

Sustainable management in turfgrass systems: Survivability during drought via minimal irrigation and simulating nitrous oxide emissions with process-based models

by

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B.S., South China Agricultural University, 2016

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AN ABSTRACT OF A DISSERTATION

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DOCTOR OF PHILOSOPHY

Department of Horticulture and Natural Resources
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Abstract

Reductions of water and nitrogen (N) inputs have long been important topics for sustainable turfgrass management. Facing rising challenges of water crises and climate change, more research is needed on such topics. With increasing city water shortages and water restrictions on turfgrasses in the U.S., it is important to research strategies to preserve C3 and C4 turfgrasses during prolonged drought. In addition, to guide the best irrigation and N-fertilization management strategies of turfgrass for the mitigation of global warming in this century, process-based models, such as DAYCENT and DeNitrification-DeComposition (DNDC), become important tools, which simulate nitrous oxide (N_2O , an important greenhouse gas and ozone-depleting gas) and soil carbon sequestration. To find strategies for alleviating drought stress during prolonged drought with imposed water restrictions, the objectives in the first part of the dissertation were to (1) evaluate turfgrass performance during drought and recovery among irrigation levels, and (2) determine minimum water amounts for turfgrass during prolonged drought that allow for acceptable recovery. Two independent studies were conducted on C3 and C4 turfgrasses, respectively, using irrigation much lower than recommendation levels during 2 summers of drought under a rainout shelter. Results indicated that during severe drought and imposed water restrictions, minimal weekly irrigation of at least 20 to 30% reference evapotranspiration (ET_0) and 40 to 50% ET_0 could reduce turfgrass damage and conserve water in zoysiagrass (C4; *Zoysia japonica* Steud., hereafter referred to as zoysia) and tall fescue (C3; *Festuca arundinacea* Schreb.), respectively. The failure of Kentucky bluegrass (C3; *Poa pratensis* L.) to survive extended drought was possibly related to being first-year sod. To inform and guide irrigation and N-fertilization management of turfgrass for global warming mitigation, the objectives of the second part of this dissertation were to 1) calibrate DAYCENT and DNDC

for N₂O emissions from Meyer zoysia; 2) validate and test the two calibrated models and compare their prediction accuracies; and 3) predict long-term N₂O emissions, C sequestration, and global warming potential (GWP) of different irrigation and N-fertilization practices. A combination of global sensitivity analysis and a Bayesian method was used to calibrate DAYCENT and DNDC. After calibration, both models were validated using field measurements from two studies of zoysia. Validation results indicated DAYCENT ($R^2 = 0.22$ to 0.89 ; relative RMSE = 36 to 171%) outperformed DNDC ($R^2 = 0.01$ to 0.38 ; relative RMSE = 119 to 193%) in biweekly N₂O fluxes. Annual N₂O emission estimates obtained from validation of DAYCENT were within -49 to +26% of annual estimates interpolated from measurements, whereas DNDC simulations generally underestimated N₂O emissions by up to -86%. Results indicated DAYCENT, but not DNDC, can adequately simulate the impacts of irrigation and N-fertilization practices on N₂O emissions in C4 turfgrasses such as zoysia. When assuming no further climate change, the validated DAYCENT model predicted that the typically recommended N-fertilization and irrigation practice in fairway zoysia turf would reduce net GWP by encouraging soil carbon sequestration in the first 40 years of establishment, better than no N-fertilization, after which reducing N and water inputs would be beneficial in mitigating increases of N₂O emissions and net GWP. A medium global warming scenario would accelerate increases in N₂O emissions and GWP, especially with higher N and water inputs.

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for N₂O emissions from Meyer zoysia; 2) validate and test the two calibrated models and compare their prediction accuracies; and 3) predict long-term N₂O emissions, C sequestration, and global warming potential (GWP) of different irrigation and N-fertilization practices. A combination of global sensitivity analysis and a Bayesian method was used to calibrate DAYCENT and DNDC. After calibration, both models were validated using field measurements from two studies of zoysia. Validation results indicated DAYCENT ($R^2 = 0.22$ to 0.89 ; relative RMSE = 36 to 171%) outperformed DNDC ($R^2 = 0.01$ to 0.38 ; relative RMSE = 119 to 193%) in biweekly N₂O fluxes. Annual N₂O emission estimates obtained from validation of DAYCENT were within -49 to +26% of annual estimates interpolated from measurements, whereas DNDC simulations generally underestimated N₂O emissions by up to -86%. Results indicated DAYCENT, but not DNDC, can adequately simulate the impacts of irrigation and N-fertilization practices on N₂O emissions in C4 turfgrasses such as zoysia. When assuming no further climate change, the validated DAYCENT model predicted that the typically recommended N-fertilization and irrigation practice in fairway zoysia turf would reduce net GWP by encouraging soil carbon sequestration in the first 40 years of establishment, better than no N-fertilization, after which reducing N and water inputs would be beneficial in mitigating increases of N₂O emissions and net GWP. A medium global warming scenario would accelerate increases in N₂O emissions and GWP, especially with higher N and water inputs.

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Dedication

I dedicated this work to my father and mother for their endless love.

Chapter 1 - Minimum water requirements of cool-season turfgrasses for survival and recovery after prolonged drought

ABSTRACT

Water restrictions may be imposed on irrigation during drought with little regard for damage to turfgrass. Minimal irrigation that may result in dormancy during prolonged drought but allows for recovery thereafter may save water and prevent expensive reestablishment. Our objectives were to: 1) evaluate turfgrass quality and performance during drought and recovery among irrigation levels; and 2) determine minimum water amounts in turfgrass during drought that allow for acceptable recovery. Sodded ‘Seed Research 8650’ tall fescue (TF, *Lolium arundinaceum* (Schreb.) Darbysh.) and a ‘Mallard’ and ‘Ridgeline’ Kentucky bluegrass blend (KB, *Poa pratensis* L.) were watered with 0-50% reference evapotranspiration (ET_o) replacement during two summers under rainout shelters near Manhattan, KS. Soil moisture, percentage green cover, normalized difference vegetation index, and turfgrass quality were measured weekly. After fall sodding, TF recovered fully after 60-83 d dry downs in both years even without water inputs. However, KB in all ET_o treatments did not recover in either year. Irrigation at 50% ET_o maintained TF above minimally acceptable quality 15-43 d longer than 0% ET_o during drought, resulted in recovery 17-18 d faster, and reduced water inputs by 38% compared with 80% ET_o , which is usually recommended for well-watered TF. Results indicate TF is better adapted than KB to prolonged drought in the first summer after fall sodding.

INTRODUCTION

In the United States, 42% of all freshwater withdrawals are attributed to agricultural irrigation (Dieter et al., 2018). The total area of irrigated turfgrass is 5 to 10 million ha, which is about 20-43% of the total cropland irrigated area (Milesi, Elvidge, & Nemani, 2009). Along with rising water demand, increasing frequencies and scales of extreme weather events such as drought could disrupt water availability for crop irrigation (Hatfield, 2017). Therefore, water shortages caused by increasing anthropological demands, limited water supplies, and natural drought pose significant challenges to the turfgrass industry (Gelernter, Stowell, Johnson, Brown, & Beditz, 2015).

About 68% of total turfgrass area is composed of residential lawns (Milesi et al., 2009). To conserve water, water restrictions are usually imposed by limiting irrigation to specific hours within a day and/or days within a week, regardless of dynamics in weather or the water requirements of turfgrass (Boyer, Dukes, Duerr, & Bliznyuk, 2018). Unfortunately, such strategies can inadvertently result in overwatering, and the effectiveness of water restrictions has been studied very little (Boyer et al., 2018). When water is severely restricted or even prohibited for irrigation during prolonged drought, stressed turfgrass may fail to recover thereafter, resulting in significant reestablishment costs and a loss of environmental benefits (e.g. cooling effects, reductions in airborne dust and soil erosion) (Beard, 1973).

Tall fescue (TF, *Festuca arundinacea* Schreb.) and Kentucky bluegrass (KB, *Poa pratensis* L.) are popular cool-season turfgrasses for lawns in the transition zone of the U.S. because of their good drought resistance (Qian, Fry, & Upham, 1997; Huang & Fu, 2000; Fry & Huang, 2004; Fu, Fry, & Huang, 2004; Su, Bremer, Keeley, & Fry, 2008). The amount of water required to maintain at or below acceptable quality varies between TF and KB, and even among cultivars of each species (Fu et al., 2004; Lewis, Bremer, Keeley, & Fry, 2012; Richardson, Karcher, Hignight, & Hignight, 2012; Gómez-Armayones, Kvalbein, Aamlid, & Knox, 2018). For example, research at the same location as ours indicated KB required 100% evapotranspiration replacement (ET_a , measured with microlysimeters) to maintain minimally

acceptable turfgrass quality during summer, whereas TF required only 60-80% ET_a replacement (Fu et al., 2004). In Arkansas, maintaining 40% green cover required 43% and 55% less irrigation in drought-resistant vs. drought-sensitive cultivars of TF and KB, respectively (Richardson et al., 2012).

If sufficient water is unavailable to maintain either desired levels of turf quality or some level of green cover during drought or water restrictions, irrigating with less water that allows partial or complete dormancy but keeps plants alive for recovery may be an alternative strategy (Steinke et al., 2010; Monje-Jiménez, Egea, & Pérez-Urrestarazu, 2019). In a dormant state, turfgrass leaves die but crowns and buds can survive droughty periods via osmotic adjustment, resulting in regrowth when soil moisture becomes adequate (Beard, 1973; Qian & Fry, 1997; Fry & Huang, 2004). Previous studies have indicated that limited water applications to turfgrass during drought can mitigate the severity of drought stress and result in good recovery upon rewatering (Karcher, Richardson, Hignight, & Rush, 2008; Richardson, Karcher, Hignight, & Rush, 2008, 2009; Leksungnoen, Johnson, & Kjelgren, 2012; Lewis et al., 2012; Richardson et al., 2012; Goldsby, Bremer, Fry, & Keeley, 2015). Although about 40% reference evapotranspiration (ET_o) has been recommended to allow for cool-season turfgrass survival during drought-induced dormancy in California (Mediterranean climate), quantitative information is limited in the literature regarding minimal water requirements to allow for recovery of cool-season turfgrasses after prolonged drought (Harivandi, Baird, Hartin, Henry, & Shaw, 2009).

Given the increasing frequencies of water restrictions for irrigation of turfgrass during droughty periods, there is a need for more technological and scientific solutions that conserve water while enhancing survival of turfgrasses (Gelernter et al., 2015; Boyer et al., 2018). A logical next step is to evaluate the minimal water requirements of cool-season turfgrasses during prolonged drought that may result in dormancy but also allow for acceptable recovery. Therefore, the objectives of this study were to: 1) determine the minimum water amounts in two cool-season turfgrasses, TF and KB, during drought that allow for an acceptable

recovery; and 2) evaluate turfgrass quality and performance during drought and recovery among various irrigation levels.

METHODS AND MATERIALS

A blend of ‘Mallard’ and ‘Ridgeline’ KB sod and a ‘Seed Research 8650’ TF sod were used at Rocky Ford Turfgrass Research Center near Manhattan, Kansas (39°13’53’’N, 96°34’51’’W). Mallard and Ridgeline KB are classified as Compact America and Compact Midnight types, respectively (Brilman, 2009). The soil was a Chase silty clay loam (fine, smectitic, mesic Aquertic Argiudoll; 10% sand and 28% clay). Sod of KB and TF was installed on 28 Sept. and 10 Oct., respectively, in 2016 under a rainout shelter with a commercial greenhouse design but open sides for air exchange (Thermolator; Agra Tech Inc., Pittsburg, CA). Berms and rain gutters were installed along the length of the shelter to prevent water invasion on the ground as well as to channel water runoff from the roof away from the plots. A new clear greenhouse film (Warp's Flex-O-Glass® Greenhouse Films -6 Mil 4-Year UV Clear Film, Warp Bros., Chicago, IL) was installed during the drought period in 2017, permitting 90% transmission of photosynthetically active radiation (PAR) as measured with a ceptometer (LP-80, Decagon Devices Inc.).

During the 2017 experiment, the KB sod failed to recover from the drought. Therefore, new sod of the same KB blend described above was obtained and installed on 13 Oct. 2017 under an automatic rainout shelter that became available about 100 m north of the greenhouse-designed shelter used in the first year. The original TF sod, which had fully recovered from the drought in the first summer, was also relocated on 3 Oct. to the automated rainout shelter. During the summer drought period, the automatic rainout shelter covered the whole study area when the precipitation reached 0.25 mm and retracted an hour after rainfall ceased (Bremer, Lee, Su, & Keeley, 2011).

This study had a 2 x 6 factorial treatment structure and a split-plot design structure with whole plots (two species) arranged in a randomized complete block design for a total of

48 plots in the study. Each cool-season turfgrass was randomly assigned to a strip (i.e. whole plot) in each of the 4 blocks (i.e. 4 replicates of each irrigation treatment within a species). Six irrigation treatments were randomly assigned to subplots (1.4 x 1.2 m each in 2017 and 1.1 x 1.2 m in 2018) of a whole plot: 0%, 10%, 20%, 30%, 40%, and 50% ET_o replacement using daily on-site weather data (<http://mesonet.k-state.edu/>; some weather data are shown in Fig. 1.1) and the American Society of Civil Engineers (ASCE) standardized reference ET_o equation (Walter et al., 2001). Irrigation was applied once a week by hand with a wand attached to a meter (Model 03N31, GPI, Inc., Wichita, KS).

In 2017, an 83-day dry down period (1 June to 22 Aug) was followed by a 40-day well-watered (two to three times a week to field capacity) phase with the plastic removed. In 2018, the dry down was shortened to a 60-day dry down period (4 June to 3 Aug), due in part to the death of KB during the longer dry down in the first year, but also to match dry down periods reported in other prolonged drought studies (Steinke et al., 2010; Goldsby et al., 2015). In 2018, the automatic rainout shelter was turned on during the 60-day dry down period and recovery was evaluated during a 50-day well-watered period.

Maintenance

Cool-season turfgrasses were mowed at 9 cm once to twice per week following the one-third rule with a rotary mower (Hoyle, 2017), and clippings were removed. Starter fertilizer was applied at 48.9 kg P ha⁻¹ (18-24-12; LESCO) on 26 Oct. 2016, and polymer-coated urea (41-0-0; Duration 120 d, Koch Agronomic Services LLC) was applied at 48.9 kg N ha⁻¹ on 20 Apr. 2017. Urea (Thrive Branded Fertilizer, Mears Fertilizer Inc.) was applied to TF at 44.0 kg N ha⁻¹ on 11 Sept. 2017, for rapid recovery after the dry down, before being transferred to automatic rainout shelter on 3 Oct. After the relocation in 2017, fertilizer (16-4-8; Lebanon Seaboard corp.) and urea were applied at 48.9 kg N ha⁻¹ (5.4 kg P ha⁻¹) and 34.2 kg N ha⁻¹ to both turfgrasses on 13 Oct. and 3 Nov., respectively. Urea was applied at 44.0 kg N ha⁻¹ on 26 May, and (NH₄)₂SO₄ was applied at 44.0 kg N ha⁻¹ on 31 Aug. 2018.

For preventative control of bluegrass billbug (*Sphenophorus parvulus* Gyllenhal) larvae in cool-season turfgrasses, imidacloprid (Merit 0.5 G, Bayer Environmental Science) was applied to the entire site at 0.39 kg a.i. ha⁻¹ on 26 May, 2017 and 2018. In 2018, a billbug trap was installed across the south side of the rainout shelter to monitor adult billbug populations. Bifenthrin (Crosscheck, LESCO) was applied at 0.13 kg a.i. ha⁻¹ on 15 May 2018 to control adult billbugs. Trichlorfon (Dylox 6.2 Granular, Bayer Environmental Science) was applied at 9.1 kg a.i. ha⁻¹ on 3 June 2018 after mild billbug damage was observed only in several KB plots, and the damage ceased before the dry period began.

For control of common dandelion (*Taraxacum officinale* Wigg.) and other broadleaf weeds, a mixture of carfentrazone-ethyl, 2,4-D, mecoprop-p acid, and dicamba acid (SpeedZone, PBI Gordon Corporation) was applied at 1.3 kg a.i. ha⁻¹ on 6 June 2017. For preventative control of brown patch, summer patch, and other diseases, trifloxystrobin (Compass, Bayer Environmental Science) was applied at 0.38 kg a.i. ha⁻¹ on 12 June and 12 July in 2017.

Data collection

All measurements were taken weekly for soil volumetric water content (VWC), turfgrass quality (TQ), normalized difference vegetation index (NDVI), and percentage green cover (PGC). Soil VWC was measured at 0 to 7.6 cm in two random locations within each plot using handheld time-domain-reflectometry equipment (FieldScout TDR 300 Soil Moisture Meter, Spectrum Technologies). Turfgrass quality was evaluated on a numeric rating scale from 1 to 9 (1 = dead turf, 9 = uniform, green and dense turf, and 6 = minimally acceptable turf for use in home lawns) according to color, texture, density, and uniformity (Morris & Shearman, 1998). A handheld active optical sensor (RapidScan CS-45, Holland Scientific) was used to measure NDVI. Reflectance measurements of the sensor were centered at wavelengths of 670 (Red) and 780 (NIR) nm, which allowed for computing NDVI [(NIR-Red)/(NIR+Red)]. Each measurement was obtained at handheld height (~0.9 m)

to scan about 80% of each plot, with readouts of the average value of NDVI. Images for measuring PGC were taken with a Nikon D5000 digital camera (26-mm focal length, an f-stop of 5.6, 1/125 sec exposure time, and 800 ISO-speed; Nikon Inc.) using a lighted camera box (51 cm x 61 cm x 56 cm). Images were analyzed by the method of Karcher & Richardson (2005) (SigmaScan Pro v. 5.0, SPSS Science Marketing Dept.), using threshold ranges of 48-110 for hue and 0-100 for saturation in both species.

Statistical analysis

Irrigation treatment and species main effects and their interactions within each measurement (i.e. VWC, TQ, PGC, NDVI) were analyzed first. Since overall performance between TF and KB was dramatically different within each dry down and recovery period (TQ, PGC, and NDVI were always significantly higher in any irrigation treatment of TF than that of KB), main effects were analyzed separately for TF and KB. Each measurement was analyzed in a mixed model with irrigation and date as fixed effects, block as a random effect, and date as a repeated measure for each dry down and recovery period of each year using PROC GLIMMIX (SAS 9.4m6, SAS Institute). Different variance-covariance structures {compound symmetry [CS], autoregressive [AR(1)], toeplitz [TOEP], heterogeneous compound symmetry [CSH], heterogeneous autoregressive [ARH(1)], heterogeneous Toeplitz [TOEPH], ante-dependence [ANTE(1)], and unstructured (UN)} were investigated to properly fit the models. Irrigation treatment effects were then analyzed on each measurement date for each species using PROC GLIMMIX.

To evaluate and compare turfgrass performance among ET_o treatments during the dry down and recovery periods, values of PGC (30, 40, 50, and 60%), an objective measure, were combined with respective values of TQ (3, 4, 5, and 6), a subjective measure that encompasses more than green cover (e.g., uniformity, texture). The mean numbers of days were compared for which all the plots in each treatment remained above (during dry downs) and were required to recover to (after resuming full irrigation, excluding KB) certain

thresholds of turfgrass performance ($TQ > 4$ and $PGC > 40$; $TQ > 5$ and $PGC > 50$; $TQ > 6$ and $PGC > 60$) using PROC GLIMMIX (irrigation treatment as a fixed effect, block as a random effect). For individual TF plots that never dropped below the abovementioned TQ and PGC thresholds during the dry downs, the total length of each respective dry down was used. Similarly, for individual TF plots that never recovered to a specific threshold of TQ and PGC, the total length of each respective recovery period was used. Comparisons of mean weekly irrigation application amounts over the 2 years were analyzed among irrigation treatments using PROC GLIMMIX (irrigation as a fixed effect, week and year as random effects).

RESULTS AND DISCUSSION

Irrigation main effects on TF and KB during prolonged drought

As expected, VWC, PGC, TQ, and NDVI generally declined with irrigation level in TF during both years of drought (Table 1; Fig. 1.2, 1.3). Specifically, TF in 50% ET_0 plots averaged higher VWC, PGC, TQ, and NDVI than in 0% to 20% ET_0 plots in both years (Table 1). In general, TF irrigated at 50% ET_0 consistently maintained the highest PGC among irrigation treatments during prolonged drought in both years (Fig. 1.2, 1.3). In TF irrigated at $\leq 10\%$ ET_0 , PGC declined faster, falling below 50% ET_0 plots approximately 3-4 weeks after initiation of the dry downs and averaging lower than TF irrigated at $> 30\%$ ET_0 in both years. During both dry downs, PGC averaged 19-26% higher in 50% ET_0 than in 0% ET_0 . None of the irrigation treatments incurred complete dormancy in TF ($TQ < 2$ and $PGC < \sim 3\%$), even after 83 and 60 days of drought in 2017 and 2018, respectively. This was probably because of the drought avoidance mechanism of deep rooting in TF, which exploits soil water in the lower soil profile to alleviate drought stress (Qian et al., 1997; Huang & Fu, 2000; Fry & Huang, 2004; Su et al., 2008). Deep soil at the research sites also likely assisted TF in maintaining PGC during drought periods (Beard, 1973; Bremer, Su, Keeley, & Fry, 2006; Leksungnoen et al., 2012). Another study conducted at the same research site as ours

also found zoysiagrass fully recovered from two months of drought, even with no water inputs (Hong, Bremer, & Keeley, 2020).

Kentucky bluegrass in all irrigation treatments went into complete dormancy during the drought periods in both years ($TQ < 2$ and $PGC < \sim 3\%$) (Fig. 1.4, 1.5). During the dry down, PGC of KB averaged approximately 8% higher in 50% ET_o than in 0% ET_o in 2017, although average differences were not significant among irrigation treatments in 2018 (Table 2). In 2017, KB irrigated at 50% ET_o generally maintained the highest VWC, PGC, TQ, and NDVI among irrigation treatments, and did not go dormant until 2-3 weeks after KB plots in 0 and 10% ET_o (Fig. 1.4). In 2018, PGC and NDVI remained higher in 20% to 50% ET_o than 0% ET_o for the first three weeks of the dry down in KB, but differences diminished among irrigation treatments thereafter (Fig. 1.5). However, there were never any significant differences in TQ among irrigation treatments during the entire dry down in 2018, nor were there any significant irrigation main effects in PGC, TQ, or NDVI across the season despite differences in VWC (Table 2). The reason for fewer differences in KB performance among irrigation treatments during drought in 2018 is uncertain, but it may have been related to higher temperatures in 2018 than 2017 (Fig. 1.1). More discussion about the different performances of KB between two years is included in the next section.

In general, KB in all irrigation treatments declined into dormancy in about 9 weeks in 2017 and 6 weeks in 2018 (Fig. 1.4, 1.5). Soil moisture (VWC) began to increase in 10% to 50% ET_o plots later in the dry downs as KB went into dormancy, probably because plants were no longer transpiring water but were still receiving irrigation. The declines into dormancy in KB during the dry downs in our study are similar to Leksungnoen et al. (2012), who reported that KB went into complete dormancy within five weeks after irrigation cessation in silt loam soils of a high desert climate. Dormancy during drought and heat stress is a more typical survival mechanism in KB than TF (Fry & Huang, 2004). Therefore, the decline into dormancy of KB during the dry downs may have been a function of its drought-tolerance mechanism during the hot Kansas summers (Goldsby et al., 2015).

Drought endurance

In general, drought stress symptoms occurred earlier in KB than TF, and TF performed better than KB (Fig. 1.2-1.5). This is similar to previous studies, both at the same research site as ours and at other locations (Fu et al., 2004; Bremer et al., 2006; Leksungnoen et al., 2012). For example, Fu et al. (2004) reported that when irrigated at 20% ET_a during the first year of drought, TQ in ‘Falcon II’ TF remained acceptable for ~50 days and never dropped below a rating of 5 during a 3-month study, while ‘Brilliant’ KB (a Compact America type) remained acceptable for less than 15 days and was completely dormant after <50 days.

In our study, TF at 50% ET_o maintained above minimally acceptable quality (both $TQ>6$ and $PGC>60$) for 82 days in 2017 and 45 days in 2018, which was 43 and 15 days longer than plots without water (0% ET_o) in respective years (Table 3). Even when watered at only 10% ET_o , TF maintained minimally acceptable quality for 46 and 29 days in 2017 and 2018, respectively. In contrast, KB at 50% ET_o maintained acceptable quality only for 18 days in 2017, and 12 days in 2018 (Table 4). These results suggest that in real-world scenarios, intermittent rainfall could allow for the maintenance of acceptable quality turfgrass for lengthy periods at significantly reduced irrigation rates, especially in TF.

In drought scenarios where water for irrigation of turfgrass is severely restricted, allowing PGC and TQ to decline below what is normally “minimally acceptable” may be a viable strategy to reduce irrigation levels. In other words, each level of deficit irrigation could be applied longer if lower PGC and TQ were acceptable. For example, TF plots at 20% ET_o maintained above minimally acceptable quality ($PGC>60$ and $TQ>6$) for 51 and 33 days in 2017 and 2018, respectively (Table 3). Thereafter, these plots declined below minimally acceptable but yet were all maintained at $PGC>40$ and $TQ>4$ for 82 and 47 days in 2017 and 2018, respectively, which were statistically similar to 50% ET_o plots. Although $PGC>40$ and $TQ>4$ was less than minimally acceptable, it maintained some greenness in the canopy.

Twelve TF cultivars were estimated to reach 50 PGC after 47-51 days without irrigation in Oregon (Karcher et al., 2008). In our study, all TF plots without water maintained both $PGC > 50$ and $TQ > 5$ for 33-46 days (Table 3). Deep soil profiles at both research sites likely assisted TF in exploiting soil water and maintaining PGC during the dry downs. To be noted, without periodical water recharge, TF has high ET_o rates and often dies after all available soil water is depleted (Qian et al., 1997; Huang & Fu, 2000; Fu et al., 2004; Leksungnoen et al., 2012). However, with intermittent rainfall or at least limited water applications during drought, recovery of TF could be encouraged as discussed in the next section.

As for KB, when irrigated at 50% ET_o it maintained above minimally acceptable quality ($PGC > 60$ and $TQ > 6$) for 12 to 18 days, but during the next ~10 days at 50% ET_o the quality declined to less than acceptable although some canopy greenness was maintained ($TQ > 3$ and $PGC > 30$) (Table 4). Other researchers reported that Mallard KB, which was also used in our study, was estimated to reach 50 PGC after 32-45 days without irrigation in the first summer after it was seeded in Oregon (Richardson et al., 2008, 2009). In the first year of an earlier 2-year study conducted under the same rainout shelter as ours, 30 cultivars of KB maintained 75 PGC for an estimated 21-41 days and 25 PGC for 44-54 days with negligible water inputs (~2.5 cm water, Goldsby et al., 2015). One difference between the Goldsby et al. (2015) study and ours is that KB had been seeded >3 years earlier in their study, while in ours KB had been sodded in the previous fall, about 8 months before the dry downs began. It is possible that KB may have weaker drought resistance in the first summer after fall sodding compared with fall seeded or to more established stands of KB.

The cause of the more rapid decline of KB in 2018 than in 2017 (Table 4; Fig. 1.4, 1.5) is uncertain but may have been related to a number of factors. First, as mentioned earlier, temperatures averaged 1.3 °C higher in the spring and summer of 2018 than in 2017 (13 April to 20 Aug., Fig. 1.1), which may have weakened KB in 2018. Kentucky bluegrass may be more susceptible to damage from prolonged drought stress when it is coupled with heat stress

in the summer (Jiang & Huang, 2000). Second, fall sodding of KB prior to the 2018 study was 15 days later than for the 2017 study, resulting in less time for KB to establish before the drought study began in 2018. Third, spring N fertilization occurred one month later in 2018 than 2017, resulting in only nine compared with 42 days between spring N fertilization and the beginning of the dry down in 2018 and 2017, respectively. This may have reduced carbohydrate reserves in KB in 2018, especially in tandem with higher temperatures in 2018 than in 2017 (late April to June; Fig. 1.1). Nitrogen triggers rapid growth in cool-season grasses in spring, which may consume carbohydrate supply and make KB more vulnerable to intense drought stress (Beard, 1973). Finally, billbug damage possibly contributed to the faster rate of decline in KB during 2018, although the leaf firing during the dry down was much more uniform than the billbug damage, which was patchy.

Recovery after prolonged drought

After drought, TF recovered to acceptable quality in both years among all irrigation treatments including at 0% ET_0 (Table 3). In 2017, all TF plots irrigated at 50% ET_0 during the dry down recovered to acceptable quality within one week after resuming full irrigation. This rapid recovery in 50% ET_0 plots was 18-28 days earlier than TF irrigated at 0% to 20% ET_0 during the dry down. Plots at 50% ET_0 also averaged higher across PGC, TQ, and NDVI than plots of 0% to 20% ET_0 during the 2017 recovery (Table 1). In 2018, TF at 50% ET_0 did not recover to acceptable quality until 30 days after resuming full irrigation, which was ~3 weeks longer than in 2017 (Table 3). Furthermore, the recovery in 50% ET_0 was not significantly faster than plots with lower irrigation, nor did PGC and NDVI average significantly higher in 50% ET_0 than any other irrigation treatment (Table 1 and 3). Slower, more variable recovery among irrigation treatments in the second year (2018) was probably because the same TF sod was used in both years, and cumulative drought stress may have depleted the carbohydrate reserves by the end of the dry down in the second year (Huang & Fu, 2000; Fu, Fry, & Huang, 2007; Leksungnoen et al., 2012).

Although dormancy is considered a drought resistance strategy, KB did not recover from prolonged drought stress in any irrigation treatment in either year of our study. This was surprising because KB typically exhibits good drought tolerance, including in studies conducted at our location (Fu et al., 2004; Lewis et al., 2012; Goldsby et al., 2015; Braun, Bremer, & Hoyle, 2020). For example, in earlier research conducted under the same rainout shelter as our study in 2017, ‘America’ KB (a Compact America type) went dormant during a 41-day dry down without water inputs during the first summer after fall seeding, but then recovered fully (Braun et al., 2020). Similarly, in earlier research conducted under the other rainout shelter we used in 2018, KB went dormant during an 82-day dry down with negligible water inputs but also recovered fully thereafter although the recovery was slow (58-148 d) (Goldsby et al., 2015). One difference between those studies (Goldsby et al., 2015, Braun et al., 2020) and ours is that they were both seeded KB, while ours was sodded. After >1 yr since it had been sodded in the previous spring, Brilliant KB irrigated with 20% ET_a during the summer gradually recovered after full irrigation was resumed, although it was severely damaged by billbugs and heat in the second year (Fu et al., 2004). Therefore, besides possible cultivar effects, the failure of KB to survive extended drought in our study may have been related to its being sodded for less than one year (~8 months), whereas most drought studies have been conducted on more established KB (Fu et al., 2004; Leksungnoen et al., 2012; Goldsby et al., 2015). Information is limited in the scientific literature about the survivability of KB sod exposed to severe drought in the first summer after fall sodding. It is possible that factors such as greater irrigation frequency, shorter drought durations, earlier fall sodding, and more moderate air temperatures during the fall and spring establishment periods may improve the performance and survivability of KB during prolonged droughts in the first year after sodding (Brown, Devitt, & Morris, 2004; Huang & Wang, 2005; Gómez-Armayones et al., 2018; Monje-Jiménez et al., 2019). More research is warranted on this topic.

Amount of water saved

This section is specific to TF since it recovered from all levels of reduced irrigation (0 to 50% ET_o). Discussion of water savings in KB is less relevant to our study because KB did not recover from any irrigation level, as discussed above.

Irrigation at 50% ET_o averaged 19.0 mm wk^{-1} over the two years of dry downs in our study (Table 5). Compared with 100% ET_o , this saved 23.7 cm of water during the 83-d dry down in the first year (2017). More conservatively, if compared with irrigation at 80% ET_o , which is typically recommended for cool-season turfgrasses (Brown et al., 2004; Beard & Kenna, 2008), then irrigation at 50% ET_o saved 14.2 cm of water in the first year. Notably, as mentioned above, 50% ET_o maintained acceptable quality in TF during the entire dry down in the first year, probably due in part to the deep soils at our research site (Fig. 1.2; Table 3).

In the second year, irrigation at 50% ET_o saved 17.0 cm and 10.2 cm compared with irrigation at 100% and 80% ET_o , respectively, during the 60-d dry down. However, minimally acceptable quality was maintained in TF for only 45 d at 50% ET_o in the second year (Table 3); recall the same TF sod was used in both years. Other researchers have reported that cool-season turfgrasses, including TF and KB, performed more poorly in the second consecutive year of drought stress than in the first year (Fu et al., 2004; Braun et al., 2020). Fu et al. (2004) reported more water was needed in the second year of drought to maintain minimally acceptable quality for a similar period, which supports our findings. However, our results indicate that if turf quality is allowed to decrease below minimally acceptable, irrigating TF at 50% ET_o in the second year of severe drought would save water while maintaining some greenness in the canopy for nearly two months (i.e., $PGC > 30$ and $TQ > 3$) and fully recover thereafter (Fig. 1.3; Table 3).

Irrigation below 50% ET_o could save additional water, but lower turfgrass performance would be expected. Decreasing irrigation by 10% ET_o increments saved an average of 3.5 mm wk^{-1} over our 2-yr experiment (Table 5). This translates to saving about 3.0 cm for two months during the summer, equivalent to 4,200 m^3 of water for the irrigated

roughs of a typical 18-hole golf course in the United States (median 14.0 ha or an equivalent area of residential lawns) (Gelernter, Stowell, Johnson, & Brown, 2017). Decreases in irrigation below 50%, in 10% ET_o increments, generally resulted in gradual, often insignificant decreases in PGC, TQ, and NDVI (Table 1-3). For example, when irrigation in TF was reduced from 50% to 40% ET_o , PGC never decreased by more than 16% in either year, and differences in PGC between 50% and 40% ET_o were never significant (Fig. 1.2, 1.3).

Conclusions

Minimum water applications (0-50% ET_o) to maintain various levels of quality and encourage survival during prolonged drought varied between TF and KB. For example, in both years TF maintained higher quality longer than KB as the prolonged dry downs progressed in the deep soil of the research site. During the first summer after fall sodding, TF with no water inputs (irrigation or precipitation) retained some greenness throughout an 83-d dry down in the first year and, after being resodded to another location, fully recovered from a 60-day drought in the second year. Conversely, in both years of the study, KB did not survive dry downs at any irrigation level (0% to 50% ET_o) in the first summer after being sodded.

Our results indicated that higher amounts of deficit irrigation (i.e., from 0% to 50% ET_o) improved the performance of TF and KB during hot, prolonged drought periods of summer. In 50% ET_o , PGC averaged approximately 8.4% higher in KB and 19-25% higher in TF than in 0% ET_o over the dry downs in the two years. Higher deficit irrigation maintained acceptable quality for longer periods in TF than lower deficit irrigation levels, which could help capitalize on periodic rainfall in real-world scenarios.

Results indicate that if expectations for turf quality in TF are lowered to below what is normally considered “minimally acceptable” ($TQ=6$), then irrigation can be reduced and significant amounts of water conserved. For example, during the 83-d dry down in year one,

14.2 to 23.7 cm less water was applied at 50% ET_0 than if it had been irrigated at 80% and 100% ET_0 , respectively. Higher irrigation during the drought period also improved TF performance and recovery rate during recovery, although TF at all irrigation levels eventually recovered fully. Recovery in TF at 50% ET_0 was 2.5 weeks earlier than 0% ET_0 .

