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The importance of land in resource criticality assessment methods: A first step towards characterising supply risk

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Abstract

Land is a key resource for human activities under growing pressure. Resource criticality assessment methods investigate the extent to which a resource may become a limiting factor according to various dimensions, including geological, economic and geopolitical availability. They have been applied to resources like minerals, fossil fuels, biotic material or water, but none consider land resources, i.e. natural land units providing space and support for human activities. Based on two recognised criticality methods developed by i) the Yale University and ii) the Joint Research Centre of the European Commission, this study aims to develop spatialized land supply risk indexes at country level. The accessibility of raw resources can be quantified and compared using the supply risk index. The specific characteristics of land call for certain adaptations of the criticality approach, and are designed to ensure comparability between resources. The main adaptations include the definition of land stress and the internal land concentration index. Land stress represents the physical availability of land, while internal land concentration relates to the concentration of landowners within a country. Finally, land supply risk indexes are computed for 76 countries, including 24 European countries for which the results of the two criticality methods are compared. Comparison points to divergences in the countries ranking for land accessibility, thus underlining the importance of methodological choices in the construction of the indexes. Data quality is discussed for European countries with the JRC method, and the use of alternative data sources reveals that it may lead to differences in absolute values, although the ranking of countries with low or high land supply risk does not change.

Finally, this work covers a gap in criticality methods by including land resources. These resources can be critical for certain countries, and are essential for human activities such as food or energy production.

Keywords

Land stress; regionalised index; resource accessibility; environmental assessment; land concentration

Glossary

EEA	European Environmental Agency
EOL RIR	End of Life Recycling Input Rate
FAO	Food and Agriculture Organisation
FDI	Foreign Direct Investment
HDI	Human Development Index
HHI	Herfindahl-Hirschman Index
HLD	Human Land Demand
ILC	Internal Land Concentration

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IUCN	International Union for Conservation of Nature
JRC	Joint Research Centre
LAQ	Land Administration Quality
Lrecycling	Land recycling
LS	Land Stress
OECD	Organisation for Economic Cooperation and Development
PA	Protected Area
PS	Political Stability
SI	Substitution Index
SR	Supply Risk
UL	Unusable land
UNDP	United Nation Development Program
UNEP	United Nation Environment Program
WCMC	World Conservation Monitoring Center
WDPA	World Database on Protected Area
WGI	World Governance Indicator

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1) Introduction

From a global perspective, land is a limited resource, submitted to growing pressure. The United Nations estimate that 20% of the Earth's total land area has been degraded only between 2000 and 2015 (United Nation, 2020). Steffen et al. (2015) estimated that forest areas have already shrunk by 38% worldwide since the Holocene, with major impacts on climate and biodiversity (Newbold et al., 2016). Within the planetary boundary framework, the "land system change" boundary is even considered to have been crossed in certain regions (Rockström et al., 2009; Steffen et al., 2015). The increase in the need for areas for human activities also leads to conflicts in land use for different economic activities. These conflicts emerge particularly for urban and agricultural use, where increasing urbanisation consumes more and more land, while it is necessary to preserve agricultural fields in the surrounding areas (Gardi et al., 2015; van Vliet et al., 2017). Conflicts also arise between agricultural use and the expansion of renewable energies that require large areas such as photovoltaic systems or energy crops (Nonhebel, 2005; Rulli et al., 2016; Smith et al., 2010). Studies on the water-energy-land-food nexus acknowledge the role of land as a crucial resource (Ringler et al., 2013), which can become critical for human activities.

The United Nation define land as "a delineable area of the earth's terrestrial surface, encompassing all attributes of the biosphere immediately above or below this surface".

Land provides physical support and habitat for species and is essential for biodiversity (Foley et al., 2005). About 85% of eukaryotic species are terrestrial (Pimm & Raven, 2000), and land-use change is one of the main drivers of biodiversity extinction, by altering the quantity and quality of species' habitats (Millenium Ecosystem Assessment, 2005). Land also supports the provision of essential ecosystem services for humanity such as regulation of biochemical and biophysical cycles or fibre and food provision (Tilman et al., 2002).

Land resource is defined by the Food and Agriculture Organization (FAO) as "the physical, biotic, environmental, infrastructural and socio-economic components of a natural land unit" (FAO, 2022).

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It is to be distinguished from soil, the "top layer of the earth's crust formed by mineral particles, organic matter, water, air and living organisms" (European Commission, 2006), which provides other functions such as water and nutrient filtering, among others (Sonderegger et al., 2017). Land, as a resource, provides space and physical support for human activity (Sonderegger et al., 2017). This study focuses specifically on these characteristics, i.e. the subset "natural land unit" of the FAO definition. Therefore, from now in this paper the term land resource will refer to the faculty of land to provide space and support for human activities.

Land competition in scientific literature has been widely investigated regarding land use and land use changes (Fritsche et al., 2010). Although these studies examine the drivers behind land use changes (Lambin & Meyfroidt, 2011), they mostly tend to focus on the environmental consequences of land use changes such as carbon storage (Valin et al., 2015) or biodiversity loss (Reidsma et al., 2006). Indeed, in general, they do not consider the potential inaccessibility of land as a limiting factor for economic activities.

Nevertheless, there is growing interest towards the criticality assessment of a wide range of resources (Schrijvers et al., 2020). Criticality methods evaluate the economic and technical dependency on a certain material, as well as the probability of supply disruptions, for a defined stakeholder group and within a certain time frame (Schrijvers et al., 2020).

Criticality assessment methods first propose to quantify a supply risk index, which represents the possibility of supply disruption for a given material, depending on its geological, technological, economic, social, or geopolitical availability. Recent studies propose the use of the supply risk index to develop new characterisation factors for environmental assessment methods such as Life Cycle Assessment (LCA), thus making it possible to consider the accessibility of resources as a complement to other available environmental impact assessment methods (Santillán-Saldivar et al., 2022). Criticality assessment methods also involve a second dimension related to the impact of supply restrictions, which analyses the substitution and importance of the use of the study material (importance can be economic, strategic, etc.) (Schrijvers et al., 2020).

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Criticality was initially intended for non-energetic mineral resources to help secure the supply of key resources for specific industries (Graedel et al., 2015), like low carbon energy technologies. The methods were later extended to fossil fuels, biotic materials (Arendt et al., 2020; Bach et al., 2017) and even water (Sonderegger et al., 2015), to allow for comparability between resources. Regarding land, Goswami & Nishad (2018) defined a land supply risk index per country solely based on arable land availability and demand, ignoring socio-economic parameters that can influence land accessibility, such as land governance or transaction restrictions. This approach also addressed the use of land for food purposes exclusively. Meylan et al. (2021) developed land criticality indicators (supply risk and impact of supply restriction), but only focused on soil nutrient availability for agriculture, without considering other types of land use such as urban or forest. Moreover, this study was just conducted for three agricultural locations without considering a global coverage.

This paper aims at providing a proof of concept on the interest of including land resource in criticality assessment methods, next to other resources. For this purpose, land supply risk indexes are developed at the country level, based on existing criticality methods: i) to ensure comparability across resources and ii) to discuss the importance of methodological choices.

Section 2 describes the criticality methods used to develop the land supply risk index, as well as the main data sources. Section 3 provides an analysis of the land supply risk index for countries across the world and a comparison of the two criticality methods for some European countries. Finally, Section 4 discusses the applicability, uncertainty and limitations of the new index, as well as the possibility of extension of the concept developed in this paper to other criticality methods.

