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Membres du jury :

Gerhard KRINNER, Directeur de Recherche, au Laboratoire de Glaciologie et Géophysique de l'Environnement (LGGE) - Grenoble - Rapporteur

Markus REICHSTEIN, Directeur de Recherche, à l'Institut Max Planck de Biogéochimie - Jena (Allemagne) - Rapporteur

Philippe CIAIS, Directeur de Recherche, à l'Université Versailles Saint-Quentin-en-Yvelines/Laboratoire des Sciences, du Climat et de l'Environnement (LSCE) - Gif/Yvette - Directeur de Recherche

Catherine OTTLE, Directeur de Recherche, à l'Université Versailles Saint-Quentin-en-Yvelines/Laboratoire des Sciences, du Climat et de l'Environnement (LSCE) - Gif/Yvette - Co-Directeur de Recherche

Aaron BOONE, Chargé de Recherche, au Centre National de Recherches Météorologiques (CNRM) - Toulouse - Examineur

Philippe BOUSQUET, Professeur des Universités, à l'Université Versailles Saint-Quentin-en-Yvelines/Laboratoire des Sciences, du Climat et de l'Environnement (LSCE) - Gif/Yvette - Examineur

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Contents

Summary.....	I
1. Introduction.....	1
1.1 Carbon cycle in the northern high-latitude ecosystems	1
1.2 Site-level monitoring of atmosphere-biosphere exchanges	3
1.3 The overview of model evaluation	5
1.4 The overview of snow model development.....	6
1.5 Objectives and structure.....	10
2. Systematic errors in a land surface model across biomes inferred from eddy covariance observations on multiple time scales.....	12
2.1 Introduction.....	12
2.2 Data and Methods	14
2.2.1 Eddy covariance data.....	14
2.2.2 Simulation protocol	14
2.2.3 Methodologies	16
2.2.3.1 Singular system analysis.....	16
2.2.3.2 ANN error model	17
2.2.3.3 The configurations of ANN error modeling	19
2.3. Results and Discussion	22
2.3.1 RMSE-R on three different timescales (Case WT).....	22
2.3.2 Error transferability across different timescales (Case CT)	25
2.3.3 Error spatial transferability (Case S)	25
2.3.3.1 Original time series	25
2.3.3.2 Different timescales	26
2.3.4 Error transferability between water and carbon fluxes	28
2.4 Conclusions and Outlooks	30
3. Controls on winter ecosystem respiration in temperate and boreal ecosystems	32
4. Development and evaluation of ORCHIDEE snow model using point observations at SNOWMIP sites and regional snow observations	50
4.1 Introduction.....	50

4.2 Model description	51
4.2.1 ORC-O snow processes	51
4.2.2 ORC-N snow processes	52
4.2.2.1 Snow layering	52
4.2.2.2 Energy balance equations	54
4.2.2.3 Liquid-water treatment	54
4.2.2.4 Mass balance equation	55
4.2.2.5 Snow compaction	56
4.2.2.6 Snow albedo	56
4.2.2.7 Roughness length	58
4.3. Metrics for snow evaluation	58
4.3.1 Snow cover accuracy (SCA)	58
4.3.2 Mean Absolute Error (MAE)	58
4.3.3 Mean Error (ME)	59
4.3.4 Index of agreement (IOA)	59
4.4. Dataset	59
4.4.1 SNOWMIP1 sites	59
4.4.1.1 Col de Porte (CDP, 1993-1995)	59
4.4.1.2 Weissfluhjoch (WFJ, 1992-1993)	60
4.4.2 SNOWMIP2 sites	60
4.4.3 Canadian climate stations	61
4.5. ORC-N Snow model evaluation at SnowMIP sites	62
4.5.1 SCD, SWE, snow depth and snow density at open sites	62
4.5.2 Snow albedo	64
4.5.3 Snowmelt runoff	65
4.5.4 Snow surface temperature	65
4.5.5 Snow simulation at needleleaf forest sites	65
4.5.6 Sensitivity tests	67
4.6 Model regional evaluation	69
4.6.1 Model driving forcing	69
4.6.2 Mean Spatial patterns	70
4.6.3 Temporal variability	72
4.6.3.1 Intra-annual variability	72
4.6.3.2 Interannual variability	72
4.6.4 Factors influencing snow model bias	73
4.7 Conclusions	77
5. High temperature frequency impacts on snow simulations and snow model evaluation over Northern Hemisphere	78
5.1 Introduction	78
5.2. Datasets	80
5.2.1 GooseBay (GSB) site	80
5.2.2 Canadian Meteorological Centre (CMC) daily snow depth (SD) analysis data	81

5.2.3 Global snow SWE products (version 1.0)	82
5.3. Methodology	83
5.3.1 ORCHIDEE simulation protocols	83
5.3.2 Sensitivity of snow simulations to the diurnal cycle of temperature	84
5.3.3 Evaluation of modeled SWE	85
5.3.3.1 Spatially integrated SWE	85
5.3.3.2 Spatial variation in SWE	86
5.3.4 Temperature sensitivity of Snow Cover Days (SCDs)	86
5.4. Sub-daily variability impacts on snow simulations	89
5.4.1 Snow model results with vs. without sub-daily temperature variability	89
5.4.2 Sensitivity analysis of sub-daily temperature variability	89
5.5 Evaluation of modeled SWE	91
5.5.1 Spatially integrated results	91
5.5.2 Spatial variation in SWE	96
5.6 Temperature sensitivity of snow cover days	98
5.7 Conclusions and perspectives	100
6. Conclusion and perspectives	103
References	107
Appendix A	133
Appendix B	134
Appendix C	139

List of Figures

Figure 1.1 A global overview of eddy covariance sites.....	4
Figure 1.2 A model structure classification with respect to the snow temperature and solar radiation absorption.....	11
Figure 2.1 Spatial distribution of the chosen sites colored by their respective plant function type.	15
Figure 2.2 The conceptual diagram of ANN operation.	19
Figure 2.3 The histogram of RMSE-R on the original time series (a: O-O), at three timescales (b: D-D, c: A-A and d: I-I) and across timescales (b: D-A and D-I; c: A-D and A-I; d: I-D and I-I) for H, LE, GPP, Reco and NEE.....	23
Figure 2.4 Matrix of the average RMSE-R from all pairs in both Case S5 (diagonal) and Case S6 (non-diagonal) for H, LE, NEE, GPP and Reco.	27
Figure 2.5 The whisker box of RMSE-R in Case S1 for H, LE, GPP, Reco and NEE on the original time series and reconstructed time series at three different characteristic timescales.....	29
Figure 4.1 The soil model coupled with a one layer snow model in ORC-O (a) and a three-layer snow model in ORC-N (b).	53
Figure 4.2 The spatial distribution of climate stations with mean winter (December to February) snow depth (a) and mean snow cover days (b) during the period 1989-2005.	62
Figure 4.3 Comparison of observed and simulated snow depth, SWE and density at (a) CDP (1993-1994), (b) CDP (1994-1995), (c) WFJ (1992-1993).	63
Figure 4.4 Comparison of observed and modeled snow albedo (a) CDP (1994-1995), (b) WFJ (1992-1993).	64
Figure 4.5 Comparison of daily snow melt runoff at (a) CDP (1994-1995) and (b) WFJ (1992-1993).	66
Figure 4.7 Comparison of SWE at (a) open and (b) forested sites in SNOWMIP2. Each circle represents the SWE per site per observation.	68
Figure 4.8 Spatial distribution of the mean difference between ERA-interim and observed total snowfall (a) and winter (December to February) air temperature (b) during the period 1989-2005.....	70
Figure 4.9 Spatial patterns of mean (1989-2005) annual snow depth error (ME) for ORC-N driven by (a) IERA and (b) IERA_TP, and the spatial patterns of mean (1989-2005) snow cover days error (ME) for ORC-N driven by (c) IERA and (d) IERA_TP.	71

Across Canada, our results indicate that both models overall perform better in capturing spatial and temporal patterns of snow given IERA_TP forcing compared to IERA forcing (e.g. Table 4.3).	73
Figure 4.10 Mean (1989-2005) half-monthly observed snow depth (cm) (A), mean half-monthly snow depth error (ME) (cm) for IERA (B) and IERA_TP (C), and mean snow cover accuracy for IERA (D) and IERA_TP (E) in different regions.....	74
Figure 4.12 Index of agreement (IOA) between interannual observed and ORC-N simulated (IERA and IERA_TP) snow characters (SMEAN, SMAX, SCD, TSL_F and TSL_L) during the period from 1989 to 2005 in four different regions and across Canada.....	76
Figure 5.1 A scheme graph showing impacts of different shapes of sub-daily temperature variability on SWE simulations.	79
Figure 5.2 The graph showing the hyperbolic tangent curve fitted between relative snow cover duration (n) and temperature	88
Figure 5.3 (a) The comparison between modeled SWE driven by the meteorological data with (ORC-O_M and ORC-N_M) and without (ORC-O_C and ORC-N_M) sub-daily temperature variability at Goose Bay site during the period 1974-1980.....	90
Figure 5.4 The mean CVs of DTR (a: spring and d: winter), simulated SWE (b: spring and e: winter) and SCDs (c: spring and f: winter) averaged from 1989 to 1995 across three different meteorological datasets	92
Figure 5.5 The mean relative change in spring SWE (a and b), spring SCDs (c and d), winter SWE (e and f) and winter SCDs (g and h) in both DTR-P and DTR-T domains.	93
Figure 5.6 The frequency distributions of CVs of spring (a) and winter (b) SWE and SCDs in two ensemble simulations.	94
Figure 5.7 Mean monthly SWE (in km ³) averaged from 1999 to 2009 at different latitude bands in (a) Eurasia and (b) North America (NA)	95
Figure 5.8 The RMSE and IOA (index of agreement) between interannual anomalies of modeled and observed seasonal (spring and winter) SWE during the period 1999-2009 in Eurasia (a and b) and NA (c and d).	96
Figure 5.9 The spatial pattern of mean spring and winter SWE (in mm) averaged from 1999 to 2009 for Globsnow (a and e), CMC (b and f), ORC-O (c and g) and ORC-N (d and h).	97
Figure 5.10 The spatial pattern of IQR of spring and winter SWE (in mm) during the period from 1999 to 2009 for Globsnow (a and e), CMC (b and f), ORC-O (c and g) and ORC-N (d and h).	98
Figure 5.11 The spatial pattern of seasonal SWE RMSE reduction during the period 1999-2009 based on Globsnow (a: spring and c: winter) and CMC (b: spring and d: winter).	99

Figure 5.12 The spatial pattern of extreme sensitivity (s_0), actual sensitivity (s_{actual}) and the difference between seasonal T_{mean} and T_0 for CMC (a: spring and d: winter), ORC-O (b: spring and e: winter) and ORC-N (c: spring and f: winter).....	101
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List of Tables

Table 2.1 The number of sites belonging to each PFT x climate group. Climate group is defined according to aggregated Koppen-Geiger classification.	15
Table 2.3 The configuration of spatial transferability of ANN correction	22
Table 2.4 Random flux measurement error, RMSE (root mean square error) of ORCHIDEE flux variables and their ANN-corrected values during the year 2000 in Howland forest.....	25
Table 4.2 Bias and RMSE for the SnowMIP1 sites	63
Table 4.3 Summary of mean annual snow depth error (ME) and mean snow cover days error (ME), and the median absolute error (MAE) between the observed and modeled (driven by both IERA and IERA_TP) annual snow depth and snow cover days during the period from 1989 to 2005 in different regions and across Canada.	73
Table 5.1 The slope, IOA (index of agreement, see details in Chapter 4), R^2 and MAD comparison between modeled (ORC-O and ORC-N) and observed (CMC) $T_{mean} - T_0$, s_0 , and s_T in both spring and winter season.	102
Table B1. List of site ID, latitude, longitude, PFT and climate of the sites used in the analysis.....	138

Summary

This thesis is to evaluate and develop a land surface model ORCHIDEE (**O**rganizing **C**arbon and **H**ydrology **I**n **D**ynamic **E**cosyst**E**ms). In the first part, ORCHIDEE model on multiple timescales is evaluated by a novel methodology linking Artificial Neural Networks to Singular System Analysis. Our model evaluation, which is characterized by quantifying the model bias (or systematic errors in ORCHIDEE), is different from the conventional approach that could be mixed up by random errors from the observations. Furthermore, a global eddy covariance network including numerous on-line observations of carbon, water and heat fluxes across a range of biomes and timescales used in this thesis provides an unprecedented opportunity to assess systematic errors in a model like ORCHIDEE. The joint analysis of observations and simulations from ORCHIDEE uncovers the characteristics of systematic errors (or model bias) at and across timescales in different plant function types and climate groups, which provide important knowledge for the future developments of ORCHIDEE parametrizations.

To have an understanding of snow effects on the present and future carbon fluxes, ORCHIDEE with a snow model that can capture snow dynamics should be developed. In the second part, before the snow model development, a site-synthesis analysis of winter ecosystem respiration and its controls among different vegetation types based on eddy covariance sites located in mid- and high-latitude regions has been conducted. Snow impacts on winter carbon cycling was not directly observed due to unavailable in-situ snow data, but the results show the non-negligible role of winter respiration in annual carbon budget and the superiority of soil temperature compared to air temperature in controlling the temporal variation of winter respiration, which is possibly due to snow insulating effect.

The standard snow model in ORCHIDEE, which adopts a mixed (or composite) single-layer snow/top soil structure, is a simple bucket snow model with constant snow density, which has been shown to bias snow simulations. Thus, in the third part, the internal snow processes (heat consumption/release due to snow melting/refreezing; water infiltration between 3 snow layers, solar radiation absorption at each snow layer) were included into standard ORCHIDEE. Moreover, a new forest albedo parameterization was implemented in ORCHIDEE accounting for the leaf area index. In the third and final parts, this newly developed snow model has been validated based on both site and continental levels. The results show a significant improved ability of new snow model in capturing observed snow pack properties (e.g. snow depth, snow water equivalent, snowmelt runoff and surface albedo) at the site level (SNOWMIP sites and Canada climate stations) and spatial and temporal variations of snow water equivalent on the continental scale according to two large-scale available snow products (CMC and GlobSnow). In addition, impacts of forcing data time resolution on snow simulations were highlighted, which pointed out that correct description of

Summary

high frequency variability (e.g. diurnal cycle) in the forcing dataset is necessary and important for accurate snow simulation.

1. Introduction

1.1 Carbon cycle in the northern high-latitude ecosystems

Global surface air temperature has increased substantially since about 1980 (Alley et al., 2003; Johannessen et al., 2004). Recent studies have revealed surface air temperature increases on the average of 0.6°C per decade since 1985 over land north of 62 °N (Polyakov et al., 2002) and 0.35°C per decade from 1970 to 2000 for terrestrial regions between 50 and 70°N (Serreze and Francis, 2006, Euskirchen et al., 2007). Northern high latitudes, encompassing the Arctic, Subarctic and Boreal zones, have been identified as a region where the ongoing global climate change will have earlier and stronger impacts than in other regions of the globe (Chapin et al., 2000; Serreze et al., 2000). A critical component of the Arctic response to climate warming is the carbon (C) cycle, with important reservoirs in northern high latitude regions, mainly in soils (Gruber et al., 2004; McGuire et al., 2009) , including frozen soils (Tarnocai et al. 2009). For example, the estimate of between 1400 and 1850 Pg C soil C stored in both surface (0-3 m) and deeper soils (McGuire et al., 2009) is more than half of global estimates that only consider surface soil (e.g. 2300 Pg C estimated for 0-3 m by Jobbagy and Jackson, 2000). Much of this soil organic carbon is stored in peatlands and in permafrost soils since their wet or cold physical conditions have prevented the decomposition of SOC (Hobbie et al., 2000; McGuire et al. 2009). In addition, the vegetation C storage has been estimated to be in the range of 60-70 Pg C (McGuire et al., 2009), which accounted for 10% and 20% of the world's vegetation C. Given these C reservoirs, the processes of C sequestration from and C release to the atmosphere can have important implications for global climate (Grosse et al., 2011).

An increasing number of studies (e.g. Heikkinen et al., 2004; Corradi et al., 2005; Aurela et al., 2004; Johansson et al., 2006; Oechel et al., 2000; Barr et al., 2007; Dunn et al., 2007) have attempted to quantify the carbon fluxes between atmosphere and biosphere in the high latitudes. The methods currently being used to estimate fluxes are top-down atmospheric inversions, in which fluxes over large regions are derived from a set of observations on atmospheric CO₂ concentration via an atmospheric transport model, (e.g. Dargaville et al., 2002), , and bottom-up models (regional up-scaling of in-situ flux or stock measurements using GIS, remote sensing and gridded climate information), or process-based terrestrial biosphere models (TBMs, e.g. McGuire et al., 2000; Sitch et al., 2007). While, atmospheric inversions can not reveal information about the underlying processes and therefore do not allow for future fluxes predictions, the TBMs can thus become the best option for this purpose. However, current TBMs need to be improved since they might not fully account for the underlying processes or factors in regulating the carbon exchanges in the high latitude ecosystems (Dargaville et al., 2002; Sitch et al., 2007). One of the main factors affecting

carbon processes in mid- and high latitude ecosystems is snow cover, which is present during a large part of the year.

Both in-situ measurements and large scale analysis have shown that there is a high degree of spatial and temporal variability in the C exchanges in the high latitudes, and the drivers are primarily vegetation dynamics and soil moisture conditions (McGuire et al., 2009). The seasonal snow cover was found to be highly correlated with the timings of the spring greenness (e.g. Myneni et al., 1997) and is also one of the factors affecting the soil moisture in the growing season (e.g. Karl et al., 1993; Liston et al., 2002). For example, using data from a transect of 6 measurement sites, Chen et al. (2008) found that soil moisture increased from 20% to 90% along a snow depth gradient from 0.2 to 1.5 m in the eastern Qinghai-Tibet Plateau. The effects of snow phenology (the date of snow melt and accumulation and snow depth) on C fluxes can be manifested through modifying or altering plant phenology, soil thermal regimes and microbial activities. The date of snow melt can affect the date of initiation of cambial activity (wood production) in the tree. For instance, later snow melt in the Siberian subarctic may significantly decrease the wood tissue growth, which could partly explain the degraded correlation between tree ring width and summer temperature dynamic after the 1960s (Kirdyanov et al., 2003; Vaganov et al., 1999). In tundra ecosystems, growing-season rates of C uptake have been shown to be closely related to the timing of snow melt, with earlier snowmelt resulting in greater uptake of atmospheric CO₂ (Aurela et al., 2004; Groendahl et al., 2007). For example, Grippa et al. (2005) reported that higher satellite-derived normalized difference vegetation index (NDVI) are significantly correlated with thicker snow packs and later snow melt over Central Siberia, suggesting the importance of snow-related winter processes on the vegetation development and on the carbon cycle in the boreal regions. This is also confirmed by Peng et al. (2010) in arid and semiarid regions in China, who found that positive correlations exist between mean winter snow depth and spring NDVI. In addition, deeper snow pack can insulate soil from extreme cold air temperature (Walker et al., 1999; Groffman et al., 2001; Schimel et al., 2004; Freppaz et al., 2008) and allows soil heterotrophic microbial activity (e.g. Brooks and Williams, 1999; Schimel et al., 2004; Monson et al., 2006), which contributes to CO₂ emissions during the snow-covered period.

The snow can also interact with other factors (e.g. fire, land use change) in regulating ecosystem carbon balance, for example, earlier snow melt has been found to increase the wild fire frequencies in the western U. S. (Westerling et al., 2006). Observed winter albedo in boreal forest varies between 0.11 (conifer stands) and 0.21 (deciduous forests) (Betts and Ball, 1997). This is much closer to summer albedo (0.08-0.15) than to the winter albedo of short-statured vegetation (0.5-0.8). Then the expansion of boreal forests or even shrubland, into a region now covered by short-vegetation (e.g. tundra, Chapin et al., 2005) would lead to a substantial heating of the atmosphere, a response that could possibly accelerate the replacement of short- vegetation by forest and profoundly affect the carbon dynamics (Bonan et al., 1995; McFadden et al., 1998; Chapin et al., 2000).

However, it is still not clear that the northern ecosystems respond to the snow dynamics in the same way mentioned above. For example, a recent study (Humphreys and Lafleur, 2011) conducted in two low arctic sites in central Canada did not support the hypothesis (Aurela et al., 2004; Groendahl et al., 2007) that earlier snow melt date can lead to greater C sequestration in the following growing season. Instead the change in leaf area was found to be a dominant factor in regulating the inter-annual variability of net carbon exchanges. Rogers et al. (2011) found a nonlinear response of C fluxes to winter snow accumulation, which demonstrates the complexity of high arctic ecosystems responses to changes in snow (or winter precipitation). To have a thorough understanding of the effects of snow parameters on the present and future carbon fluxes, terrestrial ecosystem models with a snow model that can capture the complex snow dynamics is thus necessary. This is one of the goals of this PhD dissertation.

1.2 Site-level monitoring of atmosphere-biosphere exchanges

Numerous techniques exist for studying CO₂ exchanges between biosphere and atmosphere, e.g. atmospheric inversion approach at the continental and global scales (Tans et al., 1990; Ciais et al., 1995; Denning et al., 1996), satellite-based estimation method on the basis of the algorithms driven by reflected and emitted radiation measurements (Running et al., 1999; Cramer et al., 1999), or soil carbon and biomass surveys (Kauppi et al., 1992; Gower et al., 1999). Compared to these methods, the eddy covariance method, a micrometeorological technique, provides a direct measure of local water, energy and carbon fluxes between vegetated canopy and the atmosphere (Baldocchi et al., 1988; Foken and Wichura, 1996; Aubinet et al., 2000; Baldocchi et al., 2008), which is achieved through measuring the covariance between fluctuations in vertical wind velocity and the mixing ratio of trace gases of interest (Aubinet et al., 2000; Baldocchi, 2003; Massman and Lee, 2002). The temporal information of the fluxes can be produced on a range of time scales (hour, days, seasons and years) with a minimum disturbance to the underlying vegetation. Another attribute of this method is that it can sample a relatively large area of land extending through the flux footprint around the tower (ranging between 100 and 1000 m) (Gockede et al., 2004). However, the application of eddy covariance method is generally restricted to the locations with relatively flat terrain and vegetation that extends horizontally about 100 times the sampling height (Baldocchi et al., 2001). In addition, it is also very important to consider the canopy storage effects, conditions of insufficient turbulence at night (friction velocity u^* correction, c. f. Papale et al., 2006) and lack of energy balance closure (Oncley et al., 2007; Twine et al., 2000; Wilson et al., 2002).

The data of flux measurements are subject to a variety of quality control and criterion (Foken and Wichura, 1996; Rebmann et al., 2005), causing data gaps in the data records, typically reaching 30 to 40% on an annual basis (Falge et al., 2001; Moffat et al. 2007). For obtaining continuous long-term monitoring data, gap-filling is unavoidable. A series of methods ranging from purely empirical (e.g. Papale and Valentini, 2003; Stauch and Jarvis, 2006) to process-based (Gove and Hollinger, 2006) and semi-empirical methods have been

developed to fill the half hourly data (for a comprehensive overview, see Moffat et al., 2007). The eddy covariance data used in this thesis was preprocessed using both neural networks (Papale and Valentini, 2003) and data-adaptive look-up table approach (Reichstein et al., 2005), which are shown to have the lowest error rates in the gaps (Falge et al., 2001; Moffat et al., 2007; Papale et al., 2006).

Another shortcoming is that only NEE (net carbon exchange) is measured by the eddy covariance technique. The partitioning of NEE into its component fluxes (GPP: gross primary productivity and R_{eco} : ecosystem respiration) is also a priority for model evaluation and prediction. This partition is needed so as to derive mechanistic understanding attributed to temporal and spatial variations in NEE (Falge et al., 2002; Law et al., 2002). The estimates of terrestrial carbon exchanges from space, (for example as estimated with the MODIS sensors on the TERRA and AQUA satellites), are GPP rather than NEE (Running et al., 2004). The partition of GPP from NEE can make the eddy covariance network a tool for validating satellite-derived GPP and upscaling techniques (Beer et al., 2010). Furthermore, providing GPP can benefit the parameterization of canopy-level photosynthesis in the TBMs (Braswell et al., 2005; Reichstein et al., 2003). The separation of R_{eco} from NEE enables us to further understand the sensitivity of respiration processes to temperature, which is central for quantifying the climate-carbon cycle feedback (e.g. Mahecha et al., 2010).

In the past decade, over four hundred eddy covariance sites on the global scale have been set up to measure water, energy and carbon fluxes together with ancillary meteorological, soil and plant variables. The eddy covariance data (Figure 1.1) used in the thesis were downloaded from the La Thuile FLUXNET website (<http://www.fluxdata.org/>), which have gathered over 960 site years across the global. They include a broad representation of vegetation types, climates and disturbance stages. These dense eddy covariance sites on a global scale provide us with an excellent opportunity to investigate winter carbon cycling and its controls (see Chapter 3).

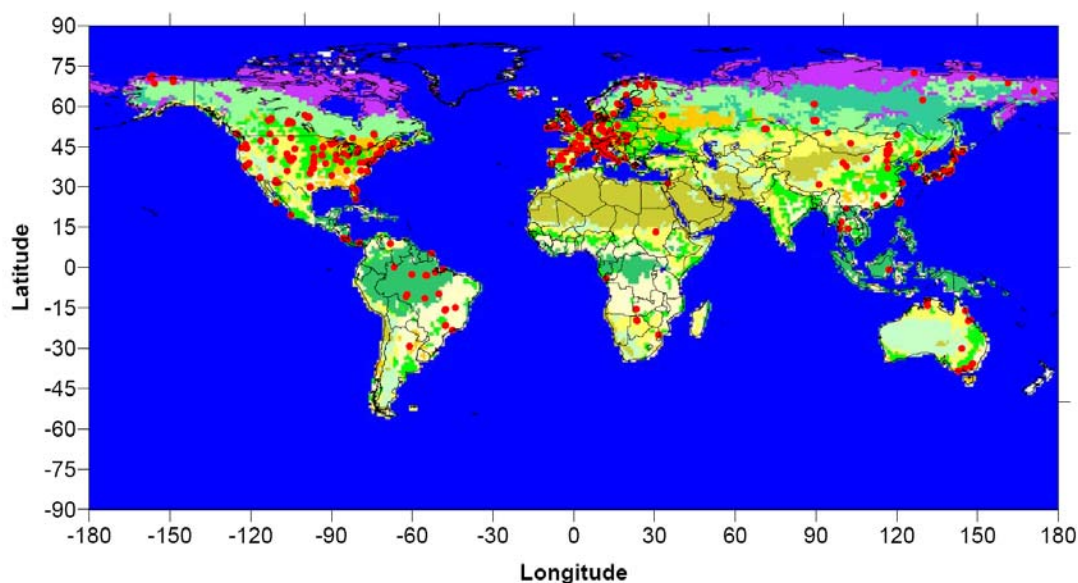


Figure 1.1 A global overview of eddy covariance sites (up to 2007, from Baldocchi et al., 2008)

1.3 The overview of model evaluation

A model synthesizes our understanding of a given system (e.g. biosphere) through a series of mathematical formulations, which are implemented in a computer program. If all of theoretical behaviors of the system are explicitly included, the model would be too complex to run on any existing computer. Hence, for practical purposes, simplifications are made so that the system has reduced complexity and computing requirements. Moreover, most physical processes occurred at microscopic scales and are necessarily parametrized when considering macroscales (like atmospheric turbulence). By reducing the level of details, it becomes necessary to introduce macroscale parameters and describe the processes in a more reduced (i.e. more parameterized) form. More importantly, different applications require different levels of complexity to represent the same system (Butts et al., 2004).

The evaluation of a model is not as clear-cut as a simple search for “falsification”. Two fundamentally different methods are followed to evaluate the models. The first method is to assess the degree to which a model is physically based and accounts for real-world processes and their interactions. The second method is to attempt to quantify model errors in simulations of particular variables or processes in the model i.e. terrestrial biosphere models, to consider the possible causes for those errors and try to understand the nature of the interactions within the model. In this thesis, we are focused on the second type of model (terrestrial biosphere model) evaluation. On the one hand, it can show us whether such errors make a given model “unusable” in answering specific questions; on the other hand, it can scrutinize our current understanding of the biosphere’s responses to meteorological variables and thereby is an important step for further developing environmental theory (Mahecha et al., 2009). In order to evaluate models, “observations” can be direct in-situ observations (e.g. in Chapter 2 the eddy covariance measurements) and can also be a product of a data assimilation system (they are the outcome of a combination of observed data, given a model). For example, in Chapter 5, the snow variable from Canadian Meteorological Centre (CMC) daily snow depth analysis data is used as ‘observation’ for snow model evaluation.

There exists a range of techniques or methodologies for evaluating TBMs. The simplest way is to summarize the total model-observations mismatch using “a single misfit number” (Evans, 2003), which provide a limited insight into the quality of a model. Classical model evaluation also embraces residual analysis (Medlyn et al., 2005). The rationale behind this, is that the coincidence of patterns in the residuals and certain variables elucidate potential problems in the model. Recently, many studies revisited the issue of model evaluation in the time-frequency domain and stated that the model-observations agreement is a matter of timescale (e.g. Braswell et al., 2005; Siqueria et al., 2006; Mahecha et al., 2010). They consider that a time-evolving variable can be described as the sum of a variability of fluctuations on different time scales of characteristic variability. These studies consider that a time-evolving variable can be described as the sum of a variability of fluctuations on different time scales of characteristic variability. For example, the observed variability in NEE (net ecosystem exchange) from eddy covariance measurements ranges from hourly, diurnal,

synoptic, seasonal-annual, to decadal periodicities (e.g. Katul et al., 2001; Stoy et al., 2005; Mahecha et al., 2007; Qin et al., 2008; Stoy et al., 2009). Above-mentioned techniques applied to model evaluation, often mix up errors (or the uncertainties) related to model structure and parameter values with the observation errors. To highlight model structural deficiencies, some studies (e.g. Butts et al., 2004; Abramowitz, 2005; Abramowitz et al., 2007, 2008) open a new window. For example, an ensemble of model structures within the same modeling tool is created to evaluate the model structural uncertainty on the simulations (e.g. Butts et al., 2004). Abramowitz et al. (2007, 2008) used an empirical model (artificial neural network) to detect systematic errors in the eddy covariance fluxes simulated by TBMs and suggested that these errors could only be reduced through model structural improvements. To highlight model deficiencies on multiple timescales, an artificial neural network combined with a time series decomposition method is thus used to diagnose model bias in a TBM using a dense network of eddy covariance sites on a global scale (see Chapter 2).

1.4 The overview of snow model development

Snow plays an important role in governing the Earth's global energy and water budgets due to its high albedo, low thermal conductivity, and considerable spatial and temporal variability (Zhang, 2004). Snow cover is one of the most highly varying hydrological quantities on the Earth's surface, with the Northern Hemisphere mean monthly snow covered land area ranging from about 7% to 40% during the annual cycle (Gutzler and Rosen, 1995). Both models and data showed that snow cover has a profound effect on the local and possibly remote climate via changes in the surface energy balance (e.g. Yeh et al., 1983). Locally, the energy demanded by snowmelt can significantly cool the surface and the overlying air (Dewey, 1977; Namias, 1985; Baker et al., 1992; Groisman et al., 1994). Thus surface air temperature forecasts from numerical weather forecasting are very sensitive to the snow cover extent and thickness. For example, improvement of snow physics in the NCEP (National Centers for Environmental Prediction) ETA operational forecast model substantially reduced a 2 m daytime air temperature cold bias for snow-covered areas (Mitchell et al., 2002). Remotely, early season Eurasian snow cover variations are associated with dominant modes of mid-latitude variability in the Northern Hemisphere winter (Cohen and Entekhabi, 1999). In addition, some observational studies (e.g. Bamzai and Shukla, 1999; Lo and Clark, 2002) also showed that the antecedent snow mass or snow cover extent has an inverse relationship with Asian and North American summer monsoon intensity.

Because of its low thermal conductivity, snow is a strong insulator of the soil and impedes the depth and severity of soil freezing (Lynch-Stieglitz, 1994; Sud and Mocko, 1999). Where there is significant snow cover in the winter, the mean annual ground surface temperature is warmer than the mean annual air temperature owing to the insulating effect of the snow. Changes in the rate of accumulation, duration, timing, density, and amount of snow cover during the winter season play an important role in determining how the air temperature signal propagates into the ground. Stieglitz et al. (2003) showed that changes in below ground

temperature can be influenced as much by temporal variations of snow cover as by changes in the near-surface air temperature in North Slope of Alaska, and hence emphasized the role of snow cover changes in the thawing of arctic permafrost. In addition, the water budget is also significantly modified through snowmelt processes. Being a water store, snow plays an important role in springtime runoff generation and flood production, and can provide a substantial component of the annual water budget. In many northern latitude regions (e.g., California), spring meltwater from the winter snowpack is the greatest source of water in the annual soil moisture budget (Aguado, 1985). Therefore, it is important to accurately represent snow characteristics in the models. Through comparing spring snow albedo feedback among 17 climate models, Qu and Hall (2006) showed that the large divergence in simulations of snow albedo feedback was mainly attributed to the differing parameterizations of snow processes in the model.

Up to now, many types of snow models have already been developed for various applications such as hydrology, global atmospheric circulation models and avalanche forecasting. The degree of complexity of these models is highly variable, ranging from simple temperature-index or degree day index models, through land surface schemes of intermediate complexity (e.g. ISBA [Douville et al., 1995] or CLASS [Brown et al., 2003]), to complex snow-physics models (e.g. CROCUS [Brun et al., 1989], SNOWPACK [Bartelt and Lehning, 2002]). The level of complexity of snow models is characterized by the following criteria: the number of snow layers, the adopted physical equations, liquid water treatment and snow density parameterization.

All of these snow models with different complexity can be classified into two main categories: temperature-index (or degree-days) model and energy balance model. Temperature index models, which are primarily designed for snowmelt modeling in river forecasting, are based on the assumed relationship between the ablation and air temperature expressed in the form of the positive temperature sums (Hock, 2003). Nowadays, they still gain the wide use because of easy availability of air temperature data and relatively easy interpolation and forecasting possibilities of air temperature (Ohmura, 2001; Hock, 2003). Most operational runoff models such as SRM-model (Martinec and Rango, 1986) and SHE-model (Boggild et al., 1999) rely on temperature-index methods for melt modeling. They are often also used in reconstructions of historical snow records for climate studies and evaluation of climate models (Brown and Goodison, 1996; Brown et al., 2003). However, its empirical melting factor linking air temperature and melting rate has the large spatial and temporal variations (Hock, 2003), which can be affected by the factors such as albedo (Kuusisto, 1980), short wave radiation (Singh and Kumar, 1996), and topographic features. In spite of their wide application in hydrology, temperature index models are not sufficient for avalanche forecasting and atmospheric models. For avalanche forecasting, snow models have to predict the evolving structure of the snow pack. For atmospheric models, snow models should supply energy and mass flux boundary conditions, and also provide snow albedo and surface temperature for constraining the radiative flux (Jin et al., 1999; Essery and Etchevers, 2004). To achieve these, many physically based snow schemes have been developed to describe the

mass and energy balance inside the snow pack and the interaction between the snow surface and atmosphere (e.g. Brun et al., 1989; Anderson, 1976; Loth and Graf, 1993; Sun et al., 1999). For example, CROCUS designed for avalanche forecasting (Brun et al., 1989) calculates the type and size of the ice crystals in each layer of the snow pack and its change is based on a set of parameterizations describing the different types of snow metamorphisms (equi-temperature, medium- and high-temperature gradient and wet snow). Besides these, CROCUS also considers other snow internal processes such as heat diffusion, percolation of liquid water, internal snow melt and refreezing, snow compaction due to overweight and absorption of solar radiation in each snow layer.

