# SIMULATION OF THE WATER BALANCE IN A PERENNIAL GROUNDCOVER CORN INTERCROP WITH THE STICS CROP MODEL

by

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# LIST OF ABBREVIATIONS

**E**: evaporation

**ET**: evapotranspiration

**KBG**: Kentucky Bluegrass

**LAI**: leaf area index

**NSE**: Nash-Sutcliffe efficiency

**p-bias**: percent bias

**PGC**: perennial groundcover

**PM**: post maturity phase

**PP**: pre-planting phase

**RegenPGC**: Regenerating America's working landscapes to Enhance Natural Resources and Public Goods through Perennial Groundcover

**RP**: reproductive phase

**STICS**: Scientific, Technical and Interdisciplinary simulator of soil-Crop System functioning (model)

**SWC**: soil water content

**T**: transpiration

**USM** : Unit of simulation

**VG**: vegetative phase

## CHAPTER 1: General Introduction

Annual commodity agriculture relies on practices that leave land exposed to degradation for multiple months of the year. Uncovered soil in fallow croplands is susceptible to erosion and nutrient leaching. Through wind and water erosion, millions of tons of soil are lost from working lands in the Midwest every year. Soil loss has both economic and environmental implications, with soil loss costing the US an estimated $37.6 billion annually and contributing to environmental crises like the dead zone in the Gulf of Mexico (Rabotyagov et al. 2014; Uri 2000). Degraded soils have decreased nutrient content, lowered water-holding capacity, high levels of soil compaction, and diminished physical properties (Baumhardt, Stewart, and Sainju 2015). Poor management choices and prioritization of yield over ecosystem wellbeing has damaged croplands worldwide (Pravalie et al. 2021).

One strategy to mitigate soil degradation is cover cropping, which provides multiple benefits including nutrient retention, erosion reduction, increasing soil organic matter, and improved soil structure (Chen et al. 2022). Although proven to mitigate erosion and nutrient loss, farmers often choose not use cover crops for reasons, including: lack of information, too few growing days for establishment, or increased management complexity (Ingram 2023). To overcome these limitations of annual cover crops, some have proposed perennial ground cover (PGC), which would provide year-long coverage on crop lands with a single planting (Moore et al. 2019). Examples of existing systems include PGC alongside perennial crops in alley cropping practices as well as in vegetable production (Kolota and Adamczewska-Sowinska 2013; Gamble et al. 2019). Intercropping trials include annual grain production, where there is a great need for more sustainable land management (Flynn et al. 2013; Martin, Greyson, and Gordon 1999; Eberlein, Sheaffer, and Oliveira 1992; Zemenchik et al. 2000).

The USDA-funded project *Regenerating America's Working Landscapes to Enhance Natural Resources and Public Goods through Perennial Groundcover* (RegenPGC) is developing a perennial groundcover to enhance ecosystem services in the Midwest. This project is still in its development stage, and PGC has been applied in limited field trials aimed at working through a variety of implementation challenges before encouraging large-scale adoption (Bartel et al. 2022; Flynn et al. 2013; Kimmelshue, Goggi, and Moore 2022). Management of the groundcover is important for limiting resource competition, especially water, nutrient, and light resources. Other concerns exist around grass establishment, suppression during the growing season, and potential pest refugia (Bartel et al. 2022; Moore et al. 2019; Schlautman et al. 2021). There is an added layer of complexity when another species is introduced into the growing space, so understanding each sphere of interaction will ensure a design that is mutually beneficial to both ground cover and crop (Moore et al. 2019). A method to examine these interactions is through crop models, where one can explore management decisions without the time and expense of in-field trials.

Process-based crop models are helpful in projecting yield with theoretical changes to the environment. They allow users to better understand the implications of management choices or uncover potentially unforeseen relationships and reactions within the system. Models can broaden one's understanding of a system and help formalize and quantify relationships in the ecosystem. Within a model the complexities of a natural system are simplified into equations and priority is given to the parts which are under study. Crop models have a variety of applications, including forecasting yield, simulating the effects of climate change on cropping systems, exploring land use change, or investigating soil nutrient dynamics, to name a few (Ewert et al. 2005; Rehman et al. 2023; Singh et al. 2014; Teixeira et al. 2018; Y. Zhang et al. 2013). Models can help inform both management choices and policy decisions, leading to more informed decisions about land use.

As one would expect, there are different models for different uses. In the case of PGC, intercropping capabilities are integral for modeling the system, but most crop growth models do not allow the simulation of intercropping. Some existing models have been modified to roughly simulate intercrop, but without explicit formalisms built into the model (Della Chiesa et al. 2022; Kimball et al. 2019; Pierre et al. 2023), while others models like APSIM are currently being modified to incorporate intercropping (Berghuijs et al. 2021; Lagerquist et al. 2024). The STICS model, however, already incorporates intercropping formalisms and has been used in a variety of conditions, making it the most mature intercropping model suitable for simulating PGC (Brisson et al. 2004b; Kherif et al. 2022; Traore et al. 2022; Vezy et al. 2023).

The focus of this research is on resource competition for water between corn and PGC, in this case Kentucky Bluegrass (KBG). The crop model STICS is used to examine the water balance of the system. Understanding the water demands of PGC is crucial for developing a non-competitive system. The PGC species should occupy a different niche within the system, so it is not competing with the primary cash crop, potentially threatening yield. These niches can include things like seasonality of the species, as well as physiological traits such as aboveground biomass and root growth. Modeling the water balance for corn and KBG will provide insight to crop yield, since water stress during particular stages of corn development has direct impact on yield (Mladenova et al. 2017). Water stress is just one of many potential competitive interactions between KBG and corn, with nutrient and light resources also being areas of concern. These modeling efforts will help growers know in what scenarios and at which point in the season water competition is highest and poses the most risk for the crop. Early season water uptake by KBG may reduce soil moisture and restrict corn growth in the spring, potentially decreasing grain yield. Alternatively, experiments have shown groundcover increasing infiltration and soil moisture retention throughout the growing season (Baker et al. 2022; Wiggans et al. 2012a). We will examine STICS' ability to simulate PGC effects on water balance to determine its efficacy in modeling the PGC system and as a way to explore under what conditions competition for soil moisture negatively impacts corn grain yield.

The STICS model is a daily timestep model driven by climatic data, soil type, and management decisions. Model outputs include crop development and water and nitrogen balances (Brisson et al. 2004b). The model comprises a set of standard formalisms found in other crop models but is unique in its adaptability to many crops (Brisson et al. 2004b). STICS was adapted for intercropping and utilizes a simplified system that models resource partitioning by breaking the crops into dominant and understory canopies, with a sunlit and shaded subcategory for the understory. The amount of light resource acquired by each canopy section drives the plant growth, water, and nitrogen balances (Brisson et al. 2004b).

The standard version of STICS includes parameterizations for a variety of crop species, ranging from banana, to corn, to miscanthus. KBG is not an existing plant file in STICS, but analogous plant files are available. Tall fescue, another cool-season grass, is a species suitable as a starting point from which to begin KBG calibration. There are some important morphological differences between KBG and tall fescue that affect water dynamics in the system. Most important is the root system, which is deeper in tall fescue than KBG and thus can access more moisture at depth and creates more competition for corn. Many parameters between the grasses are analogous, but to simulate the PGC system using KBG a novel plant file was required.

To adapt STICS to a novel plant file, multiple years of data are needed. Agronomic data for turfgrass data are limited, and what are available tend to focus on factors that are important to turf such as visual metrics of greenness rather than physiological and morphological measurements. Existing PGC field trials provide very limited measured data on the groundcover, focusing instead on the main crop measures such as yield or the shade-avoidance response from corn (Bartel et al. 2022; Wiggans et al. 2012a). PGC field trials do not currently have sufficient data to calibrate the STICS model to KBG. A bucket lysimeter study of KBG growth in Loveland, CO (Y. Zhang et al. 2013) includes measurements of evapotranspiration (ET), deep percolation, N content of grass clippings, and aboveground biomass from clippings. These data are from a highly maintained KBG turf field that had regularly mowing, irrigation, and fertilization. PGC, in contrast, receives little management throughout the season. It would be preferable to calibrate with PGC field data, but these were the best data that could be obtained.

Once STICS is parameterized to KBG, the new plant file can be used in the intercrop simulation with corn. Data from a study near Ames, IA by Wiggans et al. was used to evaluate model performance and determine whether STICS is a suitable model for capturing trends in the water balance of a corn-based PGC system (Wiggans et al. 2012a; 2012b).

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# CHAPTER 2: Calibration of STICS to Kentucky Bluegrass turf experimental data

ABSTRACT

Increasing the provision of ecosystem services by adopting cropping systems compatible with conventional commodity agriculture is highly attractive. One such approach is to add perennial groundcover to the grain systems that dominate the working lands of the Midwest. There is the need for process-based crop models that can simulate PGC intercropping and elucidate the circumstances when PGC will compete for resources with the primary crop, reducing grain yield. The STICS model is used to simulate a corn-PGC system. The focus of this research is on competition for soil moisture between the PGC and corn. The first step is to create a plant file for Kentucky Bluegrass and to calibrate the model. Data from Zhang et al. (2013) were used to parameterize a Kentucky Bluegrass plant file and calibrate the model to measurements of annual ET, clipping biomass, percolation, and nitrate leaching. The STICS model predicted annual ET well, but less satisfactory results for clipping yield, percolation, and leaching. There were significant limitations in the model's ability to implement management practices typical of turf grass which limited the model performance.

KEY WORDS

crop model, STICS, intercrop, perennial groundcover, Kentucky Bluegrass

## INTRODUCTION

Conventional agriculture in the Midwest has reduced the provision of many natural ecosystem services, processes that we rely on to support and sustain human life (Swinton et al. 2007; W. Zhang et al. 2007). Through the simplification of our landscapes, we have aggravated problems like soil erosion, nutrient leaching, and biodiversity loss (Barros-Rodríguez et al. 2021; Baumhardt, Stewart, and Sainju 2015; Kehoe et al. 2017). Continuing with these practices will further degrade the landscape and limit the productivity of our agricultural systems (Thaler, Larsen, and Yu 2021).

In response to these issues, current research is focused on reintroducing ecosystem services to conventional agriculture. The RegenPGC project led by Iowa State University is using perennial groundcover (PGC) on working lands in the Midwest to address diminished ecosystem services. The PGC is selected to be a species complementary to the cash crop, occupying different niches in the growing space. Ideally, it will would reach its peak growth in the cooler months of spring and become semi-dormant in the summer months (Moore et al. 2019). Having a living mulch on the ground year-round is expected to improve soil retention and reduce runoff (Siller, Albrecht, and Jokela 2016). The PGC is expected to increase infiltration during precipitation events and year-round ground cover will limit evaporation from the soil (Baker et al. 2022; Moore et al. 2019; Schlautman et al. 2021). The intercropped species can, however, introduce unwanted competition with the primary crop. Early-season nitrogen uptake can limit what is available to the main crop, and water uptake by PGC, especially before primary crop planting, can introduce stress on the crop, limiting grain yield (Berti et al. 2017; Dale and Daniels 1995; Liedgens, Frossard, and Richner 2004; Martin, Greyson, and Gordon 1999; Peterson, Berti, and Samarappuli 2019; Thorup-Kristensen 1993).

For PGC to fulfill its promise and be widely adopted, it cannot result in a significant yield loss, so understanding the potential areas of competition will inform management and create a more robust and resilient system. There are several ongoing PGC field trials, but it is nearly impossible to have data and records on all the potential situations where PGC interacts with the crop. Therein lies the importance of models in PGC research efforts. Models can expose interactions or outcomes in a variety of user-controlled scenarios, and they can also be used as a decision-making tool based on those outcomes. To simulate a grain-PGC system, we need a model with intercropping capabilities. Most crop models do not have these formalisms, and at best include ways to approximate an intercrop but are not explicitly made for that purpose (Della Chiesa et al. 2022; Pierre et al. 2023). The STICS model was adapted to intercropping and has been applied to intercrop systems all over the globe (Brisson et al. 2004b; Kherif et al. 2022; Traore et al. 2022; Vezy et al. 2023). For PGC, STICS will require plant files for both the main crop and the ground cover, and thus experimental data are required to calibrate and validate the model.

Field trials of PGC grown with corn and soybeans are currently underway throughout the Midwest. There are several iterations of PGC, including multiple types of groundcover such as Sandburg bluegrass (*Poa secunda*), bulbous bluegrass (*Poa bulbosa*), and Kentucky bluegrass (*Poa pratensis*) (Moore et al. 2019). In this instance of PGC, we are discussing a Kentucky bluegrass (KBG) and corn combination. To parameterize PGC in STICS, several years of data from a site and a range of relevant measurements are needed. These data are currently being collected from PGC field sites, but they are not yet available for use. RegenPGC field trials primarily focus on the cash crop, with fewer data collected on the PGC. The focus of the current field trials is on yield, water use efficiency, shade avoidance response, or other metrics pertaining to the main crop (Bartel et al. 2022; Moore et al. 2019; Wiggans et al. 2012a). To adapt STICS to PGC, we also require data on KBG. An extensive search of the literature revealed only one study that included relevant nutrient, moisture, and growth data.