2) Materials and methods

There is no scientific consensus on which method to use for criticality assessment (Hackenhaar et al., 2022; Schrijvers et al., 2020; Sonderegger et al., 2020). Methods may differ depending on the social, economic, geopolitical or governance components considered, and how they are aggregated into single indicator. For this reason, two methods are selected and compared to develop land supply risk indexes at country level. The choice of the criticality methods is explained below with a description of their main features. Adaptations of these methods are then proposed to include the specificities related to land resources, and to present a land supply risk index covering a maximum of countries at both the European and global level.

2.1) Choice of the criticality methods

Among the 39 criticality methods reviewed by Schrijvers et al., (2020), two methods were selected, i.e., the Yale method, initially developed by Graedel et al., (2012), and the Joint Research Centre (JRC) of the European commission method (Blengini et al., 2017). These two methods are recognized in the scientific community for their scientific robustness (data quality, uncertainty, peer-reviewing), transparency (traceability of modelling and documentation, reproducibility), applicability (technical feasibility, data availability,…) and high level of acceptance (by policy-maker, industry, academia) (Hackenhaar et al., 2022). In addition, they both provide a single aggregated supply risk index according to medium-term temporal perspective (5 – 10 years) at a national scale (Schrijvers et al., 2020).

The Yale method is one of the first criticality methods developed. Additionally, to the supply risk index, it considers two other criticality dimensions, i.e. i) vulnerability to supply restriction, expressing the impact of resource supply restriction on the system and ii) environmental implication which addresses the environmental impact of a resource extraction and processing. It provides criticality factors for 86 available mineral and fossil resources. Although it has been conceptualised at national and global levels, it has mainly been implemented at global level (Myers et al., 2019). Sonderegger et al. (2015) adapted this method for water criticality for 512 counties from 159 countries. In the same line, the Yale method is selected here to compute land supply risk index.

The JRC method, developed for European Union (EU) Countries, has been designed with the support of many stakeholders and experts (Blengini et al., 2017). It covers a wide range of resources

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(i.e., 80 types of material) including biotic ones. It also entails a criticality dimension named Economic Importance, which expresses the impact of resource supply restriction on the EU economy.

If the two criticality methods have the same temporal perspective, short to medium term, they differ in term of spatial coverage, global level for Yale, and only the countries of the EU for the JRC method. Moreover, they rely on contrasting methodological choices in terms of the criticality dimensions taken into account and the way in which they are aggregated, as described in Table 1 and Table 2.

Other methods could have been investigated, including those recommended by the LCA community (Berger et al., 2020; Sonderegger et al., 2020) such as GeoPolRisk (Santillán-Saldivar et al., 2022) and ESSENZ (Bach et al., 2016), or the SCARCE method (Arendt et al., 2020) which builds on the ESSENZ method. As the objective here is to make initial proposals to include land criticality, they were not included in this study.

2.2) Adaptations of the Yale and JRC Supply Risk (SR) dimension

In this paper, the other dimensions considered next to Supply Risk, i.e. Vulnerability to Supply restriction and Environmental Implication in Yale, and Economic Importance in JRC, are not taken into account.

The Supply Risk (SR) index from the Yale method relies on three components, i.e. i) geological, technological and economic, ii) social and regulatory and iii) geopolitical (see Table 1). Each component is assessed by relevant indexes. Some of these indexes are similar to those found in the JRC method (see Table 2). Both methods share indexes of Supply Concentration and World Governance Indicator (see Table 1, Table 2). Furthermore, the Depletion Time index from Yale includes a recycling parameter (Graedel et al., 2012), while the JRC includes an explicit recycling parameter (Table 2).

Nevertheless, the two methods also differ on several parameters. Firstly, the JRC method does not take into account the biophysical scarcity of resources related to their geological availability.

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Secondly, contrary to the Yale method, the JRC method involves additional economic indexes, i.e. transaction restriction and an import reliance ratio. Finally, it comprises a substitution index, which Yale does not include in the SR criticality dimension, but in the Vulnerability to Supply Restriction dimension.

To extend the SR framework to land resources, every SR component for mineral resources is adapted to land in both methods, when appropriate. This ensures comparability between resources, in accordance with what Sonderegger et al. (2015) conducted for water, based on the Yale method. As land is a local resource, its accessibility (depending on economic or social parameter) is likely to be influenced by local drivers. The developed land SR are hence computed at the country level in both methods.

Table 1 describes the adaptations of the Yale method to quantify a land SR index. The geological, technological and economic component is transformed into a spatial, technological and economic component, assessed by a Land Stress (LS) index. As land is not a by-product of other activities, the Companion Metal Fraction index is not relevant for this resource, and not considered here.

The social and regulatory component for land is composed of the Human Development Index (HDI) and a Land Administration Quality (LAQ) index. The latter has been chosen instead of the Policy Potential Index, which is specific to mineral resources (Graedel et al., 2012).

Regarding the geopolitical component, the index of Political Stability (PS) is maintained. Yet, since land is not a transportable good and no globalised market exists, the Global Supply Concentration index is converted into an Internal Land Concentration (ILC) index.

Table 1 : Adaptation of the Supply Risk indexes for mineral resources to land for the Yale method. Parameters in black are those common to the Yale and JRC land Supply Risk. The numbers in brackets refer to the sections in which the calculation of the indexes is detailed.

Yale Supply Risk	
Original parameter for mineral resources	**Adaptation to the land resource**
Geological, technological and	Spatial, technological and economic

economic		
Depletion Time	**Land Stress (2.2.1)**	**LS**
Companion Metal Fraction	-	
Social and Regulatory	Social and Regulatory	
Policy Potential Index	**Land Administration Quality (2.2.3)**	**LAQ**
Human Development Index	**Human Development Index (2.2.4)**	**HDI**
Geopolitical	Geopolitical	
Global Supply Concentration	**Internal Land Concentration (2.2.2)**	**ILC**
Political Stability	Political Stability (2.2.5)	PS

The Yale SR ranges between 0 and 100, with 100 indicating highest SR. All indexes also vary between 0 and 100. To fit into this range of values, they are rescaled when needed (see section 2.2.8).

Table 2 inventories the adaptations of the JRC method. Again, no Global Supply Concentration or Import Reliance indexes are needed. As with the Yale method, regional supply concentration is also converted into Internal Land Concentration.

For mineral resources SR, the JRC method does not consider a geological stress. However, as land is a local resource and supply shortage can occur due to a limited physical quantity of land, the LS index was included in the JRC land SR.

The initial JRC SR involves governance indexes, which reflect country governance in general. However, the JRC notes that the use of resource-specific governance indexes is preferred (Blengini et al., 2017). Therefore, the LAQ index is used as a proxy for land governance within a country.

Specific indexes for transaction restriction and recycling parameters are developed for land, and the Substitution Index is transformed into an adaptation capacity index, assessed by the HDI.

Table 2 : Adaptation of the Supply Risk indexes for mineral resources to land for the JRC method. Parameters in black are those common to the Yale and JRC land Supply Risk. The numbers in brackets refer to the sections in which the calculation of the indexes is detailed.

JRC Supply Risk		
Original parameter for mineral resources	**Adaptation to the land resource**	
Import Reliance	-	
Global import country concentration	-	

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-	**Land Stress (2.2.1)**	**LS**
EU import concentration	**Internal Land Concentration (2.2.2)**	**ILC**
World Governance Indicator	**Land Administration Quality (2.2.3)**	**LAQ**
Trade restriction	Land transaction restriction (2.2.6)	t_{land}
End of Life Recycling Input Rate	Land Recycling (2.2.7)	$L_{recycling}$
Substitution Index	**Human Development Index (2.2.4)**	**HDI**

Theoretically, the JRC SR values for mineral resources can range between 0 and 20, but the data used all range between 0 and 10, with 10 indicating highest SR. Again, each index is rescaled when necessary according to the initial JRC methods (see section 2.2.8).

