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Comparing Two Agricultural Nitrogen Leaching Models for the Central Valley, USA

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List of Abbreviations

ABBREVIATION	DEFINITION
ACR	Agriculture Commissioner Report
APN	Assessor Parcel Number
CAML	California Augmented Multisource Landcover
CDF	California Department of Forestry and Fire
CMAQ	Community Multiscale Air Quality
CV	Central Valley
CV-GNLM	Central Valley – Groundwater Nitrogen Loading Model
CV-SWAT	Central Valley – Soil Water Assessment Tool
DWR	Department of Water Resources
EPA	United States Environmental Protection Agency
FMMP	Farming Mapping and Monitoring Program
GW	Groundwater
HRU	Hydrological Respond Unit
MPEP TEAM	“Management Practices Evaluation Program” - Team
MSLC	Multisource Land Cover
SAV	Sacramento Valley
SJV	San Joaquin Valley
TLB	Tulare Lake Basin
UC - DAVIS	University of California – Davis
U.S.	United States
USDA	United States Department of Agriculture
WHO	World Health Organization

Abstract

Nitrogen (N) concentrations increase in aquifer systems in the Central Valley (CV) in California, US, presenting a risk for human health and the environment. Intensive irrigated and fertilized agriculture is a big contributor for this development. To outline and protect most vulnerable regions, the CV-SWAT (Soil & Water Assessment Tool) and CV-GNLM (Groundwater Nitrogen Loading Model) were developed, deriving two different results for N leaching to groundwater. This work compares the results of the models for the most cultivated crops in the CV, outlining the main differences resulting in different N groundwater leaching and gives recommendations for adjusting CV-GNLM. A focus lies on the comparison of land use, N in harvested crops, fertilization and organic nitrogen pools.

Land use is found to be different between CV-SWAT and CV-GNLM due to various time and source of the obtained data, which has no impact on crop specific leaching rates. Lower modelled N in harvested crops and higher fertilizer rates are identified as main reasons for an overall higher loading to groundwater in CV-GNLM. Adjusting N harvest rates with recent obtained data for crop yields has little impact, whereas the conversion factor from crop yield to N amounts is identified as decisive factor. Higher N in fertilizer in CV-GNLM is due to modelled manure application which underlie high variations and uncertainties throughout the CV. It is found that N storage as stable organic N in the soil is not negligible for annual crops and N storage in tissue of perennial crops is significant. Therefore, their implementation in CV-GNLM's N mass balance is recommended to derive to more realistic N groundwater loadings.

Possible reason for the discrepancy between the models include the outdated result from CV-SWAT. Implementations of parameters from CV-SWAT for stable organic N and N in perennial tissue should therefore be expanded to all crops present in the CV with the most recent results available. In order to adjust CV-GNLM, it is recommended to further investigate how the changes are applicable for the historic context.

Keywords: nitrate leaching, groundwater, modelling, agriculture, Central Valley

Zusammenfassung

Steigende Nitratkonzentrationen in den Aquifers im Central Valley (CV) in Kalifornien, US stellen ein hohes Risiko für die Gesundheit der Bevölkerung und die Umwelt da. Intensive, bewässerte Landwirtschaft trägt maßgebend zu dieser Entwicklung bei. Um anfällige Regionen hervorzuheben und besser zu schützen, wurden das CV-SWAT (Soil Water Assement Tool) und das CV-GNLM (Groundwater Nitrogen Loading Model) erstellt, die zu unterschiedlichen Ergebnissen von Stickstoffversickerung gelangen. Diese Studie vergleicht die Ergebnisse der beiden unterschiedlichen Modelle für die am häufigsten kultivierten Feldfrüchte im CV, arbeitet die wesentlichen Gründe für die unterschiedlichen Ergebnisse heraus und gibt Vorschläge zur Anpassung von CV-GNLM.

Die Landnutzung ist unterschiedlich zwischen CV-SWAT und CV-GNLM aufgrund der zeitlichen Differenz und die Quelle der benutzten Daten. Der Unterschied weist keine Auswirkung auf die Feldfrucht spezifische Nitratversickerungsrate auf. Geringere Mengen an modellierten Stickstoff in Ernten und erhöhte Rate von Düngung sind die Hauptgründe für die höhere modellierte Nitratversickerung in CV-GNLM. Anpassung der Ernte – Stickstoffraten mit neuesten Daten von Erntemengen hat wenig Auswirkung, wobei der Konversionsfaktor von Erträgen zu enthaltenen Stickstoffmengen als ausschlaggebend erkannt wurde. Mehr Stickstoff in Düngung im CV-GNLM kann mit der modellierten Gülledüngung begründet werden, wobei diese eine hohen Variation und Ungenauigkeit im CV unterliegt. Es ist erkannt worden, dass Stickstoffspeicherung in stabilen organischen Material im Boden für jährliche Feldfrüchte nicht vernachlässigbar ist und die Stickstoffspeicherung in Gewebe von mehrjährigen Feldfrüchten signifikant ist. Daher ist deren Einführung in CV-GNLM's Massebilanz empfohlen, um genauere Ergebnisse für die modellierte Stickstoffversickerung zu erzielen.

Grund für die Abweichung der beiden Modelle liegt auch an den veralteten Resultaten von CV-SWAT. Die Einführung von CV-SWAT's Parametern von stabilen organischen Stickstoff und Stickstoff in mehrjährigen Gewebe sollte daher mit den aktuellsten Ergebnissen durchgeführt und auf alle im CV angebauten Feldfrüchten erweitert werden. Um CV-GNLM anzupassen, ist es empfehlenswert zu erforschen, wie und ob die Veränderungen für historische Ergebnisse anzuwenden sind.

Stichworte: Nitratauswaschung, Grundwasser, Modellierung, Agrarkultur, Central Valley

1. Introduction

1.1 Nitrogen in groundwater

Nitrogen is a major component for plant growth. Although about 78% of the atmosphere is nitrogen gas (N_2), for plants it is often a limiting factor. For plant and animal use, nitrogen (N) has to be in form of reactive nitrogen, including inorganic reduced forms (e.g., NH_3, NH^{4+}), inorganic oxidized forms (e.g., NO_x, HNO_3, N_2O, NO_3^-) and organic compounds (e.g., urea). Historically, biological fixation (microbes & legumes) and decomposition supplied plants with its nitrogen demand. In the 20th century, a drastic increasing population asked for sufficient and affordable crop production, which was met among other things through intensive fertilization with manure and synthetic fertilizers (Galloway and Cowling, 2002).

Over the decades, common fertilization, irrigation, and soil management practices had an increasingly negative impact. Nitrate is of particular concern since it dissolves easily in water and thus, is easily transported on varies water pathways. Globally, cases of eutrophication of aquatic bodies by surface runoff, air pollution through toxic emission and nitrate (NO_3^-) leaching into groundwater related to agriculture are increasingly reported (Sutton et al., 2011). The latter is not only an environmental concern but also one of human health, as drinking water is often retrieved from groundwater aquifers. Nitrate-contaminated drinking water can cause methemoglobinemia for infants and other health issues for human (Ward et al., 2018). The U.S. Environmental Protection Agency (EPA, 2018) puts the drinking water limit of Nitrate - N in the United States to a concentration of 10 mg/L. This concentration is approximately equivalent to the 50 mg/L NO_3^- or 11.3 mg/L NO_3^- - N set by the World Health Organization (Ward et al., 2018). Harding et al. (1963) reported the problem of nitrogen leaching from agriculture in the Central Valley in the USA in the 1960s.

Because of the complexity of nitrate loading (across space and time) and of nitrate transport and related uncertainties, it is challenging to assess the groundwater contamination due to nitrate contamination (Vadiati et al., 2016). It has been the effort of the last years to minimize the uncertainties and to better understand sources and pathways of nitrate to better protect groundwater aquifers. Therefore, in the last two decades, the field of computer science advanced rapidly and enabled hydrologists to model groundwater pollution more accurately. Nevertheless, there are substantial variations between different models approaches and it is debatable which model is most suitable for which situation and scale (Haghbin et al., 2021).

1.2 Problem and Objective

Nitrate concentrations are also increasing in the aquifers of the Central Valley (CV), perhaps due to the permeable soils and intensive agriculture that can increase the risk of nitrate leaching (Burow et al. 2013). In order to specify most vulnerable areas, predict future loading rates and to find best possible measures against a continuing negative trend of groundwater contamination, different models were developed for the CV (Viers et al., 2012; MPEP Team, 2019).

Many commonly used models are based on mass balance equations. Especially in agricultural ecosystems, balancing water or nutrient equations (like nitrogen or phosphorous) are used in many studies to illustrate in- and outputs of a system (Linke, 2018; Ransom et al., 2017; Harter et al., 2017). On the one hand, these methods highlight the major pathways clearly, however on the other hand they simplify the underlying processes and transformations. Therefore, mass balances are mostly applied in large scale investigations, where small scale pathways and transformations become less important. If other terms are known, it is useful to quantify one unknown variable, rather than investigating underlying processes. Depending on the data available, researchers need to deviate between making assumptions and/ or adapting the resolution of their model. As a result, modelling requires to balance the uncertainty against the accuracy depending on the available data and the research aim (Beven, 1995; Haghbin et al., 2021). Because of the big scales in agricultural ecosystems, mass balances are often used in this context to evaluate the nitrate loading to groundwater.

The “Central Valley – Groundwater Nitrogen Loading Model” (CV-GNLM), developed in 2012, is based on a mass balance approach and aims to assess the nitrate loading to groundwater (Viers et al., 2012). Thereby it initially focused on the historical change of agriculture change of land use, irrigation, and fertilization practices. It does not include climate or soil data, but relies exclusively on empirical review, archive records and farmers expertise. The alternative computational model “Soil Water Assessment Tool” (SWAT), further developed for the CV, requires detailed data and for the entire CV immense computer power and calculation time. It does not consider historic changes in land use, but includes climate variability. Both models come up with different results for nitrate leaching under the root zone. This brings up the question, where exactly the conceptual differences lie, and inaccuracies occur.

Therefore, this study aims to improve the accuracy of calculated nitrate leaching of the latest version of the mass balance based in the CV-GNLM model by comparing it with the physically more detailed CV-SWAT model. For this, comparable variables, in- and outputs and crops are identified and evaluated in detail to determine the inaccuracy and uncertainties in the CV-GNLM model. Furthermore, possible improvements are worked out and recommendations are given how to adjust the CV-GNLM groundwater leaching results closer to the ones of CV-SWAT.

2. Theoretical Background

2.1 Study Area

The CV in California in the US also known as the Great Valley of California is with 20,000 square miles (~52,000 km^2), a notable geographical depression in the world. The valley has a centered position in California and is bounded by the Cascade Range to the north, the Sierra Nevada to the east, the Tehachapi Mountains to the south, and the Coastal Ranges and San Francisco Bay to the west (Figure 1).

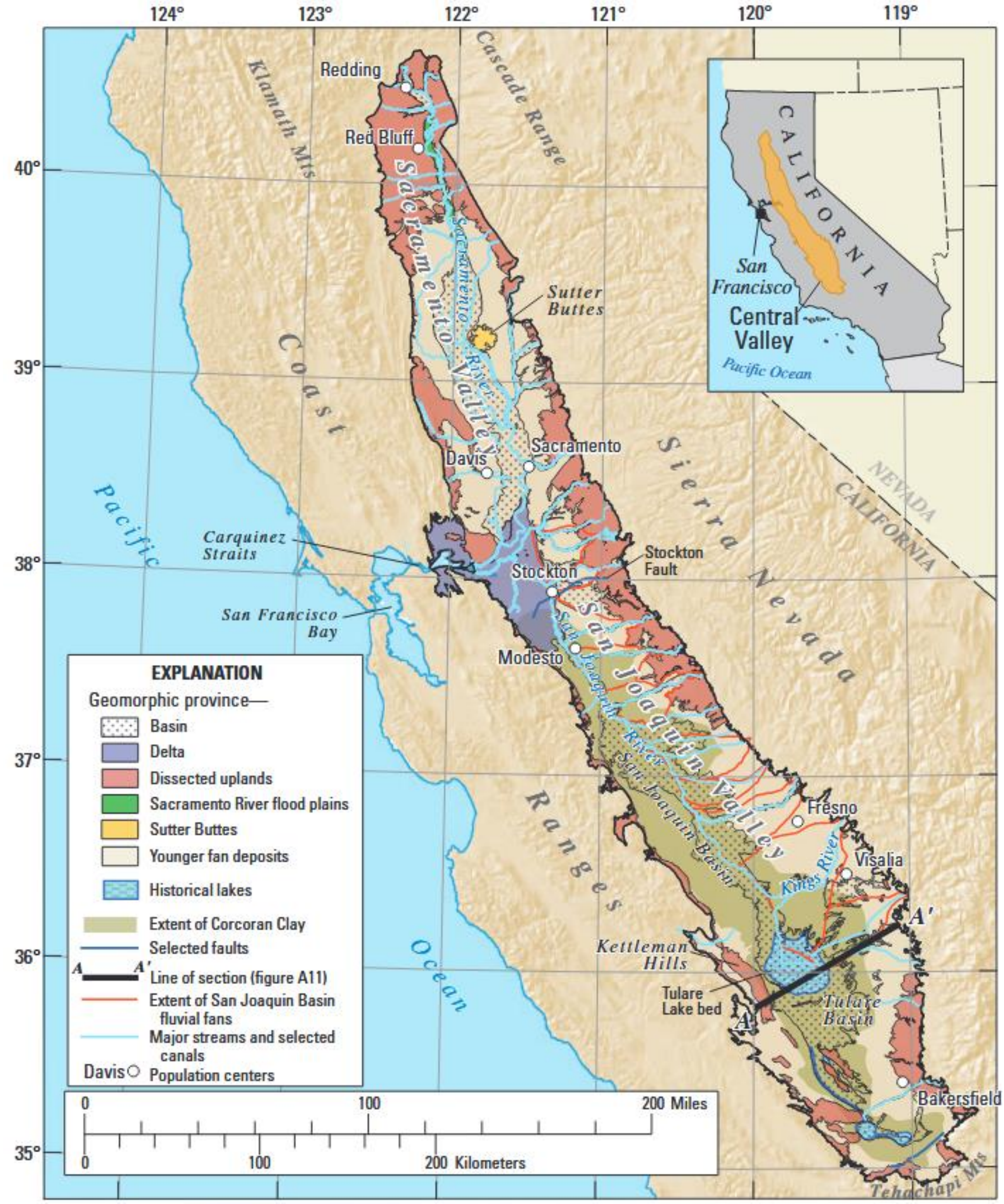

Figure 1: Shaded relief of the Central Valley in California, US. Derived from U.S. Geological Survey National Elevation Dataset, 2006.

The CV can be divided into the “Sacramento Valley” (SAV), which occupy one-third in the north and the southern two-thirds known as the “San Joaquin Valley”. The latter is further split into the “San Joaquin Basin” (SJV) and the “Tulare Lake Basin” (TLB). The Sacramento and San Joaquin River drain the water from the surrounding mountains and ranges through the valley and meet with several eastside streams from the Sierra Nevada. After the Delta area, the combined discharge flows through the Carquinez Strait into San Francisco Bay and the Pacific Ocean.

The climate in the CV is arid-to-semiarid hot, Mediterranean. Precipitation in the SAV varies between 330 – 660 mm annually, whereas precipitation in the SJV is only expected to be between 127 – 460 mm/a. About 85% of the precipitation falls from November to April, though December to February are the wettest months. In this time, the valley is prone to flooding. Besides that, high evapotranspiration results in very hot and dry summers, when most of the state is in water deficiency. The number of droughts are increasing in the last decades (Faunt et al., 2009; California Water Science Center, U.S. Geological Survey, 2022).

Farrar and Bertoldi (1988) describe the Central Valley as “virtually one large sediment-filled between Coast Ranges and the Sierra Nevada”. In Figure 2, it can be seen that the sediment lies over a westward-sloping basement rocks, being the subsurface continuation of the Sierra Nevada.

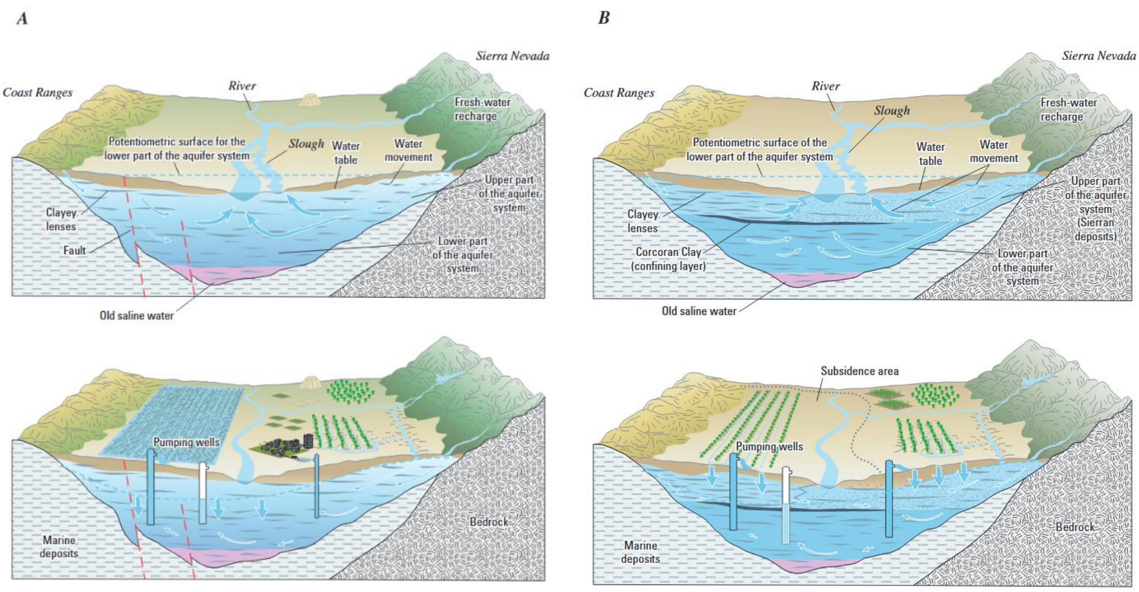

Figure 2: Pre- and post- development of A, Sacramento Valley. B, Central part of the San Joaquin Valley, California. From: Faunt, 2009.

Above the bedrock lies a thick layer of deep marine, deltaic and continental sediment. The deposits vary from zero in the east to more than 15,200 m deep on the western edge. Continental sediments, carried by streams from surrounding mountains and ranges filled the valley with sand and gravel, mixed with clay and silt up to a depth of 730 m today. Alluvial fans have developed on all sides of the CV, leaving the coarse-grained sediments rather at the valley margin, some more than 300 m thick.

These deposits of the CV form a complex aquifer system, consisting of unconfined, semi-confined and confined aquifers. Clay lenses, accumulated by lakes during the Pleistocene, are distributed throughout the CV. These lenses have low permeability but are generally not vertically extensive or laterally continuous. This clay is often referred to as “Corcoran Clay” (Page und Bertoldi, 1983; Farrar and Bertoldi, 1988). In the western San Joaquin valley, a continuous and thicker Corcoran clay layer divides the groundwater flow into an upper semi-confined and lower confined aquifer. An increasing number of wells above and under this layer, increased the hydraulic conductivity between these aquifers (Faunt et al. 2009).

Overall, there are considerable variation of deposits throughout the CV and conclusively as well their hydraulic conductivity and groundwater availability (Page and Bertoldi, 1983). Because of high temporal and spatial variability of precipitation, runoff, and surface water availability in the CV, the population depends on groundwater as reliable water source. To secure agricultural development and population growth in the water-deficient valley, large scale hydrologic systems were engineered. When surface water (dams and surface water diversions) does not meet the water demand, groundwater is used to fill the imbalance (Faunt et al., 2009). Because of the fertile soil, the long growing season and the irrigation system, a big variety of crops is grown and harvested two or three times in a year on a single field.

Additionally, changing market conditions (development of global market and cheaper production of grain production elsewhere in the world) and better transportation facilities (e.g., railroads) had the result that crops like almonds, pistachios and more than half of all the grapes grown in the US are coming from the SJV. Today around 50 different crops are cultivated in the CV (MPEP Team 2019). Agriculture is the dominant land user in the CV (~60% of floor area) and a main economic driver for the region (Faunt et al., 2009).

It is not surprising that a long history of agricultural and urban development influenced the groundwater in the CV. Faunt et al. (2009) simulated the water budget (surface and groundwater) and concluded that intensive pumping for irrigation water results in a change in aquifer storage. Consequently, water level changes (dominantly declines, rises in some areas) which alters groundwater flow rates and directions and influences the flow exchange with streams and surface waters as illustrated in Figure 2. This development results in extensive loss of riparian vegetation and wildlife habitat. Additionally, aquifer – system compaction and land subsidence are further results from groundwater pumping (Farrar and Bertoldi, 1988; Galloway et al., 1999). Another problem, not connected with the available water quantity but with the water quality is the leaching of nitrate. As mentioned before, part of the pumped groundwater used for irrigation, infiltrates back to the ground. Hence, this water takes up the highly soluble and mobile nitrate, originated from fertilizers and transports it into the groundwater. Although this effect varies across the CV, it becomes an increasing problem throughout the state. Mainly, shallow aquifers are effected which are used as drinking water supply in rural areas, constituting a health risk for the population (Burow et al., 2013). This paper will elaborate and investigate this phenomenon of GW leaching further.

2.2 Nitrogen mass balance in agriculture

Nitrogen is needed as part of nucleotides and proteins and is therefore essential for all life. For plant growth, it can be a limiting factor for growth and productivity as any other nutrient. Although N makes up 79% of our air in form of N_2, only a few natural processes can break the strong triple bond between the two Nitrogen atoms and transforming it to available form for plants in soil. For once, lightning can break this bond with its immense heat, but more commonly N is made available by N_2 – fixing microbes which are capable to convert N_2 to NH_3. The discovery of the Haber – Bosch process which forms Ammonia (NH_3) under high pressure and heat from CH_4 and N_2, revolutionized agriculture fertilizer practices. The capability to produce N – fertilizer, enabled agriculture to increase its crop yield, meaning more food can be produced on less area. In the last century, this high productivity enabled to sustain the increasing world population while relieving pressure on land clearance. In agriculture as well as in in other ecosystems, the N cycle is highly complex. Since Nitrogen is not present in rocks as most other necessary nutrients, it must derive from other sources. The form in which N is delivered is of major importance since that depends on how available it is to organisms and plants, and how mobile it is and therefore vulnerable to loss through hydrological and gaseous pathways (Robertson and Vitousek, 2009; Schimel and Bennett, 2004; Pang and Letey, 2000).

Robertson and Vitousek (2009) explain in detail the different sources, pathways, and transformation processes of Nitrogen in the soil. Nitrogen deposition through rainwater and from dry deposition is a minor contribution and in most natural ecosystems N_2 – fixation through plants and microbes are the major N source. If not carried out by harvest, the N gets replenished when organic matter is decomposing and returned to the soil. This natural cycle is interrupted in agriculture, by removing N through harvest of yield, leading to an N deficit in the soil for future plants. There are essential three possibilities for farmers to replace N loss: 1st to include N-fixing crops in rotation (historically most common, but little efficient), 2nd returning removed N in form of manure which is derived from grazing animals from pasture or 3rd to add synthetic fertilizer. Whereas the first option is commonly used in organic farming by including N fixing winter crops, this strategy includes additional costs which precluded their widespread (Pang and Letey, 2000). Manure input can be provided where there are animal farms nearby or combined with crop production. Since N ingested is mostly excreted, manure application is suited as fertilizer (Robertson and Vitousek, 2009). According to Allen (2008), the introduction of legumes, crop rotation and manure application to balance the N loss from harvest, greatly contributed to an increase of crop yields in the preindustrial Britain. Today, agricultural businesses are structured more linear in the sense that farmers are more specialized. (It is more profitable to grow one specific crop or only concentrate on animal farming than to run a "mixed farm system". On the other hand, these operations are not efficient with their nutrient management.) As a result, feed and livestock are produced far from each other, making it expensive to transport the manure back to feed production and closing the N cycle. This spatial disconnect makes the third option the most lucrative one for farmers, operating an intensive cropping system. Synthetic fertilizer are "[…] easy to transport, readily available, and relatively inexpensive…" (Robertson and Vitousek, 2009, 102).

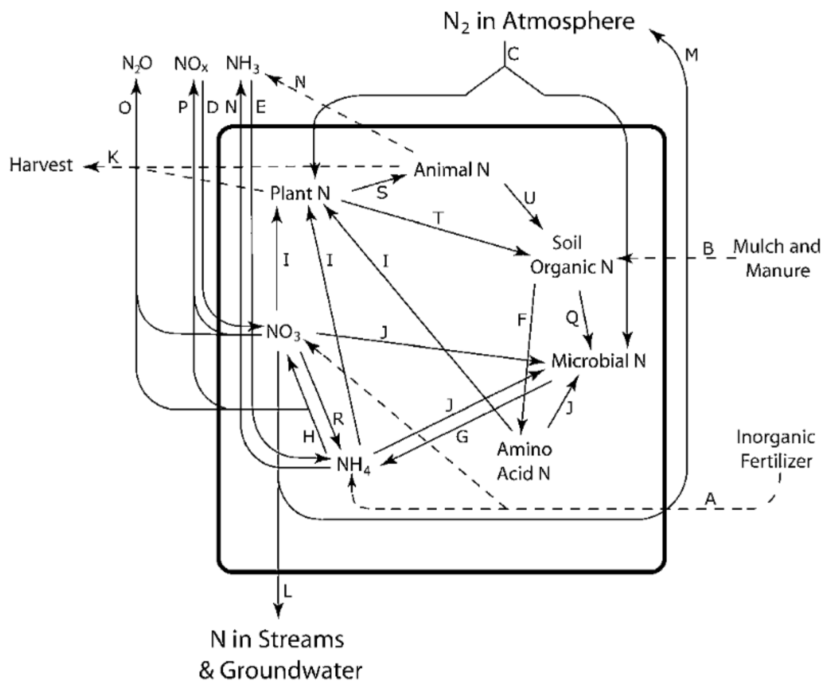

Figure 3: Pathways of nitrogen (N) in a substantial simplification of the N cycle. Solid lines indicate transformations occurring in all ecosystems, whereas dashed lines indicate processes particular to agricultural systems. From Robertson & Vitousek (2009).

Cassman, Dobermann and Walters (2002) state that this practice comes with great environmental costs since less than half of the applied N is recovered in crops. Consequently, the rest is lost to the environment with pathways like surface runoff in rivers, lakes and oceans, atmospheric loss and leaching to groundwater. In order to improve management practices and reducing harm to the environment from N loss, it is vital to understand and quantify those highly complex pathways and transformation processes (Robertson et al., 2008). Figure 3 shows a simplified version of the N cycle in agricultural ecosystems, whereas the dotted lines represent stream flows, not present in natural systems.

Nitrogen inputs are inorganic fertilizer (arrow A in Figure 3), organic fertilizer like mulch and manure (B), N_2 fixation (C) and atmospheric deposition (D & E). Fertilizer inputs are depending on the management practice. Synthetic fertilizer (mostly inorganic N and urea) are instantly available for plants, whereas organic fertilizer needs to be processed by microorganisms before its N is available for uptake. The process of mineralization (F & G) describes the transformation from organic forms to soluble and plant available form, including amino acids by extracellular enzymes. Although already available for plants, most amino acids are further transformed to inorganic form (Schimel & Bennet, 2004). Nitrification (H) is the process of further oxidation of the less mobile NH_4^+ to more mobile NO_2^- (nitrite) and further to NO_3^- (nitrate). As an anion, nitrate is easier receivable for roots and transported to groundwater. Process I in Figure 3 shows the uptake by plants, mostly in the form of nitrate (NO_3^-) (Jackson, 1997). The counter transformation of immobilization (J) is driven by microbes, also in need of N, thus competing with the demand of the plants. On the other hand, through immobilization, N is retained from loss to the environment and can be made available at a later point through mineralization again (Schimel and Bennet, 2004).

Outputs of N in an agricultural ecosystem is for once the harvest (K) and leaching to surface and groundwater (L) as mentioned above. Hence its negative charge, nitrate is highly soluble in water and therefore moves easily with it through soil to groundwater or other hydrological pathways. Di and Cameron (2002) state that this phenomenon can be observed in all agricultural ecosystems, but especially when crops or pasture is fertilized and irrigated. Other pathways for N loss are gaseous. Denitrification to N_2 (M) removes available N from the ecosystem and returns it to the atmosphere. Little is known about the magnitude of this flux and is often quantified by the difference of the other fluxes. Nevertheless, except in flooded soils like in wetlands, denitrification losses are rather small and harmless to the environment since the high content of N_2 in air. NH_3 volatilization (N) is the loss from manure, soils, and plants. It mostly occurs shortly after fertilization and can be especially high when anhydrous NH_3 (liquid manure, urea) is applied under dry soil conditions (Schjoerring, 1998). In the process of denitrification and nitrification, a small fraction is emitted to the atmosphere as N_2O (from denitrification) and NO_x (from nitrification) (O, P; Figure 3). Although the overall loss is rather small from agricultural ecosystems, the emission from nitrogen oxides must not be underestimated (Xiao et al., 2021).

2.3 Modelling Nitrogen groundwater content

2.3.1 General

Modelling is the attempt to describe natural processes based on input variables, model parameters and initial conditions. Because in hydrological systems and especially in groundwater systems, extensive measurements on large scale are often either physically not possible or very expensive, the tool of modelling gives us a possibility to fill research gaps (De Jong and Van Joolingen,1998). In the last decades, hydrological models have been used increasingly to not only understand natural processes but also to study the effect of different future management scenarios. This approach enables researchers to make predictions in ungauged catchments and to make predictions of possible future changes in climate, land use and management practices (Beven, 2001; Williams, 1995). In the context of groundwater, the field shifted its focus in the last decades. Whereas in the late 20th century many studies focused on modelling leakage of point sources and their spreading in a groundwater body, in the last decades the focus lies on non-point pollutants. As mentioned before, N in surface and groundwater becomes increasingly an environmental and health risk (U.S. Environmental Protection Agency, Office of Water, 2018). Therefore, more effort is put in understanding leakage processes and quantifying N loading from varies sources.

Liu et al. (1997) describes that there are many different forms of modelling N transport and transformations but that they can basically divided in physical and empirical modelling. Physical modelling relies on site-specific (model) parameters and measurements. It is important to keep in mind that this data may not be complete or inaccurate for which the theory of the model may or may not be complete (Worrall and Burt 1999). The empirical modelling on the other hand relies exclusively on empirical literature. With this model more general contexts and connections are explained, but it is unable to make more side specific predictions. In most cases, a “structural model” is used which uses both kinds (physical and empirical) of modelling (Liu et al., 1997).

Since the accuracy and reliability of hydrological modelling is highly dependent on the computing power available, new approaches and extend of hydrological models arise with the increasing performance of modern computers. A rather new method are the “Soft Computing” (SC) models such as as fuzzy logic (FL)-based models, artificial neural network (ANN), support vector machines (SVM), self-organized mapping (SOM), decision trees (DT) and random forest (RF) (Srinivasan et al., 2018; Sharafati et al., 2021). It gets further stated that those approaches have high potential to improve accuracy of predictions of groundwater pollution sources but also still needs a lot of improvement. The problem of land use change over time at the same location is given as an example. It makes it difficult for machine learning applications to apply mechanisms for which there is not enough data. Future research in this field will need to update the time lag between observed data, modelling, and predictions (Sharafati et al., 2021). In the CV where the problem of Nitrate leaching in groundwater is an acknowledged problem, Ransom et al. (2017) predict and visualize nitrate concentrations with a hybrid machine learning model (boosted regression tree). This method not only calculates N concentrations but also highlights which variables serves as good predictors.

With all these different methods and approaches how to model N loading to groundwater (GW), it is a good question to ask which model to use. According to Gharari and Razavi (2018), ideally one would have a full- dimensional process representation, based on a perfect understanding of the processes, their heterogeneity, and their spatio-temporal scale dependency. Unfortunately, as stated before, some of that information are often not available in hydrological modelling and the bigger the scale, the more effort to reflect heterogeneity. Beven (1995) states that it is inadequate to transfer a small-scale model on a bigger scale by using “effective” parameter values, but to incorporate hydrological heterogeneity. On the other hand, a more precise model, also needs more data to feed. If those are not available, it is obsolete to develop a high resolution model. At the end, it is a question about what one wants to answer, which scale is from interest and what data is available.

2.3.2 GNLM

The “Groundwater Nitrogen Loading Model” (GNLM) was developed in the framework of the report “Nitrogen Sources and Loading to Groundwater in the Central Valley” by Viers et al. (2012) and further updated multiple times. In order to make sources of N loading to the GW more comprehensible for the public by presenting N pollution sources, a field scale mass balance approach was chosen. This was done not only for irrigated crops but also for other land uses. After reviewing the results with literature, those N loading rates were then applied for large scale areas like the SAV, SJV and the TLB. A special emphasis was put on the change of land use from 1945 to 2007. The travel time from nitrate source to the GW water level and to the next well is typically years, decades to centuries and more. Therefore, to assess current and future GW quality in wells and at the interface to streams, one need to know historic N losses to the water table and their historic timeline (Harter et al., 2017).

The mass balance approach is conceptual one of the simplest methods to model transport of a material whereas the analysis is zero-dimensional. Mass fluxes in and out of a control volume are aggregated. It is therefore a simple accounting method, not considering transformation processes within the control volume how they would occur in nature.

$$\Delta \boldsymbol{Storage} = \boldsymbol{N_{Inputs}} - \boldsymbol{N_{Outputs}} \tag{1}$$

Where:

$$\boldsymbol{N_{Inputs}} = \boldsymbol{N_{deposition}} + \boldsymbol{N_{irrigation}} + \boldsymbol{N_{synthetic}} + \boldsymbol{N_{LandApplied}} + \boldsymbol{N_{manure\_sale}} \tag{2}$$

$$\boldsymbol{N_{Outputs}} = \boldsymbol{N_{harvest}} + \boldsymbol{N_{runoff}} + \boldsymbol{N_{atm\_Loss}} + \boldsymbol{N_{GW\_nondirect}} \tag{3}$$

The control volume comprises of 50x50 m cells and N fluxes are calculated for one year, whereas time periods of 15 years are summarized by the same land use (crop and fertilizer application). In order to make spatial comparison more comprehensible, amounts are presented in loadings instead of concentrations (kg N/ha/yr).

INPUT

Since the report "Nitrogen Fertilizer Loading to Groundwater in the Central Valley" (Harter et al., 2017) deals with different time periods, a focus of it was to obtain the necessary and reliable data for each variable. Since this paper only takes the most recent time period into account, only the data collection of this period will be elaborated.

The land cover map is composed of different sources of information. Agricultural land use information is taken from the Department of Water Resources and the Pesticide Use report. Urban areas are combination of urban areas from Farmland Mapping and Monitoring Program (FMMP) and the CDF (California Department of Forestry and Fire) Multisource Land Cover (MSLC) layer. Furthermore, natural lands are taken from the MSLC layer if an area is neither agricultural nor urban. All these layers together combined result in the "California Augmented Multisource Landcover" (CAML) at 50x50m resolution.

$N_{Deposition}$: Nitrogen deposition through rain and atmosphere

N deposition can vary spatially, especially dry deposition which are rarely measured. Large scale estimates are therefore mostly based on modeling. In this report the data from the "Community Multiscale Air Quality" (CMAQ) model is used, developed by the U.S. EPA. The models highest resolution is a 4km grid and estimates were updated by Bobbink et al. (2010), taking measured rates more accurately with into account.

$N_{Irrigation}$: Nitrogen content in irrigation water

The nitrogen content in irrigation water can vary greatly throughout the CV. For once, because of the amount of irrigation water applied and secondly, for the N content in that water. The GW use for irrigation and the amounts of nitrate in groundwater is derived from Boyle et al. (2012), providing nitrate-nitrogen application rates through measurements from public supply wells for 2000 - 2009 (Viers et al., 2012).

$N_{Fertilizer}$: Nitrogen content in synthetic fertilizer applied

This information was obtained by interviewing experts, growers, reviewing literature for most recent published fertilizer practices for major crops in California (Rosenstock et al., 2014; Viers et al., 2012) and investigating fertilizer sales in the time period, published by "California Department of Food and Agriculture" (https://www.cdfa.ca.gov/is/ffldrs/Fertilizer_Tonnage.html).

$N_{landApplied}$: Nitrogen content in manure fertilizer from inside the raster

Manure mainly derives from dairy operations, beef lots and poultry and swine manure. CV-GNLM differentiates between manure application on cropland within dairies and outside of dairies. This was determined, whether cropland is located within raster associated with a dairy's reported "assessor parcel numbers" (APNs). All manure applications are distributed proportional to typical fertilizer N applied for that specific crop on that specific field. Where dairy farmers also own cropland ("dairy cropland"), it is assumed that liquid manure accounts for 2/3 total fertilizer application for field crops like corn (often double cropped with winter grain) and 1/3 for grain and hay crops. The amount of available liquid manure on dairy cropland was calculated by determining the amount of N excreted minus the amount of N in atmospheric losses prior to land application minus the amount of N exported from the dairy facility. The amounts in this calculation are derived from EPA 2005 dairy database, evaluated by Viers et al. (2012) and Pettygrove et al. (2010). Taking with into account the "support stock" (calves and heifers), a total of 198 kg N/yr per an adult cow was determined. The size of herds was obtained from "United States Department of Agriculture" (USDA) agricultural census data from 2007 from which the total amount of excreted manure could be calculated. The amount of N, lost to the atmosphere prior to application are at 38% (EPA, 2003). Final amounts of manure application on dairy cropland is taking the overall N demand of each crop and $N_{Synthetic}$ application with into account. It is common practice among farmers, that although manure would meet crops N demand, instead or in addition synthetic fertilizer is added on the field because of the "uncertainty about short- and long-term release of plant available forms of N from organic sources" (Harter et al., 2017). The amount of manure N applied to a dairy cropland raster was therefore calculated:

$$NlandApplied_i = \frac{Nfertilizer_i}{\sum_{i=1}^{n} Nfertilizer_i} * \sum_{dairy} NlandApplied \tag{4}$$

i = raster cell

Outside of dairy croplands, amounts available for manure application is based on manure sales (explained in detail further on). Exported manure is mostly in form of dried or composted manure solids which is besides of field crops and grain and hay crops, additionally applied to perennial crops and alfalfa (Viers et al., 2012). The export of manure is obtained from UC-Davis's Dairy Annual Report Database v2012. In some cases, reported values are higher than calculated amounts (62% of excreted manure) in which case the median value of N export from dairy operation was used. If that amount was still higher than 62%, amounts were further reduced to 62% of initial excreted manure, leaving no manure available for the corresponding dairy cropland. It is further stated that due to high transportation costs, exported manure rarely leaves the county (Viers et al., 2012).

It is assumed that solid manure application outside of dairy cropland is always applied in addition to synthetic fertilizer (Harter et al., 2017).

Table A - 1 (Appendix A) gives a detailed overview of crops receiving manure in the column "GNLM: LUdriven N source_Dairy" whereas "1" indicates application of liquid manure on dairy cropland and "2" application of solid exported manure

N_{manure_sale}: Nitrogen content in manure fertilizer from outside the raster

As mentioned above, the manure N export from dairy facilities is obtained by UC Davis Dairy Annual Report Database v2012. For the period of interest, the focus is on the records of each dairy from 2007. The atmospheric loss of 38% prior to application was taken with into account.

$$NmanureSale_{i,j} = \frac{Nexport_j}{AreaNexport_j} \quad (5)$$

Where $N_{manureSale}$ stands for exported manure in kg N/ha/yr for raster cell i receiving exported manure in county j.

