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Agro-ecosystem modeling can aid in the optimization of biomass feedstock supply

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ABSTRACT

Recent European Directives promoted the development of biofuels, requesting mandatory limits to their emissions ot greenhouse gases (GHG). Second-generation biofuels based on lignocellulosic biomass are prime candidates but their GHG emissions are variable and uncertain. Agro-ecosystem modeling can capture them and the performance of biofuel feedstocks.

This study aimed at optimizing feedstock supply for a bioethanol unit in France, from agricultural residues, annual and perennial crops. Their productivity and environmental impacts were modelled on a regional scale using geo-referenced data on soil properties, crop management, land-use and future weather data. Several supply scenarios were tested. Cereal straw was the most efficient feedstock but had a low availability, and only miscanthus could meet the bioethanol plant's demand. Sorghum combined poor yields and high GHG emissions compared by miscanthus and triticale. A mix of three biomass sources used less than 3% of the regional agricultural land while abating GHG emissions by 60%.

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Software availability

Name of software: CERES-EGC
Developer: Benoît GABRIELLE, INRA EcoSys, 78850 Thiverval-Grignon, France
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Phone: (+33) 1 30 81 55 51, Fax: (+33) 1 30 81 55 63
Year first available: 1998
Hardware required: no special requirements
Software required: None
Availability and cost: - freely available on request at: https://ecosys.versailles-grignon.inra.fr/ceres_mais/ceres.html - Source code is also accessible from the Source Sup development forge: https://sourcesup.renater.fr/projects/ceres-egc/
Program language: Fortran77 (and R)
Program size: 33 Mb

1. Introduction

The European Union recently promoted the use of biofuels to mitigate GHG emissions and substitute fossil energy sources, setting ambitious targets for 2020 with its renewable energy directive (RED) (European Parliament, 2009a). As a consequence, the demand for biomass supply is likely to increase several-fold in the near future, in particular for biofuel production. However, another directive (the fuel quality directive) also set stringent environmental constraints on future biofuel chains, imposing minimum GHG abatement thresholds compared to fossil resources. For example, a threshold of 60% is set for biofuels commercialized from 2018 onwards (European Parliament, 2009b). Also, energy crops used for biomass feedstock production cannot be established on protected areas or lands with a high biodiversity value or high soil organic carbon content (European Parliament, 2009b). Since currently commercial biofuels (referred to as 1st generation biofuels) are fraught with high emissions of nitrous oxide (N_2O) (Smeets et al., 2010; Smith and Searchinger, 2012) and of CO_2 due to land-use change (LUC) effects (Humpenöder et al., 2013; Searchinger et al., 2008) they are unlikely to meet these criteria. Expectations are thus high for the 2nd generation of biofuels, which is based on lignocellulosic biomass as opposed to food crops. Possible sources of lignocellulosic biomass range from agricultural and forest residues to purpose-grown annual and perennial crops.

Abbreviations: CAP, common agricultural policy; DM, dry matter; GCM, general circulation model; GHG, greenhouse gas; GIS, geographical information system; GWP, global warming potential; LCA, life cycle assessment; LUC, land use change; RED, renewable energy directive; SU, simulation unit; UAL, utilized agricultural land.

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Agricultural residues such as cereal straw appear as prime candidates (Lal, 2009), since they are considered as residues from food production, which restricts their environmental burden to the operations specific to straw harvesting and handling. Annual crops with appropriate management may also be interesting candidate feedstocks: cereals such as Triticale (*x Triticosecale Wittmack*), as well as forage sorghum (*Sorghum bicolor L. Moench*) may be silage-harvested before their grains are set or mature, thereby maximizing biomass production compared to food or feed end-uses. *Miscanthus x Giganteus* (hereafter referred to as miscanthus) is a perennial sterile herbaceous and rhizomatous C4 crop of the *Poacea* family, which originates from Asia. It is characterized by high potential yields (in the 10–30 t DM ha^{-1} range) and lower N_2O emissions than arable food crops (Davis et al., 2010; Drewer et al., 2012). As a grass species, miscanthus was shown to sequester C in soil, but the strength of this sink varies across sites and plantation age (Cadoux et al., 2012; Clifton-Brown et al., 2007). When cultivated in degraded lands, miscanthus is likely to improve soil quality, resulting in a valuable co-benefit (Don et al., 2012; Gauder et al., 2012b).

Overall, lignocellulosic crops combine the advantages of high dry matter yields, low levels of agricultural inputs and low GHG emissions, resulting in a low GHG intensity compared to 1st generation feedstocks (Don et al., 2012). However, their environmental and agronomic performances are largely determined by soil and climate conditions (Dufossé et al., 2013; Van der Hilst et al., 2012) implying a precise knowledge of their geographical distributions (Gasol et al., 2011). Also, it is likely that 2nd generation biofuel conversion units will use several types of biomass feedstocks since their annual demand will be large (e.g., 0.73 Mt dry matter per year; Aden et al., 2002). Optimizing the feedstock supply chains for these units would be greatly facilitated by the capacity to model feedstock performance depending on various possible mixtures and establishment scenarios (e.g., on marginal land, current cropland or set-aside land for purpose-grown crops, Gelfand et al., 2013).