The aggregation of all indexes into the SR index is performed in accordance with the original resource criticality method.

The Yale land SR of a country (c) ($land\ SR_{yale,c}$) is thus the weighted average of all parameters (see Eq. (1)). For mineral resources, the weighting coefficients are all equal. However in their water SR framework, Sonderegger et al. (2015) gave more weight to the water stress parameter, arguing that the physical availability of water can only be partly mitigated by governance and geopolitical parameters. This reasoning was applied to land, and the weights given to the parameters for the Yale land SR are the same as those in Sonderegger et al (2015).

$$land\ SR_{yale,c} = \frac{1}{2} LS_{yale,c} + \frac{1}{4}\left(\frac{LAQ_{yale,c} + HDI_{yale,c}}{2}\right) + \frac{1}{4}\left(\frac{PS_{yale,c} + ILC_{yale,c}}{2}\right) \quad (1)$$

The JRC land SR of a country c ($land\ SR_{jrc,c}$) is obtained by multiplying all parameters (see Eq. (2) and Eq. (3)).

$$land\ SR_{jrc,c} = \mathrm{LS}_{jrc,c} * (ILC_{LAQ,t})_c * \left(1 - L_{recycling,c}\right) * (1 - HDI_c) \quad (2)$$

With:

$$ILC_{LAQ,t} = ILC_c * LAQ_{jrc} * t_{land,c}$$

(3)

The calculations and statistical analysis are performed using the python pandas packages (The pandas development team, 2022) and country-converter (Stadler, 2017) to compute the land SR per countries.

Statistical analysis is performed using the Spearman correlation coefficient (Spearman, 1904) to compare the two approaches. The next section details the computation of each index.

2.3) Description of indexes

2.2.1) Land Stress index (LS)

Resource scarcity indicators express the balance between resource supply and demand (Graedel et al., 2012). To date an indicator reflecting the land resource scarcity of a country by considering all types of land use does not exist.

Hence, a new indicator at the country level is proposed. This LS index includes all types of land use and is based on a land demand to availability approach, without considering land quality, according to one of the latest consensus-based methods developed for water resource, i.e. the water stress index AWARE (Boulay et al., 2018). AWARE is a water stress index representing the relative available water remaining per area in a watershed, after the needs of humans and aquatic ecosystems have been met. Using the same approach, the LS index is defined as the ratio of human land demand (HLD) over available land minus protected areas (Eq.(4)), following the recommendations of (Hélias, 2020) on the shape of the AWARE equation:

$$LS = \frac{HLD}{A_{tot} - UL - PA}$$

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(4)

With:

- HLD: Human Land Demand, i.e.: artificial surfaces, herbaceous and woody crops (perennial crops and managed forests) (ha)
- A_{tot}: Available land, i.e.: total land cover (ha)
- UL: Unusable land, i.e.: permanent snow and glacier land cover (ha)
- PA: Protected Area, i.e.: areas where human activities do not occur (ha)

For the LS to be computed, it is necessary to define the parameters of the equation based on a typology of land cover. Land cover is the biophysical aspect of the land surface (FAOSTAT, 2021), whereas land use concerns the activities that take place on the land for the purpose of economic production (FAOSTAT, 2020). As the proposed method should be applicable to any country and does not distinguish between land use types, the FAOSTAT land cover database was chosen (FAOSTAT, 2021), where land cover classification is based on the System of Environmental-Economic Accounting land cover (United Nations, 2014). Table 3 details how the land cover classes are allocated to the LS parameters.

The HLD parameter entails the land areas transformed by human activities. Land cover types that are exploited by human activities but not transformed are not considered in this category, such as forests or grasslands. The woody crop land cover encompasses both perennial crops (orchard, palm tree plantations, *etc*.) and managed forests (Christmas tree plantation, *etc*.). The UL parameter describes the land resources that are not usable, for example due to extreme weather conditions or access difficulties. These areas should therefore be removed from the available land areas.

Table 3 : Land cover classes from the CCI_LC dataset included in the Land Stress parameters. HLD: Human Land Demand; A_{tot}: Available land; UL: Unusable Land.

Land Stress (LS)	FAOSTAT CCI_LC land cover class

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parameter	
HLD	• Artificial surfaces • Herbaceous crops • Woody crops
A_{tot}	• Artificial surfaces • Herbaceous crops • Woody crops • Grasslands • Tree-covered areas • Mangroves • Shrub-covered areas • Shrubs and/or herbaceous vegetation, aquatic or regularly flooded • Sparsely natural vegetated areas • Terrestrial barren lands • Permanent snow and glaciers
UL	• Permanent snow and glaciers

In addition, it is necessary to secure land surfaces to maintain terrestrial ecosystems. Concurrently with studies on water scarcity (Hoekstra et al., 2012; Kummu et al., 2010) and the AWARE methodology (Boulay et al., 2018) a certain amount of land is dedicated to ecosystem requirements. The surface of protected areas of a country, from the World Database of Protected Areas (UNEP-WCMMC & IUCN, 2022), is used as a proxy for this parameter. This database uses the International Union for Conservation of Nature (IUCN) classification for protected areas (Dudley, 2008) where areas of type I, IIa and Ib correspond to areas where no further human interventions can take place (see Supplementary Material Table A.2). Hence, only these three types of protected areas are considered in the PA parameter.

According to Eq. (4), the LS varies between 0 and 1. The higher the LS, the higher the land SR. The LS index is rescaled for both methods (see Supplementary Material Table A.1).

2.2.2) Internal Land Concentration (ILC)

The more a resource supply is concentrated, the higher the SR due to dependence on a small number of suppliers. Since land is not transportable, no global market supply concentration index exists. However, within a country, land ownership concentration can prevent access to land and thus increase the land SR (Paulino, 2014). An ILC index is thus introduced.

To be consistent with mineral resources assessment, the Herfindahl-Hirschman Index (HHI) is used. The HHI is a widespread market concentration indicator in economy (Federal Trade Comission & Department of Justice, 2006). In this case, land market shares per agricultural farms in a given country are taken.

The FAO agricultural census (FAOSTAT, 2022) provides, per country, the number of agricultural farms per farm size class, and total surface area per class, which are used to compute the ILC index:

$$ILC = \sum_{c} \overline{ms_c}^2 * N_c \tag{5}$$

With:

- c: class of farm size (ha)
- N_c: number of farm of class c
- $\overline{ms_c}$: average Utilized Agricultural Land (UAL) share for the farm size class c :

$$\overline{ms_c} = \frac{\overline{UAL_c}}{UAL_{tot}} = \frac{UAL_{c,tot}}{N_c * UAL_{tot}} \tag{6}$$

- $UAL_{c,tot}$: total UAL of farm class c within the country (ha)
- UAL_{tot}: total country UAL (ha)

Combining Eq. (5) and Eq. (6) results in Eq. (7):

$$ILC = \sum_{c} \left(\frac{UAL_{c,tot}}{UAL_{tot}}\right)^2 * \frac{1}{N_c} \tag{7}$$

ILC varies between 0 and 10 000. The higher the ILC, the higher the land SR. For the Yale method, ILC values are rescaled (see Supplementary Material Table A.2). The values for European countries remain below 7.3 and thus match with the JRC value range; therefore the index does not need to be rescaled for the JRC method.

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2.2.3) Land Administration Quality (LAQ)

Poor land governance or land administration can prevent access to land and change its uses (Sikor et al., 2013), thus increasing the land SR in a country. It is therefore an important parameter to consider within the land SR framework.