In the family of physically based snow models, the following three factors could be identified as being the main reasons for model divergence in snow simulations (Slater et al., 2001): 1) turbulent exchanges between snow surface and the atmosphere; 2) the snow albedo parameterization, which mainly controls the amount of energy incident on and available on the snowpack; 3) the structure and thermal properties of the snow. Firstly, the parameterization of transfer coefficients often used in the snow model follows that of Louis (1979), and the specific implementation could differ (e.g. Pan et al., 1994; Abdella and McFarlane, 1996; Viterbo et al., 1999). The treatment of roughness length on snow covered vegetation also differ among the models, for example, the roughness length is significantly reduced in the presence of snow in ISBA-ES (Boone et al., 2002), and snow is prescribed to be no impacts on roughness length in SECHIBA (Ducoudre et al., 1993) snow model. In addition, blowing snow parameterizations for purposes of either snow redistribution or sublimation might not be included in most of the snow models, which are supposed to significantly affect ablation processes in some locations (Pomeroy et al., 1998; Pomeroy and Essery, 1999). The important of blowing snow conditions could be site-specific, for example, a recent study by E. Brun (not published) showed that SWE simulation at a Russia site was not affected so much after including this parameterization into CROCUS. Secondly, at the local scale, the principles of snow albedo have been well established (e.g. Wiscombe and Warren, 1980; Warren and Wiscombe, 1980) with spectral dependence, grain size and type, and contamination being important factors. A variety of methods for parameterizing snow albedo within a model have been used, ranging from fixed values (e.g. MAPS [Smirnova et al., 1997]) to calculations making allowance for temperature (e.g. BASE [Slater et al., 1998]), age (e.g. ISBA [Douville et al., 1995], SECHIBA [de Rosnay and Polcher, 1999]), extinction coefficients (e.g. ISBA-ES [Boone et al., 2002]) and solar zenith angle (e.g. BATS [Yang et al., 1997]). The snow albedo range among models are different, for example, BASE, SECHIBA (de Rosnay and Polcher, 1999) and UKMO (Warrilow and Buckley, 1989) have a range of 0.75-0.50 and CROCUS, BATS, and ISBA-ES have a range of 0.85-0.50. In Slater et al. (2001) study, the snow albedo alone can not explain all the scatter in modeled SWE since it must be considered in combination with fractional cover to determine the amount of solar radiation absorbed by the whole surface. Most of the models especially for the purpose of GCM studies often define fractional snow cover as the proportion of the grid square that the atmosphere actually sees as being covered with the snow and then use this for grid-box

albedo calculations. Regardless of how fractional snow cover is parameterized (e.g. Roesch et al., 2001), it could have a significant different effect depending upon snow model structure (Slater et al., 2001, Figure 1.2). For example, in a model with an explicit snow layer (the snow layer modeled separately from the soil, with their own temperature and hydrological conditions, e.g. ISBA-ES [Boone et al., 2002]), a fractional snow cover of 10% could have significant impact on the snow simulation in comparison with a fraction snow cover of 10% in a model with a composite snowpack (SECHIBA [de Rosnay and Polcher, 1999]). In the former case, snow temperature could stay low because of high snow albedo, however, in the latter case, the snow and soil are considered to be homogenous horizontally, and the lower albedo of the soil has a direct influence on the absorbed energy available to the snow temperature calculation. To account for this, some studies (e.g. Liston, 2004; Liston and Hemstra, 2011) adopts the physically realistic approach of performing separate albedo and surface energy balance calculations over the snow covered and snow free portions of each model grid cell. Finally, the model structure of the snow model plays an important role in determining energy availability as well as determining how that energy is used (Figure 1.2), for example, the difference in albedo calculation between explicit and composite schemes. Slater et al. (2001) found that the results from UKMO and MOSES (Cox et al., 1999) provide an example of underlying structure could produce simulation differences. Both models are implicit schemes, and the difference between two models is that UKMO uses a bulk temperature of surface snow/soil layer for turbulent calculations and MOSES uses a surface skin temperature. Hence, turbulent fluxes make greater contribution to snowmelt and MOSES tends to melt snow faster than UKMO does. The use of a skin temperature makes the model more responsive to the forcing (Viterbo and Belljaars, 1995). In addition, the scheme of snow layering and the way in parameterizing snow internal processes (e.g. snow density, snow thermal conductivity) also could make contributions to simulation differences. For example, Kowalczyk (unpublished manuscript) notes that the impact of altering the heat capacity of modeled snow by comparing a one-layer to a three-layer scheme using the same physics. Because of the higher heat capacity of the single-layer model, snowmelt is delayed when compared with the three-layer models, and the impact on subsurface hydrological behavior is also evident.

Recently, the second phase of SNOWMIP project (The Snow Model Intercomparison Project) has been conducted among available physically based snow models in order to understand the snow processes under the canopy (Rutter et al., 2009). The magnitude of snow accumulation and the timing and rate of snow ablation are very different between forested and non-forested sites (e.g. Hardy et al., 1997; Musselman et al., 2008). The difference could be mainly attributed to forest canopy characteristics: e.g. snow interception capacity by canopy, canopy shading induced changed turbulent fluxes, for example, Veatch et al. (2009) investigated influences of forest canopy density on snowpack accumulation through an intensive snow depth and density survey in a mid-latitude montane environment in northern New Mexico and found that the maximum snow accumulation in the forests was well correlated with forest canopy density. The percentage of canopy coverage could also modify

the forest canopy albedo, which affects the snow evolution in the forested regions. There are more and more studies towards modeling snow accumulation and ablation processes in the forested environments (e.g. Gelfan et al., 2004; Andreadis et al., 2009; Ni-Meister and Gao, 2011). The main idea of this modeling approach is to adjust the energy fluxes upon the under-canopy snow and the efficiency of snow interception by the canopy. For example, after considering impacts of heterogeneous and clumped forest structure on underlying snow simulation, Ni-Meister and Gao (2011) found the long wave radiation incident upon the underlying snow surface is reduced, which resulted in lowered snowmelt rates and better agreement with the observations. All of these studies suggested that another vertical layer is needed to resolve the snow simulations under the canopy. Up to now, several snow projects (PILPS2, SNOWMIP and SNOWMIP2) have been initiated to evaluate and understand the snow model performance, and these projects are valuable for our identification of processes important for the various applications of snow models, and also provide us the guidelines for further snow model development.

1.5 Objectives and structure

The overarching goal of this PhD thesis is to evaluate the ORCHIDEE: **OR**ganizing **C**arbon and **H**ydrology **I**n **D**ynamic **E**cosyst**E**ms land surface model and contribute to the simulation of the carbon cycle in cold regions in ORCHIDEE. For that purpose, the model is first evaluated against dense eddy covariance sites on a global scale and a new snow model has then been developed and incorporated in ORCHIDEE, as well as evaluation of this new snow model at both site and continental levels. An additional focus was also given to the analysis of winter carbon cycle based on eddy covariance site measurements. The aim was to understand the potential role of snow in temperate and boreal ecosystemson respiration processes. The main findings are summarized in the following chapters:

Chapter 2 presents a developed methodology to quantify ORCHIDEE model structural deficiencies on different timescales using multi-year measurements made over 100 eddy covariance sites on a global scale. The joint analysis of the observation and model data uncovers the characteristics of model bias among different plant function types and climate zones, which could serve as an aid in the future ORCHIDEE model process refinement.

Before performing snow model developments, Chapter 3 presents the exploration of carbon cycling and its controls in the cold season at mid- and high-latitude ecosystems based on eddy covariance sites. This study confirms an important component of winter carbon cycling in the annual carbon budget in the northern ecosystems.

Chapter 4 presents the development and validation of a new snow model in ORCHIDEE at the site scale. The current single layer snow model is replaced with a three-layer snow model. The snow physics processes inspired from the ISBA-ES land surface model were

included in a three-layer snow model, such as snow water melting and refreezing, solar radiation absorption within each snow layer.

Chapter 5 aims to further validate this newly parameterized snow model on a continental scale against two available snow products (GlobSnow and CMC). Besides, it explores impacts of the forcing data with different high frequency variability on snow simulations.

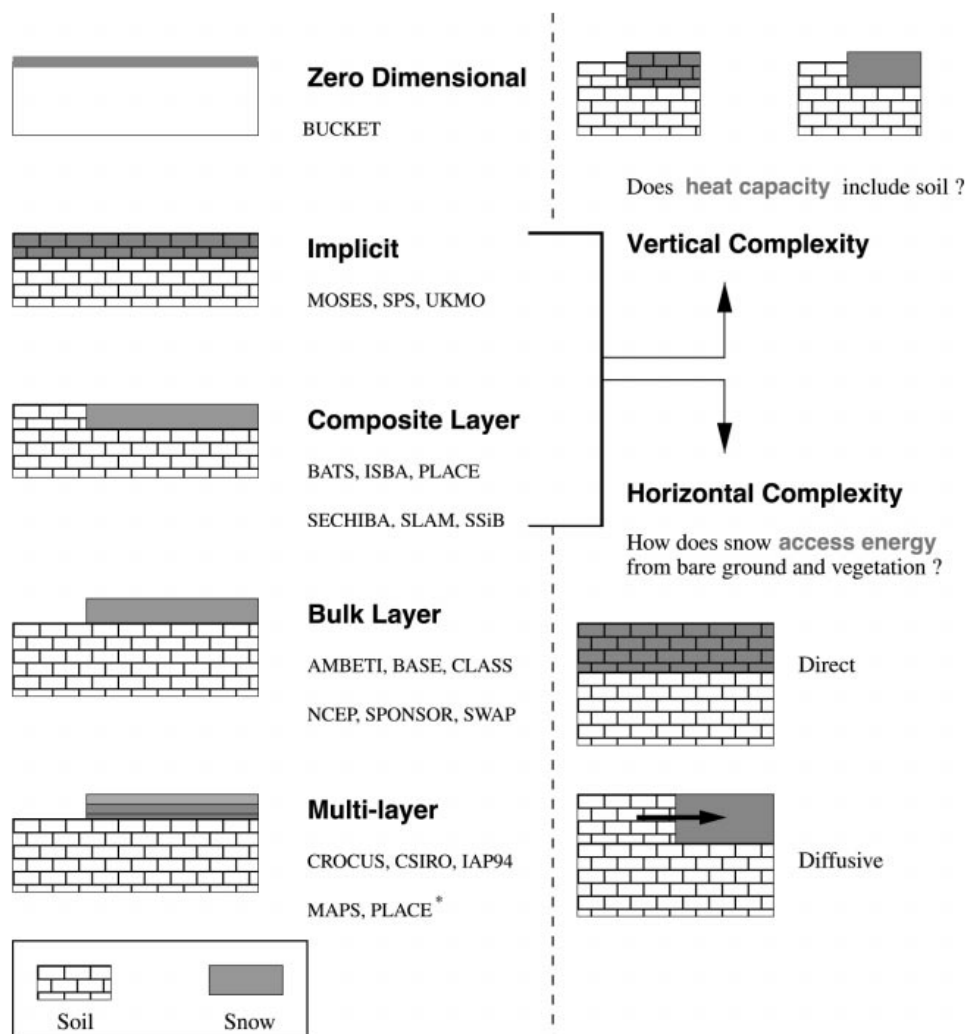


Figure 1.2 A model structure classification with respect to the snow temperature and solar radiation absorption from Slater et al. (2001). A zero-dimensional scheme computes temperature via an energy balance over a uniform surface. An implicit scheme assumes an even cover of snow upon the grid square and makes compensations to its soil and vegetation surface properties to allow for the mass of snow. A composite layer model will track various quantities for its snow cover, such as fractional cover, but snow temperature is equal to that of the first soil layer, which may eventually become 100% snow. Implicit and composite schemes can then include variations in horizontal and/or vertical complexity. Bulk layer and multilayer models include a one-layer or multiple-layer snowpack sitting above the soil system, respectively.

2. Systematic errors in a land surface model across biomes inferred from eddy covariance observations on multiple time scales

Characterization of model bias in land surface models (LSM) can highlight model deficiencies and provide great insights into the model development. In this study, we use neural networks to evaluate the portion of model bias in a particular flux from a land surface model (ORCHIDEE: ORganising Carbon and Hydrology in Dynamic EcosystEms) that can be described as a non-linear function of the simulated flux and simultaneous meteorological drivers. Multi-year flux measurements made over 125 eddy covariance sites, which cover 7 different plant function types (PFTs) and 5 climate groups, provides an excellent opportunity to characterize the model bias in ORCHIDEE. In this study, we determined whether the model bias in five flux variables (H: sensible heat, LE: latent heat, NEE: net ecosystem exchange, GPP: gross primary productivity and R_{eco} : ecosystem respiration) are transferable within and between three different time scales (diurnal, annual and interannual), and between sites (categorized by PFTs and climate groups).

Within each timescale at the site level, the transferability of model bias (or error transferability) is larger for annual and interannual timescales than for the diurnal timescale, but little error transferability is found across timescales in all flux variables examined. Timescale separation is thus very necessary for both model evaluation and developments. For all PFTs, variables and timescale components, model bias is found to be transferable between sites within the same PFT and climate group. This suggests that model improvements based on specific eddy covariance sites can be used to enhance the model behavior at other sites within the same PFT and climate group. In addition, some error transferability is also found between water and carbon fluxes. However, in contrary to diurnal timescale and the original time series, the transferability of model bias across all PFTs or climate groups is not always found on longer time scales (annual and interannual).

2.1 Introduction

The FLUXNET global eddy covariance (EC) network now contains numerous on-line observations of CO₂, water, and heat fluxes across a range of biomes and timescales (Baldocchi et al., 2001; Baldocchi, 2008), with more than 965 site years in La Thuile dataset (<http://www.fluxdata.org>). In spite of this, land surface modelers still continue to use only a few sites for model evaluation, selected for instance to represent specific plant function types (PFTs) (e.g. Krinner et al., 2005). To assess model performances, error metrics such as root mean square errors (Taylor, 2001) are often employed to summarize model-observations mismatch. However, these error metrics not only contain systematic errors of a model (or

model bias) associated with structural deficiency in the model representation of physical and biological processes, in model initialisation (Carvalhais et al. 2008), or in the value of model parameters, but also includes errors in model inputs as well as random and systematic errors in EC measurements (Richardson et al., 2006; Lasslop et al., 2008; Abramowitz et al., 2007). It is well known that random errors are statistical fluctuations (in either direction) in the data, which could be reduced through averaging a large number of observations. By contrast, systematic errors, which are difficult to be determined, are reproducible inaccuracies that are consistently in the same direction. In this study, we focused on systematic errors of a model (or model bias), which should be distinguished from model-observations mismatch (referenced to ORCHIDEE errors) that consists of both random and systematic errors from model and observations.

In order to characterize model bias, recent studies (Dekker et al., 2001; Abramowitz, 2005) successfully demonstrated the value of explicitly modelling model bias using artificial neural network (ANN) techniques. The idea is to establish a functional relationship between meteorological inputs (ANN inputs) and model-observations mismatch (ANN output) in a particular flux at a specific eddy covariance site by means of supervised training by ANN (named as ANN error model). This error model is then applied to predict model-observations mismatch in an evaluation dataset not used for training on the same site. The model bias could then be enlightened by comparing observed and modelled model-observations mismatch in the evaluation dataset. However, the model bias could not always be fully quantified since ANN inputs might be limited by both data availability and our current understanding of underlying processes (e.g. Jung et al., 2011). But this methodology could potentially provide us great insights into an issue that to what extent model bias is shared (or transferable) between simulations of different environments, which may help us to define directions for model improvement. This has been proposed and achieved in Abramowitz et al. (2007), which incorporate several sites simultaneously in ANN training and evaluation datasets. Abramowitz et al. (2007) examined spatial transferability of model bias within and across two vegetation types, and investigated the degree to which improvement of land surface models derived from a given site can be applied to other sites within the same vegetation type. They found that model bias in both sensible heat flux and latent heat flux can be transferred within and across different vegetation types. However, they did not account for variation within a vegetation type that exists across different climate regimes. In addition, because of the coupling of photosynthesis and transpiration at ecosystem level, it is also important to investigate error transferability between CO₂ and H₂O fluxes.

Previous studies (e.g. Siqueira et al., 2006; Mahecha et al., 2010a; Wang et al., 2011) reported model-observations mismatch on different timescales in different ecosystem types, and pointed out that a large relative share of model-observations mismatch occurs at long timescales, e.g. typically on annual to interannual timescales. However, the systematic coherent structure of model-observations mismatch in timescale domain is still poorly understood. Equipped with the knowledge of to what extent the model bias could be transferred within each timescale, modellers would be able to make well informed decisions

on necessary developments. Hence, one could prioritize new parameterisations in order to decrease model bias. Further, it is important to know whether improving a model for a process on a given timescale (e.g. diurnal variability of photosynthesis) also results in a better fit to observations on another timescale (e.g. seasonal or interannual variability of photosynthesis).

Thus, in this study, we aim to understand that to what extent model bias could be shared or transferred in both space and timescale domains. To achieve this, a land surface model ORCHIDEE (ORganising Carbon and Hydrology in Dynamic EcosystEms) is used. ORCHIDEE is a Soil-Vegetation-Atmosphere-Transfer model, coupled to an ecosystem carbon model, which can simulate energy, water and carbon exchanges between atmosphere and biosphere on different timescales, ranging from hours to centuries (Krinner et al., 2005). The simulations from ORCHIDEE have been evaluated against eddy covariance data on different timescales in different PFTs (Krinner et al., 2005; Mahecha et al., 2010a). Here, we integrate a time series decomposition method (Singular System Analysis: SSA, Mahecha et al. 2007, 2010a) and Artificial Neural Network (ANN, Papale et al., 2003; Moffat et al., 2010) to quantify error transferability in both space and timescale domains using ~500 site-years of eddy covariance data from 125 sites across the globe in FLUXNET database. The scientific questions addressed in this study are:

- (1) Are model bias transferable within and across time scales?
- (2) Are model bias transferable within and across PFTs and climate regimes on different timescales?
- (3) Is the model bias in terrestrial-atmosphere water fluxes transferable to CO₂ fluxes?

2.2 Data and Methods

2.2.1 Eddy covariance data

In this study, flux and meteorological drivers on half-hourly time steps are from Version 2 of the FLUXNET La Thuile dataset (<http://www.fluxdata.org>), and hourly time steps aggregated from half-hourly ones are used. The site with at least three years and yearly data coverage above 70% has been included in this study. A total of 125 sites and 500 site years were selected for the present study. For each site, climate is defined according to aggregated Koppen-Geiger classification (cf. <http://www.fluxdata.org>); vegetation class is from IGBP definitions, which is then classified to the corresponding PFT in ORCHIDEE. The distribution of studied sites with respect to PFT and climate groups is displayed in Table 2.1, and the spatial distributions are shown in Figure 2.1. In this study, shrubs and wetlands are not considered because ORCHIDEE did not have the corresponding PFT and related model parameterizations.

2.2.2 Simulation protocol

ORCHIDEE model was driven with meteorological data measured on site. Our site selection criterion allows data gap in meteorological forcing (Sect. 2.2.1), and the gap-filling

algorithms (Appendix A) were then applied to create continuous forcing data for model simulation.

Climate group/PFT	GRA	CRO	BoENF	TeENF	TeEBF	TeDBF	TrEBF
Boreal	1	0	18	0	0	1	0
Temperate	14	5	0	10	2	6	0
Temperate-continental	4	6	0	9	0	10	0
Subtropical- Mediterranean	5	4	0	9	4	9	0
Tropical	0	0	0	0	0	0	8

GRA: grassland; CRO: cropland; BoENF: boreal evergreen needleleaf forests; TeENF: temperate evergreen needleleaf forests; TeEBF: temperate evergreen broadleaf forests; TeDBF: temperate deciduous broadleaf forests; TrEBF: tropical evergreen broadleaf forests.

Table 2.1 The number of sites belonging to each PFT x climate group. Climate group is defined according to aggregated Koppen-Geiger classification.

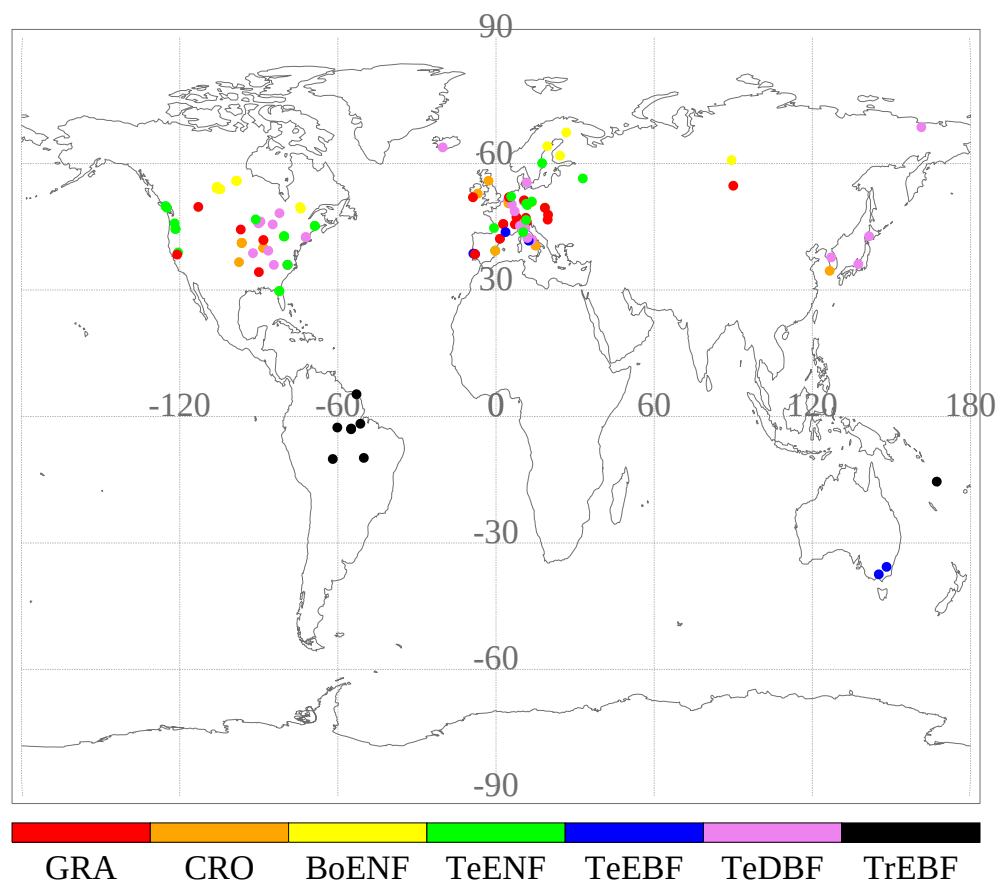


Figure 2.1 Spatial distribution of the chosen sites colored by their respective plant function type.

The PFT for each site was prescribed in the model by using parameters that most closely

represent the site vegetation and climate (Table B1). The soil and biomass carbon pools at each site are brought to the steady state by recycling over the observed period of meteorological data. Site history in terms of management was not prescribed in the simulations.

2.2.3 Methodologies

2.2.3.1 Singular system analysis

Observed and modeled time series can be described as sets of additively superimposed subsignals, which is based on the assumption that these subsignals are characterized by characteristic scales of variability. Any time series is thus described as sets of additively superimposed subsignals,

$$Y = \sum_{f=1}^F X_f \quad (2.1)$$

where f is the index over contained (and discretely separable) characteristic frequencies. We used ‘Singular System Analysis’ (SSA, Golyandina et al., 2001; Ghil et al., 2002) to extract subsignals X_f , which has already been employed to explore daily eddy covariance ecosystem-biosphere fluxes (e.g. Mahecha et al., 2007, 2010a). Here, we only summarize the two steps of SSA, and technical details could be found in the Appendix B of Mahecha et al. (2010a).

The first step is time series decomposition. The idea is to embed the time lagged windows of the time series to its trajectory space. This embedding space can be decomposed into a set of empirical orthogonal functions and associated principle components (Ghil et al., 2002). Each component is characterized by one single oscillatory mode, and has a simple representation in the frequency domain.

The second step is time series reconstruction. The time series can be partly retrieved from a set of principle components based on user’s choice. A reconstruction is based on few selected components that are characterized by complementary frequencies. Each reconstructed time series can be described by a set of subsignals X_f each of which belongs to a well defined frequency bin.

In order to reconstruct time series with characteristic timescales, three bins (Bin A: diurnal timescale; Bin B: annual timescale and Bin C: interannual timescale) are chosen respectively (Table 2.2). The chosen bin boundaries are accessible to an ecological discussion.

In order to reconstruct the time series characterized by diurnal variability, the time series on the hourly time step is used. Given the fact that a great burden on the computer memory would be encountered if SSA is applied over hourly time series, we split it into a series of subsets with each subset containing 60 days (each subset has a total of 1440 data points). Hence, a local SSA (Table 2.2) is deployed for retrieving the diurnal variability, which is summarized as follows,

- Define a continuous window of length $W \ll N$ ($W = 1440$, equal to ~60 days) on hourly time series and the windows are centered $0.5W, 1.5W \dots N-0.5W$.

- Apply SSA on each window separately, and identify the diurnal SSA component in each window based on Bin A (Table 2.2) and ignore the rest, such that contains the diurnal variability.
- Merge the locally reconstructed time series.

For the time series characterized by annual and interannual variability, we perform a global SSA (Table 2.2) on the time series on the daily time step, which is aggregated from its hourly one. The reconstructions of annual and interannual variability are based on Bin B and Bin C (Table 2.2), respectively.

Our site selection criterion allows data gaps in observed fluxes, but not in simulated fluxes since data gaps in meteorological forcing used for driving ORCHIDEE have already been gap-filled (Appendix A). The data gap in both hourly and daily time series is filled by SSA-gap-filling procedure (c.f. Appendix B in Mahecha et al., 2010a). Note that the SSA-gapfilling procedure would not be performed on the time series if its gap fraction is above 30%.

Global SSA			Local SSA	
	Upper Limit (Day)	Lower Limit (Day)	Upper Limit (Hour)	Lower Limit (Hour)
Bin C	maximum	513.7	maximum	218.8
Bin B	513.7	259.3	218.8	125.7
	259.3	130.9	125.7	72.4
	130.9	66.1	72.4	41.6
	66.1	33.4	41.6	23.9
	33.4	16.9	Bin A	23.9
	16.9	8.5		13.8
	8.5	4.3		7.9
	4.3	2.2		4.6
	2.2	minimum	2.6	2.6
				minimum

The discretization for both global and local SSA is approximately equidistant in the log domain. Bin A, Bin B, and Bin C are used to reconstruct the time series characterized by diurnal, annual and interannual variability, respectively.

Table 2.2 The Limits of the applied timescale binning schemes.

2.2.3.2 ANN error model

ANN are well adapted to solve nonlinear problems and are designed to capitalize on the inherent statistical relationships among the input and output variables. The type of ANN applied here is the feed-forward multilayer perceptron (MLP) neural network that allows for nonlinear mapping of sets of input data to a set of appropriate output. The nonlinear mapping model consists of nodes that are organized in three or more layers (an input layer and an output layer with one or more hidden layers). Any nodes, i and j in two consecutive layers are connected with a synaptic weights w_{ij} determined through training the system (Melesse and Hanley, 2005). For each node in the hidden layer, it calculates a weighted sum of all of its

inputs z_i (Eq. 2.2) and then uses transfer function (hyperbolic tangent function $f(x) = \tanh(x)$ ranging from -1 to 1) to produce the output z_j of node j in the hidden layer (Eq. 2.3).

$$x_j = \sum_{i \in \text{Inputs}(j)} w_{ij} \cdot z_i \quad (2.2)$$

$$z_j = f(x_j) = f\left(\sum_{i \in \text{Inputs}(j)} w_{ij} \cdot z_i\right) \quad (2.3)$$

For the nodes in the output layer, the linear transfer function is used to calculate the output value. In this study, we choose two hidden layers, each with five nodes.

The target of ANN error modeling is ORCHIDEE errors, being defined by the differences of modeled and observed fluxes, a vector containing hourly data. Training and evaluation of the ANN is performed on ORCHIDEE errors (Figure 2.2). The training phase determines the weights through establishing empirical relationships between ORCHIDEE errors and a combination of input predictors, including meteorological drivers and simulated ORCHIDEE flux. The parameterized ANN model with fixed weights after training will be referred to as the ANN error model. The evaluation phase uses these weights (or ANN error model) to predict ORCHIDEE errors from the input predictors within a subset of the data (an evaluation dataset) that is not used for the training phase. In the evaluation dataset, for each flux, the root mean square error reduction (RMSE-R) as a surrogate of transferability of model bias (or error transferability) is then defined as:

$$RMSE - R = 1 - \frac{\sqrt{\sum_{i=1}^n \varepsilon_{ANN}^2}}{\sqrt{\sum_{i=1}^n \varepsilon_{Ori}^2}} \quad (2.4)$$

where ε_{ANN} and ε_{Ori} are ORCHIDEE errors with and without ANN-modeled, respectively.

In addition, all variables in both the input and output layers of ANN have been rescaled into a $[-1, 1]$ interval, and then the variable in the output layer has been scaled back to its original units before performing error calculations. In the cases where the variables in the training and evaluation datasets have the same order of magnitude and unit (e.g. error transferability investigation within a timescale), the variables in the two datasets are normalized together; otherwise, the variables in the two datasets are normalized separately (e.g. error transferability investigation across timescales, and between latent heat flux and GPP). This is done given the fact that ANN is not robust extrapolation tool, that is to say, an ANN error model trained on the variable with an order of magnitude (e.g. interannual timescale) could be problematic in data extrapolation of another variable in an evaluation dataset with a higher order of magnitude (e.g. diurnal timescale).

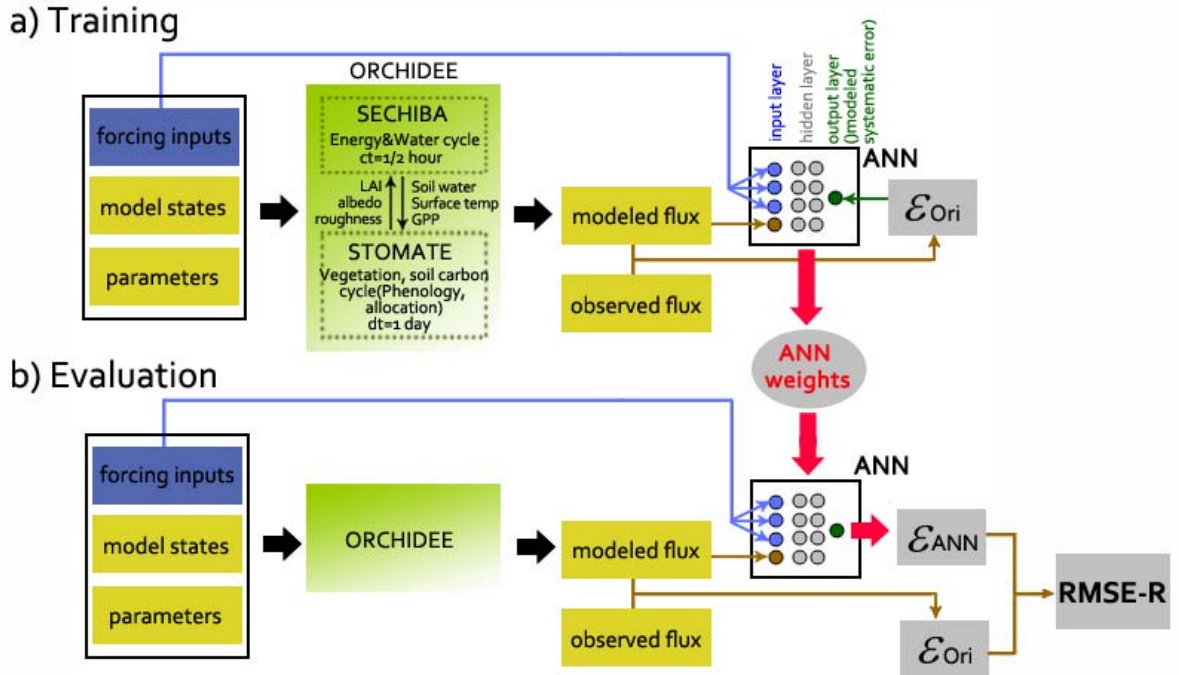


Figure 2.2 The conceptual diagram of ANN operation. Two steps are involved in the ANN error modeling. (a) The training phase is to find a parameterized ANN error model with fixed weights (or nonlinear regression parameters) that characterize the relationships between ANN inputs and ANN output presented in training dataset; (b) the evaluation phase is to apply this ANN error model to compute ANN-modeled error and RMSE-R in the evaluation dataset.

The training procedure, which adjusts the connection weights of the network through error back-propagation based on the steepest descent method, is recognized as a crucial step in ANN error model framework. To avoid over-fitting, a 20% subset of the training dataset called the test dataset is used to assess the performance of the ANN training process at every stage of learning (Scardi, 2001). Training is stopped when the error within the test dataset begins to increase, i.e. the model starts to lose prediction or generalization ability by overtraining. The training procedure is also sensitive to how the training dataset is built and initial weights linking the nodes between the input layer and the first hidden layer (Abramowitz et al., 2007; Morshed and Kaluarachchi, 1998). To overcome this, we divide each variable (or node) in the input layer into different value ranges (or classes) according to their respective data distribution (e.g. van Wijk and Bouten, 1999), and then build the training set in such a way that it would randomly select data from each combination of classes. 10 training sets are thus created in this way, and for each of 10 training sets, the ANN has been trained 5 times starting from different initial weights. In total, 50 ANNs have been trained and the mean ensemble is used.

2.2.3.3 The configurations of ANN error modeling

The original and reconstructed time series on three different characteristic timescales (diurnal, annual and interannual) are used in the ANN error model. The ORCHIDEE errors from both original and reconstructed time series are then modeled by the ANN as a function of four drivers in their respective original and reconstructed forms. We should be in the mind that the main purpose of this study is not to quantify the absolute value of model bias but to understand model bias transferability in both spatial and timescale domains. Moreover, our choice of explanatory variables is constrained by the fact that a variable must be available at all sites. Based on this principle, we chose three meteorological drivers (T_a : air temperature, VPD: vapor pressure deficit, R_g : incoming shortwave radiation), and the simulated ORCHIDEE flux as ANN inputs. The three instantaneous meteorological inputs (T_a , VPD and R_g) were selected because they have been shown to explain the majority of variation in modeled instantaneous carbon and water fluxes on the one hand (van Wijk and Bouten, 1999). On the other hand, these three variables have also been demonstrated to deliver the broad and universal nature of the model bias in a systematic sensitivity study, which is aimed to determine the optimal set of ANN inputs in carrying the greatest correction (Abramowitz et al., 2007). Other variables, such as diffuse PPFD, soil temperature and soil moisture are not considered since they are not available for all sites. In addition, the soil depth where soil temperature and moisture measurements occur is not uniform across sites. To avoid any bias due to data gap filling methods by La Thuile data processing system (c.f. www.fluxdata.org) in computing ORCHIDEE errors, only time steps with actual measurements are used in ANN error model performed upon the original time series.

The errors on five flux variables are investigated: sensible heat flux (H), latent heat flux (LE), gross primary productivity (GPP), ecosystem respiration (R_{eco}) and net ecosystem exchange of CO_2 (NEE). Note that GPP and R_{eco} are not measured but separated from NEE using the method of Reichstein et al. (2005) based upon an empirical model. Therefore, any systematic errors in the flux-partitioning algorithm of Reichstein et al. (2005) will contribute to ORCHIDEE errors for these two gross fluxes. We examine the ability of the ANN driven by meteorological variables and by the simulated ORCHIDEE flux to estimate RMSE-R for the following configurations:

Case WT: Transfer of ANN-modeled error within a time scale at each site. For example, at each site, using reconstructed time series on diurnal timescale, we train an ANN to model error on selected data from half of the time series and then use this error model to estimate RMSE-R in another half. This is also performed upon the original time series. The number of sites is 125.

Case CT: Transfer of ANN-modeled error across time scales at each site. For example, at each site, using the reconstructed time series on diurnal timescale, we train an ANN error model on the entire time series, and then use this error model to estimate RMSE-R on the entire reconstructed time series on both annual and interannual timescales. The number of sites is 125.

Case S: Transfer of ANN-modeled error across spatial scale (Table 2.3):

Case S1: We train an ANN error model on the entire time series using two-thirds of the sites belonging to a class consisting of a specific PFT (e.g. grassland) and a specific climate group (e.g. temperate), and then apply this error model to estimate RMSE-R on the entire time series of the other one-third of the sites from the same class. This is a test of error spatial transferability within a PFT and a climate group. The number of classes is 15.

Case S2: We train an ANN error model on the entire time series using all sites belonging to a class consisting of a specific PFT (e.g. grassland) and a specific climate group (e.g. temperate), and then apply this error model to estimate RMSE-R on the entire time series of all sites belonging to a class consisting of the same PFT (e.g. grassland) but a different climate group (e.g. tropical). This is a test of error transferability within one PFT and between climate groups. The number of classes is 24.

Case S3: We train an ANN error model on the entire time series using all sites belonging to a class consisting of a specific PFT (e.g. grassland) and a specific climate group (e.g. temperate), and then apply this error model to estimate RMSE-R on the entire time series of all sites belonging to a class consisting of a different PFT (e.g. cropland) but the same climate group (e.g. temperate). This is a test of PFT spatial transferability within each climate group. The number of classes is 44.

Case S4: We train an ANN error model on the entire time series using all sites belonging to a class consisting of a specific PFT (e.g. grassland) and a specific climate group (e.g. temperate), and then apply this error model to estimate RMSE-R on the entire time series of all sites belonging to a class consisting of a different PFT (e.g. cropland) and a different climate group (e.g. tropical). This is a test of both PFT and climate group spatial transferability. The number of classes is 210.

The error spatial transferability for the above four cases is investigated on both original and reconstructed time series with three characteristic timescales. In addition, to be comparable to Abramowitz et al. (2007), who did not take into account any site classification based on climate group, we also investigated two additional cases of error spatial transferability based on the original time series:

Case S5: We train an ANN error model on the time series from two-third of all sites belonging to a specific PFT (e.g. grassland) and then apply this error model to estimate RMSE-R on the time series of the other one-third of sites from the same PFT. This is a test of spatial transferability within a PFT.

Case S6: We train an ANN error model on the entire time series from all sites belonging to a specific PFT (e.g. grassland) and then apply this error model to estimate RMSE-R on the entire time series of all sites from different PFT. This is a test of PFT spatial transferability.

Case FF: Transferability of ANN-modeled error between LE and GPP:

Within each site based on original and reconstructed time series with three characteristic timescales, we trained an ANN error model on the time series of LE and applied this error model to estimate RMSE-R on the time series of GPP. Then the reverse, estimating RMSE-R in LE is from an ANN error model trained in GPP. This is a test of flux variable transferability.

We should be aware of the fact that ANN-modeled error in this study not only contains the errors originating from the model itself (or model bias) but also include other errors related to flux data measurements and data processing (e.g. Billesbach, 2011). Fortunately, the data from La Thuile dataset used in this study underwent a standardized preprocessing based on friction velocity (u^*) filter and despiking of half hourly flux data (Papale et al., 2006), and these observed-related errors such as selective systematic errors of flux during calm nocturnal periods (Goulden et al., 1996) might contribute less to total ANN-modeled errors. However, a general lack of energy balance closure (Wilson et al., 2002; Foken, 2008) at eddy covariance sites could still be a remaining problem. Since the magnitude and causes of energy balance imbalance likely vary among sites and timescales (e.g. Barr et al., 2006; Wilson et al., 2002), we did not make any corrections to the LE and H measurements performed in Jung et al. (2011). Abramowitz et al (2007) demonstrated that ANN-modeled error predominantly originates from the model itself rather than observations when comparing ANN-modeled errors in H and LE of different land surface models. Thus, ANN-modeled error might be mainly attributed to model itself rather than observational error.

