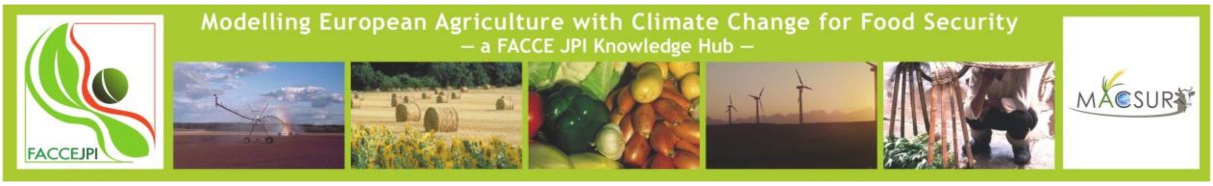

FACCE MACSUR

D-L1.1.2 Report

Gianni Bellocchi[1]*,

[1] UMR Ecosystème Prairial, INRA, VetAgroSup, 63000 Clermont-Ferrand, France
…

*gianni.bellocchi@inra.fr

Instrument:	Joint Programming Initiative
Topic:	Agriculture, Food Security, and Climate Change
Project:	Modelling European Agriculture with Climate Change for Food Security (FACCE-MACSUR)
Start date of project:	1 May 2015 (phase 2)
Duration:	24 months
Theme, Work Package:	LiveM 1
Deliverable reference num.:	D-L1.1.2
Deliverable lead partner:	INRA
Due date of deliverable:	month 20
Submission date:	2017–04–16
Confidential till:	**YYYY-MM-DD (only the abstract may be published)**

Revision	Changes	Date
1.0	First Release	2017-04-16

Abstract/Executive summary

A model-based methodology for vulnerability assessment in agriculture is illustrated, with applications to grassland sites and large regions, which reflects the experiences of MACSUR-LiveM (linked to other projects and initiatives). The most recent developments include a multi-metric indicator for assessing the adaptive capacity of agricultural districts, whose potential is illustrated with an exemplary application to the pilot case study of Arborea (Italy).

Introduction

The work developed in the frame of MACSUR LiveM-Task L1.1 (with links to other projects and initiatives) concerns approaches to assess vulnerability of grassland ecosystems to climate and global changes (mostly with applications in Europe).

Methods for vulnerability assessments

According to IPCC (2001), vulnerability is the degree to which a system is susceptible to, or unable to cope with, adverse effects of climate change, including climate variability and extremes. This means that, in a climate change context, the vulnerability of a system is determined by the potential impact (exposure of a system to hazardous climatic factors plus sensitivity of a system to these factors) and the coping (adaptive) capacity, which is the impact that may occur given projected changes and the degree to which adjustments in practices, processes or structures can moderate or offset the potential damages. The above definition accounts for the long-term nature of the climate problem (by including the adaptive capacity) and for the heterogeneity and complexity of the hazard (by including an exposure factor).

Vulnerability of biophysical systems erects a “doctrinal” edifice (Figure 1) with three foundational pillars assessing it: exposure to hazardous events, sensitivity of the system to such events, and the capacity to cope to both. These three pillars serve as placeholders for research, application and decisional aspects. They are powerful tools for defining the complete vulnerability issue: if one pillar is weak, then the system as a whole is vulnerable. Most vulnerability assessment efforts focus on only one or two pillars at a time.