The LAQ index from the World Bank comprises five dimensions, i.e., i) reliability of infrastructure, ii) transparency of information, iii) geographic coverage of land ownership registration and cadastral mapping, iv) land dispute resolution and v) equal access to property right (World Bank, 2020). In the Yale method, the LAQ index is part of the Social and Regulatory component, while it is a proxy for land governance in the JRC method.

The index ranges between 0 and 1, with 1 being highest LAQ. The higher the LAQ, the lower the land SR and the index is therefore constructed in this way (see Supplementary Material Table A.2). The index is rescaled for the Yale method (see Supplementary Material Table A.2).

2.2.4) Human Development Index (HDI)

In the initial JRC method for mineral resources, a substitution index reduces the SR. For a given mineral, substitutes are determined by expert judgement, and the substitution index is calculated according to the market shares and availability of each of its substitutes.

As with water, there are no direct substitutes for a lack of land resources. However, it is possible to implement technologies or economic strategies to adapt to the lack of resources. Therefore the resource Substitution index is replaced with an index describing adaptation capacity to resource shortages.

The HDI, defined by the United Nations Development Programme (UNDP 2020), has been used in certain water vulnerability, criticality or impact assessments (e.g. Sonderegger et al., 2015; Sullivan, 2011) to describe the capacity of adaptation to water shortage. The higher the HDI, the higher the country's capacity to develop technical or organisational solutions to prevent or respond to water

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shortage. The same idea can be applied to land: the more economic and educational strength a country has, the more it will be able to find solutions to land scarcity, either technical (e.g. vertical farming if agricultural land is scarce) or economic (e.g. importing food or energy if agricultural land is scarce). The HDI is therefore used in the JRC method to describe this process.

In the Yale method for mineral resources, the HDI is applied to assess the social and regulatory dimension of SR (Graedel et al., 2012). However for mineral resources, a high HDI is considered to increase the resource SR. In the case of land, a high HDI describes a good social and regulatory context in a country, diminishing the Yale land SR (Sikor et al., 2013).

In this case, both the Yale and JRC method integrate the HDI, but as a proxy for distinct factor, i.e. the social and regulatory capacity for Yale and adaptation capacity for the JRC.

HDI ranges from 1 to 0, with 1 indicating highest HDI. The higher the HDI, the lower the land SR and the index is therefore constructed in this way (see Supplementary Material Table A.2). The index is rescaled for the Yale method (see Supplementary Material Table A.2).

2.2.5) Political Stability (PS)

In the Yale method for mineral resources, PS of countries is accounted for as politically unstable nations present higher risk of resource supply disruption (Graedel et al., 2012). The same reasoning applies to land. Indeed, land tenure rights and PS are strongly interrelated (Russet, 2011), the higher the PS, the better land tenure rights are respected and therefore the access to land guaranteed. To assess land tenure right respect, which influences access to land, a PS index is included, based on a sub-index of the Worldwide Governance Indicators. This Political Stability and absence of Violence/Terrorism index describes "the capacity of the government to effectively formulate and implement sound policies" (Kaufmann et al., 2010).

The PS index ranges from 1 to 0, with 1 indicating highest PS. The lower a country's PS, the higher its SR and the index is therefore constructed in this way (see Supplementary Material Table A.2). Rescaling is needed for the Yale method (see Supplementary Material Table A.2).

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2.2.6) Land transaction restriction

The land transaction restriction parameter is comparable to the trade parameter in the initial JRC method, which takes into account how export restrictions and trade agreements can lead to the decrease or increase of the SR for a given material. If a country applies foreign land acquisition restrictions, it increases the land SR for other countries.

The OECD Foreign Direct Investment Restrictiveness Index (FDI index) (Kalinova et al., 2010) assesses country restrictions on foreign investments according to economic sectors. The FDI index relies on four pillars, i.e. i) foreign equity limits, ii) screening and approval, iii) restriction on key foreign personnel/directors and iv) other restrictions.

The fourth pillar involves an "acquisition of land for business purposes" dimension, which is assigned five times more weight than for other dimensions in the agricultural sector of the OECD framework. As the value of the "acquisition of land for business purposes" dimension is not available, the fourth pillar of the FDI index is thus used as a land transaction restriction parameter. The parameter varies between 0 and 0.1 and is rescaled (see Supplementary Material Table A.2). The higher the value the higher the SR, the index is constructed in this way (see Supplementary Material Table A.2).

2.2.7) Land recycling

The land recycling index is comparable to the End-of-Life Recycling Input Rate from the initial JRC method, which reflects that the recycling of material tends to decrease the demand in raw material, thus decreasing the SR.

Land recycling can be defined as the reuse of land for a new purpose instead of consuming new land area (European Environment Agency, 2019a) thus relieving pressure on the land resource and therefore reducing the land SR of a country. The land recycling index from EEA measures this process for European countries (European Environment Agency, 2019b). The index computes over the years the land surface transformations, taking into account three dynamics: i) land consumption (the transformation of agricultural or wild land surfaces into artificial surfaces); ii) artificial land densification (the addition of new buildings to pre-artificialized surfaces) and iii) land reutilisation (the reutilisation of previously artificialized surfaces for new constructions). The indicator was calculated by the European Environment Agency between the years 2006 and 2012. To obtain a yearly rate (%.year^{-1}), the original indicator is divided by 6. The index ranges from 0 to 1. 1 indicates highest land recycling. Here the higher the land recycling index, the lower the JRC land SR.

2.2.8) Data sources

In this study, the data used for the computation of the SR are all at the country level. Table 4 describes the main data sources for each index, as well as their temporal and geographical coverages.

Table 4 : Data sources for the land Supply Risk indexes

Index	Data source	Data year	Number of country
Land Stress (LS)	FAOSTAT land cover statistic (CCI_LC dataset) (FAOSTAT, 2021) World Database on Protected Areas (UNEP-WCMC & IUCN, 2022)	2019 2022	228 230
Land Administration Quality (LAQ)	Doing Business, (World Bank, 2020)	2019	230
Internal Land Concentration (ILC)	FAOSTAT agricultural censuses (FAOSTAT, 2022)	2005-2015	88
Human Development Index (HDI)	United Nation Development Program (United Nation, 2020)	2019	187
Political Stability (PS)	Worlwide Governance Indicator (Kaufmann et al., 2010)	2020	201
Land transaction restriction (t_{land})	FDI restriction index, Organisation for Economic Cooperation and Development (OECD) (Kalinova et al., 2010)	2020	83
Land recycling ($L_{recycling}$)	European Environmental Agency (European Environment Agency, 2019b)	2006-2012	27

All data sets are updated on a yearly basis, except for the World Database on Protected Areas which is updated each month; FAOSTAT agricultural census is updated every ten years while the land recycling index, has never been updated at all.

To analyse data sensitivity, a second version of the JRC SR index is calculated using European data for the LS and ILC indexes. The use of the LUCAS land cover dataset (Ballin et al., 2018), allows for the computation of a new Land Stress for European countries with more detailed land cover data, based on 22 land cover classes, instead of 11 (see Supplementary Material Table A.3). For ILC, European statistics on farm size are used (Eurostat, 2019).

The land cover and agricultural census data are publically available via the Eurostat data portal.

All data produced in this paper are available at: https://doi.org/10.57745/RALP5G

3) Results

Firstly, the Yale land SR results are reported by country at the global level. These indexes are then compared to those of the JRC for European countries. The contribution of each index in the results is also considered, with a particular focus on land stress. Finally, a comparison of the two data sets for the JRC methods is provided.

3.1) Land SR with worldwide coverage

Worldwide SR scores were only calculated with the Yale method as the JRC method requires data that were only available for European countries. Yale land SR were calculated for 76 countries as illustrated in Figure 1. The limiting data sources is the Internal Land Concentration index (see Table 4).