Unfortunately, KB failed to recover in both years of the study, even at 50% ET_0 replacement. The reasons for the failure of KB to recover are not certain, but it may be related to whether KB was well-established (e.g. establishment time, sodded vs. seeded); previous research at our site revealed that seeded KB survived prolonged drought (Goldsby et al., 2015), including in the first summer after seeding (Braun et al., 2020). Additional research is needed to investigate factors that may impact the survival of KB sod during prolonged drought in the first year after sodding, such as various drought durations, irrigation levels, and irrigation frequencies.

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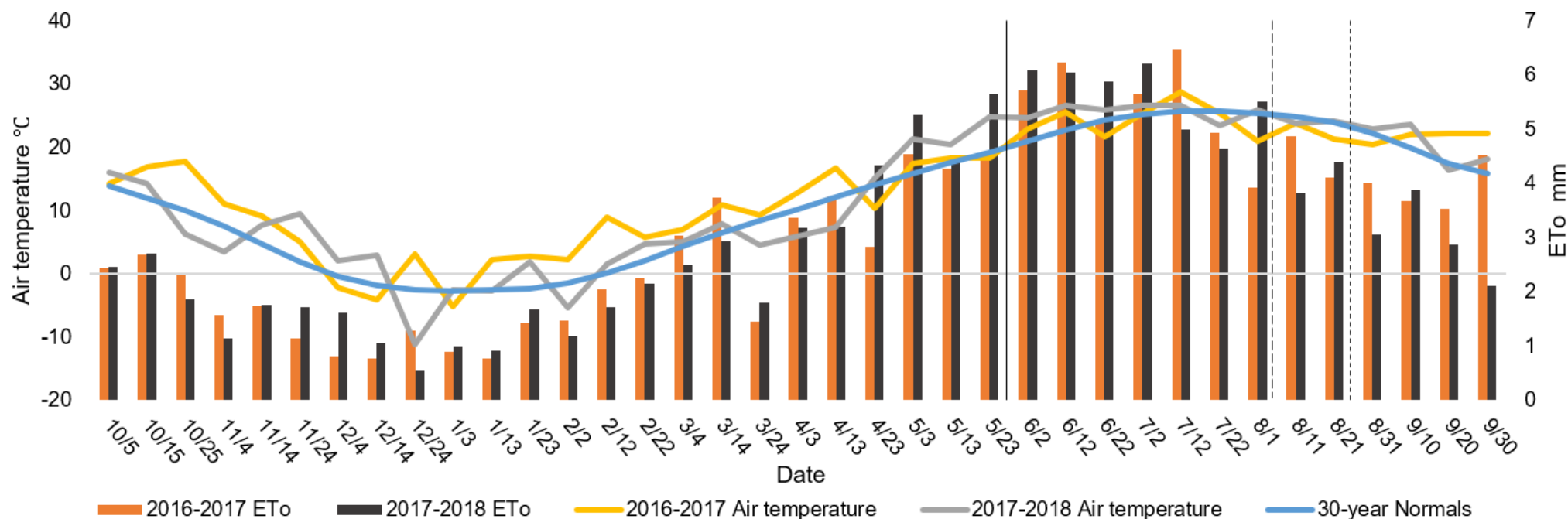


Figure 1.1. Ten-day averages of daily maximum and minimum air temperature and daily grass reference evapotranspiration (ET_o) from an on-site weather station during the study years. The blue line denotes 10-day averages of 1981-2010 daily air temperature normals from a NOAA weather station (~2.5 km from the research site). The solid vertical line denotes the start of dry down (1 June 2017; 4 June 2018); short- and long-dashed lines denote the start of recovery period in 2017 (23 Aug.) and 2018 (3 Aug.), respectively.

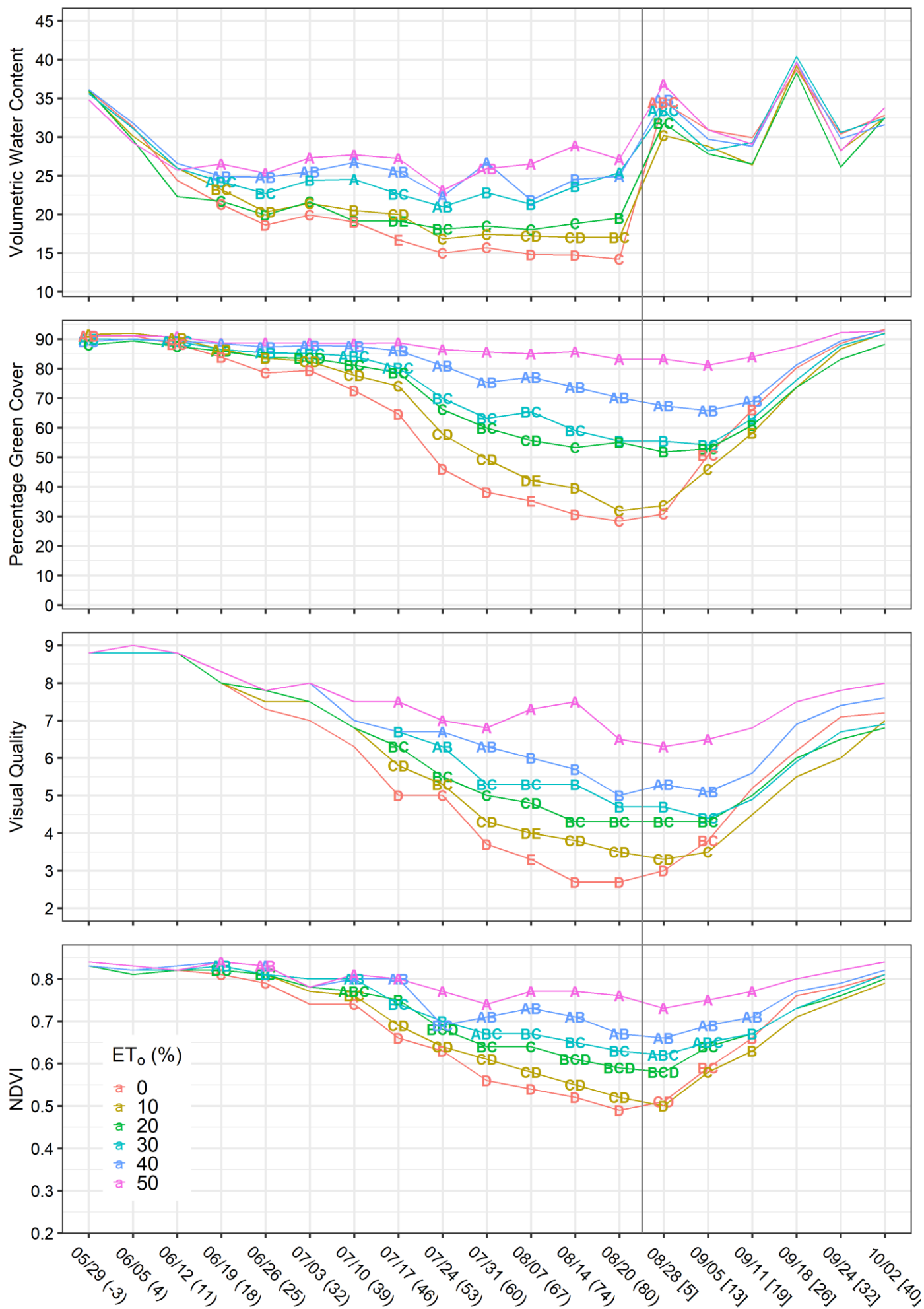


Figure 1.2. Volumetric soil water content, percentage green cover, visual quality, and normalized difference vegetation index (NDVI) of tall fescue irrigated by 0 to 50% reference evapotranspiration (ET_o) treatments in 2017. Numbers in parentheses on x-axis denote days before (negative) or after (positive) the beginning of dry down. Numbers in square brackets denote days after the recovery (full irrigation; to the right of the vertical line). Means with no letter in common within a measurement and day are significantly different ($P < 0.05$).

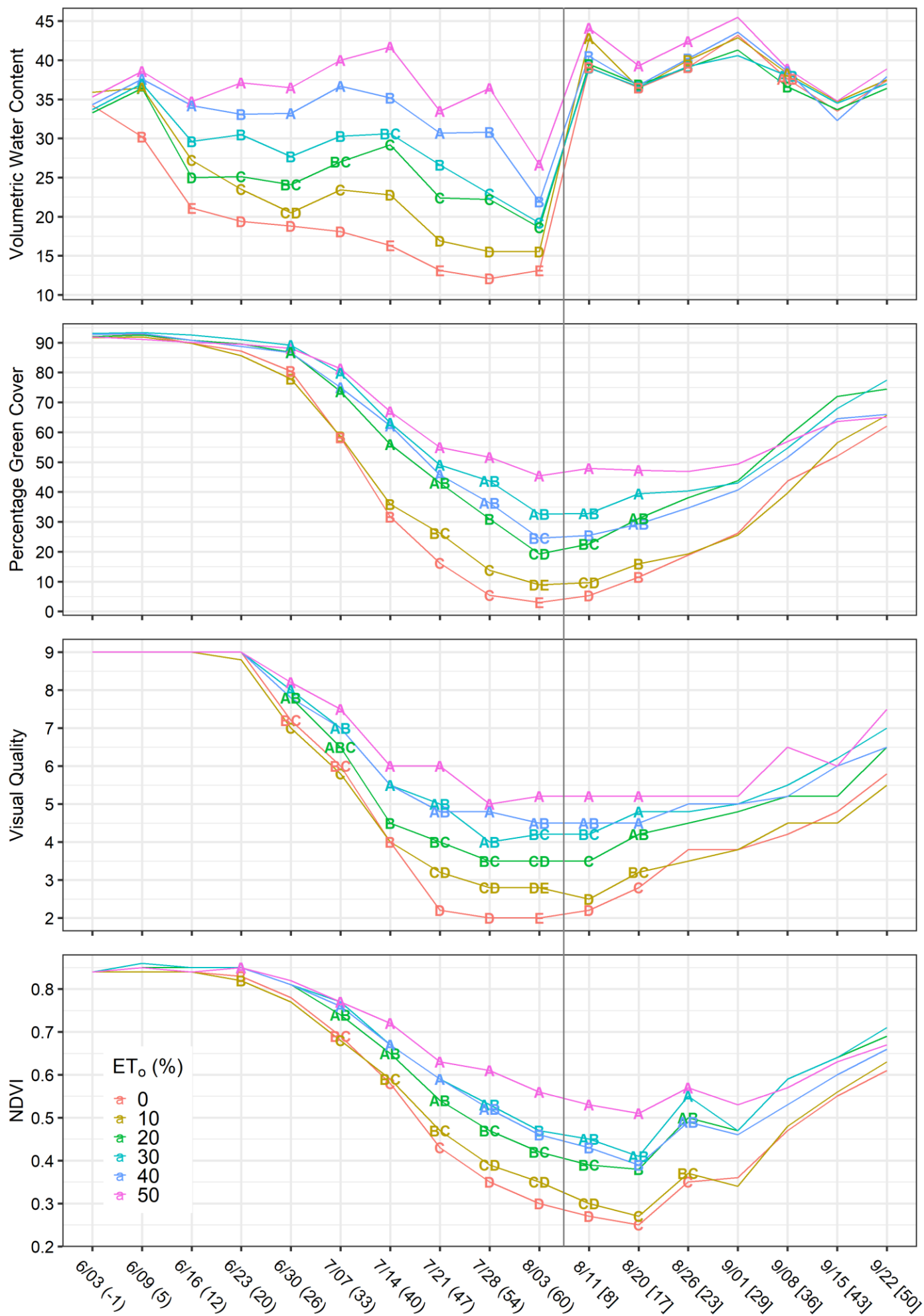


Figure 1.3. Volumetric soil water content, percentage green cover, visual quality, and normalized difference vegetation index (NDVI) of tall fescue irrigated by 0 to 50% reference evapotranspiration (ET_o) treatments in 2018. Numbers in parentheses on x-axis denote days before (negative) or after (positive) the beginning of dry down. Numbers in square brackets denote days after the recovery (full irrigation; to the right of the vertical line). Means with no letter in common within a measurement and day are significantly different ($P < 0.05$).

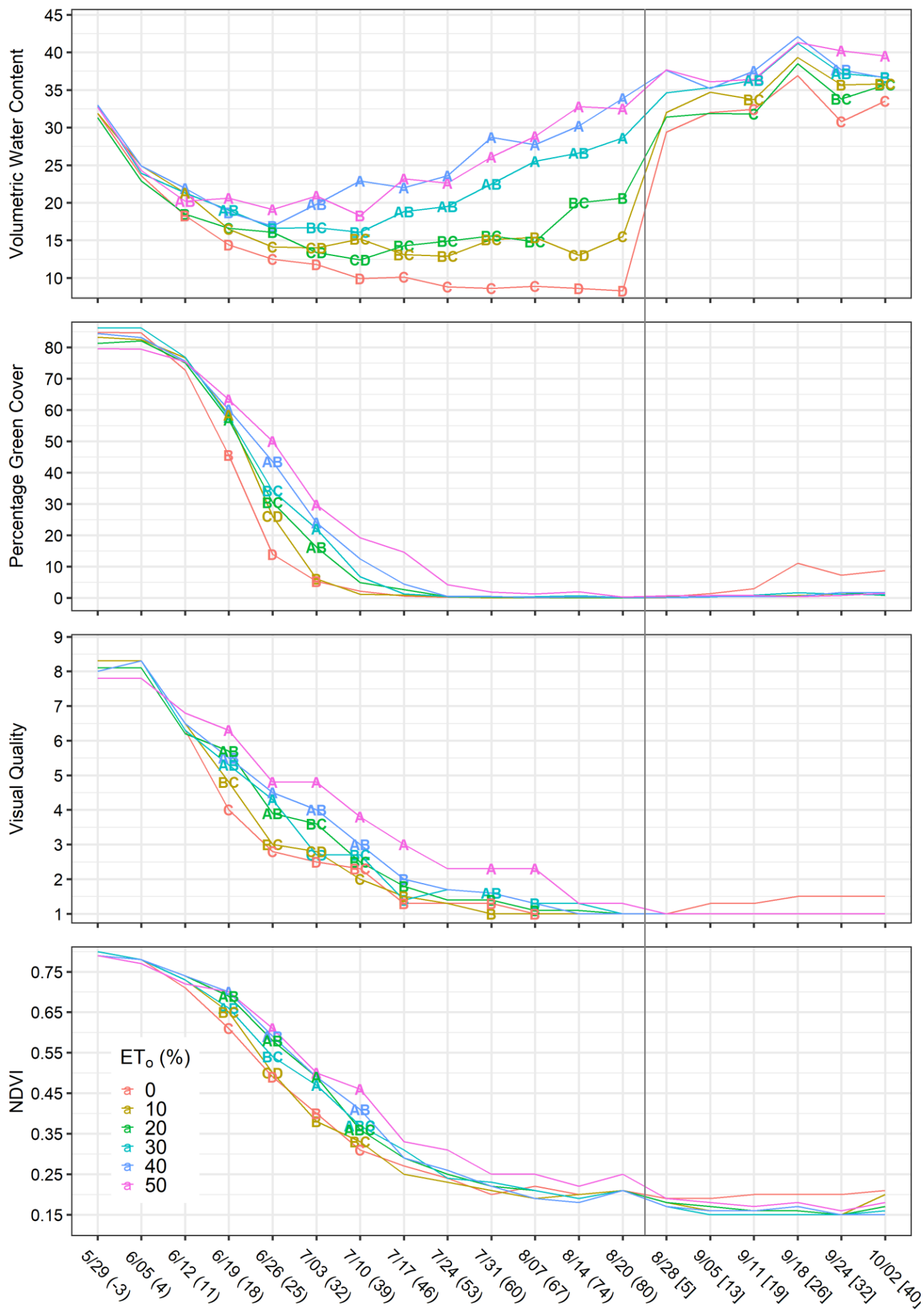


Figure 1.4. Volumetric soil water content, percentage green cover, visual quality, and normalized difference vegetation index (NDVI) of Kentucky bluegrass irrigated by 0 to 50% reference evapotranspiration (ET_o) treatments during dry down periods in 2017. Numbers in parentheses on x-axis denote days before (negative) or after (positive) the beginning of dry down. Numbers in square brackets denote days after the recovery (full irrigation; to the right of the vertical line). Means with no letter in common within a measurement and day are significantly different ($P < 0.05$).

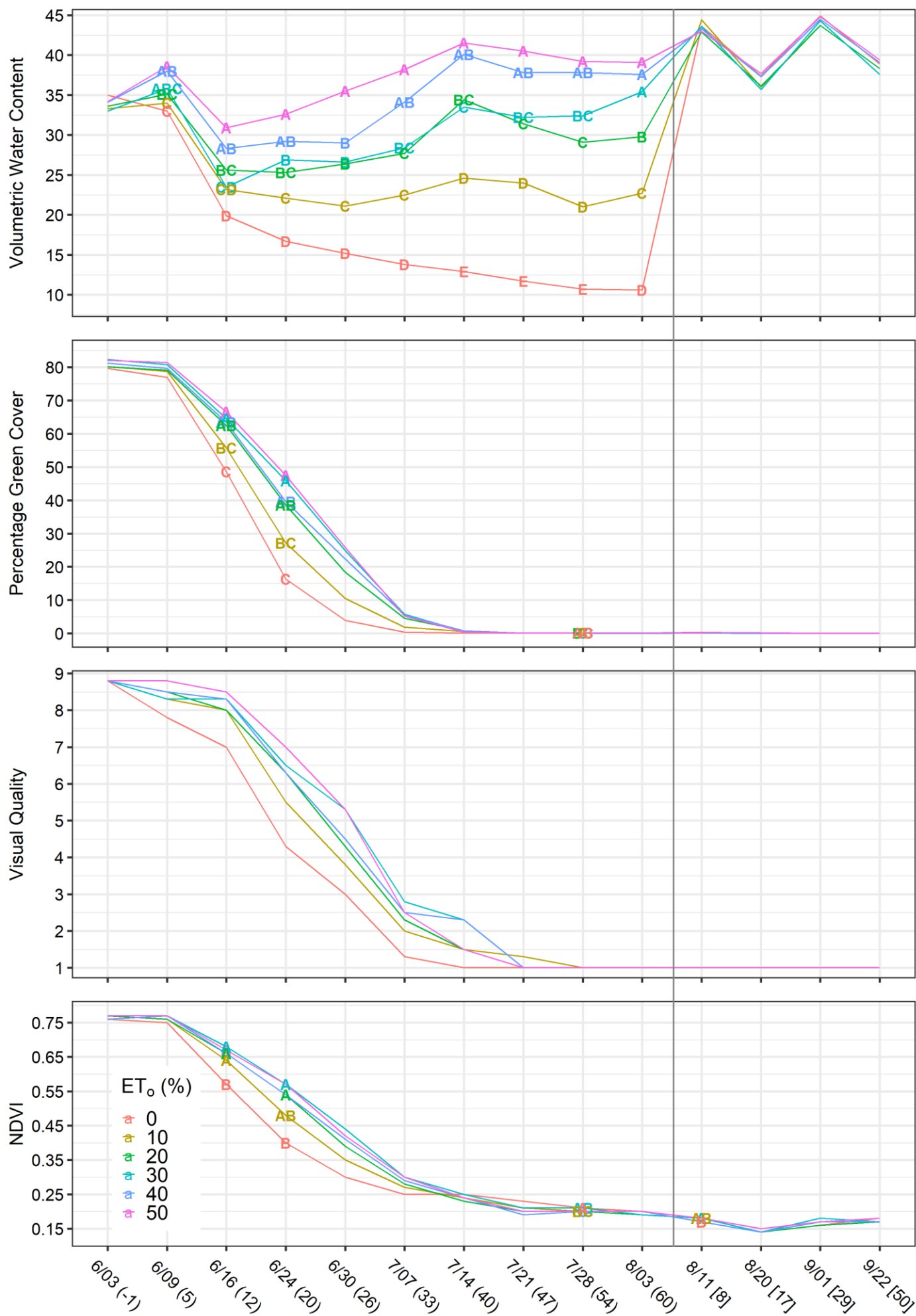


Figure 1.5. Volumetric soil water content, percentage green cover, visual quality, and normalized difference vegetation index (NDVI) of Kentucky bluegrass irrigated by 0 to 50% reference evapotranspiration (ET_o) treatments during dry down periods in 2018. Numbers in parentheses on x-axis denote days before (negative) or after (positive) the beginning of dry down. Numbers in square brackets denote days after the recovery (full irrigation; to the right of the vertical line). Means with no letter in common within a measurement and day are significantly different ($P < 0.05$).

Table 1.1. Irrigation main effects on mean separations of volumetric water content (VWC), turfgrass quality (TQ), percentage green cover (PGC), and normalized difference vegetation index (NDVI) of tall fescue over prolonged dry down and recovery periods in 2017 and 2018.

ET _o ^a	VWC ^b	2017 Dry down (83 d)			2018 Dry down (60 d)			
		PGC	TQ ^c	NDVI ^d	VWC	PGC	TQ	NDVI
50%	27.3 A ****	87.8 A ****	7.7 A ****	0.80 A ****	36.0 A ****	75.1 A ****	7.4 A ****	0.75 A **
40%	25.9 AB	83.7 A	7.2 B	0.77 AB	32.8 B	69.6 AB	7.0 AB	0.72 AB
30%	24.6 B	77.1 B	7.0 BC	0.75 BC	28.8 C	72.7 AB	7.0 AB	0.73 AB
20%	21.7 C	74.5 BC	6.7 CD	0.73 CD	26.3 D	67.4 B	6.6 BC	0.70 BC
10%	21.7 C	69.1 C	6.4 DE	0.71 DE	23.8 E	58.0 C	6.1 CD	0.66 CD
0%	20.0 C	62.3 D	6.0 E	0.69 E	19.6 F	55.7 C	6.0 D	0.65 D
	VWC	2017 Recovery (40 d)			2018 Recovery (50 d)			
		PGC	TQ	NDVI	VWC	PGC	TQ	NDVI
50%	33.0	86.8 A*	7.1 A*	0.78 A*	40.5 A*	53.9	5.9 A*	0.57
40%	32.3	80.3 AB	6.4 AB	0.75 AB	38.5 B	44.6	5.3 A	0.51
30%	32.3	74.2 ABC	5.7 BC	0.72 ABC	37.8 B	50.8	5.4 A	0.55
20%	30.5	68.4 BC	5.5 BC	0.70 BC	37.6 B	48.7	4.9 AB	0.52
10%	30.9	65.1 C	5.0 C	0.66 C	39.0 AB	33.2	3.9 B	0.42
0%	32.8	71.0 BC	5.6 BC	0.70 BC	38.0 B	31.4	3.9 B	0.41

*, **, ***, **** Significant at the 0.05, 0.01, 0.001, and 0.0001 probability levels, respectively. Means with no letter in common are significantly different (Fisher's LSD).

a Irrigation treatments as percentages of reference evapotranspiration replacement.

b Volumetric water content (%) measures the volume of water per unit bulk volume of soil across 7.6-cm depth.

c Turfgrass quality based on a 1 to 9 scale, with 1 = dead, 6 = minimally acceptable, and 9 = uniform, green, dense turfgrasses.

d NDVI = (NIR-Red)/(NIR+Red). Red peaks at 670nm and NIR at 780nm.

Table 1.2. Irrigation main effects on mean separations of volumetric water content (VWC), turfgrass quality (TQ), percentage green cover (PGC), and normalized difference vegetation index (NDVI) of Kentucky bluegrass over dry down periods in 2017 and 2018.

ET _o ^a	2017 (83 d)				2018 (60 d)			
	VWC ^b	PGC	TQ ^c	NDVI ^d	VWC	PGC	TQ	NDVI
50%	24.8 A ****	32.4 A *	4.2 A ****	0.473 A **	37.0 A ****	30.9	4.5	0.44
40%	24.5 A	30.0 AB	3.7 B	0.451 AB	34.6 A	29.3	4.4	0.43
30%	21.8 AB	28.8 ABC	3.5 BCD	0.440 BC	30.8 B	30.5	4.5	0.44
20%	18.3 BC	27.1 BC	3.5 BC	0.447 ABC	29.8 B	28.4	4.3	0.42
10%	17.1 C	25.8 BC	3.3 CD	0.419 C	24.8 C	25.5	4.1	0.41
0%	13.5 D	23.9 C	3.2 D	0.418 C	17.9 D	22.6	3.6	0.39

*, **, ***, **** Significant at the 0.05, 0.01, 0.001, and 0.0001 probability levels, respectively. Means with no letter in common are significantly different (Fisher's LSD).

a Irrigation treatment as percentages of reference evapotranspiration replacement.

b Volumetric water content (%) measures the volume of water per unit bulk volume of soil across 7.6-cm depth.

c Turfgrass quality based on a 1 to 9 scale, with 1 = dead, 6 = minimally acceptable, and 9 = uniform, green, dense turfgrasses.

d NDVI = (NIR-Red)/(NIR+Red). Red peaks at 670nm and NIR at 780nm.

Table 1.3. Average days for which tall fescue with minimal irrigation maintained different thresholds of turf quality during the dry down period and thereafter recovered to acceptable quality during the recovery periods in 2017 (83 d dry down) and in 2018 (60 d dry down).

ET _o ^a	2017				
	PGC>60 and TQ>6	PGC>50 and TQ>5	PGC>40 and TQ>4	PGC>30 and TQ>3	PGC>60 and TQ>6
	Days-dry down				Days-recovery
50%	82.3 A ^b	83.0 A	83.0 A	83.0	6.5 B
40%	72.3 AB	77.7 AB	83.0 A	83.0	18.2 AB
30%	60.0 BCb	77.7 ABa	80.0 Aa	83.0 a	22.2 AB
20%	51.3 CDc	65.8 Bb	82.3 Aa	82.3 a	27.8 A
10%	46.0 DEd	53.0 Cc	67.0 Bb	76.0 a	34.5 A
0%	39.0 Ec	46.0 Cbc	57.7 Cab	70.0 a	24.5 A
	2018				
	Days-dry down				Days-recovery
50%	45.0 Ab	51.8 Aab	51.8 Aab	58.5 Aa	29.3
40%	36.5 Bc	43.5 BCb	45.3 ABb	52.0 ABa	46.5
30%	36.5 Bc	45.3 ABb	50.3 Aab	57.0 Aa	41.3
20%	33.0 Bb	36.5 CDb	47.0 ABa	48.8 Ba	43.0
10%	29.5 Bc	33.0 Dbc	36.5 BCab	40.0 Ca	50.0
0%	29.5 Bb	33.0 Db	33.0 Cb	38.3 Ca	46.5

a Irrigation treatments as percentages of reference evapotranspiration replacement.

b Means with no letter in common are significantly different between irrigation treatments (upper case letters within a column and year) and between quality thresholds (lower case letters within a row) under the same irrigation treatment (Fisher's LSD, $P < 0.05$).

Table 1.4. Average days for which Kentucky bluegrass with minimal irrigation maintained different turf quality during dry down periods of 2017 and 2018.

ET _o ^a	PGC>60 and TQ>6	PGC>50 and TQ>5	PGC>40 and TQ>4	PGC>30 and TQ>3
Days-2017				
50%	18.0 b ^b	23.3 Aab	28.5 Aa	28.5 Aa
40%	14.5 b	18.0 Bb	23.3 ABa	26.8 ABa
30%	12.8 b	16.3 Bcb	21.5 ABCa	25.0 ABa
20%	13.6 b	19.5 ABa	21.5 ABCa	22.3 ABCa
10%	11.0 c	14.5 Bcb	18.0 BCa	18.0 Ca
0%	11.0 b	12.8 Cb	14.5 Cb	20.0 BCa
Days-2018				
50%	12.3 c	15.5 Abc	19.5 ab	21.5 Aa
40%	12.0 b	12.0 ABb	14.0 b	21.5 Aa
30%	10.3 c	16.0 Ab	18.0 ab	21.5 Aa
20%	10.3 c	12.3 ABbc	16.0 ab	17.5 ABa
10%	8.5	10.3 BC	12.3	14.0 B
0%	6.8 b	6.8 Cb	12.0 a	14.0 Ba

a Irrigation treatments as percentages of reference evapotranspiration replacement.

b Means with no letter in common are significantly different between irrigation treatments (upper case letters within a column and year) and between quality thresholds (lower case letters within a row) under the same irrigation treatment (Fisher's LSD, $P < 0.05$).

Table 1.5. Average weekly and monthly irrigation application equivalent of reference evapotranspiration (ET_o) for cool-season grass during droughts of the 2-yr study.

ET _o ^a	Weekly	Monthly		Cumulative	
		June	July	2017 (83 d)	2018 (60 d)
		mm			
100%	38.6	158.4	184.2	473.2	339.3
80%	30.9	126.7	147.4	378.6	271.4
50%	19.0 A ****	79.2	92.1	236.6	169.7
40%	15.1 B	63.4	73.7	189.3	135.7
30%	11.2 C	47.5	55.3	142.0	101.8
20%	7.4 D	31.7	36.8	94.6	67.9
10%	3.5 E	15.8	18.4	47.3	33.9

**** Significant at the 0.0001 probability level. Mean separations are conducted on weekly irrigation treatment amounts only from 10 to 50% ET_o (Fisher's LSD).

a Irrigation treatments as percentages of reference evapotranspiration replacement.

Chapter 2 - Minimum water requirements of Japanese lawngrass (*Zoysia japonica* Steud.) for survival during prolonged drought

ABSTRACT

Water restrictions on irrigation are rarely science-based and may cause irreversible damage to turfgrass or inadvertently waste water. Our objectives were to evaluate effects of minimum water applications to 'Meyer' Japanese lawngrass (*Zoysia japonica* Steud.) on: 1) canopy performance during prolonged drought and; 2) survival and recovery thereafter. Meyer was watered with 0 to 30% reference evapotranspiration (ET_o) replacement for two months in two consecutive summers under a rainout shelter near Manhattan, KS. Soil moisture and canopy performance [normalized difference vegetation index (NDVI), percent green cover (PGC), and turfgrass quality] were measured weekly. Results indicated 20 to 30% ET_o slowed the decline in canopy performance compared with no water inputs. Irrigation at 30% ET_o maintained Meyer at >75 PGC throughout the first year, but even Meyer at 0 and 5% ET_o recovered after full irrigation resumed. In the second year, 30% ET_o maintained Meyer at >25 PGC throughout the drought and recovered thereafter, but plots with 0 and 5% ET_o only recovered to 30-42 PGC after 50 d of full irrigation. Reducing irrigation from the recommended 60% ET_o for warm-season turfgrasses to 30% ET_o saved 9-11 cm of water; further reductions to 20% ET_o saved another 3-4 cm during the 2-month droughts with insignificant additional PGC reductions (<18%). During severe drought with imposed water restrictions, minimal weekly irrigation of at least 20~30% ET_o in Meyer Japanese lawngrass could reduce turfgrass damage and conserve water.

INTRODUCTION

The turfgrass industry is confronted with challenges from anthropogenic water shortages caused by increasing population and industrial demands, and changing patterns of water balance on the continent due to climate change (Barros & Field, 2014; Gelernter, Stowell, Johnson, Brown, & Beditz, 2015; Hatfield, 2017). As one solution to conserving water, local water restrictions have been imposed on stakeholders including residential homeowners; in the U.S., about 68% of total turfgrass area is composed of residential lawns (Milesi, Elvidge, & Nemani, 2009). Water restrictions usually limit irrigation to specific hours within a day and/or days within a week (varying from 1 to 3 days wk⁻¹) (Boyer, Dukes, Duerr, & Bliznyuk, 2018). With few controls on water application amounts, restrictions can inadvertently promote overwatering (Survis, Root, & Pathak, 2017; Boyer et al., 2018). Furthermore, water restrictions do not factor in differences in water requirements among turfgrass species and cultivars, or dynamics in weather conditions that can dramatically affect the water requirements (Survis et al., 2017; Boyer et al., 2018). Additionally, damage to turfgrass during long-term water restrictions may result in a failure to recover after prolonged drought and heat stress (Hong, Bremer, & Keeley, 2020). This can lead to significant reestablishment costs (e.g., seeding/sodding, human labor, extra water for new turf establishment) and a loss of environmental benefits (e.g. cooling effects, reducing airborne pollutants and soil erosion) (Stier, Steinke, Ervin, Higginson, & McMaugh, 2013).

Previous studies have investigated water application amounts for maintaining acceptable quality during drought, but few have determined minimum water requirements that, while perhaps resulting in reduced quality and even dormancy, would keep turfgrass alive during summer drought stress and allow for recovery after resuming irrigation (Beard & Sifers, 1997; Brown, Devitt, & Morris, 2004; Fu, Fry, & Huang, 2004; Zhang, Unruh, & Kenworthy, 2013; Wherley, Heitholt, Chandra, & Skulkaew, 2014; Hejl, Wherley, White, Thomas, & Fontanier, 2016; Braun & Bremer, 2018; Monje-Jiménez, Egea, & Pérez-Urrestarazu, 2019; Monje-Jiménez, Pérez-Urrestarazu, & Egea, 2019; Hong et al., 2020). In

the U.S. transition zone, reducing irrigation from the commonly recommended 80% to 50% ET_o during drought maintained above minimally acceptable quality >45 d in tall fescue (*Lolium arundinaceum* (Schreb.) Darbysh.), which then recovered within 7-29 d after resuming full irrigation (Hong et al., 2020). In a Mediterranean-type climate in California, U.S., one-half (40% ET_o) and one-third (20% ET_o) of commonly recommended irrigation amounts of 80% and 60% ET_o in cool- and warm-season turfgrasses, respectively, could allow for their survival (Harivandi, Baird, Hartin, Henry, & Shaw, 2009). Warm-season grasses have demonstrated strong drought resistance in many studies (Beard & Sifers, 1997; Qian & Fry, 1997; Huang, Duncan, & Carrow, 1997; Steinke & Chalmers, 2010; Cathey, Kruse, Sinclair, & Dukes, 2013; Wherley et al., 2014; Hejl et al., 2016; Braun & Bremer, 2018; Monje-Jiménez, Egea, et al., 2019; Monje-Jiménez, Pérez-Urrestarazu, et al., 2019). Hybrid bermudagrass (*Cynodon dactylon* (L.) Pers. x *C. transvaalensis* Burt Davy) irrigated with ≥30% ET_o outperformed bermudagrass receiving no irrigation in terms of maintaining minimally acceptable quality, and ensured autumn recovery after the second year of summer drought stress (Hejl et al., 2016). This indicates limited vs. no water applications during drought could mitigate drought stress severity and benefit the subsequent recovery.

As the most economically important *Zoysia* spp. cultivar in the U.S., ‘Meyer’ Japanese lawngrass (*Zoysia japonica* Steud.) has been identified as both a drought tolerant and cold hardy warm-season turf species that is suitable to the climate of the U.S. transition zone (Qian & Fry, 1997; Fu, Fry, & Huang, 2007; Patton, Schwartz, & Kenworthy, 2017). However, water requirements of *Zoysia* spp. cultivars to maintain minimally acceptable turfgrass quality has varied from 14-33% ET_o, to 80%-120% ET_o and 80% ET_a (microlysimeter measurements) in the summer, depending on cultivars, mowing height, precipitation, and geographic location (Fu et al., 2004; Zhang et al., 2013; Wherley et al., 2014; Braun & Bremer, 2018; Culpepper, Young, & Wherley, 2020).

