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Towards an assessment of adaptive capacity of the European agricultural sector to droughts

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ABSTRACT

Analyses of climate change vulnerability and risk have been steadily evolving, and have moved from an impact-focused towards a more risk-based approach. In the risk and vulnerability communities, the relevance of resilience and adaptive capacity (AC) are increasingly emphasized. Another emerging analytical framework is the idea of assessing AC and resilience in terms of the Sustainable Livelihoods Approach (SLA), which studies welfare as a function of multiple forms of assets ('capital') that systems and agents may utilize to both recover as well as increase resilience in the future. We assess a new method for assessing AC at a sectoral level and operationalize AC measurement based on an SLA to assess the ability of the European agricultural sector to adapt to extreme droughts. We create a set of indicators which highlight areas of high or low AC, forecast to estimated times the world will reach 2° of warming using Shared Socioeconomic Pathway (SSP) and Representative Concentration Pathway (RCP) scenarios to drive AC indicator projections based on a fixed effects model. We find that based on this approach, Central and Northern Europe rank higher in overall capacity than countries on the periphery, and projections to 2 °C do not change results to a large degree. We critically reflect on the use of this approach and suggest possible use cases for results in larger studies of sectoral vulnerability, and highlight key data gaps and the need for a stronger empirical basis for selection of indicators, which constrain our ability to assess AC.

Practical Implications

As climate change is predicted to have major impacts in the future, particularly upon the agricultural sector in some regions of the EU, this work attempts to move beyond biophysical impacts to assess the capacity of these regions to adapt to change. Southern areas face the possibility of increased droughts, and increased warm and dry conditions are forecast for southern and central Europe, with the possibility of up to 10% losses in crop yields by 2080. These assessments underscore the need to further investigate the potential impacts on the broader socioecological system. One possible avenue lies in emerging risk methodologies, which emphasize assessing the socio-ecological system as a whole. Our work provides an assessment of the adaptive capacity of the agricultural sector of the EU facing drought hazard.

Adaptive capacity (AC), ''the ability to adjust, take advantage of opportunities, or cope with consequences. (IPCC, 2014),'' has been assessed before on both a global and regional level, but the research methods, sectors of study, and spatial scales have differed greatly. This work can be seen as a first step, and while the process of assessing AC is still in relative infancy at this scale and for individual sectors, it presents valuable avenues for further research and a valid option for a way to convey important information to stakeholders and to emphasize the ideas of risk based analysis and the resilience of systems to change.

The Sustainable Livelihoods Approach has been utilized in previous AC assessments and provides a broad framework for organizing the different forms of assets to which people have access, and helps describe the use to which these assets may be put. SLA was developed conceptually by Ellis (2000) and views livelihoods strategies as made of activities that are invented, adapted and adopted in response to changing availability to five types of capacities or assets:

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1. Human capacity: the education, skills and health of household members.
2. Social capacity: reciprocal claims on others by virtue of social relationships and networks, close social bonds that aid cooperative action and social bridging and linking via which ideas and resources are accessed.
3. Natural capital: the natural resource base such as productivity of land, and actions to sustain productivity, as well as water and biological resources.
4. Physical capacity: items produced by economic activity from other types of capital; this may include infrastructure and equipment.
5. Financial capacity: the level, variability and diversity of income sources and access to other financial resources that combine to contribute to wealth.

Based on the SLA framework, we assemble an index of adaptive capacity consisting of human, natural, physical, and financial capacities, based on both theoretical and empirical links of proxy indicators as drivers of adaptive capacity. The selected indicators can be found in Table 1. These indicators are aggregated at a national level to provide an indication of areas with high or low adaptive capacity of the agricultural sector, and allows for comparisons between EU countries, shown in Fig. 1. Countries in the central European region are found to have higher overall adaptive capacity than those on the periphery to the south and east. France scored strongly in all four capital estimates, and has the highest overall capacity index value, whereas Germany, which did not over- or under-perform in any particular category, but was usually near to the median value, results in a more moderate score. Southern and eastern countries suffer from a lack of physical and human (and to a lesser extent, natural) capacity compared to the core, however there is some bolstering of values from financial capital, where southern drought-prone countries score highly due to strong insurance mechanisms.

As discussed in Section 2, adaptive capacity is only one factor for the impact of extreme events, and when combined with exposure and hazard, produces an estimate of vulnerability. AC can be projected via the use of scenarios describing possible futures, and combined with estimates of future biophysical impacts. Due to the new and novel aspects of our AC assessment, uncertainties and lack of consistent and high-resolution data limits the predictive power of this first order estimate of vulnerability, but we can demonstrate how future work building off of the concepts discussed here can be used. Combining the AC index with estimates of drought hazard impacts from the EPIC model results in an estimate of crop-specific future vulnerability to drought, seen in Fig. 2 below, for varying RCP/SSP combinations.

While this assessment differs from previous ones in its sector- and hazard-specific nature, the use of such a framework provides a basis upon which to frame the organization of AC into four distinct capacities; human, natural, physical, and financial. Due to the specific nature of the assessment, key indicators derived from the SLA framework differ greatly compared to previous AC assessments, which were much broader in nature and used more abstract proxy variables. A more focused approach may provide a clearer picture which is more relevant for the actual hazards facing the agricultural sector, and provide a more accurate assessment of the system's ability to cope with future changes. While our results agree to some extent with previous assessments, findings should not be seen as completely robust, due to a lack of data, and the limitations of the indicator approach to allow for consideration of all possible contributors to adaptive capacity.

The capitals framework does well to illustrate the various assets people or systems have to adapt to change, and goes beyond current vulnerability assessments which view capacities as physical and/or financial capitals with commensurable assets, but how to incorporate the more abstract notions of adaptive capacity and inform probabilistic risk assessments is still an open question Using such a framework to describe capacities is a valuable effort, in that it conveys the idea that the ability of people and systems to adapt to change goes beyond just having fiscal resources or physical goods to help, but that human assets and social bonds, as well as the natural environment, are all critical to facing a changing future climate.

1. Introduction

As disaster impacts continue to increase (IPCC, 2012) amid the threat of climate change – reiterated by broad scientific consensus – there is a growing importance on developing strategies to reduce vulnerability to both current and future extreme events (IPCC, 2012). As emphasized in the latest IPCC Assessment Report, a changing climate will amplify existing risks and create new ones which are unevenly distributed, with greater impacts on disadvantaged communities at all levels of development (Chambwera et al., 2014). In order to effectively make decisions regarding adaptation to future changes, policymakers need an approach which can link climate-driven impacts and scenarios for the future with greater understanding of the overall system in question, such as governance, equity, economic assessments and the diverse set of possible responses to future risks, to both highlight areas that may be vulnerable now and in the future, and recommend policy options to increase resilience (IPCC, 2014).

Risk, as used in the study of extreme events, is a function of vulnerability, exposure, and a hazard. Vulnerability, the propensity of a system to be adversely affected (IPCC, 2012) is influenced by adaptive capacity (AC), "the ability to adjust, take advantage of opportunities, or cope with consequences (IPCC, 2014)." The main challenge in being able to assess adaptive capacity is being able to reveal it, as it is a latent property of a system, only emerging once a system is subject to external stress or shock (Engle, 2011). This

Table 1
Adaptive capacity indicators used in assessment of agricultural sector of the EU.

Human capital	Natural capital	Physical capital	Financial capital
Percentage of farm managers with full agricultural training	Productivity of land	Value of buildings and machines	Total farm cash flow
Farm managers/owners with other gainful employment	Irrigation prevalence	Total current assets (e.g. non-breeding livestock, stores of agricultural products)	Farm solvency
Number of scientists working in agricultural sector	Fertilizer use	Total breeding livestock assets	Crop insurance index score

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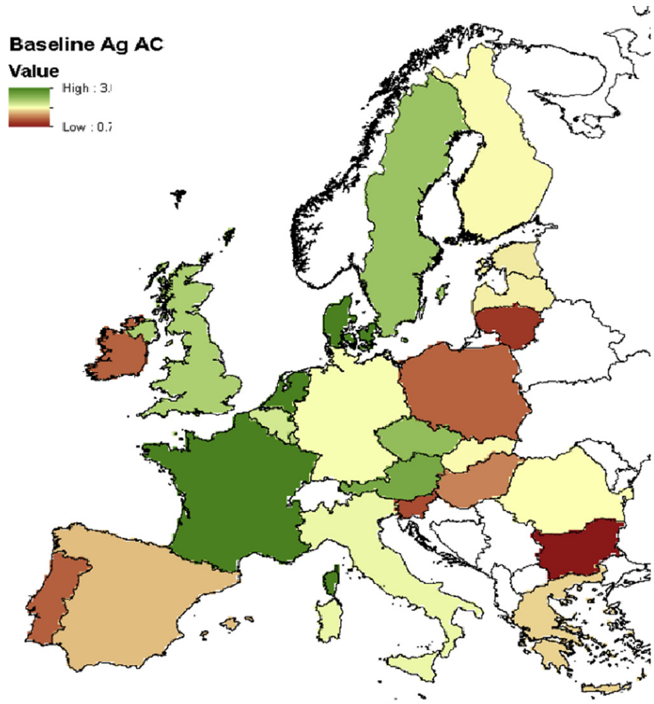

Fig. 1. Aggregate baseline adaptive capacity index for the agricultural sector of the EU.

challenge is made all the more difficult by the fact that the specific factors that determine adaptive capacity are scale, place, and system specific, such that it is difficult to generalise a set of key factors which, if universally improved, would universally enhance adaptive capacity (Tol & Yohe, 2007; Vincent, 2007).

There are various methods which may be used to uncover this latency, all of which essentially entail learning from the past. These methods range from using case studies and temporal analogues (Bussey et al., 2010; Keskitalo et al., 2011; Ford et al., 2010), focus groups and semi-structured interviews (Ivey et al., 2004; Hahn et al., 2009; Engle and Lemos, 2010), to quantitative indicator based approaches (Yohe and Tol, 2002; Fraser et al., 2012).