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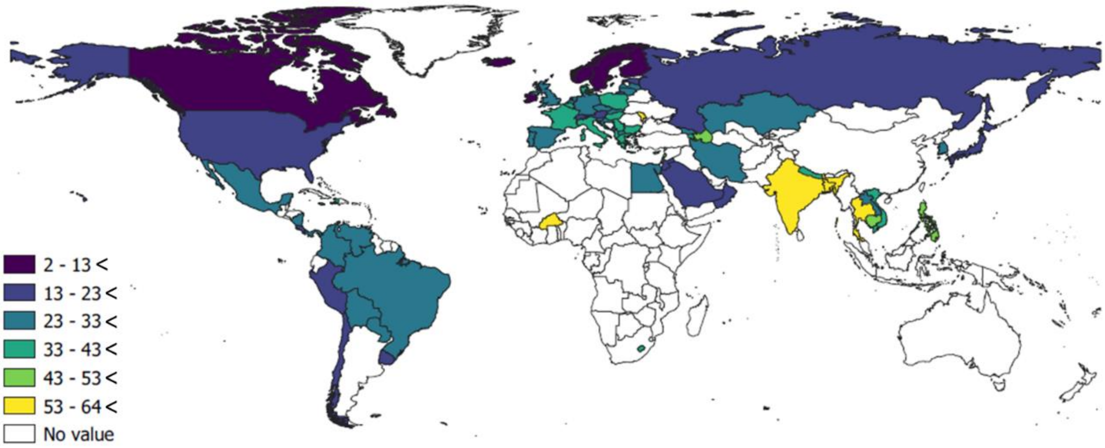

Figure 1 : Land Supply Risk with the Yale method (linear equal interval length clustering). The higher the land Supply Risk, the higher the risk of land not being accessible in a country. No values are due to lack of data.

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Yale Land SR ranges from 2.6 (Iceland) to 63.2 (Bangladesh), the world average being 29. Countries with the highest Yale land SR (land SR > 53) are Bangladesh, Moldova, Burkina Faso, India and Thailand. These results are explained both by a spatially scarce resource and by low geopolitical stability. These countries have Land Stress higher than 63 while the world average is 32 (see Figure 1). They also have Political Stability lower than 32 while the world average is 52.

In contrast, developed countries with a low land stress, and strong political stability have the smallest Yale land SR (land SR < 13) such as Iceland, Norway, Sweden, Canada, Finland, Ireland and Switzerland. However, the indexes do not all point in the same direction and countries with similar Yale land SR may have strong disparities. Results are further analysed by breaking down the Yale land SRs of five countries with similar values and above the world average (29.5) but with differing sub-index profiles (see Table 5).

Table 5 : Land Supply Risk and sub-indexes values for 5 countries chosen for illustrative purposes

Country	Land Supply Risk	Land Stress	Land Administration Quality	Human Development Index	Political Stability	Internal Land Concentration
Denma rk	**41**	71	81	94	81	0.15
Greece	**37**	38	15	88	51	0.27
Vietna	**38**	41	46	70	44	0.00

m						
Azerbaijan	**43**	51	58	75	21	0.07
Seychelles	**36**	50	70	80	71	10.48

Denmark has a high Land Stress, which is balanced by high Land Administration Quality, Human Development Index and Political Stability. Greece has a similar Yale land SR to Denmark but with a much lower Land Stress. In this case, very low Land Administration Quality and moderate Political Stability counterbalance this low Land Stress. In the case of Azerbaijan, a very low Political Stability explains why the SR value is close to that of Denmark, but with a much lower Land Stress.

Vietnam and Greece have similar SR and similar Land Stress and Political Stability. However, Vietnam has a moderate Land Administration Quality and Human Development Index, whereas Greece has a very low Land Administration Quality and a rather high Human Development Index. The average of the two indexes therefore results in similar values for both countries.

All the aforementioned countries have low Internal Land Concentration values, while it is much higher for the Seychelles. However, the average of Political Stability and Internal Land Concentration tends to decrease the effect of low Internal Land Concentration values, which is why the Seychelles have a lower SR with very high Internal Land Concentration.

3.2) Comparison at the European scale

With the JRC method the results are available for 24 countries of the European Union (see **Error! Reference source not found.**-B). Values range from 0.03 (Finland) to 10.9 (Luxembourg).

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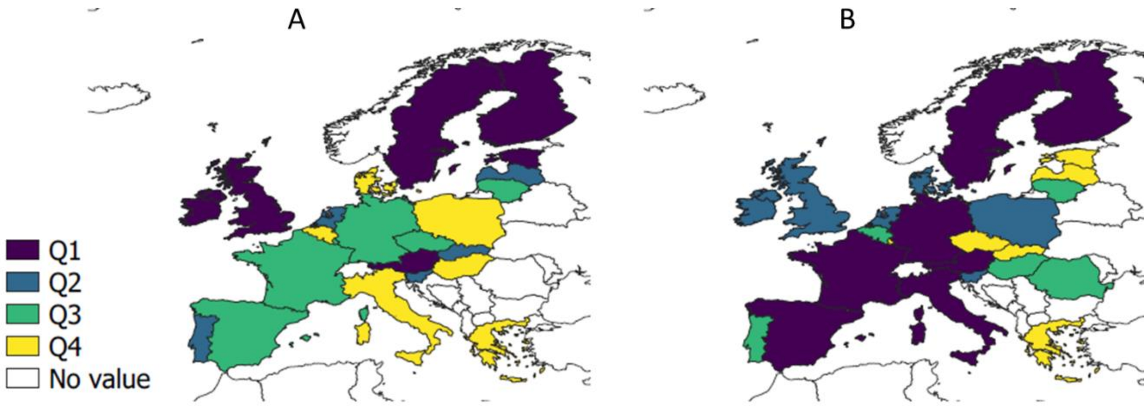

Figure 2 : Land Supply Risk in Europe with the method from Yale (A) and JRC (B) (equal length interval clustering). The higher the land Supply Risk, the higher the risk of land not being accessible. Q1 to Q4 are the quartile of land Supply Risk distribution, i.e. country belonging to the Q1 class have the lowest land Supply Risk, those to Q4 the highest. No values are due to lack of data.

These results are quite different from those computed with the Yale method as reported in Figure 2-A. The Spearman correlation coefficient between the two methods is 0.21, confirming that the two methods obtain different SR rankings.

Countries with the highest Yale land SR in Europe are Hungary, Denmark, Poland, Greece, Belgium and Italy. Those with the lowest Yale land SR are Sweden, Finland, Ireland, Estonia, Austria and the United Kingdom.

Luxembourg, Estonia, Slovakia, Greece, Czech Republic and Latvia have the highest JRC land SR. These countries have high to very high Internal Land Concentration, low FDI restriction and/or Land Recycling rates, and low Land Administration Quality or Human Development Index. Those with the lowest JRC land SR are Finland, Sweden, Austria, Italy, France, Spain and Germany. These latter countries have low FDI restrictions and Internal land Concentration, and moderate to high Land Administration Quality and/or Human Development Index.

Countries that have either high Internal Land Concentration (Estonia, Latvia, Luxembourg, Slovakia), high land transaction restrictions (Estonia, Latvia) or high Land Recycling rates (Italy, France, Poland and Spain) present the highest ranking discrepancies in the land SR score ranking between the Yale and the JRC methods.

The JRC method is more sensitive to Internal Land Concentration due to its aggregation formula. Land transaction restriction and land recycling parameters add further information about land SR, implying that countries with extreme values for these three factors present significant differences in ranking between the criticality methods.