$N_{harvest}$: Nitrogen content in harvested crop

N removal in harvested crop is calculated in two steps. First, amounts of yield for each year and county was taken from the ACR (Agriculture commissioner report). Secondly, the amounts of yield are converted in N removed by using the USDA Crop nutrient tool. N harvest rates were estimated for each crop for each county and time period. An arithmetic mean was then computed for the mean harvest rate for each crop and in each county (Viers et al. 2012).

N_{runoff}: Nitrogen content in surface runoff water

In the Technical Report 2, Viers et al. (2012) set the surface runoff losses to streams to general 14 kg N/ha/yr and lean their assumption on the study from Beaulac und Reckhow (1982). Although this study focused on the U.S midwest, it is argued that this source is widely cited.

N_{atm_loss}: Nitrogen lost to atmosphere due to denitrification.

N emission rates are obtained from literature review:

- N_2O: 1% The default emissions factor of direct field emissions used by the IPCC (Intergovernmental Panel on Climate Change) (Klein et al., 2006).
- N_2: 1.8% This emissions factor is based on the average N_2:N_2O ratio reported in agricultural sites (Schlesinger, 2009)
- NH_3: 3.6% Average emissions measured from 10 California fields (Goodrich et al., 2009)
- NO_X: 2.1% Average emissions across 8 crops and 20 sites (Matson, 1997)

The total of 8.5% of all applied N is rounded up to 10% and is argued to be reasonable (Harter et al., 2017)

As a result:

$$\boldsymbol{N_{atmLoss}} = \boldsymbol{0.1} * (\boldsymbol{N_{deposition}} + \boldsymbol{N_{irrigation}} + \boldsymbol{N_{synthetic}} + \boldsymbol{N_{LandApplied}} + \boldsymbol{N_{manure\_sale}}) \quad (6)$$

$N_{GW\_nondirect}$: Nitrogen leaching to groundwater from irrigated agricultural land (excludes leaching from septic tanks and urban areas). This variable is unknown and is the aim to be calculated with the mass balance approach, explained in more detail in the next paragraph.

OUTPUT

Harter et al. (2017) argue that due to the arid conditions in the CV no significant measurable increase in soil organic matter have been recorded over the past 65 years. It is therefore negligibly small:

$$\Delta \boldsymbol{Storage} = \mathbf{0} \tag{7}$$

Conclusive, from the previous equations:

$$\boldsymbol{N_{Inputs}} = \boldsymbol{N_{Outputs}} \tag{8}$$

Following equation is obtained when re-arranging the N mass balance for the potential nitrogen loading to groundwater:

$$\begin{aligned} \boldsymbol{N_{GW\_nondirect}} = {} & (\boldsymbol{N_{deposition}} + \boldsymbol{N_{irrigation}} + \boldsymbol{N_{synthetic}} + \boldsymbol{N_{LandApplied}} \\ & + \boldsymbol{N_{manure\_sale}}) - (\boldsymbol{N_{harvest}} + \boldsymbol{N_{runoff}} + \boldsymbol{N_{atm\_Loss}}) \end{aligned} \tag{9}$$

All variables on the right-hand side have been accounted for and estimated on various spatial and temporal scales. By solving this mass balance for each raster in all the regions, possible and major contributor for nitrogen loading in groundwater are concluded (Harter et al., 2017).

2.3.3 CV-SWAT

The Soil & Water Assessment Tool (SWAT) is a model to simulate the quantity and quality of surface and groundwater. With its implementation of climate, soil, and land cover, it can model impacts from different land use and management practices. It is therefore used globally to prevent soil erosion, assess non-point sources and for the management of watersheds (Arnold et al., 2012).

In the framework of this work, the updated version "CV-SWAT" (Central Valley – Soil Water Assessment Tool) was used. This version was programmed by the MPEP team, to make it more suitable for the conditions in the Central Valley. The model was modified with diverse cropping systems, soils, management practices, yields, and climates unique to the region. This allowed the modelers to accurately represent the land cover and use in the CV and to distinguish regional differences more accurately (Formation Environmental, 2021).

Since this work focuses on the N-Balance of agricultural used land and only this data was used, a focus is put on how CV- SWAT deals with Nitrogen in- and outputs and their different transformation processes.

INPUT

Climate data is from major importance for CV-SWAT. It requires daily information on solar radiation, relative humidity, wind speed, air temperature and precipitation not only to accurately map the water cycle but also to simulate physical processes to plant growth, evapotranspiration, nutrient uptake and cycling. This information is obtained from the closest weather station from the "California Irrigation Management Information System" (CIMIS).

Soil information were taken over from Natural Resources Conservation Service (NRCS). Their beta version is based on data mainly retrieved from field samples taken from soil pits (pedons), hence the name "PEDON" for the soil database.

Land use information include crop type, crop growth parameters, management practice (planting and harvesting date, tillage, nitrogen application, irrigation) (Formation Environment, 2019).

Calibration

In the report "Groundwater Protection Values" (Formation Environment, 2021), the MPEP team elaborates in particular how crop growth was calibrated. Growth is calculated as a function of solar radiation (derived from climate data), nitrogen and water uptake. Biomass and yield production result from these components. Parameters used in the model describing growth and yield were obtained from literature (Geisseler, 2016, 2021) and were adjusted in an iterative process. Pathways of Nitrogen were calibrated as followed:

1) As explained in previous chapter, denitrification processes are highly complex and dependent on many other factors in the soil. Since it was assumed that N_2O emissions are roughly 50% of total denitrification emissions, denitrification processes were calibrated to roughly 2% or less of the N fertilizer input. This value also depends on the calculated moisture content in the soil. Note that N_2O emissions can vary greatly between less than 20% to more than 50% of total denitrification according to Cuhel et al. (2010) and Weier et al. (1993).
2) Ammonia volatilization, the conversion from NH_3 to NO_3 is linked strongly to denitrification since both processes are dependent on the same factors. After calibration, volatilization targeted closer to 1-2% of applied N, with crop-specific differences due to management practices.
3) CV-SWAT takes N storage in perennial plant biomass into account. (MPEP Team, 2019) defines that this pathway is "controlled in part by calibrating crops to take up an appropriate total amount of N in a growing season and ensuring that the proper amount of N is removed with harvested materials".
4) N lost in surface runoff was not calibrated additionally. Since SWAT is a model especially programmed to model runoff processes, it was assumed that it is already well suited for simulating these processes (Krysanova und White, 2015).
5) Organic N stored in soil organic matter was divided into three different "pool". "Fresh plant residue" is divided in mobile Nitrate (80%) and "active organic N" (20%). This pool can either mineralize to nitrate (mobile), depending on soil parameters (e.g moisture) or become "stable organic N". CV-SWAT tries to equilibrate the amount of humus N in the "active pool" to 2%, therefor 98% remains stable and is inaccessible for plants. As a result, crops with high organic residues can lead to accumulation of organic soil (MPEP Team, 2019).

Besides Nitrogen pathways, also crop management was calibrated. Since the report of MPEP (2019) investigated the impact of different management practices on groundwater contamination, an emphasis was put on N application and irrigation. Those parameters were calibrated with the "Irrigation and Nitrogen Management Plan" (INMP) and "Nitrogen Management Plan" (NMP) created and pulled together by growers in the CV. It will not be further elaborated in here since only the "baseline" scenario is used for comparison.

At the end of the calibration process, an overall catalogue was the result, representing for each crop any possible combination of soil, climate, and land use. Every of those outcomes are expressed in a "hydrological response unit" (HRU) (Formation Environment, 2021).

OUTPUT

The output file contains extensive information for each unique HRU, among other the amount of N [kg/ha] at the bottom of the root zone for each time step. Although SWAT gives results in daily time steps, those are summarized in monthly and yearly time steps since the analysis would exceed the workload of the report (MPEP Team, 2019). Note that N load describes N at the bottom of the root zone, which does not necessarily reflect amounts infiltrating in the groundwater. Furthermore, all components are presented as loads (kg/ha/time) not as concentrations since it reflects better agricultural activity. Concentrations are highly linked to water use efficiency, meaning if water gets used more efficiently, N concentrations leaching to GW are getting higher. This should be kept in mind, since two different HRU's with the same N load to GW could have much different N concentrations infiltrating (Formation Environment, 2021). Crop productivity is based on reported yields from growers from 2016. N content in harvested crops is determined with the help of works from Geisseler (2016) and Geisseler and Horwarth (undated) (MPEP Team, 2019).

The Formation Environment (2021) team argues that with comparison to literature and field values, CV-SWAT ensures reasonable and conservative estimates of N loads across a 30-year model period in varies regions in the CV.

2.3.4 Model Comparison

As elaborated in previous chapters, CV-GNLM and CV-SWAT take different approaches to estimate nitrate loading leaching rates to GW. Thus, results differ from each other throughout the CV and for crops. UC-Davis developed a tool to compare results of nitrate loading of CV-GNLM and CV-SWAT. It is accessible under http://subsurface.gr/joomla/SWAT/SWAT_GNLM_perCrop_v2.html and allows the user to choose between different basins, crops and loading scenario. The tool shows the 5, 25, 50, 75 and 95 percentile of the distribution nitrate loading for the selected crop. Figure 4 shows nitrate loading rates from CV-GNLM and CV-SWAT for almonds in SAV over time.

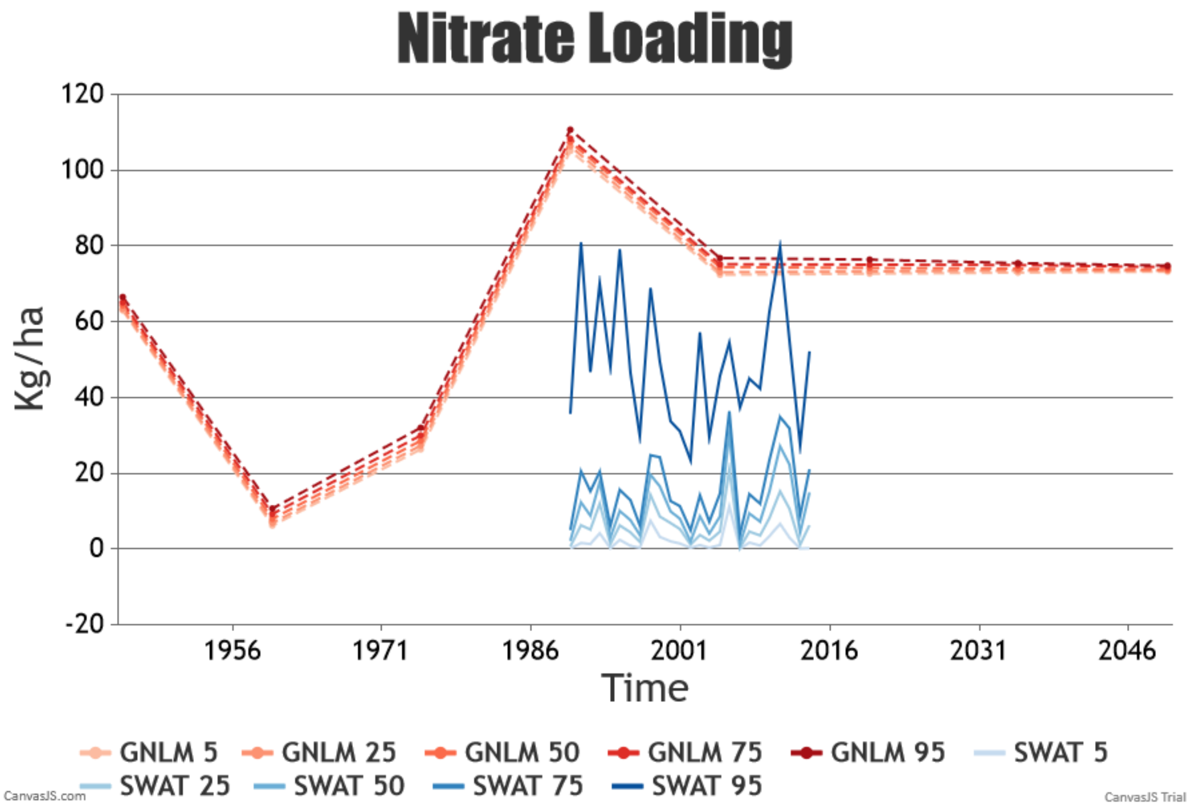

Figure 4: Comparison of nitrate leaching to groundwater between CV-GNLM and CV-SWAT. Taken from UC-Davis groundwater tool: http://subsurface.gr/joomla/SWAT/SWAT_GNLM_perCrop_v2.html.

The results illustrate that the models have significant discrepancies. CV-GNLM has constant increasing N loading from 1960 until 1990 to stay constant from 2000. CV-SWAT on the other hand fluctuates more and has significantly less N loading for most of the period. It is the motivation of this study to investigate in detail which variables and parameters of the models are most significant for the big difference. Furthermore, feasible adjustments for CV-GNLM are researched.

3. Method

3.1 Comparison

To find out how CV-GNLM needs to be updated to be more compatible with CV-SWAT, differences were identified and analyzed. In the following chapter different categories which were compared are pointed out and described in more detail. The data worked with in this report contains the output data from CV-GNLM from 2017 and output data from CV-SWAT from 2020. The data was provided by supervising professor Dr. Thomas Harter.

3.1.1 Land Use

A first challenge to overcome was the different area used by the two models. Although both models concentrate on the intensive agricultural areas of the CV, including the Sacramento Valley, the San Joaquin Valley and the Tulare Lake Basin, there are differences in the areas included. Besides some difference in the boundaries between the valleys, the major difference is that CV-SWAT includes the entire watershed and sub basins of streams and rivers. Those areas are negligible for the N-balance. Therefore, regions, not included in CV-GNLM, were cut from CV-SWAT and borders between valleys were unified. Figure 5 illustrates this adaptation. Map A) shows in light brown the area used by CV-GNLM. The model does not separate throughout the different regions and focuses on the agricultural intensive valley without the surrounding area. CV-SWAT on the other hand divides the valley in three regions and includes the corresponding watershed, shown in red (SAV), blue (SJV) and green (TLB).

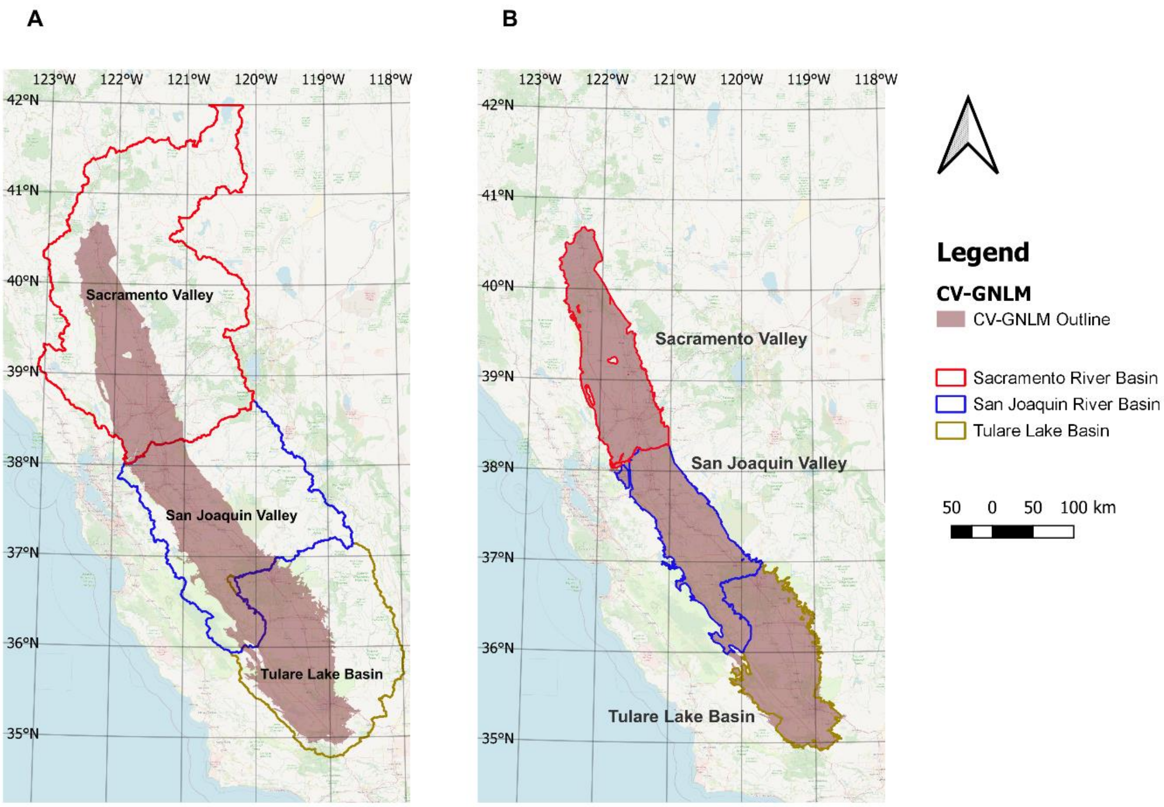

Figure 5: Maps of A) Initial Area used from both models and B) Unified Outlines for comparison.

To make a land use comparison expressive, unified outlines were created. The created outlines shown in Figure 5 B) only include areas, present in both models. Due to that, areas like at 39.2°N, 121.9°W (national park “Caldwell Hills”) or foothills from the coastal ranges at 38.9°N, 122.1°W are excluded. These outlines were further used to cut out the original land use shape files from both models.

In a second step, the different land use was analyzed. Both models use different land cover types. CV-GNLM uses over 200 different land covers, whereas CV-SWAT model focuses on 22 main crops (95% of agriculture; partly subdivided in multiple species or plant stages) and few land cover types for natural vegetation and urban landscapes (MPEP Team, 2019). In order to compare the area of the land use, crops were categorized in sixteen groups as it was done in the CV-GNLM report:

- No data
- Urban
- Native Vegetation
- Pasture
- Barren
- Water
- Citrus and Subtropical
- Deciduous Fruits and Nuts
- Field Crops
- Corn, Sorghum, Sudan
- Grain
- Alfalfa
- Semiagricultural and Incidental to Agriculture
- Truck, Nursery and Berry Crops
- Rice
- Vineyard

The CV-SWAT land cover types were assigned to a corresponding land cover from CV-GNLM and accordingly categorized. Since CV-GNLM uses land cover data from 2005 and CV-SWAT from 2014, different results were expected. A detailed overview of allotment of crops from CV-GNLM and CV-SWAT is found in Table A - 1 in Appendix A.

3.1.2 Balance

In this chapter, modeled N pathways from both models were compared, categorized in N inputs and outputs and an N mass balance was calculated. Therefore, decisive differences and variables are highlighted. Since results are different for each crop, it is crucial to analyze each crop separately. To do so, the dataset was reduced to the most recent time period, relevant variables and a choice of crops.

CV-SWAT models varies scenarios of different management practice of which one needed to be chosen. From the options: “baseline”; “moderate fertilization & high irrigation”; “high fertilization & moderate irrigation”; “high fertilization & high irrigation”, the “baseline” scenario was chosen, as it is best comparable with CV-GNLM settings. The timeframe of the obtained data includes averages from the years 2003 – 2007 for CV-GNLM (applied for each year equal) and data from 1990 – 2014 for CV-SWAT, whereas yearly results were used for further calculations.

Because an analysis and comparison of all crops would exceed the frame of this thesis, most cultivated crops as listed by the MPEP Team (2019) are used for further comparison:

1. Almonds
2. Pistachios
3. Tomatoes
4. Walnuts
5. Vineyards (wine, table and raisin grapes)

6. Oranges
7. Cotton
8. Corn (silage)
9. Wheat (silage)
10. Onion & Garlic
11. Mandarins
12. Beans
13. Peaches
14. Wheat Grain
15. Carrot
16. Sunflower
17. Pomegranate
18. Oates
19. Nectarines
20. Cherries

As a first step to analyze both models N budget, a general N-Balance with variables in both models was set up. For this purpose, all balance components from CV-GNLM were adopted. In addition, variables from CV-SWAT were categorized to close its N balance.

$$\boldsymbol{N_{IN}} = \boldsymbol{N_{Deposition}} + \boldsymbol{N_{Irrigation}} + \boldsymbol{N_{Synthetic}} + \boldsymbol{N_{Manure}} \tag{10}$$

$$\begin{aligned}\boldsymbol{N_{OUT}} = \boldsymbol{N_{Harvest}} + \boldsymbol{N_{Perennial\ Tissue}} + \boldsymbol{N_{Runoff}} + \boldsymbol{N_{Atm.Loss}} + \boldsymbol{N_{Active\ Org.}} \\ + \boldsymbol{N_{Stable\ Org.}} + \boldsymbol{N_{GW-Leaching}}\end{aligned} \tag{11}$$

$$\boldsymbol{N_{IN}} = \boldsymbol{N_{OUT}} \tag{12}$$

Table 1 illustrates how each component of the balance is calculated. For a correct method, several meetings with members of the MPEP team from UC Davis in California were held to insure correct understanding for N movement through the model. The calculation of N in perennial tissue assumes that all plant residues are mineralized. This assumption is accurate for most HRU's states CV-SWAT expert Kenneth Miller (personal communication, 2022).

Table 1: Determination of categories for the N balance for CV-GNLM and CV-SWAT.

BALANCE	CATEGORY	GNLM	SWAT
IN	Deposition	*Ndeposition*	*NRAIN, NFIX*
	Irrigation	*Nirrigation*	-
	Synthetic Fertilizer	*Nsynthetic*	*N_APP (+ N_AUTO) + NGRZ + NCFERT*
	Manure Fertilizer	*NlandApplied + NmanureSale*	-
OUT	Harvest	*Nharvest_actual*	*YLD * removal coefficient (if Harvest > 0.8* Nup, then 0.8 * Nup is used for Harvest)*
	Perennial Tissue	-	*NUP – Nharvest – F_MN*
	Runoff	*Nrunoff_actual*	*NSURQ + NLATQ + ORGN + LNO3 +*
	Atm. Loss	*NatmLoss (10% from inputs)*	*DNIT*
	Active Org.	-	*0.2 * F_FM – A_MN – A_SN*
	Stable Org.	-	*A_SN*
	GW-Leaching	*GW_nondirect;*	*NO3L*

Variables of CV-GNLM got explained in the previous chapter. (Arnold et al., 2012) gives detailed explanation of SWAT variables:

NRAIN: Nitrate added to soil profile by rain (kg N/ha).

NFIX: Nitrogen fixation (kg N/ha) in time step. Amount of nitrogen fixed by legumes during the time step.

N_APP: Nitrogen fertilizer applied (kg/N/ha). Total amount of Nitrogen (mineral and manure) applied in regular fertilizer operations during the time step.

N_AUTO: Nitrogen fertilizer auto-applied (kgn/ha. Total amount of Nitrogen (mineral and organic) auto applied during time step.

NGRZ: Nitrogen applied during grazing operations (kg N/ha). Total amount of Nitrogen (mineral and organic) added to soil during time step.

NCFERT: Nitrogen applied during continuous fertilizer operation (kg N/ha). Total amount of Nitrogen (mineral and organic) added to soil by continuous fertilizer operation during time step.

YLD: Harvested yield (metric tons/ha). The model partitions yield from the total biomass on a daily basis (and reports it). However, the actual yield is not known until it is harvested. The harvested yield is reported as dry weight.

Removal coefficient: coefficient, calculated and provided by the "Formation Environment" team to convert amounts of yield into amount of N harvested (for each crop), based on works from Geisseler (, 2016, 2021). Detailed conversion factors for each land use in CV-SWAT is found in Table A - 2.

NUP: Plant uptake of nitrogen (kg N/ha) during time step.

ORGN: Organic N yield (kg N/ha). Organic nitrogen transported out of the HRU and into the reach during the time step

NSURQ: NO3 in surface runoff (kg N/ha). Nitrate transported with surface runoff into the reach during the time step

NLATQ: NO3 in lateral flow (kg N/ha). Nitrate transported by lateral flow into the reach during time step

NO3L: NO3 leaching from soil profile (kg N/ha). Nitrate that leaches past the bottom of the soil profile during time step. The nitrate is not tracked through the shallow aquifer.

NO3GW: NO3 transported into main channel in the groundwater loading from the HRU (kg N/ha)

F-MN: Fresh organic to mineral N (kg N/ha). Mineralization of nitrogen from the fresh residue pool during the time step.

A-MN: Active organic to mineral N (kg N/ha). Movement of nitrogen from the active organic pool to the nitrate pool during the time step.

A-SN: Active organic to stable organic N (kg N/ha). Movement of nitrogen from the active organic pool to the stable organic pool during the time step.

NLATQ: NO_3in lateral flow (kg N/ha). Nitrate transported by lateral flow into the reach during the time step.

It is assumed that for both models, the N balance is closed:

$$\boldsymbol{N_{Balance}} = \boldsymbol{0} = \boldsymbol{N_{IN}} - \boldsymbol{N_{OUT}} \tag{13}$$

Conclusive:

$$\begin{aligned}\boldsymbol{N_{Balance}} = {} & (\boldsymbol{N_{Deposition}} + \boldsymbol{N_{Irrigation}}\boldsymbol{N_{Synthetic}} + \boldsymbol{N_{Manure}}) - (\boldsymbol{N_{Harvest}} \\ & + \boldsymbol{N_{Perennial\,Tissue}} + \boldsymbol{N_{Runoff}} + \boldsymbol{N_{Atm.Loss}} + \boldsymbol{N_{Active\,Org.}} \\ & + \boldsymbol{N_{Stable\,Org.}} + \boldsymbol{N_{GW-Leaching}})\end{aligned} \tag{14}$$

This calculation was carried out to validate the accuracy of the obtained data. Hence CV-GNLM calculation of "$N_{GW\text{-}Leaching}$" is based on the mass balance shown in equation *(9)*, it is expected to be zero.

As a second step, a comparison of the two models for each parameter highlights the most important variables and differences between the models are pointed out. Suggestions on how to adjust $N_{GW\text{-}Leaching}$ were derived and further developed. For this purpose, median values were calculated for each variable from all data in the CV for each crop type.

3.1.3 Harvest & Fertilizer Application

The amount of Nitrogen (kgN/ha/yr) contained by harvested crops is calculated for both models separately. CV-GNLM includes amounts of $N_{Harvest}$ in the model itself and is based on studies and conversion with farmers and experts for each crop as elaborated in previous chapters. For CV-SWAT on the other hand, $N_{Harvest}$ amounts need to be calculated as depicted in Table 1. The condition that if calculated $N_{Harvest}$ exceeds 80% of NUP, the latter is used as $N_{Harvest}$, is implemented by recommendations of Kenneth Miller (personal communication, 2022). Differences will be pointed out and discussed further on.

Based on previous discoveries, the variable "N-Application" is further analyzed. Especially because of the more distinct application rates of manure in CV-GNLM, it is important to distinguish between synthetic fertilizer and manure application.

Both evaluations were carried out for each crop, comparing the two models. For CV-GNLM, data from the timeframe 2003 – 2007 (most recent), sorted by crop was used. The whole time frame from 1990 – 2014 is used for CV-SWAT. Since CV-SWAT applies the same land use and management practice over the whole time frame, the difference in the amount of years and different time frame in general does not influence the results in this case.

3.2 Adaptation

After filtering out the most influential variables on $N_{GW\text{-}Leaching}$, possible solutions to adapt CV-GNLM were investigated. For once, the influence of updating CV-GNLM harvest data is explored. Another attempt for adaptation is the implementation of different organic N pools.

3.2.1 Data Adaptation

The N content in harvested crop was identified being a decisive factor. Two approaches are tried to adapt the harvest rates closer to the ones in CV-SWAT. For once, to update the data of harvested crop amounts with the newest published data from the USDA.

The three regions defined previously, intersect with 20 counties in the CV:

- Sacramento Valley (SCV):
    - Butte
    - Colusa
    - Glenn
    - Placer
    - Sacramento
    - Shasta
    - Solano
    - Sutter
    - Tehama
    - Yolo
    - Yuba
- (Northern) San Joaquin Valley (NSJV or SJV):
    - Contra Costa
    - Madera
    - Merced
    - San Joaquin
    - Stanislaus
- Tulare Lake Basin (TLB):
    - Fresno
    - Kern
    - Kings

- Tulare

For each county, the amounts of harvested crops from the years 2018, 2019 and 2020 were downloaded from the USDA Statistics Service (https://www.nass.usda.gov/Statistics_by_State/California/Publications/AgComm/index.php).

Secondly, the conversion from the amounts of yield (harvested crop) to N amounts is updated. For CV-GNLM the USDA "Crop Nutrient Tool" was used to convert yield weight to N amounts (https://plantsorig.sc.egov.usda.gov/npk/main). Recent studies from Geisseler (2021) present updated N content in harvested plant parts. The impact of this change on the amount of N leaching to GW is analyzed and evaluated. Since CV-SWAT also uses studies from Geisseler to convert crop weight to N amounts, this approach is promising to bring the two models closer to equal results for N GW-leaching.

3.2.2 Organic Nitrogen Pools

A main difference identified between CV-GNLM and CV-SWAT is the modeling of N transformation processes. These processes are closely interrelated with water content in the soil and the soil composition itself (Jackson, 1997). Thus, it can only be modelled by CV-SWAT. Figure 6 gives an overview of how organic N is cycled through the system and how it is calculated. It is investigated what the impact and long term influence of different organic N pools are by calculating yearly averages and accumulation over the modelled timeframe of CV-SWAT.

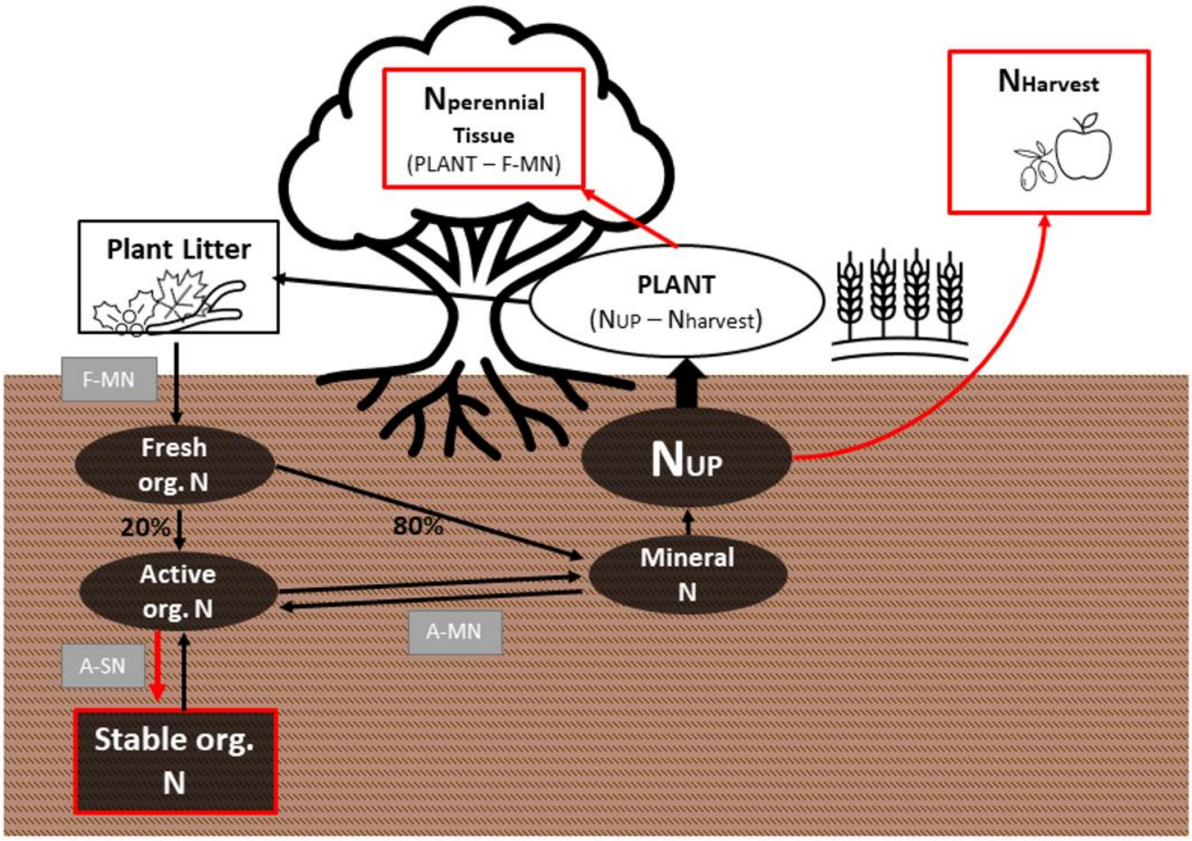

Figure 6: Concept of CV-SWAT's modelling of organic N pools. In red marked arrows indicate components leaving the yearly N cycle.

Furthermore, N taking up by the plant and not used for crop production is studied in more detail for different crop types. N content of leaves and perennial tissues (stem, roots, bark, etc.) is investigated in more detail for varies plants. Especially for perennial crops, this could be an additional component of CV-GNLM's N balance which is not taken into account yet. The calculation of each parameter can be taken from Table 1.

4. Results

4.1 Comparison

In the following chapter, the results from the model comparison are illustrated and explained. For many variables, the comparison of both models is carried out for each crop. For clarity reasons, results are presented exemplary for one crop (almonds) whereas the extensive results for all crops are found in Appendix B.

4.1.1 Land Use

Crop types were identified, matched, and categorized. A detailed overview of this process is found in Appendix A, Table A - 1. In Figure 7, these results are illustrated. It is visible that agricultural activity is similar. In both models, vineyards are concentrated in the TLB around Fresno, areas around Modesto in the San Joaquin Valley are dominated by "Deciduous Fruits and Nuts" and "rice" crops are cultivated north of Sacramento. Also, areas of "Pasture" and "Native Vegetation" roughly match. It also gets clear, that although locations of dense cultivations are made visible in land use maps like in Figure 7, it does not give a good impression of the actual area from each category. Therefore, a more detailed analysis of area distribution was carried out.

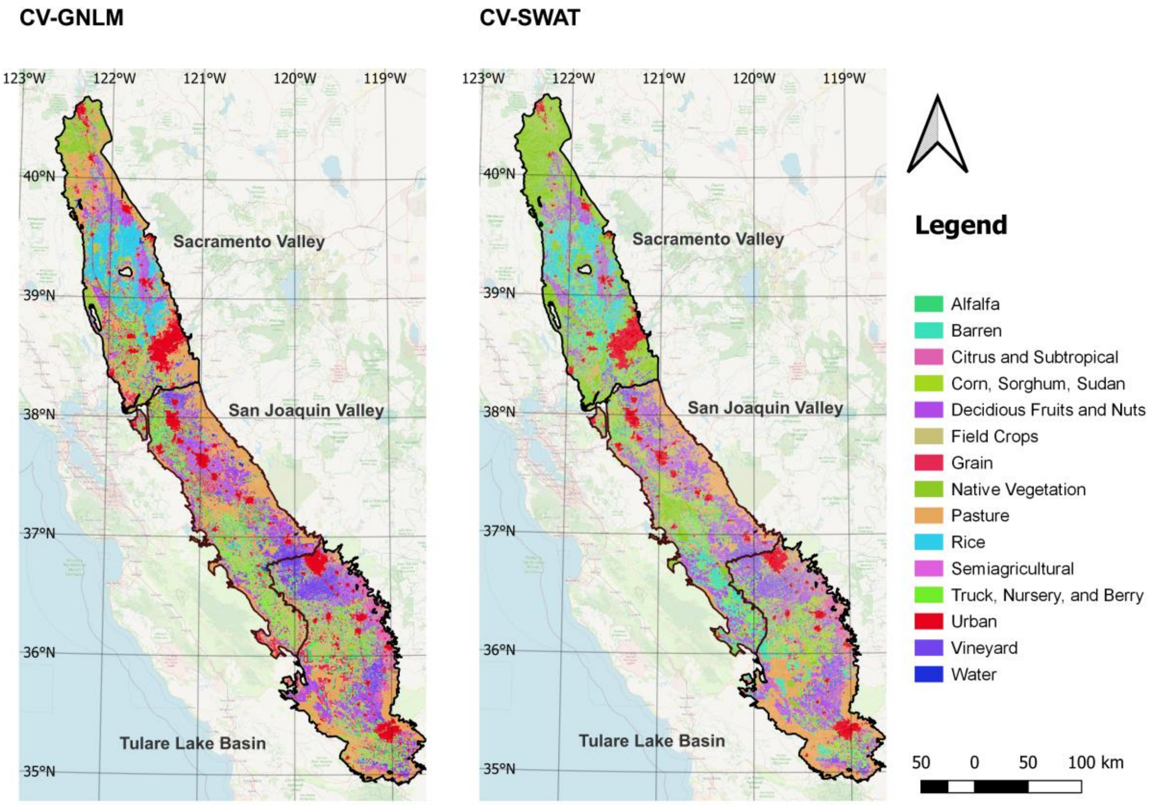

Figure 7: Map of categorized land use comparison of CV-GNLM (left) and CV-SWAT (right.

Since the dataset for CV-SWAT was too large to merge together, each region is observed separately. Figure 8 displays this comparison between the models in form of bar plots. There are some major differences between the two models which occur in all of the regions. For once, it points out that CV-SWAT has no area designated to semiagriculture and water which account up to 1500 km^2 and 1900 km^2 respectively in the TLB. Furthermore, the area for land use category “Barren” is always higher in CV-SWAT. It constantly lies over 1000 km^2 and exceeds the area from CV-GNLM four times in the Sacramento Valley until up to twelve times more in the Tulare Lake Basin.

The same trend is observed for “Truck, Nursery and Berry Crops” which is in all CV regions multiple times higher for CV-SWAT than for CV-GNLM. On the other hand, water intensive crops in the categories “field crops” and “grain” have more area in CV-GNLM, especially in the SJV (2200 km^2; five times more) and TLB (2275 km^2; 3.5 times more). Surprisingly, the category “urban” differ between the models. Urban area in the SJV accounts up to 1500 km^2 in CV-GNLM, 670 km^2 more than in CV-SWAT. In the SAV and TLB on the other hand, it is CV-SWAT which models twice and three times more the area for this land use. Same observation can be made for “Vineyards”, diverging between the models and the regions. The two categories “Alfalfa” and “Barren” are the only land uses, which remain in the same proportion between the two models throughout the different regions.

