

The World's Largest Open Access Agricultural & Applied Economics Digital Library

This document is discoverable and free to researchers across the globe due to the work of AgEcon Search.

Help ensure our sustainability.

Give to AgEcon Search

AgEcon Search http://ageconsearch.umn.edu aesearch@umn.edu

Papers downloaded from **AgEcon Search** may be used for non-commercial purposes and personal study only. No other use, including posting to another Internet site, is permitted without permission from the copyright owner (not AgEcon Search), or as allowed under the provisions of Fair Use, U.S. Copyright Act, Title 17 U.S.C.

No endorsement of AgEcon Search or its fundraising activities by the author(s) of the following work or their employer(s) is intended or implied.



Proceedings of the 6th Symposium on Agri-Tech Economics for Sustainable Futures

18 – 19th September 2023, Harper Adams University, Newport, United Kingdom.

> Global Institute for Agri-Tech Economics, Food, Land and Agribusiness Management Department, Harper Adams University

Global Institute for Agri-Tech Economics

https://www.harper-adams.ac.uk/research/giate/

Site-specific calculation of corn bioethanol carbon footprint with Life Cycle Assessment

Karen D. Ponieman^{AB*}, Rodolfo Bongiovanni^A, Martin L. Battaglia^D, Jorge A. Hilbert^E, Pablo A. Cipriotti^C, Gabriel Espósito^F

^A Rural Engineering Institute, National Institute of Agricultural Technology, INTA, Argentina
^B School of Agriculture - EPG, University of Buenos Aires / CONICET, Argentina
^C The Nature Conservancy
^D Energy & Environmental Consulting Services
^E School of Agriculture - IFEVA, University of Buenos Aires / CONICET, Argentina
^F National University of Río Cuarto, Argentina

Abstract

The agricultural stage is a hotspot in the carbon footprint (CF) of the production of corn bioethanol and, within this stage, the production and use of nitrogen fertilisers is the subprocess that has the greatest incidence. The current research project aims to incorporate the environmental impacts in the analysis of optimum nitrogen fertiliser rates, in addition to the agricultural and economic outputs that have been widely used in previous studies. We seek to obtain functions that describe the CF at different nitrogen rates, topographic positions and climatic conditions, incorporating them as objective functions in multiobjective optimization procedures. In order to achieve this aim, the first step is to quantify the corn bioethanol CF with Life Cycle Assessment (LCA) methodology, for fertilisation and yield data at a site-specific scale. On-farm research trials were conducted in 18 corn fields where agricultural producers applied up to 6 levels of strip nitrogen fertilisation, through an elevation gradient, in 5 crop seasons distributed over 12 years, in the centre-south region of Córdoba province, Argentina. The corn transportation and its industrial process were considered as fixed subsystems for this research. The LCA methodology follows the ISO 14067:2018 standard and the Intergovernmental Panel on Climate Change (IPCC) guidelines (2019). The R software was used to process the large datasets. A bioethanol corn CF map at a site-specific scale was achieved. As opposed to a single CF value per field, assessing the CF at a site-specific scale allows us to explore the within-field variability caused by different input rates, its interaction with environmental factors and crop yields. Spatial and temporal statistical analysis is needed to understand the relation between nitrogen fertilisation and corn bioethanol CF. Furthermore, we expect to consider the function that best represents this relation in the definition of optimum site-specific nitrogen rate.

Keywords

Carbon footprint; life cycle assessment; corn bioethanol; precision agriculture; site-specific management.

Presenter Profile

Karen Ponieman holds a Bachelor's degree in Environmental Sciences from the University of Buenos Aires. Since April 2020, she is a PhD student in Agricultural Sciences at the University of Buenos Aires and a Doctoral fellow from the National Scientific and Technical Research Council (CONICET) and the National Agricultural Technology Institute (INTA). Her PhD project focuses on the multiobjective optimisation of nitrogen fertilisation rate on corn in Argentina to simultaneously meet minimum carbon footprint and maximum agricultural and economic outputs at site-specific scale. Her research is part of the Environmental Footprints Platform and of the Bioenergy project at INTA.