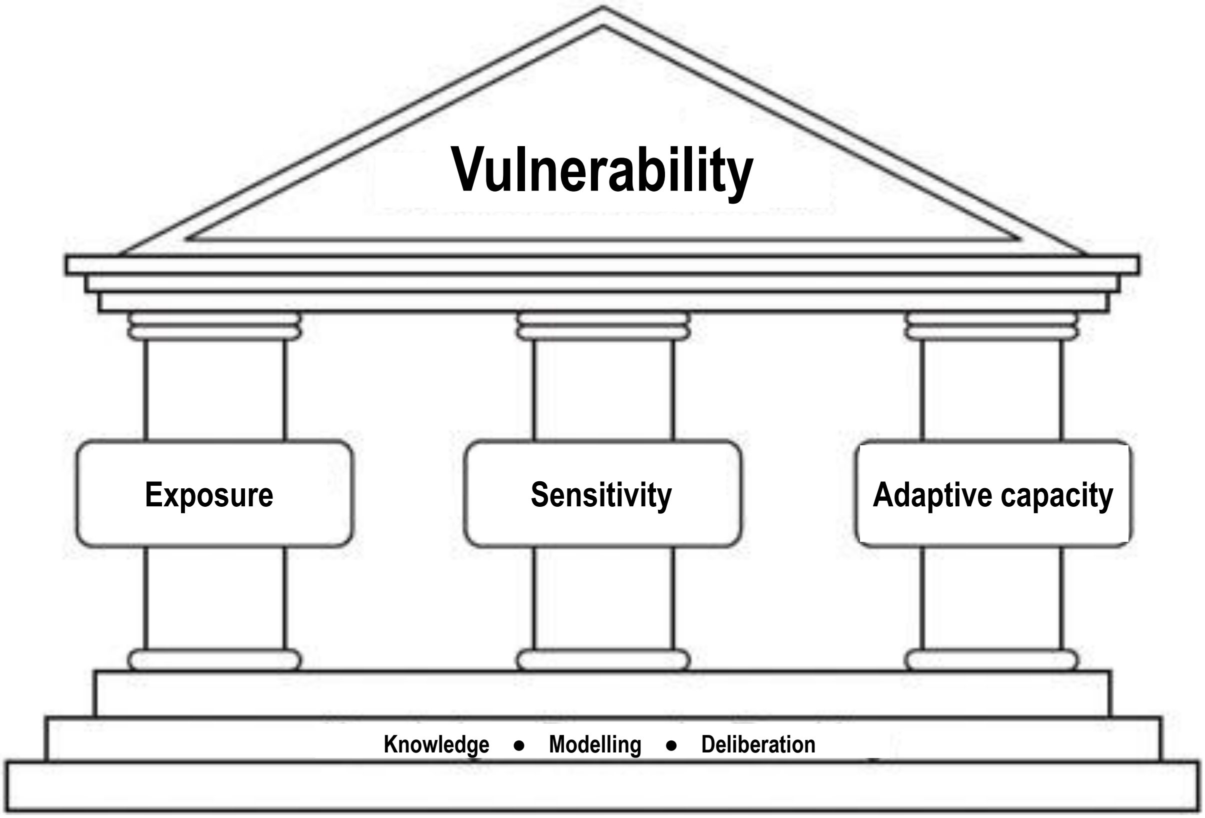

Figure 1. The three pillar of vulnerability and the foundation of vulnerability assessment.

Figure 1 depicts the pillars resting on an organizational foundation that embodies attributes of research and decision schemes: increase of knowledge (scientific research), application of modelling tools, and deliberation as a process to take decisions through a consensus of multiple actors being involved. Pillars and organizational foundation are interrelated: the overall effectiveness of vulnerability assessment is limited if advances in one area are not accompanied by corresponding advances in the others. On the one hand, pillars represent points to be monitored to explain the reason(s) why a system is vulnerable. On the other hand, they provide targets to intervene on (both immediately and in the future) to (try to) reduce vulnerability. The three pillars are moving targets as knowledge, modelling practices and deliberation approaches evolve with the evolution of socio-economic scenarios, climate models, downscaling techniques, impact models, deliberation approaches, etc.

Conventionally, vulnerability assessment is achieved through ‘top down’ or ‘scenario-led’ methods, which focus on developing fine scale climate data from coarse scale Global Climate Models. The resulting local-scale scenarios are fed into impact models to determine vulnerabilities. Although climate models are constantly being improved, they are not able to estimate future climate conditions with a high degree of confidence. In addition, outputs from different climate models often differ, presenting users with a range of possible climate futures to consider, and ultimately a wide range of possible impacts and adaptation responses. The users will be faced with the problem of deciding which model they should use. Even with improvements in climate modelling, uncertainties will remain. The process whereby uncertainty accumulates throughout the process of climate change projection and impact assessment has been described as a “cascade of uncertainty” or the “uncertainty explosion” (after Boe, 2007). This cascade of uncertainty produces a range of possible outcomes rather than best guesses (Figure 2).