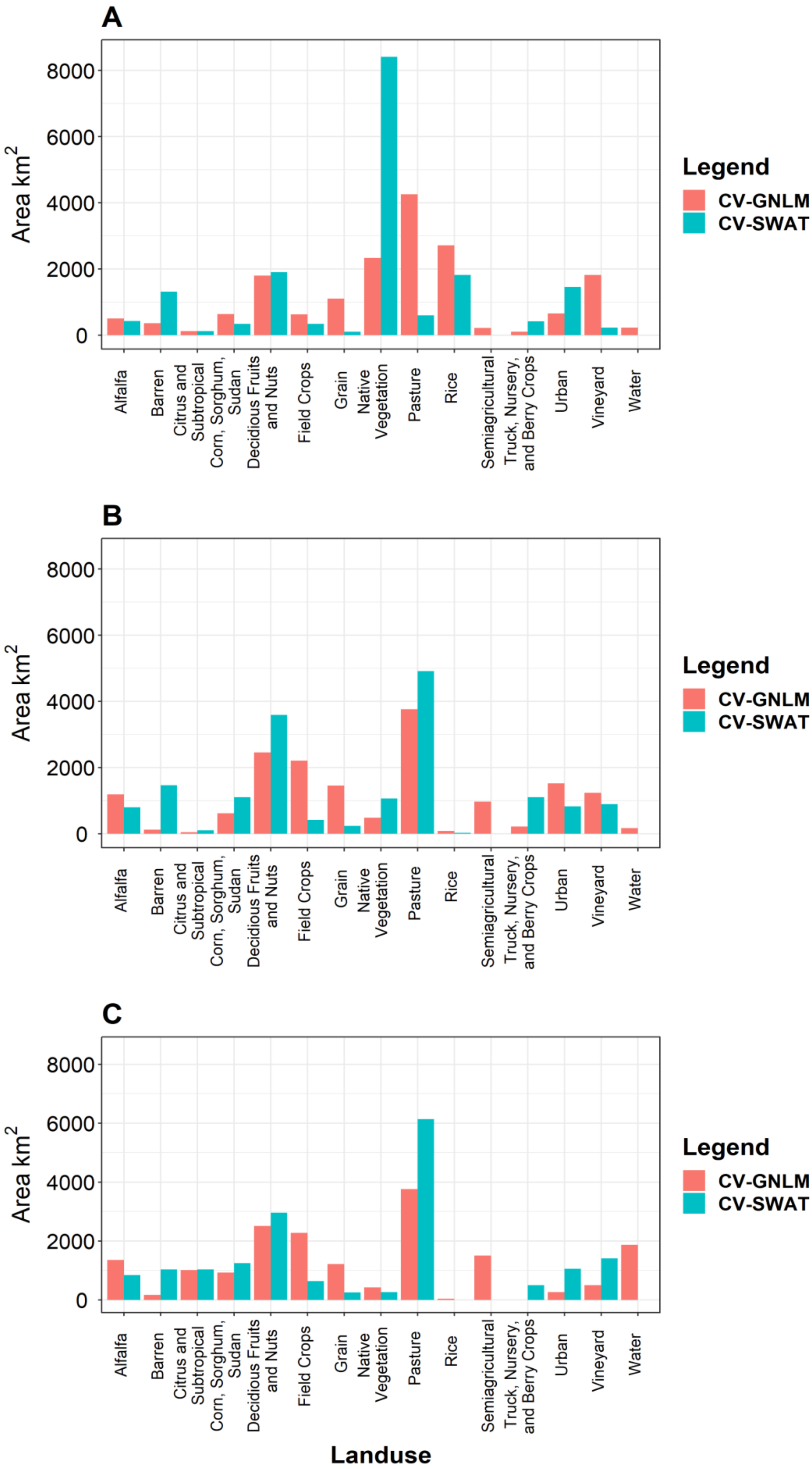

Figure 8: Comparison of categorized land use of CV-GNLM and CV-SWAT for each region in the Central Valley (A: Sacramento Valley; B: San Joaquin Valley; C: Tulare Lake Basin).

Having a closer look on each region, it points out that there are specific differences between the models in each region. For the Sacramento Valley, "Native Vegetation" for instance takes more than three times more the area in CV-SWAT than in CV-GNLM. In contrast, CV-GNLM's area for pasture counts 4250 km^2, whereas only 600 km^2 for CV-SWAT. Furthermore, CV-GNLM models vineyards for roughly 1800 km^2, eight times more than CV-SWAT. As already indicated in Figure 8, main cultivated crops in the Sacramento Valley are Rice (GNLM ~1000 km^2 more than SWAT) and Deciduous Fruits and Nuts, with an area of ~1850 km^2 respectively.

Table 2 compares the total areas of both models and each region. This highlights how comparable the land use amounts are.

Table 2: Total area of the Sacramento Valley, San Joaquin Valley and Tulare Lake Basin in the land use comparison of CV-GNLM and CV-SWAT.

MODEL	SAV [KM^2]	SJV [KM^2]	TLB [KM^2]
CV-GNLM	17 438	16 518	17 853
CV-SWAT	17 438	16 538	17 406

The SJV longitude extend from 36°N in the very south to 38.2°N in the top with a total area of 16 518 km^2. The land use differ greatly in comparison to the SAV. For once, much less native vegetation is registered, whereas the area of pasture remain in the same magnitude for CV-GNLM (~3800 km^2). Though, CV-SWAT even exceeds this area by over 1000 km^2. Here it gets obvious that main cultivations are different for each model. For CV-SWAT, deciduous fruits and nuts (3590 km^2), barren (1460 km^2), and "Corn, Sorghum, Sudan" (1100 km^2) are cultivations, occupying most areas. "Deciduous fruits and nuts" is also highest category for CV-GNLM (2455 km^2), though it is followed by "field crops" (2210 km^2) and "grain" (1460 km^2), being four times and six times higher than in CV-SWAT. "Citrus and Subtropical" and "Rice" play a subordinate role in this region with each less than 100 km^2.

The TLB, south of the SJV extend south to 34.9°N. Table 2 shows that the total area differ by 447 km^2. Although on a total area of 17 853 km^2 (CV-GNLM) this difference is only 2.5%, it is to be discussed where the difference comes from since the same total area as in the other regions was expected. "Citrus and Subtropical" are with an area of ~1000 km^2 in both models most represented in the TLB. Also "Corn, Sorghum, Sudan" and "Deciduous Fruits and Nuts" are rather equally represented by the models (CV-SWAT ~300 km^2 more). Furthermore, the nitrogen fixing grass "Alfalfa" has the highest area in TLB in comparison with the other regions with 1353 km^2 in CV-GNLM and 847 km^2 in CV-SWAT. Only a negligible area of 0.055 km^2 is used for "Truck, Nursery and Berry Crops" in CV-GNLM. For the same category it is 500 km^2 for CV-SWAT.

4.1.2 Balance

After comparing categorized land use distributions, a detailed analysis for specific crops was required in order to assess the reason for different $N_{GW\text{-}Leaching}$ results of the two models. As explained in the method, 20 crops which account for 95% of all agricultural used land were chosen for the investigation. The different variables were assigned to in- and outputs as elaborated in chapter 3.1.2 in Table 1. Here, the differences between the models for each crop are shown and characteristics of single crops are highlighted. For the sake of a good overview, only a few example results are shown here, whereas the detailed results are presented in Appendix B.

Figure 9 illustrates the N mass balance results calculated according to equation *(13)* for CV-GNLM and CV-SWAT. The highlighted "zero" stands for the result: IN = OUT. When the N mass balance is positive, IN > OUT and if negative, IN < OUT. Whereas N mass balance is constantly zero for all crops for CV-

GNLM, the balance varies in CV-SWAT. For almonds, median balance lies at 0.5 kgN/ha/yr, ranging from 2.6 to -1.5 kgN/ha/yr. The extent of this variation is different throughout the crops.

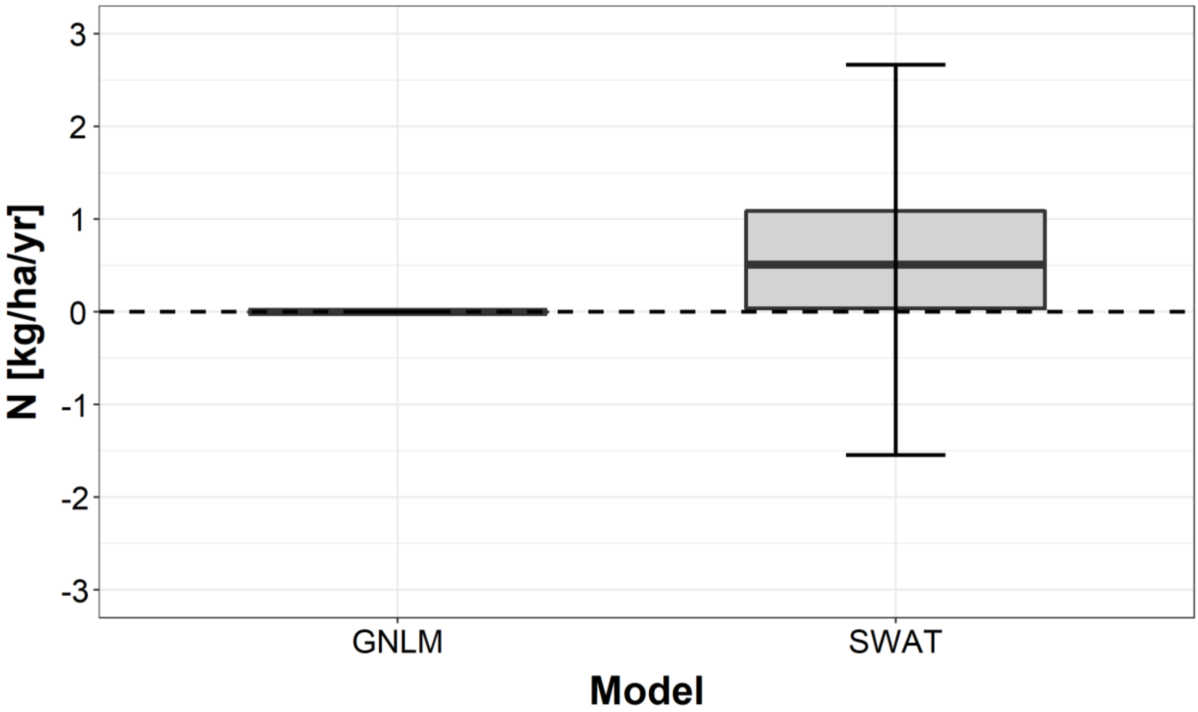

Figure 9: Almonds N-Balance (IN - OUT including GW-leaching) for CV-GNLM and CV-SWAT.

The variance of the balance for CV-SWAT is rather low for almonds, beans, cherries, pistachios and vineyards. It stands out that especially for annual crops, like carrots corn, onion and garlic, tomatoes and wheat the variance can range from 70 to -60 kgN/ha/yr, although the median mostly lies between 0 – 5 kgN/ha/yr. An exception is the crop orange where the median lies at ~60 kgN/ha/yr.

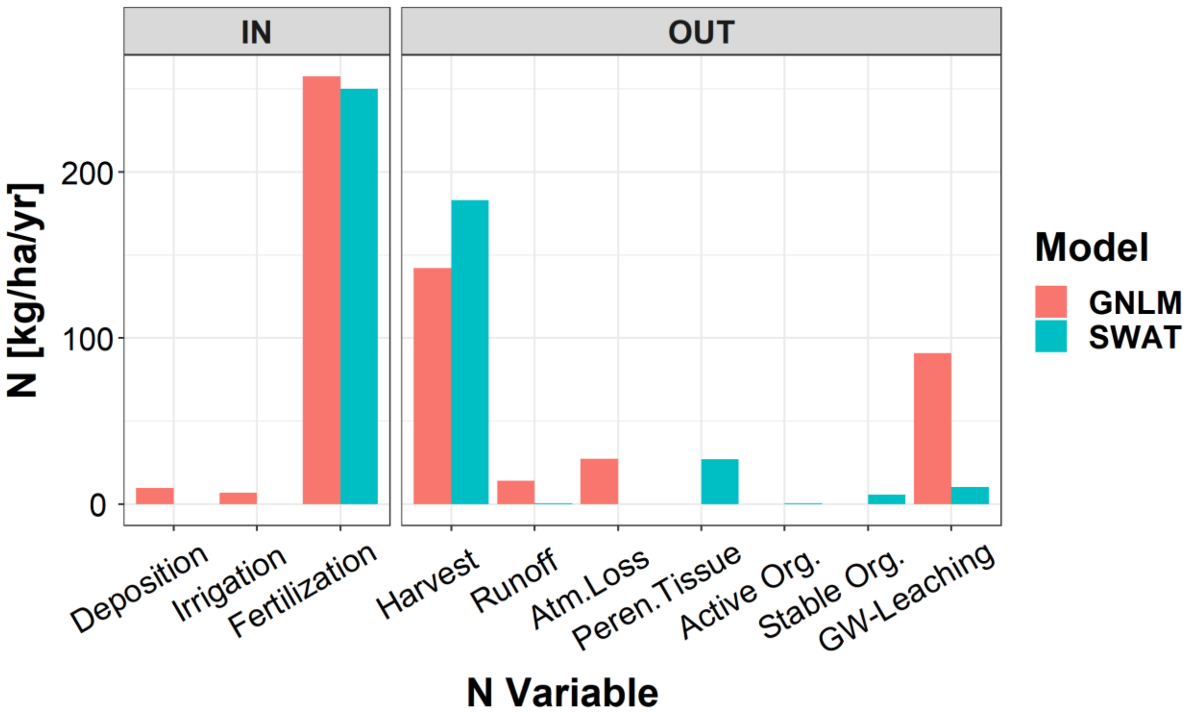

Figure 10: Detailed comparison between CV-GNLM and CV-SWAT of all in- and output variables for almonds.

To evaluate the difference between CV-GNLM and CV-SWAT, a more visible comparison between all the variables is displayed in Figure 10. There, one can see in more detail, how variables of the models differ between one another. For clarity, the bar plot divides the variables into “IN” and “OUT” to illustrate to which side of the balance each variable belongs. It stands out that some variables are only present in one model or the other. In general, N – input through atmospheric deposition or irrigation water is only present in CV-GNLM with the exception of beans for atmospheric deposition (here used also to designate plant nitrogen fixation by leguminous plants, such as beans). Same applies for “atmospheric loss” (being always 10% of all inputs for CV-GNLM) and whereas “runoff” is fixed to 14 kgN/ha/yr for CV-GNLM for all crops, it is much less in CV-SWAT, though variations are observable throughout different crops. Variables concerning organic N like active organic N and stable organic N are only present for CV-SWAT. For the example of almonds in Figure 10, both organic N sinks (active and stable) lie under 10 kgN/ha/yr. Another parameter only present in CV-SWAT is perennial tissue (“Peren. Tissue”) which lies in the case of almonds at around 38 kgN/ha/yr. This parameter varies significantly between the investigated crops and is in the case of carrots and sunflowers even negative (exemplarily for carrots seen in Figure 11.) A more detailed look on these parameters is taken in the next chapter.

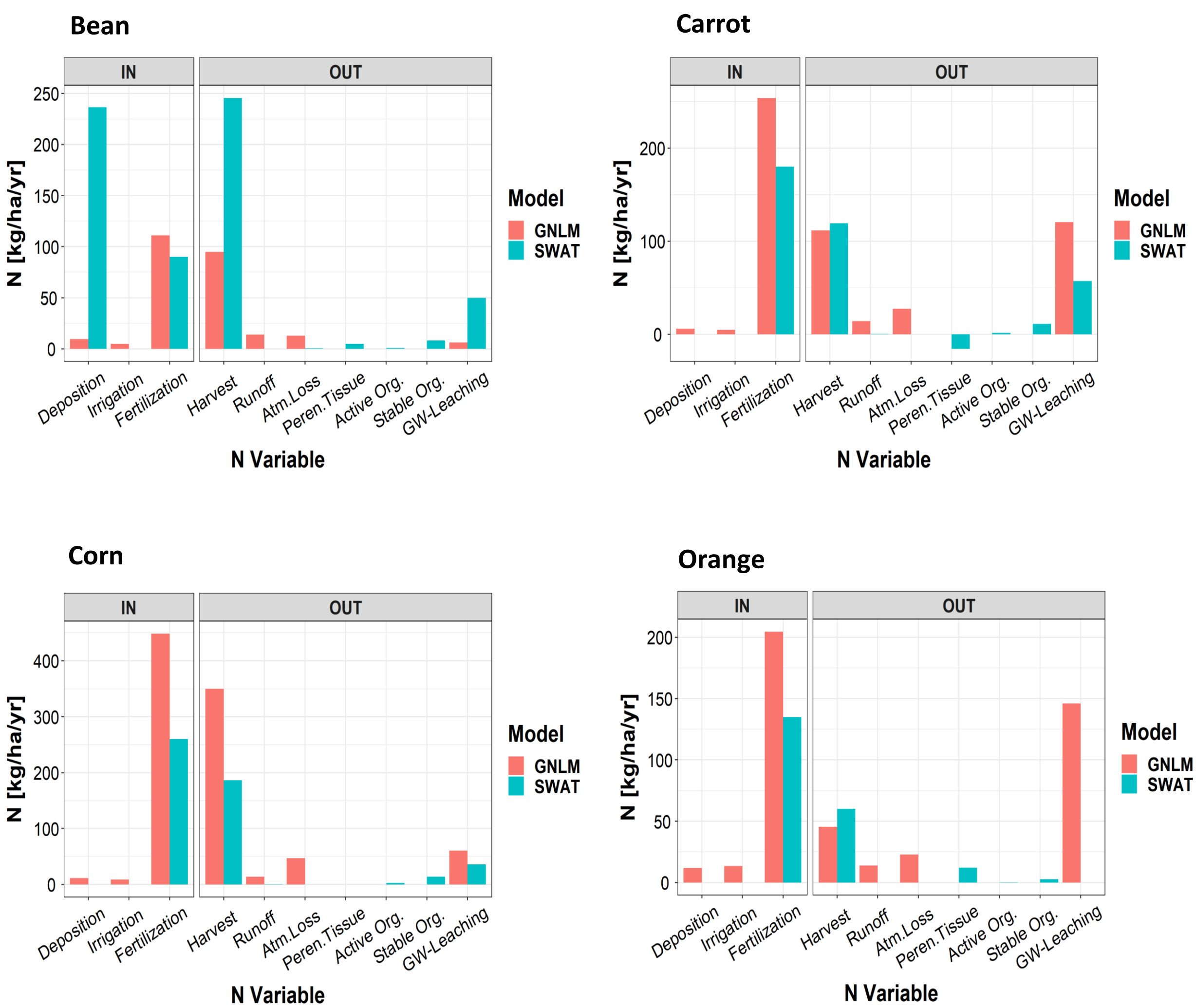

Figure 11: Detailed comparison between CV-GNLM and CV-SWAT of all in- and output variables for bean, carrot, corn and orange.

Comparing the two models throughout all crops, it stands out that the variable “Fertilization” is the highest input and “Harvest” the biggest output of Nitrogen in the balance (except for “beans”). The other main observation being that “GW-leaching” is always higher in CV-GNLM, except for beans, oats and Onion & Garlic. The magnitude of difference varies throughout the crops. In the following paragraph detail differences between the crops will be investigated.

For almonds (Figure 10) both models have a fertilization rate of >250 kgN/ha/yr. Though CV-GNLM models a much lower harvest rate (~40 kgN/ha/yr less), resulting in GW-leaching five times higher than in CV-SWAT. The results from beans in Figure 11Figure B - 5 stand out since it is the only crop for which CV-SWAT models atmospheric deposition, exceeding the amount from CV-GNLM by far. Although the N amount for the variable “harvest” is proportional larger as well, a surplus of N results in more GW-leaching for CV-SWAT. “Corn” it is one of the only crop types, where CV-GNLM models higher harvest rates than CV-SWAT. Still more GW-leaching can be observed in CV-GNLM as seen in Figure 11. Oranges stand out since CV-GNLM models fertilization > 200kgN/ha/yr (50 kgN/ha/yr more than CV-SWAT), though lower harvest rates, resulting in high amounts of GW-leaching (CV-GNLM). On the other hand, CV-SWAT is modelling no GW-leaching. As mentioned before, also the balance for oranges is off by a median of ~60 kgN/ha/yr in CV-SWAT. For oranges and wheat grain, CV-SWT models no $N_{GW\text{-}Leaching}$, whereas CV-GNLM not for oats. In general, $N_{GW\text{-}Leaching}$ is higher in CV-GNLM for most crops.

4.1.3 Harvest & Fertilizer Application

It was established in the previous chapter, that “Harvest” and “Fertilization” have the biggest impact on the in- and outputs of the N balance. Therefore, these two parameters will be investigated in more detail. Figure 12 examines the distribution of harvest rates of both models for almonds. For other investigated crops, results are found in Appendix B.

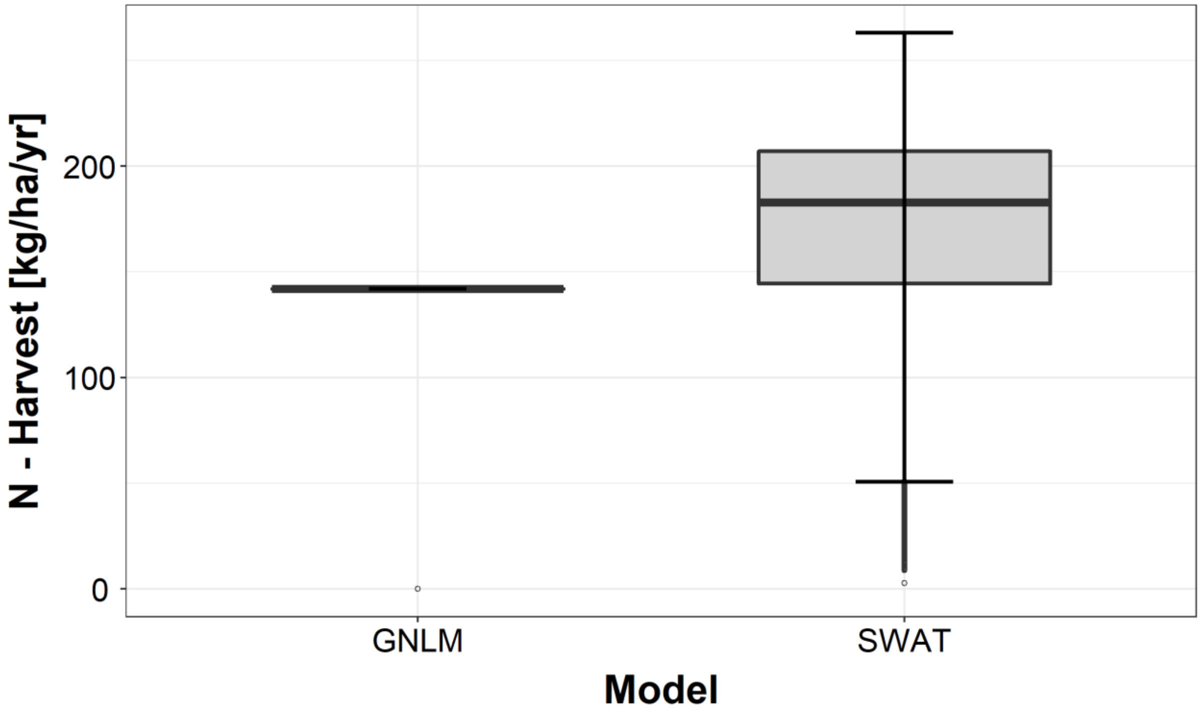

Figure 12: Detailed analysis of N- harvest for almonds.

For the comparison of harvest rates, it stands out that whereas CV-GNLM has one fixed value for the whole crop type throughout the CV, harvest rate from CV-SWAT has deviations. As elaborated before, harvest rates are mostly higher in CV-SWAT, confirmed by the median value. Lower deviation values or extreme outliers might be lower than the one from CV-GNLM in some cases. In the case of almonds, $N_{Harvest}$ lies at 142 kgN/ha/yr whereas the median from SWAT lies at 183 kgN/ha/yr with the 1st and 3rd quantile being 145 and 207 kgN/ha/yr respectively. Harvest rates are higher for CV-SWAT throughout all crops, except for "corn" and onion & garlic. The variance of $N_{Harvest}$ in CV-SWAT differ from crop to crop.

Table 3 examines the fertilizer application further for both models for almonds. It gets clear that it is important to distinguish between the two fertilizer methods, since they can vary greatly. Although overall fertilization is higher in CV-GNLM (Figure 10), CV-GNLM median synthetic application is 4 kgN/ha/yr lower than CV-SWAT's, whereas the average is higher. Furthermore, CV-GNLM's synthetic fertilizer application ranges from zero to 246 kgN/ha/y, whereas from 85 to 250 kgN/ha/yr for CV-SWAT. Nevertheless, standard deviation and variance is much higher in CV-SWAT. Besides for beans, oats and vineyards where the same trend is observed, standard deviation and variance is mostly zero for CV-SWAT since only one fixed value is set for synthetic application (same minimum, maximum, median and mean value).

Table 3: Statistical summary of different fertilizer applications (synthetic and manure) of both models for almonds. Results are depicted in kgN/ha/yr.

MODEL	FERTILIZER	MIN	MAX	MEDIAN	MEAN	SD	VARIANCE
GNLM	Synthetic	0	246	246	245.5	8.7	76
	Manure	0	3851.5	11.7	13.9	26.6	710
SWAT	Synthetic	85	250	250	220.9	62.9	3957.8
	Manure	0	0	0	0	0	0

Additionally, CV-SWAT has no manure applications for almonds. This applies for all investigated crops. Median and average manure application in CV-GNLM are 11.7 and 13.9 kgN/ha/yr respectively for almonds. It stands out that extreme outliers are present, the minimum being zero and maximum value being 3852 kgN/ha/yr. A variance of 710 kgN/ha/yr indicates a high dispersion of results. Many perennial crops like cherries, peaches, pistachios and vineyards have similar results for manure in CV-GNLM. Manure results of CV-GNLM for corn and wheat application range from zero to multiple hundred thousand. Median application lie for both crops at 11.7 kgN/ha/yr, averages are 357.3 and 192.6 kgN/ha/yr respectively resulting in enormous high standard deviation and variance.

4.2 Adaptation

4.2.1 New Data

Figure 13 shows the harvest rates in kgN/ha/yr of crop type almond in CV-GNLM. The boxplot on the left side shows harvest rates with the new data from ACR of 2018, 2019 and 2020. On the right side results from the old data set is shown as known from previous graphs. As explained in previous chapters, harvest rates from CV-GNLM are averaged throughout a time period and the CV resulting in one unified value, being at 142 kgN/ha/yr for almonds.

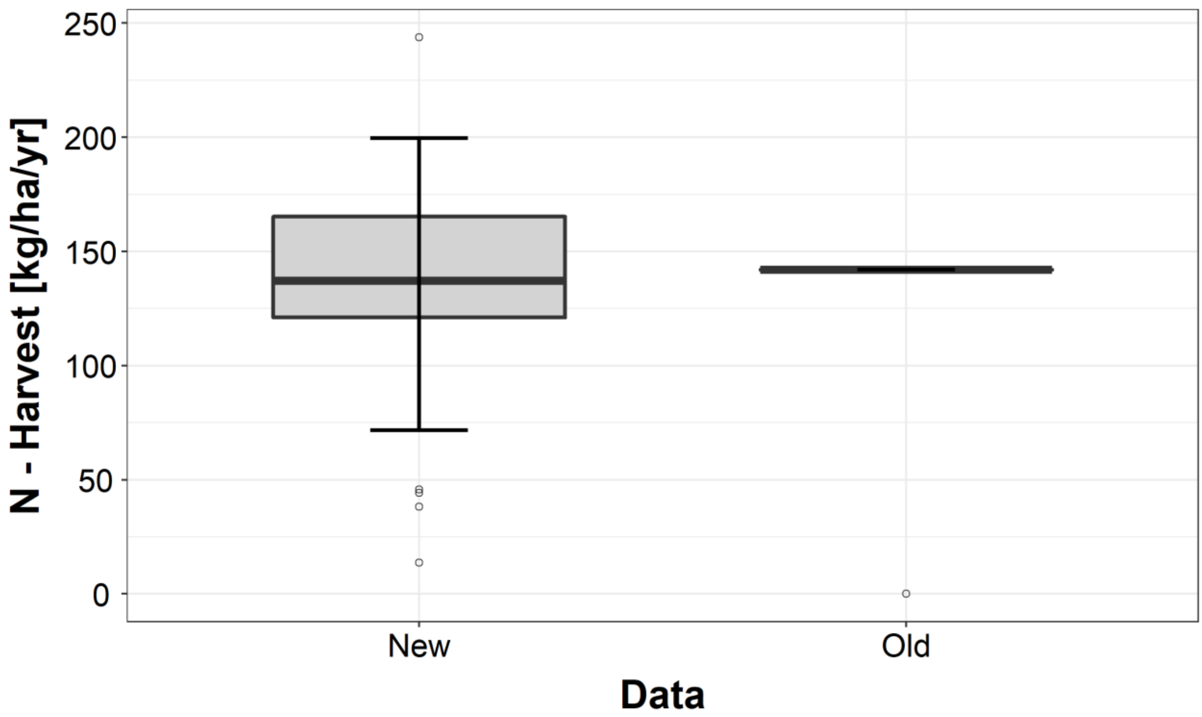

Figure 13: Comparison of the new and old data set for CV-GNLM harvest rates. Example almonds.

For the new calculated harvest rates, the median value is similar to the value of the old data set. In fact, it is less by 6.47 kgN/ha/yr. The variance stretches from ~75 kgN/ha/yr to 200 kgN/ha/yr. Few outliers are noticeable above and below the whiskers (min = 18 kgN/ha/yr; max = 240 kgN/ha/yr). Appendix B shows the results of each crop. To make the results from all crops visible in one graph, the variation between N harvested [kgN/ha/yr] of the new and old data was calculated:

If the variation results in a negative value, harvest rates are lower with the new data set and vice versa. Figure 14 shows the results of the variation for all crops. The “zero” line is highlighted, indicating the value, where harvest rates are equal. One can see that for almonds the median is slightly lower, but the variance can also be higher as seen in Figure 13. Similar results are seen for beans (with huge outliers), carrots, walnuts, and wheat. Pistachios and cotton have less variance and median value of N harvest rates are ~50kgN/ha/yr less with the new data set than with the old one. The same accounts for Onion & Garlic, though the variance is greater and reaches into a positive variation of N harvest. The median values for oats and oranges lie on the threshold line with an equal variance reaching to both sides.

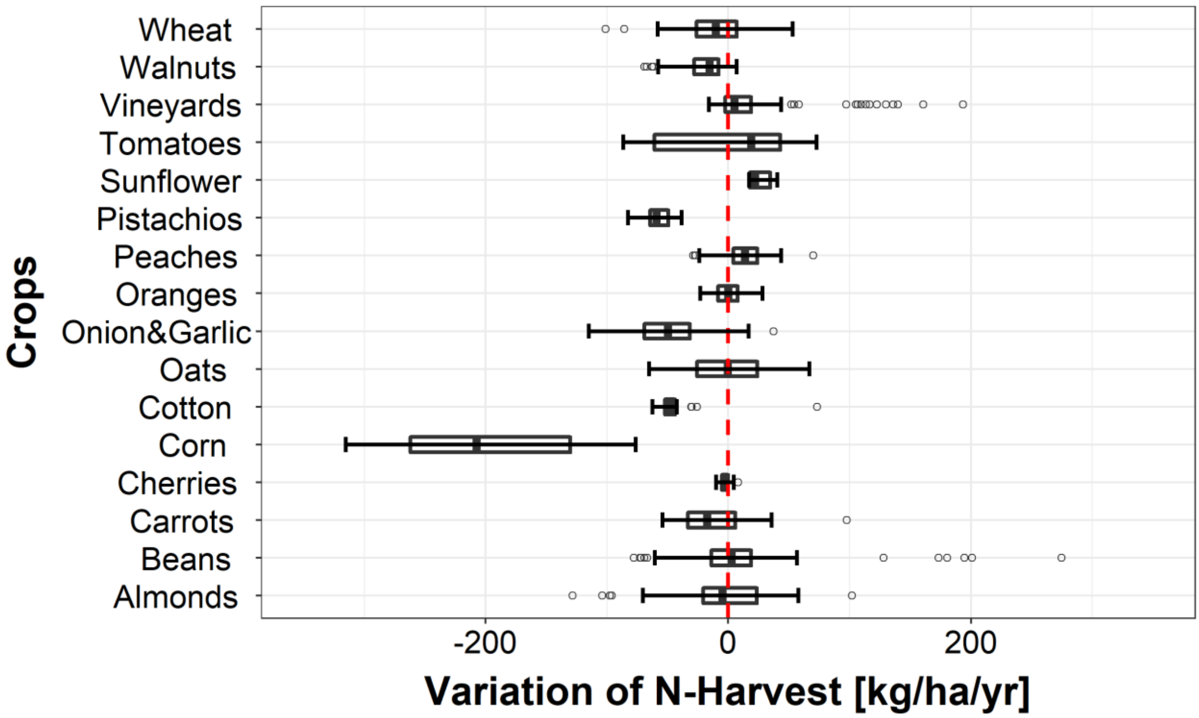

Figure 14: Variation of harvest rates between new and old data set of CV-GNLM for all crops.

Data adaptation resulted in an increased $N_{Harvest}$ for sunflowers with a small variance from the median. Tomatoes and vineyards results in an overall positive variation of $N_{Harvest}$, though with a big variance and outliers. "Corn" shows an exception. The change in data and harvest conversion resulted in an unproportioned decrease of $N_{Harvest}$ by ~210 kgN/ha/yr with a variance ranging from -320 kgN/ha/yr to -80 kgN/ha/yr.

4.2.2 Organic Nitrogen Pools

Different organic N pools were compared throughout different crops. Figure 15, Figure 16 and Figure 17 illustrate N accumulation of active organic N, stable organic N and N in perennial tissue for different crops. Table 4 summarizes the average yearly accumulation rates for each organic pool and each crop represented in the graphs.

Table 4: Average yearly accumulation of active organic N, stable organic N and perennial tissue growth for a variation of crops in kgN/ha/yr.

AVG. ACCUMULATION	ALMOND	YOUNG ALMOND	ORANGE	PEACH	TOMATO	VINEYARD	TABLE GRAPES	GRAIN
ACTIVE ORG. N	0.63	0.91	0.30	0.38	1.79	0.21	0.17	1.44
STABLE ORG. N	5.65	7.74	2.60	3.35	10.42	1.67	1.56	7.77
PEREN. TIS. N	38.04	5.60	12.21	56.95	6.91	17.97	22.64	4.93

After 24 years, accumulation ranges from 4.3 (table grapes) to 44.85 kgN/ha (tomato). It stands out that the accumulation does not proceed linear, but with periods of stagnation and even depletion. "Grain" is a good example for this, where in the years 1994, 2004 and 2010 short periods of depletion are followed by a steep increase of accumulated active organic N. Young and adult almonds stagnate or slightly decrease from year 2001 on. Peach, orange, vineyard and table grape have very low active organic N accumulation raters, yearly averages ranges from 0.17 to 0.38 kgN/ha/yr. A close look reveals that for these crops a stagnation is seen from year 2001 as well. Figure 16 displays accumulation of stable organic N in CV-SWAT over the same period. The range of total accumulation after 24 years is in a different magnitude, ranging from 48.93 to 260.5 kgN/ha. Though stable organic N accumulates much more continuous than for active organic N, it does not increase linear.

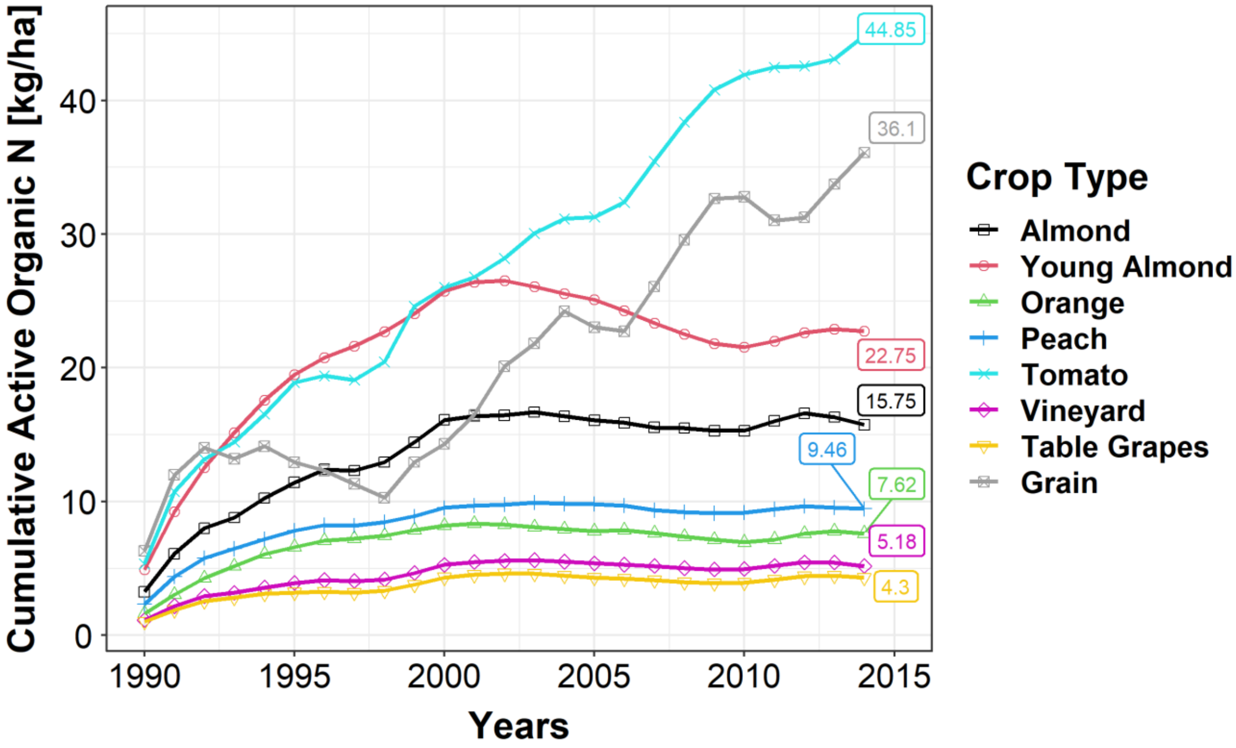

Figure 15: Accumulation of active organic N in CV-SWAT over 24 years.

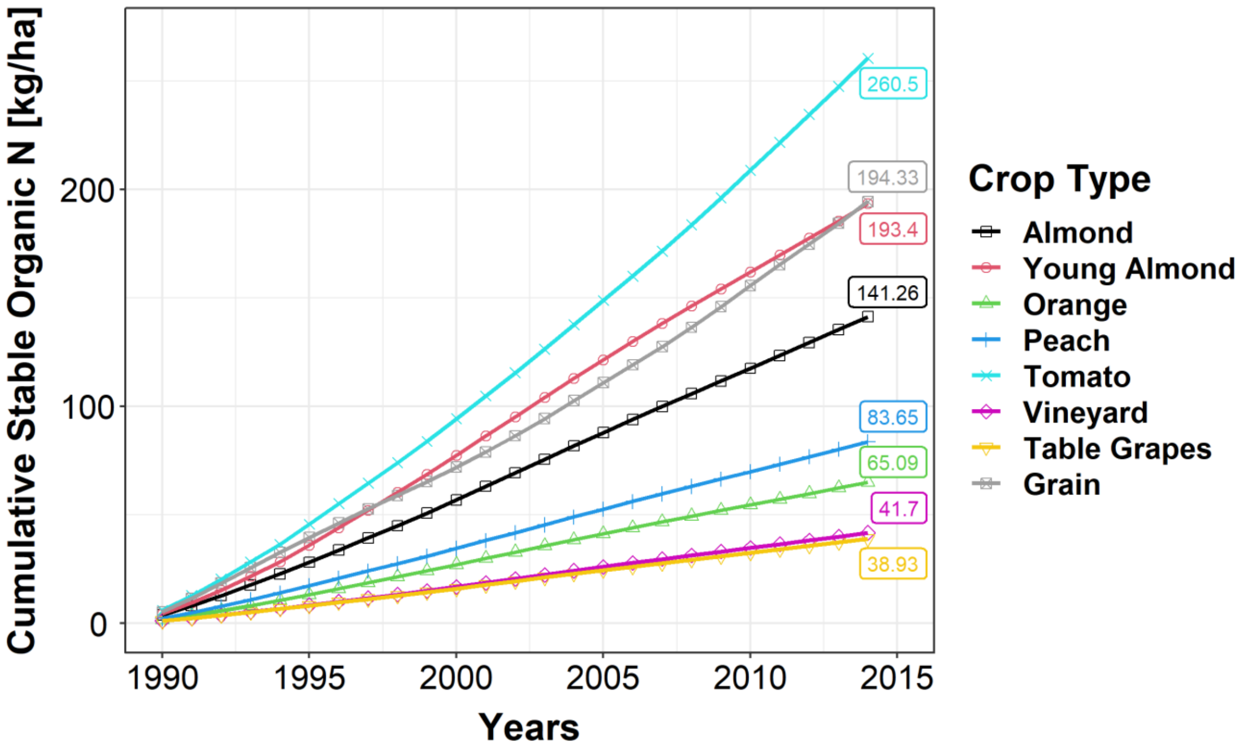

Figure 16: Accumulation of stable organic N in CV-SWAT over 24 years.