* Corresponding Author: Karen Ponieman, INTA-CONICET-FAUBA, Buenos Aires, Argentina, email: <u>ponieman.karen@inta.gob.ar</u>, <u>kponieman@agro.uba.ar</u>

Introduction

The term carbon footprint (CF) has been widely used as an indicator to quantify the human pressure on the environment (Hoekstra & Wiedmann, 2014). The CF measures the greenhouse gases (GHG) emissions per unit of outcome produced (Kim & Dale, 2008; Kraatz et al., 2013; Boone et al., 2016; Xu & Lan, 2016; Arrieta et al., 2018; Mekonnen et al., 2018). Due to the fact that the manufacture of a product requires the use of multiple raw materials, energy and transportation, the identification of the GHG emissions throughout the entire process is necessary for an integral and systematic analysis. The Life Cycle Assessment (LCA) methodology is one of the most known methodologies to calculate and compare CFs and other environmental impact indicators across different regions and a long time. The International Organization for Standardization (ISO) has two sets of standards (14040 & 14060) that provide tools for the assessment. The LCA of a product takes into account the environmental impact throughout all the stages of the production process, such as the production and transportation of raw materials from the field to the industry, the manufacture, its use and the residues generated after its use (Hauschild et al., 2018; Roy & Dutta, 2019).

Biofuels emerge as an alternative to reduce carbon dioxide emissions resulting from the extraction and use of fossil fuels and to contribute to the Sustainable Development Goals of the United Nations Agenda (United Nations, 2015). The agricultural stage is a hotspot in the production of corn bioethanol (Pieragostini et al., 2014; Moreira et al., 2020; Bongiovanni & Tuninetti, 2021; Hilbert et al., 2021) and, within this stage, the production and use of nitrogen fertilisers is the sub-process that has the greatest incidence in the total corn CF (Ma et al., 2012; Wang et al., 2015; Yan et al., 2015; Qi et al., 2018; Piñero et al., 2019; Bongiovanni & Tuninetti, 2021; Hilbert et al., 2021; Lee et al., 2021). However, the use of appropriate nitrogen fertiliser rates is a key factor for obtaining high yields in corn (Adeyemi et al., 2020; Agyin-Birikorang et al., 2020; Seleiman et al., 2021). That is why it is very important to optimise the use of fertilisers, and the CF is an adequate indicator as it considers not only the GHG emissions but also the amount of output generated with those inputs.

Sustainable intensification of agriculture pursues high product demand by optimising agricultural management and reducing its impact on the environment, by means of increases in the yield per area with less or same use of inputs (Rosales Álvarez et al., 2004; Andrade, 2020; Cassman & Grassini, 2020). In this context, Precision Agriculture (PA) is a technology that generates the nexus between the need for a more intensified agricultural production and that of increasing concerns regarding environmental sustainability (Muschietti-Piana & Zubillaga, 2014; Finger et al., 2019). Variable fertilisation rate is a PA technology that allows the application of the optimum rate in each specific site, according to the crop requirements and soil variability in each production field. Consequently, it can reduce nitrogen loss to the environment and increase the nitrogen use efficiency and crop and economic yields (Bongiovanni & Lowenberg-Deboer, 2004; Gregoret et al., 2006; Albarenque et al., 2016; Muschietti-Piana et al., 2018).

Although the environmental impacts caused by different PA technologies with site-specific management in comparison with a uniform management have been studied in corn (Brown, 2013; Balafoutis et al., 2017), those studies did not consider the environmental indicators in the decision-making process; they just assessed the impact after the management strategy had been already implemented. Instead, the current research project aims to incorporate the

environmental impacts in the analysis, in addition to the agricultural and economic outputs that have been widely used in previous studies. We seek to obtain functions that describe the CF at different nitrogen rates, topographic positions and climatic conditions, incorporating them as objective functions in multiobjective optimization procedures. In order to achieve this aim, the first step is to quantify the corn bioethanol CF with LCA methodology, for fertilisation and yield data at a site-specific scale. Here we will focus on this specific objective.