Case type	Full type name	Num. of classes
Case S1	spatial transferability within a PFT and a climate group	15
Case S2	climate group spatial transferability within a PFT	24
Case S3	PFT spatial transferability within a climate group	44
Case S4	PFT and climate group spatial transitivity	210
Case S5	spatial transferability within a PFT	7
Case S6	PFT spatial transitivity	42

Table 2.3 The configuration of spatial transferability of ANN correction

2.3. Results and Discussion

2.3.1 RMSE-R on three different timescales (Case WT)

Figure 2.3 shows RMSE-R for each flux variable within each time scale using ANN error modeling. All sites ($n = 125$) are pooled to generate the histogram of RMSE-R for each flux at each time scale. When comparing the range of median RMSE-Rs from all flux variables across different timescales (Figure 2.3), we found that the interannual timescale is always associated with the largest RMSE-R (range of median values: 36-61%; which means that 36-61 percent of ORCHIDEE error in the evaluation dataset has been reduced by ANN error modeling), whereas the diurnal timescale has the smallest RMSE-R (16-36%). The annual time scale has the intermediate values (17%-44%; Figure 2.3). Our results suggest that climate-dependent processes controlling fluxes are better represented by ORCHIDEE in the

short timescales than in the long timescales. Previous studies documented that the land surface model (LSM) tends to fail in replicating interannual variation of carbon and water fluxes (Siqueira et al., 2006; Urbanski et al., 2007; Mahecha et al., 2010a). That the highest RMSE-R was found on the interannual timescale for all fluxes investigated (Figure 2.3) implies that long timescales can be significantly improved if their model bias related to the meteorological variables used in ANN error model can be largely removed by the model refinement. This is consistent with previous findings (e.g. Hui et al., 2003; Sierra et al., 2009) that climate is an important driver of interannual variability of terrestrial fluxes.

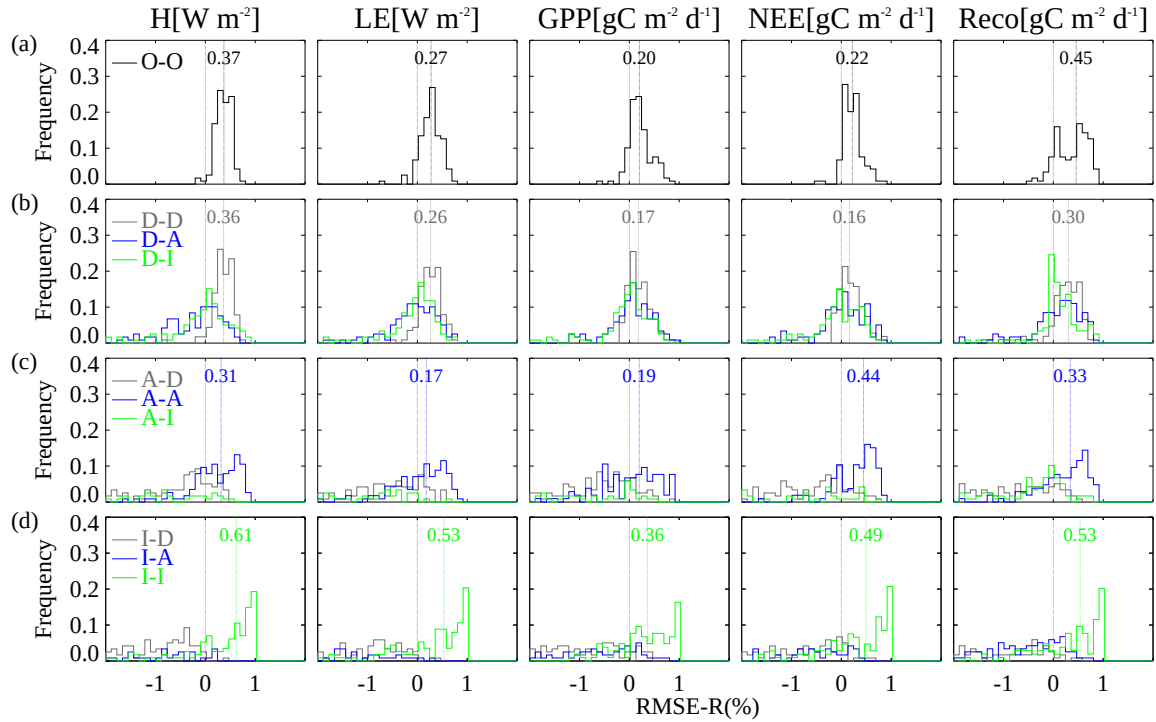


Figure 2.3 The histogram of RMSE-R on the original time series (a: O-O), at three timescales (b: D-D, c: A-A and d: I-I) and across timescales (b: D-A and D-I; c: A-D and A-I; d: I-D and I-I) for H, LE, GPP, Reco and NEE. O is the original time series, and D, A and I represent the time series on diurnal, annual and interannual timescales respectively. An ANN error model is trained on one timescale (e.g. D) and then evaluated on another timescale (e.g. A) to get RMSE-R in A from D (D-A). The value on the graph represents the median value of the histogram of RMSE-R.

The small RMSE-R on a diurnal timescale, particularly, for GPP and NEE reflects the ability of ORCHIDEE to resolve fast CO₂ exchange processes using canopy turbulent theories, largely driven by radiation. Diurnally, GPP and NEE have a lower RMSE-R than H, LE and R_{eco} . This may be expected due to the fact that the observed high model bias in H can be related to the use of a single energy budget for both vegetation and soil (Krinner et al., 2005). The source of higher model bias in R_{eco} can be related to the possibility that heterotrophic respiration in ORCHIDEE is calculated using daily mean temperature without resolving its diurnal variability. Another cause of concern is the unrealistic representation of soil carbon

states in natural ecosystems, which is based on soil carbon equilibrium hypothesis when initializing soil carbon pools at the site level (Williams et al., 2009; Pietsch and Hasenauer, 2006; Wutzler and Reichstein, 2007; Carvalhais et al., 2008, 2010). In addition, the observed high RMSE-R in H and LE could also be associated with the systematic errors contributed by a general lack of energy balance closure at eddy covariance sites (Wilson et al., 2002; Foken, 2008). Moreover, our results suggest that considering only the model bias in the original time series (range of median values: 20-45%) can mask large residual model bias on interannual (36-61%) timescales. Not separating timescale in model evaluations may thus lead to an optimistic assessment of model behaviors on longer timescales because of error cancellation across timescales (Mahecha et al., 2010a), that may also translate into flawed estimates of the carbon climate feedbacks (Wang et al., 2010; Mahecha et al., 2010b). We also found that the distribution of RMSE-R on interannual timescale is much more spread than other timescales, and one of the possibilities could be the accuracy of extracted interannual variability by SSA based on relatively short time series length in La Thuile FLUXNET dataset. For example, Mahecha et al. (2010a) explored interannual timescale using the five-year time series of carbon and water fluxes and found that the uncertainty of subsignal separation is very large and does not allow assessing the interannual variability. This emphasized the necessity of continued flux monitoring for understanding longer-term carbon and water flux variability, and the use of other long-term variables such as basal area growth from tree ring records (Briffa et al., 2008).

To have an idea of the fraction of systematic errors that could be accounted for by ANN error modeling, based on original time series, we made a comparison between RMSE in the fluxes after ANN error modeling and the random flux errors in a temperate deciduous forest site at Howland. The random flux errors were estimated by comparing the results of two eddy covariance towers installed near one another during the year 2000 (Hollinger and Richardson, 2005) (Table 2.4). This comparison showed that the RMSE after ANN error modeling remain more than two times larger in absolute value than the random flux errors (Table 2.4). For example, ANN error modeling can strongly reduce the RMSE on yearly H (W m^{-2}), LE (W m^{-2}) and NEE ($\text{umol m}^{-2} \text{s}^{-1}$) RMSE to 45.8, 43.2 and 3.18. But the residual RMSE is still higher than their respective random flux errors (19.5, 16.5 and 1.5) (Table 2.4). This might be related to the fact that only considering climate drivers as ANN input variables is inadequate, other variables such as delayed response to external forcings (e.g. van der Molen et al., 2011), soil moisture (Niu et al., 2011) and management activities (crop rotations, irrigation, fertilization) in particular for crops and managed forests (e.g. Jaksic et al., 2006; Peichl et al., 2011; Smith et al., 2010) could also be important. In Howland, for example, the inclusion of soil temperature as another ANN driver, an input recognized as an important regulator of carbon exchange during soil thawing period in the Howland forest ecosystem (Hollinger et al., 1999), can further reduce RMSE of ORCHIDEE errors in NEE by 5% (Table 2.4). It should be noted that the random flux errors could vary between sites and the fraction of systematic errors accounted for by ANN error model is then site-dependent. But the model bias removed in this

study might be beyond the random flux errors on most of EC sites, since ANN input drivers could be limited by both data availability and our understanding of the underlying processes.

Flux variable	Howl. 2 tower	ORCHIDEE	ANN1	ANN2	(ANN1-ANN2)/ANN1 (%)
H (W m^{-2})	19.5	129.1	45.8	45.3	1.1
LE (W m^{-2})	16.5	73.9	43.2	42.1	2.5
NEE ($\text{umol m}^{-2} \text{s}^{-1}$)	1.5	4.93	3.18	3.02	5.0

Howl. 2 tower data from Hollinger and Richardson (2005), where random errors are estimated using simultaneous measurements from two flux towers separated by around 775 m. ANN1 is the root mean square error of the ANN model with air temperature, global radiation, vapor pressure deficit and modeled output as drivers; ANN2 is the same with ANN1 but with soil temperature in surface layer as another driver.

Table 2.4 Random flux measurement error, RMSE (root mean square error) of ORCHIDEE flux variables and their ANN-corrected values during the year 2000 in Howland forest.

2.3.2 Error transferability across different timescales (Case CT)

To investigate whether ANN-modeled errors are transferable across different timescales, we examined whether ANN error model constructed at one timescale could be useful to reduce ORCHIDEE errors on other timescales. Figure 2.3b-d shows that ANN-modeled errors on one timescale are not transferable to other timescales, reflected by the near zero or even negative median RMSE-R (meaning a decrease in the fit of the data to the ANN error model) (Figure 2.3b-d). We also observed a widening of the frequency of RMSE-R, indicating different results across sites. This poor error transferability across timescales is evident in other studies, for example, Siqueira et al. (2006) demonstrated that the model justified for resolving fast CO_2 and H_2O exchange processes using canopy turbulent theories can not necessarily translate into improved predictive skills on all timescales. Mahecha et al. (2007) also showed that a clear hysteretic curve between pure annual components of NEE and air temperature is significantly affected by adding the interannual component to the annual cycles, and emphasizing potential differences in the response of NEE to temperature on different timescales. Poor timescale transferability of model biases for ORCHIDEE found in this study also implies that this model can capture most of time scale-independent behaviors in ecosystem flux simulations (Baldocchi et al., 2001; Katul et al., 2001; Stoy et al., 2009), though large RMSE-R still existed when transferring errors within annual or interannual timescales as mentioned in Sect. 2.3.1.

2.3.3 Error spatial transferability (Case S)

2.3.3.1 Original time series

In Abramowitz et al. (2007), only two different PFTs and 13 eddy covariance sites were used to investigate the spatial transferability of ANN-modeled errors based on an original time series. In this study, we extended this approach through the use of 125 sites distributed across 7 PFTs. Based on an original time series, the median RMSE-R from all scenarios in both Case S5 (spatial transferability within a PFT, $n = 7$) and Case S6 (PFT spatial transferability, $n = 42$) for different fluxes are displayed in the diagonal and non-diagonal terms of the matrix in Figure 2.4, respectively. Case S5 analysis suggested that the median RMSE-R in H (W m^{-2}), LE (W m^{-2}), GPP ($\text{g C m}^{-2} \text{ d}^{-1}$), R_{eco} ($\text{g C m}^{-2} \text{ d}^{-1}$) and NEE ($\text{g C m}^{-2} \text{ d}^{-1}$) is of 38, 30, 18, 26 and 18% respectively. For GPP and NEE, cropland (32% and 34%) and BoENF (33% and 27%) have the highest RMSE-R in Case S5. For the cropland that covers any kind of cultivated species without distinction, this can be expected since crop in the parameterization of crop phenology in ORCHIDEE is the one of generic herbaceous vegetation, and does not account for management practices and crop variety-dependent parameters (Smith et al., 2010; Li et al., 2011). Case S6 analysis (PFT spatial transferability) suggests most of RMSE-R in H and LE across PFTs are positive (Figure 2.4), indicating that ANN error modeling does improve the prior ORCHIDEE model simulation. This was also found by Abramowitz et al (2007) study when comparing H and LE across grassland and conifers for all of the land surface models they considered. This means that ANN-modeled errors in H and in LE based on the original time series are relatively insensitive to PFT. By contrast, the picture of RMSE-R in GPP and NEE is different. For example, based on the constructed ANN error model in TrEBF, ANN produces a marginal or negative RMSE-R in GPP for other PFTs (Figure 2.4; that is degradation from the prior ORCHIDEE simulation). This suggests that the ORCHIDEE model has some capability in simulating PFT-specific carbon fluxes based on the original time series.

2.3.3.2 Different timescales

As shown in whisker boxes of Figure 2.5, the median RMSE-R from all classes in Case S1 (spatial transferability within a PFT and a climate group, $n = 15$) was always positive at all time scales for each flux variable. The comparison between Case S1 on Y axis and other cases on X axis (Case 2: $n = 24$, Case 3: $n = 44$ and Case 4: $n = 210$) is also shown in Figure 2.5. The 1:1 line (Figure 2.5) showed that the median RMSE-R in Case S1 ($n = 15$) is larger in all other cases on all investigated timescales. Meanwhile, RMSE-R is often found to be negative (that is the model misfit is increased after applying the ANN error model) or near zero on annual and interannual timescales in all cases except Case S1. In contrary, on diurnal timescale, the median RMSE-R of all classes within each case was always positive for each flux variable, which is comparable to the ANN error model applied on the original time series (Figure 2.5). This can be expected due to the fact that the short timescale (diurnal) carries the largest spectral power among the investigated three characteristic timescales and most of the variability in the original time series can be accounted for by its short timescale part.

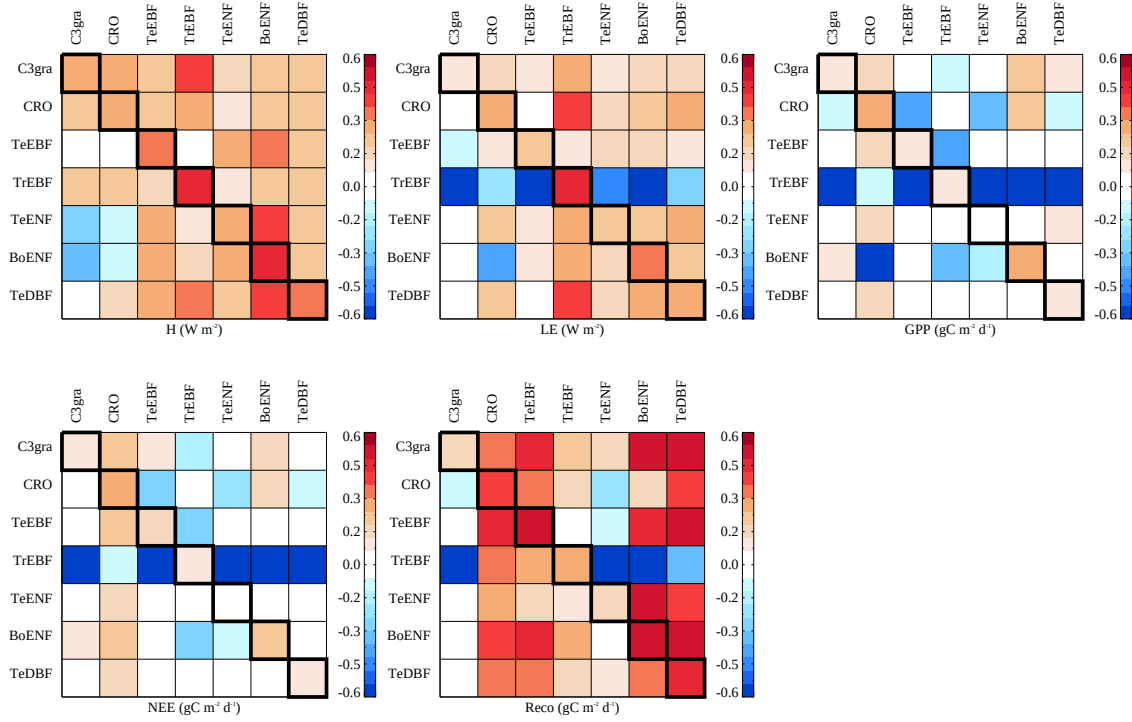


Figure 2.4 Matrix of the average RMSE-R from all pairs in both Case S5 (diagonal) and Case S6 (non-diagonal) for H, LE, NEE, GPP and Reco. A single ANN is trained on vertical PFT (e.g. CRO) and then tested on horizontal PFT (e.g. TeENF) to get RMSE-R in TeENF from CRO.

Firstly, Case S1 analysis suggested that ANN-modeled error is transferable within a PFT and within a climate group at all timescales. This means that each PFT/climate group has specific features that the model is not able to reproduce, and thus suggests that better model performance could be achievable by improving the parameterization at the level of PFT/climate group. This result implies that model improvement based on specific eddy covariance sites can enhance the model behavior at other sites within the same PFT and the same climate group. This is a key result showing the non-local character of eddy- flux point-scale observations to improve the description of fluxes through process-based modeling. It provides evidence for mapping national or regional water, carbon and energy fluxes using PFT (from satellite observations) and climate data (e.g. Jung et al., 2011). Theoretically, the information on error transferability in a PFT and a climate group could also be used to optimize the future network designed for carbon and water studies through better locating the sites. The ANN-modeled errors are less transferable across sites belonging to different climate groups (Case S2, S3) and different PFTs (Case S3, S4) especially on the annual and interannual timescales, as shown by the reduced or negative error transferability e.g. in LE and NEE (Figure 2.5). This result suggests that PFT alone cannot describe the representation of ecosystem functioning on the long timescale, and that the ORCHIDEE model would benefit from accounting for more detailed climate groups in addition to PFT for its parameterization. This is similar to results from field observations on hundreds of plots showing ecoregion (primarily delimited by climate, e.g. seasonal high and low temperatures,

precipitation) differences in forest type productivity, carbon pools, and recovery from disturbance for a given forest type (Hudiburg et al. 2009).

Secondly, there is little error transferability on annual and interannual timescales (Case S2, Case S3, and Case S4). In contrast, positive error transferability is often found on the diurnal timescale in Case S4, which is consistent with the spatial error transferability (Case S5 and Case S6) using the original time series. The ANN-modeled errors of the short timescale are much less sensitive to PFT or climate group than the errors of the longer timescales, which is notably for H , LE and R_{eco} (Figure 2.5). However, this does not mean that the model has a better ability to characterize the main processes driving the fluxes on longer timescales. In fact, larger relative model-observation mismatch have already been observed on longer timescales (annual and interannual) compared to shorter time scales (diurnal). One of the possibilities is that on the diurnal cycle, the variations in water and carbon fluxes are largely forced by daily rhythms in climatic controls (i.e. solar radiation, air temperature and humidity) (Baldocchi, 1997). While, the longer timescales might be more affected by climate through site-specific slowly varying ‘biotic’ variables (e.g. soil carbon, leaf area) (Richardson et al., 2007; Stoy et al., 2009; Jung et al., 2011), land use history, disturbance history, fertility and also including the delayed responses to environmental variation (Schimel et al., 2005). In addition, the accuracy of extracted interannual variability by SSA using relatively short time series in La Thuile dataset could also be questioned (see Sect 2.3.1).

2.3.4 Error transferability between water and carbon fluxes

It is established that photosynthesis and transpiration are tightly correlated through stomatal control at the leaf level, and this has been observed at the ecosystem level (Irvine et al. 2008, Law et al. 2006, Beer et al. 2009), with PFT differences in water-use efficiency (GPP/LE, which includes evaporation). In the ORCHIDEE model, photosynthesis and transpiration are coupled through stomatal conductance (Krinner et al., 2005). To test whether the error transferability revealed in previous cases also existed between photosynthesis and transpiration, we use an ANN error model from LE (or GPP) to estimate RMSE-R in GPP (or LE) at each site. The ANN-modeled errors are transferable from LE to GPP and vice versa using both the original time series and reconstructed time series on diurnal timescale. For example, considering all of the sites together ($n = 125$), constructed ANN error model on LE can have a median RMSE-R of 21% (original time series) and 20% (time series on the diurnal timescale) in GPP, and conversely, a median RMSE-R of 18% and 16% were achieved in LE from ANN error model trained on GPP. This confirms that the nature of ANN-modeled errors is transferable between GPP and LE on the diurnal timescale, which suggested that an improvement of representation of GPP (or LE) parameterization in ORCHIDEE can probably improve accuracy of simulated LE (or GPP).

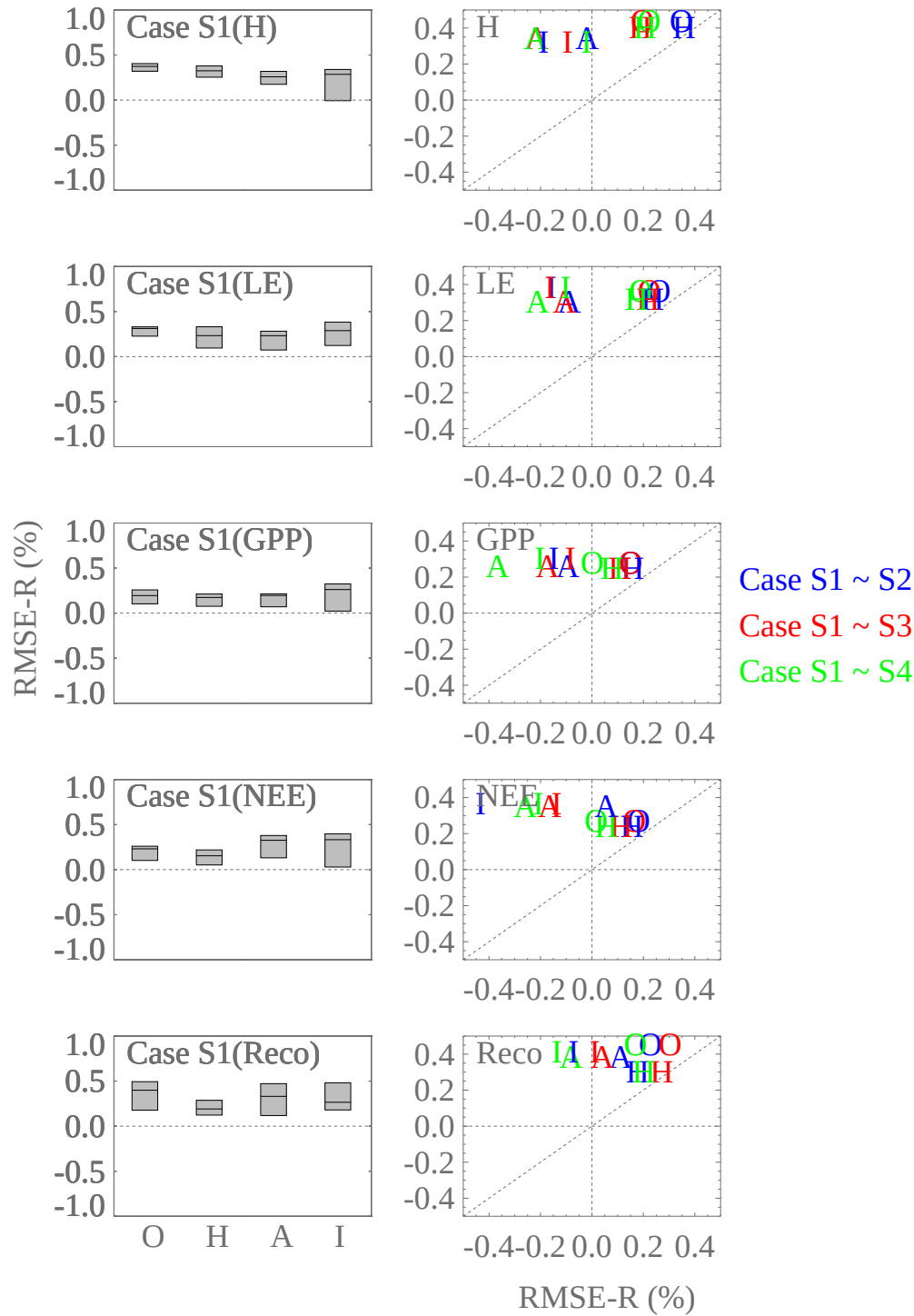


Figure 2.5 The whisker box of RMSE-R in Case S1 for H, LE, GPP, Reco and NEE on the original time series and reconstructed time series at three different characteristics timescales. The scatter plots for Case S2 vs. Case S1, Case S3 vs. Case S1 and Case S4 vs. Case S1 were also shown. O, H, A and I represent the original time series, reconstructed time series at diurnal, annual and interannual timescales, respectively. The whisker box is consisted of median value (solid line), 25% percent and 75% percent of the data.

In addition, we found again that error transferability was marginal when considering long timescales (annual and interannual). For example, at annual and interannual timescales, a median of RMSE-R in GPP from ANN error model trained on LE are 5% and 1% ($n = 125$), and ANN error model from GPP on LE are -7% and -1% ($n=125$), respectively. This may reflect some decoupling between GPP and LE on an annual timescale, for instance the transpiration fraction of LE can vary seasonally (Irvine et al. 2004). However, we can not conclude that ANN-modeled errors are not transferable between these two variables on annual and interannual timescales, since our ANN error model did not include other drivers (e.g. seasonal dynamics of vegetation growth and soil moisture) as ANN inputs, which are regarded as important factors controlling LE and GPP in long timescales (Beer et al., 2009; Daly et al., 2009; Irvine et al. 2004).

2.4 Conclusions and Outlooks

Our study demonstrates the ability of a neural network-based technique to quantify the transferability of model bias across sites as advocated by Abramowitz et al. (2007). Combined with a time series decomposition method, this methodology was also successfully extended to explore the transferability of model bias in timescale domain. This could enable land surface model (LSM) community to have an idea of the theoretical bound for the space of model improvement and model uncertainties reduction. Within each timescale, lower error transferability was always found on the diurnal timescale than long timescales (annual and interannual). Meanwhile, the processes regulating on different timescales are different, which can also be implied from near-zero or even negative error transferability across timescales. This further emphasize that more and more attention in model evaluation and development should be paid in timescale domain, and not separating timescale can lead to a biased estimate of model behaviors on long timescales.

Thanks to a global eddy covariance network, we can apply this methodology in an extended space domain, which is delimited by PFT and climate groups. This can provide the clues on how much of the benefits could be obtained for overall model performance from site-based model refinement. Our analysis showed that model improvement achieved on the sites in a specific PFT and a specific climate group could translate into improved model simulations at other sites belonging to the same PFT and the same climate group. This is a non-local character of eddy flux point observations to improve flux simulations through process-based modeling.

In this study, the mode bias is only partially characterized because ANN inputs could be restricted by both data availability and poor understanding of some underlying processes. Meanwhile, long timescale separation from the original time series by SSA is unstable, and long term eddy covariance records are thus very necessary, which could facilitate improved representation of interannual variability in current LSMs. As longer records of fluxes become available, and inclusion of other variables such as moisture become available (e.g. from

remote sensing), this methodology shows promise for diagnosing model weaknesses and prioritizing improvements to the models.

3. Controls on winter ecosystem respiration in temperate and boreal ecosystems

Winter CO₂ fluxes represent an important component of the annual carbon budget in northern ecosystems. Understanding winter respiration processes and their responses to climate change is also central to our ability to assess terrestrial carbon cycle and climate feedbacks in the future. However, the factors influencing the spatial and temporal patterns of winter ecosystem respiration (R_{eco}) of northern ecosystems are poorly understood. For this reason, we analyzed eddy covariance flux data from 57 ecosystem sites ranging from ~35° N to ~70° N. Deciduous forests (DBF) were characterized by the highest winter R_{eco} rates (0.90 ± 0.39 g C m⁻² d⁻¹), when winter is defined as the period during which daily air temperature remains below 0 °C. By contrast, arctic wetland (AWET) had the lowest winter R_{eco} rates (0.02 ± 0.02 g C m⁻² d⁻¹). Mixed forests (MF), evergreen needle-leaved forests (ENF), grasslands (GRA), croplands (CRO) and boreal wetland (BWET) were characterized by intermediate winter R_{eco} rates (g C m⁻² d⁻¹) of $0.70(\pm 0.33)$, $0.60(\pm 0.38)$, $0.62(\pm 0.43)$, $0.49(\pm 0.22)$ and $0.27(\pm 0.08)$, respectively. Our cross site analysis showed that winter air (T_{air}) and soil (T_{soil}) temperature played a dominating role in determining the spatial patterns of winter R_{eco} in both forest and managed ecosystems (GRA and CRO). Besides temperature, the seasonal amplitude of the leaf area index (LAI), inferred from satellite observation, or growing season gross primary productivity (GPP_{gs}), which we use here as a proxy for the amount of carbon available for R_{eco} in the subsequent winter, played a marginal role in CO₂ emissions from forest ecosystems. We found that winter R_{eco} sensitivity to temperature variation across space (Q_S) was higher than the one over time (interannual, Q_T). This can be expected due to the fact that Q_S not only accounts for climate gradients across sites but also for (positively correlated) substrate spatial variability. Thus, if the models estimate future warming impacts on R_{eco} based on Q_S rather than Q_T , this could overestimate the impact of temperature changes.

Controls on winter ecosystem respiration in temperate and boreal ecosystems

T. Wang¹, P. Ciais¹, S. L. Piao², C. Ottlé¹, P. Brender¹, F. Maignan¹, A. Arain³, A. Cescatti⁴, D. Gianelle⁵, C. Gough⁶, L. Gu⁷, P. Lafleur⁸, T. Laurila⁹, B. Marcolla¹⁰, H. Margolis¹¹, L. Montagnani^{12,13}, E. Moors¹⁴, N. Saigusa¹⁵, T. Vesala¹⁶, G. Wohlfahrt¹⁷, C. Koven¹⁸, A. Black¹⁹, E. Dellwik²⁰, A. Don²¹, D. Hollinger²², A. Knohl²³, R. Monson²⁴, J. Munger²⁵, A. Suyker²⁶, A. Varlagin²⁷, and S. Verma²⁶

¹LSCE/IPSL, UMR8212, CEA-CNRS-UVSQ – Unité Mixte de Recherche, CE L'Orme des Merisiers, Gif-sur-Yvette 91191, France

²Department of Ecology, College of Urban and Environmental Science, and Key Laboratory for Earth Surface Processes of the Ministry of Education, Peking University, Beijing 100871, China

³School of Geography and Earth Sciences, McMaster University, Hamilton, ON, L8S 4K1, Canada

⁴Climate Change Unit, Inst. for Environment and Sustainability, European Commission, DG joint Research Centre, Ispra, Italy

⁵IASMA, Research and Innovation Centre, Fondazione Edmund Mach, Viote del Monte Bondone, Trento, 38040, Italy

⁶Department of Biology, Virginia Commonwealth University, P.O. Box 842012, 1000 West Cary St. Richmond, VA 23284-2012, USA

⁷Environmental Sciences Division, Oak Ridge National Laboratory, Oak Ridge, TN 37831, USA

⁸Department of Geography, Trent University, Peterborough, Ontario K9J 7B8, Canada

⁹Finnish Meteorological Institute, P.O. Box 503, 00101 Helsinki, Finland

¹⁰Edmund Mach Foundation, Research and Innovation Center, 38010 S. Michele all' Adige, Trento, Italy

¹¹Centre d'Étude de la Forêt, Faculté de Foresterie, de Géographie et de Géomatique, Université Laval, Québec, QC, G1V 0A6, Canada

¹²Autonomous Province of Bolzano, Forest Services and Agency for the Environment, Bolzano, Italy

¹³Free University of Bolzano, Faculty of Science and Technology, Bolzano, Italy

¹⁴Alterra Wageningen UR, Wageningen, 6700 AA, The Netherlands

¹⁵Center for Global Environmental Research, National Institute for Environmental Studies, 16-2 Onogawa, Tsukuba 305-8506, Japan

¹⁶Department of Physics, University of Helsinki, P.O. Box 48, 00014, Finland

¹⁷University of Innsbruck, Institute of Ecology Sternwartestrasse 15, Innsbruck 6020, Austria

¹⁸Lawrence Berkeley National Lab, Berkeley 94720, CA, USA

¹⁹Faculty of Land and Food systems, University of British Columbia, Vancouver, British Columbia, V6T 1Z4, Canada

²⁰Wind Energy Division, Risoe National Laboratory for Sustainable Energy, Technical University of Denmark, P.O. Box 49, 4000 Roskilde, Denmark

²¹Johann Heinrich von Thünen Inst., Inst. of Agricultural Climate Research, Bundesallee 50, 38116 Braunschweig, Germany

²²Northern Research Station, USDA Forest Service, 271 Mast Rd, Durham, NH 03824, USA

²³Chair of Bioclimatology, Büsgen Institute, Georg-August University of Göttingen, Germany

²⁴Department of Ecology and Evolutionary Biology, University of Colorado, Boulder, CO 80309, USA

²⁵Division of Engineering and Applied Science, Department of Earth and Planetary Science, Harvard University, Cambridge, MA 02138, USA

²⁶School of Natural Resources, University of Nebraska-Lincoln, Lincoln, NE 68583, USA

²⁷A. N. Severtsov Institute of Ecology and Evolution, Russia Academy of Sciences, Leninsky Prospect 33, Moscow, 117071, Russia

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Correspondence to: T. Wang
(tao.wang@lsce.ipsl.fr)

Abstract. Winter CO₂ fluxes represent an important component of the annual carbon budget in northern ecosystems. Understanding winter respiration processes and their responses to climate change is also central to our ability to assess terrestrial carbon cycle and climate feedbacks in the future. However, the factors influencing the spatial and temporal patterns of winter ecosystem respiration (R_{eco}) of northern ecosystems are poorly understood. For this reason, we analyzed eddy covariance flux data from 57 ecosystem sites ranging from $\sim 35^\circ\text{N}$ to $\sim 70^\circ\text{N}$. Deciduous forests were characterized by the highest winter R_{eco} rates ($0.90 \pm 0.39 \text{ g C m}^{-2} \text{ d}^{-1}$), when winter is defined as the period during which daily air temperature remains below 0°C . By contrast, arctic wetlands had the lowest winter R_{eco} rates ($0.02 \pm 0.02 \text{ g C m}^{-2} \text{ d}^{-1}$). Mixed forests, evergreen needle-leaved forests, grasslands, croplands and boreal wetlands were characterized by intermediate winter R_{eco} rates ($\text{g C m}^{-2} \text{ d}^{-1}$) of $0.70(\pm 0.33)$, $0.60(\pm 0.38)$, $0.62(\pm 0.43)$, $0.49(\pm 0.22)$ and $0.27(\pm 0.08)$, respectively. Our cross site analysis showed that winter air (T_{air}) and soil (T_{soil}) temperature played a dominating role in determining the spatial patterns of winter R_{eco} in both forest and managed ecosystems (grasslands and croplands). Besides temperature, the seasonal amplitude of the leaf area index (LAI), inferred from satellite observation, or growing season gross primary productivity, which we use here as a proxy for the amount of recent carbon available for R_{eco} in the subsequent winter, played a marginal role in winter CO₂ emissions from forest ecosystems. We found that winter R_{eco} sensitivity to temperature variation across space (Q_S) was higher than the one over time (interannual, Q_T). This can be expected because Q_S not only accounts for climate gradients across sites but also for (positively correlated) the spatial variability of substrate quantity. Thus, if the models estimate future warming impacts on R_{eco} based on Q_S rather than Q_T , this could overestimate the impact of temperature changes.

1 Introduction

The processes controlling the winter carbon cycle of northern ecosystems, which is mainly ecosystem respiration (R_{eco}), have received much less attention than processes active during the growing season. The longstanding view of marginal wintertime biological activity (e.g. Coyne and Kelley, 1971; Steudler et al., 1989) proposes that winter respiration is very small compared to growing season respiration. Recent field studies suggest a different picture by demonstrating the larger than expected wintertime respiration rates in Arctic tundra, bog, and mountain ecosystems (e.g. Oechel et al., 1997; Fahnestock et al., 1998; Grogan and Chapin, 1999; Panikov and Dedysh, 2000; Aurela et al., 2002; Monson et al., 2006; Bergeron et al., 2007). These studies suggest that winter R_{eco} should not be ignored when attempting to

quantify and understand the annual carbon balance of terrestrial ecosystems (Hobbie et al., 2000; Grogan and Jonasson, 2005; Johansson et al., 2006). However, due to the large carbon storage and heterogeneity of northern ecosystems, winter R_{eco} remains incompletely understood given the limited spatial representativeness of individual-site studies.

In general, mid and high-latitude ecosystems contain large amounts of soil carbon (Post et al., 1982; Tarnocai et al., 2009), which implies that these ecosystems could provide a significant positive feedback to climate change if warming stimulates soil carbon decomposition and CO₂ release to the atmosphere (Friedlingstein et al., 2006). The increased high-latitude warming projected by climate models includes winter warming (Serreze et al., 2000; Giorgi et al., 2001) and has already been observed over the past 30 yr (IPCC, 2007). The response of the soil organic carbon (SOC) balance to warming differs widely among coupled climate-carbon models (Friedlingstein et al., 2006). This is because the net balance in these models depends on two fluxes of opposite directions: the litter input that may increase under warming if vegetation net primary productivity increases, and the soil carbon microbial decomposition rate that also responds positively to warming (e.g. Jones et al., 2005). Therefore, it is important to disentangle how temperature and vegetation productivity separately affect winter respiration. Previous studies (e.g. Klein and Schimel, 1995; Hobbie, 1996; Mikan et al., 2002; Grogan et al., 2001; Grogan and Jonasson, 2005) were concentrated on the site-level or landscape-level. For example, Grogan and Jonasson (2005) found that both the amount of substrate available for respiration and soil temperature (T_{soil}) determine landscape-level variation of winter R_{eco} of birch forest and heath tundra. These studies are valuable for understanding site-specific or landscape-level processes, but their results cannot be readily extrapolated across sites and climate gradients to infer regional sensitivities.

