

Long-term biophysical conditions and carbon dynamics of a temperate swamp in Southern
Ontario, Canada

by

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Examining Committee Membership

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Author's Declaration

This thesis consists of material all of which I authored or co-authored: see Statement of Contributions included in the thesis. This is a true copy of the thesis, including any required final revisions, as accepted by my examiners.

I understand that my thesis may be made electronically available to the public.

Statement of Contributions

Unlike the traditional thesis format, this submission has been compiled as a collection of written scholarly work (manuscripts). Three independent manuscripts to be submitted for publication are presented as chapters 2, 3 and 4 of this thesis. As a result, repeated information may be included.

Tentative titles and authorship of future publications:

Manuscript 1: Process-based modelling of multi-decade carbon dynamics of a cool temperate swamp. Authors: Afolabi, O.L., He, H. and Strack, M. (submitted to Journal of Biogeosciences)

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Manuscript 3: Seasonal and annual shifts in temperate swamp biophysical conditions and carbon dioxide exchange under a changing climate. Afolabi, O.L., He, H., Fletcher, C. and Strack, M.

Afolabi O.L conducted the field design and setup, data collection and processing, model setup, data analysis, and wrote the thesis chapters. All the manuscripts and the other contents of this thesis were written by Afolabi O.L. and reviewed by M. Strack, H. He and C. Fletcher

Abstract

In Canada, wetlands cover a land area of $1.5 \times 10^6 \text{ km}^2$ and store $\sim 129 \text{ Pg C}$. However, the carbon (C) cycling of swamps has been understudied even though they store substantial quantity of C in their biomass and can also accumulate peat. In particular, southern Ontario swamps are estimated to hold $\sim 1.1 \text{ Pg C}$ under distinct hydroclimatic conditions. Previous studies on temperate swamp C fluxes were mostly based on short-term (< 5 years) field measurements that limit our understanding of the multi-decadal dynamics that exist between this ecosystem's C flux and biophysical conditions. To elucidate the long-term interactions and feedbacks that are important to temperate swamp C dynamics, a process-based model (CoupModel) was used to simulate plant processes, energy, water and C fluxes in one of the most well-preserved swamps in southern Ontario over 78-year period (1983–2060). CoupModel reasonably simulated the C flux and controlling variables when validated with compiled historic field measurements (1983–2023) with coefficient of determination (R^2) values of 0.60, 0.95 & 0.61 for soil respiration, surface soil temperature (0–5 cm) and water table level (WTL). Systematic calibration of the initialized model for Beverly Swamp with the Generalized Likelihood Uncertainty Estimation (GLUE) approach moderately reduced the uncertainty associated with modelling processes and assisted in identifying the important parameters that greatly influence temperate swamp C flux simulations. Plant-related processes and hydrological variables exerted the strongest control on the simulation of carbon dioxide (CO_2) efflux through soil respiration. The forcing of the GLUE calibrated CoupModel with an ensemble of climate projections downscaled from earth system models (ESMs) under shared socio-economic pathway (SSP5) by mid-century (2060) produced a decline in the swamp's C uptake capacity as net ecosystem exchange (NEE) of CO_2 . Relative to the reference period of 1983–2002, the projected increase in mean air temperature ($4.3 \pm 0.8 \text{ }^\circ\text{C}$) and precipitation ($0.2 \pm 0.1 \text{ mm}$) by 2050s triggered increase in 5 cm deep soil temperature, vapor pressure deficit, and evapotranspiration at Beverly Swamp. These changes to the swamp's thermal and hydrological conditions dropped its WTL and VMC. Consequently, drier and warmer conditions raised the swamp's CO_2 efflux through ecosystem respiration, while its GPP

moderately increased. These bidirectional feedbacks contributed to a reduction in the swamp's net C uptake (NEE) by the 2050s but it mostly still maintained its net C sink role. While uncertainty in future climate projections and model fit limit our confidence in the precise estimate of future carbon exchange, it was clear that seasonal timing of warming and precipitation played an important role in the swamp response, with coincident declines in precipitation and warming temperatures in summer that caused water stress for plants. Results from this long-term study will help improve our understanding of the important ecohydrological interactions and feedbacks that drive the C cycle of temperate swamps, and their contributions to regional terrestrial C and water cycles. This will help inform decision making on the role of swamp peatlands as nature-based climate solutions through improved understanding of their net C exchange with the atmosphere.

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Dedication

I dedicate the thesis to the LORD almighty for granting me the strength to complete my program at the University of Waterloo.

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Chapter 1. Introduction and literature review

1.1 INTRODUCTION

Wetlands in North America are important to regional carbon (C) inventories as they cover a land area of ~2.2 million and store approximately 161 PgC (Kolka et al., 2018). Over 80% (129 Pg C) of the region's wetland stocks are located in Canada where they contribute to annual carbon dioxide (CO₂) uptake of ~64 TgC (Kolka et al., 2018). In particular, the swamp class, defined as a wetland with woody vegetation cover of more than 30% relative to their land area (National Wetland Working Group, 1997) also contribute to these C stocks and fluxes (Tarnocai (2006) . The swamp class is characterized by poorly drained soil and plant types that are adapted to the fluctuating water table and minerotrophic conditions (Davidson et al., 2022, 2024). Swamps exist on mineral soils or as peat-based ecosystems (National Wetland Working Group, 1997). Swamps that exist as peatlands hold higher organic C contents than mineral soils because C is stored in both living (above and below) biomass and in the peat layer that has accreted over centuries to millennial from the imbalance of primary productivity exceeding decomposition (Belyea & Clymo, 2001). Carbon sequestration, peat accumulation, decomposition and other C cycling processes in swamps are largely mediated by hydro-climatic conditions (e.g. temperature and soil moisture) (Davidson et al., 2019; Gutenberg et al., 2019; Kendall et al., 2020). This is linked to the strong coupling between the C and hydrology cycles in soil, vegetation, atmosphere transfers (Gentine et al., 2019; Helbig et al., 2020; Waddington et al., 2015). Furthermore, swamp C cycle processes are also sensitive to the thermal regime because of its influence on important ecosystem processes (e.g., soil respiration, phenology and transpiration) and biophysical conditions (Davidson & Janssens, 2006; Medlyn et al., 2011; Smith & Woo, 1986).

However, predicted climate changes (Bonsal et al., 2019; Zhang et al., 2019) are expected to disrupt the thermal and hydrologic conditions supporting the C balance processes of swamps in the temperate region (Trettin et al., 2005). Yet, most studies of C cycling in swamps to date are short term with limited ability to contribute to understanding of the ecosystem's response to longer term climate changes. Furthermore, bidirectional feedbacks between the climate and

swamp C cycle will play an important role in determining the ecosystem's future as net C source or sink. Therefore, this thesis assessed the long-term interactions and feedbacks that exists between biophysical conditions and C flux in a temperate swamp using a biophysical modelling approach. This thesis is structured to include a literature review, three chapters that are presented in manuscript format, and a final chapter that includes conclusions, study limitations, and future research sections.

1.2 LITERATURE REVIEW

1.2.1 Carbon cycling in mid-latitude swamps

Unlike other wetlands, swamps are characterized by a dense canopy cover of trees that are adapted to different levels of inundation varying from seasonal to permanent flooded conditions (Davidson et al., 2022; Kendall et al., 2020; Sleeter et al., 2017). The distinct vegetation cover of swamps in the form of trees (both deciduous and coniferous) and shrubs confer this forested ecosystem with high vegetative productivity and litter deposition (Mitsch et al., 1991; Sleeter et al., 2017). Aboveground CO₂ gross fixation via photosynthesis (GPP) is the dominant C influx of swamps as the sequestered C is stored in the biomass of trees and shrubs (Sleeter et al., 2017). The GPP rate of swamps reflect the different canopy types and climates that vary across regions, ranging from 1700 gC m⁻² yr⁻¹ to 3000 gC m⁻² yr⁻¹ in temperate and subtropical regions, respectively (Aguilos et al., 2020; Botkin et al., 1970; Shoemaker et al., 2015).

The deposition of above and below ground litter by swamps is the major source of soil organic matter (Kendall et al., 2020) (see Figure 1-1). However, the quality and quantity of litter produced by this ecosystem is dependent on plant functional groups and climate (Stoler & Relyea, 2020). Litter inputs of 112–537 g dry mass m⁻² yr⁻¹ have been reported in temperate swamps (Kendall et al., 2020; Mitsch et al., 1991; Santia & Strack, 2024), with mixed forest canopy recording higher litter input than deciduous and coniferous plant cover, and deciduous canopies producing more litter than coniferous in temperate regions (Jevon et al., 2022). In contrast, a study (Santia & Strack, 2024) of 12 swamp sites in Southern Ontario did not report

any difference in litterfall quantity between deciduous and coniferous plant cover. Instead, their litter quality represented by the carbon to nitrogen ratio (C:N) reflected the different canopy types with reported values ranging from 31 to 98 across the studied swamps (Kendall et al., 2020; Santia & Strack, 2024; Wang et al., 2015). The litter abundance and quality in swamps make important contribution of substrate to soil respiration processes, as heterotrophic mineralization and subsequent CO₂ efflux from wetlands require sufficient substrate (Kendall et al., 2020; Sleeter et al., 2017).



Figure 1-1. Litter deposition and collection at Beverly swamp in Southern Ontario, Canada

Ecosystem respiration (i.e., total contributions from both heterotrophic and autotrophic respiration) is the main route of CO₂ efflux from swamps and other forested wetlands (Aguilos et al., 2020). However, soil respiration (heterotrophic and root respiration), which is the largest component of ecosystem respiration (Reco) is more commonly measured in swamps (Davidson et al., 2019; 2024). Soil respiration rates of 0.4 to 12 gC m⁻² d⁻¹ have been observed in temperate swamps across Canada and the US (Clair et al., 2002; Dalva et al., 2001; Davidson et al., 2019; Kendall et al., 2020; Koh et al., 2009; Webster et al., 2014). This broad range of soil respiration rates can be linked to the differences in climate, hydrogeomorphic setting, plant functional type cover and their substrates, microbial community, and other important conditions that drive

these processes (Davidson et al., 2019; Gutenberg et al., 2019; Kendall et al., 2020; Sleeter et al., 2017). Even though Reco is a major CO₂ efflux from swamps, the substantial assimilation of C in the form of GPP ensures that these ecosystems retain their net C sink status. Measured net CO₂ uptake of swamps and other forested wetlands, represented by net ecosystem exchange (NEE) ranges from -124 gC m⁻² y⁻¹ to -1131 gC m⁻² y⁻¹ in both temperate and subtropical regions, where negative values indicate uptake of CO₂ by the ecosystem from the atmosphere (Aguilos et al., 2020; Botkin et al., 1970; Shoemaker et al., 2015).

1.2.2 Important controls on temperate swamp carbon cycle

Carbon sequestration in the live biomass, peat accumulation and other C cycling processes in swamps are largely mediated by hydrology because of the unique connection between hydrology, soil, vegetation and atmospheric transfers of C (Gentine et al., 2019; Helbig et al., 2020; Trettin et al., 2005; Waddington et al., 2015). This coupling that occurs between hydrological conditions affect the redox status (Bridgham et al., 2013), nutrient distribution (Komor, 1994), soil chemistry (Kendall et al., 2020), vegetation distribution (Mitsch et al., 1991; Sleeter et al., 2017), microbial richness and diversity (Nunes et al., 2015) and other important variables associated with rates of C cycling in swamps.

Water availability for these processes is directly influenced by the hydroperiod of swamps which is a function of its water balance components, climate, geomorphology and prevailing subsurface (e.g., soil) conditions (Mitsch & Gosselink, 2015). The water balance of swamps is dependent on total water inputs and outputs presented in equation (1):

$$\Delta S = P - ET + (R_{in} - R_{out}) + (GWin - GWout) \quad (1)$$

where ΔS represents water storage of the swamp, ET represents evapotranspiration (evaporation & transpiration), R_{in} and R_{out} are surface runoff inflow and outflow of the wetland, respectively, and $GWin$ and $GWout$ represents groundwater inflow and outflow of the wetland.

The dominance of each component to the water balance depends on the swamp's hydrogeomorphic setting, which describes swamp's position in the landscape (Duval & Waddington, 2018; McCarter et al., 2024).

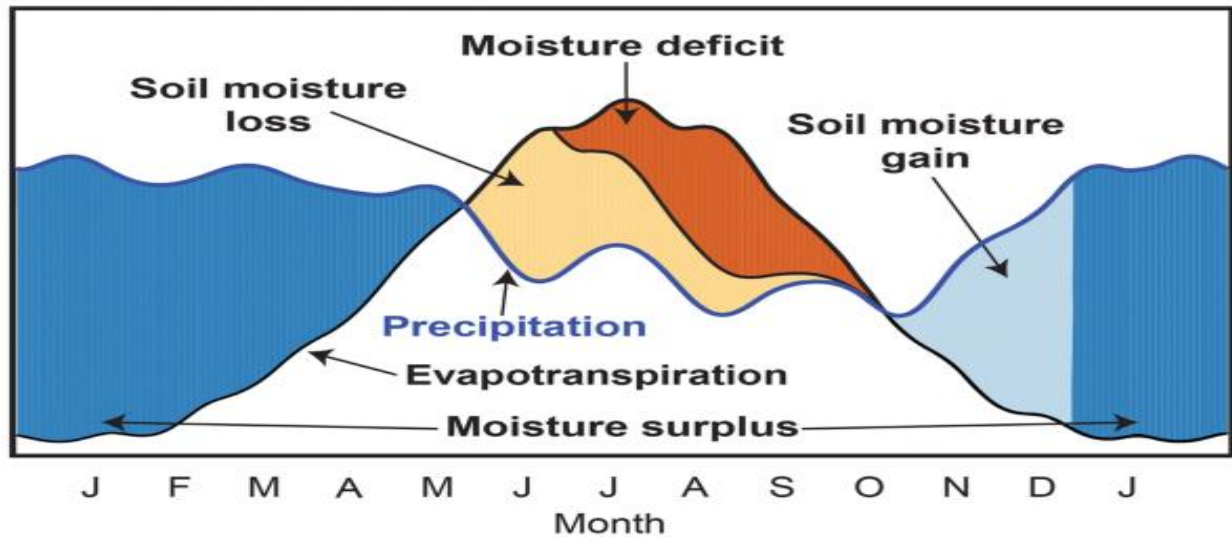


Figure 1-2. Typical hydropattern of temperate swamp water table level during winter, spring, summer and autumn seasons (Adapted from (Berkowitz et al., 2020))

Swamps are known to rely on different water sources to sustain their ecological processes (Berkowitz et al., 2020; McCarter et al., 2024; Roulet, 1990). A temperate swamp's annual hydropattern (Figure 1-2) is typified by water table rise in winter, autumn and spring in response to low evapotranspiration, increased precipitation in autumn and snow melt in spring, followed by water table draw-down during the summer growing season that coincides with high evapotranspiration (Berkowitz et al., 2020; Woo & Valverde, 1981). Dense vegetation cover and non-limiting moisture conditions support high evapotranspiration rates in swamps (Munro, 1986). This effect is pronounced in a region like southern Ontario where evapotranspiration losses exceeds precipitation during growing season (Whiteley & Irwin, 1986), and water table level can drop to as low as 65 cm below the surface during extremely dry summers that coincide with high evapotranspiration rates (Munro, 1984; Smith & Woo, 1986; Warren et al., 2001). However, the seasonal distribution of water table position may differ in swamps with unique water balance components (e.g., spring-fed saturation) that are

less dependent on flood water and precipitation supplies and water loss through evapotranspiration (Roulet, 1990). A swamp's unique hydroperiod and its associated flow regime influence vegetation, particularly tree and shrub, distribution across the ecosystem (Berkowitz et al., 2020; Sleeter et al., 2017; Woo & Valverde, 1981). Some of the woody species supported by swamp water table regimes are red maple (*Acer rubrum*), white cedar (*Thuja occidentalis*), tamarack (*Larix laricina*), aspen (*Populus tremuloides*), hemlock (*Tsuga spp*), green ash (*Fraxinus pennsylvanica*) and Nuttall oak (*Quercus texana*) (Berkowitz et al., 2020; Sleeter et al., 2017; Waddington et al., 1993; Woo & Valverde, 1981; see Fig. 1-3 for images of swamp vegetation)



Figure 1-3. Snow cover and typical vegetation at a temperate swamp in Southern Ontario

In addition to the influence of moisture on plant distribution and land-surface energy exchange through evapotranspiration, swamp moisture content also affects peat thermal processes because of its effect on soil heat capacity and thermal conductivity (Dimitrov et al., 2010; Smith & Woo, 1986). This is important to soil respiration processes and CO₂ emission (Dimitrov et al., 2010) because microbes that mediate decomposition are sensitive to temperature change and heat transfer (Lloyd & Taylor, 1994). Heat transfer through vertical conduction is known to be the dominant exchange component in swamp soil (Smith & Woo,

1986). Snowpack in winter may also affect the thermal regime of swamps by serving as insulation for the soil (Contosta et al., 2016) (see Figure 1-3 for swamp snow cover image). This process dampens freezing conditions underneath the snow layer and supports warmer soil temperature for organic matter decomposition even during winter periods (Contosta et al., 2016). Conversely, the wet peat layer supports cooler conditions in swamps during warm periods because of its poor heat conducting properties (Smith & Woo, 1986). These cool and saturated conditions in peat layers slow microbial decomposition rates (Blodau, 2002; Limpens et al., 2008). Changes to hydrological conditions have been reported to have strong constraint on microbial communities that mineralize peat soil (Nunes et al., 2015). Overall, swamp hydrology has a strong control on important biophysical conditions that produce feedbacks to C cycling in this ecosystem.

1.2.3 Modelling the biophysical conditions and carbon dynamics of mid-latitude swamps

In an attempt to understand the important interactions and feedbacks that exist between biophysical and biogeochemical conditions in swamps, field observations (Davidson et al., 2019; Kendall et al., 2020; Munro, 1979; Word et al., 2022), laboratory experiments (Webster et al., 2014), and modelling approaches (Munro et al., 2000; Sleeter et al., 2017; Yuan et al., 2023) have been applied to this ecosystem as the three complement each other. Observations provide background knowledge of ecosystem functions, while models improve our understanding of the processes encapsulated in observations (explanatory function), discover unobserved aspects (heuristic application) and also predict future changes (Metzger et al., 2016a; Mozafari et al., 2023; Wu et al., 2011). However, continuous field measurements and model applications in long-term studies (< 10 years) of temperate swamps are lagging when compared to tropical swamps or even other temperate wetland types (Davidson et al., 2019, 2022; Kendall et al., 2020). Temperate swamps are largely understudied and underestimated (Davidson et al., 2022); these knowledge gaps in temperate swamp C cycling processes were reflected in the exclusion of the peat swamp class from the Canadian Model for Peatlands (CaMP) because of data sparsity for calibration and validation (Bona et al., 2020). Ultimately,

the dearth of information and data on temperate swamps limits our ability to fully assess their role in regional C cycling and how they can be protected under a changing climate.

The few studies that exist on temperate swamps focused on micrometeorology measurements (Munro, 1986; 1987), soil hydraulics and hydrology (Munro, 1982; Woo & Valverde, 1981; Word et al., 2022), soil temperature simulations (Smith & Woo, 1986), vegetation surveys (Harper et al., 2022; Mitsch et al., 1991; Spencer, 1991) and other biophysical investigations of individual temperate swamps. However, only selected studies have attempted to understand the biogeochemical cycles (e.g., C stocks and fluxes) that occur in temperate swamps in Canada (Davidson et al., 2019; Kendall et al., 2021) or the interactions between these cycles and abiotic components, which can be simultaneously studied with a modeling approach. Numerous studies have adopted Arrhenius-based functions and other statistical models to simulate soil respiration rates and other C balance components of wetlands and other ecosystems (Lloyd & Taylor, 1994; Rowson et al., 2013). However, because these models are empirical and conceptual in nature, they are inherently not designed to capture important dynamic mechanisms that drive C fluxes within and between atmosphere-vegetation-soil transfers (Korzukhin et al., 1996; Reichstein & Beer, 2008; Yuan et al., 2023). These limitations restrict our understanding of the complex interactions and feedbacks that occur in temperate swamps.

Sleeter et al. (2017) adopted an integrated modelling approach using the Land Use and Carbon Scenario Simulator (LUCAS) to estimate historic (30 years) impacts of land change and other management practices on the C balance of Great Dismal Swamp. The integrated system also included process-based models (e.g., Integrated Biosphere Simulator, IBIS) because of their ability to simulate important underlying dynamic processes (e.g., C allocation) and the resultant feedbacks to the system. Process-based models are applicable to the current stage of knowledge development (Fourcaud et al., 2008; Korzukhin et al., 1996) in swamps where the focus is directed at elucidating the important interactions and processes driving C exchange in this ecosystem (Yuan et al., 2023). Munro et al. (2000) applied a process-based model, the Canadian Land Surface Scheme (CLASS), to understand the energy and water fluxes of a

temperate swamp in southern Ontario as part of the land surface processes in regional and global climate models. However, the study of Munro et al. (2000) was focused on specific processes (e.g., land surface water and energy fluxes) and did not couple both the biophysical and biogeochemical cycles in temperate swamps. More integrated, process-oriented ecosystem models (e.g., CoupModel, DNDC, Ecosys, and Lund-Potsdam-Jena) have been used to simulate important plant processes, water and energy exchange mechanisms and C fluxes across Europe and other parts of the globe with high success rate when validated with observations (He, et al., 2023; Kim et al., 2016; Metzger et al., 2016a; Mezbahuddin et al., 2016; Wania et al., 2009; Wu et al., 2013; Wu et al., 2011). However, these process-based models have not been tested in temperate swamps where the hydroperiods and vegetation cover are different from other wetlands classes including bogs, fens and marshes.

Process-based models heavily rely on forcing variables and exact boundary conditions to simulate important processes in forested ecosystems that may be difficult to delineate because of measurement limitations (Munro et al., 2000; Svensson et al., 2008; Yuan et al., 2023). This model category also require well-defined parameter values (Silva et al., 2024), but the course of assigning parameter values to important processes in data sparse ecosystems such as temperate swamps can be challenging. Thus, this creates parameter uncertainty when simulating temperate swamp C fluxes and its controlling conditions. Uncertainty in swamp C flux modelling is also introduced from field observations that are used for calibration and validation processes. Large spatial variability, varying measurement techniques for different study periods, and overall scarcity of measurements influence C flux modelling outcomes (Jansson, 2012; Wu et al., 2019). In addition, the limited modelling studies on temperate swamps to date may also create uncertainties when selecting the appropriate model structure for simulating swamp C balance. Consequently, these uncertainties, which are linked to parameterization, field measurement error and model structure may affect the C modelling process of this ecosystem and also compound uncertainty in future predictions that are expected to distort existing ecosystem interactions and feedbacks under climate change.

1.2.4 Climate predictions and swamp carbon dynamics

Climate change, defined as an alteration to weather distribution over a long time attributed to anthropogenic emission of greenhouse gases (GHGs) (IPCC, 2021), is expected to significantly impact the hydro-climatic conditions supporting C storage in the live biomass and peat soils of swamps (Kendall et al., 2020; Trettin et al., 2005). Approximately, one-third of boreal and temperate peatland soil organic C may be irrecoverable within the required mid-century timeframe (i.e., 2050 as defined to align with Paris Agreement commitments) for climate change mitigation if they are lost (Goldstein et al., 2020). Average air temperature across Canada is expected to increase by up to 6 °C relative to 1986–2005 averages at the end of the century under a high emission scenario (RCP8.5) (Zhang et al., 2019), while mean annual precipitation across Canada is expected to increase by 24% by the end of the century (Bonsal et al., 2019). In Ontario, annual maximum daily temperature is also expected to increase by up to 6 °C under RCP 8.5 by the year 2100, which will reduce the number of frost days by up to 50 days (Wazneh et al., 2020). Furthermore, the region's total annual precipitation will rise by 16% under RCP 8.5 by 2100, while the number of days with heavy precipitation (>10 mm) will increase by 5 days by the end of the century (Wazneh et al., 2020)

At the catchment scale, Sultana & Coulibaly (2011) relied on downscaled Global Climate Change Model (GCM) outputs to drive the Mike SHE model towards understanding how climate change will impact the hydrology of Spencer Creek, a creek in southern Ontario that feeds Beverly Swamp, by 2050s. In their study, they predicted an increase of up to 2–3 °C in annual minimum and maximum daily temperature, 16% rise in total precipitation, 1–10% increase in evapotranspiration, 1–5% decrease in snow storage and 0.5–6% decrease in groundwater recharge by the 2050s (2046–2060). Similarly, Grillakis et al. (2011) assessed the impacts of climate change on Spencer Creek by forcing semi-distributed rainfall-runoff models with downscaled future temperature and precipitation products of the North America Regional Climate Change Assessment Program (NARCCAP) for the 2050s (2040–2069). Their study arrived at similar increases of 16% for precipitation and 2.3 °C for air temperature for these years and predicted 3.3% increase in the frequency of extremely dry and wet conditions.

With increased annual precipitation predictions for the region (Wazneh et al., 2020), swamps may be flooded. Flooding conditions are expected to reduce both GPP and Reco rates in swamps (Freeman et al., 2001; Middleton, 2020; Pezeshki, 1991, 2001). However, the impact of these projections may vary on seasonal scales where more precipitation is expected during the wetter seasons and with reduced precipitation possible during the drier conditions in summer (Zhang et al., 2019). During drier seasons and warmer conditions, increased soil respiration will diminish the effectiveness of swamps as C sinks (Gutenberg et al., 2019; Kendall et al., 2020). However, warming and prolonged growing seasons and rising atmospheric CO₂ concentrations may spike GPP (Gallego-Sala et al., 2018; von Buttlar et al., 2018), thus balancing the C loss of this ecosystem. Conversely, warm conditions may not translate to a higher GPP rate because the peak of summer also coincides with high evaporative demand and plant stress (Helbig et al., 2019; 2020; Medlyn et al., 2011). This may be exacerbated by plant's acclimation to warmer conditions and nutrient constraints that will hinder productivity in these ecosystems (Medlyn et al., 2011).

Although the climate projections highlighted above are relevant for predicting the hydro-climatic conditions affecting southern Ontario hydrology, they cannot be directly translated to future C flux of swamps because the studies did not establish any relationship between climate change predictions and swamp C flux or stocks. Tarnocai (2006) assessed the impacts of climate change on Canadian peatlands with a peatland sensitivity model and concluded that 60% of peatland areas and 51% of organic C mass in Canadian peatlands will be affected by climate change. Despite the relevance of the study, Davidson et al. (2022) observed that the swamp land cover (5120 km²) used for the research was likely underestimated. This underestimation reflects the lack of studies on temperate swamps relative to other peatlands (e.g., bogs and fens) and the uncertainty involved in estimating the C stocks and fluxes of this ecosystem (Davidson et al., 2022; Dazé et al., 2022).

1.3 OBJECTIVES

To address the identified research gaps, this PhD thesis aims to assess the long-term C dynamics and biophysical controls of temperate swamps using a biophysical modelling

approach. In particular, Beverly Swamp (see section 1.3.1 for more detailed description of the swamp) in southern Ontario will be used as a case study because it is one of the largest, well-preserved swamps of the region. To achieve this aim, the objectives are to:

- i. Elucidate the multi-decadal C dynamics of a temperate swamp peatland and the important biotic and abiotic interactions and feedbacks that drive the C biogeochemical cycle of this ecosystem (Chapter two)
- ii. Undertake an uncertainty analysis of the simulated swamp C flux and controls of Beverly swamp (Chapter three)
- iii. Examine how climate change will affect Beverly swamp's biophysical conditions and carbon cycling processes in the 2050s (Chapter four)

1.3.1 Beverly swamp as a case study

Beverly Swamp is located in northwest Hamilton (43.366N, 80.120W), southern Ontario, Canada, and it is one of the largest, well-preserved temperate swamps in the region. Beverly Swamp is under the management of Hamilton Conservation Authority (HCA, 2020a) (see Figure 1-4 below for map).

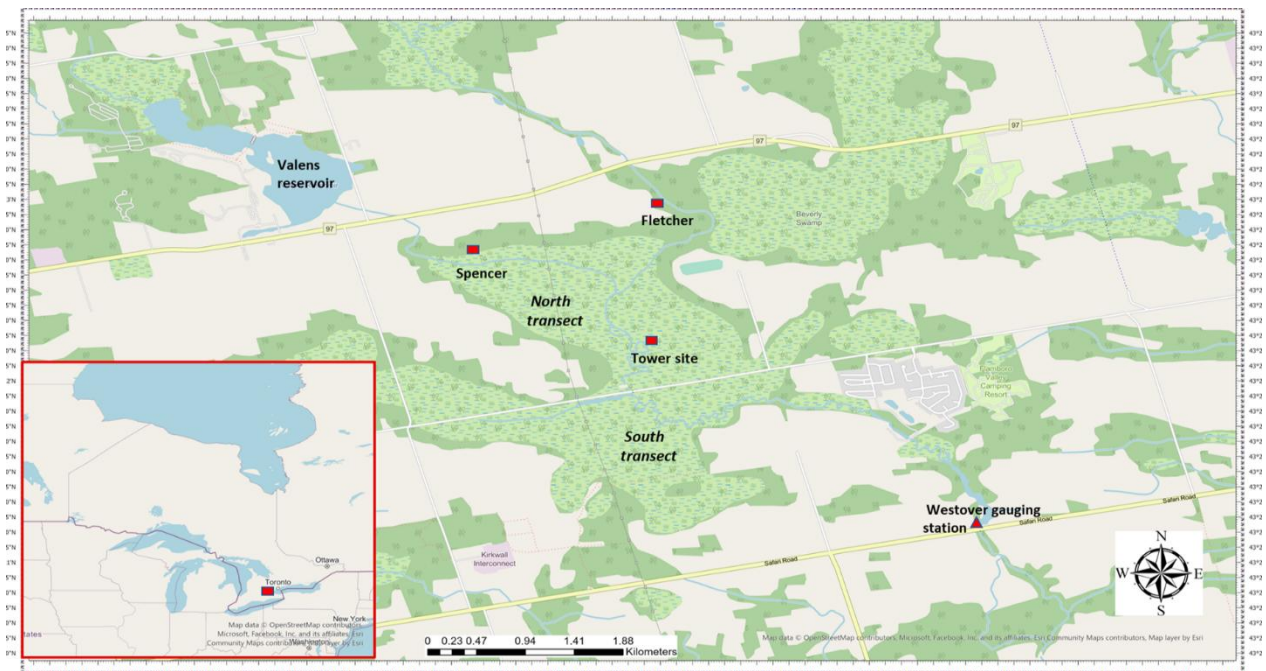


Figure 1-4. Map of Beverly Swamp in southern Ontario, Canada

The swamp is minerotrophic in nature and covers a land area of $\sim 20 \text{ km}^2$ (Munro 1984; 1987). According to the Köppen classification, Beverly Swamp is in the humid continental climatic zone with an annual total precipitation of 973 mm and annual average temperature of 7.6°C (Canadian Climate Normals 1980-2010, 2024), Millgrove station; Environment Canada, 2024) and accumulated peat depth ranging from 30 to 150 cm across the different sections of the swamp (Warren et al., 2001; Woo & Valverde, 1981).

The swamp is sustained by a perched water table that is underlined by an impermeable marl layer (Woo, 1987), and is fed by the Spencer creek and its tributary, Fletcher and with the former influenced by reservoir operations upstream (Woo & Valverde, 1981). The 0.76 km^2 Valens reservoir was created by a dam that regulates water flow along the Spencer Creek (HCA, 2020b). During summer, water is mostly stored in the Valens reservoir to maintain water level for recreational and agricultural activities, which consequently affect water levels in the swamp. In autumn (October–November), water is discharged into the swamp to minimize upstream flooding or reservoir failure (HCA, 2020b; Macrae et al., 2011). Snowmelt in spring, evaporation reduction after summer and reservoir water release in autumn contribute

to the swamp flooding for ~8 months, while water table drawdown for 4 months during the summer growing season supports diverse vegetation growth (Woo & Valverde, 1981). The vegetation canopy of the swamp is mixed with almost equal standing biomass of deciduous and coniferous trees in the northern section and mostly deciduous trees in the southern part (Munro, 1979). The swamp also has some important ground flora (e.g., ferns, sedges and vines) but they are mostly scanty because of the closed canopy structure of the swamp (Welch, 1985). Overall, this study focused on the northern part of the swamp because most data acquisition has been completed in this portion. Further details of the site characteristics are listed in Table 1-1 below.

Table 1-1 Beverly Swamp site characteristics

	Value	Source
<i>Location and Meteorological variables</i>		
Lat, Lon	43.36N, 80.11W	(Munro, 1979)
Swamp size	~20 km ²	(Hamilton Conservation Authority, 2020a; Munro, 1979)
Altitude	265-270 m	(McCarter et al., 2024)
Mean Annual temp	7.6°C	(Environment Canada, 2024)
Mean Annual Precipitation	973 mm	(Environment Canada, 2024)
Mean Annual Evaporation	554-752 mm	(Valverde, 1978; M. Woo & Valverde, 1981)
Plant characteristics		
Major tree species (mixed forest)	silver maple (<i>Acer saccharinum</i>), red maple (<i>Acer rubrum</i>) white cedar (<i>Cedar occidentalis</i>), birch (<i>Betula papyrifera</i>), black ash (<i>Fraxinus nigra</i>), aspen (<i>Populus tremuloides</i>), elm (<i>Ulmus americana</i>), alder (<i>Alnus rugosa</i>)	(Hamilton Conservation Authority, 2020a; Thambipillai, 1998; Welch, 1985)
Ground understory vegetation	Fens and Sedges	(Welch, 1985)

Average stand age in 1980	40-52 yrs	(Hamilton Conservation Authority, 2020a; Welch, 1985)
Average-Max canopy height	5.22-10 m	(Hamilton Conservation Authority, 2020a; Munro et al., 2000; Thambipillai, 1998)
Root depth	0.3 – 0.4 m	(Hamilton Conservation Authority, 2020a; Munro et al., 2000; Thambipillai, 1998)
Leaf Area Index (LAI)	5 to 6	(Hamilton Conservation Authority, 2020a; Thambipillai, 1998)
Stand density	6317-8125 trees/ha	(Hamilton Conservation Authority, 2020a; Thambipillai, 1998; Welch, 1985)
Basal area	25-52 m ² /ha	(Hamilton Conservation Authority, 2020a; Welch, 1985)
Average litter C/N ratio	31	(Santia & Strack, 2024)
Plant C (1979- 1987)	~ 9009 gC m ⁻²	(Munro, 1989; Munro et al., 2000; Welch, 1985)
Foliage C	1171.17 gC m ⁻²	(Welch, 1985)
Stem C	6936.93 gCm ⁻²	(Welch, 1985)
Root C	900.9 gC m ⁻² yr ⁻¹	(Welch, 1985)
Net Primary Productivity	~1145 gC m ⁻² yr ⁻¹	(Welch, 1985)
Litter production	250-350 g m ⁻² yr ⁻¹	(Welch, 1985) (Santia & Strack, 2024)
<i>Phenology</i>		
Leaf emergence day	145	(Thambipillai, 1998)
Leaf emergence temp	5 °C	(Thambipillai, 1998)
Optimum day number	167	(Thambipillai, 1998)
Litterfall commencement day	270	(Thambipillai, 1998)
Canopy extinction value	0.33-0.7	(Thambipillai, 1998)
<i>Soil variables</i>		
Soil type	Sapric peat	(Munro et al., 2000)
peat depth	~85 (cm)	(Munro et al., 2000; Valverde, 1978; Woo & Valverde, 1981)
Soil pH	6.0 - 7.7	(Spencer, 1991)
Soil pore volume	80-85 vol%	(Czerneda, 1985; Munro, 1982, 1984; Munro et al., 2000)
Soil bulk density	0.18-0.22 g cm ⁻³	(Czerneda, 1985; Munro, 1982, 1984); Waddington et al. (Unpublished data)

Total soil C content in upper 50 cm	$37894 \pm 14854 \text{ gC m}^{-2}$	Waddington et al. (Unpublished data, 1998); (McCarter et al., 2024)
Total soil C content in top 150 cm	$16600 \pm 6400 \text{ gC m}^{-2}$ to $106800 \pm 2800 \text{ gC m}^{-2}$	Waddington et al. (Unpublished data); (McCarter et al., 2024)
Soil C/N ratio	18-26	(DeSimone, 2009)
Soil nitrate	$0.43\text{-}7.41 \text{ g NO}_3\text{-N gsoil}^{-1}$	(DeSimone, 2009)

Chapter 2. Process-based modelling of multi-decade carbon dynamics of a cool temperate swamp

2.1 OVERVIEW

Swamps are important wetlands globally, but temperate swamps have been understudied even though they store substantial quantity of carbon (C) in their biomass and can accumulate peat. In particular, Southern Ontario (SON) swamps are estimated to store ~1.1 Pg C under distinct hydroclimatic conditions. Previous studies on temperate swamp C fluxes are mostly based on short-term (<5 years) field measurements that limit our understanding of the multi-decadal dynamics that exist between this ecosystem's C flux and biophysical conditions. To elucidate the long-term interactions and feedbacks that are important to temperate swamp C dynamics, we adopted a process-based model (CoupModel) to simulate daily plant processes, energy, water and C fluxes in one of the most well-preserved swamps in SON over a 40-year period (1983-2023). CoupModel reasonably simulated the C flux and controlling variables with coefficient of determination (R^2) values of 0.60, 0.95 & 0.61 for soil respiration, surface soil temperature (0-5cm) and water table level (WTL) when validated with field measurements. Over the simulation period, the swamp's C uptake capacity as net ecosystem exchange declined but it maintained a net C sink in most years. This declining trend can be attributed to a consistent rise in soil respiration (11% per decade) that is likely to continue with future climate change predictions. Overall, the study shows that process-based models are effective tools for improving our understanding of long-term C dynamics of temperate swamps. It also reflected the importance of inter-annual and inter-seasonal changes in biotic and abiotic conditions on temperate swamp C dynamics.

2.2 INTRODUCTION

Wetlands in Canada cover a land area of $1.5 \times 10^6 \text{ km}^2$ and hold 129 Pg C (Kolka et al., 2018). The Canadian wetlands classification system separates wetlands into five classes, where swamps are wetlands with woody vegetation cover of more than 30% relative to their land area (National Wetland Working Group, 1997). Swamps in southern Ontario occupy ~87% of the region's total wetland area with a C stock of ~ 1.1 billion tonnes stored in their biomass and soil layer that has accreted over the years as vegetative productivity exceeds the rate of decomposition in this ecosystem (Byun et al., 2018). The C biogeochemical cycle in swamps is substantially mediated by hydro-climatic conditions (e.g. water table level and temperature) (Davidson et al., 2019; Gutenberg et al., 2019). This is linked to the outstanding coupling between these conditions and C cycling processes in the atmosphere, soil and vegetation (Gentine et al., 2019; Helbig et al., 2020; Waddington et al., 2015), as energy exchanges and mass transfer processes occur between these components (Silva et al., 2024).

Hydrology influences vegetation distribution, microbial richness, nutrient and fluvial C transport, decomposition and other important C cycling operations in swamps and other wetlands (Berkowitz et al., 2020; Dalva & Moore, 1991; Middleton, 2020; Mitsch et al., 1991; Nunes et al., 2015; Sleeter et al., 2017; Turetsky et al., 2014). Meanwhile, respiration, phenology, photosynthesis and other important C flux processes are sensitive to thermal regimes (Davidson & Janssens, 2006a; Medlyn et al., 2011; Smith & Woo, 1986). Ultimately, these interactions corroborate the strong control of biophysical processes on swamp C cycle. However, because temperate swamps are largely understudied and underestimated (Davidson et al., 2022), continuous field measurements and model applications to long-term C studies (i.e., multi-decadal time scale) in temperate swamps are lagging when compared to tropical swamps or even other temperate wetland types (Davidson et al., 2022; Kendall et al., 2020; Warner & Asada, 2006). These knowledge gaps in temperate swamp C cycling processes were reflected in the exclusion of peat swamp class from the Canadian Peatland Model because of data scarcity for calibration and validation (Bona et al., 2020).

Recent studies (Davidson et al., 2019; Kendall et al., 2020; Sleeter et al., 2017) have attempted to fill-up these knowledge gaps with field measurements on temperate swamp C stocks and

fluxes and their controlling conditions. Results from these field studies suggest that certain abiotic conditions such as water table level (WTL) and air/soil temperature are important controls on temperate swamp soil respiration rate. However, because the studies are mostly short-term (> 5 years), they are unable to capture the impact of regional multidecadal disturbances (e.g., climate change). These long-term changes may have impacted climatic regimes (Rudra et al., 2023) and C cycling processes of swamps in the region but were not reported by existing short-term studies. Consequently, this knowledge gap in long-term studies limits our understanding of the role of this ecosystem in regional C cycling and how they can be protected under a changing climate.

Modelling approaches have been adopted to support field studies and circumvent long-term data sparsity on wetlands (Bona et al., 2020; Ju et al., 2006) but few are focused on temperate swamp C flux. (Sleeter et al., 2017) adopted an integrated modelling approach, the Land Use and Carbon Scenario Simulator (LUCAS) to estimate historic (30 years) impacts of land use change and other management practices on the C balance of the Great Dismal Swamp. The integrated system of Sleeter et al. (2017 & 2022) also included process-based models (e.g. Integrated Biosphere Simulator, IBIS) because of their ability to simulate important underlying dynamic processes (e.g., C allocation) and the resultant feedbacks. Process-based models are applicable to the current stage of knowledge development (Korzukhin et al., 1996) on temperate swamps and are relevant to long-term studies that will improve our understating of this ecosystem (Yuan et al., 2023).

Integrated process-based models (e.g., CoupModel) have been adopted in other peatland types (e.g., bogs and fens) to simulate important plant processes, water and energy exchange mechanisms and C fluxes across the globe with reasonable performance when validated with observations (He et al., 2021; Metzger et al., 2016b; Wu et al., 2013). However, CoupModel has not been tested in temperate swamps where the hydroperiods, vegetation cover and other biophysical conditions are different from bogs, fens, and marshes. To fill-up these long-term knowledge gaps in temperate swamp C dynamics, this study therefore applied CoupModel to improve our understanding of the interactions that occur between biotic and abiotic components of temperate swamps and the resultant effect on C cycling processes.

Consequently, the objectives of this paper are to: i) evaluate the ability of a process-based model (CoupModel) to simulate important plant processes, water, energy and C fluxes of temperate swamps, ii) improve understanding of the long-term C flux dynamics of a temperate swamp, and iii) describe the seasonal and inter-annual interrelationships between C flux components and important biophysical controls.

2.3 MATERIALS AND METHODS

2.3.1 Study site description

Beverly swamp is located in Northwest Hamilton (43.366N, 80.12W), Southern Ontario, Canada and is one of the most well-preserved temperate swamps under the management of Hamilton Conservation Authority (Hamilton Conservation Authority, 2020a) (see Figure 1-4). The swamp is minerotrophic in nature and covers a land area of ~20 km² (Munro, 1984, 1987). According to the Koppen classification, Beverly Swamp is in the humid continental climatic zone with an annual average precipitation (973 mm) and temperature (7.6 °C) (*Canadian Climate Normals 1980-2010*, 2024), Millgrove station) and accumulated peat depth ranging from 30 to 150 cm across the different sections of the swamp (Warren et al., 2001; Woo & Valverde, 1981). Further details of the site characteristics are listed in Appendix 2-1. The swamp is sustained by a perched water table that is underlined by an impermeable marl layer (Woo, 1987), and is drained by two major streams namely, Fletcher and Spencer but with the latter influenced by reservoir operations upstream (Woo & Valverde, 1981). The 0.76 km² Valens reservoir was created by a dam that regulates water flow along the Spencer Creek (Hamilton Conservation Authority, 2020b). During summer, water is mostly stored in the Valens reservoir to maintain water level for recreational and agricultural activities which consequently affect water levels in the swamp. In autumn (October – November), water is discharged into the swamp to minimize upstream flooding or reservoir failure (Hamilton Conservation Authority, 2020b; Macrae et al., 2011). Snowmelt in spring, evaporation reduction after summer and reservoir water release in autumn contribute to the swamp flooding for 8 months, while water table drawdown for 4 months during the summer growing season supports diverse vegetation growth (Woo & Valverde, 1981). The vegetation canopy of the

swamp is almost mixed with equal standing biomass of deciduous and coniferous in the northern section and mostly deciduous trees in the southern part (Munro, 1979). The swamp also has some important ground flora (e.g., ferns and vines) but they are mostly scanty because of the closed canopy structure of the swamp (Welch, 1985). Overall, this study focused on the northern part of the swamp because most data acquisition has been completed in this portion.

2.3.2 Datasets

Observation data for model forcing, calibration and validation processes were sourced from existing studies, government databases (e.g., Environment Canada) that ranged from the 1983 to more recent on-going field measurements (July 2022 to present) as presented below. We compiled all the major data published historically from Beverly swamp to evaluate the model in detail. Split-value technique was used for calibration and validation, where historic datasets (mostly in the 1980s) were usually used during parameter tuning and more recent measurements in 2020s to validate model simulations. For the calibration process (parameter tuning), default model parameters values of CoupModel (Jansson & Karlberg, 2004) and those obtained from field measurements, lab experiments and literature (see Appendix 2-3 for list of sources) were used to improve the match of the simulated to observed variables. The adjusted parameters are highlighted in Appendix 2-3.

2.3.2.1 Climatic datasets

A dataset of 40-year duration (Jan 1983 to May 2023) of daily climatic variables (air temperature, precipitation, wind speed, relative humidity and global radiation) from nearby weather stations within a 25km radius of the swamp (e.g. Valens, Christie Conservation, HamiltonRBG CS and Hamilton A) was compiled using “weathercan in r” (LaZerte & Albers, 2018; R Core Team, 2021). In addition, meteorological measurements sourced from (Munro, 1979, 1980, 1987; Munro et al., 2000) were also employed for gap-filling during 1983-1986, and other suitable products such as Ontario in-filled climate data (1983-2005) (Ontario Government, 2019) and NASA Power Project (1986-2023) (Sparks, 2018) were used to

support precipitation and global radiation datasets, respectively. All the described climatic variables were used as dynamic inputs for driving the model.

2.3.2.2 Lateral water input

For the simulation, we used stream discharge records at Westover gauging station (south of the swamp) in Spencer Creek (See Figure 2-1 above) as a proxy for the lateral water input to the swamp since there are no accessible records of the dam's flow regulation into the swamp. The gauging station data were downloaded from the Water Survey of Canada (https://wateroffice.ec.gc.ca/mainmenu/historical_data_index_e.html)

2.3.2.3 Energy fluxes, water table level & snow depth (August 1983-July 1987)

Historic hourly measurements (Figure 2-1, BS_Tower) of net radiation, ground heat, sensible heat, latent heat fluxes derived by Bowen ratio surface energy approach were used. Other variables such as soil temperature (0–5 cm) and water table level were obtained from (Munro et al., 2000). Detailed measurement methodologies are published in (Munro et al., 2000) and other publications by Munro referenced therein.

2.3.2.4 Soil respiration, soil organic carbon (1998-2023)

Bi-weekly soil CO₂ flux measurements obtained by closed opaque chamber method and analyzed with gas chromatograph (1998-2000) or measured directly with LI-COR portable greenhouse gas analyzer (LI-7810) were sourced from (Davidson et al., 2019; Schmidt & Strack, 2026), respectively. While soil organic carbon (SOC) measurements of depths 0–150 cm (analyzed with loss on ignition approach) were received from (McCarter et al., 2024; Waddington, Unpublished) for the same period. SOC measurements were used for the initialization process of CoupModel (See section 2.4.2).

2.3.2.5 Additional data (June 2022 to July 2023)

More recent field measurements were also undertaken for model evaluation (June 2022 to July 2023). Thermocouples (Type E) at depths 5, 10, 30 and 40 cm for soil temperature, TDR probes (Campbell Scientific, CS616) at soil depths 5 and 30 cm for volumetric water content of the

soil, and tipping bucket rain gauge (TR-525M) were installed and logged every hour with a CR1000 powered by solar panel installed adjacent to C flux collar transects in the swamp. Groundwater wells made from 5 cm diameter and 155 cm long PVC pipes were installed across the swamp with water level logged hourly with pressure transducers (Levellogger, Solinst). Outputs of the level loggers were barometrically corrected before use with pressure measurements on-site or from nearby weather stations (HamiltonRBG CS and Hamilton A). Litterfall was collected with traps made from 50 cm x 50 cm wooden frames elevated above the ground surface on wooden legs of 1 m long, and fitted with fabric of 1 mm mesh size. A litter trap each was installed at the center of four 20 m x 50 m plots positioned along a 200 m transect in the Spencer and Fletcher sections of Beverly swamp. These traps were located along the 4 cardinal directions from the center of the C flux collar (similar to (Kendall et al., 2020)). Collected litterfalls were retrieved bi-weekly, dried at 65 °C for 48 hrs and thereafter weighed and analyzed for their carbon and nitrogen contents (Details are provided in (Santia & Strack, 2024)). Litter decomposition bags made from 1 mm fiber mesh were separately filled with 10 g of dried litterfall and understory vegetation, respectively and thereafter buried in close proximity to C flux collars, water table wells and litterfall traps to estimate the decomposition rate constant. The above-described measurements (Figure 2-1., northern transect) were used as additional datasets for the different aspects of modelling (e.g., driving variables, parameter estimation and validation).