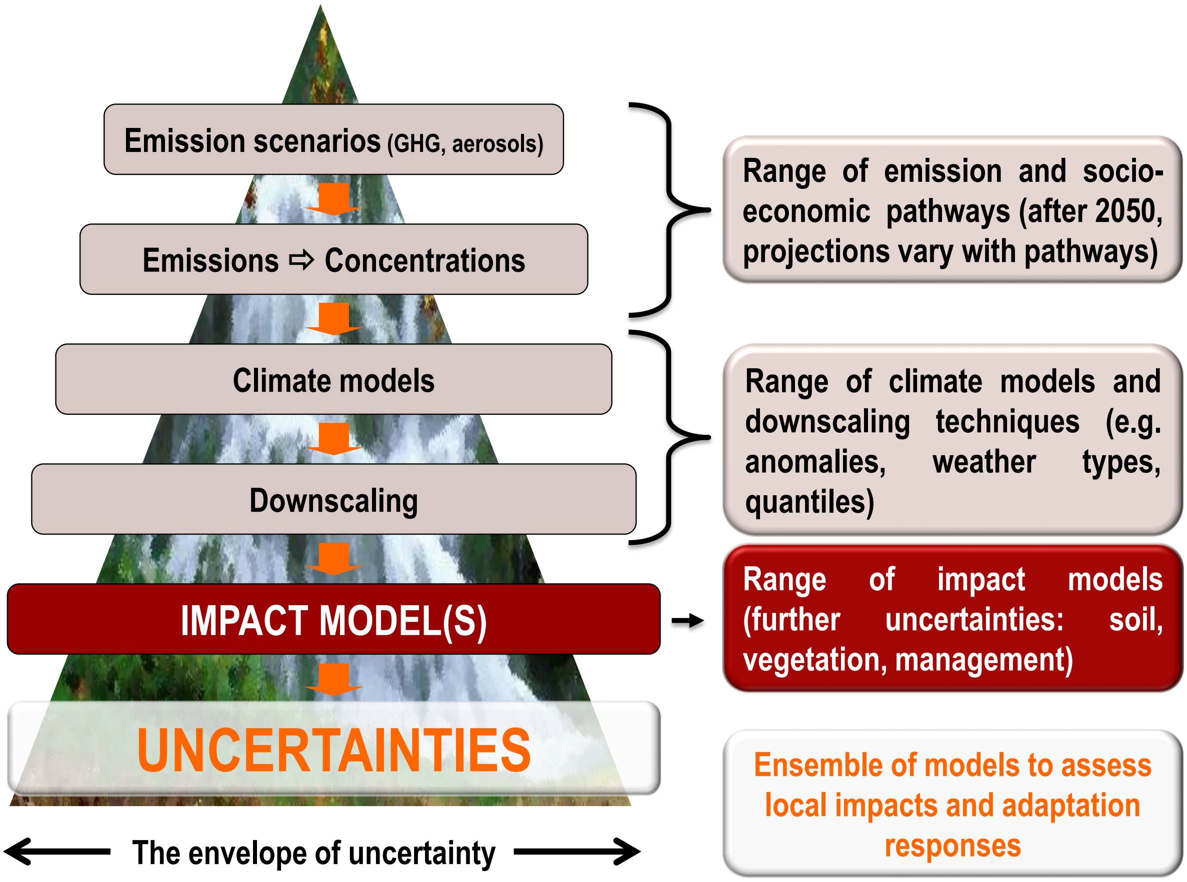

Figure 2. The uncertainty cascade.

This has urged for benchmarking actions at an international level, where estimation of process-oriented epistemic uncertainties is done by running several models supposed to simulate the same reality (ensemble modelling) so as to generate an expanded envelope of uncertainty. Model ensembles were used for yield predictions with annual crop monocultures (e.g. maize: Bassu et al., 2014; rice: Li et al., 2015; wheat: Ruane et al., 2016), but to a much lesser extent for crop rotations (Kollas et al., 2015) and grasslands (e.g. Sándor et al., 2015, 2017)

MACSUR-LiveM experience

We referred to a systemic approach, which considers the grassland ecosystem as a homogeneous plot whose components are vegetation, soil, climate and farming practices. The latter may include the presence of grazing animals. To account for the interactions existing among these components and their evolution over time, modelling tools were used, which simulates production and environmental performances of grassland ecosystems. Obtained under current and future climatic forcing, model outputs were exploited to generate indicators of vulnerability accounting for exposure to climate, sensitivity of the system to this exposure, and its adaptive capacity.

Grassland models were evaluated with data from a variety of grassland sites in Europe and Israel (Sándor et al., 2017), characterized for their exposure to weather hazards with two metrics: aridity and heat waves. Figure 3 shows that the two Mediterranean sites of Matta and Sassari fall in a fanciful “danger zone”, marked by arid conditions and high frequency of heat waves.

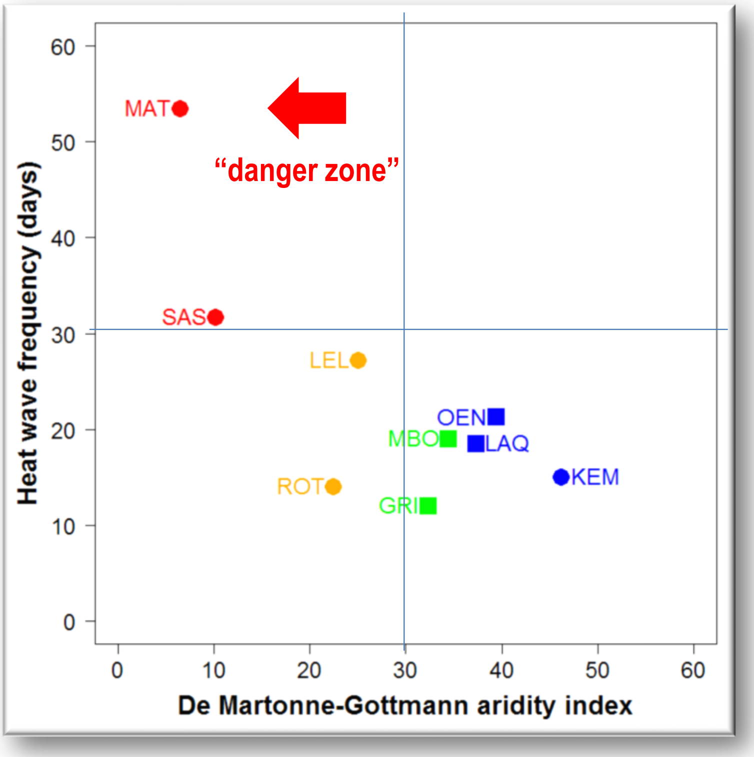

Figure 3. Classification of grassland sites (black squares: grassland sites equipped with eddy covariance system; green circles: other grassland sites) with respect to De Martonne-Gottmann aridity index (extreme aridity, 0≤) and heat wave days frequency (no heat waves, 0≤). GRI: Grillenburg (Germany), KEM: Kempten (Germany), LAQ: Laqueuille (France), LEL: Lelystad (The Netherlands), MAT: Matta (Israel), MBO: Monte Bondone (Italy), OEN: Oensingen (Switzerland), ROT: Rothamsted (United Kingdom), SAS: Sassari (Italy). Figure adapted from Sándor et al. (2017).