Eddy covariance measurements of CO₂ fluxes have been collected continuously, together with climate variables, at many sites in temperate, boreal and arctic ecosystems, and are available in the FLUXNET database (Baldocchi et al., 2001; Baldocchi, 2008). These data represent a valuable source of information for the analysis of the spatial and temporal variability of winter R_{eco} . In this study, we focus on Northern Hemisphere sites from $\sim 35^\circ\text{N}$ to $\sim 70^\circ\text{N}$, covering a climate gradient of 24°C of mean annual temperature. In the first part, we investigate the importance of winter R_{eco} and its contribution to annual R_{eco} for different ecosystem types. The results are based on five different definitions of the winter season, having different temporal and thermal thresholds. In the second part, we analyze the temperature dependency of winter daily R_{eco} at each site, using an Arrhenius type model. We also consider a total of 218 site-years that have been aggregated to quantify the sensitivity of anomalies of winter R_{eco} to temperature on the temporal (interannual) scale. This sensitivity to temperature variation over time is hypothesized to be lower than the one across space given that

the latter not only accounts for direct climate effects, but also site productivity (Mahecha et al., 2010; Wang et al., 2010). Finally, in an attempt to improve our understanding of spatial controls on winter R_{eco} , we examine the relationships between winter R_{eco} , climate variables and productivity-related variables across sites.

2 Materials and methods

2.1 Data sources

2.1.1 Eddy covariance flux data

The eddy covariance data used in this study are extracted from the La Thuile FLUXNET synthesis database which contains 965 site years processed according to standardized protocols (Papale et al., 2006) (<http://www.fluxdata.org>). The processing of this dataset is based on friction velocity (u^*) filter and despiking of half hourly flux data, which would be expected to reduce the bias of flux measurements during the calm night and winter stable stratification period. Daily cumulative values of Net Ecosystem Exchange (NEE, $\text{g C m}^{-2} \text{ day}^{-1}$) are retrieved from the half hourly values included in the database, where a positive NEE represents a carbon release and a negative NEE a carbon uptake. The NEE time series can be partitioned into gross primary productivity (GPP) and ecosystem respiration (R_{eco}). The flux-partitioning algorithm, which is implemented in La Thuile FLUXNET database, uses short-term temperature sensitivities to extrapolate night-time respiration to daytime. This approach avoids significantly biased estimates of R_{eco} that can be obtained using long-term temperature sensitivities affected by confounding factors such as growth dynamics (Reichstein et al., 2005). T_{air} , T_{soil} and soil moisture in upper layer (between 2 and 10 cm depth), precipitation, GPP and ancillary observations of maximum LAI from site measurements were also used in this study.

Of the 200 sites located north of 35°N , we identified a subset of sites meeting the following criteria:

- having at least two years of T_{air} , upper T_{soil} , precipitation, NEE, GPP and R_{eco} data;
- having a winter duration (according to definition D_AT0: T_{air} below 0°C , Sect. 2.2) longer than 15 days;
- having more than 70 % of data coverage, both at the annual scale and during the winter period defined by D_AT0.

This resulted in a total of 57 sites, and 218 site years of data being selected, covering evergreen needleleaf forests (ENF), deciduous broadleaf forests (DBF), mixed forests (MF), boreal wetlands (BWET), arctic wetlands (AWET), croplands (CRO) and grasslands (GRA) (the number of site years are 78, 54, 17, 11, 5, 20 and 33, respectively) (Table 1).

Nearly one third (20) of the selected 57 sites employed open-path infrared gas analyzers (IRGA) for measuring CO_2 concentrations (Table 1), which are known to underestimate CO_2 emissions in cold conditions due to self-heating of the open-path IRGAs (Burba et al., 2006; Hirata et al., 2007; Lafleur and Humphreys, 2007). The effects of self-heating can be corrected for in post-processing (Burba et al., 2008), however while some studies found these corrections to improve the correspondence with concurrent closed-path CO_2 flux measurements (Burba et al., 2006, 2008; Grelle and Burba, 2007; Järvi et al., 2009), others did not (Wohlfahrt et al., 2008a; Haslwanter et al., 2009). The reasons for these mixed results are unclear at present; they may be partly attributed to differences in environmental conditions (Haslwanter et al., 2009), partly to the deployment of the open-path analyser. For example, the correction after Burba et al. (2008) applies to a vertical setup only, while many researchers prefer to tilt their open-path IRGAs in order to speed up drying of the lower window after wetting. Given these uncertainties, we decided not to correct open-path CO_2 flux measurements for the effect of self-heating in the present study. In an attempt to quantify how much this may bias our results we compared the parameters of Eq. (1) optimised for sites with open- and closed-path IRGAs separately. Both parameters (E_0, R_{ecoref}) were found to be not statistically significantly different (e.g. E_0 : open- vs. closed-path: 85.6 vs. 83.0 kJ mol^{-1} ; R_{ecoref} : open- vs. closed-path: 0.9 vs. 1.1 $\text{g C m}^{-2} \text{ d}^{-1}$ when investigating $T_{\text{air}}-R_{\text{eco}}$ relationship based on winter definition D_AT0), suggesting that any bias due to the IRGA design is small in the present study.

2.1.2 LAI dataset

Information on the leaf area index (LAI) was retrieved for each investigated site from MODIS-Aqua satellite data downloaded from the ORNL-DAAC MODIS – Collection-5 LAI data (MYD15A2) (<https://daac.ornl.gov>). These LAI data, which are only available after the year 2000, have a spatial resolution of 1 km and a temporal resolution of 8-days. They also include quality control (QC) information about cloud and data processing conditions. Only LAI data without significant cloud contamination described in the LAI user's guide (<http://landweb.nascom.nasa.gov>) within an area of $1 \times 1 \text{ km}$ centered on each site were retained for each 8-day period to obtain the maximum and minimum LAI values for each site year. The seasonal amplitude (ΔLAI) is defined as the difference between maximum and minimum of LAI and can be considered as a proxy for recent carbon inputs to soil, i.e. substrate available for sustaining winter R_{eco} . In-situ ΔLAI can not be retrieved since the majority of minimum LAI measurements are not reported in La Thuile ancillary dataset. It should be noted that in-situ LAI substitution with MODIS-LAI at 1 km resolution can introduce uncertainty, whose magnitude is dependent on the size of the eddy covariance tower footprint and the landscape heterogeneity

Table 1. General characterization of study sites used in this study.

Site	Type	Lat.	Lon.	Index	Ann. Precip. (mm)	Ann. Temp. (°C)	WLEN (D_AT0) (SD) (d)	Δ LAI (SD) (m ² m ⁻²)	R_{eco} (D_AT0) (SD) (g C m ⁻² d ⁻¹)	R_{eco} (D_TM) (SD) (g C m ⁻² d ⁻¹)	Available years	Reference
AT-Neu*	GRA	47.1	11.3	1	852	6.5	116(16)	5.8(0.4)	1.24(0.12)	1.06(0.24)	2002–2005	Wohlfahrt et al. (2008b)
BE-Vie	MF	50.3	6.0	2	1065	7.4	71(35)	5.4(0.2)	1.02(0.16)	1.10(0.16)	1996–2002	Aubinet et al. (2001)
CA-Ca1	ENF	49.9	−125.3	3	1369	9.9	54	5.6	1.33	1.48	2001	Humphreys et al. (2006)
CA-Ca2*	ENF	49.9	−125.3	4	1474	9.9	39(31)	4.4(0.7)	0.82(0.13)	1.24(0.22)	2001, 2004	Humphreys et al. (2006)
CA-Let	GRA	49.7	−112.9	5	398	5.4	138(13)	1.1(0.5)	0.22(0.08)	0.17(0.06)	1998–2004	Flanagan et al. (2002); Flanagan and Johnson (2005)
CA-Mer	BWET	45.4	−75.5	6	891	6.1	128(22)	5.5(0.3)	0.32(0.03)	0.29(0.04)	1998–2004	Lafleur et al. (2003)
CA-Oas	DBF	53.6	−106.2	7	429	0.3	169(17)	6.0(0.2)	0.50(0.06)	0.33(0.07)	1997–2003	Black et al. (2000)
CA-Obs	ENF	54.0	−105.1	8	406	0.8	185(15)	3.9(0.2)	0.47(0.04)	0.27(0.04)	1999–2004	–
CA-Ojp	ENF	53.9	−104.7	9	431	0.1	176(13)	3.0(0.4)	0.24(0.02)	0.12(0.03)	1999–2004	Kljun et al. (2006)
CA-Qcu*	ENF	49.3	−74.0	10	950	0.1	175(15)	2.2(0.2)	0.22(0.06)	0.13(0.01)	2001–2005	Giasson et al. (2006)
CA-Qfo	ENF	49.7	−74.3	11	962	−0.4	172(19)	4.0(0.2)	0.44(0.07)	0.28(0.06)	2003–2005	Bergeron et al. (2007)
CA-SJ1*	ENF	53.9	−104.7	12	430	0.1	181(15)	2.3(0.2)	0.14(0.05)	0.08(0.04)	2001–2004	–
CA-SJ2	ENF	53.9	−104.6	13	430	0.1	197	1.3(0.5)	0.09(0.00)	0.02(0.01)	2003–2004	–
CA-TP4*	ENF	42.7	−80.4	14	936	8.7	107(8)	5.8(0.1)	0.66(0.06)	0.67(0.02)	2003–2004	Arain and Restrepo-Coupe (2005)
CA-WP1*	MF	55.0	−112.5	15	461	1.1	159(7)	3.9(0.3)	0.22(0.02)	0.12(0.00)	2003–2004	Syed et al. (2006); Flanagan and Syed (2011)
CH-Oe1*	GRA	47.3	7.7	16	945	9.1	85(28)	2.4(0.4)	0.83(0.24)	0.87(0.24)	2002–2005	Ammann et al. (2007)
CN-HaM*	GRA	37.4	101.2	17	577	−0.8	182	4.7	0.08	0.02	2002	Kato et al. (2006)
CZ-BK1	ENF	49.5	18.5	18	1026	4.7	112(19)	5.8(0.6)	0.54(0.07)	0.57(0.06)	2004–2005	–
DE-Bay	ENF	50.1	11.9	19	1159	5.2	127(32)		1.22(0.21)	1.20(0.13)	1997–1998	–
DE-Geb*	CRO	51.1	10.9	20	444	8.7	87(7)	5.7(0.6)	0.57(0.27)	0.59(0.28)	2004–2005	Kutsch et al. (2010b)
DE-Hai	DBF	51.1	10.5	21	780	7.2	74(22)	6.2(0.3)	1.01(0.12)	1.06(0.15)	2001–2004	Knohl et al. (2003); Kutsch et al. (2010a)
DE-Meh	GRA	51.3	10.7	22	695	7.8	96(20)	5.1(0.7)	0.54(0.06)	0.57(0.09)	2003–2005	–
DE-Tha	ENF	51.0	13.6	23	643	8.1	85(21)	5.7(0.5)	0.94(0.18)	1.00(0.10)	1996–2002	Grunwald and Bernhofer (2007)
DK-Sor	DBF	55.5	11.6	24	573	8.0	71(35)	5.8(0.2)	1.44(0.25)	1.62(0.22)	1996–1998	Pilegaard et al. (2003)
FI-Hyy	ENF	61.8	24.3	25	620	2.2	153(21)	5.9(0.6)	0.55(0.11)	0.47(0.14)	2000–2001 1996–1998, 2000–2002,	Suni et al. (2003b)
FI-Kaa	BWET	69.1	27.3	26	454	−1.4	191(13)	1.5(0.1)	0.18(0.06)	0.15(0.06)	2000, 2003–2005	Aurela et al. (2002)
FI-Sod	ENF	67.4	26.6	27	525	−1.1	183(14)	2.2(0.2)	0.42(0.09)	0.32(0.18)	2000–2001, 2003–2005	Suni et al. (2003a)

within the footprint. Besides this, the satellite product might give large errors for evergreen needleleaf forests during the winter season, for example, the in-situ LAI at RU-Fyo site (spruce evergreen forest) was around 3.0 (m² m⁻²) but the MODIS-derived LAI value is almost near zero. When comparing maximum LAI, we found that the coefficient of determination (r^2) between satellite and in-situ measurements was 0.48 (root mean square = 1.67, $n = 52$, data not shown). Given the uncertainties in satellite-derived Δ LAI, mean daily gross primary productivity during the growing season (May–October) (GPP_{gs}) at site level was also used as a proxy for recent carbon inputs to the soil.

2.2 Winter season definition

In this study, we focus on carbon cycling during the freezing period of the year, which has been rarely explored in previous meta-data analyses (e.g. Yuan et al., 2009; Migliavacca et al., 2011). The winter seasons defined below are thus referenced to the freezing period of the year. Four winter season definitions were tested to estimate the effect of this arbitrary choice: D_AT0, D_AT-2, D_AT-5 and D_AT-10 are defined as the period during which the 10-day smoothed daily T_{air}

remained below 0 °C, −2 °C, −5 °C and −10 °C for at least five consecutive days, which allowed for year-to-year variability in winter length since these definitions are based on each site year. We also include the established climatological winter (D_TM), which is defined as the three cold months December, January and February, hence implying the same winter onset and duration at each site.

2.3 Definitions of winter R_{eco} ratios and winter R_{eco} temperature dependency

2.3.1 Winter R_{eco} ratios definition

We investigated two types of winter R_{eco} ratios, one (RWCR) is defined as the ratio of winter cumulative R_{eco} (g C m⁻²) to annual cumulative R_{eco} (g C m⁻²) and the other (RWRR) is calculated as the ratio of mean winter R_{eco} rates (g C m⁻² d⁻¹) to mean annual R_{eco} rates (g C m⁻² d⁻¹). Both of the ratios are expressed in percentage (%). RWRR is used to represent winter average metabolism relative to the annual level. Although RWCR only differs from RWRR by the inclusion of winter duration, providing RWCR for each ecosystem can indicate the role of winter season in the annual

Table 1. Continued.

Site	Type	Lat.	Lon.	Index	Ann. Precip. (mm)	Ann. Temp. (°C)	WLEN (D_AT0) (SD) (d)	Δ LAI (SD) (m ² m ⁻²)	R_{eco} (D_AT0) (SD) (g C m ⁻² d ⁻¹)	R_{eco} (D_TM) (SD) (g C m ⁻² d ⁻¹)	Available years	Reference
FR-Hes	DBF	48.7	7.1	28	793	9.2	57(31)	5.8(0.5)	1.00(0.22)	1.17(0.24)	1997–1998, 2001–2003	Granier et al. (2000)
HU-Bug*	GRA	46.7	19.6	29	555	10.5	92(3)	1.5(0.1)	0.42(0.14)	0.45(0.14)	2002–2005	–
IT-Amp*	GRA	41.9	13.6	30	945	10.6	93(23)	2.0(0.2)	1.10(0.64)	0.97(0.24)	2002–2004	Gilmanov et al. (2007)
IT-Col	DBF	41.8	13.6	31	971	7.3	83(53)	6.3(0.4)	0.72(0.00)	0.75(0.15)	1996, 2000	–
IT-MBo*	GRA	46.0	11.0	32	1185	5.4	141(29)	5.8(0.4)	0.91(0.12)	0.84(0.20)	2003–2005	Marcolla and Cescatti (2005); Gianelle et al. (2009)
IT-Ren	ENF	46.6	11.4	33	965	6.2	150(19)	5.4(0.2)	0.38(0.07)	0.31(0.13)	2001–2005	Montagnani et al. (2009)
JP-Tak	DBF	36.1	137.4	34	1024	6.5	123(16)	6.2(0.1)	0.58(0.17)	0.53(0.17)	2000–2003	–
JP-Tom*	MF	42.7	141.5	35	1156	6.7	114(14)	6.0(0.3)	0.51(0.02)	0.46(0.05)	2001–2002	–
NL-Loo	ENF	52.2	5.7	36	786	9.4	63(34)	5.7(0.5)	1.54(0.74)	2.06(0.43)	1996, 1998, 2002	Dolman et al. (2002)
RU-Fyo	ENF	56.5	32.9	37	671	4.4	143(19)	5.9(0.4)	0.91(0.19)	0.78(0.27)	1998–2004	Milyukova et al. (2002)
US-Atq*	AWET	70.5	–157.4	38	93	–12.3	254(14)	0.9(0.1)	0.02(0.01)	0.00(0.00)	2003–2005	–
US-Bkg*	GRA	44.3	–96.8	39	586	6.0	124(5)	1.8(0.1)	0.15(0.07)	0.13(0.09)	2004–2005	Gilmanov et al. (2005)
US-Bo1*	CRO	40.0	–88.3	40	991	11.0	96(18)	4.5(0.4)	0.22(0.07)	0.40(0.26)	1996–1998, 2001–2002	Meyers and Hollinger (2004)
US-Bo2*	CRO	40.0	–88.3	41	991	11.0	84(14)	4.5(0.4)	0.50(0.50)	0.53(0.49)	2004–2005	Meyers and Hollinger (2004)
US-Ha1	DBF	42.5	–72.2	42	1071	6.6	110(16)	–	1.43(0.44)	1.34(0.43)	1991–1992, 1994–1997	Urbanski et al. (2007)
US-Ho1	ENF	45.2	–68.7	43	1070	5.3	130(16)	5.5(0.2)	0.62(0.13)	0.52(0.13)	1996–2002	Hollinger et al. (2004)
US-IB2*	GRA	41.8	–88.2	44	930	9.0	103(15)	1.7(0.3)	0.38(0.04)	0.37(0.13)	2004–2005	–
US-Ivo	AWET	68.5	–155.8	45	304	–8.3	239(26)	2.0(0.1)	0.03(0.03)	0.03(0.02)	2003–2004	–
US-LPH	DBF	42.5	–72.2	46	1071	6.7	119(11)	6.1(0.2)	0.81(0.19)	0.75(0.21)	2002–2004	Borken et al. (2006)
US-MMS*	DBF	39.3	–86.4	47	1032	10.9	77(12)	5.9(0.1)	0.87(0.12)	0.91(0.18)	2000–2004	Schmid et al. (2000)
US-MOz*	DBF	38.7	–92.2	48	878	13.5	64(26)	6.4(0.2)	0.76(0.38)	0.91(0.21)	2004–2005	Gu et al. (2006)
US-NR1	ENF	40.0	–105.5	49	595	0.4	169(41)	4.3(0.2)	0.77(0.19)	0.64(0.27)	1999, 2002	Monson et al. (2002)
US-Ne1	CRO	41.2	–96.5	50	790	10.1	92(10)	2.3(0.3)	0.61(0.03)	0.62(0.03)	2001–2004	Verma et al. (2005)
US-Ne2	CRO	41.2	–96.5	51	789	10.1	95(9)	2.1(0.2)	0.58(0.11)	0.59(0.12)	2002–2004	Verma et al. (2005)
US-Ne3	CRO	41.2	–96.4	52	784	10.1	94(8)	2.2(0.4)	0.59(0.10)	0.55(0.06)	2001–2004	Verma et al. (2005)
US-PFa	MF	45.9	–90.3	53	823	4.3	141(1)	–	0.55(0.08)	0.53(0.12)	1996–1998	Ricciuto et al. (2008)
US-Syv	MF	46.2	–89.3	54	826	3.8	148(20)	6.3(0.2)	0.52(0.32)	0.42(0.36)	2002, 2004–2005	Desai et al. (2005)
US-UMB	DBF	45.6	–84.7	55	803	5.8	121(21)	6.4(0.2)	0.77(0.09)	0.77(0.05)	1999–2002	Gough et al. (2008)
US-WCr	DBF	45.8	–90.1	56	787	4.0	140(17)	6.0(0.2)	0.58(0.19)	0.45(0.17)	1999–2002, 2004–2005	Cook et al. (2004)
US-Wrc	ENF	45.8	–122.0	57	2452	9.5	70	5.7	1.08	0.82	2000	–

Type: DBF: deciduous broadleaf forests; ENF: evergreen needleleaf forests; GRA: grasslands; CRO: croplands; BWET and AWET are boreal and arctic wetlands, respectively; MF (mixed forests).

* denotes the sites that use open-path gas analyzer.

Lat. and Lon. are latitude and longitude, respectively.

Annual precip. and Annual temp. represent annual total precipitation and mean annual temperature, respectively.

WLEN is the winter length (unit: day).

Δ LAI: the average difference between maximum and minimum of MODIS LAI (m² m⁻²) from corresponding available years, and the MODIS LAI data is only available after year 2000.

R_{eco} is mean winter R_{eco} rates (g C m⁻² d⁻¹) for D_AT0 (air temperature <0 °C) and D_TM (December–February) over available years, respectively.

SD is standard deviation.

carbon budget. One-way variance analysis (ANOVA) was employed to examine whether winter R_{eco} ratios (or winter R_{eco}) were different among ecosystem types. Before ANOVA, the data sets were tested for normality using one-sample Kolmogorov-Smirnov test (K-S test). Both of the statistical analyses were performed using SPSS statistical package (SPSS windows, version 17.0, SPSS Inc.).

2.3.2 Winter R_{eco} sensitivity to temperature variation over time

Owing to the short length of R_{eco} and temperature records, temporal correlations between winter R_{eco} and predictor temperature are not applicable for studying the interannual (temporal) sensitivity of R_{eco} to temperature in detail at

each site. Instead, we calculated mean winter R_{eco} rates (g C m⁻² d⁻¹) and mean winter temperature anomalies at each site year, which was achieved by removing the multi-year mean winter R_{eco} rates and mean winter temperature from their respective mean annual values. A least squares regression was then performed between all site-year anomalies of mean winter R_{eco} rates and mean winter temperature in order to quantify the response of winter R_{eco} to interannual variations in temperature (or Q_T , winter R_{eco} sensitivity to temperature variation over time; g C m⁻² d⁻¹ °C⁻¹). For each winter season definition and each vegetation type using winter definition D_AT0, Q_T is calculated and its uncertainty is estimated using a bootstrapping algorithm (random resampling with replacement) with 500 draws.

2.3.3 Arrhenius equation to describe the temperature dependency of R_{eco}

The temperature dependency of winter R_{eco} within- and across-sites was analyzed using an Arrhenius type equation (Lloyd and Taylor, 1994):

$$R_{\text{eco}} = R_{\text{ecoref}} \exp\left(\frac{E_0}{R} \left(\frac{1}{T_{\text{ref}}} - \frac{1}{T}\right)\right) \quad (1)$$

where R_{ecoref} ($\text{g C m}^{-2} \text{d}^{-1}$) represents a reference respiration rate at the reference temperature (T_{ref} , 273.15 K) related both to the amount of substrate available for decomposers, and its quality (Lloyd and Taylor, 1994). E_0 (kJ mol^{-1}) is the activation energy parameter and represents the R_{eco} sensitivity to temperature, R the universal gas constant and T is temperature (K). Model parameters (E_0, R_{ecoref}) were estimated using the Levenberg-Marquardt method, implemented in the IDL library (Interactive Data Language 8.0), a non-linear regression analysis that optimizes model parameters finding the minimum of a defined cost function. The cost function used here is the sum of squared residuals. The standard errors of model parameters (E_0, R_{ecoref}) were estimated using a bootstrapping algorithm (random resampling with replacement) with 500 draws.

In order to obtain site-year-specific parameters (E_0, R_{ecoref}), half-hourly nighttime NEE over the defined winter season (Sect. 2.2) was regressed against the corresponding nighttime T_{air} and T_{soil} based on Eq. (1). This is done given that daytime R_{eco} is derived from NEE based on the temperature sensitivity of nighttime NEE in the La Thuile dataset (Reichstein et al., 2005). It should be noted that other analyses in this study are based on daily R_{eco} values. The parameters (E_0, R_{ecoref}) from the site years were then averaged to get site-specific values based on the criterion that both the relative error of site-year-specific E_0 and R_{ecoref} is less than 50 % and E_0 estimates were within an acceptable range (0–450 kJ mol^{-1}).

Across sites, we investigate two different temperature dependencies of winter R_{eco} across space using Eq. (1). The first one uses a fixed value of R_{ecoref} across sites in Eq. (1). The second one allows R_{ecoref} to vary across sites, relying on the assumption that R_{ecoref} might have different values for different substrates (Ågren, 2000). To achieve this, mean winter temperature was regressed against mean winter R_{eco} rates divided by site-specific R_{ecoref} , which is provided by above-mentioned within-site analysis. This analysis is conducted towards all winter definitions and all vegetation types using winter definition D.AT0.

Across sites, Eq. (1) was also reformulated by adding the dependency of R_{ecoref} on ΔLAI ($\text{m}^2 \text{m}^{-2}$) or GPP_{gs} ($\text{g C m}^{-2} \text{d}^{-1}$) in forest ecosystems. Winter R_{eco} rates ($\text{g C m}^{-2} \text{d}^{-1}$) can thus be expressed by:

$$R_{\text{eco}} = (A_{\text{air}}S + B_{\text{air}}) \exp\left[\frac{E_{0,\text{air}}}{R} \left(\frac{1}{T_{\text{ref}}} - \frac{1}{(T_{\text{air}} + T_{\text{ref}})}\right)\right] \quad (2)$$

$$R_{\text{eco}} = (A_{\text{soil}}S + B_{\text{soil}}) \exp\left[\frac{E_{0,\text{soil}}}{R} \left(\frac{1}{T_{\text{ref}}} - \frac{1}{(T_{\text{soil}} + T_{\text{ref}})}\right)\right] \quad (3)$$

where S stands for substrate and represents either ΔLAI ($\text{m}^2 \text{m}^{-2}$) or GPP_{gs} ($\text{g C m}^{-2} \text{d}^{-1}$). $E_{0,\text{air}}$, $E_{0,\text{soil}}$, A_{air} , A_{soil} , B_{air} and B_{soil} are fitted parameters. To test the effect of soil carbon stock, besides ΔLAI (or GPP_{gs}), soil carbon stock is also linearly added in the same way as ΔLAI (or GPP_{gs}) into Eqs. (2) and (3). The model accuracy was then assessed by a cross-validation technique: one site at a time was excluded using the remaining subset for training and the excluded for validation and the model was fitted against the training set and then applied to calculate the modeled value for the validation set.

3 Results and discussion

3.1 Winter R_{eco} and its ratio to annual R_{eco} among ecosystem types

Figure 1 shows the frequency distribution of winter cumulative R_{eco} and RWCR based on the two winter definitions D.AT0 and D.TM. These histograms contain data from all site-years. The winter cumulative R_{eco} (g C m^{-2}) for D.TM and D.AT0 ranges from 0.5 to 201.5 (median, 25th and 75th percentiles: 51.2, 24.1 and 78.0) and from 2.3 to 229.2 (64.8, 37.8 and 90.9), respectively. The RWCR (%) varies from 0.01 to 18.2 (5.3, 3.8 and 7.7) and from 0.7 to 22.5 (8.4, 5.9 and 10.4) for D.TM and D.AT0, respectively.

Table 2 provides the statistics of mean winter R_{eco} rates and winter cumulative R_{eco} for different ecosystem types using winter definition D.AT0 and D.TM. The values for other winter definitions (D.AT-2, D.AT-5 and D.AT-10) are shown in Table A1 in the Appendix. As shown in Table 2, deciduous broadleaf forests have the highest winter R_{eco} and arctic wetlands have the lowest. Both boreal and arctic wetlands have a smaller winter R_{eco} (mean rates and cumulative) when using the definition D.TM (90 days) compared to definition D.AT0 (151 and 248 days). This can be expected due to the fact that microbial activity decreases rapidly as T_{soil} descends towards -5°C (Clein and Schimel, 1995) and arctic wetlands exhibit the lowest T_{soil} (e.g. D.AT0: US-Ivo: -4.9°C and US-Atq: -11.3°C). Besides the low temperature constraint, anaerobic conditions pose another constraint on microbial respiration because of oxygen limitation. For example, boreal wetlands with relatively high T_{soil} (CA-Mer: -0.3°C and FI-Kaa: -1.1°C) has lower mean respiration rate compared to other ecosystem types except arctic wetlands. Both mean winter R_{eco} rates and winter cumulative R_{eco} are expected to decrease when the winter definition was changed from D.AT-2 to D.AT-10 (Table A1). Consistent with D.AT0 and D.TM, the highest and lowest mean winter R_{eco} rates (winter cumulative R_{eco}) were always found in deciduous broadleaf forests and arctic wetlands if using other winter definitions (Table A1).

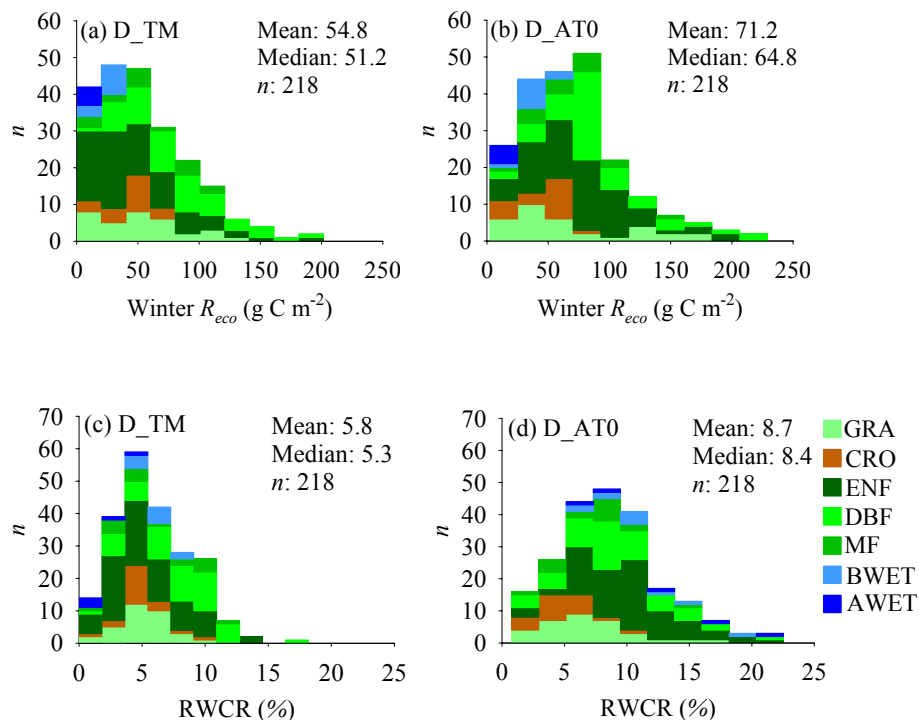


Fig. 1. Frequency histograms of winter cumulative R_{eco} and the ratio of winter cumulative R_{eco} to annual cumulative R_{eco} (RWCR) (%) according to winter definition D_TM (December–February) and D_AT0 (air temperature $<0^{\circ}\text{C}$) across all of the site-years. n is the number of site years.

The RWCR (%) varies among ecosystem types (Table 2). Using definition D_AT0, the highest RWCR values are found in both arctic and boreal wetlands and the lowest values in grasslands and croplands (Table 2). In contrast, when using the D_TM definition with a much shorter winter duration in high latitudes, both arctic and boreal wetlands have a lower RWCR (Table 2). Compared to the RWCR, the RWRR (%) is less varied among different ecosystem types but shows a higher relative value for ecosystems with large permanent biomass such as forests, indicating the contribution of autotrophic respiration. Arctic wetlands have much lower RWRR in D_TM than D_AT0, which can be related to the possibility that the microbial activity is much more constrained by very low temperatures in D_TM (T_{soil} : -15.9°C) than D_AT0 (T_{soil} : -11.3°C). Similar to the RWCR, both croplands and grasslands have the relatively lower RWRR values (Table 2), which may be related to management practices that remove the plant residuals fuelling winter respiration.

Except winter definition D_TM, the RWCR increases with latitude (e.g. D_AT0: $r = 0.33$, $p < 0.05$, $n = 57$) since winter is often longer at higher-latitude sites (e.g. D_AT0: $r = 0.51$, $p < 0.01$). This pattern can be also found if grasslands and croplands are separated from forests (data not shown). The increase of the RWCR with latitude is not found in D_TM due to its constant winter duration. These results im-

ply that winter R_{eco} in colder regions carries a higher relative contribution to annual cumulative R_{eco} , due to its longer duration, than at warmer sites and thus further stresses the importance of winter R_{eco} for the carbon balance of alpine, arctic and boreal ecosystems (e.g. Oechel et al., 1997; Fahnestock et al., 1998; Bergeron et al., 2007; Wohlfahrt et al., 2008b). In this respect, we suggest that the established climatological winter season (December through February) should not be chosen to represent the role of winter time for annual carbon balances of seasonally cold sites. Due to sparse data for cold regions in global FLUXNET, the RWCR (4.9–13.2 %) using D_AT0 is on average lower in this study than in previous works (15–50 %) by Zimov et al. (1996) and Fahnestock et al. (1998), focused on arctic ecosystems.

3.2 Temperature sensitivity of winter R_{eco}

3.2.1 Temperature sensitivity of winter R_{eco} at the site level

Under the winter definition D_AT0, across sites, values of the reference respiration rate R_{ecoref} (g C m⁻² d⁻¹) and activation energy E_0 (kJ mol⁻¹) range from 0.17 to 1.74 and from 5.1 to 50.8, respectively, when T_{air} is used as the predictor, and from 0.17 to 1.43 and from 26.5 to 192.6 when T_{soil} is used. Across sites, R_{ecoref} was found to increase with ΔLAI

Table 2. Summary statistics of mean winter R_{eco} rates ($\text{g C m}^{-2} \text{d}^{-1}$), winter cumulative R_{eco} (g C m^{-2}), RWRR values (%) and RWCR values (%) with winter definitions D_AT0 (air temperature $< 0^\circ \text{C}$) and D_TM (December–February) across ecosystem types.

Vegetation type	D_AT0						D_TM				
	Num	Winter Length	Winter cumulative R_{eco}	RWCR	Mean Winter R_{eco} rates	RWRR	Num	Winter cumulative R_{eco}	RWCR	Mean Winter R_{eco} rates	RWRR
		Mean (SD) d	Mean (SD) (g C m^{-2})	Mean (SD) (%)	Mean (SD) ($\text{g C m}^{-2} \text{d}^{-1}$)	Mean (SD) (%)		Mean (SD) (g C m^{-2})	Mean (SD) (%)	Mean (SD) ($\text{g C m}^{-2} \text{d}^{-1}$)	Mean (SD) (%)
DBF	54	106 ^{ab} (42)	89.0 ^b (44.7)	8.9 ^{abc} (4.0)	0.90 ^c (0.39)	31.7 ^b (11.6)	54	85.1 ^c (42.7)	7.8 ^b (3.1)	0.95 ^c (0.47)	31.6 ^b (12.7)
ENF	78	144 ^{ab} (45)	76.3 ^b (40.4)	9.9 ^{bc} (3.9)	0.60 ^{bc} (0.38)	26.0 ^{ab} (8.4)	78	65.4 ^{bc} (53.6)	6.2 ^b (3.4)	0.73 ^{bc} (0.60)	25.0 ^b (13.9)
MF	17	113 ^{ab} (44)	68.4 ^b (33.4)	7.3 ^{ab} (3.1)	0.70 ^{bc} (0.33)	26.0 ^{ab} (10.4)	17	67.5 ^{bc} (35.8)	6.7 ^b (3.3)	0.75 ^{bc} (0.41)	27.1 ^b (13.5)
GRA	33	114 ^{ab} (29)	67.6 ^b (50.1)	6.8 ^{ab} (3.4)	0.62 ^{ab} (0.43)	22.4 ^{ab} (9.3)	33	50.0 ^{abc} (34.7)	4.9 ^{ab} (2.1)	0.56 ^{abc} (0.39)	20.5 ^b (8.5)
CRO	20	93 ^a (12)	45.3 ^{ab} (20.8)	4.9 ^a (1.9)	0.49 ^{abc} (0.22)	19.4 ^{ab} (7.5)	20	46.1 ^{abc} (19.7)	5.0 ^{ab} (1.9)	0.51 ^{abc} (0.22)	20.3 ^{ab} (7.9)
BWET	11	151 ^b (37)	38.6 ^{ab} (11.5)	10.8 ^{bc} (3.7)	0.27 ^{ab} (0.08)	25.8 ^a (4.3)	11	21.6 ^{ab} (7.6)	5.7 ^b (1.1)	0.24 ^{ab} (0.08)	23.1 ^b (4.7)
AWET	5	248 ^c (18)	6.0 ^a (4.4)	13.2 ^c (6.4)	0.02 ^a (0.02)	19.5 ^a (9.4)	5	1.1 ^a (1.6)	1.7 ^a (1.7)	0.01 ^a (0.02)	6.8 ^a (7.1)

ENF, DBF, MF, GRA, CRO, BWET and AWET represent evergreen needle leaf forests, deciduous broadleaf forests, mixed forests, grasslands, croplands, boreal wetlands and arctic wetlands, respectively.

RWCR and RWRR is the ratio of winter cumulative R_{eco} (g C m^{-2}) to annual cumulative R_{eco} (g C m^{-2}) and the ratio of mean winter R_{eco} rates ($\text{g C m}^{-2} \text{d}^{-1}$) to mean annual R_{eco} rates ($\text{g C m}^{-2} \text{d}^{-1}$), respectively.

SD is standard deviation. Mean (± 1 SD) within a column followed by different letters (a, b and c) were significantly different ($p < 0.05$).

Data normality was tested using one-sample Kolmogorov-Smirnov (K-S test) without the Dallal-Wilkinson-Lilliefors correction and the distribution of the data pooled from all of the site years is not significant from the normal distribution except winter R_{eco} rates in D_TM ($p = 0.013$, $n = 218$). However, if K-S test with correction is used, the data in all of the cases did not conform to the normal distribution. We should thus take cautions about the existence of the risk of violation of assumptions of ANOVA.