2.3.3 CoupModel

CoupModel was adopted for this study to simulate the historic C flux of the swamp and the controls driving its C cycle. CoupModel is an assemblage of many sub-modules for radiation and precipitation interception, evaporation and transpiration, snow and surface water pools, soil temperature and heat fluxes, plant growth and maintenance, soil hydraulics and soil organic C decomposition (He et al., 2021; Jansson & Karlberg, 2004; Jansson, 2012) as presented in Figure 2-2 below (*see also eqs. A1- A52 in Appendix 2-2 for details of functions used to simulate the processes*). It is a detailed one-dimensional coupled heat and mass transfer model designed to simulate the hydrological and thermal conditions of terrestrial ecosystems

and the respective biological processes that constrain C flux in soil, vegetation and atmosphere (Wu et al., 2011). The representation of processes in CoupModel is based on the laws of conservation of energy and mass and flows of thermal energy (Fourier's law) and water (Darcy's law) that results from concentration differences in temperature and water potential (Jansson & Moon, 2001). In addition, a preferential flow option is also included for ecosystems (e.g., swamps) where tree roots and other organic materials support a by-pass through macropores of soil matrix flow system (Jansson et al., 2005). Detailed description of the model can be accessed in Jansson & Karlberg (2004); Jansson, (2012) and other publications referenced therein.

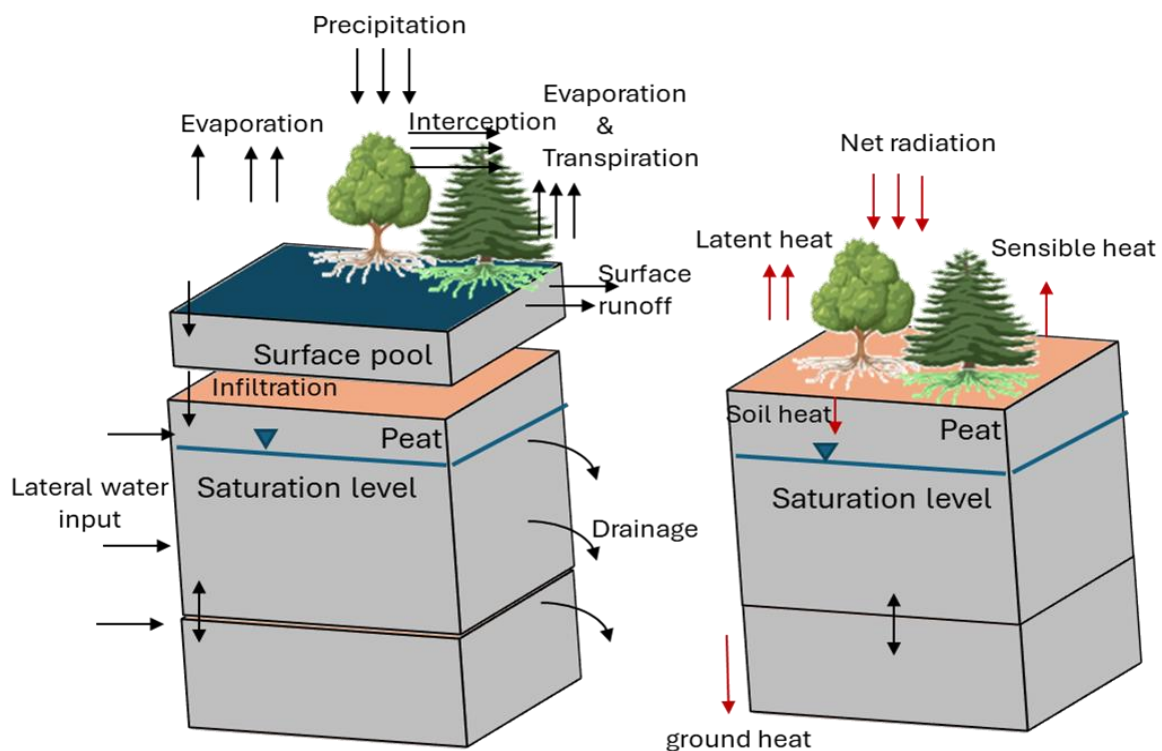


Figure 2-1. Important hydrological (left) and energy flux processes (right) of CoupModel for Beverly swamp (modified from He et al. (2023)).

2.3.4 Model structure, design, initial and boundary conditions

CoupModel version 6.2.2 was used to simulate the swamp's hydrology, energy and C fluxes at a daily time resolution from January 01, 1983 to May 30, 2023. Simulations were started

five years (1978–1982) prior to study period (1983) with repeated meteorological datasets of first 5 years (1983–1987) to allow the system to adapt to site conditions and make it less dependent on initial values as adopted by (Metzger et al., 2016a, 2016b). The soil profile for Beverly swamp was divided into thirteen layers varying in thickness between 5 cm (0-30 cm), 10 cm (30-50 cm), 15 cm (50-80 cm), 20 cm (80 – 120 cm) and 30 cm (120 – 150 cm) intervals (ST2 in Appendix 2-2). We simulated ~1 m peat depth because the topmost layer of the swamp has an average peat layer of 85 cm (50-100 cm thick) that is underlined by an almost impermeable marl layer (Munro et al., 2000). Sub-modules of global radiation and precipitation interception, surface pool formulation and snowmelt were used to define the swamp's soil surface boundary conditions (Jansson & Karlberg, 2004; Metzger et al., 2016a). Energy fluxes (net radiation, sensitive and latent) of the swamp were simulated by an iterative solution of the energy balance that captures the feedback between moisture availability and temperature (eqs. A1-A4 in Appendix 2-2). However, for soil surface temperature, convection was switched off because previous research (Smith & Woo, 1986) has shown that vertical conduction is the dominant heat flow mechanism in Beverly Swamp. Annual average air temperature and amplitude of 7.64 °C and 12 °C, respectively were adopted for estimating the bottom boundary conditions for heat conduction in Beverly Swamp (eqs. A9-A11 in Appendix 2-2). This heat conduction, energy fluxes and air temperature also interacted with other simulated processes (e.g., snow pack). Details of the specific equations and parameters used can be found in Appendices 2-2 and 2-3.

2.3.4.1 Soil hydraulic and lateral water flow at Beverly swamp

The van Genuchten Model (vGM) soil water retention curve (van Genuchten, 1980) (eq. A14) was used to represent the soil water potential and soil moisture content relationships of the swamp's 13 soil layers, while the Mualem equation (Mualem, 1976) (eq. A15) defined the unsaturated hydraulic conductivity of the swamp's soil (eqs. A12-A22 in Appendix 2-2). These two functions were used to simulate vertical water movement through the swamp's soil matrix as it conforms with Darcy's law (Richards, 1931). Values of van Genuchten's empirical parameters used for the simulation were estimated with pedotransfer functions (Letts et al.,

2000; Liu & Lennartz, 2019) using dry bulk density measurements (Czerneda, 1985; Munro, 1982). Residual water content and wilting point parameters were estimated from literature (Dimitrov et al., 2010; Letts et al., 2000; Menberu et al., 2021).

The perched nature of the swamp supports water accumulation, and the point of soil saturation (water table level, WTL) as it rises above the drainage datum is marked by continuous saturation from the WTL to the marl layer which signifies the bottom of the soil profile. Hydraulic conductivity at the marl layer is as low as 0.86 mm/day (McCarter et al., 2024; Warren et al., 2001) with no significant interaction with regional groundwater flow (Macrae et al., 2011; Valverde, 1978). As the simulated WTL rises over the marked drainage datum (e.g., WL in draining Fletcher and Spencer streams), water efflux of the saturated peat layers above the marked level was linearly simulated (eq. A22) (Metzger et al., 2016a). The addition and loss of water from adjacent soil layer was used to maintain saturation level in simulation similar to ground water field measurements (Metzger, 2015). The swamp's runoff was driven by the generated water pool at soil surface that accumulates when water in the surface layer of the soil is transmitted upwards during completely saturated condition, and when throughfall exceeds the rate of infiltration. Ultimately, runoff was a function of the water produced in the surface pool and the estimation of the swamp's soil moisture depended on water storage and temperature (Metzger et al., 2015, 2016a; Wu et al., 2011). In addition to the simulations above, a two-domain approach (not ordinary Darcy's flow) that takes into consideration a bypass of the micropore soil matrix flow system (Jansson et al., 2005) was also tested for the flow process at Beverly Swamp (equations A19 – A21, Appendix 2-2).

2.3.4.2 Vegetation and soil organic carbon of the swamp

In CoupModel, vegetation was represented by an "explicitly bigleaf" model (5-10 m height) with a single representative canopy layer characterized by the closed canopy structure (LAI of ~5-6) in the swamp with a root depth of ~30 cm (*Appendix 2-1*). No understory vegetation was simulated since cover was low and thus insignificant for the simulated C and hydrology fluxes. The plants represented in the model are divided into different parts of leaf, stem, root, grain and mobile pools but for this simulation, grain allocation was excluded because of its

insignificant contribution in non-agricultural settings (Metzger et al., 2016b). The initial vegetation conditions used for the simulation were based on the field measurements computed in Appendix 2-1. The light-use efficiency sub-model, which considers the proportionality between plant growth and global radiation and the limitations imposed by moisture availability, temperature and nitrogen supply was used to simulate the swamp's photosynthetic rate and C assimilation of the swamp's vegetation (eq A23 - A26 & A39 - A43) (Jansson & Karlberg, 2004; Wu et al., 2011). A fixed N approach was used, which means that the nutrient limitation for the plant growth was implicitly included in the specified light use efficiency parameter. The model simulated LAI dynamically as a function of total mass of leaf and other plant properties (eq A41). This option ensures that seasonal and inter-annual changes in environmental conditions are reflected in LAI just as this plant characteristics feedback to micrometeorological conditions that consequently alter local climate and hydrology in the model. Plant respiration simulation for the swamp is assumed to be a function of both maintenance and growth and was estimated from the functional trait coefficients (Amthor, 1984; Amthor & Baldocchi, 2001; Cannell & Thornley, 2000; Jansson & Karlberg, 2004) of the swamp species and was further regulated by air temperature. (See eqs. A23-A44, Appendices 2-2 and 2-3 for model equations and parameters that are related to plant processes). The SOC initialization process for Beverly swamp was based on methods adopted by several previous studies that define conditions in the soil layer (Dangal et al., 2022; He et al., 2023; Metzger et al., 2015, 2016a) and not the common "spin-up" approach. Spin-ups will not produce realistic results for this simulation because "equilibrium" may not be achieved in disturbed (i.e. known peat extraction, road and transmission line construction) peat soils like Beverly swamp where the humified pool will take multiple decades to restabilize (Byun et al., 2018; Woo, 1979; Woo, 1987), thus affecting SOC pool and fluxes (Nemo et al., 2017). To account for this in CoupModel, the swamp's SOC was partitioned into 13 layers (See ST2 of Appendix 2-2 for initial C layers). The initial C and nitrogen content per layer were assigned by measurements and partitioned into two SOC pools (litter and slow turn over/recalcitrant) for each of the layers based on their C:N ratio and extent of humification (DeSimone, 2009; Schmidt & Strack, 2026; Wang et al., 2015; Webster et al., 2014). This was to ensure that the

specified initial conditions fulfilled the measured total C per layer. Beverly swamp's measured total C storage of $\sim 98 \text{ kg/m}^2$ (McCarter et al., 2024; Waddington et al., unpublished) were separated by reported soil C:N values into active and passive pools to represent the fast and slow turnover rates, respectively. Consequently, high or low C:N for a given soil layer means more fast or slow cycling SOC pool will be initialized, respectively. The swamp's SOC pool at different depths were partitioned into the two major pools in a manner that is almost at equilibrium for defined parameter coalescence which eventually generates a realistic fit to soil respiration (Dangal et al., 2022; He, et al., 2023; Metzger et al., 2015, 2016a). For the simulation, decomposition of fast and slow turnover pools were estimated by first-order rate process that is limited by substrate quality, moisture availability and temperature (Jansson et al., 2008; Metzger et al., 2015; Wu et al., 2011) (See eqs. A44 – A52). Temperature sensitivity of microbial decomposition was described by the Q10 response function given in eq. A46, while that of moisture was controlled by different moisture limits that constraint microbial decomposition when soil is either too dry or too wet decomposition (eq A47) (Metzger et al., 2016b). Therefore, as the swamp litter decomposes, CO_2 is emitted, and soil organic matter is formed. Further decomposition of humus under oxic and more favorable condition (e.g. moderately low moisture contents) produces only CO_2 . Also at deeper soil layers, moisture saturated conditions, lower soil temperature and less labile organic matter lower the decomposition rate. Because a static displacement of organic matter between layers was used for this study, there was no downward displacement of C at deeper layers. This means that the model structure did not account for vertical peat C movement (He et al., 2023; Jansson & Karlberg, 2004). See eqs. A44-A52 in Appendices 2-2 and 2-3 for sub-model functions and parameter values used in SOC simulation.

2.3.5 Statistical analysis of model performance and trend analysis

To analyze the performance of simulated variables against measurements, the coefficient of determination (R^2) was used to quantify the degree to which variability in field measurements can be explained by simulated variables, while root mean square error (RMSE) statistics was adopted to measure the standard deviation of the residuals (simulated errors). Trend analysis

of long-term simulated variables was completed with the Mann-Kendall statistics (Kendall, 1948; Mann, 1945). This rank-based non-parametric test detects upward and downward monotonic trends in time series. For the study, 95% confidence level ($p = <0.05$) was adopted to test the null hypothesis, while tau (-1:+1) determined the direction of the trend. In addition to this, the Sen's slope (Sen, 1968) was employed to quantify the magnitude of the trend by estimating the median of the slopes in the time series. All the described statistical analysis were completed in the R statistical software (Lemon, 2006; Pohlert, 2023; R Core Team, 2021).

2.4 RESULTS

2.4.1 Trends of model driving variables

Statistical analysis of weather station datasets around Beverly Swamp showed a mean air temperature of 8.1 °C with ~0.4 °C increase every decade over the simulation period (January 1983 - June 2023; Figure 2-2a & ST3 in Appendix 2-4). The years 2012 and 1993 were the warmest and coolest with mean temperature values of 10.4 °C and 6.5 °C, respectively, while on a monthly resolution, January and July were the coldest and hottest months (SF1 in Appendix 2-4). The upward air temperature trend of the swamp was more pronounced during winter and early spring seasons (SF1). Recorded average annual precipitation (rainfall and snow) was 902 mm (Figure 2-2b) with ~62% (modelled) of this penetrating the canopy as throughfall. Highest rainfall of 1200 mm was recorded in the year 1996, while lowest occurred in 2007 (414 mm). The swamp had the largest and lowest amounts of rainfall in summer and winter seasons, respectively. However, receding trends were observed in summer and the reverse in winter for the study period (SF1 in Appendix 2-4). Overall, the precipitation pattern had a slightly decreasing signal of 0.1 mm/day per decade (Jan 1983 – May 2023) (ST3 in Appendix 2-4).

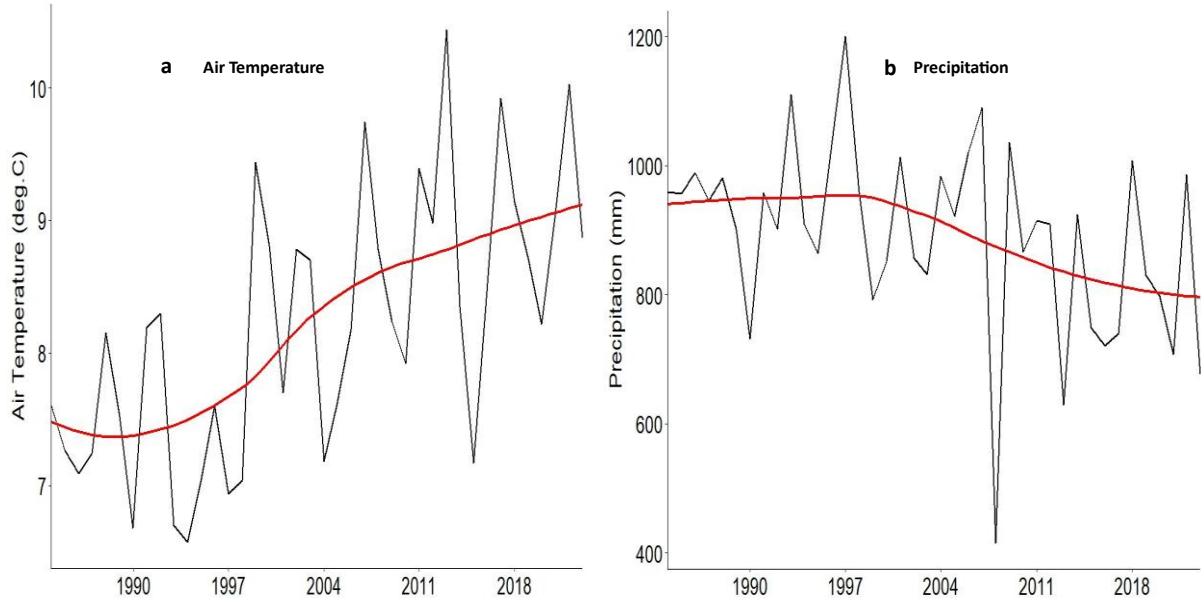


Figure 2-2. Annual air temperature and precipitation trends of swamp area. Red line shows the direction of the trend

The mean values over the simulation period of other driving weather variables, namely global radiation, wind speed and relative humidity were $13.5 \text{ MJ m}^{-2} \text{ day}^{-1}$, 3.3 m s^{-1} and 74.8% respectively, all representative of the humid continental climate zone where the swamp is located. Overall, slight and strong downward trends were observed for global radiation and windspeed respectively, while no statistically significant trend was recorded for relative humidity (ST3 in Appendix 2-4). Mean surface discharge measurement of 0.86 mm day^{-1} was recorded for the swamp with the highest and lowest peaks in 2008 and 1989, respectively (SF2 in Appendix 2-4) which reflected in the swamp's lateral water flow simulation. Similar to precipitation, surface discharge measurement followed a declining trend (0.02 mm d^{-1} per decade) (ST3 in Appendix 2-4). Aggregating precipitation, surface water level and groundwater records show that the swamp's hydropattern has a mostly rain induced saturation (SF3 in Appendix 2-4).

2.4.2 Validation and trend analysis of simulated environmental controls and C flux variables

2.4.2.1 Soil temperature

CoupModel simulated soil temperature in the swamp effectively and all seasons were well replicated when compared to observations. Validation of soil temperature simulations with historic measurements listed in section 2.3 produced R^2 values of 0.94 and 0.92 and root mean square error (RMSE) of 2.2 °C and 2.0 °C at 5 cm and 30 cm depths, respectively (Figure 2-3a, 3c). This shows that CoupModel performed slightly better in simulating the soil's top layer when compared to the deeper sections (>30 cm). For the simulation, an amplitude of 7–10 °C was recorded for soil temperature across depths. During the summer months (June – August), mean soil temperature (0–5 cm) was approximately 18.7 °C with a peak in July (SF8b in Appendix 2-4). Especially for the top layer, there was a direct relationship between the swamp's soil temperature and atmospheric temperature, but the amplitude dampened with soil depth. Over the 40-year simulated period, the modelled soil temperature increase of 0.35 °C per decade was almost on the same magnitude with air temperature (ST3 in Appendix 2-4). See SF6 in Appendix 2-4 for soil calibration chart.

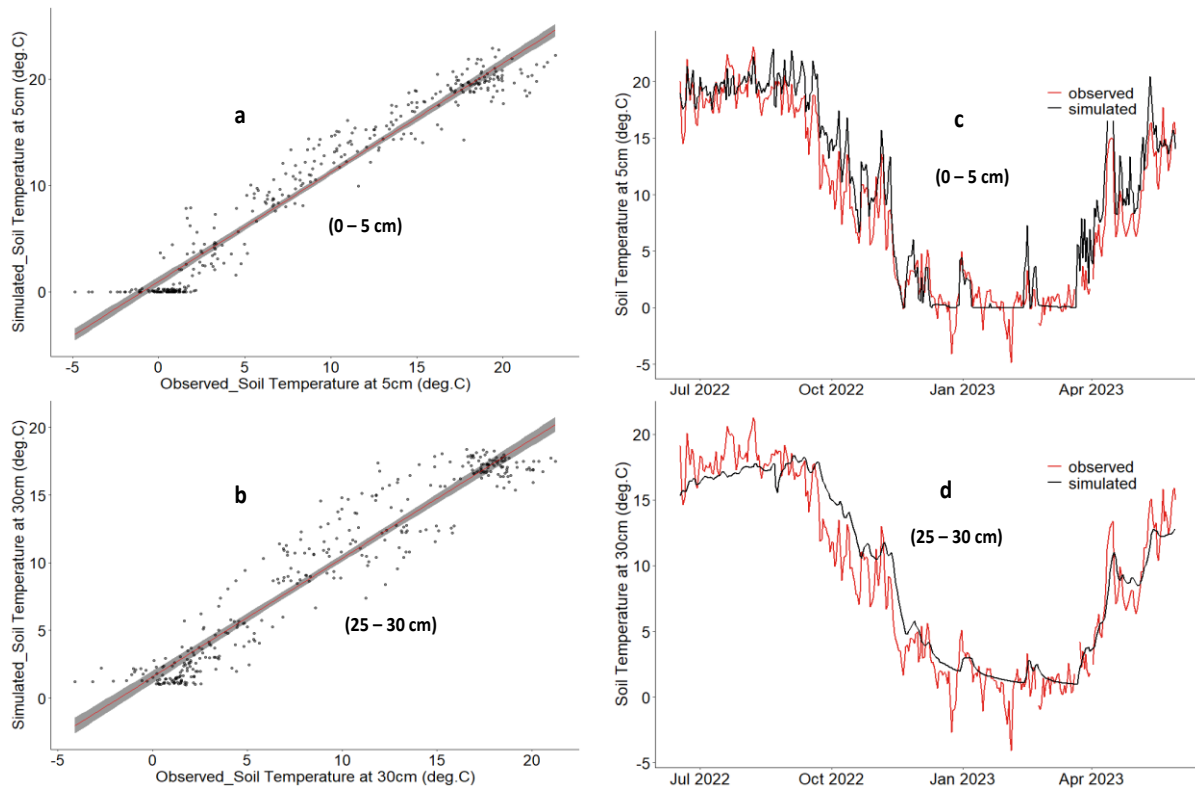


Figure 2-3. (a, b, c & d). Scatter and times series plots of validated soil temperature at 5 cm and 30 cm, respectively from June 2022 - May 2023. See supplementary Figure (SF6 in Appendix 2-4) for calibration period

2.4.2.2 Water availability, energy fluxes & snow depth

The water table level (WTL) of the swamp is a function of precipitation, evapotranspiration (ET), and surface and subsurface net water exchange. For the simulation period, two-thirds of the precipitation received in the swamp was lost as ET, while total runoff (drainage and surface runoff), which mostly followed precipitation patterns, accounted for 31% of the water balance.

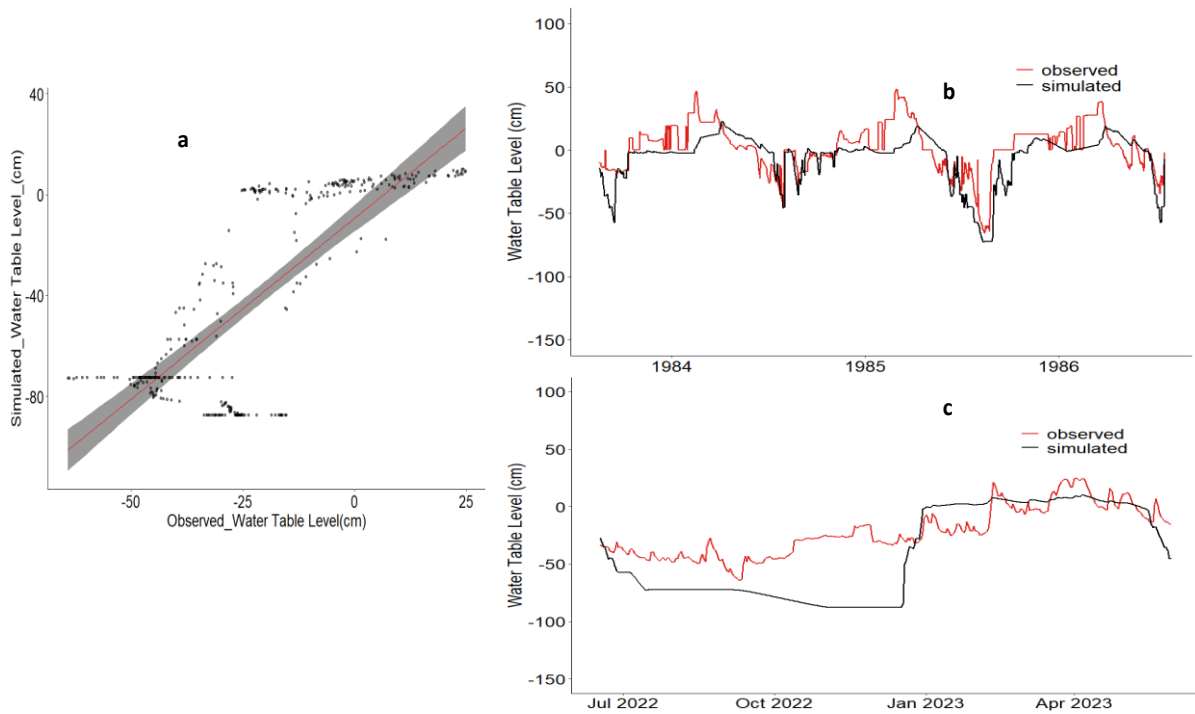


Figure 2-4. Validation (a & c) of Water Table Level (June, 2022 – May, 2023) and calibration period (b) Aug 1983- July 1986

The WTL was reasonably simulated (Figure 2-4) but the match to measured data was not of the same magnitude as that of soil temperature. This reduced match cascaded from the underestimation of WTL for most of the seasons during the calibration period and from July to December (summer and autumn) during the validation. When the simulated WTL of the swamp was validated with recent field measurement (June 2022–May, 2023), the R^2 was 0.6 and RMSE was 32 cm (Figure 2-5a). On average, the driest WTL (-47.1 cm) occurred during late summer, while the wettest condition was immediately after snow melt in April (standing water 13.9 cm deep) (Figure 2-4 & SF7d in Appendix 2-4). Even though peak precipitation was in summer (SF2b in Appendix 2-4), the swamp’s water table was less responsive to these events because of its quick removal through ET. Over the simulated 40-year period, the WTL of the swamp moved deeper by ~4.3 cm every decade (ST3 in Appendix 2-4). This may deepen the vadose zone if the trend continues into the future.

Comparing the simulated amount of water per unit volume (VMC) at surface (0-5 cm) and middle (25-30 cm) layers to observed values produced R^2 values of 0.8 & 0.5 and RMSE of 6% and 12%, respectively (Figure 2-5 and 2-6). In the 0-5 cm layer, simulated values tended to overestimate VMC in winter and spring (Figure 2-7a), while at 25-30 cm depth, summer VMC was underestimated (Figure 2-7b). Over the simulated period, VMC ranged from 51% to 86% (0-30 cm) but soil moisture levels at the soil surface layer (0-5 cm) showed more variability when compared to the deeper layers (65-80 cm) with narrower range of 82 – 85% (SF8e in Appendix 2-4). However, this variability was less pronounced on an annual resolution. Highest soil moisture contents were simulated during the winter and spring seasons (82-86%), while the lowest was observed for summer and autumn periods (67-82%). VMC mostly emulated the WTL pattern of the swamp with a declining pattern of ~2% per decade (ST3 in Appendix 2-4), which made less water available for biochemical processes. Because VMC measurements were only made from June 2022 until present, available datasets are not enough to validate VMC simulations as all data was used in the calibration process.

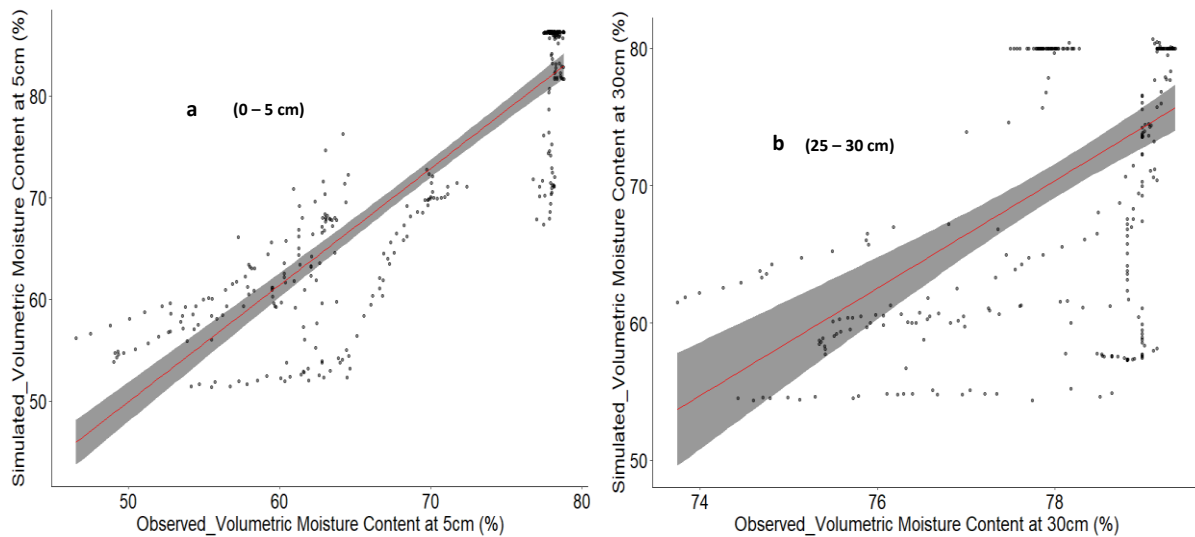


Figure 2-5. Scatter (a & b) plots of measured VMC against simulated at surface (0-5cm) and middle (25-30 cm) soil layers (June 2022 – May 2023)

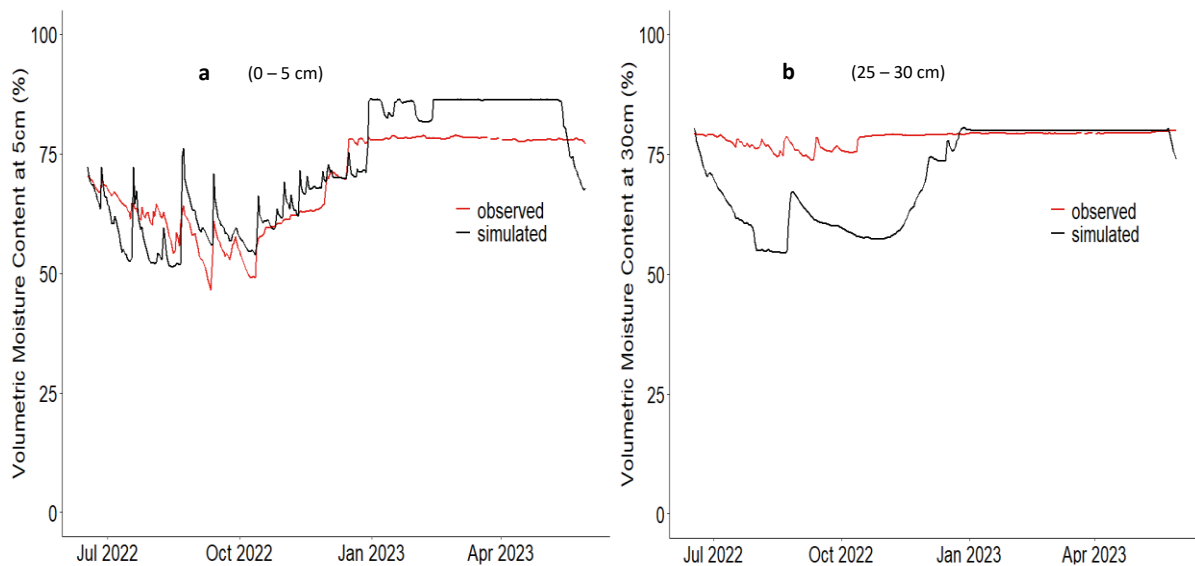


Figure 2-6. Time series (a & b) plots of measured VMC against simulated at surface (0-5cm) and middle (25-30 cm) soil layers (June 2022 – May 2023)

Even though the hydrological variables (WTL and VMC) described above were reasonably simulated for one-domain (ordinary Darcy's flow) modelling structure, the validation statistics slightly improved when tested with two-domain approach (soil matrix by-pass) described in section 2.4.1. R^2 and RMSE of simulated WTL increased to 0.63 and 26 cm, while that of VMC (0-5 cm) increased to 0.86 and 6.8% respectively. This suggests that preferential flow regime through the surface peat layers of the swamp is equally important in describing its soil water hydraulics.

Energy exchanges between the swamp and atmosphere impact the ecosystem's water balance and other hydroclimatic conditions. Cumulatively, net radiation around the swamp was approximately one-half of global radiation received in the area. Net radiation partitioning into latent, sensible and ground heat fluxes varied seasonally (See SF4 in Appendix 2-4). During winter, more energy was partitioned into sensible heat flux than latent heat flux, but this changed during summer months with Bowen ratio as low as 0.2 as more energy was partitioned into latent heat flux. The peak of summer was marked with high vapour pressure deficit and evapotranspiration (ET) rate of ~4 mm/day (Fig 2-7 & SF7f in Appendix 2-4) while this pattern is the reverse (almost zero ET) in winter with high albedo and when soil moisture and radiation

were limiting. Seasonality in ET rates were reflected in the swamp's water table level (SF7d&f in Appendix 2-4). Over the simulation period, ET rose slightly by 0.03 mm per decade (ST3 in Appendix 2-4) with implications for swamp's water availability especially in the peak of summer when water is also in high demand for photosynthesis and heterotrophic respiration.

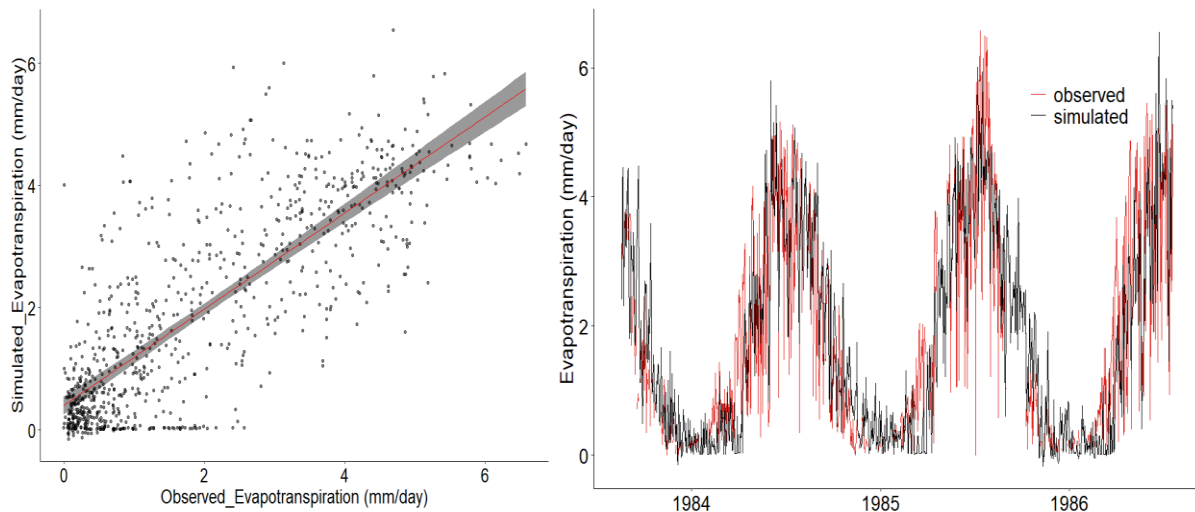


Figure 2-7. Scatter plot and time series of daily modelled and observed evapotranspiration (Aug 1983 – July 1986)

Snow depth of the swamp was also simulated by CoupModel to understand the contribution of snowmelt (especially in spring) to the swamp's hydrological cycle and soil heat flow processes in different seasons. R^2 value of 0.5 and RMSE of 15 cm were estimated when simulated snow depth (1983-1986) was compared with observations. The snow cover of the swamp started around the last day of November and completely disappeared by mid-April (SF5 in Appendix 2-4). Snow depth of the simulated period is between 0–100 cm. The swamp's soil was generally not frozen during the winter period (as shown in Figures 4 & SF6b in Appendix 2-4) because of the insulating properties of deposited snow on swamp soil. Over the simulated period, snow depth during the winter aligned with overall warming trend with a ~20% (1.5 cm) reduction every decade (ST1 in Appendix 2-4). Furthermore, the frequency of early snowmelt increased in the later period (2009 onwards) of the simulation with implications on the

hydrology and thermal conditions of the swamp and eventual impacts on C fluxes (SF5 in Appendix 2-4).

2.4.2.3 Carbon flux

Only soil respiration (root and heterotrophic respiration) was validated for C flux simulations because of field measurement limitations. Comparing simulated soil respiration fit with field measurements resulted in R^2 and RMSE results of 0.6 and $2.9 \text{ g C m}^{-2} \text{ d}^{-1}$, respectively (Figure 2-8 a & c). Daily mean soil respiration for the period was $3.7 \text{ g C m}^{-2} \text{ d}^{-1}$. However, this varied among seasons with values of $0\text{--}2 \text{ g C m}^{-2} \text{ d}^{-1}$ during winter and a maximum of $\sim 8 \text{ g C m}^{-2} \text{ d}^{-1}$ in summer (Figure 2-9 & SF 8a in Appendix 2-4). Higher soil respiration in summer coincided with drier and warmer conditions as water table level decreased and soil temperature increased. Peak gross primary production (GPP) also occurred during the summer (June-August) with more CO_2 intake as canopy leaves fully emerge for photosynthesis. The swamp NEE was positive for many months except from May to October where GPP exceeded the rate of Reco allowing the swamp to act as a net CO_2 sink NEE of -1 to $-11 \text{ g C m}^{-2} \text{ d}^{-1}$.

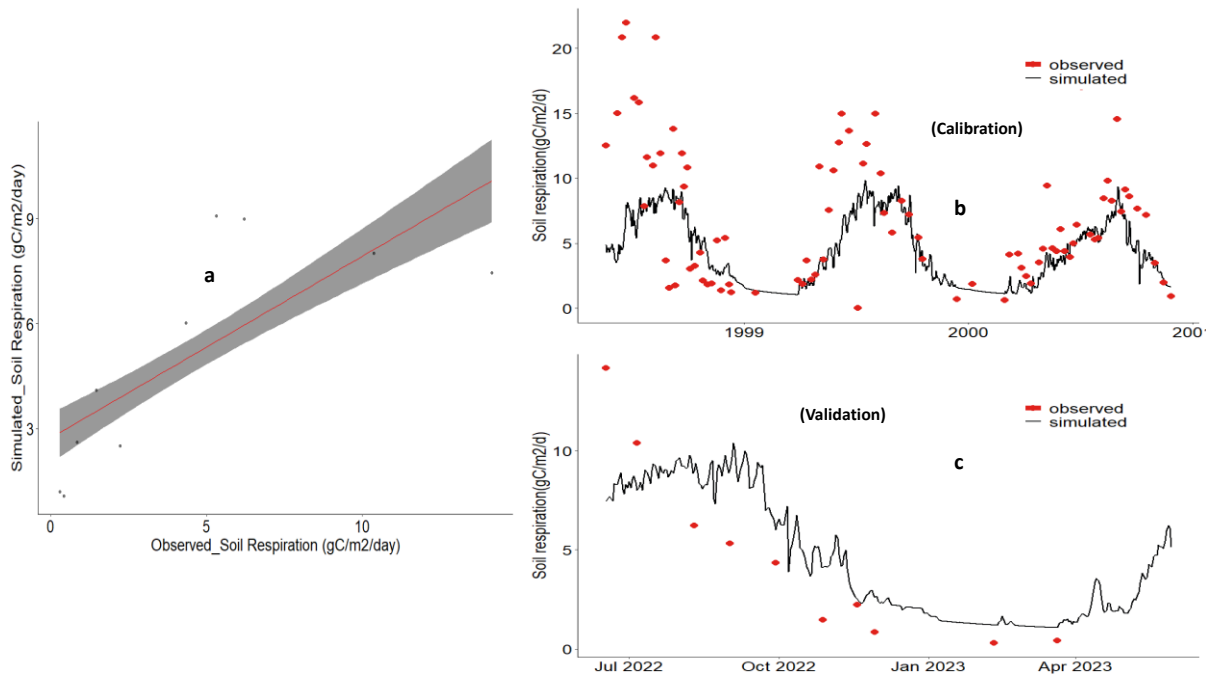


Figure 2-8. Validation (a & c) of simulated soil respiration rates (June, 2022 – May, 2023) and calibration period (b, May 1998- Dec 2000)

Average annual gross primary productivity (GPP), Ecosystem Respiration (autotrophic and heterotrophic respiration, Reco) and Net Ecosystem Exchange (NEE) for the simulated years are $2606 \pm 163 \text{ g C m}^{-2} \text{ y}^{-1}$, $1902 \pm 266 \text{ g C m}^{-2} \text{ y}^{-1}$ and $-704 \pm 268 \text{ g C m}^{-2} \text{ y}^{-1}$, respectively, where negative NEE indicates uptake by the swamp. On a multi-decadal scale, GPP and Reco followed upward trends of 1 % (GPP) and 11 % (Reco) every decade, while NEE was less negative (21% change per decade) for the study period (ST3 in Appendix 2-4). Over the 40-year simulation period, the swamp was mostly a net C sink (~93%) as presented in ST1 & SF8 in Appendix 2-4 even though soil respiration rates increased during this period.

2.5 DISCUSSION

2.5.1 Evaluation of simulations & sources of uncertainties

CoupModel numerically simulated the long-term plant processes, energy, water, and carbon fluxes at Beverly swamp. The results presented in section 2.4 shows that the model is capable

of reproducing critical interactions and feedbacks that prevails between biophysical processes and the C cycle in temperate swamps even over a space of 40 years. CoupModel effectively simulated the swamp's soil temperature with minimal error throughout the study period (Figure 2-2a to 2-2d) and moderately captured the hydrological conditions of the swamp (Figure 2-3). During the summer months, a greater mismatch was observed between the modeled and observed WTL of the validation period than the calibration period. This difference can be linked to very dry conditions (annual precipitation record of 616 mm compared to average over the modelled period of ~900mm) during the validation period. Because the model was mostly trained with wet years during the calibration period (1983 – 1986), it was not able to exactly capture the extremely dry conditions presented in the validation period, although it still estimated WTL with reasonable accuracy (R^2 of 0.6). The diminished simulation performance of WTL during the summer and autumn seasons, which cascaded into winter, may also be associated with surface runoff shortage during this period. Inflow to the swamp is controlled by the upstream Valens reservoir, for which discharge data was unavailable. It is likely that downstream proxy lateral runoff data used (section 2.3.2.2) as driving variable for the simulation did not properly account for water control and release into swamp from Valens reservoir during summer and autumn seasons, thus reducing the run-off component of the swamp's water balance and hydrological simulation as whole. Underestimation of WTL may also have originated from seasonal and interannual changes in the swamp's interactions with drainage streams (Fletcher and Spencer). Beverly swamp has been reported to lose water to Fletcher creek during wet years and seasons with the reverse occurring during dry years and seasons (McCarter et al., 2024; Warren et al., 2001). These complex hydrological changes were not captured in the modelling process and may have also contributed to the underestimation of latent heat flux during these periods since this variable is also dependent on moisture availability. Furthermore, we relied on pedotransfer functions based on bulk density to estimate soil retention parameters (section 2.3.4.1.) instead of direct field measurement. As an implication, VMC was underestimated for the simulation, with this underestimation particularly reflected in the middle soil layer at 25–30 cm (Fig 2-6d), which is an important boundary for ecohydrological processes in swamps (Kendall et al., 2020; Sleeter et al., 2017).

Overall, the lower performance of the model in simulating some of the swamp's hydrological processes is linked to the uncertainties in measurements, parameter estimates, and model structure that is inherent to the one-dimensional design of CoupModel. One-dimensional design aims to mostly capture vertical and not spatially distributed transport and complicated phase change processes (Kalantari et al., 2012). For instance, snow disappearance in the open canopy section of the swamp during winter season (Smith & Woo, 1986) may not have been properly accounted for in the simulation. This limitation may have affected energy partitioning in winter and contributed to the overestimation of sensible and ground heat fluxes during this season explaining some of the mismatch in snow accumulation simulations and soil thermal processes in winter.

Despite some mismatch between simulated and observed hydrological conditions, CoupModel reproduced important C fluxes of the swamp. Simulated average annual GPP, Reco and NEE values at Beverly swamp (section 2.4.2.3) were in line with existing studies of similar ecosystem even though there are no field measurements of the variables at Beverly swamp to validate these simulations. For instance, annual NEE range of -124 to -1131 g C m⁻² y⁻¹; GPP 1700 to 3000 g C m⁻² y⁻¹ and Reco 800 to 1000 g C m⁻² y⁻¹ were reported for treed swamps in temperate and subtropical regions (Aguilos et al., 2020; Bernal & Mitsch, 2012; Botkin et al., 1970; Shoemaker et al., 2015). The model's performance was slightly diminished in soil respiration simulation, a compendium of many complex processes and interactions (figure 8a - 8c). The period of validation for soil respiration simulation (June 2022-May 2023) was better reproduced (represented by R² and RMSE values) than the calibration period (1998-2000). This difference may be associated with the measurement techniques, frequency and length of measurements, and spatial variability of soil respiration data measurements (Davidson et al., 2019; Schmidt & Strack, 2026) employed for the calibration and validation periods. The highlighted factors have been reported to produce uncertainty in soil respiration and other biogeochemical field measurements (Butterbach-Bahl et al., 2016; Denmead, 2008) that consequently extend into model evaluation when field measurements are used. On a seasonal scale, simulated soil respiration was cumulatively (calibration period) underestimated for

summer & autumn relative to the other two seasons (Figures 2-8b & 2-8c). This may be linked to the underestimation of simulated swamp's WTL and moisture deficit during these periods (Figures 2-5 to 2-6) because of the strong control water availability has on C flux. Excessive moisture deficit is known to cause plant stress, disrupt microbial and enzymatic activities in soil (Nunes et al., 2015; von Buttlar et al., 2018), ultimately reducing soil respiration (root and heterotrophic) rate in the swamp.

2.5.2 Analysis of the interrelationships between C flux and biophysical conditions

The results of the long-term simulations presented in section 2.4 shows that there is a strong relationship between the swamp's C flux and controlling biophysical conditions. In particular, periodic changes in the swamp's biotic processes, hydrological and thermal conditions significantly imprinted on carbon assimilation and losses from the ecosystem. Here, we discuss these interactions with a focus on the largest contributor to ecosystem respiration, soil respiration because it is the only C flux component that was validated with measurement for the study.

2.5.2.1 Biotic controls on soil respiration

Soil respiration was reasonably simulated by the model (Figure 2-8) with trends coinciding with other modelled biotic variables (e.g. gross primary production, GPP). On a multidecadal scale, both simulated soil respiration and GPP followed an upward trend (ST3 & SF2 in Appendix 2-4.). However, the extent of the relationship between the two variables was dependent on the time scale considered. The relationship between soil respiration and GPP is of interest because GPP symbolizes the main C influx of the swamp and has been shown to exert some control on soil respiration in forested ecosystem (Högberg et al., 2001; Kendall et al., 2020). GPP is indicative of the swamp's tree canopy structure, which ultimately determines substrate quality (e.g. litter fall and root exudates) and availability for soil respiration processes, as heterotrophic mineralization and subsequent CO₂ efflux from wetlands require plant residues (Blodau, 2002; Kendall et al., 2020; Reichstein & Beer, 2008). Root respiration

(autotrophic respiration) and priming effects of roots in SOM also contribute to soil respiration and may account for 40-60% of total soil respiration in temperate regions (Högberg et al., 2001; Kuzyakov, 2006; Reichstein & Beer, 2008). These interconnectivities explain why periods of high plant productivity on both daily and monthly time scales often translated to increased soil respiration.

In contrast, the relationship between GPP and soil respiration was weaker in the spring and autumn seasons with soil respiration rate picking up faster after snowmelt than GPP rates and not falling as quickly as GPP during autumnal senescence. The rate of change of GPP in these periods was constrained by phenological processes of gradual leaf emergence and decline as senescence commences, respectively. Because Beverly swamp has a mixed canopy structure, the evergreen plants of the swamp minimized some of the lags in the shoulder months with their ability to commence photosynthesis earlier than deciduous vegetation and also prolong the process into late autumn (Helbig et al., 2019; Spafford et al., 2023; Wehr et al., 2016). Overall, plant processes and the distinct canopy structure of Beverly swamp significantly contributed to the simulated swamp's respiration processes even though existing field studies (Davidson et al., 2019) did not account for this component.

2.5.2.2 Water balance influence on swamp's soil respiration processes

Soil respiration also mimicked changes in WTL and the extent of the relationship was similar for interannual and seasonal time scales (ST3 and SF7 in Appendix 2-4). WTL has been reported by field observations to be a major mediator of C cycle processes in swamps (Davidson et al., 2019; Juszczak et al., 2013) because it moderates oxygen diffusion in soil profile (Rowson et al., 2013; Waddington et al., 2015) and demarcates oxic and anoxic zones of the soil profile. Therefore, dry (WTL of -36.9 cm to -15.9 cm, 2018-2022) and wet (WTL of 4.2cm to 0.08 cm, 1992-1994) years coincided with higher ($1517\text{--}1639\text{ g C m}^{-2}\text{ y}^{-1}$) and lower ($1106\text{--}1222\text{ g C m}^{-2}\text{ y}^{-1}$) soil respiration, respectively (SF7c in Appendix 2-4). This is line with existing field studies (Davidson et al., 2019) on Beverly swamp that have shown that drier peat conditions enlarge the oxic layer and increase mineralization rates of organic matter, thus enhancing aerobic respiration and CO₂ efflux. In addition, prolonged dry conditions may

support greater rooting depth (Munro, 1984), which in turn increases root respiration and overall soil respiration. However, there were years (e.g., 2008) when a greater than average drop in WTL (> -11.9 cm) did not translate into rapid CO₂ efflux from the swamp, and on the reverse, slight increase in WTL translated to high CO₂ emission from flux. The first condition may have resulted from substrate unavailability or excess moisture deficit, which affected substrate diffusion, biochemical and physiological activities in microbial activities (Grant & Rochette, 1994; Moyano et al., 2013; Zhang et al., 2018), while the latter observation may be linked to “birch effect” (Zhu & Cheng, 2013) when dry years (1998-1999) were followed by relatively high CO₂ efflux even with high water table level (2000).