Methods

Study site

The study site is located in the centre-south region of Córdoba Province, Argentina (Figure 1). Córdoba province is a major corn producer in Argentina, with a total production that represents more than a third of the total corn production in the country. Moreover, the main corn starch bioethanol production plants are located in this area, which produce most of the bioethanol in Argentina (MINEM, 2021).



Figure 1: Location of the 18 study sites and the main bioethanol plants in Córdoba Province, Argentina.

Experiment design

The georeferenced database has 18 maize real field cases where agricultural producers applied up to 6 levels of strip nitrogen fertilisation, through an elevation gradient, in 5 crop seasons distributed over 12 years, in the centre-south region of Córdoba province. Each crop season covers the period between July 1 and June 30 of the following year, and the study period is from the year 1998 through 2010. The elevation gradient was assessed with digital elevation maps. From it, a topographic index (CTI) was calculated (Tarboton, 1997). It has been demonstrated that CTI index is a good indicator of water accumulations and organic carbon in soil (Schmidt & Persson, 2003; Liu et al., 2006; Terra et al., 2006; Huang et al., 2008). Three topographic zones were classified in each one of the 18 fields. The minimum value, the two

terciles and the maximum value of CTI were considered as threshold values for the zone classification. Higher values of CTI index correspond to lower zones within the field, whereas lower values of CTI index correspond to higher zones. The daily precipitation was recorded with a manual rain gauge in each field and the accumulated precipitation (PP_{ACUM}) was calculated during each corn season. In addition, the historical average value of accumulated precipitation (PP_{HISTORIC ACUM}) was collected for that same period, considering the series of years that each field had a record. Then, a Precipitation Index (IPP; IPP=PP_{ACUM}/PP_{HISTORIC ACUM}) was calculated to identify wet or dry years with respect to the historical values of each field. Half of the trials presented values higher and lower than 1, wet or dry seasons respectively; being a value of 1 a combination of location per campaign with normal rainfall for the crop season.

The agricultural management in each field followed standard practices widely adopted in the region (i.e. planting date, plant density, crop protection, weed control, rotations, etc.). Thus, corn management was assumed to be constant during the study period, and this information was obtained from technical reports of the magazine Márgenes Agropecuarios (2010). Yield data were obtained with AgLeader yield monitor and georeferenced by GPS with RTK (Real Time Kinematic) precision technology.

On-farm research trials were carried out according to Bouder & Nielsen (2000). The area of the fields is 10 hectares on average (ranging from 4 to 16 ha). In each field, 4 to 6 fertilisation rates were applied in strips including an unfertilized control. The width of the strips was the same width of the combine harvester (9 metres) and the length was the field. Rectangular grids were created as polygons on top of the observations, in order to normalise the dataset. The maximum rates reached in each trial ranged between 115 and 288 kg N ha⁻¹, and the plant stands were never subjected to a nitrogen limitation. The nitrogen fertilisation source was urea (46-0-0) applied in the moment when the crop presented between V4 and V6 (Abendroth et al., 2011).

Data of the transportation of raw material from the field to the industry and of the industrial process were provided by a biorefinery located in Villa María, Córdoba, Argentina. Annual data correspond to the crop season 2020/2021, and these are considered to be representative of the transportation of raw material and of the industrial process of corn bioethanol in Argentina. Ninety-two percent of the trucks travelled less than 250 km per trip transporting the raw material from the fields directly or indirectly to the industry. The corn transportation and its industrial process were considered as fixed subsystems for this research, because the industry has a processing capacity independent of the crop yield.