Taking the gross primary production (GPP) as an indicator, we assessed the sensitivity of different grassland models to increasing concentrations of atmospheric CO_2 (Figure 4 for Oensingen, Switzerland). The increase of 25% of GPP wit doubling CO_2 concentration roughly matches what is known from literature for C3 plants (e.g. Ainsworth and Roger, 2007). However, the variability across models is high, which means that we can expect different results with using different models.

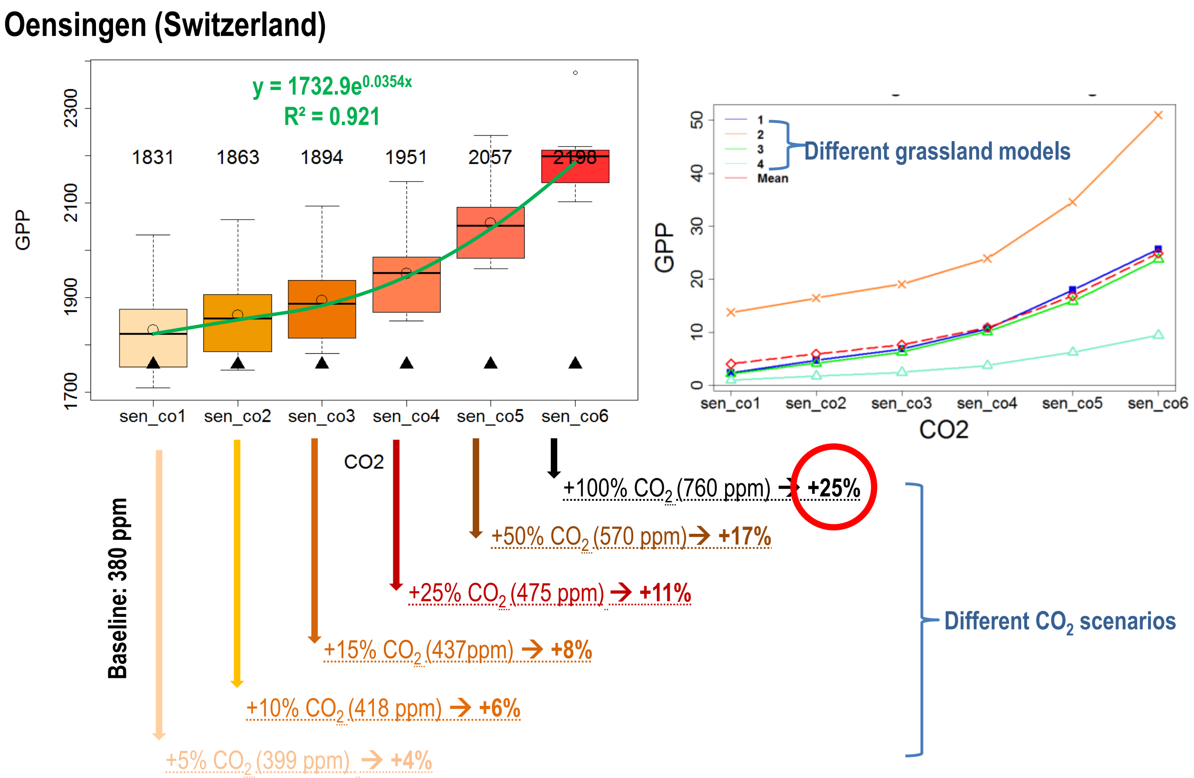

Figure 4. Simulated effects of [CO_2] on the yearly values of gross primary production (GPP) with four models at Oensingen (Switzerland). Figure adapted from Sándor et al. (2015).

Such a big variability in the responses from different models was also observed when the sensitivity to temperature and precipitation variations was assessed (Figure 5 for Oensingen, Switzerland).