Similar to WTL, soil respiration also reflected the changes to soil VMC (0 – 30 cm, Figure 2-7). VMC represents the readily available water for photosynthetic activities and near surface microbial and enzymatic processes in the vadose zone (<40 cm) (Seneviratne et al., 2010; Webster et al., 2014). Water movement processes in this layer are particularly relevant to the vegetation physiology of Beverly swamp with shallow tree roots (depth of ~ 30 cm) because of its influence on soil water infiltration and evapotranspiration processes (Munro et al., 2000). High productivity ($17\text{--}20$ g C m⁻² d⁻¹), CO₂ efflux ($5\text{--}8$ g C m⁻² d⁻¹) and water table drawdown (-47.1 cm to -10.7 cm) during the summer period coincided with a VMC range of 67–80%. However, there were periods in the simulation (e.g 2007) when a significant drop in WTL did not produce VMC loss of the same magnitude. Similar conditions were observed by (Munro, 1984; Word et al., 2022) in their field measurements and they attributed this to the unique soil water retention properties of swamp peat. This illustrates the potential disconnect between near surface VMC and the water table, resulting in the VMC being the dominant driver of soil respiration. Overall, simulated VMC of the swamp soil followed a declining trend throughout the 40-year simulation ($\sim 1.8\%$ per decade) aligning with a predicted increase in soil respiration over the same period.

Moisture availability in Beverly swamp was dependent on the seasonal balance between precipitation and ET. ET is an important component of the swamp’s water budget as it couples water balance and energy fluxes. Partitioning simulated ET into different components over the

simulated period shows that ~47% was lost from transpiration while the remaining was accounted for by soil evaporation (15%) and interception (38%). Simulated ET rates of this study were consistent with other studies at Beverly swamp area (Munro, 1979; Sultana & Coulibaly, 2011) that reported an average daily peak of 2.5 to 4 mm in summer season. Unlike bogs and fens with mostly understory vegetation cover (Kellner, 2001), the ET pattern (SF6f in Appendix 2-4) of the swamp reflected the unique phenological changes of its canopy structure. ET commenced after snowmelt when moisture and energy to drive the process were not limiting and the swamp's vegetation emerged. High ET rates in summer coincided with water table drawdown and this persisted until the end of August even with high precipitation during these months. Over the study period, the warming temperature trend contributed to early snowmelt and greater ET in the spring season. However, the opposite was observed in the summer months when high evaporative demand did not match simulated actual ET (SF6f in Appendix 2-4). The decoupling between potential and actual ET rates in summer at the end of the simulation period may be attributed to moisture limitations as water level dropped below the root zone (30–40 cm) and increased stomata resistance of plants cover (Munro, 1979; Valverde, 1978). These interactions shows that plant processes and land-surface exchanges are important to water availability in the swamp and consequently soil respiration.

2.5.2.3 Soil temperature and snow depth influence on soil respiration

Simulated soil temperature (0–5cm) ranked highest in explaining soil respiration with the strongest relationship on a seasonal resolution . This aligns with field observations at Beverly swamp (Davidson et al., 2019) and other studies that have related soil respiration to soil temperature, especially in a non-limiting moisture condition like swamps (Lloyd & Taylor, 1994; Moore & Dalva, 1993; Rowson et al., 2013). Important soil respiration related processes such as plant productivity, phenology, C allocation, litter decomposition and heterotrophic respiration are dependent on air and soil temperature (Medlyn et al., 2011) because of its influence on the reaction kinetics of these biological processes (Davidson & Janssens, 2006). This effect is particularly pronounced in temperate regions where estimated Q_{10} values are ≥ 2 , thus making the SOM cycling more sensitive to temperature increase (Byun et al., 2021).

However, there were some exceptions to the strong positive relationship between the two variables. In some instances, slightly warm years (2018 & 2019) triggered massive C flux and at other times, extremely warm years (e.g., 2017) did not translate into excessive C flux. This hysteresis may be explained by interactions with other influential factors (e.g., moisture availability, substrate quantity and quality, and microbial community) (Moyano et al., 2013). Simulated soil temperature mostly followed the seasonality of air temperature and WTL movements with corresponding effect on soil respiration (SF2 & SF7 in Appendix 2-4). However, some hysteresis existed between air and soil temperature of the swamp during the winter period when the snowpack provided thermal insulation for the soil, thus dampening the response of the soil to air temperature changes. In warmer seasons, the canopy cover of the swamp produced some cooling effect on the soil, thus decoupling the direct relationship between atmospheric and soil temperature. Overall, temperature had a strong control on important processes that affected the swamp's soil respiration rates. This control is expected to increase with rising temperatures that prolongs growing season, triggers early snowmelt, increases evapotranspiration, and also increases respiration rates in shoulder seasons.

2.6 CONCLUSION

The 40-year C flux simulation at Beverly swamp is one of the few multidecadal modelling studies on temperate swamp peatlands. This study validated existing field measurement findings that plant processes and thermal and hydrologic conditions are important controls on the C dynamics of temperate swamps even on a long-term basis. CoupModel reliably simulated important biophysical conditions in the swamp and the swamp's C cycle processes, thus suggesting that the process-based model is well adapted to diverse peatland ecosystems (including swamps). However, the adoption of a more robust calibration process and uncertainty analysis may further improve the simulation process for better constraint on the simulated variables. Nevertheless, this research demonstrated that swamp category is an important contributor to temperate peatland C cycle as the swamp maintained its net C sink status ($-704 \pm 268 \text{ g C m}^{-2} \text{ y}^{-1}$) for the simulation period even with rising soil respiration ($\sim 13\%$ per decade) and less negative NEE values in response to warming soils during this period. This

was made possible by increased GPP rates (1% per decade) which offset some of the C losses by soil respiration. However, these existing dynamics may be altered under future warmer climate predictions for southern Ontario because of the strong coupling between swamp C cycle processes and hydroclimatic conditions. Consequently, it is important for future studies to understand the influence of climate change on this ecosystem towards informing management practices and decision making to protect temperate swamp C stocks.

Chapter 3

Global parameter sensitivity analysis of modelling water, energy and carbon dynamics in a temperate swamp

3.1 OVERVIEW

Forested peatlands cover a land area of $7 \times 10^5 \text{ km}^2$ and store $\sim 77 \text{ Pg C}$ in Canada. However, the carbon (C) cycling of forested peatlands, particularly swamps, has been understudied. Few modelling studies have been done on temperate swamp C cycling partly because of the scarcity of field measurements in this ecosystem. These gaps create uncertainties in modeling the C dynamics of temperate swamps and consequently limit our understanding of this ecosystem. To improve our understanding of the processes, interactions and feedbacks that mediate temperate swamp C cycling, we simulated the long-term (40 years) plant processes, energy, water and C fluxes of Beverly Swamp, a well-preserved swamp in Southern Ontario using a process-based model (CoupModel). CoupModel v6 was systematically calibrated for Beverly Swamp using the Generalized Likelihood Uncertainty Estimate (GLUE) method. The GLUE method moderately reduced the uncertainty associated with modelling processes linked to swamp C cycle, and reasonably improved the simulation outcome when compared to the initial manual calibration. Global sensitivity analysis of the parameters identified the important parameters that greatly influence temperate swamp C flux simulations and the interconnections that exist between simulated variables and parameters. Plant-related processes and hydrological variables exerted the strongest control on soil respiration simulation. However, these dynamics may be altered as climate continues to warm in coming decades. Results from this study provide valuable knowledge for predicting the fate of swamp C cycle in the region under a changing climate

3.2 INTRODUCTION

Temperate swamps are known to contribute substantially to the peatland C cycle even though the coverage of this ecosystem is largely underestimated and understudied (Davidson et al., 2022; Kendall et al., 2020). A recent modelling study indicated that many aspects of a swamps thermal, hydrological and biogeochemical conditions could be adequately modelled, gaining insight into the ecosystem's response to disturbance (see chapter 2); however, parameter estimation remained difficult given the scarcity of previous studies in swamps. Process-based models have been widely applied to diverse ecosystems because of their ability to simulate important interactions and feedbacks between biophysical processes and biogeochemical cycles (He et al., 2016; Wang et al., 2022). This model class heavily relies on forcing variables and exact boundary conditions to simulate important processes in forested ecosystems that may be difficult to delineate because of measurement limitations (Munro et al., 2000; Svensson et al., 2008; Yuan et al., 2023). Process-based models also require well-defined parameter values (Silva et al., 2024) but the course of assigning parameter values to important processes in data sparse ecosystems such as temperate swamps can be challenging, thus creating parameter uncertainty when simulating temperate swamp C fluxes and its controlling conditions (see Chapter 2). Uncertainty in swamp C flux modelling is also introduced from field observations that are used for calibration and validation processes. Large spatial variability across temperate swamps, scaling of instantaneous measurements to daily resolution, varying measurement techniques for different study periods, and overall scarcity of measurements influence C flux modelling outcomes (see chapter 2). Furthermore, observation sparsity and limited modelling studies on swamps to date may also create uncertainties when selecting the appropriate model structure for simulating swamp C balance. Consequently, these uncertainties that are linked to parameterization, field measurement error and model structure all affect the C modelling process of this ecosystem.

Modelling studies have shown that there are interrelationships between biogeochemical and biophysical processes in peatlands. (Metzger et al., 2016b, 2016a) showed that simulated C flux variables (e.g., ecosystem respiration and gross primary productivity) are linked to diverse

ecohydrological processes (e.g., soil moisture content, soil heat flow, and phenological changes). These interconnections and feedbacks were reflected in the sensitivities of simulated water, energy and C fluxes to diverse process categories such as plant growth and development, soil hydrology, organic matter decomposition, and soil thermal processes. In a similar manner, (Yuan et al., 2023) also noted in their modelling study on tropical swamps that plant-related parameters significantly influenced the energy and C fluxes of their studied area. Understanding the interrelationships and feedbacks that exist within and between biophysical and biogeochemical processes and their parameters through sensitivity analysis is important for model calibration (especially parameter specification) (Muleta & Nicklow, 2005). However, these interactions are not well studied in temperate swamps.

The modelling study of Afolabi et al. (see chapter 2) attempted to fill some of these knowledge gaps by highlighting the relationships between soil respiration and biophysical controls over four decades in a temperate swamp. However, their study did not quantify the uncertainties associated with measurements used as driving variables and for defining boundary conditions. For instance, they relied on proxy gauging station data to quantify the lateral water influx of a nearby dam and creeks into the studied swamp. This data source may introduce uncertainties in the swamp's boundary conditions. In addition, because Afolabi et al (see chapter 2) relied on local sensitivity analysis (one-at-a-time) approaches for their study, some of the non-linear and multi-process interactions may not have been captured. These interactions are important in swamps where a single parameter can influence multiple processes (Yuan et al., 2023). To improve on the limitations of local sensitivity analysis, the global sensitivity analysis (GSA) approach has been adopted by many modelling studies (KC et al., 2021; Wu et al., 2019). Instead of varying just an input or parameter and holding others constant, GSA simultaneously varies all the selected parameters and inputs of a model to help study all plausible interactions between parameters and processes (Hamby, 1994). This procedure assists in identifying sensitive and important parameters that are required for calibration and also the assignment of uncertainty level to individual model inputs and parameters as uncertainty analysis is an essential aspect of any modelling process.

Uncertainty analysis accounts for all the sources of uncertainty and their influence on modeling outcomes that consequently determine the usefulness of model predictions (Muleta & Nicklow, 2005). Although the study by Afolabi et al (see chapter 2) is one of the pioneering modelling studies on the long-term C dynamics of temperate swamps, no uncertainty analysis was undertaken for their modeling study. These limitations restrict our understanding of the dynamic interactions that occur in swamp C cycle that may be pertinent to ranking important processes for field measurement campaigns and parameterizing the swamp category of wetlands in large scale models (e.g., CLASSIC and CAMP) (Bona et al., 2020; Melton et al., 2020).

To improve on the highlighted limitations above, this study undertook an uncertainty analysis of simulated swamp C flux and controls by CoupModel using the Generalized Likelihood Uncertainty Estimation (GLUE) approach. The GLUE method is a systematic approach that captures all sources of uncertainties (Yang et al., 2018) and it is based on the principles of equifinality that finds the plausible combinations of models, parameters and variables that are acceptable for reproducing C flux processes and controlling conditions (Beven, 2006; Beven & Freer, 2001). Consequently, the objectives of this study were to: i) complete a global sensitivity analysis and model calibration with multiple variables (e.g., soil respiration, water table level and leaf area index, ii) present acceptable model structure and parameter distribution for simulating temperate swamp C, which would be an important foundation for predicting future climate change impacts on this ecosystem, iii) identify parameter equifinality and the influence of these parameters on simulated variables, iv) evaluate GLUE performance for simulated variables and suggest measurement variables that will improve our understanding of the soil respiration process in temperate swamps, and v) analyze the sensitivity of swamp C fluxes to changes in lateral water inputs.

Based on literature, we hypothesize that the application of GLUE methodology will improve the initial simulations of Afolabi et al. (*In press, Chapter 2*). We expect that the parameters related to soil organic C decomposition, soil thermal conditions, hydrology, and plant

processes will significantly affect soil respiration simulations. We also hypothesize that the swamp's C flux will be responsive to variation in lateral water fluxes.

3.3 MATERIALS AND METHODS

3.3.1 Brief description of study location

Beverly Swamp is a minerotrophic forested wetland situated in Southwest Ontario, Canada (43.366N, 80.12W) with an elevation range of 265 to 270 m. The 2000 ha swamp is a product of an underlying impermeable marl layer that is situated in a double dolomite bedrock depression (Woo, 1987). This unique formation supports a perched water table and the accumulation of ~85 cm peat layer as vegetative productivity exceeded the rate of decomposition (Munro, 1979; Woo & Valverde, 1981). Beverly Swamp is located within the humid continental climate zone with an annual average temperature of 7.6 °C and precipitation of 973 mm (*Canadian Climate Normals 1980-2010*, 2024), Millgrove station). The swamp has a heterogenous canopy cover of both deciduous (e.g., red maple and birch) and coniferous vegetation (e.g., white cedar), and it is mainly drained by two streams, namely Spencer and Fletcher located in the northwest and northeast portions of the swamp, respectively (Woo & Valverde, 1981; Woo, 1987). Detailed description of the site can be found in Appendix 2-1; (Woo & Valverde, 1981) and other publications cited therein.

3.3.2 Field measurements used for study

3.3.2.1 Forcing variables and initializing measurements

Forty years of daily meteorological measurements (Jan 1983 - May 2023), including, precipitation, air temperature, wind speed, relative humidity, and global radiation were collected from weather stations located within 25 km radius of the swamp (e.g. Valens, Christie Conservation, HamiltonRBG CS and Hamilton A) (see Table 3-1). Additional observation data sourced from (Munro, 1987, 1989; Munro et al., 2000) were also employed for gap-filling during 1983 - 1986. Other suitable meteorological products such as Ontario in-filled climate data (1983 - 2005) (Ontario Government, 2019), NASA Power Project (1986-2023) (Sparks,

2018) and CWEEDS (1986-2023) solar radiation product of Environment Canada were used to support precipitation and global radiation datasets, respectively as shown in Table 3-1.

Table 3-1. Forcing and initialization variables for CoupModel

Table 3-1 Forcing and initialization variables for CoupModel

Variable	Period	Temporal resolution	Data source	Remarks
Air temperature	Jan 1983-May 2023	Daily	Weather station Munro 1987, 1989 and Munro et al., 2000	Details of collection method are available on Environment Canada's website < https://climate.weather.gc.ca/historical_data/search_historic_data_e.html >. Additional collection approach for support data are described in Munro 1987, 1989 & Munro et al., 2000
Precipitation	Jan 1983-May 2023	Daily	Weather station Munro 1987, 1989 and Munro et al., 2000	As described above
Wind speed	Jan 1983-May 2023	Daily	Weather station Munro 1987, 1989 and Munro et al., 2000	As described above

Relative humidity	Jan 1983-May 2023	Daily	Weather station Munro 1987, 1989 and Munro et al., 2000	As described above
Global radiation	Jan 1983-May 2023	Daily	NASA Power & CWEEDS Environment Canada product Munro 1987, 1989 and Munro et al., 2000	Approach adopted by NASA Power (Sparks, 2018) and Environment Canada (https://climate.weather.gc.ca/prods_servs/engineering_e.html). Addition data collection approach is described in Munro 1987, 1989 and Munro et al., 2000
Volumetric discharge (flow)	Jan 1983-May 2023	Daily	Westover gauging station	Details of collection method are available on Water Survey Canada < https://wateroffice.ec.gc.ca/mainmenu/historical_data_index_e.html >
C content per soil layer	1998-2000	One time	McCarter et al., 2024; Waddington et al. (unpublished)	Analyzed with loss on ignition approach

The climatic variables described were used as dynamic driving variables for CoupModel, while a streamflow dataset from Westover gauging station at the exit of swamp was used as proxy for lateral flow input into the swamp because of the unavailability of this information. To quantify the inconsistencies associated with the lateral flow proxy data assumption, an uncertainty analysis was undertaken for this input variable, which was introduced into the model as average flow input defined by the parameter of Gwsourceflow, q_{sof} (see section 3.4.2

for details). For the initialization process, soil organic carbon (SOC) measurements of depths 0–150 cm that were analyzed with loss on ignition approach ((McCarter et al., 2024); Waddington et al., unpublished) was used in the model. Details of other site characteristics used for the initialization process are included in Appendix 2-1

3.3.2.2 Measurements used for calibration and validation process

Hourly soil temperature measurements obtained by thermocouples (Type E) at depths (0 – 40 cm); groundwater table level data (barometrically corrected) collected by pressure transducer (Solinst levellogger); and volumetric moisture contents (0-30 cm) of the soil measured by installed Campbell Scientific (CS616) probes across the swamp were used as calibration and validation datasets. Details of compiled calibration and validation datasets are presented in Table 3-2

Table 3-2 Observational datasets for calibration (cal) and validation (val)

Variable	Period	Time scale	Mean $\pm$ Std	Data source	Remarks on approach
Soil temperature	1983-1987 (cal); 2022 - 2023 (val)	Daily	Cal: 5.9 ± 6 °C Val (5cm): 9.0 ± 7.6 °C Val (30cm): 9.0 ± 6.9 °C	Field measurement	Obtained with thermocouple installation. See Munro 1987, Munro 1989; Munro et al., 2000; Afolabi et al. (see chapter 2) for details
Water Table Level	1983-1987(cal); 2022 - 2023 (cal)	Daily	Cal: -2 ± 19 cm Val: 22 ± 21 cm	Field measurement	Obtained with pressure transducer (water level loggers). See Munro 1987, Munro 1989; Munro et al., 2000; Afolabi et al. (see chapter 2) for details
Volumetric Moisture Content	2022- 2023	Daily	VMC5: $69 \pm 9.5\%$ VMC 30: $78 \pm 15\%$	Field measurement	Obtained with corrected time-domain measurement method. See Afolabi et al. (see chapter 2) for details

Soil respiration	1998-2000(cal); 2022-2023(val)	Bi-weekly	Cal:10.3±7.6 gC/m ² /d val:4.4±5.4 gC/m ² /d	(Davidson et al., 2019; Schmidt & Strack, 2026)	Obtained with closed opaque chamber method. Spatial variability of same day measurements are ±3.7 gC/m ² /d for cal and ±1.8 gC/m ² /d for val period
Net radiation	1983 - 1987	Daily	7.7 x 10 ⁶ ±5.7x 10 ⁶ J/m ² /day	Munro 1987, Munro 1989 and Munro et al., 2000	Obtained with Bowen ratio approach
Latent Heat	1983 - 1987	Daily	4.7 x 10 ⁶ ±4 x 10 ⁶ J/m ² /day	Munro 1987, Munro 1989 and Munro et al., 2000	Obtained with Bowen ratio approach
Sensible Heat	1983 - 1987	Daily	2.5 x 10 ⁶ ±1.6 x 10 ⁶ J/m ² /day	Munro 1987, Munro 1989 and Munro et al., 2000	Obtained with Bowen ratio approach
LAI	1998	seasonally	3.9±1.9	Thambipillai 1998	Obtained with ground-based measurements and hemispherical photography
Snow Depth	1983 - 1987	seasonally	24±16 cm	Munro 1987, Munro 1989 and Munro et al., 2000	Obtained during snow survey

Additional datasets were sourced from existing studies as compiled in *Table 3-2*. Bi-weekly soil CO₂ flux measurements were obtained by closed opaque chamber method and analyzed with gas chromatograph (1998-2000) or measured directly (2022-2023) with LI-COR portable greenhouse gas analyzer (LI-7810) (Davidson et al., 2019; Schmidt & Strack, 2026). Historic

hourly measurements of net radiation, ground heat, sensible heat, latent heat fluxes derived by Bowen ratio surface energy and additional measurements of water table level, soil temperature (0–5 cm) and snow depth were sourced from (Munro, 1987, 1989; Munro et al., 2000). Compilation of measured Leaf Area Index (1998) by direct measurement and hemispherical photography were sourced from (Thambipillai, 1998). Detailed measurement methodologies are published in the papers compiled in Table 3-2.

3.3.3 Modelling approach

3.3.3.1 CoupModel description

CoupModel (coupled model), a one-dimensional coupled heat and mass transfer model that simulates thermal and hydrological conditions of ecosystems and the adjoining biological processes that mediates C exchange between the atmosphere, vegetation and soil environment (He et al., 2021; Jansson & Moon, 2001; Jansson & Karlberg, 2004), was adopted for this study. Estimation of heat and water flow processes in CoupModel are based on the laws of conservation of energy and mass, and flows of thermal energy (Fourier's law) and water (Richard's equation) created by gradient differences in temperature and water potential. C balance simulations and plant development in the model are products of the interactions between plants and forcing hydroclimatic variables (Svensson et al., 2008). CoupModel consists of many biotic and abiotic sub-modules for radiation and precipitation interception, evaporation and transpiration, snow and surface water pools, soil temperature and heat fluxes, plant growth and maintenance, soil hydraulics, and soil organic C decomposition (Jansson & Moon, 2001; Jansson & Karlberg, 2004; Metzger et al., 2016b, 2016a; Jansson, 2012) (Figure 3-1) (*see eqs. A1- A52 of Appendices 2-3 and 2-4 for details of functions used to simulate the processes*). Detailed description of the model can be accessed in (Jansson & Karlberg, 2004; Jansson, 2012) and other publications referenced therein.

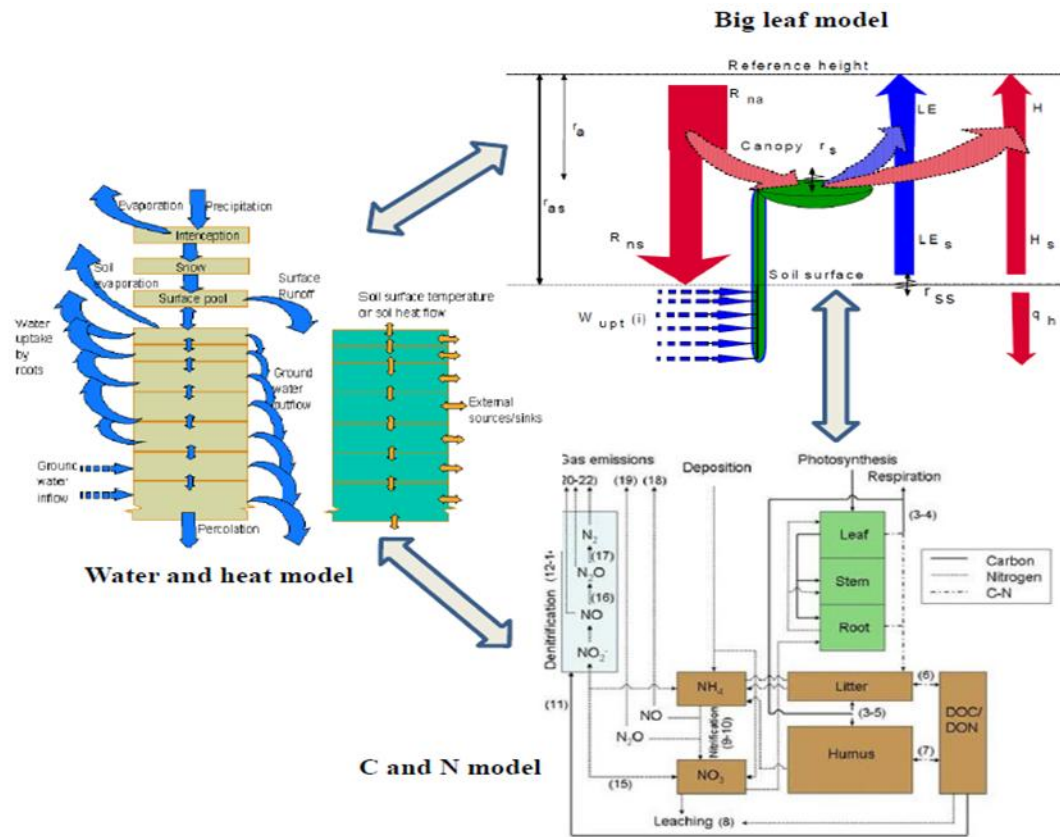


Figure 3-1. Conceptual diagram of the coupled components in CoupModel (modified from (He et al., 2023)). Note that only the processes relevant to C flux modeling were adopted for this study.

3.3.3.2 Model design and setup for Beverly Swamp

The model set-up and parameterization for this study is based on the previous use of CoupModel at Beverly Swamp as described in Afolabi et al. (see chapter 2). Parameter assignment was informed by field measurements, lab experiments, literature values, experience from single runs (Afolabi et al., see chapter 2) and default model values. See Table 3-3 and Appendices 2-3

3.3.4 Sensitivity analysis and calibration process using the GLUE Approach

Field measurements of 1983–1986 and 1998–2000 were used for parameter sensitivity analysis and calibration, while those of 2022–2023 were adopted for validation. The single run of the initialized model described in Afolabi et al (see chapter 2) for the swamp provided the

foundation for this study. To select the parameters for the multiple run analysis, an initial screening (sensitivity analysis) of 90 identified parameters (see Appendices 3-5) representing diverse processes related to plant growth and development, water, energy and C flux processes was completed with the one-factor-at-a-time (OAT) approach described by (Lenhart et al., 2002). The process thereafter reduced the final number of selected parameters for calibration to 38 based on their importance and sensitivity to C flux processes, while the remaining ones were held static for the runs (see Table 3-3 for details).

The prior range of parameters presented for GLUE analysis were defined in such a manner to cover anticipated posterior value (Svensson et al., 2008) (See Appendix 3-6 for extent of uncertainty coverage before applying constraints). Thereafter, a total of 35,000 *Monte Carlo* simulations of random uniform sampling were implemented for the study to generate both prior and posterior distributions covering a broad range of C balance conditions in the swamp. The process assisted in locating possible sets of models, parameters and variables that generate ensemble simulations that match observations (Wu et al., 2013). The ensembles were split into behavioral and non-behavioral simulations (Metzger et al., 2016a) based on their consistent performance as acceptable solutions that fit well with the multiple observed variables described in section 3.3.2. Consequently, those that fall below set threshold (see section 3.4.1 below) were discarded while the ones above were accepted as behavioral simulations. Posterior parameter intervals of between 5th to 95th percentile of the distribution of parameter values of accepted runs were considered for the study. These posterior distributions generated after applying the acceptance thresholds were compared to the prior distribution to identify sensitive parameters.

3.3.4.1 Performance Indices, set thresholds and interrelationships

Simulations produced above were constrained to field measurements through the setting of multiple acceptance criteria in the form of performance indices, namely, coefficient of determination (R^2) and Mean Error (ME). These two indices have been shown by previous uncertainty studies with the GLUE approach in CoupModel (Metzger et al., 2016a; Wang et al., 2022; Wu et al., 2019) to be effective in capturing all the seasonality and interannual

variabilities embedded in simulated and observed datasets with strong influence on the overall process of sensitivity analysis and calibration. R^2 describes the strength of the relationship that exists between simulated and field measurements by estimating the extent that the variability in simulated data explains that of observations using a regression line (Kalantari et al., 2012). R^2 is particularly independent of the data scale being considered and the value produced by this statistical index falls with the range of 0 and 1. ME, which tests the bias of the simulation, is the average of all errors generated from the difference between simulated and observed variables as it represents the magnitude of the difference.

For the selection of behavioral models and for the calibration process, measured soil temperature, hydrological measurements (water table level and volumetric moisture content), C fluxes (soil respiration), energy fluxes (net radiation, latent heat and sensible heat), plant properties (LAI), and snow depth were used to constrain the simulations. The setting of the constraining thresholds was inspired by the uncertainty estimated from field measurements (*see Table 3-2*) and previous single run experience described in Afolabi et al. (chapter 2). In particular, thresholds of $R^2 > 0.80$ for soil temperature, $R^2 > 0.7$ for LAI, $R^2 > 0.5$ for net radiation flux, $R^2 > 0.4$ for VMC and soil respiration, $R^2 > 0.3$ water table level and latent heat flux, $R^2 > 0.1$ for sensible heat flux, snow depth and surface pool were set as criteria to constrain the selection of acceptable runs. In addition, estimated uncertainty measurement of soil respiration was considered in assigning ME constraint for the simulation. Where ME of ± 0.5 and $\pm 3 \text{ g C/m}^2/\text{d}$ were used to constrain the model for both the validation and calibration periods, respectively. Additional ME constraint was only applied to soil respiration because it is the only C flux that was validated for the study and the main C flux variable in the study with much interest for improvement. Furthermore, the simultaneous R^2 and ME constraints on all the variables led to the rejection of the 35,000 runs.

The constraining process was achieved in multiple steps. The above described R^2 and ME thresholds were applied to soil respiration and each of the variables (controls) in a stepwise manner to test the level of constraint each of the variables has on behavioral model selection and soil respiration in particular. Thereafter, all the multiple constraints of the measurement

were simultaneously applied. In addition, equifinality (Eq_{jk}) between the calibrated parameters of diverse process categories was determined by summing their covariance (R^2) as presented in equation 1a (Metzger et al., 2016a; Wu et al., 2019). Only cases where correlation ≥ 0.4 were considered for the analysis.

$$Eq_{jk} = \sum 2 \times \frac{2^{10 \times R_{jk}^2} j \neq k}{10} \quad \text{Equation. 1a}$$

where R_{jk} is the correlation between the parameters j and k

For initial identification of sensitive parameters, Wilcoxon signed rank and Kolmogorov-Smirnov tests were applied to detect the difference between prior and posterior parameters distribution and to also identify the posterior parameters that have been transformed from uniform distribution. In addition, a range ratio index of posterior to prior distribution was also computed after calibration (Wu et al., 2019). After the identification of sensitive parameters, the contribution (importance) of sensitive parameters to the performance of selected simulated variables outputs was quantified using the Lindeman, Merenda and Gold (LMG) approach (Johnson, 2000; Lindeman et al., 1980; Wu et al., 2019). LMG method is an averaging over ordering method that quantifies the proportion of total variance (R^2) explained by each dependent variable (i.e., model parameters in this case). In this study, the relative weight of the sensitive parameters in the form of proportion of averaged R^2 across the orderings are predictors of studied variables (Equation 1b).

$$LMG(x_k) = \frac{1}{p} \sum_{j=0}^{p-1} \left(\sum_{\substack{S \subseteq \{x_1, \dots, x_p\} \setminus \{x_k\} \\ n(S)=j}} \frac{seqR^2(\{x_k\}|S)}{\binom{p-1}{j}} \right) \quad \text{Equation 1b}$$

Where $seqR^2(\{X_k\}|S)$ represents R^2 summation when regressor $\{X_k\}$ is being added to regression model with the set of regressors S . The implementation of the LMG approach was done with the R package “relaimpo” (Groemping, 2006). Consequently, the completion of the process helped identify and rank sensitive parameters.

3.3.4.2 Lateral input variation

To quantify the uncertainty associated with lateral water flow, which is largely influenced by Valens dam and the two creeks draining Beverly swamp, measurements from Westover gauging station were used to specify the prior parameter range representing this variable in CoupModel. This parameter ($G_{\text{sourceflow}}$, q_{sof}) was calibrated as part of the GLUE process and further varied at different sensitivities ($\pm 10\%$, $\pm 25\%$, $\pm 50\%$) as a separate experiment in the study to test the response of C flux variables to these changes. Selection of sensitivity range for testing was informed by existing hydrological studies in the swamp area (McCarter et al., 2024; Sultana & Coulibaly, 2011).

3.4 RESULTS

3.4.1 Calibrated parameters and sensitivities

The GLUE Calibration process transformed most of the uniform parameter distribution of the prior to other distributions (e.g. normal and log normal) in the posterior. Out of the 38 parameters selected for calibration, 17 showed a very significant difference ($p < 0.05$) between prior uniform distribution and posterior distribution before multicriteria constraint. However, this number increased to 24 after selection of behavioral models as shown in *Table 3-3*. The sensitive parameters resulting from the calibration procedure were linked to diverse biotic and abiotic categories controlling plant properties, soil organic processes, soil thermal dynamics, soil water storage and transport, land surface energy exchanges, and other physical processes. In particular, all the parameters in the soil organic matter category showed significant sensitivity with reduced posterior mean for litter (K_l) and humus (K_h) decomposition rates but an increase for surface litter decomposition (L_l) after calibration.

Table 3-3 Prior and posterior parameter distribution after calibration (See Appendices 2-3 and 2-4 for parameter definitions)

Parameter	Symbol	Prior range		Prior mean	Post mean	Range ratio ¹
		min	Max			
Plant Processes						
MCoefCoarseRoot	k _{mrespcoarseroot}	0.0001	0.02	0.01	0.004	0.93
RadEfficiency	e _L	2.8	4	3.40	3.33	0.96
Leafc1	l _{c1}	0.1	0.4	0.25	0.24	0.77
LeafRate1	l _{Lc1}	0.00001	0.01	0.01	0.001	0.6
LeafRate2	l _{Lc2}	0.01	0.1	0.06	0.06	0.97
GrowthCoef	k _{gresp}	0.1	0.3	0.20	0.19	0.93
LAI enh Coef	LAI _{enhcoef}	0	1	0.50	0.65	0.85
MobileAlloCoef	m _{retain}	0.3	0.95	0.63	0.85	0.6
Rootlowestdepth	p _{zroot}	-0.5	-0.2	-0.35	-0.34	0.94
SpecificLeafArea	p _{l,sp}	50	120	85	90	0.95
AlbedoV	a _{veg}	10	20	15	14	0.69
Soil Organic Processes						
RateCoefHumus	k _h	0.000001	0.0001	5E-05	0.004	0.37
RateCoefLitter1	k _l	0.0001	0.01	0.005	0.01	0.44
RateCoefSurfL1	l _{l1}	0.5	1	0.75	0.90	0.91
land surface exchange processes						
Albedo Wet	a _{wet}	10	20	15	14	0.9
Conduct VPD	g _{vpd}	10	200	105	115	0.81
Conduct Max	g _{max}	0.009	0.05	0.03	0.03	0.96
Conduct Ris	g _{ris}	3E+06	7E+06	5E+06	5E+06	0.74
KBMinusOne	kB ⁻¹	1.5	3	2.25	2.29	0.81
Maximal Cover	c _{max}	0.75	1	0.88	0.87	0.95
Surface and Soil Water Processes						
PrecA0Corr	C _{rain}	1	1.15	1.08	1.06	0.78
TempCoefA	t _{WA}	0.1	3	1.55	1.57	0.87
Airmincontent	q _{Amin}	0	5	2.5	1.73	0.7

¹ Range ratio is the posterior parameter distribution relative to the prior

SPMaxCover	p_{maxt}	0.5	1	0.75	0.80	0.88
SurfPoolMax	W_{pmax}	50	200	125	91	0.89
GWSourceLayer	q_{sol}	1	4	2.5	2.72	0.95
Total conductivity (1)	k_{sat1}	50	2100	1075	1090	0.92
Total conductivity (6)	k_{sat6}	6	30	18	20	0.95
GWSourceFlow	q_{sof}	0	1.6	0.8	0.36	0.71
DrainSpacing	d_p	50	2500	1275	1107	0.9
Soil Thermal & Other Abiotic Processes						
ThScaleLog(1)	X_{hf}	-0.5	0.5	0	-0.06	0.99
MeltCoefAirTemp	m_T	1	3	2	2.32	0.87
ThetaPowerCoef	$p_{\theta p}$	0.2	2	1.1	0.99	0.95
Saturation activity	$p_{q\text{Satact}}$	0.05	0.5	0.28	0.35	0.89
Thetaupperange	$p_{q\text{Upp}}$	3	20	12	13	0.82
Theta Lower Range	$p_{q\text{Low}}$	3	20	12	12	0.83
TemQ10Bas	$t_{p\text{Q10bas}}$	20	35	28	27	0.9
TemQ10	t_{Q10}	1.5	3	2.3	2.2	0.97

Comparing the ratio of mean posterior distribution to prior (range ratio) in *Table 3-3*, RateCoefHumus (K_h , 0.37, decomposition rate of humus), RateCoefLitter (K_l , 0.44, decomposition rate of litter), LeafRate1 (l_{LC1} , 0.60, leaf litter fall), MobileAlloCoef (m_{retain} , 0.60, mobile allocation of the vegetation) and AlbedoV (a_{veg} , 0.69, albedo of the vegetation) showed the largest changes. This result is not unprecedented because K_l and K_h parameters are important to the decomposition of labile C and the recalcitrant humus layer of peat soil, respectively, thus influencing soil C efflux. Conversely, a decrease was observed in the posterior distribution value of l_{LC1} parameter after calibration. l_{LC1} constrains the leaf litter fall process during non-autumnal period with strong influence on litter abundance and the rate at which it disappears or is transferred to humus. Posterior distribution value of m_{retain} parameter increased after calibration with more allocation to mobile C pool. m_{retain} influences the storage of non-structural carbohydrates and its allocation during the non-growing season or under extreme conditions (Jansson & Karlberg, 2004). This parameter therefore has a strong relationship with forest gross primary productivity. The calibration process produced a lower

posterior mean value for a_{veg} parameter, which affects the amount of shortwave radiation that is reflected from the heterogeneous canopy structure of Beverly Swamp. a_{veg} is a major driver of energy flux partitioning of land-surface energy exchange, which eventually affects thermal conditions and evapotranspiration mechanisms in forested ecosystems. Overall, the presented results of the global sensitivity and calibration process assisted in identifying sensitive parameters and the parameter distribution for modelling water, energy and C fluxes in temperate swamp ecosystems.

3.4.1.1 Equifinality of parameters

Parameter equifinality is at the core of the GLUE approach in identifying parameter sets and interactions that reasonably describe important processes in the modelled system. Summation of R^2 generated from the correlation matrix of calibrated parameters (*see Appendix 3-7 for matrix*) described in section 3.3.4 was used to compute the equifinality of this modelling experiment. The overall equifinality of the parameters was categorized into five process groups namely, plant properties, soil organic matter processes, energy balance drivers, soil water processes and soil thermal and other abiotic processes as presented in Figure 3-2.

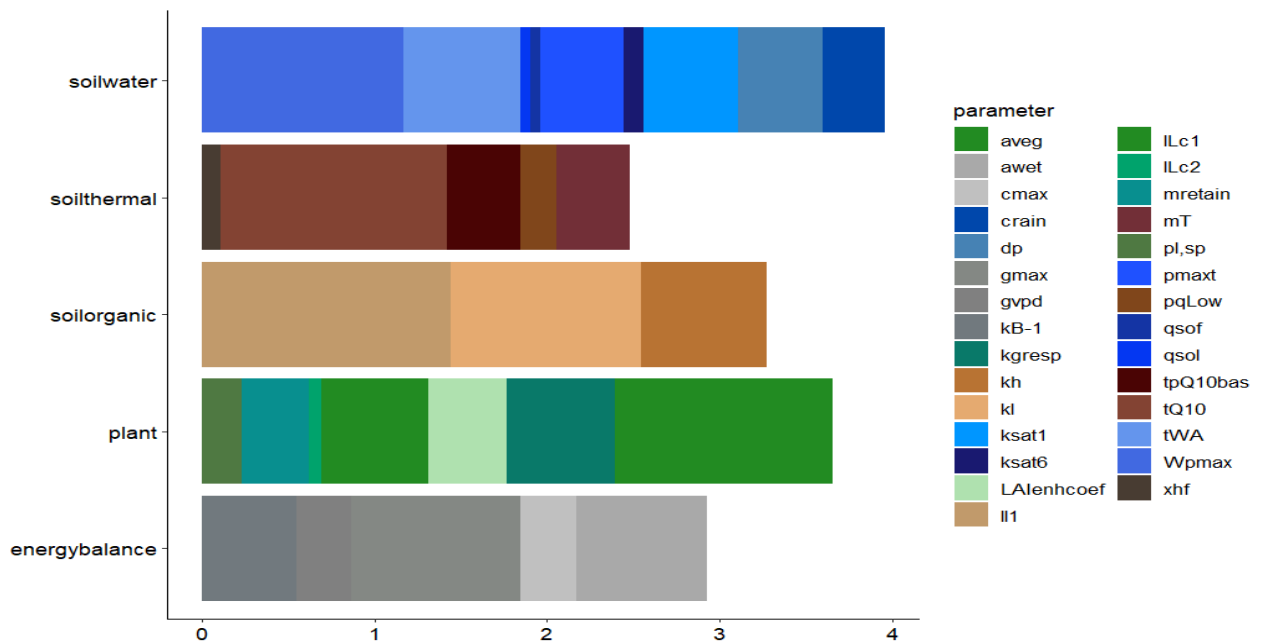


Figure 3-2. Mean equifinality of calibrated parameter-process categories

Considering the average of each category highlighted above, parameters related to soil water processes ranked highest with average equifinality value of 3.96. Within this category, SurfacPoolMax ($W_{pmax}10.5$) accounted for the most equifinality. The category linked to plant processes ranked the next with had mean equifinality value of 3.7, and a_{veg} (8.9) had the highest equifinality in this group. Parameters in the soil organic matter class were estimated to have an average equifinality of 3.3 with the combination of k_1 (4.33) and l_{h1} (3.3) accounting for almost 80 percent of the total equifinality in the group. Energy balance category (2.9) and soil thermal and other abiotic group (2.5) had the lowest mean equifinality for the computed correlation matrix. Generally, more equifinality was observed between parameters of the same process category than those of other categories.

3.4.1.2 Parameter influence on variable simulation

In determining the influence of sensitive parameters on simulated variables, the normalized relative weight (R^2 average) of the parameters derived from the LMG method (described in section 3.3) and their contribution to model performance are presented in Figure 3-3.

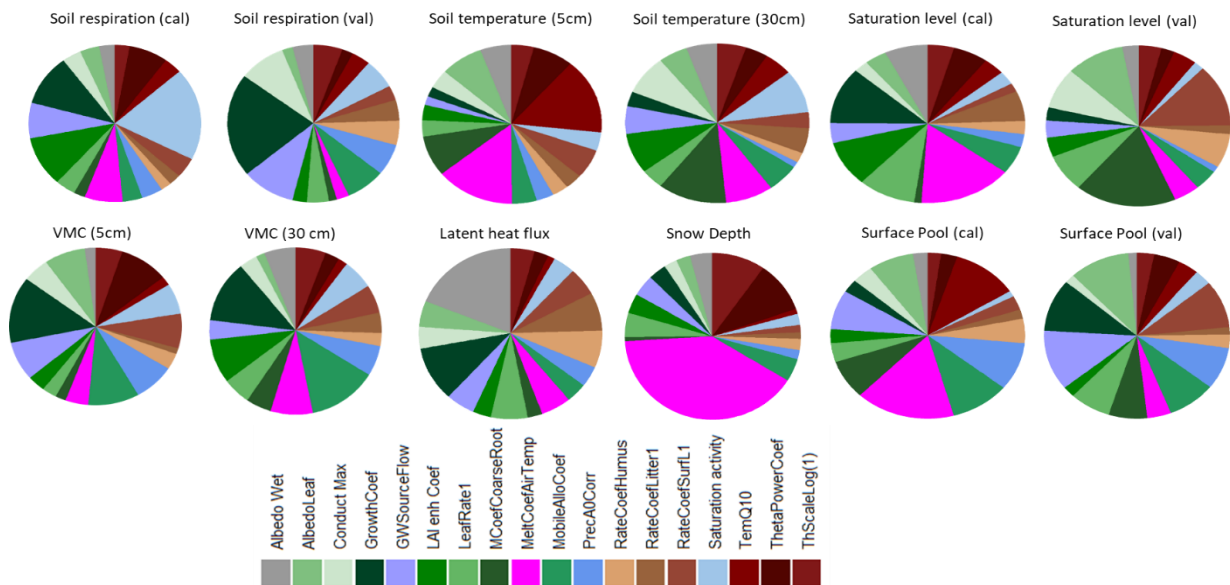


Figure 3-3. Parameter contribution to variable performance (R^2), where cal & val represents calibration and validation periods, respectively. See also Appendix 3-8 for details and also the definition of parameters

The simulated variables showed sensitivities to parameters of different categories but the parameters representing plant growth (Growthcoef , k_{gresp}), soil water drainage/input (GWSourceFlow , q_{sof}) processes and snow melt (MeltCoefAirTemp , m_T) exerted the strongest influence on all the simulated variables. Soil respiration simulations were most sensitive to plant growth (k_{gresp}), soil moisture response function (saturation activity, $p_{q\text{Satact}}$) and soil water drainage (q_{sof}) parameters but with some variations between the calibration (1998-2000) and validation (2022-2023) period. The calibration period showed high sensitivity to both $p_{q\text{Satact}}$ and k_{gresp} parameters, while q_{sof} and k_{gresp} parameters were the highest for the validation period. For the simulation of hydrological variables (saturation level, volumetric moisture content and surface pool), plant related coefficients (McoefCoarseRoot , $k_{\text{mrespcoarseroot}}$; k_{gresp} ; MobielAlloCoef , m_{retain}), snow melt (m_T) and soil water drainage (q_{sof}) parameters contributed the most to explaining the variability in these simulated variables. However, the parameter sensitivity differed for both the calibration and validation periods for both the saturation level and surface pool simulations. The variability in net radiation, latent heat and sensible heat flux simulations were most explained by parameters representing radiation properties (albedo wet, a_{wet}) and soil moisture response ($p_{q\text{Satact}}$, thetapowercoef , $p_{\theta p}$). Respiration response function of temperature (t_{Q10}), respiration parameter of coarse root ($k_{\text{mrespcoarseroot}}$) and snowmelt related coefficient (m_T) parameters ranked top in explaining the variabilities in soil temperature and snow depth simulations, while plant related parameters ($\text{LAI}_{\text{enhcoef}}$ and $k_{\text{mrespcoarseroot}}$) ranked the most in explaining the variability in LAI. Overall, parameters of diverse process categories exerted influence on C, water and energy flux modelling performance at Beverly Swamp. This influence was more prominent in situations where parameters and variables shared the same process category.

3.4.2 Evaluation of model performance following the GLUE approach to parameter estimation

The systematic GLUE approach assisted in identifying the ensemble sets of parameters with the highest likelihood to match measurement data in section 3.3.3.2. Out of the 35,000 prior simulations that were completed, only 30 ensembles were accepted as behavioral simulations

for the posterior distribution after applying all the stringent multicriteria thresholds adopted for the experiment. The ensemble mean of the posterior models performed better than that of the simulations generated by the prior distribution as represented by Table 4.

Table 3-4 Performance (R^2) of prior and posterior models

Variable	N	Distribution prior selection =35000			Distribution post selection =30		
		Mean	CV	Range	Mean	CV	Range
Soil temperature (5cm) cal	707	0.86	0.20	0.93	0.89	0.01	0.05
Soil temperature (5cm) val	343	0.92	0.20	0.97	0.93	0.02	0.07
Soil temperature (30cm) val	344	0.88	0.20	0.94	0.90	0.02	0.07
Saturation level (cal)	1066	0.48	0.37	0.73	0.55	0.25	0.53
Saturation level (val)	348	0.35	0.74	0.78	0.65	0.04	0.15
VMC (5cm)	346	0.45	0.59	0.94	0.78	0.09	0.27
VMC (30cm)	346	0.16	1.28	0.74	0.52	0.12	0.27
Soil respiration (cal)	88	0.25	0.41	0.63	0.30	0.16	0.32
Soil respiration (val)	10	0.43	0.49	0.98	0.72	0.18	0.45
Net radiation	840	0.70	0.20	0.76	0.73	0.01	0.05
Latent heat flux	840	0.41	0.36	0.71	0.50	0.18	0.45
Sensible heat flux	840	0.20	0.38	0.50	0.24	0.17	0.41
Leaf area index	57	0.50	0.47	0.93	0.74	0.06	0.13
Snow depth	36	0.54	0.23	0.71	0.52	0.13	0.40
Surface pool (cal)	1067	0.09	0.96	0.48	0.24	0.38	0.54
Surface pool (val)	347	0.42	0.34	0.84	0.54	0.27	0.49

**CV represents coefficient of variation while cal and val denote calibration and validation periods*

3.4.2.1 Soil respiration

The GLUE approach reduced the uncertainty of posterior soil respiration simulations (Table 3-4). Soil respiration simulations showed significant improvement as represented by the changes in mean R^2 (0.43 to 0.72) and ME (-2 to 0 $\text{gC m}^{-2} \text{d}^{-1}$) in prior and posterior models, respectively during the validation period. In fact, soil respiration showed the greatest observed improvement after multiple constraints compared to the other studied variables. This is an indicator of higher uncertainties in simulating soil respiration. The accepted models were mostly able to represent the seasonality in soil respiration of both the calibration and validation periods (Figure 3-4). However, some of the peaks in soil respiration rate in late spring and early summer were not well captured by the posterior model ensemble when compared to field measurement. This mismatch is not unexpected because soil respiration is highly influenced by plant processes, hydrology, and thermal conditions, so the inadequacies from the simulation of these controls will cascade into soil respiration and other C flux simulations.