In addition, with the Yale method a higher weight was assigned to Land Stress, while it is more easily offset by other factors in the JRC method; therefore this also accounts for differences in ranking.

3.3) Results for the Land Stress (LS)

The LS index are calculated for 228 countries, and vary from $4.8E^{-4}$ (Iceland) to 0.87 (Pitcairn Island in the South Pacific), indicating contrasting results worldwide (see **Error! Reference source not found.**).

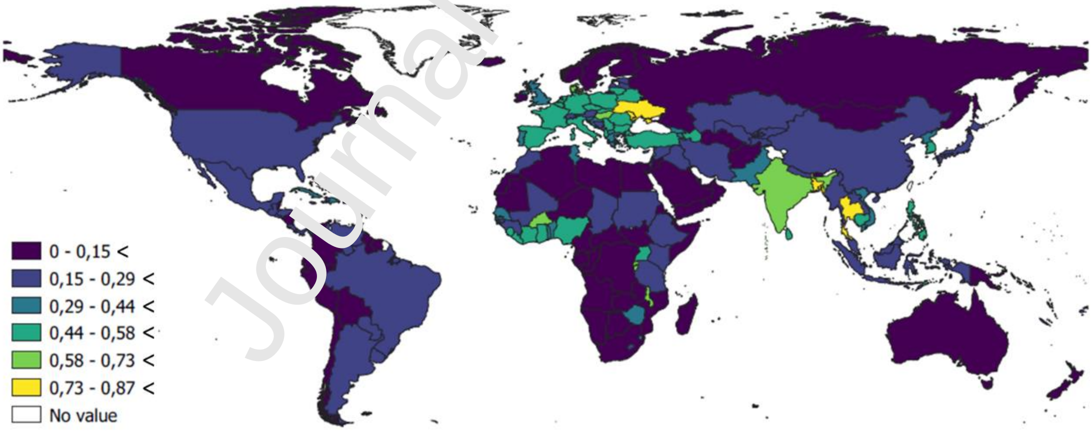

Figure 3 : Land Stress world map (linear equal interval length clustering). The higher the Land Stress, the higher the proportion of human land used in proportion to country area. No values are due to lack of data.

The countries with the highest LS values (LS > 0.73) are of three types. The first consists of very small countries with a total area smaller than 600 km^2 (e.g., Pitcairn Island, Nauru, Monaco, San Marino Island, Kiribati, the Vatican, Tokelau, Tuvalu and Norfolk Island), for which the high LS is due to little land availability in general. The second type includes countries with a very large agricultural

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area (Herbaceous crop > 68 % of the total area), which explains their high LS (e.g., Moldova, Ukraine and Bangladesh). Finally, Thailand combines both large areas of cultivated land, and vast protected areas, thus entailing a high LS.

From a global perspective, the highest LS are found in Europe, the southern part of West-Africa, South and South-East Asia.

In Europe, high LS values are first explained by the high rate of built-up areas, with highest rates in Germany and Belgium. Moreover, in Europe, all countries with high LS scores have a very high surface coverage of herbaceous crops compared to the world average, except for Spain and Italy where woody crops predominate. Finally, Luxembourg has a very high rate of protected areas.

In the southern part of West Africa, the high LS scores are not due to artificial surfaces (the proportion of which is very low) but to large areas of crops, well above the world average, except for Ghana, Liberia and Ivory Coast where the high rate of perennial crops or managed forest areas explains the high values for LS.

In South and South East Asia, the trends are similar to West Africa, i.e. high rates of cultivated land explain the high LS. Thailand and Vietnam also have large areas of perennial crops, which increase their LS. In addition, India and Pakistan have large areas that are not usable because of snow and ice cover, which further increase their LS. Finally, Thailand and Cambodia have large protected areas, which also increase the LS.

According to the Land Stress equation (Eq.(4)), the higher the permanent snow surfaces, the higher the Land Stress. However, countries with high rates of permanent snow surfaces such as Norway, Canada, Switzerland and Iceland also have among the lowest land stress index. Therefore, their Land Stress are not explained by their high surfaces of permanent snow, but by their lower rates of agricultural and artificial land surfaces.

3.4) Effect of data sources for European countries

With data from Eurostat, the JRC land SR are on average 112% higher than with FAOSTAT data (**Error! Reference source not found.**). Countries with the largest discrepancy are Finland and Sweden. However, the country ranking is not particularly altered; indeed the Spearman correlation coefficient between land SR with data from Eurostat and FAOSTAT is 0.88.

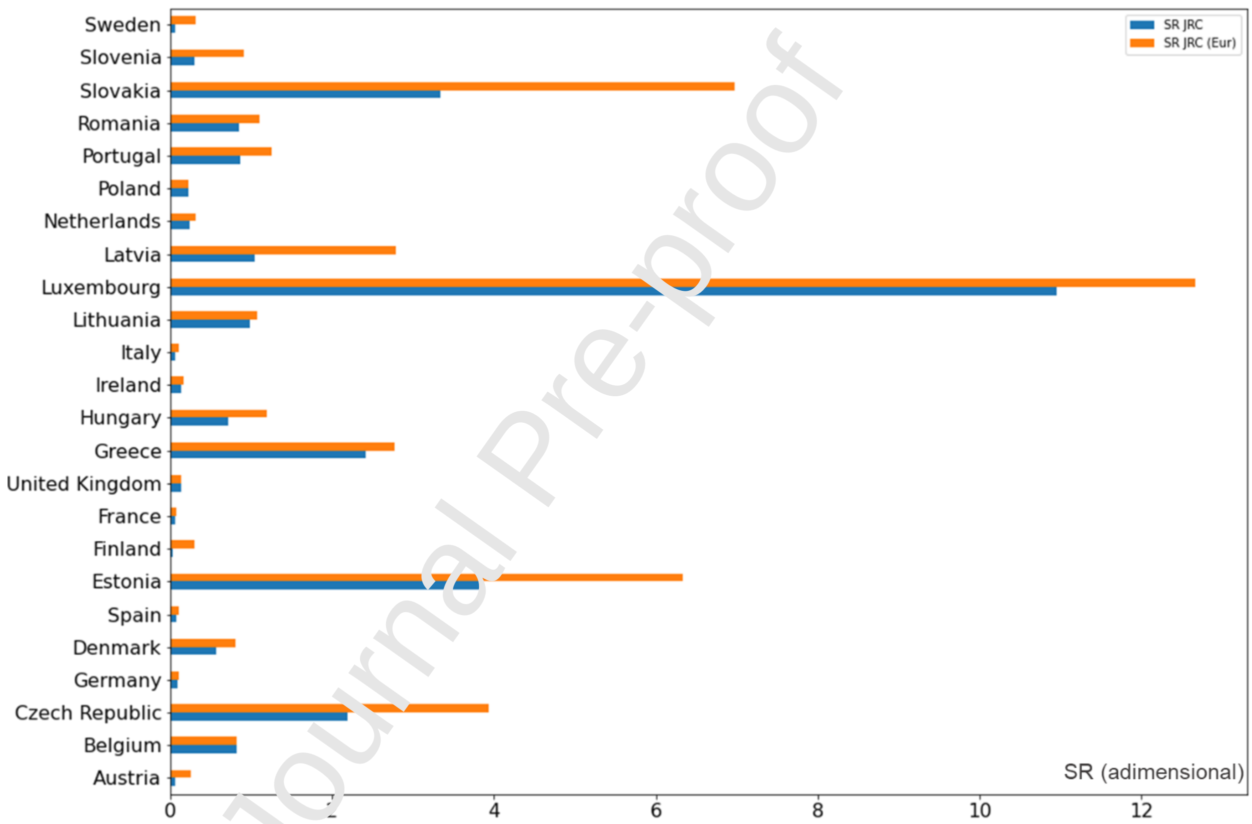

Figure 4 : Comparison of land Supply Risk (SR) with the Joint Research Center (JRC) method for European countries, with FAOSTAT data (SR JRC - blue bars), and Eurostat data (SR JRC (Eur) - orange bars).