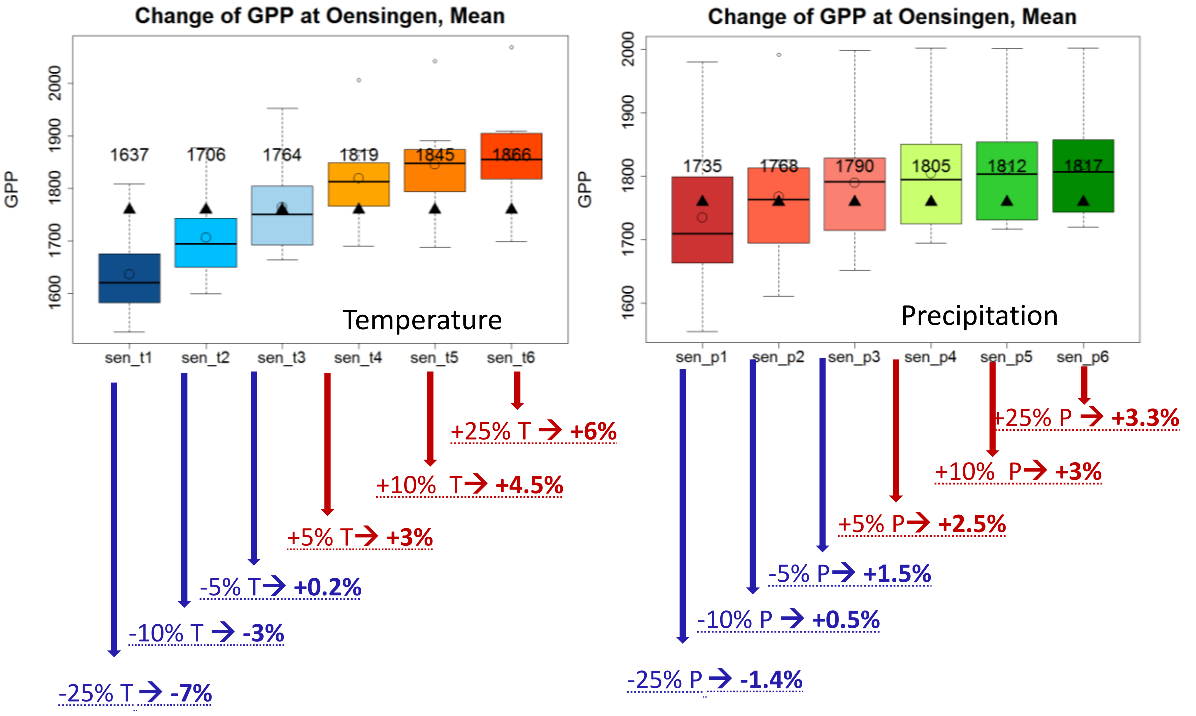

Figure 5. Simulated effects of temperature and precipitation on the yearly values of gross primary production (GPP) with four models at Oensingen (Switzerland). Figure adapted from Sándor et al. (2015).

This difference among models is reflected in their performance when outputs are compared to observational data (Figure 6 for Oensingen, Switzerland). Globally wide, the envelope of results become wider in 2003, that is, an extreme year in terms of both aridity and heat waves.

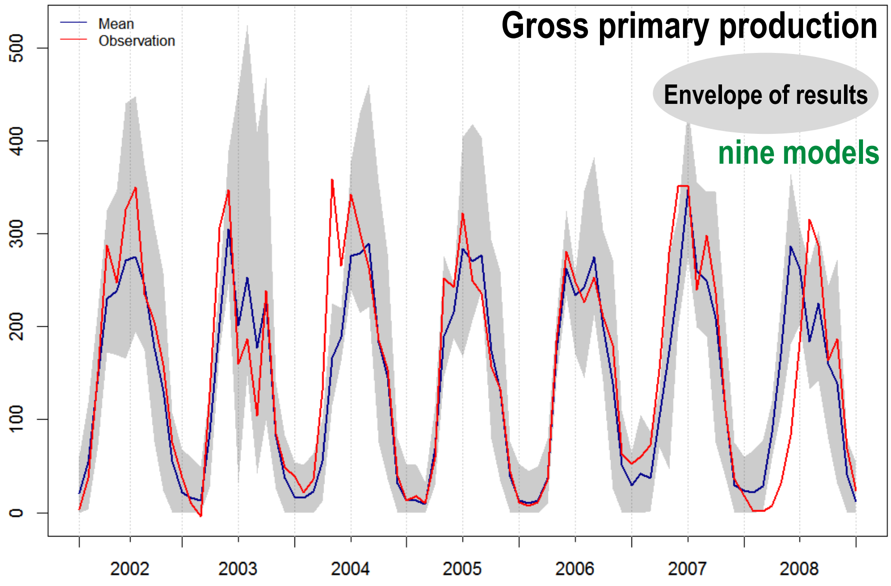

Figure 6. Temporal course of simulated (nine models) and observed gross primary production (GPP, g C m^{-2} week^{-1}) at Oensingen (Switzerland) for 2002-2008. Figure adapted from Ma et al. (2014).

Other than being used at specific sites, models are also used to assess vulnerability of grasslands at large scales, e.g. the European scale. In the approach implemented in the frame of the EU-FP7 AnimalChange (http://www.animalchange.eu), two Representative Concentration Pathways of future atmospheric CO_2 concentrations (RCP 8.5, the most pessimistic, and RCP4.5, an intermediate one) were used to input two climate models, which generated long series of transient climate change data, projected at the horizon 2100. Together with grassland management data, simulations were run at a resolution of 25 km with PaSim within a high-performance computing cluster. The characterization of the weather series showed an expected increased exposure to arid conditions in Europe in the future (Figure 7, Bellocchi et al., 2014). The combination IPSL-CM5 model/RCP 4.5 is an exception for some areas of England, Central and Eastern Europe (where reduced aridity was estimated).