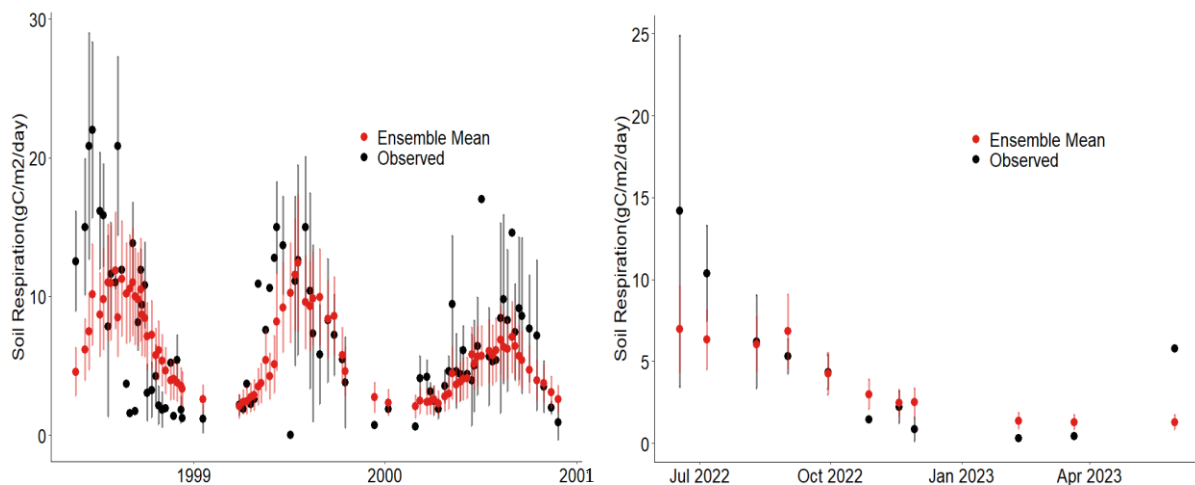


Figure 3-4. Plot of observation against ensemble mean of simulated soil respiration for calibration and validation periods. Error bars in black reflect the standard deviation of measured soil respiration (black), while those in red represent the standard deviation of the acceptable models

Compared to the calibration period, soil respiration was better simulated in the validation period with less uncertainty than the calibrated period (R^2 of 0.3 and ME: $-1.1 \text{ gCm}^{-2}\text{d}^{-1}$). This may be linked to measurement error, difference in collection approach and spatial variability

during this period and the uncertainties that also cascaded from controlling variables. The magnitude of uncertainty related to measurements was also reflected by the spatial variability of soil respiration data across the installed soil fluxing sampling locations with standard deviation values of $3.7 \text{ gCm}^{-2}\text{d}^{-1}$ for calibration (1998 – 2000) and $1.8 \text{ gCm}^{-2}\text{d}^{-1}$ (2022 – 2023) for the validation periods.

3.4.2.2 Hydrological simulations of the swamp

The calibration process significantly improved the simulation performance of the hydrological variables (i.e., water table level and volumetric moisture content) and to a greater extent than soil temperature. This is an indication that the simulation of the hydrological variables is more uncertain than that of soil temperature. In comparison to the prior models, saturation level and surface pool (water table level) simulations showed higher mean R^2 (0.65; 0.54) and reduced ME (0.02m; -5 mm) in the posterior model ensemble, respectively for the validation period as shown in *Table 3-4*. However, the partitioning of WTL shows that saturation level was better simulated than surface pool (see *Table 3-3* and *Figure 3-5*). For the saturation level and surface pool simulations, the validation period was better simulated than calibration period. Peak drought generated during very dry summer and autumn years (1985 and 2022) were not well captured in the saturation level simulations. These, and other inaccurate representations in the system's behavior, cumulatively made simulated saturated level slightly lower than that of observation. Similar underestimation was also observed in the surface pool simulation when compared to the observed data. Some of these inadequacies may be linked to that the fact the model was mostly trained with wet years during the calibration period (1983 – 1986), so it was unable to fully capture the extremely dry conditions presented in the validation period (e.g., 2022)

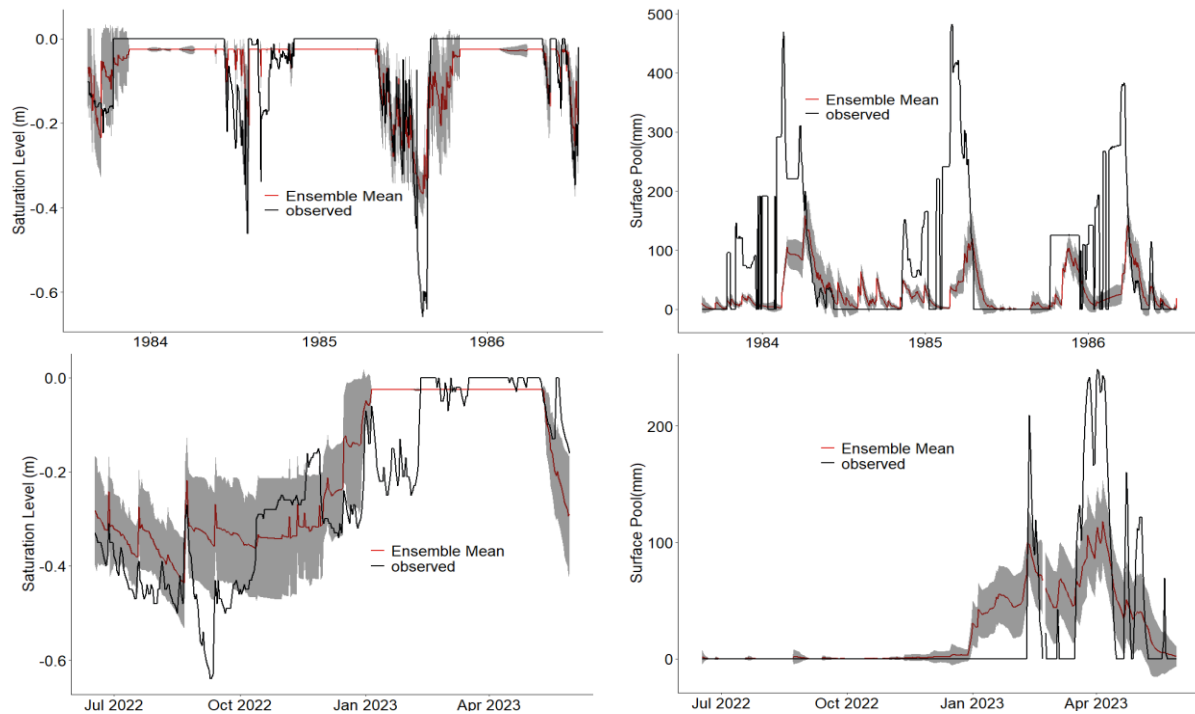


Figure 3-5. Observation versus ensemble mean of saturation and surface pool simulations for calibration (a) and validation (b) periods

For the posterior model, R^2 value of simulated VMC at 5 cm (0.45 to 0.78) and 30 cm (0.16 to 0.52) increased but ME values also increased. The 5 cm VMC matched better with observation than that of 30 cm with mean R^2 of ≥ 0.63 and ≥ 0.41 , respectively. However, more moisture deficit was simulated for the topsoil than that of middle layer as presented in *Appendix 3-9*

3.4.2.3 Soil temperature and snow simulation

Overall, posterior simulation of soil temperature ranked highest when compared to measured data with 90–93 % of the variability in measured soil temperature explained by those of the simulated (see Table 4). This is an improvement from the initial R^2 range of 0.88–0.92 in the prior distribution with middle layer (30 cm) showing more evident improvement than the surface layer (5 cm). For the accepted simulations, soil temperature at the two layers were overestimated during the summer seasons, while the lowest temperatures in winter were not perfectly captured (See *Appendix 3-10*). The overestimation in summer may be linked to moisture underestimation during this period, which results in more partitioning into sensible

heat than latent heat. Also, the pattern of snow disappearance may not be well represented in the model so this may have affected model-observation fit during winter. Unlike soil temperature simulation, the GLUE approach did not result in a significant difference in snow depth simulation. Instead, a slight reduction in fit to measured data (R^2 from 0.54 to 0.52) was observed in the posterior. This reduction may be associated with the overestimation of snow accumulation in the first year of the simulated period and the seasonal mismatch that results from snow accumulation and disappearance during the winter season (See Appendix 3-10).

3.4.2.4 Energy balance performance

The performance of all the simulated energy flux components, namely net radiation latent heat and sensible heat fluxes improved after calibration as shown by their R^2 values. However, latent heat flux experienced the most improvement from mean R^2 of 0.4 to 0.5 and reduction in mean error from $-7.95 \times 10^5 \text{ J m}^{-2} \text{ d}^{-1}$ to $-4.60 \times 10^5 \text{ J m}^{-2} \text{ d}^{-1}$ (see Table 3-4). Most of the measured seasons were captured well by the posterior model except for the underestimation during the spring season of the calibration period (see Appendix 3-10). This underestimation in spring led to the partitioning of more energy to sensible heat flux. Generally, sensible heat flux simulation did not perform as well as latent heat flux, with overestimation in summer and autumn and underestimation in spring when compared to measured data. This cumulatively contributed to the mismatch between observed and simulated sensible heat flux with mean R^2 and ME values of 0.24 and $1.2 \times 10^5 \text{ J m}^{-2} \text{ d}^{-1}$, respectively. Net radiation had the highest mean R^2 (0.73) and ME ($1.21 \times 10^6 \text{ J m}^{-2} \text{ d}^{-1}$) among the three simulated energy fluxes. The high R^2 value can be linked to the good fit between simulated and observed data for most of the calibrated period. However, there was some underestimation and overestimation of net radiation during spring and summer seasons, respectively in some of the studied years (e.g., spring 1984). This seasonal mismatch was then also reflected in simulated latent and sensible heat fluxes.

3.4.3 Experiment of constraining variables on soil respiration flux

When the R^2 constraints described in section 3.3 were applied to only soil respiration, ~53% of the prior simulations were rejected (Figure 3-6). The stepwise addition of soil thermal, hydrological, and plant variable constraints to soil respiration led to model rejection rates of 53% (constrained for soil temperature in addition to soil respiration), 53% (snow depth), 91% (WTL), 92% (VMC) and 85% (LAI). Although VMC showed the strongest individual constraint on acceptance rate, the combination of soil water related variables (WTL and VMC) produced a stronger model rejection value of 96%.

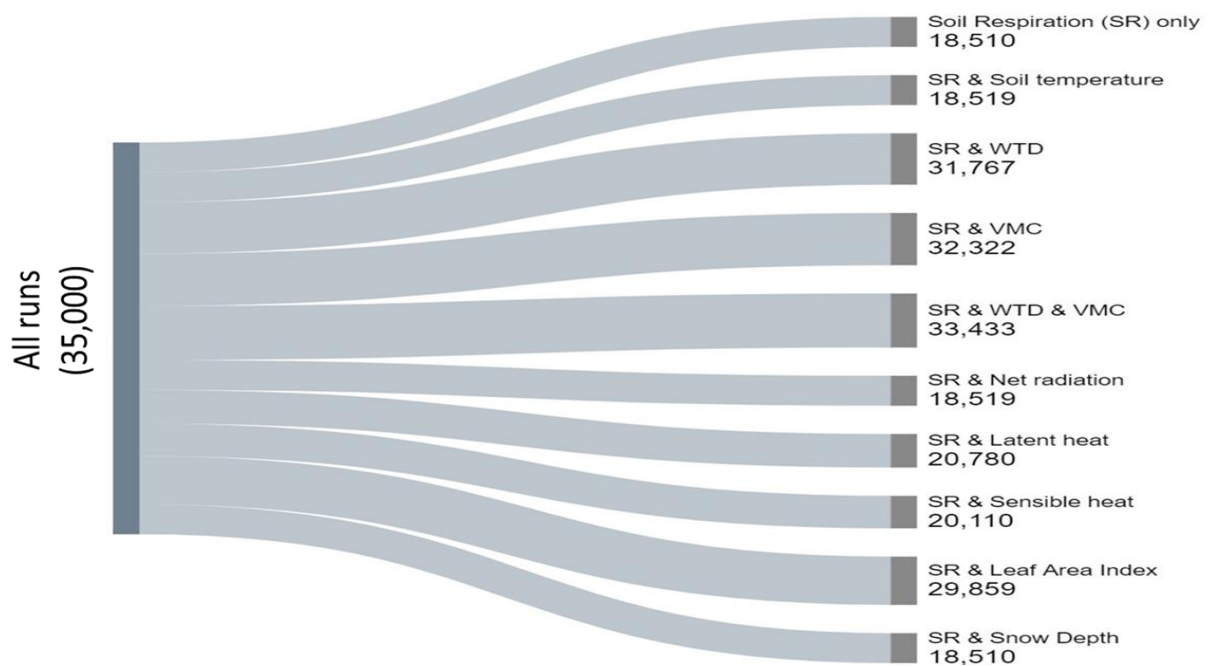


Figure 3-6. Number of rejected runs after R^2 constraint on simulated variables

For the energy flux variables, combining soil respiration constraints with these variables produced rejection rates of 53% (net radiation), 59% (latent heat) and 57% (sensible heat flux). This shows that latent heat flux produced the strongest constraint on the acceptance rate of the behavioral models for energy fluxes. This may be linked to the uniqueness of latent heat flux in representing the energy flux component of evapotranspiration that couples both energy and water balance. A similar result was observed for all the variables when ME constraint was

added to the R^2 constraint of soil respiration as presented in Appendix 3-11. However, LAI ranked higher than VMC or WTL in constraining the prior simulations.

3.4.4 Importance of lateral water flux

Lateral flow is an important variable for defining boundary conditions for modelling energy, water and carbon fluxes in Beverly Swamp. The variation experiment of lateral water input ($\pm 10\%$, $\pm 25\%$ and $\pm 50\%$) showed that gross primary productivity, ecosystem respiration and net ecosystem exchange simulations were responsive to lateral water flux changes as shown in figure 3-7. One-tenth and one-quarter increase in lateral input resulted in $\leq 1\%$ increase in GPP and Reco and 1% increase in NEE, while one-half increase raised GPP, Reco and NEE values by 2.5%, 2% and 4%, respectively. For the reverse experiment, one-tenth reduction in the lateral input led to less than 1% decline in GPP, Reco and NEE, while one-quarter and one-half reduction in water flux further declined GPP by 2%-5%, Reco by 2%-4% and NEE by 4% -6% respectively. This experiment shows that the swamp's C flux showed minimal sensitivity to changes in lateral water input.

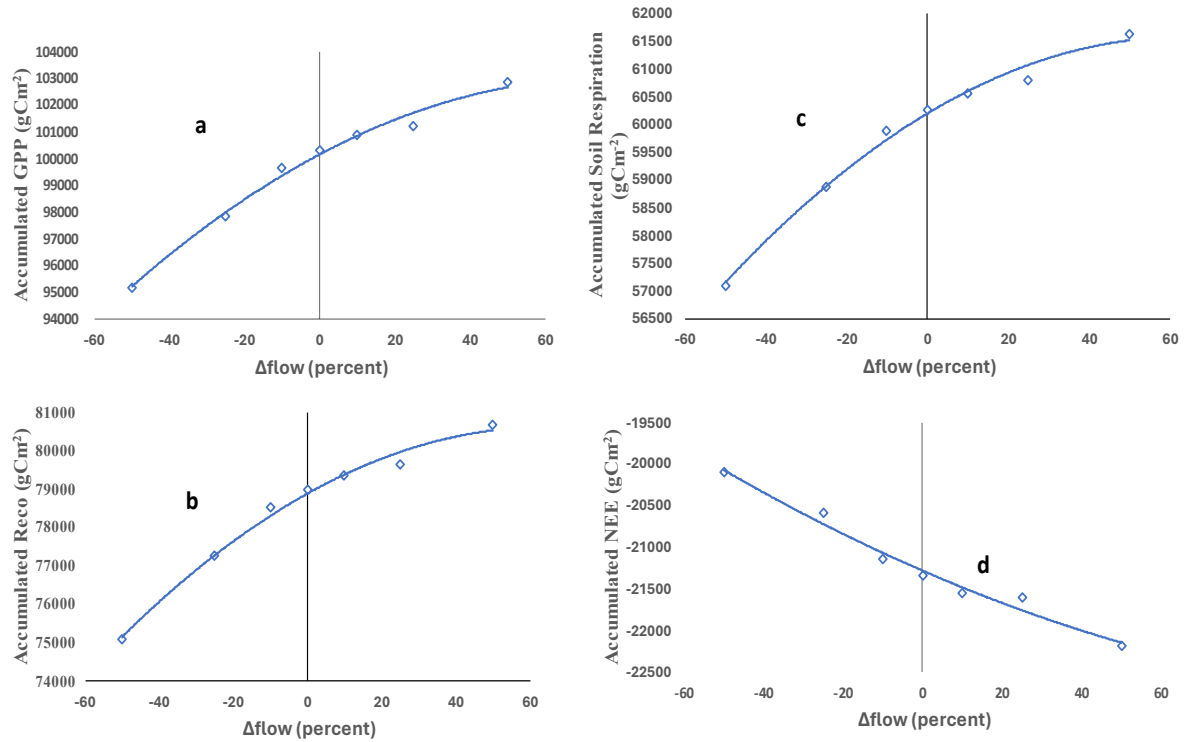


Figure 3-7. Response of Accumulated GPP (a), ecosystem respiration (b), soil respiration (c) and NEE (d) to lateral water input variation over 40 years (1983 – 2023)

3.5 DISCUSSION

The adoption of the GLUE approach for this study reduced the uncertainties associated with temperate swamp C modelling as highlighted in Section 3.4. This confirms part of the hypothesis presented in the introduction section of this study that GLUE will reduce model uncertainties. Global sensitivity analysis and calibration process of GLUE assisted in mapping parameter distribution, constraining boundary conditions and identifying sensitive and important parameters for simulating water, energy and C fluxes in a temperate swamp peatland. The approach reduced the margin of parameter uncertainty in this ecosystem, where parameter values required for modelling C flux and relevant controls are not readily available (Yuan et al., 2023). Critical boundary conditions such as later water flux was better constrained by the process than when parameterization was done one at a time (e.g., Afolabi et al., in press). In addition to the GLUE results, the sensitivity analysis experiments of constraining variables for

soil respiration and C flux response to lateral flow variation (*section 3.4*) also confirmed our other hypotheses on the interconnections that exist between the different ecohydrological processes within this temperate swamp ecosystem. However, the extent of the interactions and the contribution of each process category to C flux and biophysical conditions simulation varied.

3.5.1 Parameter-process influence on soil respiration simulation

As described in the Results (Section 3.4), soil respiration simulations were mostly sensitive to plant growth respiration (k_{gresp}), soil moisture response function (p_{qSatact}) and soil water drainage (q_{sof}) parameters. k_{gresp} coefficient, which represents the concentration of C efflux per C assimilated as structural dry matter, constrains autotrophic respiration in the model (Jansson & Karlberg, 2004; Lavigne & Ryan, 1997). k_{gresp} is dependent on plant functional traits, canopy age and size (Schmiede et al., 2023) and is linked to many critical processes such as plant productivity, tissue nitrogen content, root respiration and rhizosphere (Litton et al., 2007; Ryan, 1990) that control soil respiration processes in swamps. This finding is consistent with other studies that reported the strong influence of this parameter on C flux variables (Hanson et al., 2000; Metzger et al., 2016b). The other two parameters that soil respiration responded to with strong sensitivity were hydrology related. Numerous studies have shown that hydrology is a strong mediator of soil respiration as it exerts control on almost all the processes related to soil respiration in temperate swamps (Davidson et al., 2019; Kendall et al., 2020). In particular, the parameter soil water drainage (q_{sof}), which represents later water flow input into the swamp, displayed strong influence on soil respiration. The importance of this parameter corroborates the results of other modelling studies (Ju et al., 2006; Tonkin et al., 2018) and the findings of the lateral flow variation experiment in section 3.4. Lateral water flux is an important part of the soil water balance of Beverly Swamp with water sources from Fletcher and Spencer creeks that drain the swamp, and the influence of regulated flow supplies from Valens dam upstream of the swamp (McCarter et al., 2024; Woo & Valverde, 1981). Flow variation of this water flux showed that soil respiration and other C flux components are sensitive to lateral flow variation even though at a reduced magnitude. Nevertheless, the 3% increase in soil respiration

rates when lateral flow was increased from 0 to 50% can be attributed to soil moisture abundance that was initially limiting. Moisture deficit impedes plant productivity, substrate availability, microbial activities and other mechanisms constraining soil respiration process (Blodau, 2002; Limpens et al., 2008). Therefore, future disturbances from dam operations and climate change that alter lateral flow regimes of the swamp is also expected to offset its C dynamics. Further, while the lateral flow experiment presented here represents shifts in plant and microbial activity in response to resulting soil moisture change, persistent shifts to lateral flow regimes could result in succession of the plant community (Tonkin et al., 2018) that would have consequent impacts on swamp C cycling.

Even though the simulation performance of soil respiration was influenced by plant and hydrology related parameters, there were variations in the parameter influence for the calibration (1998-2000) and validation (2022-2023) periods. The greater sensitivity of the calibration period to soil moisture response function ($p_{qSatact}$) and plant growth respiration (k_{gresp}), and that of validation to soil water drainage (q_{sof}) and plant growth respiration k_{gresp} parameters may be linked to the spatial variability that exist in swamps. The different sections of Beverly Swamp have distinct hydrogeomorphic settings that influence the hydrology and vegetation distribution of the swamp (Davidson et al., 2019; McCarter et al., 2024; Woo & Valverde, 1981). Therefore, the collection of soil respiration measurements at different points in the swamp with distinct local ecohydrological characteristics may have introduced the variability in soil respiration data used for calibration and validation. In addition, inter-annual variability may also have affected the water availability of the study periods and its effect on soil respiration process. Consequently, this finding possibly explains the origin of the spatial variability in field measurements, which cascaded into the model assessment process.

3.5.2 Parameter equifinality in swamp C flux model

In addition to parameters' influence on model performance, the result of parameter equifinality described in *section 3.4.1.1* was also used to understand the interactions between plant processes, soil organic matter cycling, hydrological processes, energy flux drivers, soil thermal conditions, and other abiotic processes in Bevely Swamp. Substantial parameter equifinality

was observed in the modelling of the swamp's water fluxes, energy balance and C flux components. Some of the parameters showed single interconnection, while others showed high equifinality. Parameters related to soil water (SPMaxCover, $p_{\max}$; SurfPoolMax, $W_{p\max}$) and plant (LeafRate1, l_{Lc1}) process categories ranked highest in equifinality. This result is in line with the findings (Yuan et al., 2023) where they observed that swamp C flux variables were sensitive to plant (phenology) parameters. The equifinality analysis confirms that the interactions between sets of parameters take priority over individual parameters when modelling swamp C flux and its controls. The set of parameters presented in the Results section will be relevant to the calibration of other temperate swamp C models. However, the high equifinality of this modelling exercise may reduce the chance of isolating specific C flux-related parameter values for modelling experiments in other temperate swamps (Sierra et al., 2015). In the event where a single parameter is selected for calibration, the parameter range of others that share the same equifinality may be affected (Wang et al., 2022; Wu et al., 2019). Also, because the selection of constraining criteria is somewhat subjective, the adoption of different sets of indices aside from R^2 and ME may affect the outcome of the calibration and sensitivity analysis process (Metzger et al., 2016a). Therefore, caution should be taken when transferring single parameter value of Beverly Swamp to other temperate swamps. Nevertheless, the parameter ranges of the posterior distributions are applicable to the modelling of other temperate swamp systems.

3.5.3 Simulation evaluation and constraining variables for soil respiration

The GLUE process moderately improved the performance of almost all the simulated variables when compared to field measurements and to the previous results of Afolabi et al. (see chapter 2). Behavioral models of soil respiration were able to reasonably capture the seasonality of both the calibration and validation periods. However, some of the uncertainties in other simulated variables (e.g., hydrological variables) may have affected soil respiration estimates. This hypothesis was confirmed by the stepwise constraint experiment on soil respiration (section 3.3) that showed that associated biophysical conditions strongly affected the acceptance or rejection rate of soil respiration simulations. LAI and hydrological variables

(WTL and VMC) displayed the strongest influence on soil respiration simulations. This finding is consistent with field measurement studies that have shown that plant properties and hydrological conditions have very strong interconnections with soil respiration processes in temperate peatlands (Juszczak et al., 2013; Kendall et al., 2020; Sleeter et al., 2017). LAI is an important plant parameter in regional and global biogeochemical models because it reflects important biological conditions and processes of forested ecosystems such as canopy type, canopy structure and phenological changes (Bréda, 2003; Malone et al., 2015). LAI is a major input for estimating radiation interception and energy balance (Munro et al., 2000), canopy C assimilation (Barclay, 1998), scaling between leaf resistance for water use efficiency and CO₂ absorption (McWilliam et al., 1993) and the simulation of evapotranspiration (Malone et al., 2015), which is an important component of water and energy balance. Hydrological variables (WTL & VMC) have also been reported by many studies to have strong influence on soil respiration processes in peatlands (e.g., (Davidson et al., 2019; Kendall et al., 2020; Waddington et al., 2015). Hydrological conditions moderate microbial abundance and activities, plant distribution, root growth, nutrient availability and other mechanisms that control soil respiration in wetlands (Harper et al., 2022; Mitsch et al., 1991; Nunes et al., 2015; Pezeshki, 1991). Importantly, moisture abundance partitions swamp soils into oxic and anoxic zones and this determines the rate of peat decomposition and ultimate CO₂ efflux into the atmosphere through soil respiration (Blodau, 2002; Limpens et al., 2008; Middleton, 2020). Consequently, the finding of this experiment will inform both modelling studies on important biophysical and biogeochemical interactions, and field measurement campaigns on the relevant variables that should be measured alongside C flux. Furthermore, the adopted behavioral models with reduced uncertainty; high simulation performance will be an important tool for understanding future interactions and feedbacks of biophysical and biogeochemical processes in temperate swamps.

3.6 CONCLUSION

This research is one of the pioneering uncertainty modelling studies on temperate swamp peatland C dynamics, where large knowledge gaps have cumulated into substantial

uncertainties in estimating the water, energy and C fluxes of this ecosystem. The adoption of the GLUE approach for uncertainty analysis assisted in achieving multiple objectives of identifying important ecohydrological processes in temperate swamp, systematically calibrating CoupModel for Beverly Swamp, improving the model performance in simulating C flux and its associated controls, and ultimately reducing the uncertainties of the modelling process. Uncertainty analysis is an important aspect of modelling experiments because it determines the usefulness of the modelling outcomes and the transferability of the modelling components (e.g., structure and parameters) to other temperate swamps. Therefore, the results of this study will inform model structure selection and parameterization of large scale ecological models (e.g., CLASSIC and CaMP) when simulating swamp C flux at regional and global scales. Some of the important parameters and soil respiration constraining variables (e.g., WTL, VMC and LAI) that were identified in this study will help inform the choice of variables to be measured in the field for C related studies. Furthermore, the lateral flow variation experiment may also guide relevant authorities (e.g., conservation authorities) on the best approach for managing flow regulation into Beverly Swamp and similar systems towards preserving the swamp's C stocks. This is important for future planning where climate change risk may affect the hydrological and thermal conditions of the swamp, and its C balance. In addition, the behavioral models generated by the GLUE approach will be useful tools for estimating the effects of climate change on the swamp's C flux and controlling variables.

3.6.1 Study limitations and recommendations

Although the GLUE approach assisted in reducing some of the uncertainty associated with the C flux modelling experiment at Beverly Swamp, the study is not without limitations. The rejection of all the 35,000 runs when R^2 and ME constraints were simultaneously applied to all the simulated variables (see section 3.3.4) may be an indicator of a defect in the model structure adopted for this study that does not fully capture processes relevant for swamp C cycling. Therefore, there is the need for future studies to test alternative model structures that may capture better the biophysical conditions and C flux dynamics of the studied swamp, especially for the C flux and hydrological components (WTL and VMC). The uncertainty approach

adopted for this study is heavily dependent on multiple variable constraints, therefore shortage of long-term field measurements for calibration and validation in some of the variables may have affected the analysis. In particular, the inclusion of high resolution multi-decadal long-term field measurements of Reco, GPP & NEE for additional variable constraint may have improved the modelling process. These measurements will help reduce the high equifinality observed for Beverly Swamp, as high equifinality can be an indication of using insufficient data for calibration (Sierra et al., 2015). Furthermore, the installation of a gauging station at the entrance of the swamp may improve the estimation of lateral influx and the effect of Valens dam and the two creeks on the swamp. Additional measurements to support estimation of important parameters such as growth respiration of swamp vegetation and decomposition rates of litter and humus may further reduce parameter uncertainty in the modelling process.

The posterior parameter distribution generated from the calibration process is dependent on the variables used for constraining the model, adopted performance thresholds, and other parameters selected for calibration. Therefore, the outcome of this uncertainty analysis may change if these conditions are altered. Also, because the model structure selected for the simulation of water fluxes, energy balance and C flux components in CoupModel is based on theoretical knowledge of swamp biophysical processes and experience from existing studies, there is some level of subjectiveness in selecting the appropriate model structure for the study (Metzger et al., 2016a; Wang et al., 2022). However, increased understanding of swamp processes and availability of additional measurements for testing the model's structure will assist in reducing the uncertainty associated with this modelling component.

Chapter 4. Seasonal and annual shifts in temperate swamp biophysical conditions and carbon dioxide (CO₂) exchange under a changing climate

4.1 OVERVIEW

Peatlands in North America are important to regional carbon (C) inventories. Carbon storage and other C cycling processes in peatlands rely on unique hydroclimatic conditions that may be altered under climate change. In particular, the hydroclimatic conditions that support the storage of ~1.1 Pg C in swamps across southern Ontario are susceptible to climate change impacts resulting in a shift in the C balance of this ecosystem. These future changes may produce complex biophysical interactions and bidirectional climate feedbacks. To understand the C dynamics of temperate swamp peatlands under a changing climate, this study assessed the response of swamp biophysical conditions and C flux to mid-century (2050s) climate conditions at a swamp in southern Ontario. A previously calibrated, process-based ecosystem model (CoupModel) was forced with an ensemble of climate projections downscaled from earth system models (ESMs) under shared socio-economic pathway (SSP5) by 2060. Relative to the reference period of 1983–2002, the projected increase in mean air temperature (4.3 ± 0.8 °C) and precipitation (0.2 ± 0.1 mm) by 2050s triggered $41 \pm 11\%$, $18 \pm 8\%$ and $13 \pm 3\%$ increase in 5 cm deep soil temperature, vapor pressure deficit, and evapotranspiration respectively at the swamp. These changes to the swamp's thermal and hydrological conditions dropped its water table level by 12 ± 2 cm and volumetric soil moisture content by $10 \pm 1\%$. Consequently, drier and warmer conditions raised the swamp's CO₂ efflux through ecosystem respiration (Reco) by $30 \pm 2\%$, while its gross primary production moderately increased by $4 \pm 2\%$. These bidirectional feedbacks contributed to an offset in the swamp's C balance resulting in $62 \pm 8\%$ reduction in net CO₂ uptake (net ecosystem exchange). While uncertainty in future climate projections and model fit limit our confidence in the precise estimate of future carbon exchange, it was clear that seasonal timing of warming

and precipitation played an important role in the swamp response, with coincident declines in precipitation and warming temperatures in summer resulting in water stress for plants. Our results show that the future C dynamics of temperate swamp are dependent on complex ecohydrological interactions and feedbacks between hydroclimatic conditions and biotic variables. This study will help inform decision making on the role of swamp peatlands as nature-based climate solutions through improved understanding of their net C exchange with the atmosphere by midcentury.

4.2 INTRODUCTION

Forested peatlands in North America are important to regional carbon (C) inventories as they account for 63% (~82 PgC) of all peatland C stocks of the region (Kolka et al., 2018) and have been identified as potential nature-based climate solutions for climate change mitigation (Drever et al., 2022; Fargione et al., 2024; Strack et al., 2022). This unique ecosystem is created from the imbalance of primary productivity exceeding decomposition, thus supporting long-term terrestrial C storage (Belyea & Clymo, 2001). Photosynthesis, soil organic matter decomposition and other C cycling processes in forested peatlands are dependent on moisture availability and suitable thermal conditions (Davidson et al., 2019; McCarter et al., 2024; Mitsch et al., 1991; Sleeter et al., 2017; Webster et al., 2014) that ensures this ecosystem remains as a net C sink.

Swamps account for an uncertain portion of forested peatland area in Canada (Davidson et al., 2022) but have been identified as the dominant wetland class in southern Ontario (Byun et al., 2018). The hydroclimatic conditions supporting C storage of ~1.1 PgC in southern Ontario swamp peatlands may be disrupted under climate change (Chapter 2; Trettin et al., 2005). The mean temperature of the region is predicted to increase by 2–5 °C by the middle of the century, while precipitation may rise by up to 17% especially for non-growing seasons (Grillakis et al., 2011; Sultana & Coulibaly, 2011; Zhu et al., 2020). Warmer atmospheric condition in southern Ontario will shorten the duration of snow cover (Wazneh et al., 2020) and support an increase in evapotranspiration (ET) rate by 10%, thus reducing groundwater recharge by ~6% in the region (Sultana & Coulibaly, 2011). These future predictions are expected to greatly disrupt

the biophysical conditions supporting the C sequestration functions of peatlands (Goldstein et al., 2020; Harris et al., 2021).

Drier and warmer soil layers in peatlands are expected to increase soil aeration and microbial activities that accelerate peat mineralization (Davidson & Janssens, 2006b; von Buttlar et al., 2018), thus supporting more CO₂ efflux into the atmosphere. Also, high ET rates and reduced precipitation during the growing season may disrupt water availability for photosynthetic activities and consequently lower the C assimilation rate of peatland vegetation (Helbig et al., 2020). Greater ET may also affect the water use efficiency pattern of wetland ecosystems thereby costing them more water for C assimilation (Li et al., 2024; Pan et al., 2018). Conversely, negative climate feedbacks may occur in the region as rising atmospheric CO₂ concentration and warmer conditions increase carboxylation (Farquhar et al., 1980; Medlyn et al., 2002; von Buttlar et al., 2018), prolong the growing season (Helbig et al., 2019; Polgar & Primack, 2011) and ultimately increase primary production in forested peatlands. Increased CO₂ concentration may also affect transpiration rates in wetlands through stomatal conductance as plants have to moderate between absorbing more atmospheric CO₂ and losing water during the process (Medlyn et al., 2011). Even though climate change is expected to have significant impact on the C sequestration function of temperate swamp peatlands, studies have only focused on the historic long-term trends of this ecosystem (Afolabi et al., see chapter 2) or at best, the potential impacts of climate change on swamp hydrology in temperate region (Grillakis et al., 2011; Sultana & Coulibaly, 2011) without connecting it to the C biogeochemical cycle. These knowledge gaps limit our understanding of the vulnerability of this ecosystem to climate change impacts and its resilience under long-term disturbances. Therefore, to better inform our understanding about the preservation of the C sequestration functions of forested peatlands, this study assessed the effect of climate change on temperate forested peatland C dynamics. To achieve this, we i) analyzed the downscaled climate projections of the swamp area under the shared socioeconomic pathway, SSP5 ii) examined the response of the swamp's C balance components and controlling hydroclimatic conditions to predicted future climate by using a coupled ecohydrology and biogeochemical model

previously calibrated for the swamp, and iii) elucidated the important ecohydrological interactions and feedbacks that arose in this future modelling experiment. Based on theoretical knowledge and literature review, we hypothesize that predicted warmer temperature by midcentury would increase soil temperature, vapor pressure deficit, and evapotranspiration rates. This drier condition would be balanced by greater precipitation as projected for the area. Consequently, warmer and drier conditions would support an increase in ecosystem respiration resulting in less net C uptake in the swamp.

4.3 MATERIALS AND METHODS

4.3.1 Brief description of study location

The study site is a well-preserved 20 km² forested peatland (Beverly Swamp) that is located in the Spencer Creek Watershed of southern Ontario under the management of Hamilton Conservation Authority. The swamp resides in the humid continental climate zone with annual maximum and minimum temperature of 12.9 °C and 2.9 °C and precipitation of 962 mm (Canadian Climate Normals 1980-2010, 2024), Millgrove station; Environment Canada, 2024), respectively. The swamp is underlined by an impermeable marl layer (Woo, 1987), and is drained by two major streams namely, Fletcher and Spencer, with the latter influenced by reservoir operations upstream (Woo & Valverde, 1981). This unique formation supports a perched water table and the accumulation of a well-decomposed ~85 cm peat layer (Munro, 1979; Woo & Valverde, 1981). The hydropattern of the swamp is marked with water table rise in response to snowmelt in spring, evaporation-driven water table reduction by the end of summer, and reservoir water release in autumn that contributes to the swamp flooding for ~8 months from autumn through to early summer. The swamp's water table drawdown for 4 months during growing season supports diverse vegetation growth (Woo & Valverde, 1981). Beverly Swamp has a heterogenous canopy cover of both deciduous (e.g., red maple and birch) and coniferous vegetation (e.g., white cedar) (Woo & Valverde, 1981; Woo, 1987). Detailed description of the site can be found in chapter 1 of this thesis; Woo and Valverde (1981) and other publications cited therein on Beverly Swamp.

4.3.2 Modelling approach

4.3.2.1 Forcing environmental variables

For future climate predictions, multivariate bias corrected (Cannon et al., 2018; Francois et al., 2020) daily mean air temperature and precipitation variables under shared socioeconomic pathway (SSP5-8.5) (Riahi et al., 2017) were used as driving climatic variables for the modelling experiment. Outputs were derived from downscaled (10 km) earth systems model (ESM) ensembles generated by the Pacific Climate Impact Consortium (PCIC). SSP5 was considered because it is consistent with near to mid-term projections up to 2050 with no significant changes among the important variables of all the scenarios (air temperature and precipitation) (Hawkins & Sutton, 2009; Schwalm et al., 2020). These mid-century projections of SSP5 are very relevant to ongoing climate change mitigation efforts because it matches with current global CO₂ emissions (Schwalm et al., 2020). The future climate outputs were sourced from regional subsets of 11 ESMs (Curry et al., 2023). Thereafter, five downscaled ensemble ESMs (BCC-CSM2-MR, CanESM5, ECEarth3Veg, GFDL-ESM4 and MIROC-ES2L) that represent the 5th, 50th and 95th percentiles of the 11 ensemble subsets were selected as forcing model outputs. This selection was achieved by computing the changes in temperature (ΔT) and precipitation (ΔP) as the difference between the mean of 20-year reference period (1986–2005) and that of the future prediction (2041–2060) (see Appendix 4-1 for list of the 11 ESMs). Thereafter, the ESMs representing 5th, 50th and 95th percentiles of the differences (ΔT and ΔP) for the 11 ESMs were computed as a matrix combination (see Table 4-1 below). These ESM combinations of air temperature and precipitation were used as future forcing variables for the process-oriented ecological model adopted for this study, and the variability of the ecological model outputs resulting from the different ESMs ensembles were represented by standard deviation ($\pm$ SD) when computing the means.

Table 4-1 Matrix of selected EMS combinations

Air temperature	Precipitation	Combination id
5 th percentile (GFDL_ESM4)	5 th percentile (BCC-CSM2-MR)	V1
5 th percentile (GFDL_ESM4)	95 th percentile (ECEarth3Veg)	V2
95 th percentile (CanESM5)	5 th percentile (BCC-CSM2-MR)	V3
95 th percentile (CanESM5)	95 th percentile (ECEarth3Veg)	V4
50 th percentile (BCC-CSM2-MR)	50 th percentile (MIROC-ES2L)	V5

To ensure that the seasonality of the selected EMSs was consistent with measured air temperature and precipitation datasets (see Chapter 2, Section 2.3 for details of historic measured data), the distributions of the measured variables (1986–2005) were analyzed against each ESM outputs with quantile-quantile (Q-Q) plot and Cumulative Distribution Function (CDF) tests in R statistical software (Millard, 2013; R Core Team, 2021). The analyses assisted in identifying the consistency of the ESMs with measurements (see Appendix 4-2 for details).

This future experiment of climate change only included mean air temperature and precipitation projections because existing studies around the swamp area (e.g. Grillakis et al., 2011) have identified these two variables as major drivers of hydrology in the Spencer Creek watershed. In addition, the Pacific Climate Impact Consortium platform only has the future projection of these two variables (Cannon, 2018). Other driving variables derived from 1983–2023 (see Afolabi et al., In press for details), namely relative humidity, wind speed and global radiation data were repeated for the future simulations, as they are not expected to significantly affect our modelling experiment. Future lateral input into the swamp was introduced into the model as a calibrated parameter from Afolabi et al. (In press). The calibrated value was held constant for this study because the sensitivity analysis of Afolabi et al. (see chapter 2) has shown that the swamp’s C flux variables (e.g., ecosystem respiration) were not very responsive to the changes from this water balance component.

4.3.2.2 CoupModel design and setup for Beverly Swamp

A coupled heat and mass transfer model (CoupModel) that simulates thermal and hydrological conditions of ecosystems and the adjoining biological processes that mediates C exchange between the atmosphere, vegetation and soil environment (He et al., 2021; Jansson & Karlberg, 2004) was adopted for this study. The simulation of heat and water flows in CoupModel are based on the laws of conservation of energy and mass, and flows of thermal energy (Fourier's law) and water (Richard's equation) created by gradient difference in temperature and water potential. C balance simulations and plant development in the model are products of the interactions between plants and forcing hydroclimatic variables (Svensson et al., 2008). For this study, a single vegetation (overstory) layer without understory was simulated because the swamp is characterized by a closed canopy structure (LAI of ~5-6) that does not support abundant understory (Welch, 1985). Consequently, the contribution of the understory to the simulated C and hydrology fluxes will be insignificant.

CoupModel consists of many biotic and abiotic sub-modules for radiation and precipitation interception, evaporation and transpiration, snow and surface water pools, soil temperature and heat fluxes, plant growth and maintenance, soil hydraulics, and soil organic C decomposition (He et al., 2021; Jansson & Moon, 2001; Jansson & Karlberg, 2004; Metzger et al., 2016a; Jansson, 2012) (see eqs. A1- A52 of Appendix 2-4 for details of functions used to simulate the processes). Detailed description of the model can be accessed in Jansson & Karlberg (2004), Jansson, (2012) and other publications referenced therein.

Details of site characteristics used for the initialization process are included in Afolabi et al. (chapters 1 & 2). The model set-up and parameterization for this study is based on previous use of CoupModel at Beverly Swamp as described in Afolabi et al. (chapter 2). Acceptable model generated from the initialization and calibration of CoupModel at Beverly Swamp using the Generalized Likelihood Uncertainty Estimation (GLUE) approach (See Appendix 4-3 for posterior parameter values used and Afolabi In press for more detailed description) was forced with the climatic variables described in section 2.2.1 to simulate plant processes, water, energy and carbon fluxes at Beverly swamp from January 1983 to December 2060.

Trend analysis of long-term simulated variables was completed with the Mann-Kendall statistics (Kendall, 1948; Mann, 1945) using R statistical software (Pohlert, 2023; R Core Team, 2021). This rank-based non-parametric test detects upward and downward monotonic trends in time series. For this study, 95% confidence level ($p = <0.05$) was adopted to test the null hypothesis, while tau (-1:+1) determined the direction of the trend.

4.4 RESULTS

4.4.1 Multi-model projections of swamps climatic conditions

Analysis of the multi-model projections of climatic variables in Beverly Swamp showed that mean air temperature followed a positive trend (See Table 4-2) when tested with Mann-Kendall statistical test. Relative to a 20-year reference period (1983–2002), mean air temperature of the area increased by 4.3 ± 0.8 °C under SSP5 pathway by the middle of the century (2041–2060). However, the extent of change differed among the ensemble ESM members with CanESM5 projecting the highest increase ($+5.7$ °C) and GFDL-ESM4 the lowest ($+3.3$ °C). On a seasonal resolution, the greatest warming of $+5.7 \pm 0.2$ °C was projected during the winter season (Dec – Feb), while spring (Mar – May), summer (Jun – Aug) and fall (Sept – Nov) seasons were warmer by $+3.9 \pm 1$ °C, $+4.0 \pm 0.3$ °C and $+4.7 \pm 0.1$ °C, respectively by the middle of the century (Figure 4-1).

Table 4-2 Midcentury trends of ESM forcing variables and simulated biophysical and C flux conditions at Beverly swamp. Mean $\pm$ SD represents the standard deviation of the ensemble mean and spread of the years being averaged

Data type	Variable name	1983-2002	2041-2060	Mean change	$\Delta\%$ by 2050s	Trend direction
Forcing Variables (downscaled ESMs)	Mean air temperature ($^{\circ}\text{C}$)	7.7 ± 0.8	12 ± 0.8	4.3 ± 0.8	56.2 ± 10	positive
	Precipitation (mm)	2.6 ± 0.3	2.8 ± 0.1	0.2 ± 0.1	8 ± 5	positive
Simulated Variables by CoupModel	Soil temperature ($^{\circ}\text{C}$)	7.3 ± 0	10.3 ± 0.81	3 ± 0.8	41 ± 11	positive
	Vapor pressure deficit (VPD) (Pa)	359 ± 0	± 29	65 ± 29	18 ± 8	positive
	Evapotranspiration (ET) (mm)	2.2 ± 0	2.5 ± 0.06	0.3 ± 0.06	13 ± 3	positive
	Water Table Level (cm)	-11 ± 0	-23 ± 2	-12 ± 2	-101 ± 19	negative
	Volumetric Moisture Content (VMC) (%)	70 ± 0	60 ± 0.9	-10 ± 0.9	-14 ± 1	negative
	Snow depth (cm)	7 ± 0	3 ± 1	-4 ± 1	-63 ± 19	negative
	Ecosystem Respiration (Reco) ($\text{g}/\text{m}^2/\text{day}$)	6.9 ± 0	9 ± 0.2	2.1 ± 0.2	29.4 ± 2	positive
	Gross Primary Productivity (GPP) ($\text{g C}/\text{m}^2/\text{day}$)	9.7 ± 0	10 ± 0.2	0.3 ± 0.2	4 ± 2	positive
	Net Ecosystem Exchange (NEE) ($\text{g}/\text{m}^2/\text{day}$)	-2.7 ± 0	-1 ± 0.2	1.6 ± 0.2	62 ± 8	positive
	Water use efficiency ($\text{gC}/\text{kgH}_2\text{O}$)	4.5 ± 0	4.1 ± 0.1	-0.4 ± 0.1	-7.7 ± 2	negative
*Trend direction is determined by Mann-Kendall Trend Test. All the analyzed trends were significant with $p < 0.05$						

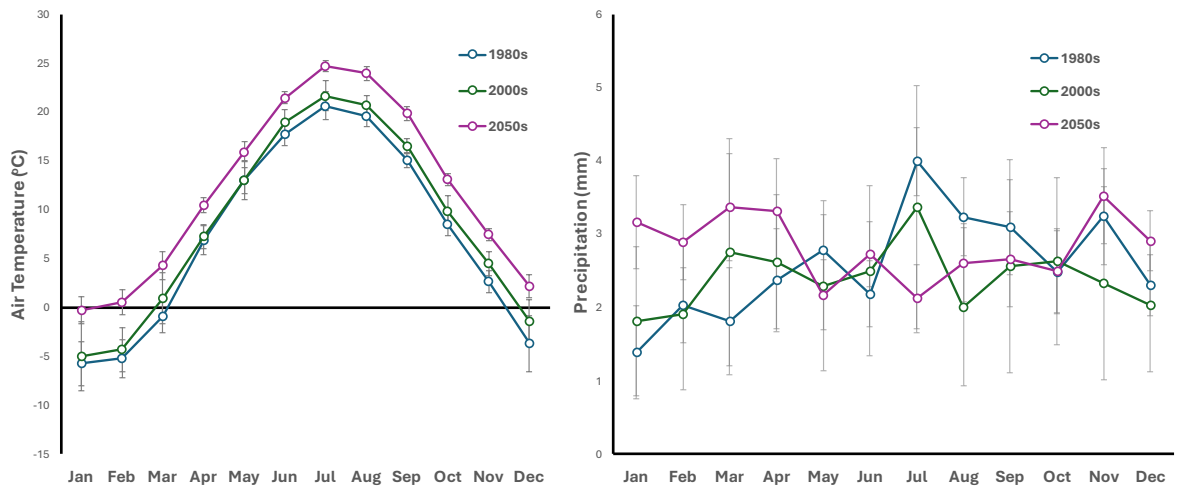


Figure 4-1. Monthly changes in mean air temperature (left) and precipitation (right) during the 1980s (1983 -1992), 2000s (2003 – 2012) and 2050s (2043 – 2052)

Across the ESMs, the precipitation at Beverly Swamp increased by 0.2 ± 0.1 mm by mid-century with ECEarth3Veg and BCC-CSM2-MR projecting the highest (+0.3 mm) and the lowest (+0.1 mm) respectively. However, the projected signal was divergent across the seasons. Greater precipitation of $65 \pm 45\%$ and $34 \pm 44\%$ were observed in winter and spring, respectively, while lower precipitation of $-13 \pm 29\%$ and $-2 \pm 9\%$ were observed during the summer and fall seasons respectively. This mixed signal on monthly scales shows that an increasing precipitation annual trend by 2050 does not guarantee water availability, especially during the summer months when water is needed for biochemical processes in the swamp. Analyzing these different scales helps to disentangle the response of the swamp's biophysical variables to future climatic changes.