Carbon footprint calculation

LCA methodology was used to calculate the CF in each square polygon of the regular grid. The LCA methodology follows the ISO 14067:2018 standard and the Intergovernmental Panel on Climate Change (IPCC) guidelines (2019). The R software was used to process the large datasets. The LCA recognizes four main stages, which are: the definition of the objective and scope of the system to study; life cycle inventory analysis, which collects the relevant inputs and outputs of the system; the evaluation of the environmental impacts generated by the use of inputs and outputs; and the interpretation of the impacts in each phase of the inventory.

The functional unit was 1 MJ of corn bioethanol at the industry's gate, according to the Renewable Energy Directive 2018/2001 (European Union, 2018). In the bioethanol production process, not only biofuel was generated, but also other by-products. The emissions that

correspond to each by-product were assigned according to the energy criteria. The resulting bioethanol CF was expressed as $gCO_2eq MJ^{-1}$.

The GHG emissions were estimated by multiplying the consumption quantities of each input to the corresponding Emission Factor (EF) obtained from databases. The EF for the use of fertilisers, crop residues and the use of fuels in agricultural machinery and transportation of raw materials were obtained from IPCC Guidelines (2019) Tier 1; the EF for the production of fuels was obtained from Hilbert & Caratori (2021); the EF for the production of fertilisers and agrochemicals, and the production of inputs for the industrial stage, were obtained from Biograce V4; the EF for the seed production was obtained from EcoInvent 3.7. It was assumed that there was no soil carbon sequestration, because all fields have more than 20 years of continuous agriculture, hence the system was considered to be stabilised (ISO, 2018; IPCC, 2019).

The impact category evaluated was global warming. The impact assessment method used was the Global Warming Potential method (GWP) with a horizon of 100 years; based on the IPCC Fifth Assessment Report (IPCC, 2013). The GWP considered were for the three main GHGs: Carbon Dioxide CO_2 , Methane CH_4 and Nitrous Oxide N_2O (IPCC, 2013).

Results

A bioethanol corn CF map at a site-specific scale was achieved. Figure 2 illustrates the results, taking field number 14, randomly, as an example. Both yield and CF values for each nitrogen rate present differences in wet and dry seasons (Figure 3). Moreover, there may be differences in yield and CF values among topographic zones (Figure 4). Nevertheless, statistical analyses are needed.



Figure 2: Topographic index (CTI), strip fertilisation nitrogen (N) rates, corn yields and corn bioethanol carbon footprint (CF) values at a site-specific scale in a typical field of the area.



Figure 3: Scatter plot of median corn yield and median bioethanol CF for each nitrogen rate, considering data from 18 field trials. Blue circles: wet seasons. Red triangles: dry seasons.



Figure 4: Scatter plot of median corn yield and median bioethanol CF for each nitrogen rate, considering data from 18 field trials. Circles: wet seasons. Triangles: dry seasons. Grey: high zone. Orange: middle zone. Brown: low zone.

Discussion and conclusion

The resulting maps are a very useful tool as CF data can be related with yield and fertilisation data, as well as with topographic and climatic conditions in order to analyse the spatial and temporal variability of CF within and among fields. As opposed to a single CF value per field,

assessing the CF at a site-specific scale allows us to explore the within-field variability caused by different input rates, its interaction with environmental factors and crop yields. Furthermore, it allows us to consider the CF as an indicator in the definition of PA strategies.

A wide variety of studies around the world have demonstrated a negative correlation between crop yield and its CF (Yan et al., 2015; Arrieta et al., 2018; Zhang et al., 2018; Zhang et al., 2021). This relation is affected by the use of inputs. As the use of inputs increases, so does the yield, reducing the associated CF (Zhang et al., 2018, Zhang et al., 2021), until reaching a threshold. Above this threshold, the addition of more inputs does not increase the crop yield, which can result in a higher CF (Yan et al., 2015). Therefore, it is relevant to calculate the CF at a site-specific scale to optimise the fertilisation rate with PA.