Data from a study by Zhang, et al. (2013), examining turfgrass management practices using the DAYCENT model were obtained from the corresponding author. These data were collected from a three-year bucket lysimeter study in Loveland, CO. Unlike most turfgrass studies that focus on visual metrics of turf performance, these data include biomass accumulation, evapotranspiration (ET), deep percolation, clipping N content, and nitrate leaching. For STICS' parameterization, focus was on the water balance measurements, in this case ET, percolation, and biomass growth.

## METHODS AND MATERIALS

Data for model calibration were provided from a study by Zhang et al. Data were collected for three years, 1993-1995, from three bucket lysimeters on an 8-year old KBG stand in Loveland, CO. The soil was Fort Collins loam (fine-loamy, mixed, superactive, mesic Aridic Haplustalf; 29% clay, 54% sand, 17% silt) (Y. Zhang et al. 2013).

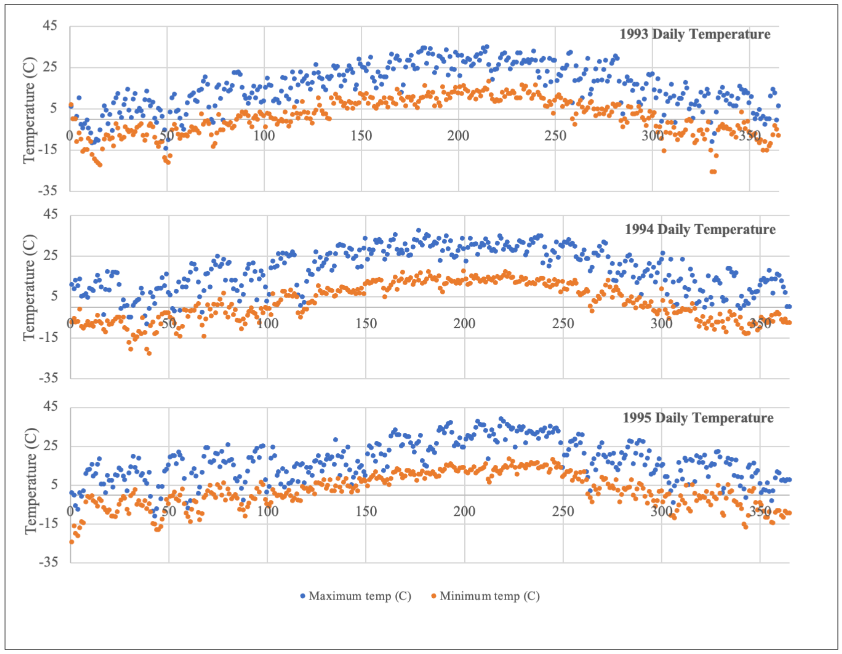


*Figure 1: Minimum and maximum temperatures in Loveland, CO, 1993-1995.*

Each bucket lysimeter was 80cm deep, with 60cm of soil and 20cm for drainage catchment. Precipitation, cumulative ET, N content of grass clippings, aboveground biomass, and cumulative deep percolation were measured weekly throughout the growing season. Weather data came from the Loveland mesonet site, LOV01 *The Ole Golfcourse of Loveland* (40.42, -105.1). Values of minimum and maximum temperature, precipitation, solar radiation, windspeed, and vapor pressure were required for the model. (Figure 1) To “spin up” the model to represent a mature KBG stand, 8 years of KBG growth were simulated before the study years of interest.

The KBG stand was a highly maintained turf, receiving consistent irrigation, mowing, and fertilization. Grass was irrigated twice a week starting in the third week of April and continuing until the last week of October with irrigation amounts chosen to provide 100% of reference ET. Irrigation is specified by day of year and amount to be applied in mm. Turf was mowed once a week at a cutting height of 5.1cm, with all clippings returned to the soil. In the STICS simulation, grass cutting was controlled according to residual biomass and residual leaf area index (LAI) through the cut crop management option. Sulfur-coated urea was used to fertilize the turf in multiple applications throughout the growing season. In STICS, fertilization was simulated using urea with variable rates throughout the season and amongst the growing years. In years 1993, 1994, and 1995, growing season N-fertilizer application totaled 187, 122, and 164 kg N ha$^{-1}$, respectively.

*Table 1: Monthly precipitation (mm) in Loveland, CO.*

| | **1993** | | **1994** | | **1995** | |
|---|---|---|---|---|---|---|
| | Precip. | Irrig. | Precip, | Irrig. | Precip. | Irrig. |
| **Jan** | 9.5 | - | 10.4 | - | 5 | - |
| **Feb** | 20.9 | - | 20.5 | - | 23.9 | - |
| **Mar** | 36.2 | - | 13.6 | - | 18 | - |
| **Apr** | 54.3 | 99 | 64.2 | 65 | 80 | 88 |
| **May** | 28.8 | 188 | 32.2 | 151 | 172.7 | 109 |
| **June** | 64.9 | 186 | 73.9 | 143 | 87 | 164 |
| **July** | 26.5 | 212 | 27.1 | 135 | 20.4 | 214 |
| **Aug** | 24.5 | 213 | 44.8 | 147 | 4.4 | 200 |
| **Sept** | 68.8 | 130 | 18.4 | 97 | 47.2 | 123 |
| **Oct** | 51.3 | 90 | 21.3 | 57 | 112 | 105 |
| **Nov** | 30.7 | - | 18.6 | - | 17.2 | - |
| **Dec** | 4.3 | - | 8 | - | 3.4 | - |

Parameters for the plant file were obtained through review of the literature, comparison with analogous crops in STICS, and tuning within a range of values. A base file of tall fescue was copied and then modified to calibrate KBG. Calibration schemes are provided in the *Conceptual Framework, Equations, and uses of the STICS soil-crop model* book and table 16.3 was used for calibration (APPENDIX 3: Calibration scheme for KBG). Without observed LAI or phenological stage data, step 6 was first completed, and then steps 1, 2, 3, 4, and 5. Priority was given to parameters and variables that pertained to water balances, and sections such as yield formation, yield quality, and nitrogen use were kept the same as the original fescue values. LAI, biomass growth, and root growth were the primary targets for calibration.

Model variables pertaining to the water balance were tracked for each study year, Table 2. Not all output parameters were activated in the simulation, with optional parameters such as ineffective irrigation, capillary rise, mole drainage, and leaf interception turned off. These options were not used for this primary calibration to reduce the number of parameters that needed calibrating and simplify the water balance. Soil evaporation, transpiration, and mulch interception were combined to represent the total flux for ET from the system. Mulch interception is controlled by percent coverage of mulch and its wettability.

Extensive input to the management files was also necessary to simulate the turfgrass accurately. Unique management files were made for each study year to accommodate specific irrigation amounts, cutting dates, and varying fertilizer schedules.

*Table 2: STICS water balance. Recreated from Beaudoin et al. 2022.*

| **STICS Water Balance** | |
|---|---|
| **Inputs** | **Outputs** |
| Initial water content | Final water content |
| Precipitation | Evaporation |
| Irrigation | Transpiration |
| | Runoff |
| | Capillary rise* |
| | Deep infiltration |
| | Mole drainage* |
| | Leaf interception* |
| | Mulch interception |
| | Ineffective irrigation* |
| *option to turn on/off. Simulations were run with options off. | |

Observed evapotranspiration and clipping weight data from 1993 and 1994 were compared with model outputs and used to adjust model parameters to minimize the error between the observed and simulated outputs.

RESULTS

Outputs for ET, clipping yield, and deep percolation were compared against measured KBG data. The model simulated ET most accurately, with clipping yield and deep percolation yielding less good results. Nash-Sutcliffe Efficiency (NSE) and percent-bias (p-bias) measures of model accuracy were calculated for each output variable. NSE is a dimensionless measure of the residual variance in the simulated data compared to residual variance in measured data, where a value between 0 and 1 ( $0 \leq NSE \leq 1$) is considered good, and an NSE < 0 indicates the mean of the measured data is a better predictor than the model (Moriasi et al. 2007; Yang et al. 2014). P-bias determines the tendency of the simulated data to be larger or smaller than the observed data. A small p-bias value is favorable, with zero as the optimum value. Positive p-bias values indicate model underestimation, and negative values indicate model overestimation (Moriasi et al. 2007).

Modeled outputs follow the same general trends observed in the measured data for ET but did not capture all high and low peaks. The turf was irrigated with 100% reference ET, so the model did not simulate almost any water stress. Within the model, daily transpiration is equal to root uptake, so under non-stressed conditions the rate of transpiration was more consistent and did not simulate peaks seen in the field data, which may be attributed to some water stress on hot days. Simulated cumulative ET values of 731, 699, and 675mm were recorded for 1993, 1994, and 1995, respectively. These are close to measured values in each of the three study years, which had recorded total ET values of 738, 738, and 693mm. The 1993 modeled ET closely followed measured data throughout the growing season (NSE=0.92, p-bias=0.97%). The 1994 modeled ET did not capture the fluctuations early in the season but predictions were more accurate at the end of the growing season (NSE=0.41, p-bias 5.3%). Similarly, 1995 modeled ET had fewer fluctuations throughout the season than the measured data but generally followed the trend of the observations (NSE=0.47, p-bias=2.6%) (Figure 3)

Clipping yields were consistently underestimated by STICS. Model outputs were only 77%, 78%, and 68% of the total observed yield for each study year, respectively (Figure 4). The 1993 growing season exhibited large clipping weights in the spring, likely due to spring fertilization and milder spring temperatures compared to the other study years (Y. Zhang et al. 2013). These large observed values were not simulated by STICS, but cuttings through July and August of 1993 were close to the measured values (NSE= - 0.72, p-bias=23.4%). 1994 and 1995 measured clipping had sporadically large clipping yields throughout the season that were not simulated by the model (1994: NSE= -0.81, p-bias=21.7%) (1995: NSE= -2.5, p-bias= 31.6). Each simulation consistently had a much larger first cut in the spring than seen in the measured data. This is likely due to the high radiation-use-efficiency parameter values needed to simulate the rapid biomass accumulation between cuttings. Further tuning of vernalization or emergence parameters might mitigate this discrepancy, but significant efforts to tune these parameters were not effective.

Simulation of deep percolation was underestimated in 1993 (333mm total modeled vs. 434 mm total observed) and overestimated for 1994 and 1995 (270 mm total modeled vs. 133 mm total observed, 409 mm total modeled vs. 292 mm total observed, respectively) (Figure 3). Parameters for percolation were not calibrated to these data, so discrepancies were likely. STICS did not capture large percolation events in the measured data, but rather had more frequent, small events, than what were measured in situ. Formalisms related to pore space were not activated in the soil file, which would affect water movement throughout the soil profile. If more data on soil were available, parameterizing these formalisms would likely improve model performance. 1993: NSE=0.33, p-bias=23.3%. 1994: NSE= -1.5, p-bias= -103. 1995: NSE=0.40, p-bias= -40. (Figure 2)

Simulated runoff for all three study years was zero, with suppression occurring because of mulch and vegetation on the soil surface. Field data on runoff was only available for the 1993 season, which had a total annual runoff value of 173mm. No data were available for 1994 and 1995.

Nitrate leaching was also not accurately simulated by STICS and was significantly overestimated (p-bias= -39,185) (Table 3). Leaching events coincided with percolation at the base of the soil profile, but leaching values were unrealistically large per drainage event. A potential source of error is incorrect root density, which could have limited nitrogen uptake if underestimated. Field data on roots would be valuable for a more accurate simulation. Parameters governing nitrogen use were also not calibrated to observed data but rather adopted from the STICS fescue plant file. Further tuning of the plant file with emphasis on nitrogen use could potentially improve these metrics. One study on STICS' simulation of nitrate leaching found poorer model performance for leaching and drainage variables in the continuous simulations than the annual simulations due to propagation of error between USMs (Schnebelen et al. 2004). Erroneous simulations in the spin-up year USMs could have compounded error in the study year simulations.

