256,503
LS	32,299	26,137	36,997
LFP	2,891	7,438	238,765
NPP_{act}	797,528	736,505	809,317
NPP_h	502,835	371,689	236,704
ATT	479,100	405,191	610,629
LTI	102,964	145,146	1,100,288
LPS	35,190	33,575	532,265
FTI	184,407	40,375	49,167
FII	178,854	35,542	46,320
Fnren	0	73,247	190,925
Lnren	0	123	113,276
FEROI	1.031	1.475	0.302
NPP-EROI	3.127	4.621	0.728
IF-EROI	1.082	1.633	2.418
EF-EROI	21.530	15.292	0.346
AE-EROI	0.478	0.449	0.201
E	0.617	0.688	0.768

Energy of Internal Loops

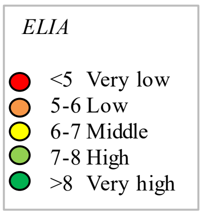
Coefficients			
Coef.	1860	1956	2000
β_1	0.630	0.505	0.297
β_2	0.370	0.495	0.703
β_3	0.385	0.100	0.081
β_4	0.615	0.900	0.919
β_5	0.517	0.613	0.412
β_6	0.483	0.387	0.588
β_7	0.030	0.120	0.058
β_8	0.970	0.880	0.942
β_9	0.065	0.073	0.882
β_{10}	0.935	0.927	0.118
β_{11}	0.082	0.222	0.866
β_{12}	0.918	0.778	0.134
α_1	0.500	0.031	0.007
α_2	0.500	0.494	0.448
γ_L	0.500	0.500	0.493
γ_B	0.500	0.500	0.259
k_1	0.517	0.682	0.761
k_2	0.426	0.269	0.189
k_3	0.057	0.049	0.050
I	0.644	0.359	0.209

Information of Energy Flows

$E{\cdot}I$ Vallès



Energy-Landscape Integrated Analysis			
Indicator	1860	1956	2000
$E{\cdot}I$	0.397	0.247	0.161
ELIA	0.773	0.586	0.464



Land Covers in each period of time						
Land Cover	Percentages			ha		
	1860	1956	1999	1860	1956	1999
Forest and Scrubland	36.5%	58.6%	56.6%	3,461	5,557	5,366
Grassland and Wasteland	2.9%	3.0%	2.7%	274	283	257
Dry cropland	20.1%	31.3%	16.1%	1,906	2,967	1,531
Irrigated cropland	1.6%	0.0%	2.6%	151	0	245
Vineyard land	36.4%	2.4%	0.2%	3,453	228	16
Water bodies	1.6%	1.4%	1.1%	152	134	101
Urban areas and Unproductive	0.6%	3.4%	20.8%	55	320	1,970
No data	0.4%	0.0%	0.0%	34	0	0
L	0.72	0.50	0.38	9,486	9,488	9,486

Landscape Functional Structure

Appendix F. Energy-Landscape Integrated Analysis (ELIA) in Decatur (USA)

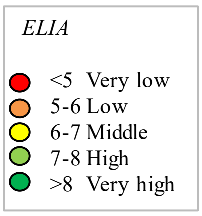
Energy flows (GJ)			
Flows	1880	1954	1997
FEI	3,765	2,600	588
UB	5,117,902	3,870,672	8,069,514
FW	0	0	0
FBR	3,958	221,361	555,306
LBR	315,722	2,471,749	3,267,254
FFP	84,192	1,294,623	3,651,131
LEI	66,285	360,994	360,024
LW	0	0	0
LS	170,361	0	0
LFP	4,486	55,260	77,016
NPP_{act}	5,521,775	7,858,405	15,543,204
NPP_{h}	403,873	3,987,733	7,473,690
ATT	5,295,986	4,094,633	8,625,408
LTI	382,008	2,832,743	3,627,278
LPS	174,847	55,260	77,016
FTI	178,084	223,961	555,894
FII	174,319	221,361	555,306
Fnren	2,131	274,403	945,008
Lnren	0	1,692	73,093
FEROI	0.23	0.44	0.89
NPP-EROI	14.17	2.57	3.72
IF-EROI	0.28	0.50	0.98
EF-EROI	1.27	3.71	10.34
AE-EROI	0.016	0.195	0.304
E	0.942	0.765	0.736

Energy of Internal Loops

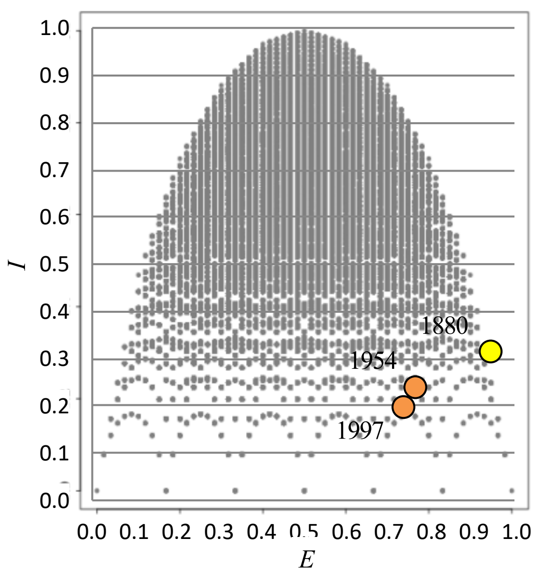
Coefficients			
Coef.	1880	1954	1997
β_1	0.073	0.507	0.481
β_2	0.927	0.493	0.519
β_3	0.034	0.055	0.064
β_4	0.966	0.945	0.936
β_5	0.208	0.325	0.489
β_6	0.792	0.675	0.511
β_7	0.021	0.012	0.001
β_8	0.979	0.988	0.999
β_9	0.174	0.127	0.099
β_{10}	0.826	0.873	0.901
β_{11}	0.026	1.000	1.000
β_{12}	0.974	0.000	0.000
α_1	0.319	0.005	0.000
α_2	0.500	0.498	0.416
γ_L	0.500	0.500	0.500
γ_B	0.500	0.500	0.500
k_1	0.913	0.590	0.679
k_2	0.057	0.410	0.321
k_3	0.030	0.000	0.000
I	0.316	0.239	0.196