As mentioned above, few studies have quantified the potential benefits of applying minimal water amounts that could preserve turfgrass while conserving water during

prolonged drought. Therefore, the objectives of this field study were to evaluate in Meyer: 1) the effects of minimum water amounts on canopy performance during prolonged drought periods; and 2) survival and recovery thereafter.

METHODS AND MATERIALS

The research was conducted under an automatic rainout shelter in 2017 and 2018 at Rocky Ford Turfgrass Research Center near Manhattan, Kansas (39°13'53''N, 96°34'51''W). Meyer was used in this study because it is tolerant to cold and therefore the most widespread *Zoysia* spp. cultivar in the transition zone of the U.S. (Patton et al., 2017). It was sodded on 4 June 2013. The soil was a Chase silty clay loam (fine, smectitic, mesic Aquertic Argiudoll; 15.6% sand and 22.2% clay). During drought periods, the automatic rainout shelter would cover the whole study area when rainfall reached 0.25 mm and retract one hour after rainfall ceased (Bremer, Lee, Su, & Keeley, 2011). Outside of the summer drought periods, the rainout shelter remained off the plot area, which received precipitation and, if necessary, irrigation.

This study was a one-way treatment structure in a randomized complete block design of total 28 plots (1.14 x 1.23 m each) in 2017 and 2018. The irrigation treatments in each of 4 blocks (replicates) were: 0, 5, 10, 15, 20, 25, and 30% ET_o replacement using daily on-site weather data (<http://mesonet.k-state.edu/>) and the American Society of Civil Engineers (ASCE) standardized ET_o equation (Walter et al., 2001). Irrigation was applied once per week by hand with a wand attached to a meter (Model 03N31, GPI, Inc., Wichita, KS). The drought periods were for 56 d (8 June to 3 Aug.) in 2017 and 60 d (4 June to 3 Aug.) in 2018 followed by full irrigation (two to three times a week to field capacity) for 39 d in 2017 and 50 d in 2018. On 30 June and 19 July 2017, and 3 June 2018, 6.4-mm irrigation was applied to all plots to incorporate trichlorfon (Dylox 6.2 Granular, Bayer Environmental Science), which was applied after damage by billbugs (*Sphenophorus parvulus* Gyllenhal) was observed.

Maintenance

Meyer Japanese lawnglass was maintained at a 5.1-cm mowing height with a rotary mower and clippings were removed. It was fertilized with urea (Thrive Branded Fertilizer, Mears Fertilizer Inc.) at 48.9 kg N ha⁻¹ on 26 May and 29 Aug., 2017. To improve the recovery from a 2-year drought study previously conducted on the same study area, and the insect damage during the 2017 drought, additional polymer-coated urea (41-0-0; slow-release duration 120, Koch Agronomic Services) was applied at 48.9 kg N ha⁻¹ on 20 Apr. and 29 Aug., 2017. Urea was applied at 44.0 kg N ha⁻¹ on 26 May, and (NH₄)₂SO₄ was applied at 44.0 kg N ha⁻¹ on 31 Aug., 2018.

For preventative control of billbug larvae, chlorantraniliprole (Acelepryn, Syngenta Crop Protection LLC) was applied at 0.26 kg a.i. ha⁻¹ on 26 May 2017; and imidacloprid (Merit 0.5 G, Bayer Environmental Science) was applied at 0.39 kg a.i. ha⁻¹ on 26 May, 2018. Trichlorfon was applied at 9.1 kg a.i. ha⁻¹ on the dates previously mentioned after billbug damage was observed. In 2018, A billbug trap was installed across the south side of the rainout shelter to monitor adult billbug movement. Bifenthrin (Crosscheck, LESCO) was applied at 0.13 kg a.i. ha⁻¹ on 15 May 2018 to target billbug adults.

For control of common dandelion (*Taraxacum officinale* Wigg.) and other broadleaf weeds, a mixture of dimethylamine salt of propionic acid, 2,4-D acid, and dicamba (Trimec bentgrass formula, PBI Gordon Corporation) was applied at 0.76 kg a.i. ha⁻¹ on 11 Apr. 2017. For preventative control of large patch, triticonazole (Triton FLO, Bayer Environmental Science) was applied at 0.88 kg a.i. ha⁻¹ and Flutolanil (Prostar 70WG, Bayer Environmental Science) was applied at 3.97 kg a.i. ha⁻¹ on 15 Sept. and 13 Oct. 2017, respectively.

Data collection

Measurements were taken weekly for soil volumetric water content (VWC), turfgrass quality (TQ), NDVI, and PGC. Soil VWC was measured at 0 to 7.6 cm in two random

locations within each plot using a handheld time-domain-reflectometry instrument (FieldScout TDR 300 Soil Moisture Meter, Spectrum Technologies). Turfgrass quality was evaluated on a numeric rating scale from 1 to 9 (1 = completely brown turf, 9 = uniform, green and dense turf, and 6 = minimally acceptable turf for use in home lawns) according to color, texture, density, and uniformity (Morris & Shearman, 1998). A handheld active optical sensor (RapidScan CS-45, Holland Scientific) was used to measure NDVI. Reflectance measurements of the sensor were centered at wavelengths of 670 (Red) and 780 (NIR) nm, which allowed for computing NDVI $[(\text{NIR}-\text{Red})/(\text{NIR}+\text{Red})]$. Each measurement was obtained at handheld height (~ 0.9 m) to scan about 80% of each plot, with readouts of the average value of NDVI. Images for measuring PGC were taken with a Nikon D5000 digital camera (26-mm focal length, f-stop of 5.6, 1/125 sec exposure time, and 800 ISO-speed; Nikon Inc.) using a lighted camera box (51 cm x 61 cm x 56 cm). Images were analyzed by the method of Richardson, Karcher, & Purcell (2001) (SigmaScan Pro v. 5.0, SPSS Science Marketing Dept.), using threshold ranges of 48-110 for hue and 0-100 for saturation.

Statistical analysis

Irrigation main effects on all variables were evaluated for each drought and recovery period of each year with dates being repeated measures, and were also analyzed on each measurement date. Monthly rates of decline (%) of each variable were compared among irrigation treatments in each year. Mean weekly irrigation amounts (ET_o) over the 2-month periods of two years were compared among irrigation treatments (irrigation treatment as a fixed effect; weekly irrigation amounts (ET_o) were analyzed as replicates across the 2-year study, with week and year treated as random effects). The means were separated when irrigation treatment was statistically significant using the Fisher's protected least square difference (LSD) test ($P < 0.05$). All analysis was completed by PROC GLIMMIX (SAS Studio 3.8, SAS Institute).

RESULTS AND DISCUSSION

Minimal irrigation during prolonged drought and subsequent recovery

Meyer remained partially green even without water inputs during a two-month drought period in the first year ($PGC > \sim 30\%$; Fig 2.1B). In the second year, Meyer in all treatments survived although some of the drier plots went dormant ($PGC < 3\%$) during the two-month drought (Fig 2.2B). Similar results were reported for 10-month established *Z. japonica* (new sod installed each year) without water inputs in Texas, where PGC decreased by 97% and 68% during 60-day dry downs in two successive years (Steinke & Chalmers, 2010). In our study, Meyer irrigated at 30% ET_0 maintained PGC above 75% and 25% during the drought periods in 2017 and 2018, respectively, while Meyer at 0% ET_0 declined towards 30% and 0% PGC by the end of each respective drought. In all, soil moisture and all canopy measurements in 30% ET_0 plots averaged higher than that of 0% ET_0 plots during drought in both years (Table 2.1). This indicates that Meyer Japanese lawngrass receiving as little as 30% ET_0 weekly from irrigation or rainfall could maintain at least partial green coverage during periods of drought, which is similar to Zhang et al.'s findings (2013) where rainfed *Z. japonica* and *Z. matrella* (*Zoysia matrella* (L.) Merr.) cultivars had improved quality when supplemented with 25% ET_0 compared with 3% ET_0 , twice per week using a linear gradient irrigation system in Jay, FL, U.S..

Canopy performance (NDVI, TQ, and PGC) generally declined among ET_0 treatments as the drought progressed in each year (Fig. 2.1-2.2, B,C,D). During the first month of the drought within each year, there were no significant differences among ET_0 treatments in the rates of decline in canopy performance (except PGC in 2018) (Table 2.2). This was probably because VWC started high in all ET_0 treatments and Meyer had not depleted available water in the soil profile, at least until later in the first month. Furthermore, leaves of C4 grasses would not heavily fire until transpirable water is fully exhausted (Cathey et al., 2013). This may be related in part to leaf water potential, which did not significantly increase in Meyer until $VWC < 16\%$ in a greenhouse study conducted at the same location as ours (Qian & Fry,

1997). The deep soil with high available water capacity at our research site may have delayed the drought stress in the first month, and then osmotic adjustment may have enabled Meyer to endure drought even without water inputs (Salter, Berry, & Williams, 1966; Qian & Fry, 1996; Huang et al., 1997; Qian & Fry, 1997; Qian, Fry, & Upham, 1997; Huang, 1999; Patton et al., 2017).

As drought extended into a second month, declines in PGC, NDVI, and TQ were less in high than in low ET_0 treatments (e.g. 20-30% vs. 0% ET_0) (Table 2.2). Irrigation at 20-30% ET_0 maintained higher soil moisture, which likely mitigated drought stress in the second month compared with 0% ET_0 (Fig. 2.1-2.2, A). Therefore, although irrigation at 20-30% ET_0 did not prevent a decline in canopy performance, it preserved enough soil moisture to improve canopy performance compared with Meyer with no water inputs, especially during the second month of the dry down in each year. The detrimental effects of no vs. minimal irrigation (e.g., 20-30% ET_0 in our study) on C4 turfgrass performance would likely be more evident or begin earlier where soils are shallow or compacted (Steinke, Chalmers, Thomas, & White, 2011).

The overall performance of Meyer declined faster in 2018 than 2017 (Table 2.2; Fig. 2.1-2.2, B,C,D). It is possible the carbohydrate reservoir of Meyer had been largely depleted during the drought in 2017, and had not completely recovered by the beginning of the study in 2018. Nitrogen was not applied as recommended during June or July (Fagerness, 2001), which was during the restricted irrigation treatments, to prevent possible confounding effects. This lack of mid-summer N fertilization may have reduced the nutrient uptake efficiency of Meyer during its optimal growth window (Carey et al., 2012; Miller, Earlywine, Braun, Fry, & Kennelly, 2016), resulted in a weakened root system (Huang et al., 1997; Qian et al., 1997; Fu et al., 2007), and diminished its ability to fully recover by the beginning of 2018 drought. This effect was probably exacerbated by a relatively short recovery period between the end of the drought in late summer 2017 and the beginning of the drought in late spring 2018 in this warm-season turfgrass, which typically goes dormant in early fall (Sept.-Oct.) and reemerges

from dormancy in mid-spring (Apr.-May) in Kansas when thatch and soil temperatures are between 16 and 25 °C (Miller et al., 2016). Evidence for an incomplete recovery is the slightly lower PGC (~80-90%) at the beginning of drought in 2018 than that in 2017 (Fig. 2.1-2.2, B). A similar phenomenon was observed in non-irrigated, rainfed ‘Jamur’ *Z. japonica*, which maintained season-long TQ>6 in the first year, but its quality declined in the second year (TQ=3-6; Culpepper et al., 2020).

In 2017, VWC increased in all ET_o treatments on 5 July because 6.4 mm of water had been applied to all plots to incorporate trichlorfon on 30 June (Fig. 2.1A). This water application delayed the normal weekly irrigation treatments by 3 d, which were accordingly applied on 3 July. Thus, the increase in VWC on 5 July was partially an artifact of measuring VWC only 2 d after irrigation treatments were applied instead of the usual 5 d in 2017. Other smaller increases in VWC were observed on some days in both years (Fig. 2.1-2.2, A), including after water was applied to all plots on 19 July, 2017, to incorporate trichlorfon. Other causes for VWC increases are less evident but may have been related to occasionally wide fluctuations in weekly ET_o demand and possibly hydraulic lift that supplemented the VWC from Meyer’s roots lower in the soil profile, below where VWC was measured (Qian & Fry, 1996; Qian et al., 1997; Huang, 1999).

In our study, plots of 30% ET_o maintained both average PGC>60 and TQ>6 for 42 d in 2017 and 12 d in 2018 (Fig. 2.1-2.2, B,C). In an earlier study at our location, Meyer required 60% ET_a to maintain season-long TQ above 4 to 5 (Fu et al., 2004). However, minimally acceptable quality (TQ=5) of *Z. japonica* and *Z. matrella* cultivars (excluding Meyer) was maintained with 14 to 33% ET_o when irrigated twice per week during the summer using a linear gradient irrigation system adjusted for effective rainfall in Dallas, TX, U.S. (Wherley et al., 2014). Those same *Zoysia* spp. cultivars were maintained at similar TQ (~5) with natural rainfall plus 37% ET_o twice per week for three years in Jay, FL (Zhang et al., 2013). Meyer has been reported as a higher water user among *Zoysia* spp. cultivars, while newer cultivars have shown better drought resistance (Patton et al., 2017). Apart from

cultivar differences, irrigation frequency may affect drought resistance, especially among different soil types. For instance, runoff can easily occur in fine-textured soil, and water holding capacity is low in sandy soil (Wherley et al., 2014; Monje-Jiménez, Pérez-Urrestarazu, et al., 2019). The effects of irrigation frequency and soil types on minimal irrigation amounts during severe drought will require additional research (Qian & Fry, 1996; Brown et al., 2004; Monje-Jiménez, Pérez-Urrestarazu, et al., 2019; Hong et al., 2020).

In both years, Meyer recovered from the drought although the recovery was substantially weaker in the second year (Table 2.1). For example, PGC, TQ, and NDVI increased to statistically similar levels among all irrigation treatments by 4 and 8 d after resuming full irrigation in 2017 and 2018, respectively (Fig. 2.1-2.2, B,C,D). However, PGC, TQ, and NDVI rebounded faster and remained higher throughout the recovery of 2017 compared with 2018. Surprisingly, Meyer with 0% and 5% ET_0 recovered to ~60 PGC only after 4 d of full irrigation in 2017, but only recovered to 30-42 PGC after 50 d of full irrigation in 2018. Plots irrigated with 30% ET_0 recovered to averages of both $PGC > 60$ and $TQ > 6$ in 4 d and 36 d in 2017 and 2018, respectively. The slower recovery of Meyer in 2018 was likely a result of its reduced performance during the drought in 2018 than in 2017, which was likely caused by less carbohydrate reserve, as discussed earlier. This resulted in dormancy in 0% and 5% ET_0 Meyer by the end of the drought in 2018, which slowed the recovery afterwards. Slower recovery after a second year of drought stress was also observed in *Z. japonica* and bermudagrass in other studies (Hejl et al., 2016; Braun & Bremer, 2018; Monje-Jiménez, Pérez-Urrestarazu, et al., 2019; Culpepper et al., 2020). Conversely, two to three months of dry downs following deficit irrigation during summer in successive years resulted in dormancy but did not affect the recovery capacity of a bermudagrass fairway in Spain (Subtropical Genuine Mediterranean climate; Monje-Jiménez, Egea, et al., 2019). In our study, the recovery of Meyer generally trended higher among plots that received more irrigation during the drought periods, especially in the second year, although differences were usually insignificant among treatments during the recovery in both years.

Amount of water saved

Irrigation at 30% ET_0 averaged 11.4 mm wk^{-1} over the two years of drought (Table 2.3). Compared with 100% ET_0 , this saved 26.6 and 21.4 cm of water during the two summer months in 2017 and 2018, respectively. More conservatively, if compared with 60% ET_0 , which is typically recommended for warm-season grasses (Beard & Kenna, 2008; Harivandi et al., 2009), 30% ET_0 still saved 11.4 and 9.2 cm of water in 2017 and 2018, respectively. Irrigating Meyer at 30% ET_0 maintained quality with $PGC > 75\%$ and $> 25\%$ during the droughts in 2017 and 2018, respectively (Fig. 2.1-2.2, B). This indicates that while saving water, 30% ET_0 could maintain adequate quality of Meyer during the first-year summer of prolonged drought. If less than “minimally” adequate quality is acceptable, 30% ET_0 could still preserve some greenness in the second year of prolonged drought although recovery could be slower than in the first year. Presumably, intermittent precipitation could supplement 30% ET_0 irrigation and improve turfgrass quality in either of these scenarios. For example, most *Z. japonica* and *Z. matrella* cultivars maintained season-long TQ between 4 and 5 with rainfall plus 25% ET_0 (Zhang et al., 2013). Jamur *Z. japonica* maintained season-long $TQ > 6$ merely with rainfall (153 mm, $\sim 40\%$ ET_0) in the first year, but required supplemental irrigation to maintain $TQ = 6$ (totaled 284 mm, $\sim 61\%$ ET_0) in the second year (Culpepper et al., 2020). Fu et al. (2004) also reported more water was needed to maintain season-long minimally acceptable quality of C3 and C4 grasses in the second year of drought, which supports our findings. Nevertheless, 30% ET_0 in our study allowed autumn recovery after the droughts in both years; 30% ET_0 plots recovered to averages of both $PGC > 60$ and $TQ > 6$ in 4 and 36 d in 2017 and 2018, respectively.

Mean PGC was never significantly lower in 20-25% ET_0 than in 30% ET_0 plots throughout 2017 or in the first 54 d of the drought in 2018, although PGC varied by as much as 18% among 20-30% ET_0 plots (Fig. 2.1-2.2, B). As mentioned above, *Z. japonica* cultivars except Meyer had comparable TQ when irrigated with 14%-33% or at 37% ET_0 at different

locations (Zhang et al., 2013; Wherley et al., 2014). Our study indicates reducing irrigation from 30% to 25% or 20% ET_0 could conserve additional water while having few negative effects on PGC (Table 2.1 and 2.2). For example, reducing irrigation by 5% ET_0 (e.g., from 30% to 25%) saved an additional 1.9 mm wk^{-1} , or about 1.63 cm during the two-month summer droughts. This translates to about 2,282 m^3 of water savings for an average 14.0 ha. of irrigated roughs (or an equivalent area of residential lawns) in a typical 18-hole golf course (Gelernter, Stowell, Johnson, & Brown, 2017). The findings of this paper can apply to both golf course roughs and home lawns because of similar management practices. Furthermore, policymakers may conserve more water during prolonged droughts by restricting irrigation of Meyer to 20-30% ET_0 rather than imposing traditional restrictions, especially for high irrigators (Survis et al., 2017; Boyer et al., 2018).

Conclusions

Minimal water inputs of as little as 20 to 30% ET_0 replacement could improve Meyer performance during drought and enhance survival and recovery compared with no water inputs. Irrigation at 30% ET_0 maintained >75 PGC in Meyer throughout and beyond the 2-month drought in the first year, while 0% and 5% ET_0 Meyer declined to 30 PGC but recovered to ~60 PGC after 4 d of full irrigation. In the second year, Meyer at 30% ET_0 maintained >60 PGC for ~2 weeks and >25 PGC throughout the 2-month drought, and recovered to >60 PGC within 5 weeks after resuming full irrigation. However, Meyer at 0% and 5% ET_0 went dormant and only recovered to 30-42 PGC after 50 d of full irrigation in the second consecutive year of prolonged drought.

Using 30% ET_0 instead of 60% ET_0 , which is typically recommended for warm-season turfgrasses, saved 11.4 and 9.2 cm water in a silty clay loam soil during the 2-month summer droughts in 2017 and 2018, respectively. An additional 3.1-3.8 cm of water was saved by reducing irrigation from 30% to 20% ET_0 , with insignificant additional impacts on PGC (<18% reduction). However, our results indicate that impacts on turfgrass performance

could be more severe in a second consecutive year of prolonged drought, if irrigation is continued at these minimal irrigation levels. Additional research is needed to investigate potential effects of soil types, irrigation frequencies and amounts, and drought durations on minimum irrigation thresholds for maintaining turfgrass survival and recovery after severe droughts, including in other species.

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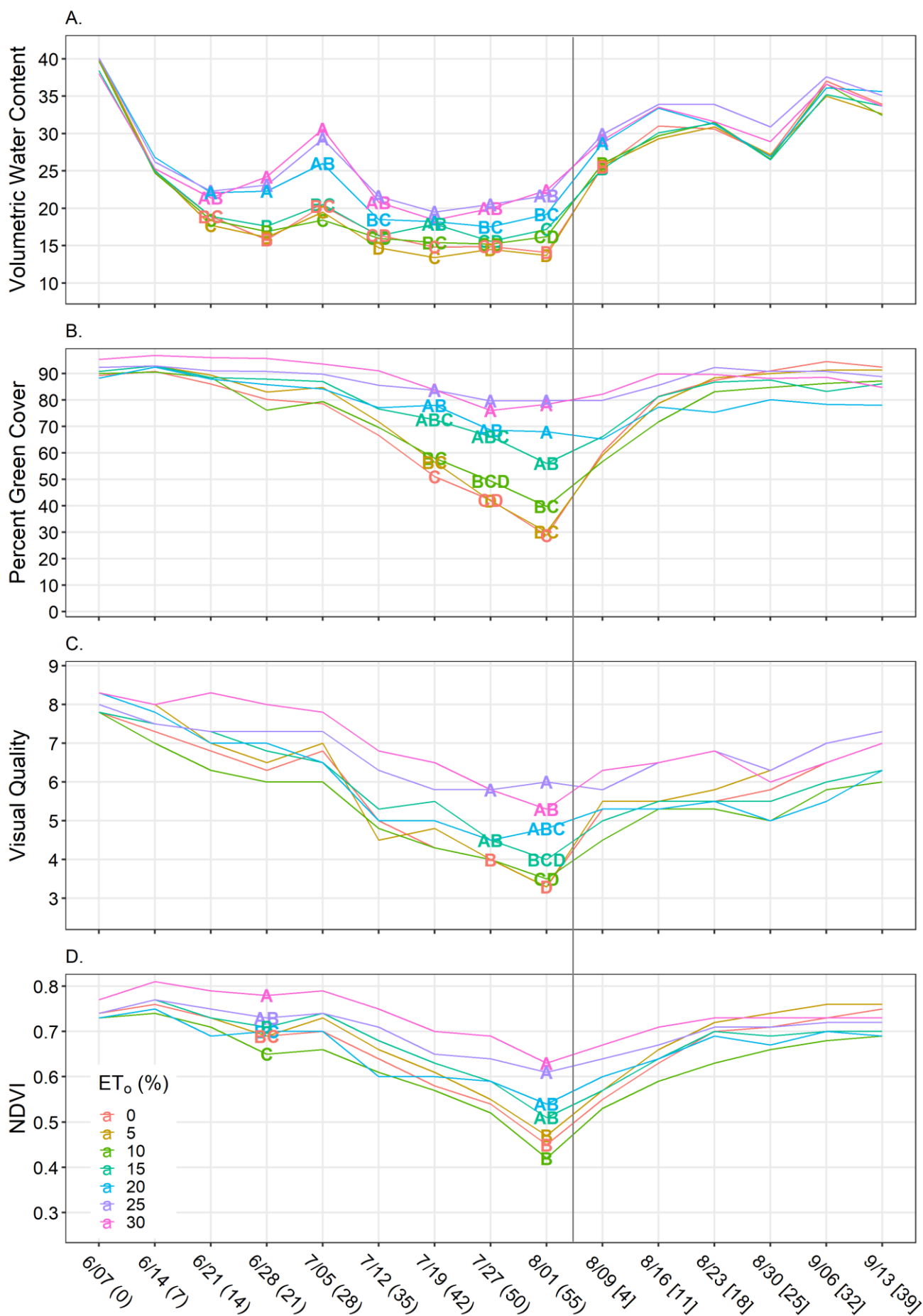


Figure 2.1. Volumetric water content (A, $\text{cm}^3 \text{ cm}^{-3}$), percent green cover (B), turfgrass quality (C), and normalized difference vegetation index (NDVI, D) of Japanese lawngrass irrigated at 0 to 30% evapotranspiration (ET_0) replacement treatments in 2017. Number in parentheses on the x-axis denotes days after the beginning of drought. Number in square brackets denotes days after full irrigation was resumed (denoted by vertical line). Means with no letter in common within a measurement and day are significantly different; means on days without letters were not significantly different ($P < 0.05$).

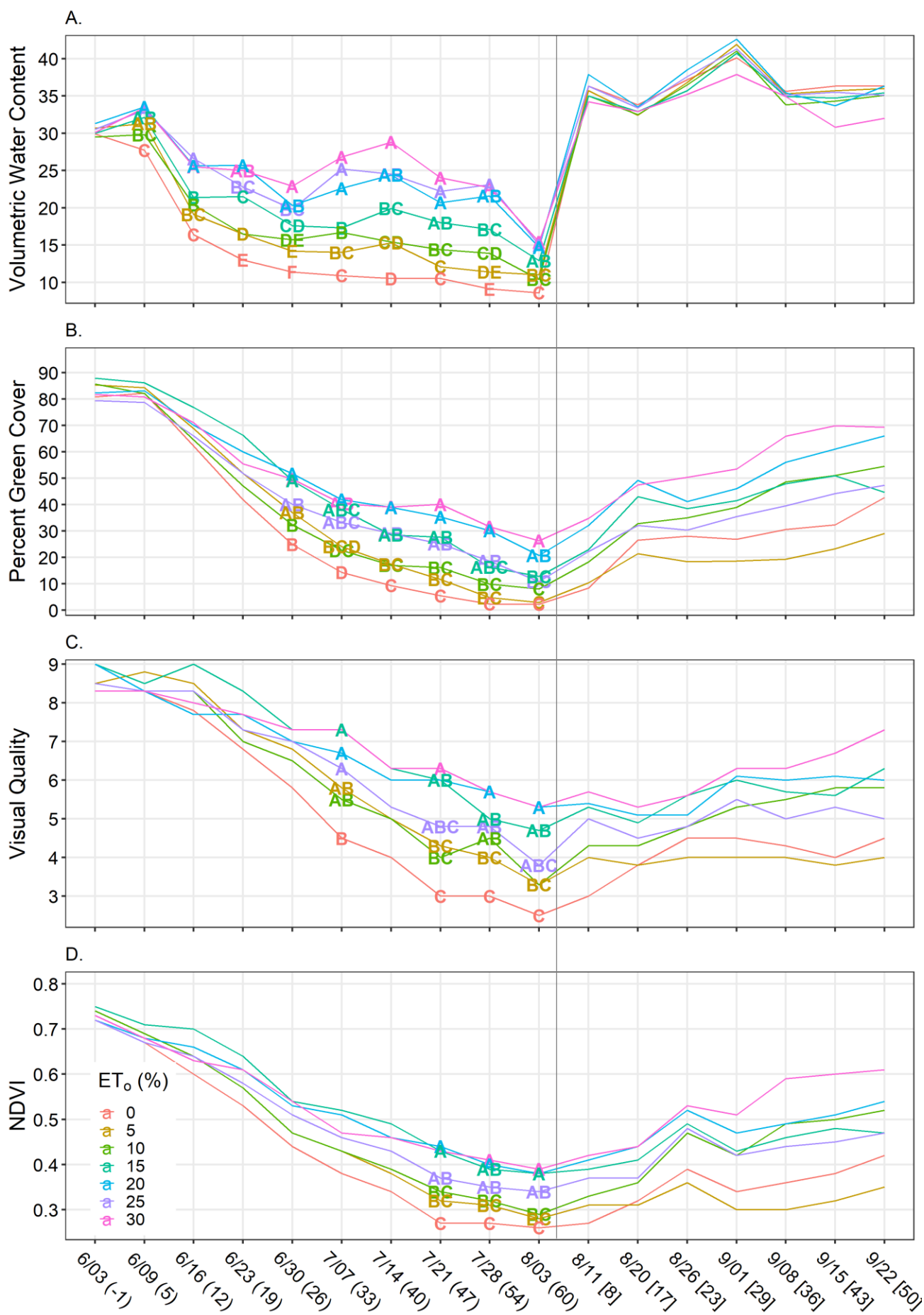


Figure 2.2. Volumetric water content (A, $\text{cm}^3 \text{ cm}^{-3}$), percent green cover (B), turfgrass quality (C), and normalized difference vegetation index (NDVI, D) of Japanese lawngrass irrigated at 0 to 30% evapotranspiration (ET_0) replacement treatments in 2018. Number in parentheses on the x-axis denotes days before (negative) or after (positive) the beginning of drought. Number in square brackets denotes days after full irrigation was resumed (denoted by vertical line). Means with no letter in common within a measurement and day are significantly different; means on days without letters were not significantly different ($P < 0.05$).

Table 2.1. Irrigation main effects on volumetric water content (VWC), turfgrass quality (TQ), percent green cover (PGC), and normalized difference vegetation index (NDVI) of Japanese lawngrass over the drought and recovery periods in 2017 and 2018.

ET _o ^a	2017 Drought period (55 d)				2018 Drought period (60 d)			
	VWC ^b	PGC	TQ ^c	NDVI ^d	VWC	PGC	TQ	NDVI
30%	19.1 A ^e	83.8 A	6.5 AB	0.67 A	22.7 A	53.9 A	7.2 AB	0.57 A
25%	19.7 A	85.2 A	6.7 A	0.65 A	20.5 A	43.3 ABC	6.4 ABC	0.55 A
20%	18.0 A	76.4 AB	6.3 ABC	0.64 AB	19.4 A	52.8 A	7.1 AB	0.58 A
15%	15.9 B	71.0 AB	5.8 BCD	0.58 ABC	15.5 B	51.6 AB	7.3 A	0.58 A
10%	15.2 BC	61.8 BC	5.4 D	0.54 C	12.6 BC	38.5 BC	6.1 BC	0.53 AB
5%	13.8 C	54.1 C	5.6 CD	0.55 BC	9.8 CD	38.8 BC	6.2 ABC	0.53 AB
0%	14.8 BC	54.8 C	5.2 D	0.55 C	7.4 D	32.5 C	5.4 C	0.49 B
<i>P</i>	***	**	**	*	***	*	*	*
	2017 Recovery (39 d)				2018 Recovery (50 d)			
30%	33.2	85.1	6.6	0.71	34.2	52.9	5.7	0.45
25%	33.7	86.0	6.5	0.68	35.2	35.0	4.9	0.36
20%	32.8	73.4	5.8	0.65	36.4	48.3	5.7	0.45
15%	29.9	78.6	5.7	0.65	34.8	35.6	5.6	0.40
10%	31.3	74.7	5.3	0.62	34.4	37.0	4.5	0.35
5%	30.0	78.7	6.4	0.67	35.1	19.8	4.3	0.34
0%	31.1	79.8	6.2	0.65	35.7	25.9	3.9	0.32

*, **, *** Significant at the 0.05, 0.01, and 0.001 probability levels, respectively.

a Percent of evapotranspiration (ET_o) replacement.

b Volumetric water content (cm³cm⁻³) measures the volume of water per unit bulk volume of soil across 7.6-cm depth.

c Turfgrass quality based on a 1 to 9 scale, with 1 = dead, 6 = minimally acceptable, and 9 = uniform, green, dense turfgrass.

d NDVI = (NIR-Red)/(NIR+Red). Red peaks at 670nm and NIR at 780nm.

e Means with no letter in common are significantly different (Fisher's protected LSD).

Table 2.2. Monthly rates of decline (%) of volumetric water content (VWC), turfgrass quality (TQ), percent green cover (PGC), and normalized difference vegetation index (NDVI) of Japanese lawngrass during the drought periods in 2017 and 2018.

ET _o ^a	VWC		PGC		TQ		NDVI	
	1 st month ^b	2 nd month ^c	1 st month	2 nd month	1 st month	2 nd month	1 st month	2 nd month
2017								
30%	19.5% D	26.60%	1.90%	16.7% C	5.60%	32.6% BC	2.40%	20.7% B
25%	26.9% CD	24.90%	2.80%	12.3% C	9.40%	17.5% D	0.40%	19.3% B
20%	35.0% BC	25.30%	4.20%	20.5% C	19.80%	27.4% CD	3.10%	22.7% B
15%	46.3% AB	14.40%	4.20%	35.4% BC	16.10%	38.1% BC	0.40%	30.5% AB
10%	53.7% A	11.60%	11.70%	50.2% AB	22.30%	41.7% AB	9.80%	35.8% A
5%	51.4% A	28.30%	6.50%	64.3% A	14.90%	53.6% A	1.00%	36.3% A
0%	48.9% A	25.30%	11.80%	65.8% A	12.50%	53.0% A	4.60%	35.9% A
<i>P</i>	***			**		***		*
2018								
30%	23.6% E	3.2% ABC	38.6% C	38.3% D	7.80%	23.3% C	25.70%	24.8% C
25%	34.9% D	-16.4% C	48.3% BC	57.7% CD	17.40%	31.9% BC	29.10%	30.4% BC
20%	35.3% D	-5.2% BC	36.2% C	40.5% D	20.60%	19.3% C	26.20%	24.1% C
15%	41.1% CD	4.2% ABC	46.0% BC	67.5% BC	18.70%	31.6% BC	29.60%	26.6% BC
10%	46.9% BC	10.6% AB	62.6% AB	76.8% ABC	22.60%	31.7% BC	35.80%	33.1% AB
5%	53.7% AB	20.3% A	56.6% AB	87.1% AB	20.20%	39.9% AB	36.80%	32.9% AB
0%	61.9% A	19.7% A	68.6% A	91.3% A	31.40%	47.5% A	38.90%	38.4% A
<i>P</i>	***	*	**	***		*		**

*, **, *** Significant at the 0.05, 0.01, and 0.001 probability levels, respectively.

a Percent of evapotranspiration (ET_o) replacement.

b Defined as (Day 0 - Day 28)/Day 0% in 2017, (Day -1 - Day 26)/(Day -1) in 2018.

c Defined as (Day 28 - Day 55)/Day 28 in 2017, (Day 26 - Day 54)/Day 26 in 2018.

Table 2.3. Irrigation amounts applied to Japanese lawngrass based on reference evapotranspiration (ET_o), calculated by weekly and monthly averages over the drought periods in both years, and cumulative during the drought period in each year.

ET _o	Weekly	Monthly	Cumulative	
			2017 (56 d)	2018 (55 d)
%	----- mm -----			
100	43.2	185.2	379.5	305.7
60	25.9	111.1	227.7	183.4
30	11.4 A ****	55.6	113.8	91.7
25	9.5 B	46.3	94.9	76.4
20	7.6 C	37.0	75.9	61.1
15	5.7 D	27.8	56.9	45.9
10	3.8 E	18.5	37.9	30.6
5	1.9 F	9.3	19.0	15.3

**** Significant at 0.0001 probability level. Mean separations were conducted on weekly irrigation treatment amounts only from 5 to 30% ET_o (Fisher's protected LSD).