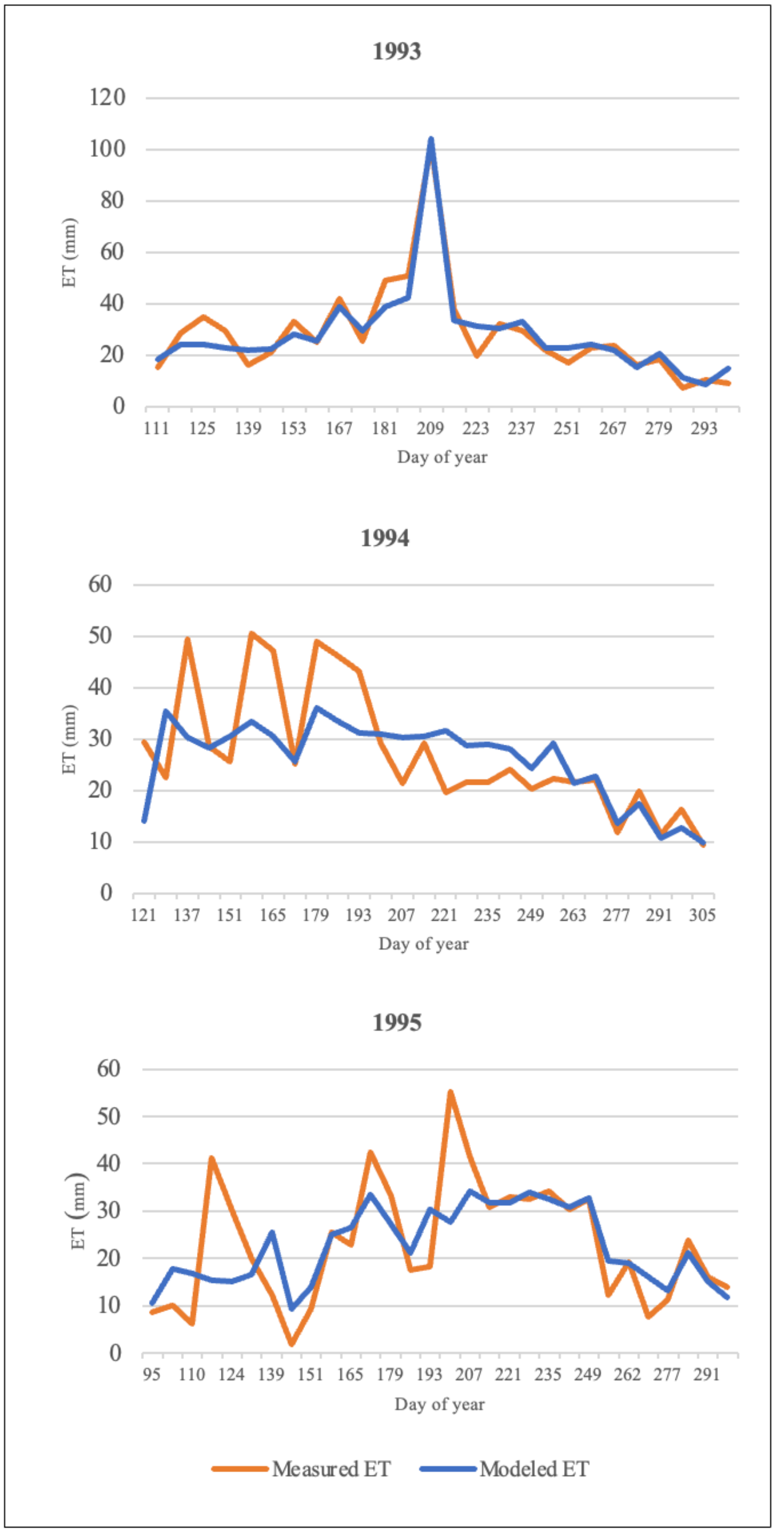


*Figure 2: Measured vs. modeled ET for KBG turf. Loveland, CO*

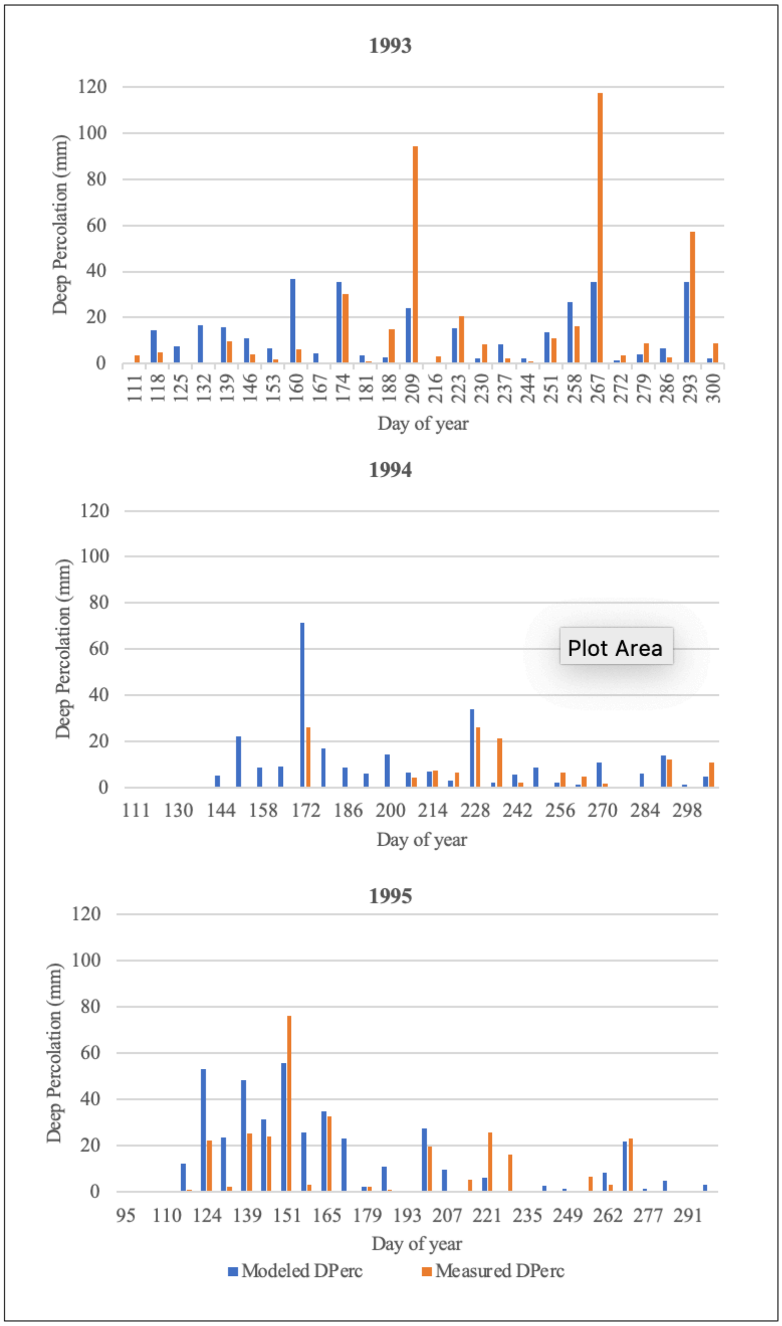


*Figure 3: Measured vs. modeled deep percolation for KBG turf, Loveland, CO.*

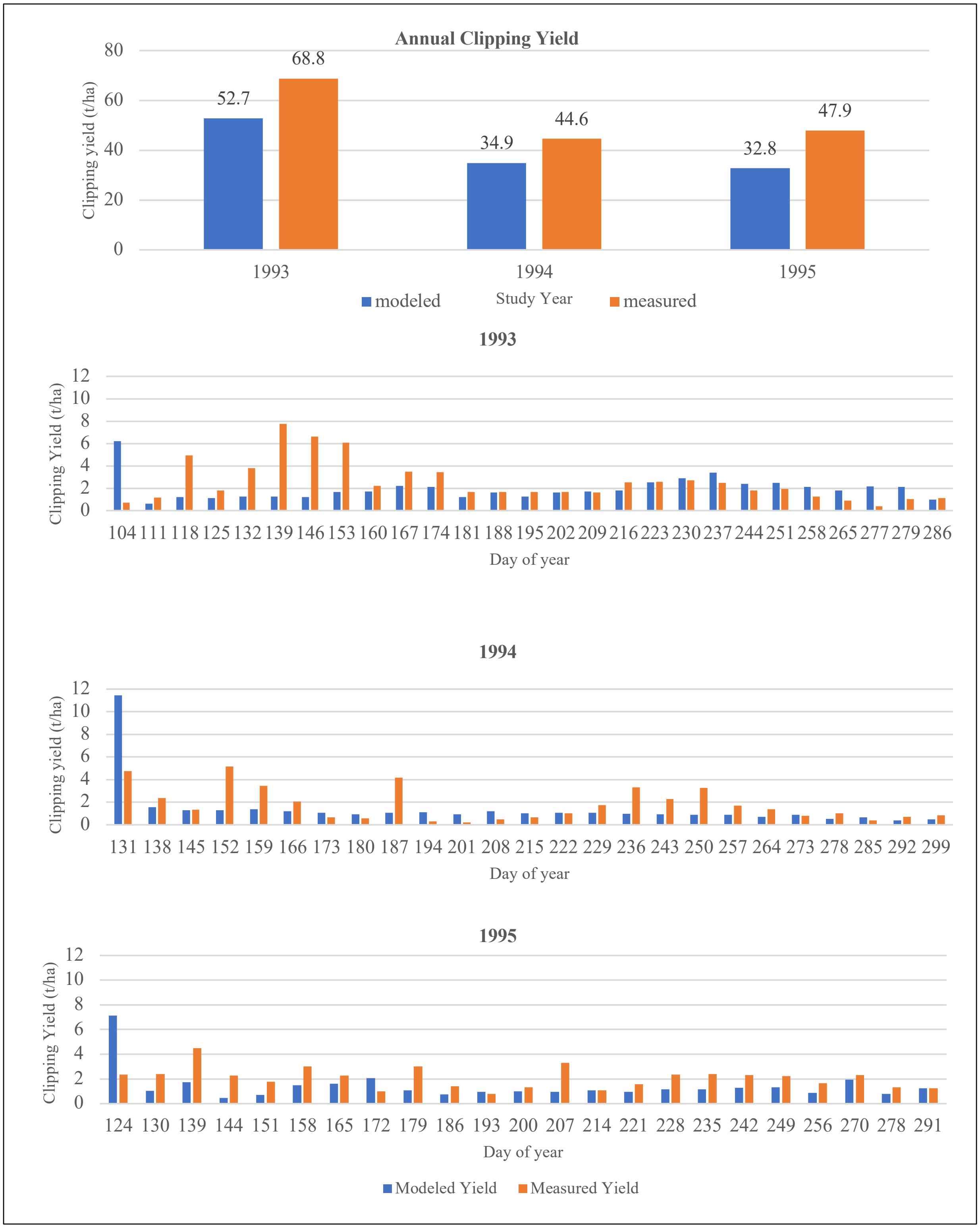


*Figure 4: Modeled vs. measured clipping yield for KBG turf. Loveland, CO*

*Table 3: Annual nitrate leaching for KBG turf. Loveland, CO*

| | 1993 | 1994 | 1995 |
|---|---|---|---|
| **Measured (g/m$^2$)** | 0.03 | 0.08 | 0.03 |
| **Modeled (g/m$^2$)** | 14.3 | 21.4 | 19.3 |

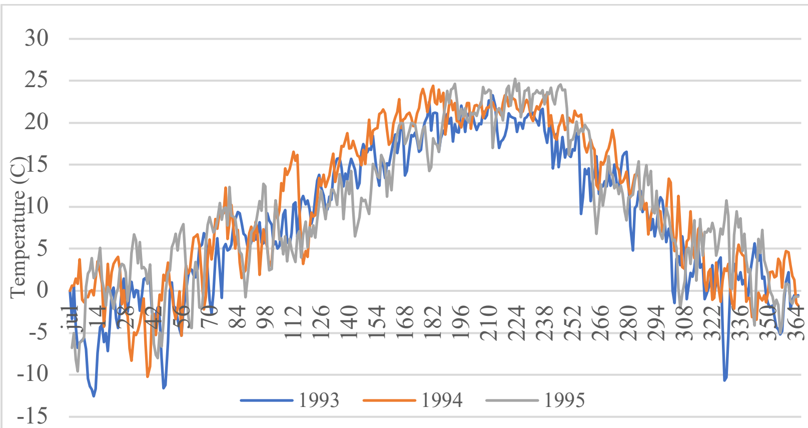


*Figure 5: Soil temperature in top 10cm in KBG turf. Loveland, CO*

DISCUSSION

The STICS model was designed to simulate corn and wheat, with the goal of creating a model that could be applied to many crops with general and cultivar-specific parameters. It is a deterministic, process-based model that simulates both crop and soil processes, with user inputs controlling plant traits, management choices, climate, and soil (Beaudoin et al. 2022). While considered a "general" model that can be applied to any crop, it is not particularly suited to simulating turfgrasses because of the management techniques that are required for turf. The process of calibrating STICS to the data from Zhang et al. (2013) was convoluted and involved some important limitations which undoubtedly affected the quality of calibration.

Model calibration is the process in which model parameters are tuned to reduce error between simulated and observed data. (Wallach et al. 2021). Some parameters in STICS are measurable values (i.e., biomass or specific leaf area), whereas others are impossible to measure and must be calibrated (Beaudoin et al. 2022). To parameterize Kentucky Bluegrass, known values from literature were used to populate measurable parameters, while calibration methods were necessary for the more theoretical parameters. See appendix 2 for a full list of plant parameters.