Due to the date of the experiment data available, we do not focus on the value of the CF itself, but we do highlight the functionality of the LCA methodology to calculate a site-specific corn bioethanol CF and its potential optimisation with PA technologies. By analysing the relation between nitrogen fertilisation and corn bioethanol CF with spatial statistics, in the next steps of the current research project we expect to assess if the CF responds differently to the addition of nitrogen fertilisation in seasons with different rainfall and across different management zones. Moreover, we expect to include the function that best represents this relation as an objective function in multiobjective optimization problems. This approach will allow the determination of the optimum nitrogen fertilisation rate with which, simultaneously, CF is minimum and agricultural yields and economic returns are maximum.

References

- Abendroth, L.J., Elmore, R.W., Boyer, M.J., & Marlay, S.K. 2011. Corn growth and development. PMR 1009. Iowa State University Extension, Ames, Iowa.
- Adeyemi, O., Keshavarz-Afshar, R., Jahanzad, E., Battaglia, M. L., Luo, Y., & Sadeghpour, A. 2020. Effect of wheat cover crop and split nitrogen application on corn yield and nitrogen use efficiency. Agronomy, 10(8), 2–11.
- Agyin-Birikorang, S., Tindjina, I., Adu-Gyamfi, R., Dauda, H. W., Fuseini, A. R. A., & Singh, U. 2020. Agronomic effectiveness of urea deep placement technology for upland maize production. Nutrient Cycling in Agroecosystems, 116(2), 179–193.
- Albarenque, S. M., Basso, B., Caviglia, O. P., & Melchiori, R. J. M. 2016. Spatio-temporal nitrogen fertilizer response in maize: Field study and modeling approach. Agronomy Journal, 108(5), 2110–2122.
- Andrade, F. H. 2020. Los desafíos de la agricultura global. Ediciones INTA.
- Arrieta, E. M., Cuchietti, A., Cabrol, D., & González, A. D. 2018. Greenhouse gas emissions and energy efficiencies for soybeans and maize cultivated in different agronomic zones: A case study of Argentina. Science of the Total Environment, 625, 199–208.
- Balafoutis, A., Beck, B., Fountas, S., Vangeyte, J., Van Der Wal, T., Soto, I., Gómez-Barbero, M., Barnes, A., & Eory, V. 2017. Precision agriculture technologies positively contributing to ghg emissions mitigation, farm productivity and economics. Sustainability (Switzerland), 9(8), 1–28.
- Bongiovanni, R., & Lowenberg-Deboer, J. 2004. Precision agriculture and sustainability. Precision Agriculture, 5(4), 359–387.
- Bongiovanni, & Tuninetti. 2021. Huella de Carbono y Huella energética del etanol anhidro, producido en una mini destilería "Minidest" en origen. Revista de Investigaciones Agropecuarias, 1–15.
- Boone, L., Van linden, V., De Meester, S., Vandecasteele, B., Muylle, H., Roldán-Ruiz, I., Nemecek, T., & Dewulf, J. 2016. Environmental life cycle assessment of grain maize production: An analysis of factors causing variability. Science of the Total Environment, 553, 551–564.
- Brouder, S., & Nielsen, R. 2000. On-Farm Research. In J. Lowenberg-Deboer, K. Erickson, & K. A. Vogel (Eds.), Precision Farming Profitability (pp. 103–112). Purdue University, West Lafayatte, IN.