Chapter 3 - Simulations of Nitrous Oxide Emissions and Global Warming Potential in a C4 Turfgrass System: Comparing the DAYCENT and DNDC Models

ABSTRACT

Nitrous oxide (N_2O) is an ozone depleting gas and important greenhouse gas (GHG) that has been implicated in global climate change. Irrigated and N-fertilized turfgrass systems cover large areas of land and emit N_2O . DAYCENT and DeNitrification-DeComposition (DNDC) are two widely used process-based models that predict GHG fluxes in agricultural lands. Despite of large number of studies applying these models, they have not been applied to C4 turfgrasses. Our objectives were to 1) calibrate DAYCENT and DNDC for N_2O emissions from ‘Meyer’ zoysiagrass (*Zoysia japonica* Steud., hereafter referred to as zoysia); 2) validate and test the two calibrated models and compare their prediction accuracies; and 3) predict long-term N_2O emissions, C sequestration, and global warming potential (GWP) of different irrigation and N-fertilization practices. A combination of global sensitivity analysis and a Bayesian method was used to calibrate DAYCENT and DNDC. After calibration, both models were validated using field measurements from two studies of zoysia. Validation results indicated DAYCENT ($R^2 = 0.22$ to 0.89 ; relative RMSE = 36 to 171%) outperformed DNDC ($R^2 = 0.01$ to 0.38 ; relative RMSE = 119 to 193%) in biweekly N_2O fluxes. Annual N_2O emission estimates obtained from validation of DAYCENT were within -49 to +26% of annual estimates interpolated from measurements, whereas DNDC simulations generally underestimated N_2O emissions by up to -86%. Results indicated DAYCENT, but not DNDC, can adequately simulate the impacts of irrigation and N-fertilization practices on N_2O emissions in C4 turfgrasses such as zoysia. When assuming no further climate change, the validated DAYCENT model predicted that the typically recommended N-fertilization and irrigation practice in fairway zoysia turf would reduce net

GWP by encouraging soil carbon sequestration in the first 40 years of establishment, better than no N-fertilization, after which reducing N and water inputs would be beneficial in mitigating increases of N₂O emissions and net GWP. A medium global warming scenario would accelerate increases in N₂O emissions and GWP, especially with higher N and water inputs.

INTRODUCTION

With rapid urbanization worldwide, turfgrass has been extensively utilized because of its significant economic, environmental, and human health benefits to society (Stier et al., 2013). This has resulted in large areas of land covered with turfgrass including golf courses, athletic fields, residential lawns, campus and public landscapes, cemeteries, and roadsides. Based on a global golf course inventory from the National Golf Foundation, there were 38,864 golf courses in 209 of the 249 countries globally by 2018 (The R&A, 2019). In the U.S., there was an estimated 13–20 million ha of turfgrass, from which irrigated turfgrass accounted for 5–10 million ha, making it the largest irrigated crop (Milesi et al., 2005, 2009).

Zoysiagrass

Zoysiagrass (zoysia), as a C4 turf species that originated from East Asia and the Pacific islands, has been well adapted to the climate of the transition zone and warm regions in the U.S., and is increasingly preferred for its minimal maintenance characteristics (Patton et al., 2017). While zoysia accounts for 2% (10,375 ha) of the maintained turfgrass in golf courses across the U.S., the share is higher in the transition zone (8%) and its popularity is increasing in the southeastern U.S. (Gelernter et al., 2017; Patton et al., 2017). From 2005 to 2015, the use of zoysia in U.S. golf courses increased by 67%, more than any other turfgrass species including seashore paspalum (*Paspalum vaginatum* Sw.) and tall fescue (*Festuca arundinacea* Schreb.) which increased by 53% and 20%, respectively, while the use of other turfgrass species has decreased (Gelernter et al., 2017).

Nitrous oxide emissions

Nitrous oxide (N_2O) is a greenhouse gas (GHG) with greater than a hundred-year live period. Atmospheric N_2O concentrations have increased more than 20% since pre-industrial times, to 331 ppb by 2018, with the fastest growth occurring since the 1980s (Ciais et al., 2014; Davidson & Kanter, 2014; Tian et al., 2020). With an estimated 100-yr global warming potential (GWP) of 265–310 times that of CO_2 , N_2O is currently the single most ozone-depleting gas and is expected to remain so throughout this century (Ciais et al., 2014; Ravishankara et al., 2009).

From the 1980s to 2016, anthropogenic sources of N_2O emissions steadily increased from 5.6 to 7.3 Tg N yr^{-1} , whereas the N_2O emissions from natural sources were relatively stable (9.9 to 9.7 Tg N yr^{-1}) (Tian et al., 2020). During this period, agriculture accounted for more than 71% of the increase in anthropogenic N_2O emissions, which was mainly attributed to nitrogenous fertilization (Tian et al., 2020). For most agricultural croplands, N_2O emissions increase in an exponential rather than a linear trend in response to synthetic N fertilizer inputs, indicating N inputs exceed crop needs (Ciais et al., 2014; Davidson & Kanter, 2014; Shcherbak et al., 2014).

Nitrous oxide emissions data are relatively limited from turfgrass systems, as reported in a comprehensive review by Braun & Bremer (2018b). Turfgrass systems are typically irrigated and fertilized with synthetic and/or organic nitrogen, which may result in significant N_2O emissions (Braun & Bremer, 2018a, 2018b; Bremer, 2006). Emissions of N_2O differ among grass species because of their varying N uptake abilities and different influences on soil N_2O formation (Bowatte et al., 2014, 2018; Bowman et al., 2002; Hamido et al., 2016). However, turfgrass systems also can be a net sink for CO_2 and retain N, and the net GWP of turfgrass systems may be reduced by tuning management practices over the years (Braun & Bremer, 2019; Chen et al., 2018; Gu et al., 2015; Qian et al., 2003; Qian & Follett, 2012; Tidåker et al., 2017; Zhang, Qian,

Bremer et al., 2013). For example, previous studies have revealed significant effects of N-fertilization and irrigation management on N₂O emissions in zoysia over two years and C sequestration over three years (Braun & Bremer, 2018a, 2019).

Process-based models

To monitor and estimate the impacts of atmospheric N₂O on GWP, continuous long-term measurements of N₂O emissions are needed but they are expensive and time-consuming, including the majority of research that has been conducted with static chambers (Braun & Bremer, 2018b). Alternatively, process-based models have been an important tool to apply the current state of biogeochemical knowledge to estimate and explain spatial and temporal patterns of GHG fluxes from various ecosystems, which can aid the understanding of biogeochemical processes and advise decision making for the ecosystems. DAYCENT and DeNitrification-DeComposition (DNDC) models are two of the most widely used daily time-step process-based models that simulate C and N cycles, plant yield, and GHG fluxes in ecosystems including crop/grass lands, rice paddies, forests, savannahs, and wetlands from field to global scales (Del Grosso et al., 2009; Del Grosso & Parton, 2019; Gilhespy et al., 2014; Yang et al., 2021).

DAYCENT is a daily time-step version derived from the CENTURY biogeochemical model (Del Grosso & Parton, 2019; Parton et al., 1998). DAYCENT adopts a “Hole-in-the-pipe” concept where nitrification and denitrification depend on the soil matrix and factors that control soil N flow and partitioning of N species (Bouwman, 1998; Parton et al., 2001). DAYCENT has been validated in C3 turfgrasses including its estimates of biomass, N₂O emissions, and SOC (Bandaranayake et al., 2003; Braun & Bremer, 2018b; Qian et al., 2003; Zhang, Qian, Bremer, et al., 2013; Zhang, Qian, Mecham, et al., 2013).

DNDC was developed to simulate N₂O emissions (Giltrap et al., 2010; Li et al., 2000). Since then, many versions have been developed for specific conditions around the world (Gillespie et al., 2014). DNDC implements an “anaerobic balloon” concept so that the proportions of aerobic and anaerobic soil sites are quantified for nitrification and denitrification, respectively (Li et al., 2000). DNDC has been applied for N₂O simulations in urban lawns, but has rarely been calibrated and validated for any specific turfgrass species (Gu et al., 2015).

Model comparisons

Process-based model comparisons, including between DAYCENT and DNDC, have been conducted on agricultural crops but not, to our knowledge, in turfgrass systems (Brilli et al., 2017; Dutta et al., 2017; Gaillard et al., 2018; Li et al., 2005; G. Wang & Chen, 2012; Wang et al., 2020; Yue et al., 2019; Zimmermann et al., 2018). Although DAYCENT is of intermediate complexity and DNDC’s complexity is relatively greater, comparisons of their fit in N₂O simulation in croplands have been mixed (Del Grosso et al., 2020; Ehrhardt et al., 2018). In addition to model comparisons, model uncertainty and sensitivity analyses have been useful for improving process-based models to eventually advise crop management and inform policymaking (Ehrhardt et al., 2018; Gaillard et al., 2018; Gurung et al., 2020; Wang & Chen, 2012; Zhang et al., 2020). Recently, the Bayesian theorem coupled with certain Monte Carlo techniques has been a popular approach to quantify uncertainties in the outputs of process-based models (Gurung et al., 2020; G. Wang & Chen, 2012; Zhang et al., 2020).

The thorough acquisition of N₂O emissions data from measurements in zoysia provided a unique opportunity to calibrate, validate, test, and compare process-based models for a C4 turfgrass (Braun & Bremer, 2018a; Lewis & Bremer, 2013). Process-based models need to be

calibrated for accuracy with detailed inputs, which to date has not been conducted for C4 turfgrasses such as zoysia, and the parameterizations for C4 turfgrass' characteristics would be different from C3 turfgrass (Del Grosso et al., 2011, 2020; Ehrhardt et al., 2018). Similarly, GWP of different management intensities have been simulated by both DAYCENT and DNDC in C3 but not C4 turfgrasses (Gu et al., 2015; Zhang, Qian, Bremer, et al., 2013). Comparisons between DAYCENT and DNDC in their ability to simulate effects on GHG fluxes from different turfgrass management regimes would help determine the best model for long-term predictions of N₂O emissions and GWP and best management practices for mitigating GHG fluxes in zoysia turf.

Therefore, using field measurements from Braun & Bremer (2018a) and Lewis & Bremer (2013), the objectives of this study were to:

1. Calibrate the DAYCENT and DNDC models for N₂O emissions from zoysia through a Bayesian and Monte Carlo method;
2. Validate and test the two calibrated models and compare their prediction accuracies;
3. Predict long-term N₂O emissions and C sequestration in fairway zoysia and the impacts (GWP) of different irrigation and N-fertilization practices.

METHODS AND MATERIALS

Field experiment datasets

Data from Braun & Bremer (2018a) were used to calibrate and validate the DAYCENT and DNDC models. Those authors conducted a field experiment from 2013 to 2016 under an automated rainout shelter that allowed for precise control of irrigation according to reference

evapotranspiration (ET_o) of on-site weather data (<http://mesonet.k-state.edu>). The soil was a Chase silty clay loam (fine, smectitic, mesic Aquertic Argiudoll). ‘Meyer’ zoysia (*Zoysia japonica* Steud.) was sodded on 4 June 2013 at KSU Turfgrass Research Center near Manhattan, Kansas (39°13’53’’N, 96°34’51’’W). Meyer was maintained at a fairway height (2.54 cm) and clippings were returned to the soil.

In the Braun & Bremer (2018a) study during 2015–2016, six treatments included combinations of N fertilizer (0 or 98 kg ha⁻¹ yr⁻¹ [urea or poly-coated urea]) and irrigation (Medium [66%–68% ET_o] and Low [33%–45% ET_o]). Specifically, the six treatments included granular urea and medium irrigation (Urea_Medium), granular urea and low irrigation (Urea_Low), poly-coated urea and medium irrigation (PCU_Medium), poly-coated urea and low irrigation (PCU_Low), no fertilization and medium irrigation (None_Medium), and no fertilization and low irrigation (None_Low).

Braun & Bremer (2018a) conducted 69 measurement events of soil volumetric water content (VWC), soil temperature, N₂O emissions, soil ammonia (NH₄), and soil nitrate (NO₃). Soil C and bulk density at 0–30 cm depth were measured at the start and end of the study (Braun & Bremer, 2019). In the present study, data from the Urea_Medium treatment (a regular, typically recommended irrigation and N-fertilization regime in zoysia) was used to calibrate both the DAYCENT and DNDC models. Data from the other N-fertilization and irrigation treatments (Urea_Low, PCU_Medium, PCU_Low, None_Medium, and None_Low) was used for model validations.

An earlier N₂O emissions study conducted on Meyer zoysia from 2006 to 2008 at a nearby site at the KSU Turfgrass Research Center was also used for model validation (Lewis & Bremer, 2013). Soil temperature, VWC, soil NH₄, soil NO₃, and N₂O fluxes were measured on 58 dates.

Soil C, texture, and bulk density at 0-15 cm depth were measured at the start of the study. The Meyer zoysia in that study was established in May 2005, fertilized with urea at 100 kg N ha⁻¹ yr⁻¹, and maintained at a lawn height (7.5 cm). In both Meyer zoysia studies described above (Braun & Bremer, 2018a; Lewis & Bremer, 2013), more frequent measurements (e.g., one to three days) after fertilization events were conducted.

DAYCENT initial parameterization

The version used in this paper was also used by the U.S. Environmental Protection Agency (U.S. EPA, 2021). Information on weather, soil, and management practices was required for model simulations. Daily maximum and minimum temperatures and precipitation were obtained from the onsite mesonet station for 2013-2021 and from the closest NOAA weather station GHCND:USC00148259 (<https://www.ncdc.noaa.gov/cdo-web/datatools/findstation>) for 1983-2012; onsite weather data were not available prior to 2013. For the DAYCENT soil file, the soil pH was set at 7.0, and bulk density at 0-10 cm and 10-30 cm depths was 1.42 and 1.51 g cm⁻³, respectively, based on measurements by Braun & Bremer (2019). Two soil cores from the upper 30-cm depth were taken at the study site to represent average soil texture of the soil profile (0-210 cm), based on which bulk density (30-210 cm), saturation conductivity (0-210 cm), field capacity and wilting point (0-210 cm) were calculated using Soil Water Characteristics v.6.02.74 (Saxton & Rawls, 2006; <https://hrsl.ba.ars.usda.gov/soilwater/Index.htm>). The Meyer zoysia root profile was set to 90-cm depth and the relative distribution was determined by an earlier field study at the same research center (Qian et al., 1997). The upper 30 cm organic matter was estimated with measured SOC using a 58% factor (Combs & Nathan, 1998). In the DAYCENT

site file, the initial surface 20-cm SOC pools were adjusted to be within 1% of the mean SOC measured before the experiment period (Braun & Bremer, 2019).

Using default parameters, historical land use at the research site was simulated as the surrounding, regional tallgrass prairie for 5000 years to reach equilibrium (spin-up period), followed by C3 turfgrass with regular maintenance from the 1970s until the experimental period with C4 zoysia from 2014 to 2016. The parameterization of C3 turfgrasses had been accomplished by others (Golubiewski, 2006; Zhang, Qian, Mecham, et al., 2013), and was used for the period with C3 turfgrass at our site. During the period with zoysia, turfgrass management practices of fertilization, irrigation, and mowing events were scheduled as documented by Braun & Bremer (2018a). Urea fertilization was modeled as a one-time input of NH_4 into the soil. PCU (90-day release) was modeled as 45 events of equal NH_4 input with a 2-day interval (Salman et al., 1989). Each irrigation event was scheduled with specific documented amounts (Braun & Bremer, 2018a). Mowing was treated as a harvest event in the model that returns the 10% aboveground biomass (clippings) as litter, according to clippings collected from zoysia turf in the field at the research center in 2020 (Fig. A11) and previous research (Bowman et al., 2002; Qian et al., 2003; Trappe et al., 2011).

A new crop was parameterized as zoysia and added to the DAYCENT crop file. The following parameters were adjusted before the Bayesian calibration because they can be directly measured or derived from measurements and were relatively insensitive to model outputs compared with parameters in Table 3.1 according to the global sensitivity analysis as described in a later section (Zhang et al., 2020). Belowground C allocation parameters [Table A1; CFRTCW(2), CFRTCN(2)] and shoot and root death rates [Table A1; FSDETH(1), RDRJ, RDRM] were adjusted based on biomass measurements at the research center in 2020 (Fig. A10,

A11) and research on Meyer zoysia (Patton et al., 2007). Leaf lignin content was set at 6% (Hale et al., 2009; Hamido et al., 2016). Lignin content of roots was set at 24.3% based on lab analysis of Meyer zoysia root and rhizome samples at a 10-cm depth (Sluiter et al., 2008). Boundary parameters of C/N ratio were adjusted by fitting model outputs of leaf and root C/N ratios within the ranges of field samples (Fig. A12) analyzed at the Kansas State University Soil Testing Laboratory.

DNDC initial parameterization

DNDC v.9.5, the most used version, was used in this study (<http://www.dndc.sr.unh.edu/>). The same weather data, optimal temperature (30 °C), grain fraction (0.1%), soil texture, field capacity, wilting point, and pH were set in DNDC as in DAYCENT described above. Land use was set to be “Moist grassland/pasture” and soil texture was “Silty clay loam”. Initial surface 20-cm SOC was adjusted to be within 1% of the mean measured SOC (Braun & Bremer, 2019). The experimental period followed a 2-year spin-up period (Zhang et al., 2015).

Irrigation, fertilization, and mowing events were scheduled the same as in the DAYCENT model. “Days for total N release” (slow-release rate) was set at 90 for the PCU treatment. Clipping return was scheduled as a fixed amount of manure amendment at each mowing event so that the annual amendment matched the model output of the annual cut leaf amount. Ranges of crop C allocation parameters were based on Meyer zoysia field biomass measurements in 2020 and previous research of Meyer zoysia (Patton et al., 2007) (Table 3.2).

DAYCENT and DNDNC were calibrated using the same processes of sensitivity analysis and Bayesian calibration as detailed below.

Global sensitivity analysis

As a very comprehensive global sensitivity analysis method, Sobol is variance-based, model-independent, and computationally efficient for complex models, such as process-based models (Gurung et al., 2020; Qin et al., 2016; Sobol, 2001; Zhang et al., 2020). Therefore, it has been used as a prior step to identify parameters with the relatively high influence (i.e., explaining a high proportion of the variance) for model outputs, so that other insensitive parameters can be fixed at the next-step of Bayesian model analysis (Gurung et al., 2020; Wang & Chen, 2012; Zhang et al., 2020).

Sobol requires independence of parameters. However, DNDC parameters of fractions of leaf, stem, and root are dependent (sum of 0.999; Grain fraction = 0.001). A new parameter, leaf ratio (leaf biomass to aboveground biomass) was therefore induced as a random variable to set DNDC parameters of leaf and stem fractions (Table 3.2; Leaf_ratio). Stem C/N was set to be the same as Leaf C/N in the DNDC model. Twenty-five parameters of DAYCENT and seven parameters of DNDC were analyzed by the Sobol method and ranked by the total sensitivity indices (total effect) for simulations of VWC, NH₄, NO₃, and N₂O, respectively (Table A1, A5; Fig. A1, A5). The number of simulations equaled to the product of $n=1000$ and $k+2$ (k is the number of parameters) to ensure numerical stability (Saltelli et al., 1999).

Bayesian calibration

Nine sensitive (Sobol total indices ≥ 0.025) DAYCENT parameters (Table 3.1) and the seven abovementioned DNDC parameters (given the limited number of parameters that are relevant and adjustable; Table 3.2) were calibrated using the Bayes' theorem with the sampling importance resampling (SIR) method. Other parameters in both models were kept at the default

values. The joint posterior (post-calibration) distribution $p(\theta|Y)$ can be statically inferred by Eq. (1) (Vrugt, 2016; Zhang et al., 2020).

$$p(\theta|Y) \propto p(\theta)L(\theta|Y) \quad (1)$$

where, $p(\theta)$ is the prior (before-calibration) distribution of parameters; the likelihood $L(\theta|Y)$ is determined from the probability distribution of the residuals between observed (Y) and modeled responses.

SIR is a direct Monte Carlo method and the coupling of SIR and Bayes' theorem was detailed by Gurung et al. (2020). In brief, after exhaustive simulations of a million parameter sets (each parameter was randomly drawn from a uniform distribution with a prior range; Table 3.1 and 3.2), each parameter set was weighted by the summation of likelihood of the model outputs and observations. Root mean square error between simulations and observations was used to estimate hyperparameter (sigma in the Gaussian likelihood formula) in each run (Gurung et al. 2020). The Monte Carlo approach (one thousand draws from the one-million parameter sets based on likelihood weights) was used to estimate marginal posterior distributions of parameter values and model outputs (Gurung et al. 2020). The best parameter set was determined by the maximum sum of likelihood of simulations of daily VWC, NH_4 , NO_3 , and biweekly N_2O in zoysia under regular management treatment (Urea_Medium) (Braun & Bremer, 2018a). Given the temporally heterogeneous nature of N_2O , the biweekly N_2O instead of daily N_2O values from simulations and measurements were used for calibration. The daily emissions of N_2O simulated by process-based models may be lagged or led (Brilli et al., 2017; W. N. Smith et al., 2008; Yue et al., 2019). At calibration, the best parameter set was determined by the maximum sum of likelihood containing biweekly N_2O averages, which resulted in better model validation of both biweekly and daily N_2O than that containing daily N_2O (data not shown).

Model evaluations

By adopting the best parameter set for Urea_Medium (Braun & Bremer, 2018a), both DAYCENT and DNDC models were respectively validated using data from other irrigation and N-fertilization treatments in the same study, and from an independent study (Lewis & Bremer, 2013). DNDC and DAYCENT simulations in calibration and validation phases were evaluated for time-series fitness for measurements using coefficient of determination (R^2), model efficiency (ME) in Eq. (2), relative root mean square error (RRMSE) in Eq. (3), and relative mean difference (RMD) in Eq. (4) (Necpálová et al., 2015; Yue et al., 2019; Zhang et al., 2015). Annual N_2O emissions of both models were also compared with measurements. After linear interpolation of observations, biweekly N_2O averages, annual N_2O emissions, and standard errors of observations were calculated.

$$1 - \frac{\sum_{i=1}^n (S_i - O_i)^2}{\sum_{i=1}^n (O_i - \bar{O})^2} \quad (2)$$

$$\frac{1}{\bar{O}} \sqrt{\frac{1}{n} \sum_{i=1}^n (S_i - O_i)^2} \quad (3)$$

$$\frac{1}{\bar{O}} (\bar{S} - \bar{O}) \quad (4)$$

where, n is the number of observations; S_i and O_i represent the i^{th} simulated value from the models and the respective observed value; and $\bar{S}$ and $\bar{O}$ represent the mean of the simulated and observed value.

Predictions in future weather

Using the validated model of DAYCENT and/or DNDC, annual N_2O and soil C were projected in fairway zoysia for the next 80 years (2021-2100) under different management

practices based on a baseline weather scenario, which uses 1983-2021 local historical data assuming no further climate change and CO₂ concentration at current level [418.9 ppm (NOAA, 2021)]. To consider climate change under the Shared Socioeconomic Pathway (SSP) scenario of medium challenges to mitigation and adaptation (SSP2-4.5) (O'Neill et al., 2016), five global downscaled (0.25 degree resolution) future weather models (GFDL-ESM4, MIROC-ES2L, EC-Earth3-Veg-LR, MPI-ESM1-2-LR, ACCESS-ESM1-5) were selected and downloaded from the Coupled Model Intercomparison Project Phase 6 (CMIP6) (<https://www.nccs.nasa.gov/services/data-collections/land-based-products/nex-gddp-cmip6>). Under the CMIP6 SSP2-4.5 climate scenario, global CO₂ concentration was assumed to linearly increase till 602.8 ppm in 2100 (Meinshausen et al., 2020).

GWP from mowing, irrigation, fertilizer, pesticides, and GHG fluxes was calculated for different management practices based on their C equivalents (Braun & Bremer, 2019; Gu et al., 2015). GWP from applications of pesticides and fungicide was the same for all management practices. Net GWP was calculated from GWP of turfgrass management and emissions of N₂O (GWP = 298 CO₂) and CH₄ (GWP = 25 CO₂) minus C sequestration (Braun & Bremer, 2019; Gu et al., 2015; Zhang, Qian, Bremer, et al., 2013). Negative net GWP means the turf sward is a sink for atmospheric C while positive net GWP means the turf is a source for atmospheric C. Cumulative net GWP was the aggregation of net annual GWP since the first year of prediction.

All analyses and figures within this manuscript were conducted and produced by the R program (R Core Team, 2021).

RESULTS

DAYCENT simulation

Sensitivity

Rankings of sensitivity of the DAYCENT parameters to model outputs are presented in Fig. A1 (parameters are defined in Table A1). Top sensitive parameters (total sensitivity indices ≥ 0.025) were listed in Table A2. All NH_4 , NO_3 , and N_2O outputs were sensitive to PRDX(1) and FAVAIL(1). Both N_2O and VWC were sensitive to FWLOSS(4). Both N_2O and NH_4 were sensitive to MINO3. Additionally, MAXNIT affected NH_4 ; FALLRT affected VWC; WFPSNIP, N2N2OA, and NADJWP affected N_2O .

Posterior distributions of sensitive parameters and their correlations

Posterior distributions of most parameters except FALLRT, MAXNIT, and N2N2OA were well informed by the Bayesian calibration compared to their prior distributions (Fig. A2). PRDX(1), NADJWP, and FWLOSS(4) exhibited their highest probability at their upper or lower bounds despite that their full prior ranges represented reasonable limits. Correlations between the sensitive parameters were low ranging from nearly none to weakly moderate (i.e., WFPSNIP and N2N2OA or NADJWP; Fig. A3).

Calibration and prediction uncertainty

The patterns of DAYCENT simulated and measured daily N_2O within the calibration dataset (Urea_Medium) were well matched, although the three highest N_2O peaks caused by fertilization were underestimated (Fig. A4). Prediction uncertainty of daily N_2O emissions was significantly reduced with the posterior parameter distribution compared with using random parameters

(priors). The resulting 95% prediction interval was narrow and it well enclosed most observations.

Both using the calibrated parameters, the biweekly N₂O simulation was better than the daily simulation within the calibration dataset (Urea_Medium) (Fig. 3.1, A4; Table 3.3, A3). The calibrated DAYCENT model described the biweekly N₂O data well with strong R² and ME, weakly moderate RRMSE, and low RMD (Table 3.3). Notably, daily N₂O flux simulations still performed adequately (e.g., R²=0.25-0.71), close to the simulations of biweekly N₂O flux (e.g., R²=0.25-0.89). Annual N₂O simulation of Urea_Medium was within 8% of the estimate based on field measurements by Braun & Bremer (2018a) (Fig 3.2). See other calibration results of daily soil temperature, VWC, NH₄, NO₃, N₂O in Table A3.

Validation

In general, biweekly N₂O validation of the calibrated DAYCENT model performed well when applied to the remaining five treatments but especially in Urea_Low, PCU_Medium, and None_Medium with strong R² and ME, low to weakly moderate RRMSE, and low RMD (Fig. 3.1; Table 3.3). Their annual N₂O simulations were within -49 to +26% of the estimates derived from field measurements (Fig 3.2). As for model validation using the independent dataset of Lewis and Bremer (2013), DAYCENT underestimated the biweekly N₂O peak at fertilization in July 2006 and the snowmelt peak in Feb. 2007 (Fig 3.3). There were under- and over-estimations of N₂O around N fertilization events in 2007. Although model validation performed poorly for the independent study (Table 3.3), the annual N₂O simulation was within 10% of annual estimates interpolated from the measurement (Fig 3.3). See other validation results of daily soil temperature, VWC, NH₄, NO₃, N₂O in Table A3.

DNDC simulation

Sensibility

Maximum_yield, Leaf_C/N, and Leaf_ratio were the sensitive parameters for simulations of soil VWC, NH₄, NO₃, and N₂O (Table A5; Fig. A5). In addition, both VWC and NH₄ were sensitive to Accumulative_temperature, NO₃ was sensitive to Root_fraction, and VWC was sensitive to Water_requirement.

Posterior distribution of parameters and their correlation

Posterior distributions of DNDC parameters Maximum_yield, Accumulative_temperature, Water_requirement, and Leaf_C/N were informed by the Bayesian calibration compared to their prior distributions (Fig. A6). Maximum_yield exhibited their highest probability at their upper bounds. Correlations between the seven DNDC parameters were low ($r < 0.4$; Fig. A7).

Calibration and prediction uncertainty

After calibration, the DNDC generally underestimated daily and biweekly N₂O emissions of the calibration dataset (Urea_Medium) during the growing seasons (Fig. 3.4, A8; Table 3.4, A6). The DNDC simulation was relatively invariable except for high pulses only around fertilization events. One simulated pulse underestimated daily N₂O in July 2015, while one highly overestimated daily N₂O in July 2016. The prior uncertainty of daily N₂O emissions from DNDC was narrow, which was relatively similar to 95% prediction interval using posterior likelihood parameter distributions.

Although roughly matching the biweekly N₂O flux patterns of measured Urea_Medium, the calibrated DNDC model inadequately described the calibration data. While results indicated a moderate R², the ME was negative (inferior to mean of the data), RRMSE was high, and the RMD was negative (underestimation) (Table 3.4). Accordingly, DNDC underestimated annual N₂O emissions in the calibration dataset (Urea_Medium) by 17 to 48% compared with field measurements (Fig 3.5). See other calibration results of daily soil temperature, VWC, NH₄, NO₃, N₂O in Table A6.

Validation

Compared to the calibration, simulated N₂O fluxes with DNDC were less accurate in the validation tests using data from the other five treatments in Braun & Bremer (2018a), especially in PCU and no (None) N fertilizations (Fig 3.4; Table 3.4). Annual N₂O simulations from DNDC underestimated that of field measurements by 25 to 86% among the five treatments (Fig 3.5).

As for model validation using the independent dataset of Lewis and Bremer (2013), DNDC underestimated N₂O peak emissions after N fertilization in July 2006 and a snowmelt peak in Feb. 2007 (Fig 3.3). There were N₂O overestimations around N fertilization events in 2007. Model validation for DNDC performed better for the independent study than for validation tests with the five treatments described above, as indicated by higher R², RMD, and higher and positive ME, although RRMSE is higher (Table 3.4). Annual N₂O simulations with DNDC underestimated that from field measurements by up to 49% (Fig 3.3). See other validation results of daily soil temperature, VWC, NH₄, NO₃, N₂O in Table A6.

Predictions in future weather

Because of better validation results from DAYCENT than DNDC, the DAYCENT model was used to predict long-term N₂O emissions (Fig. 3.6, A14), C sequestration (Fig. A13), and the cumulative net GWP of different irrigation and N-fertilization practices in zoysia (Fig. 3.7). Under baseline weather conditions, annual N₂O emissions from zoysia without fertilization would decrease to be at a low rate between 1 to 1.5 kg N ha⁻¹ yr⁻¹ till the end of the century (Fig. 3.6). In contrast, annual N₂O emissions would continuously increase if zoysia is fertilized (98 kg N ha⁻¹ yr⁻¹) regardless of N-fertilizer forms, but using PCU or Low irrigation could occasionally reduce N₂O emissions in some years (Fig. 3.6). However, low irrigation would have lower cumulative net GWP than medium irrigation after the 2030s regardless of N fertilization (Fig. 3.7).

Cumulative net GWP in zoysia with N fertilization would decrease faster than with no N fertilization by the late 2050s. Thereafter, net GWP in zoysia with N fertilization would increase faster than and surpass that of no N practices (Fig. 3.7), indicating a net negative effect of long-term fixed-amount N fertilization. In other words, the net annual GWP from N-fertilized zoysia would be negative until late 2050s, with greater absolute values (atmospheric CO₂ absorbing capacity) than with no fertilization, and then increase to be positive. PCU fertilization would have lower net annual GWP than Urea fertilization after the late 2050s.

As for the medium climate change scenario (SSP2-4.5), the trends and rankings among the six management practices in predictions of their N₂O emissions and cumulative GWP were the same under the five selected future weather datasets as under the baseline weather (data not shown). Given the slight bias of the calibrated DAYCENT in Urea_Low, PCU_Medium, and None Low (Table 3.3, RMD), there could be limitations in the long-term predictions in these

three management regimes. To illustrate the effects of climate change on future N₂O emissions (Fig. 3.8) and cumulative GWP (Fig. 3.9), Urea_Medium and None_Medium were used to represent moderate- (regular) and low-intensity management regimes. Compared to under the baseline weather, there would be positive feedbacks in N₂O emissions and cumulative GWP under climate change (SSP2-4.5), especially in moderate-intensity management regime. As a result, cumulative GWP of Urea_Medium would cross over (offset) that of None_Medium earlier (>20 yr) than under the baseline weather.

DISCUSSION

Model comparisons

DAYCENT daily and biweekly N₂O simulations were better than that of DNDC (Fig. A4, A8; Table A3, A6, daily and biweekly N₂O), partly because DAYCENT better simulated the background emissions (i.e., no N fertilization: None_Medium and None_Low). Smaller RMSE and better simulations of background emissions have also been reported by others in DAYCENT compared to DNDC (Zimmermann et al., 2018). Simulations of annual N₂O emissions with DAYCENT fitted fairly well for the annual N₂O estimates interpolated from field measurements, much better than that of DNDC. Half of the DAYCENT annual N₂O emissions (7 out of 14) were within one standard error of annual estimates interpolated from field measurements in all calibration and validation datasets (Fig 3.2, 3.3). In contrast, only one of 14 DNDC annual N₂O emissions was within one standard error of annual estimates (Fig. 3.3, 3.5). Previous studies have also shown that both daily and annual N₂O simulations of DAYCENT outperformed that of DNDC in croplands and grasslands in various locations worldwide (Gaillard et al., 2018; Yue et al., 2019; Zimmermann et al., 2018).

DNDC's significant bias of underestimating N_2O can be attributed to large underestimations of soil N (Table A6, Study 1 and 2; NH_4 RMD < -88%, NO_3 RMD < -69%) and underestimation of surface soil C (Fig. A9) that provides dissolved organic C for denitrification (Cui et al., 2012). Underestimated N_2O emissions by DNDC has been reported in agricultural cropping systems (Gaillard et al., 2018; Yue et al., 2019). Similar to our findings (Table A6; biweekly N_2O ME), the negative model efficiency (inferior to N_2O average) of DNDC was also reported (Gaillard et al., 2018; Zhang et al., 2015).

The calibrated DAYCENT from this study produced average annual N_2O emissions within 3.2% of field measurements from zoysia (mathematically equals to RMD of Biweekly N_2O , Urea_Medium; Table 3.3). Zhang, Qian, Bremer, et al. (2013) calibrated DAYCENT and produced average annual N_2O emissions within 8% and 16% of field measurements from perennial ryegrass and Kentucky bluegrass, respectively. This implied the advantages of algorithmic (Bayes' theorem and SIR) over empirical (manual trial) calibration. Given that N_2O emissions varied among grass species (Bowatte et al., 2014, 2018), future research can compare relative impacts on N_2O emissions of different turf species/cultivars and management practices including N fertilization (e.g., amount, timing, fertigation or not, organic form or not) and irrigation (Braun & Bremer, 2018a, 2018b; Głab et al., 2020; Ning et al., 2019; Tidåker et al., 2017; Wang et al., 2014; Zanardo et al., 2016; Zhang, Qian, Bremer, et al., 2013).

Process-based model limitations

One difficulty of calibrating process-based models is to calibrate shared parameters that are sensitive to multiple output variables. In this study, three (i.e., Maximum_yield, Leaf_C/N, and Leaf_ratio) out of seven parameters in DNDC were sensitive for predicting all variables, whereas

two [i.e., PRDX(1) and FAVAIL(1)] out of nine in DAYCENT were sensitive for NH_4 , NO_3 , and N_2O . Therefore, it is difficult to find the optimal value of each parameter when fitting many variables (e.g. VWC, NH_4 , NO_3 , and N_2O) simultaneously (Wang & Chen, 2012). For example, the optimal calibrated value of Leaf_C/N fell far away from the peak of marginal posterior distribution (Fig. A6; Table 3.1).