There is no one-size-fits-all process for model calibration, and model users must first consider which parameters are of greatest concern. This decision can be made by considering the observed data available. There are several obstacles that arise when deciding how to proceed with calibration, but no one method is perfect. Process-based models like STICS have myriad parameters and it is not possible to calibrate every parameter. Furthermore, limited amounts of observed data will determine which parameters a user can calibrate (Beaudoin et al. 2022). Users must also decide the method by which they plan to calibrate the model, as there are many options here, too. The process of tuning an individual parameter and then checking its corresponding output is tedious but provides a greater level of control than using built-in optimization tools that often have a steep learning curve (Wallach et al. 2021). This method also lets the user consider reasonable ranges for parameter values that maintain some physiological sense. Optimization tools may find the best fit, but it can come at the cost of using parameter values that are far outside the bounds of reality. (Wallach et al. 2021)

To calibrate the KBG file, parameters influencing LAI, biomass, and water balance were prioritized. Other parameters regarding nitrogen balance and yield were taken from an analogous plant file in STICS, in this case, tall fescue. The STICS user guide provides calibration schemes based on what data are available for calibration. We used the pattern from table 16.3 in the STICS conceptual framework book (Beaudoin et al. 2022) and followed the recommended procedure for the case that no LAI or phenological data were available. First step 6, then 1, 2, 3, 4, and 5 were completed as data were available.

Another grass file, timothy, had been previously parameterized by Jego et al. (2013) from the same original tall fescue plant file that we began with for KBG. As reference, the timothy file was studied to determine which parameters were altered to simulate a new grass. This provided further framework for which parameters might be useful to tune.

When applying the KBG plant file to simulate an intercrop, certain formalisms must be selected. These include the radiation transfers option for canopy microclimate, the resistance approach for crop water requirements, and the Shuttleworth-Wallace approach for energy balance calculations. Some, but not all of these are already calibrated for the sole-crop KBG plant file.

Before tuning the plant file, management files were created for the KBG turf. This step is where many sources of error were introduced. To simulate a weekly mowing, the cut crop formalism was activated in the management file. Throughout each growing season there were up to 27 mowing dates. If more than 11 cutting events were added to a *unit of simulation* (USM) the simulation would report no plant growth for the whole season. To work around this problem, each study year was broken into three separate USMs that could be run successively and accommodate all the cuttings.

When linking USMs, STICS carries over soil organic matter and crop residue values into the next simulation, which allows users to more accurately model soil dynamics over time (Beaudoin et al. 2022). It also transfers crop status with variables such as LAI and biomass carried over, however other outputs are recalculated at the start of each USM. These recalculated variables were discovered on a trial-and-error basis, as irregular patterns in crop growth appeared in the chained USMs. For example, leaf lifespan restarted at zero in the beginning of each USM, causing large drops in LAI once the end of the lifespan was reached and all leaves present at the start of the USM senesced at once (Figure 11). The crop would also recalculate the emergence stage, beginning at the juvenile stage for each USM. The juvenile stage uses different growth parameters than the vegetative stage, causing slower growth at the start of the second and third USMs.

STICS' simulation of ET had cumulative values close to those observed but captured less fluctuation throughout the growing season. To achieve these results, parameters pertaining to mulch decomposition were altered because a significant layer of un-decomposed biomass was limiting soil evaporation and transpiration. Turf clippings typically decompose rapidly, but STICS' general decomposition parameters were not tuned for this use and total decomposition was nearly zero (Kopp and Guillard 2004). Once decomposition between cuttings was increased, the total evaporative flux from the system was much closer to observed values.

The discrepancies between linked USMs likely account for slowed biomass accumulation and poor agreement between modeled and observed clipping yield. Extensive tuning was done on parameters regulating LAI and shoot biomass growth, especially *dlaimaxbrut*, *dlaimin*, and radiation use efficiency parameters *efcroijuv*, *efcroiveg*, and *efcroirepro* (Table 4). Some of these parameters were modified to values outside their typical range to compensate for regular mowing but would not be appropriate parameter values for a non-mowed grass like that grown for PGC.

*Table 4: STICS parameters for KBG versus original tall fescue parameter values*

| | ***dlaimaxbrut*** | ***dlaimin*** | ***efcroijuv*** | ***efcroiveg*** | ***efcroirepro*** |
|---|---|---|---|---|---|
| **Mowed KBG** | 0.00047 | 0.3 | 5 | 10 | 4 |
| **Tall fescue** | $8 \times 10^{-6}$ | 0 | 2 | 2.5 | 2.2 |

*dlaimaxbrut*: maximum rate of daily LAI increase
*dlaimin*: accelerating parameter for LAI growth
*efcroijuv*: maximum radiation use efficiency during the juvenile stage
*efcroiveg*: maximum radiation use efficiency during the vegetative stage
*efcroirepro*: maximum radiation use efficiency during the reproductive stage

Nitrate leaching in this simulation also produced egregiously over-estimated values. Reported values from Qian et al. had inconsistent units, so further clarification would be necessary for calibration. In the context of turfgrass, the STICS simulated leaching values were not within a reasonable range. Leached N was simulated as 76%, 175%, and 188% of total applied N for the three study years, respectively. Leaching is closely tied to percolation at the base of the soil profile, and STICS' overestimation of percolation in 1994 and 1995 intensified the error in leaching outputs for those two years. Studies suggest nitrate leaching in turf can range from 0.6-16% of applied NO3-N, depending on type of fertilizer, irrigation/precipitation, and time of application (Guillard and Kopp 2004; Petrovic 1990), however STICS' values are far outside this range. When examining the nitrate leaching for the spin up years, the total amount of N leached accounted for anywhere between about 10-85% of applied nitrate, with smaller values from the later spin-up years when the plant became more established. This trend, however, stopped once the study years were broken into three USMs. This erroneous simulation could possibly be attributed to the chained USMs, or the change in management between the spin-up USMs and the study-year USMs, namely biweekly versus weekly mowing.

## CONCLUSION

STICS is not well suited for modeling turfgrass, especially with its limitations in implementing management styles typical of turf. If more than 11 cutting events were permitted, a more accurate calibration could be done since there would be continuity throughout a single USM. When parameterizing a highly maintained turf, many parameters will not be appropriate in simulations without similar management, so using this plant file in other applications is somewhat limited.

STICS simulated the annual ET well for the three study years but did not achieve good results for biomass accumulation between cuttings. There were also discrepancies regarding percolation and nitrate leaching, which may be improved by tuning nitrogen-use parameters or spending more time parameterizing the pore-space formalisms in the soil file.

It would be useful for future iterations of STICS to expand the cut crop formalism option to allow users to simulate turf. Decomposition parameters specific to turf clippings could also be explored more. Another route to explore is the implementation of chemical suppression in STICS, which is not currently a management practice in the model.

As there are limitations to management inputs, there are also fundamental limitations to models' formalisms. Like many crop models, STICS is limited to a 1-D world, where a plant's access to water is not horizontally distributed, but rather plants have equal access to resources per "bucket" of soil moisture (Beaudoin et al. 2022). In the context of these simplified systems, it is even more important to make sure aspects like soil, management practices, and plant characteristics are parameterized as accurately as possible. Future work could further parameterize the roots of KBG so their distribution allows appropriate access to each "bucket" of water. If we can ensure that all the pieces of the model are calibrated to the best possible values, then we can use this simplified version of the world to represent our system. When using crop models, it is valuable to understand how they simplify natural processes so that one makes the most suitable choice for their simulation.

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**CHAPTER 3: Exploring PGC water balance trends in STICS**

INTRODUCTION

Incorporating intercrops into industrial agriculture is a new approach for restoring lost ecosystem services to the landscape. Projects like RegenPGC aim to create intercrop systems with straightforward implementation and management so the cost to farmers is minimum, but the benefits are great (Moore et al. 2019; Schlautman et al. 2021). RegenPGC field trials are being run throughout the Midwest, and simultaneously, modeling efforts are exploring the potential scenarios where the groundcover and main crop might interact (Bartel et al. 2022; Flynn et al. 2013; Kimmelshue, Goggi, and Moore 2022). Models are powerful tools that can run through many conditions and explore outcomes from user-controlled scenarios. Resource competition between the perennial groundcover (PGC) and main crop is a concern for growers, so these modeling efforts are geared toward simulating whether PGC water use poses a threat to corn growth. Water stress during certain stages of corn growth can damage grain yield, so minimizing the competition is imperative (Mladenova et al. 2017). To model the RegenPGC system, intercropping capabilities are required. The STICS model is unique in its ability to simulate intercrops, which is uncommon amongst crop models.

In this instance of PGC, we are simulating corn grown with Kentucky bluegrass (KBG). The STICS model was designed to be generic and allow users to simulate any crop, with users having access to all plant parameters (Beaudoin et al. 2022). We calibrated STICS to KBG observations to create a novel plant file. The existing selection of plant files had an option for tall fescue, from which we tuned the file to represent KBG.

Once a KBG plant file was created, the intercrop simulation could proceed. Data from a study by Wiggans et al. (2012a) were used to investigate how well STICS could replicate the trends in plant water use and soil moisture observed *in situ*. This study measured volumetric soil water content (SWC), yield, and reproductive water use in a KBG-corn intercrop and a conventional corn control (Wiggans et al.

2012a). The study took place over three years, during which there were two seasons with above-average precipitation, 2008 and 2010, and another year (2009) with average rainfall. In 2010, however, spring was drier than typical, whereas 2008 and 2009 had more than typical spring precipitation (Table 6). The timing of precipitation is considered important because early-season water use by PGC is a concern. Reduction of antecedent soil moisture going into the corn growing season may hinder establishment of the main crop and in a dry year, reduce crop growth and grain yield.

## METHODS AND MATERIALS

To implement an intercrop in STICS, plant files are required for both the main crop and associated crop. The Kentucky bluegrass (KBG) is present for the duration of the USM, so it was designated as the main crop and corn as the associated crop (a necessary STICS formalism). Weather and soil files were created for the Iowa State University Sorenson research farm in Boone County, near Ames, IA. The site sits on a Nicollet soil (fine-loamy, mixed, superactive, mesic Aquic Hapludolls). Weather from 2008-2010 used for the simulation were obtained from a nearby Iowa mesonet site (Ames-AEI ISU-RDF (Boone County, BOOI4)).

KBG was planted in the fall of 2007 in 20cm rows (Wiggans et al. 2012a). The following spring, Pioneer 34A20 hybrid corn was planted at a density of 8.2 plants/m in 0.76m rows according to the planting and fertilization rates described in Table 5. A control plot with no PGC was also planted at the same time. Each spring, two applications of glyphosate were applied to the PGC to suppress growth. This process cannot be simulated in STICS, but a cutting right before corn planting was used as proxy for suppression. For both the control plot and the KBG plot, STICS was run as a series of successive USMs so that soil data and crop status carried over into the next year.

Field measurements on volumetric soil water content, reproductive corn transpiration, and grain yield, among others, were collected over the three study years, 2008-2010. These measurements were used to assess STICS' ability to capture water balance trends.

Formalisms required to simulate intercropping were selected in the plant file, including the water requirement resistive approach, true density root profile, and radiative transfer option, and planting structure was turned on in the management file.

*Table 5: Fertilization schedule for KBG-corn intercrop in Ames, IA.*

| | Planting Date | Fertilization date | Fertilizer Rate (Urea ammonium nitrate, kg N/ha) |
|---|---|---|---|
| 2008 | May 16 | June 19 | 202 |
| 2009 | May 5 | May 5, June 4 | 39, 168 |
| 2010 | April 29 | April 29, June 1 | 39, 168 |

RESULTS

Intercrop simulations were run to determine whether STICS could simulate water balance patterns that were observed in field trials. Overall, STICS outputs followed the trends observed in the field, but not with great fidelity. Of the three study years, 2008 and 2010 had well-above average precipitation, and 2009 had average precipitation.

In 2008 and 2010, volumetric SWC at 15 cm trended higher in the KBG plot than the control plot for in field-collected measurements (Wiggans et al. 2012a). In 2008, measured data showed the KBG plot had 4% higher SWC at the reproductive phase (RP) and 6% higher post maturity (PM). STICS simulated 8% higher SWC in the KBG plot during RP but only 0.28% higher during PM (Figure 7). In 2010, field measurements showed a 3.96% higher SWC in the KBG plot for the RP and 8.6% higher SWC during PM.  STICS simulated a SWC 3.93% higher in the KBG plot for the RP and only 1.77% higher value PM (Figure 9) In general, STICS followed the trends measured *in situ*, but did not accurately predict the magnitude of the observations.

Simulations of transpiration during RP were consistently underpredicted by STICS. The 2009 season was an especially errant simulation, with transpiration simulated in the control plot 82% smaller than measured, and the KBG plot value 69% smaller (Table 7). Transpiration in 2008 and 2010, both years with above-average precipitation, was also underpredicted but to a lesser degree.