The results from grain and young almonds illustrates this where young almond's accumulation exceeds the one from grain in 1994 but are equal again in 2014. Average yearly accumulation ranges from 1.56 to 10.42 kgN/ha/yr. It stands out that results after 24 years are in the same descending order for active and stable organic accumulation, table grapes having the lowest and tomatoes the highest accumulation of N. As for active organic N, also results from stable organic N show that table grapes, vineyards, oranges and peaches are clustered together with low accumulation rates.

Figure 17 shows the cumulative accumulation of N in perennial tissue. Results are in a higher magnitude than previous results of this chapter. Lowest values is 123.16 kgN/ha for grain after 24 years with an average yearly increase of 4.93. Highest N accumulation in perennial tissue is seen in "Peach" with 1423.63 kgN/ha in 2014 (after 24yrs) with a rather linear increase of an average 56.95 kgN/ha/yr. Almonds have the second highest results with 951 kgN/ha (avg. of 38.04 kgN/ha/yr), followed by table grapes with 566 kgN/ha (avg. of 22.64 kgN/ha/yr) and vineyard with 449 kgN/ha (avg. of 17.94 kgN/ha/yr). Grain, young almonds and tomatoes have rather low perennial tissue growth with an average increase between 4.93 and 6.91 kgN/ha/yr. Besides for grain and almond, graphs proceed rather linear.

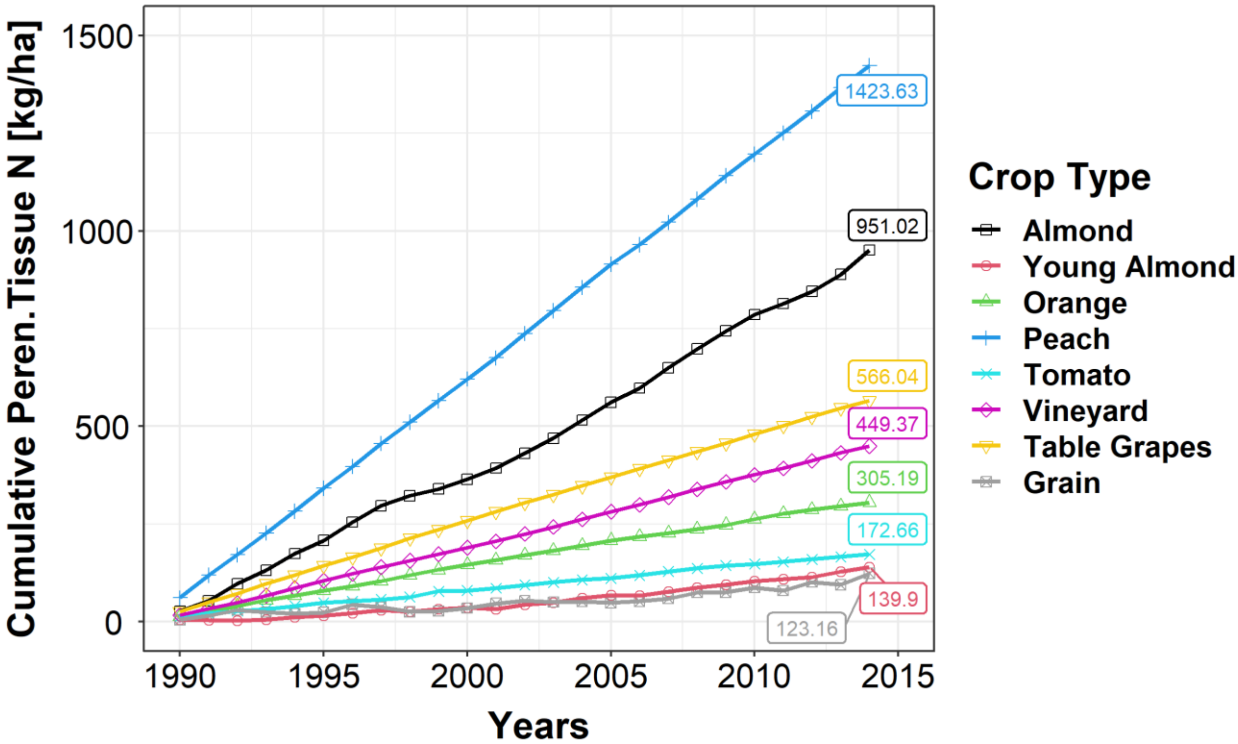

Figure 17: Accumulation of N in perennial Tissue in CV-SWAT over 24 years.

Overall, cumulative results of different organic N pools over the period of 24 years are very different in magnitude. Furthermore, within the same N pool, cumulative results and yearly averages differ greatly throughout different crop types. These results will be discussed further on.

5. Discussion

5.1 Comparison

In the following chapter, the results from the model comparison are discussed and put in perspective.

5.1.1 Land Use

Although both models results focus on the agricultural land in the CV, they use different inputs. CV-SWAT not only focuses on the nitrogen but on phosphorous and the entire water balance as well. Therefore, it includes the whole watershed which expands beyond the agricultural used land (MPEP Team, 2019). Since there are three major watersheds: Sacramento Valley, San Joaquin Valley and Tulare Lake Basin, the spatial domain was divided accordingly. Thus, the different outlines for the models emerge.

To analyze the different outcomes of the land use, one needs to distinct between 1) the difference between the models and 2) the difference between the regions. Firstly, CV-SWAT uses land use dataset from a 2014 summer season, derived from the Department of Water Resources (DWR) published 2016 (MPEP Team, 2019). CV-GNLM on the other hand compiles its land use map from varies sources, based on the earlier version of the "California Augmented Multisource Land cover" (CAML). For once, agricultural land use was obtained as well from the DWR from the years 1997 (County of Monterey) to 2006 (County of Kern) and the Pesticide Use Report from 2008. Additional information on urban and natural land cover was obtained from the Farmland Mapping and Monitoring Program (FMMP) and the Multi-Source Land Cover (MSLC) to derive to the overall CAML 2010 (Viers et al., 2012).

Results showed that CV-SWAT has a significant less amount of field crops and grain which are water intensive crops (Hattendorf et al., 1988). In Figure 18, statewide precipitation anomalies for California can be seen. Johnsen (2021) demonstrates that droughts return periodically and were observed back to 1950 (in comparison with 1990-2020 average).

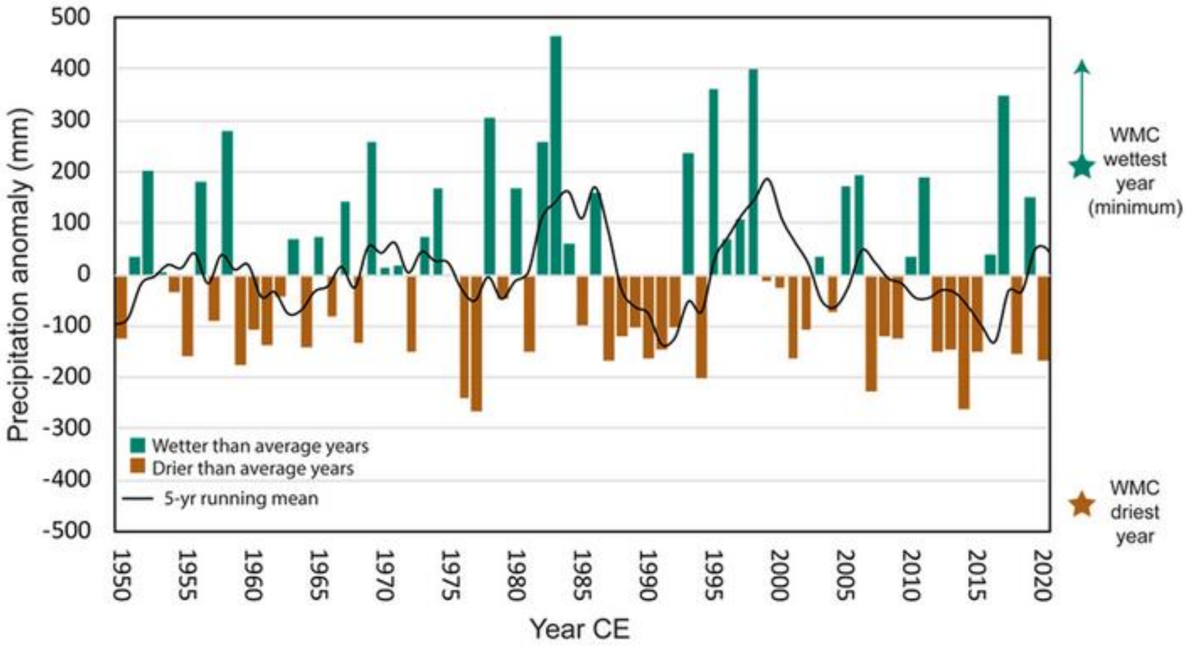

Figure 18: Statewide precipitation anomalies for California from 1950 - 2020 relative to 1990-2020 average (black line). From: (Johnson 2021).

Focusing on the last two decades, it stands out that in the beginning of the 2000's no persistent extreme drought took place and that 2005 and 2006 were even rather wet years. The years 2010 to 2015 on the other hand present a historic period of partly extreme droughts. Due to droughts, groundwater levels decline and wells are threaten to run dry. Although shallow domestic wells are more vulnerable, also irrigation wells are threatened to run dry or to have lower pumping capacity regionally (Scanlon et al., 2012; Perrone und Jasechko, 2017). Niles und Hammond Wagner (2019) point out that according to their survey in Yolo County, farmers are aware of the problem of groundwater depletion. Be it by personal conviction, environmental circumstances or governmental policies – many farmers changed their fruit cultivation, management strategies or irrigation technique in the last years to adapt to drought conditions. One can expect that the decrease in field crops and grain in all three regions is due to farmer's drought adaptation. It is debatable why the most water intensive crop corn is even more represented in the drier San Joaquin Valley and Tulare Lake Basin in 2014. MPEP Team (2019) show in their Appendix Table C-1 that in the Sacramento Valley corn is cultivated for its grain, whereas in SJV and TLB mainly for silage. There is a higher density of dairy corrals in central and south of CV as mentioned in table 11.101 in Harter et al. (2017) (in SJV and TLB, 789 and 616 facilities respectively, in SAC only 130). It is assumed that farmers rely on corn for silage as feed source for dairy farms in these regions, explaining the increasing amount of corn cultivation in the SJV and TLB.

In the Sacramento Valley, the major difference between the models is the discrepancy in "native vegetation" and "pasture". One explanation could be the persistent drought which did not make it profitable anymore to keep vast land of pasture and return it to "native vegetation". The discrepancy of the category "water" is explained by the fact that the CV-SWAT report (MPEP Team, 2019) does not take water with into account. "Wetlands" was established to be regarded as native vegetation as seen in Appendix A, Table A - 1. Therefore, area regarded as water in CV-GNLM is often counted as native vegetation in CV-SWAT, explaining the discrepancy partly. Furthermore, besides in SJV, an increase in urban area is seen comparing CV-GNLM and CV-SWAT. One reason could be that population and therefore urban area has grown in the decade. Johnson et al. (2022) state though that the population growth of California has decreased dramatically in recent decades, indicating that it is more likely that the additional information to urban land use from FMMP included in CV-GNLM lead to different results in urban land cover. A visible example of this can be seen in Figure 7, where the "Interstate Highway 5" is displayed in the CV-GNLM map and not in CV-SWAT.

The general difference of crop cultivation throughout the regions in both models is explained by the climatic difference in the CV. The north of the Sacramento Valley is not yet heavily used by agriculture and gives room for more native vegetation. Rice finds best growing conditions in the more humid Sacramento Valley whereas deciduous trees, nuts, citrus and subtropical crops grow better in the warmer SJV and TLB.

CV-SWAT has in all regions higher amounts of unfertilized land like native vegetation and barren and less fertilizer intensive crops as field crops and grain. One could conclude that because CV-SWAT's different land use, associated with less fertilizer application, overall less N is put in the system and therefore potential $N_{GW\text{-}Leaching}$. It was therefore important, that further analysis of model comparison is carried out not in total N amounts, but area specific, meaning converted N going in or out per unit of area in a specific time step.

5.1.2 Balance

Because both models use very different approaches to derive to amounts of N leaching to the GW, a N mass balance was calculated to prove its fidelity. As equations *(8)* and *(9)* point out, balance results for CV-GNLM were expected to be zero. Results of all crops confirmed this assumption. This is expected, since CV-GNLM calculates $N_{GW\text{-}leaching}$ based on a N mass balance as shown in equation *(9)*. Therefore, the balance results in zero unavoidably (Viers et al., 2012).

CV-SWAT on the other hand, uses extensive data, exceeding N correlated parameters like topography, soils and climate. Since all these parameters are decisive for plants growth and therefore N uptake, they all have indirect impact on the N balance. By far, not all parameters necessary for CV-SWAT were available. Although the CV-SWAT database contains default values for many crops, they were found to be partly unfitting for conditions in California. Therefore, multiple crop growth parameters, variables of the N dynamics and crop productivity underwent a repeating process of calibration and validation. A repeated process of hard data validation (comparing simulated values with observed data) and soft data validation (simulated values are compared to literature review) should ensure liable model results (MPEP Team, 2019). All N in and outputs should be accounted for. As results from Figure 9 (Almond as example) show, this is not the case. A median positive balance indicates more N going in than out as it is the case for all crops. This surprising results are difficult to explain since multiple errors can be the cause. Intensive research and multiple meetings and discussions with members from the MPEP team should exclude the possibility that the variables in Table 1, calculating CV-SWAT's N mass balance are flawed. Multiple revisions of parameters and redefining variables did not solve the problem. More likely is the assumption that the data is still with small deviations and errors. This research was conducted with CV-SWAT data from 2020. It should be highlighted, that in the meantime updated and more recent data were implemented which should be more precise. Unfortunately, this data set could not be made accessible in the timeframe of this research. It would be interesting to find out if the outdated data set is causing the imbalance and should be investigated in future research. Another possible reason for the unbalance could be the manual adaptation by the MPEP team of some $N_{Harvest}$ results. Through the mentioned soft and hard data validation, the MPEP team adapted $N_{Harvest}$ if yield * conversion factor > 0.8 * N_{UP}. Then, 0.8 * N_{UP} is used as result for $N_{Harvest}$. According to Kenneth Miller (personal communication, 2022), this adaptation could lead to a disparity in the N mass balance.

Not only is the median not zero, but a high variance in the balance especially for annual crops indicate regional differences. The results of $N_{Harvest}$ showed big variances for crops in CV-SWAT as well whereas other values are fixed ($N_{Fertilizer}$). It is speculative whether there is a correlation between the variance of $N_{Harvest}$ and overall N mass balance, especially since variations are not in the same ratio (i.e. corn: N mass balance ranges from 39 – (-) 37 kgN/ha/yr [difference of 76], whereas harvest rate ranges from 85 - 255 kgN/ha/yr [difference of 170]).

Results from Figure 10 unfold the difference in structure and focus of variables between the models. It stands out that variables like atmospheric deposition and loss is neglected by CV-SWAT. Both parameters are less than 50 kgN/ha/yr for all crops (CV-GNLM), making them minor contributor for the N mass balance. (Robertson und Vitousek, 2009) confirm this observation. It is arguable if the negligence of this parameters in CV-SWAT is justifiable. On the one hand atmospheric deposition and loss are variables which make the model more true to nature and possibly more accurate. (Bobbink et al., 2010) and (Pardo et al., 2011) state that N deposition has significant impact on plant diversity and will have an increasing effect on plant growth in the future with increasing pollution of N gases. On the other hand, atmospheric deposition through rain and air is very difficult to measure and regional differences are not captured from the CMAQ by EPA which has a 4km grid accuracy. Also for $N_{atm.Loss}$, it is challenging to quantify amounts reliable. Although Harter et al. (2017) give reasonable explanation for atmospheric loss being 10% of all N inputs, an uncertainty remains. One could argue for CV-SWAT that the focus on specifying decisive parameters is more important than including inaccurate variables with little impact. Since $N_{Depostion} < N_{Atm.Loss}$ (in most cases), the implementation of these parameters as in CV-GNLM would result in a negative N mass balance. “Beans” represent an exception for this observation. As the results for “beans” in Figure B - 5 show higher $N_{Depostion}$ in CV-SWAT. This is due to the fact that CV-GNLM does not take N fixation through leguminous crops (like beans) with into account in the N mass balance. Harter et al. (2017) identify “alfalfa” and “clover” as main leguminous crops in the CV. “The uncertainties in the amount of N fixation by these legume crops relative to harvested nitrogen, and relative to (small amounts of) fertilizer nitrogen (synthetic or manure) applied, is too uncertain to arrive at reasonable N leaching estimates” (Harter et al., 2017, p.67). Hence, field measurements reported in literature for N leaching under the root zone from alfalfa and clover is used as final estimate for $N_{GW\text{-}Leaching}$ for these crops. For the sake of completeness and to be better comparable with CV-SWAT, it is recommended to proceed with “beans” the same way as for “alfalfa” and “clover”. Since only a very small amount of land use is taken by beans (<3%) (MPEP Team, 2019), the overall impact of $N_{GW\text{-}Leaching}$ is expected to be rather small.

Another parameter solely present in CV-GNLM is N input through irrigation water. As in the theoretical framework explained, levels of N in irrigation water vary greatly throughout the CV and depth of the wells. Especially water from shallow, unconfined aquifer systems are likely to increase in future (Boyle et al., 2012). Although $N_{Irrigation}$ is less than 10 kgN/ha/yr in median for most crops, for certain regions especially in the SJV and TLB it could become a more relevant factor in future, hence the increasing N loads in GW. N_{Runoff} results are collectively up to 10x less for CV-SWAT. For CV-GNLM the fixed value of 14 kgN/ha/yr is taken from literature review (Viers et al., 2012) whereas CV-SWAT models runoff as a result of topography, soil and climate data. One can assume that especially on the regional spatial scale, CV-SWAT is more precise in this regard. Since this parameter varies widely, it is difficult to implement one value for the whole CV or for a crop type (since dependable from other parameters not taken into account from CV-GNLM). Since a lower N_{Runoff} would result in more $N_{GW\text{-}Leaching}$, adapting this variable would not result in a more precise result for $N_{GW\text{-}Leaching}$.

Organic N in- and outputs like active organic N, stable organic N and perennial tissue growth is only considered by CV-SWAT since these parameters are highly dependent by soil and climate and therefore vary spatially and temporally throughout the CV (Miller und Geisseler, 2018; Pang und Letey, 2000). Harter et al. (2017) assume that given the arid climate and intensive agricultural land use, accumulation of soil organic matter is negligible as expressed in equation *(7)*. This assumption is further investigated, since organic active N, stable organic N and N in perennial tissue are N outputs in the N mass balance which could possibly contribute in lowering $N_{GW\text{-}Leaching}$ in CV-GNLM. Results of perennial tissue were highlighted for oats and sunflower since a negative values are observed in Figure B - 17 and Figure B - 32. The calculation of perennial tissue assumes that all of fresh residues is mineralized again. If this is not the case, “F-MN” is aimed too high for the calculation of N in perennial tissue, possibly resulting in a negative growth of perennial tissue. In nature this is unrealistic, besides the fact that neither oats nor sunflowers are perennial crops in the first place.

Figure 10 show that $N_{Harvest}$ and $N_{Fertilization}$ are the most important variables in both models. This is noticeable not only for “almonds” but for all crop types. In the theoretical framework and methods it was established how both models calculate $N_{Harvest}$. Identified as major components of the N mass balance, these variables will be investigated and further discussed in the next chapter.

The discrepancy of $N_{Gw\text{-}Leaching}$ between the two models for all crop types highlight once more the importance and need to adjust CV-GNLM’s N mass balance.

5.1.3 Harvest & Fertilizer Application

Results in Figure 12 and corresponding graphs for other crops in the Appendix B show a higher variance of $N_{Harvest}$ for CV-SWAT. This is due to the fact that CV-GNLM calculates averages yield of crops through the CV and CV-SWAT not. Furthermore a higher median harvest rate is observed in CV-SWAT for almost all investigated crops. Whether the period of the obtained data and/or different conversion tools used for N conversion is causing this difference, is investigated further in a later chapter. Exceptions for general higher harvest rates in CV-SWAT are corn and onion & garlic. This is caused by the fact that in CV-GNLM, corn is double cropped with winter wheat in most cases, especially in the TLB (Harter et al., 2017). Since yearly results are displayed, they include $N_{Harvest}$ and $N_{Fertilizer}$ for both crops, hence results are higher for CV-GNLM. The same is true for onion and garlic. Whereas CV-GNLM accounts for both crops and add them together, CV-SWAT only takes onions with into account as seen in Appendix A, Table A - 1. It is stated that the MPEP Team already adjusted this in newest version of CV-SWAT and implemented double cropping of corn and wheat with manure application for certain areas in the CV (Kenneth Miller, personal communication, 2022). Therefore, it is from high interest to update this research with newest CV-SWAT data and to investigate whether results change.

As pointed out in the results of Figure 10, the median overall fertilizer rate from CV-GNLM exceeds the one from CV-SWAT frequently. In the results major differences between N_{Manure} and $N_{Synthetic}$ between CV-GNLM and CV-SWAT are pointed out.

$N_{Synthetic}$ is often found to be lower in average in CV-GNLM as in CV-SWAT. Since both models rely on fertilizer reports from ACR, it is expected to be due to increasing synthetic fertilizer application practices over the years as stated from Harter et al. (2017). It is highlighted by Harter et al. (2017) that $N_{Synthetic}$ is likely to be overestimated in CV-GNLM due to possible over reporting. As explained in the theoretical framework, CV-GNLM bases its synthetic fertilizer application on fertilizer sales in the counties. It was observed in multiple cases that sales were occasionally accounted for twice. Once when sold from the distributer to a "middleman" and a second times when sold to the end user. Although not highlighted in the reports of CV-SWAT, one can expect that the same inaccuracy accounts for CV-SWAT, since its synthetic fertilizer amounts are taken from ACR as well.

The fact that CV-GNLM has higher manure application is explained by the method. How Viers et al. (2012) and Harter et al. (2017) derive to manure application on and off dairy cropland is elaborated in the theoretical framework. Crops like field crops (e.g. corn) and grain and hay crops receive high manure application as they receive liquid manure on dairy cropland. It is argued that significant amounts of those crop acreages are actually "off-dairy" and probably not using manure as fertilizer addition. Therefore, estimates are likely to overestimate N_{Manure} and underestimating $N_{Synthetic}$ as the amounts get adjusted accordingly (Viers et al., 2012). $N_{Synthtetic}$'s variance in CV-GNLM is explained by this adaptation of fertilizer application. For crops like almonds, receiving exported manure in form of dried and composted solids off dairy land, a higher overall fertilizer rate is observed since N_{Manure} is applied additionally to $N_{Synthteic}$. Although it is common practice to add $N_{Synthetic}$ to N_{Manure} to ensure N availability for the crops in crucial growth periods (Harter et al., 2017), it is likely that farmers would adjust their application in praxis for economic and ecological reasons (Pang and Letey, 2000). It is therefore argued that N_{Manure} is often overestimated for field crops, grain and hay crops, perennial crops and alfalfa off dairy cropland.

For all crops with N_{Manure} application a variance is recorded in CV-GNLM based on the fact that throughout the CV, dairy facilities are distributed unequally, being highest in the TLB (Viers et al., 2012). Additionally, each dairy operation has different amounts N_{Manure} available (based on the amount of life stock), influencing the amounts applied for each county. Because results are displayed per crop and not per region, mentioned crop types not only have the highest N_{Manure} application in general but also a high standard deviation, variance and ranges between minimum and maximum as seen in corresponding tables of Table 3 for CV-GNLM (Appendix B). Because in the SAV, less dairy facilities are present (Viers et al. 2012), less N_{Manure} is applied here. Therefore, often less overall fertilizer is applied here with amount of yield being similar. Harter et al. (2017) states that as a result, nitrogen use efficiency (NUE) varies greatly throughout the CV in CV-GNLM, being highest in SAV (since lowest N_{Manure} application) which is not necessarily true in reality.

CV-SWAT on the other hand, records no N_{Manure} application for any crop, since no parameter could be defined which represents this input. MPEP Team (2019) states that it takes N application rates from the "nitrogen use report" of 2016 with into account which includes all mineral fertilizer, manure and compost fertilizer and any N in irrigation water. In neither report of MPEP Team (2019) or Formation Environmental (2021) it gets further elaborated how N_{Manure} is implemented. Kenneth Miller (personal communication, 2022) states that in the updated version of CV-SWAT, double cropping of corn and grain for silage with N_{Manure} application was implemented. In the frame of this study, it cannot be investigated further, since only output data was provided and no further inside how each variable was defined for each crop is available.

It is established that N_{Manure} application has significant regional differences and is often overestimated in CV-GNLM, whereas CV-SWAT almost neglects it completely. Although adapting N_{Manure} applications according to CV-SWAT would decrease $N_{GW\text{-}Leaching}$, it is concluded that this would not be a justifiable adaptation. Viers et al. (2012) and Harter et al. (2017) put significant effort into determining N_{Manure} as precise as possible. Although uncertainties and inaccuracies remain, it is argued that for a majority of cropland, N_{Manure} is modelled closely to realistic practices. Van der Schans et al. (2009) and Harter et al. (2002) highlight the impact of manure application on the GW quality in irrigated agriculture. Therefore, it is indispensable to implement this factor for GW-leaching models.

5.2 Adaptation

5.2.1 New Data

The implementation of more recent data from the ACR is shown exemplary for almonds in Figure 13 (for other crops found in Appendix B), whereas Figure 14 gives an overall overview for all crops. For most crops, median $N_{Harvest}$ is lower for the new calculated values. Since the aim is to lower $N_{GW\text{-}Leaching}$, the opposite was achieved. The high variance for the new data stands out, which is explained by the many different species for one crop in the USDA's National Agricultural Statistics Service (https://www.nass.usda.gov/Statistics_by_State/California/Publications/AgComm/index.php). In the Appendix A, Table A - 3 lists which crop species are compared with which crop from CV-GNLM. In the example of "beans" nine different species get compared to the averaged $N_{Harvest}$ from CV-GNLM. In the ACR it is distinguished between yields of different species, different further processing and counties throughout CV. It is obvious that this leads to a high variation of N content. Geisseler (2021) distinguishes partly between species which is implemented in the calculation. As an example: "grapes raisin", "grapes wine" and "grapes table" have different conversion rate which are taken with into account for the new data results, but not in CV-GNLM. Nevertheless, for most crops the median $N_{Harvest}$ does not change significantly, indicating that conversion rates of USDA's Crop Nutrient Tool and conversions from Geisseler (2021) do not differ greatly. Further research in the crop nutrient tool reveals that values contained in the database supporting the tool are derived from various sources and values reflect national averages. The USDA lists as their data sources (https://plantsorig.sc.egov.usda.gov/npk/NutrientSources) varies nationwide research, dating from 1959 to 2000 with many being prior to 1980. Since the research from Geisseler (2021) illustrates crop averages specifically from California and more recent crop yields, it is arguable that conversions with Geisseler's results are more accurate. An important factor not to neglect when converting crop yields to N content is the role of moisture content in the crops. Both USDA conversion tool and Geisseler emphasize the moisture content of the crop yield when showing N content in amount of yield per area. This gets clear when comparing table grapes with raisins in Geisseler (2016) where N in table grapes is 2.26 lbs/tons whereas N in raisins is 10.1 lbs/ton (at moisture of 15%). Through the process of drying, the crop becomes lighter, whereas the nutrient content stays the same, thus increasing the N content per weight. Mulvaney und Devkota (2020) confirm the importance of moisture content in yield/area data and point out that frequent mistakes are made in the conversion. Since the moisture content is unknown in the provided data of crop yields in ACR, the accuracy of the N conversion remains uncertain.

In Figure 14, the crop corn stands out, $N_{Harvest}$ being significantly lower than in the new data than in the old CV-GNLM data set. One can take from Appendix A, Table A - 3 that in CV-GNLM "corn" is double cropped with grain (mostly as winter wheat). Since $N_{Harvest}$ displays N removed per year, N amounts in the yield of both crops are included in CV-GNLM whereas only different kind of corn (silage, grain & sweet corn) is included in the new calculated dataset. Among farmers in the CV, especially in the TLB, it is common practice to till a field twice a year, especially for the purpose of silage (Harter et al., 2017), making the setting of double cropping a realistic scenario.

Overall, results from Figure 13 and Figure 14 show, that median yields for each crop throughout the CV do not differ significantly between 2005 and more recent obtained data. It is concluded that neither the implementation of new data, nor the conversion with Geisseler (2021) is a suitable adaptation for CV-GNLM to increase $N_{Harvest}$ amounts for crops to be better comparable with CV-SWAT. Although the implementation of the whole spectrum of crop yields would better reflect the variety of crop yields throughout the CV, it would also mean a significant increase in workload and calculation time. Since it is found out, that there is no significant difference between amounts of yields between the beginnings of the 2000's to the 2020's, the different result in $N_{Harvest}$ between CV-GNLM and CV-SWAT is concluded to be due to the "conversion coefficient" used by MPEP Team (2019). This coefficient was provided by the MPEP team, but unfortunately it is not further elaborated how the coefficient was prepared in neither CV-SWAT report.

It is recommended to further investigate why the conversion coefficient result in higher $N_{Harvest}$ rates. It would be feasible to adjust $N_{Harvest}$ with determined yields in CV-GNLM and calculate its N content with the conversion coefficient, thus adjusting the $N_{Harvest}$ rates accordingly to CV-SWAT's. It is assumed to be a reasonable solution to decrease CV-GNLM's $N_{GW\text{-}Leaching}$. In order to implement this procedure for historic values from CV-GNLM as well, further research is necessary to investigate if the conversion coefficient is applicable for historic yields in the CV.

5.2.2 Organic Nitrogen Pools

The complexity of transformation processes of organic N in soil was touched in the theoretical framework. Results from Figure 15, Figure 16 and Figure 17 illustrate the relevance of active organic N and stable organic N in the soil and N uptake from plants for perennial tissue.

Active organic N describes the N content in soil which is in the process of transformation from fresh organic matter to mineralized N through microbial organisms as fungus and bacteria (Robertson and Vitousek, 2009). An accumulation of active organic N therefore indicates high microbial biomass and activity, which is regarded as an indicator of healthy soil (Doran and Parkin, 1996). Accumulation over 24 years in the active organic N pool ranges between a maximum of 44.85 kgN/ha for tomatoes and a minimum of 4.3 kgN/ha for table grapes. This shows that the storage of active organic N is very crop dependable. That active N in soil is highly dependable of land use and agricultural management practices is also confirmed by Dilly et al. (2003). It stands out in Figure 15 that accumulation of active organic N is highest for annual crops like tomatoes and grain. Common management practice for annual crops is the plowing under the soil of plant residues like roots and stems after harvest, increasing the organic N content in the soil. Entry et al. (1997) confirms this observation by highlighting the dependency of organic by-products and microbiological activity. It should be mentioned that microbiological activity is additionally dependable from the soil. Verberne et al. (1990) explain that the rate of mineralization is lower in fine texture soils. Furthermore, climate (precipitation and temperature) plays a key role in soil respiration, N mineralization and microbial biomass (Franzluebbers et al., 2001). Changing soil and climate conditions is expected to be the reason for the fluctuating average yearly accumulation rates for tomatoes and grain, for which in occasional years even a decrease in active organic N is observed. Since in this analysis only average values throughout the CV per crop are taken into account, regional differences of soil and climate are not visible. Note, that there can be significant regional differences for the accumulation of active organic N throughout the CV for the same crop. It stands out that from the year 2000/2001 to 2014, accumulation rates stagnate. This especially applies for young almonds, having highest yearly increase until 2000 but then decreasing and stagnating in accumulation. One attempt to explain the change in the behavior could be climate. Figure 18 shows that since the 2000's, climate is increasingly becoming drier. Findings from Franzluebbers et al. (2001) indicate though that increasing precipitation lower soil microbial biomass, thus it is expected to be higher in dry conditions. Additionally, no change is observable in the rather wet years 2005 and 2010, indicating that change in climate is not the reason for stagnating active organic N accumulation for perennial crops. It remains questionable why active organic N stagnates for perennial crops from the year 2000 on.

Comparing young almonds and grain illustrate that the accumulation does not proceed linear. Total accumulation after 24 years varies from 260.5 kgN/ha for tomatoes to 38.93 kgN/ha for table grapes, being in average four times higher than accumulation of active organic N. Like for active organic N, stable organic N is highest for annual crops (tomato and grain). This is explained by the fact that stable organic N is a product of active organic N as Figure 6 illustrates. It is therefore a product of the addition of fresh organic matter to the soil (Kelley and Stevenson, 1995). As previous stated, more organic matter is added to the soil yearly with annual crops for land use. Thus, it is not surprising that perennial crops have very low rates of N trapped in the soil. For perennial crops, no residues get plowed under but it is a common management practice to let plant residues like leaves and woodchips cover the soil to decrease water loss from soil through evaporation (Sinkevičienė et al., 2009). Because of above described transformation processes, this material might also accumulate as stable organic N although not in the same amounts than for annual crops. As Harter et al. (2017) mention, NUE is different for each crop and region and therefore also the N content in plant residues. Thus, N in stable organic pool differs depending which plant residues are applied to the soil. This applies for perennial crops as for annual crops alike.

In general, the arid to semi-arid climate in the CV is not promoting high accumulation of organic material in the soil. "No significant measurable increases in soil organic matter have been recorded over the past 65 years" (Harter et al. 2017, p.63) leads to the assumption for the CV-GNLM that N storage in soil is negligible. Although Figure 15 and Figure 16 show that accumulation of organic N (active and stable) is present in the model of CV-SWAT, yearly averages are so low that it is difficult to confirm yearly accumulations with measurements. Comparing active and stable organic N with other variables of the N – balance in Figure 10, it gets clear that they have little to no impact on the yearly balance and $N_{GW\text{-}Leaching}$ for perennial crops. Nevertheless, for annual crops, average yearly accumulation can exceed 10 kgN/ha/yr. Parameters like $N_{Deposition}$, $N_{Atm.Loss}$, $N_{Irrigation}$ and N_{Runoff} have low impact as well but are still implemented in the N mass balance. It can be argued that the implementation of stable organic N for annual crops would make results more precise and should not be missing. This would lower $N_{GW\text{-}Leaching}$, adjusting CV-GNLM more towards the results of CV-SWAT.

Discussing results from Figure 17, it is important to highlight that accumulation of N in perennial tissue are in a different magnitude than for active and stable organic N in soil, ranging from 1423.63 kgN/ha for peaches to 123.16 kgN/ha for grain. Accumulation over 24 years does not proceed linear. Factors affecting plant N uptake include type of crop, source, timing and rate of fertilizer, environmental factors like soil and climate and management practice (Recous et al., 1988; Raun and Johnson, 1999). Because all of these factors can vary even for the same crop over the CV and over the period of 24 years, it is logical that yearly tissue growth differ between the years. Since annual crops do not have perennial tissue growth, it is questionable why tomato and grain have average yearly storage in tissue of 6.91 kgN/ha/yr and 4.93 kgN/ha/yr respectively (Table 4). Although these amounts are negligible, it was expected to be zero. Since perennial tissue is calculated by subtracting N_{UP} by F-MN (plant residues), a possible explanation could be that N_{UP} is partly defined too high or F-MN too low in CV-SWAT and further calibrations are necessary. As detailed inside is missing on how these parameters were determined for each crop, one can only speculate that this is the reason. Since an updated version of CV-SWAT is already available, it can be assumed that these parameters were further revised. It is therefore recommended to determine perennial tissue growth for crops again when updated data is available. Furthermore, it stands out from Table 4 that for perennial crops, growth of perennial tissue differentiates widely. This is a logical consequence hence different N uptake of crops. Therefore, it is concluded that is vital to distinguish between different perennial crops and not summarize all perennial crops together. Table 4 states an average yearly N uptake in perennial tissue of 38.04 kgN/ha/yr for almonds. If incorporated in the N-balance of CV-SWAT, this would decrease $N_{GW\text{-}Leaching}$ significantly from 90.92 kgN/ha/yr to 52.04 kg/ha/yr. It is therefore concluded, that the implementation of perennial tissue growth as an output of CV-GNLM's N mass balance has the potential to lower $N_{GW\text{-}Leaching}$ for perennial crops. As crops as almonds and pistachios make up a substantial amount of agricultural used land in the CV (MPEP Team 2019), this adaptation could potentially have a significant impact of modeled $N_{GW\text{-}Leaching}$ throughout the CV. Since this research focuses on the most recent period from CV-GNLM, further research is required to find out the impact on groundwater leaching in the previous years. More research is needed to investigate if N uptake in perennial tissue from past periods are comparable with those from today.

6. Conclusion

The objective was to identify key differences and parameters between CV-GNLM and CV-SWAT which result in the difference of modelled N leaching to GW and to work out possible adaptions for CV-GNLM, adjusting overestimated GW loading.

For once, a land use analysis revealed that land use not only varies over the time period 2000 to 2016, but also throughout the CV. In all regions, CV-GNLM land use shows more field crops and grain due to adaptation to drier climate and regulations. The fact that CV-SWAT has more native vegetation and barren land, is assumed to be due to the same reason. As a result, CV-SWAT has less area where fertilizer intensive crops are grown, resulting in less total amount of N available for $N_{GW\text{-}Leaching}$. Further analysis and comparison were therefore carried out in amounts per area per year. The difference in land use throughout the CV attributes to the different climate in the CV. Whereas rice can grow in the more humid SAV, whereas citrus and subtropical crops are cultivated in the hotter and drier TLB. Corn is grown in the south even though it is water intensive, for the purpose of silage to serve as feed for livestock.

An N mass balance for both models indicate that CV-GNLM accounts for all in- and outputs. CV-SWAT records an imbalance between in- and outputs which could imply an inaccuracy for $N_{GW\text{-}Leaching}$ as well. Detailed comparison of all model parameters show that both models have different focus. Whereas CV-SWAT does not include $N_{Deposition}$ or $N_{Atm.Loss}$, neither $N_{Irrigation}$, CV-GNLM neglects organic N in soil (active and stable) and N content in perennial tissue. $N_{Fertilizer}$ and $N_{Harvest}$ are identified as most influential N in- and outputs. A focus on these variables revealed that $N_{Harvest}$ shows a high variance for CV-SWAT due to implementation of regional differences of crop yields and species. It is discovered that the implementation of updated crop yields and an updated conversion of N content in crops has little impact on average $N_{Harvest}$ in CV-GNLM. Although the implementation of regional crop yields could increase the accuracy of CV-GNLM (regional differences in crop growth), it is not feasible for the adaption of historic data, since no data is available prior to 1980. Rather, it is recommended to apply CV-SWAT's conversion coefficient to derive to comparable $N_{Harvest}$, thus lowering significantly $N_{GW\text{-}Leaching}$ of CV-GNLM. Further research is necessary, whether the conversion coefficient is applicable on historic data of crop yields. Separation of $N_{Fertilizer}$ into $N_{Synthetic}$ and N_{Manure} revealed that higher amounts of $N_{Fertilizer}$ in CV-GNLM is caused by modelled amounts of N_{Manure}. Additional N_{Manure} application on crops outside of dairy cropland leads to overestimation of applied $N_{Fertilizer}$ with high variance throughout the CV due to regional differences of size and number of dairy facilities and exported manure.