While DAYCENT parameters that control and affect mineralization, nitrification, and denitrification are adjustable for users, the DNDC parameters that are relevant and available in the input file are limited to be crop-related (DNDC, 2017). This hinders users to calibrate DNDC to the optimal for different conditions. Notably, users currently cannot create a C4 perennial grass in DNDC without changing the programming code (Deng, personal communication, 2021). Except for the parameters in Table 3.2, other differences regarding crop growth dynamics between C3 and C4 crops were hard-coded. The simulated biomass (Fig. A10) and soil NH_4 and NO_3 were lower than measured values, partly because annual N demand in DNDC was highly overestimated for zoysia ($338 \text{ Kg N ha}^{-1} \text{ yr}^{-1}$), which was based on crop biomass and C/N and yet unadjustable.

The Bayesian calibration in this study generally reduces the uncertainty of parameters. Note that this study accounted for the uncertainty of parameters but not that of the measurements and model structures (Zhang et al., 2015). However, the narrow range of prior uncertainty of DNDC parameters did not enclose most observations, and the Bayesian calibration reduced the uncertainty to a low extent (Fig. A8). These indicated the model inefficiency of DNDC could be related to the model structure more greatly than to parameters. Here, the model parameter posterior uncertainty of DAYCENT was wider than that of DNDC (Fig. A4, A8), which was similar to previous comparison results (Wang & Chen, 2012).

DAYCENT performed nearly as poorly as DNDC in the model validation using an independent study (Lewis & Bremer, 2013), which was inferior to DAYCENT's validation of Braun & Bremer (2018a) (Table 3.3, 3.4). DAYCENT underestimated N_2O in low irrigation treatments especially when it was unfertilized (Fig. 3.1, 3.3), although simulations of soil NH_4 , NO_3 were occasionally similar between fertilized and unfertilized treatments (Table A3). As discussed above, DNDC overall underestimated N_2O emissions especially when unfertilized or fertilized with PCU. The imperfect parameterization of DAYCENT and DNDC can be attributed to the structural limitation regarding N_2O responses to fertilization (e.g., no N, slow-release N) and low irrigation practices. So far, most process-based models have been calibrated for grasslands and intensively managed agricultural croplands with a limited range of soil and climate conditions (Zhang & Yu, 2021).

Future model improvements

Bayesian calibration with SIR resulted in the posterior distributions of parameters in the calibration scenario of this study. The posterior distributions of key sensitive parameters (e.g., Maximum_yield in DNDC, PRDX(1) in DAYCENT; Fig. A2, A6) may need to be reconsidered along with local measurements before being used to confine prior ranges for calibrations at other locations given that N_2O fitting of both models has been affected by varying climate and soil conditions in a collection of studies (Brilli et al., 2017; Dutta et al., 2017; Zhang & Yu, 2021; Zimmermann et al., 2018). Further improvements are needed in model equations relevant to and parameterizations of FALLRT, MAXNIT, and N2N2OA in DAYCENT (Table 3.1), and Root_fraction, Leaf_ratio, and Root_C/N in DNDC (Table 3.2). Both Maximum_yield of DNDC and PRDX(1) of DAYCENT were calibrated to be at the upper extremes of their theoretical

bounds, which indicated both models need further improvements in algorithms regarding crop phenology and carbon allocation (Fig. A10-A12). In the calibration dataset (Urea_Medium treatment), the three highest N₂O fluxes were outside the DAYCENT posterior prediction and two of them were outside the prior uncertainty, which indicated a need for model structure improvement for daily high fluxes after fertilization. Model structure improvement is needed in DNDC because many observations were outside the prior uncertainty interval predicted by DNDC.

Using process-based models for executive recommendations regarding N₂O emissions has been based on an annual temporal resolution. Although outperforming DNDC, DAYCENT still underestimated N₂O peak fluxes following N fertilizations, which was also reported in other grasslands (Fuchs et al., 2020; Zimmermann et al., 2018). Both DNDC and DAYCENT models generally performed better in biweekly and annual N₂O emissions than daily N₂O fluxes. The accuracy and reliability in N₂O daily responses to N fertilization needs to be improved in process-based models (Brilli et al., 2017; Xin et al., 2019).

Our results affirmed findings from other studies that both DNDC and DAYCENT underestimated VWC (Table A3; A6) because both models trigger quick drainage when soil water is above field capacity (Brilli et al., 2017; Fuchs et al., 2020; Gaillard et al., 2018; Smith et al., 2008). This, coupled with underestimated SOC by both models to different extents (Fig. A9), could result in low (DAYCENT) to high (DNDC) underestimation of denitrification and therefore, underestimation of N₂O emissions (Cui et al., 2012). More detailed and realistic representation of soil water movement should be incorporated into process-based models (Smith et al., 2020), which is important to further improve the processes of nitrification and denitrification in models (Brilli et al., 2017). Other efforts included coupling agroecosystem

models herein with hydrological models such as Soil & Water Assessment Tool (SWAT) (Wang et al., 2020). While further understanding and representation of the denitrification processes are needed (Del Grosso et al., 2020), process-based models may also be substantially improved in describing N₂O emissions of various practices, particularly low-intensity management regimes (e.g., low irrigation, slow-released N inputs) (Brilli et al., 2017; Xin et al., 2019). As low-input management is increasingly being advocated, more data from different management practices and diverse crop systems, including turfgrass in different soil and climate conditions, need to be used to calibrate the existing models. Model structural improvements are also needed regarding responses to unconventional fertilization (e.g., no N, slow-release N) and low irrigation practices.

Predictions in future weather

Assuming no further climate change, N₂O emissions from fertilized zoysia (98 kg N ha⁻¹ yr⁻¹) are predicted to increase to between 6 to 8 kg N ha⁻¹ yr⁻¹ after 80 yr from present (Fig. 3.6). This is higher than the DNDC-predicted N₂O emissions (2.5 kg N ha⁻¹ yr⁻¹) from lawns in Nashville (TN, USA) after 75 yr, which would mainly be due to lower N inputs (47.5 kg N ha⁻¹ yr⁻¹) (Gu et al., 2015). Between the present and 2060, the net GWP of zoysia under regular maintenance (Urea_Medium) at the study location is predicted to continuously decline (Fig. 3.7), which indicates the soil C sequestration due to biomass production and decomposition would outweigh the GWP of turfgrass management and N₂O emissions. Low to regular maintenance would sequester 16.4 to 41.3 Mg C ha⁻¹ in zoysia soil by 2060 (40 yr from 2021; Fig. A13). Carbon sequestration in another study was estimated at 32.1 to 32.6 Mg ha⁻¹ over 40 yr at 0-20

cm soil where Kentucky bluegrass turfgrass was maintained (Zhang, Qian, Mecham, et al., 2013). This was within the range of C sequestration in our study.

While producing more N_2O (Fig. 3.6), N fertilization in zoysia would result in greater biomass production (data not shown) and greater reductions in net annual GWP during the next 40 years (2020-2060; Fig. 3.7). Thereafter, the net annual GWP of all practices would become positive as indicated by inflections in cumulative GWP, especially those with N fertilization. Therefore, as turfgrass ages and C sequestration slows down after 2060 (Fig. A13), reducing N fertilization rates and/or using slow-release N sources in zoysia should work in favor of mitigating GWP by reducing the slope of the incline in N_2O emissions over the years (Fig. 3.6, 3.7). These findings generally agree with the trend of GWP estimations in C3 lawns (KS and CO, USA), where C sequestration was predicted to gradually taper off and reach a plateau (Bandaranayake et al., 2003; Gu et al., 2015; Qian et al., 2003; Zhang, Qian, Bremer, et al., 2013) and net GWP would reverse to become positive after 20 yr (Zhang, Qian, Bremer, et al., 2013). In warmer places such as Nashville, TN (USA), the net annual GWP of turfgrass lawns may be always positive regardless of maintenance intensity because the C sequestration of the location could not offset the GWP from GHG emissions and lawn maintenance (Gu et al., 2015).

The background N_2O emissions (None_Medium) would be higher under the medium climate change scenario (SSP2-4.5) than under the baseline weather. This is because N_2O emissions would be accelerated by enhanced soil nitrification and denitrification from increasing temperatures, which would surpass N_2O reductions caused by increased nitrogen uptake from increased biomass production (data not shown) resulting from increasing atmospheric CO_2 concentrations and temperatures (Ciais et al., 2014; Tian et al., 2020). Such positive feedback from global warming is amplified in fertilized lands because of the nonlinear response of N_2O

emissions to N inputs and increasing microbial processes caused by long-term nitrogen accumulation in soil (Shcherbak et al., 2014; Tian et al., 2020). This is shown by the increasing gap of N₂O emissions from Urea_Medium zoysia between under the medium climate change scenario and under the baseline weather (Fig. 3.8). Compared to the baseline weather, global warming can accelerate the increase of GWP (Fig. 3.9) caused by increased N₂O emissions mentioned above and earlier C saturation regardless of maintenance intensity (Fig. A15). Such earlier C saturation was also predicted globally by Shi et al. (2021) including in the mid-western U.S. (RCP6 scenario).

Conclusions

The DAYCENT and DNDC models were parameterized, calibrated, and validated for N₂O emissions using zoysia characteristics and field measurements of two published studies that included the most comprehensive N₂O datasets of C4 turfgrass to date. Daily and biweekly N₂O fluxes, and annual N₂O emissions were well modelled by DAYCENT in the calibration phase and the model was validated adequately. In contrast, the N₂O flux simulations in DNDC were generally poor and underestimated. In C4 turfgrass such as zoysia, DAYCENT can adequately simulate the impacts of different irrigation and N-fertilization practices on biweekly and annual N₂O emissions, better than DNDC.

Given the climate and soils (two soil textures) at the study site and the baseline weather, the validated DAYCENT model predicted that regular N-fertilization and irrigation practice in fairway zoysia turf would reduce net GWP by encouraging SOC sequestration for about the next 40 years, after which reducing N inputs would be beneficial in mitigating increases in net GWP.

A medium climate change scenario would accelerate the increases of N₂O emissions and GWP, with greater extents for higher intensity management practices.

Although having a great fit in some variables (e.g., soil temperature), both DAYCENT and DNDC require improvements in their representation of low-intensity management regimes (e.g., low irrigation, no N or slow-release N fertilization) and in daily simulations of soil water, NH₄, and NO₃, which would be critical to substantially optimize N₂O daily simulations. More site-specific calibrations across multiple locations would also improve regional simulations of N₂O emissions from turfgrass and strengthen policy decisions in the future.

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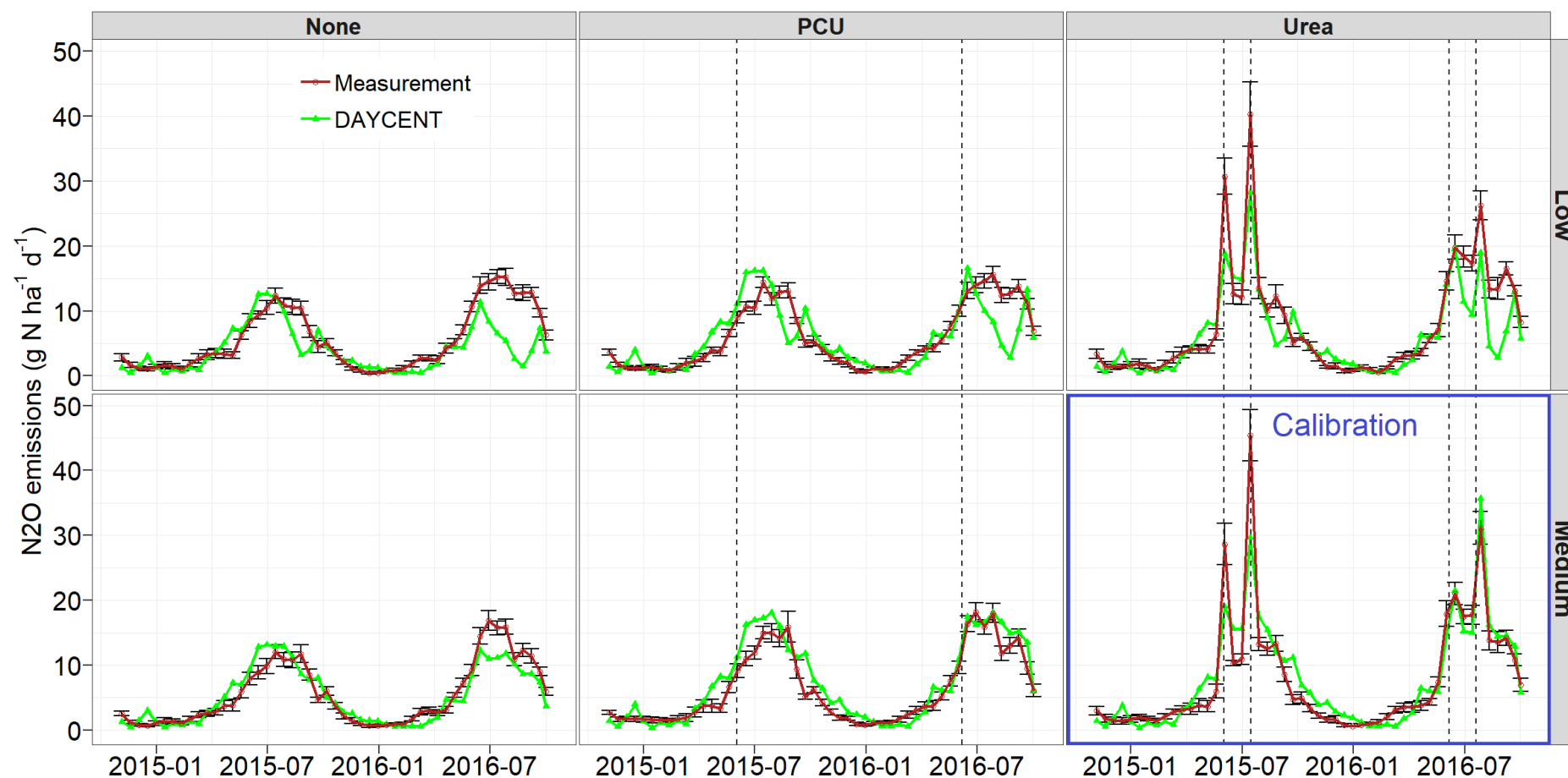


Figure 3.1. Biweekly N_2O emission estimates from DAYCENT and from field measurements in management regimes of three N fertilizations (columns; none=no N, PCU=poly-coated urea, and urea=granular urea) and two irrigations (rows; low=33-45% ET_0 and medium=66-68% ET_0). Error bar represents one standard error above and below measurement mean.

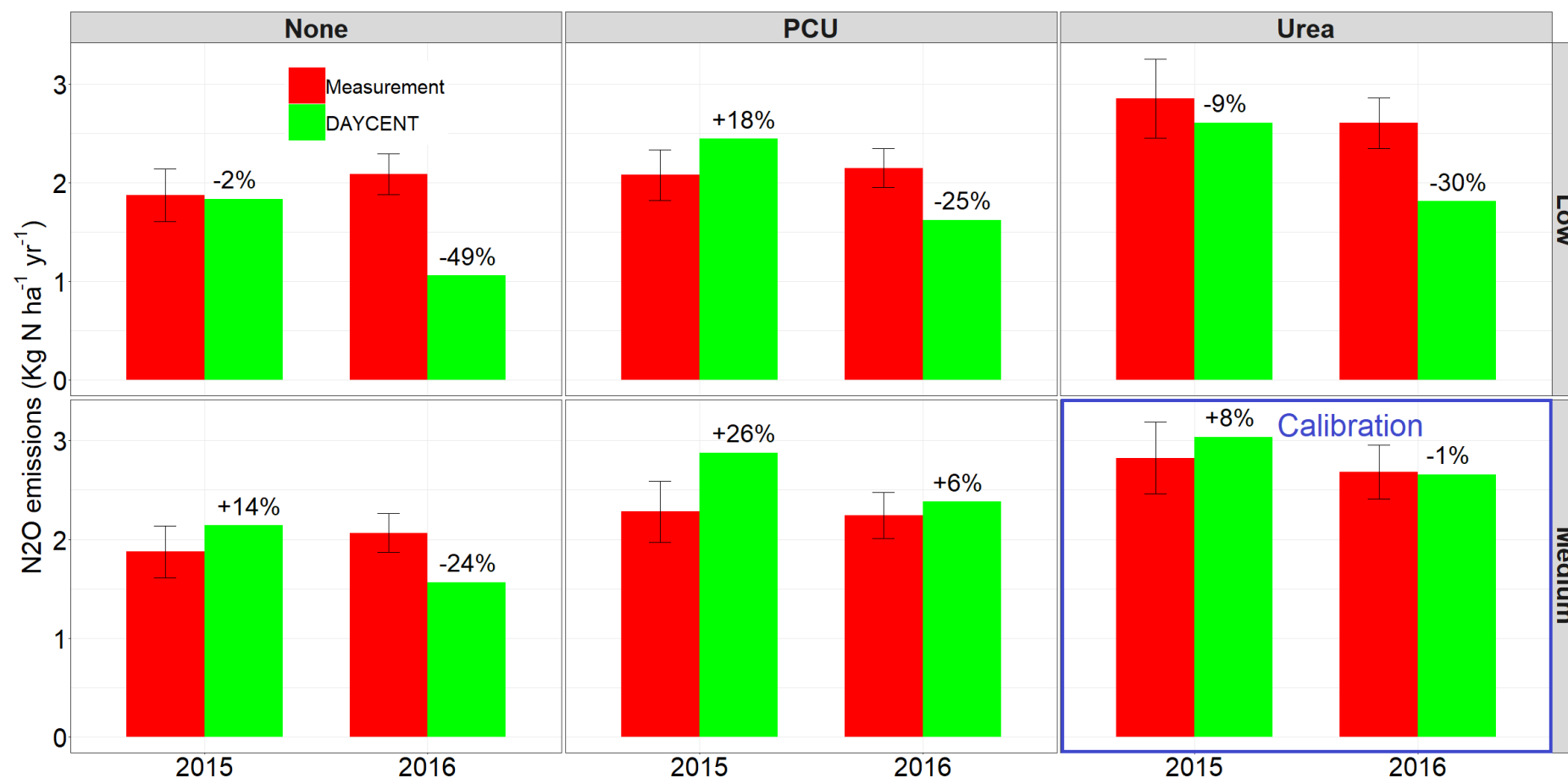


Figure 3.2. Annual N₂O emission estimates from DAYCENT and from field measurements in management regimes of three fertilizations (columns) and two irrigations (rows). Data during Oct. - Dec., 2014 were combined in the 2015 estimates. Percentages above green bars represent relative differences of simulation compared to measurement means. Error bar represents one standard error above and below measurement mean.

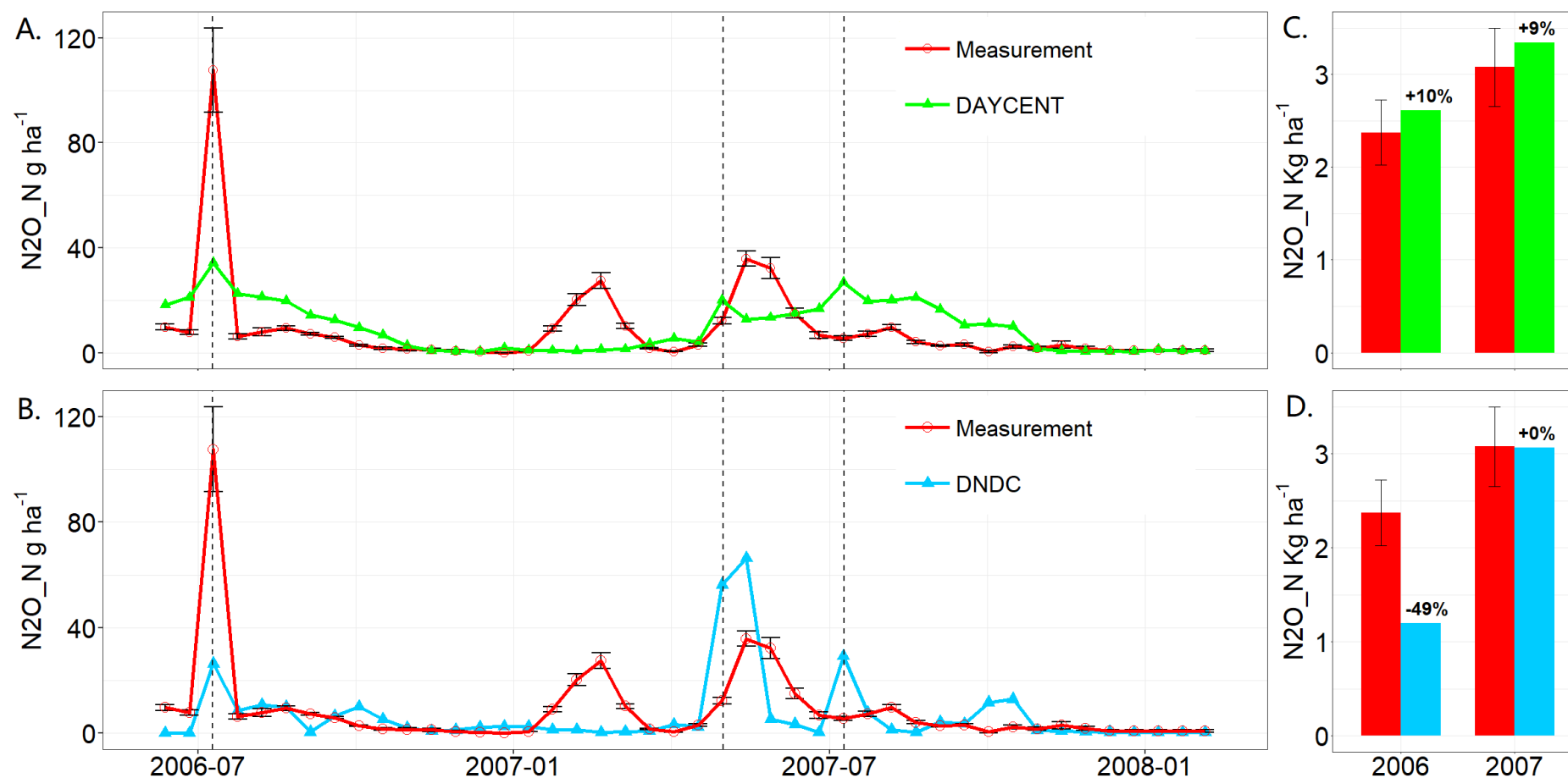


Figure 3.3. Biweekly N_2O emission estimates from DAYCENT (A) and DNDC (B) and from field measurement values in the independent dataset (Lewis and Bremer, 2013). Annual N_2O emission estimates from DAYCENT (C) and DNDC (D) simulations and from field measurements (data during Jan. - Feb., 2008 were combined in 2007). Percent within bars of model estimate represents relative difference of simulation from measurement mean. Error bar represents one standard error above and below measurement mean.

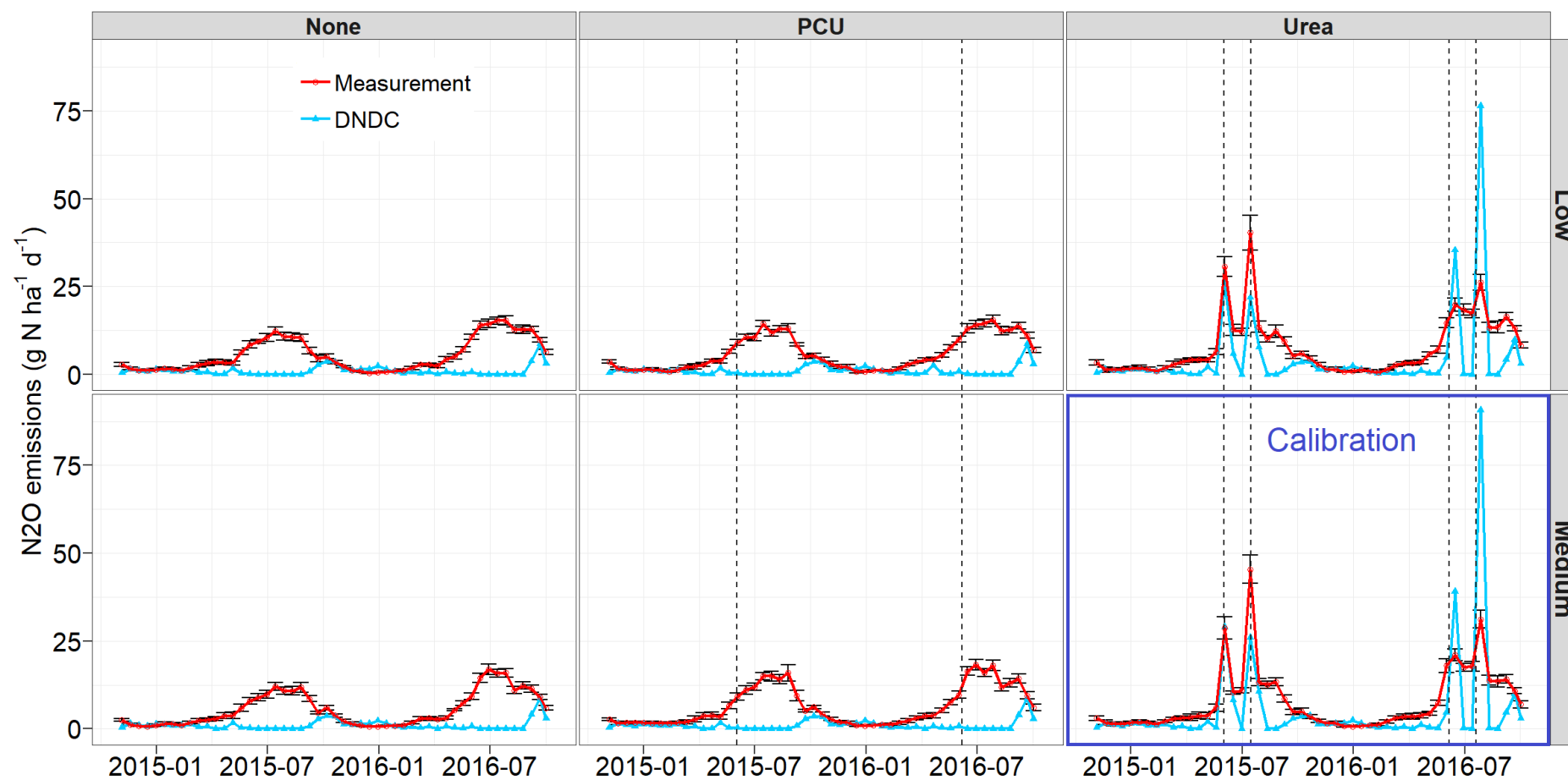


Figure 3.4. Biweekly N_2O emission estimates from DNDC and from field measurement in management regimes of three fertilizations (columns) and two irrigations (rows). Error bar represents one standard error above and below measurement mean.

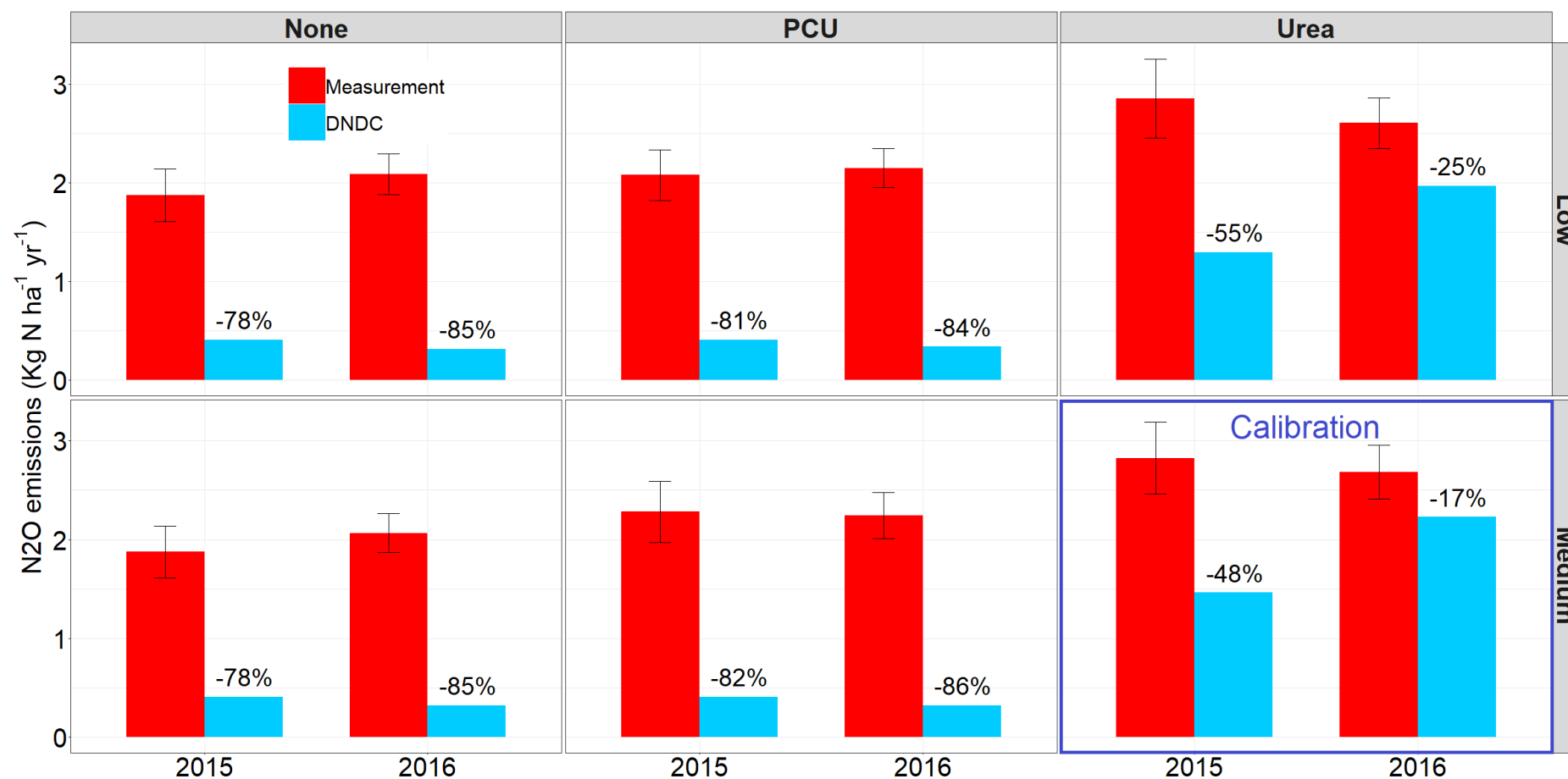


Figure 3.5. Annual N₂O emission estimates from DNDC and from field measurements in management regimes of three fertilizations (columns) and two irrigations (rows). Data during Oct. - Dec., 2014 were combined in 2015 estimates. Percentages above blue bars represent relative differences of simulation compared to measurement means. Error bar represents one standard error above and below measurement mean.

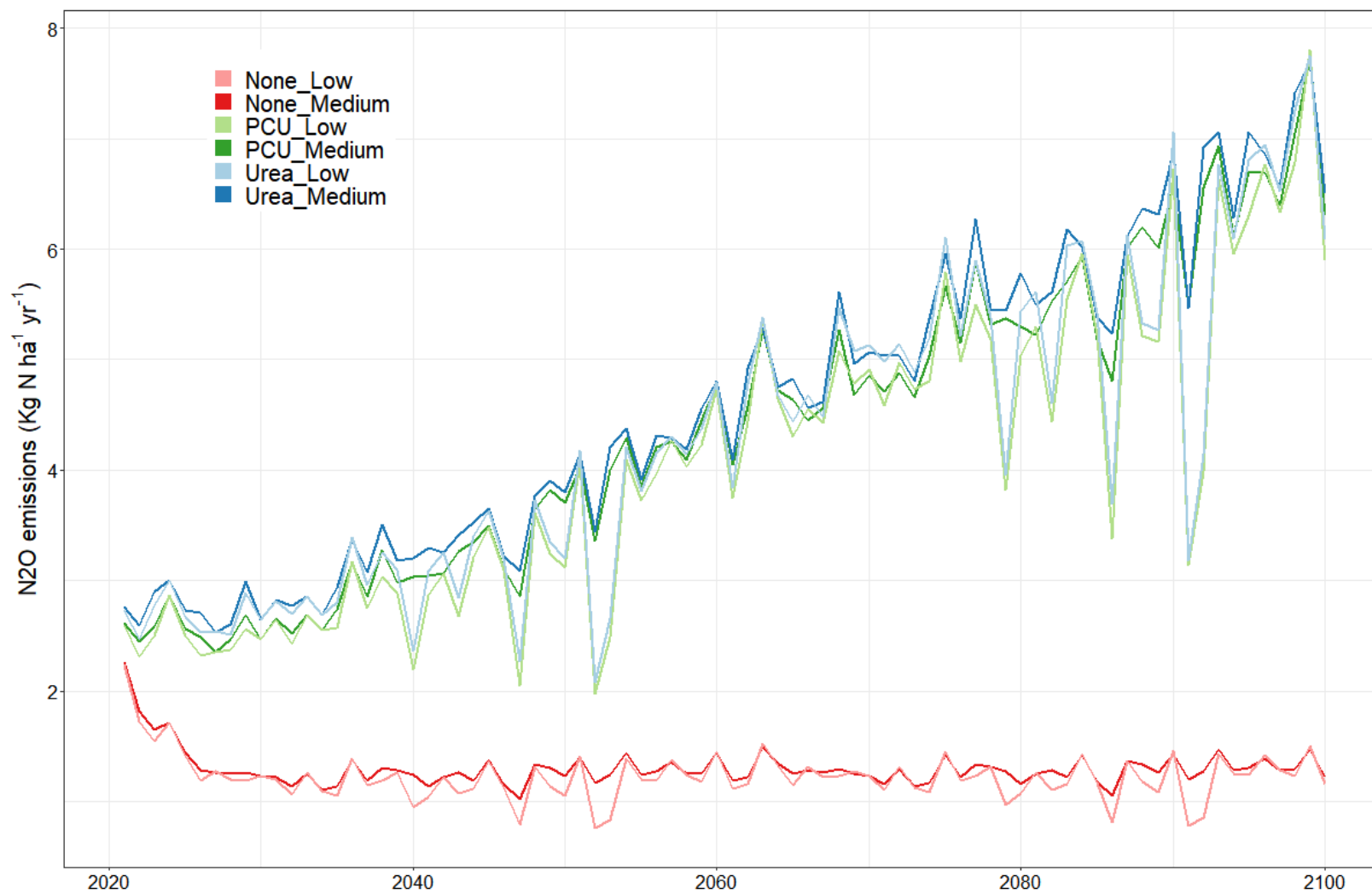


Figure 3.6. 2021-2100 projection of annual N₂O emissions for six management practices in fairway zoysiagrass under baseline weather using the validated DAYCENT model.