We do not have field-measured ET values, but total ET values simulated by STICS were within a reasonable range for corn fields in the Midwest (Kimball et al. 2019). The split between evaporation and transpiration, however, is not well simulated. STICS predicts a nearly equal split, while literature shows us transpiration is the greater part of total ET (Wang et al. 2021; Xiao et al. 2016) (Table 8). This discrepancy could be further investigated if more above-ground biomass data were available to assess if STICS was properly simulating those metrics.

Lastly, STICS simulation of yield was close to observed values, but it is difficult to say whether the agreement was achieved through an accurate simulation of the system or through compensating errors. In the field, the KBG plot had lower yields in 2008 and 2010, and a slightly higher yield in 2009. STICS predicted lower yields in the KBG plot for all three study years, 10.31 t/ha vs 8.33 t/ha, 10.59 t/ha vs. 9.53 t/ha, and 10.59 t/ha vs 7.60 t/ha for control vs. KBG plot, respectively (Figure 10). Observed values for the three years were as follows: 11.13 t/ha vs. 7.88 t/ha, 10.11 t/ha vs. 10.87 t/ha, and 10.68 t/ha vs 7.72 t/ha for control vs. KBG.

## DISCUSSION

The KBG plant file was modified for use in an intercrop USM. STICS requires specific formalisms to be selected for intercropping, and adjustments were required for leaf growth and biomass parameters that were over-tuned to compensate for management practices in the mowed turf. The adjusted parameters mostly include those listed in Table 4. These parameters were reset to values in the analogous tall fescue plant file for this PGC simulation.

This exercise was primarily done to determine STICS' suitability for simulating a PGC system. There were not sufficient measurements for a calibration, so emphasis was placed on evaluating whether STICS correctly predicted the water balance trends and interactions between the two species observed in field trials. With limited observations, it is premature to say whether STICS detected differences between a control plot and KBG plot, or if the trends were coincidence.

To better evaluate the model, additional measurements such as accumulated biomass, rooting characteristics, and ET are required for both the corn and PGC. This would provide a fuller picture of the system and allow us to determine the source of output mismatch. There are also limitations to STICS' ability to implement all the management practices typical in a PGC system. Notably, PGC suppression through herbicide application in the spring cannot currently be modeled. The Wiggans et al. (2012a) field trial used two applications of glyphosate each spring to suppress PGC growth. In STICS, we implemented a cutting of the grass before the corn planting date, but the KBG is not suppressed by a cut in the same way an herbicide would inhibit growth. This would likely introduce more resource competition for the corn.

STICS simulation of SWC somewhat followed trends, typically showing a higher SWC value in the KBG plots than their control plot counterpart. The differences between PGC and control plots were not, however, of the same magnitude as those measured in the field. The model predicted much larger differences in SWC between plots during RP than what was observed, especially in 2008 and 2009. These two years measured a SWC difference of 4% and 3%, respectively, whereas the model predicted an 8% and 25% difference between plots The 2009 RP SWC in STICS was opposite to the trend in the measured data, where a slightly lower SWC in the KBG was observed, but the model predicted the KBG had 25% higher SWC than the control (Figure 7, Figure 8). Both RPs for 2008 and 2009 had slightly below-average rainfall, while 2010 had more than double the typical rainfall over the RP.

*Table 6: Monthly air temperature and precipitation, with 30-yr averages. Copied from Wiggans et al. 2012a*

**Table 1. Average monthly air temperature and precipitation collected approximately 2 km from the experimental site†. Thirty-year averages were computed from data collected between 1975 and 2004.**

| | Air temperature | | | | Precipitation | | | |
|---|---|---|---|---|---|---|---|---|
| Month | 2008 | 2009 | 2010 | 30-yr | 2008 | 2009 | 2010 | 30-yr |
| | °C | | | | mm | | | |
| Mar. | 1.0 | 3.8 | 4.0 | 2.8 | 71 | 103 | 38 | 53 |
| Apr. | 8.4 | 9.2 | 13.0 | 10.3 | 130 | 116 | 100 | 93 |
| May | 15.2 | 16.0 | 15.9 | 16.5 | 216 | 104 | 89 | 112 |
| June | 21.2 | 20.8 | 21.8 | 21.4 | 271 | 104 | 312 | 119 |
| July | 23.2 | 20.5 | 23.9 | 23.5 | 234 | 70 | 122 | 112 |
| Aug. | 21.5 | 20.9 | 23.8 | 22.1 | 53 | 123 | 396 | 120 |
| Sept. | 17.9 | 18.1 | 17.5 | 18.1 | 78 | 24 | 126 | 76 |
| Oct. | 11.6 | 7.9 | 13.3 | 11.1 | 92 | 186 | 12 | 61 |
| Nov. | 3.1 | 7.0 | 4.0 | 2.6 | 66 | 34 | 58 | 51 |

†NWS COOP site Ames 8WSW (near Ames, IA).

Trends for SWC were also over-predicted in PM by STICS in 2008 and 2009. In 2010, STICS predicted the opposite trend than what was observed in the field, with a higher SWC content in the control plot than the KBG plot. During PM in 2010 rainfall was below-average, whereas in 2008 and 2009 PM rainfall was above-average. Whether the rainfall was above or below average does not seem to be a predictor of whether the model will capture the correct trend in SWC.

Modeled transpiration over RP was consistently underpredicted by STICS, and to a significant degree. The overall annual ET values simulated by STICS were reasonable (Table 8), but the split between E and T was almost 50:50 E:T in some cases (Suyker and Verma 2009). A study by (Xiao et al. 2016) measured the split between E and T for corn at 13% and 87%, respectively, and another study by (Wang et al. 2021) calculated the split as 19% and 81% between E and T. In the model, actual transpiration is the minimum of either crop water needs or soil water supply (Kimball et al. 2019) In 2009, the simulated transpiration value was especially underestimated, but the SWC values were similar to those of the other two years. This would suggest the water demands of the crop are being underestimated by STICS rather than there being a lack of soil moisture.

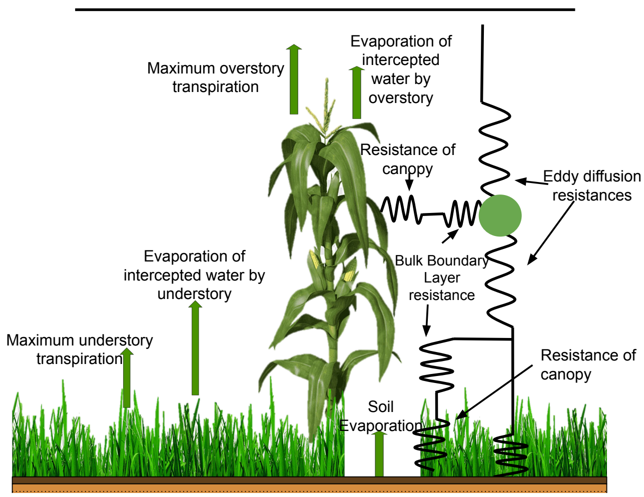


*Figure 6: Resistance scheme in STICS. Recreated from Beaudoin et al, 2022.*

When using the intercrop formalism, STICS requires the resistive approach based on the Shuttleworth and Wallace resistive scheme. It consists of five evaporative fluxes, three net radiation budgets, and three types of resistances (Beaudoin et al. 2022). This approach takes into account the microclimate's effect on water requirements, such as the decreased vapor pressure deficit due to understory transpiration (Brisson et al. 2004a). In an evaluation 29 crop models comparing the simulation of corn ET under varying levels of input, Kimball et al. (2019) found that STICS' Shuttleworth and Wallace calculations for ET performed better when more input data were available to calibrate the model. The improved performance occurred when measurements for LAI, biomass, yield, soil moisture, and daily ET were used to calibrate the model. Our simulation was driven only by soil type, weather, and management choices, so outputs would likely be improved with more data from the field.

STICS' outputs for yield followed the trends of observed data in 2008 and 2010, but not 2009. For 2008 and 2010, the yield in the control plots was greater than the yield of KBG plots. The KBG plot had a slightly greater yield in 2009, which the model did not predict. In the model, grain filling is dependent on canopy growth rate, which is calculated with net radiation values (Beaudoin et al. 2022). Without more information on metrics that would represent the canopy like aboveground biomass or LAI, it is not possible to speculate why yield did or did not follow the observed trends.

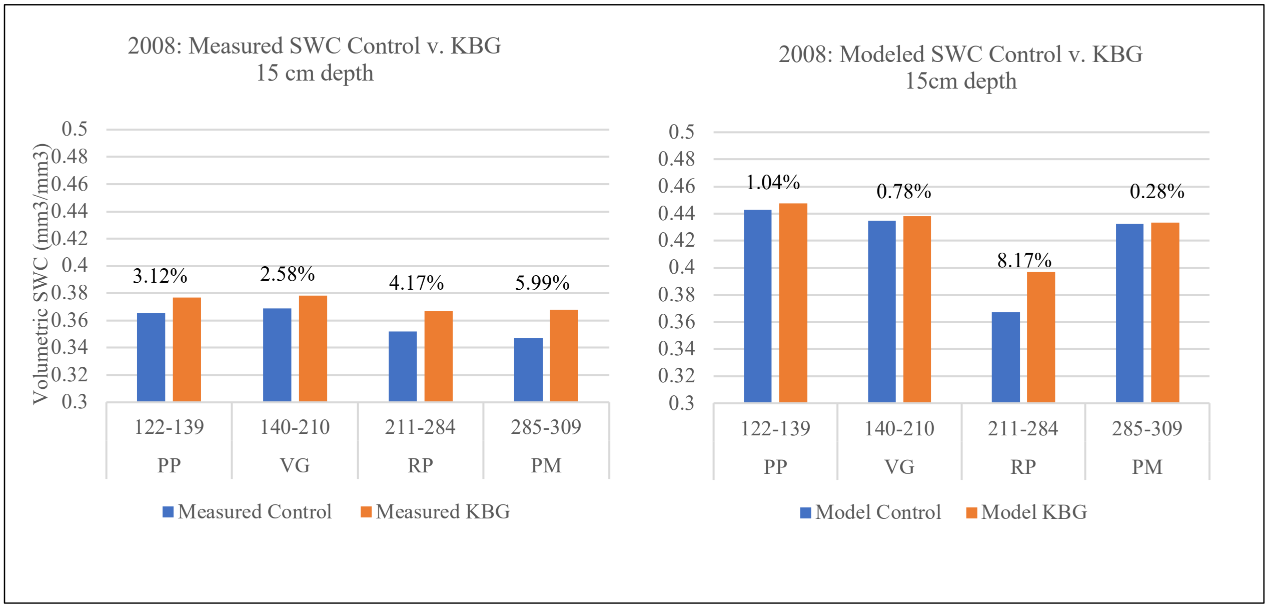


*Figure 7: 2008 volumetric soil water content for field-measured control vs. KBG and modeled control vs. KBG. Includes percent difference between plots. Ames, IA. PP= pre-planting, VG= vegetative, RP= reproductive, PM= post maturity*

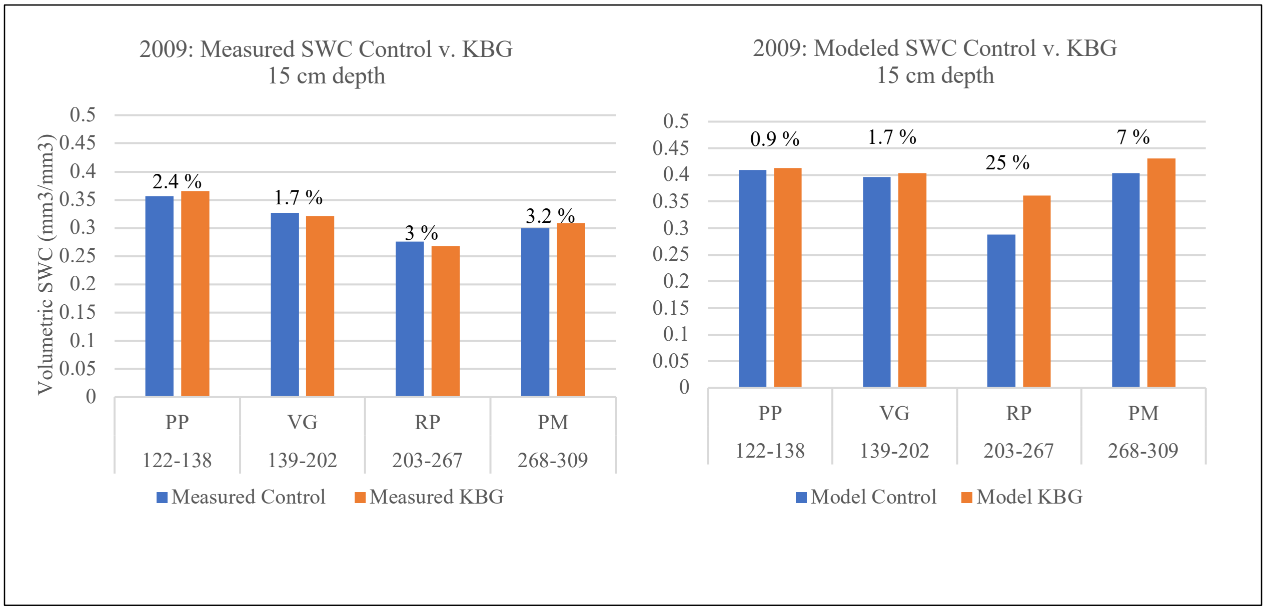


*Figure 8: 2009 volumetric soil water content for field-measured control vs. KBG and modeled control vs. KBG. Includes percent difference between plots. Ames, IA. PP= pre-planting, VG= vegetative, RP= reproductive, PM= post maturity*