The Land Stress calculated with Eurostat data are on average 24% lower than with FAOSTAT data. Examination of the ranking difference reveals that only Ireland presents an increase in Land Stress with Eurostat data, whereas Portugal and Slovenia present the strongest decrease (Supplementary material Figure A.1). The Spearman correlation coefficient in this case is 0.92.

On the contrary, the Internal Land Concentration calculated with the Eurostat agricultural census are on average 125% higher than with FAOSTAT data. This result is partly due to data structure. The

Eurostat classification considers 9 farm size classes, while the FAOSTAT classification considers 14. Therefore, the Utilised Agricultural Land share per farm size class mathematically increases, which translates into much higher Herfindahl-Hirschman Index (see Eq. (7)).

Here the Scandinavian countries present the highest discrepancy (Supplementary material Figure A.2). The Spearman correlation coefficient is 0.89.

Therefore, the countries with the highest JRC land SR discrepancy between the two data sources are those with the largest difference in Internal Land Concentration values.

Using second data source highlights a strong sensitivity for the agricultural census data, but does not significantly modify the relative ranking of countries

4) Discussion

An approach was developed to quantify spatialized land SR indexes at global and European levels. The objective was twofold, i.e. i) to consider land resources in criticality methods as previously performed for other resources and ii) to discuss the choices in terms of criticality methods used and data sources.

The method has been successfully applied in many countries around the world, and the resulting indexes have clearly confirmed strong contrasts between countries in terms of land SR. These results open up promising application perspectives, even though certain improvements could be made from a methodological and operational point of view. These issues are discussed below.

4.1) Applicability

The land SR index is the first step toward the integration of land resources in criticality assessment methods. This is especially relevant for technologies or sectors that require mineral resources as well as land. For photovoltaic production systems for instance, mineral criticality assessments have been conducted (Guzik et al., 2022) without considering the land resource,

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although it is now an identified limiting resource (Nonhebel, 2005). Criticality assessment in the agriculture sector could also benefit from the land SR as it would allow the issues of land (Gardi et al., 2015), water, fossil fuels and mineral criticality such as phosphorus (Cordell & Neset, 2014) to be addressed jointly. The nexus frameworks between food, energy, water and land (Nie et al., 2018; Ringler et al., 2013) could therefore be enhanced by the land SR index that quantifies the level of accessibility of land in a country.

The land SR index could also be integrated to product assessment methods like Life Cycle Assessment (LCA) using land at different locations around the globe during its life cycle. Currently, work is underway to include criticality measures in LCA (Berger et al., 2020; Cimprich et al., 2019; Santillán-Saldivar et al., 2021; Sonderegger et al., 2020; Sonnemann et al., 2015). The LCA method already accounts for land use and environmental impacts of land use change. It also quantifies the amount of land required for a product. Furthermore, the inclusion of the land SR as characterisation factor could provide complementary information on how critical a system can be relative to the land resource. However, this would require the spatialization of land use flows at the country level to be more systematic in LCA databases.

4.2) Data availability

Further versions of the SR can be calculated, because most of the indexes are updated on a yearly basis. Concerning the Land Stress index, a temporal series of the index could also be computed to analyse past tendencies in physical availability of land. To assist in decision making and scenario analysis, further development of the Land Stress or Internal Land Concentration index could also be based on prospective instead of past data.

Regarding spatial variability, the land SR index could be computed at a finer resolution than the country, which is recommended for criticality assessments (Ioannidou et al., 2019). For instance, the Land Stress index could be computed at finer scale using remote sensing databases. However,

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regarding the other parameters, such as the influence of local governance or commercial factors on land accessibility, data availability at sub-country scale could become an issue.

4.3) Model assumptions

4.3.1) Land Stress

Another assumption concerns the classification of grasslands. In this work, grasslands have not been counted as land consumed by human activities, but this remains a strong and debatable assumption. A first possible distinction could be made between permanent and non-permanent grasslands. As the latter occur between two crops, the land should be considered as consumed by human activities. However, even among permanent grasslands, some may be fertilised and highly managed while others are much closer to natural ecosystems with minimal human intervention. A finer distinction between the different types of grasslands and their allocation between areas consumed or not by human activities would therefore be more relevant and could change the land stress results for countries with high grassland rates such as Ireland or New-Zealand.

A third limitation of the Land Stress index is that the protected area values originate from a different database to that of the other Land Stress parameters. This may cause compatibility problems. Protected areas can overlap with other types of land covers, leading to a potential overlap between parameters from Eq. (4). It is assumed that the chosen categories of protected areas (type I and II) are not crops or artificial land cover, and that the overlap with unusable land represents a minority of surface areas. Finally, the World Database on Protected Areas states that IUCN classification is known only for a third of the areas listed. The Protected Area parameter is thus potentially underestimated, which would lead to higher land SR.

The use of protected areas is also conceptually questionable. First, they have been used as a proxy to describe areas left for ecosystem requirement, where no human economic activities occurs. However, humans in the purpose of protecting biodiversity often manage protected areas. Therefore, protected areas could include areas that are not directly used for economic activities, but

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where human interventions take place in favour of biodiversity. Secondly, protected areas are based on human decisions, and can be far from terrestrial ecosystem requirements. The importance of ecoregions for global biodiversity or areas needing conservation per country (Allan et al., 2022) could be another choice in further versions of the Land Stress index to represent crucial areas for ecosystem functioning or determining a threshold not to cross.

4.3.2) Internal Land Concentration Index

The Internal Land Concentration Index seems to be driven by the country surface. Indeed, only six countries have an Internal Land Concentration value above 10, and they are all small islands. A further version of the model could consider weighting this index by the country population to avoid this country size bias.

In addition, several farms can be under the same ownership, thus the area per farm would not correctly represent the land market concentration. For example Brazil has a high land concentration (Paulino, 2014), which does not appear in the data. Such detailed agricultural census studies exist for some countries (Glass et al., 2019; Paulino, 2014) but no globally consistent data were found.

Furthermore, only agricultural land is taken into account with these data. However the majority of land surface areas used by humans are for agricultural purposes (FAOSTAT, 2020).

Finally, the Herfindahl-Hirschman Index ranges from 0 to 10,000. For mineral resources, the Herfindahl-Hirschman Index assesses the concentration of market shares of supplier countries (i.e. dozens of suppliers), while the land adaptation considers the market shares of landowners in a country (i.e. thousands of landowners). The orders of magnitude of this index are therefore very different according to the two types of resources. Hence, for JRC, the Herfindahl-Hirschman Index for mineral resources is scaled by dividing it by 10 000, while the Internal Land Concentration index is not rescaled. For Yale, the affine normalisation that was chosen flattens all the values due to the existence of extreme values, thus resulting in indexes that are all very close. The affine normalisation does not provide more weight to the extreme values of market concentration, as is the case for

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water or mineral resources (Graedel et al., 2012; Sonderegger et al., 2015). However, in the absence of a function defined by a biophysical or socio-economic relationship, normalisation was performed in the simplest manner. Due to these differences in values, the comparison between land and mineral resources is limited for both methods.