- Brown, R. M. 2013. Economic Optimization and Precision Agriculture: A Carbon Footprint Story. Agricultural Economics.
- Cassman, K. G., & Grassini, P. 2020. A global perspective on sustainable intensification research. Nature Sustainability, 3(4), 262–268.
- European Union. 2018. Directive (EU) 2018/2001 of the European Parliament and of the Council of the 11 December 2018 on the promotion of the use of energy from renewable sources. Official Journal of the European Union, 328, 82–209.
- Finger, R., Swinton, S. M., El Benni, N., & Walter, A. 2019. Precision Farming at the Nexus of Agricultural Production and the Environment. Annual Review of Resource Economics, 11, 313–335.
- Gregoret, M. C., Dardanelli, J., Bongiovanni, R., & Díaz-Zorita, M. 2006. Modelo de respuesta sitioespecífica del maíz al nitrógeno y agua edáfica en un haplustol. Ciencia Del Suelo, 24(2), 147–159.
- Hauschild, M. Z., Rosenbaum, R. K., & Olsen, S. I. 2018. Life Cycle Assessment: Theory and Practice. In M. Z. Hauschild, R. K. Rosenbaum, & S. I. Olsen (Eds.), Life Cycle Assessment: Theory and Practice. Springer.
- Hilbert, J. A., Manosalva, J. A., & Ponieman, K. 2021. Estudios sobre biorefinerías de maíz en la Argentina. Proceeding of the 9th International Conference on Life Cycle Assessment.
- Hilbert, J. A., & Caratori, L. 2021. El potencial de los biocombustibles argentinos para contribuir al cumplimiento de las contribuciones de Argentina en el marco del Acuerdo de París (Issue July).
- Hoekstra, A. Y., & Wiedmann, T. O. 2014. Humanity's unsustainable environmental footprint. Science, 344(6188), 1114–1117.
- Huang, X., Wang, L., Yang, L., & Kravchenko, A. N. (2008). Management effects on relationships of crop yields with topography represented by wetness index and precipitation. Agronomy Journal, 100(5), 1463–1471.
- IPCC. 2013. Fifth Assessment Report. https://www.ipcc.ch/site/assets/uploads/2018/02/WG1AR5_all_final.pdf
- IPCC. 2019. 2019 Refinement to the 2006 IPCC Guidelines for National Greenhouse Gas Inventories (E. Calvo Buendia, K. Tanabe, A. Kranjc, J. Baasansuren, M. Fukuda, S. Ngarize, A. Osako, Y. Pyrozhenko, P. Shermanau, & S. Federici (eds.)). IPCC, Switzerland.
- ISO. 2018. ISO 14067: Greenhouse gases Carbon footprint of products Requirements and guidelines for quantification. International Organization for Standardization.
- Kim, S., & Dale, B. E. 2008. Life cycle assessment of fuel ethanol derived from corn grain via dry milling. Bioresource Technology, 99(12), 5250–5260.
- Kraatz, S., Sinistore, J. C., & Reinemann, D. J. 2013. Energy intensity and global warming potential of corn grain ethanol production in Wisconsin (USA). Food and Energy Security, 2(3), 207–219.
- Lee, U., Kwon, H., Wu, M., & Wang, M. 2021. Retrospective analysis of the U.S. corn ethanol industry for 2005–2019: implications for greenhouse gas emission reductions. Biofuels, Bioproducts and Biorefining, 1–14.
- Liu, Y., Swinton, S. M., & Miller, N. R. (2006). Is site-specific yield response consistent over time? Does it pay? American Journal of Agricultural Economics, 88(2), 471–483.
- Ma, B. L., Liang, B. C., Biswas, D. K., Morrison, M. J., & McLaughlin, N. B. 2012. The carbon footprint of maize production as affected by nitrogen fertilizer and maize-legume rotations. Nutrient Cycling in Agroecosystems, 94(1), 15–31.
- Márgenes Agropecuarios. 2010. Los números del campo. Márgenes Agropecuarios, 25(299).
- Mekonnen, M. M., Romanelli, T. L., Ray, C., Hoekstra, A. Y., Liska, A. J., & Neale, C. M. U. 2018. Water, Energy, and Carbon Footprints of Bioethanol from the U.S. and Brazil. Environmental Science and Technology, 52, 14508–14518.
- MINEM. 2021. Datos Energía Estadísticas de biodiesel y bioetanol. Ministerio de Energía y Minería de La Nación Argentina. http://datos.minem.gob.ar/dataset/estadisticas-de-biodiesel-ybioetanol
- Moreira, M. M. R., Seabra, J. E. A., Lynd, L. R., Arantes, S. M., Cunha, M. P., & Guilhoto, J. J. M. 2020. Socioenvironmental and land-use impacts of double-cropped maize ethanol in Brazil. Nature Sustainability, 3(3), 209–216.
- Muschietti-Piana, M. del P., Cipriotti, P. A., Urricariet, S., Peralta, N. R., & Niborski, M. (2018). Using site-specific nitrogen management in rainfed corn to reduce the risk of nitrate leaching. Agricultural Water Management, 199, 61–70.
- Muschietti-Piana, M. del P., & Zubillaga, M. M. 2014. Agricultura de precisión y GEI: efecto de la fertilización