Information of Energy Flows

Energy-Landscape Integrated Analysis			
Indicator	1880	1954	1997
E·I	0.298	0.183	0.144
ELIA	0.638	0.573	0.528



E·I Decatur



Land Covers in each period of time						
Land Cover	Percentages			ha		
	1880	1954	1997	1880	1954	1997
Cropland area	3.1%	54.8%	50.9%	6,897	127,571	117,702
Woodland and scrub area	0.4%	0.7%	0.9%	940	1,534	2,034
Pastureland area	68.6%	39.4%	44.3%	154,342	91,656	102,434
Unproductive area	28.0%	5.1%	4.0%	62,930	11,834	9,270
L	0.54	0.64	0.63	225,108	232,596	231,440

Landscape Functional Structure

Appendix G. Energy-Landscape Integrated Analysis (ELIA) in Nemaha (USA)

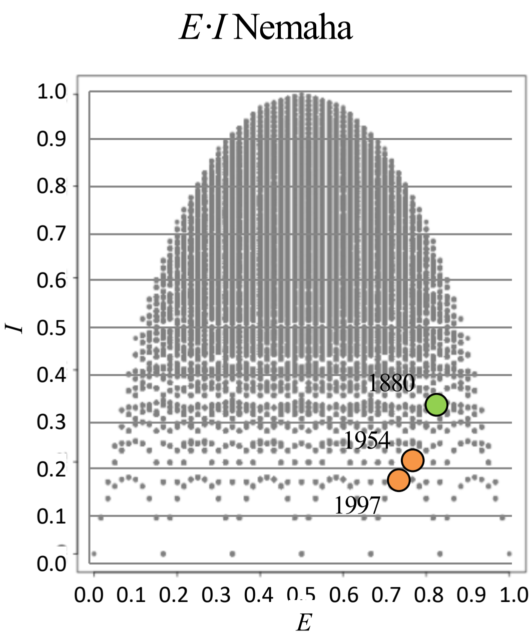
Energy flows (GJ)			
Flows	1880	1954	1997
FEI	7,738	442	974
UB	8,545,047	6,465,310	11,815,548
FW	0	0	0
FBR	129,081	289,133	804,481
LBR	3,163,476	3,984,999	4,306,294
FFP	852,230	2,305,320	5,514,030
LEI	698,160	372,124	363,360
LW	0	0	0
LS	744,384	0	0
LFP	90,156	103,429	171,392
NPP_{act}	12,689,834	13,044,762	22,440,353
NPP_h	4,144,787	6,579,451	10,624,805
ATT	9,426,249	6,754,885	12,621,003
LTI	3,861,637	4,357,123	4,669,654
LPS	834,540	103,429	171,392
FTI	881,202	289,575	805,455
FII	873,465	289,133	804,481
Fnren	29,497	546,002	1,723,604
Lnren	0	2,083	106,346
FEROI	0.236	0.518	1.038
NPP-EROI	3.174	2.807	4.099
IF-EROI	0.286	0.564	1.112
EF-EROI	1.335	6.465	15.605
AE-EROI	0.075	0.217	0.329
E	0.821	0.765	0.734

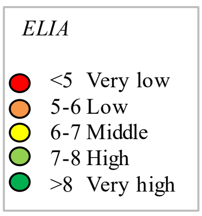
Energy of Internal Loops

Coefficients			
Coef.	1880	1954	1997
β_1	0.327	0.504	0.473
β_2	0.673	0.496	0.527
β_3	0.093	0.043	0.064
β_4	0.907	0.957	0.936
β_5	0.206	0.350	0.519
β_6	0.794	0.650	0.481
β_7	0.009	0.002	0.001
β_8	0.991	0.998	0.999
β_9	0.181	0.085	0.078
β_{10}	0.819	0.915	0.922
β_{11}	0.108	1.000	1.000
β_{12}	0.892	0.000	0.000
α_1	0.104	0.000	0.000
α_2	0.500	0.497	0.387
γ_L	0.500	0.500	0.500
γ_B	0.500	0.500	0.500
k_1	0.679	0.602	0.698
k_2	0.262	0.398	0.302
k_3	0.059	0.000	0.000
I	0.336	0.218	0.177

Information of Energy Flows

Energy-Landscape Integrated Analysis			
Indicator	1880	1954	1997
E·I	0.276	0.167	0.130
ELIA	0.704	0.575	0.533





Land Covers in each period of time						
Land Cover	Percentages			ha		
	1880	1954	1997	1880	1954	1997
Cropland area	24.3%	59.1%	53.9%	45,632	109,166	100,291
Woodland and scrub area	4.5%	4.9%	4.6%	8,510	8,992	8,612
Pastureland area	57.1%	30.9%	36.3%	107,273	57,026	67,619
Unproductive area	14.1%	5.2%	5.2%	26,543	9,530	9,717
L	0.78	0.70	0.72	187,957	184,714	186,239

Landscape Functional Structure