4.4.2 Soil temperature and snow depth

Similar to air temperature, surface soil temperature (5 cm) of the swamp followed an increasing pattern (Table 4-2). Mean annual soil surface temperature rose from 7.3 ± 0 °C to 10.3 ± 0.8 °C between 1980s and 2050s. On a seasonal scale, the highest change in surface (5cm) soil temperature was experienced during winter (0.1 ± 0.2 °C to 1.7 ± 0.9 °C) followed by fall (8.8

$\pm 4^{\circ}\text{C}$ to $12.9 \pm 4^{\circ}\text{C}$), spring ($5.2 \pm 4^{\circ}\text{C}$ to $7.9 \pm 3.5^{\circ}\text{C}$) and summer ($14 \pm 1.2^{\circ}\text{C}$ to $18.3 \pm 2^{\circ}\text{C}$) seasons respectively (see Figure 4-2).

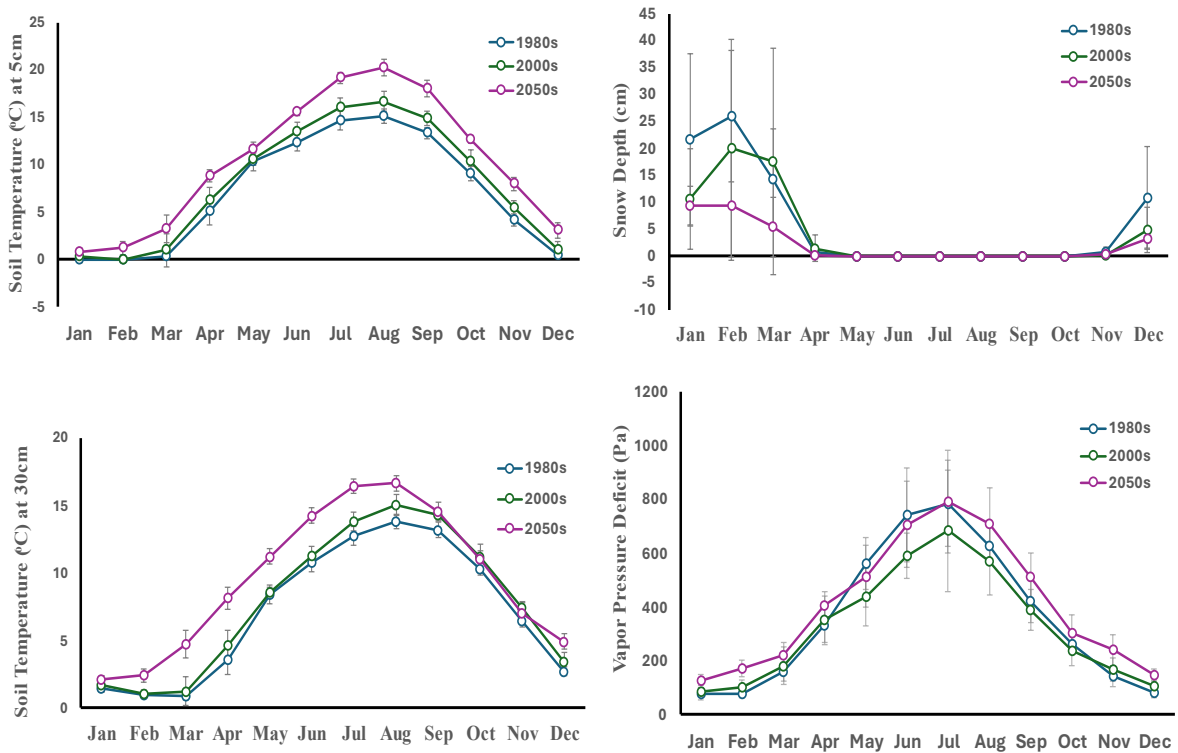


Figure 4-2. Monthly changes in average soil temperature at 5 cm and 30 cm (upper and lower left), snow depth (upper right) and vapor pressure deficit (lower right) during the 1980s (1983 - 1992), 2000s (2003 – 2012) and 2050s (2043 – 2052)

The deeper soil layer (30 cm) of the swamp also showed a similar extent of warming ($+7.3 \pm 0^{\circ}\text{C}$ to $+9.4 \pm 0.6^{\circ}\text{C}$) but with slight dampening in temperature amplitude (Table 4-2). As presented in Figure 4-2, the highest warming was predicted in the spring season ($+87 \pm 3\%$) by mid-century. Unlike the surface soil temperature, winter ($+85 \pm 42\%$) and summer ($+27 \pm 5\%$) seasons reported more drastic increase than fall ($+9 \pm 2\%$) seasons at 30 cm depth in the soil. This may be linked to the stronger sensitivity of deeper layers to oscillating phase change (frost – thaw) that results from thinner snowpacks and early snowmelt in spring. In addition, extremely dry conditions at the peak of summer may reduce moisture contents for cooling

during at the peak of summer. With warmer air and soil, the swamp's snow depth followed a declining trend over the simulation period (1983-2060). Annual daily average snow depth decreased from 6.8 ± 0 cm in the 1980s to 2.5 ± 1.3 cm by mid-century with different magnitudes on monthly resolution. The largest reduction in snow depth occurred during April (-74%) and December (-71%), followed by the February (-64 %) (Figure 4-2). These results show that the swamp is expected to experience warmer soil conditions and receding snow depth by mid-century.

4.4.3 Evaporative demand and swamp's water balance

Vapor pressure deficit (VPD), the difference between atmospheric saturated vapor pressure and actual pressure deficit representing the atmosphere's water holding capacity, was simulated with CoupModel over the study period (1983–2060). Similar to air temperature, VPD followed an upward pattern (Table 4-1) as warmer atmospheric conditions are known to increase VPD. VPD increased by 11.3 % (359 ± 0 Pa to 424 ± 29 Pa) from the 1980s to 2050s. Although summer had the highest seasonal VPD values (735 ± 169 Pa) by midcentury, the VPD at the beginning of summer (June) reduced by 37 Pa even though the average of the season mildly increased (17 ± 48 Pa) (Figure 4-2). Other seasons namely, winter ($+70 \pm 18$ Pa), autumn ($+76 \pm 25$ Pa) and spring ($+27 \pm 53$ Pa) experienced an increase by 2050. These VPD trends show that warmer temperature by midcentury affected the difference between saturated and atmospheric vapor pressure with implications on transpiration and other plant activities.

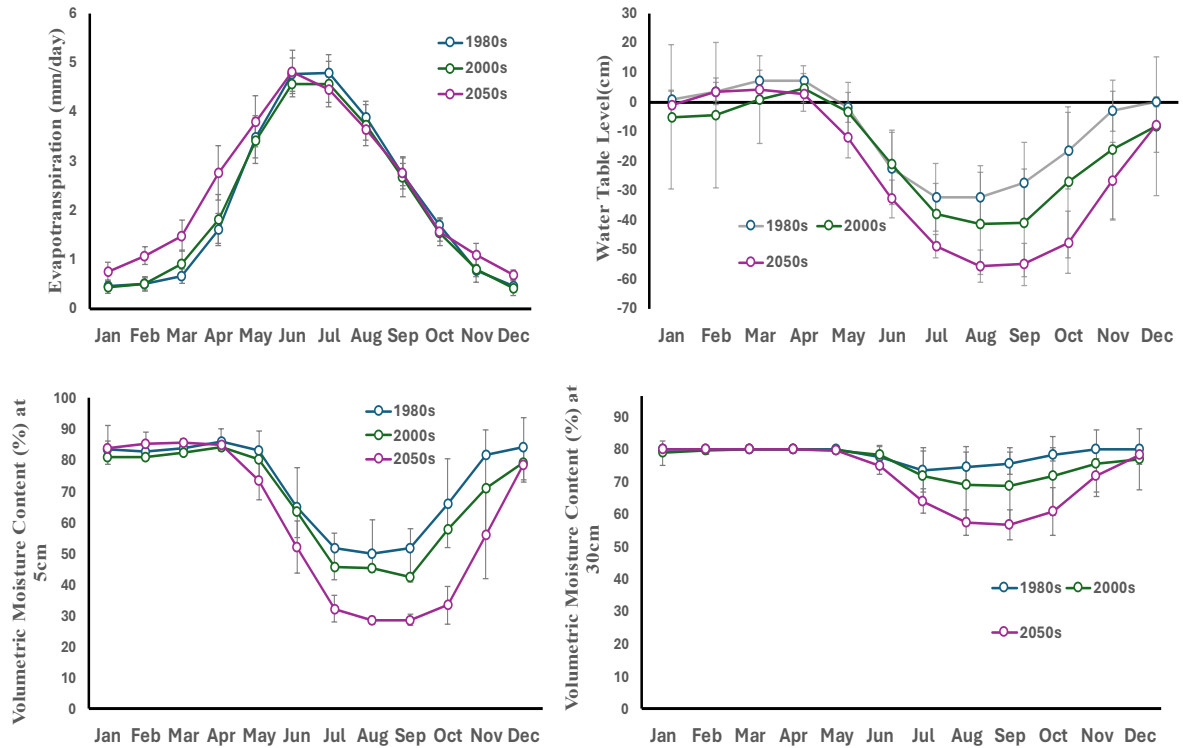


Figure 4-3. Monthly changes in average evapotranspiration (upper left), volumetric moisture at 5cm (lower left), water table level (upper right) and volumetric moisture at 30 cm (lower right) during the 1980s (1983 -1992), 2000s (2003 – 2012) and 2050s (2043 – 2052)

Because VPD drives evapotranspiration (ET) when there is a difference between atmospheric vapor pressure and saturated vapor pressure, ET rates followed an identical trend to VPD (Table 4-1). Daily ET rates also increased from 2.2 ± 0 mm to 2.5 ± 0.1 mm ($13 \pm 3\%$) during the study period with the highest mean ET value in summer (4.7 ± 0.1 mm/day) and lowest in winter (0.5 ± 0.1 mm/day) (see Figure 4-3). However, on a seasonal resolution, daily ET rates were reduced during the summer season from 4.5 ± 0.4 mm/day to 4.3 ± 0.5 mm/day, while ET rates increased ($11 \pm 20\%$ to $75 \pm 28\%$) during the other seasons (fall, spring and winter) for the study period.

The simulated WT level of the swamp also followed a declining trend reflecting the water balance component (Table 4-1). Mean annual WT of the swamp declined from -11 ± 0 cm (where negative values indicate a depth below the surface) to -23 ± 2 cm over the study period,

with the deepest WT level in summer season ($-45 \pm 9\text{cm}$) and the highest in spring ($-1.5 \pm 7\text{cm}$) by mid-century (Figure 4-3). Overall, the fall and summer seasons were the driest by mid-century. Because there is a direct relationship between the swamp's VMC and WTL, the swamp's mean annual VMC at 5cm ($70 \pm 0\%$ to $60 \pm 0.1\%$) and 30cm ($77 \pm 0\%$ to $72 \pm 1\%$) followed declining trends from 1980s to 2050s that is reflective of the rising water loss through ET. The magnitude of change differed for the different layers of soil with the reduction doubling at 5 cm ($-14 \pm 1.3\%$) when compared to the soil layer at 30 cm ($-7 \pm 1.3\%$). For the 5cm VMC simulation, greatest decline was observed during the fall ($-41 \pm 8\%$) and summer seasons ($-32 \pm 10\%$) while the spring ($-3 \pm 6\%$) and winter ($-1 \pm 4\%$) seasons recorded the lowest change. Ultimately, the declining trends of both the volumetric moisture contents and WT level of the swamp shows that water availability will recede by mid-century while the thickness of the aerated soil layer will increase, particularly in summer.

4.4.4 Carbon exchange and water use efficiency

The C assimilation of the swamp in the form of gross primary production (GPP) increased by $4 \pm 2\%$ from annual average of $9.7 \pm 0\text{ gC m}^{-2}\text{ d}^{-1}$ to $10 \pm 0.2\text{ gC m}^{-2}\text{ d}^{-1}$ during the 78 years simulation period (Table 4-1). Peak GPP was in summer but with a receding ($-14 \pm 3.4\%$) trend by 2050s and increase during the spring ($36 \pm 7.6\%$) and fall ($22 \pm 5.2\%$) seasons (Figure 4-4). This seasonal pattern predicts a shift towards an early onset of photosynthesis during spring and prolonged growing season into autumn, but that this extended growing season is largely balanced by declining GPP in midsummer.

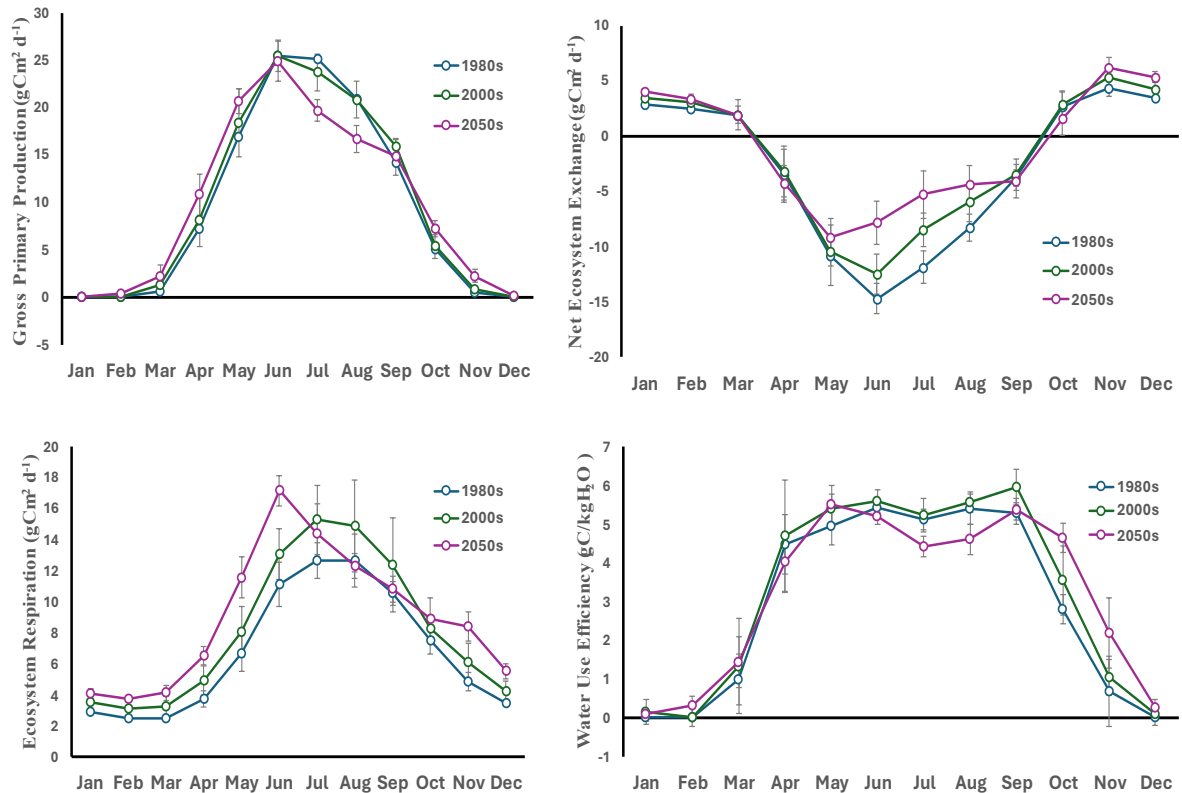


Figure 4-4. Monthly changes in average GPP (upper left), Reco (lower left), NEE (upper right) and WUE at 30 cm (lower right) during the 1980s (1983 -1992), 2000s (2003 – 2012) and 2050s (2043 – 2052)

As GPP of the swamp is predicted to increase, C loss in the form of ecosystem respiration (Reco) also spiked by the end of the study period (Table 4-1). Mean daily soil respiration increased by $29 \pm 2.3\%$ from $6.9 \pm 0 \text{ gC m}^{-2} \text{d}^{-1}$ to $9 \pm 0.2 \text{ gC m}^{-2} \text{d}^{-1}$ by the middle of the century. Even though Reco increased during all the seasons, spring season had the highest increase ($72 \pm 1.2\%$) in the 2050s when compared to 1980s. This pattern of a greater increase in Reco compared to GPP was reflected in the less negative predictions of net ecosystem exchange (NEE) simulations by mid-century (Figure 4-4). The mean NEE value of the swamp changed from $-2.7 \pm 0 \text{ gC m}^{-2} \text{d}^{-1}$ in the 1980s to $-1.0 \pm 0.2 \text{ gC m}^{-2} \text{d}^{-1}$ by the end of the study period (2050s). Across the seasons, the highest NEE change ($-50 \pm 4\%$) over the simulation period

was in summer with dwindling C intake from $-11.6 \text{ gC m}^{-2} \text{ d}^{-1}$ to $-5.8 \text{ gC m}^{-2} \text{ d}^{-1}$. The spring season also experienced a less negative ($7.4 \pm 16\%$) NEE, while more positive NEE values that reflect C loss were predicted during the fall season (1.07 ± 3.5 to $1.24 \pm 4.2 \text{ gC m}^{-2} \text{ d}^{-1}$). Overall, CoupModel predictions showed that the swamp's C intake was reduced by the 2050s but it still maintained a net C sink status.

In addition to GPP's contribution to the swamp's water balance described above, GPP was also used to compute the water use efficiency (WUE) of the swamp's canopy. WUE represents the canopy's water requirement for C assimilation which is computed as the proportion of GPP to ET. For the simulation period (1983–2060), the swamp's mean water use efficiency declined by $\sim 7.7 \pm 2\%$ from $4.5 \pm 0 \text{ gC/kgH}_2\text{O}$ to $4.1 \pm 0.1 \text{ gC/kgH}_2\text{O}$ (Table 4-1). This trend reflects the relatively high increase in ET and only moderate increase in GPP by mid-century indicating that the swamp's canopy will be less efficient in its water use. At the seasonal scale, peak WUE was in summer, which coincided with high GPP and ET rates (Figure 4-4). However, by mid-century, WUE declined ($5.3 \text{ gCkg}^{-1}\text{H}_2\text{O}$ to $4.7 \text{ gCkg}^{-1}\text{H}_2\text{O}$) during the summer period and increased during the fall (46%) and spring (6.3%) seasons. This seasonal distribution shows that less water will be needed for C assimilation in the spring and fall seasons even with an overall predicted decline in WUE on an annual scale.

4.5 DISCUSSION

4.5.1 Important interactions and feedbacks under future climate predictions

The mid-century simulations of biophysical conditions and C fluxes with CoupModel in Beverly Swamp, a mixed wood swamp with a shallow peat layer in Southern Ontario supported our hypotheses that changes in the swamp's future climatic conditions would affect important interactions and feedbacks in the swamp's C cycle and hydrological conditions. Warmer mean air temperature ($4.3 \pm 0.8 \text{ }^\circ\text{C}$) by 2050s raised daily average VPD of the swamp area by 18%. This VPD prediction is in line with the Clausius-Clapeyron relationship that suggests that higher atmospheric temperature will increase saturated vapor pressure (Massmann et al., 2019), thus expanding the gradient between atmospheric and saturated vapor pressure around

the peatland. Higher VPD affected critical hydrological fluxes such as ET that are important for maintaining the peatland's carbon balance (Helbig et al., 2020). Rising VPD over the simulation period triggered an increase in ET of a similar magnitude. This forecast is consistent with VPD and ET estimates for peatlands in Canada (Helbig et al., 2020) and in particular, our ET estimates are similar to the projections of (Grillakis et al., 2011; Sultana & Coulibaly, 2011) for the Beverly Swamp area by 2050s. However, a decoupling of VPD and ET was observed during the summer and fall seasons by midcentury (*Section 3.3*). For instance, even though VPD increased (+13 %) during summer peak (August), ET responded with a decline (-6%) for the same period. This difference can be linked to moisture limitations for ET processes during summer when the swamp's water table drawdown goes beyond the main rooting zone (30 cm – 40 cm) where plants access water for transpiration (Munro et al., 2000). In addition, excessive VPD values during summer have been reported to trigger increased stomata resistance that reduces water transfer to the atmosphere in the form of ET (Schönbeck et al., 2022). This plant physiological response reduces water stress, and it is important for water availability in the swamp because plant transpiration is a major water balance component of the swamp (Afolabi et al., see chapter 2)

Even though ET water loss in Beverly Swamp is predicted by CoupModel to spike by 2050s, a predicted similar increase (+11 ± 4%) in annual precipitation may balance this water loss. However, the projected seasonal distribution of precipitation does not coincide with peak ET summer rates when water is required for many biochemical processes in the swamp (e.g., photosynthesis). The highest precipitation increase is expected to occur in winter (65%) and spring (35%) seasons where minimal plant productivity and respiration processes that balance the swamp's C flux transpire. Instead, precipitation rates are expected to decline by 14% in summer with daily mean rate of 2.5 mm/day by midcentury, while predicted ET rate will be 4.3 mm/day even with 4% decline over the study period. This difference shows that a water deficit is expected as these two variables represent the major water balance components of the swamp. There is the possibility that the contributions of other water balance components such as lateral water inputs from streams feeding and draining the swamp (McCarter et al., 2024;

Woo & Valverde, 1981) may make up for this component. However, because the contribution of the lateral flow input is small (~ 0.86 mm/day) (Afolabi et al., see chapter 3) and high ET predictions of the catchment area is also expected to affect the streams, it is unlikely that water loss during the summer months will be matched with water input. In addition, the predictions of shallower snowpack and early snowmelt in the swamp will hasten the loss of this water source to ET. Consequently, these changes to the swamp's water balance components were reflected in the shift of the water table from 11 cm below the surface to 23 cm by 2050s accompanied by a reduction in mean annual soil VMC from 70% to 60%. These hydrological changes led to predicted shifts in the swamp's vegetative productivity and carbon loss in the form ecosystem respiration.

4.5.2 Beverly Swamp's carbon balance under future climate predictions

The predicted changes in the swamp's hydrological components and thermal regimes also reflected in its CO₂ balance. The increase (+4%) in GPP rate over the study period can be attributed to warmer and drier conditions (Table 4-1). Warmer climatic conditions have been reported by experimental and paleoclimatic studies to prolong growing season (Gallego-Sala et al., 2018; Helbig et al., 2019a; Polgar & Primack, 2011), speed up carboxylation rates and electron transport in plants (Farquhar et al., 1980; Medlyn et al., 2002; von Buttlar et al., 2018) and also increase the growth of specific plant organs (e.g., roots, stems) in peatlands (Lindborg et al., 2021). Even though the GPP of Beverly Swamp followed an increasing trend by midcentury, summer GPP rate at peak plant growth was marked with a decline (-14%). This change can be attributed to moisture deficit during summer with deeper water table level (-46cm) and lower soil moisture contents. Moisture deficit triggers partial stomata closure and lower carboxylation rate in plant, thus reducing carbon assimilate during very dry conditions and high vapor pressure deficit (Fu et al., 2022). Canopy ET is known to aid local cooling (Bonan, 2008), thus, the predicted ET decline (-4%) and reduction in its corresponding cooling during growing season may also have exacerbated plant stress and contributed to lower GPP rate during this period. Despite the summer decline in GPP rates over the study period, the increasing trend simulated by CoupModel compensated for it with an increase in spring (+36

%) and (+23 %) autumn seasons. These seasonal changes in GPP rate reflected the swamp's modification to its phenological strategy under changing climate and how future hydrological adjustments affected this biological process. A thinner simulated snowpack and warmer spring season encouraged the early release of moisture for photosynthesis, while warmer conditions in autumn prolonged the growing season. Ultimately, these changes increased the annual C assimilation rate of the swamp.

Although the swamp's C uptake rose over the simulated period, carbon loss through ecosystem respiration (autotrophic and heterotrophic) increased at a faster rate with a 30% rise by the 2050s (Table 4-1). High vegetative productivity comes along with increases in litter inputs for decomposition and more root respiration (Lindborg et al., 2021). The addition of C efflux from older recalcitrant organic matter of the swamp also contributed to more positive climate feedback by midcentury. This result is not unprecedented because warmer temperature speeds up microbial breakdown of organic matter and therefore warmer soils increased heterotrophic respiration (Davidson & Janssens, 2006). Although ecosystem respiration (Reco) increased over the simulated period, a decline was observed at the peak of summer (August) even with air temperature of 24 °C and 5 cm soil temperature of 20 °C. This decline can be attributed to moisture limitation that affected heterotrophic respiration during this period. Insufficient soil moisture may affect solute transport, rhizosphere deposition, macrofauna community activity and also disrupt microbial activities, as the biochemical processes of these biotic components require moisture (Reichstein & Beer, 2008). The extensive increase in Reco during the spring (72%) and autumn (23%) seasons significantly contributed to the rising trend observed annually in the swamp. Rising R_{eco} trend by 2050s during spring can be linked to warmer soil layers, less snow accumulation and early snowmelt that also coincided with early onset of ET that created drier conditions during this period. These findings are consistent with previous studies on the swamp (Davidson et al., 2019) that reported faster peat mineralization under warmer and drier conditions.

The balance between the swamp's C assimilation (GPP) and loss (Reco) that is represented by net ecosystem exchange (NEE) had a trend of declining net CO₂ uptake over the study period.

This diminished C uptake capability of the swamp is linked to the spike in R_{eco} and moderate increase in GPP by 2050s. The C balance offset was particularly strong during summer with NEE dropping by 63%. This signifies rapid reduction in net CO₂ uptake in the swamp by midcentury but with the peatland still maintaining its net C sink role. These findings agree with global and regional projection (end of century) of reduced C uptake by northern peatlands under a high emission scenario (RCP 8.5) (Qiu et al., 2020). However, the declining trend of our WUE estimate into the future is different from the projections of other studies (e.g Keenan et al., 2013)). It is possible that the inclusion of rising CO₂ concentration in the modelling experiment may have reversed the direction of our simulated WUE (Pan et al., 2018).

4.5.3 Important study assumptions and limitations

Even though the midcentury simulations of this study have provided valuable understanding of future peatland-C cycle processes in the temperate region, we also acknowledge that the predictions are not without limitations. Uncertainties embedded in climate predictions (Hawkins & Sutton, 2009; Palmer & Stevens, 2019) and the post-processing approach (Maraun et al., 2017) adopted for the forcing variables may have cascaded into the modelling process of this study. However, we expect that the adoption of a multi-model ensemble of climatic variables should help reduce some of the uncertainties from climate predictions. Additional uncertainty may have originated from the atmospheric CO₂ concentration used for this study, as this modelling experiment was based on the default atmospheric CO₂ concentration (354ppm) of CoupModel (Jansson & Karlberg, 2004). Rising atmospheric CO₂ concentration, i.e., CO₂ fertilization is expected to affect GPP and transpiration rates of forested ecosystems (Medlyn et al., 2011) but this was not considered for the study. Because constant nitrogen concentration was used for this study, nitrogen deposition through transboundary nitrogen transport was not captured in this modelling experiment. Nitrogen enrichment has been reported to accelerate biological processes in forested ecosystems of southern Ontario (Watmough, 2010).

Ecosystem response to climate change may also involve successional shifts in plant community composition (Tonkin et al., 2018). Based on previous multidecadal canopy projections of

Beverly Swamp (Welch, 1985), our study assumed that the swamp will maintain the same canopy composition over the simulated period. However, future disturbances or other unforeseen conditions may affect the swamp's canopy composition, thus altering its biophysical and biogeochemical conditions. Our modelling experiment also relied on constant lateral water input even though this may change in the future. We do not expect the future changes in lateral water input to significantly affect our C flux modelling outcomes because the sensitivity analysis of Afolabi et al. (see chapter 2) demonstrated that the swamp's C flux was not really affected when this parameter was varied by $\pm 10\%$, $\pm 25\%$ and $\pm 50\%$. Even though previous studies (e.g., Grillakis et al., 2011) have shown that air temperature and precipitation are the main hydrological drivers of the catchment (Spencer) where Beverly Swamp is located, it is also possible that the inclusion of future predictions of additional forcing variables (wind speed, global radiation and relative humidity) may have affected the outcomes of the study. Furthermore, we did not consider the roles of methane (CH_4) and dissolved organic carbon (DOC) that may also affect the future C balance of this ecosystem. Drier conditions in summer may reduce CH_4 emissions (Davidson et al., 2019), while less snowpack during the spring season may disrupt DOC losses from the swamp (Warren et al., 2001)

4.6 CONCLUSION

The forcing of a calibrated swamp peatland model (CoupModel) with climate predictions by this study is important for improving our understanding of the future role of swamp peatlands in regional terrestrial C and water cycles. Simulation of critical interactions and feedback between the swamp's thermal and hydrological conditions and the C cycle demonstrated that changes in climatic conditions have a strong constraint on future forested peatland C and water balance. The increasing trend for ET, an important water balance component of the swamp contributed to drier conditions by 2050s, but the magnitude was dampened by distinct ecohydrological responses. High ET rate with moderate GPP increase ensured that the swamp's C assimilation rate was less water efficient by midcentury. Drier conditions with high ET rate also spiked C loss through Reco from the swamp, thus producing a positive climate feedback. Consequently, the swamp's net C uptake dwindled by the 2050s but it still

maintained its net C sink role. This modelling experiment produced a future outlook of the complex interactions and feedbacks that are expected in temperate forested peatlands. We anticipate that these findings will help inform water and C management practices that are required to maintain the swamp's C storage functions even under a changing climate by midcentury.

Chapter 5. Conclusions, Research Significance, Study Limitations and Future Research Needs

5.1 STUDY CONCLUSIONS

This 78-year (1983–2060) simulation of biophysical conditions and C flux at Beverly Swamp is one of the few multidecadal modelling studies on temperate swamp peatlands. The historic (1983–2023) simulations validated existing field measurement findings that plant processes and thermal and hydrologic conditions are important controls on the C dynamics of temperate swamps even on a long-term basis. CoupModel reliably simulated important biophysical conditions in the swamp and the swamp's C cycle processes, thus suggesting that the process-based model is well adapted to diverse peatland ecosystems, including swamps (Objective i, Chapter 2). This research also demonstrated that the swamp wetland class is an important contributor to temperate peatland C cycle as the swamp maintained its net C sink status ($-704 \pm 268 \text{ g C m}^{-2} \text{ y}^{-1}$) for the simulation period even with rising soil respiration ($\sim 13\%$ per decade) and less negative NEE values in response to warming soils during the historic period simulation (1983–2023). The maintenance of a net C sink was made possible by increased GPP rates (1% per decade) that offset some of the C losses by soil respiration. However, some of these dynamics changed by mid-century (2050s) when CoupModel was forced with future climate predictions under SSP5 pathway.

Midcentury simulation of critical interactions and feedback between the swamp's thermal and hydrological conditions and the C cycle demonstrated that changes in climatic conditions have a strong constraint on future forested peatland C and water balance (Objective iii, Chapter 4). A trend of increasing ET, an important water balance component of the swamp, contributed to drier conditions by 2050s, but the magnitude was dampened by distinct ecohydrological responses. High ET rate with moderate GPP increase ensured that the swamp's C assimilation rate was less water efficient by midcentury. Drier conditions with high ET rate also resulted in greater C loss through ecosystem respiration from the swamp, thus producing a positive climate feedback. Consequently, the swamp's net C uptake dwindled by the 2050s, but it still

maintained its net C sink for most of the years. These results accentuate how seasonal shifts in biophysical conditions (e.g., precipitation and ET) under changing climate can significantly affect the water and C cycles in temperate swamps (Objective iii, Chapter 4). Overall, the modelling experiment produced a future outlook of the complex interactions and feedbacks that are expected to drive the response of C cycling in temperate forested peatlands in response to a warming climate. It is anticipated that these findings will help inform water and C management practices that are required to maintain the swamp's C storage functions even under a changing climate by midcentury.

For this modeling experiment at Beverly Swamp, large knowledge gaps on temperate swamps cumulated into substantial uncertainties in estimating the water, energy and C fluxes of this ecosystem. However, the adoption of the Generalized Likelihood Uncertainty Estimation (GLUE) approach for uncertainty analysis assisted in achieving multiple objectives of identifying important ecohydrological processes in temperate swamps, systematically calibrating CoupModel for Beverly Swamp, improving the model performance in simulating C flux and its associated controls, and ultimately reducing the uncertainties of the modelling process (Objective ii, Chapter 3). Uncertainty analysis is an important aspect of modelling experiments because it determines the usefulness of the modelling outcomes and the transferability of the modelling components (e.g., structure and parameters) to other temperate swamps. Therefore, the results of this study will inform model structure selection and parameterization of large-scale ecological models (e.g., CLASSIC and CaMP) when simulating swamp C flux at regional and global scales. Some of the important parameters and soil respiration constraining variables that were identified in this study, including water table level, soil volumetric moisture content, and leaf area index, will help inform the choice of variables to be measured in the field for C related studies. Furthermore, the lateral water flow variation experiment may also guide relevant authorities (e.g., conservation authorities) on the best approach for managing flow regulation into Beverly Swamp and similar systems towards preserving the swamp's C stocks. This is important for future planning where climate change risk may affect the hydrological and thermal conditions of the swamp, and its C balance.

5.2 STUDY LIMITATIONS

5.2.1 Important study limitations of uncertainty analysis with GLUE

Although the GLUE approach assisted in reducing the uncertainty associated with the C flux modelling experiment at Beverly Swamp, the study is not without limitations. The uncertainty approach adopted for this study is heavily dependent on multiple variable constraints, therefore shortage of long-term field measurements for calibration and validation in some of the variables may have affected the analysis (See Chapter 3 for details). Additional measurements to support estimation of important parameters, such as growth respiration of swamp vegetation, may further reduce parameter uncertainty in the modelling process. Therefore, the outcome of this uncertainty analysis may change if these conditions are altered. Also, because the model structure selected for the simulation of water fluxes, energy balance and C flux components in CoupModel is based on theoretical knowledge of swamp biophysical processes and experience from existing studies, there is some level of subjectiveness in selecting the appropriate model structure and constraints for the study. However, increased understanding of swamp processes and availability of additional measurements for testing the model's structure will assist in reducing the uncertainty associated with this modelling component. (See Chapter 3 for details)

5.2.2 Important study limitations of future projection of Beverly Swamp C exchange

Even though the midcentury simulations of this study have provided valuable understanding of future peatland-C cycle processes in the temperate region, the research also acknowledges that the predictions are not without limitations. Uncertainties embedded in climate predictions (Hawkins & Sutton, 2009; Palmer & Stevens, 2019) and the post-processing approach (Maraun et al., 2017) adopted for the forcing variables may have cascaded into the modelling process of this study. However, it is expected that the adoption of a multi-model ensemble of climatic variables should help reduce some of the uncertainties from climate predictions. Additional uncertainty may have originated from the atmospheric CO₂ concentration used for this study, as this modelling experiment was based on CoupModel's default atmospheric CO₂ concentration parameter of 354 ppm. Rising atmospheric CO₂ concentration, i.e., CO₂

fertilization, is expected to affect GPP and transpiration rates of forested ecosystems (Medlyn et al., 2011) but this was not included in this experiment. Further, because constant nitrogen concentration was used for this study, nitrogen deposition through transboundary nitrogen transport was not captured in this modelling experiment. Nitrogen enrichment has been reported to accelerate biological processes in forested ecosystems of southern Ontario (Watmough, 2010).

Ecosystem response to climate change may also involve successional shifts in plant community composition (Tonkins et al., 2018). Based on previous multidecadal canopy projections of Beverly Swamp (Welch, 1985), this study assumed that the swamp would maintain the same canopy composition over the simulated period. However, future disturbances or other unforeseen conditions may affect the swamp's canopy composition, thus altering its biophysical and biogeochemical conditions. This modelling experiment also relied on constant lateral water input even though this may change in the future. The study does not expect the future changes in lateral water input to significantly affect our C flux modelling outcomes because the sensitivity analysis of Chapter 3 demonstrated that the swamp's C flux was largely unaffected when this parameter was varied by $\pm 10\%$, $\pm 25\%$ and $\pm 50\%$. Even though previous studies (e.g., Grillakis et al., 2011) have shown that air temperature and precipitation are the main hydrological drivers of the catchment (Spencer) where Beverly Swamp is located, it is also possible that the inclusion of future predictions for additional forcing variables (e.g., wind speed, global radiation and relative humidity) may have affected the outcomes of the study.

5.3 Future research needs for temperate swamp carbon exchange

Based on the highlighted limitations above, undertaking further research on the following areas will improve our understanding of the C flux dynamics and biophysical conditions at Beverly Swamp and other temperate swamps:

- i. **Maintaining long-term ecological research sites.** Even though this modelling experiment would not have been possible without access to historical datasets, the modelling outcome would have improved if relevant variables had been measured

continuously throughout the study period. In particular, high resolution multi-decade field measurements of C cycle components including Reco, GPP and NEE will help to better constraint the modelling process and improve our understanding of the ecosystem under a changing climate. Also, the installation of a gauging station at the entrance of the swamp for estimating lateral influx and the effect of Valens dam on the swamp will also improve data availability for the modelling the water balance components of the swamp. Additional measurements to support estimation of important parameters such as soil water retention, growth respiration of swamp vegetation, and decomposition rates of litter and humus alongside access to local measurements of long-term forcing variables (e.g., global radiation) will assist in reducing the uncertainties that were associated with the modelling exercise.

- ii. **Measurement and simulation of other C balance components (e.g. CH₄ and fluvial carbon input and output).** Because this study is focused on CO₂ flux, it is also important to investigate how other C balance components such as methane flux (CH₄) and net dissolved organic carbon (DOC) export will contribute to the C dynamics of temperate swamps. Therefore, continuous measurements of these variables and their adoption in modelling experiments is highly recommended.
- iii. **Other modelling considerations.** It is important for future studies to explore the effect of important biogeochemical alterations (e.g., nitrogen and carbon fertilization) on the swamp's C dynamics because some studies (see section 5.2) have shown that these processes can influence C and water fluxes in forested ecosystems. Furthermore, it is possible that the coupling of a spatially distributed component to CoupModel will better represent some of the spatial variation in hydrology and C cycling that are unique to the swamp. However, this may also introduce more uncertainties into the modelling process. In addition, there is the need for future studies to test alternative model structures that may capture better the biophysical conditions and C flux dynamics of

the studied swamp, especially for the C flux and hydrological components (WTL and VMC).

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APPENDICES

Appendix 2-1 (ST1) Beverly Swamp Site Characteristics

	Value	Source
<i>Location and Meteorological variables</i>		
Lat, Lon	43.36N, 80.11W	(Munro, 1979)
Swamp size	~20 km ²	(Hamilton Conservation Authority, 2020a; Munro, 1979)
Altitude	265-270 m	(McCarter et al., 2024)
Mean Annual temp	7.6°C	(Environment Canada, 2024)
Mean Annual Precipitation	973 mm	(Environment Canada, 2024)
Mean Annual Evaporation	554-752 mm	(Valverde, 1978; M. Woo & Valverde, 1981)
Plant characteristics		
Major tree species (mixed forest)	silver maple (<i>Acer saccharinum</i>), red maple (<i>Acer rubrum</i>) white cedar (<i>Cedar occidentalis</i>), birch (<i>Betula papyrifera</i>), black ash (<i>Fraxinus nigra</i>), aspen (<i>Populus tremuloides</i>), elm (<i>Ulmus americana</i>), alder (<i>Alnus rugosa</i>)	(Hamilton Conservation Authority, 2020a; Thambipillai, 1998; Welch, 1985)
Ground understory vegetation	Fens and Sedges	(Welch, 1985)
Average stand age in 1980	40-52 yrs	(Hamilton Conservation Authority, 2020a; Welch, 1985)
Average-Max canopy height	5.22-10 m	(Hamilton Conservation Authority, 2020a; Munro et al., 2000; Thambipillai, 1998)
Root depth	0.3 – 0.4 m	(Hamilton Conservation Authority, 2020a; Munro et al., 2000; Thambipillai, 1998)
Leaf Area Index (LAI)	5 to 6	(Hamilton Conservation Authority, 2020a; Thambipillai, 1998)
Stand density	6317-8125 trees/ha	(Hamilton Conservation Authority, 2020a; Thambipillai, 1998; Welch, 1985)
Basal area	25-52 m ² /ha	Welch, 1985; HCA (2021)
Average litter C/N ratio	30-93	Santia et al. (2023) & Wang et al. (2015)
Average veg C/N ratio	45.6	Wang et al. (2015)
Microbe C/N ration	6-7	Wang et al. (2015)
Plant C (1979- 1987)	~ 9009 gC m ⁻²	Welch (1985); Munro (1989); Munro et al (2000)

Foliage C	1171.17 gC m ⁻²	Welch (1985)
Stem C	6936.93 gCm ⁻²	Welch (1985)
Root C	900.9 gC m ⁻² yr ⁻¹	Welch (1985)
Net Primary Productivity	~1145 gC m ⁻² yr ⁻¹	Welch (1985)
Litter production	250-350 g m ⁻² yr ⁻¹	Welch (1985)
Leaf longevity	0.45-8.9 years	Kanda et al (1996) & Withington et al (2006)
<i>Phenology</i>		
Leaf emergence day	145	Thambipillai (1998)
Leaf emergence temp	5 °C	Thambipillai (1998)
Optimum day number	167	Thambipillai (1998)
Litterfall commencement	270	Thambipillai (1998)
Canopy extinction value	0.33-0.7	Thambipillai (1998)
<i>Soil variables</i>		
Soil type	Sapric peat	Munro et al (2000)
peat depth	~85 (cm)	Munro et al (2000); Valverde (1978); Woo & Valverde (1981)
Soil pH	6.0 - 7.7	Spencer (1991)
Soil pore volume	80-85 vol%	Czerneda (1985); Munro (1982); Munro, 1984 & Munro et al., 2000
Soil bulk density	0.18-0.22 g cm ⁻³	Czerneda (1985); Munro (1982); Munro (1984); Waddington et al. (Unpublished data)
Total soil C content in upper 50 cm	37894 ± 14854 gC m ⁻²	Waddington et al. (Unpublished data, 1998); McCarter et al. (2024)
Total soil C content in top 150 cm	16600 ± 6400 gC m ⁻² to 106800 ± 2800 gC m ⁻²	Waddington et al. (Unpublished data); McCarter et al. (2024)
Soil C/N ratio	18-26	DeSimone (2009); Cools et al (2014)*; Webster et al. (2014); Wang et al. (2015)
Soil nitrate	0.43-7.41 g NO ₃ -N gsoil ⁻¹	DeSimone (2009)

* Estimate from Cools et al. (2014) is based on the characterization of Beverly Swamp soil as Sapric, while ± signifies the standard deviation

Appendix 2-2: Detailed model design, structure and equations in CoupModel

1. Soil surface energy balance

Energy balance is important to land surface exchanges in CoupModel. In computing the energy fluxes, total net radiation ($R_{n,tot}$) was calculated from net longwave radiation and shortwave incoming radiation R_{is} . $LWin$ was estimated from meteorological measurements using Konzelmann et al. (1994) function, while R_{is} is one of the driving variables of the model. The fluxes were partitioned in CoupModel according to the surface energy balance (eq.A1),

$$\underbrace{\underbrace{\sigma(\varepsilon_s(T_s + 273.15)^4)}_{LW_{out}} - \underbrace{\varepsilon_a(T_a + 273.15)^4}_d}_{R_{n,tot}} + (1 - a_r)R_{is} = H + LE + q_h + \frac{dF}{dt} \quad (eq. A1)$$

where LW_{out} is the longwave radiation emitted from the ground calculated by using simulated temperature of soil surface, T_s with consideration of snow surface temperatures in winter. $LWin$ represents the incoming longwave radiation from the atmosphere which is based on measured air temperature, T_a (forcing variable). σ is the Stefan-Boltzmann constant and is the ε_s emissivity of the ground. Atmospheric emissivity ε_a is estimated from Konzelmann et al (1994) function. The surface albedo of ground a_r was simulated by considering the dynamic area cover of peat soil and snow. Peat soil albedo was set to 7% as measured by Munro et al. (2010). The snow approach used in the study follows Gustafsson et al. (2001) where snow albedo was assumed to be a function of snow age with 90% for newly formed snow which decreased to 40% c.a. 1 month time. CoupModel partitioned $R_{n,tot}$ into latent (LE), sensible (H) and soil heat flux (q_h) fluxes respectively. Change energy storage (dF/dt) within the measured reference height ($Z_{ref}= 1.5m$) and soil surface was assumed to be zero in the study.

The model calculated H and LE between the soil surface and reference level of meteorological inputs from gradients of temperature and vapour pressure respectively

$$H_s = \rho_a c_p \frac{T_s - T_a}{r_{as}} \quad (eq. A2)$$

$$LE = \frac{\rho_a c_p}{\gamma} \frac{(e_{surf} - e_a)}{r_{as}} \quad (eq. A3)$$

$$q_h = k_h \frac{T_s - T_l}{\frac{\Delta z_l}{2}} \quad (eq. A4)$$

Where ρ_a is the soil density, c_p is the air heat capacity, γ is the psychrometric constant, e_{surf} is the vapour pressure of the soil surface, e_a is the actual vapour pressure of the atmosphere (forcing variable), aerodynamic resistance above the soil surface r_{as} which was assumed to be the same for sensible and latent heat flux. Under neutral conditions, r_{as} (eqs. 2 & 3) was calculated as a function of wind speed and temperature gradients,

$$r_{as} = \frac{1}{k^2 u} \ln \left(\frac{z_{ref}-d}{z_{OM}} \right) \ln \left(\frac{z_{ref}-d}{z_{OH}} \right) \quad (\text{eq. A5})$$

Where measured wind speed, u (forcing variable) was given at the reference height, k (=0.4) is von Karman's constant, d is the displacement height ($d=0$), z_{OM} and z_{OH} are the roughness length for momentum and heat respectively. Under non-neutral conditions, eq. (A5) was further corrected with the Monin-Obukhov stability function (Beljaars and Holtslag 1991). This involves a dimensionless factor kB^{-1} . In this study, $kB^{-1} = 2.3$ was obtained from the synthesized value from available measured peatland data (Humphreys et al., 2006)

Alvenas and Jansson (1997) scheme was used to account for the non-equilibrium effects of rapid moisture fluctuations close to the soil surface. This was done by modifying e_{surf} by an available factor that is driven by soil moisture availability (eq. A7) calculated by water balance at the first soil layer (eq. A8)

$$e_{surf} = e(T_s) * \exp \left(\frac{\psi M w g e_c}{R(T_s + 273.15)} \right) \quad (\text{eq. A6})$$

$$e_c = 10^{(-\delta \psi_g)} \quad (\text{eq. A7})$$

$$\delta_s(t) = \max(-2, \min(1, \delta_s(t-1) + (P - E)\Delta t)) \quad (\text{eq. A8})$$

Where $e(T_s)^*$ is the saturated vapor pressure at the surface temperature T_s , ψ is the mean soil water potential in the topsoil layer, g is the gravity constant, and R is the gas constant, e_c is an empirical correction factor that compensates for the differences between the mean soil moisture potential in the top-soil layer and the soil moisture potential at the surface, defined as eq. (A7), eq. (A8) calculates the water balance and was assumed to vary from a deficient of -2mm to a surplus of +1mm at one timestep t , where δ_s and ψ_g are parameters.

2. Soil temperature

Soil heat flux q_h in eq. (A1) was further used to calculate the soil temperature profile by considering heat conduction and convection flow (eqs. A9-A11),

$$q_h = -k_h \frac{\partial T_s}{\partial z} + C_w T_s q_w \quad (\text{eq. A9})$$

$$k_h = h_1 + h_2 \Theta \quad (\text{eq. A10})$$

$$\frac{\partial (CT)}{\partial t} - L_f \rho \frac{\partial \theta_i}{\partial t} = \frac{\partial}{\partial z} (-q_h) \quad (\text{eq. A11})$$

Where dT/dz is the gradient of soil temperature with depth, k_h is the thermal conductivity of peat soil calculated by an empirical approach of de Vries (1975), assuming proportional to the soil water content, Θ and h_1 and h_2 are parameters (eq. 10). The subscript h in eq. (A9) is heat, w is liquid water, i and f in eq. (A11) refer to ice and freezing respectively, t is time, C is heat capacity, L_f is latent heat of melting. In this study model default values were used for the snow and soil frost modules.

3. Soil water flow

The soil water process (eqs. A12-A13) was described based on the matrix flow and bypass flow,

$$q_w = -k_w \left(\frac{\partial \psi}{\partial z} - 1 \right) + q_{\text{bypass}} \quad (\text{eq. A12})$$

$$\frac{\partial \theta}{\partial t} = - \frac{\partial q_w}{\partial z} \quad (\text{eq. A13})$$

Where q_w is the water flow flux, k_w is the unsaturated hydraulic conductivity, ψ is the water tension/potential and q_{bypass} is the bypass flow.

The soil water retention curve was based on the van Genuchten (1980) approach

$$S_e = \frac{1}{(1 + (\alpha \psi)^n)^m} = \frac{\theta - \theta_r}{\theta_s - \theta_r} \quad (\text{eq. A14})$$

Where S_e is the effective saturated water content, α , n , m are van Genuchten parameters ($m=1-1/n$), θ_r is the residual water content, θ_s is the saturated water content.