nitrogenada. In Suelos, producción agropecuaria y cambio climático, avances en la Argentina (pp. 105–127). Ministerio de Agricultura Ganadería y Pesca, Presidencia de la Nación.

- Pieragostini, C., Aguirre, P., & Mussati, M. C. 2014. Life cycle assessment of corn-based ethanol production in Argentina. Science of the Total Environment, 472, 212–225.
- Piñero, P., Sevenster, M., Lutter, S., Giljum, S., Gutschlhofer, J., & Schmelz, D. 2019. Technical documentation of the Sustainable Consumption and Production Hotspots Analysis Tool (SCP-HAT) (Issue September).
- Qi, J. Y., Yang, S. T., Xue, J. F., Liu, C. X., Du, T. Q., Hao, J. P., & Cui, F. Z. 2018. Response of carbon footprint of spring maize production to cultivation patterns in the Loess Plateau, China. Journal of Cleaner Production, 187, 525–536.
- Rosales Álvarez, R. A., Apaza Mamani, E., & Bonilla Londoño, A. 2004. Economía de la producción de bienes agrícolas. Teoría y aplicaciones. CEDE, 2004(34).
- Roy, P., & Dutta, A. 2019. Life Cycle Assessment (LCA) of Bioethanol Produced From Different Food Crops: Economic and Environmental Impacts. In Bioethanol Production from Food Crops (pp. 385–399). Elsevier Inc.
- Schmidt, F., & Persson, A. (2003). Precision Agriculture, 4 (Vol. 179, Issue 192). www.jti.slu.se
- Seleiman, M. F., Almutairi, K. F., Alotaibi, M., Shami, A., Alhammad, B. A., & Battaglia, M. L. 2021. Nano-Fertilization as an Emerging Fertilization Technique: Why Can Modern Agriculture Benefit from Its Use? Plants, 10(2).
- Tarboton, D. G. (1997). A new method for the determination of flow directions and upslope areas in grid digital elevation models. Water Resources Research, 33(2), 309–319. https://doi.org/10.1029/96WR03137
- Terra, J. A., Shaw, J. N., Reeves, D. W., Raper, R. L., van Santen, E., Schwab, E. B., & Mask, P. L. (2006). Soil Management and Landscape Variability Affects Field-Scale Cotton Productivity. Soil Science Society of America Journal, 70(1), 98–107.
- United Nations. 2015. Sustainable Development Goals. https://www.un.org/sustainabledevelopment/sustainable-development-goals/
- Wang, H., Yang, Y., Zhang, X., & Tian, G. 2015. Carbon footprint analysis for mechanization of maize production based on life cycle assessment: A case study in Jilin Province, China. Sustainability (Switzerland), 7(11), 15772–15784.
- Xu, X., & Lan, Y. 2016. Spatial and temporal patterns of carbon footprints of grain crops in China. Journal of Cleaner Production, 146, 218–227.
- Yan, M., Cheng, K., Luo, T., Yan, Y., Pan, G., & Rees, R. M. 2015. Carbon footprint of grain crop production in China -Based on farm survey data. Journal of Cleaner Production, 104, 130–138.