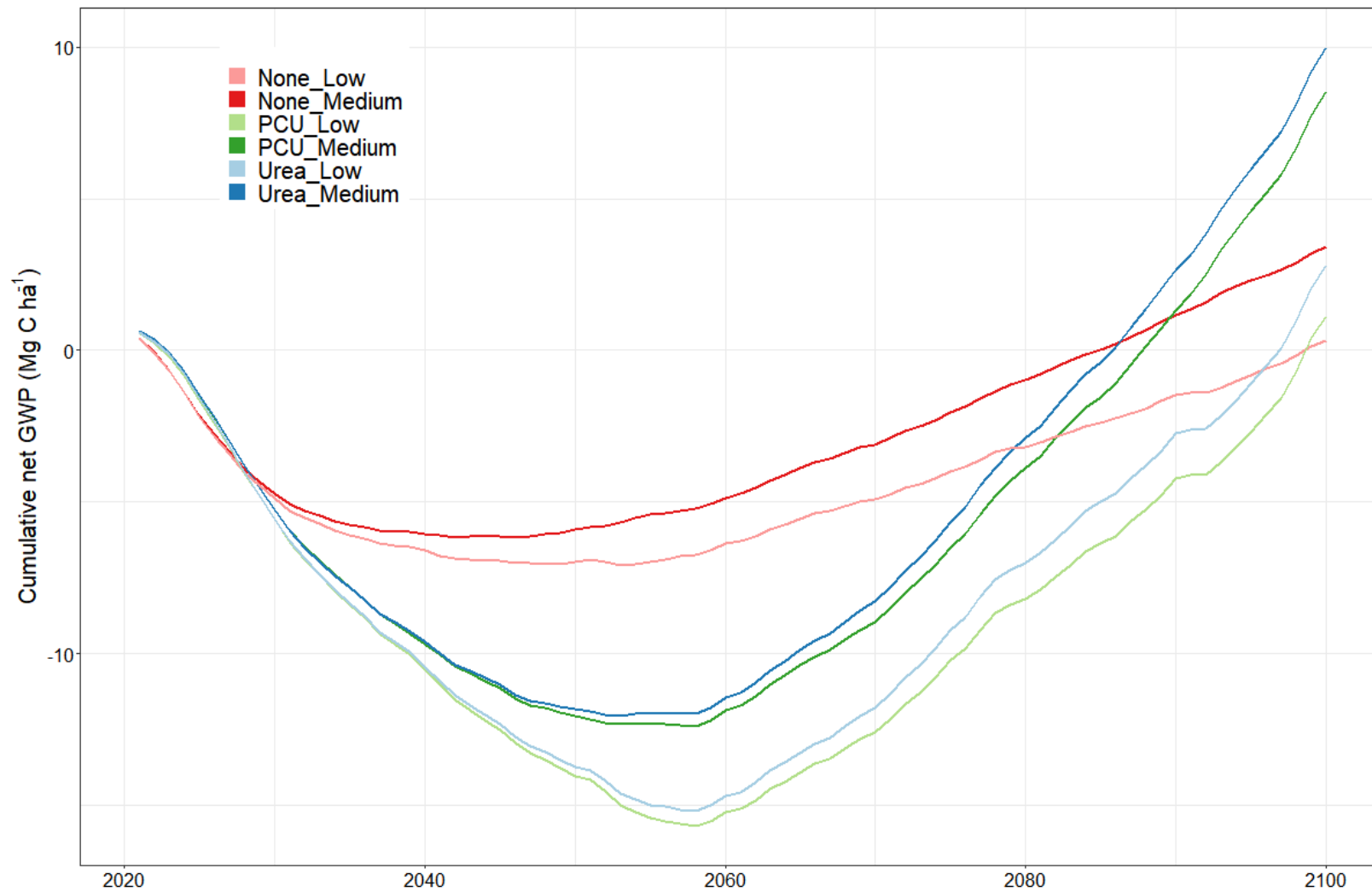


Figure 3.7. 2021-2100 cumulative net global warming potential (GWP) for six management practices in fairway zoysiagrass under baseline weather using the validated DAYCENT model.

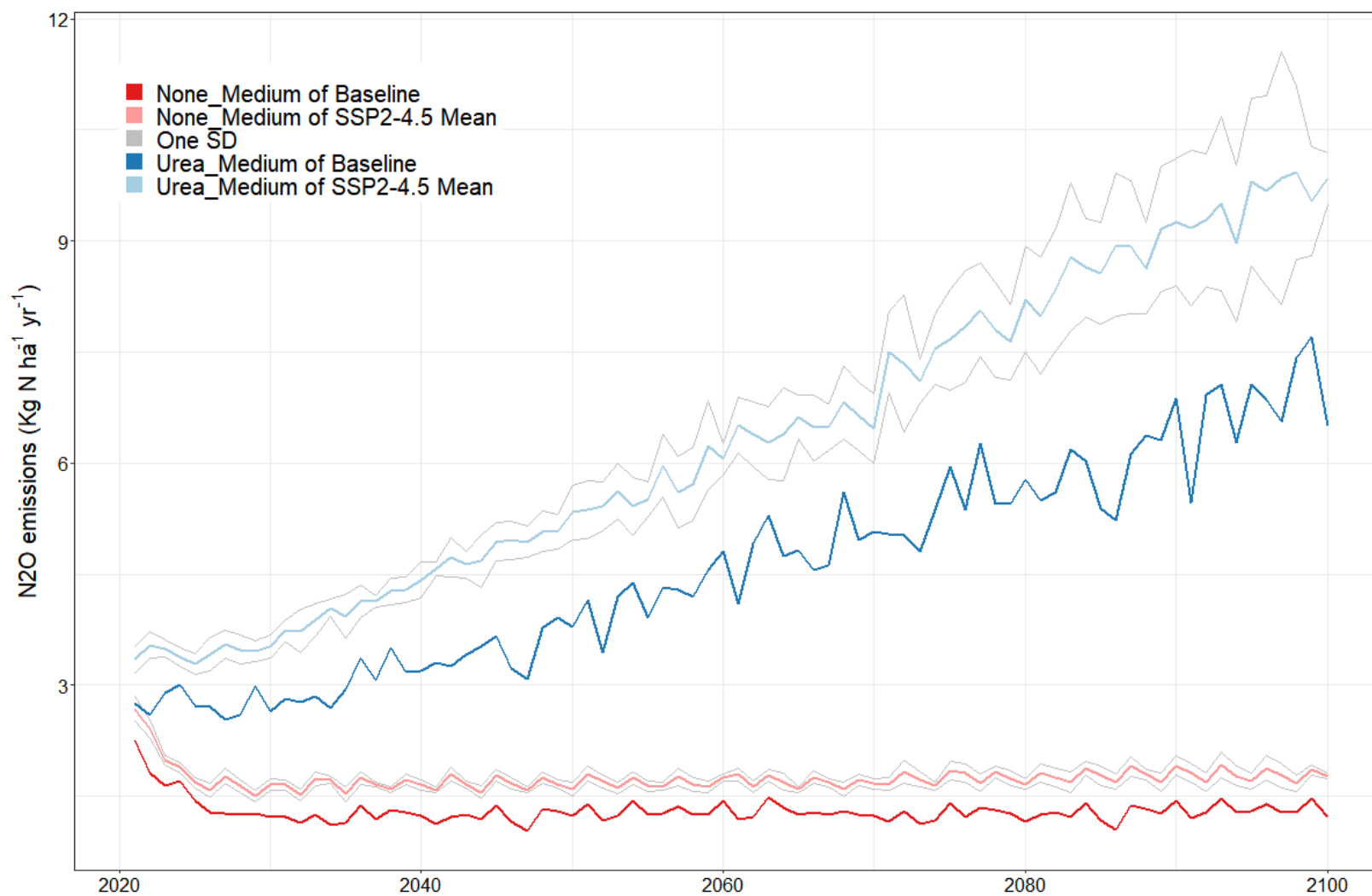


Figure 3.8. 2021-2100 projection of annual N₂O emissions for regular (Urea_Medium) and low (None_Medium) intensity maintenance in fairway zoysiagrass under baseline weather and a medium climate change scenario (SSP2-4.5) using the validated DAYCENT model

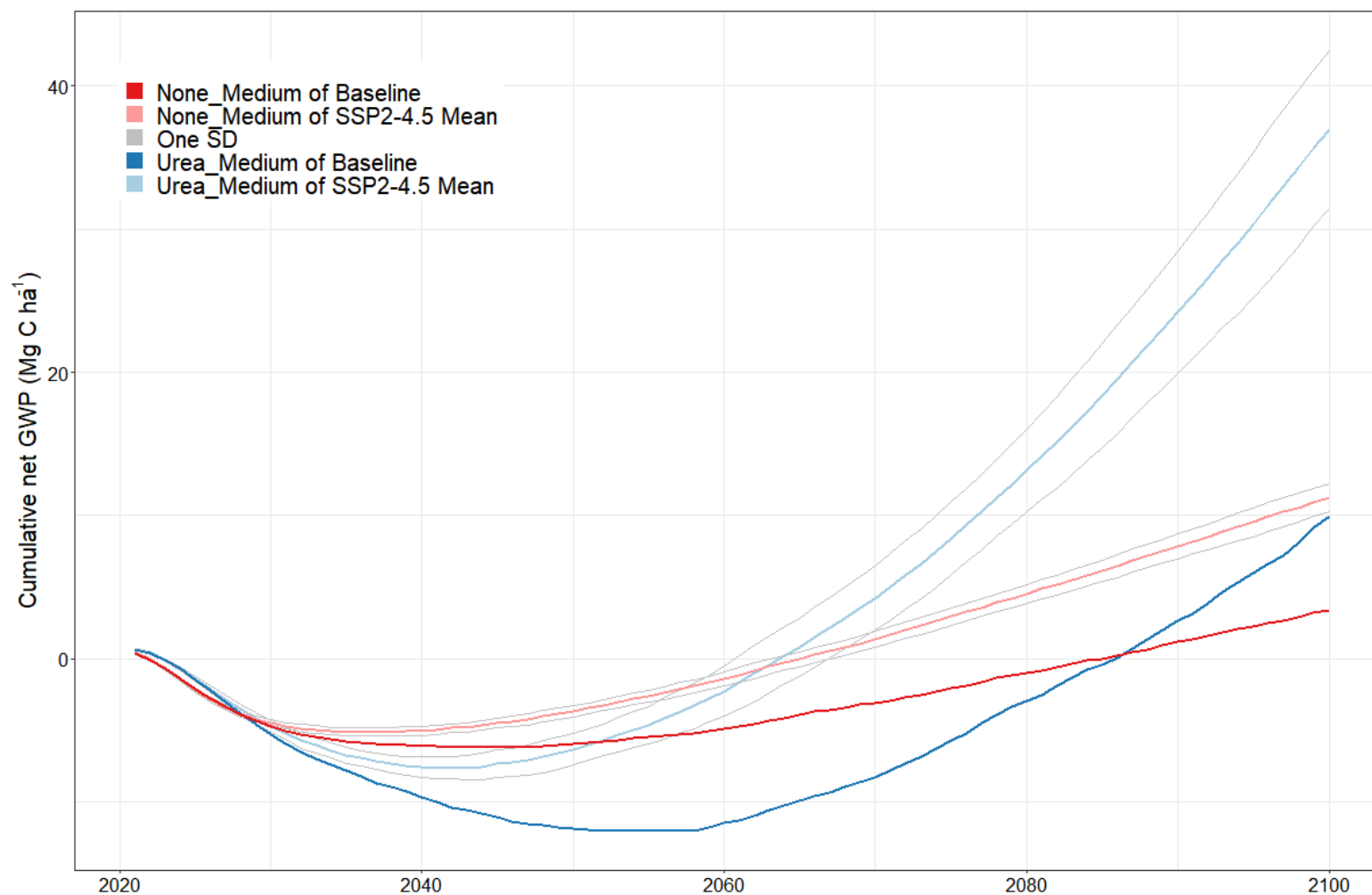


Figure 3.9. 2021-2100 projection of cumulative net global warming potential (GWP) for regular (Urea_Medium) and low (None_Medium) intensity maintenance in fairway zoysiagrass under baseline weather and a medium climate change scenario (SSP2-4.5) using the validated DAYCENT model.

Table 3.1. Prior uniform distribution of sensitive parameters in DAYCENT and their calibrated values.

Parameter	Definition	Lower bound	Upper bound	Reference	Input file	Calibrated Value
PRDX(1)	Coefficient for calculating total monthly potential production as a function of solar radiation outside the atmosphere. It functions as a radiation use efficiency scalar on potential production.	1	4	(Hartman et al., 2018)	crop.100	3.826
FALLRT	Fall rate (fraction of standing dead which falls each month)	0.01	0.9	(Hartman et al., 2018)	crop.100	0.808
MINO3	Fraction of new net mineralization that goes to NO ₃ (0.0- 1.0).	0.05	0.4	(Gaillard et al., 2018)	site.100	0.140
MAXNIT	maximum daily nitrification amount (gN/m ² /day)	0.1	4	(Necpálová et al., 2015)	site.100	3.769
NADJWP	Minimum fraction nitrified N lost as N ₂ O at wilting point	0.001	0.012	(Gaillard et al., 2018)	site.100	0.012
N2N2OA	N ₂ /N ₂ O ratio adjustment factor for computing the N ₂ /N ₂ O ratio during non-flooded conditions. Values > 1.0 increase this ratio, values (0.0-1.0) decrease this ratio.	0.01	2	(Gaillard et al., 2018)	site.100	0.813
WFPSNIP	Adjustment on inflection point for the water filled pore space effect on denitrification curve (< 1.0 allow denitrification to occur at lower soil water content; > 1.0 require wetter conditions for denitrification)	0.85	1.15	(Gaillard et al., 2018)	site.100	0.955
FAVAIL(1)	Fraction of N available per day to plants.	0.01	0.5	(Necpálová et al., 2015)	fix.100	0.163
FWLOSS(4)	Scaling factor for potential evapotranspiration.	0.6	0.9	(Allen et al., 1998; Braun & Bremer, 2018a; Fu et al., 2004)	fix.100	0.602

Table 3.2. Prior uniform distribution of DNDC parameters and their calibrated values.

Parameter	Definition	Lower bound	Upper bound	Reference	Calibrated Value
Maximum_yield	The maximum biomass productions for grain (0.1% of total biomass) under optimum growing conditions (kg C/ha)	2	15	Measurement	14.482
Accumulative_temperature	Accumulative air temperature from seeding till maturity of the crop (0 °C base)	3441	4434	Local weather data	3838.292
Water_requirement	Amount of water needed for the crop to produce a unit of dry matter of biomass (g water/g dry matter)	120	320	(Qin et al., 2013)	164.621
Leaf_ratio	Leaf biomass / (stem biomass + leaf biomass)	0.4	0.99	Measurement; (Patton et al., 2007)	0.689
Root_fraction	Root fraction of a plant	0.1	0.4	Measurement; (Patton et al., 2007)	0.344
Leaf_C/N	Leaf C/N ratio	15	45	Measurement	44.759
Root_C/N	Root C/N ratio	39	90	Measurement	39.739

Table 3.3. Model evaluation of DAYCENT simulations of biweekly N₂O (coefficient of determination [R²], model efficiency [ME], relative root mean square error [RRMSE], and relative mean difference [RMD]).

Study	Dataset	Fertilization_Irrigation	R ²	ME	RRMSE	RMD
(Braun & Bremer, 2018a)	Calibration	Urea_Medium	0.8483	0.8460	0.4469	0.0320
		Urea_Low	0.7958	0.7386	0.5482	-0.1919
		PCU_Medium	0.8906	0.8210	0.3597	0.1599
		PCU_Low	0.5763	0.5255	0.5547	-0.0391
	Validation	None_Medium	0.8178	0.8123	0.3677	-0.0625
(Lewis & Bremer, 2013)		None_Low	0.4734	0.3626	0.6606	-0.2714
		Urea_Medium	0.2248	0.2197	1.7096	0.0917

Table 3.4. Model evaluation of DNDC simulations of biweekly N₂O (coefficient of determination [R²], model efficiency [ME], relative root mean square error [RRMSE], and relative mean difference [RMD]).

Study	Dataset	Fertilization_Irrigation	R ²	ME	RRMSE	RMD
(Braun & Bremer, 2018a)	Calibration	Urea_Medium	0.4291	-0.5543	1.4197	-0.3331
		Urea_Low	0.3834	-0.4691	1.2995	-0.4061
	Validation	PCU_Medium	0.0237	-1.125	1.2391	-0.8371
		PCU_Low	0.0109	-1.1972	1.1936	-0.8215
		None_Medium	0.0181	-1.0992	1.2297	-0.8131
(Lewis & Bremer, 2013)		None_Low	0.0152	-1.1483	1.2128	-0.8142
		Urea_Medium	0.1635	0.0073	1.9284	-0.2173

Appendix A - Supplemental Data for Chapter 3

Table A1. Definition and prior bounds (uniform distribution) of DAYCENT parameters.

Parameter	Definition	Lower bound	Upper bound	Reference
PRDX(1)	Coefficient for calculating total monthly potential production as a function of solar radiation outside the atmosphere. It functions as a radiation use efficiency scalar on potential production.	1	4	(Hartman et al., 2018)
FSDETH(1)	Maximum shoot death rate at very dry soil conditions (fraction/month)	0.05	0.9	(Hartman et al., 2018)
FALLRT	Fall rate (fraction of standing dead which falls each month)	0.01	0.9	(Hartman et al., 2018)
RDRM	Maximum mature fine root death rate at very dry soil conditions (fraction/month)	0.05	0.9	(Hartman et al., 2018)
RDRJ	Maximum juvenile fine root death rate at very dry soil conditions (fraction/month)	0.05	0.9	(Hartman et al., 2018)
CFRTCW(2)	Minimum fraction of C allocated to roots with no water stress	0.1	0.5	Measurement
CFRTCW(2)	Minimum fraction of C allocated to roots with no nutrient stress	0.1	0.5	Measurement
WSCOEF(1)	Water Stress Coefficient used to calculate the water stress multiplier on potential growth based on the relative water content of the wettest soil layer in rooting zone	0.2	0.5	(Hartman et al., 2018)
WSCOEF(2)	Water Stress Coefficient used to calculate the water stress multiplier on potential growth based on the relative water content of the wettest soil layer in rooting zone	6	30	(Hartman et al., 2018)
BIOMAX	Aboveground biomass level above which the minimum and maximum C/E ratios of new shoot increments equal pramn(*,2) and pramx(*,2) respectively.	200	800	(Hartman et al., 2018)
PRBMN(1,1)	(N, intercept) parameter for computing minimum C/N ratio for belowground matter as a linear function of annual precipitation.	30	50	Measurement
PRBMX(1,1)	(N, intercept) parameter for computing maximum C/N ratio for belowground matter as a linear function of annual precipitation.	50	100	Measurement
PRAMX(1,1)	Maximum aboveground C/N ratio with zero biomass.	18	40	Measurement
PRAMX(1,2)	Maximum aboveground C/N ratio with biomass > biomas.	26	50	
PRAMN(1,1)	Minimum aboveground C/N ratio with zero biomass.	9	18	
PRAMN(1,2)	Minimum aboveground C/N ratio with biomass > biomas.	15	26	

MINO3	Fraction of new net mineralization that goes to NO3 (0.0- 1.0).	0.05	0.4	(Gaillard et al. 2018)
NCOEFF	Minimum water/temperature limitation coefficient for nitrify	0.01	0.08	(Necpálová et al. 2015; Rafique et al. 2013)
MAXNIT	maximum daily nitrification amount (gN/m2/day)	0.1	4	(Necpálová et al. 2015)
NADJFC	maximum proportion of nitrified N lost as N2O @ field capacity	0.012	0.05	(Gaillard et al. 2018)
NADJWP	Minimum fraction nitrified N lost as N2O at wilting point	0.001	0.012	(Gaillard et al. 2018)
N2N2OA	N2/N2O ratio adjustment factor for computing the N2/N2O ratio during non-flooded conditions. Values > 1.0 increase this ratio, values (0.0-1.0) decrease this ratio.	0.01	2	(Gaillard et al. 2018)
WFPSNIP	Adjustment on inflection point for the water filled pore space effect on denitrification curve (< 1.0 allow denitrification to occur at lower soil water content; > 1.0 require wetter conditions for denitrification)	0.85	1.15	(Gaillard et al. 2018)
FAVAIL(1)	Fraction of N available per day to plants.	0.01	0.5	(Necpálová et al. 2015)
FWLOSS(4)	Scaling factor for potential evapotranspiration.	0.6	0.9	(Allen et al. 1998; Braun and Bremer 2018)

Table A2. Sensitive DAYCENT parameters for daily simulations of soil VWC, NH₄, NO₃, and N₂O. Parameters and prior bounds are defined in Table A1.

Variable	Parameter	Total effect index	Lower 95% CI ^a	Higher 95% CI
VWC	FWLOSS(4)	0.9465	0.8849	1.0085
	FALLRT	0.0491	0.0435	0.0554
NH ₄	PRDX(1)	0.6191	0.5673	0.6734
	FAVAIL(1)	0.2070	0.1850	0.2312
	MINO3	0.1953	0.1745	0.2183
	MAXNIT	0.1922	0.1717	0.2148
NO ₃	PRDX(1)	0.7748	0.7168	0.8345
	FAVAIL(1)	0.2064	0.1846	0.2306
N ₂ O	WFPSNIP	0.5508	0.5027	0.6017
	N2N2OA	0.2936	0.2638	0.3261
	NADJWP	0.1379	0.1228	0.1547
	PRDX(1)	0.0807	0.0716	0.0909
	FWLOSS(4)	0.0627	0.0556	0.0707
	FAVAIL(1)	0.0391	0.0347	0.0442
	MINO3	0.0294	0.0260	0.0332

a Confidence interval.

Table A3. Model evaluation of DAYCENT simulations of daily soil temperature, VWC, NH₄, NO₃, N₂O (daily and biweekly). Coefficient of determination (R²), model efficiency (ME), relative root mean square error (RRMSE), and relative mean difference (RMD).

Study	Variable	Treatment	RRMSE	RMD	R ²	ME
1 (Braun & Bremer, 2018a)	Soil temperature	Urea_Medium	0.0999	0.0134	0.9572	0.9484
		Urea_Low	0.1017	0.0146	0.9565	0.9456
		Polymer-coated urea_Medium	0.1026	0.0115	0.9546	0.9446
		Polymer-coated urea_Low	0.1019	0.0139	0.9564	0.9451
		No Fertilization_Medium	0.1029	0.0227	0.9569	0.9454
		No Fertilization_Low	0.1022	0.0237	0.9587	0.9454
	VWC	Urea_Medium	0.2602	-0.2091	0.0484	-2.0855
		Urea_Low	0.2738	-0.1947	0.1518	-1.2947
		Polymer-coated urea_Medium	0.2684	-0.2165	0.0089	-2.5684
		Polymer-coated urea_Low	0.2794	-0.2049	0.1391	-1.5801
		No Fertilization_Medium	0.2748	-0.2245	0.0081	-2.7077
		No Fertilization_Low	0.3062	-0.2440	0.0623	-3.4479
	NH ₄	Urea_Medium	0.6915	-0.1293	0.0603	-5.1562
		Urea_Low	0.6594	-0.2040	0.1263	-4.4393
		Polymer-coated urea_Medium	0.4287	-0.3352	0.0044	-1.8773
		Polymer-coated urea_Low	0.4552	-0.3572	0.0046	-1.9255
		No Fertilization_Medium	0.5742	-0.5101	0.0506	-3.6653
		No Fertilization_Low	0.6075	-0.5417	0.0356	-4.1755
	NO ₃	Urea_Medium	0.6971	-0.0463	0.2929	0.2894
		Urea_Low	0.5863	-0.0329	0.1732	-0.0696
		Polymer-coated urea_Medium	0.4579	0.0349	0.0053	-0.4263
		Polymer-coated urea_Low	0.5208	0.0493	0.0027	-0.9764
		No Fertilization_Medium	0.4096	-0.1468	0.0025	-0.9182
		No Fertilization_Low	0.4961	-0.1595	0.0125	-0.9299
	Daily N ₂ O	Urea_Medium	1.3582	-0.1927	0.5911	0.4629
		Urea_Low	1.2704	-0.3519	0.6832	0.4531
		Polymer-coated urea_Medium	0.3653	0.0996	0.7125	0.6336
		Polymer-coated urea_Low	0.5104	-0.1461	0.3694	0.1885
		No Fertilization_Medium	0.3629	-0.1114	0.6710	0.6352
		No Fertilization_Low	0.6055	-0.3509	0.3137	-0.0757
	Biweekly N ₂ O	Urea_Medium	0.4469	0.0320	0.8483	0.8460
		Urea_Low	0.5482	-0.1919	0.7958	0.7386
		Polymer-coated urea_Medium	0.3597	0.1599	0.8906	0.8210
		Polymer-coated urea_Low	0.5547	-0.0391	0.5763	0.5255
		No Fertilization_Medium	0.3677	-0.0625	0.8178	0.8123
		No Fertilization_Low	0.6606	-0.2714	0.4734	0.3626

2 (Lewis & Bremer, 2013)	Soil	Urea_Regular irrigation	0.1365	-0.0694	0.9739	0.9467
	temperature					
	VWC	Urea_Regular irrigation	0.2591	-0.1221	0.0532	-0.4460
	NH4	Urea_Regular irrigation	1.0233	0.3117	0.4165	0.3302
	NO3	Urea_Regular irrigation	0.9545	-0.6990	0.0405	-1.0884
	Daily N2O	Urea_Regular irrigation	3.1283	0.0748	0.2473	0.2057
	Biweekly N2O	Urea_Regular irrigation	1.7096	0.0917	0.2248	0.2197

Table A4. Definition and prior bounds (uniform distribution) of DNDC parameters.

Parameter	Definition	Lower bound	Upper bound	Reference
Maximum_yield	The maximum biomass productions for grain (0.1% of total biomass) under optimum growing conditions (kg C/ha)	2	15	Measurement
Accumulative_temperature	Accumulative air temperature from seeding till maturity of the crop (°C)	3441	4434	(Patton et al. 2006)
Water_requirement	Amount of water needed for the crop to produce a unit of dry matter of biomass (g water/g dry matter)	120	320	(Qin et al. 2013)
Leaf_ratio	Leaf biomass / (stem biomass + leaf biomass)	0.4	0.99	Measurement
Root_fraction	Root fraction of a plant	0.1	0.4	Measurement
Leaf_C/N	Leaf C/N ratio	15	45	Measurement
Root_C/N	Root C/N ratio	39	90	Measurement

Table A5. Sensitive parameters for DNDC daily simulations of soil VWC, NH₄, NO₃, and N₂O. Parameters and prior bounds are defined in Table A4.

Variable	Parameter	Total effect index	Lower 95% CI ^a	Higher 95% CI
VWC	Leaf_C/N	0.3966	0.3586	0.4375
	Maximum_yield	0.3775	0.3410	0.4170
	Leaf_ratio	0.1855	0.1657	0.2075
	Accumulative_temperature	0.0359	0.0318	0.0406
	Water_requirement	0.0288	0.0255	0.0325
NH ₄	Maximum_yield	0.7166	0.6606	0.7747
	Accumulative_temperature	0.1317	0.1172	0.1478
	Leaf_C/N	0.1105	0.0983	0.1242
	Leaf_ratio	0.0928	0.0824	0.1044
NO ₃	Maximum_yield	0.9713	0.9095	1.0333
	Leaf_C/N	0.3932	0.3554	0.4339
	Root_fraction	0.0801	0.0711	0.0902
	Leaf_ratio	0.0309	0.0274	0.0349
N ₂ O	Maximum_yield	0.9237	0.8623	0.9856
	Leaf_C/N	0.1731	0.1544	0.1938
	Leaf_ratio	0.0286	0.0253	0.0323

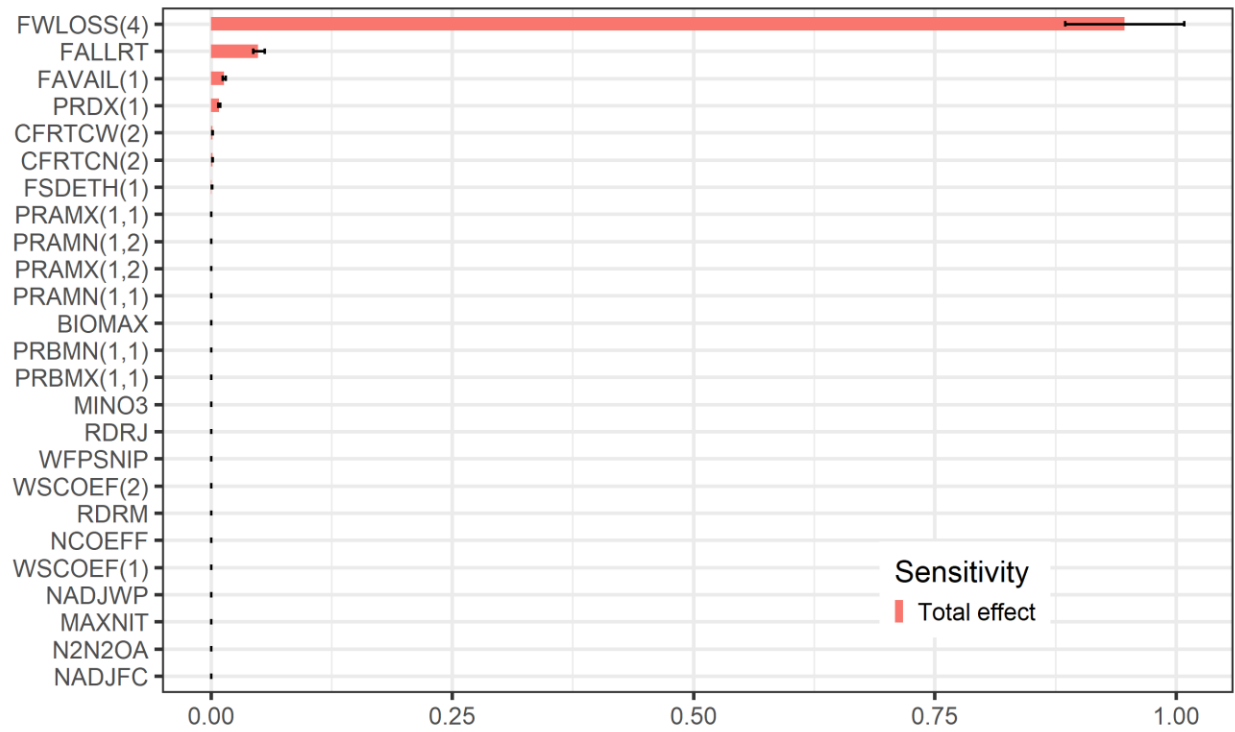
^a Confidence interval.

Table A6. Model evaluation of DNDC simulations of daily soil temperature, VWC, NH₄, NO₃, N₂O (daily and biweekly). Coefficient of determination (R²), model efficiency (ME), relative root mean square error (RRMSE), and relative mean difference (RMD).