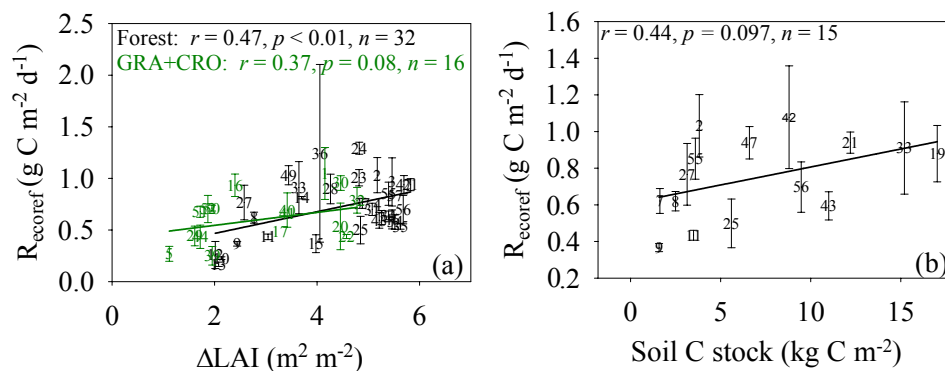


Fig. 2. The relationship between reference winter respiration (R_{ecoref}) calculated from the Arrhenius function and ΔLAI ($\text{m}^2 \text{m}^{-2}$) (a) and total soil carbon stock (kg C m^{-2}) (b) across sites. The site-specific R_{ecoref} is averaged from its site years, and its error bar is the standard deviation of R_{ecoref} over the site-years. All values are calculated according to winter definition D_AT0.

(Fig. 2a) (or GPP_{gs}, data not shown) both in the forests and in grasslands and croplands. These results indicate that substrate availability, for which ΔLAI and GPP_{gs} are taken as proxies, exerts a significant positive control on R_{ecoref} across sites, and thus supports the conclusions of Grogan and Jonasson (2005) who found that R_{ecoref} was significantly reduced after removing plant and litter in a birch and heath tundra. We also found that R_{ecoref} is marginally correlated with total soil carbon stock in forest ecosystems (Fig. 2b). We did not perform the same analysis for grasslands and croplands due to their limited number of samples ($n = 5$). Based on the forest ecosystems our results support previous studies (Grogan et al., 2001; Nobrega and Grogan, 2007), which suggested that winter soil respiration is more derived from easier decomposable carbon (e.g. litter) than bulk soil organic matter

(SOC). This can be expected due to the fact that total soil carbon stock reflects the fraction of slow and passive compounds, which do not contribute much to R_{eco} . However, SOC, which is buried beneath the active layer in frozen soils, has found to be labile and could be respired in case of permafrost thawing (Dutta et al., 2006; Nowinski et al., 2010). The decomposition of this old but labile SOC is of concern for future warming (on decadal scale), although this process is masked by the faster C cycling of fresh litter (on seasonal to interannual scale).

Our analysis shows that the arctic permafrost site US-Atq has the lowest E_0 in all winter definitions (e.g. D_AT0: 26.5 kJ mol^{-1}). This can be attributed to the fact that substrate availability for microbial respiration (Ostroumov and Siebert, 1996; Mikan et al., 2002) can be significantly

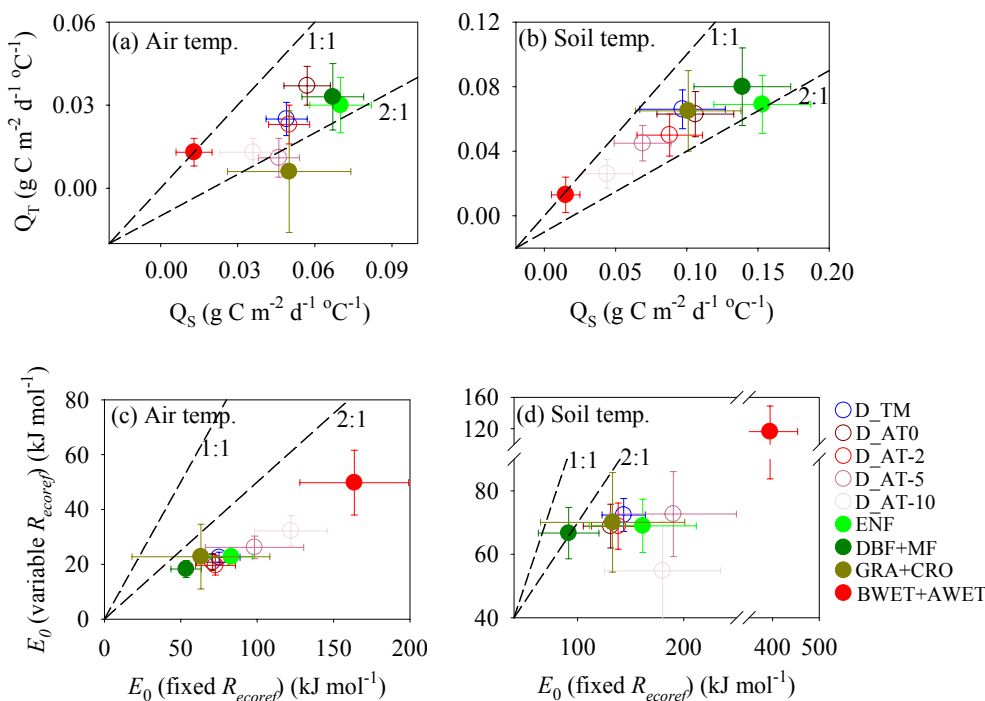


Fig. 3. The winter R_{eco} sensitivity to temperature variation across space and the one over time is compared across different winter definitions and vegetation types, using both air (a) and soil (b) temperature, and two different types of winter R_{eco} sensitivity to temperature variation across space calculated from the Arrhenius function are also compared using both air (c) and soil (d) temperature. The values from vegetation type are calculated according to winter definition D_AT0.

reduced if the soil reaches a critical freezing temperature (e.g. D_AT0: US-Atq: -11.3°C) in which microorganisms can be in a state of anabiosis (e.g. -10°C in Vorobyova et al., 1997). In contrast, another arctic permafrost site (US-Ivo) had a comparably high activation energy (e.g. D_AT0: 66.3 kJ mol^{-1}) presumably due to higher T_{soil} (e.g. D_AT0: -4.9°C). Our understanding of winter R_{eco} controls in arctic permafrost regions is still very poor since only two permafrost sites are included in this study. This calls for further studies of different permafrost (e.g. continuous, discontinuous, and sporadic etc., Jorgenson et al., 2001; Zhang, 2005), vegetation types (e.g. Eugster et al., 2005) and in particular the different responses to freezing of oxic and anoxic systems underlain by permafrost.

3.2.2 Winter R_{eco} sensitivity to temperature variation over time

Our analysis shows that winter R_{eco} anomalies positively correlated with winter T_{soil} anomalies, which explained more variability (e.g. D_AT0: $r = 0.40$, $p < 0.01$, $n = 218$; D_TM: $r = 0.37$, $p < 0.01$, $n = 218$, data not shown) than T_{air} (e.g. D_AT0: $r = 0.30$, $p < 0.01$, $n = 218$; D_TM: $r = 0.22$, $p < 0.01$, $n = 218$, data not shown). This is also found when using other winter definitions (data not shown). The explained variance by the temperature is very low, but this anal-

ysis might suggest that T_{soil} was superior to T_{air} in explaining anomalies in winter R_{eco} likely because of the influence of snow cover which acts as a thermal insulator controlling soil microbial activity (Zhang, 2005). This is consistent with the results of a six-year record of eddy covariance measurements at the Niwot Ridge Ameriflux site in the Rocky Mountains, where Monson et al. (2006) showed that interannual variability of net carbon exchange is less controlled by T_{air} anomalies than by T_{soil} anomalies, which in turn were controlled by snow depth. To verify this observation with our dataset, daily snow water equivalent from AMSR-E/Aqua (Kelly et al., 2004) was used but no significant relationship between anomalies of snow water equivalent and winter R_{eco} could be found (data not shown). This could be expected since the snow characteristics at site level can not be truly reflected by a remote sensing product at a spatial resolution of $25 \times 25\text{ km}^2$. In addition, we found no significant relationship, with r always close to zero, between winter R_{eco} and winter precipitation anomalies (e.g. D_AT0: $p = 0.49$; D_TM: $p = 0.71$) and no correlation with ΔLAI anomalies (e.g. D_AT0: $p = 0.44$; D_TM: $p = 0.82$) and GPP_{gs} (e.g. D_AT0: $p = 0.34$; D_TM: $p = 0.69$). This was also found if forest ecosystems and managed ecosystems (grasslands and croplands) were considered separately (data not shown).

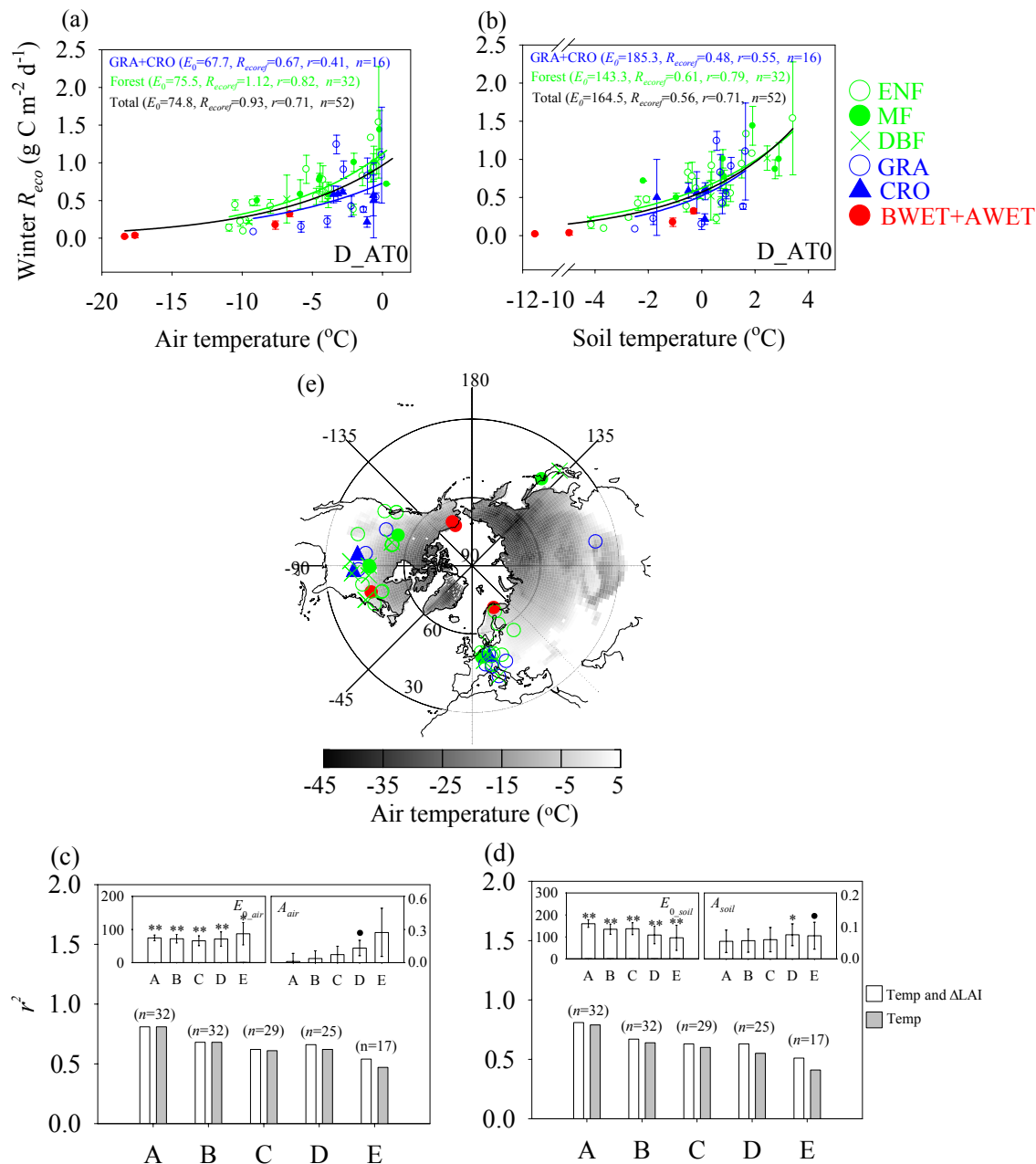


Fig. 4. Relationships between winter air temperature **(a)**, soil temperature **(b)** and R_{eco} using winter definition D_AT0. The coefficient of determination (r^2) between the Arrhenius models with and without ΔLAI is compared using air temperature **(c)** and soil temperature **(d)** respectively in the forest ecosystems. A, B, C, D, and E in both **(c)** and **(d)** denote winter definitions D_TM, D_AT0, D_AT-2, D_AT-5 and D_AT-10, respectively. The spatial distribution of eddy covariance sites is displayed in **(e)**. Winter air temperature from 1 December to 28 February is used as the background in **(e)**. Significance levels are indicated as **, * and • representing $p < 0.01$, 0.05 and 0.1, respectively.

3.2.3 The comparison between winter R_{eco} sensitivity to temperature variation across space and over time

Our analysis shows that the winter R_{eco} sensitivity to variation of T_{air} or T_{soil} across space (Q_S ; g C m⁻² d⁻¹ °C⁻¹), defined as the slope of a linear regression between mean win-

ter R_{eco} rates and mean winter T_{air} or T_{soil} across all sites is higher than Q_T (winter R_{eco} sensitivity to temperature variation over time) among different winter definitions (Fig. 3a and b). In addition, we categorized the sites by vegetation types for the winter definition D_AT0, and the difference between these two temperature sensitivities can also be found in

all ecosystem types except boreal and arctic wetlands (Fig. 3a and b). No difference for the wetland (boreal and arctic wetlands) category may be due to the low number of the samples in wetland ($n = 4$). The same differences between the two temperature sensitivities can also be obtained if sites are categorized by vegetation types according to other winter definitions (data not shown).

The differences between these two winter R_{eco} temperature sensitivities are due to the fact that Q_T is mainly driven by direct climate effects, but Q_S not only accounts for gradients of climate affecting decomposition, but also reflects gradients in ecosystem state (e.g. soil C pools) in space (Hibbard et al., 2005) or the degree of adaptation of microorganisms to low temperatures. To test this hypothesis, we regressed mean winter R_{eco} rates ($\text{g C m}^{-2} \text{d}^{-1}$) divided by site-specific R_{ecoref} provided by the within-site analysis (Sect. 3.2.1) against mean winter T_{air} or T_{soil} using the Arrhenius function. As shown in Fig. 3c and d, activation energies (E_0 , kJ mol^{-1}) were much smaller when using site-specific R_{ecoref} in all winter definitions and all vegetation types based on winter definition D_AT0. This is consistent with the findings of recent studies (Mahecha et al., 2010; Wang et al., 2010), which showed that the temperature sensitivity (Q_{10}) became much smaller after removing the influence of confounding effects imposed by substrate availability. Furthermore, from a multiple regression analysis conducted between mean winter R_{eco} rates and both mean winter temperature and ΔLAI (or GPP_{gs}) across sites, we found that Q_S became smaller if ΔLAI (or GPP_{gs}) was included (data not shown). For example, for winter defined as D_AT0, Q_S (SD) calculated as a function of T_{soil} changed from 0.11(0.03) to 0.08(0.03) after ΔLAI was included as an additional predictor. However, the Q_S after including ΔLAI (D_AT0: 0.08 ± 0.03) remains larger than its corresponding Q_T (D_AT0: 0.05 ± 0.01), which can be expected due to the possibility that ΔLAI only partly accounts for inter-site variation in substrate availability (Sect. 3.2.1). This might imply that Q_S can become closer to Q_T if spatial gradients in substrates can be mostly taken into account.

The temperature sensitivity of respiration is a key parameter controlling carbon-climate feedbacks in coupled models (Friedlingstein et al., 2006). A fixed value of temperature sensitivity, obtained from meta-analysis of spatial data (Raich and Schlesinger, 1992; Lloyd and Taylor, 1994) is often incorporated in these models (e.g. Cox et al., 2000; Friedlingstein et al., 2006). If Q_S rather than Q_T is used for winter R_{eco} , then, the current generation of models will likely overestimate the effect of future warming on soil C pools. However, great care should be taken into this extrapolation when using Q_T obtained from soil temperature. On the one hand, in La Thuile dataset, the soil temperature measurement depth is not uniform across sites (the range is from 2 to 10 cm). On the other hand, the active layer where winter R_{eco} occurs might be shallow and its depth might not necessarily coincide with the one for which soil temperature was

provided in the dataset. These two factors might contribute to the biased estimate of actual temperature response of winter R_{eco} (e.g. Reichstein and Beer, 2008; Subke and Bahn, 2010).

3.3 Environmental and biotical controls on winter R_{eco} across sites

Since grasslands and croplands are heavily affected by human management on a short-term (e.g. seasonal and annual) basis, we conducted two separate cross site analyses, one for forests and the other for both grasslands and croplands. Wetland sites were not included in the analysis since the number of the samples suited for our winter R_{eco} study in La Thuile dataset is too small ($n = 4$).

Under all winter definitions, winter R_{eco} is found to increase exponentially with increasing T_{air} and T_{soil} (Fig. 4a and b) across sites. On the basis of the aforementioned results (Sect. 3.2.1), a linear dependence of the reference respiration on ΔLAI or GPP_{gs} was included (Eqs. 2 and 3). We only explored ΔLAI or GPP_{gs} effects in the forest ecosystems since ΔLAI or GPP_{gs} may be weak indicators of recent carbon inputs to the soil in grasslands and croplands (Fig. 2a), where much of the produced carbon is exported from the sites.

As shown in Fig. 4c and d, when integrated over five different winter definitions, the coefficients of determination for Eqs. (2) and (3) range from 0.54 to 0.82 and from 0.51 to 0.81, while the root mean square errors are within the range of 0.17–0.22 and 0.17–0.22 $\text{g C m}^{-2} \text{d}^{-1}$, respectively (data not shown). A cross validation of the regression models in Eqs. (2) and (3) shows that 50–79 % and 48–76 % of winter R_{eco} variance can be explained by Eqs. (2) and (3). Both equations empirically describe the spatial variability of winter R_{eco} and thus have predictive power to extrapolate winter R_{eco} to the continental scale. Given that temperature is the dominant controlling factor of winter R_{eco} across sites and co-varies with other potential drivers, we regressed the residuals of Eqs. (2) and (3) against the total precipitation during winter period (winter precipitation) to determine if this alternative driver could explain additional variance. There was no significant correlation between the residuals and winter precipitation using all winter definitions (e.g. D_AT0: Eq. (2): $r = 0.00$, $p = 0.632$; Eq. (3): $r = 0.01$, $p = 0.901$, data not shown). The lack of a significant correlation between winter precipitation and winter R_{eco} may be explained as follows. First, precipitation effects on respiration can be manifested through its influences on soil moisture (e.g. Migliavacca et al., 2011). Since most of the sites in this study are expected to be covered by snow thanks to a freezing or below freezing temperature-threshold based winter definition, precipitation is expected to influence soil moisture to a lesser extent. For example, at site AT-Neu where upper soil moisture data were available, soil moisture (%) is almost constant (50.5 ± 2.0) during the period from day 322 of year 2002 to

day 108 of year 2003, which is within the range of winter definition D_AT0. In this respect, the role of winter precipitation in regulating R_{eco} is not as evident as in the growing season (e.g. Migliavacca et al., 2011). Second, winter snowfall (solid precipitation) is one of many variables controlling snow depth, which was found to regulate T_{soil} and microbial respiration under the snow pack when using T_{air} as a predictor of winter R_{eco} (e.g. Groffman et al., 2001; Grogan and Jonasson, 2006; Monson et al., 2006; Nobrega and Grogan, 2007). Snow depth is not simply related to winter snowfall since it is influenced by local factors such as topography (e.g. Liston, 2004), wind speed (e.g. Li and Pomeroy, 1997), vegetation structure (e.g. Li and Pomeroy, 1997; Rutter et al., 2009), sublimation and melting. This justifies neglecting precipitation in our temperature response model (Eqs. 2 and 3).

Our results also showed that the inclusion of ΔLAI can only make a marginal improvement in winter R_{eco} prediction of forest ecosystems (Fig. 4c and d), which was also observed if both total soil carbon stock and ΔLAI or GPP_{gs} was included (data not shown). This may be related to the fact that aboveground respiration from tree biomass can still accounts for a significant fraction of winter R_{eco} (e.g. the reported values are below 10 % or even higher than 50 %, Monson et al., 2005; Davidson and Janssens, 2006), thus reducing the fraction of heterotrophic respiration on winter R_{eco} using the substrates such as litter. It would also suggest that both recent aboveground carbon inputs (approximated by ΔLAI or GPP_{gs}) and soil carbon stock can not fully account for substrate availability (Fig. 2a and b), and belowground carbon inputs such as the senescence of fine roots and the supply of dissolved organic carbon or nitrogen (e.g. Edwards et al., 2006; Larsen et al., 2007) might play a role. Most notably, the substrates for winter soil respiration can be provided by the dead biomass of mycorrhizal fungi and other rhizospheric microbial cells that die at the autumn-winter transition period following the nighttime soil freezing.

4 Conclusions

The availability of meteorological and eddy covariance flux data across different ecosystems opens a new opportunity to quantify winter R_{eco} and its spatial and temporal controls across North Hemisphere ecosystems. Given four different winter definitions, based on temperature below the freezing point, we found an increase in the ratio of winter to annual cumulative respiration towards higher latitude, due to the longer winters that occur at high latitudes. Therefore, due to the importance of winter processes in the carbon balance, it is important to better represent winter R_{eco} in current terrestrial carbon cycle models. The large number of sites now available provides an important source of information to improve winter carbon cycle. Our empirical characterization of temperature controls on winter R_{eco} implies that winter

R_{eco} temperature sensitivity obtained on spatial and temporal scales should be treated differently. The winter R_{eco} sensitivity to temperature variation across space (Q_S) was always found to be higher than the one over time (Q_T) among different winter definitions and among different vegetation types except for the wetlands which had a limited sample size. Our result also imply that Q_S can become closer to its Q_T if spatial gradients in inter-site substrates can be more and more taken into account. Thus, if extrapolated to future warming, the winter R_{eco} temperature sensitivity to warming obtained from spatial gradients will be exaggerated without fully considering the spatial difference in substrate availability.

Temperature is an overwhelming factor in determining the spatial variation of winter R_{eco} in forests and grasslands and croplands. Although recent carbon inputs from aboveground marginally account for winter R_{eco} spatial variation, inter-site substrate availability (or biotic factors) does seem to be important since ΔLAI or GPP_{gs} do partly account for the difference in reference respiration across sites. Indeed, the biotic controls of winter R_{eco} were not fully explored in this study, which needs further investigation by considering belowground carbon inputs such as recently-killed rhizospheric microbial biomass and the senescence of fine roots. It should be noted that our results are mainly based on forest ecosystems and that winter carbon cycling in arctic ecosystems with limited sample size in La Thuile dataset characterized by long winters and large soil carbon pools are still not well understood. Furthermore, snow cover effects on winter R_{eco} were only explored using satellite-derived snow products, and these should be further investigated in future studies in which more in-situ snow data are available.

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Appendix A

Table A1. Winter R_{eco} rates ($\text{g C m}^{-2} \text{ d}^{-1}$) comparison among different winter definitions.

Site	Type	Lat.	Lon.	D_TM	D_AT0		D_AT-2		D_AT-5		D_AT-10	
				R_{eco} (SD) ($\text{g C m}^{-2} \text{ d}^{-1}$)	WLEN (SD) (d)	R_{eco} (SD) ($\text{g C m}^{-2} \text{ d}^{-1}$)	WLEN (SD) (d)	R_{eco} (SD) ($\text{g C m}^{-2} \text{ d}^{-1}$)	WLEN (SD) (d)	R_{eco} (SD) ($\text{g C m}^{-2} \text{ d}^{-1}$)	WLEN (SD) (d)	R_{eco} (SD) ($\text{g C m}^{-2} \text{ d}^{-1}$)
AT-Neu	GRA	47.1	11.3	1.06(0.24)	116(16)	1.24(0.12)	92(32)	1.04(0.34)	62(22)	1.04(0.43)	–	–
BE-Vie	MF	50.3	6.0	1.10(0.16)	71(35)	1.02(0.16)	57(28)	0.89(0.15)	17	0.43	–	–
CA-Ca1	ENF	49.9	–125.3	1.48	54	1.33	–	–	–	–	–	–
CA-Ca2	ENF	49.9	–125.3	1.24(0.22)	39(31)	0.82(0.13)	–	–	–	–	–	–
CA-Let	GRA	49.7	–112.9	0.17(0.06)	138(13)	0.22(0.08)	120(21)	0.21(0.07)	100(32)	0.19(0.10)	61(37)	0.14(0.07)
CA-Mer	BWET	45.4	–75.5	0.29(0.04)	128(22)	0.32(0.03)	112(22)	0.30(0.04)	93(14)	0.28(0.04)	57(22)	0.24(0.03)
CA-Oas	DBF	53.6	–106.2	0.33(0.07)	169(17)	0.50(0.06)	157(21)	0.46(0.08)	141(13)	0.40(0.10)	101(18)	0.34(0.07)
CA-Obs	ENF	54.0	–105.1	0.27(0.04)	185(15)	0.47(0.04)	168(18)	0.42(0.04)	145(15)	0.35(0.06)	114(13)	0.30(0.03)
CA-Ojp	ENF	53.9	–104.7	0.12(0.03)	176(13)	0.24(0.02)	164(18)	0.21(0.04)	145(14)	0.17(0.05)	116(13)	0.14(0.03)
CA-Qcu	ENF	49.3	–74.0	0.13(0.01)	175(15)	0.22(0.06)	154(14)	0.19(0.04)	137(21)	0.17(0.05)	104(16)	0.12(0.01)
CA-Qfo	ENF	49.7	–74.3	0.28(0.06)	172(19)	0.44(0.07)	149(14)	0.39(0.07)	139(13)	0.37(0.05)	102(10)	0.30(0.04)
CA-SJ1	ENF	53.9	–104.7	0.08(0.04)	181(15)	0.14(0.05)	172(19)	0.13(0.04)	146(20)	0.09(0.04)	121(8)	0.08(0.04)
CA-SJ2	ENF	53.9	–104.6	0.02(0.01)	197	0.09(0.00)	167(4)	0.06(0.01)	137(17)	0.03(0.02)	123(7)	0.03(0.01)
CA-TP4	ENF	42.7	–80.4	0.67(0.02)	107(8)	0.66(0.06)	99(8)	0.65(0.04)	61(30)	0.52(0.14)	19	0.43
CA-WP1	MF	55.0	–112.5	0.12(0.00)	159(7)	0.22(0.02)	155(6)	0.21(0.02)	143(16)	0.19(0.05)	103(28)	0.14(0.02)
CH-Oe1	GRA	47.3	7.7	0.87(0.24)	85(28)	0.83(0.24)	58(13)	0.84(0.24)	43	0.73	–	–
CN-HaM	GRA	37.4	101.2	0.02	182	0.08	159	0.06	148	0.06	98(12)	0.03(0.01)
CZ-BK1	ENF	49.5	18.5	0.57(0.06)	112(19)	0.54(0.07)	105(22)	0.53(0.08)	47(1)	0.56(0.03)	–	–
DE-Bay	ENF	50.1	11.9	1.20(0.13)	127(32)	1.22(0.21)	77(30)	1.18(0.15)	91	1.11	–	–
DE-Geb	CRO	51.1	10.9	0.59(0.28)	87(7)	0.57(0.27)	34(26)	0.45(0.12)	–	–	–	–
DE-Hai	DBF	51.1	10.5	1.06(0.15)	74(22)	1.01(0.12)	68(21)	1.01(0.14)	76	0.92	–	–
DE-Meh	GRA	51.3	10.7	0.57(0.09)	96(20)	0.54(0.06)	81(4)	0.47(0.12)	–	–	–	–
DE-Tha	ENF	51.0	13.6	1.00(0.10)	85(21)	0.94(0.18)	53(29)	0.87(0.12)	48(38)	0.85(0.06)	–	–
DK-Sor	DBF	55.5	11.6	1.62(0.22)	71(35)	1.44(0.25)	63(33)	1.39(0.32)	–	–	–	–
FI-Hyy	ENF	61.8	24.3	0.47(0.14)	153(21)	0.55(0.11)	132(25)	0.50(0.13)	99(26)	0.44(0.13)	48(14)	0.42(0.13)
FI-Kaa	BWET	69.1	27.3	0.15(0.06)	191(13)	0.18(0.06)	182(9)	0.17(0.06)	147(16)	0.15(0.05)	100(19)	0.13(0.04)
FI-Sod	ENF	67.4	26.6	0.32(0.18)	183(14)	0.42(0.10)	166(9)	0.40(0.10)	146(15)	0.35(0.15)	113(11)	0.30(0.19)
FR-Hes	DBF	48.7	7.1	1.17(0.24)	57(31)	1.00(0.22)	55(28)	1.04(0.18)	–	–	–	–
HU-Bug	GRA	46.7	19.6	0.45(0.14)	92(3)	0.42(0.14)	67(25)	0.42(0.13)	33(26)	0.41(0.19)	–	–
IT-Amp	GRA	41.9	13.6	0.97(0.24)	93(23)	1.10(0.64)	43(32)	0.43(0.08)	24	0.23	–	–
IT-Col	DBF	41.8	13.6	0.75(0.15)	83(53)	0.72(0.00)	101	0.67	–	–	–	–
IT-Mbo	GRA	46.0	11.0	0.84(0.20)	141(29)	0.91(0.12)	98(19)	0.78(0.23)	68(37)	0.77(0.18)	–	–
IT-Ren	ENF	46.6	11.4	0.31(0.13)	150(19)	0.38(0.07)	118(21)	0.32(0.15)	58(35)	0.29(0.18)	–	–
JP-Tak	DBF	36.1	137.4	0.53(0.17)	123(16)	0.58(0.17)	94(11)	0.52(0.17)	77(7)	0.50(0.16)	–	–
JP-Tom	MF	42.7	141.5	0.46(0.05)	114(14)	0.51(0.02)	93(14)	0.47(0.03)	55(36)	0.46(0.06)	–	–
NL-Loo	ENF	52.2	5.7	2.06(0.43)	63(34)	1.54(0.74)	46(36)	1.41(1.02)	16	0.69	–	–
RU-Fyo	ENF	56.5	32.9	0.78(0.27)	143(19)	0.91(0.19)	130(10)	0.86(0.21)	101(29)	0.81(0.25)	62(30)	0.62(0.15)
US-Atq	AWET	70.5	–157.4	0.00(0.00)	254(14)	0.02(0.01)	231(10)	0.01(0.00)	219(3)	0.01(0.00)	185(5)	0.01(0.00)
US-Bkg	GRA	44.3	–96.8	0.13(0.10)	124(5)	0.15(0.07)	117(0)	0.14(0.08)	104(14)	0.12(0.05)	59(35)	0.11(0.05)
US-Bo1	CRO	40.0	–88.3	0.40(0.26)	96(18)	0.22(0.07)	69(28)	0.20(0.11)	31(10)	0.15(0.18)	–	–
US-Bo2	CRO	40.0	–88.3	0.53(0.49)	84(14)	0.50(0.50)	68(29)	0.53(0.47)	–	–	–	–
US-Ha1	DBF	42.5	–72.2	1.34(0.43)	110(16)	1.43(0.44)	88(3)	1.35(0.54)	59(13)	1.23(0.38)	32	1.19
US-Ho1	ENF	45.2	–68.7	0.52(0.13)	130(16)	0.62(0.13)	109(16)	0.53(0.10)	80(20)	0.46(0.11)	38(20)	0.29(0.05)
US-IB2	GRA	41.8	–88.2	0.37(0.13)	103(15)	0.38(0.04)	67(28)	0.34(0.09)	60(29)	0.34(0.07)	–	–
US-Ivo	AWET	68.5	–155.8	0.03(0.02)	239(26)	0.03(0.03)	233(25)	0.03(0.02)	223(21)	0.02(0.02)	186(7)	0.02(0.01)
US-LPH	DBF	42.5	–72.2	0.75(0.21)	119(11)	0.81(0.19)	113(15)	0.79(0.20)	87(10)	0.74(0.19)	26(6)	0.62(0.28)
US-MMS	DBF	39.3	–86.4	0.91(0.18)	77(12)	0.87(0.12)	60(21)	0.84(0.12)	25(9)	0.75(0.21)	–	–
US-Moz	DBF	38.7	–92.2	0.91(0.21)	64(26)	0.76(0.38)	37	0.50	–	–	–	–
US-NR1	ENF	40.0	–105.5	0.64(0.27)	169(41)	0.77(0.19)	150(19)	0.73(0.24)	131(38)	0.70(0.22)	72	0.44
US-Ne1	CRO	41.2	–96.5	0.62(0.03)	92(10)	0.61(0.03)	73(25)	0.58(0.05)	57(17)	0.59(0.08)	–	–
US-Ne2	CRO	41.2	–96.5	0.59(0.12)	95(9)	0.58(0.11)	79(22)	0.55(0.10)	52(17)	0.51(0.12)	–	–
US-Ne3	CRO	41.2	–96.4	0.55(0.06)	94(8)	0.59(0.10)	79(17)	0.55(0.10)	58(17)	0.54(0.14)	18	0.32
US-PFa	MF	45.9	–90.3	0.53(0.12)	141(1)	0.55(0.08)	137(1)	0.54(0.09)	112(24)	0.51(0.07)	44(17)	0.44(0.15)
US-Syv	MF	46.2	–89.3	0.42(0.36)	148(20)	0.52(0.32)	131(12)	0.43(0.36)	110(29)	0.40(0.33)	87(21)	0.32(0.44)
US-UMB	DBF	45.6	–84.7	0.77(0.05)	121(21)	0.77(0.09)	110(17)	0.76(0.09)	82(17)	0.71(0.08)	53	0.73
US-WCr	DBF	45.8	–90.1	0.45(0.17)	140(17)	0.58(0.19)	118(23)	0.50(0.17)	101(17)	0.44(0.16)	73(11)	0.40(0.17)
US-Wrc	ENF	45.8	–122.0	0.84	70	1.08	–	–	–	–	–	–

Type: DBF: deciduous broadleaf forests; ENF: evergreen needleleaf forests; GRA: grasslands; CRO: croplands; BWET and AWET are boreal and arctic wetlands respectively; MF (mixed forests).

Lat. and Lon. are latitude and longitude, respectively.

WLEN is the winter length (unit: day).

R_{eco} is mean winter R_{eco} rates ($\text{g C m}^{-2} \text{ d}^{-1}$).

D_AT0, D_AT-2, D_AT-5 and D_AT-10 are defined as the period during which the 10 day smoothed air temperature remained below 0°C , -2°C , -5°C and -10°C for at least five consecutive days; D_TM is defined as the 90-day period from 1 December to 28 February.

SD is standard deviation.



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4. Development and evaluation of ORCHIDEE snow model using point observations at SNOWMIP sites and regional snow observations

4.1 Introduction

In Chapter 3, winter carbon cycling plays an important role in annual carbon budget in seasonal snow-covered ecosystems, and the superiority of soil temperature over air temperature in regulating interannual variations of winter respiration might indicate the potential role of snow. To have a thorough understanding of snow effects on the present and future carbon fluxes, terrestrial ecosystem models with a correct snow model that can capture snow dynamics processes is very necessary, which is the purpose of this chapter.

Snow covers nearly half of the North Hemisphere land surface during winter (Robinson et al., 1993; Lemke et al., 2007). Due to its large seasonal variability and distinct physical properties (i.e. high albedo, low thermal conductivity and roughness length), snow has been quantified to give a strong positive feedback on climate in both observation and modeling studies (Groisman et al., 1994; Qu and Hall, 2006; Femandes et al., 2009; Flanner et al., 2010). Snow is also recognized as an important storage component of the hydrological cycle, especially in mountainous regions, which can contribute to a large percentage of total annual water supplies. In addition, they can also act as a moisture bank for some ecosystems, whose vegetation activities are dependent on spring snowmelt (i.e. semi-arid and arid cold regions, Peng et al., 2010, Tahir et al., 2011).

In terms of modeling efforts, snow models with variable degree of complexity are developed, which ranged from simple degree-day models (e.g. Hock, 2003), through land surface schemes of intermediate complexity (i.e. ISBA [Douville et al., 1995]), to complex snow-physic models (i.e. SNOWPACK [e.g. Rasmus et al., 2007]). To evaluate the overall performance of these models designed for different purposes, snow model intercomparison projects (e.g. Phase 2(d) of The Project for Intercomparison of Land-surface Parameterization Schemes, Slater et al., 2001); Snow Model Intercomparison Project (SnowMIP: Etchevers et al., 2002; SnowMIP2: Rutter et al., 2009)) have been initialized, the results of which provide detailed assessment of various snow schemes and the guidelines for improvement of future snow modeling. In PILPS2 (d), SECHIBA (Ducoudré et al., 1993), the hydrological module of the terrestrial biosphere model ORCHIDEE (Organizing Carbon and Hydrology in Dynamic Ecosystems) (Krinner et al., 2005), was shown to be able to capture the broad pattern of snow accumulation and ablation in comparison to observations at grassland sites. However, SECHIBA tends to display lower SWE (snow water equivalent) and shorter snow cover duration than many of the other snow models involved in PILPS 2(d). This was not surprising since the treatment of snow in SECHIBA is simple; there is a single snow layer without parameterization of snow internal processes e.g. liquid water refreezing, variable

snow density. Improved snow parameterizations in the snow module of SECHIBA for building confidence in snow simulation is thus necessary to improve the regional climate simulations, in particular the coupling with General Circulation Models (GCMs) study.