Our work here tests a new method to move beyond biophysical impacts and assess the ability of EU member states to adapt to future changes. While research for the European Union focuses heavily on biophysical impacts, the vulnerability and adaptive capacity is not as well understood, especially at a sectoral level, which until now has not received much focus in terms of assessing AC. We address this question by developing a new index of adaptive capacity for the EU, focused specifically on the agricultural sector and drought hazard, as a part of the Impact2C project, which aimed to estimate the impacts of two degrees Celsius of climate change on Europe. Our approach addresses issues inherent in previous assessments of AC via the use of the Sustainable Livelihoods Approach (SLA) as a deductive framework and by projecting AC forward using a scenario-based approach. The resulting AC index highlights a number of areas where member states may be able to improve, or may be adequately prepared to cope with impacts. We then demonstrate how such estimates can be incorporated into larger assessments of vulnerability, using drought in the EU as a test-case, and discuss uncertainties and limitations in the approach.

The paper is organized as follows: Section 2 provides an overview of previous work on assessing adaptive capacity, and Section 3 addresses the methodological approach to assessing biophysical impacts, adaptive capacity and vulnerability and projecting these values to future time periods. Section 4 presents results of adaptive capacity and vulnerability assessment to the EU agricultural sector, with Section 5 discussing the science policy implications of our results as well as adaptive capacity and vulnerability more generally, and Section 6 providing conclusions.

2. Quantitative indicators of adaptive capacity: a review

There is now a relatively large body of literature describing various climate change vulnerability assessments, most of which adopt the IPCC framing of vulnerability as being a function of exposure, sensitivity, and adaptive capacity. The focus of our review here is on the main methodological characteristics of how adaptive capacity has been operationalized, i.e. the deductive basis on which the drivers of adaptive capacity are thought to derive, the way in which proxy indicators for these drivers have been selected, and whether or not adaptive capacity has been projected forward. Table 2 summarises these methodological characteristics.

An analysis of Table 2 highlights three key methodological issues which we have addressed in this work. The first issue is that there are very few studies that have employed a sound theory upon which to base their analysis of adaptive capacity. To date there are only five studies that could be said to adopt a sound theory for understanding AC and how it is shaped. These studies are those of Nelson et al. (2005, 2007, 2010b), Gbetibouo and Ringler (2009), and Antwi-Agyei et al. (2012), and they all employ the sustainable livelihoods theory of Ellis (2000). The sustainable livelihoods theory is described in more detail in the methodology section below.

The second issue is that, of the nine studies which analyse future vulnerability, only five of them project AC forward, and one of those five, Moss et al. (2002), simply projects AC forward by using an integrated assessment model to estimate values for the indicators that constitute their model. This model of AC has very little statistical or theoretical basis for the drivers and proxy indicators of AC. Of the other four studies, the projection of AC is carried out on the basis of expert judgement of the drivers of AC, and as such they all lack a coherent theory. Metzger et al. (2006), in assessing the vulnerability of a number of ecosystem services in Europe, employ largely the same approach as Moss et al. (2002), although they use different indicators and project these forward using regression models. Yohe et al. (2007) and Patt et al. (2010) both develop models for adaptive capacity based on observed relationships between impacts and various indicators, using statistical analysis to identify significant indicators of adaptive capacity, and use the model to project AC forward using projections of changes in driving variables. Fraser et al. (2012) develop a model of AC based on the statistical relationship between an adaptive capacity index and seven national-level indicators of AC, selected based on expert knowledge. They then apply this model to project AC forward by using readily available projections of the indicators. Their results are rather mixed but do show some promise in explaining adaptive capacity. The work in Patt et al. (2010) is shown to explain just over half the variance in numbers killed or affected by disasters. The advantage of the statistical approach taken by Yohe et al. (2007), Patt et al. (2010), and Fraser et al. (2012), is that at least some idea of the statistical power of the AC models is obtained.

A third issue addressed is the scope of adaptive capacity in terms of sectors and hazards addressed. Many previous regional or global assessments of AC have used a single generalized estimate of AC to assess vulnerability to climate impacts more broadly, without focusing on specific hazards or sectors affected. Acosta et al. (2013) and Dunford et al. (2014) among others use a single index of AC made up of parameters such as the number of patents

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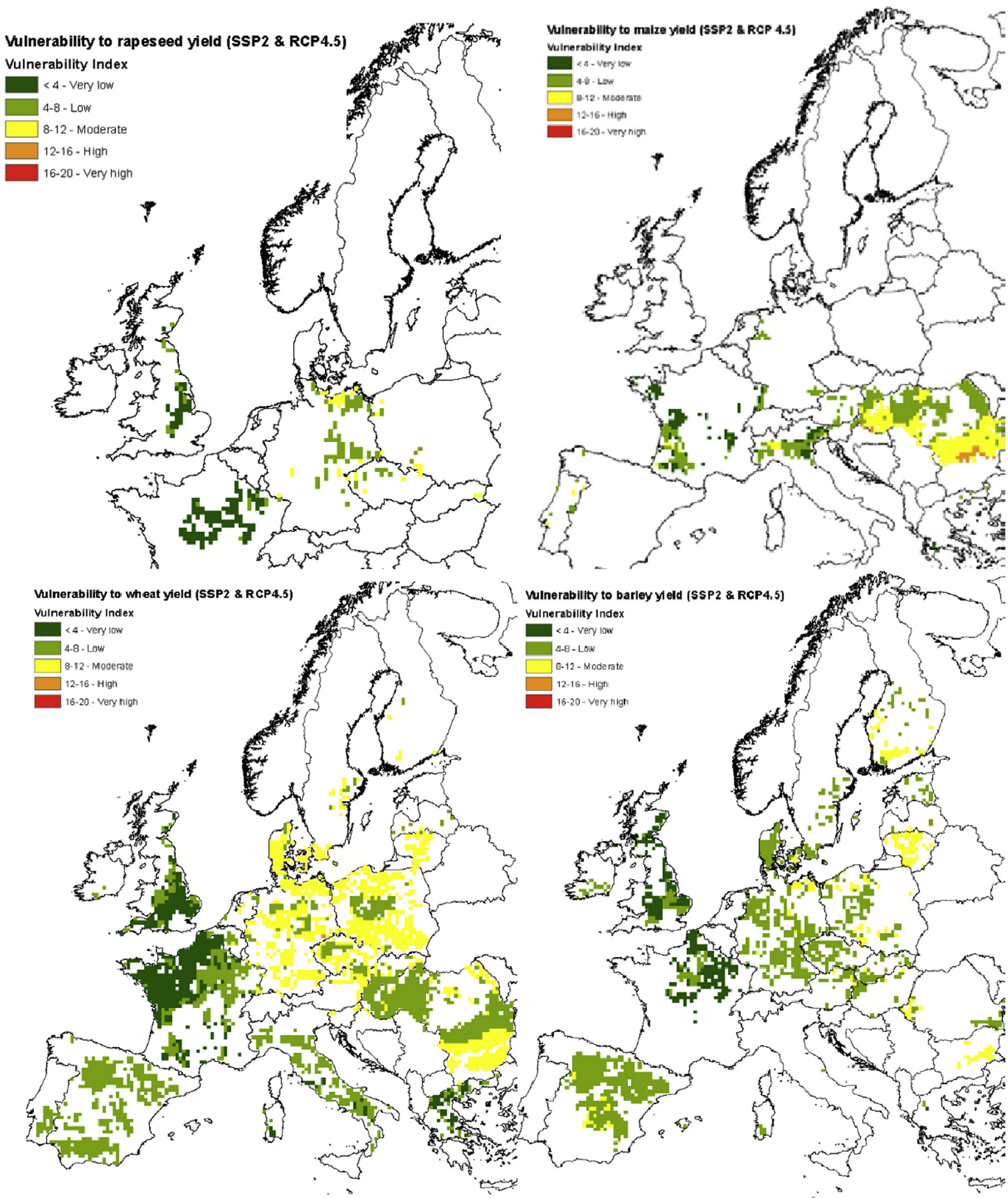

Fig. 2. Example vulnerability estimates produced with sector-specific adaptive capacity estimates, for the vulnerability of various crops to drought hazard, using SSP 2 and RCP 4.5 to create future scenarios of capacity and crop yield.

issued within a country and telephone or internet access to reflect various capacity, and apply this broader index to multiple hazards. In this work, we focus explicitly on the agricultural sector of the European Union, and assess adaptive capacity to a single hazard, drought, in a manner similar to Nelson et al. (2010b).

3. Methodology

Developing indicators of AC via a quantitative approach can be generalized to a three stage process, the first being the establishment of a deductive basis upon which to understand the drivers

Table 2
Summary of key methodological characteristics of vulnerability assessments using quantitative indicators to operationalize adaptive capacity.