4.3.3) Political Stability

In the Yale method, the PS index is used to account for the fact that land access is better guaranteed in politically stable countries, as it is the case with other resources (Graedel et al., 2012; Sonderegger et al., 2015). More specifically, it is assumed that PS is a proxy to assess land tenure right access in a country, considering that the more stable a country is, the more land rights are respected (Russet, 2011). However, this proxy remains generic and, other more specific indicators on the protection of land tenure rights exist, such as the Sustainable Development Goal (SDG) 1.4.2 "Proportion of total adult population with secure tenure rights to land" (United Nations, 2021). This indicator currently covers 33 countries, but could be used in future work on land criticality if its scope is extended.

4.3.4) Method comparison

In all cases, it is essential that the methodological framework for computing supply risk remains the same for all resources to ensure consistency and comparability. The comparison between the Yale and JRC approaches points out how results can be completely different from one method to the other, as highlighted in the literature (Berger et al., 2020; Cimprich et al., 2019; Sonderegger et al., 2020).

The land Stress index was given more weight in the Yale methods, to ensure comparability with the water criticality methodology from Sonderegger et al., (2015), whereas it has the same weight as other indexes in the JRC methods. Therefore, the Yale method rather focuses on the spatial accessibility of land. However, on one hand, this choice remains based on expert judgement; and different ways of weighting the land SR parameters could be considered for the Yale method. On the

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other hand, the influence of internal land market concentration is assigned more importance within the JRC method because this parameter is merged with the country political stability in the Yale method. Furthermore, the JRC focuses more on the institutional context of a country that determines land accessibility by including land recycling and transaction restriction parameters that are determined by political institutions. With this in mind, the restriction of land acquisition by foreign investments is considered to increase the land supply risk of a country, in the same way as for mineral resources. However, this relationship depends on the point of view. Indeed, for a country, the accessibility to its own land is higher if foreign capital does not have access to land; therefore its land supply risk is decreased if there are restrictions on land acquisition by foreign capital. More conceptually, the JRC method considers the acquisition of natural resources in foreign countries by European countries to be beneficial, which seems questionable from an ethical point of view.

The two methods also differ according to their aggregation methods. The linear aggregation of the components in the Yale method dampens the index variability (Graedel et al., 2012; Sonderegger et al., 2015), whereas, in the JRC method, the multiplication of all indexes amplifies small component variations.

In the Yale method, the weighted average aggregation of the indexes requires for the rescaling of many indexes. For this purpose, different mathematical functions can be used, the choice of which can change the ranking of the indicators, thus adding a layer of subjectivity to the model.

Finally, for mineral resources, the SR dimension of the JRC method involves a substitution index, which was transformed into an adaptation index for land. With the Yale method, the substitution index is included in the Vulnerability to Supply Restriction dimension. Hence, the JRC SR dimension overlaps with the Vulnerability to Supply Restriction dimension from Yale; this fact should be kept in mind when comparing the two methods.

"Other methods could have been investigated, including those recommended by the LCA community (Berger et al., 2020; Sonderegger et al., 2020) such as GeoPolRisk (Santillán-Saldivar et al., 2022) and ESSENZ (Bach et al., 2016), or the SCARCE method (Arendt et al., 2020) which builds on the ESSENZ method. As the objective here is to make initial proposals to include land criticality, they could be studied at a future stage".

4.4) Extending the concept to other criticality methods

Existing criticality methods do not have the same goal and scope, indicators, nor aggregation method, which explains the great variability in their results (Schrijvers et al., 2020). This variability was observed when applying the criticality concept to land with two known criticality methods. Nevertheless, other recognised methods exist (Hackenhaar et al., 2022), including those recommended for use in LCA (Sonderegger et al., 2020), such as GeoPolRisk (Santillán-Saldivar et al., 2022) and ESSENZ (Bach et al., 2016). The concept of land criticality could also be included in these methods, with some adjustments.

The GeoPolRisk method is more import based, with a focus on resource concentration and geopolitical factors in supplier countries (Cimprich et al., 2019). In order to adapt it to the land resource, the main adjustment would be to change the aggregation formula, which is based on the physical flows of resource imports and exports from countries and cannot be used as it is for a resource that is not transportable.

The ESSENZ method includes several other factors such as price volatility or demand growth for instance. Adapting this method to the land resource, the main adjustment would be to develop these factors for land. Price volatility could be computed on the basis of land prices in countries, but the demand growth parameter would require further investigation on how translating this concept to land. Moreover, ESSENZ does not provides a single aggregated Supply Risk index, and it is at a global scale. In order to have an aggregated SR index per country, the works of the SCARCE method (Arendt et al., 2020) could be used, which adapts ESSENZ to the country scale by providing a single indicator of SR.

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The adaption of criticality frameworks to the land resource highlighted the variability among criticality methods, and adapting the concept with other criticality methods would be one of the next research perspectives.

5) Conclusion

In this study, the development and analysis of indexes quantifying access to land according to biophysical, economic and social factors proved the interest of extending the supply risk concept to the land resource. These methodological developments have been performed in line with the criticality methods of Yale and JRC, to ensure comparability across resources. The developed land SRs are available by country. They allow for the quantification of risks related to potential inaccessibility of land resources and for disparities between countries to be revealed. This index can be used Quantifying this supply risk is all the more important as more and more human activities rely on access to land resources such as food, energy or material production.

However, the developed index can still be further improved and several perspectives have been opened. A promising direction would be the integration of land quality parameters, based on soil characteristics such as biochemical contents or degradation states. Integration of such information would allow to consider that even if access to land is possible, it may be unsuitable to support certain human activities such as agriculture. As not all human activities require the same land quality, this would imply a differentiation in the land SR per land use types. This could provide better information on the state of land resource within countries.

Finally, to extend and further develop the concept, its integration in other renowned criticality methods would be an interesting approach. As each method has its own specificities, it will require to develop new criticality factors, and may involve to adapt aggregation formulas.

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CRediT authorship contribution statement

Lazare Deteix: Conceptualization; Methodology; Investigation; Software; Data Curation; Writing-Original Draft. **Thibault Salou:** Conceptualization; Methodology; Investigation; Validation; Supervision; Writing-Review & Editing. **Sophie Drogué:** Conceptualization; Validation. **Eléonore Loiseau:** Conceptualization; Methodology; Investigation; Validation; Supervision; Writing-Review & Editing; Project administration.

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Declaration of competing interest

The authors declare no competing interests.

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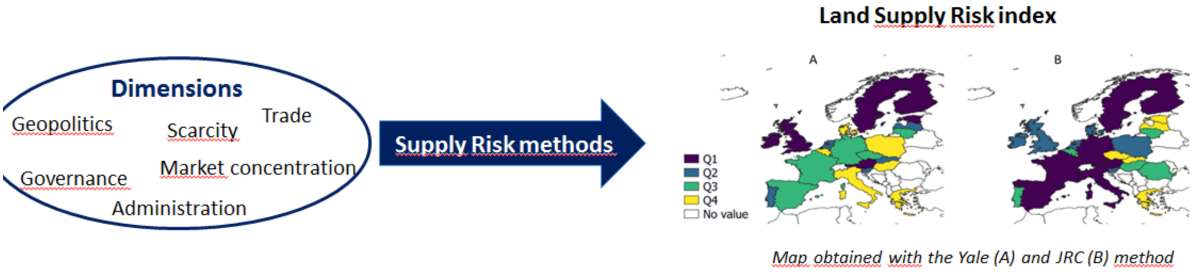

Graphical abstract

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Highlights

- Land is a key resource for human activities, which is under growing pressure
- Land is still not considered in criticality methods along with other resources
- Regionalised land supply risk indices are built, adapting two criticality methods
- The results show that land can be a critical resource for certain countries
- Data quality and conceptual choices are discussed, comparing methods and data sets

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