Implementation of active organic N pool in CV-GNLM is concluded to be redundant. For once, because of soil and climate dependency and hence significant regional differences. Second, it was found that even for annual crops, active organic N is less than 2 kgN/ha/yr. This amount is so low, that it is below measurable detection and therefore cannot be proven by field measurements. For stable organic N on the other hand, different results for annual and perennial crops are found. Whereas for perennial crops, stable organic N accumulation is small, up to over 10 kgN/ha/yr are stored as stable organic N for annual crop. It is argued that this could have an impact on the overall N mass balance in CV-GNLM and lower $N_{GW\text{-}Leaching}$. Further research is recommended to investigate if this implementation applies for modelling historic land uses in CV-GNLM.

Findings show that N uptake for growth of perennial tissue is a significant N output over time. For perennial crops like peaches, $N_{GW\text{-}Leaching}$ could be reduced by up to 56 kgN/ha/yr. Although this adaption only has an impact on perennial crops, it is expected to have a high impact since large amounts of land use are used by perennial crops like almonds and pistachios in the CV. For future research it is recommended to establish average yearly N uptake of perennial tissue for each perennial crop with most recent output data from CV-SWAT available. Hence these results are derived from modeled parameters based on recent obtained data, it is recommended to further study if this implementation is applicable for historic data. If confirmed, this adaptation has high potential of adjusting $N_{GW\text{-}Leaching}$ from CV-GNLM closer to results from CV-SWAT for the majority of agricultural used land in the CV.

In conclusion, following list clarifies the recommendations for further research and implementation in CV-GNLM

- Update to most recent data (2018-2021) not necessary
- Implementation of active organic N is redundant
- Implementing CV-SWATs conversion coefficient in CV-GNLM conversion from crop yield to $N_{Harvest}$
- Implementation of stable organic N for annual crops
- Implementation of N uptake in tissue for perennial crops
  - Merged together as parameter “organic N”
  - Further research required, finding out the impact on $N_{GW\text{-}Leaching}$ in previous years

These recommendations have high potential of adjusting results from CV-GNLM. Higher outputs of harvest and organic N results in lower $N_{GW\text{-}Leaching}$. Therefore, results of CV-GNLM and CV-SWAT match better and are more comparable.

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Appendix A: Land Use

Table A - 1: Comparison of CV-GNLM and CV-SWAT land cover types, overall categorization and indicator if CV-GNLM land use is driven by dairy sources (0=no; 1=liquid manure on dairy cropland; 2=solid manure off dairy cropland).

CAML CODE/GNLM RASTER VALUE	DWR/CAML/GNLM LAND COVER TYPE	GNLM: LUDRIVEN N SOURCE_DAIRY	CAML ALSO IN DWR 2014 LAND USE SURVEY?	CIG-MPEP CV-SWAT LAND COVER TYPE ("CROP2014_FINAL")	CIG-MPEP CV-SWAT RASTER TERM	GROUPED CLASSIFICATION
0	No data	0	No			No data
500	No Access	0	No			No data
1440	Not surveyed	0	No			No data
2161	(Unknown referent)	0	No			No data
2600	Out of area	0	No			No data
1	Urban (backcasted)	0	No	Urban	URML	Urban
53	Urban	0	Yes	Urban	URML	Urban
2027	Greenhouse	0	No	Urban	URML	Urban
2100	Urban	0	Yes	Urban	URML	Urban
2110	Commercial	0	No	Urban	URML	Urban
2111	Offices	0	No	Urban	URML	Urban
2112	Hotels	0	No	Urban	URML	Urban
2113	Motels	0	No	Urban	URML	Urban
2114	RV Parking	0	No	Urban	URML	Urban
2115	Institutions	0	No	Urban	URML	Urban
2116	Schools	0	No	Urban	URML	Urban
2117	Municipal buildings	0	No	Urban	URML	Urban
2118	Miscellaneous high water use	0	No	Urban	URML	Urban
2120	Industrial	0	No	Urban	URML	Urban

2121	Manufacturing	0	No	Urban	URML	Urban
2122	Extractive Industries	0	No	Urban	URML	Urban
2123	Storage and distribution	0	No	Urban	URML	Urban
2126	Saw Mills	0	No	Urban	URML	Urban
2127	Oil refineries	0	No	Urban	URML	Urban
2128	Paper mills	0	No	Urban	URML	Urban
2129	Meat Packing Plants	0	No	Urban	URML	Urban
2130	Urban landscape	0	Yes	Urban	URML	Urban
2131	Lawn - irrigated	0	No	Urban	URML	Urban
2132	Golf course	0	No	Urban	URML	Urban
2133	Ornamental landscape	0	No	Urban	URML	Urban
2134	Cemeteries - irrigated	0	No	Urban	URML	Urban
2135	Cemeteries - non-irrigated	0	No	Urban	URML	Urban
2140	Residential	0	No	Urban	URML	Urban
2141	Single family > 1 acre	0	No	Urban	URML	Urban
2142	Single family 1-8 units/acre	0	No	Urban	URML	Urban
2143	Multiple family	0	No	Urban	URML	Urban
2144	Trailer Courts	0	No	Urban	URML	Urban
212910	Steel mill	0	No	Urban	URML	Urban
212911	Fruit and Vegetable cannery	0	No	Urban	URML	Urban
212912	Miscellaneous high water use	0	No	Urban	URML	Urban

212913	Sewage treatment plant	0	No	Urban	URML	Urban
212914	Waste accumulation sites	0	No	Urban	URML	Urban
212915	Wind farms/solar farms	0	No	Urban	URML	Urban
2	Natural Vegetation (backcasted)	0	No	Range Grass	RNGE	Native Vegetation
4	Alkali Desert Scrub	0	No	Range Grass	RNGE	Native Vegetation
5	Aspen	0	No	Evergreen Forest	FRSE	Native Vegetation
7	Bitterbrush	0	No	Range Grass	RNGE	Native Vegetation
8	Blue Oak-Foothill Pine	0	No	Pine Trees	PINE	Native Vegetation
9	Blue Oak Woodland	0	No	Evergreen Forest	FRSE	Native Vegetation
10	Coastal Oak Woodland	0	No	Evergreen Forest	FRSE	Native Vegetation
11	Closed-Cone Pine-Cypress	0	No	Pine Trees	PINE	Native Vegetation
12	Chamise-Redshank Chaparral	0	No	Range - Brush	RNGB	Native Vegetation
13	Coastal Scrub	0	No	Range - Brush	RNGB	Native Vegetation
14	Douglas-Fir	0	No	Pine Trees	PINE	Native Vegetation
15	Desert Riparian	0	No	Wetlands	WETL	Native Vegetation
17	Desert Scrub	0	No	Range - Brush	RNGB	Native Vegetation
18	Desert Succulent Shrub	0	No	Range - Brush	RNGB	Native Vegetation
20	Eastside Pine	0	No	Pine Trees	PINE	Native Vegetation
22	Freshwater Emergent Wetland	0	No	Wetlands	WETL	Native Vegetation

24	Jeffrey Pine	0	No	Pine Trees	PINE	Native Vegetation
25	Joshua Tree	0	No	Pine Trees	PINE	Native Vegetation
26	Juniper	0	No	Evergreen Forest	FRSE	Native Vegetation
27	Klamath Mixed Conifer	0	No	Evergreen Forest	FRSE	Native Vegetation
29	Lodgepole Pine	0	No	Pine Trees	PINE	Native Vegetation
30	Low Sage	0	No	Range - Brush	RNGB	Native Vegetation
32	Mixed Chaparral	0	No	Range - Brush	RNGB	Native Vegetation
34	Montane Chaparral	0	No	Range - Brush	RNGB	Native Vegetation
35	Montane Hardwood-Conifer	0	No	Evergreen Forest	FRSE	Native Vegetation
36	Montane Hardwood	0	No	Evergreen Forest	FRSE	Native Vegetation
37	Montane Riparian	0	No	Wetlands	WETL	Native Vegetation
40	Pinyon-Juniper	0	No	Range - Brush	RNGB	Native Vegetation
41	Palm Oasis	0	No	Range - Brush	RNGB	Native Vegetation
42	Ponderosa Pine	0	No	Pine Trees	PINE	Native Vegetation
44	Redwood	0	No	Evergreen Forest	FRSE	Native Vegetation
45	Red Fir	0	No	Evergreen Forest	FRSE	Native Vegetation
48	Subalpine Conifer	0	No	Evergreen Forest	FRSE	Native Vegetation
49	Saline Emergent Wetland	0	No	Wetlands	WETL	Native Vegetation
50	Sagebrush	0	No	Range - Brush	RNGB	Native Vegetation
51	Sierran Mixed Conifer	0	No	Evergreen Forest	FRSE	Native Vegetation
55	Valley Oak Woodland	0	No	Evergreen Forest	FRSE	Native Vegetation
56	Valley Foothill Riparian	0	No	Evergreen Forest	FRSE	Native Vegetation
58	White Fir	0	No	Evergreen Forest	FRSE	Native Vegetation

59	Wet Meadow	0	No	Evergreen Forest	FRSE	Native Vegetation
62	Undetermined Shrub Type	0	No	Range - Brush	RNGB	Native Vegetation
63	Undetermined Conifer Type	0	No	Range - Brush	RNGB	Native Vegetation
77	Eucalyptus	0	No	Range - Brush	RNGB	Native Vegetation
310	Eucalyptus	0	No	Range - Brush	RNGB	Native Vegetation
1420	Native Vegetation (unsegregated)	0	No	Range Grass	RNGE	Native Vegetation
1430	Riparian Vegetation	0	No	Wetlands	WETL	Native Vegetation
1431	Riparian Marsh	0	No	Wetlands	WETL	Native Vegetation
1432	Riparian Meadow	0	No	Wetlands	WETL	Native Vegetation
1433	Riparian Tree	0	No	Wetlands	WETL	Native Vegetation
1434	Riparian seasonal duck marsh	0	No	Wetlands	WETL	Native Vegetation
1435	Riparian permanent duck marsh	0	No	Wetlands	WETL	Native Vegetation
1450	Native Vegetation	0	No	Range - Brush	RNGB	Native Vegetation
1452	Light Brush	0	No	Range - Brush	RNGB	Native Vegetation
1453	Medium Brush	0	No	Range - Brush	RNGB	Native Vegetation
1454	Heavy Brush	0	No	Range - Brush	RNGB	Native Vegetation
1455	Brush and Timber	0	No	Range - Brush	RNGB	Native Vegetation
1456	Forest	0	No	Evergreen Forest	FRSE	Native Vegetation
3	Annual Grassland	0	No	Non Irrigated Pasture	PASN†	Pasture
39	Perennial Grassland	0	No	Non Irrigated Pasture	PASN†	Pasture
72	Non-Irrigated Pasture	0	No	Non Irrigated Pasture	PASN†	Pasture
1451	Grassland	0	No	Non Irrigated Pasture	PASN†	Pasture
1457	Oak grassland	0	No	Non Irrigated Pasture	PASN†	Pasture

1600	Pasture	1	Yes	Pasture	PAST	Pasture
1414	Salt Flats	0	No	Barren	BARR	Barren
1415	Sand dunes	0	No	Barren	BARR	Barren
2150	Vacant	0	No	Barren	BARR	Barren
1603	Mixed pasture	1	Yes	Low Productive Pasture; Moderate Pasture; High Productive Pasture, Grass	PASL†;PASM†; PASI†; HAY	Pasture
1604	Native Pasture	0	No	Non Irrigated Pasture	PASN†	Pasture
1605	Induced high water table native pasture	0	No	Non Irrigated Pasture	PASN†	Pasture
1606	Miscellaneous grasses	0	No	Non Irrigated Pasture	PASN†	Pasture
1607	Turf farms	0	No	Low Productive Pasture; Moderate Pasture; High Productive Pasture	PASL†;PASM†; PASI†;	Pasture
6	Barren	0	No	Barren	BARR	Barren
901	Idle – Cropped Past 3 Years	0	Yes	Idle	BARR	Barren
902	Idle – New Lands	0	Yes	Idle	BARR	Barren
1410	Barren and Wasteland	0	No	Idle	BARR	Barren
1411	Dry stream channels	0	No	Idle	BARR	Barren
1412	Mine Tailings	0	No	Idle	BARR	Barren
1413	Barren Land	0	No	Idle	BARR	Barren
2151	Unpaved	0	No	Idle	BARR	Barren
2152	Vacant unlisted	0	No	Idle	BARR	Barren

2153	Railroad right of way	0	No	Idle	BARR	Barren
2154	Paved areas	0	No	Idle	BARR	Barren
2156	Airport runways	0	No	Idle	BARR	Barren
19	Desert Wash	0	No	Idle	BARR	Water
21	Estuarine	0	No	Managed Wetland	WETL	Water
28	Lacustrine	0	No	Managed Wetland	WETL	Water
31	Marine	0	No	Managed Wetland	WETL	Water
43	Riverine	0	No	Managed Wetland	WETL	Water
57	Water	0	No	Managed Wetland	WETL	Water
1460	Water Surface	0	No	Managed Wetland	WETL	Water
1461	River	0	No	Managed Wetland	WETL	Water
1462	Water channel	0	No	Managed Wetland	WETL	Water
1464	Freshwater lake, reservoir	0	No	Managed Wetland	WETL	Water
1465	Brackish water	0	No	Managed Wetland	WETL	Water
300	Citrus and Subtropical (Also Miscellaneous subtropical and jojoba)	2	Yes	Citrus (per Table 4)	ORAN**	Citrus and Subtropical
301	Grapefruit	2	No	Citrus	ORAN**	Citrus and Subtropical
302	Lemons	2	No	Citrus	ORAN**	Citrus and Subtropical
303	Oranges	2	No	Citrus	ORAN**	Citrus and Subtropical
304	Dates	0	Yes	Citrus (per Table 4)	ORAN**	Citrus and Subtropical
305	Avocados	2	Yes	Citrus (per Table 4)	ORAN**	Citrus and Subtropical
306	Olives	2	Yes	Olives	OLIV	Citrus and Subtropical
308	Kiwis	2	Yes	Kiwis	GRAK†	Citrus and Subtropical

400	Deciduous Fruits and Nuts	2	Yes	Almonds (see Table 4: Miscellaneous Deciduous)	ALMD	Decidious Fruits and Nuts
401	Mixed deciduous (Apples)	2	Yes	Apple	APPL	Decidious Fruits and Nuts
402	Apricots	2	Yes	Plums, Prunes and Apricots	ALML	Decidious Fruits and Nuts
403	Cherries	2	Yes	Cherries	ALMC*	Decidious Fruits and Nuts
405	Peaches and Nectarines	2	Yes	Peaches and Nectarines	ALMP*	Decidious Fruits and Nuts
406	Pears	2	Yes	Apple (see Table 4: Pears)	APPL	Decidious Fruits and Nuts
407	Plums	2	Yes	Plums, Prunes and Apricots	ALML*	Decidious Fruits and Nuts
408	Prunes	2	Yes	Plums, Prunes and Apricots	ALML	Decidious Fruits and Nuts
409	Figs	2	No	Bush Berries	AGBR**	Decidious Fruits and Nuts
412	Almonds	2	Yes	Almonds; Almonds Young	ALMD; ALMY	Decidious Fruits and Nuts
414	Pistachios	2	Yes	Pistachios	ALMI*	Decidious Fruits and Nuts
413	Walnuts	2	Yes	Walnuts	WALN	Decidious Fruits and Nuts
600	Field Crops (includes Flax, Hops, Castor Beans, Miscellaneous Field, and Millet)	1	Yes	Corn, Sorghum and Sudan (see Table 4: Miscellaneous Field Crops)	CORN	Field Crops
601	Cotton	1	Yes	Cotton	COTS	Field Crops
602	Safflower	2	Yes	Safflower	SUNS*	Field Crops
605	Sugar Beets	1	No	Bush Berries	AGBR**	Field Crops

610	Beans (dry)	2	Yes	Beans (dry)	PTBB**	Field Crops
612	Sunflowers	1	Yes	Sunflower	SUNF	Field Crops
606	Corn (Field and Sweet)	1	Yes	Corn	CORN	"Corn, Sorghum, Sudan"
607	Grain sorghum	1	No	Corn	CORN	"Corn, Sorghum, Sudan"
608	Sudan	1	No	Corn	CORN	"Corn, Sorghum, Sudan"
700	Grain and Hay (includes miscellaneous)	1	Yes	Miscellaneous Grain and Hay	HAY	Grain
701	Barley	1	No	Miscellaneous Grain and Hay	HAY	Grain
702	Wheat	1	Yes	Winter Wheat	WWHT	Grain
703	Oats	1	No	Miscellaneous Grain and Hay	HAY	Grain
1601	Alfalfa	2	Yes	Alfalfa	ALFA†	Alfalfa
1602	Clover	2	No	Alfalfa	ALFA†	Alfalfa
1901	Farmstead (with residence)	0	No	Urban	URML	Semiagricultural and Incidental to Agriculture
1902	Livestock feedlot operation	0	No	Urban	URML	Semiagricultural and Incidental to Agriculture
1903	Dairy farm	0	No	Urban	URML	Semiagricultural and Incidental to Agriculture
1904	Poultry farm	0	No	Urban	URML	Semiagricultural and Incidental to Agriculture
1905	Farmstead (without residence)	0	No	Urban	URML	Semiagricultural and Incidental to Agriculture

2000	Truck,Nursery, Berry Crops (includes cole mix, mixed, and misc. truck crops)	2	Yes	Pepper (see Table 4: Miscellaneous Truck Crops)	PEPP	"Truck, Nursery, and Berry Crops"
2001	Artichokes	2	No	Lettuce/Leafy Greens	LETT	"Truck, Nursery, and Berry Crops"
2002	Asparagus	2	No	Lettuce/Leafy Greens	LETT	"Truck, Nursery, and Berry Crops"
2003	Beans (green)	2	No	Lettuce/Leafy Greens	LETT	"Truck, Nursery, and Berry Crops"
2006	Carrots	2	Yes	Carrots	CRRT	"Truck, Nursery, and Berry Crops"
2007	Celery	2	No	Lettuce/Leafy Greens	LETT	"Truck, Nursery, and Berry Crops"
2008	Lettuce	2	No	Lettuce/Leafy Greens	LETT	"Truck, Nursery, and Berry Crops"
2009	Melons, squash, cucumbers	2	Yes	Melons, Squash and Cucumbers	CUCM	"Truck, Nursery, and Berry Crops"
2010	Onions and garlic	2	Yes	Onions	ONIO	"Truck, Nursery, and Berry Crops"
2011	Peas	2	No	Lettuce/Leafy Greens	LETT	"Truck, Nursery, and Berry Crops"
2012	Potatoes	2	Yes	Potatoes and Sweet Potatoes	POTA	"Truck, Nursery, and Berry Crops"
2013	Sweet Potatoes	2	Yes	Potatoes and Sweet Potatoes	POTA	"Truck, Nursery, and Berry Crops"
2014	Spinach	2	No	Lettuce/Leafy Greens	LETT	"Truck, Nursery, and Berry Crops"
2015	Tomatoes (processing)	2	Yes	Tomato	TOMA	"Truck, Nursery, and Berry Crops"
2016	Flowers, nursery, Christmas tree farms	0	Yes	Flowers, Nursery, and Christmas Tree Farms	MAPL**	"Truck, Nursery, and Berry Crops"
2019	Bush berries	2	Yes	Bush Berries	AGBR**	"Truck, Nursery, and Berry Crops"
2020	Strawberries	2	Yes	Pepper (see Table 4: Strawberries)	PEPP	"Truck, Nursery, and Berry Crops"
2021	Peppers	2	Yes	Peppers	PEPP	"Truck, Nursery, and Berry Crops"
2022	Broccoli	2	No	Lettuce/Leafy Greens	LETT	"Truck, Nursery, and Berry Crops"

2023	Cabbage	2	No	Cabbage	CABG	"Truck, Nursery, and Berry Crops"
2024	Cauliflower	2	No	Lettuce/Leafy Greens	LETT	"Truck, Nursery, and Berry Crops"
2025	Brussels Sprouts	2	No	Lettuce/Leafy Greens	LETT	"Truck, Nursery, and Berry Crops"
1800	Rice (includes rice & wild rice subclasses)	2	Yes	Rice; Wild Rice	RICE; RICW	Rice
2200	Vineyards (includes table grapes, wine grapes, and raisins)	2	No	Grape High Tonnage; Grape Low Tonnage; Table Grape	GRAH†; GRAL†; GRAT†	Vineyards

Land use conversion coefficient for CV-SWAT

Table A - 2: Conversion coefficient from yield to N content for crops in CV-SWAT.

LAND USE CODE (CV-SWAT)	CONVERSION FACTOR
AGRB	15.91
AGRC	25
AGRL	19.9
AGRR	14
ALFA	30
ALMC	12.5
ALMD	19
ALMI	26.6
ALML	11.25
ALMP	11
ALMY	22.5
APPL	4.4
ASPR	63
BANA	6.4
BARL	21
BARR	23.4
BBLS	16
BERM	23.4
BLUG	16
BROC	51.2
BROM	23.4
BROS	23.4
CABG	29.09
CANA	38
CANP	38
CANT	20
CASH	1.9
CASS	24.6
CAUF	41.1
CELR	19.9
CLVA	60
CLVR	65
CLVS	65
COCB	65
COCO	1.5
COCT	1.15
COFF	1.5
CORN	14
COTP	23.3
COTS	23.3
CRRT	17
CSIL	14
CUCM	21.9
CWDC	12.75
CWDW	17
CWGR	50
CWPS	42.7

CWRC	12.75
CWRW	17
DCWH	14
DLFA	30
DWHT	26.3
EGAM	16
EGGP	21.8
EUCA	1.9
FESC	23.4
FLAX	40
FPEA	37
FRSD	1.5
FRSE	1.5
FRST	1.5
GRAH	7
GRAK	8.33
GRAL	20
GRAL	21.25
GRAP	20
GRAR	1.5
GRAT	7
GRBN	29.9
GRSG	19.9
HAY	17.7
HMEL	7.1
INDN	16
JHGR	20
LBLS	16
LENT	50.6
LETT	30
LIMA	36.8
MAPL	8
MESQ	1.5
MINT	13.5
MUNG	42
OAK	1.5
OATS	31.6
OILP	1.9
OLIV	13
ONIO	15
ORAN	11
ORCD	1.9
ORCP	13.076
PAPA	500
PART	65
PASI	23
PASL	23
PASM	23
PASN	23
PASO	23
PAST	23
PEAS	41

PEPP	21.25
PEPR	18.8
PINE	1.5
PINP	6.4
PLAN	6.4
PMIL	20
PNUT	50.5
POPL	1.5
POTA	17
PTBB	180
PTBN	65
RADI	13.5
RICE	13.6
RICW	13.6
RNGB	16
RNGE	16
RUBR	1.9
RYE	28.4
RYEA	23
RYEG	22
RYER	23
SCRN	21.4
SEPT	23.4
SESB	65
SGBT	13
SGHY	19.9
SIDE	16
SOYB	65
SPAS	23.4
SPIN	54.3
SPOT	9.7
STRW	11.6
SUGC	0
SUNF	45.4
SUNS	30
SWCH	16
SWGR	50
SWHT	23.4
SWRN	16
TEFF	23.4
TIMO	23.4
TOBC	14
TOMA	24
WALN	16.36
WATR	0
WBAR	25
WETF	1.5
WETL	16
WETN	16
WILL	1.5
WMEL	11.7
WPAS	23.4

WWGR	50
WWHT	24.22

Selection of crops

Table A - 3: Selection of compared crops and their corresponding codes in each model.

CROPS	GNLM-OLD (LU CODE)	GNLM-NEW	SWAT
1. ALMONDS	412	ALMOND HULLS ALMONDS ALL	ALMD; ALMY
2. PISTACHIOS	414	PISTACHIOS	ALMI*
3. TOMATOES	2015	TOMATOES FRESH MARKET TOMATOES PROCESSING TOMATOES UNSPECIFIED	TOMA
4. WALNUTS	413	WALNUTS ENGLISH	WALN
5. VINEYARDS (WINE, TABLE & RAISIN GRAPES)	2200	GRAPES RAISIN GRAPES TABLE GRAPES WINE GRAPES UNSPECIFIED	GRAH†; GRAL†; GRAT†
6. ORANGES	303	ORANGES NAVEL ORANGES VALENCIA ORANGES UNSPECIFIED	ORAN**
7. COTTON	601	COTTON LINT PIMA COTTON LINT UNSPECIFIED COTTON LINT UPLAND COTTON SEED PLANTING COTTONSEED	COTS ➔ No results
8. CORN (SILAGE)	<u>606 (Corn & Grain)</u> 608 (Corn, Sudan, Grain)	CORN GRAIN CORN SILAGE CORN SWEET ALL	CORN
9. WHEAT (SILAGE)		SILAGE SORGHUM SILAGE	
10. ONION & GARLIC	2010	GARLIC ALL ONIONS ONIONS GREEN & SHALLOT	ONIO
11. MANDARINS	-	TANGERINES & MANDARINS	
12. BEANS	610	BEANS BLACKEYE (PEAS) BEANS DRY EDIBLE UNSPECIFIED BEANS FAVA BEANS FRESH UNSPECIFIED BEANS LIMA BABY DRY BEANS LIMA LARGE DRY BEANS LIMA UNSPECIFIED BEANS SEED BEANS SNAP UNSPECIFIED	PTBB**
13. PEACHES	405	PEACHES CLINGSTONE PEACHES FREESTONE PEACHES UNSPECIFIED	ALMP*
14. WHEAT GRAIN	<u>702 (Wheat)</u> 700 (Grain & Hay)	WHEAT ALL WHEAT SEED	WWHT
15. CARROT	2006	CARROTS FOOD SERVICE CARROTS FRESH MARKET CARROTS PROCESSING CARROTS UNSPECIFIED	CRRT
16. SUNFLOWER	612	SUNFLOWER SEED PLANTING	SUNF
17. POMEGRANATES	-	POMEGRANATES	
18. OATES	703	OATS GRAIN	HAY
19. NECTARINES	-	NECTARINES	ALMP*
20. CHERRIES	403	CHERRIES SWEET	ALMC*

Appendix B: Crop Results

Almonds

Balance

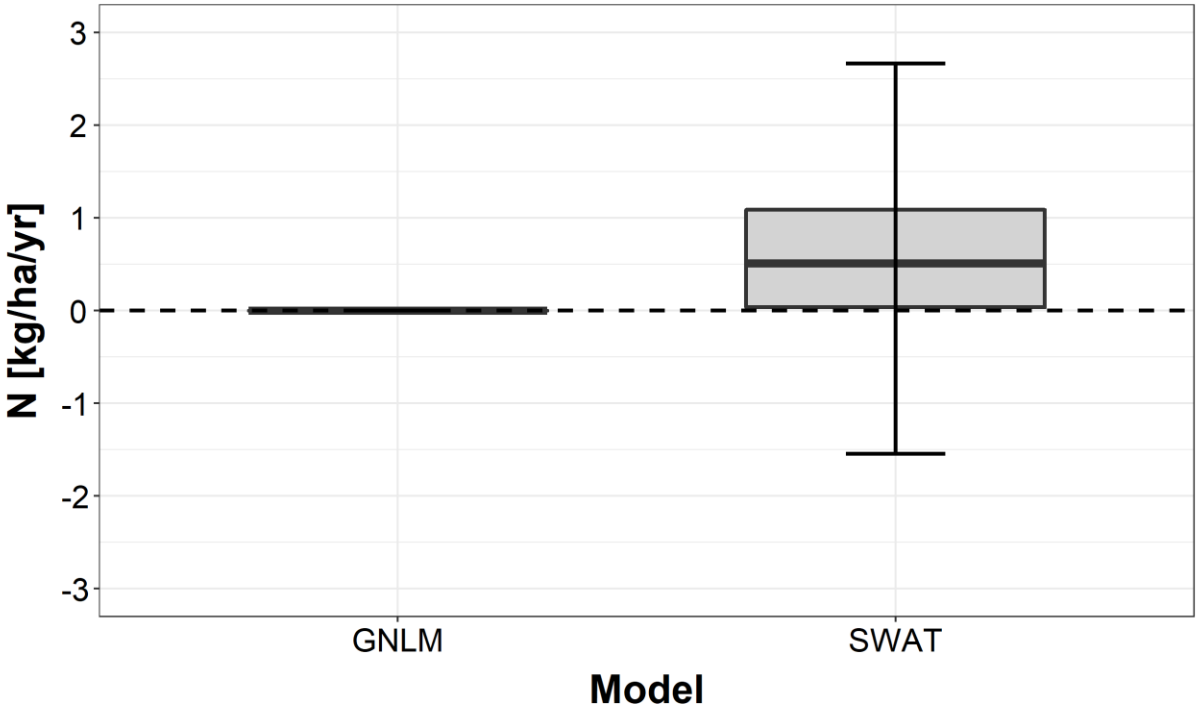

Figure B - 1: Boxplot N mass balance comparison - Almonds.

Comparison

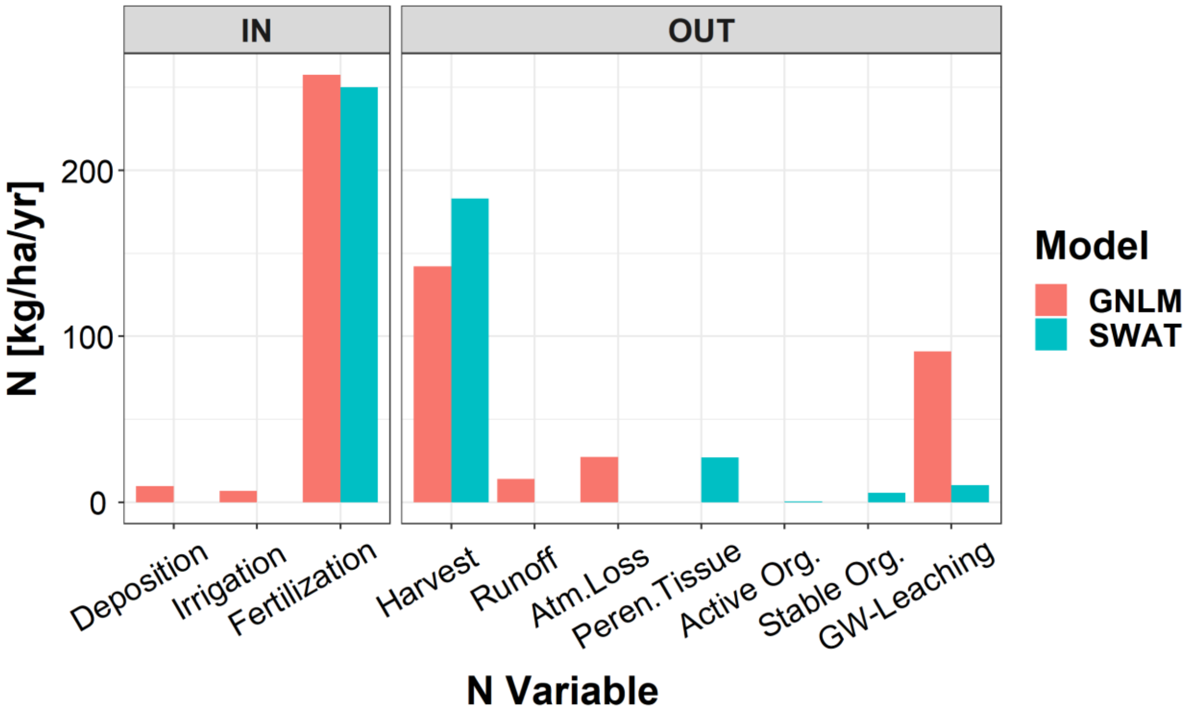

Figure B - 2: Variable comparison - Almonds.

Harvest

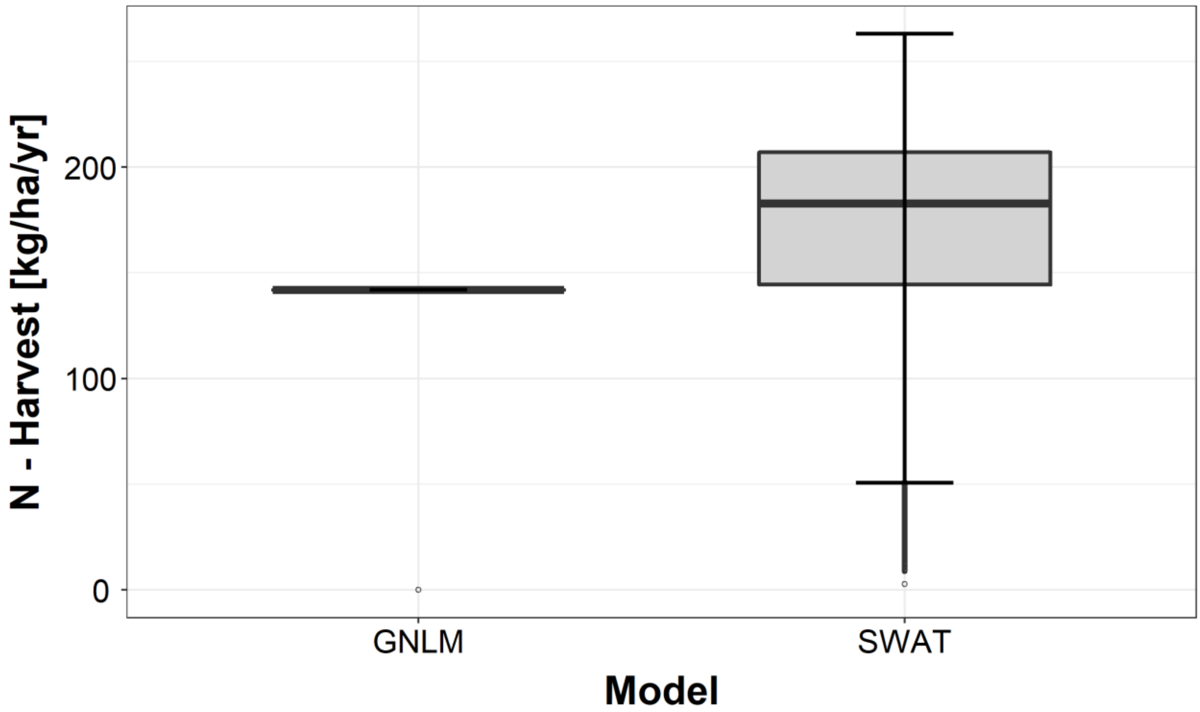

Figure B - 3: Boxplot of harvest rates comparison - Almonds.

Application

Table B - 1: Statistical analysis of fertilizer application - Almonds.

Model	Fertilizer	Min	Max	Median	Mean	SD	Variance
GNLM	Synthetic	0	246.0	246.0	245.5	8.7	76.0
GNLM	Manure	0	3851.5	11.7	13.9	26.6	710.0
SWAT	Synthetic	85	250.0	250.0	220.9	62.9	3957.8
SWAT	Manure	0	0.0	0.0	0.0	0.0	0.0

Beans

Balance

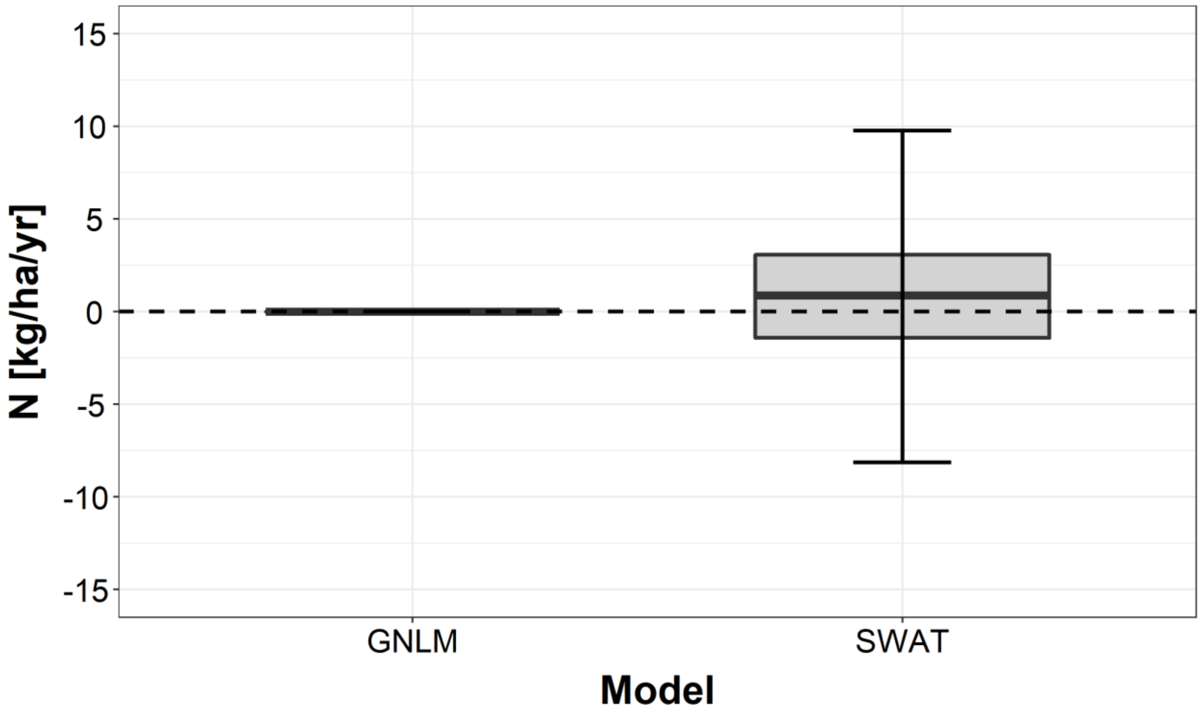

Figure B - 4: Boxplot N mass balance comparison - Beans.

Comparison

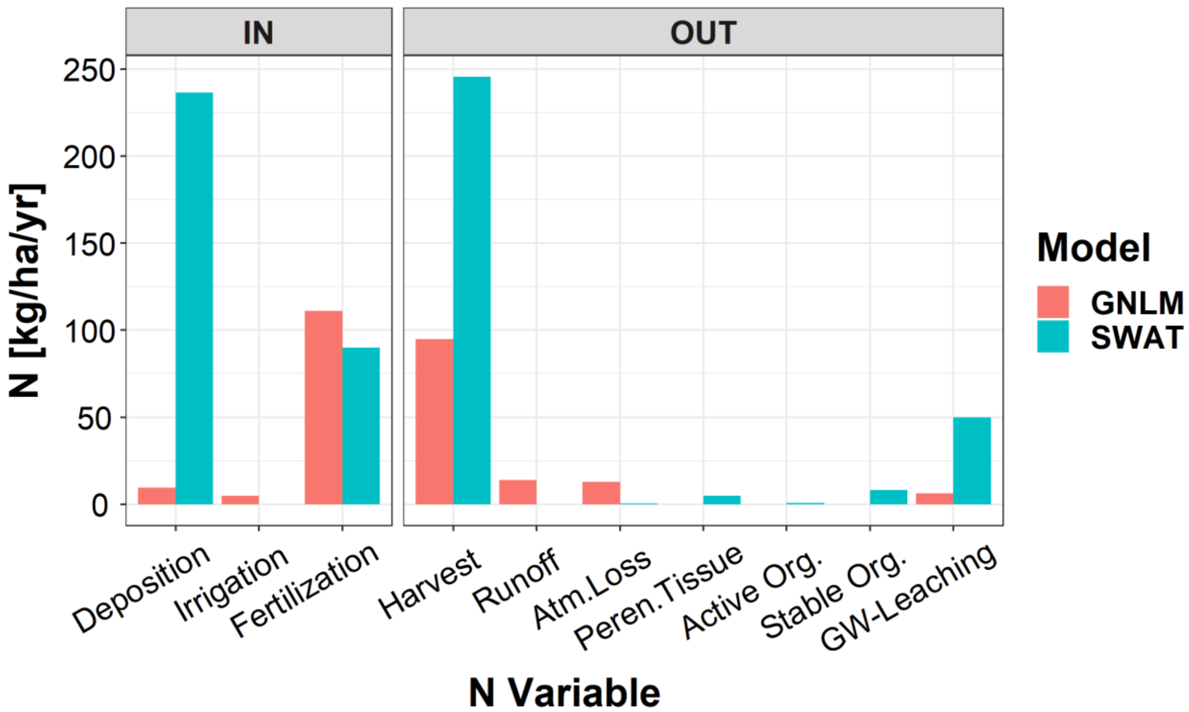

Figure B - 5: Variable comparison - Beans.