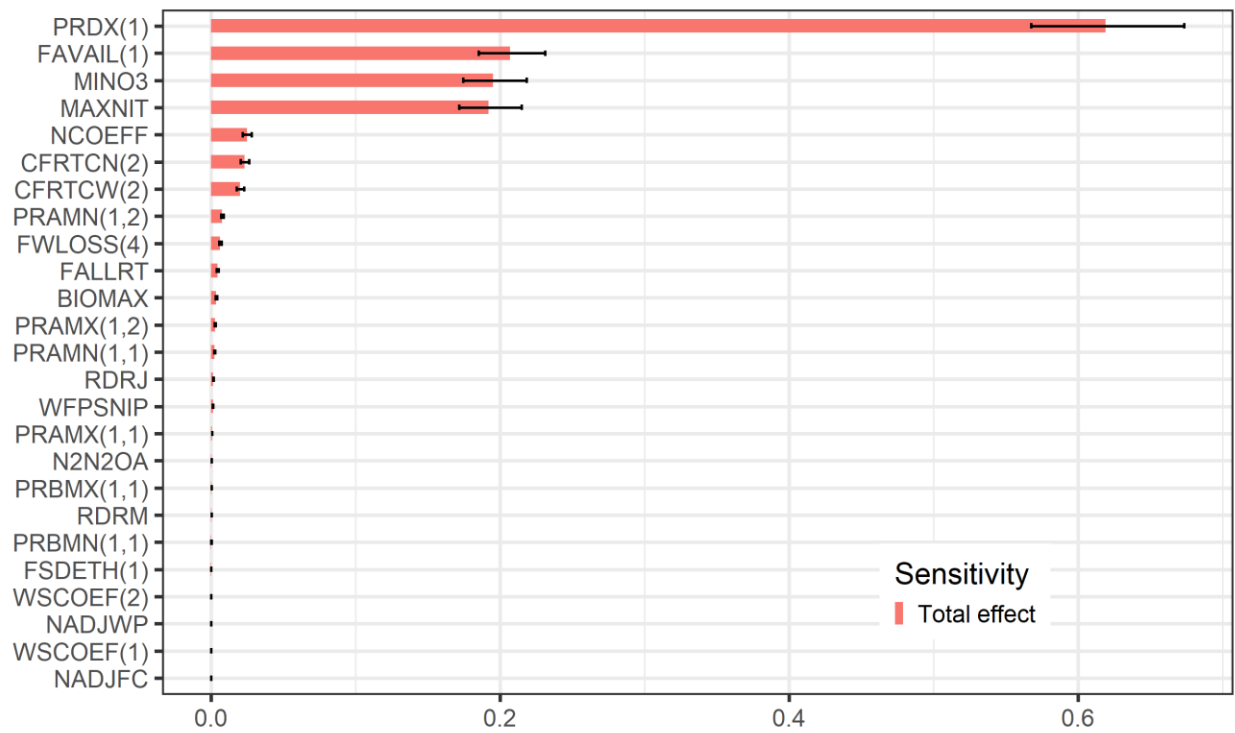
Study	Variable	Treatment	RRMSE	RMD	R ²	ME
1 (Braun & Bremer, 2018a)	Soil temperature	Urea_Medium	0.1701	0.0611	0.9359	0.8502
		Urea_Low	0.1684	0.0624	0.9336	0.8507
		Polymer-coated urea_Medium	0.1669	0.0591	0.9357	0.8534
		Polymer-coated urea_Low	0.1666	0.0617	0.9350	0.8531
		No Fertilization_Medium	0.1734	0.0685	0.9329	0.8450
		No Fertilization_Low	0.1712	0.0700	0.9334	0.8469
	VWC	Urea_Medium	0.2005	-0.1400	0.0761	-0.8326
		Urea_Low	0.1897	-0.0150	0.0035	-0.1018
		Polymer-coated urea_Medium	0.2128	-0.1610	0.0733	-1.2438
		Polymer-coated urea_Low	0.1827	-0.0392	0.0245	-0.1041
		No Fertilization_Medium	0.2211	-0.1731	0.0922	-1.3992
		No Fertilization_Low	0.1721	-0.0891	0.0502	-0.4055
	NH ₄	Urea_Medium	0.9689	-0.9042	0.0227	-11.0864
		Urea_Low	0.9634	-0.9079	0.0608	-10.6106
		Polymer-coated urea_Medium	1.0205	-0.9880	0.0371	-15.3081
		Polymer-coated urea_Low	1.0241	-0.9881	0.0406	-13.8102
		No Fertilization_Medium	1.0235	-0.9877	0.0217	-13.8226
		No Fertilization_Low	1.0238	-0.9877	0.0200	-13.6979
	NO ₃	Urea_Medium	1.1913	-0.6635	0.0258	-1.0754
		Urea_Low	1.0800	-0.6480	0.0122	-2.6290
		Polymer-coated urea_Medium	1.0183	-0.9072	0.0125	-6.0545
		Polymer-coated urea_Low	0.9973	-0.8942	0.0006	-6.2482
		No Fertilization_Medium	0.9818	-0.8893	0.0136	-10.0205
		No Fertilization_Low	0.9891	-0.8778	0.0000	-6.6731
	Daily N ₂ O	Urea_Medium	3.0674	0.0071	0.0583	-1.7393
		Urea_Low	2.6985	-0.0510	0.0734	-1.4675
		Polymer-coated urea_Medium	1.1404	-0.9030	0.0602	-2.5707
		Polymer-coated urea_Low	1.1132	-0.8938	0.0467	-2.8602
		No Fertilization_Medium	1.1411	-0.8917	0.0555	-2.6070
		No Fertilization_Low	1.1318	-0.8927	0.0569	-2.7580
	Biweekly N ₂ O	Urea_Medium	1.4197	-0.3331	0.4291	-0.5543
		Urea_Low	1.2995	-0.4061	0.3834	-0.4691
		Polymer-coated urea_Medium	1.2391	-0.8371	0.0237	-1.1250
		Polymer-coated urea_Low	1.1936	-0.8215	0.0109	-1.1972
		No Fertilization_Medium	1.2297	-0.8131	0.0181	-1.0992
		No Fertilization_Low	1.2128	-0.8142	0.0152	-1.1483

2 (Lewis & Bremer, 2013)	Soil	Urea_Regular irrigation	0.1537	0.0958	0.9624	0.9324
	temperature					
	VWC	Urea_Regular irrigation	0.2400	-0.1067	0.0399	-0.2404
	NH4	Urea_Regular irrigation	1.3175	-0.8763	0.5886	-0.1103
	NO3	Urea_Regular irrigation	1.1603	-0.9433	0.0017	-2.0859
	Daily N2O	Urea_Regular irrigation	3.8521	-0.2622	0.0007	-0.2043
	Biweekly N2O	Urea_Regular irrigation	1.9284	-0.2173	0.1635	0.0073

A. Soil VWC



B. Soil NH4



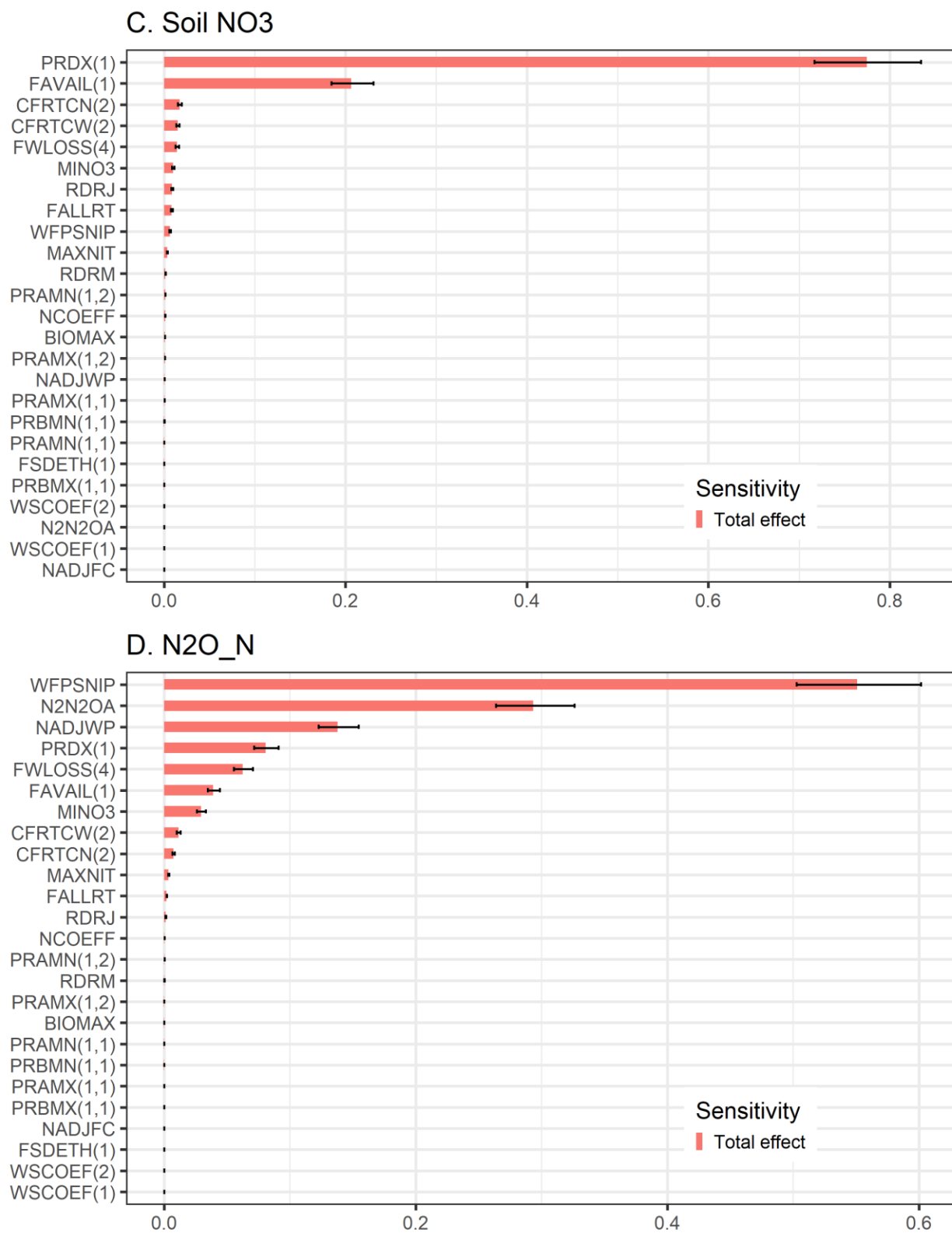


Figure A1. Relative ranking of sensitivity of DAYCENT model to parameters in simulating (A) soil volumetric water content (VWC), (B) soil ammonium (NH₄), (C) soil nitrate (NO₃), (D)

nitrous oxide (N₂O) in zoysiagrass, respectively. Parameters and prior bounds are defined in Table A1.

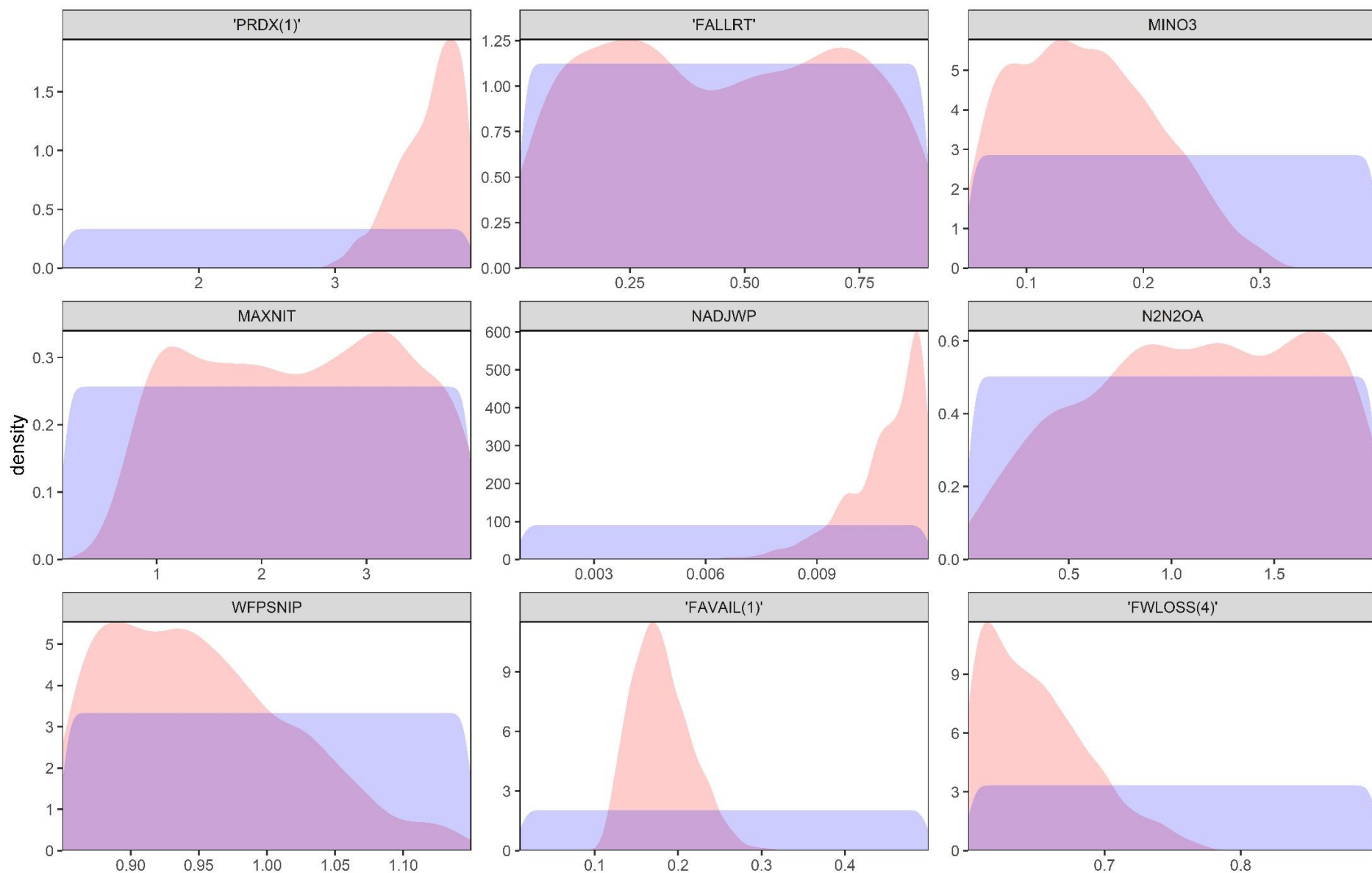


Figure A2. Marginal prior (purple) and posterior (rose) distributions of sensitive DAYCENT parameters. Parameters and prior bounds are defined in Table A1.

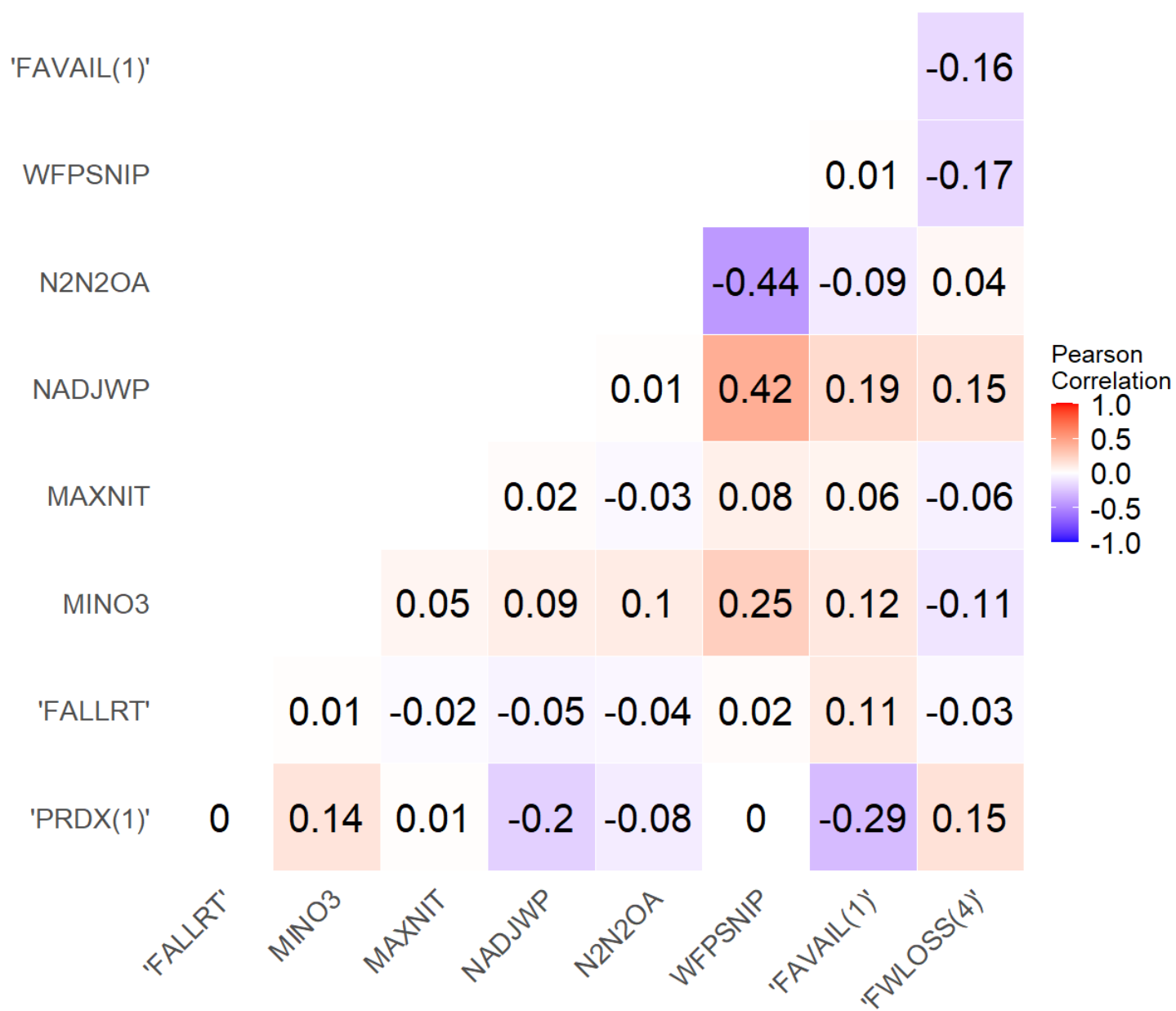


Figure A3. Correlation coefficients among DAYCENT model parameters in the posterior distributions. Parameters and prior bounds are defined in Table A1.

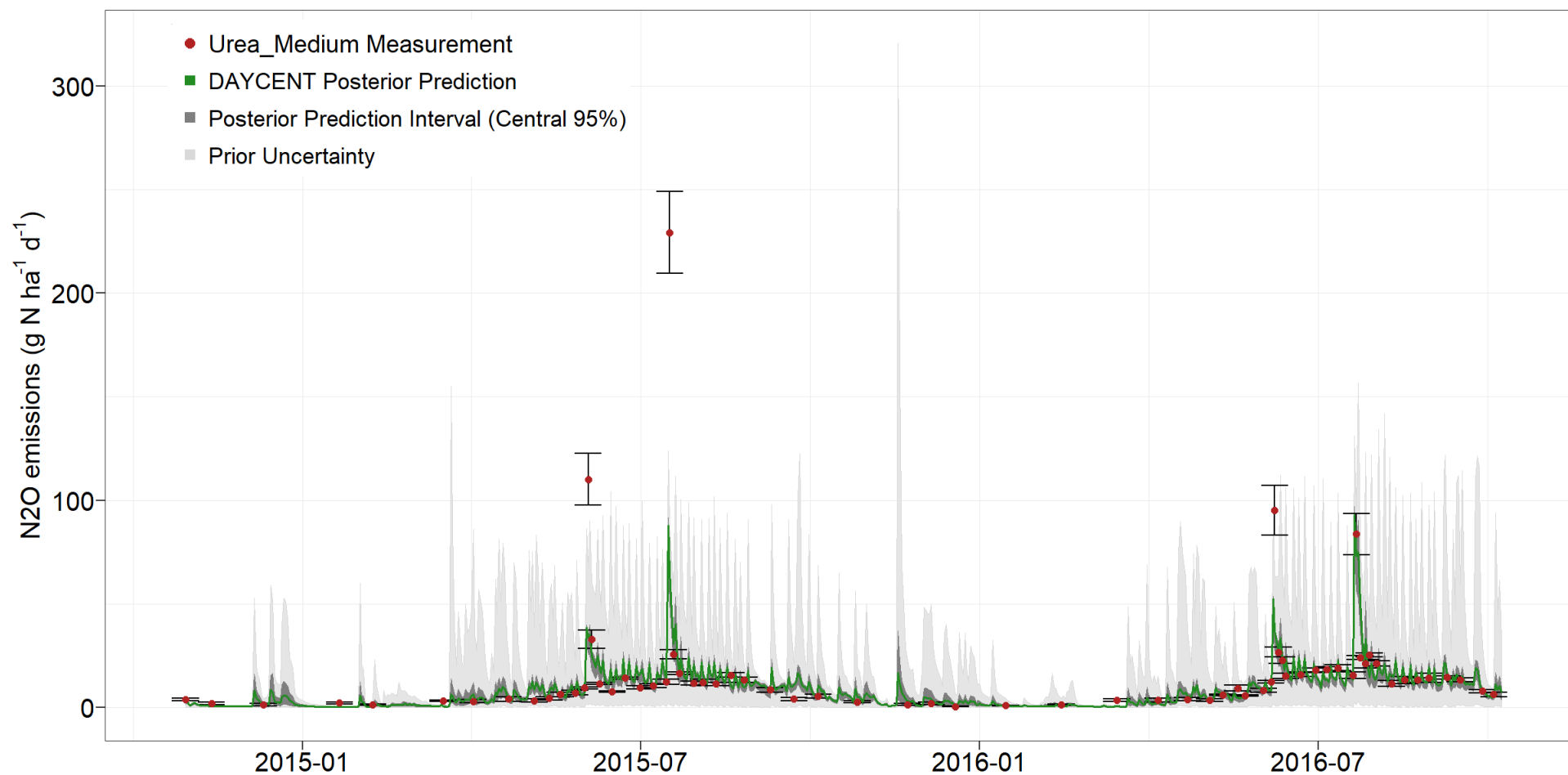
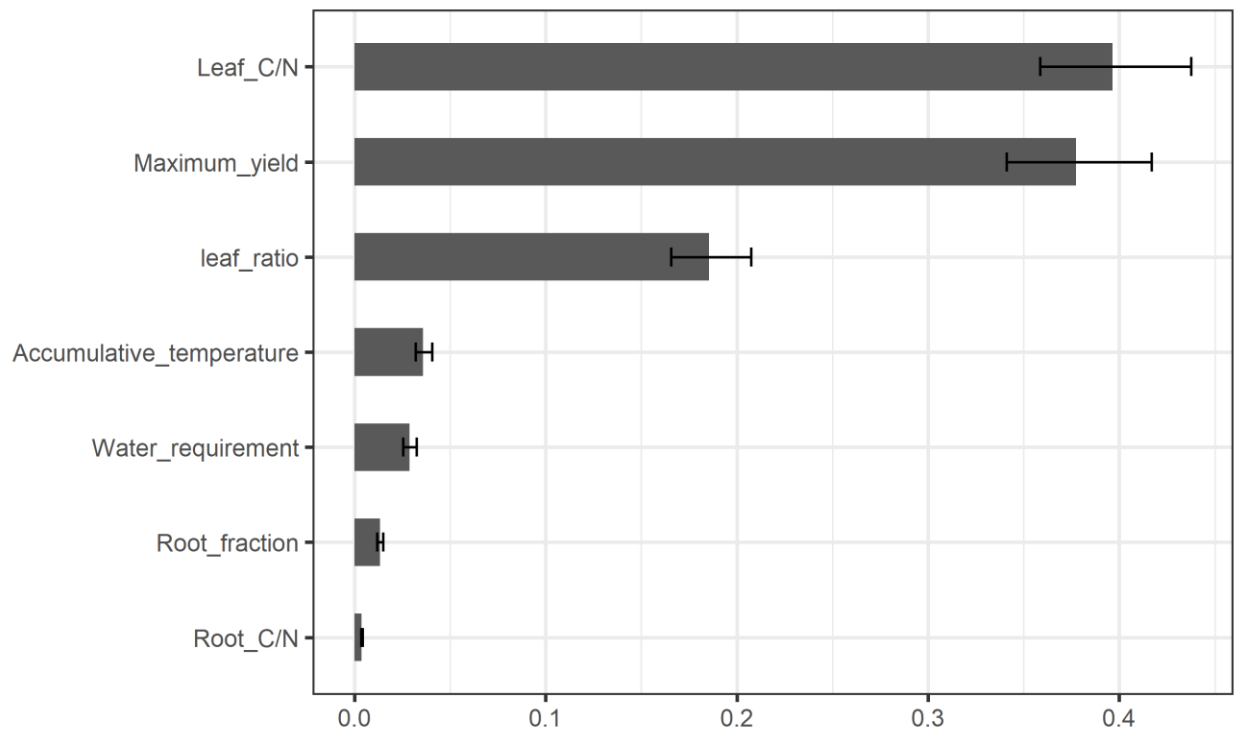
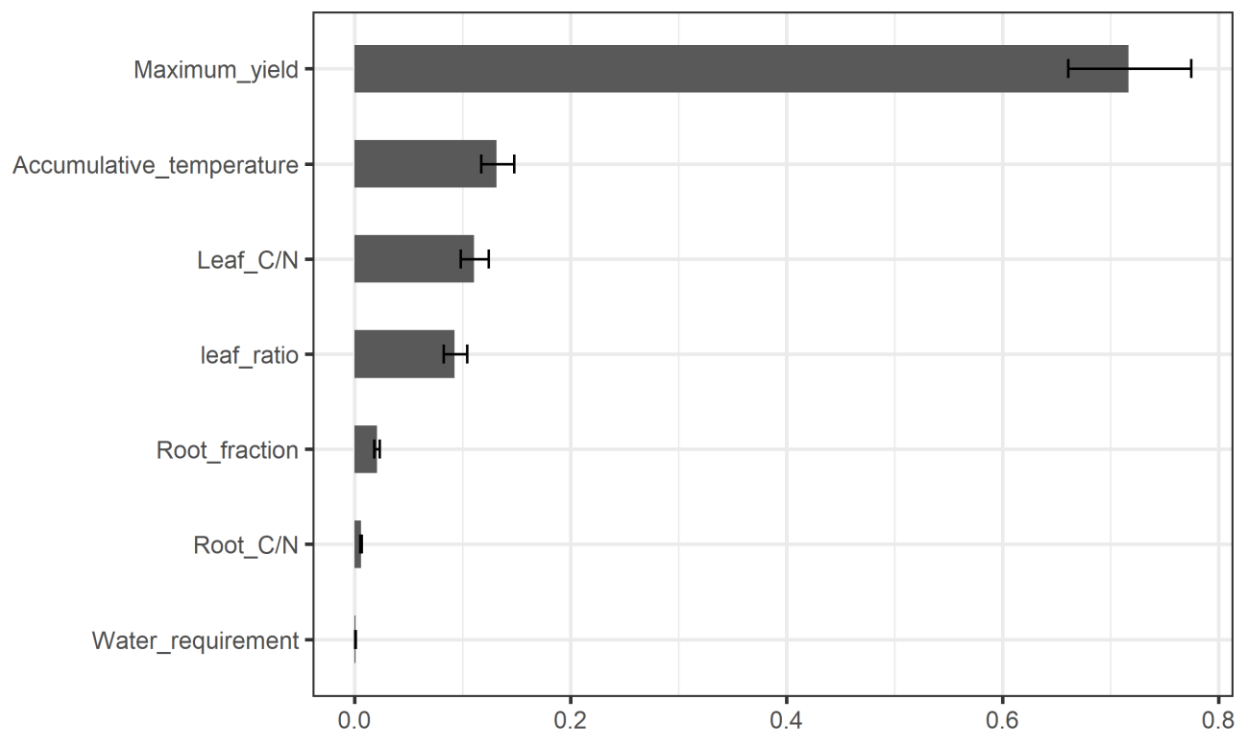


Figure A4. DAYCENT prior and posterior prediction intervals of daily N₂O emission from under the medium irrigation and urea treatment (a typical irrigation and N fertilization regime).

A. Soil VWC



B. Soil NH4



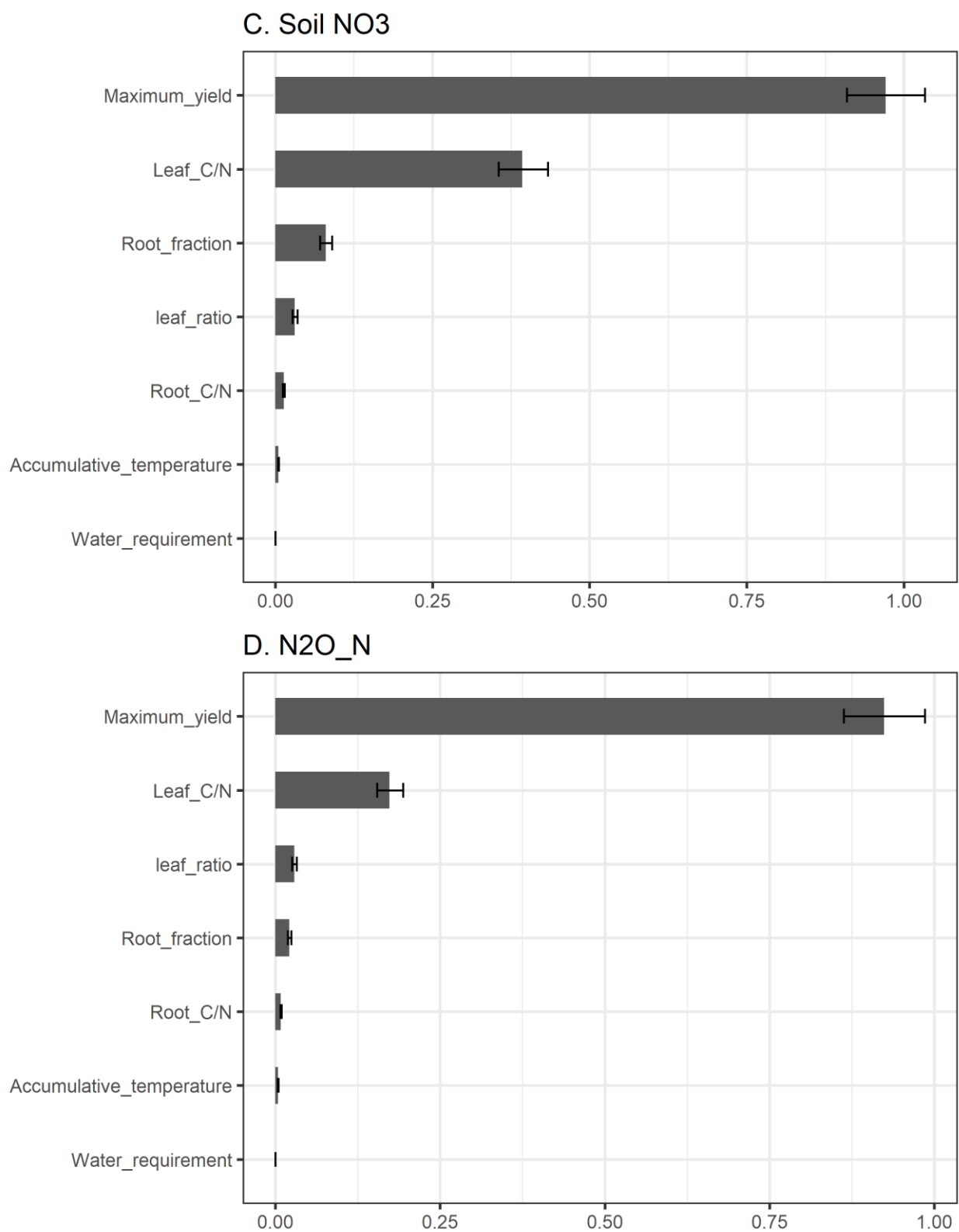


Figure A5. Relative ranking of sensitivity of DNDC model to parameters in simulating (A) soil volumetric water content (VWC), (B) soil ammonium (NH₄), (C) soil nitrate (NO₃), (D) nitrous oxide (N₂O) in zoysiagrass, respectively. Parameters and prior bounds are defined in Table A4.

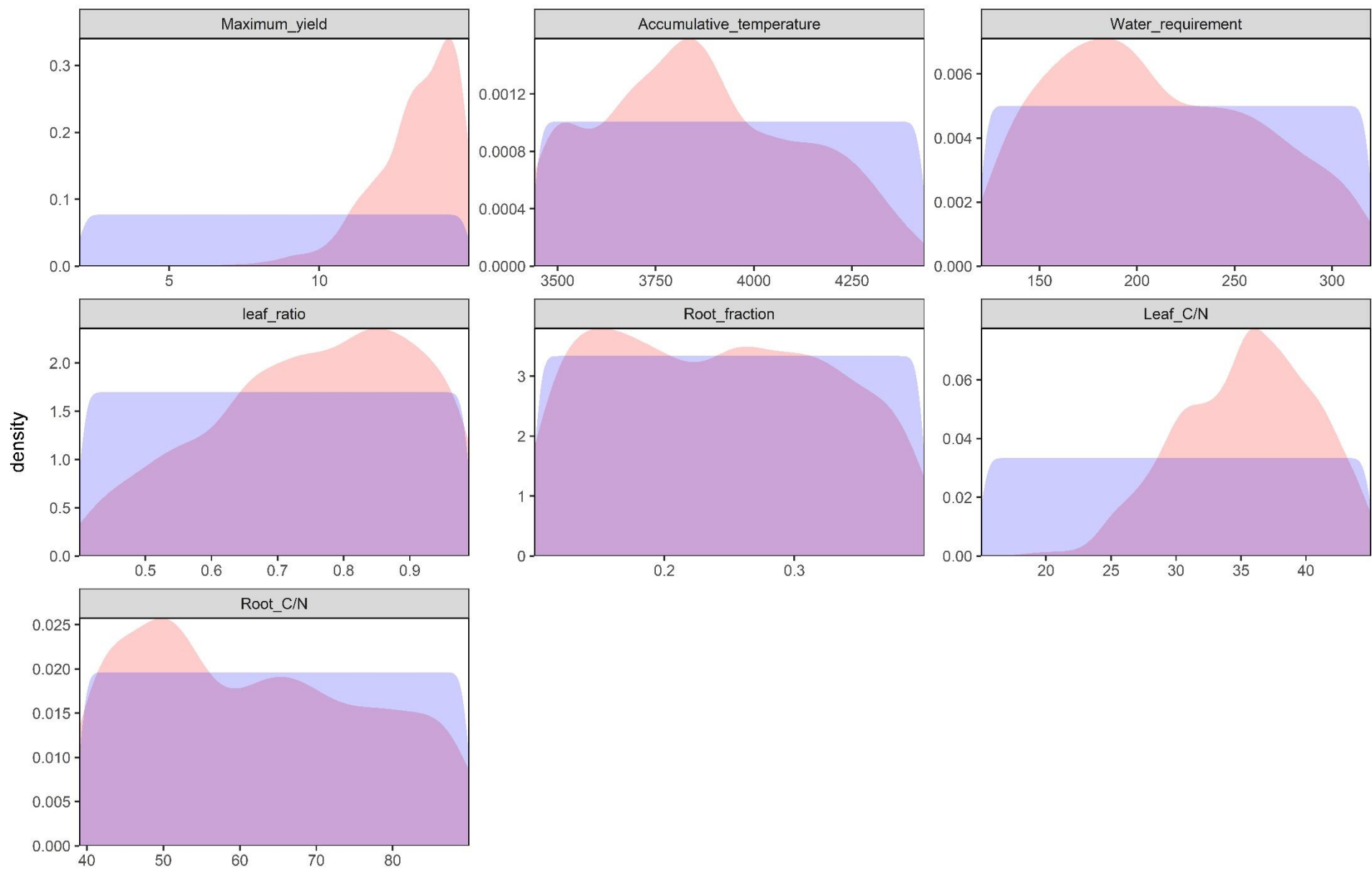


Figure A6. Marginal prior (purple) and posterior (rose) distributions of DNDC parameters. Parameters and prior bounds are defined in Table A4.

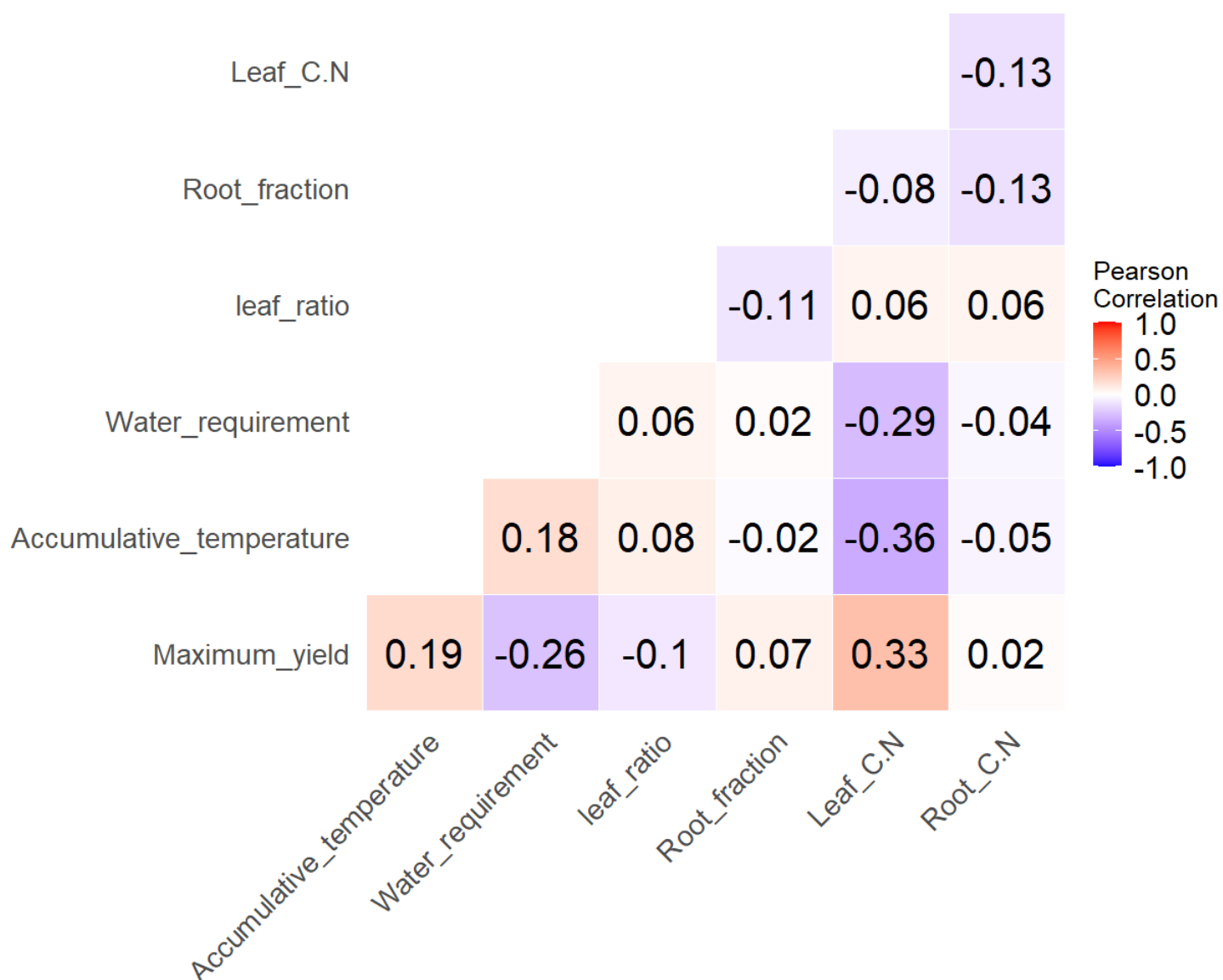


Figure A7. Correlation coefficients among DNDC model parameters in the posterior distributions. Parameters and prior bounds are defined in Table A4.