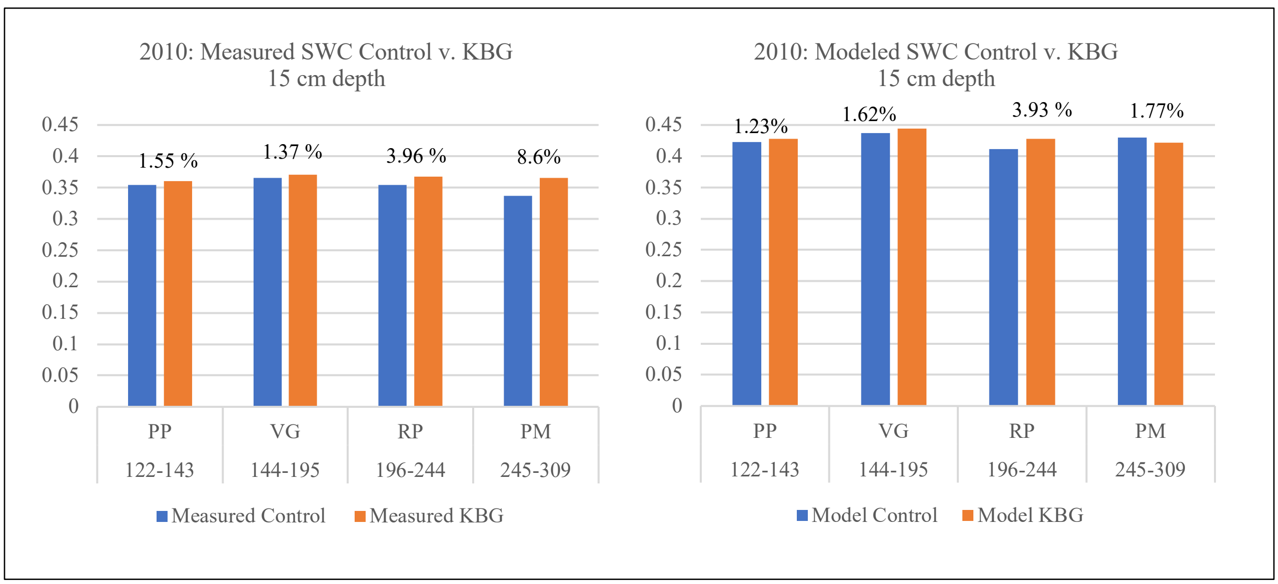


*Figure 9: 2010 Volumetric soil water content for field-measured control vs. KBG and modeled control vs. KBG. Includes percent difference between plots. Ames, IA. PP= pre-planting, VG= vegetative, RP= reproductive, PM= post maturity*

*Table 7: Measured vs. modeled reproductive stage corn transpiration, Ames, IA.*

| | **Control** | | | **KBG** | | |
|---|---|---|---|---|---|---|
| | **2008** | **2009** | **2010** | **2008** | **2009** | **2010** |
| **Measured transpiration (mm)** | 262 | 274 | 211 | 155 | 260 | 188 |
| **Modeled transpiration (mm)** | 140 | 49 | 160 | 126 | 81 | 138 |

*Table 8: Modeled total annual ET, evaporation, and corn transpiration, Ames, IA.*

| | **Control** | | | **KBG** | | |
|---|---|---|---|---|---|---|
| | **2008** | **2009** | **2010** | **2008** | **2009** | **2010** |
| **Annual ET (mm)** | 515 | 507 | 510 | 466 | 454 | 447 |
| **Evaporation (mm)** | 268 | 254 | 264 | 249 | 241 | 249 |
| **Transpiration (mm)** | 247 | 254 | 246 | 217 | 213 | 198 |

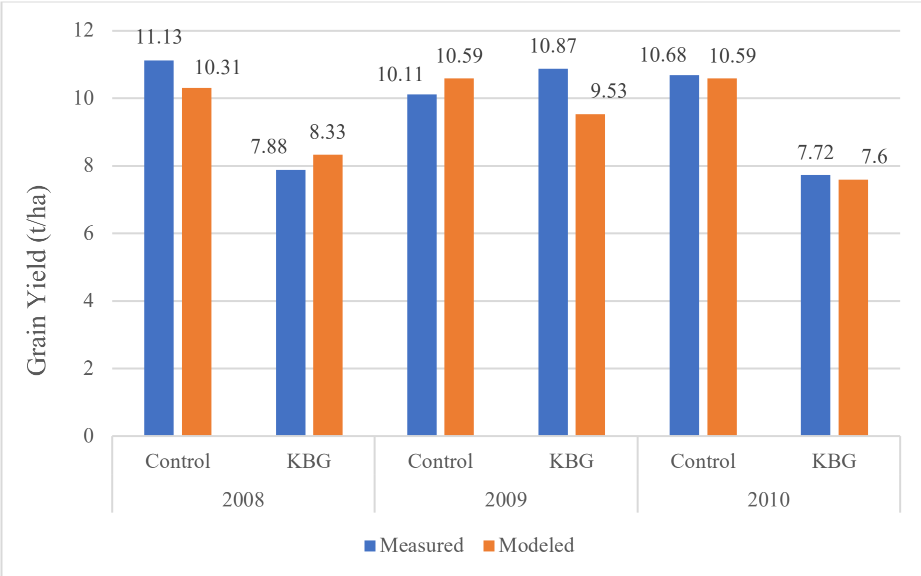


*Figure 10: Measured vs. modeled corn yield at 15% moisture content, Ames, IA.*

CONCLUSIONS

The simulation of PGC with STICS was limited by its inability to implement the typical management practices as well as a lack of data required for calibration. The model, does, however, have capabilities for simulating intercrops that are promising. The complexity of the model, however, requires many observed variables to obtain a reasonable calibration of the many model parameters.

STICS loosely followed SWC trends observed in the control and KBG plots, but whether the year was excessively rainy or dry was not correlated with whether STICS would simulate the observed trends or not. The underprediction of transpiration needs further exploration since the error is quite significant. Finally, agreement between predicted and observed yield may be the result of compensating error rather than a well-tuned model. More information on accumulated biomass and LAI will increase confidence in the yield predictions.

These preliminary results are evidence that STICS, with proper calibration, can predict intercropping yields and water balance with reasonable accuracy. As more data become available, confidence in the model's performance can be verified. For now, there is sufficient promise to justify more exploration of the STICS model and its application to the PGC system.

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**CHAPTER 4: General Conclusions**

STICS is unique in its ability to simulate intercrops, but limitations in management choices makes accurate simulations of the PGC system difficult. This was the same limitation for the KBG parameterization, which was fatally flawed by its intensive management and need for separate USMs. The KBG file had limited application outside its calibration to the mowed management, and many parameter values were reset to tall fescue values when applied to the intercrop.

With models, there is almost always a desire for more data and this research is no exception. Further use of STICS would greatly benefit from more data on both the PGC and main crop. Data collection, however, is time consuming and labor-intensive, so focus should be placed on those metrics most useful. Data on LAI, above-ground biomass, ET, yield, and soil moisture would be very useful in further calibration efforts, for both the PGC and corn. Monthly field measurements on some, or all, of these metrics would greatly aid in model calibration and performance. Data collection starting with the greening of the PGC and through post-maturity of the corn would be preferable, and with a consistent sampling site. Once these data are available, STICS will be much more useful for the needs of this project.

STICS is a highly parameterized model, with greater control afforded to the user, but it also has a steep learning curve. The preliminary results from this work are encouraging enough that further exploration of the model's intercropping formalism is warranted. With more data, future work could explore the model's built-in optimization tools or its R studio link to try different calibration methods.

**APPENDIX 1. Parameters for the simulation of cut crops**

STICS has a cut crop formalism to simulate multiple cutting events throughout the growing season. Primarily intended for forage cuts, this option allows users to cut depending on phenological stage or on a specific calendar date. If cutting on specific dates, there are further options to drive the model with cutting height or with residual LAI and residual biomass. In this case, the model was driven by residual LAI and biomass, with the cutting height determined by these parameters. The formalisms in the model to drive cuttings via cutting height limited the potential residual LAI and biomass and therefore were not suitable for the observed values we were trying to achieve.

The cut crop formalism is the best choice to simulate regular mowing in STICS, but it is not necessarily suited for this use. Turfgrass lawns are highly maintained with regular cuttings at low heights, between 2-4 inches. Even at this cutting height, residual biomass is still significant, with observed values of 3.4 t/ha (Beaudoin et al. 2022). If choosing to drive the simulation with cutting height, STICS could only simulate a maximum of 2 t/ha residual biomass due to constraints on the parameters, specifically $coefmshaut_P$ (Beaudoin et al. 2022).

Due to these limitations, driving the model with residual LAI and residual biomass is the most suitable choice. This option allows users to define residual biomass and LAI, and this is especially crucial for achieving a residual biomass of 3.4 t/ha and LAI value over 1. Plant height (*hauteur*) is determined according to equation 1 after each cut. The targeted value for cutting height is 5.1cm, but by driving the model with residual LAI and biomass cutting height is closer to 12cm. There was a tradeoff of either simulating cutting height accurately, at the cost of reasonable LAI and biomass values, or achieving good biomass and LAI values with a slightly higher cutting height. For the purpose of modeling water competition, accurate LAI and biomass values were deemed more critical.

$$hauteur(t) = hautmax_p \; x \; \left(1 - exp\left(-khaut \times \left(lai(t) + laisen(t)\right)\right)\right) + hautbase_P \qquad \text{(eqn. 1)}$$

**hauteur(t)=** height of crop (m)

**$hautbase_P$**= basal height of plant (m)

**$hautmax_p$**= maximum height of crop (m)

**laisen=** LAI of senescent leaves ($m^2/m^2$)

**$khaut_p$**= extinction coefficient connecting LAI to crop height (ND)

*(EQUATION ONLY TRUE WITH BEER'S LAW, NOT RADIATIVE TRANSFER. Beer's Law was used for KBG parameterization)

When initiating cutting events in STICS, certain criteria must be met for cuttings to proceed. Simulated values of biomass, LAI, and a harvestable fraction must be greater than the amount desired to be left in the field after cutting. If any of these criteria are not met the cut will be delayed until the requirements are satisfied. To avoid delays in cuttings, parameters relating to leaf and shoot biomass growth were significantly increased from the base plant file (Table 4). This was also an important step to simulate higher biomass clipping yields.

One of the biggest limitations to implementing a turfgrass management style is that STICS could not implement more than 11 cuts per *unit of simulation* (USM), so three USMs were needed for each study year to accommodate all 28 cuttings. While much of the data from the previous USM is carried over to the next, not all variables are translated between USMs. Importantly, leaf lifespan, parameter *durvief*, is recalculated between each USM, causing irregular drops in LAI throughout the season. Leaf lifespan is not calculated through degree days, but with an exponential-type function using cumulative Q10 units, which are about 20% of the degree-day lifespan (Kopp and Guillard 2004). The amount of plant material at the start of the USM will senesce once *durvief* is reached, therefore causing significant senescence in the middle of a USM (figure 1). The plant stage is also not carried over between each USM, so the emergence stage occurred three times in each study year. Growth parameters such as radiation use efficiency vary between plant stages, so resetting between USMs affects biomass accumulation which likely explains some of the discrepancy in modeled versus measured data.