The (un)saturated hydraulic conductivity was calculated by Mualem (1976) and modified to consider macropores (pp 63-68 in Jansson and Karlberg, 2011)

$$k_w^* = k_{\text{mat}} S_e^{(n+2+\frac{2}{\lambda})} \quad (\text{eq. A15})$$

$$k_{\text{mat}} = 10^{((\log k_{\text{sat}} - \log h_{\text{com}}) h_{\text{sens}} + \log k_{\text{sat}})} \quad (\text{eq. A16})$$

$$k_w^{**} = 10^{\left(\log(k_w^* (\theta_s - \theta_m)) + \frac{\theta - \theta_s + \theta_m}{\theta_m} \log\left(\frac{k_{\text{sat}}}{k_w^* (\theta_s - \theta_m)}\right)\right)} \quad (\text{eq. A17})$$

$$k_w = (r_{\text{AOT}} + r_{\text{AIT}} T_s) \max(k_w^{**}, k_{\text{minus}}) \quad (\text{eq. A18})$$

Where (eqs. A15-A16) accounts for the matric pores, k_w^* is the unsaturated hydraulic conductivity, k_{mat} is the saturated matrix conductivity, h_{com} and h_{sens} are parameters. The (eq. A17) additionally accounts for the conductivity in macropores, θ_m is the water content at which the macropore water flow occurs, k_{sat} is the saturated total hydraulic conductivity and $k_w^* (\theta_s - \theta_m)$ is the unsaturated hydraulic conductivity calculated by eq. (A15), the effects of temperature on hydraulic conductivity were calculated by eq. (A18), r_{AOT} and r_{AIT} are scaled parameters for temperature, k_{minus} is the minimum hydraulic conductivity parameter.

The bypass flow (eqs. A19-A21) was calculated by an empirical approach (Jansson et al., 2005)

$$q_{\text{bypass}} = \begin{cases} 0 & 0 < q_{\text{in}} < S_{\text{mat}} \\ q_{\text{in}} - q_{\text{mat}} & q_{\text{in}} \geq S_{\text{mat}} \end{cases} \quad (\text{eq. A19})$$

$$q_{\text{mat}} = \begin{cases} \max\left(k_w(\theta) \left(\frac{\partial \psi}{\partial z} + 1\right), q_{\text{in}}\right) & 0 < q_{\text{in}} < S_{\text{mat}} \\ S_{\text{mat}} & q_{\text{in}} \geq S_{\text{mat}} \end{cases} \quad (\text{eq. A20})$$

$$S_{\text{mat}} = a_{\text{scale}} a_r k_{\text{mat}} pF \quad (\text{eq. A21})$$

Where q_{in} is the infiltration rate, S_{mat} is the sorption capacity rate, k_{mat} is the maximum conductivity of the matric pores, a_r is the compartment thickness (for each layer), pF is $10^{\log}$ of the water tension ψ and a_{scale} is the sorption scaling coefficient.

The lateral flow across the swamp was calculated by Darcy-type function (He et al., 2021),

$$q_{\text{wp}} = \int_{z_p}^{z_{\text{sat}}} k_{\text{sat}} \frac{(z_{\text{sat}} - z_p)}{d_u d_p} dz \quad (\text{eq. A22})$$

Where q_{wp} is the horizontal flow rate, d_u is the unit length of the horizontal element, z_{sat} is the simulated depth of the groundwater level, k_{sat} is the saturated hydraulic conductivity of each soil layer including macropores, d_p is the distance between drainage pipes, z_p is the level of drainage pipes.

During over-saturated periods (e.g. snowmelt and heavy rainfall), the flow of water in the upper soil layer can be directed upwards and added to the surface runoff to drainage pipes. The model formed a pool of water on the soil surface when precipitation exceeded the infiltration capacity of the first soil layer. Water in the surface pool could either infiltrate with a delay into the soil profile or be lost as surface runoff, as overland flow. The flow was regulated by a first-order runoff coefficient (eq. A21)

4. Plant biotic processes

Canopy photosynthetic rate and C assimilation was estimated by light use efficiency approach,

$$C_{atm \rightarrow a} = \varepsilon_l \eta f(T_l) f(CN_l) f\left(\frac{E_{ta}}{E_{tp}}\right) R_{s,pl} \quad (eq. A23)$$

Where rate of photosynthesis ($\text{g C m}^{-2} \text{ day}^{-1}$), $C_{atm \rightarrow a}$ is a function of global radiation absorbed by the swamp's canopy $R_{s,pl}$ but ultimately this is constrained by unfavorable temperature $f(T_l)$, nitrogen $f(CN_l)$, and water $f\left(\frac{E_{ta}}{E_{tp}}\right)$ conditions. ε_l is the radiation use efficiency and η is the conversion factor from biomass to carbon

where ε_L is the radiation use efficiency and η is the conversion factor from biomass to carbon. $R_{s,pt}$ is the global radiation absorbed by canopy and $f(T_l)$, $f(CN_l)$, and $f(E_{ta}/E_{tp})$ limitations due to unfavourable temperature, nitrogen, and water conditions.

Response function for leaf temperature $f(T_l)$

$$f(T_l) = \begin{cases} 0 & T_l < p_{\max} \\ (T_l - p_{\min})/(p_{o1} - p_{\max}) & p_{\max} \leq T_l \leq p_{o1} \\ 1 & p_{o1} < T_l < p_{o2} \\ 1 - (T_l - p_{o2})/(p_{\max} - p_{o2}) & p_{o2} \leq T_l \leq p_{\max} \\ 0 & T_l > p_{\max} \end{cases} \quad (eq. A24)$$

where $p_{\min}$, p_{o1} , p_{o2} and $p_{\max}$ are parameters and T_l the leaf temperature.

Response function for fixed leaf C:N ratio $f(CN_l)$

$$f(CN_l) = p_{\text{fixedN}} \quad (eq. A25)$$

Where p_{fixedN} is a parameter.

Response function for transpiration $f(E_{ta}/E_{tp})$

$$f(E_{ta}/E_{tp}) = \frac{E_{ta}}{E_{tp}} \quad (eq. A26) \quad \text{where } E_{ta} \text{ and } E_{tp} \text{ are actual and potential transpiration}$$

Allocation of new assimilates to the leaves $C_{a \rightarrow \text{Leaf}}$

$$C_{a \rightarrow \text{Leaf}} = l_{c1} \cdot C_a \quad (\text{eq. A27}) \quad \text{where } l_{c1}, \text{ is a parameter and } C_a \text{ is the new assimilated carbon}$$

Allocation of new assimilates to the roots $C_{a \rightarrow \text{Root}}$

$$C_{a \rightarrow \text{Root}} = (1 - l_{c1}) \cdot C_a \quad (\text{eq. A28}) \quad \text{where } l_{c1}, \text{ is a parameter and } C_a \text{ the new assimilated carbon.}$$

The plant growth and maintenance respiration processes ($\text{g C m}^{-2} \text{ day}^{-1}$) are estimate by

$$C_{\text{respleaf}} = k_{\text{mrespleaf}} \cdot f(T_a) \cdot C_{\text{leaf}} + k_{\text{gresp}} \cdot C_{a \rightarrow \text{Leaf}} \quad (\text{eq. A29})$$

Where $k_{\text{mrespleaf}}$ is the maintenance coefficient for leaves, k_{gresp} is the growth respiration coefficient, $f(T_a)$ is the temperature response, $C_{a \rightarrow \text{Leaf}}$ is the carbon allocation to leaf and C_{leaf} is the carbon content of leaf. Similar methods were used for stem and root respiration estimates. In this case, the equation calculates respiration from stem and roots by substituting $k_{\text{mrespleaf}}$ with $k_{\text{mrespstem}}$, & k_{mrespoot} and using the corresponding storage pools. Respiration from the old carbon pools is estimated with the same maintenance respiration coefficients that is used for respiration from new carbon pools.

Temperature response for maintenance respiration

$$f(T) = t_{Q10}^{(T-t_{Q10}^{\text{lose}})/10} \quad (\text{eq. A30}) \quad \text{where } t_{Q10} \text{ and } t_{Q10 \text{ bas}} \text{ are parameters.}$$

Reallocation of C from leaf pool to stem pool. It is represented here as pool for senescent leaves

$$C_{\text{Leaf} \rightarrow \text{Sem}} = l_{LS} \cdot C_{\text{Leaf}} \text{ where } l_{LS} \text{ is a parameter and } C_{\text{Leaf}} \text{ the carbon in the leaf pool.}$$

Leaf C entering the surface litter pool

$$C_{\text{Leaf} \rightarrow \text{LitterSurface}} = f(T_{\text{Sum}}) \cdot f(A_l) \cdot S_{\text{newleaf}} \cdot C_{\text{Leaf}} \quad (\text{eq. A31})$$

where S_{newleaf} is a scaling factor and stem C is calculated analogously with S_{newstem}

Leaf litter fall dependence of temperature sum

$$f(T_{\text{Sum}}) = l_{Lc1} + (l_{Lc2} - l_{Lc1}) \cdot \min\left(1, \frac{\max(0, T_{\text{Sum}} - t_{L1})}{\max(1, t_{L2} - t_{L1})}\right) \quad (\text{eq. A32})$$

where t_{L1} , t_{L2} , l_{Lc1} and l_{Lc2} are parameters and T_{Sum} is the so called "dorming" temperature sum, $T_{\text{Dormsum}} \cdot T_{\text{Dormsum}}$ is calculated at the end to the growing season when air temperature is below the

threshold temperature $T_{DormTth}$, as the accumulated difference between $T_{DormTth}$ and T_a . $T_{DormTth}$ is a parameter. The stem litter rate is calculated analogously with the parameters t_{Sl} , t_{S2} , I_{Sl} and I_{Sc2} .

Leaf litter fall dependence of LAI

$$f(A_l) = e^{L_{aiEnh} \cdot A_l} \quad (\text{eq. A33})$$

where L_{aiEnh} is a parameter and A_l the leaf area index

Root C entering the soil litter pool of the corresponding layer

$$C_{Root \rightarrow Litter} = f(l_{Rc}) \cdot C_{Root} \cdot S_{newroot} \quad (\text{eq. A34})$$

where $s_{newroot}$ is a scaling factor. The root litter rate function, $f(l_{Rc})$, can be calculated with Eq. (A32) by exchanging the parameters t_{L1} , t_{L2} , l_{Lc1} and l_{Lc2} to t_{R1} , t_{R2} , l_{Rc1} and l_{Rc2} .

Litter fall from roots, leaves and stems in “old” biomass are calculated similarly to the “new” biomass but with the important exception that some of the old leaves may be retained

$$C_{OldLeaf \rightarrow LitterSurface} = f(l_{Lc}) \cdot (C_{OldLeaf} - C_{RemainLeaf}) s_{old leaf} \quad (\text{eq. A35})$$

where $s_{oldleaf}$ is a scaling factor. The litter fall for stems and roots is calculated analogously.

Fraction of the whole $C_{OldLeaf}$ pool that will be excluded from the calculation of the litterfall from the old leaves

$$C_{RemainLeaf} = C_{OldLeaf} \left(1 - \frac{1}{l_{life} - 1} \right) \quad \text{where } l_{life} \text{ is a parameter (eq. A36)}$$

Allocation to the mobile C pool for developing new leaves during litter fall

$$C_{Mobile} = (C_{Leaf \rightarrow LitterSurface} + C_{OldLeaf \rightarrow LitterSurface}) \cdot m_{retain} \quad (\text{eq. A37})$$

where m_{retain} is an allocation coefficient

Allocation from mobile C pool at leafing as an additional supply. This process goes on as long there is C left in the mobile pool.

$$C_{Mobile \rightarrow Leaf} = C_{Mobile} \cdot m_{shoot} \quad (\text{eq. A38})$$

where m_{shoot} is an allocation coefficient and C_{Mobile} the carbon in the mobile pool.

5. Plant abiotic process

Plant interception of global radiation (MJ m⁻² day⁻¹)

$$R_{s,pl} = \left(1 - e^{-k_{rn} \frac{A_l}{f_{cc}}}\right) \cdot f_{cc} (1 - a_{pl}) R_{is} \text{ (eq. A39)}$$

where k_{rn} is the light use extinction coefficient given as a single parameter common for all plants, f_{cc} is the surface canopy cover, a_{pl} is the plant albedo and R_{is} is the global radiation

Surface canopy cover (m²m⁻²)

$$f_{cc} = p_{cmax} (1 - e^{-p_{ck} A_l}) \text{ (eq. A40)}$$

Where p_{cmax} is a parameter that determines the maximum surface cover and p_{ck} is a parameter that governs the speed at which the maximum surface cover is reached. A_l is the leaf area index of the plant.

Leaf Area Index (m²m⁻²)

$$A_l = \frac{B_l}{p_{l,sp}} \text{ (eq. A41)}$$

Where $p_{l,sp}$ is a parameter estimated from specific leaf area and B_l is the total mass of leaf (i.e leaf C content in the leaves, $C_{Leaf} + C_{OldLeaf}$).

Potential transpiration (m²m⁻²)

$$L_v E_{tp} = \frac{\Delta R_n + \rho_a c_p \frac{(e_s - e_a)}{r_a}}{\Delta + \gamma \left(1 + \frac{r_s}{r_a}\right)} \text{ (eq. A42)}$$

where R_n is net radiation available for transpiration, e_s is the vapour pressure at saturation, e_a is the actual vapour pressure, ρ_a is air density, c_p is the specific heat of air at constant pressure, L_v is the latent heat of vaporisation, Δ is the slope of saturated vapour pressure versus temperature curve, γ is the psychrometer 'constant', r_s is 'effective' surface resistance and r_a is the aerodynamic resistance.

$$r_s = \frac{1}{\max(A_l g_l, 0.001)} \text{ (eq. A43)}$$

where g_l is the leaf conductance.

$$g_l = \frac{R_{is}}{R_{is} + g_{ris}} \frac{g_{max}}{1 + \frac{(e_s - e_a)}{g_{vpd}}} \text{ (eq. A43)}$$

where g_{ris} , $g_{\max}$ and g_{vpd} are parameter values, $g_{\max\text{win}}$ corresponds to g_{vpd} in winter. R_{is} , is the global radiation and $(e_s - e_a)$ the vapour pressure deficit.

6. Soil respiration process

Decomposition of soil organic matter was simulated by first-order kinetics (eqs. A44-A45),

Decomposition of the fast C pools ($\text{g C m}^{-2} \text{ day}^{-1}$)

$$C_{\text{DecompL}} = k_l \cdot f(T) \cdot f(\theta) \cdot C_{\text{labile}} \quad (\text{eq. A44})$$

where k_l is a parameter that describes the 1st order decomposition rates and $f(T)$ and $f(\theta)$ are response functions for soil temperature and moisture in the certain layer

Decomposition of the slow C pools ($\text{g C m}^{-2} \text{ day}^{-1}$)

$$C_{\text{DecompL}} = k_h \cdot f(T) \cdot f(\theta) \cdot C_{\text{refractory}} \quad (\text{eq. A45})$$

where k_h is a parameter that describes the decomposition rates and $f(T)$ and $f(\theta)$ are response functions for soil temperature and moisture in the certain layer

Response function for soil temperature

$$f(T) = t_{Q10}^{(T-t_{Q10\text{bas}})/10} \quad (\text{eq. A46})$$

Where t_{Q10} and $t_{Q10\text{bas}}$ are parameters and T is the soil temperature in the certain layer.

Response function for soil moisture was calculated by (eq. A47)

$$f(\theta) = \begin{cases} p_{\theta\text{satact}} & \theta = \theta_s \\ \min \left(\left(\frac{\theta_s - \theta}{p_{\theta Upp}} \right)^{p_{\theta p}} (1 - p_{\theta\text{satact}}) + p_{\theta\text{satact}}, \left(\frac{\theta - \theta_{\text{wilt}}}{p_{\theta\text{Low}}} \right)^{p_{\theta p}} \right) & \theta_{\text{wilt}} \leq \theta \leq \theta_s \\ 0 & \theta < \theta_{\text{wilt}} \end{cases}$$

where $p_{\theta\text{Upp}}$, $p_{\theta\text{Low}}$, $p_{\theta\text{Satact}}$ and $p_{\theta p}$ are parameters and the variables, θ_s , θ_{wilt} , and θ , are the soil moisture content at saturation, the soil moisture content at the wilting point, and the actual soil moisture content, respectively. Soil respiration was assumed to be optimal at 60% and decreased linearly with either water content above or below (Or et al., 2007). The produced CO_2 was assumed to emit directly into the atmosphere thus no transpiration of CO_2 gas in the soil profile was simulated.

Litter from inactive surface litter pool entering the fast SOC pool at continuous rate

$$C_{\text{LitterSurface} \rightarrow \text{Litter } l} = l_{l1} \cdot C_{\text{LitterSurface}} \quad (\text{eq. A48})$$

where l_{l1} is a parameter and $C_{\text{LitterSurface}}$ the carbon in the surface litter pool.

Amount of decomposition product from fast SOC pools being released as CO₂

$$C_{\text{Litter} \rightarrow \text{CO}_2} = (1 - f_{e,l}) \cdot C_{\text{DecompL}} \quad (\text{eq. A49})$$

Amount of decomposition products from fast SOC pools entering the slow decomposition pools

$$C_{\text{Litter} \rightarrow \text{refractory}} = f_{e,l} \cdot f_{h,l} \cdot C_{\text{DecompL}} \quad (\text{eq. A50})$$

Amount of decomposition products from the slow SOC pools being returned to the fast decomposition pools

$$C_{\text{Litter} \rightarrow \text{Litter}} = f_{e,l} (1 - f_{h,l}) \cdot C_{\text{DecompL}} \quad (\text{eq. A51})$$

Amount of decomposition products from the slow SOC pools being released as CO₂

$$C_{\text{refractory} \rightarrow \text{CO}_2} = f_{e,l} \cdot C_{\text{DecompL}} \quad (\text{eq. A52})$$

Where C_{DecompL} represents the decomposition rate of litter pool, $f_{e,l}$ is the efficiency of decay of litter and $f_{h,l}$ is the fraction of C and N in the labile pool that will enter the refractory C pool.

ST2: Initial Carbon and Nitrogen layers used for Beverly Swamp in Coup

Depth	Init L1C (active) (g/m2)	Init HC (passive) (g/m2)	Init L1N (active) (gN/m2)	Init HN (passive) (gN/m2)
0-5	1067.949	1220.513	30.51282	61.02564
5-10	1719.494	1965.136	49.12839	98.25678
10-15	1747.074	1996.656	49.9164	99.8328
15-20	311.4887	5161.813	8.899677	258.0906
20-25	207.8285	3444.015	5.937956	172.2007
25-30	358.1405	5934.9	10.23259	296.745
30-40	1020.338	5247.451	29.1525	262.3725
40-50	1056.745	5434.69	30.19272	271.7345
50-65	649.2692	3339.099	18.55055	166.9549
65-80	1091.221	5611.992	31.17774	280.5996
80-100	1111.299	18415.81	31.7514	920.7905
100-120	647.3291	10727.17	18.49512	536.3584
120-150	1058.263	17536.93	30.23609	876.8466

Appendix 2-3: Parameter values in CoupModel

SPM2: List of model parameters used in the model run that differ from the model default for Beverly swamp

Symbol	Parameters	Value	Units	References
Z_o	Surface roughness length	2.7±0.5	M	Munro 1987 & Munro et al 2000
P_{ral}	Air resistance inside canopy	6.7-10	s/m	Munro 1987 & Munro et al 2000
g_{max}	Maximal conductance of fully stomata	0.01-0.02	m/s	Munro 1987 & Munro et al 2000
g_{ris}	Global radiation intensity that represents half-light saturation in light response	5300000	J/m ² /day	Thambipillai, 2000
g_{vpd}	Vapour pressure deficit that corresponds to a 50% reduction of stomata conductance	125	Pa	Munro 1987 & Munro et al 2000
α_{dry}	Soil albedo when tension >104cm H ₂ O	7	%	Munro et al 2000; Thambipillai, 2000
α_{wet}	Soil albedo when tension <10cm H ₂ O	15	%	Munro et al 2000; Thambipillai, 2000
α_{leaf}	Albedo of vegetation canopy	15-16	%	Munro et al 2000; Thambipillai, 2000
kB^{-1}	Difference between the natural logarithm of surface roughness length for momentum and heat	2.5	-	Munro et al 2000; Thambipillai, 2000
θ_{sat}	Total porosity	80-85	Vol %	Czerneda, 1985 & Munro 1982
θ_m	Macroporosity	18-28	Vol %	Word et al., 2022

K_{sat}	Total saturated hydraulic conductivity ²	125-0.08	mm d-1	Gupta et al. (2023); Czerneda, 1985
α_{surf}	First-order coefficient for surface runoff	0.4	—	assumed
$P_{\theta Low}$	Lower range for moisture response	12	Vol%	assumed
$P_{\theta Low}$	Upper range for moisture response	12	Vol%	assumed
α_{scale}	The first-order coefficient for the surface runoff	0.1	—	Assumed
θ_r	Residual water content	22	Vol %	Dimitrov and Lafleur (2021); Menberu et al. (2021) ; Letts et al. (2000); Liu and Lennartz et al. (2018)
θ_{wilt}	Wilting point	30	Vol %	
W_{pmax}	Maximum amount of water stored on soil surface without causing surface runoff	200	mm	Valverde, 1978; Woo and Valverde (1981)
t_{WA}	Temperature coefficient in the temperature response function	0.59	--	Assumed
t_{WB}	Temperature coefficient in the temperature response function	0.28	--	Assumed
Δz_{humus}	The thickness of peat layer	0.85	M	Munro et al. 2000
k_{rn}	Extinction coefficient	0.52		Thambipillai, 2000

² Measured K_{sat} values were used for the simulated layers which is arranged from top to bottom

l_{life}	Max leaf lifetime	2	Years	Welch, 1985
p_{life}	Max plant lifetime	400	years	Kanda et al (1996); Withington et al. (2006)
ε_L	Radiation use efficiency for photosynthesis at optimum temperature, moisture and C-N ratio	2.8 - 4	gDw/MJ	Horn & Schulz, 2010; Wang et al., 2020
k_{gresp}	Growth respiration coefficient	0.17	Day-1	Amthor & Baldochhi (2001); Amthor 1984; Amthor 1986; Cannel & Thornley, 2000
$k_{mresp\ leaf}$	Maintenance respiration coefficient for leaves	0.002	Day-1	
$k_{mresp\ stem}$	Maintenance respiration coefficient for stem	0.0001	Day-1	
$k_{mresp\ root}$	Maintenance respiration coefficient for root	0.015	Day-1	
$k_{mresp\ croot}$	Maintenance respiration coefficient for coarse root	0.0008	Day-1	
m_{retain}	coefficient for determining allocation to mobile internal storage pool	0.9	Day-1	assumed
m_{shoot}	Coefficient for determining allocation from the mobile pool to the leaf at leafing.	0.5	Day-1	assumed
l_{Lc1}	rate coefficient for the leaf litter fall before the first threshold	0.001	Day-1	Thambipillai, 2000

	temperature sum tL1 is reached			
l_{Lc2}	rate coefficient for the leaf litter fall after the second threshold temperature sum tL2 is reached	0.05	Day-1	Thambipillai, 2000
l_{Sc1}	rate coefficient for the litter fall from stems before the first threshold temperature sum tS1 is reached	1.73e-05	Day-1	Thambipillai, 2000
k_l	First-order decomposition coefficient for labile C	0.001	Day	Field measurement (unpublished), (Literature) Kendall et al (2020)
k_h	First-order decomposition coefficient for refractory C	3 x 10-6	day	Field measurement (unpublished), Middleton et al. (2020)
l_h	Fraction of above ground residues that enter litter 1 pool	0.001	day	Kendall et al (2020)
CN_m	C:N of soil microbes	7	–	Wang et al. (2015)
C_{tot}	Total soil C at 1.5 m profile	98083	gC/m ²	Waddington et al. (unpublished data); Schmidt et al. (2024)
$C_{tot, layer}$	Total soil C for each simulated layer* ³	13623	gC/m ²	
Q_{10}	Q_{10} value for decomposition	2-3	-	Byun et al. (2021)
T_{aamp}	Amplitude of analytical air temperature	12	oC	Weather station data

³ This is an average as different values were used for different layers

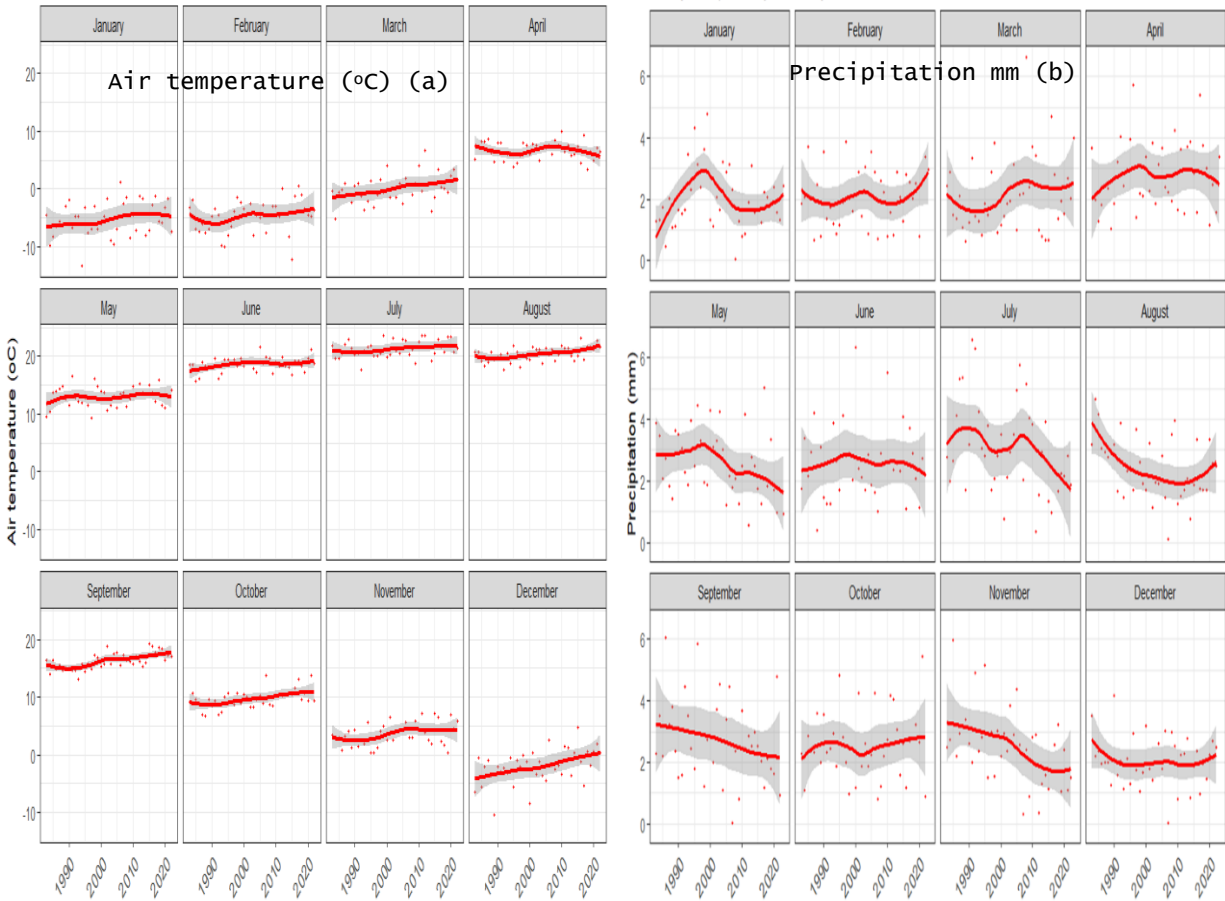
T_{amean}	Mean value in air temperature function (also for estimating lower boundary condition)	7.64	oC	Weather station data
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Appendix 2-4: Additional result statistics and charts for Chapter 2

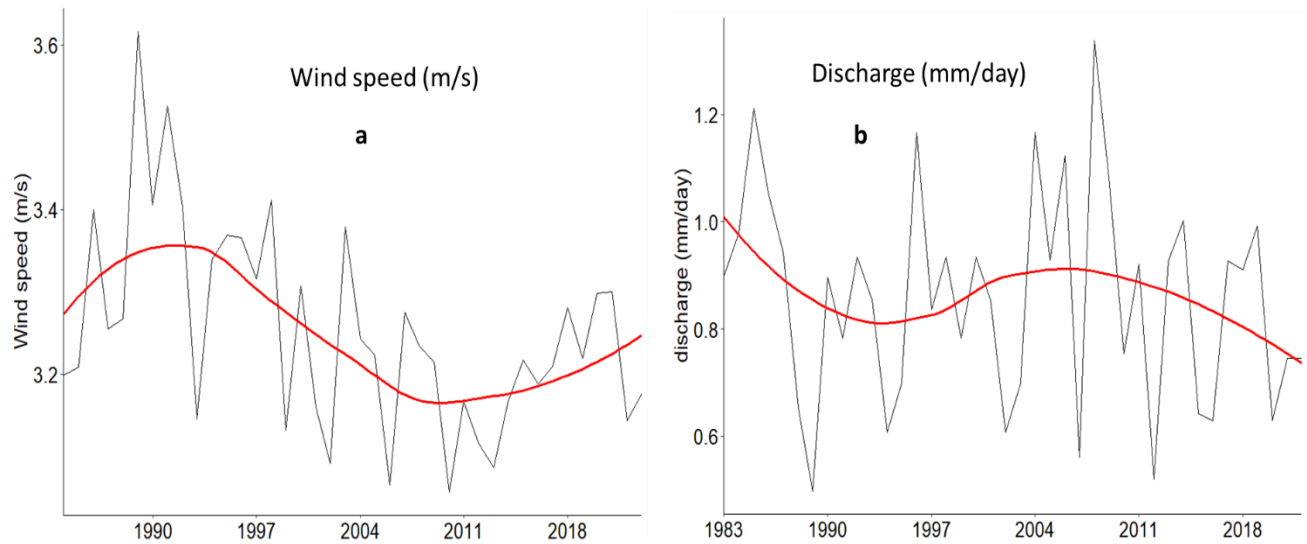
ST3: Mean decadal change in simulated variable (Jan 1983 – May 2023)

Data type	variable name	average change/decade	% change/ decade	Tau (T)	2-sided p value	Trend direction
observation	Air temperature (oC)	0.43	6	0.041	2.22E-16	Very strong positive
	precipitation (mm/year)	-0.11	-4	-0.251	0.02	Weak negative
	Global radiation (J/m2/day)	-20332.989	-0.1	-0.01	0.039135	Weak negative
	Relative Humidity (%)	0	0	0.000743	0.89	Little or no evidence
	Windspeed (m/s)	-0.04	-1.2	-0.03	1.80E-08	Very strong negative
	Discharge (mm/day)	-0.02	-2.3	-0.0321	5.0099e-08	Very strong negative
simulated	Soil respiration (g/m2/day)	0.4	11	0.12	2.22E-16	Very strong positive
	NEE (g/m2/day)	0.5	21	0.11	2.22E-16	Very strong positive
	GPP (g/m2/day)	0.05	1	0.004	0.43	Little or no evidence
	Reco (g/m2/day)	0.53	11	0.132	2.22E-16	Very strong positive
	WTL (mm)	-4.3	-50	-0.08	2.22E-16	Very strong negative
	ET (mm)	0.03	1.5	0.026	3.3379e-06	Very strong positive
	VMC (%)	-1.3	-1.8	-0.1	2.22E-16	Very strong negative
	Soil temperature (oC)	0.35	3.8	0.04	2.22E-16	Very strong positive

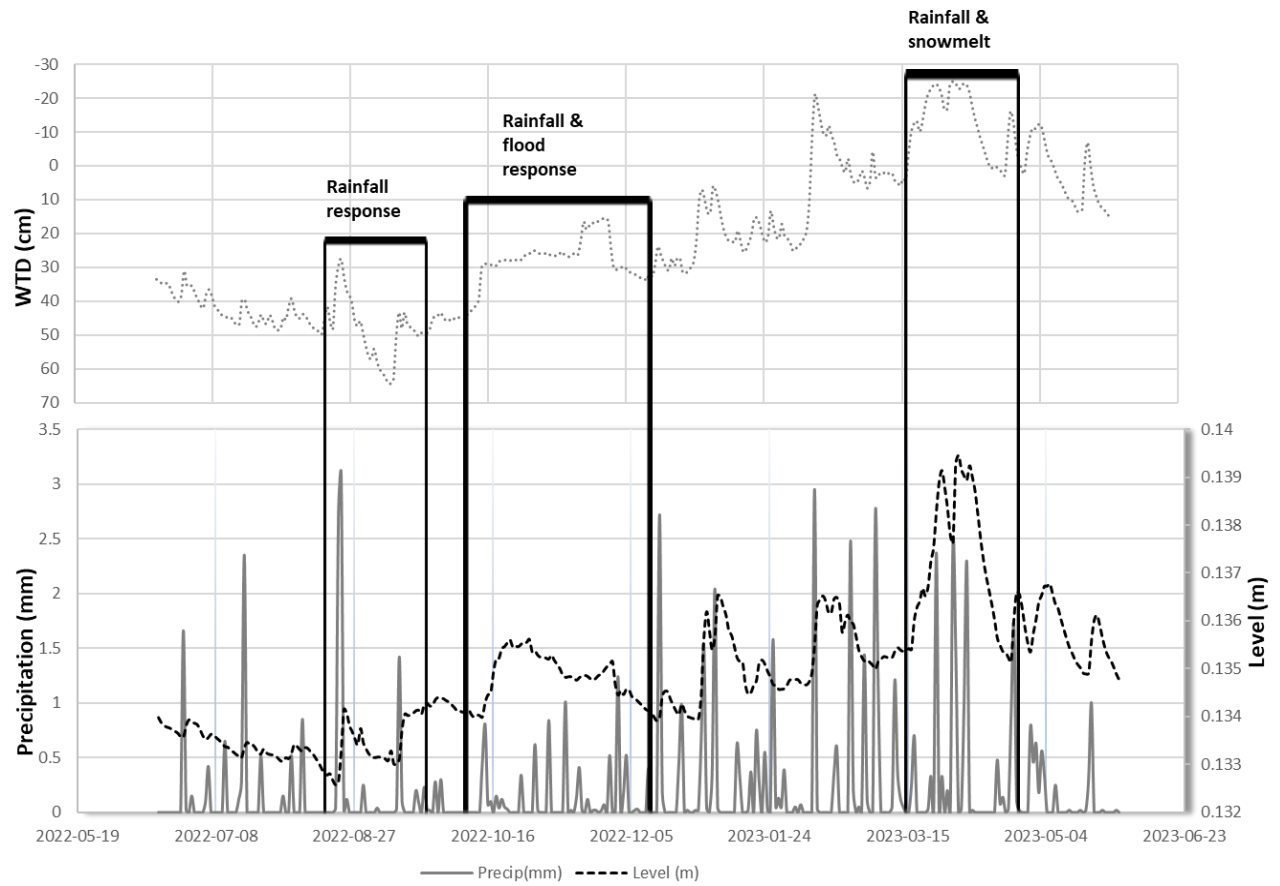
	Snow depth (cm)	-1.5	-20	-0.08	2.22E-16	Very strong negative
*tau & p value are products of Mann-Kendall Trend Test. Trend is significant when p value is <0.05 and tau specifies the direction of trend						



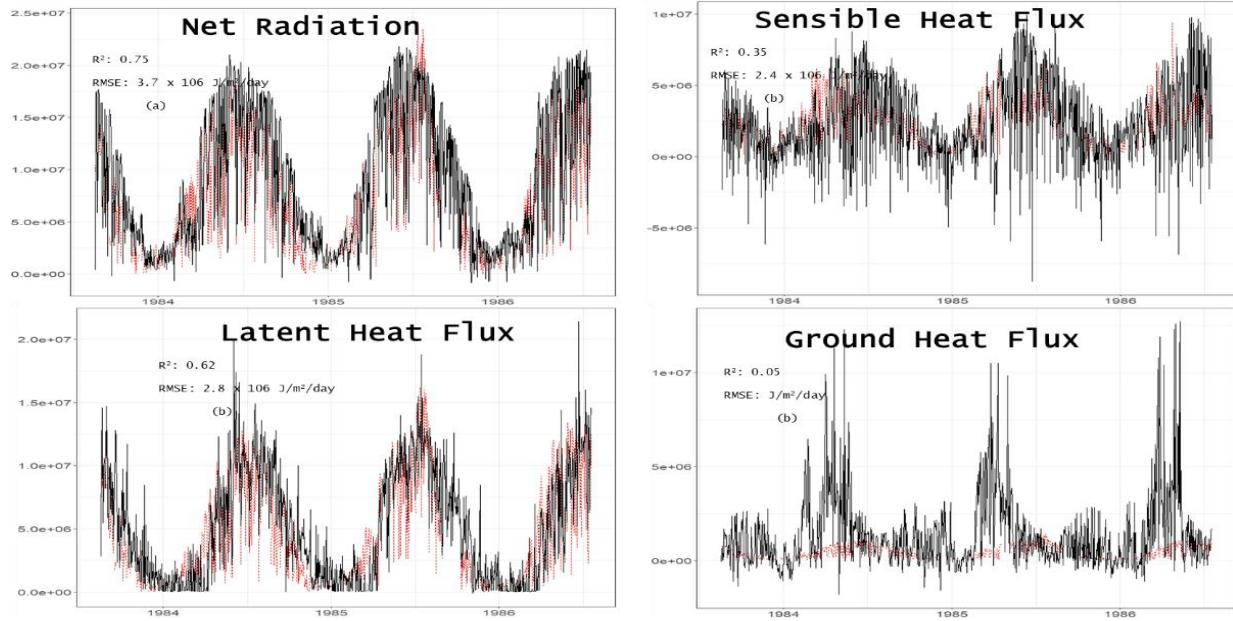
SF1: Average daily air temperature (a) and precipitation (b) by months from Jan 1983 - May 2023



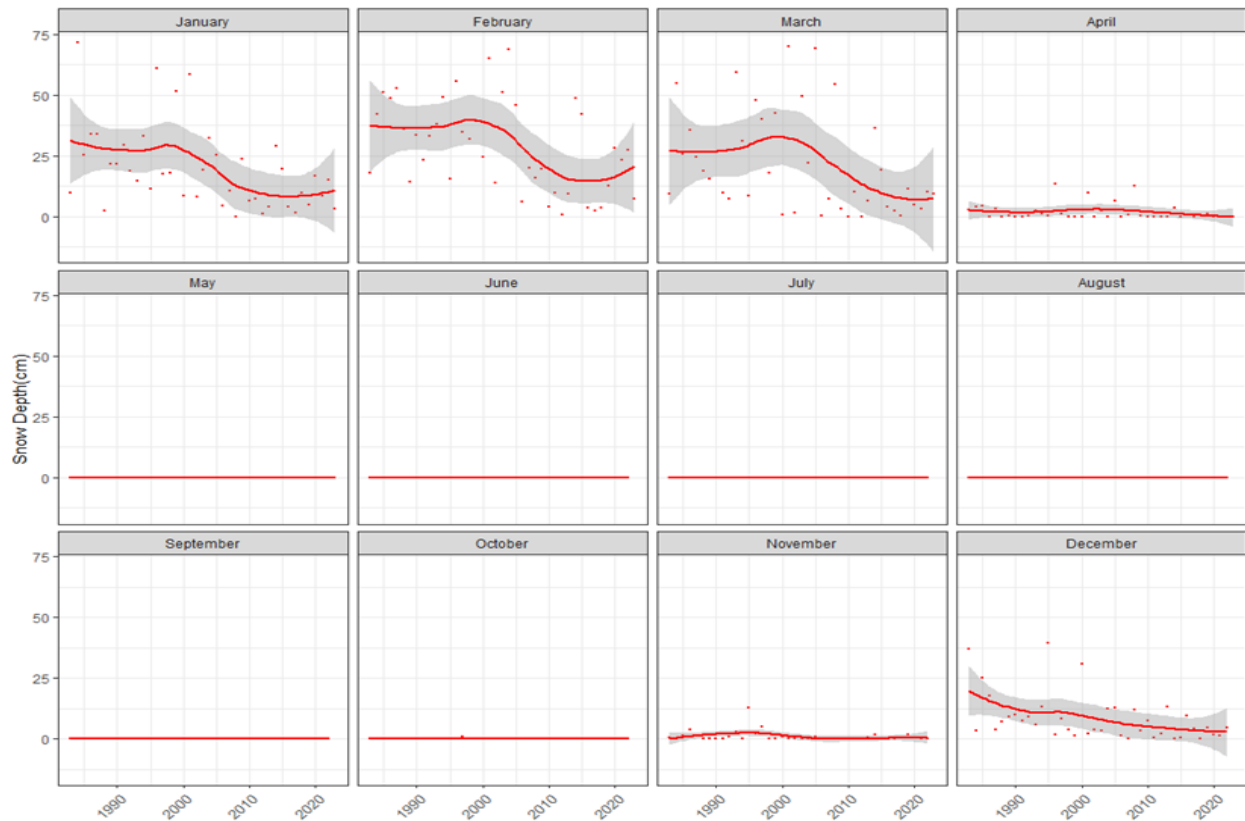
SF2: Annual windspeed (a) and surface discharge (b) trends from Jan 1983 - May 2023



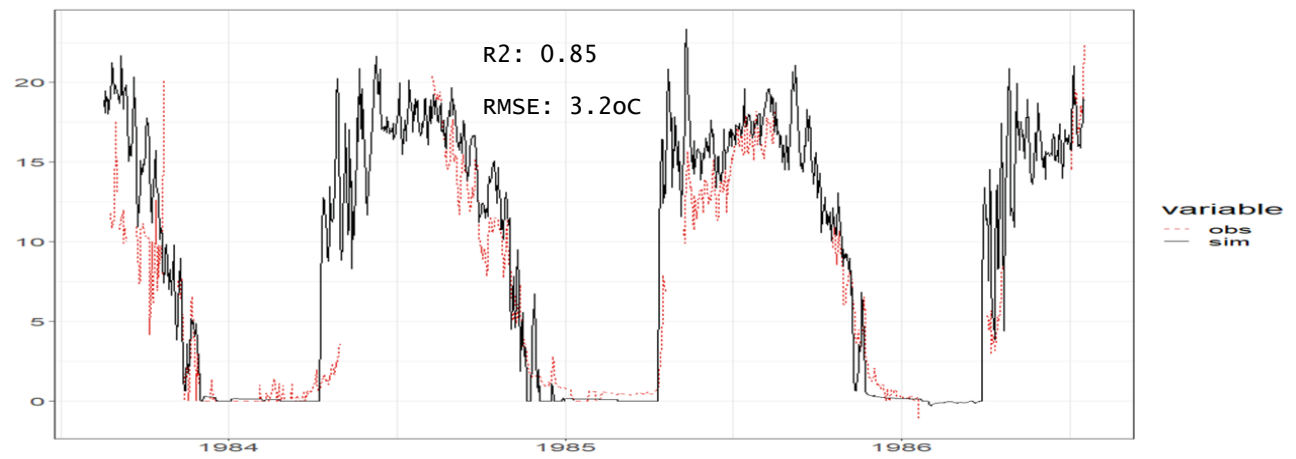
SF3: Typical hydropattern of Beverly Swamp (May 2022 – June 2023)



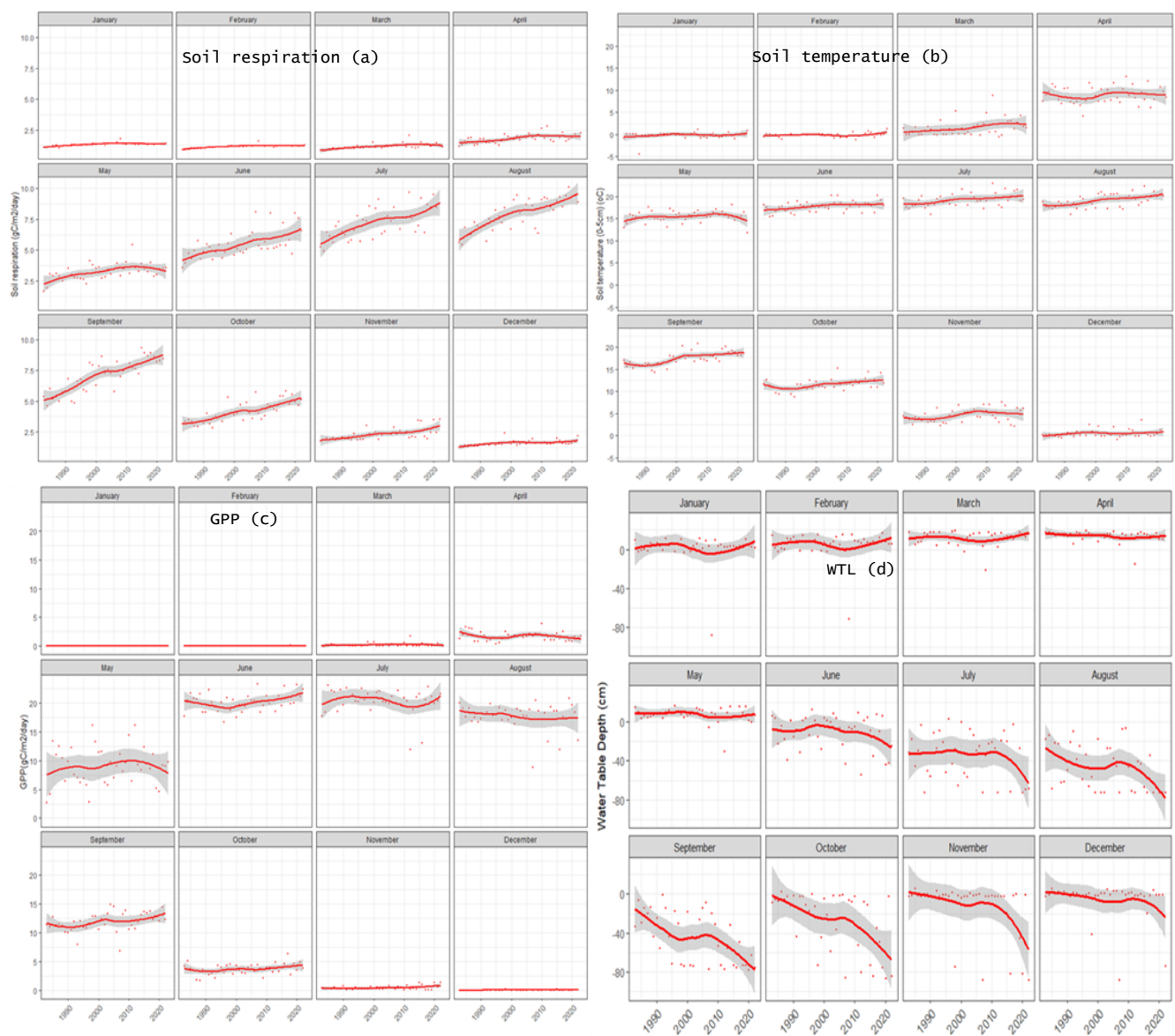
SF4: Calibration period of swamp's Energy fluxes (Aug 1983 – July 1986)

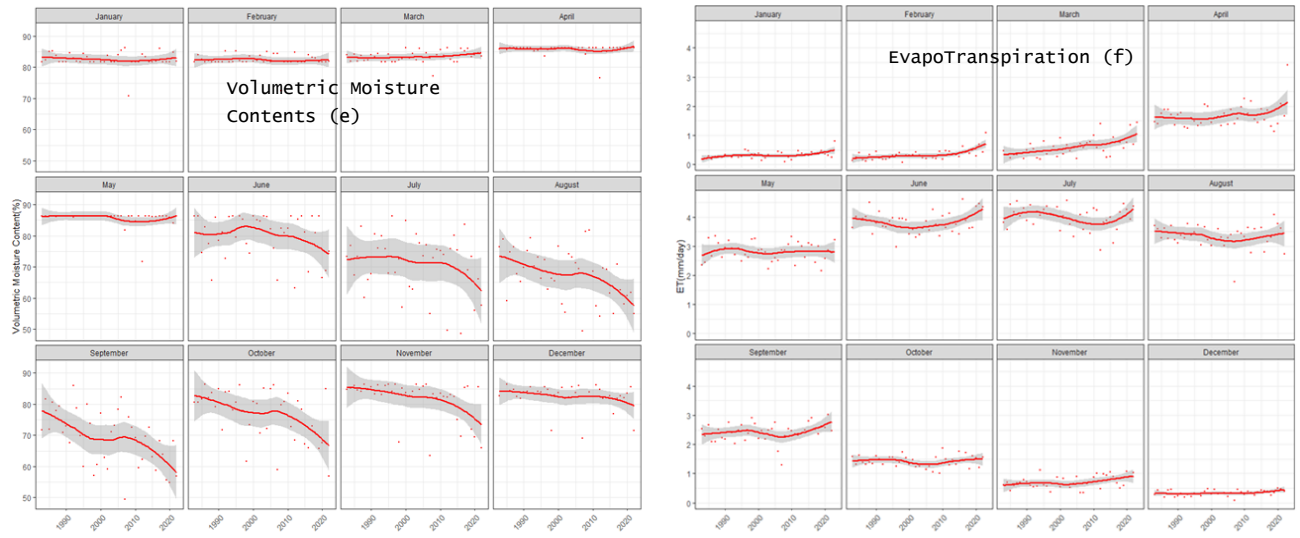


SF5: Snow trend time series of swamp (Jan 1983 – May 2023)