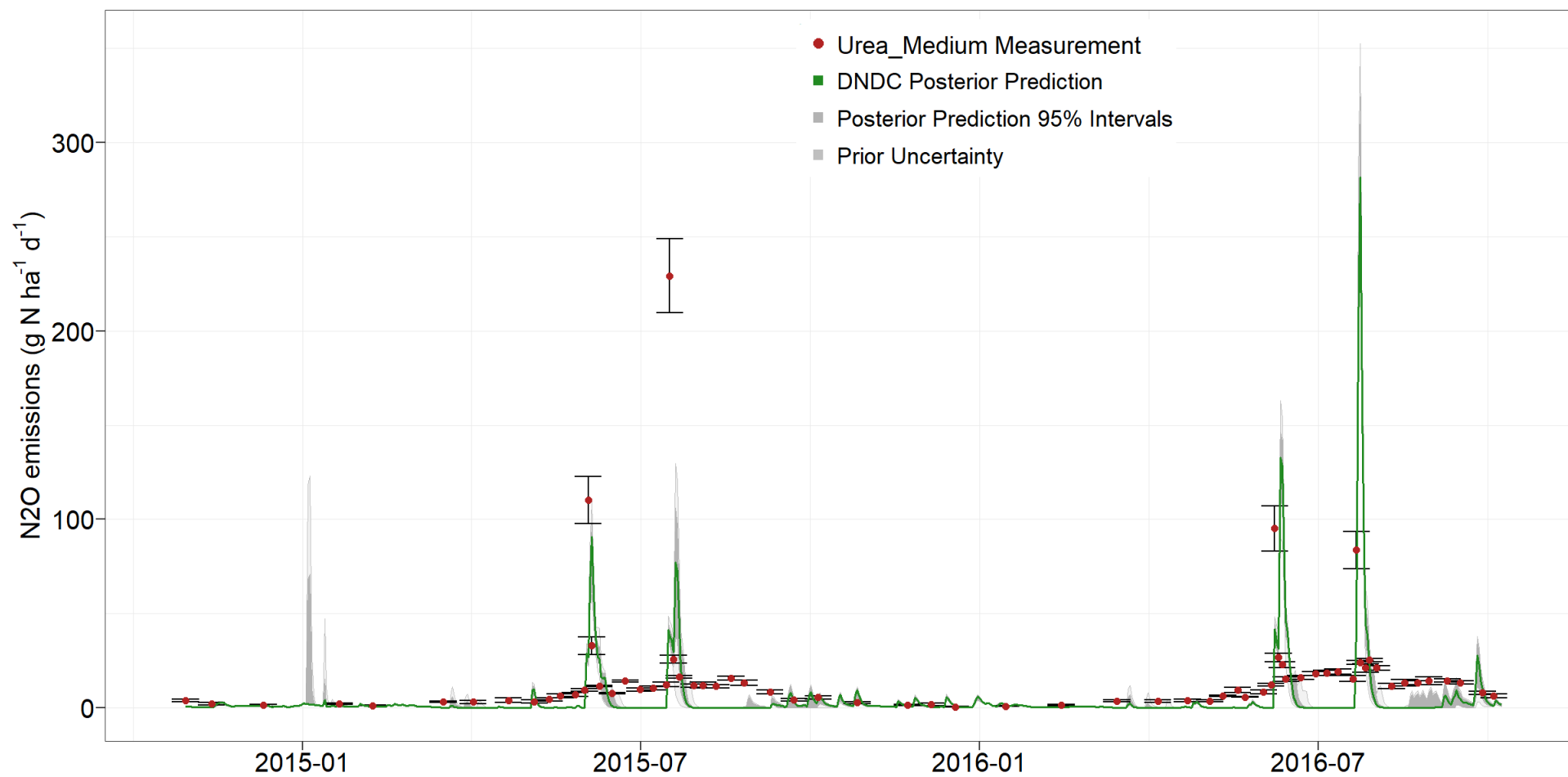


Figure A8. DNDC prior and posterior prediction intervals of daily N2O emission from under the medium irrigation and urea treatment (a typical irrigation and N fertilization regime).

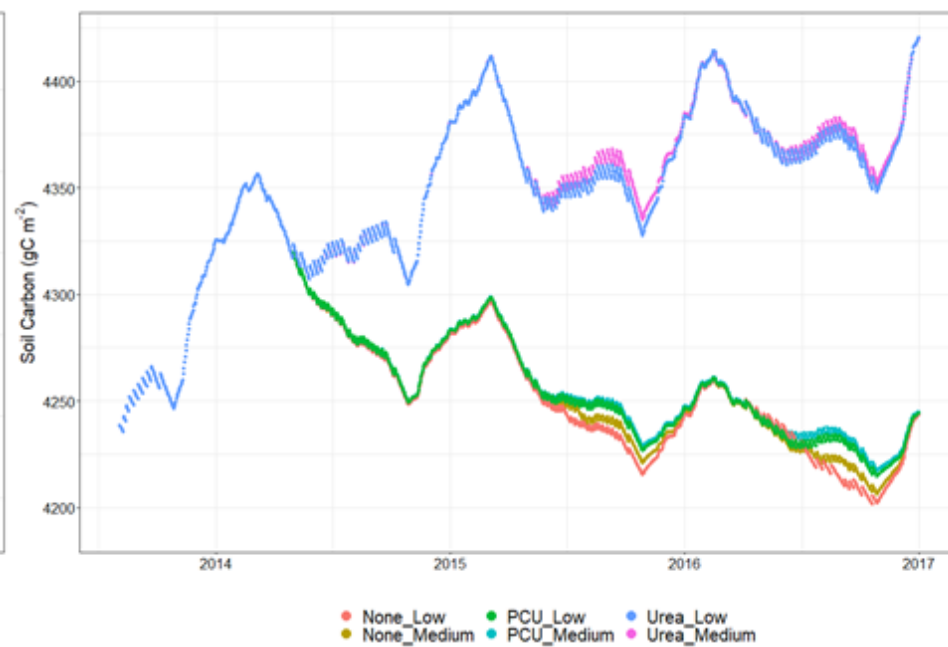
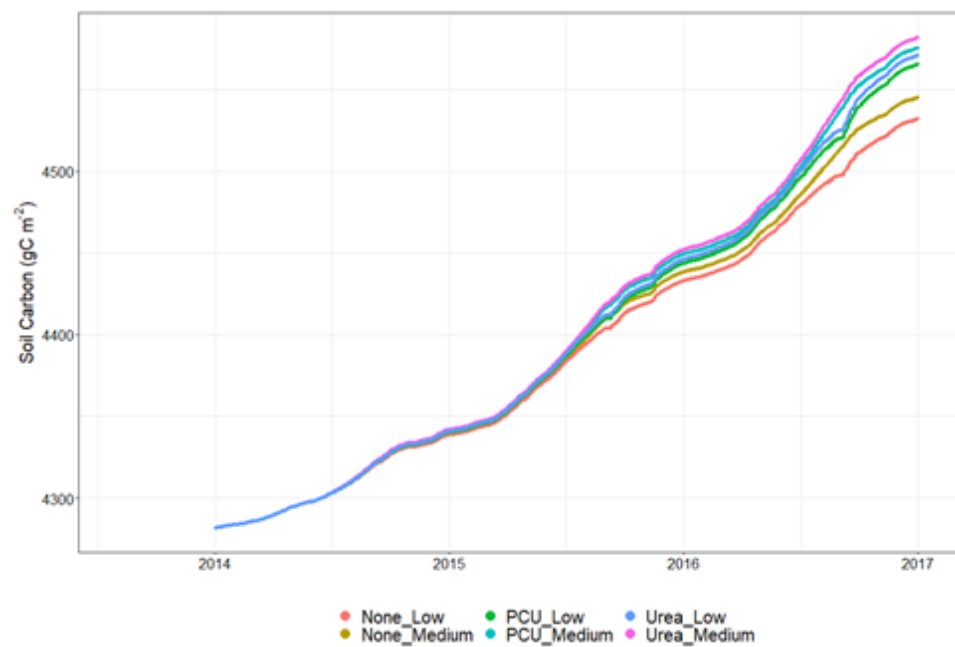
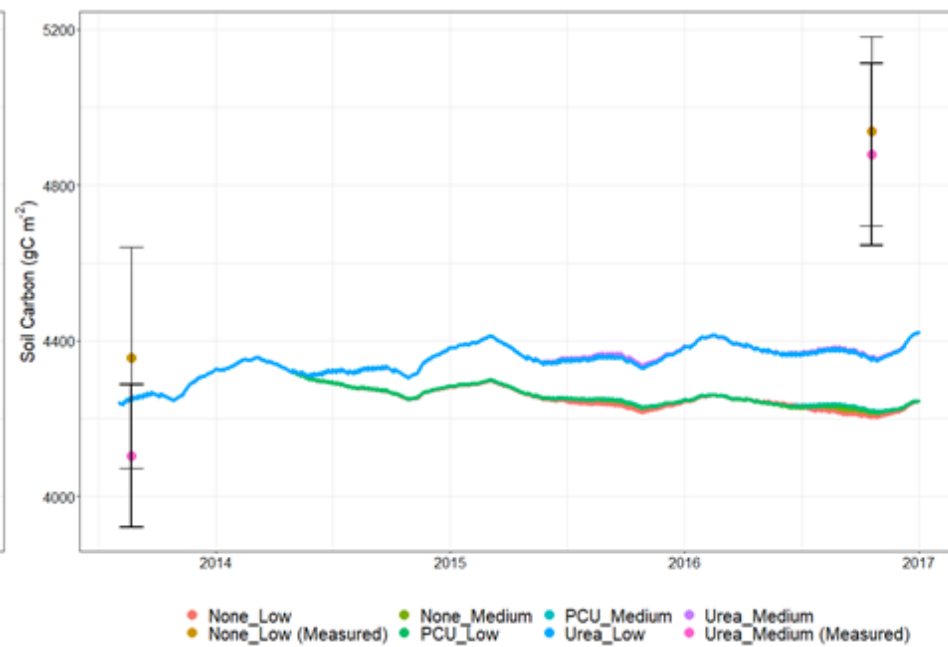
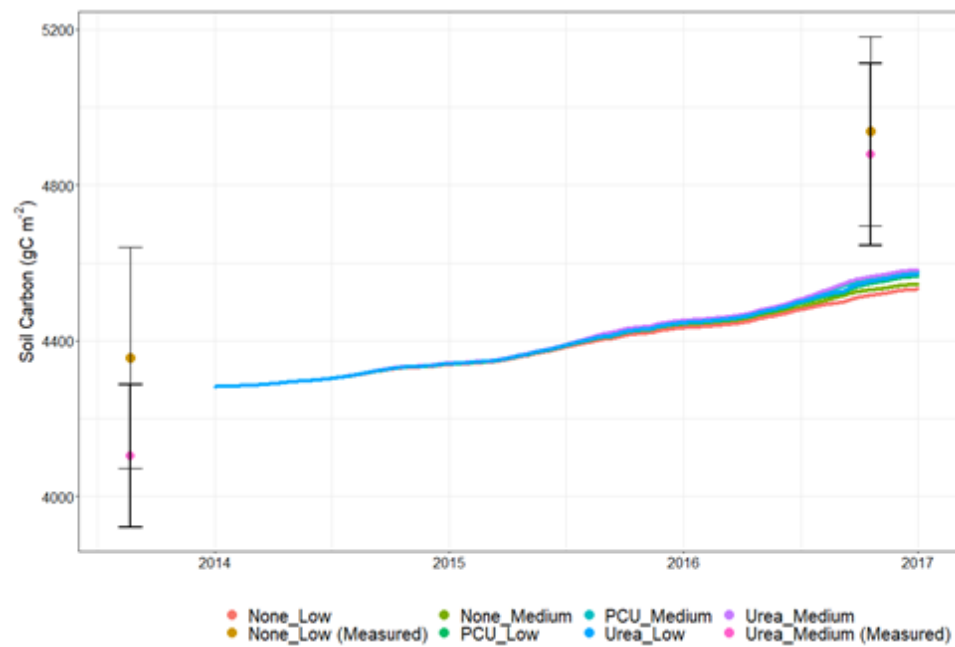


Figure A9. DAYCENT (left column) and DNDC (right column) simulations of surface 20-cm soil carbon for different management in zoysiagrass. One standard error bar of measurements is shown in the upper panels. Lower panels are the zoom-in of upper panels.

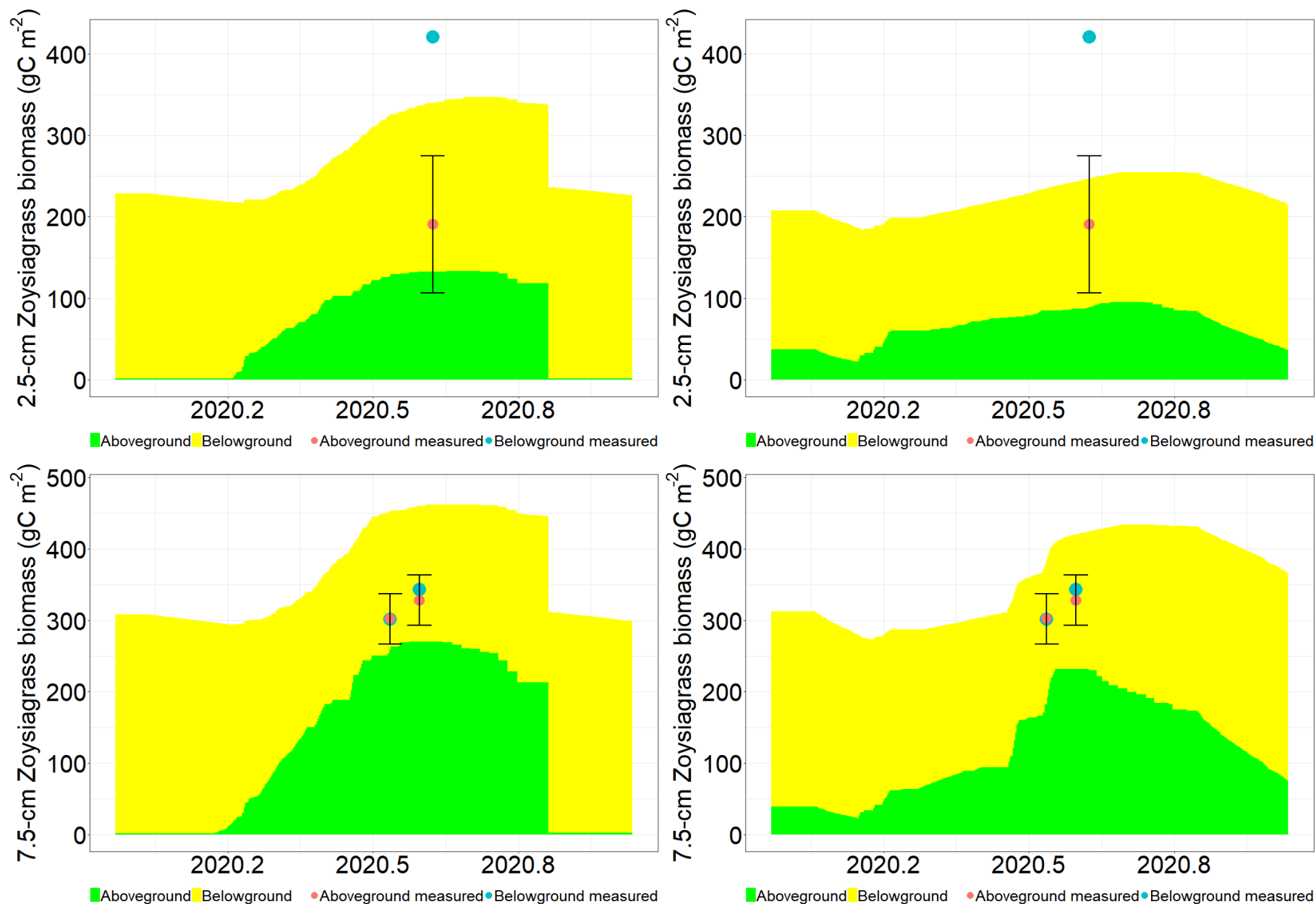


Figure A10. Zoysiagrass biomass simulated by DAYCENT (left column) and DNDC (right column) at the research center. Error bars enclose a 95% confidence interval of aboveground biomass.

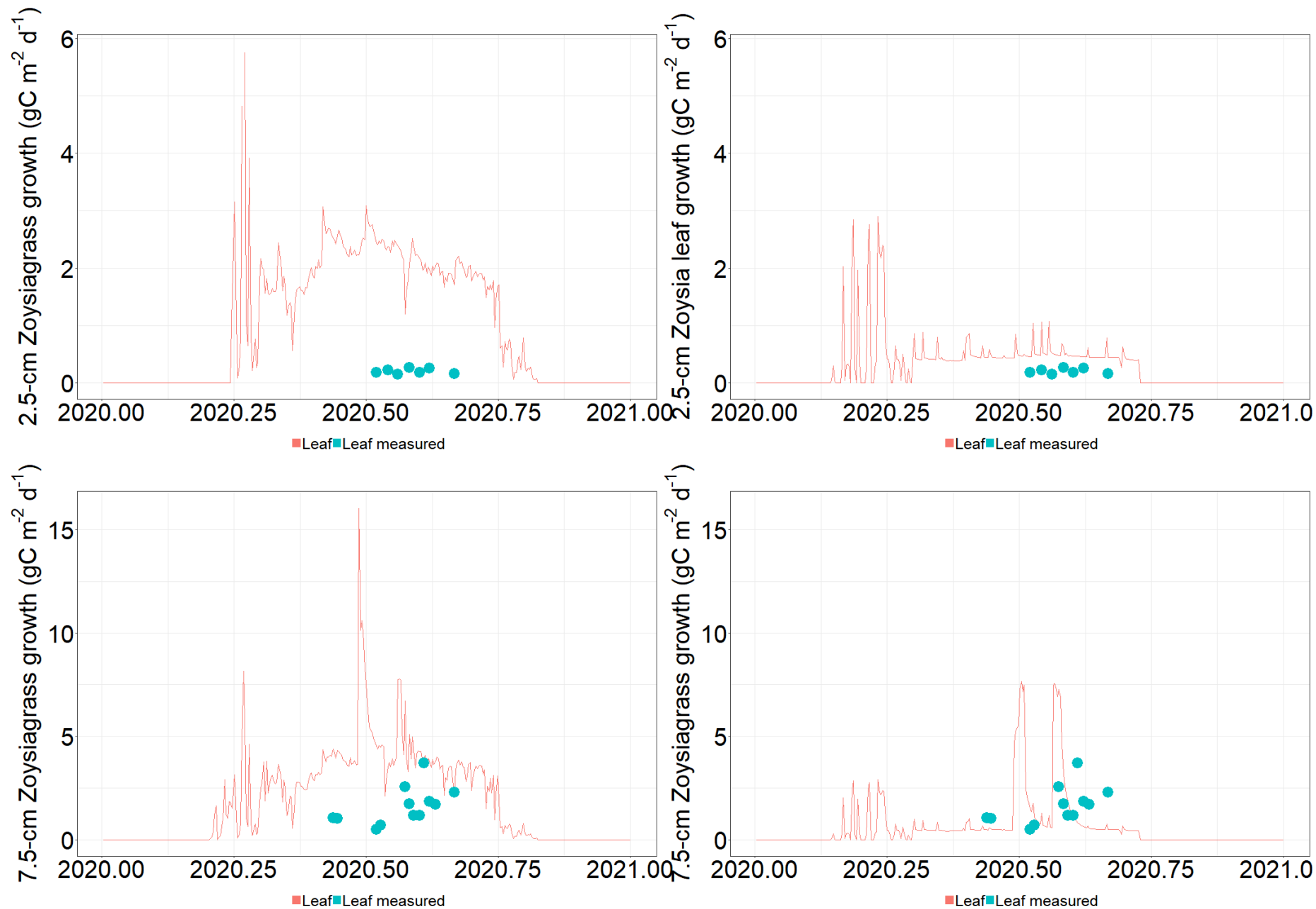


Figure A11. Zoysiagrass leaf growth rate simulated by DAYCENT (left column) and DNDC (right column) at the research center.

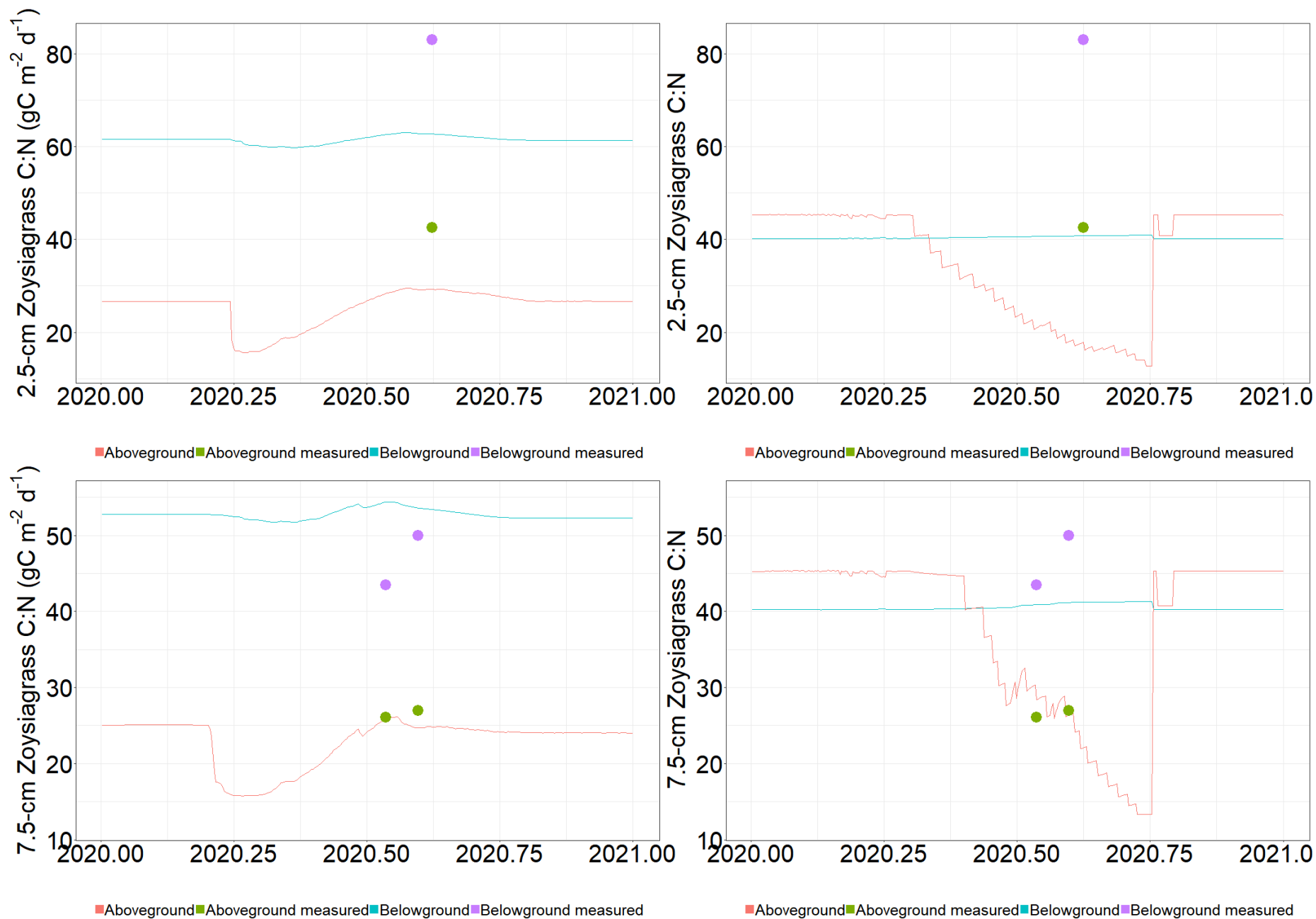


Figure A12. Zoysiagrass leaf C/N ratio simulated by DAYCENT (left column) and DNDC (right column) at the research center.

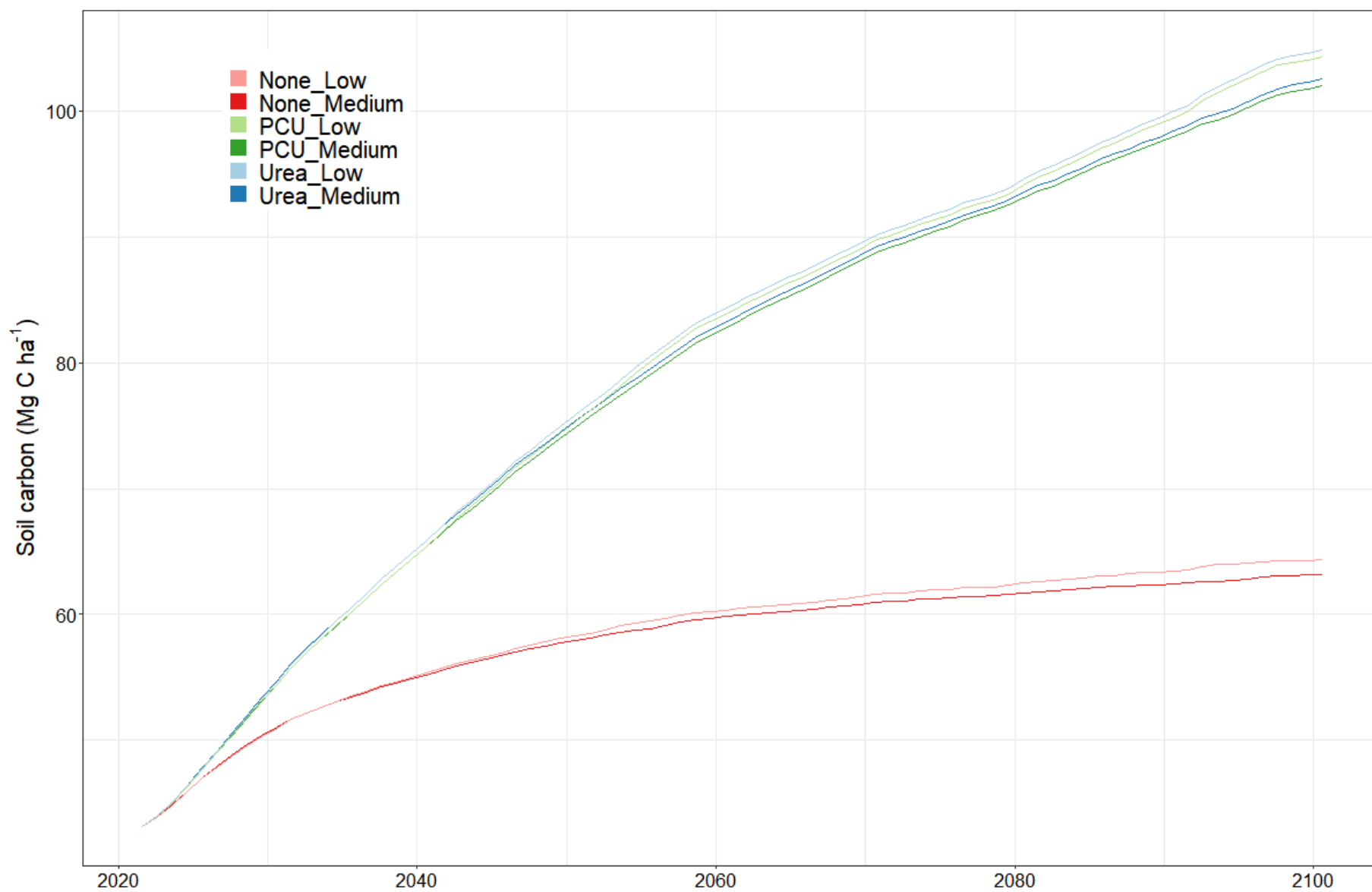


Figure A13. 2021-2100 projection of soil organic carbon for six maintenance scenarios under baseline weather using the validated DAYCENT model.

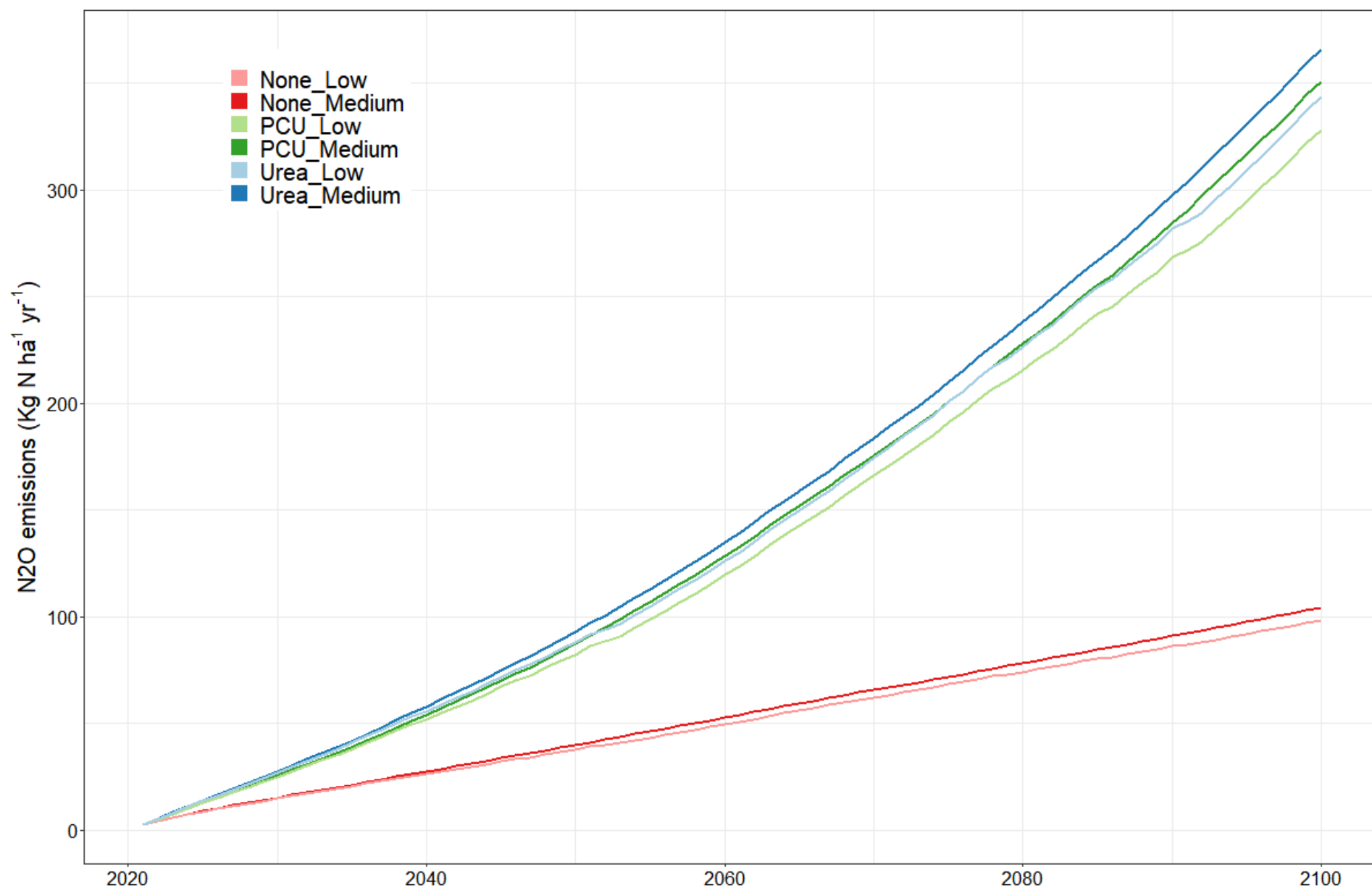


Figure A14. 2021-2100 cumulative N₂O emissions for six maintenance scenarios under baseline weather using the validated DAYCENT model.

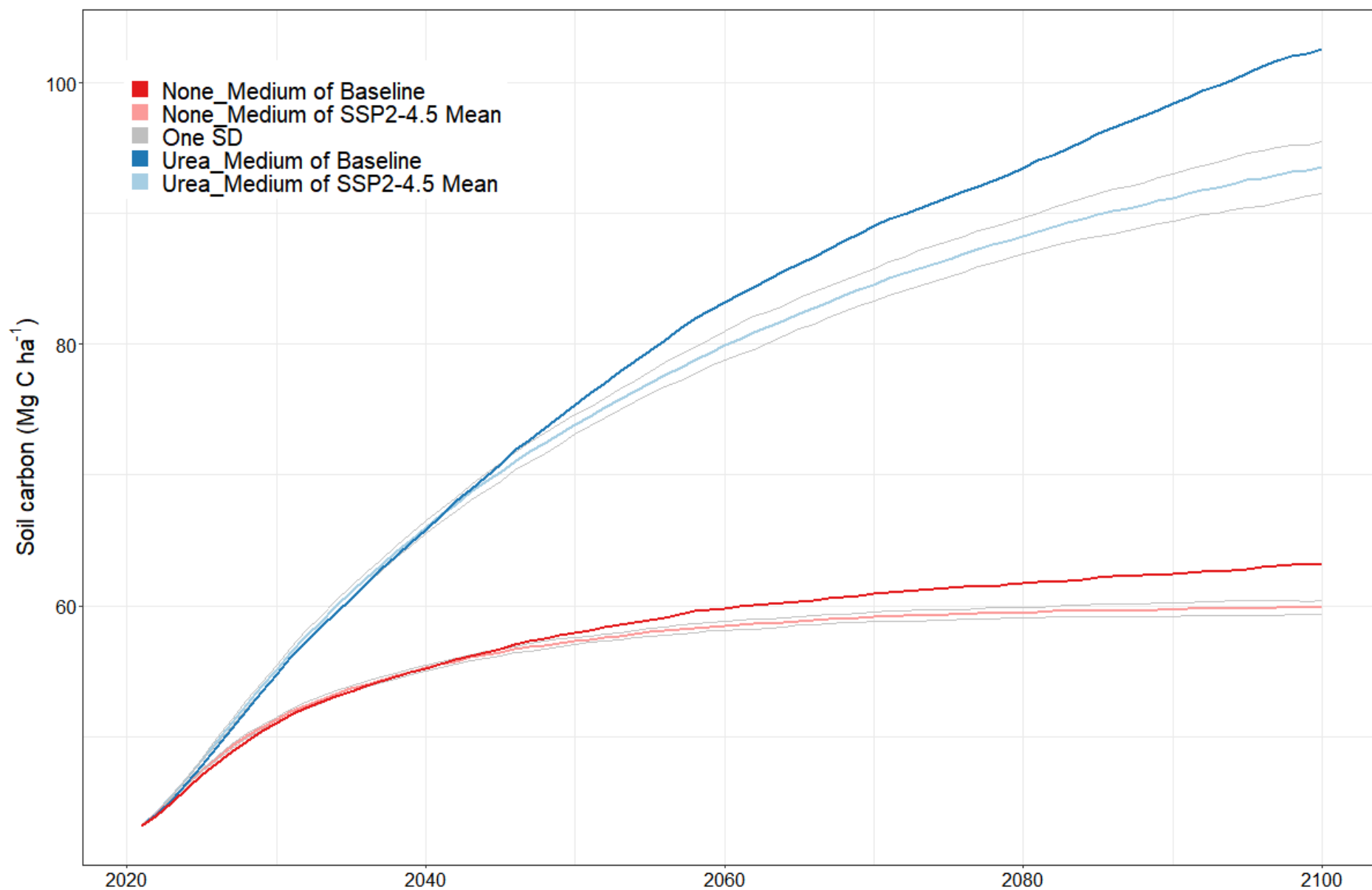


Figure A15. 2021-2100 projection of soil organic carbon for moderate (Urea_Medium) and low (None_Medium) intensity maintenance under baseline weather and medium climate change scenario (SSP2-4.5) using the validated DAYCENT model.