Harvest

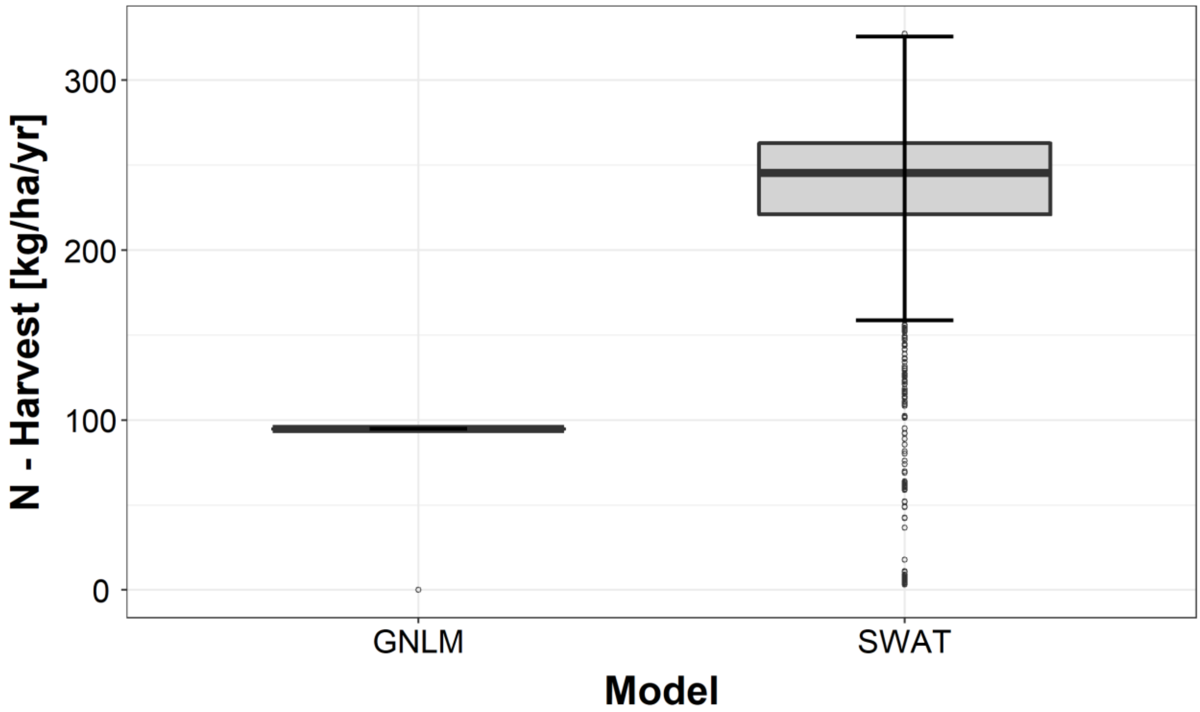

Figure B - 6: Boxplot of harvest rates comparison - Beans.

Application

Table B - 2: Statistical analysis of fertilizer application - Beans.

Model	Fertilizer	Min	Max	Median	Mean	SD	Variance
GNLM	Synthetic	0	101.5	101.5	101.3	4.6	20.7
GNLM	Manure	0	76.2	9.5	17.2	18.8	355.1
SWAT	Synthetic	50	90.0	90.0	81.7	16.2	262.1
SWAT	Manure	0	0.0	0.0	0.0	0.0	0.0

Carrots

Balance

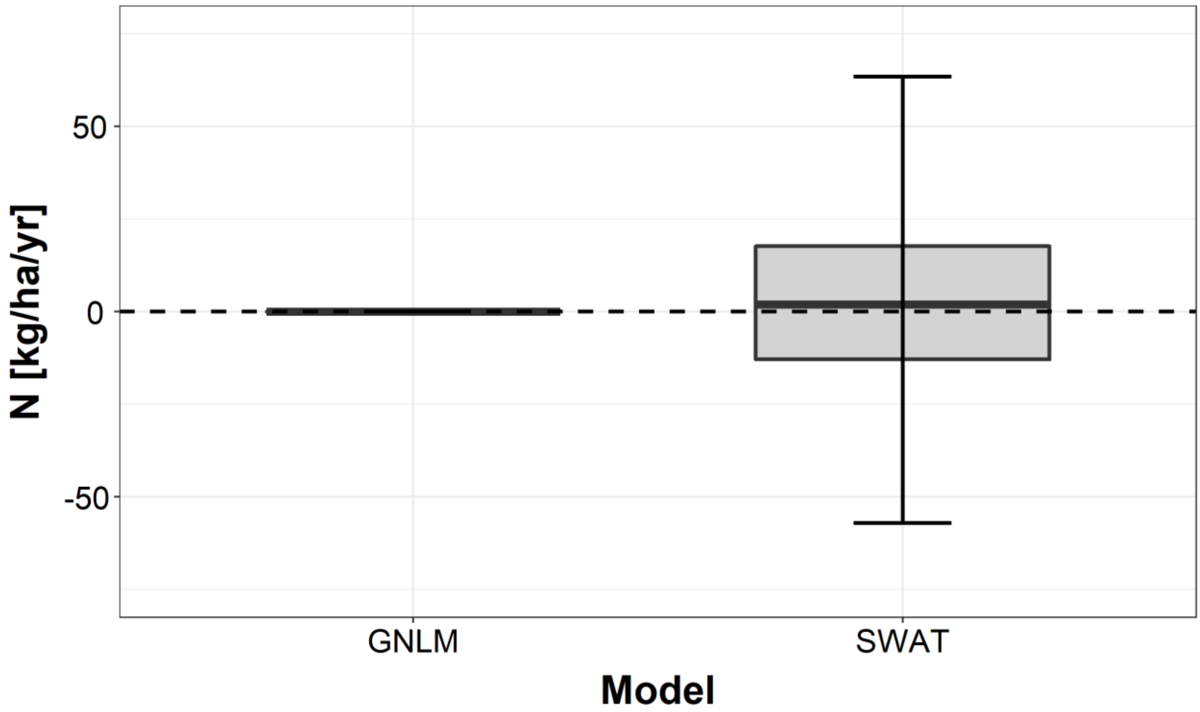

Figure B - 7: Boxplot N mass balance comparison - Carrots.

Comparison

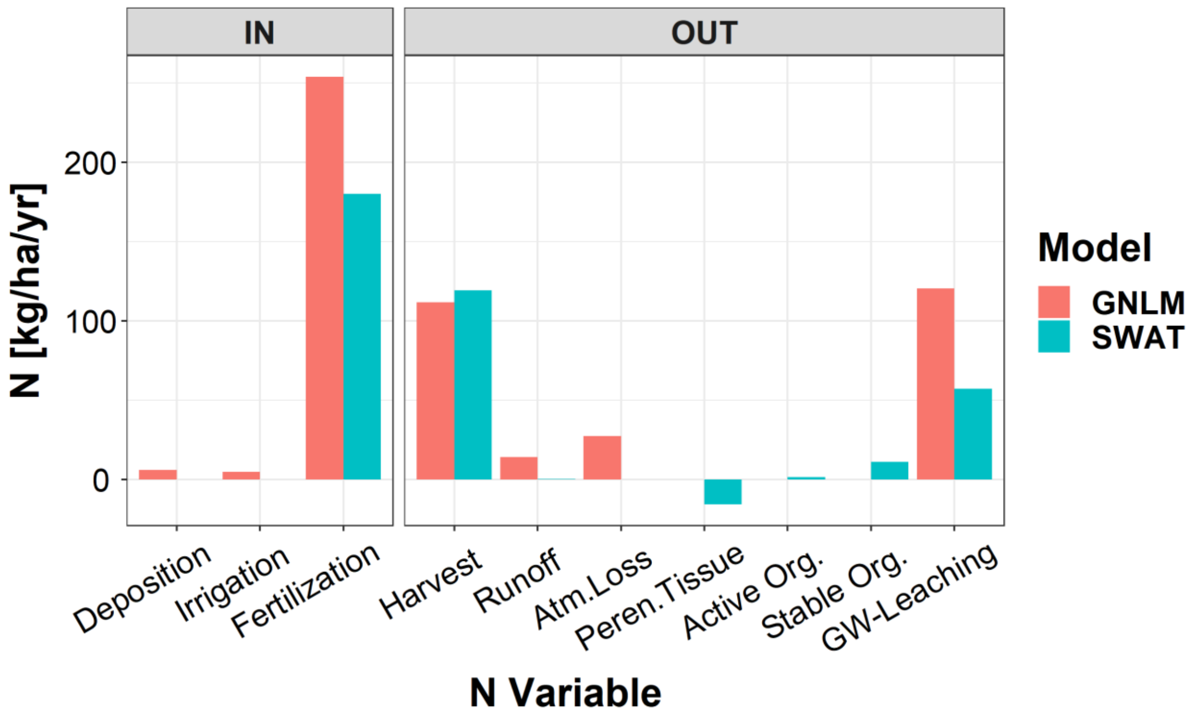

Figure B - 8: Variable comparison - Carrots.

Harvest

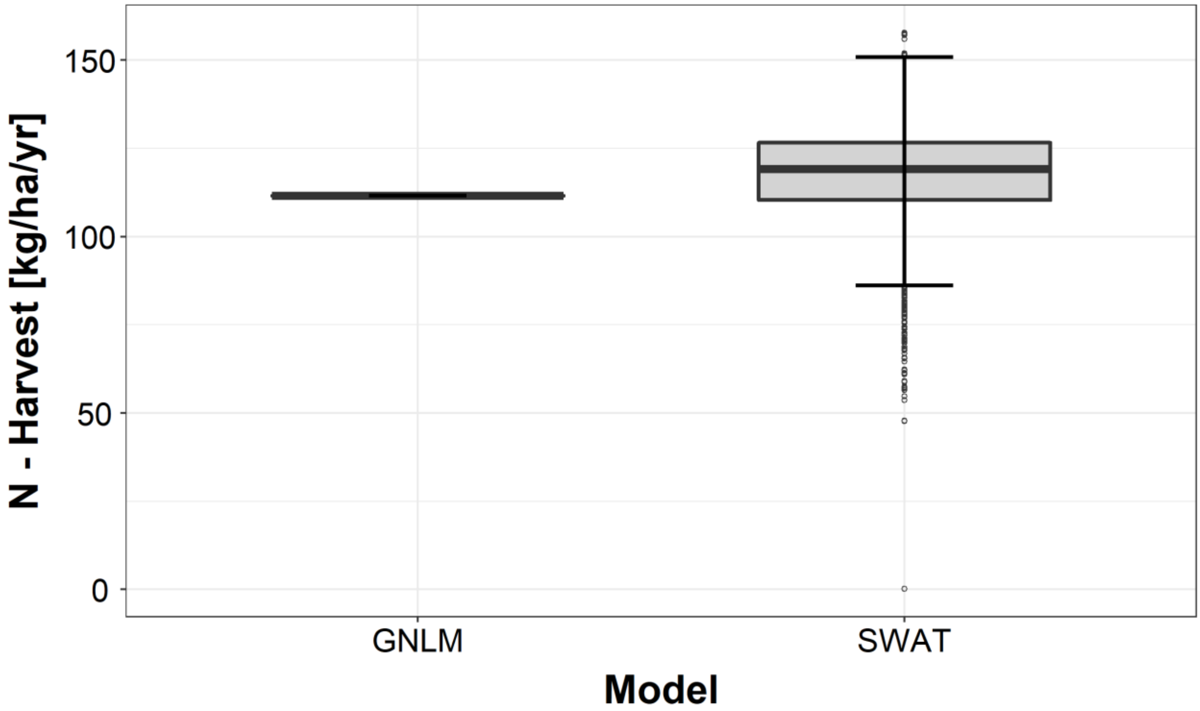

Figure B - 9: Boxplot of harvest rates comparison - Carrots.

Application

Table B - 3: Statistical analysis of fertilizer application - Carrots.

Model	Fertilizer	Min	Max	Median	Mean	SD	Variance
GNLM	Synthetic	221	242.2	242.2	242.2	0.2	0.1
GNLM	Manure	0	58.6	11.7	15.8	4.9	24.3
SWAT	Synthetic	180	180.0	180.0	180.0	0.0	0.0
SWAT	Manure	0	0.0	0.0	0.0	0.0	0.0

Cherries

Balance

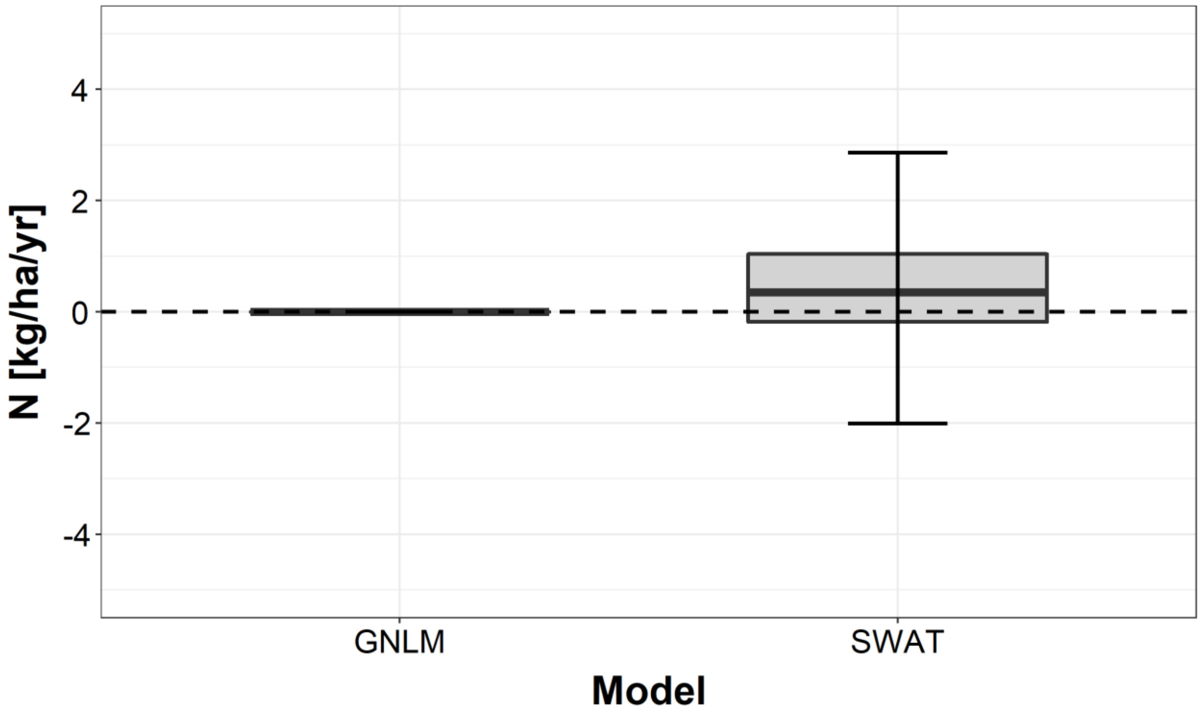

Figure B - 10: Boxplot N mass balance comparison - Cherries.

Comparison

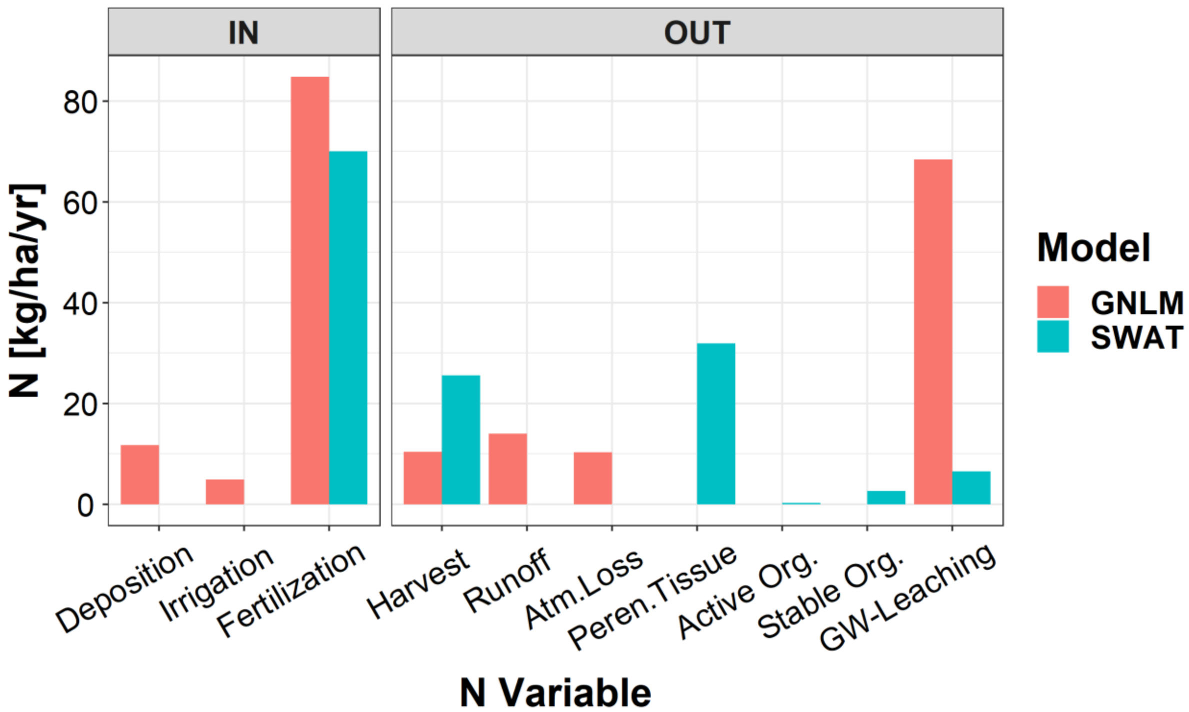

Figure B - 11: Variable comparison - Cherries.

Harvest

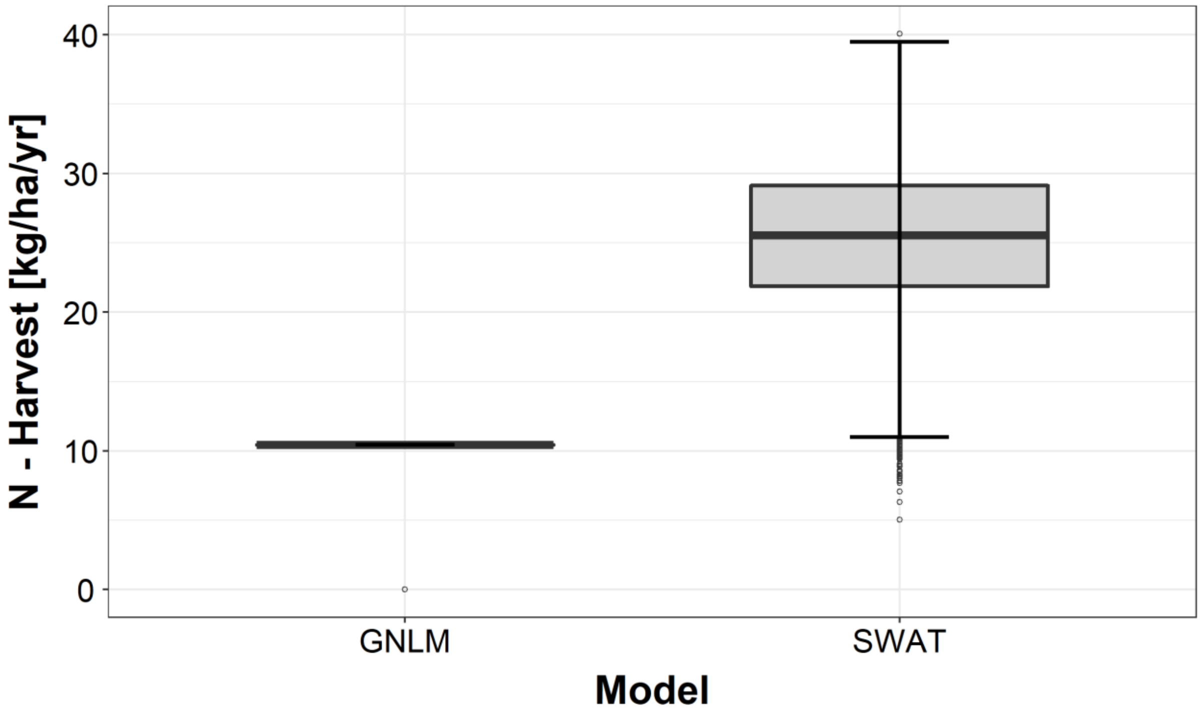

Figure B - 12: Boxplot of harvest rates comparison - Cherries.

Application

Table B - 4: Statistical analysis fertilizer application - Cherries.

Model	Fertilizer	Min	Max	Median	Mean	SD	Variance
GNLM	Synthetic	0	76.4	76.4	76.4	2.2	4.9
GNLM	Manure	0	246.3	8.4	12.2	10.5	109.9
SWAT	Synthetic	70	70.0	70.0	70.0	0.0	0.0
SWAT	Manure	0	0.0	0.0	0.0	0.0	0.0

Corn

Balance

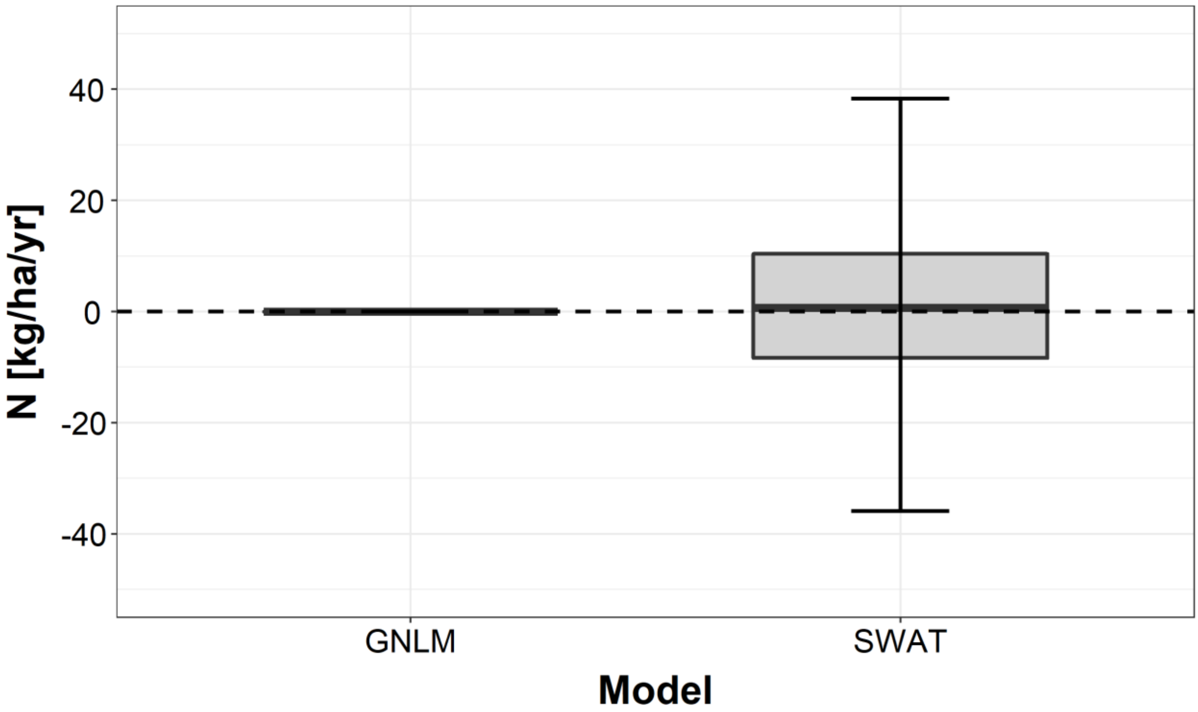

Figure B - 13: Boxplot N mass balance comparison - Corn.

Comparison

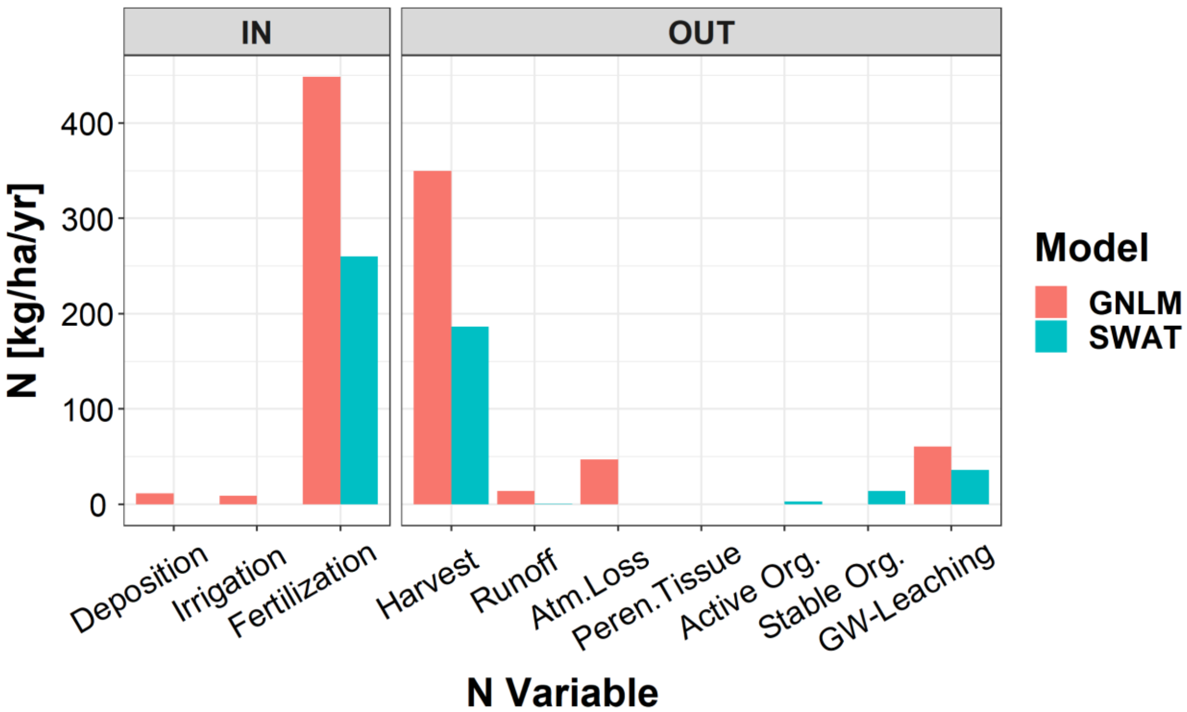

Figure B - 14: Variable comparison - Corn.

Harvest

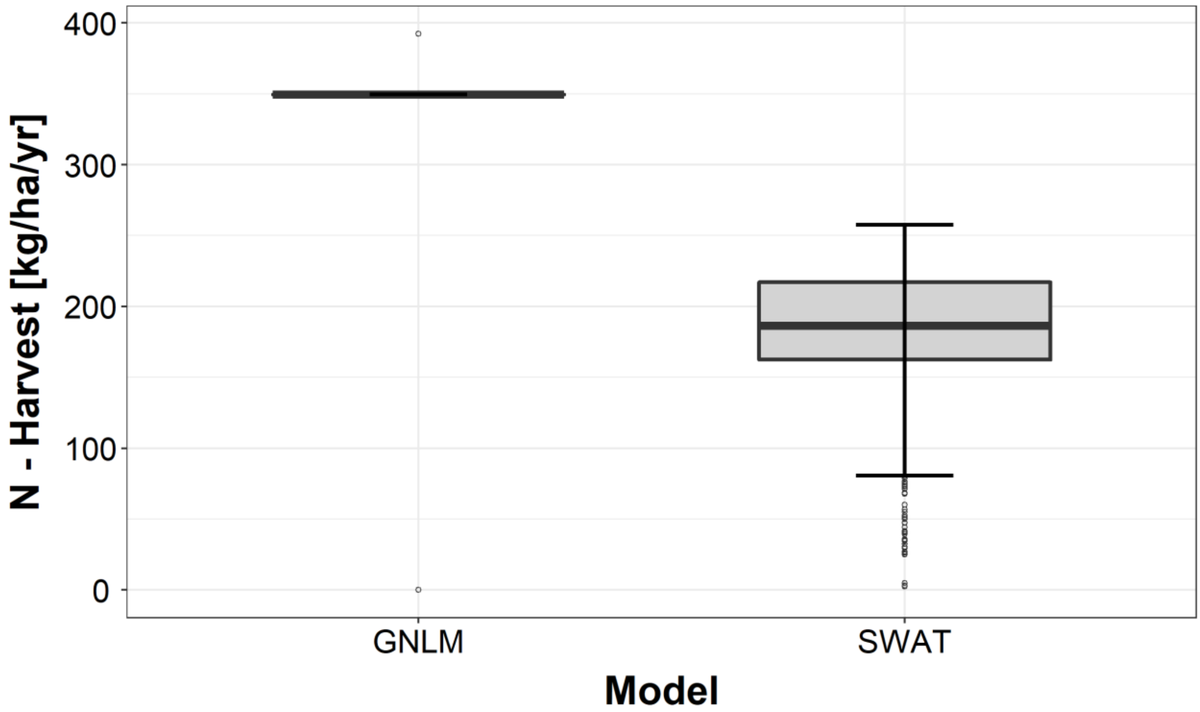

Figure B - 15: Boxplot of harvest rates comparison - Corn.

Application

Table B - 5: Statistical analysis fertilizer application - Corn.

Model	Fertilizer	Min	Max	Median	Mean	SD	Variance
GNLM	Synthetic	0	560.1	437.0	384.8	107.7	11601.4
GNLM	Manure	0	366266.8	11.7	357.3	1321.7	1746805.9
SWAT	Synthetic	260	260.0	260.0	260.0	0.0	0.0
SWAT	Manure	0	0.0	0.0	0.0	0.0	0.0

Oats

Balance

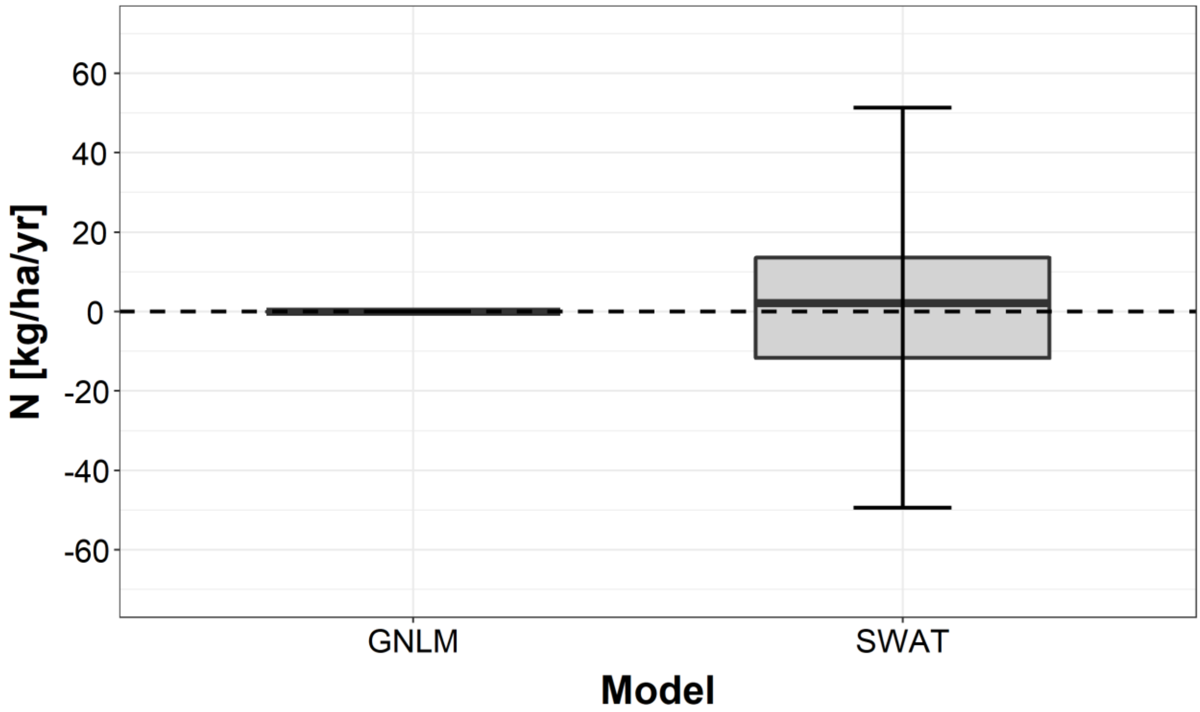

Figure B - 16: Boxplot N mass balance comparison - Oats.

Comparison

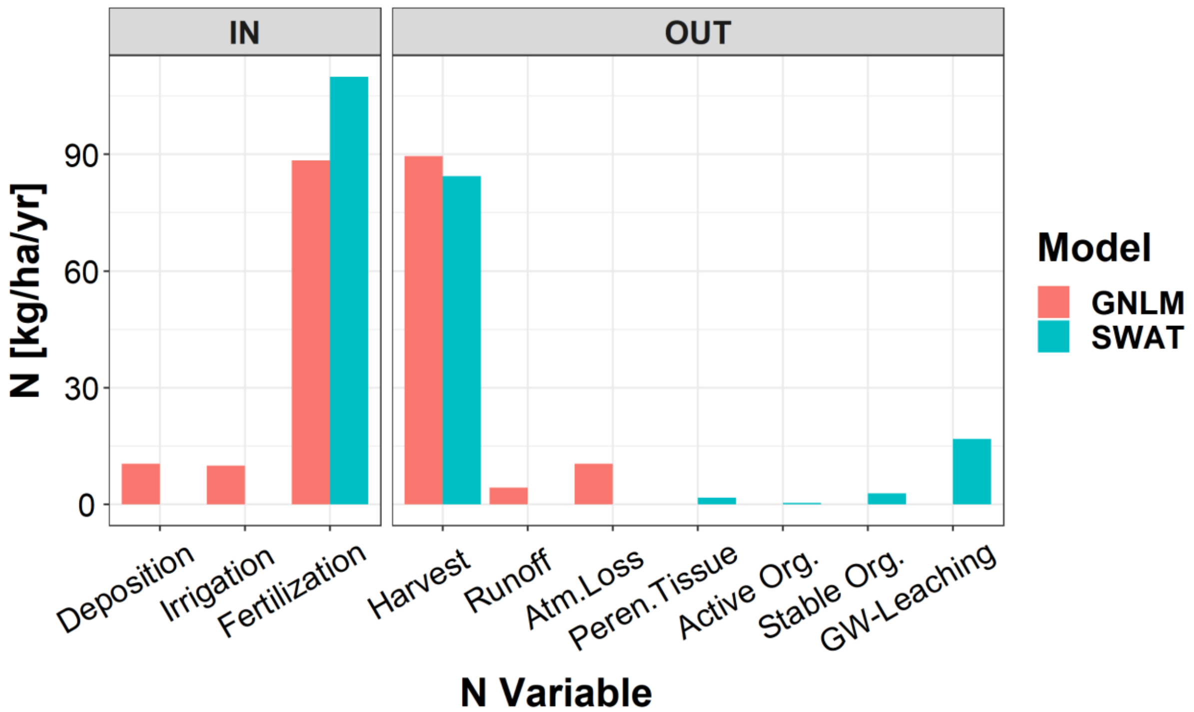

Figure B - 17: Variable comparison - Oats.

Harvest

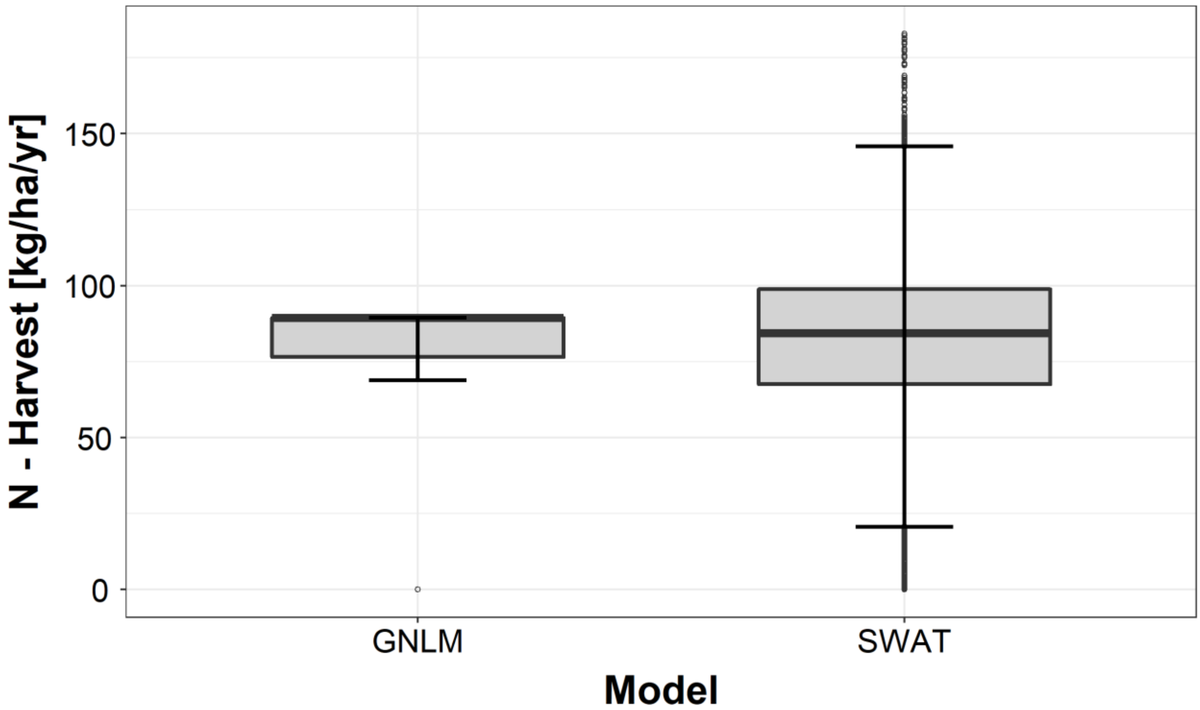

Figure B - 18: Boxplot of harvest rates comparison - Oats.

Application

Table B - 6: Statistical analysis fertilizer application - Oats.