The environmental impacts of bioenergy feedstocks are usually measured using life-cycle assessment (LCA), a widespread and comprehensive methodology. However, one of its weaknesses for such systems lies in the estimation of nitrous oxide (N_2O emissions) occurring in the agricultural fields, together with the changes in soil organic matter associated with the transition to energy crops (Cherubini and Strømman, 2011; Hoefnagels et al., 2010). Nitrous oxide is a potent greenhouse gas (GHG) whose emissions from soils are driven by N fertilization and local pedoclimatic conditions (Dufossé et al., 2013). The emissions of N_2O are therefore highly variable over time and space, a pattern which is not adequately captured by the use of fixed emission factors, as recommended in the IPCC guidelines for inventory purposes (IPCC, 2006). This leads to high uncertainties in the GHG balance of bioenergy feedstocks and chains (Smeets et al., 2010; Smith and Searchinger, 2012).

Comparison of potential lignocellulosic crops, especially in terms of GHG emissions, are widely available from field trials, covering perennial grasses as well as short rotation coppice and annual crops (Don et al., 2012; Drewer et al., 2012; Gauder et al., 2012a; Rowe et al., 2009). However, these studies only represent local situations and cannot be extrapolated to an entire feedstock supply area, especially for large-scale industrial processes such as cellulosic ethanol production. Agro-ecosystem modeling has a potential to overcome this limitation and provide estimates on this scale regarding GHG emissions or yields (Dufossé et al., 2013; Gelfand et al., 2013). For example, the biogeochemical model DAYCENT was used to compare the performance of several bioenergy crops at the field scale but only in one location (Davis et al., 2010). Spatially distributed ecosystem models are scarcer, especially for energy crops. Recent studies based on the DNDC-EUROPE model (Leip et al., 2011; Lugato et al., 2010) showed that the use of modeled estimates of N_2O emissions improved the accuracy of GHG emissions compared with the IPCC default (Tier 1) methodology (IPCC, 2006). However, this modeling of cropland did not involve bioenergy feedstocks. Other studies used geo-referenced databases to estimate the availability of land suitable to bioenergy farming, but they estimated biomass yields and GHG emissions from literature reviews or field experiments (De Wit and Faaij, 2010; Fiorese and Guariso, 2010; Fischer et al., 2010; Gasol et al., 2011). Top-down approaches were also developed for biofuel production, given the location of a bioenergy unit and an economic optimization of feedstock production and supply (Hellmann and Verburg, 2011). However, this optimization did not take land characteristics into account when distributing energy crops, assigning them a random location on local cropland. Thus, a bottom-up approach including agro-ecosystem modeling and databases managed under a geographical information systems (GIS) appears as the most accurate option to assess the environmental balance of lignocellulosic feedstocks and optimize their spatial distribution.

The objective of this paper was to assess and design optimal feedstock supply chains for a bioethanol unit, based on agro-ecosystem modeling at regional scale. Minimizing the competition with food and feed crops was also an objective in this optimization. In terms of feedstock types, this paper focuses on three purpose-grown crops, in addition to straw residues: two annual species (triticale and sorghum) and a perennial grass (miscanthus). The paper compares their performances for two different French administrative regions: Picardy and Burgundy. It builds on the methodology proposed by Dufossé et al. (2013) involving the agro-ecosystem model CERES-EGC and a set of GIS databases. The model's ability to simulate the N2O emissions and productivity of crops was already tested for wheat straw, triticale and sorghum, and miscanthus (Gabrielle et al., 2002; Gabrielle and Gagnaire, 2008; Goglio et al., 2013; Ferchaud et al., 2015).

2. Materials and methods

2.1. Regional crop modeling

Regional modeling was based on the agro-ecosystem model CERES-EGC (Gabrielle et al., 2002), which operates on a daily time step. It comprises a physical sub-model which simulates the transfer of heat, water and nitrate down the soil profile, as well as soil evaporation, plant water uptake and transpiration in relation to climatic demand (Gabrielle et al., 2002). A biological sub-model simulates the growth and phenology of the crops and a micro-biological sub-model simulates the turnover of organic matter in the ploughed layer. Direct field emissions of CO_2, N_2O, NO and NH_3 into the atmosphere are simulated with different trace gas modules (Lehuger et al., 2010, 2009). The nitrous oxide emission module simulates the production of this trace gas in soils through both the nitrification and denitrification pathways, using soil-specific, fixed proportions of these rates for the fraction of N_2O evolved (Lehuger et al., 2009). CO_2 exchanges between the soil–plant system and the atmosphere are modeled from processes ofnet photosynthesis and soil organic carbon (SOC) mineralization (Lehuger et al., 2010).

The model requires meteorological and crop management data as forcing variables, as well as soil input parameters. The latter include physical properties, soil texture characteristics and biological parameters for nitrification and denitrification processes. At the regional scale, these inputs were inferred from the 1: 1 000 000 European soil map, in which the twenty soil classes occurring in France were reduced to fourteen main soil types after an aggregation based on their characteristics (Dufossé et al., 2013). The model was run on simulation units (SU) defined by overlaying the soil map

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