Study	Temporal and spatial scale. Is AC projected forward?	Deductive basis of AC: conceptual framework, theory, or expert judgement	Indicator variable selection method: deductive, inductive, or data availability
Moss et al. (2002)	Current and future vulnerability Global scale at the national level AC is projected forward	No basis for understanding the drivers of AC	Data availability
Yohe and Tol (2002)	Current vulnerability	IPCC TAR conceptual framework	Inductive
Brooks et al. (2005)	Current vulnerability Global scale at the national level	Expert judgement	Inductive
Nelson et al. (2005) and Nelson et al. (2007)	Current vulnerability of Australian broadacre agriculture	Sustainable livelihoods theory	Deductive
Nelson et al. (2010b)	Current and future vulnerability of Australian broadacre agriculture AC is not projected forward, uses current AC as a proxy for future AC	Sustainable livelihoods theory	Deductive
Metzger et al. (2006)	Current and future vulnerability National and sub-national level AC is projected forward	Expert judgement	Deductive
Tol et al. (2007)	Current and future vulnerability National level in sub-Saharan Africa AC is projected forward	Expert judgement	Inductive
Vincent (2007)	Current vulnerability National and sub-national level	Expert judgement	Deductive
Sharma and Patwardhan (2008)	Current vulnerability District level in India	Expert judgement	Inductive
Allison et al. (2009)	Future vulnerability Global scale, National level AC not projected, used current AC as a proxy for future AC	Expert judgement	Deductive
Gbetibouo and Ringler (2009)	Future vulnerability, but AC is determined based on observed data and used as a proxy for future AC	Sustainable livelihoods theory	Deductive
Simelton et al. (2009)	Current vulnerability Province level in China	Expert judgement	Inductive
Simelton et al. (2012)	Current vulnerability Global scale at the national level	Expert judgement	Deductive
Patt et al. (2010)	Future vulnerability National level AC is projected forward	Expert judgement	Inductive
Pandey et al. (2011)	Current vulnerability National and sub-national level	Expert judgement	Deductive
Ericksen et al. (2011)	Future vulnerability National level AC not projected, used current AC as a proxy for future AC	Expert judgement	Deductive
Antwi-Agyei et al. (2012)	Current vulnerability National and sub-national level	Sustainable livelihoods theory	Data availability
Fraser et al. (2012)	Current and future vulnerability Global scale at the national level AC is projected forward	Expert judgement	Inductive

of adaptive capacity. Essentially this step is the use of a theory or conceptual framework to organize and guide the selection of proxy indicator variables. The second step follows by operationalizing this framework and selecting appropriate indicator variables. The final step pertains to how these proxies are assembled into an overall index or set of indicators, with the key issue at hand being how to determine the relative importance of the various factors selected and prioritizing or ranking them.

Within this process, there are two prevailing approaches for selecting appropriate proxies, a deductive and inductive approach (Adger and Vincent, 2005; Hinkel, 2011). A deductive approach takes a conceptual framework or expert judgment and uses it to decide which indicators are likely to be related to a driver of adaptive capacity, whereas inductive approaches choose indicators based on statistical correlation of potential indicators and empirical observations of damage or harm. While the second process is termed inductive, it should be emphasized that a deductive framework is commonly used to understand and organize drivers of AC from which candidate indicators can be chosen (Brooks et al., 2005). Assessing vulnerability to drought requires two inputs, an estimate of both biophysical impacts and adaptive capacity (Metzger et al., 2006). Combining these two indicators produces an indicator of the propensity of an area to be adversely affected by a hazard, and moves towards a risk-based framework for assessing and coping with extreme events. Building off of the overview of AC discussed above, this section outlines the approach taken to assess the adaptive capacity of the EU agricultural sector to drought, starting with our deductive basis for understanding AC, specifying how adaptive capacity is determined and projecting the newly-formed index to future time periods. We use the IPCC (2012) definition of drought as "a period of abnormally dry weather sufficiently prolonged for the lack of precipitation to case a serious hydrological imbalance (Heim, 2002)".

3.1. Establishing a deductive basis to understand drivers of AC

As mentioned above, most assessments thus far have not utilized a sound basis from which to understand AC, with only five studies surveyed utilizing a pre-existing framework. Ad hoc or expert judgement approaches suffer from a lack of comparability and statistical approaches are difficult to apply to regions or problems beyond their original intent. This necessitates the use of a framework upon which AC can be understood, allowing cross-comparisons with other studies to be made. One previously used framework is that of the Sustainable Livelihoods Approach (SLA).

The SLA utilized in previous AC assessments provides a broad-based framework for organizing the different forms of assets to which people have access, and helps describe the use to which these assets may be put. SLA was developed conceptually by Ellis (2000) and views livelihoods strategies as made of activities that are invented, adapted and adopted in response to changing availability to five types of capacities or assets:

1. Human capacity: the education, skills and health of household members.
2. Social capacity: reciprocal claims on others by virtue of social relationships and networks, close social bonds that aid cooperative action and social bridging and linking via which ideas and resources are accessed.
3. Natural capital: the natural resource base such as productivity of land, and actions to sustain productivity, as well as water and biological resources.
4. Physical capacity: items produced by economic activity from other types of capital; this may include infrastructure and equipment.
5. Financial capacity: the level, variability and diversity of income sources and access to other financial resources that combine to contribute to wealth.

This approach sees adaptive capacity as a function of the balance between the five capitals, but does not assume that capitals are entirely commensurable. While it may be possible to compensate for a lack of a certain capacity via use of others, there may exist thresholds at which a lack of capacity cannot be overcome via the substitution of other capacities. In our work, we reduce the SLA framework to focus on four asset types: human, natural, physical, and financial.

Literature review revealed little in the way of social capital indicators suiting our needs, compared to the other capital types. The objective of social capacity to incorporate institutional factors was better reflected in financial capacity, with the inclusion of drought insurance policy measures, and to a lesser extent the ability of farms to obtain credit, whereas social capital conveyed no real adaptation or coping measures, so it was removed from analysis. The institutional dimension emphasized by social capital was subsumed by financial capital, as outside sources of funding after an event, or the implementation of policy measures e.g. drought relief programs and insurance, can be seen as measures of solidarity and incorporate institutional aspects.

The SLA framework allows for a simple but well-developed way to think about complex issues in applications linked to policy and practice, and can be applied at varying levels of detail, from a broad conception framework to a tool for designing programs and or evaluate strategies. Most work thus far with SLA has been theoretical, however use of the framework to assess adaptive capacity is becoming more common, such as the work described by Keating et al. (2014), which aims at establishing quantitative indicators of community-level resilience based on an SLA approach.

3.2. Operationalizing the framework

We first established a collection of candidate indicators for AC based on proxies found to be previously used, or which are shown to be linked to AC via literature review. The review gathered a large number of potential indicators for each capital type, resulting in the need to try and identify key factors for each capital and reduce the number of proxies needed. Many assessments of AC focus on multiple hazards and address multiple sectors; using the SLA framework and focusing on only one sector, a number of initial variables literature could be disregarded. To best describe each capacity while limiting the total selection in order to be readily accessible to stakeholders and policymakers, three proxies were selected from the total pool that best reflected the various facets of each capacity type. A discussion on the selection of final proxies for each type of capacity can be found in the results section.

Emphasis was initially placed on sub-national indicators, in order to get a more accurate picture of AC, but it was found that for the vast majority of proxy data, sub-national indicators did not exist, or datasets were too incomplete to cover the entire study area. As selection of indicators was driven based on hypothesized relationships between proxies and the qualities of each capital stock, as well as empirical observations of qualities that enhance AC, many of our selections limited us to national-scale AC assessment.

3.3. Assembling proxies into an index of AC

Upon selection of the final set of indicators, each proxy was normalized (by taking the value for each observation minus the mean value, divided by variance) and combined into five capital stock indicators via equal weighting, resulting in a final index for each capacity as a value between zero and one. Combining these capacities into a single index of AC required choosing between a small number of different methods available, discussed below.

A survey of previous work on aggregating AC indices yielded a varied picture in terms of methods applied. Generally, index creation falls into three categories: (1) – expert judgment (Brooks et al., 2005; Moss et al., 2002, and others); (2) equal weighting (Vincent, 2007; O'Brien et al., 2004); and (3) the use of statistical methods such as principal component analysis (PCA), factor analysis, or use of fuzzy set theory (Nelson et al., 2010a,b; Acosta et al., 2013; Gbetibouo and Ringler, 2009). While equal weighting of proxies is commonly undertaken, the main critique is that it does not accurately represent 'true' AC values, but benefits from being easy to carry out and able to be done without extensive expert knowledge. Expert judgment improves upon equal weighting, but is difficult to carry out at a large spatial scale such as the EU, which would require a number of stakeholders and experts from various sub-regions. It can be difficult to come to any sort of consensus in terms of weighting factors, which could be compounded due to the large area (and thus number of experts) in question.

Of the remaining options, while fuzzy set theory seemed to provide a novel means of creating an index, it is not a simple process to apply, and requires a good amount of experience and familiarity with the process to carry out the assessment. Additionally, the step of fuzzy inference, which combines qualitative values, is heavily reliant on application of inference rules "designed from experience, expert knowledge, and literature sources (Acosta et al., 2013)." Thus fuzzy set theory embodies expert judgment, which would lead to the inherent problems of that approach, again namely the large spatial scope in question.

Alternatively, principal components analysis (PCA) offers a relatively easily implemented method of weighting and computing capacity indicators, which has been met with some success in the literature in the past. Nelson et al. (2010b), Gbetibouo and Ringler (2009) and Abson (2012) all successfully use PCA to create indices of AC at various scales. PCA benefits from being able to rapidly change indicators based on new/improved datasets or changing deductive frameworks. It is also easily reproducible in further research, whereas fuzzy modeling may be more difficult due to weighting and fuzzy inference rules established by expert judgment. Following the example of Nelson et al. (2010b), who compared the results of weighting via equal weights and PCA and discovered that the results from either approach were almost identical, we did our own assessment with our indicators and