Model	Fertilizer	Min	Max	Median	Mean	SD	Variance
GNLM	Synthetic	0	69.4	69.4	68.4	6.4	40.5
GNLM	Manure	0	7043.4	19.0	40.0	267.1	71317.6
SWAT	Synthetic	110	140.0	110.0	116.9	12.6	159.1
SWAT	Manure	0	0.0	0.0	0.0	0.0	0.0

Onion & Garlic

Balance

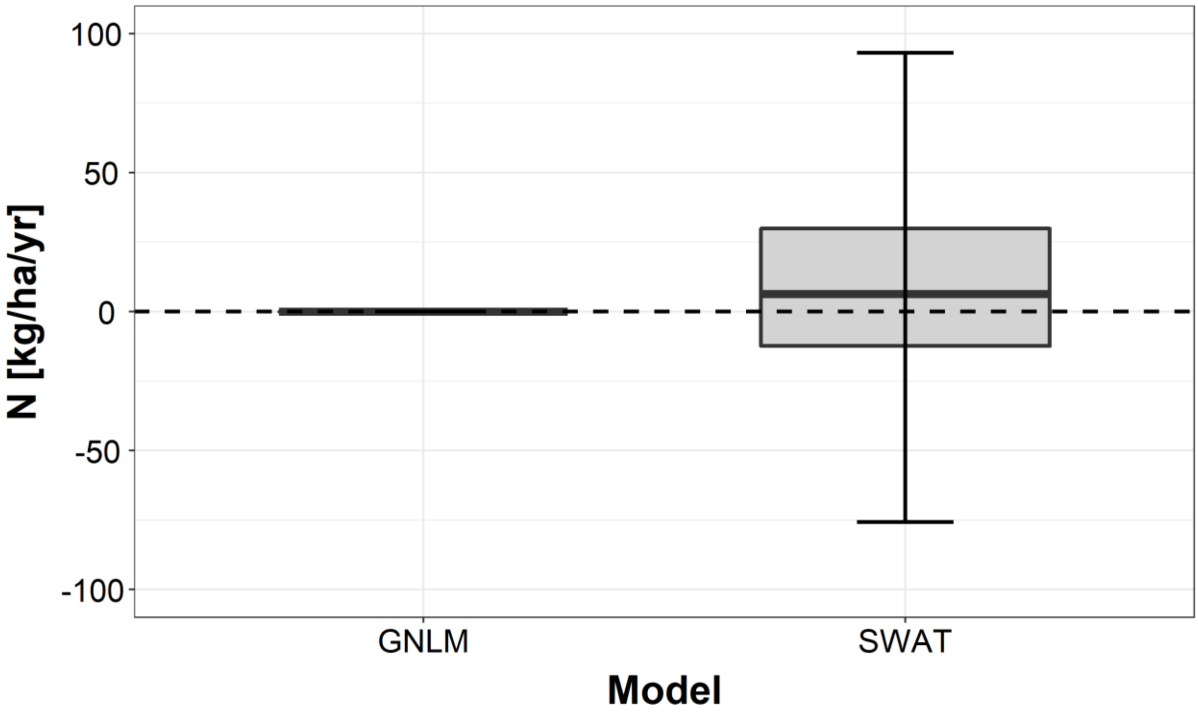

Figure B - 19: Boxplot N mass balance comparison - Onion & Garlic.

Comparison

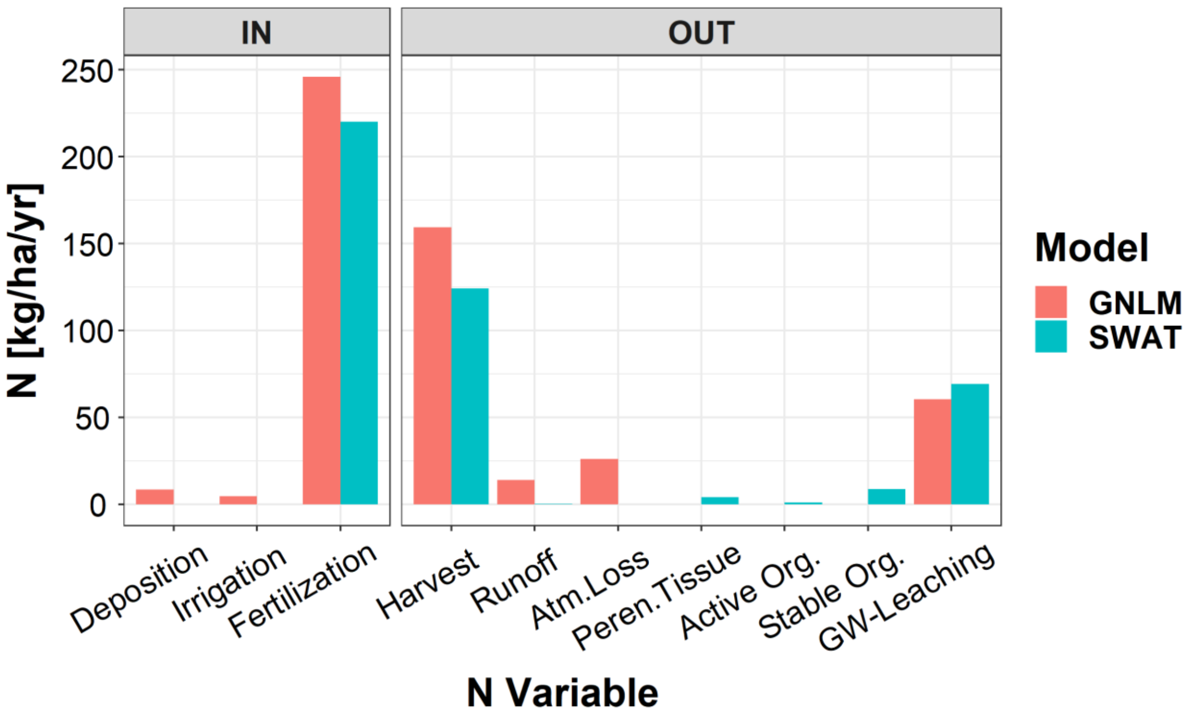

Figure B - 20: Variable comparison - Onion & Garlic.

Harvest

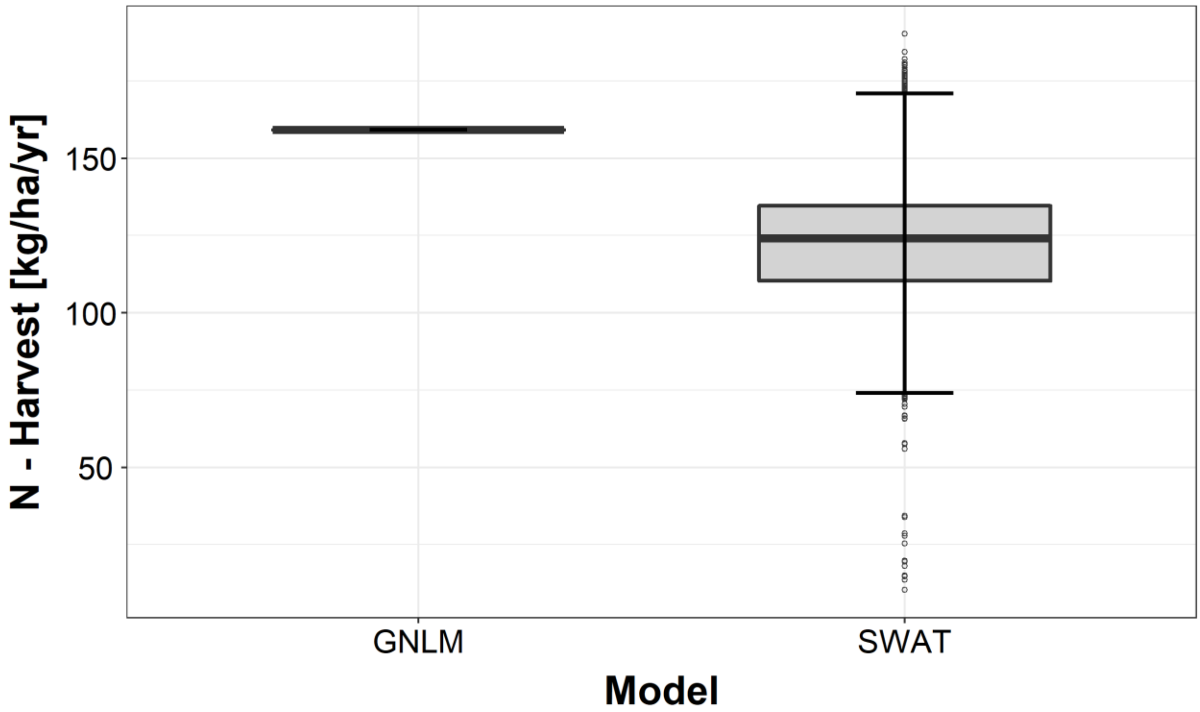

Figure B - 21: Boxplot of harvest rates comparison - Onion & Garlic.

Application

Table B - 7: Statistical analysis fertilizer application - Onion & Garlic.

Model	Fertilizer	Min	Max	Median	Mean	SD	Variance
GNLM	Synthetic	118.3	236.5	236.5	236.3	4.2	17.3
GNLM	Manure	0.0	126.1	9.5	11.4	7.1	50.8
SWAT	Synthetic	220.0	220.0	220.0	220.0	0.0	0.0
SWAT	Manure	0.0	0.0	0.0	0.0	0.0	0.0

Oranges

Balance

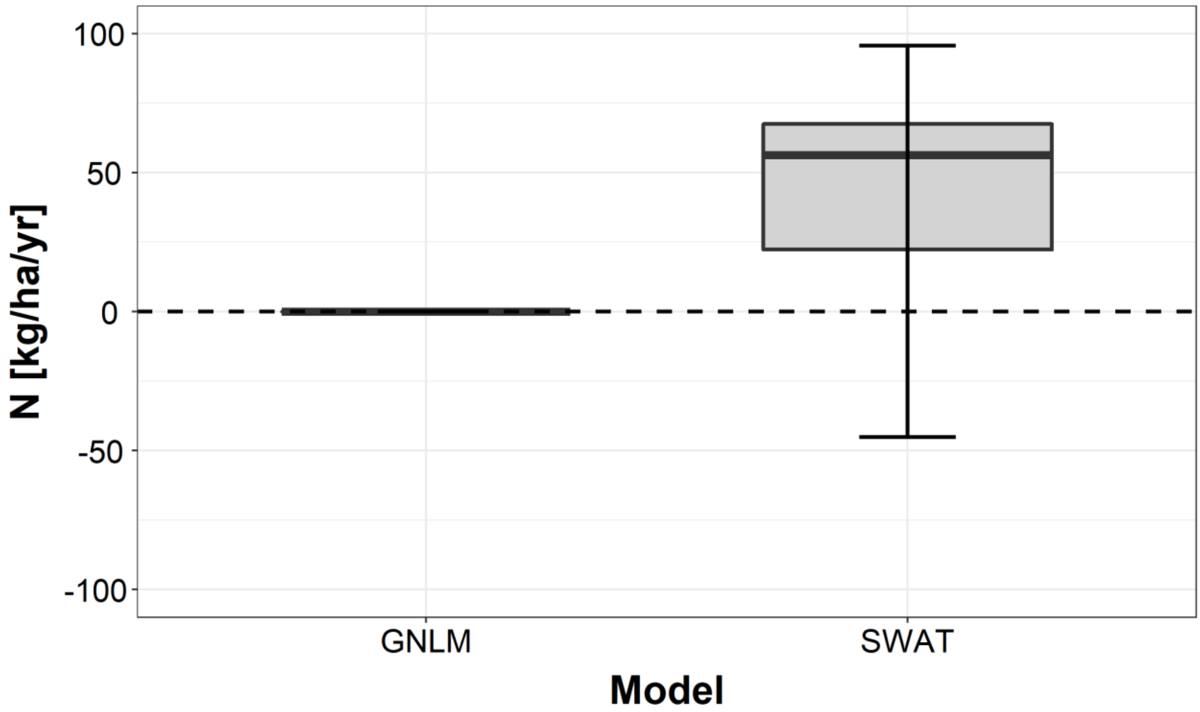

Figure B - 22: Boxplot N mass balance comparison - Oranges.

Comparison

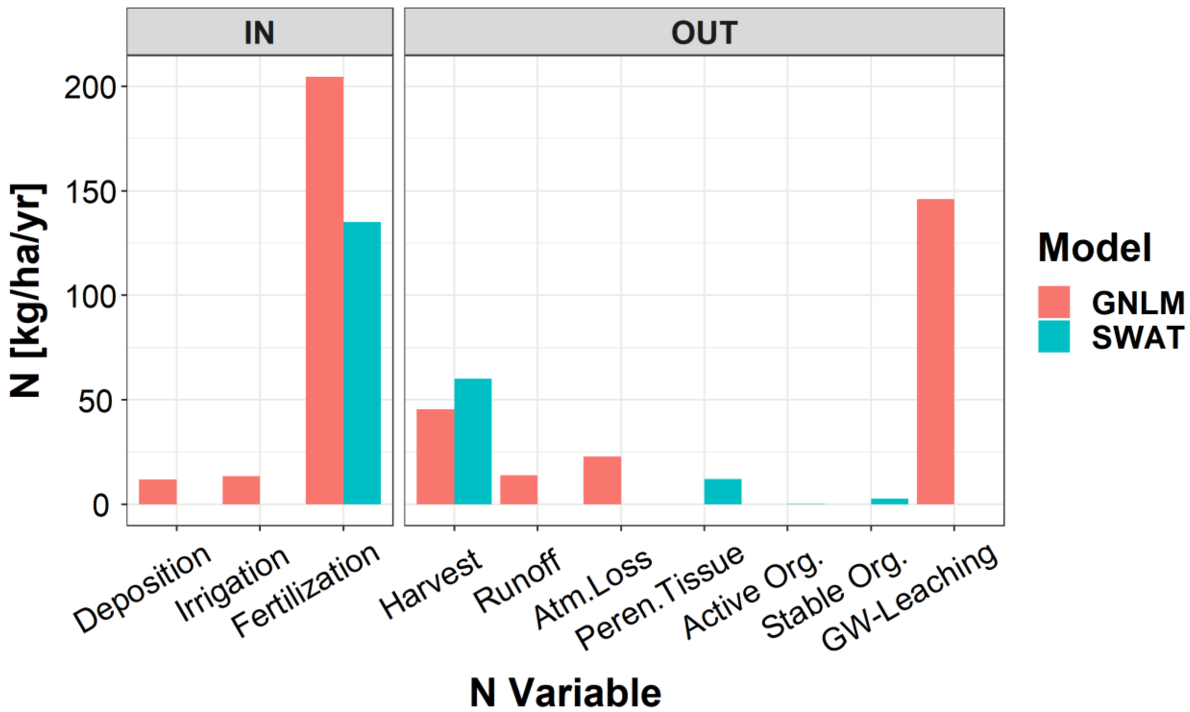

Figure B - 23: Variable comparison - Oranges.

Harvest

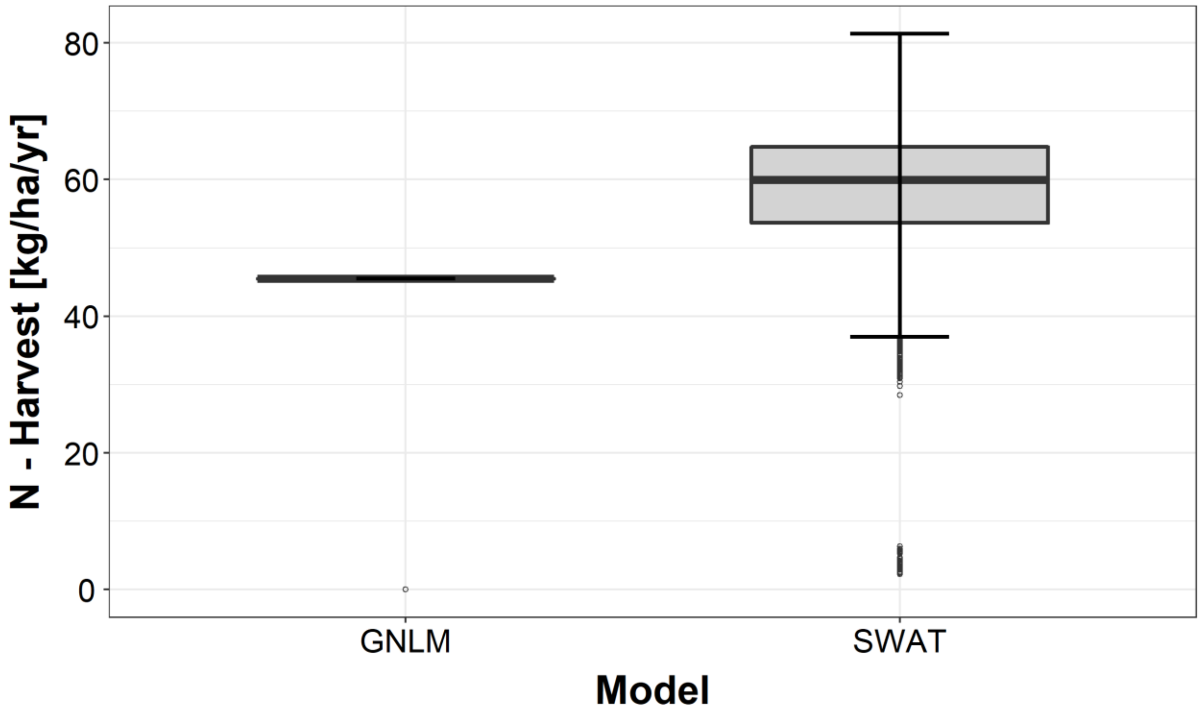

Figure B - 24: Boxplot of harvest rates comparison - Oranges.

Application

Table B - 8: Statistical analysis fertilizer application - Oranges.

Model	Fertilizer	Min	Max	Median	Mean	SD	Variance
GNLM	Synthetic	0	146.0	146.0	145.8	4.6	21.3
GNLM	Manure	0	508.1	58.6	36.3	27.1	736.5
SWAT	Synthetic	135	135.0	135.0	135.0	0.0	0.0
SWAT	Manure	0	0.0	0.0	0.0	0.0	0.0

Peaches

Balance

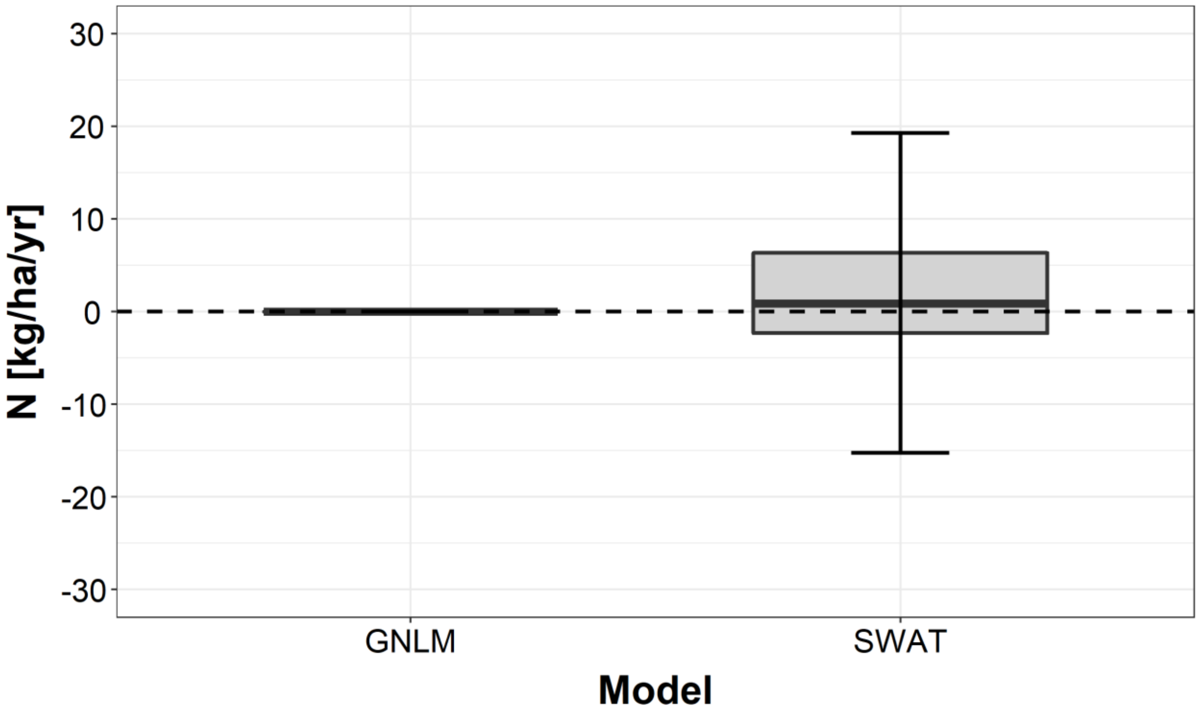

Figure B - 25: Boxplot N mass balance comparison - Peaches.

Comparison

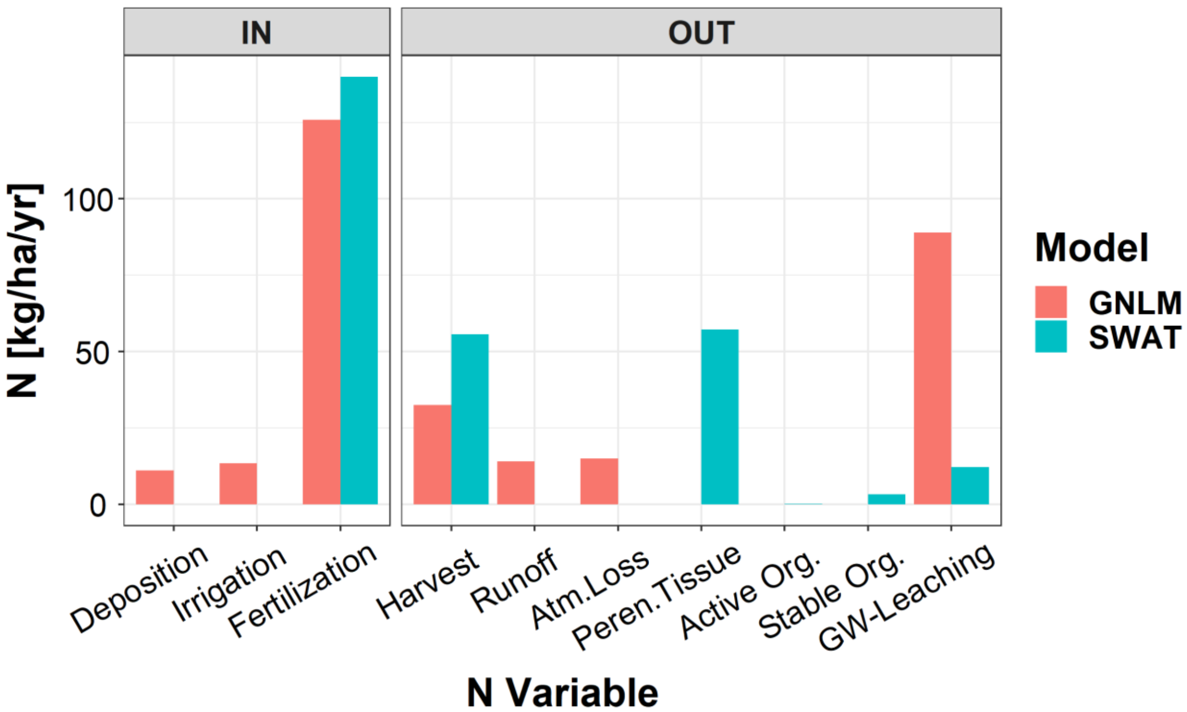

Figure B - 26: Variabel comparison - Peaches.

Harvest

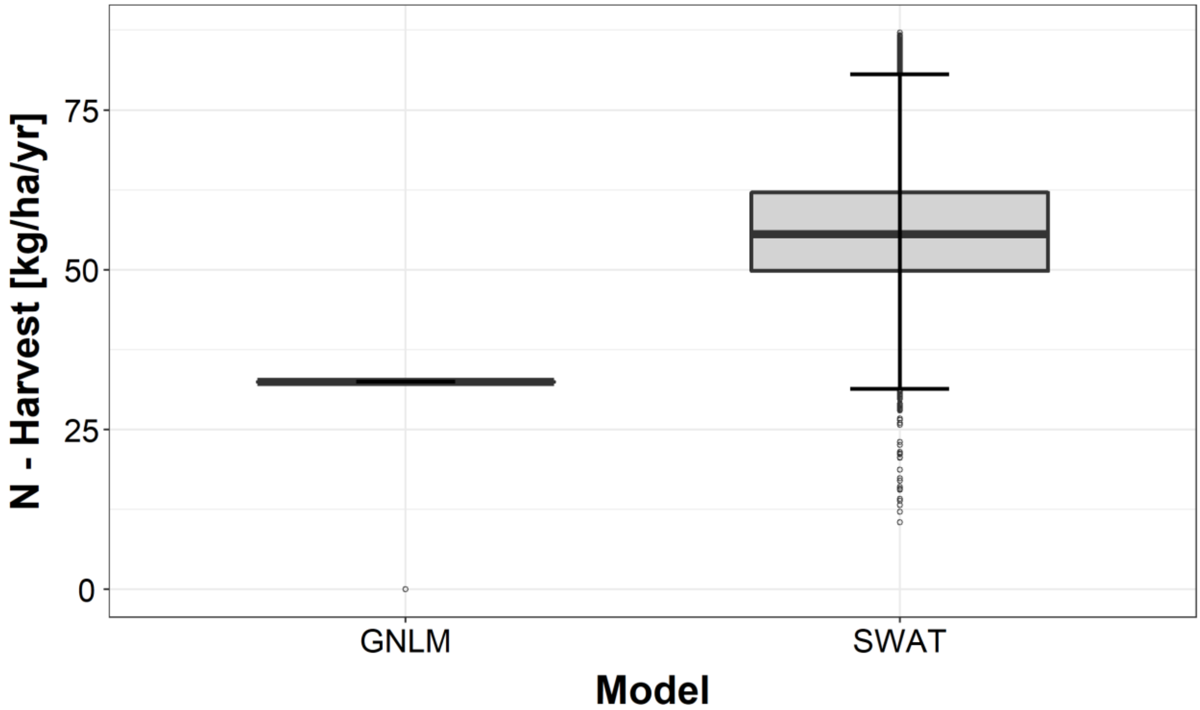

Figure B - 27: Boxplot of harvest rates comparison - Peaches.

Application

Table B - 9: Statistical analysis fertilizer application - Peaches.

Model	Fertilizer	Min	Max	Median	Mean	SD	Variance
GNLM	Synthetic	0	116.3	116.3	116.1	4.2	17.6
GNLM	Manure	0	3851.5	9.5	23.5	55.6	3089.9
SWAT	Synthetic	130	140.0	140.0	136.5	4.8	22.8
SWAT	Manure	0	0.0	0.0	0.0	0.0	0.0

Pistachios

Balance

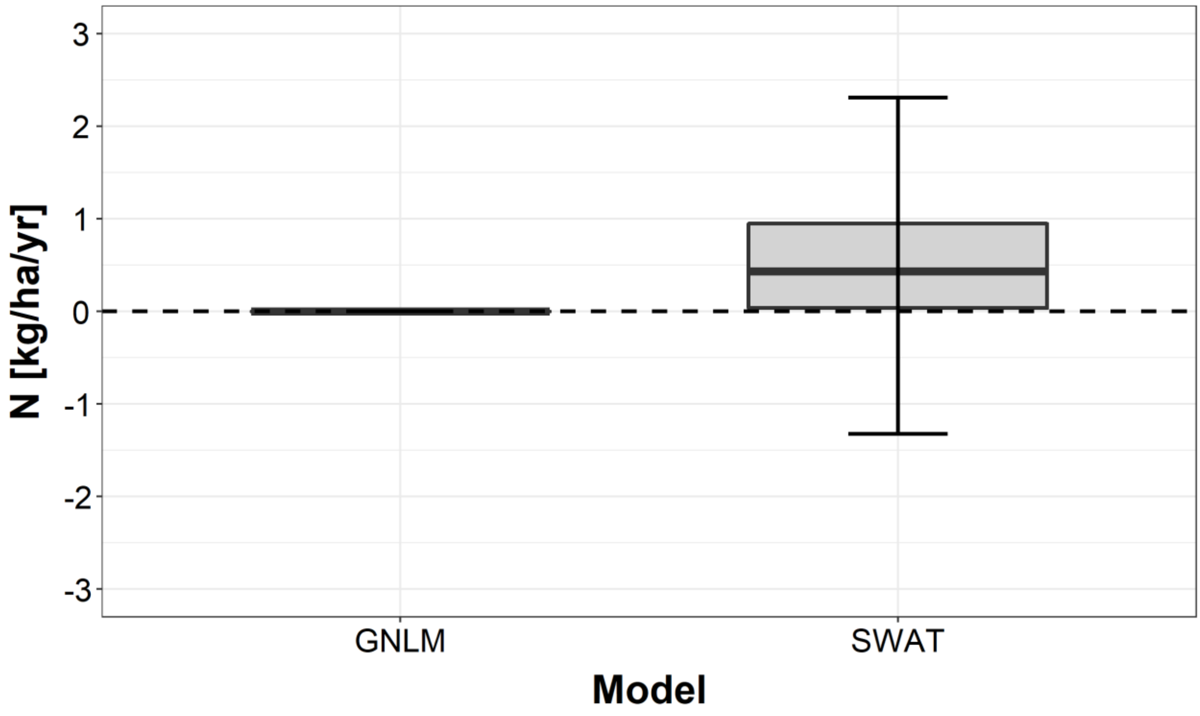

Figure B - 28: Boxplot N mass balance comparison - Pistachios.

Comparison

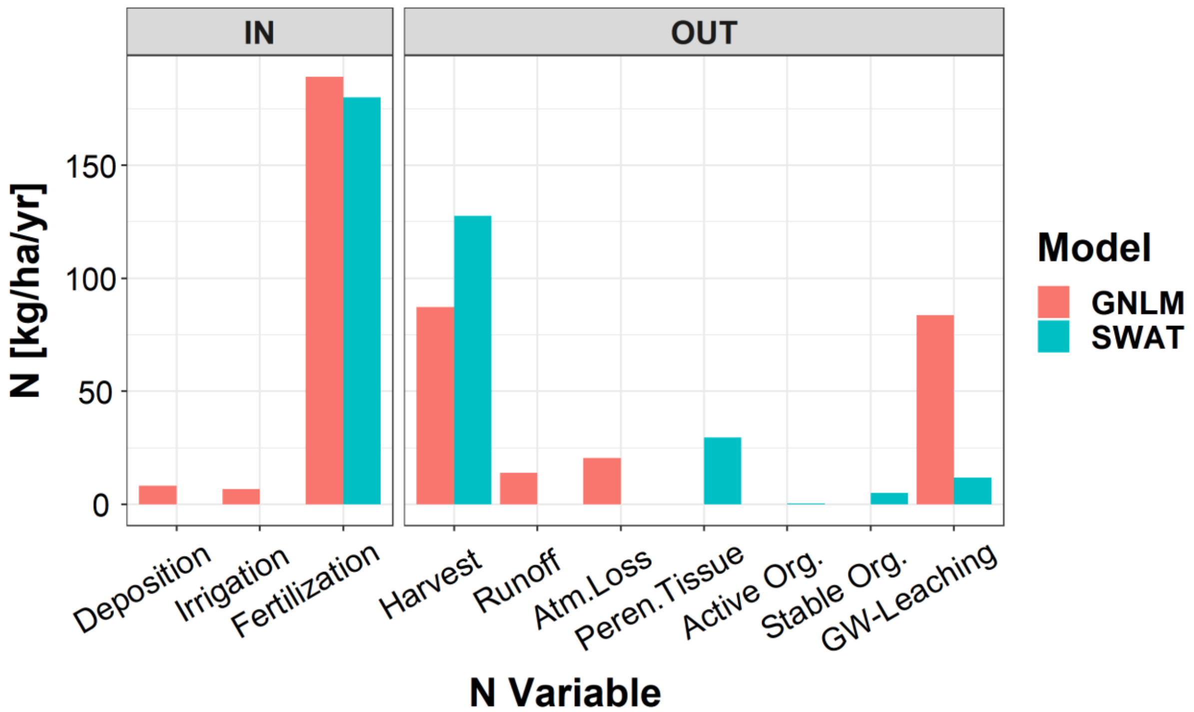

Figure B - 29: Variable comparison - Pistachios.

Harvest

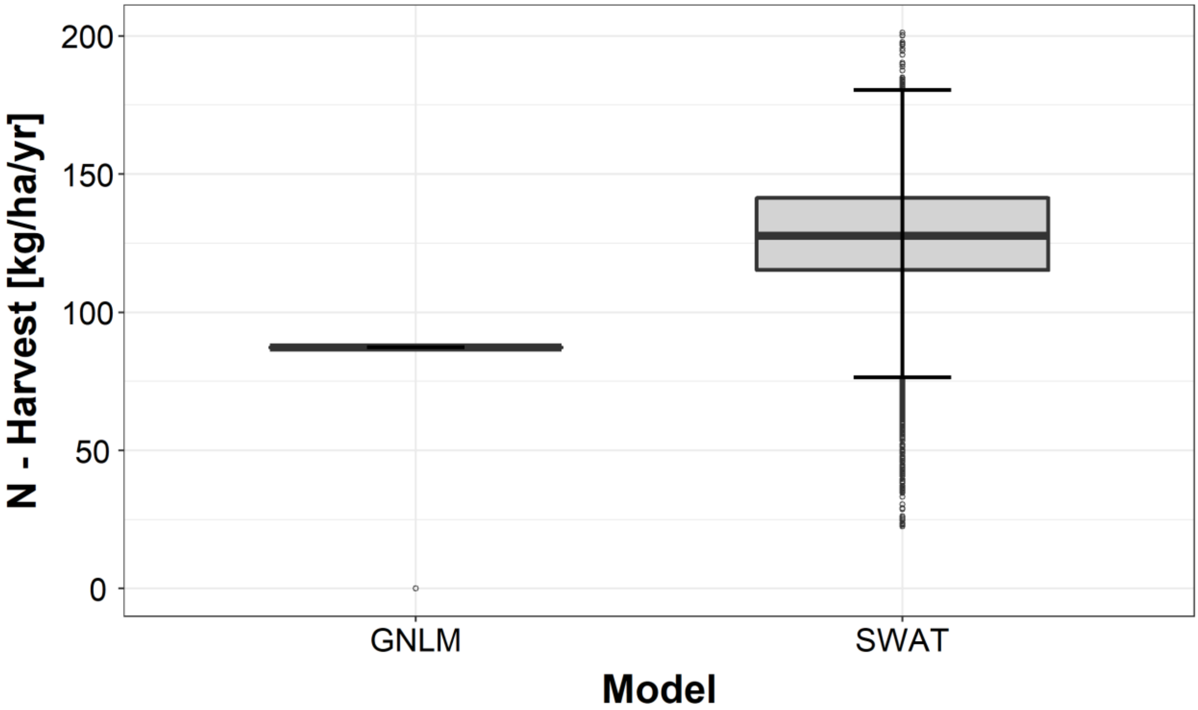

Figure B - 30: Boxplot of harvest rates comparison - Pistachios.

Application

Table B - 10: Statistical analysis fertilizer application - Pistachios.

Model	Fertilizer	Min	Max	Median	Mean	SD	Variance
GNLM	Synthetic	0	177.5	177.5	177.5	3.0	9.1
GNLM	Manure	0	242.0	11.7	16.1	13.1	172.4
SWAT	Synthetic	180	180.0	180.0	180.0	0.0	0.0
SWAT	Manure	0	0.0	0.0	0.0	0.0	0.0

Sunflower

Balance

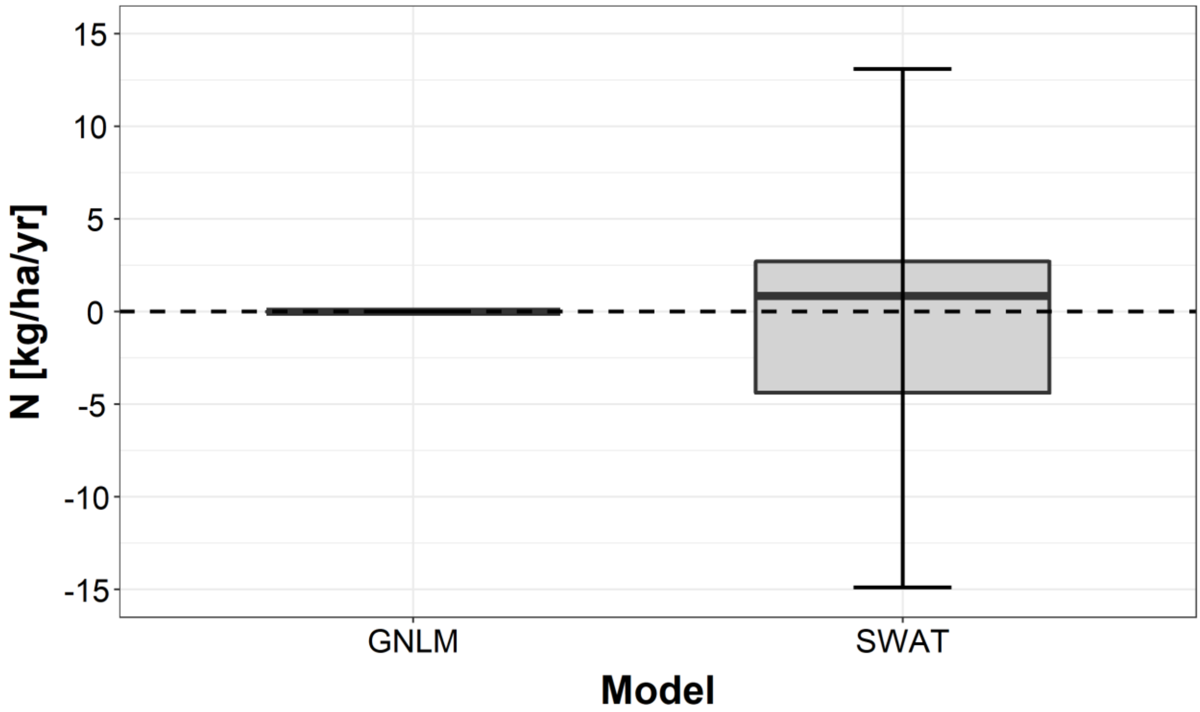

Figure B - 31: Boxplot N mass balance comparison - Sunflower.

Comparison

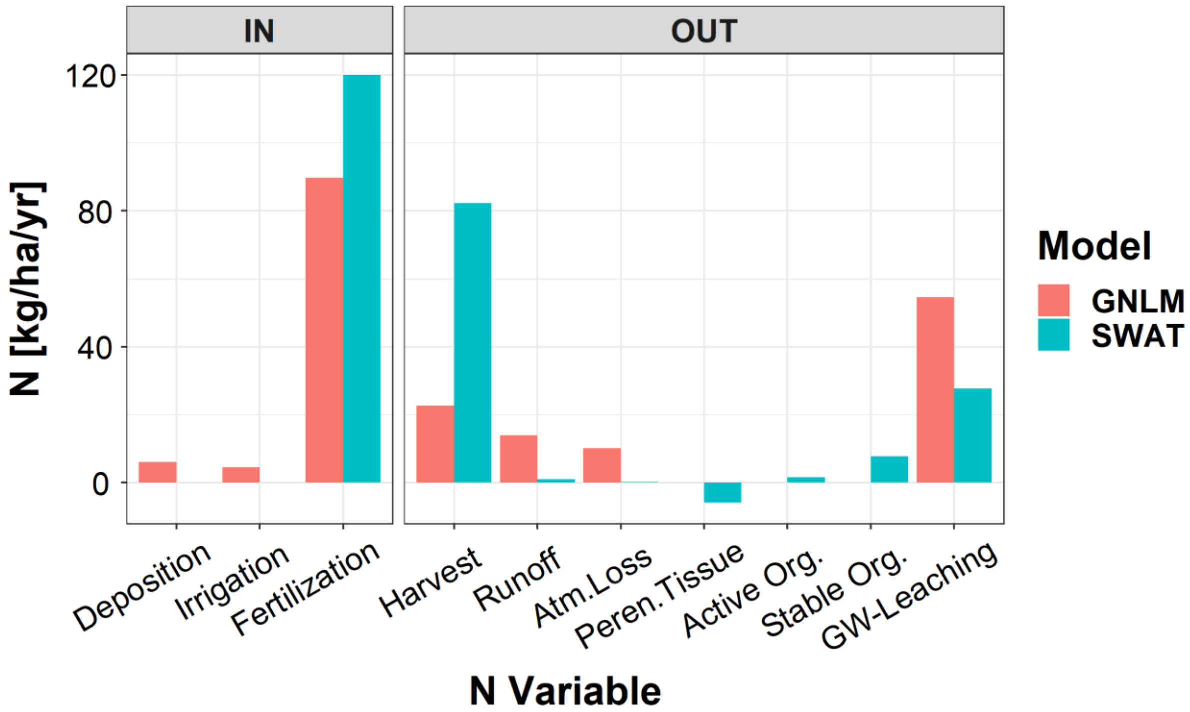

Figure B - 32: Variable comparison - Sunflowers.