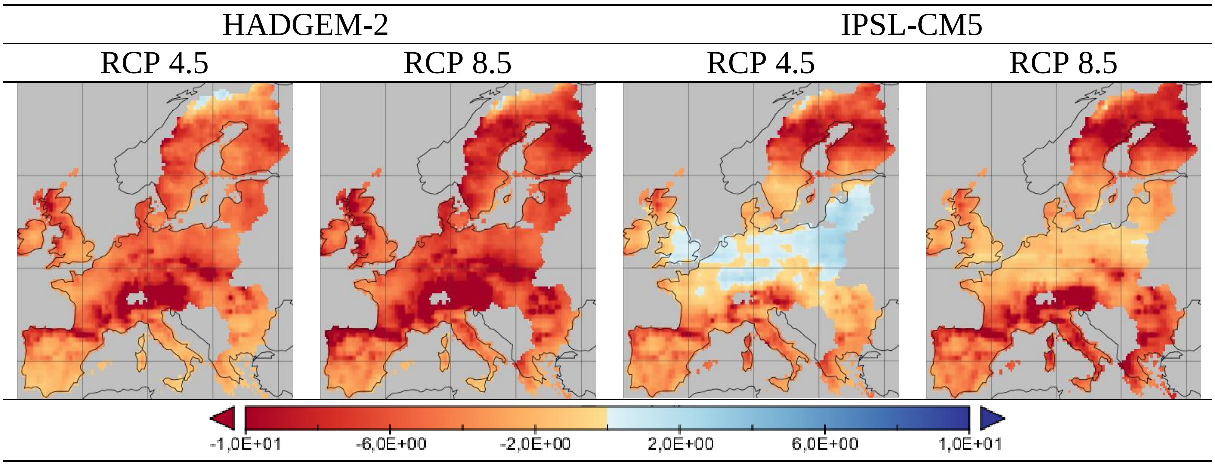

Figure 7. Difference between the mean values of the aridity index (*b*) calculated for the years 2005-2099 and 1951-2004 with *b*<25th percentile, as represented by two climate models and two RCPs. Red to bleu colours indicate growing aridity under future climate (and vice versa for red to brown colours).

For this vulnerability assessment of grasslands, we focussed on the simulated responses of gross primary production. On average, we can expect increased productivity in the future due to higher CO_2 concentrations and favourable temperature conditions. However, the inter-annual variability is also expected to increase, especially in large areas of the Mediterranean. But the question stands: is the vulnerability of European grasslands to climate change expected to increase or decrease in the future? An assessment was made with a vulnerability index known as Luers index (Luers et al., 2003), in a form derived by Lardy et al. (2014). It considers the state of the system, compared to a threshold, an exposure factor and the sensitivity of the system to that factor. This index can be calculated for a future time slice, but also for a past baseline. The ratio of the two makes the index threshold-independent and normalized on the value of 1: the higher than 1 the index the higher the vulnerability and vice versa. With the grassland model PaSim (https://www1.clermont.inra.fr/urep/modeles/pasim.htm) and two climate models, the vulnerability index indicates increased expected vulnerability in large parts of Europe (as reflected in the light blue, and yellow-brown colours).

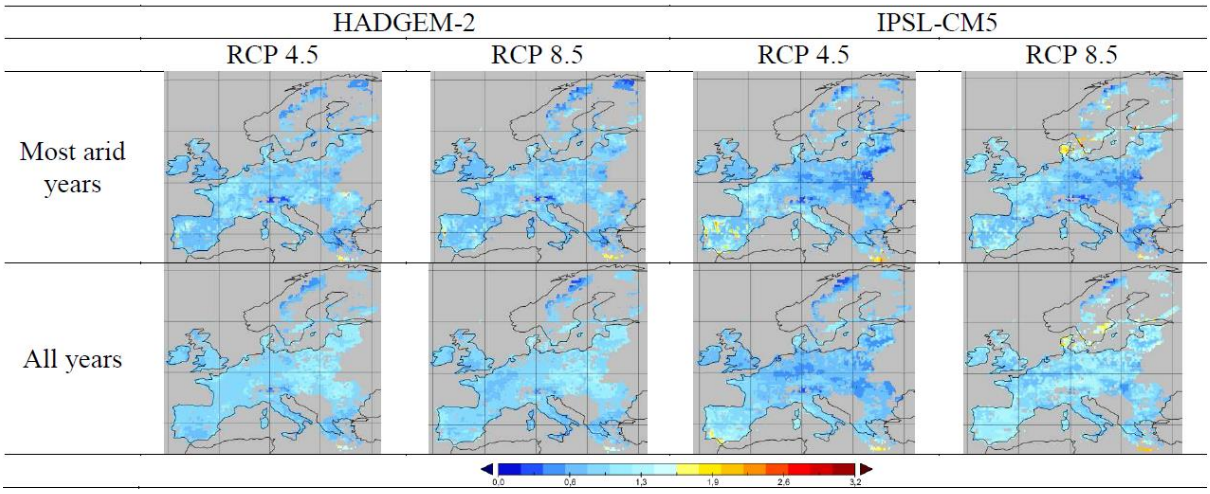

Figure 8. Luers vulnerability index for gross primary production (estimated by PaSim) in 2005-2099 for European grasslands, as represented by two climate models and two RCPs, and for two sets of years. Index values were normalized over the reference period (1951-2004). The higher the vulnerability index, the higher is the vulnerability of grassland systems to changes in climate. Light blue to brown colours indicate growing vulnerability (>1) under future climate (and vice versa for light-blue to blue colours).