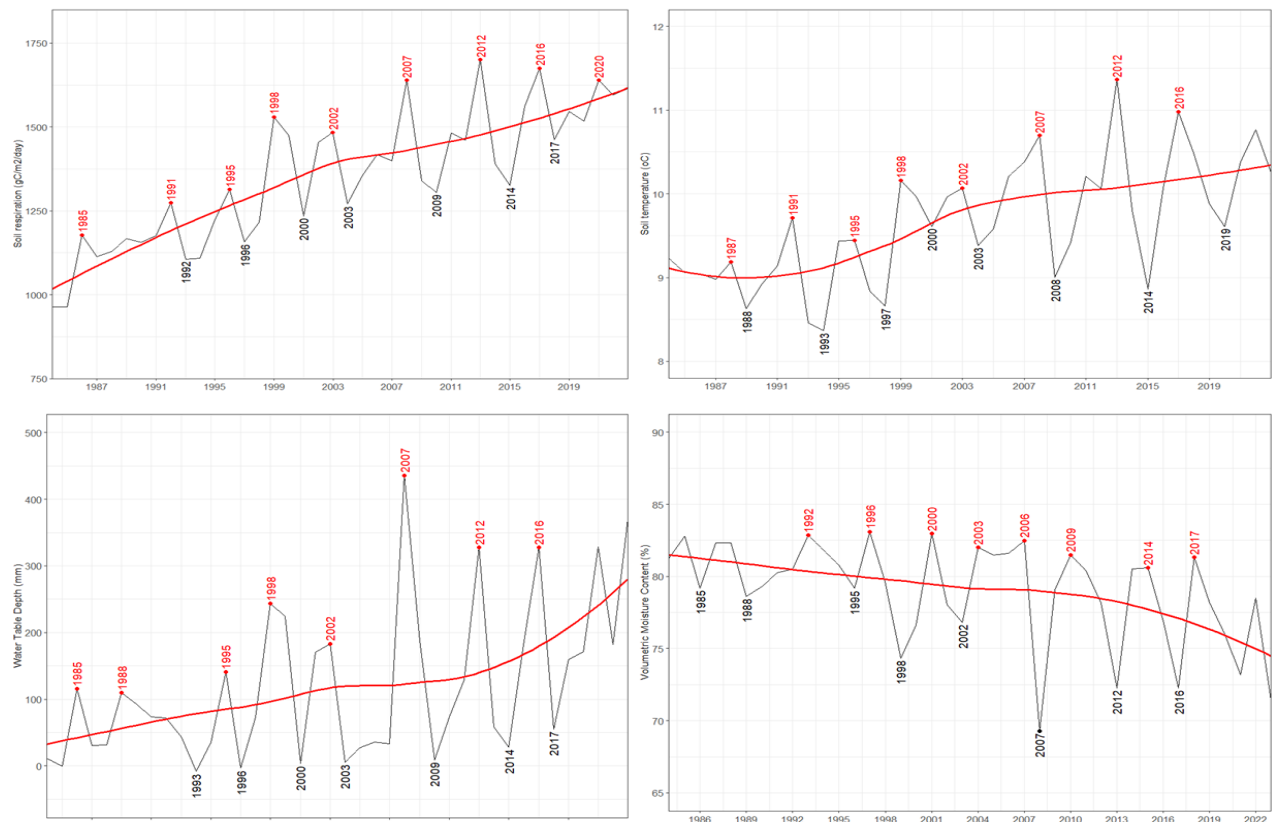


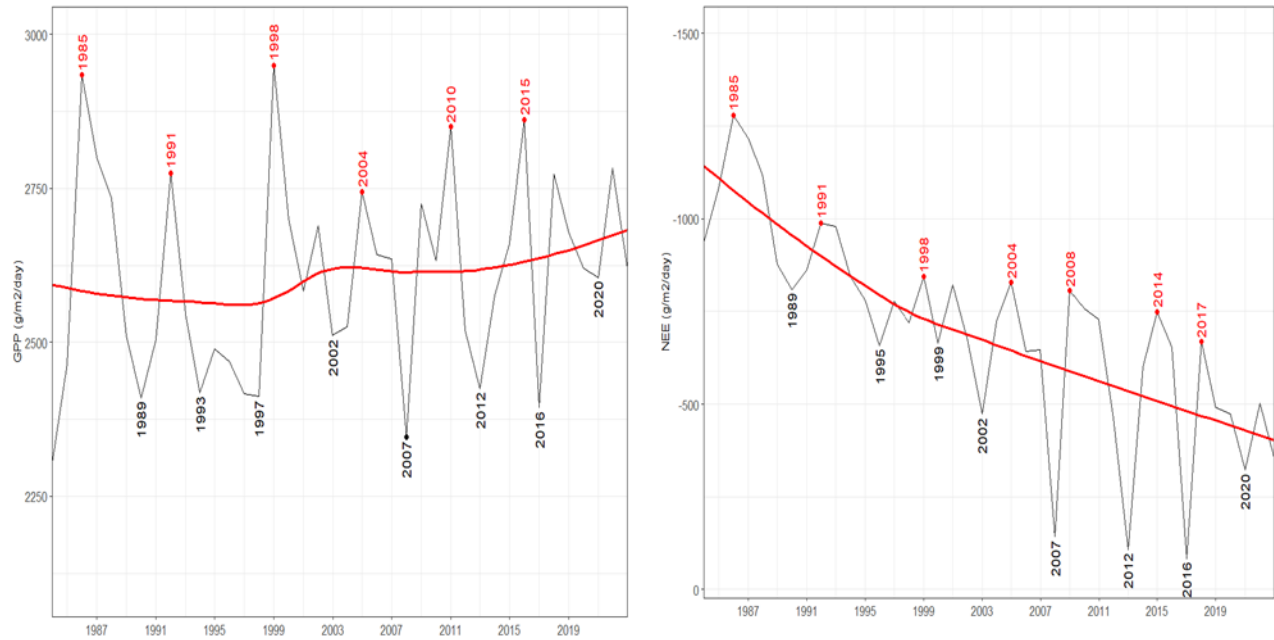
SF6: Calibration period of surface soil temperature (0-5cm) (Aug 1983- July 1986)





SF7: Simulated daily average Rs (a), soil temperature (b), GPP (c), WTL (d), VMC (e), ET (f) on monthly scale (Jan 1983 – May 2023)





SF8 Annual time series of Rs (a), Soil temperature (b), WTL (c), VMC (d), GPP (e) and NEE (f) for simulated period (Jan 1983 – May 2023)

Appendix 3-5: Result of initial parameter screening using One-at-a-time

Parameter	Temperature (1)	Temperature (6)	Saturation Level	TotalWater Content(1)	TotalWater Content(6)	Soil respiration	Radiation Net Tot	TotalLatent Flow	TotalSensible Flow	LeafArea Index(1)	Snow Depth	Surface pool
TemQ10												
TempAirMean												
Theta Lower Range												
Theta upper Range												
Reference Height												
AlbedoLeaf												
TemQ10Bas												
Albedo Dry												
Albedo Wet												
CritThresholdDry												
DrainSpacing												
PrecA0Corr												
PrecA1Corr												
MeltCoefAirTemp												
MeltCoefGlobRad												
KBMinusOne												
RaIncreaseWithLAI												
WindLessExchange Canopy												
WithinCanopyRes												
TempDiffPrec_Air												
CN Ratio Microbe												
RateCoefHumus												
RateCoefLitter1												
RateCoefSurf L1												

SaturationActivity												
AScaleSorption												
SPMaxCover												
SurfCoef												
SPCoverTotal												
SurfPoolMax												
GWSourceFlow												
GWSourceLayer												
AirMinContent												
TempCoefA												
TempCoefB												
CFrozenSurfCorr												
Maximal Cover												
Specific LeafArea												
MaxLeafLifetime												
Max Plant Lifetime												
Shoot Coef												
MobileAlloCoef												
RadEfficiency												
Leafc1												
RootWaterc1												
RootCNc1												
RootMassc1												
GrowthCoef												
MCoefLeaf												
MCoefStem												
MCoefRoot												
MCoefCoarseRoot												
LeafRate1												
LeafRate2												

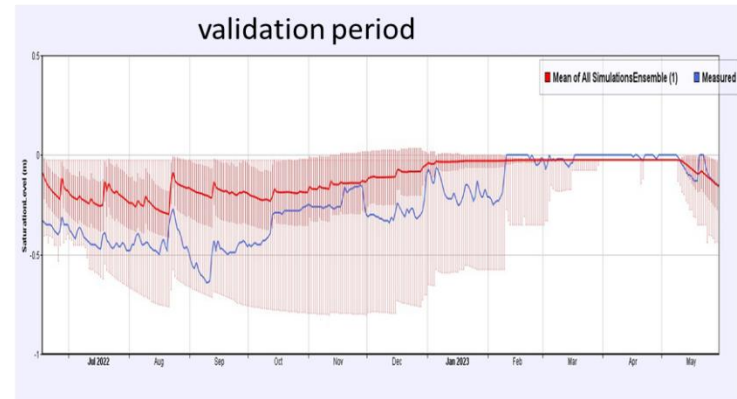
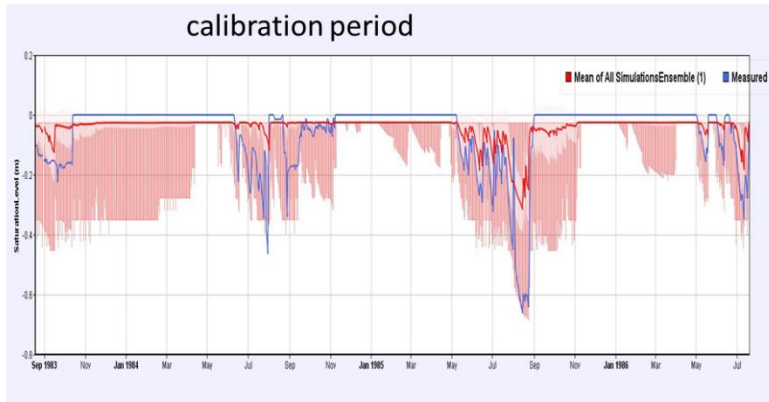
LeafTsum1												
stemRate1												
stemRate2												
StemTsum1												
RootRate1												
Rootrate2												
CoarseRootRate1												
CoarseRootRate2												
LAI enh Coef												
Roughness Min												
AirResisLAI Effect												
Conduct Ris												
Conduct VPD												
Conduct Max												
Roughness max												
n-value (1)												
n-value (6)												
n-value (9)												
n-value (11)												
Alpha(1)												
Alpha(6)												
Alpha (9)												
Alpha(11)												
Wilting point												
Residual water												
Total conductivity(1)												
Total conductivity(6)												
Total conductivity(9)												
Total conductivity(11)												

Total conductivity(12)												
n Tortuosity												
Macropore(1)												
Macropore(6)												
Macropore(9)												
Macropore(11)												
Macropore(12)												

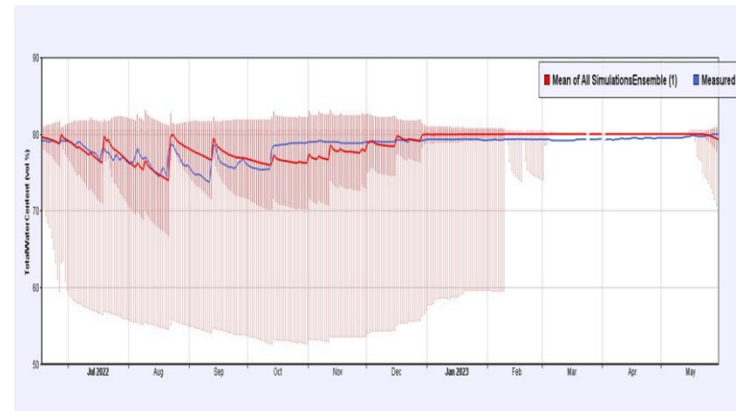
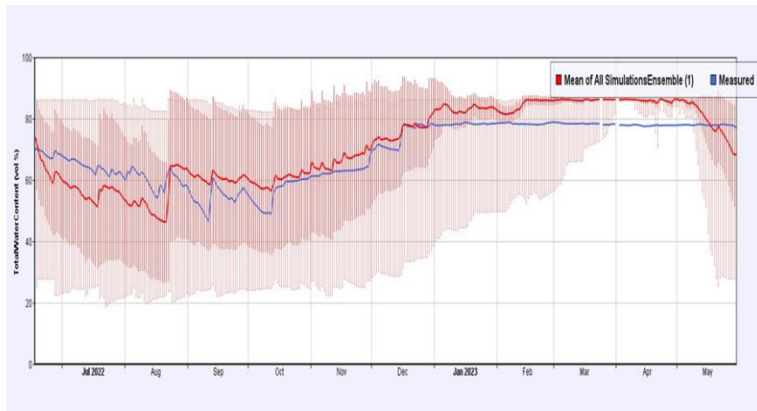
Sensitivity classes		
Class	Index	Sensitivity
I	$0.00 \leq I < 0.05$	small to negligible
II	$0.05 \leq I < 0.20$	Medium
III	$0.20 \leq I < 1.00$	High
IV	$ I \geq 1.0$	Very High

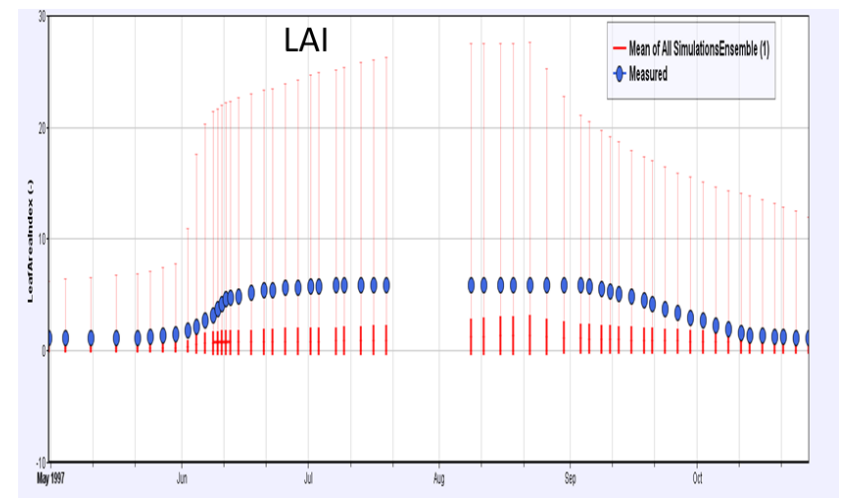
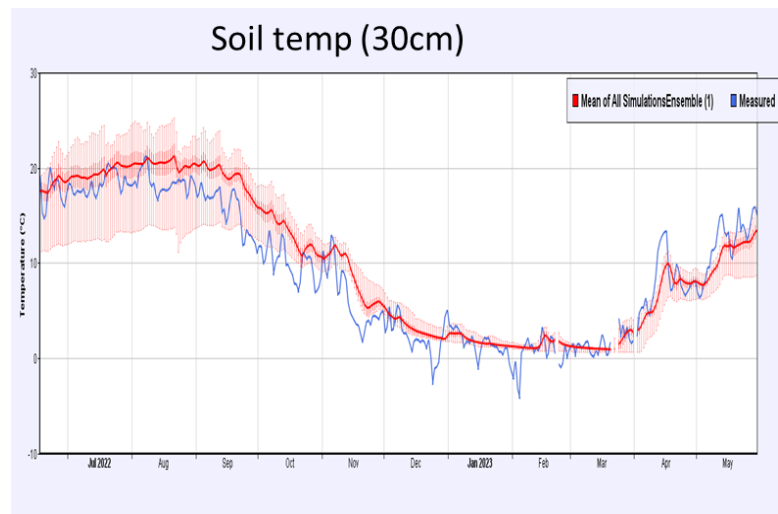
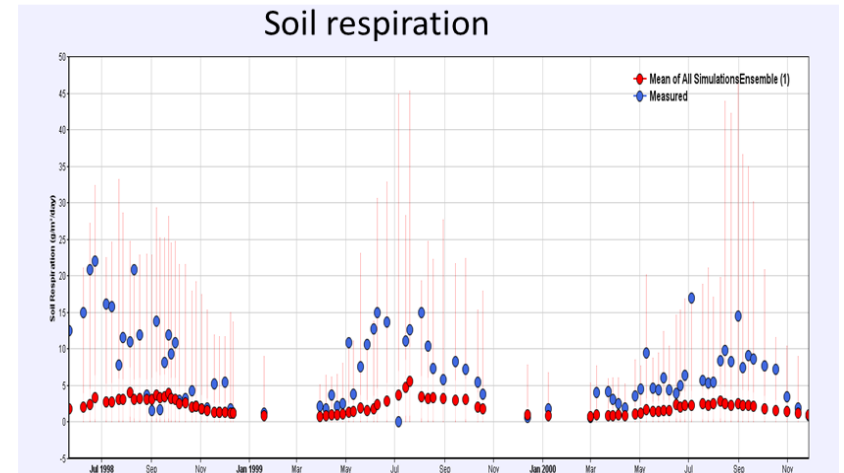
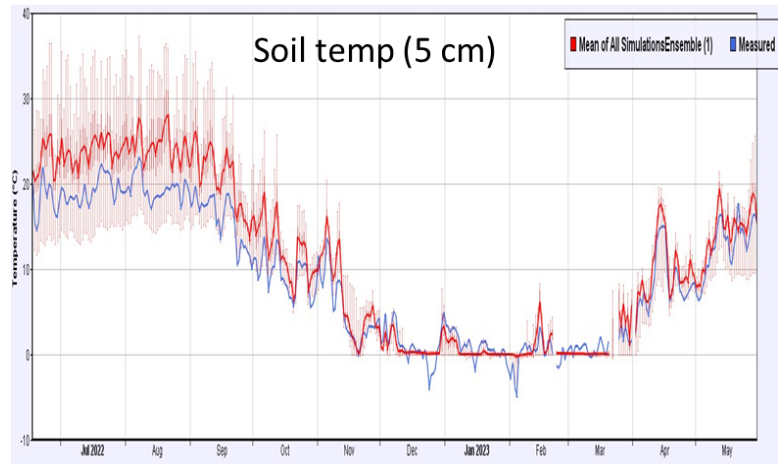
Appendix 3-6: Extent of uncertainty coverage for prior simulations (35,000) in CoupModel

saturation level (m)

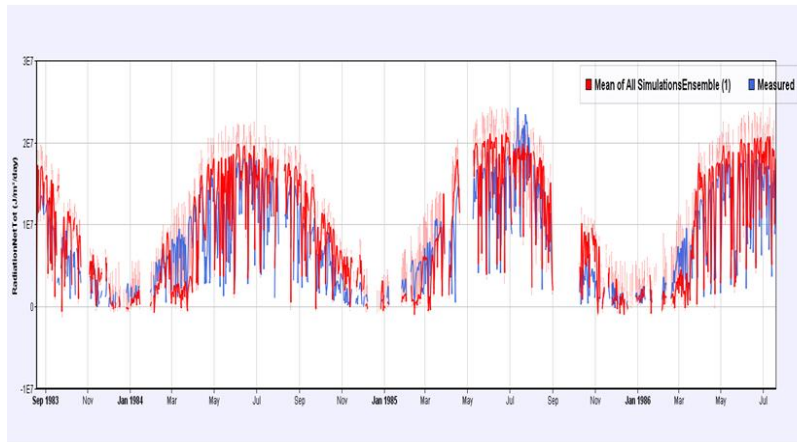


volumetric metric content (%)

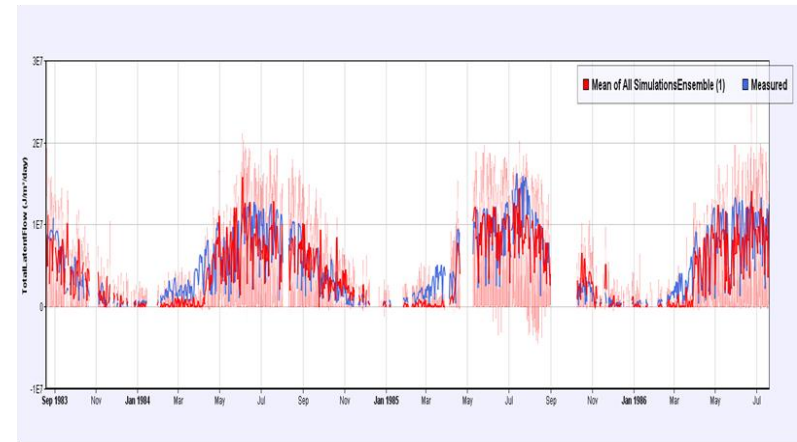




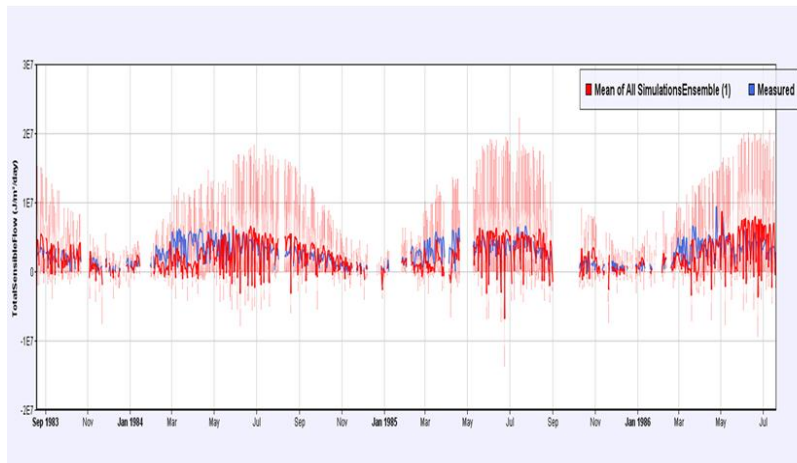
Net Radiation



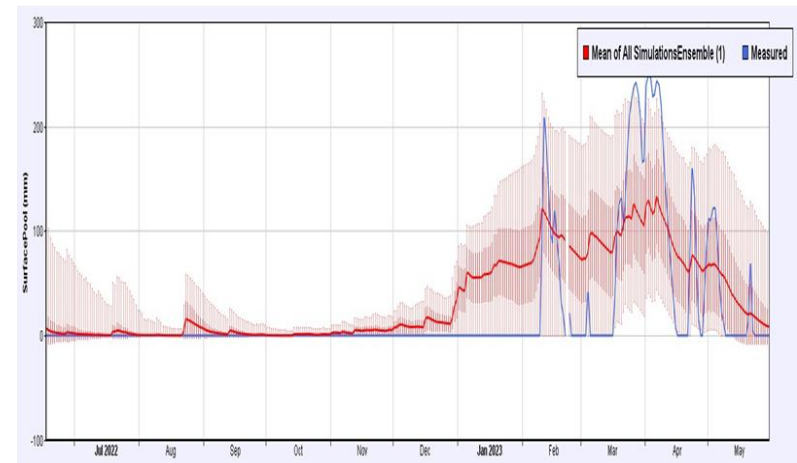
Latent Heat Flux



Sensitive heat



Surface pool



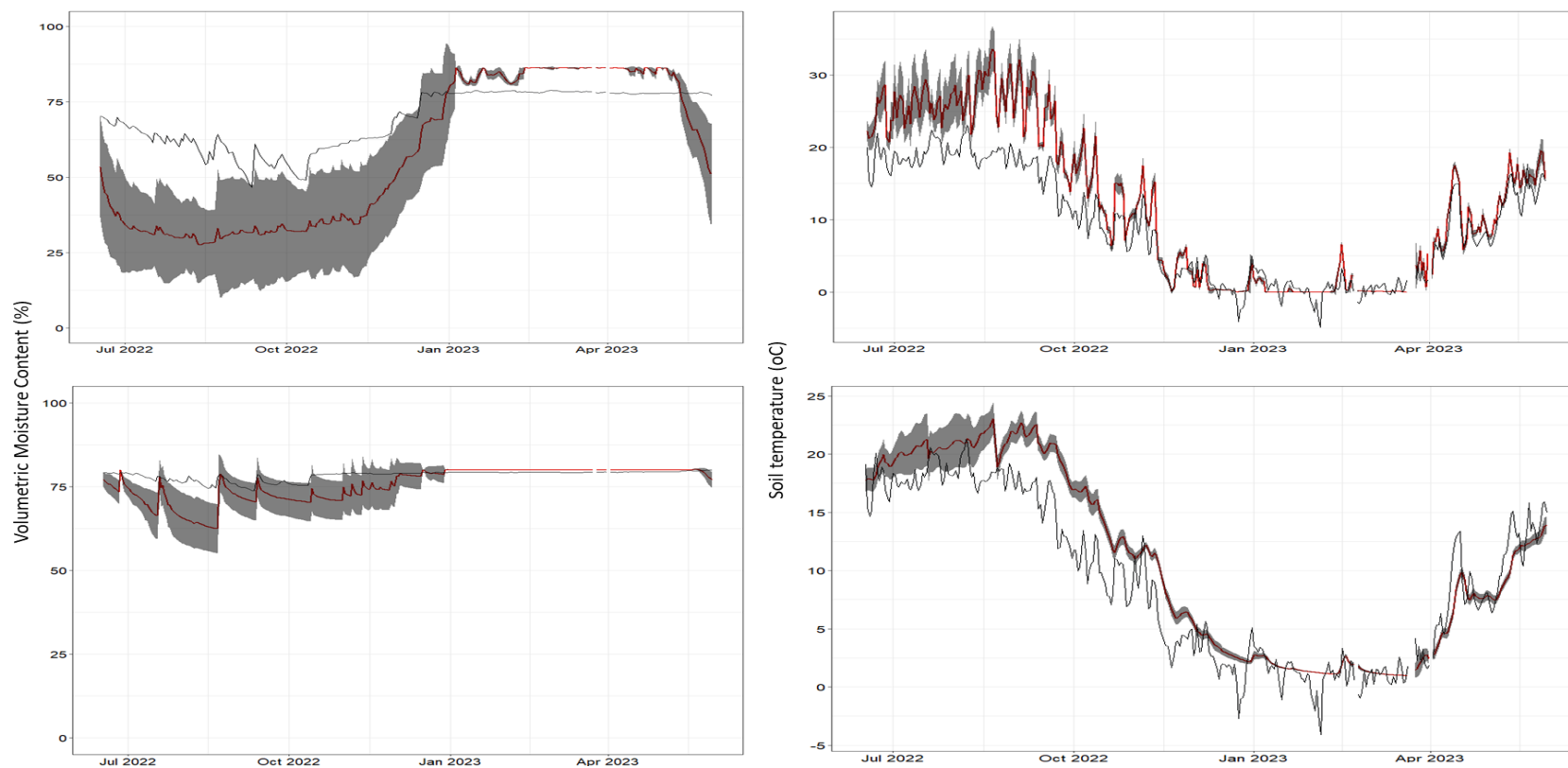
Appendix 3-7: Correlation matrix of calibrated parameters

$k_{trans,sp}$	θ_L	p_{op}	$p_{st,water}$	$p_{gl,sp}$	θ_{min}	α_{hf}	$p_{gl,low}$	$p_{st,root}$	K_h	c_{rain}	l_{cl}	t_{WA}	l_{L2}	c_{max}	$p_{1,sp}$	a_{wg}	$t_{pQ10max}$	k_1	l_1	t_{Q10}	$k_{gr,sp}$	q_{of}	g_{epd}	g_{max}	m_{rain}	KB^{-1}	m_T	a_{wet}	d_p	LAI_{anhc}	g_h	l_{L1}	p_{max}	$w_{gr,ex}$	q_{col}	K_{wet}	K_{as}		
		-0.3	-0.2	0	0	-0.3	0	0.4	0.2	0	0.1	0.1	-0.4	0.1	0	0.3	0.3	-0.2	-0.1	0	-0.5	0	0.2	0.4	0.3	0.1	0.1	0.2	0	0	0.2	0.2	-0.2	-0.1	-0.4	0	0.3	0.1	
θ_L		0	0.1	-0.1	-0.1	0	0	0	0.3	-0.1	0	0.2	0.1	0.2	0	-0.3	-0.1	0.2	-0.1	0.2	0	-0.4	0.1	-0.1	-0.1	0.2	0.4	0.3	-0.3	-0.2	0.1	0.5	-0.3	0.1	-0.3	-0.5	0.1	0	
p_{op}			0	0.2	-0.1	0.1	-0.3	0.3	0	0.1	-0.1	0.4	0.4	0	0	0.1	0.4	0.2	0.3	0.2	0	0	-0.3	-0.1	0	-0.2	-0.3	0.2	0.3	-0.2	-0.3	0	0	-0.2	0	-0.1	0.2		
$p_{st,water}$				0	-0.1	-0.3	0.3	0	-0.2	0.4	-0.1	0	-0.2	-0.1	0.2	-0.3	0	0.1	0.2	0.3	0.4	-0.2	-0.2	0.5	0.2	-0.2	0.2	0.4	-0.5	0	0.4	0	-0.2	0.3	-0.2	0	0.3		
$p_{gl,sp}$					-0.3	0	0.4	-0.2	0.1	0.4	-0.1	-0.2	0.1	0.1	0	-0.4	0.5	0.3	-0.4	0	-0.3	0	0.3	0.3	-0.4	0.1	-0.4	0.4	0.3	-0.2	-0.3	0.5	0.4	0.2	0.3	-0.1	-0.2		
θ_{min}						-0.4	-0.1	0.2	-0.2	-0.2	0.3	0.2	-0.1	-0.3	0	0.3	-0.3	-0.1	0.2	0.1	0.2	0	-0.2	-0.2	0.4	0.2	-0.1	-0.6	0	0.4	-0.1	-0.1	-0.1	-0.1	-0.1	0.3	0.1	0.2	
α_{hf}							-0.3	-0.2	0.6	-0.1	0.1	0	-0.1	0.1	-0.1	0	0.2	0	0	-0.1	0	0.1	-0.1	-0.4	-0.5	-0.2	0.1	-0.2	0.1	-0.2	0	-0.2	0.2	-0.2	0	0	-0.4		
$p_{gl,low}$								-0.1	-0.1	0.6	-0.2	-0.7	0	-0.2	0.1	-0.3	0.1	0	-0.5	0.2	0.2	-0.3	0.4	0.6	0	0	0.2	0.2	-0.3	0	-0.1	0.1	0.5	0.3	0.2	0.2	0	0.2	
$p_{st,root}$									-0.2		0.1	-0.1	0	0.1	-0.4	0.1	0.4	-0.3	0.3	0.1	-0.2	0.4	-0.2	-0.1	0	0.2	0.4	0	-0.2	0	0	-0.1	-0.2	-0.1	-0.5	-0.2	0.3	0.3	
K_h										-0.1	0	0.2	0	0.1	-0.1	-0.2	0.3	0.2	0	0.1	0.1	-0.3	0.1	-0.3	-0.4	0.2	0.1	0.1	0.2	0.2	0.3	0.3	0.3	0	-0.1	-0.2	-0.3		
c_{rain}											-0.3	-0.3	-0.2	-0.5	-0.1	-0.3	0.4	0.1	-0.2	0.2	0.5	-0.5	-0.1	0.4	-0.1	-0.1	0	0.2	0	0	-0.1	0.1	0.5	0.3	-0.1	0	0.3		
l_{cl}													0.3	-0.1	0.2	0.5	0.7	-0.2	-0.6	0.4	-0.6	-0.2	0.6	-0.2	-0.2	-0.2	-0.3	-0.3	-0.2	0	0.1	-0.1	0.2	0	-0.4	0	-0.3	0	
t_{WA}														-0.1	0.3	0.1	0.2	0	0	0.6	0	0	0.2	-0.2	-0.4	0.3	-0.1	0	-0.1	0.2	0.3	0.1	0.1	-0.1	0	0	-0.2	0	
l_{L2}															-0.1	0.1	0.2	0.2	0.2	0.1	-0.5	-0.1	-0.1	-0.1	0	-0.2	-0.2	0.3	-0.1	-0.4	-0.2	0.2	-0.2	-0.3	-0.2	-0.2	0.2		
c_{max}																0.4	-0.1	-0.1	0	0.2	-0.1	-0.5	0.5	0.2	0.1	-0.1	-0.2	-0.1	0.3	0	0	0.1	0.3	-0.1	0	0.3	-0.5	-0.4	
$p_{1,sp}$																	0.6	-0.2	-0.2	0.3	-0.4	-0.1	0.5	0	0.5	0.1	-0.3	-0.1	0.1	-0.1	0.2	0.2	0	0	-0.4	0	-0.4	-0.1	
a_{wg}																		-0.3	-0.5	0.4	-0.6	0	0.5	-0.2	-0.1	0.1	-0.2	-0.2	-0.3	0.1	0.2	-0.2	-0.3	-0.1	-0.7	-0.2	0	0.1	
$t_{pQ10max}$																		0	-0.3	0.4	-0.1	-0.2	-0.1	0	-0.4	-0.2	-0.4	0.3	0.5	-0.1	-0.4	0.3	0.4	0.3	0	0	-0.2	0.2	
k_1																			-0.2	0.4	0.1	-0.4	0.1	0.2	0.2	0.5	0.2	0.2	-0.1	-0.2	0.3	0.1	-0.1	0.1	0.1	0.2	-0.3		
l_1																					-0.1	0	0.3	-0.4	-0.2	0.3	-0.5	0	0	-0.2	0.1	0.3	-0.2	-0.3	-0.1	-0.2	0.1		
t_{Q10}																						0.1	-0.6	0.1	-0.1	0.2	0	0.2	0.1	-0.2	-0.1	0.1	0.1	0	0.6	0.2	-0.1	0.3	
$k_{gr,sp}$																								-0.5	-0.1	0.1	0.1	0.3	0.2	-0.2	-0.1	0.5	0.3	-0.4	0.1	0.1	-0.2	0.3	0.2
q_{of}																								0	-0.1	0	-0.4	-0.2	-0.2	0.1	-0.1	-0.1	-0.1	-0.1	-0.1	-0.3	0.3	0	-0.3
g_{epd}																									0	0.1	0.3	0.3	0.1	0	0.2	0.1	0	-0.1	0.3	0.4	0.2	0	
g_{max}																									0.2	0	0	0.4	-0.2	0	0.2	0	-0.1	-0.1	0	-0.1	-0.1		
m_{rain}																										0.2	0.4	-0.2	-0.2	0.4	0.4	-0.4	-0.5	0	0.2	0.2	0.2	0.2	
KB^{-1}																												0.1	-0.2	0.3	0.4	0.1	0.1	0	0	0	0.5	-0.1	
m_T																													-0.2	-0.6	-0.1	0.5	-0.4	-0.4	0.1	0	0.2	0.1	
a_{wet}																														0	-0.2	0	0.4	-0.1	0.2	-0.1	-0.3	0	
d_p																															0.3	-0.5	0.1	0.4	0	0.1	0.1	-0.2	
LAI_{anhc}																																							
g_{of}																																							
g_h																																							
l_{L1}																																							
p_{max}																																							
$w_{gr,ex}$																																							
q_{col}																																							
K_{wet}																																							

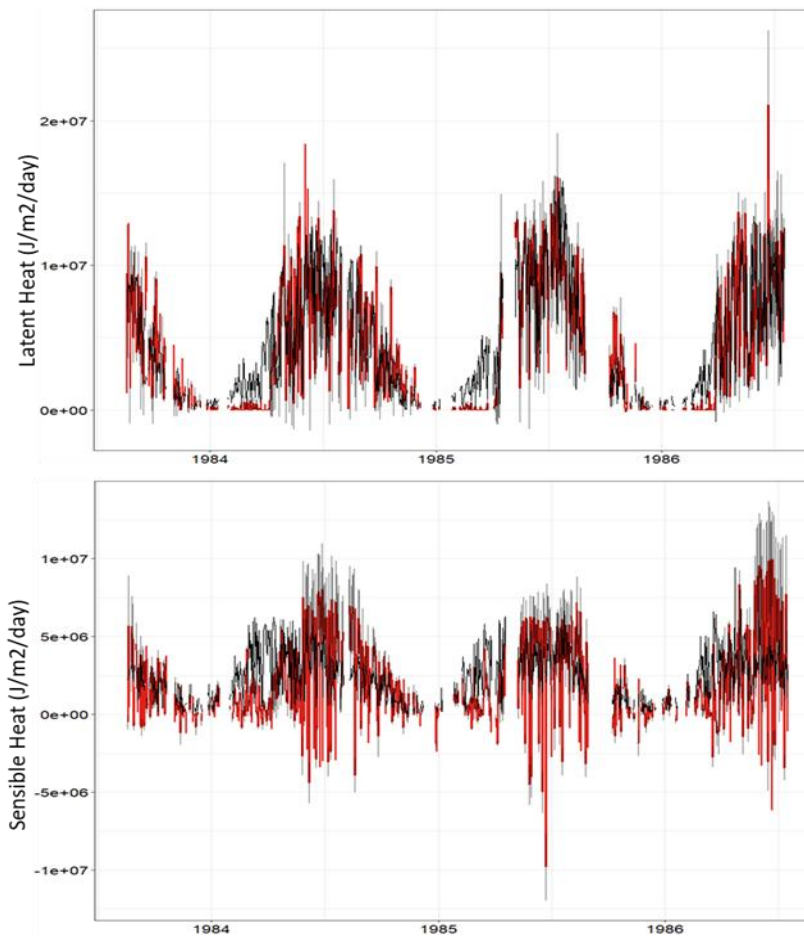
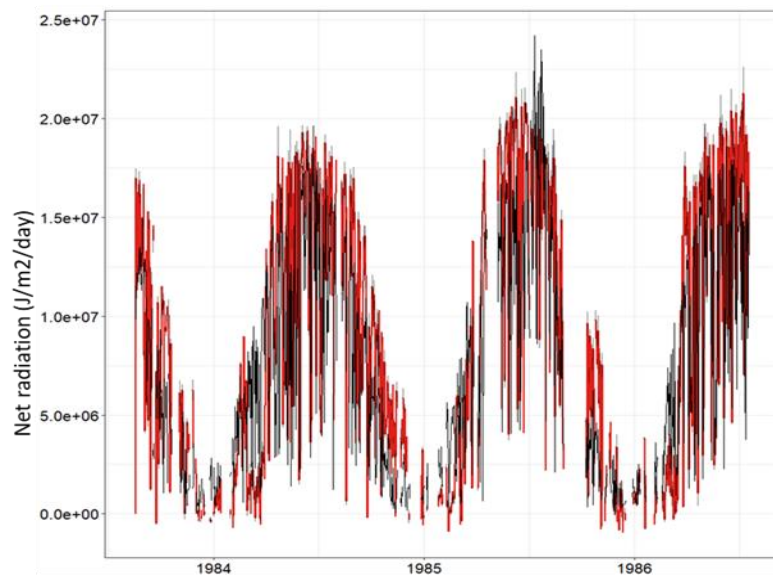
Appendix 3-8: Result of parameter contribution to variable performance with LMG Approach

Category	Parameter	Soilresp(cal)	Soilresp(val)	Stemp5	Stemp30	SL(cal)	SL	VMC5	VMC30	Nrad	LH	SH	LAI	SnowD	SP(cal)	SP(val)
plant growth	MCofCoarseRoot	2.121416	1.477459	8.237431	12.1217	1.187035	17.74539	1.958169	4.767888	6.843652	2.5908	3.96741	10.120669	0.7853312	7.533316	6.719465
water/abiotic	ThetaPowerCoef	7.31755	2.090769	7.294556	3.988291	5.82293	2.310807	9.194762	2.728837	1.641421	2.517004	13.08791	1.845788	9.9324373	2.711138	4.553528
temp and decom-abiotic	TemQ10	3.38563	3.591051	15.32889	5.032576	3.499937	4.164385	1.835659	1.754209	6.103535	1.248388	1.856529	7.562064	0.974746	11.13657	3.54019
water-abiotic	Saturation activity	19.032887	6.029802	3.726173	8.712364	2.779985	1.768566	6.311641	5.844128	13.70476	3.935608	5.333488	6.856898	2.1444549	1.165058	2.954025
soil thermal	ThScaleLog(1)	2.77317	5.571461	4.079623	5.135376	4.40426	3.929442	4.940231	5.749493	10.63224	4.292136	7.725473	8.078626	9.7169917	2.218961	3.019597
soil organic	RateCoefHumus	2.002456	4.926929	2.882412	1.993718	2.652958	6.900096	3.326349	2.480241	3.123797	6.954205	7.417158	8.072348	2.1838908	4.72409	2.614537
meteorological	PrecA0Corr	3.926877	6.32134	3.140031	1.147461	2.66219	1.225755	7.812461	5.822728	1.504695	3.863147	3.205525	1.508219	1.7608698	9.293432	8.184454
plant	AlbedoLeaf	3.637218	2.044274	7.800618	5.18149	3.673719	10.14206	7.674131	1.644069	8.028443	4.908113	5.794787	5.340018	2.5878091	7.580291	10.59164
soil organic	RateCoefLitter1	2.283223	4.270437	3.114548	5.069016	6.191558	1.756832	1.220147	3.971254	3.271041	7.293449	3.626779	8.778116	1.2721331	1.795226	1.437049
soil organic	RateCoefSurfL1	4.098293	2.965316	5.875754	3.252724	1.77197	12.68042	7.161687	5.493897	2.456879	5.269038	3.192613	2.106959	1.449582	2.74919	9.2759
plant growth	GrowthCoef	10.574973	21.048423	2.033687	2.959492	11.60148	2.642283	13.57133	11.97936	5.986806	10.26584	5.410165	7.162934	3.3258733	2.559314	10.2463
Drainage and deep perco	GWSourceFlow	7.342453	10.080261	1.7985	5.581834	4.069777	3.404689	7.94457	3.722327	11.74869	5.1041	11.87913	4.499984	4.1570726	7.660973	11.73978
transpiration (plant)	Conduct Max	3.597613	8.882092	3.841812	8.000887	2.412481	8.196215	4.953836	3.441733	7.459955	4.108898	3.651364	4.448836	2.4006713	3.50104	1.712176
plant	MobileAlloCoef	3.726829	7.44953	4.444536	5.736773	5.692012	4.188876	9.603209	12.94847	7.071648	3.708091	7.459666	2.539816	4.4515116	9.891208	8.456312
snowpack	MeltCoefAirTemp	7.115477	2.370553	14.26561	8.392565	15.5446	4.61058	4.321144	7.912447	2.800823	5.317808	5.136222	2.393013	40.1541276	16.568312	4.167339
radiation/ET	Albedo Wet	2.933628	3.97973	5.651772	5.521492	7.196675	2.909862	2.061132	5.983924	1.994771	18.91448	2.283797	1.521929	4.0062391	2.491929	1.494299
plant	LAI enh Coef	10.300507	2.741922	3.166416	8.150327	9.233269	3.870245	3.35022	8.524324	2.152355	3.188891	3.261322	11.081197	3.8636574	2.712412	2.13573
plant	LeafRate1	3.8298	4.158654	3.317631	4.021919	9.603164	7.553502	2.759323	5.230672	3.4745	6.520004	5.710656	6.082587	4.8326011	3.70754	7.157681

Appendix 3-9: observation vs ensemble mean of volumetric moisture contents (5 cm & 30cm) and soil temperature simulations



Appendix 3-10: observation vs ensemble mean of net radiation, latent and sensible heat fluxes



Appendix 3-11: Influence of constraining variables on soil respiration flux

R ² constraint (variable)	Runs # after constraint
Soil respiration only	16,490 out of 35,000
Soil respiration + soil temperature	16,481 out of 35,000
Soil respiration + saturation level	5,923 out of 35,000
Soil respiration + WTD (saturation level and surface pool)	3,233 out of 35,000
Soil respiration + VMC	2,678 out of 35,000
Soil respiration + VMC +WTD	1,567 out of 35,000
Soil respiration + Net radiation	16,490 out of 35,000
Soil respiration + latent heat flux	14,220 out of 35,000
Soil respiration + sensible heat flux	14,890 out of 35,000
Soil respiration + LAI	5141 out of 35000
Soil respiration + snow depth	16490 out of 35000
Soil respiration + surface pool only	6769 out of 35000

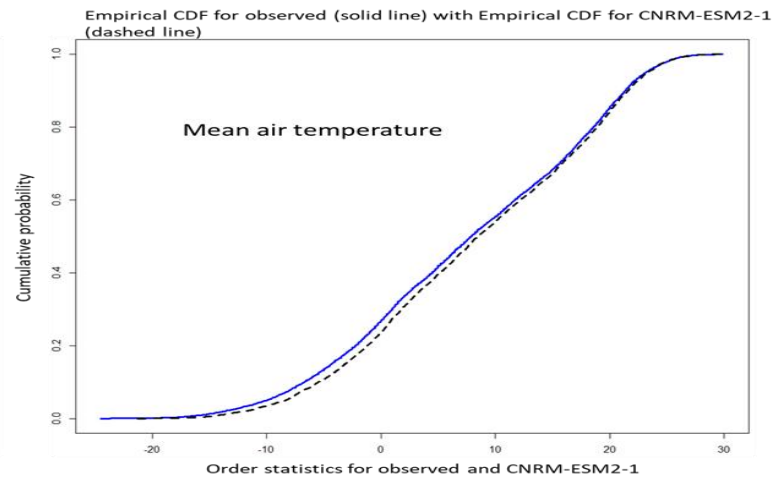
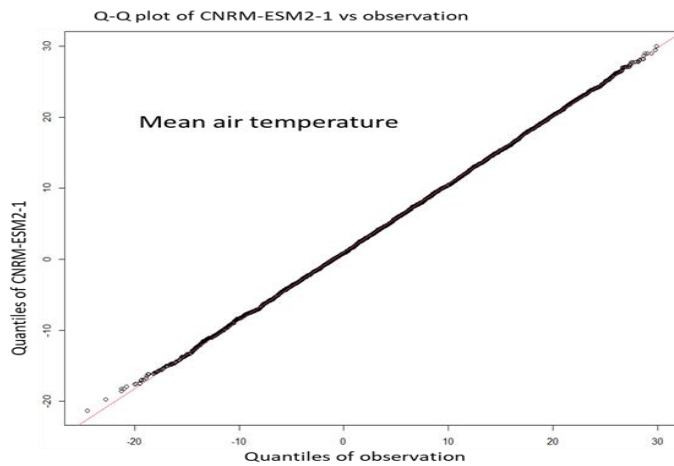
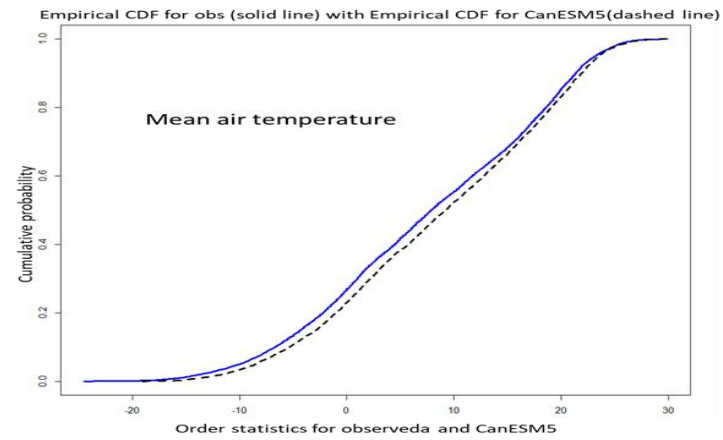
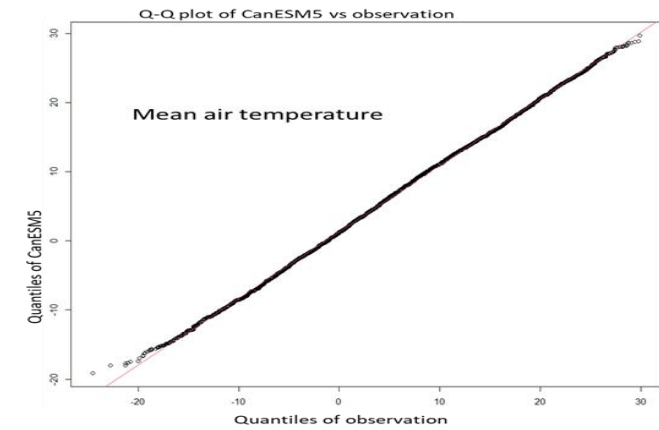
Generally, hydrological and plant productivity (LAI) variables have stronger influence than thermal variables