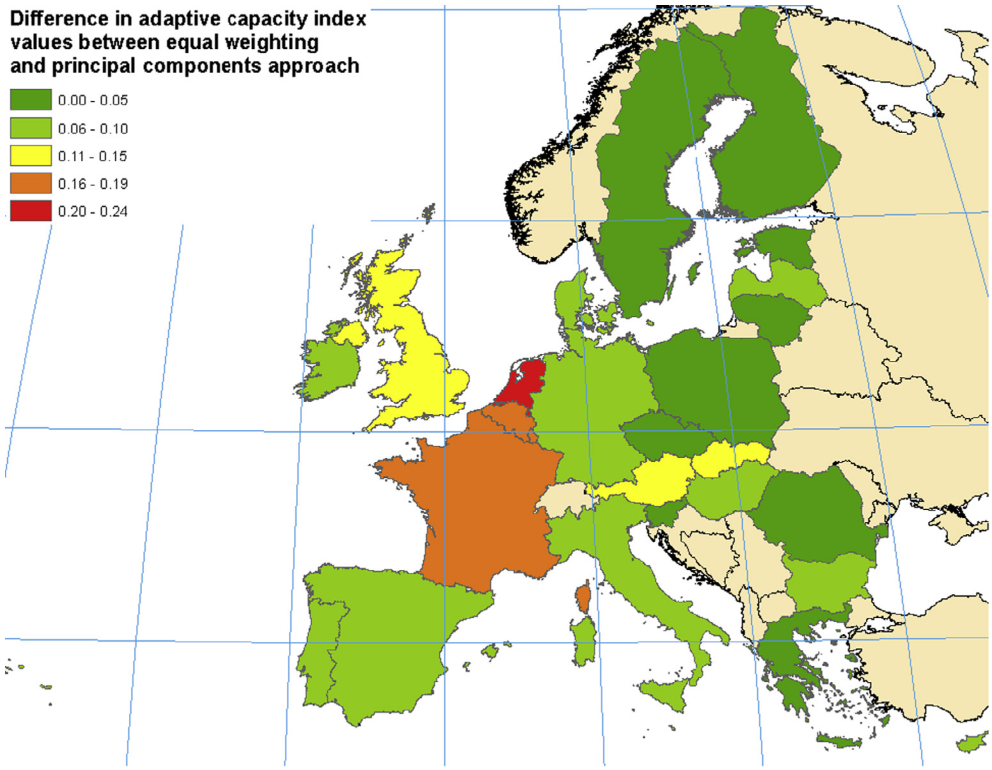

Fig. 3. Comparison of principal components analysis and equal weighting methods of indicator aggregation. Lower values indicate higher agreement between the two differing methods.

arrived at similar results. For some capacities, results of the standardized index (between 0 and 1) changed less than 0.01 on average. Similar results were found for other capitals, with results normally changing very little, especially when the classification of the index into categories (very high, high, medium, low, very low) was taken into account. Fig. 3 compares the resulting adaptive capacity indices derived by both equal weighting and PCA, and as can be seen, differences are minimal.

As previously discussed, equal weighting has the weakness of inaccurately conveying that proxies equally affect overall adaptive capacity, especially when combining various capitals (e.g. human, physical, etc.) into one index. PCA avoids this drawback, but as shown, differences in results of the two methods are minimal. This essentially negates the benefits of PCA, while drawbacks remain. PCA is more time-consuming than equal weighting, and is more difficult to communicate how results were generated to stakeholders and policymakers.

As one of the only other European-level studies, CLIMSAVE, also took an equal weighting approach, in order to maintain consistency of results and be easily relatable to previous work, as well as being easily understood by readers, we chose to use equal weighting in creation of our indices and classified results in a similar manner to the previous assessments (see, for example Dunford et al., 2014).

3.4. Projecting adaptive capacity

As mentioned previously, one of the novel features of this research was the projection of AC to a future time period, in spite of the inherent uncertainty arising from predictions of future values, which warrants discussion. Vincent (2007) emphasizes the impossibility of projecting capacities into the future with any certainty at all. As pointed out by Yohe (2001), numerous factors which influence future AC, such as demographics and technological change, also drive emissions, and thus future mitigation and possible future impacts. Vincent and Yohe make valid points, and express concern with placing too much "trust" in AC indicators, but the critiques are relatively narrow and focus on the most direct "use-case" of AC indicators without considerations for how even uncertain measurements of current and future AC can be useful to policymakers, regardless of uncertainty. Focus on conceptual use could justify the use of future predictions as it helps to introduce new concepts and possibilities to stakeholders.

We utilize Shared Socioeconomic Pathway (SSP) projections as a basis for forecasting AC into the future via panel regression (in a manner similar to Acosta et al. (2013)), in order to use scenarios which are pre-existing and are accessible to other researchers for future work and comparison. SSPs describe plausible alternative trends in society and natural systems through the end of the 21st century, both in narrative storyline form and quantitative measurements of development (O'Neill et al., 2013). Based on these narratives, the SSP database provides key indicators for financial, human, and social capitals, including national GDP estimates, population and education levels, and the share of the population living in urban environments. The SSP database contains information on projected GDP, population (e.g. absolute numbers and education levels), the levels of urban and rural population, as well as land use and agricultural production values. Similar to Acosta et al. (2013), we utilize a fixed effects model to determine the relationship between individual capital indicators and the SSP projections.

3.4.1. Panel regression approach

Panel regression was carried out for all indicator variables which were available in a time series format, and three routes of analysis were pursued:

1. A fixed effects model for individual country assessment of each indicator (dependent variable) separately, with GDP, tertiary education rate, and urban share of population as predictor variables, with time fixed effects.

2. A fixed effects model of each indicator separately using all countries, with GDP per capita, tertiary education rate, and urban share of population as predictor variables, and country fixed effects.
3. A random effects model of each indicator separately using all countries, with GDP per capita, tertiary education rate, and urban share of population as predictor variables.

The first approach, assessing the dependent variable for each country as a separate regression, allows for different changes in the dependent variable over time (i.e. different slopes for each country). However, due to an incomplete dataset and a small time series, degrees of freedom were limited to such an extent that results were not statistically significant, and projecting results to the 2 degree periods led to extreme outliers.

A second attempt was made, using the entire dataset and having country fixed effects, with the result of each indicator having the same rate of change over time, with individual y-intercepts for each country. Here we were able to obtain much higher degrees of freedom and statistically significant results. We then compared the results of the fixed effects model to a random effects model via the Hausman test, which consistently produced p-values lower than 0.05, indicating a preference for fixed effects results due to inconsistency of random effects.

The final model used to project AC indicators to the 2 degree period is as follows:

$$Y_{it} = \beta_1 \ GDP/capita_{it} + \beta_2 \ Tertiary\ Education_{it} + \beta_3 \ Urban\ Share\ of\ population_{it} + \alpha_i + u_{it}$$

where Y_{it} = Indicator for country i at time t, β_x = coefficient for predictor variables, α_i = intercept for country i, and u_{it} = error term for country i at time t.

The dependent variables used were calculated from the SSP dataset for SSPs 1, 2, and 3; GDP per capita, the tertiary education rate of the population, and the proportion of the population living in urban areas were used as predictor variables. The model was run individually for the 11 final AC indicators for which panel data was available (see Table 1; the only variable not projected was "insurance penetration," a categorical variable with no time-series data). The majority of results reflect a level of significance of 0.05, but some individual country results were found not to be statistically significant. While the projected AC indicators are in most cases statistically significant, it is good to recognize the limitations of this approach and treat them as the SSPs are intended, as scenarios or examples of possible futures, for assessing how future socio-economic changes might affect adaptive capacity. A more complete and/or lengthy dataset (in terms of time series covered) as well as a greater understanding of the drivers of each individual AC indicator, could improve the reliability of results, and remains a limitation of the panel regression approach for forecasting AC indicators.

Upon determining the functional relationships between provided SSP data and our indicators, we project AC estimates to the two degree period. As individual regional climate models (RCMs) reach two degrees over a range of time, which differs per RCM and Representative Concentration Pathway (RCP) used, we establish the "year we hit 2 degrees" to be the median year of the 30 year time slices from the RCMs. For RCP 2.6, we set 2086 as the 2 degree target year, and for RCP 4.5, the year 2056. For the time period 2000–2010 (with the exception of physical capital, which exists for years 2004–2012), indicators were regressed dependent on GDP, percent of population with tertiary education and urban share of population for SSPs 1, 2, and 3. As SSP projections are only provided in 5 or 10 year increments, GDP and population data were interpolated to the target years. After projection, the projected indicators were again aggregated via equal weighting.

4. Presentation of results

4.1. Adaptive capacity – current values

Results from the assessment of agricultural AC are presented in the following section, separated by capacity type. Maps of each capacity's indicator values are given at national scales, with values ranging between 0 and 1, with 0 being the worst, compared to all other European regions, and 1 being the best. Indicators are discussed in depth below, but are reproduced in Table 3 for conve-

Table 3
Proxy indicators used in creation of the agricultural adaptive capacity index, and a comparison of selected indicators with observed adaptation strategies/actions documented in literature review.

Indicator	Action/response
Human capacity	
Farm managers with agricultural training	Asante et al. (2012) results from study in Ghana show that increased education increases ability to respond to changes
Farm managers with other gainful activity	Pandey et al. (2007) found that income diversification was extremely important in coping with drought in rice cultivation, and Dixon et al. (2014) emphasize diversification of livelihoods as being important to coping in Ugandan agriculture.
Number of scientists	Pandey et al. (2007) emphasize that local community mechanisms such as land (re)allocation, better management of local water resources, and better forecasting and communication of forecasts help farmers cope with adverse impacts, which could be influenced by prevalence of highly knowledgeable researchers in the region. Asante et al. (2012) also emphasize that technology has a positive effect on adaptive capacity, but possibly only for those with already high adaptive capacity
Natural capacity	
Irrigation coverage	Multiple sources indicate that irrigation practices improve adaptive capacity to drought, and that drought conditions spur farmers to adapt irrigation measures, and if they are already in place, to adapt more technologically advanced and efficient measures (Schuck et al., 2005)
Productivity of land	"At farm level, some factors, like farm intensity, size and land use, can give some indication of the capacity to adapt" (Reidsma et al., 2010). Dixon et al. (2014) show that increasing productivity indicates higher adaptive capacity as well
Fertilizer use	Brooks et al. (2005) assert that areas with higher fertilizer use are less likely to be healthy and have higher adaptive capacity overall
Physical capacity	
Buildings and machines Total current assets Total livestock assets	Multiple studies (see, for example Dixon et al., 2014; Reidsma et al., 2010; Olesen et al., 2011) found that diversifying via raising livestock, as well as utilizing capital in the form of machines to intensify agricultural production, both increase capacity
Financial capacity	
Insurance penetration	Olesen et al. (2011) found crop insurance to be an "effective tool for mitigating the effect of climatic hazards during the growing season" based on a study of EU agriculture
Farm solvency Total farm cash flow	In order to satisfy the definition from Ellis (2000) as financial capacity being the level and diversity of income and access to other sources, we utilize solvency to assess farms' ability to obtain credit, and total farm cash flow

nience, along with results from key studies indicating observed or theorized link of the indicator to adaptive capacity, based on field studies. Fig. 4 shows estimated capacities at NUTS0 level, disaggregated into human, natural, physical, and financial capacities.