Maps of this type may have certain interest in terms of general tendencies but the resolution is not fine, thus they do not help much to implement adaption measures at specific territories and production districts. To make concepts of vulnerability operational, a modelling platform for vulnerability assessment was developed (Eza et al., 2015) to incorporate exposure, sensitivity and adaptive capacity (as in Fig. 1). The framework links outcomes from climate and impact models, represented as indicators of exposure and sensitivity, towards overall indicators of vulnerability. The mechanistic view of the simulation engine allows estimating production and environmental performances of a variety of grasslands. The outputs, obtained under current and projected climate forcing scenarios, are exploited to calculate vulnerability indices at a range of scales, thus facilitating the identification of vulnerable areas. The platform can serve the development of research activities around vulnerability assessment. It can integrate new advancements of basic research relative to aspects of the modelling system that can be improved to improve the sensitivity of model outputs estimated at ecosystem scales to hazardous events. Moreover, the platform can provide context for deliberative processes and decisions with the involvement of local stakeholders. This framework thus integrates scientific, technological and socio-institutional components that can become just as many research actions.

This scheme is attractive but to effectively support adaptive responses by farmers and policymakers (other than researchers), climate change adaptation must become a socially-constructed concept, where scientific knowledge and experiential knowledge (together with expectations and aspirations of stakeholders) an hybrid knowledge that could generate local answers for pervasive social problems (e.g. water pollution) beyond climate change. After Wise et al. (2014), research meta-questions include:

- How to support effective adaptive responses to climate change and stimulate proactive attitudes of farmers, policymakers & researchers
- How to co-construct the nature of the issues about climate change adaptation
    - How to identify the right questions to engage pathways within the adaptive space
- Hybrid knowledge rationale: climate change adaptation is a socially-constructed concept, where conceptualized background experience informs…
  … climate change understanding and response-abilities/capacities
  … farmers’ climate change perception driving changes in practice

Adaptation strategies aim at reducing the vulnerability of a system by reducing its exposure and/or its sensitivity to climate factors, as well as by improving the adaptive capacity through different types of levers depending on technological level and infrastructural supplies (ability), as well as information capabilities and equity dimension (awareness), and also due to economic wealth and human, institutional organization and social capital (action).

According to Metzger et al. (2006), six determinants are the basis for building a framework of adaptive capacity. Two socio-economic indicators were used to represent each determinant of adaptive capacity. The framework thus includes 12 indicators. Fuzzy logic-based rules can be used to aggregate the estimated values of the indicators to generate the adaptive capacity index. Arborea district, in the Italian island of Sardinia, is one of the MACSUR regional pilot case studies, characterized by the presence of cereals, vegetables, forage crops and pasture under both irrigated and rainfed conditions. Thanks to social dialogue with local stakeholders, indicators were collected and framed into the adaptive capacity scheme of Metzger, but the outcome is completely different. The Sardinian case, in Italy, covers a mixed production agricultural district, where dairy and extensive cow and sheep systems coexist with vegetables, and rice- and forage-growing areas. Projected climate changes may induce yield drops as well as abandonment of rainfed hill sheep areas. Price of water is problematic, with increasing irrigation costs. But some changes in the crop management could help exploiting new opportunities because of warmer autumns and winters. The dairy business is based on a cooperative settlement, for which an interesting win-win pathway is emerging, through synergies with the beef industry. Among the basic indicators for adaptive capacity, social capital metrics become prominent as well as the sensitivity of people to certain issues such as the expected impacts of climate change, which is not perceived as a specific concern in itself but one among others, such as pollution and water quality. Indicators such as female activity rates or number of telephone lines, which are in the scheme of Metzger et al. (2006), are not an issue at all. Following the model proposed by Metzger et al. (2006), 21 indicators representative of adaptive capacity were derived from an array of socio-economic and environmental priorities, initially identified by an interdisciplinary team of scientists and then extended and scored (on a rank from 1 to 5) by 31 experts (agronomic scientists, farmers, advisors and consumers). The extended list of priorities was reduced to a set of indicators that could be quantified using data from different sources. The indicators were organized into seven determinants (1 Infrastructure, 2 Technology, 3 Economic power, 4 Flexibility, 5 Knowledge, 6 Reception/Sensitivity, 7 Social capital), in turn organized in three components: Ability (1, 2), Action (3, 4) and Awareness (5, 6, 7). Calculation of AC required that 1) scores for each basic indicator be normalized and aggregated to a determinant value, 2) determinant values be aggregated to a component value, 3) component values be aggregated to an Adaptive Capacity Indicator (best, $0 \leq ACI \leq 1$, best). For that, a fuzzy logic inferring system was used based on the weighting expression of the balance of importance of the basic indicators and their aggregation into determinants and components. Favourable/unfavourable thresholds for each basic indicator were from expert knowledge and/or survey/census/literature data, while the priority scores were used to assign weighting factors. Results indicate a low-medium AC (ACI=0.61) with social capital (0.27) being the strongest determinant and economic power (0.80) the weakest. These findings (Bellocchi et al., 2017) provide essential information for enhancing our understanding on effective, locally meaningful and feasible strategies increasing the AC of Oristanese rural communities.