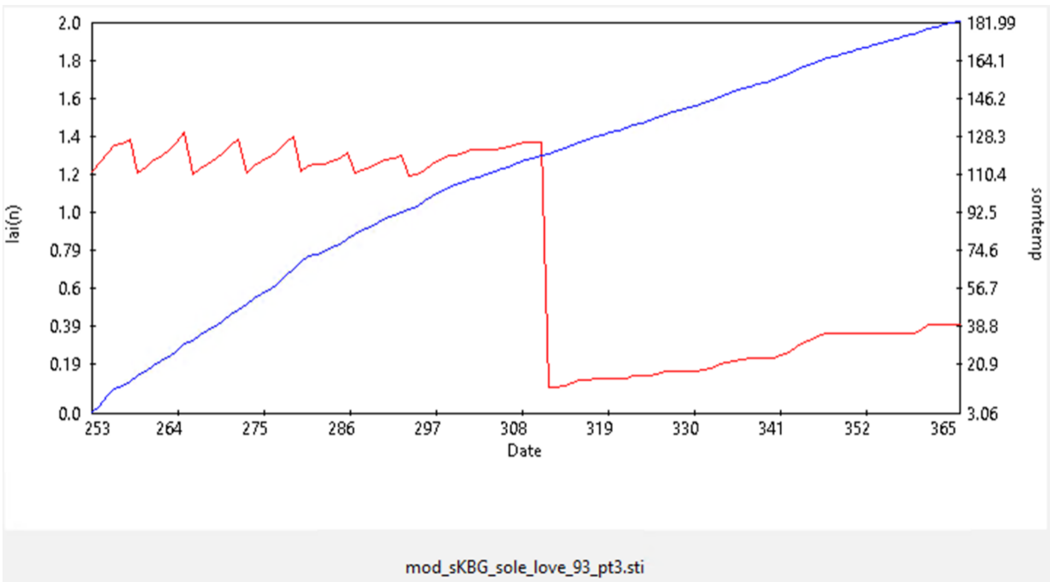


*Figure 11: LAI drop when somtemp (sum of temperatures expressed in Q10 units) reaches 120 (durvieF=120). x-axis = julian days*

Another obstacle to implementing mowings into the model is the continual accumulation of clipping mulch. Decomposition of organic matter in STICS occurs at a slower rate on the surface of the soil than organic matter incorporated into the soil. With weekly cuttings, the cut biomass quickly accumulates and very little of it decomposes, which is not consistent with the typical rapid decomposition of turf clippings (Beaudoin et al. 2022). As a result, the mulch accounts for a significant portion of the evaporative flux from the system, even outpacing evapotranspiration. Simply exporting each cut would diminish nitrogen in the soil, and therefore is not a viable solution. Decomposition parameters were not keeping pace with the decomposition rate that would be expected from turf clippings, resulting in outrageously high amounts of mulch. To accelerate decomposition, parameters FTEMr (Parameter (1/2) of the temperature function on decomposition rate of organic residues), FTEMra (Parameter (2/2) of the temperature function on decomposition rate of organic residues), and TREFr (reference temperature for decomposition of organic residues) were altered to affect temperatures at which decomposition would proceed.

With weekly mowing, root death was high and limited plant growth. To mitigate this, the formalism to turn off root death at cutting was selected. As a result, the plant had more regular growth and cuttings were not delayed as frequently. Root parameters for KBG need more attention, but a lack of observed data limited our ability to tune these parameters.

**APPENDIX 2: Plant Parameters in STICS**

This table lists plant file parameter values for species used in the sole KBG simulation and the corn variety for the intercrop. Some parameters in the KBG file were changed for the intercrop simulation.

| Chapter/formalism | Parameter | Corn (variety 34A20) | Kentucky Bluegrass (turfgrass) | Kentucky Bluegrass (intercrop) | Grass (fescue cultivar) |
|---|---|---|---|---|---|
| Development/Phasic development | tdmin | 6 | 0 | 0 | 0 |
| | tdmax | 32 | 25 | 25 | 25 |
| | codetemp | 1 | 2 | 2 | 2 |
| | codegdh | 1 | | | |
| | coeflevamf | | 1 | 1 | 1 |
| | coefamflax | | 1 | 1 | 1 |
| | coeflaxsen | | 1 | 1 | 1 |
| | coefsenlan | | 1 | 1 | 1 |
| | coeflevdrp | | 1 | 1 | 1 |
| | coefdrpmat | | 1 | 1 | 1 |
| | coefflodrp | | 1 | 1 | 1 |
| | codephot | 2 | 1 | 1 | 1 |
| | codephot_part | 2 | 2 | 2 | 2 |
| | coderetflo | 2 | 1 | 1 | 1 |
| | stressdev | | 0.2 | 0.2 | 0.2 |
| | codebfroid | 1 | 1 | 2 | 1 |
| | jvcmini | | 7 | 7 | 7 |
| | julvernal | | 274 | 274 | 274 |
| | tfroid | | 6.5 | 6.5 | 6.5 |
| | ampfroid | | 10 | 10 | 10 |
| | tdmindeb | | | | |
| | tdmaxdeb | | | | |
| | codedormance | 3 | | | |
| | ifindorm | | | | |
| | q10 | | | | |
| | idebdorm | | | | |
| | codegdhdeb | 2 | | | |
| | code_WangEngel | 2 | | | |
| | tdoptdeb | | | | |

| | | | | | |
|---|---|---|---|---|---|
| Development/Phasic development* | stlevamf | 350 | 116 | 116 | 116 |
| | stamflax | 550 | 1000 | 5000 | 800 |
| | stlevdrp | 1150 | 1000 | 1000 | 1000 |
| | stflodrp | 250 | 0 | 0 | 0 |
| | stdrpdes | 650 | 700 | 700 | 700 |
| | jvc | | 33 | 33 | 33 |
| | stdordebour | | | | |
| | sensiphot | | 0.5 | 0 | 0 |
| | phobase | | 6.3 | 6.3 | 6.3 |
| | phosat | | 20 | 20 | 20 |
| Development/Emergence and starting | tgmin | 8 | 0 | 0 | 0 |
| | codeperenne | 1 | 2 | 2 | 2 |
| | codegermin | 1 | 1 | 1 | 1 |
| | stpltger | 35 | 50 | 50 | 50 |
| | potgermi | -1.6 | -1.6 | -1.6 | -1.6 |
| | nbjgerlim | 50 | 50 | 50 | 50 |
| | propjgermin | 1 | 1 | 1 | 1 |
| | codehypo | 1 | 1 | 1 | 1 |
| | belong | 0.022 | 0.012 | 0.012 | 0.012 |
| | celong | 2.04 | 3.2 | 3.2 | 3.2 |
| | elmax | 8 | 8 | 8 | 8 |
| | nlevlim1 | 50 | 10 | 10 | 10 |
| | nlevlim2 | 50 | 50 | 50 | 50 |
| | vigueurbat | 1 | 1 | 1 | 1 |
| | laiplantule | | | | |
| | nbfeuilplant | | | | |
| | masecplantule | | | | |
| | zracplantule | | | | |
| | | | | | |
| Leaves | phyllotherme | 70 | 200 | 200 | 200 |
| | laicomp | 0 | 0 | 0 | 0 |
| | tcmin | 8 | 0 | 0 | 0 |
| | tcmax | 32 | 30 | 25 | 25 |
| | tcxstop | 35 | 40 | 30 | 30 |
| | codelaitr | 1 | 1 | 1 | 1 |
| | vlaimax | 2.2 | 2.2 | 2.2 | 2.2 |
| | pentlaimax | 5.5 | 5.5 | 5.5 | 5.5 |
| | udlaimax | 3 | 3 | 3 | 3 |

| | | | | | |
|---|---|---|---|---|---|
| | ratiodurvieI | 1 | 1 | 0.8 | 0.8 |
| | ratiosen | 0.8 | 0.2 | 0.2 | 0.8 |
| | abscission | 0 | 0.4 | 0.8 | 0.8 |
| | parazofmorte | 13 | 13 | 13 | 13 |
| | innturgmin | 0.3 | 0.3 | 0.3 | 0.3 |
| | dlaimin | 0 | 0.3 | 0.1 | 0.1 |
| | codlainet | 2 | 2 | 2 | 2 |
| | tustressmin | | | | |
| | durviesupmax | 0.4 | 0.4 | 0.4 | 0.4 |
| | codestrphot | 2 | 2 | 2 | 2 |
| | phobasesen | | | | |
| | dltamsmaxsen | | | | |
| | dltamsminsen | | | | |
| | alphaphot | | | | |
| | tauxrecouvmax | | | | |
| | tauxrecouvkmax | | | | |
| | pentrecouv | | | | |
| | infrecouv | | | | |
| Leaves* | adens | -0.12 | -0.5 | -0.5 | -0.5 |
| | bdens | 5 | 140 | 140 | 140 |
| | hautbase | 0 | 0.02 | 0.02 | 0.02 |
| | hautmax | 2.5 | 0.5 | 0.5 | 0.3 |
| | khaut | 0.7 | 0.2 | 0.1 | 0.7 |
| | durvieF | 200 | 120 | 120 | 120 |
| | stlaxsen | | | | |
| | stsenlan | | | | |
| | dlaimax | | | | |
| | dlaimaxbrut | 0.0016 | 0.00047 | 8.00E-06 | 2.26E-05 |
| | innsen | 1 | 0.2 | 1 | 1 |
| | rapsenturg | 0 | 0 | 0 | 0 |
| Shoot biomass growth | temax | 32 | 40 | 25 | 25 |
| | teoptbis | 32 | 24 | 24 | 25 |
| | efcroijuv | 1.9 | 5 | 2 | 2 |
| | efcroiveg | 3.8 | 10 | 2.5 | 2.5 |
| | efcroirepro | 3.8 | 4 | 2.2 | 2.2 |
| | remobres | 0.2 | 0.1 | 0.05 | 0.05 |
| | coefmshaut | 0 | 100 | 100 | 25 |
| Shoot biomass growth* | temin | 8 | 0 | 0 | 0 |
| | teopt | 24 | 18 | 18 | 15.274 |

| | | | | | |
|---|---|---|---|---|---|
| Radiation interception | codetransrad | 2 | 1 | 2 | 1 |

| | | | | | |
|---|---|---|---|---|---|
| | forme | 1 | | 1 | |
| | rapforme | 5 | | 2.6 | |
| | adfol | 1 | | 1 | |
| | dfolbas | 4 | | 5 | |
| | dfolhaut | 4 | | 5 | |
| Radiation interception* | extin | | 0.9 | | 0.55 |
| | ktrou | 0.5 | | 0.45 | |
| | | | | | |
| Yield formation | codeindetermin | 1 | 1 | 1 | 1 |
| | cgrain | 0.05 | 0.035 | 0.035 | 0.035 |
| | cgrainv0 | 0.111 | -0.139 | -0.139 | -0.139 |
| | irazomax | 0 | 0.879 | 0.879 | 0.879 |
| | codeir | 2 | 1 | 1 | 1 |
| | irmax | | 0.55 | 0.55 | 0.55 |
| | nboite | | | | |
| | allocfrmax | | | | |
| | afpf | | | | |
| | bfpf | | | | |
| | cfpf | | | | |
| | dfpf | | | | |
| | spfrmin | | | | |
| | spfrmax | | | | |
| | splaimin | | | | |
| | splaimax | | | | |
| | codcalinflo | 1 | | | |
| | codetremp | 1 | 1 | 1 | 1 |
| | tminremp | 0 | 0 | 0 | 0 |
| | tmaxremp | 40 | 28 | 28 | 28 |
| Yield formation* | pgrainmaxi | 0.2 | 0.01 | 0.01 | 0.01 |
| | vitpropsucre | 0 | 0 | 0 | 0 |
| | vitprophuile | 0 | 0 | 0 | 0 |
| | vitirazo | 0.011 | 0.01757 | 0.01757 | 0.01757 |
| | deshydbase | 0.008 | 0.008 | 0.008 | 0.008 |
| | nbjgrain | 20 | 30 | 30 | 30 |
| | nbgrmin | 1500 | 6000 | 6000 | 6000 |
| | nbgrmax | 4500 | 30000 | 30000 | 30000 |
| | stdrpmat | 650 | 600 | 600 | 600 |
| | vitircarb | | 0.011 | 0.011 | 0.011 |
| | vitircarbT | 0.0011 | | | |
| | afruitpot | | | | |
| | dureefruit | | | | |

| | | | | | |
|---|---|---|---|---|---|
| | stdrpnou | | | | |
| | nbinflo | | | | |
| | inflomax | | | | |
| | pentinflores | | | | |

| | | | | | |
|---|---|---|---|---|---|
| Roots | sensanox | 0 | 0 | 0 | 0 |
| | stoprac | lax | lax | lax | rec |
| | sensrsec | 0 | 0.5 | 0.5 | 0 |
| | contrdamax | 0 | 0.3 | 0.3 | 0.3 |
| | rayon | 0.02 | 0.02 | 0.02 | 0.02 |
| | codetemprac | 2 | 1 | 1 | 1 |
| | codemortalracine | 2 | 2 | 1 | 1 |
| | coefracoupe | | | 0.5 | 0.5 |
| | coderacine | 2 | 2 | 2 | 1 |
| | zlabour | | | | 25 |
| | zpente | | | | 25.5 |
| | zprlim | | | | 40 |
| | draclong | 5000 | 80 | 80 | |
| | debsenrac | 1500 | 500 | 500 | |
| | lvfront | 0.05 | 0.05 | 0.05 | |
| | longsperac | 11000 | 18182 | 18182 | |
| | codedisrac | 2 | 2 | 1 | |
| | kdisrac | | | 0.00062 | |
| | alloperirac | | | 0.23 | |
| | codazorac | 2 | 2 | 2 | |
| | minefnra | | | | |
| | minazorac | | | | |
| | maxazorac | | | | |
| | codtrophrac | 3 | 3 | 3 | |
| | repracpermax | | | | 0.85 |
| | repracpermin | | | | 0.9 |
| | krepracperm | | | | 1 |
| | repracseumax | | | | |
| | repracseumin | | | | |
| | krepracseu | | | | |
| | code_INN_root | 2 | 2 | 2 | |
| | code_rootdeposition | 2 | 2 | 2 | |
| | parazorac | | | | |
| | code_diff_root | 2 | 2 | 2 | |
| | lvmax | | | | |