Evaluation of snow processes in forests was conducted in SNOWMIP2. Rutter et al. (2009) found that the most of models compared in SNOWMIP2 could not reproduce SWE at forest sites as well as at grassland sites. The snow under the canopy can be affected by canopy snowfall interception efficiency (Hedstrom and Pomeroy, 1998; Storck et al., 2002), forest gap fraction (influences on albedo in the sky view) and below-canopy microclimate conditions (sheltered wind speed, reduced solar radiation loadings) (Hardy et al., 2004; Pomeroy and Dion, 1996; Tribbeck et al., 2006). Therefore, a fully physical-based snow model is desirable to simulate the mechanisms by which canopies transform radiation, turbulent exchange and mass exchange (Pomeroy and Dion, 1996; Hedstrom and Pomeroy, 1998; Nakai et al., 1999). In this study, modifications on the snow simulation of the SECHIBA model are made to improve forest snow albedo parameterization. Forest albedos have been documented to vary dramatically as a function of canopy cover when snow covers the ground (e.g. Ni et al., 2000).

Previous evaluation of snow model performance using in-situ snow observations was restricted to sites with few years of observation. From the results of SnowMIP2 (Rutter et al., 2009) showed that the performances of most snow models were not consistent over all sites or site years, which calls for more comprehensive snow model evaluation based on sites spanning across larger spatial and temporal scales (e.g. Pan et al., 2003; Habets et al., 2008; Parajka et al., 2010). This can be achieved with the availability of numerous in-situ snow data from meteorological surface observation networks (e.g. North America: Dyer and Mote, 2006; Austria: Parajka et al., 2010; China: Peng et al., 2010), which also provide other climate variables e.g. precipitation and temperature. However, not all variables (i.e. incoming shortwave and longwave radiation, distinction between rain and snow) necessary for snow simulation are recorded at meteorological stations, and reanalysis products (e.g. ECMWF Interim reanalysis or ERA-interim) may be used instead. The main objectives of this study are 1) to describe a new snow model incorporated into the ORCHIDEE land surface model; 2) to evaluate its performances against SNOWMIP sites for SWE, snow depth, snow density, snow albedo and snowmelt runoff; 3) to test the ability of the new snow model to capture spatial and temporal patterns of snow depth and snow cover days across 193 Canadian meteorological stations.

4.2 Model description

4.2.1 ORC-O snow processes

The standard version of the ORCHIDEE snow model, named ORC-O in the following, is a simplified approach designed for use in GCMs, where snowpack processes are ignored. It consists of a single-bucket snow mass balance with constant snow density (330 kg m^{-3}). Snow

surface temperature is derived from resolving energy budget equation taking into account incoming shortwave and longwave radiations, sensible and latent heat flux and ground heat flux in the skin layer, which is assumed to be infinitesimal with no heat capacity. When surface temperature is simulated to be above freezing, it is automatically reset to 0°C, and the excess energy is applied to melt snow. Snowmelt feeds directly runoff, since liquid water is not allowed to be stored in the snowpack. This simplification implies that the model is not capable to represent liquid water refreezing and related heat release, which can be used to warm the snow layer. A mixed snow-soil structure is assumed, which implies that temperature in the first soil layer is set equal to the snow temperature. The initial snow albedo values of bare soil and each plant functional type are prescribed, and their values are changed as both the snow ages and the amount of new snowfall. Snow albedo is then weighted by the fractional snow coverage over a grid cell (Eq. 4.13), and an abrupt drop of albedo is simulated during the ablation period when the snow becomes thin.

4.2.2 ORC-N snow processes

Previous studies have documented that the representation of snow physics inside the snowpack is critical to provide accurate energy and mass flux boundary conditions for atmospheric models (e.g. Cess et al., 1991; Yeh et al., 1983; Yang et al., 1999). Therefore, we decide to modify ORC-O in order to represent the energy and mass transfers along with snow internal processes. The new snow physics processes are parameterized following the ISBA-ES (Interaction between Soil, Biosphere and Atmosphere – Explicit Snow, Boone et al., 2004) model. ISBA-ES is an intermediate complexity snow scheme and resolve the main internal snow processes (e.g. multi-layered with thicknesses varying in time, liquid water transmission, incident radiation absorption within the snowpack) (Boone et al., 2001). The new model called here after ORC-N is presented in details in the following. The structural difference between ORC-O and ORC-N is shown in Figure 4.1.

4.2.2.1 Snow layering

The snowpack in ORC-N is modeled with three snow layers, which is shown to adequately resolve the snow thermal gradients between the top and base of the snow cover (Lynch-Stieglitz, 1994; Sun et al., 1999). In order to have a reasonable simulation of diurnal change in surface temperature, the maximum upper layer thickness is prescribed to be 5 cm (D_{j1max}). In addition, since the diurnal variation of snowpack properties is most pronounced near the snow surface, the second layer is limited at 50 cm. The definition of snow layer thickness can be found as follows (Lynch-Stieglitz, 1994; Boone, 2001).

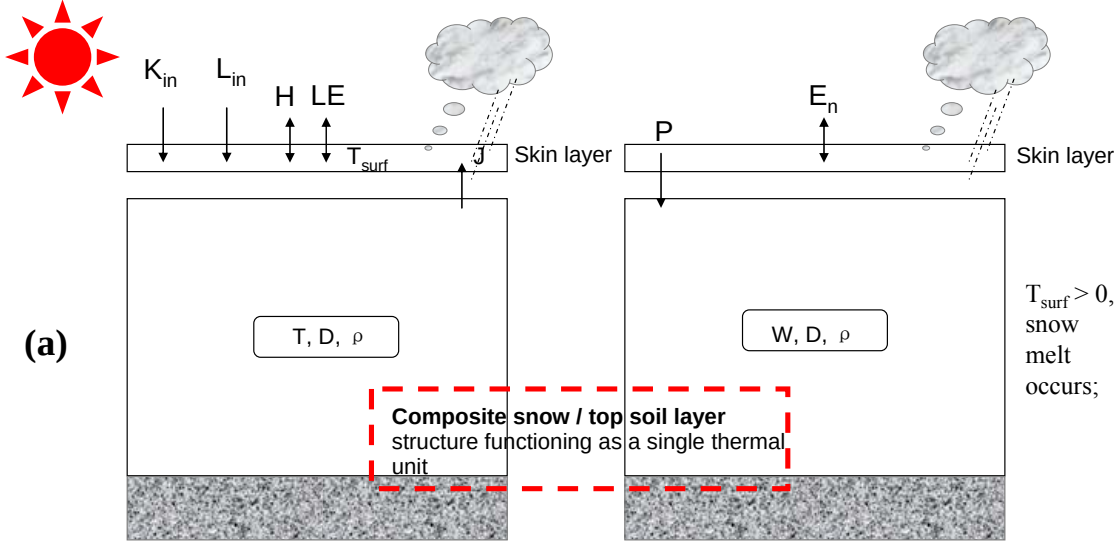
$$D_{j1} = \delta_D 0.25D_j + (1 - \delta_D)D_{j1max} \quad \text{Eq. (4.1)}$$

$$D_{j2} = \delta_D 0.50D_j + (1 - \delta_D)[0.34(D_j - D_{j1max}) + D_{j1max}](D_{j2} \leq 10D_{j1}) \quad \text{Eq. (4.2)}$$

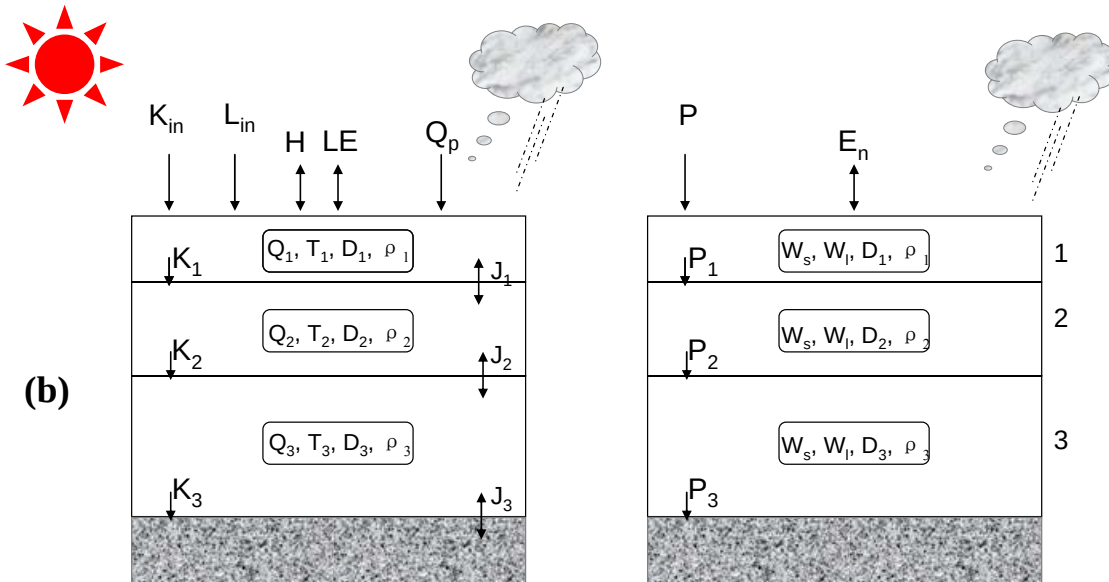
Snow model evaluation at SNOWMIP sites and regional snow observations from Canada

$$D_{j3} = D_j - D_{j1} - D_{j2} \quad \text{Eq. (4.3)}$$

D_{j1} , D_{j2} , D_{j3} and D_j are the first layer, second layer, third layer and total snow thickness (cm). δ_D is 0 and 1 respectively when D_j is above and below 20 cm.



K_{in} (short wave radiation), L_{in} (longwave radiation), H (sensible heat flux), LE (latent heat flux), J (conduction heat flux), W (SWE), D (snow depth), ρ (fixed snow density, 330), P (precipitation), E_n (evaporation), T (snow temperature), T_{surf} (skin layer temperature)



K_{in} (short wave radiation), L_{in} (longwave radiation), H (sensible heat flux), LE (latent heat flux), J (conduction heat flux), Q (snow layer heat content), Q_p (advective heat from rain and snow), W (snow layer SWE), W_l (snow layer liquid water content), D (snow layer depth), ρ (snow layer density), P (precipitation), E_n (evaporation)

Figure 4.1 The soil model coupled with a one layer snow model in ORC-O (a) and a three-layer snow model in ORC-N (b).

4.2.2.2 Energy balance equations

In ORC-O, vertical diffusion equations are used to describe the diffusion from the bottom of the soil to the skin layer, which is achieved by the implicit method through coupling one-layer snow bucket model, thermodynamic soil model to the surface energy balance (Polcher et al., 1997). We keep this snow-soil coupling scheme, and make the following modifications in ORC-N: including solar radiation absorption by each snow layer, and the first snow layer instead of the skin layer is used to calculate the surface energy balance.

At each half-hourly model time step, energy is transferred through the snow/soil column based on the vertical heat-transfer equation,

$$C_p \frac{\partial T_j}{\partial t} = \frac{\partial}{\partial z} (\kappa_j \frac{\partial T_j}{\partial z}) + \frac{\partial R}{\partial z} \quad \text{Eq. (4.4)}$$

where T_j is snow or soil temperature, z is vertical coordinate, t is time, C_p is snow or soil heat capacity ($\text{J m}^{-3} \text{K}^{-1}$). Snow C_p is the product of snow density (ρ_i , Kg m^{-3}) and the specific heat of ice ($2106 \text{ J K}^{-1} \text{ Kg}^{-1}$). For soil C_p , see Koven et al., 2009 for details. Compared to the constant value used in ORC-O, the thermal conductivity of the snow in ORC-N, κ_j ($\text{W m}^{-1} \text{K}^{-1}$) is given by,

$$\kappa_j = (0.02 + 2.50 \times 10^{-6} \rho_i^2) + (-0.06 + \frac{-2.54}{T_j - 289.99}) (\frac{P_0}{P_a}) \quad \text{Eq. (4.5)}$$

Where P_a is the atmospheric pressure in hPa and $P_0 = 1000$ hPa. The first term of Eq. (4.5) corresponds to the snow thermal conductivity (Anderson, 1976) and the second term represents the thermal conductivity from vapor transfer in the snow (Sun et al., 1999). Soil κ_j is parameterized as a function of ice content, soil moisture, soil organic matter and clay content and soil temperature (see Koven et al., 2009 for details). $R(z)$, which is not considered in ORC-O, is the solar-radiative energy source term depending on snow depth, which is determined by,

$$R(z) = R(0)(1 - \alpha)\exp(-\lambda z) \quad \text{Eq. (4.6)}$$

Where $R(0)$ (W m^{-2}) is incoming shortwave radiation, α is surface albedo, λ (m^{-1}) is the extinction coefficient for solar radiation.

4.2.2.3 Liquid-water treatment

To account for super-critical water refreezing processes out of thermodynamic equilibrium, liquid water should be allowed to coexist with ice in each snow layer. For easily tackling phase change processes, we adopt snow heat content (H_j) defined as Eq. (4.7) (e.g. Lynch-Stieglitz, 1994; Sun et al., 1999) to allow the presence of either cold (dry) or warm (wet) snow. According to Eq. (4.7), the heat content is used to diagnose the snow temperature

assuming that there is no liquid water in the snow layer. If the calculated snow temperature in Eq. (4.4) exceeds the freezing point, snow temperature is set to freezing point and liquid water content (LQW_j) is then deduced from Eq. (4.7).

$$H_j = c_{sj} D_j (T_j - T_f) - L_f (W_j - LQW_j) \quad \text{Eq. (4.7)}$$

Where W_j is the snow water equivalent at the jth layer. L_f is the latent heat fusion for ice (J kg⁻¹). T_f is the triple point temperature for water. c_{sj} is snow heat capacity at jth layer, which is parameterized as a function of snow density (ρ_j, kg m⁻³) and intrinsic density of ice (ρ_i = 920 kg m⁻³) following Verseghy (1991):

$$C_{sj} = 1.9 \times 10^6 \frac{\rho_j}{\rho_i} \quad \text{Eq. (4.8)}$$

If the calculated snow temperature in Eq. (4.4) is below freezing, liquid water in the jth layer refreezes and the energy released due to phase change is used to warm snow temperature at this layer.

4.2.2.4 Mass balance equation

The mass balance equations describe the change in total snow water equivalent, which is sum of liquid water and ice content. The contribution of water vapor is neglected because of its unimportant role in the mass balance equation (Sun et al., 1999). The mass balance at each snow layer can be expressed by Eq. (4.9).

$$\frac{\partial W_j}{\partial t} = \begin{cases} P_s + P_r - IF_j - R_j - E_n & \text{First layer (j=1)} \\ IF_{j-1} - IF_j - R_j & \text{Other layers (j=2, 3)} \end{cases} \quad \text{Eq. (4.9)}$$

In Eq. (4.9), W_j is snow water equivalent at jth layer (m), P_s and P_r are snowfall and rainfall rate (kg m⁻² s⁻¹) upon the first snow layer, R_j is runoff rate leaving jth layer (kg m⁻² s⁻¹), E_n is the sum of evaporation and sublimation rate (kg m⁻² s⁻¹). IF_j is the actual infiltration rate (m s⁻¹) at the interface between jth and (j+1)th layer. Infiltration of liquid water into the next lower layer is controlled by maximum liquid water holding capacity. As such, melt water generated in a layer will remain in that layer if the liquid water content does not exceed the layer holding capacity. Otherwise, it will infiltrate down to the next lower layer where it may either refreeze, remain in the layer in the liquid state or pass through. The maximum liquid water holding capacity is taken as a function of the snow layer density following Anderson (1976).

$$LQW_{max} = W_j [rw_{min} + (rw_{max} - rw_{min}) \max(0, \rho_t - \rho_j) / \rho_t] \quad \text{Eq. (4.10)}$$

where LQW_{jmax} is maximum water holding capacity at jth layer, the constants rw_{max} = 0.10, rw_{min} = 0.03 and ρ_i = 200 kg m⁻³.

4.2.2.5 Snow compaction

The compaction process is critically important for the evolution of density and snow depth. Snow depth is decreased by compaction and it is increased by snowfall. The local rate of change of density (increase) due to the weight of the overlying snow and settling (primarily of new snow) is parameterized following Anderson (1976) as

$$\frac{1}{\rho_j} \frac{\partial \rho_j}{\partial t} = \frac{\sigma_j}{\eta_j(T_j, \rho_j)} + a_c \exp[-b_c(T_f - T_j) - c_c \max(0, \rho_j - \rho_c)] \quad \text{Eq. (4.11)}$$

where the first term on the right-hand side of Eq. (4.11) represents overburden (the compactive viscosity term, see Eq. 4.12). The pressure of the overlying snow is represented by σ (Pa), and η is the snow viscosity (Pa s), which is an exponential function of snow temperature and density (Eq. 4.12, Mellor, 1964; Kojima, 1967). The second term represents the thermal metamorphism (Anderson, 1976) which can be significant for fresh relatively low-density snowfall. The values from Anderson (1976) are used: $a_c = 2.8 \times 10^{-6} \text{ s}^{-1}$, $b_c = 4.2 \times 10^{-2} \text{ K}^{-1}$, $C_c = 460 \text{ m}^3 \text{ kg}^{-1}$, and $\rho_c = 150 \text{ kg m}^{-3}$. The compaction constants can be treated as site-dependent calibration parameters, but they are held constant for all conditions and locations in the current model.

The snow viscosity is formulated as a function of snow density (Kojima, 1967) and temperature (Mellor, 1964) as

$$\eta_j = \eta_0 \exp[a_\eta(T_f - T_j) + b_\eta \rho_j] \quad \text{Eq. (4.12)}$$

where $\eta_0 = 3.7 \times 10^7 \text{ Pa s}$, $a_\eta = 8.1 \times 10^{-2} \text{ K}^{-1}$ and $b_\eta = 1.8 \times 10^{-2} \text{ m}^3 \text{ kg}^{-1}$. Snow settling is the dominant compaction mechanism for low density snow, whereas compaction due to overburden is the primary mechanism over long time periods and for high snow densities (Boone et al., 2002).

4.2.2.6 Snow albedo

The snow cover fraction on each grid box (f_{sg}) is a function of SWE, as given by:

$$f_{sg} = \text{SWE} / (\text{SWE} + 10) \quad \text{Eq. (4.13)}$$

At both bare soil and short vegetation sites, the snow covered albedo is parameterized using a prognostic snow albedo scheme of ISBA-ES model (Boone, 2002).

$$\begin{aligned} \alpha_{g_s}^{t+1} &= (P_n \Delta t / W_{crn})(\alpha_{\max} - \alpha_{\min}) + (1 - \omega_a) \left[\alpha^t - \frac{\tau_a \Delta t}{86400} \right] \\ &+ \omega_a \left[(\alpha_{g_s}^t - \alpha_{\min}) \exp\left(\frac{\tau_f \Delta t}{86400}\right) + \alpha_{\min} \right] \\ &(\alpha_{\min} \leq \alpha_{g_s} \leq \alpha_{\max}) \end{aligned} \quad \text{Eq. (4.14)}$$

Where α_{gs}^{t+1} and α_{gs}^t denote the albedo of current and previous time step, α_{min} and α_{max} are minimum (0.50) and maximum snow albedo (0.85) values. The maximum snow albedo value is adjusted empirically. Δt is the time step and P_s is snow fall amount (mm), A linear decrease rate is used for dry snow ($\tau_a = 0.008$ s) (Baker et al., 1990), and an exponential decrease rate ($\tau_f = 0.24$ s) is used to model the wet metamorphism (Verseghy, 1991). The weight ω_a is defined as the degree of saturation, which is defined as the ratio of snow liquid content to snow water equivalent in the surface snow layer. The snow albedo increases at a rate proportional to the snowfall. A snowfall of at least ten-centimeter water equivalent ($W_{cm} = 10$ cm) resets the snow albedo back to its maximum value. The total surface albedo on short vegetations or bare soil is then computed as the sum of snow-free background albedo ($\alpha_{g_{ns}}$) (Chalita and Treut, 1994) and snow covered albedo (α_{g_s}), weighted by the snow cover fraction (f_{sg}).

$$\alpha_{surf} = f_{sg}\alpha_{g_s} + (1 - f_{sg})\alpha_{g_{ns}} \quad \text{Eq. (4.15)}$$

At the forested sites, the total forest albedo α_{for} is computed as the sum of the closed canopy albedo α_{can} and the albedo underneath the canopy α_g , weighted with the fraction of closed canopy i.e. sky view factor (SVF) (Roesch et al., 2001), respectively:

$$\alpha_{for} = SVF\alpha_g + (1 - SVF)\alpha_{can} \quad \text{Eq. (4.16)}$$

The SVF describes the degree of canopy closure. It is defined as the fraction of sky that the ground underlying the canopy sees and has been determined by an exponential function of the LAI for both deciduous (Eq. 4.17) and evergreen (Eq. 4.18) trees.

$$SVF = e^{-0.5LAI} \quad \text{Eq. (4.17)}$$

$$SVF = e^{-1.5LAI} \quad \text{Eq. (4.18)}$$

The ground albedo α_g is computed in the same way as short vegetation (Eq. 4.14). The canopy albedo is calculated as the sum of the snow-free canopy albedo and the albedo of the snow-covered part of the canopy, weighted by their respective fractions. The snow-free canopy albedo α_{g_c} for each vegetation type is defined following Chalita and Treut (1994).

$$\alpha_{can} = f_{snc}\alpha_{snc} + (1 - f_{snc})\alpha_{g_c} \quad \text{Eq. (4.19)}$$

The fractional snow cover of the canopy f_{snc} is prescribed to be constant (0.5) in this study, however the equation 4.19 allow the albedo to vary as a function of canopy interception capacity in future studies (e.g. Roesch et al., 2001; Roesch and Erich, 2006). Finally the total grid-mean albedo is given by,

$$\alpha_{surf} = f_{sg}[f_{for}\alpha_{for} + (1 - f_{for})\alpha_g] + (1 - f_{sg})\alpha_{for_sf} \quad \text{Eq. (4.20)}$$

where f_{for} is the forest fraction. The snow free forest albedo α_{for_sf} is given by the following,

$$\alpha_{for_sf} = (1 - SVF)\alpha_{g_c} + SVF\alpha_{g_{ns}} \quad \text{Eq. (4.21)}$$

4.2.2.7 Roughness length

Snow cover is assumed to reduce the gridbox effective roughness length following the averaging method from Noilhan and Lacarrère (1995),

$$\frac{1}{\ln[z_r / z_{0t}]^2} = \frac{f_{sg}}{\ln[z_r / z_{0n}]^2} + \frac{1 - f_{sg}}{\ln[z_r / z_0]^2} \quad \text{Eq. (4.22)}$$

where z_0 is the vegetation/surface roughness length (m), z_{0n} is the snow surface roughness length baseline value (0.001 m), and z_t is the blending height (10 m in ORCHIDEE).

4.3. Metrics for snow evaluation

Specific metrics are defined below to assess the performances of the ORC-N snow model against observations. The four criteria used are presented below.

4.3.1 Snow cover accuracy (SCA)

To assess the accuracy of the ORC-N snow model to simulate the presence of snow, a snow cover accuracy metric (SCA) is used. To remove the effect of very small values, a snow depth limit of 0.05 cm is used to characterize snow presence and the results presented here is not sensitive to this threshold. SCA is defined as the sum of correctly classified days expressed as a percentage of the total number of days during the investigated period:

$$SCA = \frac{A + D}{A + B + C + D} \times 100 \quad \text{Eq. (4.23)}$$

Where A is the number of days where snow is both modeled and observed, B represents the number of days where snow is observed but not modeled, C represents the number of days where the snow is modeled but not observed, and D is the number of days when snow is neither modeled nor observed. The SCA varies from 0.0 (theoretical minimum) to 1.0 (perfect agreement between the observed and modeled values).

4.3.2 Mean Absolute Error (MAE)

The Mean Absolute error (MAE) metric is given by,

$$MAE = \frac{1}{N} \sum |O_i - P_i| \quad \text{Eq. (4.24)}$$

Where N is the number of observations, O_i is observed variable, and P_i is modeled variable.

4.3.3 Mean Error (ME)

The Mean error (ME) metric is given by,

$$ME = \frac{1}{N} \sum (P_i - O_i) \quad \text{Eq. (4.25)}$$

Where N is the number of observations, O_i is observed variable, and P_i is modeled variable.

4.3.4 Index of agreement (IOA)

The index of agreement (IOA), which was developed by Willmott (1981), is a widely used dimensionless indicator of goodness-of-fit. The index of agreement was not designed to be a measure of correlation but of the degree to which model's predictions are error free (Legates and McCabe, 1999).

$$IOA = 1 - \frac{\sum (O_i - P_i)^2}{\sum (|P_i - \bar{O}| + |O_i - \bar{O}|)^2} \quad \text{Eq. (4.26)}$$

Where O_i is observed data, P_i is modeled data and $\bar{O}$ is mean of observed data. The IOA varies from 0.0 (theoretical minimum) to 1.0 (perfect agreement between the observed and modeled values).

4.4. Dataset

Datasets for evaluation of models include three short vegetation sites of SNOWMIP1: Col de Porte (CDP), Weissfluhjoch (WFJ) and four short vegetation/forest sites from SNOWMIP2 (Rutter et al., 2009). In addition, the archive of historical observations of snowfall, rainfall, temperature and snow cover available at 193 locations in Canada over 15 years is also used to assess the model performances in simulating spatial and temporal dynamics of snow cover and snow depth.

4.4.1 SNOWMIP1 sites

4.4.1.1 Col de Porte (CDP, 1993-1995)

CDP is located within the Rhone River basin in the French Alps, which is managed by the Center for Snow Studies (CEN: Centre d'Etude de la Neige) in Grenoble, France. This site is located at 45.8 °N, 68 °E with an altitude of 1320 m, and is characterized by a flat topography with loamy soil covered with short grass. The snow often begins in November and ends at the beginning of May. Winter air temperature can occur intermittently above the freezing point throughout the winter, and rainfall episodes can thus be common during the snow season. The soil generally does not freeze. Besides hourly observations of meteorological data, hourly observed snow surface temperature from a downward-looking radiometer, hourly snow depth from an ultrasonic sensor and daily bottom runoff from

snowpack measured by a 5 m² lysimeter are also provided. In addition, the weekly observations of the snow water equivalent and snow depth are also available. This dataset has been widely used to evaluate many snow schemes (e.g. Brun et al., 1992; Douville et al., 1995; Sun et al., 1999; Essery et al., 1999; Boone and Etchevers, 2001; Essery and Etchevers, 2004; Brown et al., 2006).

4.4.1.2 Weissfluhjoch (WFJ, 1992-1993)

WFJ is a high-elevation site at 2540m with flat topography, located in the eastern Swiss Alps (46.83°N, 9.81°E) and managed by the Swiss Federal Institute for Snow and Avalanche Research. The average air temperature during the period of continuous snow cover is -2.9 °C. Rainfall does not occur from mid-October to mid-May. Snow continuously accumulates from mid-October until mid-April and then melts through May and June owing to temperatures above the melting temperature. Although this site is more windy than CDP, drifting and blowing effects are weaker (Essery and Etchevers, 2004; Brown et al., 2006). Evaluation data comprise hourly observations of snow surface temperature from an infrared thermometer, hourly observations of snow depth from an ultrasonic sensor supported by weekly and sometimes biweekly snow pit observations of the SWE and snow depth, daily snow albedo and daily snowmelt runoff. Data from this site have been used in the assessment of many snow models (e.g., Fierz and Lehning, 2000; Lehning et al., 2002; Fierz et al., 2003; Essery and Etchevers, 2004; Etchevers et al., 2004; Brown et al., 2006).

4.4.2 SNOWMIP2 sites

There are five locations in SNOWMIP2, with span maritime, taiga and alpine seasonal snowpack types (Sturm et al., 1995). In each location, two sites are identified: a forested (canopy) site and an open (no canopy) site, which were at most 4 km from each other. The meteorological forcing data (shortwave and longwave radiation, total precipitation, air temperature, humidity and wind speed) at each location is obtained from automatic weather stations except for Hyytiala, where longwave radiation was not measured. The precipitation measurements are corrected for undercatch and partitioned into rain, snow or mixed precipitation using algorithms supplied by the data providers (see details in Table 3 of Rutter et al., 2009). The physical characteristics of each location are summarized in Table 4.1 (Rutter et al., 2009). In addition, the details about the hydro-meteorological conditions at each location can also be seen in Table 4 of Rutter et al. (2009). Among all sites, Alptal was the cloudiest location on average, and recorded also the highest snowfall. The location with the next highest snowfall, Fraser, had only 57% of the total amount observed at Alptal while BERMS, had the lowest with only 22% of Alptal's amount. Alptal was the warmest location with a mean air temperature of 3°C, whereas the remaining three locations had mean air temperatures within 2°C of each other, averaging -2°C.

Snow model evaluation at SNOWMIP sites and regional snow observations from Canada

Each forest site is covered by evergreen needleleaf trees of varying heights with canopy coverage greater than 70% (see Table 5 of Rutter et al., 2009). The meteorological data were collected above the canopies. Open sites consisted of either cut grass or previously cleared forest. Deforestation occurred at the open site in 1985 at Fraser and in 2000 at BERMS. The BERMS site was subsequently scarified in 2002 and no significant regrowth was observed, while on the Fraser open site some small trees (2-4 m) have regrown. However, regrowth is very sparse at the Fraser open site and meteorological and snowpack measurements were performed at different locations in the clearings (Rutter et al., 2009).

Location	Site	Latitude	Longitude	Distance from Forest (m)	Elevation (m)	Snowpack Type (after Sturm et al., 1995)
Alptal (Switzerland)	Forest	47°03N	8°48E		1185	Alpine
	Open	47°03N	8°48E	200	1220	Alpine
BERMS (Canada)	Forest	53°55N	104°42W		579	Taiga
	Open	53°55N	104°42W	4000	579	Taiga
ASER (USA)	Forest	39°53N	105°53W		2820	Alpine
	Open	39°53N	105°53W	45	2820	Alpine
Hitsujigaoka (Japan)	Forest	42°59N	141°23E		182	Maritime
	Open	42°59N	141°23E	2500	182	Maritime
Hyytiala (Finland)	Forest	61°51N	24°17E		181	Taiga
	Open	61°51N	24°17E	500	154	Taiga

Table 4.1 Physical characteristics of study locations from SNOWIP2

4.4.3 Canadian climate stations

In order to quantify the ability of our snow models in simulating interannual and spatial variability of snow characteristics (e.g. snow depth, snow cover days), we use daily observed snow depth, minimum and maximum air temperature and precipitation (snowfall and rainfall) during the period 1989-2005 from Canada's National Climate Archive. The snow depth at each climate station is measured daily at artificially grassy sites and reported in centimeters as integer values. The climate stations satisfying the two following criteria are used in this study. At each climate station and each year, both annual data gap and winter (December-February) data gap in three variables (snow depth, air temperature and precipitation) must be below 2%. At least 8 years of data must be available during the period 1989-2005. This generates 193 Canadian climate stations. Their mean winter (November through February) snow depth and mean snow cover days (SCD) are shown in Figure 4.2a and b respectively. SCD is calculated by totaling the days when snow depth exceeds 5 mm. In addition, the whole Canada is divided into four regions (Figure 4.2c): MW: mountain and the west region, PR: the prairies, CC: central Canada and the east coast and NC: northern Canada.

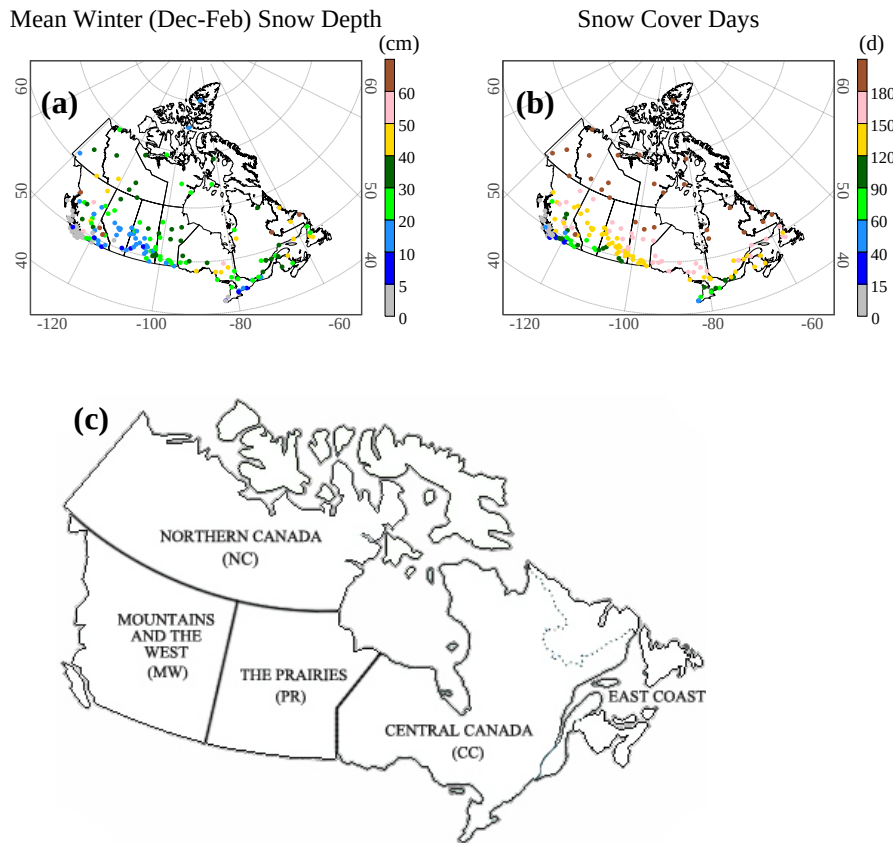


Figure 4.2 The spatial distribution of climate stations with mean winter (December to February) snow depth (a) and mean snow cover days (b) during the period 1989-2005. The whole Canada is divided into four regions (c): MW: mountain and the west region, PR: the prairies, CC: central Canada and the east coast and NC: northern Canada.

4.5. ORC-N Snow model evaluation at SnowMIP sites

4.5.1 SCD, SWE, snow depth and snow density at open sites

Comparison of observed and simulated snow characteristics (SWE, snow depth and snow density) is presented in Figure 4.3 and Table 4.2. ISBA-ES (Boone et al., 2001; Boone, 2002) is also added in the comparison, as a reference. The results clearly showed that the ORC-N simulations are comparable to ISBA-ES ones at both CDP and WFJ. The improvements compared to ORC-O in both SWE and snow depth are obvious (Figure 4.3). ORC-O could not capture the variability of snow depth since it assumes a constant snow density (330 kg m^{-3}).

Again, across short vegetation SNOWMIP2 sites (Figure 4.7a), both the coefficient of determination (R^2) and the slope between observed and modeled SWE increased from 0.05 for ORC-O to 0.65 for ORC-N, and from 0.09 for ORC-O to 0.81 for ORC-N respectively.

Snow model evaluation at SNOWMIP sites and regional snow observations from Canada

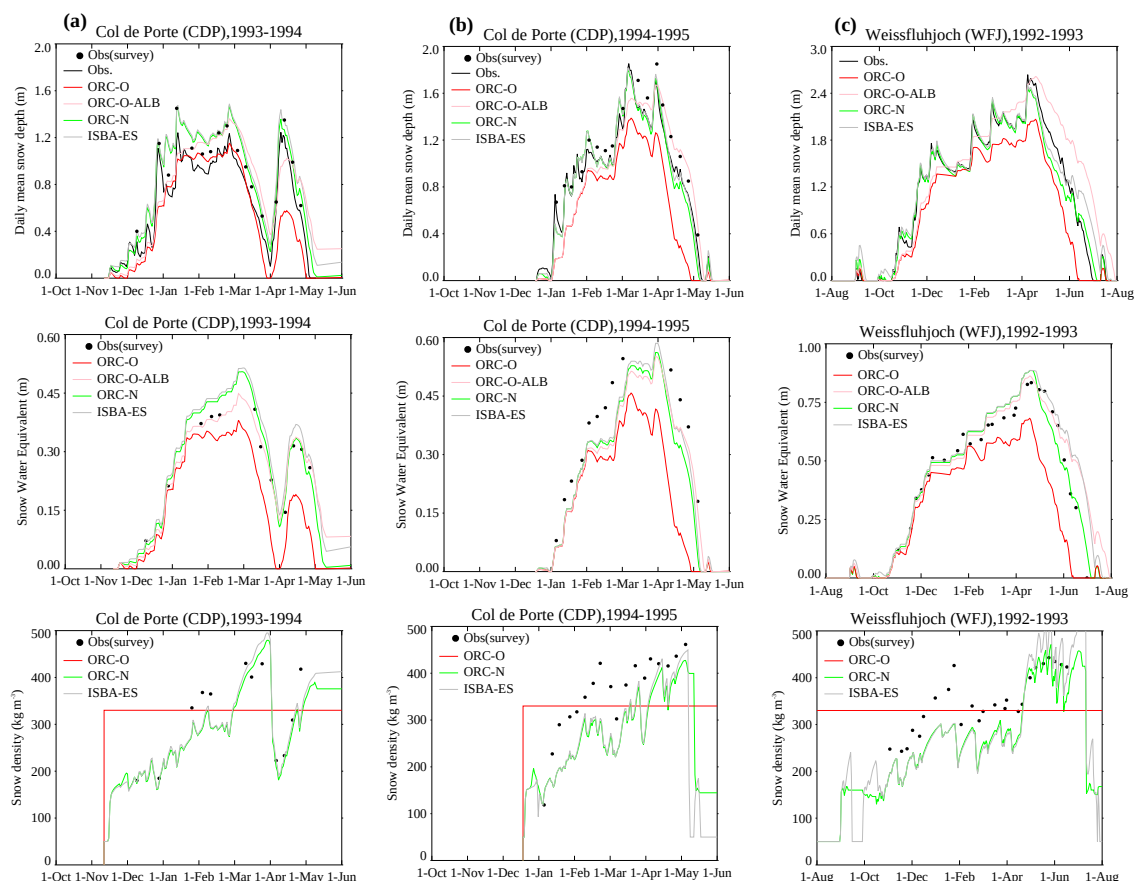


Figure 4.3 Comparison of observed and simulated snow depth, SWE and density at (a) CDP (1993-1994), (b) CDP (1994-1995), (c) WFJ (1992-1993).