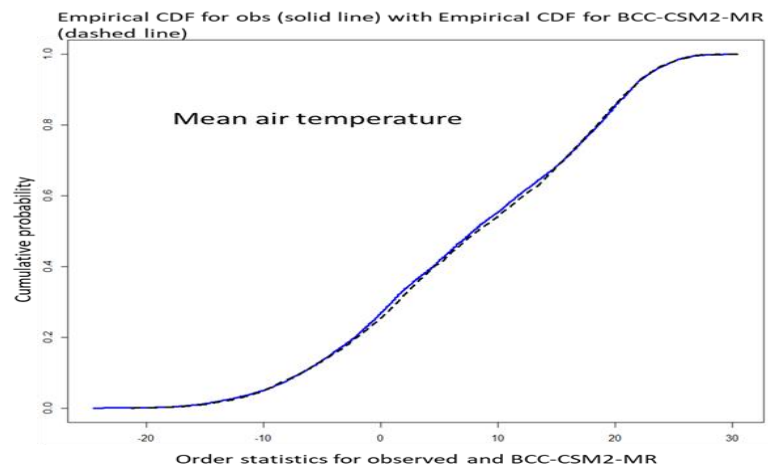
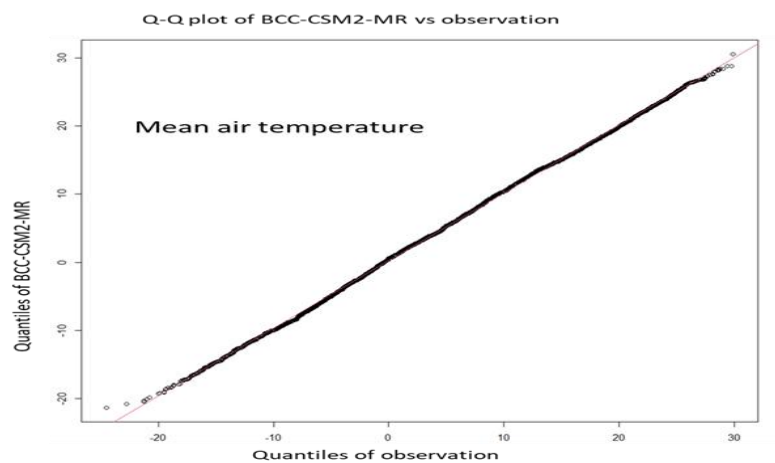
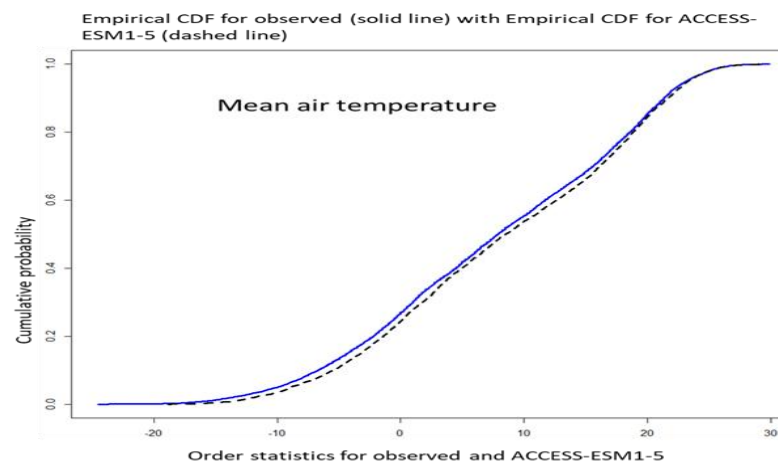
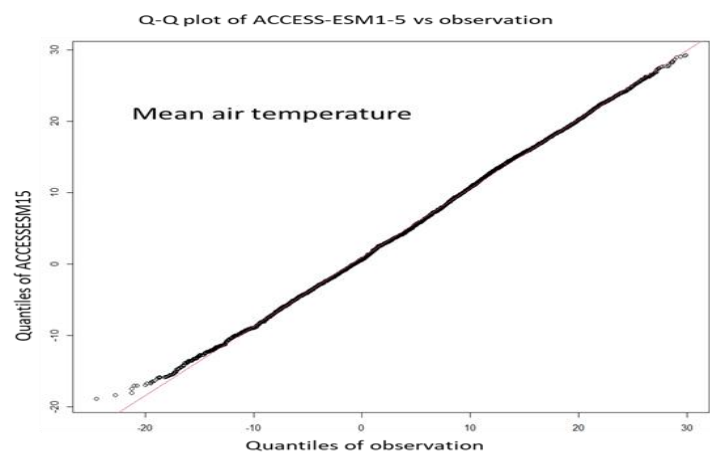
R ² & ME (soil resp) constraint	Runs # after constraint
Soil respiration only	383 out of 35,000
Soil respiration + soil temperature	380 out of 35,000
Soil respiration + saturation level	289 out of 35,000
Soil respiration + WTD (saturation level and surface pool)	189 out of 35,000
Soil respiration + VMC	228 out of 35,000
Soil respiration + VMC +WTD	133 out of 35,000
Soil respiration + Net radiation	383 out of 35,000
Soil respiration + latent heat flux	314 out of 35,000
Soil respiration + sensible heat flux	383 out of 35,000
Soil respiration + LAI	84 out of 35,000
Soil respiration + snow depth	383 out of 35,000
Soil respiration + surface pool only	254 out of 35,000
All constraints	30 out of 35,000

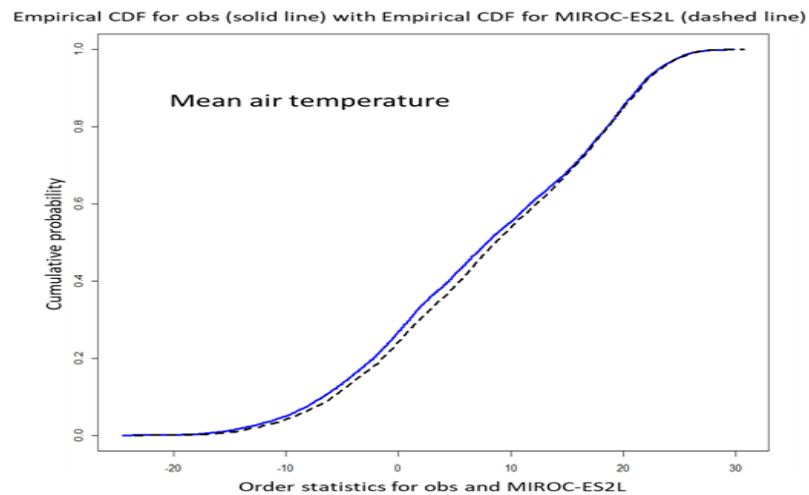
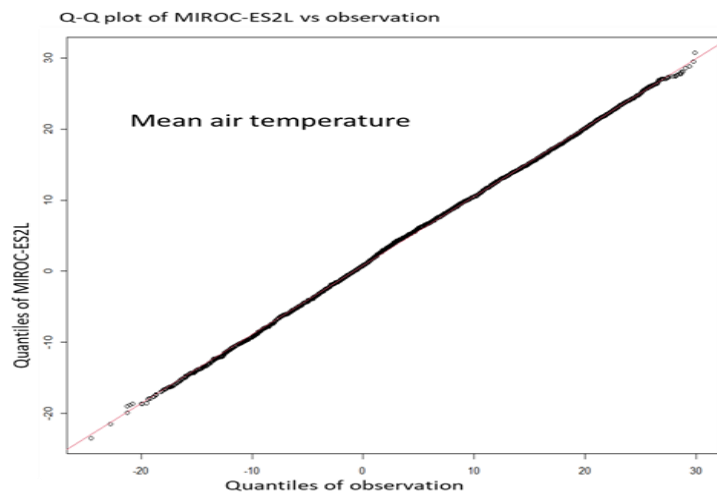
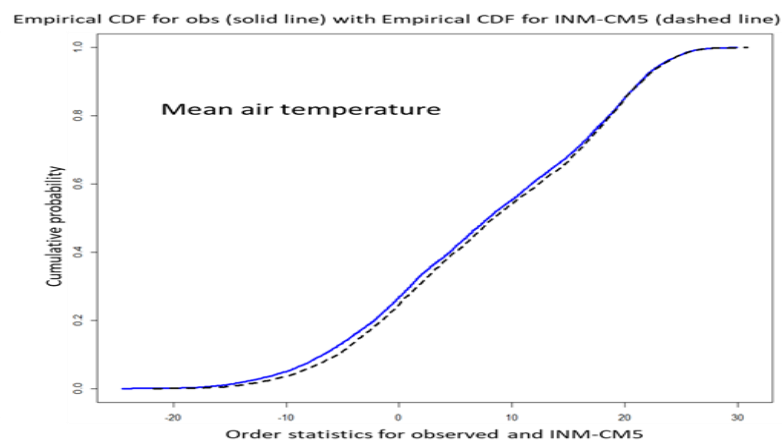
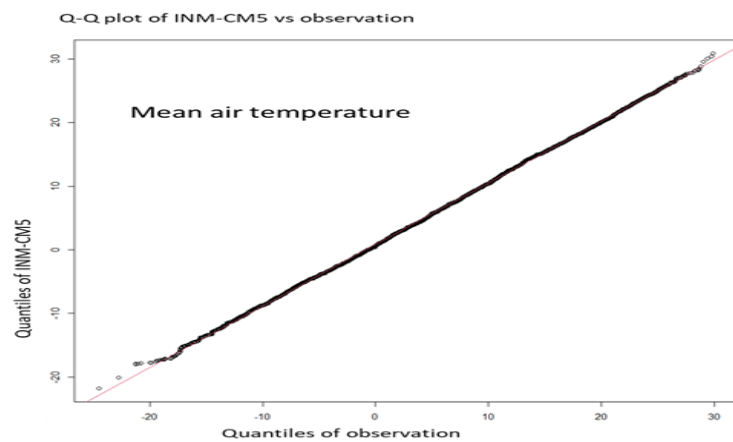
Appendix 4-1: (ΔT) and precipitation (ΔP) as the difference between the mean of 20-year reference period (1986 – 2005) that of the future prediction (2041 – 2060) of 11 ESMs

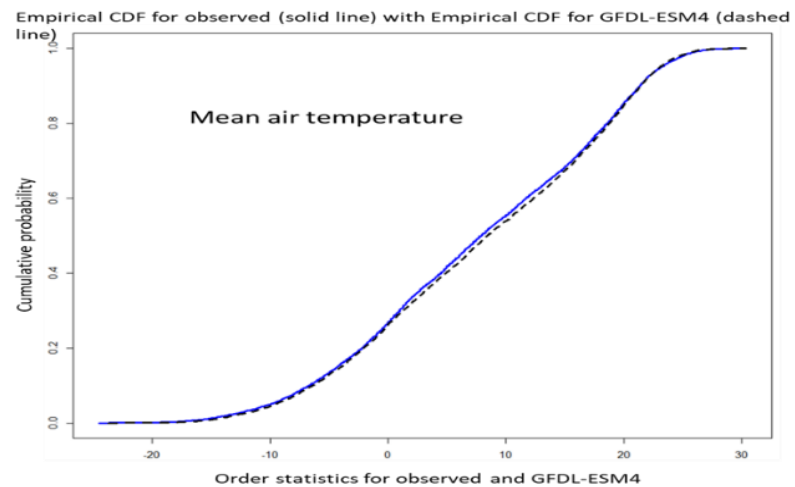
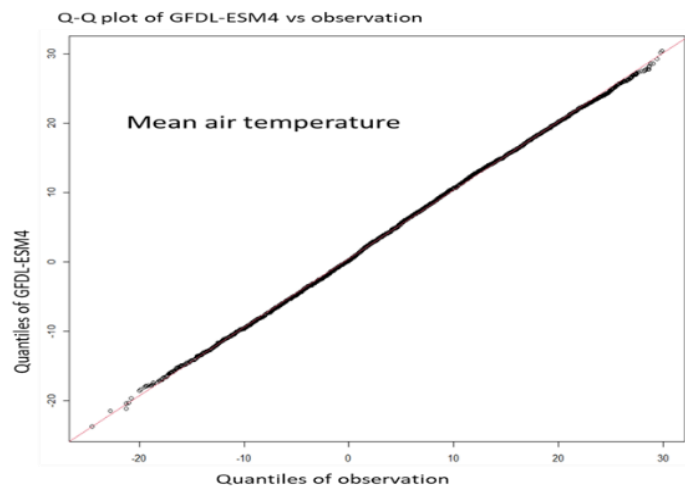
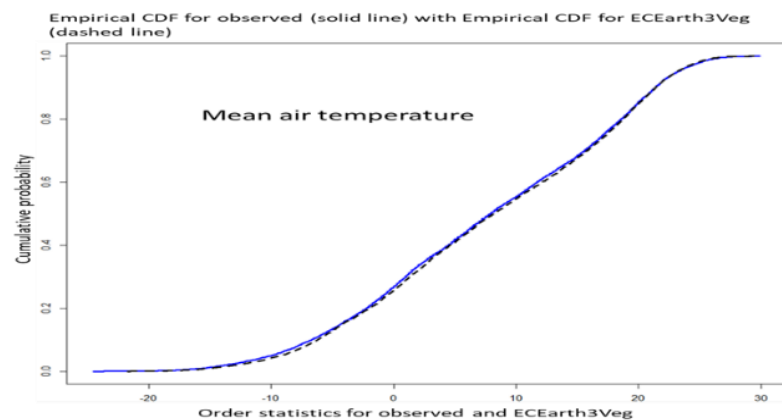
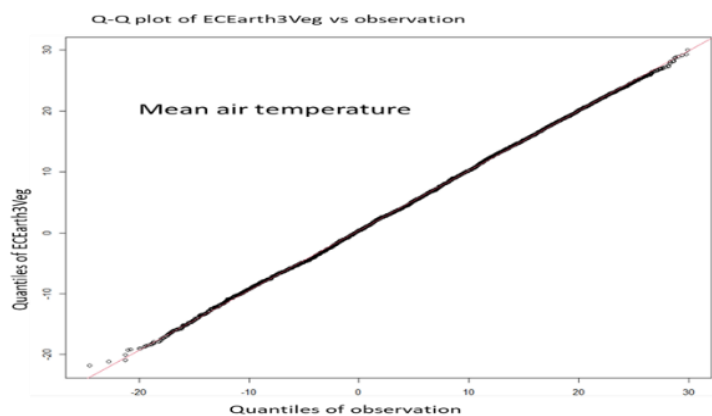
$\Delta T(^{\circ}C)$	$\Delta P(mm)$	Model
4	0.2	ACCESSES-ESM1-5
3.6	0.1	BCC-CSM2-MR
5.4	0.3	CanESM5
3.3	0.4	CNRM-ESM2-1
3.5	0.4	EC-Earth3-Veg
3	0.4	GFDL-ESM4
3.6	0.2	INM-CM5
3.8	0.2	MIROC-ES2L
3.7	0.4	MRI-ESM2
4	0.1	NorESM2-LM
6.2	0.2	UKESM1-0-LL

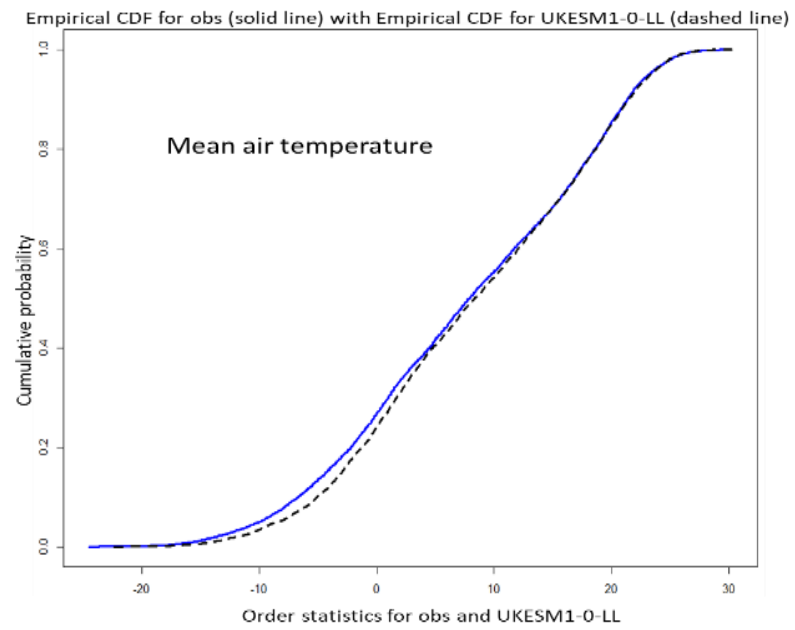
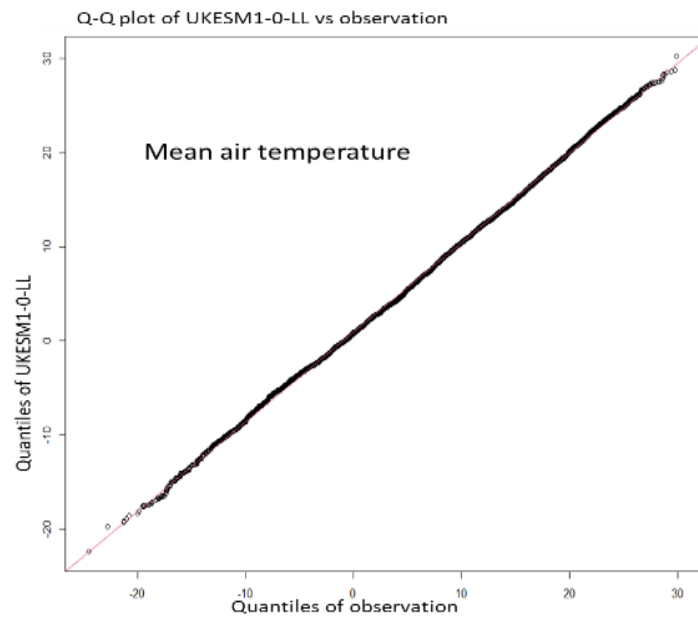
Appendix 4-2:Q-Q Plot and CDF of downscaled EMS outputs

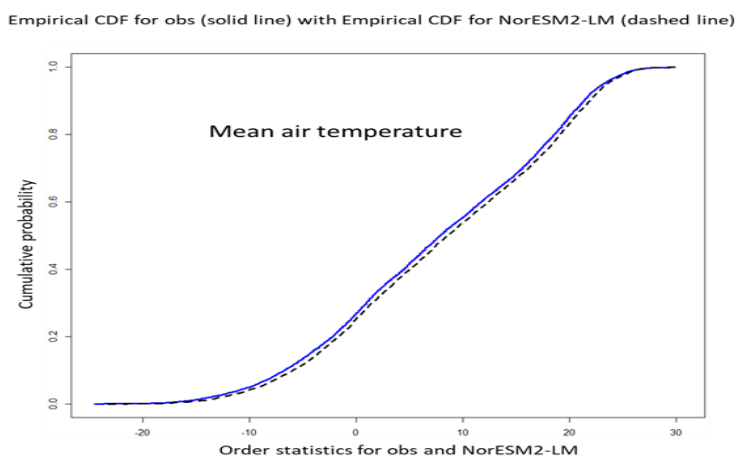
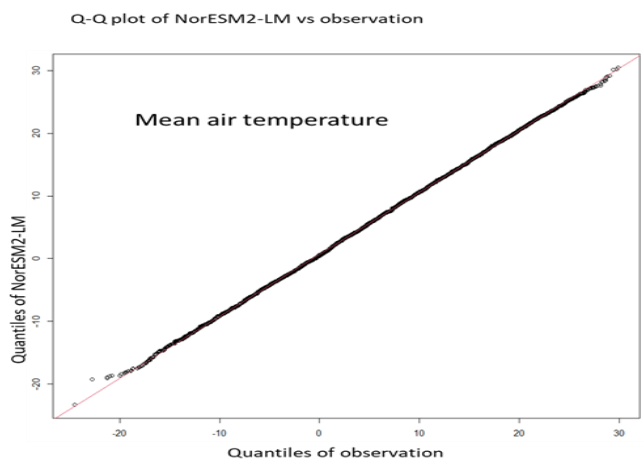
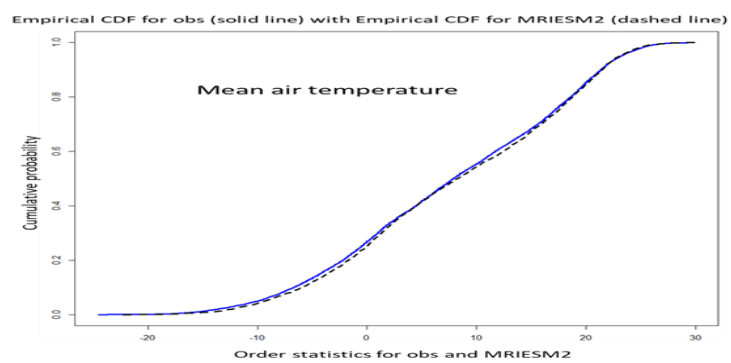
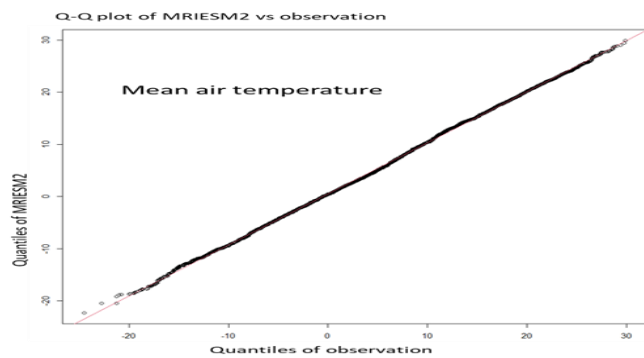




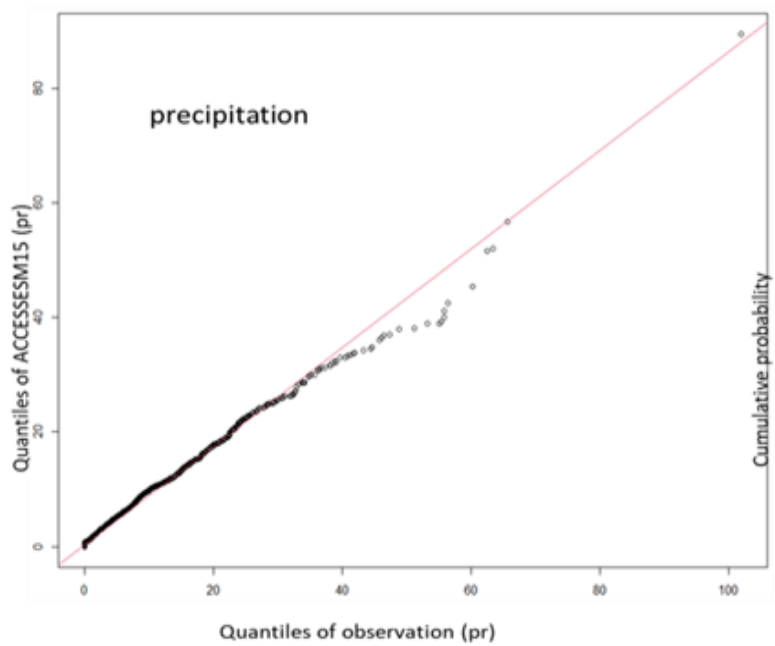




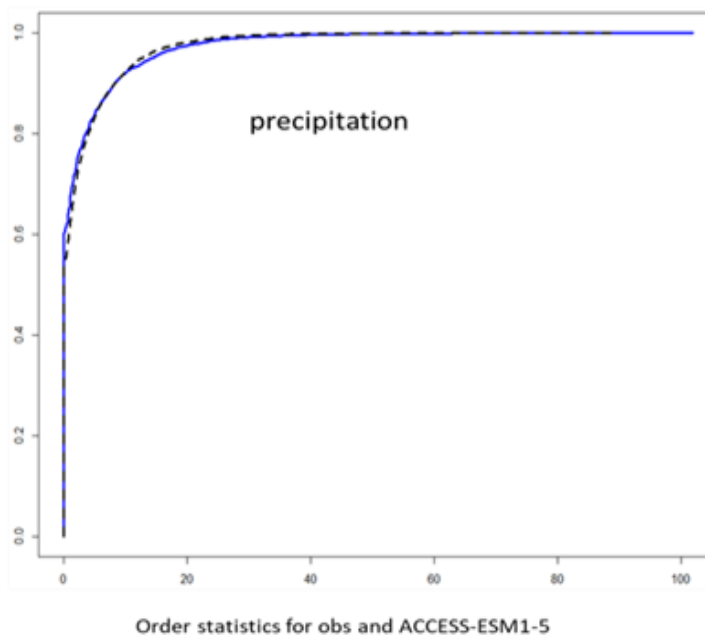


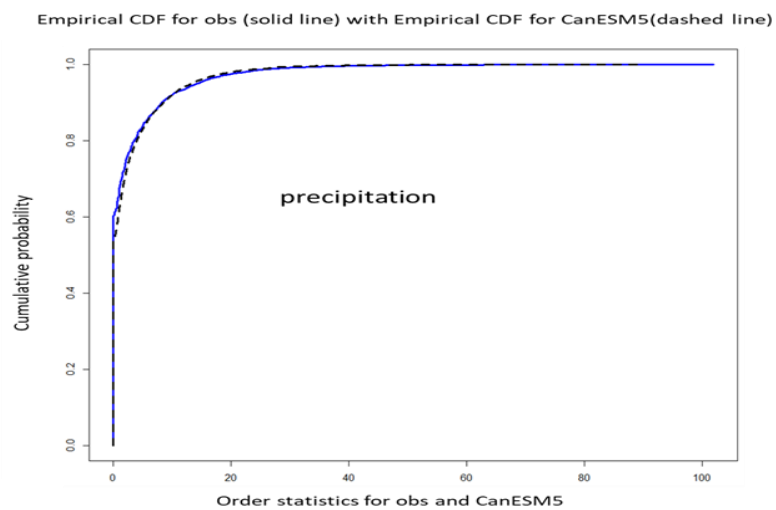
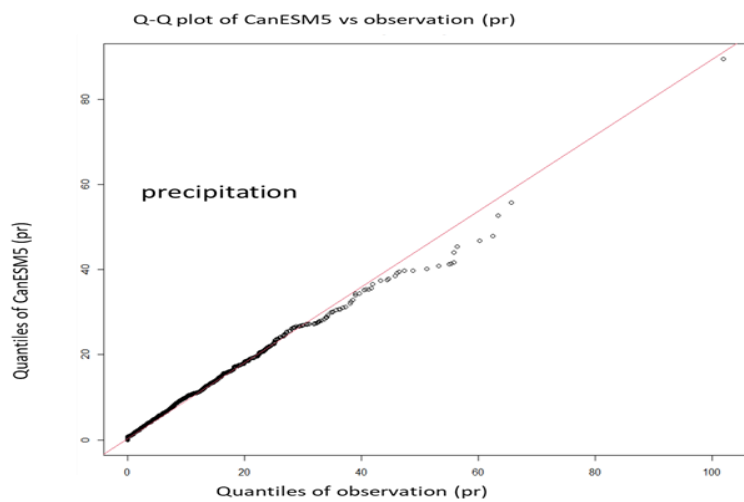
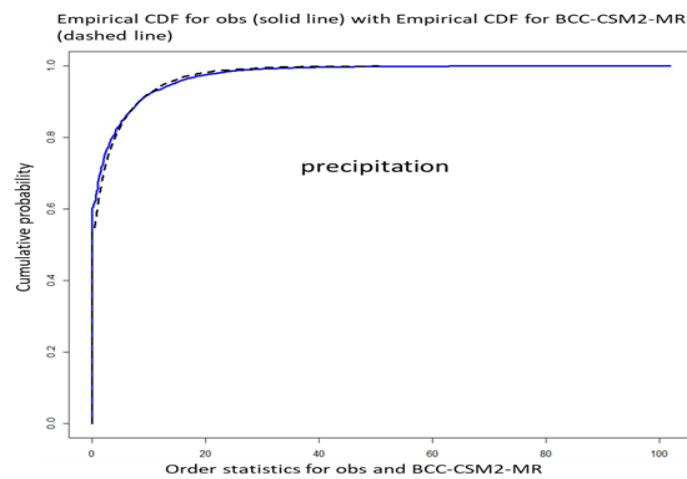
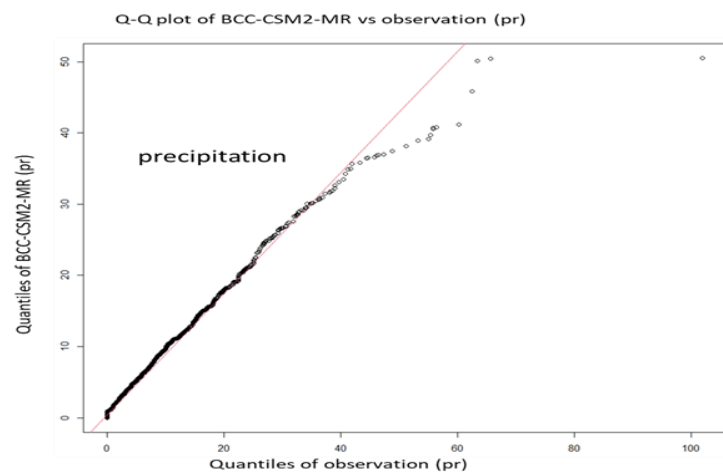


Q-Q plot of ACCESS-ESM1-5 vs observation (pr)

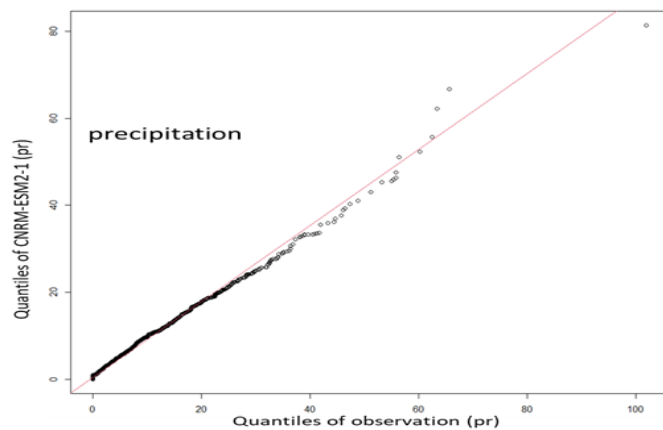


Empirical CDF for obs (solid line) with Empirical CDF for ACCESS-ESM1-5 (dashed line)

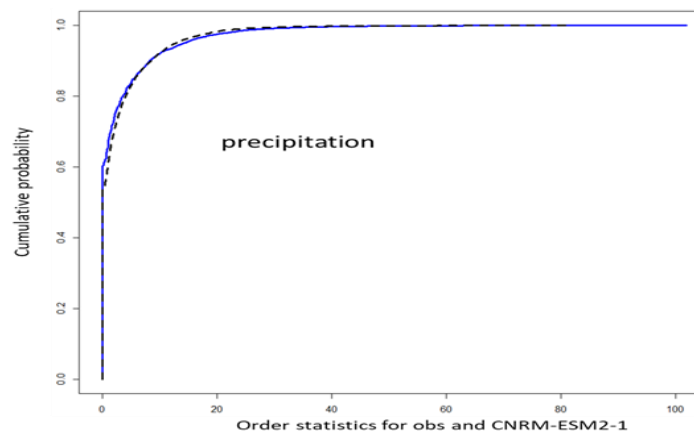




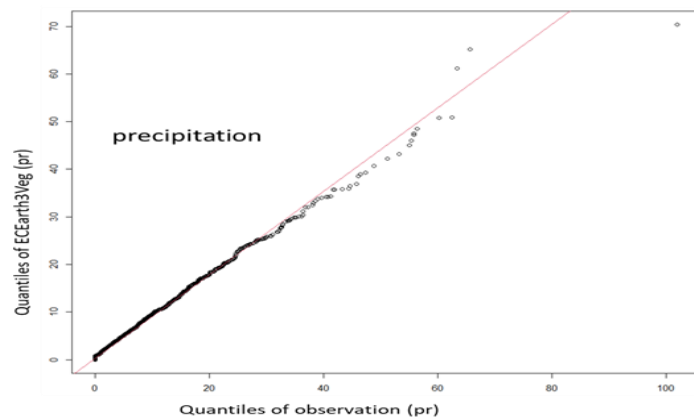
Q-Q plot of CNRM-ESM2-1 vs observation (pr)



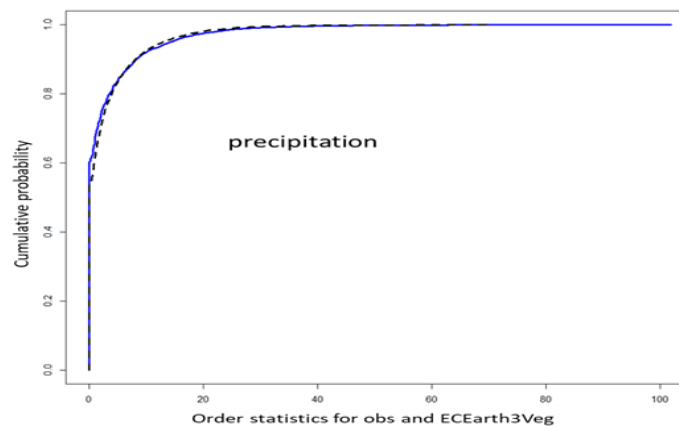
Empirical CDF for obs (solid line) with Empirical CDF for CNRM-ESM2-1 (dashed line)

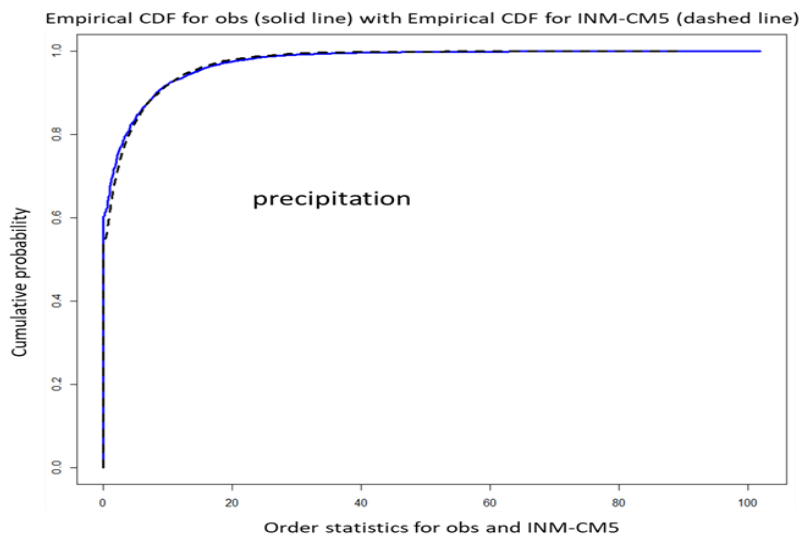
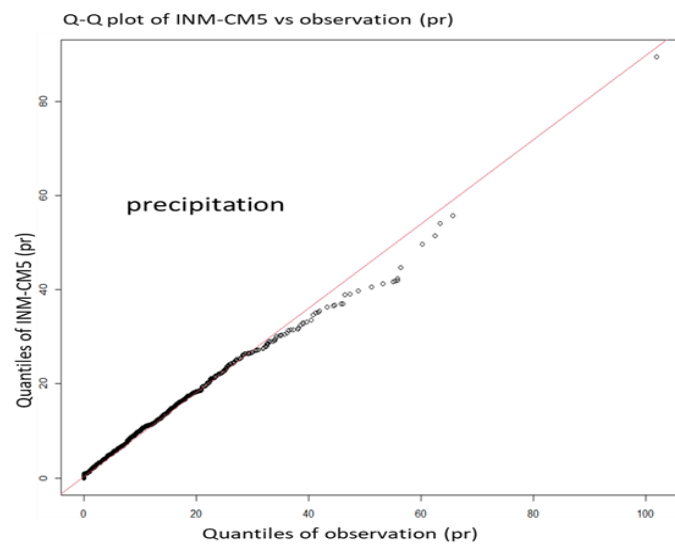
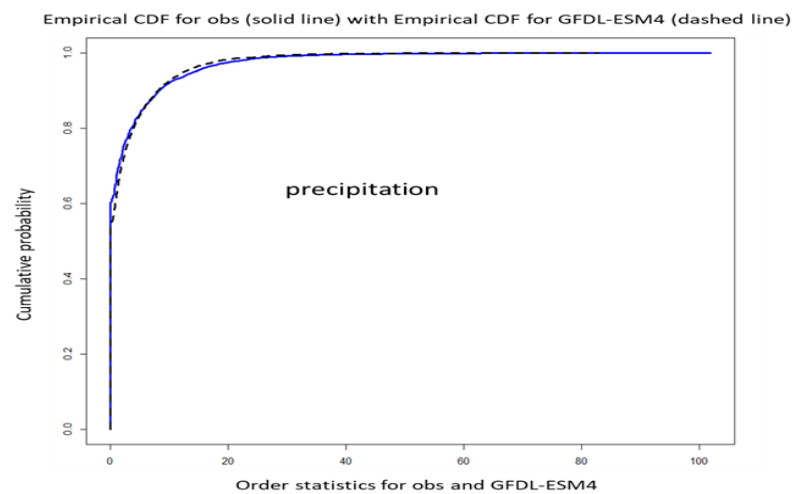
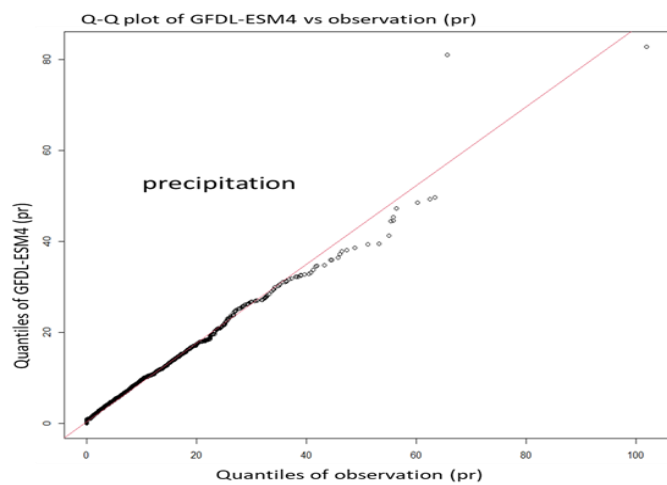


Q-Q plot of ECEarth3Veg vs observation (pr)

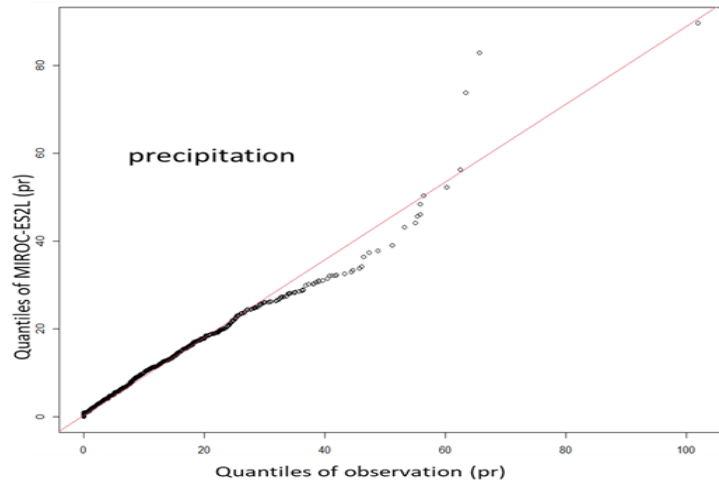


Empirical CDF for obs (solid line) with Empirical CDF for ECEarth3Veg (dashed line)

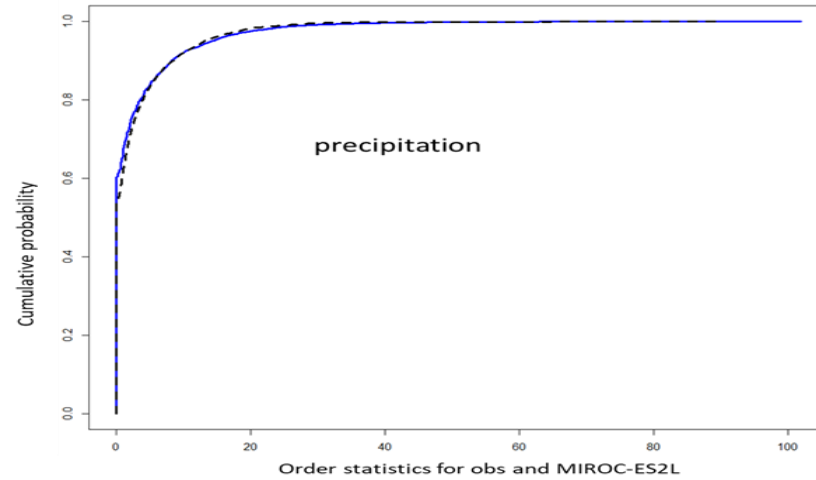




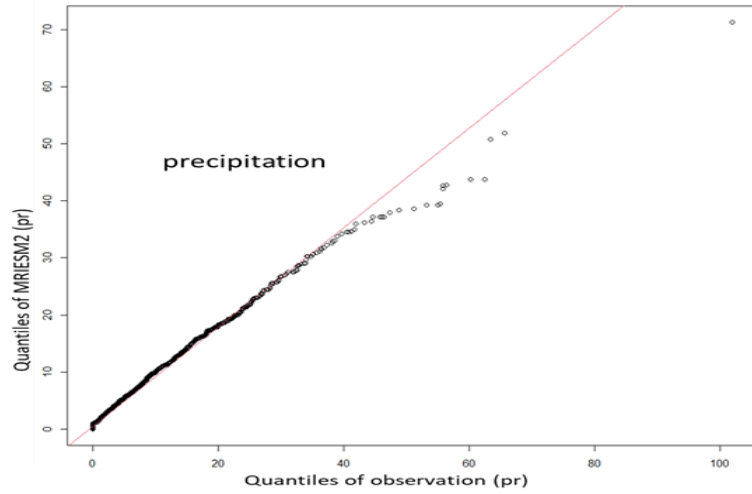
Q-Q plot of MIROC-ES2L vs observation (pr)



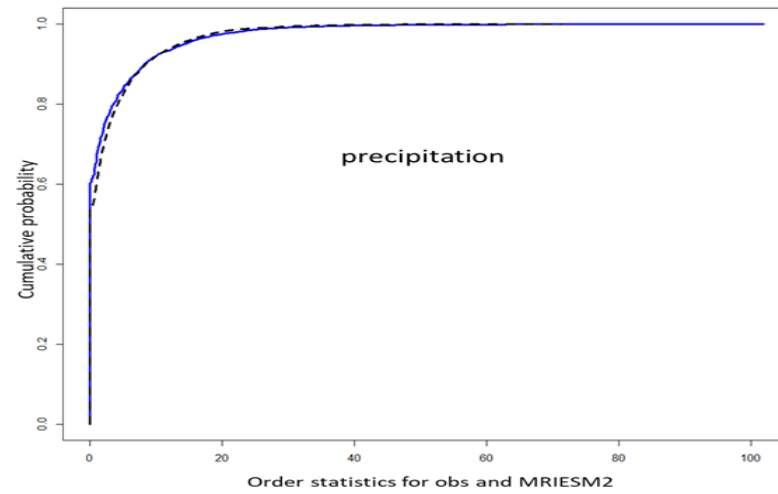
Empirical CDF for obs (solid line) with Empirical CDF for MIROC-ES2L (dashed line)

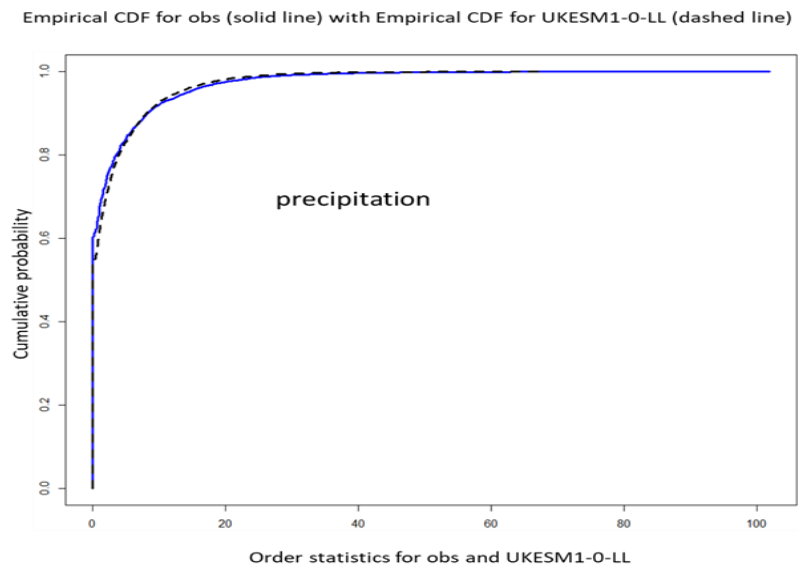
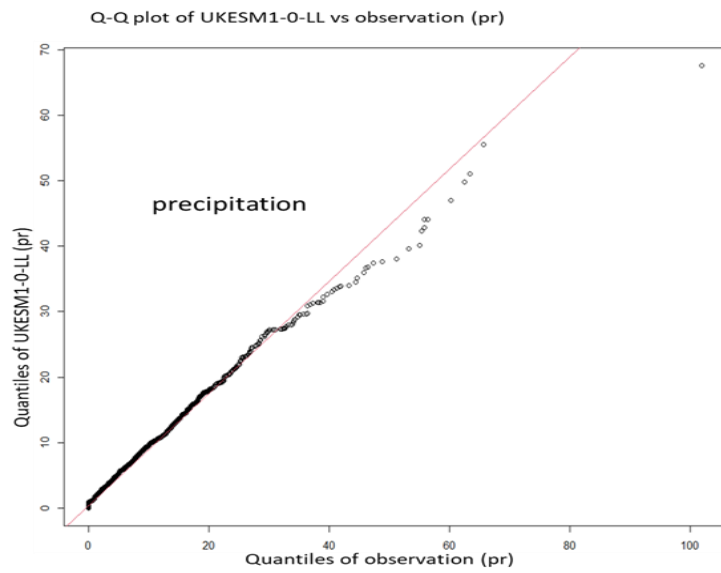
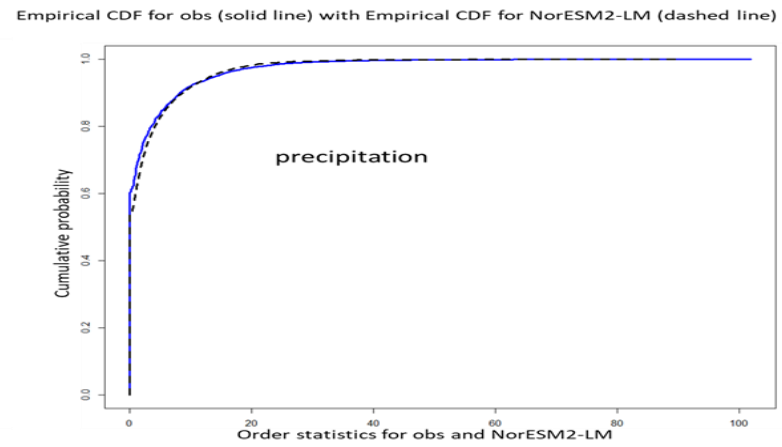
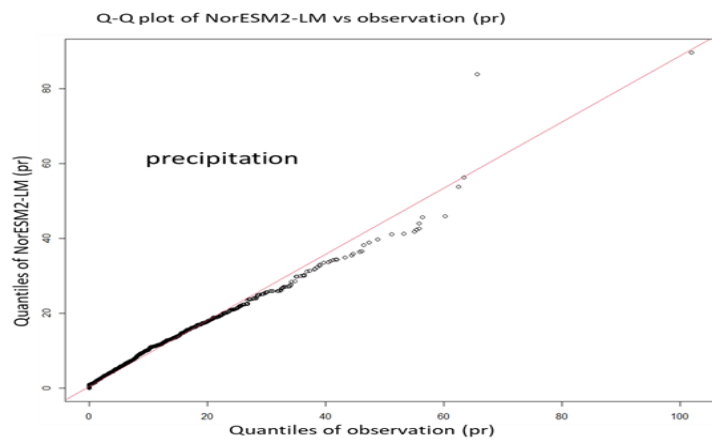


Q-Q plot of MRIESM2 vs observation (pr)



Empirical CDF for obs (solid line) with Empirical CDF for MRIESM2 (dashed line)





Appendix 4-3: Parameter value of acceptable model used for Chapter 5 simulations

Module	Parameter	symbol	value
Plant Growth	MCoefCoarseRoot	$k_{mrespcoarseroot}$	0.000237
Plant Growth	RadEfficiency	e_L	2.8271
Common abiotic responses	ThetaPowerCoef	$p_{\theta p}$	0.9407
Common abiotic responses	Saturation activity	$p_{qSatact}$	0.3127
Common abiotic responses	Thetaupperange	p_{qUpp}	17.0319
Water uptake	Airmincontent	q_{Amin}	0.002594
Soil Thermal	ThScaleLog(1)	x_{hf}	0.3242
Common abiotic responses	Theta Lower Range	p_{qLow}	7.427
Plant	Rootlowestdepth	p_{zroot}	-0.433
Soil organic processes	RateCoefHumus	k_h	1.58E-06
Meteorological Data	PrecA0Corr	c_{rain}	1.0568
Plant Growth	Leafc1	l_{c1}	0.3363
Water uptake	TempCoefA	t_{WA}	1.3128
Plant Growth	LeafRate2	l_{Lc2}	0.0112
Interception	Maximal Cover	c_{max}	0.9491
Plant	Specific LeafArea	$p_{l,sp}$	85.6142
Plant	AlbedoLeaf	a_{veg}	13.8847
Common abiotic responses	TemQ10Bas	$t_{pQ10bas}$	28.5229
Soil organic processes	RateCoefLitter1	k_l	0.00241
Soil organic processes	RateCoefSurfL1	l_{l1}	0.7137
Common abiotic responses	TemQ10	t_{Q10}	2.0963
Plant Growth	GrowthCoef	k_{gresp}	0.1199
Drainage and deep percolation	GWSourceFlow	q_{sof}	1.1463
Potential Transpiration	Conduct VPD	g_{vpd}	113.6137
Potential Transpiration	Conduct Max	g_{max}	0.0106
Plant Growth	MobileAlloCoef	m_{retain}	0.5472
Soil evaporation	KBMinusOne	k_B^{-1}	1.6421
SnowPack	MeltCoefAirTemp	m_T	2.2412
Radiation properties	Albedo Wet	a_{wet}	13.8835

Drainage and deep percolation	DrainSpacing	d_p	1250.737
Plant Growth	LAI enh Coef	$LAI_{enhcoef}$	0.1472
Potential Transpiration	Conduct Ris	g_{ris}	4.03E+06
Plant Growth	LeafRate1	l_{lc1}	6.87E-05
Surface water	SPMaxCover	p_{maxt}	0.9158
Surface water	SurfPoolMax	W_{pmax}	120.278
Drainage and deep percolation	GWSourceLayer	q_{sol}	3.933
Soil Hydraulic	Total conductivity (1)	k_{sat1}	1642.352
Soil Hydraulic	Total conductivity (6)	k_{sat6}	12.31