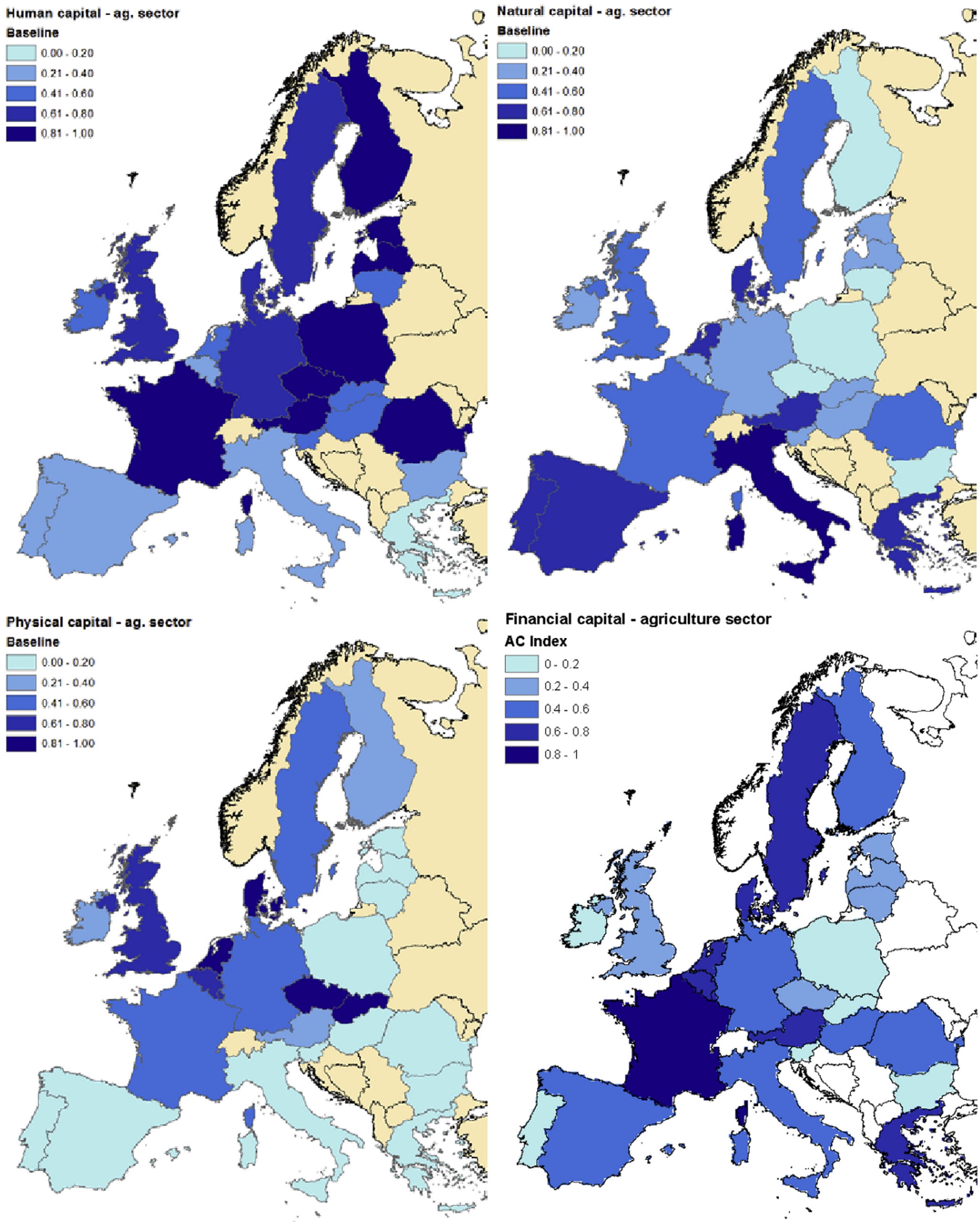

Fig. 4. Agricultural adaptive capacity of NUTS0 regions of the EU, disaggregated into (clockwise from left): human, natural, financial, and physical capacities.

4.1.1. Human capacity

Human capacity represents the education, skills, and health of household members. Since being conceptualized by early thinkers such as Adam Smith (1776), it rose to prominence during the 1960's when emphasis was placed on the skills, knowledge, and health of a labor force as a key variable in national growth rates and the earning capacity of individuals (Becker, 1975) As described by Grossman (2000), human capital contributes to income generation because "a person's stock of knowledge affects his market and non-market productivity, while his stock of health determines the total amount of time he can spend producing money earnings and commodities" (Grossman, 2000). This was further elaborated upon by Schultz (1961), who outlined five components of human capital:

1. Health facilities and services, e.g. anything affecting life expectancy, strength and vitality of people.
2. Apprenticeships and on-the-job training.
3. Formal education.
4. Study programs for adults not organized by employers, e.g. agricultural extension programs.
5. Migration to adjust to changing opportunities.

Based on the initial literature review and data collection, three factors were selected, relating to education and training, occupation, and local knowledge and innovation. While health is frequently emphasized as an important contributor to AC, indicators such as life expectancy or self-assessed health were provided at too broad a level. An indicator of the health or well-being of agricultural workers would be more relevant, but as data only existed for the population as a whole, it was disregarded in order to select indicators with a more relevant agricultural and drought hazard focus.

Education and training: Education and work-related training have been shown to contribute to individuals' earning capacity over their lifetime (Becker, 1975) and is a well-accepted principle. Evidence of this can be seen in the attention given to national education statistics and political focus on educational attainment and school retention rates. Based on indicators surveyed, the *percentage of farm managers with full agricultural training* was selected, as farms run by individuals with a more advanced level of training would be more likely to either be aware of strategies to cope with and adapt to changing conditions, as well as more likely to learn about and implement new ideas.

Diversity of farm income/changing occupation: The ability of a region to change from less profitable industries towards those with higher profits can indicate evidence of collaborative economic action and high human adaptive capacity (Nelson et al., 2007). As farms face higher risks in the future, the ability to diversify income and profit sources could be a key asset to weathering future droughts, beyond strategies which would be attempted without moving away from strictly agriculture. Diversifying farm income by switching to tourism would be an example of other gainful activity, along with other strategies. To represent this ability of farms, the indicator *Farm managers/owners with other gainful activity* was selected to represent this facet of human capital.

Local knowledge and innovation: This facet of human capacity deals with the region's possibility for technological change and greater understanding of hazards and willingness to adapt. In previous work on adaptive capacity, the amount of scientists in a population was frequently utilized as an indicator of a system's ability to understand and adapt to changing hazards and vulnerability (see, for example: Yohe and Tol, 2002; Tol and Yohe, 2007; Allison et al., 2009). For this concept, the indicator *number of scientists per* 100 K *population, working in the agricultural sector* was selected.

Generally, northern countries fare better in terms of human capital, with southern and Mediterranean countries having lower indicator values for all three selected indicators. Greece ranks lowest in percentage of workers with agricultural training, and fares poorly in both the "other gainful employment" and "scientists working in the agricultural sector", although for the latter indicator, Belgium fares worst, with a value of 0.5 per 100 K population, compared to the average value of 1.64, which heavily impacts its overall rating. Spain also lacks farms with other means of gainful activity, as well as a low education level of farm workers, dragging down its overall human capacity. Italy, while not having any one extremely low indicator value, is below average for all three proxies, resulting in its low aggregate indicator. Interestingly, Romania, which has the lowest percentage of ag. managers with full training, conversely had the highest amount of scientists in the ag. sector, and above average percentage of managers with other gainful activity, boosting its index compared to its neighbors.

4.1.2. Natural capacity

Natural capacity is a system's natural resource base: the productivity of land and the ecological resources from which we derive livelihoods. As seen from the resilience framework, natural capacity can also be utilized to lessen the impacts of disaster events. In terms of agroecosystems, natural capital takes on two important distinctions, renewable and non-renewable natural capital, with renewable being self-reproducing and self-maintaining processes, such as ecosystem goods and services like the operation of the hydrological cycle. Non-renewable capital would include fossil fuels and mineral deposits. Also relevant for agriculture are the renewable functions of soil formation and biological diversity (Cleveland, 1994). With this in mind, we separate natural capital into factors, based on Nelson et al. (2007), productivity of land and sustaining it, and conservation of ecological assets.

Indicators are chosen to complement the modeling process and results of typical biophysical impact modeling, and not duplicate factors which could be considered to be more closely related to sensitivity.

Productivity of land: As stated in Nelson et al. (2007), productivity of land "is a direct measure of one of the most immediate dimensions of natural capital contributing to the adaptive capacity of land managers. Simple measures of biophysical productivity such as crop yields and livestock turnoff relate production to the area of land." Productivity seems to present a bit of a conundrum in terms of adaptive capacity and climate change as it can be seen as being driven by or affected by a changing climate, as well as indicating coping and adaptive capacity, and here we follow the trend in literature to see resource productivity as an indication of a system's capacity (see, for example, Cleveland, 1994; Nelson et al., 2007, 2010a,b; Dixon et al., 2014). Efforts to maintain productivity are also highly relevant to drought hazard and are subsumed under this category, such as the prevalence and use of irrigation, and availability of water.

From the literature review and availability of indicators for EU level, two proxies were selected to cover this category; *productivity of land* as an indicator of productivity, and *irrigation coverage* in an attempt to assess regions' ability to maintain productivity.