| | | | | | |
|---|---|---|---|---|---|
| | rapdia | | | | |
| | RTD | | | | |
| | propracfmax | | | | |
| Roots* | croirac | 0.15 | 0.008 | 0.008 | 0.03 |

| | | | | | |
|---|---|---|---|---|---|
| Nitrogen | Vmax1 | 0.0018 | 0.0018 | 0.0018 | 0.0018 |
| | Kmabs1 | 50 | 50 | 50 | 50 |
| | Vmax2 | 0.017 | 0.05 | 0.05 | 0.05 |
| | Kmabs2 | 25,000.00 | 25000 | 25000 | 25000 |
| | adil | 3.5 | 4.8 | 4.8 | 4.8 |
| | bdil | 0.37 | 0.32 | 0.32 | 0.32 |
| | masecNmax | 1 | 1 | 1 | 1 |
| | INNmin | 0.3 | 0.3 | 0.3 | 0.3 |
| | INNimin | -0.5 | -0.5 | -0.5 | -0.5 |
| | inngrain1 | 2 | 1 | 1 | 1 |
| | inngrain2 | 2 | 1 | 1 | 1 |
| | bdilmax | 0.37 | 0.32 | 0.32 | 0.32 |
| | codeplisoleN | 2 | 2 | 2 | 2 |
| | adilmax | | | | |
| | Nmeta | 4.8 | 6.47 | 6.47 | 6.47 |
| | masecmeta | 0.04 | 0.04 | 0.04 | 0.04 |
| | Nreserve | 1.5 | 1.5 | 1.5 | 1.5 |
| | codeINN | 1 | 1 | 1 | 1 |
| | codelegume | 1 | 1 | 1 | 1 |
| | stlevdno | | | | |
| | stdnofno | | | | |
| | stfnofvino | | | | |
| | vitno | | | | |
| | profnod | | | | |
| | concNnodseuil | | | | |
| | concNrac0 | | | | |
| | concNrac100 | | | | |
| | tempnod1 | | | | |
| | tempnod2 | | | | |
| | tempnod3 | | | | |
| | tempnod4 | | | | |
| | codefixpot | 1 | 1 | 1 | 1 |
| | fixmax | | | | |
| | fixmaxveg | | | | |
| | fixmaxgr | | | | |
| | codazofruit | 2 | 2 | 2 | 2 |

| | | | | | |
|---|---|---|---|---|---|
| Water | h2ofeuilverte | 0.9 | 0.9 | 0.9 | 0.9 |
| | h2ofeuiljaune | 0.15 | 0.15 | 0.15 | 0.15 |
| | h2otigestruc | 0.6 | 0.6 | 0.6 | 0.6 |
| | h2oreserve | 0.7 | 0.7 | 0.7 | 0.7 |
| | h2ofrvert | 0.4 | 0.4 | 0.4 | 0.4 |
| | tempdeshyd | 0.005 | 0.005 | 0.005 | 0.005 |
| | codebeso | 2 | 2 | 2 | 1 |
| | kmax | | | | 1 |
| | rsmin | 175 | 200 | 200 | |
| | codeintercept | 2 | 2 | 2 | 2 |
| | mouillabil | | | | |
| | stemflowmax | | | | |
| | kstemflow | | | | |
| Water* | psisto | 12 | 15 | 15 | 12 |
| | psiturg | 5 | 4 | 4 | 1 |
| | swfacmin | 0.1 | 0.1 | 0.1 | 0.1 |
| Frost | tletale | -5 | -25 | -25 | -25 |
| | tdebgel | 0 | -10 | 0 | -5 |
| | codgellev | 1 | 2 | 2 | 2 |
| | nbfgellev | | 2 | 2 | 2 |
| | tgellev90 | | -20 | -20 | -20 |
| | codgeljuv | 1 | 2 | 2 | 2 |
| | tgeljuv90 | | -20 | -20 | -20 |
| | codgelveg | 1 | 1 | 2 | 2 |
| | tgelveg90 | | | -10 | -10 |
| | codgelflo | 1 | 2 | 2 | 2 |
| | tgelflo10 | | -4.5 | -4.5 | -4.5 |
| | tgelflo90 | | -6.5 | -6.5 | -6.5 |
| Frost* | tgellev10 | -1 | -6 | -6 | -6 |
| | tgeljuv10 | -1 | -10 | -10 | -10 |
| | tgelveg10 | -1 | | -4.5 | -4.5 |

*indicates parameter in cultivar parameter section

**APPENDIX 3: Calibration scheme for KBG**

**Table 16.3** Calibration Pattern without observed LAI or phenological stages from the STICS "redbook". (Green highlights are parameters of interest) (Beaudoin et al. 2022)

<table>
<tr><th>Step</th><th>Forcing</th><th colspan="2">Process</th><th>Parameters to calibrate</th><th>Targeted variable</th></tr>
<tr><td>1</td><td rowspan="12">LAI + emergence date</td><td colspan="2">Root growth</td><td>Croirac</td><td>zrac, HR or resmes</td></tr>
<tr><td rowspan="4">1a</td><td rowspan="4">Root Growth</td><td rowspan="4">True density</td><td>draclong, debsenrac, lvfront</td><td rowspan="3">HR, resmes, azomes, msrac, or LRACH and C&N stocks evolution (under perennial crops)</td></tr>
<tr><td>(+) activation of continuous trophic linked production: repracpermax, repracpermin, krepracperm</td></tr>
<tr><td>(+) activation of standard root distribution: kdisrac, alloperirac</td></tr>
<tr><td>(+) activation of simulation of 2 root classes (recommended for perennial crops): RTD, rapdia, propracfmax</td><td>HR, resmes, azomes, msrac, or LRACH and C&N stocks evolution (under perennial crops)</td></tr>
<tr><td rowspan="2">2</td><td rowspan="2">Biomass growth</td><td>In all situations</td><td>efcroijuv, efcroiveg, efcroirepro, teopt, teoptbis, sea, psisto</td><td>masec</td></tr>
<tr><td>Additional params for simulation of C reserves</td><td>propresP + propres + tauxmortresp</td><td>masecnp, maperenne</td></tr>
<tr><td rowspan="3">3</td><td rowspan="3">N absorption</td><td>In all situations</td><td>vmax2, inngrain1, inngrain2, INNmin</td><td>QNplante</td></tr>
<tr><td>Additional params for simulation of N partitioning (structural N, reserves and roots)</td><td>PropresPN + parazoper + parazorac + parazofmorte, parazotmorte</td><td>QNplantenp, QNperenne, QNrac</td></tr>
<tr><td>Additional params for leguminous</td><td>fixmaxveg, mixmaxgr, concNrac0, concNrac100</td><td>Qfix</td></tr>
<tr><td>4</td><td colspan="2">Elaboration of yield</td><td>vitircarb/vitircarbT, IRmax, tmaxremp, nbgrmax, pgrainmaxi, stlevdrp, stdrpmat</td><td>mafruit</td></tr>
<tr><td>5</td><td colspan="2">Elaboration of quality of harvested organs</td><td>Vitirazo, stdrpdes, tempdeshyd, deshydbase, vitprophuile, vitpropsucre</td><td>CNgrain, H2Orec, oil, sugar</td></tr>
<tr><td>6</td><td>Emergence date</td><td colspan="2">Foliage growth</td><td>dlaimaxbrut/dlaimax, tigefeuil, innturgmin, innsen, rapsenturg, psiturg, adens, durvieF, stlevamf, stamflax, jvc (annual crops) sensiphot</td><td>LAI</td></tr>
</table>

## APPENDIX 4: File names in STICS

| USM name | Climate file | Weather Station | Initializations | Management file | plant file | soil |
|---|---|---|---|---|---|---|
| KBG_sole_love_85 | Love.1985 | Loveland_sole_sta | KBG_ini | KBG_love_85_tec | KBG_sole | sol_CSU |
| KBG_sole_love_86 | Love.1986 | Loveland_sole_sta | KBG_2_ini | KBG_love_cuts_tec | KBG_sole | sol_CSU |
| KBG_sole_love_87 | Love.1987 | Loveland_sole_sta | KBG_2_ini | KBG_love_cuts_tec | KBG_sole | sol_CSU |
| KBG_sole_love_88 | Love.1988 | Loveland_sole_sta | KBG_2_ini | KBG_love_cuts_tec | KBG_sole | sol_CSU |
| KBG_sole_love_89 | Love.1989 | Loveland_sole_sta | KBG_2_ini | KBG_love_cuts_tec | KBG_sole | sol_CSU |
| KBG_sole_love_90 | Love.1990 | Loveland_sole_sta | KBG_2_ini | KBG_love_cuts_tec | KBG_sole | sol_CSU |
| KBG_sole_love_91 | Love.1991 | Loveland_sole_sta | KBG_2_ini | KBG_love_cuts_tec | KBG_sole | sol_CSU |
| KBG_sole_love_92 | Love.1992 | Loveland_sole_sta | KBG_2_ini | KBG_love_cuts_tec | KBG_sole | sol_CSU |
| KBG_sole_love_93 | Loveland.1993 | Loveland_sole_sta | KBG_2_ini | KBG_love_93_study_tec | KBG_sole | sol_CSU |
| KBG_sole_love_93_pt2 | Loveland.1993 | Loveland_sole_sta | KBG_2_ini | KBG_love_93_study_2_tec | KBG_sole | sol_CSU |
| KBG_sole_love_93_pt3 | Loveland.1993 | Loveland_sole_sta | KBG_2_ini | KBG_love_93_study_3_tec | KBG_sole | sol_CSU |
| KBG_sole_love_94 | Loveland.1994 | Loveland_sole_sta | KBG_2_ini | KBG_love_94_study_tec | KBG_sole | sol_CSU |
| KBG_sole_love_94_pt2 | Loveland.1994 | Loveland_sole_sta | KBG_2_ini | KBG_love_94_study_2_tec | KBG_sole | sol_CSU |
| KBG_sole_love_94_pt3 | Loveland.1994 | Loveland_sole_sta | KBG_2_ini | KBG_love_94_study_3_tec | KBG_sole | sol_CSU |
| KBG_sole_love_95 | Loveland.1995 | Loveland_sole_sta | KBG_2_ini | KBG_love_95_study_tec | KBG_sole | sol_CSU |
| KBG_sole_love_95_pt2 | Loveland.1995 | Loveland_sole_sta | KBG_2_ini | KBG_love_95_study_2_tec | KBG_sole | sol_CSU |
| KBG_sole_love_95_pt3 | Loveland.1995 | Loveland_sole_sta | KBG_2_ini | KBG_love_95_study_3_tec | KBG_sole | sol_CSU |
| | | | | | | |
| Maize_KBG_inter_2007 | AMW_2007 | AMW_sta | KBG_ini | prairie_inter_tec | KBG_soleV3_plt | sol_AMW |
| Maize_KBG_inter_2008 | Sorenson08-10.2008 | AMW_sta | mais_KBG_inter_2 | prairie_inter_tec | KBG_soleV3_plt | sol_AMW |
| | | | | mais_AMW_08_tec | corn_inter_plt | |
| Maize_KBG_inter_2009 | Sorenson.2009 | AMW_sta | mais_KBG_inter_2 | prairie_inter_tec | KBG_soleV3_plt | sol_AMW |
| | | | | mais_AMW_tec | corn_inter_plt | |
| Maize_KBG_inter_2010 | Sorenson08-10.2010 | AMW_sta | mais_KBG_inter_2 | prairie_inter_tec | KBG_soleV3_plt | sol_AMW |
| | | | | mais_AMW_tec | corn_inter_plt | |
| Maize_AMW | Sorenson08-10.2008 | AMW_sta | mais_AMW_ini | mais_AMW_08_tec | corn_inter_plt | sol_AMW |
| Maize_AMW_09 | Sorenson.2009 | AMW_sta | mais_AMW_ini | mais_AMW_tec | corn_inter_plt | sol_AMW |
| Maize_AMW_10 | Sorenson08-10.2010 | AMW_sta | mais_AMW_ini | mais_AMW_tec | corn_inter_plt | sol_AMW |