The preliminary results obtained for Arborea show that the approach is promising and encourages further research in this direction in other European agricultural districts.

References

Ainsworth, E.A., Rogers, A., 2007. The response of photosynthesis and stomatal conductance to rising [CO_2]: mechanisms and environmental interactions. Plant, Cell & Environment 30, 258-270.

Bassu, S., Brisson, N., Durand, J.L. et al., 2014. How do various maize crop models vary in their responses to climate change factors? Global Change Biology 20, 2301–2320.

Bellocchi, G., Ruiu, M.L., Piras, F., Roggero P.P., Seddaiu, G., 2017. Assessing priorities for enhancing adaptive capacity of agricultural systems to climate change using fuzzy logic-based approaches. MACSUR Science Conference 2017, May 22-24, Berlin, Germany. http://macsur.eu/index.php/events/macsur-science-conference-2017-may-22-24

Bellocchi, G., Viovy, N., Eza, U., Martin, R., Chang, J., 2014. Vulnerability analysis of production. AnimalChange D5.5.

Boe, J., 2007. Changement global et cycle hydrologique : Une étude de régionalisation sur la France. PhD thesis, University Paul Sabatier - Toulouse III, Toulouse (in French). https://tel.archives-ouvertes.fr/tel-00256811

Eza, U., Shtiliyanova, A., Borras, D., Bellocchi, G., Carrère, P., Martin, R., 2015. An open platform to assess vulnerabilities to climate change: An application to agricultural systems. Ecological Informatics 30, 389–396.

Kollas, C., Kersebaum, K.C., Nendel, C., et al., 2015. Crop rotation modelling - A European model intercomparison. European Journal of Agronomy 70, 98–111.

Lardy, R., Bachelet, B., Bellocchi, G., Hill, D.R.C., 2014. Towards vulnerability minimization of grassland soil organic matter using metamodels. Environmental Modelling & Software 52, 38-50.

Li T, Hasegawa T, Yin X et al., 2015. Uncertainties in predicting rice yield by current crop models under a wide range of climatic conditions. Global Change Biology 21, 1328-1341.

Luers, A.L., Lobell, D.B., Sklar, L.S., Addams, C.L., Matson, P.M., 2003. A method for quantifying vulnerability, applied to the agricultural system of the Yaqui Valley, Mexico. Global Environmental Change 13, 255-267

Ma, S., Acutis, M., Barcza, Z., Ben Touhami, H., Doro, L., Hidy, D., Köchy, M., Minet, J., Lellei-Kovács, E., Perego, A., Rolinski, S., Ruget, F., Seddaiu, G., Wu, L., Bellocchi, G., 2014. The grassland model intercomparison of the MACSUR (Modelling European Agriculture with Climate Change for Food Security) European knowledge hub. In: Ames, D.P., Quinn, N.W.T., Rizzoli, A.E. (eds.), Proceedings of the 7th International Congress on Environmental Modelling and Software, June 15-19, San Diego, CA, USA.

Metzger, M.J., Rounsevell, M.D.A., Acosta-Michlik, L., Leemans, R., Schröter, D., 2006. The vulnerability of ecosystem services to land use change. Agriculture, Ecosystems and Environment 114, 69-85.

Ruane, A.C., Hudson, N.I., Asseng, S. et al., 2016 Multi-wheat-model ensemble responses to interannual climate variability. Environmental Modelling & Software 81, 86–101.

Sándor, R., Barcza, Z., Acutis, M. et al., 2017. Multi-model simulation of soil temperature, soil water content and biomass in Euro-Mediterranean grasslands: Uncertainties and ensemble performance. European Journal of Agronomy, http://doi.org/10.1016/j.eja.2016.06.006

Sándor, R., Ma, S., Acutis, M., et al., 2015. Uncertainty in simulating biomass yield and carbon-water fluxes from grasslands under climate change. Advances in Animal Biosciences 6, 49-51.

Wise, R.M., Fazey, I., Stafford Smith, M., Park, S.E., Eakin, H.C., Archer Van Garderen, E.R.M., Campbell, B., 2014. Reconceptualising adaptation to climate change as part of pathways of change and response. Global Environmental Change 28, 389–396.