Site	Model type	Snow Depth (m)		SWE (m)		Albedo		Snowmelt Runoff (mm)	
		BIAS	RMSE	BIAS	RMSE	BIAS	RMSE	BIAS	RMSE
CDP93-94	ORC-O	-0.11	0.21	-0.09	0.10	-	-	0.25	7.9
	ORC-O-ALB	0.1	0.22	0.	0.02	-	-	2.19	7.68
	ORC-N	0.16	0.19	0.02	0.03	-	-	2.97	8.1
	ISBA-ES	0.21	0.23	0.04	0.05	-	-	3.1	8.96
CDP94-95	ORC-O	-0.26	0.32	-0.19	0.21	-0.12	0.19	0.3	10.07
	ORC-O-ALB	-0.03	0.19	-0.10	0.11	0.01	0.15	0.4	7.81
	ORC-N	-0.02	0.08	-0.10	0.11	-0.01	0.15	-0.53	5.53
	ISBA-ES	0.01	0.07	-0.08	0.09	0.09	0.12	-0.7	4.74
WFJ92-93	ORC-O	-0.23	0.32	-0.14	0.18	-0.25	0.29	-3.56	12.57
	ORC-O-ALB	0.13	0.35	0.03	0.09	-0.05	0.09	-2.91	11.54
	ORC-N	-0.02	0.12	0.01	0.05	-0.06	0.01	0.12	10.49
	ISBA-ES	0.05	0.17	0.05	0.10	-0.03	0.08	-1.27	12.38

Table 4.2 Bias and RMSE for the SnowMIP1 sites

Snow density is an important factor in the parameterization of snow thermal conductivity, which is critical for correctly simulating the soil temperature underlying snow (e.g. Sturm et al., 1997). The results for the snowpack average density at CDP and WFJ sites, as shown in Figure 4.3, reveal that both ORC-N (e.g. CDP: $R^2=0.80$) and ISBA-ES ($R^2=0.81$) are able to capture the seasonal variation in this variable. However, the snow density is underestimated in the mid-winter season (February) at both CDP site in 1994-1995 and WFJ site in 1992-1993, a bias which is related to the underestimation of snow melt by both models.

4.5.2 Snow albedo

Snow albedo measured at WFJ and CDP (1994-1995) was used to evaluate the ORC-N model. Figure 4.4 compares the daily mean observed and modeled albedo with ORC-O, ORC-N and ISBA-ES. The results show that all the models can capture the intra-seasonal variations of albedo. The snow albedo simulation in ORC-N is, however, improved compared to ORC-O, which underestimates the snow albedo and shows the largest bias among all the models (Table 4.2). The underestimated snow albedo by ORC-O mainly leads to significant biases in snow simulations (see Sect. 4.5.6). However, at CDP (1994-1995), albedo is slightly overestimated by both ORC-N and ISBA-ES, which could be related to partial obstruction of the sensor's field of view as noted by Etchevers et al., 2004. At WFJ site, a significant negative bias of around 0.15 in both ORC-N and ISBA-ES is found during the accumulation period, which is consistent with previous snow comparison studies (Essery and Etchevers, 2004; Etchevers et al., 2004; Brown et al., 2006; Shrestha et al., 2010). The main reason is attributed to the fact that the observed albedo of recent snow is around 0.95 whereas the simulated maximum albedo is 0.85 (e.g. Shrestha et al., 2010).

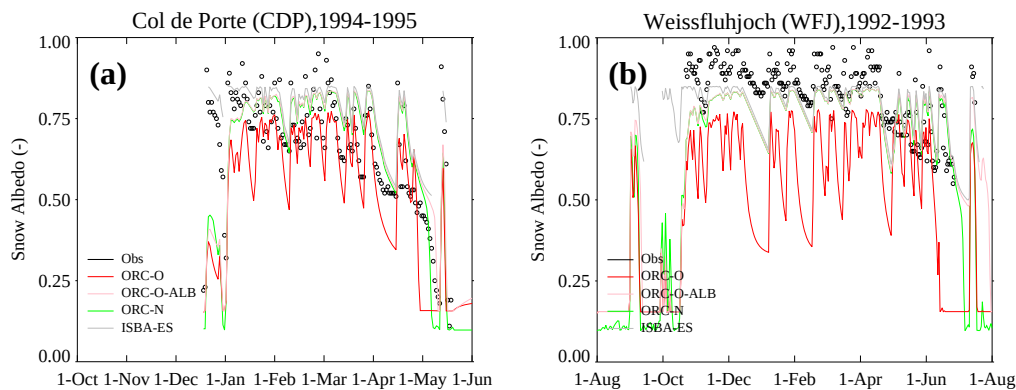


Figure 4.4 Comparison of observed and modeled snow albedo (a) CDP (1994-1995), (b) WFJ (1992-1993).

4.5.3 Snowmelt runoff

The snowmelt runoff observed at CDP (1994-1995) and WFJ (1992-1993) were also used in the model evaluation. At the WFJ site, the observations of snowmelt runoff are available only for a short period (27 April to 7 July 1993). The total snowmelt (sum of the contributions of the 3 layers) is partitioned into surface runoff and infiltration into the soil. As shown in Figure 4.5, the timing and total amount of snowmelt runoff is better simulated by both ORC-N and ISBA-ES than by ORC-O. ORC-N was found to capture the snowmelt runoff during the accumulation period, mid-season ablation and final melting season. Although the results for ORC-O also show similar runoff behavior, they include large biases during the melting season linked to too early melting (Table 4.2). Substantial improvements in snowmelt runoff simulations are achieved at both sites by ORC-N with less RMSE and bias (see Table 4.2).

4.5.4 Snow surface temperature

Snow surface temperature is an important parameter of the land surface energy balance since it plays an important role in the estimation of water vapour and heat fluxes between the snow surface, the soil and the atmosphere. The results for the hourly snow surface temperature simulations at CDP and WFJ are shown in Figure 4.6. Note that only snow cover situations were selected in the comparison. The results indicate that all models are capable of simulating snow surface temperature variability. In terms of RMSE, the improvement of surface temperature simulations in ORC-N over ORC-O is not as evident as improvements realized for snow depth and SWE. ORC-N tends to have a colder bias than ORC-O at both CDP and WFJ sites. This is related to the fact that snow albedo is underestimated in ORC-O. If the snow albedo scheme in ORC-O is replaced with the one of ISBA-ES (see details in Sect. 4.5.6), the mean temperature bias in ORC-O became closer to the bias in ORC-N. For example, at CDP site in 1993-1994 and 1994-1995, after the albedo scheme replacement in ORC-O, the mean temperature bias (K) in ORC-O is changed from -0.61 and -1.59 to -1.17 and -1.87 K respectively, which is comparable to -1.04 and -1.89 in ORC-N. The cold temperature bias of ORC-N can be explained by both the deficiency of Monin-Obukhov similarity theory used to calculate the turbulent fluxes in highly stable conditions and to the uncertainty in the roughness length of the snow surface (Brown et al., 2006). The simulations could be improved by the inclusion of windless coefficient as discussed in Brown et al. (2006).

4.5.5 Snow simulation at needleleaf forest sites

As shown in Figure 4.7b, the forest snow albedo parameterization in ORC-N shows a slight improvement in modeling needleleaf forest SWE compared to ORC-O. The overestimation of SWE by ISBA-ES could be expected since its snow albedo parameterization does not take into account the albedo masking effect by the forest. Snow

Snow model evaluation at SNOWMIP sites and regional snow observations from Canada

interception and snow unloading (melt drip and drop of the snow due to winds and bending of branches) from the canopy are not represented in all of the models. Such processes could influence forest albedo and the amount of snow falling on the ground. In this study, all forested sites present a canopy coverage of more than 70%, and the snow has been found to have little effect on needleleaf forest albedo when the tree cover exceeds 70% (Ni et al., 1996).

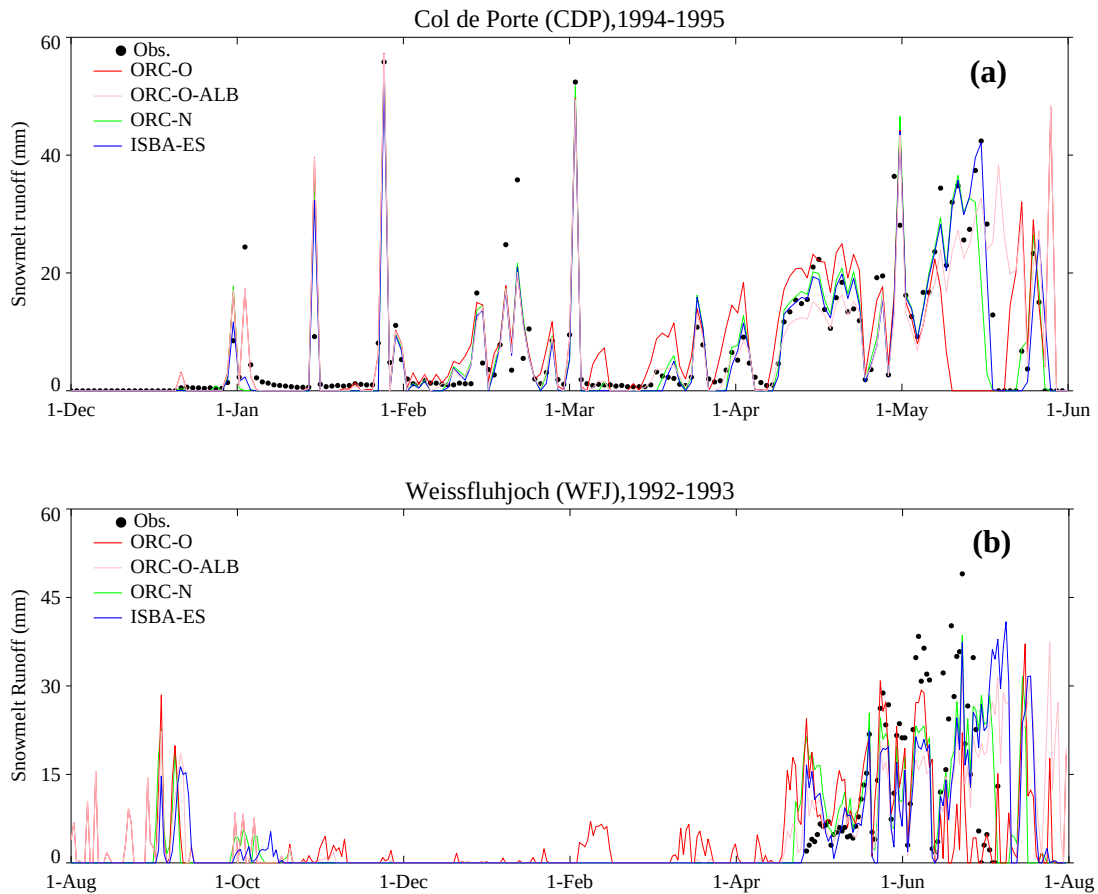


Figure 4.5 Comparison of daily snow melt runoff at (a) CDP (1994-1995) and (b) WFJ (1992-1993).

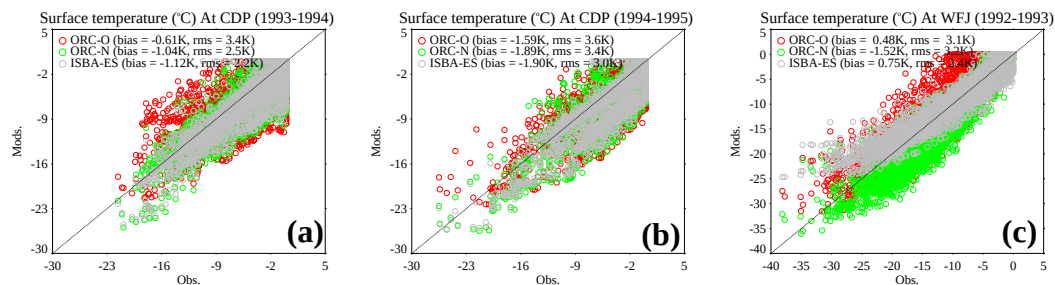


Figure 4.6 Comparison of hourly snow surface temperature at (a) CDP (1993-1994), (b) CDP (1994-1995) and (c) WFJ (1992-1993).

Our sensitivity analysis of SWE to different F_{csnow} values (the fraction of snow-covered canopy) (0.0-1.0) at the Fraser forested site has shown that F_{csnow} was not mainly responsible for the failure of the model in capturing the observed SWE, and this is also found at other sites (data not shown). Thus, the albedo effect caused by the fraction of intercepted snow could not be significant in this study.

At both Alptal and Hitsujigaoka sites, the maximum SWE is overestimated but at both BERMS and Fraser forested sites, the maximum SWE is significantly underestimated (data not shown). If the snow interception was included in the model, the model performance would be better at Alptal and Hitsujigaoka sites but might be even worse for BERMS and Fraser sites. This implied that only considering canopy snow interception might not be sufficient to account for the snow dynamics under the canopy. Alongside interception effects, needleleaf forest cover influences energy exchanges snow-atmosphere and the forest layer acts to effectively decouple the above-canopy and sub-canopy atmospheres, resulting in a large depression of turbulent energy fluxes (Harding and Pomeroy, 1996; Link and Marks, 1999). Thus, accurate simulation of snow accumulation and melting on needleleaf forest sites requires a second energy budget layer, to adjust the energy fluxes to the under-canopy snow (e.g. Ellis et al., 2010). This modification will be the subject of future work.

Our study suggest that ORC-N has shortcomings in the simulations of snow variables at dense needleleaf forest sites (larger than 70% of canopy coverage), but we still expect that benefits might be gained if albedo effect significantly contributes to the snow simulations in the deciduous forests and the needleleaf forests with sparse canopy coverage.

4.5.6 Sensitivity tests

Our study showed that SWE is always underestimated by ORC-O (Figure 4.3 and 4.7a) at open sites, an underestimation that could be mainly attributed to the simulated low albedo values (Figure 4.4). To test how large differences can be brought by the snow albedo scheme, we first replace the ORC-O snow albedo scheme with Eq. 4.14, named as ORC-O-ALB. In Eq. 4.14, the fraction of liquid water in the surface layer is used to denote the snow state (wet vs. dry), and the wet snow is parameterized to have a larger snow albedo decay rate than the dry snow. Given liquid water is not calculated in ORC-O, instead of using the fraction of liquid water in the surface layer, skin layer temperature in ORC-O is used as a proxy for snow state (wet vs. dry), i.e. snow is diagnosed as wet when skin layer temperature is above 0°C.

The new snow albedo calculated by the modified scheme is almost similar to the one implemented in ORC-N or ISBA-ES at both CDP and WFJ sites (Figure 4.4). After this replacement, ORC-O-ALB performs much better than ORC-O with less bias and RMSE in terms of SD, SWE, and snowmelt runoff (see Table 4.2). However, the improvements on snow depth in ORC-O-ALB are not as large as those observed on SWE and snowmelt runoff

(Table 4.2). The reason could be attributed to the absence of prognostic simulation of snow density in ORC-O.

Previous studies documented the fact that the existence of snow could significant change roughness length. In ORC-O, the presence of snow does not alter the roughness length (z_0), which is dependent on the vegetation height. For example, the reported z_0 is in the range of 0.01 and 0.35 mm for the fresh snow covered surfaces (Clifton et al., 2006, 2008), which is much smaller than ~ 20 mm often prescribed for short vegetations in ORCHIDE. In order to test surface roughness effects on snow simulations, we also modify the roughness length in ORC-O-ALB based on Eq. 4.22, which is named as ORC-O-ALB-ROU. After this replacement, we found that mean daily sublimation rates (JFMAM) in ORC-O-ALB-ROU at the site e.g. CDP (1994-1995) is 0.02 (mm/d), which is much lower than 0.16 (mm/d) in ORC-O-ALB. But the impacts were much smaller on SWE, SD and snowmelt runoff simulation (data not shown). This could be partly explained by the fact that the tested sites are not exposed to very windy conditions.

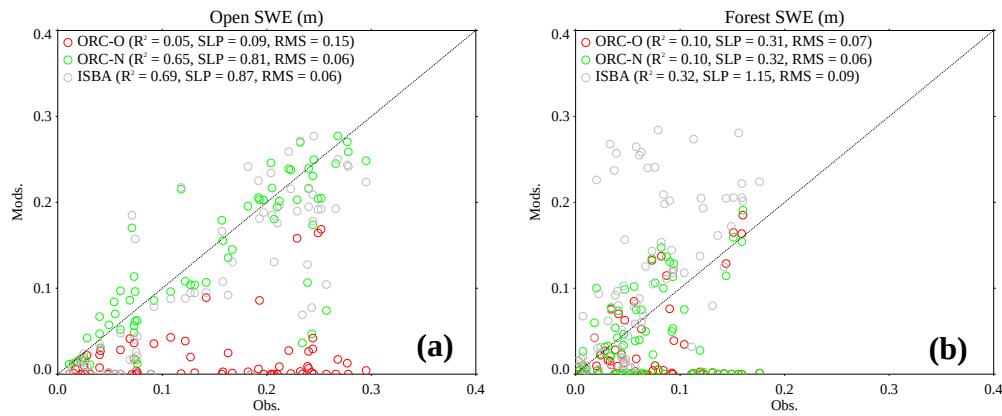


Figure 4.7 Comparison of SWE at (a) open and (b) forested sites in SNOWMIP2. Each circle represents the SWE per site per observation.

Although significant improvement could be achieved through changing the albedo scheme, the soil temperature underlying the snow pack still stays colder than the observations. For example, at CDP during the winter season (1994-1995), the soil never freezes but soil temperature is modeled as -5 °C in ORC-O and -0.1 °C in ORC-N. The cold bias of soil temperature in ORC-O can be attributed to its mixed soil-snow structure, where snow temperature is assumed to equal temperature in the first soil layer. To demonstrate this, calculation of temperature in the snow layer was separated from the underlying soil, and our results showed that the cold bias of soil temperature (-0.2 °C) disappear when snow and soil layers are separated. By comparing modeled snow results from Russia Valdai station across different degree of snow model complexity, Slater et al. (2001) also pointed out that a multilayer snow model like our ORC-N is necessary in the simulation of snow-soil interface temperature.

4.6 Model regional evaluation

In this section, the evaluation of modeled snow depth is based on in-situ snow depth data collected by Canadian meteorological stations. The forcing data used for model simulation is from IERA, which is considered given the fact that IERA forcing data agrees well with the observations (Simmons et al., 2010).

4.6.1 Model driving forcing

For each climate station and each year, both ORC-O and ORC-N are driven by two meteorological forcing gridded datasets: one is IERA and the other in which IERA precipitation (snow and rain) and temperature data were replaced with their observed daily values. IERA dataset is reported on six-hourly time step. In order to get the second dataset, temporal desegregation of observed daily precipitation (snowfall and rainfall) data to half-hourly time step was achieved using a simple uniform partition. For temperature, half-hourly temperature is generated from observed daily values of minimum and maximum air temperature by using a sine wave assuming that maximum temperature occurs at 14:00 local time and minimum temperature occurs at sunrise (Campbell and Norman, 1998). It should be noted that IERA snowfall is obtained by using a threshold air temperature of 0 °C to partition precipitation inputs and the in-situ snowfall is provided by each climate station.

After removing the bias in both IERA-derived precipitation and temperature using the values observed at each weather station, improved snow simulations can be expected (e.g. Pan et al., 2003; Parajka et al., 2010). To determine their respective contributions, the following four datasets with only precipitation or temperature replaced by the observation are generated. IERA_T_P and IERA_T_NP are IERA in which only temperature is replaced by the observation. IERA_P_P and IERA_P_NP are IERA in which snowfall and rainfall are replaced by observed values. Unlike some snow models (e.g. Pan et al., 2003), in which snowfall is calculated from total precipitation using the temperature input based on certain temperature threshold (e.g. 0 °C), snowfall amount independent from air temperature forcing can be prescribed in ORCHIDEE. To have an idea of the difference brought by these two different model structures, snowfall in IERA_T_P and IERA_P_P is partitioned from total precipitation using their own temperature fields based on zero-centigrade temperature threshold. The snowfall in IERA_T_NP and IERA_P_NP was not re-partitioned from total precipitation.

The mean difference between IERA and observed winter (December to February) air temperature and total snowfall during the period from 1989 to 2005 are shown in Figure 4.8. Compared to observed values, IERA overestimates total snowfall data in 54% of climate stations. Across Canada, a difference within the range of ± 10 mm was found in 61% of stations and differences larger than ± 40 mm could be observed in 9% of stations (Figure 4.8a). Regional differences in the percentage of total snowfall overestimation are observed. In MW region, about 72% of the stations present overestimations, and nearly all of the differences

between observed and IERA derived snowfall larger than ± 40 mm across Canada is located in this region. In PR region, nearly half of the stations are overestimated but nearly all of the differences are within ± 10 mm. In CC region, only 19% of the stations are overestimated and half of the differences are within ± 10 mm. In NC region, nearly all of the stations ($N = 14$) have been overestimated and half of the differences are within ± 10 mm. For air temperature, good agreement was observed between observation and IERA-derived values, for example, 62%, 71% and 52% of the stations where the absolute air temperature difference is less than 1°C are observed in spring (March to May), autumn (September to November) and winter (December to February) respectively. Across Canada, winter air temperature in nearly 58% of the stations is underestimated. An underestimation of IERA air temperature in winter by more than 2°C is found at the stations located in MW region (Figure 4.8b). The same cold bias is also found in spring and autumn (data not shown). Coincidentally, most of the stations in MW region overestimate total snowfall as compared with IERA (Figure 4.8a). Overall, this indicates that IERA forcing data in MW region will have a tendency to produce longer and deeper snow coverage in comparison with observed forcing.

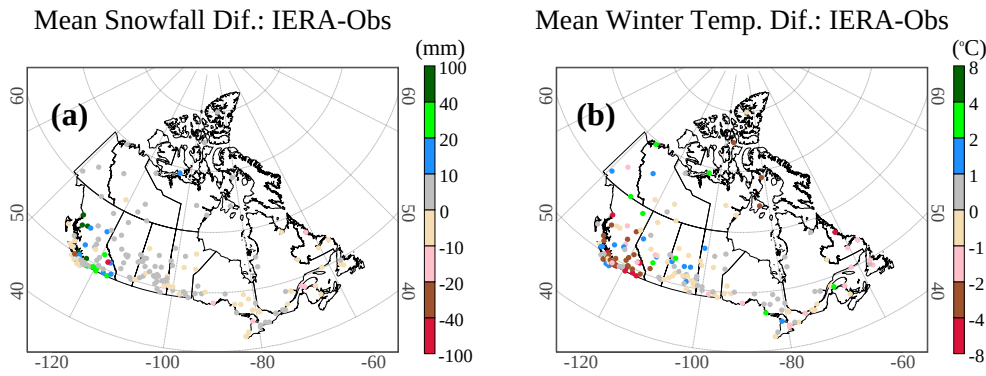


Figure 4.8 Spatial distribution of the mean difference between ERA-interim and observed total snowfall (a) and winter (December to February) air temperature (b) during the period 1989-2005.

4.6.2 Mean Spatial patterns

The spatial patterns of mean annual snow depth error (ME) (Eq. 4.25) and mean snow cover days (SCD) error over the period 1989-2005 are displayed in Figure 4.9 for the ORC-N snow model driven by both IERA and IERA_TP respectively. The values of annual snow depth ME and SCD ME over the period 1989-2005 in four different regions are also given in Table 4.3. Across all Canada sites, annual snow depth ME (cm) for IERA_TP and IERA are 2.4 and 3.7 cm. The mean SCD (d) ME for IERA_TP and IERA forcing are of 22 and 9 d respectively. For annual snow depth ME, overestimated values are found in MW and NC regions in IERA-forced simulations and MW and CC regions in IERA_TP-forced simulations (Table 4.3). In both simulations, the ORC-N showed good performances, characterized by low annual snow depth ME values in PR region (Table 4.3). The comparison between IERA and IERA_TP forced ORC-N results showed that the behavior has been significantly

Snow model evaluation at SNOWMIP sites and regional snow observations from Canada

improved in MW and NC regions using IERA_TP (Table 4.3). For example, in MW region, annual snow depth ME (cm) is reduced to 2.6 (± 6.2) with IERA_TP forcing, compared to 8.3 (± 22.5) with IERA forcing. This is mostly likely caused by the overestimation of snowfall in these two regions by IERA (Figure 4.8a). However, in CC region, annual snow depth ME has instead significantly increased in IERA_TP simulations than IERA. The same spatial pattern was also found in mean snow cover days (Table 4.3).

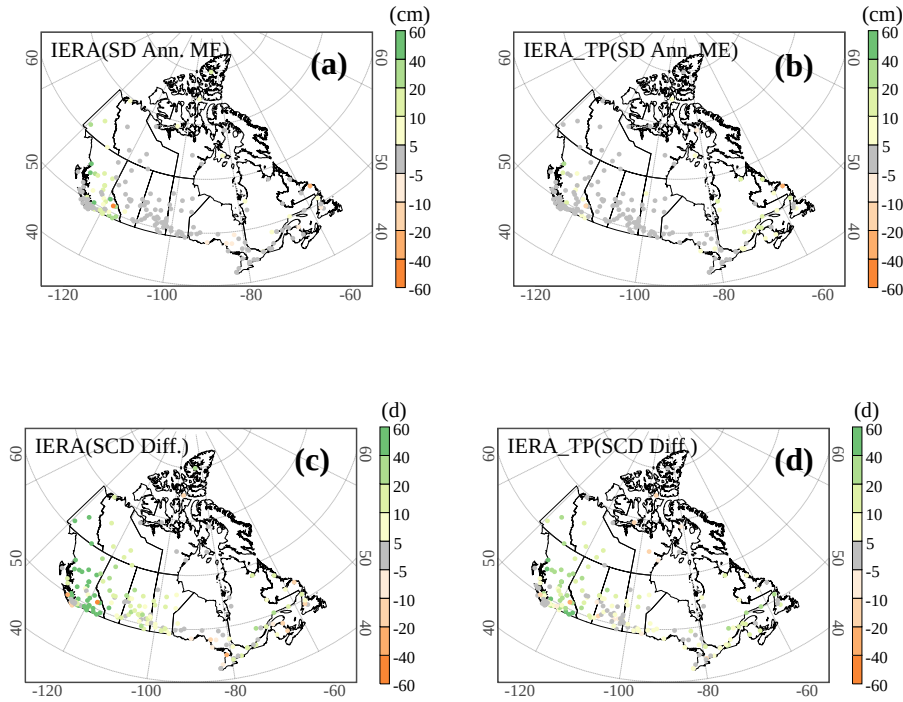


Figure 4.9 Spatial patterns of mean (1989-2005) annual snow depth error (ME) for ORC-N driven by (a) IERA and (b) IERA_TP, and the spatial patterns of mean (1989-2005) snow cover days error (ME) for ORC-N driven by (c) IERA and (d) IERA_TP.

Elevation is identified as one of the key factors in governing snow processes, and previous studies reported snow depth bias can be systematic different in low and high elevation (Sheffield et al., 2003; Habets et al., 2008; Parajka et al. 2010). However, no obvious relation between seasonal snow depth ME and altitude was found in our analysis. In contrast to 34% (209) of the stations located above 800 m in Parajka et al. (2010) study, only 6% (11) of the stations fulfill this condition in our study. In addition, the ORC-N snow model performances (e.g. annual snow depth ME) using either IERA or IERA_TP are not correlated with the elevation difference between stations and IERA grid boxes where stations resides in. This can be expected since the elevation differences (the range is from -200 to 200 m) in our analysis are not as large as those (the range can be -750 to 1000 m) found in Parajka et al. (2010) study.

4.6.3 Temporal variability

4.6.3.1 Intra-annual variability

Half-monthly observed snow depth, snow depth error and snow cover accuracy simulated by ORC-N with IERA and IERA_TP forcing in four different Canadian regions are displayed in polar plots, where a full circle corresponds to one year. As shown in Figure 4.10, snow in NC region has a prolonged duration and can persist through the early summer, while the snow in MW region has the shortest duration and the least median snow depth. In terms of median snow depth error, the ORC-N model forced by both IERA and IERA_TP has the ability in capturing the intra-annual snow depth variation (Figure 4.10b and c), though systematic snow depth bias is always found in some regions. When the SCA metrics is used, the ORC-N model from both forcings shows higher values. However, we should note that the snow cover simulated with this high accuracy does not imply a similarly high degree of accuracy for snow depth (e.g. Figure 4.10c and e). This feature was also found in ORC-O (data not shown). Spring season is found to have lower values of SCA than autumn. This suggested that the ORC-N model has a better ability to capture snow behavior during the accumulation period than during the ablation period, which is also found in ORC-O (data not shown). As expected, the SCA values in winter and summer seasons are always near unity especially in PR, CC and NC regions since winter and summer season are often characterized by the continuous snow cover and no snow cover respectively (Figure 4.10a).

4.6.3.2 Interannual variability

The observed and modeled interannual variability (IAV) of mean snow depth in four different regions over the period from 1989 to 2005 is shown in Figure 4.11. The mean annual snow depth was averaged spatially over stations located in four different regions. As shown in Figure 4.11, in both IERA and IERA_TP forced simulations the ORC-N model shows reasonable agreement with the IAV observed data in terms of the shape of interannual variation, though systematic bias in snow depth still remains. To get better insights on the ability of ORC-N model to capture snow temporal behaviors, besides annual snow depth, other snow characteristics (maximum snow depth, continuous snow cover days and transitional snowfall length) in each region are also explored and error metrics (IOA and MAE) for each snow character are given in Figure 4.12. The transitional snowfall length (TSL_F and TSL_L) is defined as the difference between the (first and last) snowfall date and the (first and last) date of continuous snow cover. For each region, the IOA (and MAE) metrics for ORC-N and observed snow variables are first calculated at each sites within this region, and then averaged to get the regional-level. Our results showed that the ORC-N model in both simulations can capture interannual variability well, except the MW region with the IERA forcing, a bias that was consistently found in above spatial and intra-annual analysis. It

Snow model evaluation at SNOWMIP sites and regional snow observations from Canada

is interesting to note that the model has a comparable IOA (MAE) between IERA and IERA_TP forced simulations in CC region, despite the fact that IERA_TP has a larger systematic bias in annual snow depth ME than IERA (Figure 4.9). This is mostly explained by the fact that in IERA simulation both under- and over-estimation of snow depth happened in CC region and the error compensating effect leads to the non-evident systematic bias in annual snow depth ME displayed by Figure 4.11.

ORC-O						ORC-N			
Snow depth (cm)									
IERA				IERA_TP		IERA		IERA_TP	
Region	N	Mean error	MAE	Mean error	MAE	Mean error	MAE	Mean error	MAE
MW	68	2.6(22.4)	3.1	-1.5(4.9)	1.1	8.3(22.6)	3.0	2.6(6.3)	1.2
PR	45	-4.7(3.5)	3.9	-2.8(3.1)	2.2	0.2(3.4)	1.8	1.0(3.2)	1.6
CC	45	-6.1(5.8)	5.7	-1.6(5.3)	3.0	-0.4(5.8)	3.1	4.9(6.0)	4.4
NC	14	-4.1(7.3)	6.1	-5.4(6.1)	5.8	5.5(8.3)	5.4	0.6(5.3)	3.2
Canada	193	-1.9(15.8)	3.7	-2.2(5.3)	2.0	3.7(15.2)	2.5	2.4(5.9)	1.8
Snow cover days (d)									
IERA				IERA_TP		IERA		IERA_TP	
Region	N	Mean error	MAE	Mean error	MAE	Mean error	MAE	Mean error	MAE
MW	68	13(44)	27	9(17)	12	42(44)	33	16(20)	15
PR	45	19(15)	18	13(12)	13	11(14)	12	4(11)	7
CC	45	17(14)	17	10(12)	11	2(14)	8	8(11)	8
NC	14	5(25)	15	19(15)	17	16(26)	14	4(17)	13
Canada	193	3(34)	19	11(15)	12	22(36)	14	9(17)	10

Table 4.3 Summary of mean annual snow depth error (ME) and mean snow cover days error (ME), and the median absolute error (MAE) between the observed and modeled (driven by both IERA and IERA_TP) annual snow depth and snow cover days during the period from 1989 to 2005 in different regions and across Canada.

4.6.4 Factors influencing snow model bias

Across the country, the MAE (median absolute error) is smaller in ORC-N than ORC-O when the snow models are driven by both IERA and IERA_TP (Table 4.3). Both ORC-O and ORC-N have a negative and positive mean annual snow depth error respectively, which could be expected since the ORC-O often underestimate snow albedo and thus snow depth. In CC region, we found that the ORC-N had a degraded performance than ORC-O when IERA_TP is used.

Across Canada, our results indicate that both models overall perform better in capturing spatial and temporal patterns of snow given IERA_TP forcing compared to IERA forcing (e.g. Table 4.3).

Snow model evaluation at SNOWMIP sites and regional snow observations from Canada

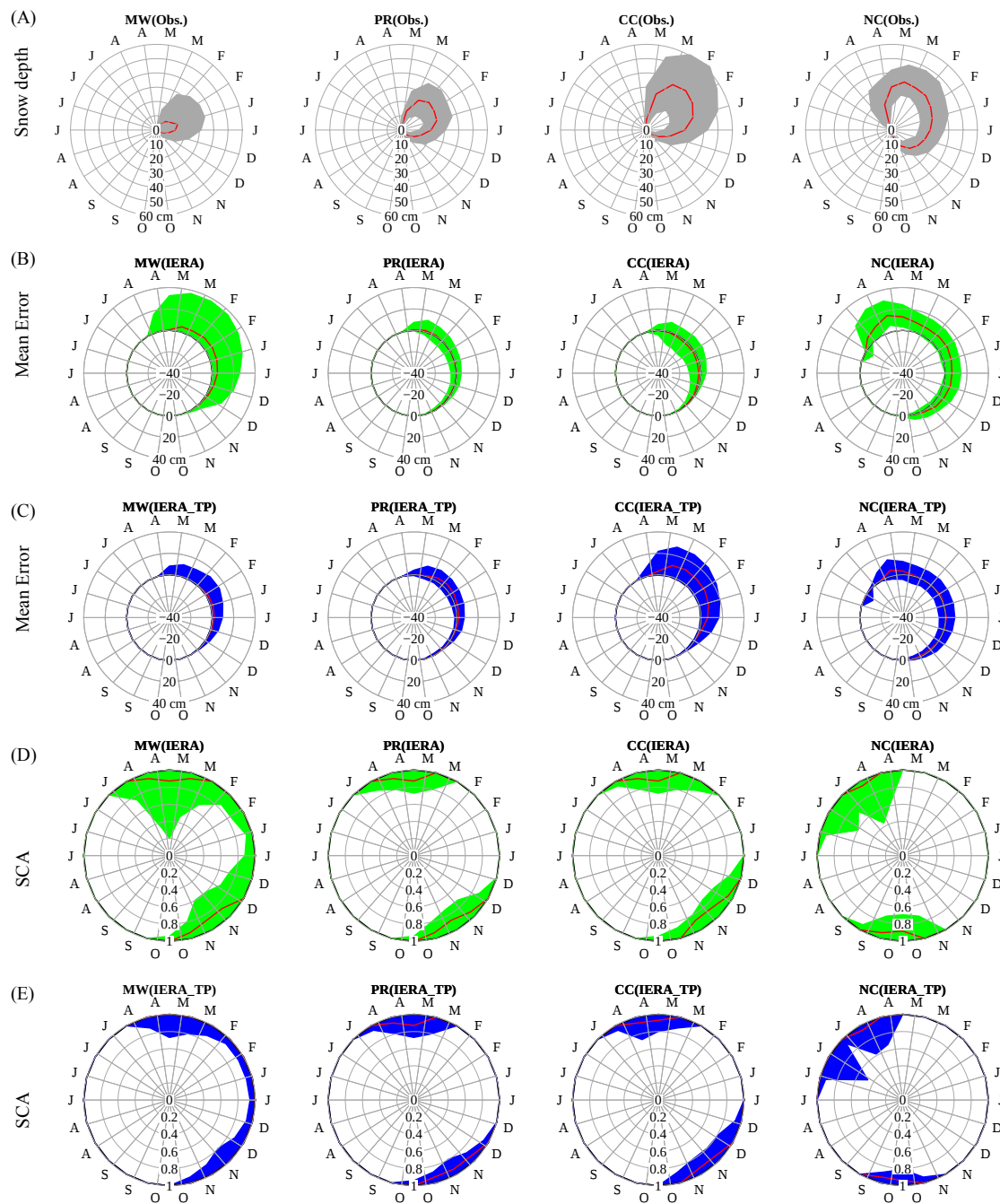


Figure 4.10 Mean (1989-2005) half-monthly observed snow depth (cm) (A), mean half-monthly snow depth error (ME) (cm) for IERA (B) and IERA_TP (C), and mean snow cover accuracy for IERA (D) and IERA_TP (E) in different regions. The data is shown in polar plots, where a full circle corresponds to 1 year. The shaded area is enveloped by the 25th and 75th of the data, and the red line denotes the median value. The snow model used here is ORC-N.

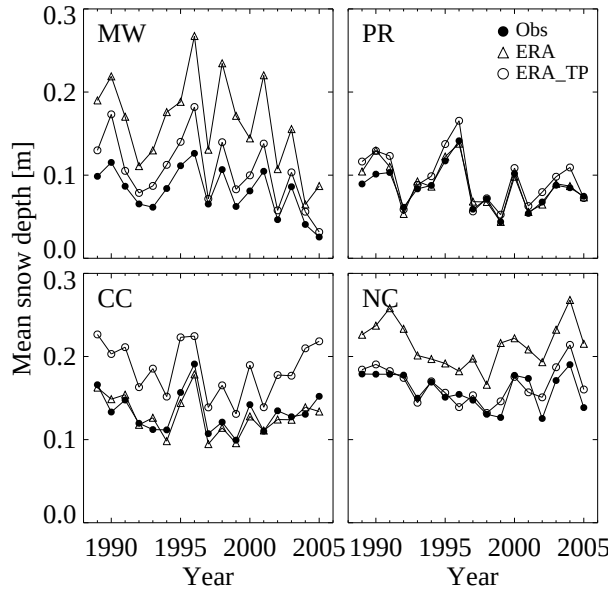


Figure 4.11 Interannual variability of annual mean snow depth from observation and modeled values from IERA and IERA_TP simulations using ORC-N in four different regions.