Ecological conservation: Ecological assets, beyond being a form of capital able to be transformed by economic activity into assets supporting agricultural production, provide a buffer against degradation and serve as a measure of biophysical health of land (Nelson et al., 2007). A review of AC work highlights various indicators relevant to this category, such as management of riparian zones, forest cover/remnant vegetation cover, forest change rates, fertilizer use, air quality measurements, groundwater recharge rates, etc. (See, for example: Nelson et al., 2010a,b; Pandey et al., 2011; Brooks et al., 2005; Moss et al., 2002). The most pertinent indicator with EU coverage for this work is *fertilizer use* from the Eurostat database, and was selected to represent ecological conservation, and is used as a proxy for ecosystem health as well as the degree of human intrusion on the natural landscape. Areas with higher fertilizer use are less likely to be healthy and have higher adaptive capacity overall (Brooks et al., 2005).

4.1.3. Physical capacity

Physical capacity reflects farm assets created through economic production processes, e.g. buildings, irrigation canals, roads, and machinery (Ellis, 2000). Most assessments of AC are focused on large regions and address multiple hazards and sectors, resulting in typical proxy indicators such as water supply and sanitation prevalence, health infrastructure, road density and built-up areas (Brooks et al., 2005; Pandey et al., 2011; Moss et al., 2002). These indicators are too broad and have little relevance to our analysis. Other works, such as Nelson, break down physical capacity into on farm assets and regional assets; while on-farm assets are clearly relevant for a discussion of drought, regional assets are less so, as proxies such as remoteness and stocks of housing in the region seem to have little relevance to adaptation to drought. As a result, we focus here on farm assets and data provided by the Farm Accountancy Data Network (FADN) periodic farm survey. For physical capacity, three indicators were selected which reflect on-farm assets and better convey the AC of farms: *value of buildings and machines, total current assets* (a measure of non-breeding livestock and other circulating capital), *and total breeding livestock assets*.

As seen, physical capital for the average farm is concentrated in mostly central European countries, which have higher indicator values than countries on the periphery, with almost no exception. A negative correlation seems to appear in regards to physical capital and financial capital, specifically agricultural value added, as countries with a higher ag. value added score generally have much lower physical capacity, but as higher GDP and industrialization is seen in countries with a lower ag. value added percentage, it does stand to reason that they would have more high intensity agriculture with more physical capital requirements.

4.1.4. Financial capacity

Financial capacity (the level, variability, and diversity of income sources, as well as access to other resources) contributes to adaptive capacity via the ease at which savings and credit can be transformed into consumption and other forms of capital via investment (Nelson et al., 2007). Income levels, for example, provide an indicator of the immediate financial resources of a farm. Other proxies, such as diversity of income generation, used in human capacity, also have relevance here. Beyond farm income and diversity, other large factors come into play, notably for agriculture, insurance and farm subsidies. These various factors contributing to financial capacity are not necessarily correlated, as can be seen below.

In order to satisfy the definition from Ellis (2000) as financial capacity being the level and diversity of income, and access to other sources, we selected three indicators which tried to cover the broad spectrum of financial capacity. To assess farm cash flow, *total farm cash flow (including subsidies)* was selected from FADN survey data, but subsidy contributions were removed from the variable, given the recent move by EU countries to change and limit the agricultural subsidy regime. To assess farms' ability to obtain credit, a ratio of assets to liabilities was used to calculate *farm solvency*, providing an indicator of profitability and creditworthiness (DG Agriculture 2011). *Crop insurance* was included via a scoring system created which indicates the availability and type of crop insurance, i.e. if crop insurance is not available at all, the value is zero; if private insurance is available, the value is 1; if there is a mix of public and private insurance, 2; and mandatory public insurance systems scored as 3; generated from data on insurance penetration from a report prepared for the European Commission DG Climate Action (Bielza et al., 2008).

At first glance, the map of financial capacity seems counterintuitive. By any other indicator of financial capacity, countries such as Germany, Sweden, the Netherlands, Great Britain, etc., should all be outpacing southern Europe, however our results convey the opposite. This observation is true, but what is important to recall is that the capacity being assessed is the financial capital of *the agricultural sector* alone. Our three indicators, total farm cash flow, farm solvency, and the drought insurance indicator, heavily favor southern EU countries. The majority of countries with strong drought insurance mechanisms (thus scoring higher) are southern, whereas northern regions have no mechanisms in place. What is not reflected in the results is the ability of the overall economy to absorb future losses due to climate change, and/or to provide assistance.

4.1.5. Aggregating capitals into an index of adaptive capacity

Values for each capital stock type were summed to create an index of overall capacity, and can be seen in Fig. 5. Countries in the central European region are found to have higher overall adaptive capacity than those on the periphery to the south and east. France scored strongly in all four capital estimates, and has the highest overall capacity index value, whereas Germany, which did not over- or underperform in any particular category, but was usually near to the median value, results in a more moderate score. Southern and eastern countries suffer from a lack of physical and human (and to a lesser extent, natural) capacity compared to the core, however there is some bolstering of values from financial capital, where southern drought-prone countries score highly due to strong insurance mechanisms.

4.2. Projecting adaptive capacity to future time periods

Discussed in Section 3.4, SSP projections were used to project capital indicators via a fixed effects regression model, to different

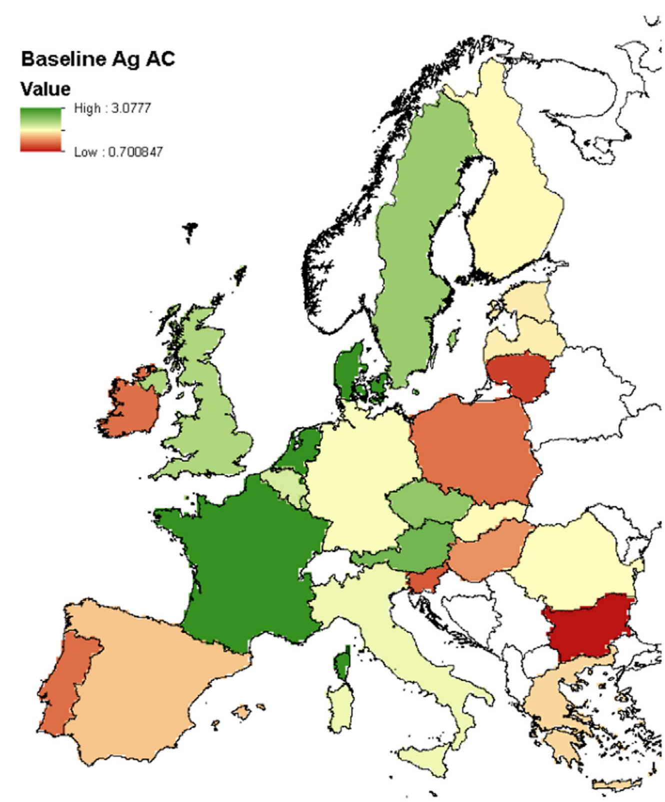

Fig. 5. Aggregate baseline adaptive capacity index for the agricultural sector.

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target years. For RCP 2.6, we set 2086 as the 2 degree target year, and for RCP 4.5, the year 2056. Example results can be seen in Fig. 6 for SSP3 and RCP 4.5. For a full set of results for all capacities for different SSP/RCP combinations, refer to Impact2C Deliverable 10.2 (2015).

While changes occur, compared to baseline AC projections, most trends in the ranking of capacities between countries stays generally the same. Natural capital erodes slightly in all countries compared to Italy and Greece, which stay the same or improve under both SSPs, while Germany, Spain and the Baltic countries as well as Sweden and Denmark all are projected to lose natural capital in all scenarios. Other countries deviate slightly based on the RCP and SSP used, although not to such a degree as those mentioned before. Under an SSP1 assumption of sustainability, physical capital is evenly distributed throughout nations, regardless of the year 2 degrees is reached, while SSP3 results in increasing capacity in the south and eastern areas, with little change to the core countries.

Trends for financial capital also remain quite similar to the baseline projection, especially in SSP1, as the southern countries