Harvest

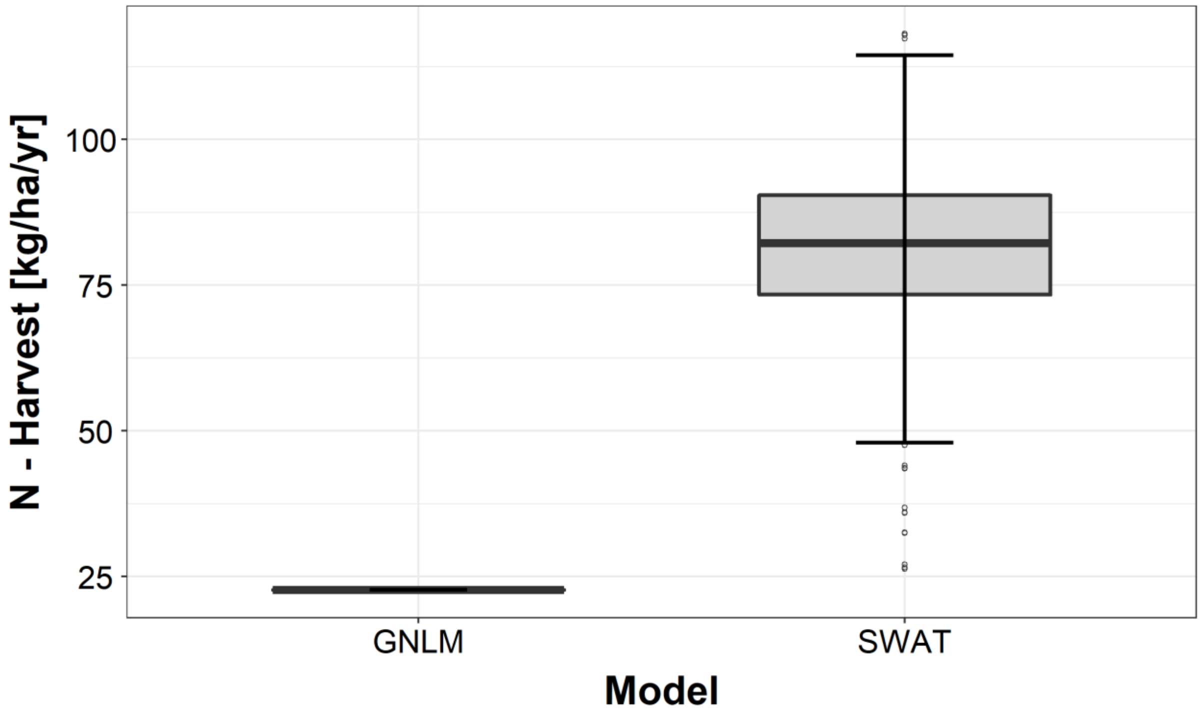

Figure B - 33: Boxplot of harvest rates comparison – Sunflower.

Application

Table B - 11: Statistical analysis fertilizer application - Sunflower.

Model	Fertilizer	Min	Max	Median	Mean	SD	Variance
GNLM	Synthetic	44.8	89.6	89.6	89.4	3.1	9.7
GNLM	Manure	0.0	1665.2	0.1	4.6	57.6	3313.1
SWAT	Synthetic	120.0	120.0	120.0	120.0	0.0	0.0
SWAT	Manure	0.0	0.0	0.0	0.0	0.0	0.0

Tomatoes

Balance

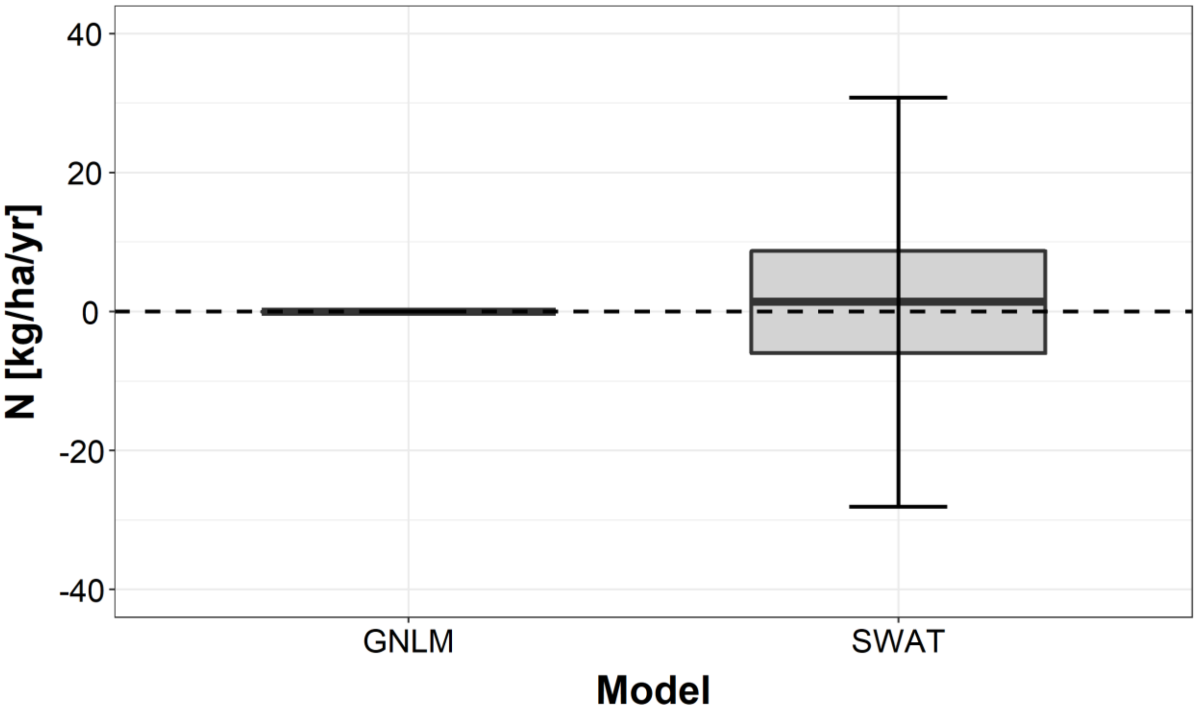

Figure B - 34: Boxplot N mass balance comparison - Tomatoes.

Comparison

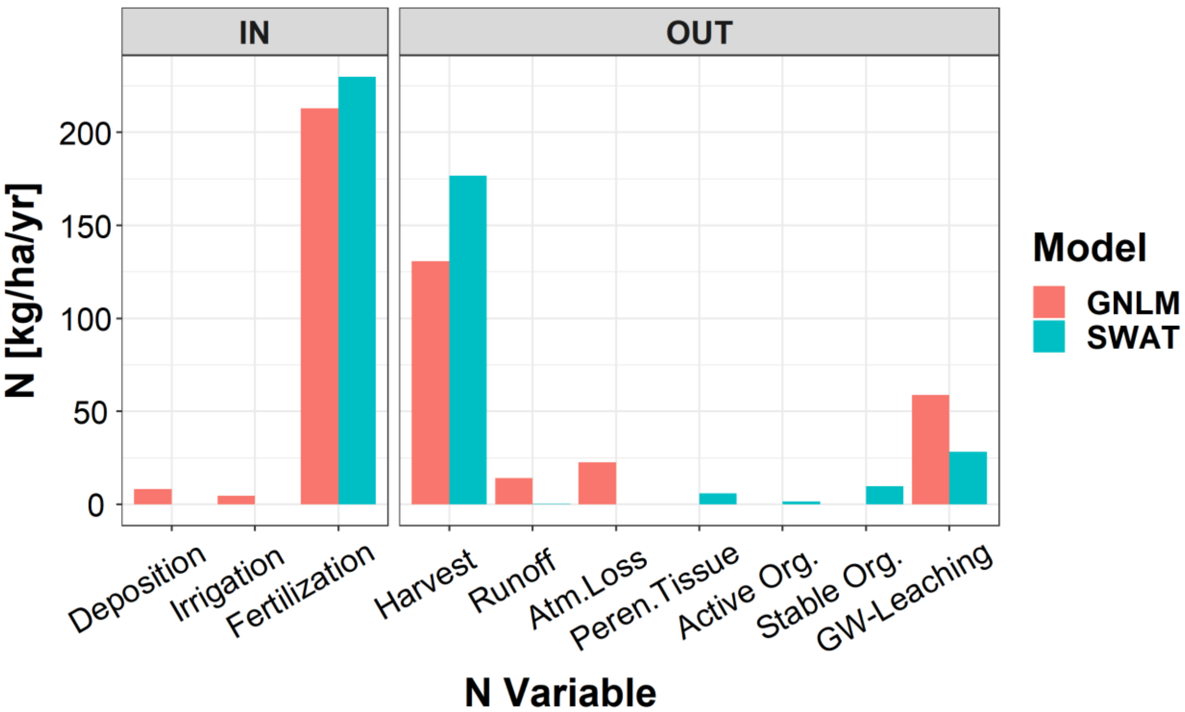

Figure B - 35: Variable comparison - Tomatoes.

Harvest

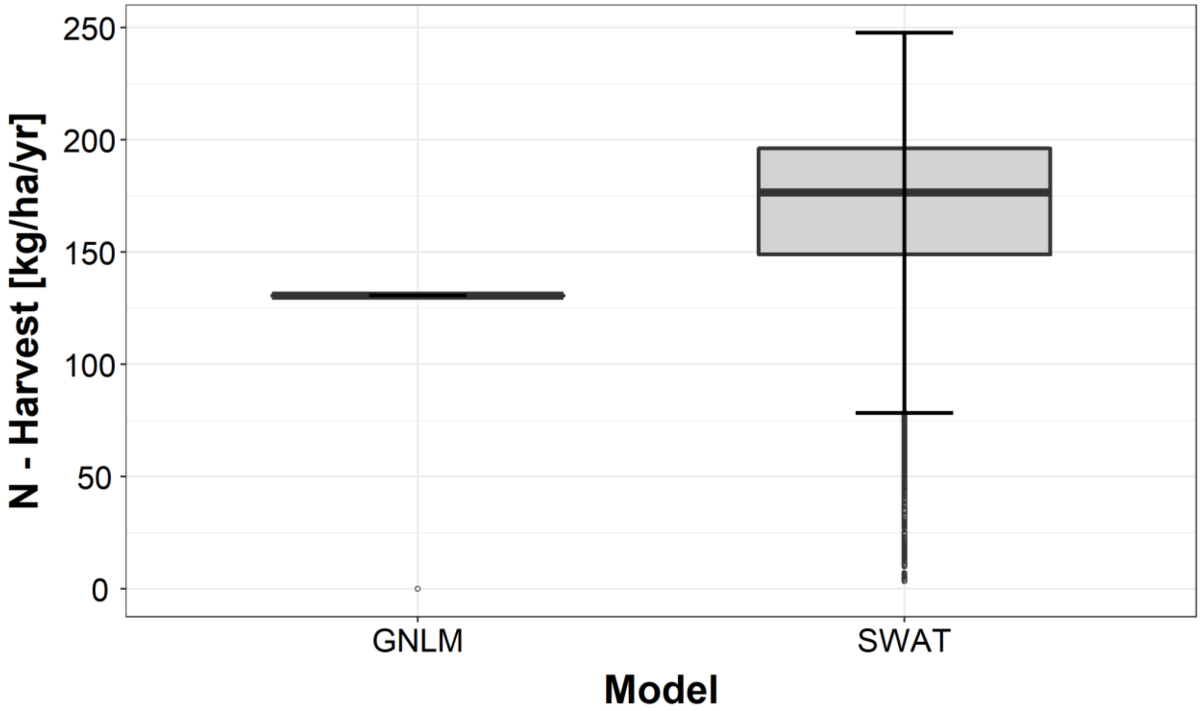

Figure B - 36: Boxplot of harvest rates comparison – Tomatoes.

Application

Table B - 12: Statistical analysis fertilizer application - Tomatoes.

Model	Fertilizer	Min	Max	Median	Mean	SD	Variance
GNLM	Synthetic	0	203.6	203.6	203.2	6.0	36.0
GNLM	Manure	0	399.6	9.5	9.3	9.8	96.7
SWAT	Synthetic	230	230.0	230.0	230.0	0.0	0.0
SWAT	Manure	0	0.0	0.0	0.0	0.0	0.0

Vineyards

Balance

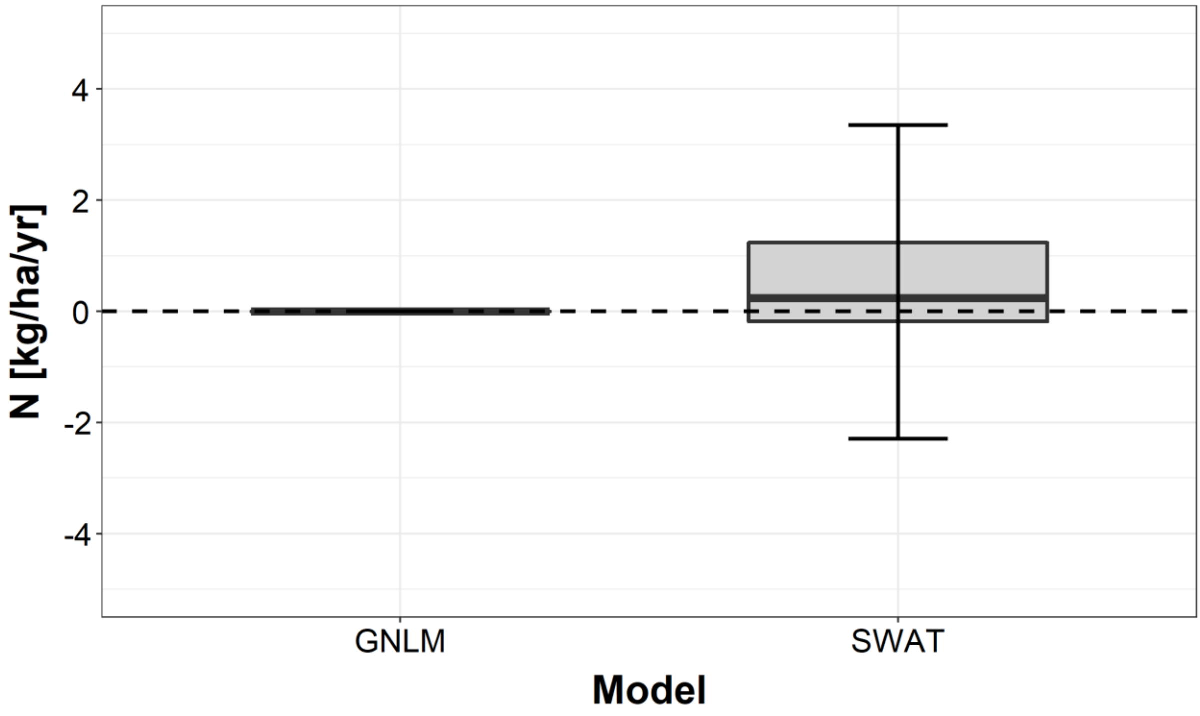

Figure B - 37: Boxplot N mass balance comparison - Vineyards.

Comparison

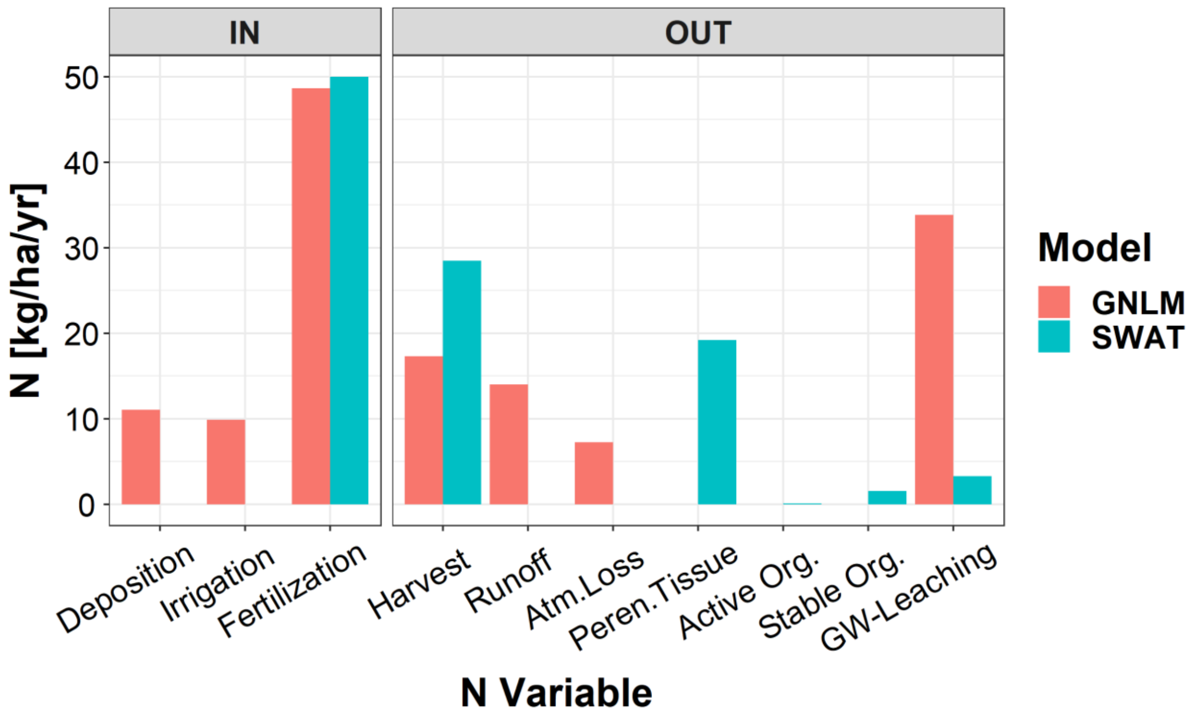

Figure B - 38: Variable comparison - Vineyards.

Harvest

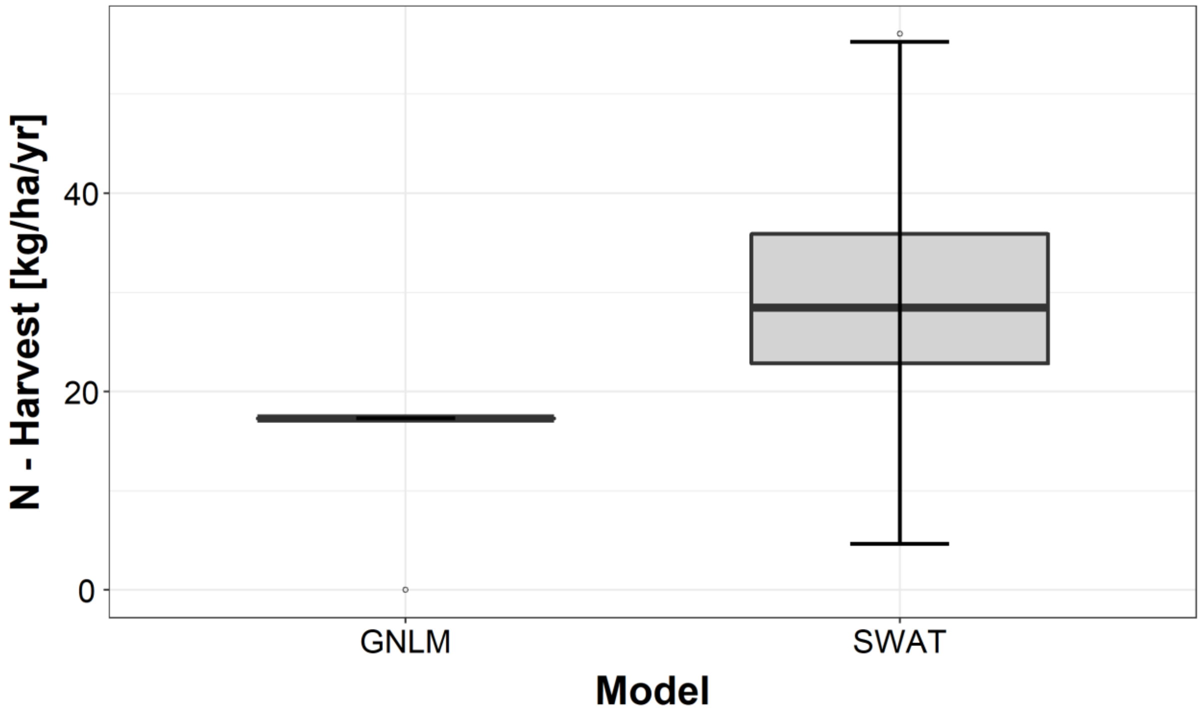

Figure B - 39: Boxplot of harvest rates comparison – Vineyards.

Application

Table B - 13: Statistical analysis fertilizer application - Vineyards.

Model	Fertilizer	Min	Max	Median	Mean	SD	Variance
GNLM	Synthetic	0	39.1	39.1	39.0	1.7	3.0
GNLM	Manure	0	4169.2	9.5	17.3	60.0	3595.2
SWAT	Synthetic	50	70.0	50.0	57.9	9.8	95.4
SWAT	Manure	0	0.0	0.0	0.0	0.0	0.0

Walnuts

Balance

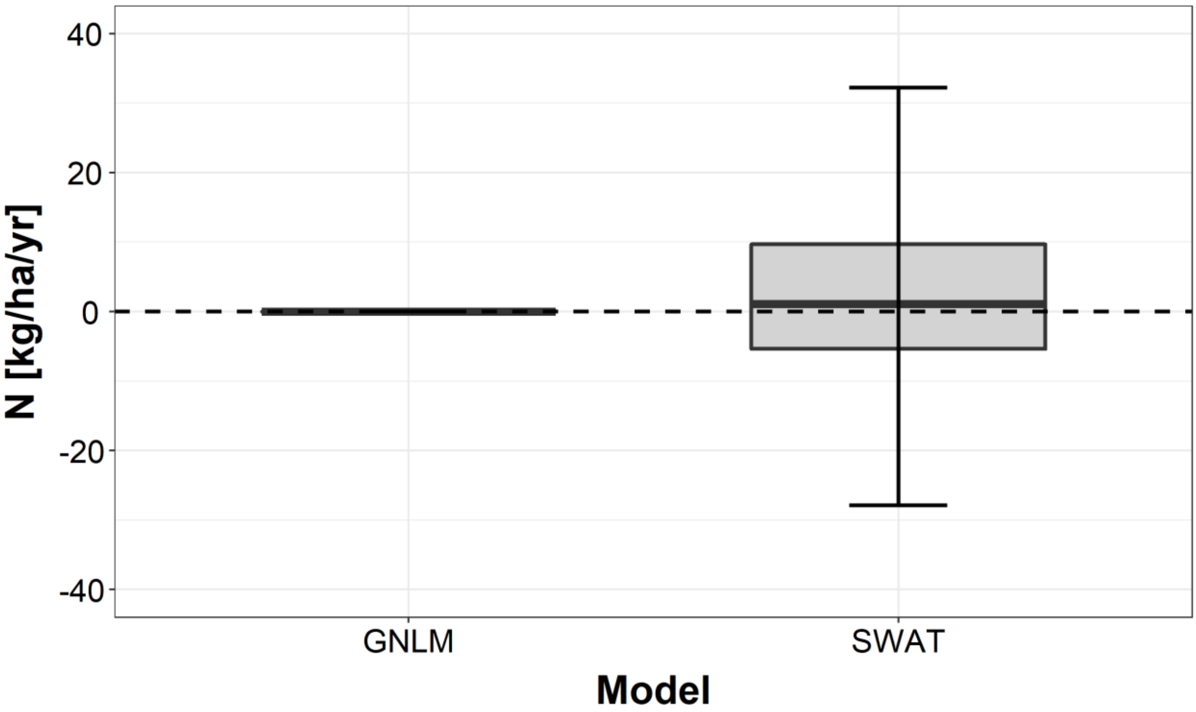

Figure B - 40: Boxplot N mass balance comparison - Walnuts.

Comparison

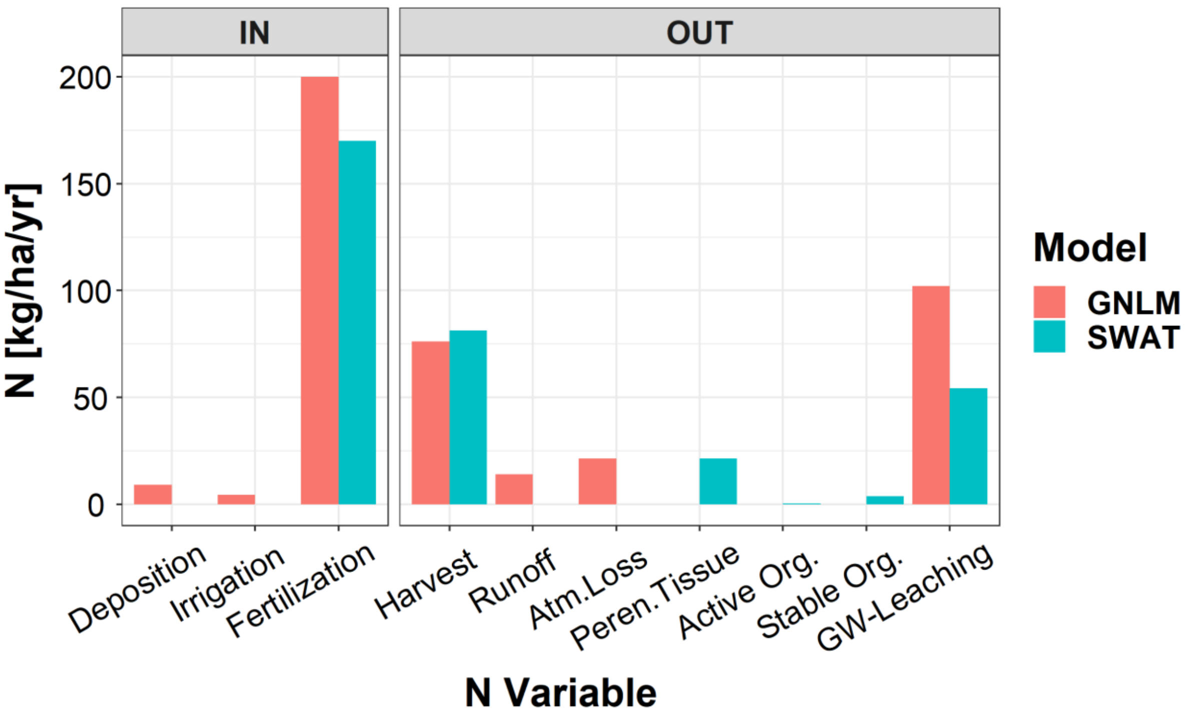

Figure B - 41: Variable comparison – Walnuts.

Harvest

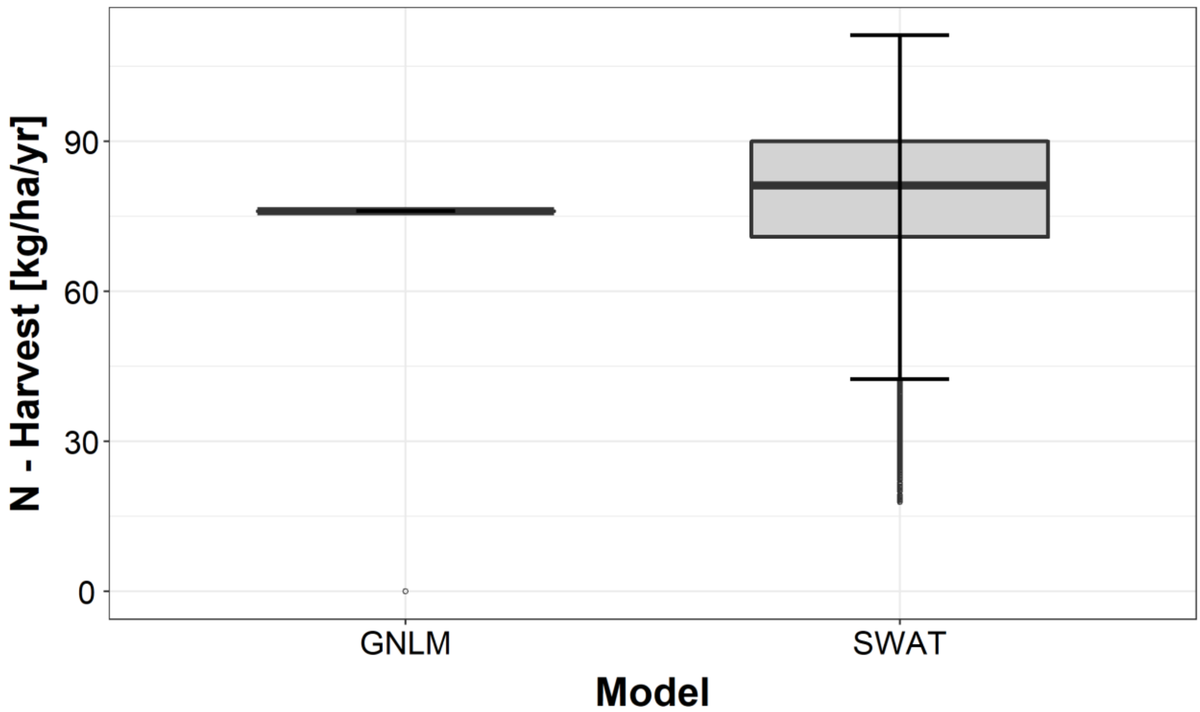

Figure B - 42: Boxplot of harvest rates comparison – Walnuts.

Application

Table B - 14: Statistical analysis fertilizer application - Walnuts.

Model	Fertilizer	Min	Max	Median	Mean	SD	Variance
GNLM	Synthetic	0	196	196.0	195.7	6.9	48.1
GNLM	Manure	0	594	4.1	13.9	20.3	411.2
SWAT	Synthetic	170	170	170.0	170.0	0.0	0.0
SWAT	Manure	0	0	0.0	0.0	0.0	0.0

Wheat – Grain

Balance

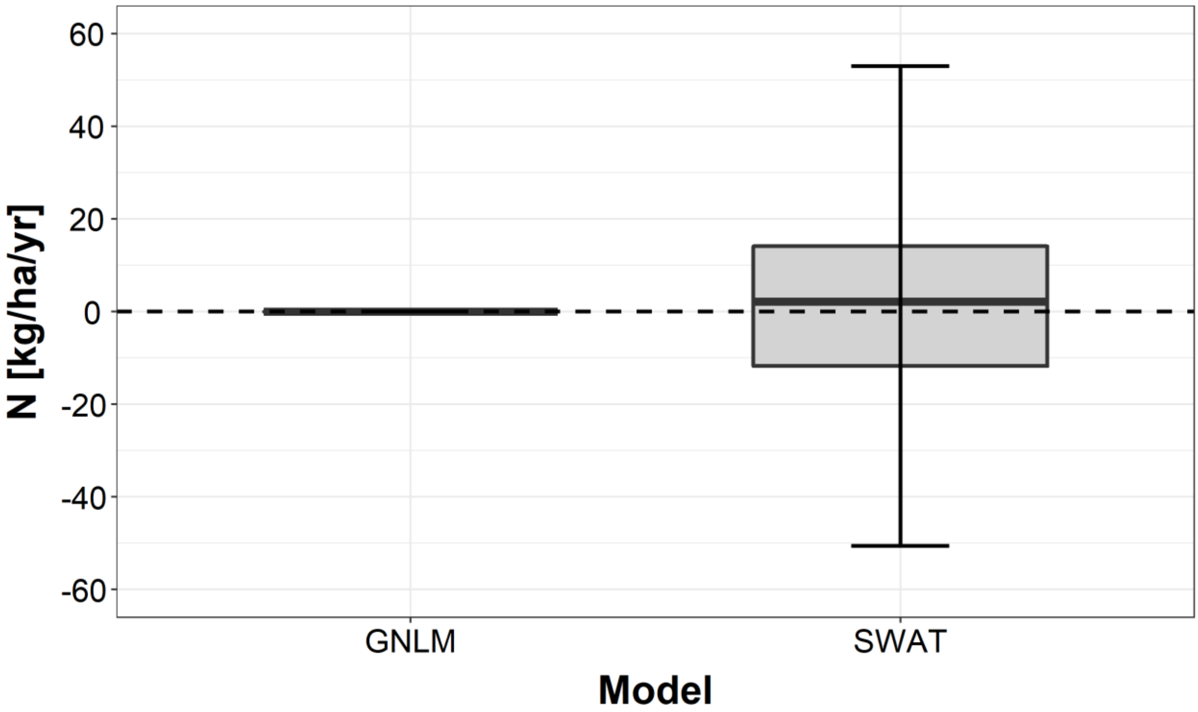

Figure B - 43: Boxplot N mass balance comparison - Wheat - Grain.

Comparison

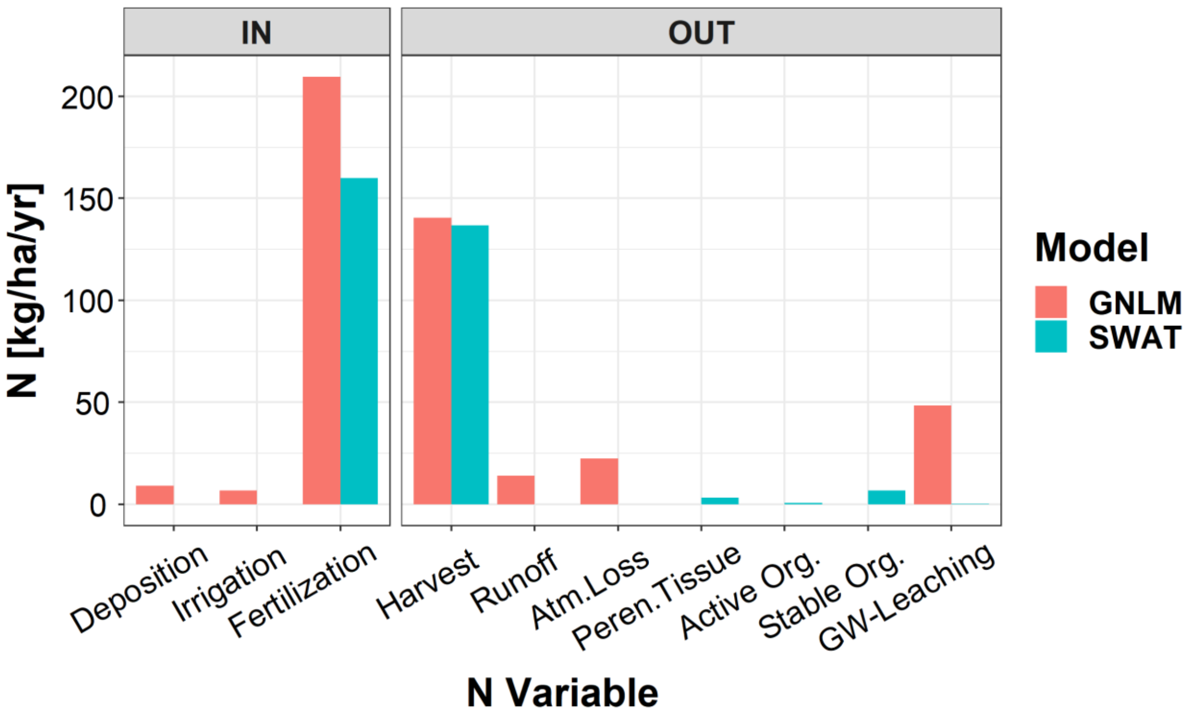

Figure B - 44: Variable comparison - Wheat-Grain.

Harvest

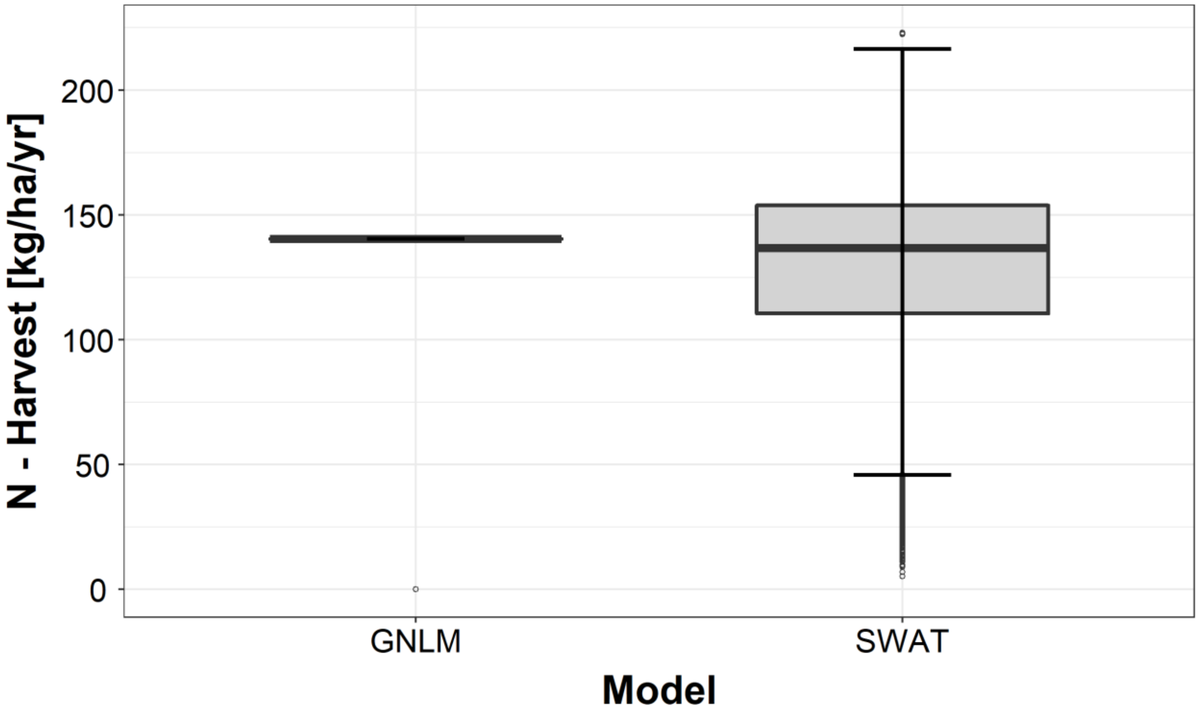

Figure B - 45: Boxplot of harvest rates comparison – Wheat-Grain.

Application

Table B - 15: Statistical analysis fertilizer application - Wheat-Grain.

Model	Fertilizer	Min	Max	Median	Mean	SD	Variance
GNLM	Synthetic	0	198.0	198.0	182.5	37.1	1378.9
GNLM	Manure	0	194430.7	11.7	191.6	674.3	454704.9
SWAT	Synthetic	160	180.0	160.0	165.9	9.1	83.3
SWAT	Manure	0	0.0	0.0	0.0	0.0	0.0

Statutory Declaration

I declare that I have authored this thesis independently and that I have not used other than the declared sources and resources.

Hiermit erkläre ich, dass die Arbeit selbständig und nur unter Verwendung der angegebenen Hilfsmittel angefertigt wurde.

Place and Date: ______________________________ Signed: ________________________

Jean-Luc Rosien