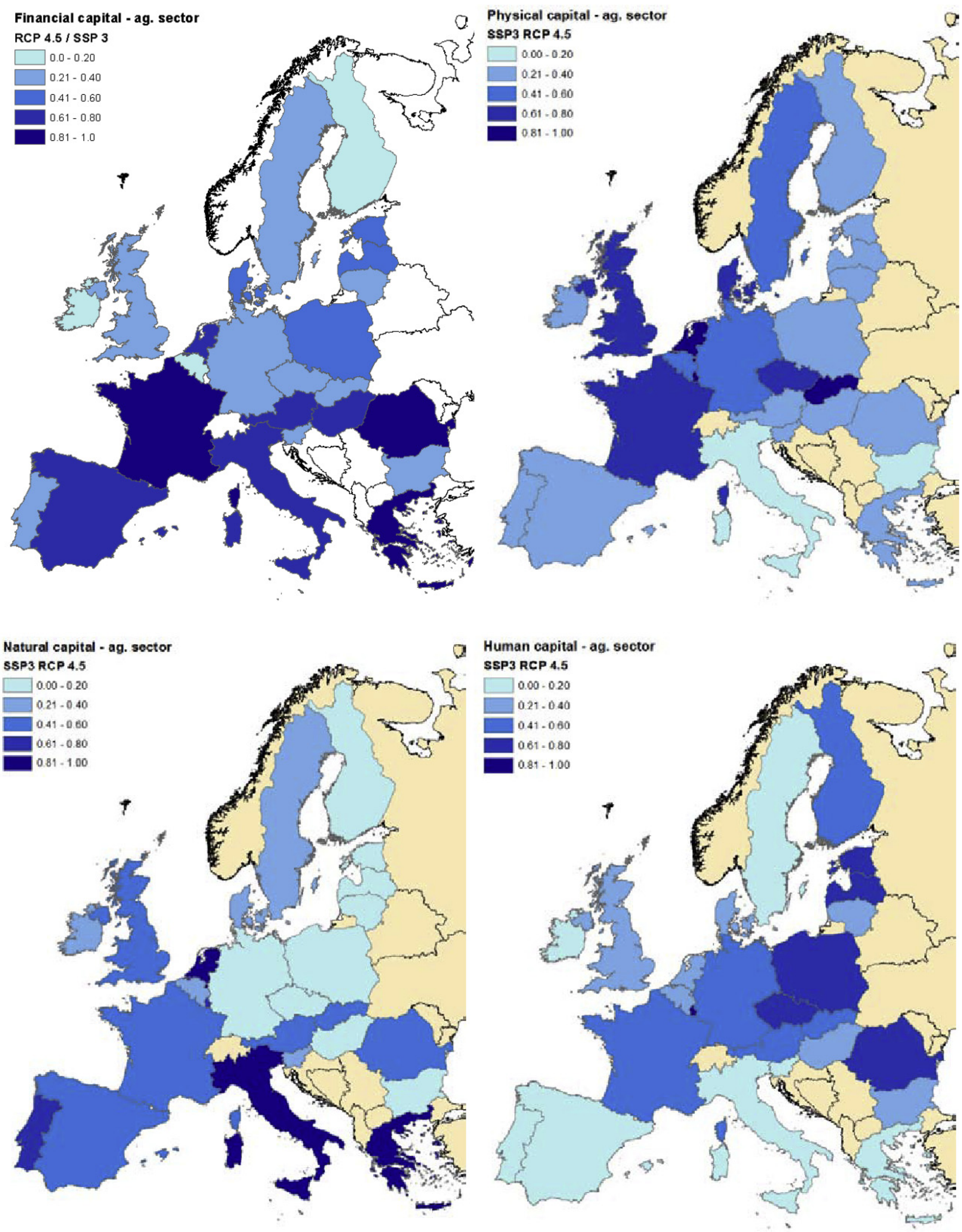

Fig. 6. Agricultural adaptive capacity of NUTS0 regions of the EU for the future using SSP3 and RCP 4.5, assuming the world reaches 2 degrees Celsius of climate change in the year 2056.

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are projected to have higher indicator values for the agricultural sector, mainly due to the use of the drought insurance indicator (which cannot be projected, as it is a matter of policy) as well as the diminishing of core countries' total cash flow (minus subsidies), which drops at a much faster rate than the south and east, with southern countries trending upwards in this regard. Again, this reflects only estimates of the *agricultural sector*, and estimates to RCP2.6 time to 2 degrees are highly uncertain when dealing with such a relatively small dataset available for prediction. Human capital projections vary highly compared to the baseline, mostly due to sharp decreases in estimates of scientists working in the ag. sector, as well as farm managers with full agricultural training. Eastern European countries retain some strength in terms of human capital, mainly because indicators of education and research and development do not fall as sharply as in western nations.

4.3. Future use: assessing vulnerability

As discussed, adaptive capacity is only one factor contributing to the damages due to extreme events, and when combined with exposure and hazard, produces an estimate of vulnerability. The following section presents an example of how AC can be inserted into a larger assessment of vulnerability. Due to the new and novel aspects of our AC assessment, uncertainties and lack of consistent and high-resolution data limits the predictive power of this first order estimate of vulnerability, but we can demonstrate how future work building off of the concepts discussed here might be used.

For our analysis, we assess vulnerability of 4 agricultural crops to increasing drought hazard: the three largest-yielding cereal crops in the EU (wheat, 44% of total cereals, corn – 21%, and barley – 19.6%) and the largest oil-producing crop, rapeseed (21 million tonnes in 2013) (Eurostat, 2015).

To produce a map of future vulnerability, estimates of future hazard and exposure are required. The EPIC (Environmental Policy Integrated Climate) model is used to predict the biophysical impacts of drought for RCP 2.6 and 4.5. Impact models were run using a number of input global/regional climate model (GCM/RCM) pairs, and combined into one multi-model ensemble (MME) for each RCP. For crop yield estimates, the absolute change in yield was calculated from historical to 2 degree periods, and the average for each RCP was found. For an elaborated description of the EPIC model and estimate of future drought hazard to the agricultural sector, refer to Impact2C Deliverable 7.2 (2014).

A region is only vulnerable to a hazard if it is exposed to it; in order to assess only exposed areas and eliminate spurious results, a pre-filtering of impact estimates was needed. For agriculture, fractional harvested area at a grid level was utilized, to only select areas which contain more than 5% of the type of crop in question. Gridded estimates were obtained from EarthStat, a collaboration between the University of Minnesota and University of British Columbia. Areas which meet the pre-selection criteria are then combined with the adaptive capacity index to estimate vulnerability to grid cells which currently produce the crop in question.

Studies of vulnerability using indicators such as we above have taken generally the same approach, notably Nelson et al. (2010b), Acosta et al. (2013) and Tinch et al. (2015), which combine indicators of AC and exposure or impact. Vulnerable areas occur when adaptive capacity is low and impacts or exposure high. Following the convention set forth in the European assessment CLIMSAVE, we use a similar logic, and combine maps of adaptive capacity and biophysical impacts via raster addition in ArcGIS. We invert our AC index scale, so that lower values indicate higher AC, combined with the absolute crop yield change measure from the EPIC model, using model outputs to calculate the change in crop yields at grid level, standardized between zero and five. We then break this down according to Dunford et al. (2014) into six discrete categories of vulnerability: very low, low, moderate, high and very high.

Both the inverse adaptive capacity measurement and impacts are scaled between zero and five, so by adding the two raster datasets for AC and impacts, and multiplying by two, we arrive at an index of vulnerability between zero and 20, broken into discrete categories as described above (See Fig. 7).

As an example for drought hazard in the EU, the vulnerability of wheat, barley, corn, and rapeseed yields to drought were assessed. To generate estimates of crop yields for the impact indicator, the ensemble mean for EPIC model runs at RCP 4.5 and 2.6 was taken, and then combined with the adaptive capacity index for SSP2 (middle of the road).(see Fig. 8).

With the exception of maize yields, the most vulnerable regions according to our approach occur mainly in central and eastern Europe, with Mediterranean countries classified as having low vulnerability to a large degree. Vulnerability of wheat and barley yields are the most pronounced in this regard, although rapeseed is moderately vulnerable in Germany near the North Sea. Maize vulnerability does not follow this trend, and is highest in Hungary and northern Bulgaria, with some small areas of France and Italy also being moderately vulnerable.

These results contradict other analyses which highlight southern Europe as facing the highest impacts under climate change (see, for example: Trnka et al., 2011; Meehl and Tebaldi, 2004; Iglesias et al., 2009), especially in regards to vulnerability affecting wheat yields, however there are indications that heat stress could

		Impact indicator value				
		1	2	3	4	5
Inverse Adaptive capacity index	1	4	6	8	10	12
	2	6	8	10	12	14
	3	8	10	12	14	16
	4	10	12	14	16	18
	5	12	14	16	18	20

Vulnerability categorical values				
0 - 4	4 - 8	8 - 12	12 - 16	16 - 20
Very low	Low	Moderate	High	Very high

Fig. 7. Approach used to combine adaptive capacity and biophysical impacts for an indicator of vulnerability.

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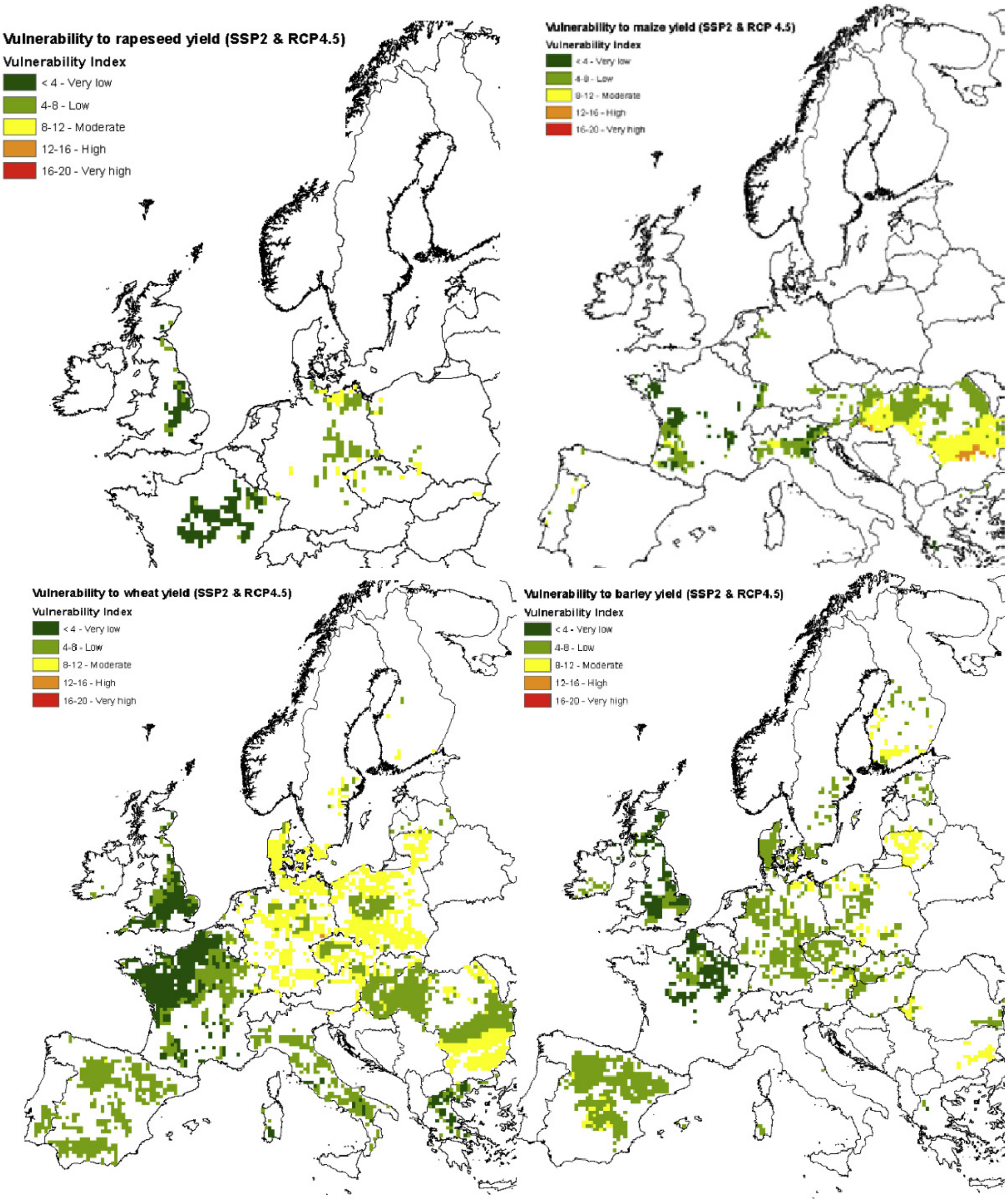

Fig. 8. Assessing vulnerability to drought affecting rapeseed, maize, wheat and barley yields under +2 degrees Celsius of global climate change. Biophysical impacts (absolute change in crop yield from historic to target years) are combined with future AC estimates, and excludes areas which have <5% harvested crop area for RCP 4.5 and SSP2.

lead to considerable loss of yield in western Europe (Semenov, 2009). Ciscar et al. (2011) also find that warmer and drier conditions by 2050 could cause moderate declines in central Europe. The IPCC's Fifth Assessment Report was similarly divided on the scale and distribution of impacts on the sub-regional level within Europe, finding disagreement over food production impacts for northern Europe, and one study predicting a decrease in production in the continental region. Some studies, using extreme climate change predictions (e.g. 5.4 degrees of warming by 2080) lead to extremely large yield losses for southern Europe, but more moderate impacts result in less severity of changes for the south, with some declines felt in central areas (Kovats et al., 2014).

There are two main explanations for these trends. The first lies in the impacts index; most pronounced in the wheat and rapeseed maps, impacts modeling results show that the highest reductions in yields under an RCP4.5 scenario will fall in France, Germany, and Poland, and other central EU countries, with yields in southern countries either not diminishing at all, or only facing a slight reduction under 2 degrees of global change. Indicator selection also plays a large part in determining overall vulnerability and this research highlights how important the process is to end results. While selection is driven by a deductive framework and reinforced by findings from studies in the field, to apply a consistent set of indicators as such a large scale limits selection possibilities.

5. Discussion

We assessed the adaptive capacity of the agricultural sector of the EU to future climate change using an indicator approach, developing a consistent set of indicators which allow for identifying differential adaptive capacity across the EU, based on a mixture of deductive and inductive approaches. The SLA framework formed the deductive basis from which to select indicators which were shown in the literature (see Table 3) to have an effect on AC. The results can be seen as an assessment of different scenarios of changing adaptive capacity at a European scale, allowing for the identification of areas of concern which should be investigated further, as well as emphasizing that impacts are not only dependent on biophysical effects, but that the socio-ecological system as a whole plays a large part in determining vulnerability, providing a different lens through which to view current and future impacts.

Even so, results are highly uncertain and should be taken with caution, due to limitations of the indicator approach at such a large scale. The need to have a small number of consistent indicators over such a large area limited the possible proxies to be used. The large study area also precluded the use of a participatory or stakeholder-driven approach, which might have highlighted other potential proxies. Lastly, assessing only a single sector's ability to cope with future changes ignores the rest of the system involved, meaning that while the sector itself may have less adaptive capacity, the entire system may be more easily able to assist in the case of extreme events, be it financially, technologically, etc. However, an indicator approach such as this helps to broadly outline future AC, but further analysis at much finer spatial scales is required to make solid conclusions about more local or sub-national levels.

As discussed, there are numerous approaches to assessing AC, based upon varying methodological frameworks. The use of a five capitals approach is not new, and has been increasing in use when assessing AC (see, for example: Tinch et al. (2015), Nelson et al. (2007, 2010b) etc.) but this is the first time an indicator approach was used to assess *sectoral* adaptive capacity at such a large scale. Previous assessments focused on a generalized indicator of adaptive capacity for the entire system, never becoming sector- or hazard-specific. Another assessment, Nelson et al. (2010a) and Nelson et al. (2010b) used the five capitals framing to assess the agricultural sector, but only for the case of Australia.

Thus assessing single sector/single hazard AC at a pan-EU level is a first, and presented difficulties. The most pressing issue was data availability and resolution. Initial literature review highlighted an extremely large number of possible proxy indicators, however the majority of these were not available as consistent measurements across countries. Here the issue of sector-specific analysis compounded this difficulty. Other assessments of EU-level AC used much more general and easily measured proxies, such as life expectancy, or number of patents issued, etc. While sectoral analysis allowed for much more precise indicators to be used, this precision and choice of sector-specific employment, infrastructure, and other data was met with difficulty in acquiring a comprehensive dataset.

Data limitations also limited the spatial resolution of analysis; a first attempt for sub-national level analysis was found to be impossible due to a lack of data coverage. Other analyses, such as Schröter et al. (2004) and ESPON (2013), were able to utilize NUTS3 resolution data, whereas our assessment was limited to a national level only. For the agricultural sector, a reasonably consistent dataset for the years 2000–2010 was compiled, with minimal missing values; enough to be able to project capital stocks via panel regression. Even so, an approach such as this needs as much consistent data as possible, and can always be improved; an expanded set of socio-economic indicators at finer spatial resolution would not only allow for more precise estimates of sub-national AC but would provide more flexibility and options in selecting the appropriate indicators.

Beyond data and methodological considerations, selecting indicators proved to be difficult. Every attempt was made to justify indicator selection based on previous use in literature as well as choosing proxies which reflected components of a resilient agro-ecosystem (as discussed by Cabell and Oelofse (2012)), but some indicators could be interpreted in multiple ways. Taking the example of value added as a percentage of GDP, it was reasoned that higher values indicate that the sector holds more importance to the broader economy, and thus would enjoy more focus and ostensibly more action to assist the sector in cases of extreme events. However, lower values seen in more industrialized countries could give the false impression that these nations would be less able to respond to an event, which may not be the case, given their higher overall GDP and ability to finance losses.

An additional means to verify indicator selection would be via the use of a more participatory approach with stakeholder consultation. These approaches are time intensive and difficult to carry out at such a large scale, due to the myriad of different stakeholders involved. Different regions and actors may highlight differing proxies than others. As the focus of this work was an indicator approach at a pan-EU level, the approach taken was considered as a better alternative to a more stakeholder-driven process. Note that this does not imply that participatory approaches are without value; using a broader indicator such as in this project, when combined with impacts mapping, would identify areas in which vulnerability may increase in the future; from there, a more focused stakeholder-based approach could be undertaken to further investigate how the local system functions and what local experts consider to be the best indicators and measurements of adaptive capacity.

Finally, while the approach was innovative in projecting AC via the use of SSP indicators, which had not yet been undertaken, the modeling and projection introduces another layer of uncertainty. The SSP and RCP scenarios themselves are not predictive but rather outline storylines for possible futures; similarly, our projections of AC indicators can be seen as furthering those storylines. A vital next step would be to further test this approach and improve upon the fixed effects model. Assuming that all countries AC indicators will change at the same rate is tenuous, and further work is needed to increase the robustness of these results; ideally, a fixed effect model for individual country assessment of each indicator would be used, possibly incorporating additional predictor variables, such as land use or other agricultural data.

6. Conclusions

This work focused on the concept of adaptive capacity for deriving an estimate of agricultural vulnerability to a 2 degree change in temperature in the EU as a part of the modeling chain of the Impact2C project, which quantified projected impacts on Europe of 2 degrees Celsius of global warming, from climate models to adaptation analyses.

The majority of previous work on the agricultural sector is presented without socio-economic considerations, which we addressed by assessment of adaptive capacity via an indicator-based approach. While other attempts have been made to quantify the AC of EU member states, to the best of our knowledge this represents the first effort to provide sector-specific indicators of AC at a national level, for the agriculture sector, beginning from a sustainable livelihoods framework that organizes adaptive capacity around various types of capacity as measured by the notion of capital. Following the example of other European research (see, for example, Tinch et al. (2015) and Acosta et al. (2013)), we selected relevant proxies for each stock type, combined indicators via equal weighting, and merged the results into a single adaptive capacity index

The mapping done in this work can serve as a first step to highlight possible vulnerability "hotspots" with the incorporation of biophysical impacts. By using outputs from impact modeling showing the change from historical to future time periods in regards to crop yields, precipitation and other relevant indicators, future vulnerability based on different possible scenarios can highlight regions that will be subject to both by high potential impacts to crops as well as low capacity of farmers to adapt to those changes. Additionally, more analysis at a regional or community level, and involving a more participatory process, can further the understanding of AC in the area, based on the assessment done here, which applies a standard methodology to the entire region allowing for standard comparisons between member states.

Assessing adaptive capacity in the context of this research faces numerous challenges. Linking climate and social science research is inherently difficult due to different approaches and spatial scales involved and this work was no exception, and highlights a number of areas in need of further research. Until now, focus has been placed on quantitative assessment of AC, but recent developments in methods for measuring AC have increased focus on more qualitative approaches, emphasizing stakeholder interaction, evaluation by practitioners and other experts, with a stronger focus towards smaller spatial scales such as the community level. Such approaches attempt to build a greater empirical basis for indicators, and the results at a local level could help to inform which indicators are useful at these higher spatial scales. In assessing AC such a level, even with a robust methodology incorporating local stakeholders and practitioners, there is a great need for better indicator data. In a recent commentary, Otto et al. (2015) emphasize the need for better quality socio-economic data, moving beyond national-level data towards finer spatial resolution, along with a need for more complete coverage of all areas over a longer time period. Our work echoes these needs, as many of the limitations in terms of indicator selection was due to a lack of data at sub-national scale, or a lack of consistency in data reporting over time, leaving us unable to project values to the future. A better understanding of adaptive capacity and an improved empirical basis for selecting indicators via more participatory approaches, coupled with improved, sub-national indicator datasets, could greatly improve the robustness of results and highlight key areas where further research is needed in order to better couple climate research with socio-economic analysis.

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