Such improvement brought by correcting IERA-derived precipitation and temperature forcing with local observations was also documented in other studies (e.g. Pan et al., 2003). To determine which factor (temperature or precipitation) contributes mostly to this improved snow simulation, we performed correlation analysis of annual snow depth ME between IERA_TP, IERA_P_NP and IERA_T_NP using ORC-N. Across all Canada sites, we found that annual snow depth ME in IERA_TP simulations has a higher correlation with the one in IERA_P_NP ($R^2 = 0.77$, $p < 0.01$) than in IERA_T_NP ($R^2 = 0.30$, $p < 0.01$). This is also found in different regions and different snow characters (e.g. seasonal snow depth ME and seasonal SCD ME) (data not shown). It suggested that the extent to which the results from IERA driven simulations match observed data is strongly related to the initial accuracy of the IERA snowfall. This can be evidently reflected in MW region, which often showed a degraded model performance in IERA simulation in both above-mentioned spatial and temporal analysis.

However, it must be noted that the bias of air temperature in IERA can be translated to an ill-estimation of snowfall amount if using precipitation partitioning scheme (IERA_P_P). For example, annual snow depth ME from IERA_TP was found to be less correlated with annual snow depth ME from IERA_P_P (using precipitation partitioning) ($R^2 = 0.25$, $p < 0.01$) than the one from IERA_P_NP (not using precipitation partitioning) ($R^2 = 0.77$, $p < 0.01$) across all Canada sites. This highlighted that even the total precipitation can be well represented in

the forcing data (IERA_P_P), the bias in air temperature can make the partition between snowfall and rainfall incorrect (e.g. Pan et al., 2003).

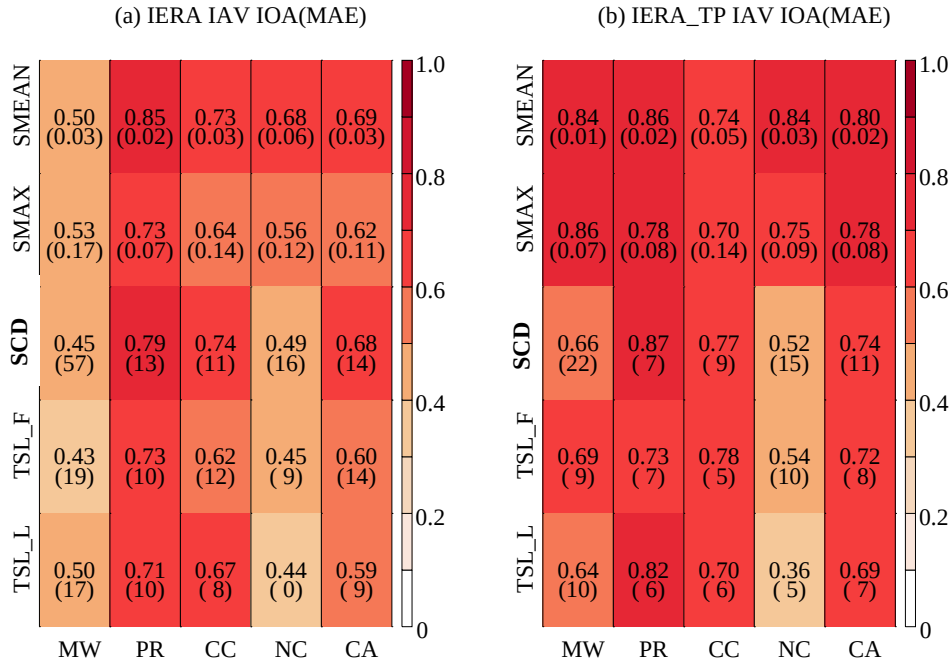


Figure 4.12 Index of agreement (IOA) between interannual observed and ORC-N simulated (IERA and IERA_TP) snow characters (SMEAN, SMAX, SCD, TSL_F and TSL_L) during the period from 1989 to 2005 in four different regions and across Canada. The units of IOA are dimensionless and their values are displayed on each grid box using the color scale. The median absolute error (MAE) for each snow character is also shown in the parenthesis, and the units of MAE for SMEAN and SMAX are the meter, and the units of MAE for SCD, TSL_F and TSL_L are days.

Besides temperature and precipitation, other climate variables can also play a significant role in snow simulation. This bias can be introduced by the incomplete substitution of climate variables (only temperature and precipitation) with local observations in IERA. To get a hint on this side, we created two subsets: one (Case 1) includes the station years where absolute annual mean temperature difference between IERA-derived and local observation is within 0.1°C and absolute annual total snowfall difference is less than 5% of the observed snowfall amount; the other (Case 2) pools the station years where absolute annual mean temperature difference is larger than 4°C and absolute annual total snowfall difference is larger than 50% of the observed snowfall. The results indicated that in IERA_TP simulation, the model has larger annual snow depth ME (6 ± 8 , $N = 91$) (cm) in Case 2 than in Case 1 (0.9 ± 5 , $N = 35$), which is also found in IERA simulation (Case1: -0.5 ± 4 , $N = 35$; Case 2: 32 ± 29 , $N = 91$). This might be related to the possibility that as IERA-obs. difference in precipitation and

temperature become large, other co-varied climate variables (e.g. incoming shortwave and long wave radiation) in IERA dataset also possibly deviate from their respective observed values, and snow simulation error related to this deviation can thus be introduced if still keeping these variables untouched in the forcing data. It is also worthwhile to mention that in Case 2, the annual snow depth ME from IERA_TP is much smaller than the annual snow depth ME from IERA, suggesting that correcting temperature and precipitation fields in IERA can make significant improvements in snow simulation.

In addition, the snow error in both IERA and IERA_TP forced simulations can also be related to the following factors. Firstly, since detailed site information (e.g. initial snow albedo, roughness length) related to snow state are lacking, causing the errors by applying the same parameterization without distinction among the stations across Canada. Secondly, snow depth instead of snow water equivalent is employed for model evaluation, and the additional bias can be brought by inaccurate estimation of snow density. This could possibly occur since the compaction constants used for snow density parameterization in the model are held constant for all stations. Thirdly, the errors in the input meteorological forcing data, can also make a contribution.

4.7 Conclusions

In conclusion, the evaluation a new three-layer snow model (ORC-N) showed a significant improvement over simple bucket snow model (ORC-O) both at SNOWMIP sites and Canada meteorological stations. The lower performances of ORC-O are mainly attributed to its underestimation of snow albedo. Replacing snow albedo scheme with the one from ISBA-ES could thus significant improve the snow simulations. However, the seasonal variation of snow depth still could not be captured by ORC-O with modified snow albedo scheme, which justifies the necessity of including snowpack physics processes as in ORC-N. In addition, under-canopy snow simulations are still not well captured even if new forest albedo parameterization takes into account leaf area index, and the result suggested that multi-layer energy budget need to be incorporated into ORCHIDEE in the future for resolving under-canopy snow processes. At Canadian meteorological stations, ORC-N showed the ability in capturing the spatial and temporal patterns of snow depth, and the correction of ERA-Interim precipitation and temperature using the local observed ones, could improve the snow simulations. Compared to ORC-N, ORC-O has a relatively larger median absolute error on this dataset. In addition, ORC-N was demonstrated to have an advantageous performance over ORC-O, and at the same time the improvement of ORC-N over ORC-O could be detected using IERA without precipitation and temperature correction by local observation. This demonstrates that ERA-Interim could be used as boundary conditions for large-scale snow simulations. In the future studies, the ORC-N can be further coupled with a frozen soil scheme (Gouttevin et al., 2011) to improve the integrated water resources management in cold and high elevated river basins.

5. High temperature frequency impacts on snow simulations and snow model evaluation over Northern Hemisphere

5.1 Introduction

Before proceeding with the comparison between observations and snow model outputs, it is necessary to understand potential impacts of meteorological forcing datasets with different frequencies on snow simulations. This is considered given the fact that compared to high frequency forcing data (e.g. sub-daily), the lower frequency (e.g. daily and monthly) data is often more preferred for snow model simulations due to its wide availability. For example, the temperature index models or degree-day models, which assume an empirical relationship between air temperatures and melting rates and is the most common approach for modeling snow melt, often calculate the *degree-day factor* by relating the amount of snow melt during a period of n daily time intervals to the sum of positive air temperatures of each daily time interval during the same period. It is well known that temperature effects on the snow cover could be reflected through two main mechanisms: changes in the percentage of precipitation falling as rain or snow (mainly occurring during the accumulation phase of the snow season) and melting events (mainly occurring in the decreasing snowpack phase). If sub-daily temperature variability is not accounted for, the snow simulations can be biased when the diurnal temperatures vary across the freezing point of water in both accumulation and melting phases of the snow season. One could also expect that different diurnal variation around the same mean daily temperature value can also exert different influences on snow melt through different exposure to above-freezing temperatures (Figure 5.1). Future climate change will likely affect not only the mean temperature but also the diurnal amplitude (Meehl et al., 2000). For example, Easterling et al. (1997) reported that the diurnal temperature range (DTR) in the boreal winter season has undergone a strong reduction during the period from 1950 to 1993. The simultaneous change in both mean temperature and daily amplitude can potentially dampen or amplify the effects on snowmelt of changes in mean temperature alone. A quantitative analysis of sub-daily temperature variability on the snowpack seasonal dynamics is not yet explored.

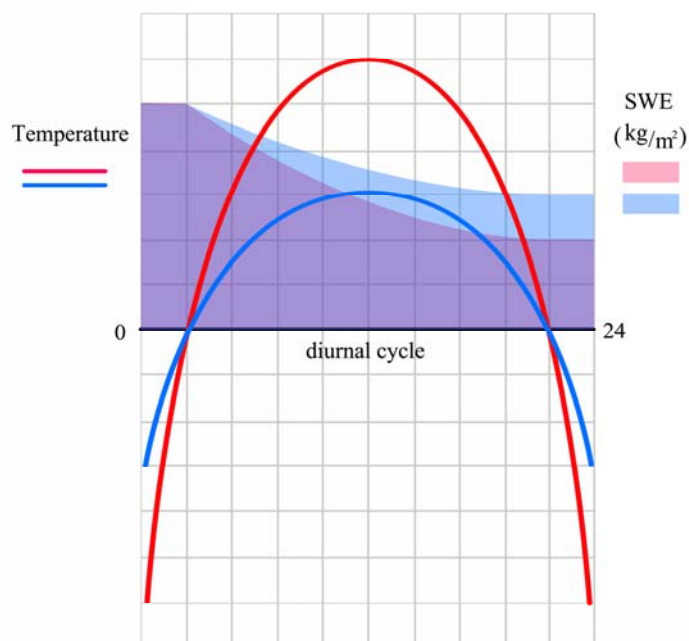


Figure 5.1 A scheme graph showing impacts of different shapes of sub-daily temperature variability on SWE simulations.

Accurate meteorological driving data is pivotal to model evaluation (e.g. Pan et al., 2003; Parajka et al., 2010), and bias in the forcing data could result in biased model evaluation. In Chapter 4, the analysis showed that the ORC-N model could more closely reproduce seasonal snow evolution than ORC-O across Canadian sites if the model is driven by in-situ temperature, precipitation, and vegetation characteristics. A better performance of ORC-N over ORC-O was also found when the model is driven by IERA (ERA-Interim, Dee et al., 2011) forcing at Canadian sites. This might suggest that IERA forcing data is adequate for snow simulation on the continental scale. Besides this, IERA datasets have been shown to agree well with Climate Research Unit and Hadley Centre analyses of monthly station temperature data (CRUTEM3) and synoptic humidity observations (HadCRUH) for both temperature and humidity variations for periods and places of overlap (Simmons et al., 2010). Precipitation in IERA also agree best with the new gauge-based Global Precipitation Climatology Centre (GPCC) and the latest combined gauge and satellite products of the Global Precipitation Climatology Project (GPCP) datasets, with IERA being significantly better than ERA-40 at capturing monthly rainfall variability (Simmons et al., 2010). IERA forcing data is thus used below to drive the off-line ORCHIDEE model and the model outputs are compared with two currently reliable estimates of large scale snow products. This section concentrates on the evaluation of modeled snow water equivalent (SWE). Snow water equivalent is defined as the amount of water that would be obtained if a column of the snow

pack was completely melted, which quantifies the amount of frozen moisture storage and determines the amount of spring melt and subsequent flooding.

It is well established that snow cover has a significant positive feedback on the temperature (e.g. Groisman et al., 1994a,b; Qu and Hall, 2006), and the strength of this feedback is expected to vary significantly for future climate scenarios (e.g. Cess et al., 1991; Randall et al., 1994; Holland and Bitz, 2003). Empirically describing the temperature sensitivity of snow cover days could hence be used to assess regional snow feedbacks. In the final section, model evaluation is also carried out based on the model's ability in depicting the temperature sensitivity of snow cover days (SCDs). The main objective of this chapter is to 1) quantify the effects of diurnal temperature amplitude (DTR) on modeled SWE and SCDs; 2) evaluate modeled SWE against two best available SWE products; 3) describe the temperature sensitivity of SCDs using two snow products, which is then used to evaluate the modeled temperature sensitivities.

5.2. Datasets

5.2.1 GooseBay (GSB) site

A full description of the data can be found in Brown et al. (2006), and a brief summary will be given here. The hourly meteorological data (air temperature, humidity, wind speed and incoming shortwave radiation) from 1969 to 1984 is observed at the Goose Bay airport (53°32'N, 60°42'W, grassland site). Downward longwave radiation was not available from the observed data and, following the approach of previous studies (Idso, 1981), was determined using the observed air temperature, relative humidity, cloud cover and opacity. Hourly precipitation data is derived from the observed 6-hourly precipitation totals corrected for wind-induced undercatch, wetting loss and trace precipitation amounts. Hourly precipitation intensity and phase were derived using a weighting scheme based on synoptic reports of precipitation type and intensity (Brown et al., 2006). The manual measurements of daily snow depth (SD) were made at the grassland of GSB airport and bi-weekly snow course measurements (SD and SWE)) were made in a sparse wooded area near the site. The snow course measurements at this forested site are not used for model validation given they might be affected by snow canopy processes. A typical annual maximum snow depth value ranges from 0.9 to 2.1 m, and January temperature average about -18°C but can drop as low as -23 °C. Snowfall typically begins in late October or November, and the snow pack can persist until the end of May. The site is relatively windy and potential blowing snow conditions are encountered around 10% of the period from December to April (Li and Pomeroy, 1997). The data have been used in previous snow model evaluations by Brown et al. (2006) and Bélair et al. (2003).

5.2.2 Canadian Meteorological Centre (CMC) daily snow depth (SD) analysis data

Northern Hemisphere daily SD data is a product from the Canadian Meteorological Centre (CMC) (Brown et al., 2010). This dataset combines surface synoptic observations, meteorological aviation reports, and special aviation reports acquired from the World Meteorological Organization (WMO) information system. This CMC dataset includes daily SD observations from 1998 through 2010. Monthly averages and monthly climatologies of SD and estimated SWE are provided. SWE for the October through June period of each year is estimated from monthly SD using a look-up table (see Table 3 in http://nsidc.org/data/docs/daac/nsidc0447_CMC_snow_depth) of monthly snow density values. The density values are from Canadian snow course observations established for various snow-climate classes (Sturm et al. 1995), and these Canadian density observations are extrapolated to snow-climate classes in all other regions of the Northern Hemisphere. The July through September time period is not processed by CMC due to a lack of observed snow density information during the time period.

A complete description of the analysis methodology and validation can be found in Brasnett (1999). The CMC snow depth data is based solely on in-situ daily SD observations, with spatial and temporal continuity provided through the temperature and precipitation fields generated by the CMC global NWP (NCEP's mesoscale numerical weather prediction) model. The CMC SD product is obtained from the following steps:

- Uses snow depth observations from all synoptic reports, metars (meteorological aviation reports) and sa's (special aviation reports).
- Analysis is updated every 6 hours using the optimum interpolation method. The effect of elevation is included in the interpolation.
- Precipitation forecasts (6 hours) from the CMC global model are used to estimate the new snowfall between analysis times. The precipitation is assumed to be snow if the analyzed screen-level temperature is less than 0°C.
- A melting algorithm removes mass from the snowpack at the rate of 0.15 mm SWE per hour per Kelvin for air temperatures above freezing.
- The analysis includes an estimate of the density of the snowpack. The density of new snow is assumed to be 100 kg m⁻³ and the snowpack gradually increases in density as it ages. The increase in density with aging stops when the density reaches 300 kg m⁻³ (210 kg m⁻³ for needleleaf forest as the canopy shelters the snowpack from wind and sunlight and snow densities are lower). Recent snow causes the density to decrease by an amount related to the mass of the new snow and the mass of the existing snowpack. During melting, the density is allowed to increase up to a maximum of 550 kg m⁻³.

- In regions where there are no observations of SD, the SD values shown in the analysis corresponds to the accumulated precipitation from the precipitation forecasts consistent with the assumptions about density from the previous paragraph.
- The analysis has a resolution of $1/3^\circ$. The error correlations used by the analysis have an e-folding distance of about 120 km horizontally and 800 m vertically.
- The scheme makes use of an analysis of screen-level temperature produced with vertical correlations taken into account.

Over most of the Arctic region there are only very few observations, so the analysis is based on estimated SD from the first guess field. In addition, SD observations over northern Canada tend to be biased to coastal locations with observing sites at open areas near airports. The snow at these sites tends to be shallower and to melt out earlier than snow in surrounding terrain. The gridded CMC SWE during the period 1979-1996, which is developed in the same way as described above, is regarded as the currently best available estimates of large-scale SWE over North America (NA), and the authors (Brown et al., 2003) have the greatest confidence in the product in ‘data rich’ areas of NA with relatively small orographic effects, mainly located east of the Rocky mountains south of 55°N . The CMC SWE dataset in North America has been widely used to evaluate Global Circulation Model (GCM) snow mass simulations in the Atmospheric Model Intercomparison Project II (AMIP II) (Frei et al., 2005), to validate the different algorithms for obtaining the GlobSnow SWE data (Sect. 5.2.3, Luoju et al., 2010) and improve the snow cover fraction in global climate models (Niu and Yang, 2007).

5.2.3 Global snow SWE products (version 1.0)

The version 1.0 (v1.0) of GlobSnow SWE product for the Northern Hemisphere, provided by European Space Agency (ESA) Data User Element (DUE), is derived from a combination of ground based data and satellite microwave radiometer-based measurements (SMMR, SSM/I and AMSR-E sensors) from 1979 until present (see details in Luoju et al., 2010). The SWE production system v1.0 utilizes SWE retrieval methodology (Pulliainen, 2006) complemented with a time-series melt-detection algorithm (Takala et al. 2009). The two algorithms are combined to produce SWE maps incorporated with information on the extent of snow cover on coarse resolution (25 x 25 km grid cells). The SWE estimates are complemented with uncertainty information on a grid cell level. The GlobSnow SWE processing system uses passive microwave observations and weather station observations collected by ECMWF in an assimilation scheme to produce maps of SWE estimates (in EASE-Grid format) over the northern hemisphere, covering all land surface areas with the exception of mountainous regions and Greenland. A semi-empirical snow emission model (Pulliainen et al., 1999) is used for interpreting the passive microwave (radiometer) observations through model inversion to the corresponding SWE estimates. The basis of the SWE processing system can be found in Pulliainen (2006). As applied for GlobSnow,

estimates of SD based on the inversion of a two frequencies (18.7 and 36.5 GHz) emission model, are first calibrated over EASE grid cells with weather station measurements of SD available. Snow grain size is used in the model as a scaling model input parameter (being determined from the input radiometer and weather station data). These values of grain size are used to construct a kriging interpolated background map of the effective grain size, including an estimate of the effective grain size error. The map is then used as input in the model inversion over the span of available radiometer observations, providing an estimate of SD. In the inversion process, the effective grain size in each grid cell is weighed with its respective error estimate. A snow density value is applied to each grid cell to connect depth to SWE. The SWE estimate map and SD map from weather station observations are combined using a Bayesian spatial assimilation approach to provide the final SWE estimates. There are three products derived for SWE: daily, weekly and monthly (Luo et al., 2010). In this study, we only used monthly SWE dataset and its error estimation for model evaluation.

Preliminary validation of GlobSnow SWE has been conducted across the sites, which are mainly distributed in Northern Eurasia, ground truth data in Finland and Central Canada. The CMC gridded SWE is also used as an independent evaluation dataset. The complete algorithm evaluation, including an overview of the algorithms, reference datasets, and the results are presented in the GlobSnow design justification file (Solberg et al., 2009). The results for Eurasia showed that GlobSnow has a tendency to systematically underestimate SWE under deep snow conditions due to a change in the microwave behavior of the snowpack.

5.3. Methodology

5.3.1 ORCHIDEE simulation protocols

The climate forcing data (air temperature, precipitation, surface pressure, specific humidity, wind speed, incoming shortwave radiation, longwave and shortwave radiations) on six-hourly time step with a spatial resolution of 0.7 degree from IERA is provided as the boundary condition for the ORCHIDEE land surface model (two versions being used, ORC-O: default ORCHIDEE version and ORC-N: new version with improved snow parameterization) to simulate snow in the Northern Hemisphere north of 40 N. Precipitation is partitioned into snowfall and rainfall using a 0°C surface air temperature threshold. Note that a bias is introduced into the snow simulations using this simple threshold value. In some snow models, a linear function is fitted over a certain temperature range (e.g. Community Atmospheric Model Version 3.0, Collins et al., 2006) between fraction of precipitation falling as snow and the near surface temperature. However, this can also introduce an error given the fact that the rain-snow phase near the surface depends upon additional factors, such as pressure, wind speed, particle size (Yuter et al., 2006, Dai, 2008).

The vegetation dynamics in ORCHIDEE is deactivated and the fraction cover of each Plant function type (PFT) is prescribed based on vegetation map with 0.7 degree resolution,

which is produced from high resolution land-cover maps such as CORINE over Europe (Heymann et al., 1993) and UMD (University of Maryland, Hansen et al., 2000). In each grid cell, the site history and the initial values for vegetation carbon pools are not known precisely. To model these initial pool values, the first year of forcing data is used cyclically over 200 years until equilibrium of the vegetation carbon pools are attained. This is done given the fact that leaf area index (LAI) is used to parameterize the sky view factor in forest snow albedo formulations.

5.3.2 Sensitivity of snow simulations to the diurnal cycle of temperature

In order to understand impacts of diurnal temperature range (DTR) and mean air temperatures on snow simulations, meteorological forcing datasets only differing by their DTR or mean daily temperature are generated from the GSWP-2 (The Second Global Soil Wetness Project) dataset. Before presenting these two ensembles, GSWP-2 is briefly described.

GSWP-2 makes corrections to the systematic biases in the fields of NCEP/DOE reanalysis (National Centers for Environmental Prediction/Department of Energy, Kanamitsu et al., 2002) of 1986-1995 by hybridization of the 3-hourly analysis with global observationally-based gridded data sets with a lower temporal resolution. This means that the atmospheric forcing data uses information from global gridded observational datasets when possible. In some cases, no adequate global observation data exist, so a pure model analysis product is used. In GSWP-2, the NCEP/DOE temperature is combined with the one in CRU (Climatic Research Unit). The monthly CRU temperatures are first corrected for the altitude difference between the CRU grid and the NCEP/DOE mean altitude derived from the GTOPO30 (Geographical Topography data at 30') data set (see details in Zhao and Dirmeyer, 2003). The monthly CRU data are then aggregated from 0.5° to 1°, and hybridized with the 3-hourly NCEP/DOE reanalyses 2-meter air temperature data by correcting the differences of monthly diurnal range and mean:

$$T_{GSWP2} = \delta(T_{NCEP} - \overline{T_{NCEP}}) + T_{CRU} \quad \text{Eq. (5.1)}$$

$$\delta = \frac{D_{CRU}}{D_{NCEP}} \quad \text{Eq. (5.2)}$$

Constrained so that: $0.5 < \delta < 2.0$, D is the monthly mean diurnal range (DTR) of the temperature, which is reported for the CRU data, and has been calculated from the original hourly data from the NCEP/DOE reanalysis. Limits are placed on the diurnal scaling factor δ to prevent unreasonable extreme temperatures (see details in Zhao and Dirmeyer, 2003).

The first ensemble uses temperature products IERA, CRU-NCEP/DOE and NCEP/DOE, adjusted to have the same daily temperature than IERA, but different DTR. The second ensemble uses the three temperature products adjusted to have the same daily DTR than IERA, but different daily temperatures. For each ensemble, the corrected temperatures combined with other meteorological fields from IERA (e.g. total precipitation, incoming shortwave

radiation and longwave radiation) are used to drive the ORCHIDEE snow model (two versions). The 0 °C temperature's threshold being used to partition total precipitation into snowfall and rainfall.

To describe the dispersion of model outputs using different meteorological datasets, the coefficient of variation (CV) of seasonal (spring and winter) SWE and SCDs for each pixel, which is defined as the ratio of standard deviation (Std) to the mean, is calculated as the following.

$$CV_s = \frac{Std(S_i)}{Mean(S_i)} (i = 1, \dots, 3) \quad \text{Eq. (5.3)}$$

Where S is the seasonal (spring and winter) SWE or SCDs from ORCHIDEE snow model. SCDs is the number of the snow cover days with at least 5 cm of snow depth. i represents different meteorological forcing dataset. The CV of DTR is also computed in the same way. The CV of mean seasonal temperature is not calculated. The temperature is on an interval scale, e.g. the coefficient of variation depends on temperature scales (Kelvin or Celsius scale). Furthermore, to quantify how DTR impacts snow simulations, the relative change of DTR and of simulated seasonal SWE and SCDs using both CRU-NCEP and NCEP forcings are calculated for each pixel. The relative change (Rel_V) of the investigated variable (V) from CRU-NCEP and NCEP is expressed as,

$$Rel_V = 2 \times \frac{V_{CRU-NCEP} - V_{NCEP}}{V_{CRU-NCEP} + V_{NCEP}} \quad \text{Eq. (5.4)}$$

Contour graph is used to visualize spatial pattern of the seasonal SWE (or SCDs), of CV in temperature-precipitation (T-P) domain and the spatial pattern of seasonal SWE (or SCDs) relative change for different DTR-P and DTR-T. The T-P domain spans across mean seasonal temperature between -45 and 6 °C and across mean daily total precipitation from 0.0 to 6.0 mm/day. The DTR-P domain spans across mean seasonal DTR from 0.4 to 2.0 and cross mean daily total precipitation from 0.0 to 6.0 mm/day, and the DTR-T domain has the same span of DTR with DTR-P and cross mean seasonal temperature between -45 and 6 °C. To generate 2D diagrams, the T-P, DTR-P and DTR-T domains are divided into 20 x 20 bins, and each bin in T-P has a 'climate resolution' of 2.5 °C and 0.4 mm/day, each bin in DTR-P has a resolution of 0.2 and 0.4 mm/day and DTR-T has a resolution of 0.2 and 2.5 °C. Geographic grid cells are then grouped into these bins according to their temperature, precipitation and DTR. Because the geographically defined (latitude-longitude) grid is not an equal-area projection, results from grid cells are weighted by the cosine of their latitude before they are summed and averaged in all of T-P, DTR-P and DTR-T domains.

5.3.3 Evaluation of modeled SWE

5.3.3.1 Spatially integrated SWE

Simulated SWE values integrated over 7 latitude bands (40-45°N, 45-50°N, 50-55°N, 55-60°N, 60-65°N, 65-70°N and >70°N) are compared to observed values. Both intra-annual and interannual variations in SWE are considered. Mean monthly (October to April) SWE values averaged from 1999 to 2009 is used to denote the intra-annual variation in SWE. For the interannual variation, seasonal (winter and spring) SWE anomalies from the 1999 to 2009 climatology are investigated. Both monthly mean SWE values and interannual anomalies in model and observations are area weighted and integrated over all grid cells designated as land whose centers lie in each latitude band. SWE is expressed volumetrically as km³ of liquid water.

5.3.3.2 Spatial variation in SWE

In order to visualize the regions where the ORC-N model SWE shows better agreement with observations, at each grid cell, the root mean square error (RMSE) is first calculated between modeled and observed seasonal (winter and spring) SWE from 1999 to 2009, and the error reduction between ORC-O and ORC-N is then computed as the following,

$$Red_{mod} = 2 \times \frac{RMSE_{ORC-O} - RMSE_{ORC-N}}{RMSE_{ORC-O} + RMSE_{ORC-N}} \quad \text{Eq. (5.5)}$$

Positive Red_{mod} values indicate that the SWE simulated by ORC-N is closer to observations than ORC-O. With regards to interannual variability of SWE, inter-quartile range (IQR) is used, which is equal to the difference between the 75% and 25% quartiles.

5.3.4 Temperature sensitivity of Snow Cover Days (SCDs)

SCDs can determine the influence of snow on the atmosphere through snow albedo feedbacks. In turn SCD is sensitive to air temperature at the start and end of the snow cover season, and less sensitive to snowfall. Up to now, the relationship between SCDs and temperature has been investigated in Alpine regions (e.g. Hantel et al., 2000; Hantel et al., 2007; Wielke et al., 2004) and Tibet plateau (Ma et al., 2010). To quantitatively analyze SCDs responses to air temperature, Hantel et al. (2000) defined n as the number of days with snow cover (5 cm is used in this study) normalized by the number of days within a month, and then describe the SCDs-temperature relationship using a hyperbolic tangent function (Figure 5.2, Eq. 5.6).

This function was chosen because it shows a large change n when T lies around zero, and n can only vary between 0 and 1. The sensitivity, s , expressed by $s = \partial n / \partial T$, is always negative, ranging from -1 and 0 (Fig. 5.2).

$$n = \frac{1}{2} \{ \tanh[2s_0(T - T_0)] + 1 \} \quad \text{Eq. (5.6)}$$

Hereinto, n and T are known, and s_0 and T_0 are the parameters to be fitted. s_0 represents the extreme temperature sensitivity (the minimum s_0 for $T = T_0$ corresponding to $n = 0.5$). T_0 is the critical temperature where the sensitivity approaches the extremum (s_0). Extreme sensitivity s_0 may not be a particularly useful parameter for the actual climate of a given station since its value is often extrapolated from the high-curvature part of the curve. Thus, by putting mean seasonal (or monthly in this study) temperature T in Eq. (5.7), the actual sensitivity s_T is thus introduced (s_T in absolute value terms is smaller or equal than s_0).

$$\frac{\partial n}{\partial T} = \frac{s_0}{\cosh^2[2s_0(T - T_0)]} \equiv s_T \quad \text{Eq. (5.7)}$$

The cost function defined in Eq. (5.8) is minimized to find the parameters s_0 and T_0 (see details in Hantel et al., 2000).

$$\sum_{i=1}^I h_i^2 \equiv J_e, J_e = J_e(s_0, T_0) \quad \text{Eq. (5.8)}$$

$$\frac{n_i - n^i}{\sigma_i} = f_i, f_i = f_i(s_0, T_0) \quad \text{Eq. (5.9)}$$

$$\frac{T_i - T^i}{\chi_i} = g_i, g_i = g_i(s_0, T_0) \quad \text{Eq. (5.10)}$$

$$(f_i^2 + g_i^2)^{1/2} = h_i, h_i = h_i(s_0, T_0) \quad \text{Eq. (5.11)}$$

where σ_i and χ_i are error levels for both n and T respectively, which we have to specify externally. For the variances (σ_i and χ_i) that specify the relative weights of the observations n_i, T_i in the cost function (Eq. 5.8) we postulate that they can be written as the product of two factors. The first (superscript a) represents the distribution error and the second (superscript b) the error scale,

$$\sigma_i = \sigma_i^a \cdot \sigma^b, \chi_i = \chi_i^a \cdot \chi^b \quad \text{Eq. (5.12)}$$

The first factor describes the distribution of the data error over the interval of the variable considered. For n and T this is from the considerations above

$$\sigma_i^a = \sigma_0 [4(1 - n_i)n_i]^{1/2}, \chi_i^a = \chi_0 \quad \text{Eq. (5.13)}$$

The constants of proportionality σ_0, χ_0 are to be chosen such that the mean weights for all n_i and all T_i are equal, i.e.

$$\sum_{i=1}^I \frac{1}{(\sigma_i^a)^2} = \frac{1}{2} \Rightarrow \sigma_0^2 = \frac{1}{2} \sum_{i=1}^I \frac{1}{(1 - n_i)n_i} \quad \text{Eq. (5.14)}$$

$$\sum_{i=1}^I \frac{1}{(\chi_i^a)^2} = \frac{1}{2} \Rightarrow \chi_0^2 = 2I \quad \text{Eq. (5.15)}$$

The second factor in products is taken as interannual variability of the observed data after removing the trend,

$$\sigma^b = v_n, \chi^b = v_T \quad \text{Eq. (5.16)}$$

The basic idea behind this method is that the interannual snow cover fluctuations could be interpreted as a substitute for long-term snow cover changes. Compared to nearly 40 and 60 years in Hantel et al. (2000) and Ma et al. (2010) studies, CMC snow product used to characterize the ‘observed’ temperature sensitivity of SCDs in spring (MAM) and winter (DJF) seasons can be available only from 1999 to 2009. This means that the interannual temperature and SCDs variability might not be sufficient enough for substituting their long-term fluctuations. Instead of using mean seasonal (spring or winter) temperature and SCDs each year (e.g. Hantel et al, 2000; Hantel et al., 2007; Wielke et al., 2004; Ma et al., 2010), monthly values in each spring or winter season from the year 1999 to 2009 are used here to describe seasonal (spring or winter) SCDs-temperature relationship. This is done considering the possibility that April and May temperatures (February and January) could be surrogates for the present and future temperature conditions during the peak of snow season.

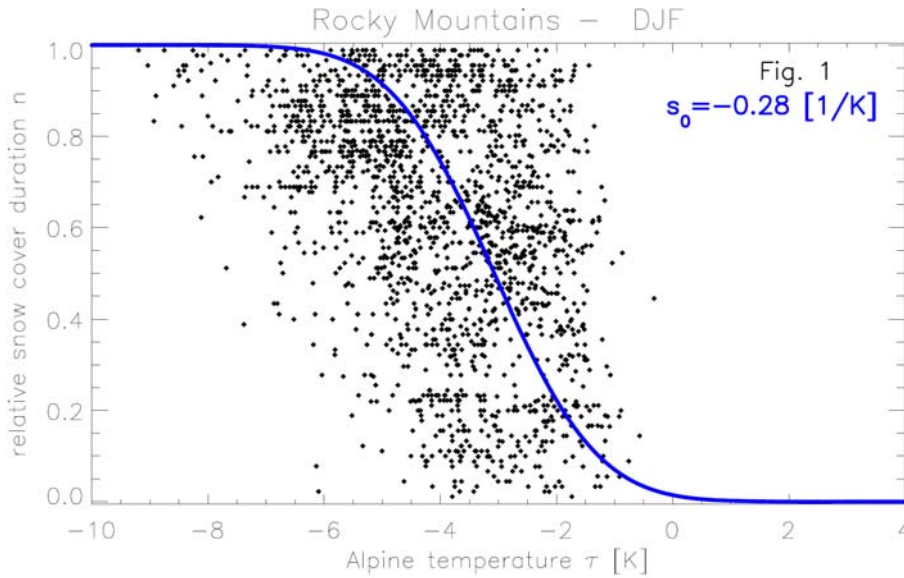


Figure 5.2 The graph showing the hyperbolic tangent curve fitted between relative snow cover duration (n) and temperature (from Wielke et al., 2004), s_0 is extreme temperature sensitivity.

5.4. Sub-daily variability impacts on snow simulations

5.4.1 Snow model results with vs. without sub-daily temperature variability

As shown in Figure 5.3a, the simulated SWE and SCDs by both ORC-O and ORC-N at Goose Bay are overestimated after removing sub-daily temperature variability. This overestimation is much more pronounced during the early spring than during the early/mid-winter season, which can be related to the fact that daily maximum air temperature in the early spring is generally higher and has a larger probability to be above freezing point than during early/mid-winter. Thus, using mean daily temperature forcing of snow models can lead to bias especially when sub-daily temperature fluctuates around the freezing point.

To further confirm the Goose Bay result, snow simulation based on ORC-N is performed over the NH north of 40 °N. The analysis shows that the modeled seasonal (spring and winter) SWE (Figure 5.3d and 5.3e) are always overestimated after removing sub-daily temperature variability if mean seasonal SWE above 5 cm is considered. This is also found in seasonal SCDs (Figure 5.3b and 5.3c). As expected, when the climate becomes warmer from winter (DJF) to spring (MAM), the overestimation of seasonal SWE and SCDs become larger (Figure 5.3b-e). The bias resulting from discarding sub-daily temperature variability is more evident in seasonal SWE than seasonal SCDs (Figure 5.3b-e). The same results are also obtained if ORC-O is used (data not shown).

5.4.2 Sensitivity analysis of sub-daily temperature variability

Section 5.4.1 suggests that inclusion of sub-daily temperature variability into snow model is necessary and more important for SWE than SCDs. A further sensitivity analysis of both SWE and SCDs to different DTR is conducted over the NH north of 40 °N using the ensemble of forcing with different DTR constructed in Section 5.3.2.

In the first ensemble simulation (3 forcing datasets with same mean daily temperature but different DTR), the pattern of CV in SWE is coherent with the one of DTR (Figure 5.4a-b and d-e), and the Pearson correlation (r) between CVs of DTR and SWE in both spring and winter season are 0.30 ($p < 0.01$) and 0.40 ($p < 0.01$) respectively. The CV of SCDs (Figure 5.4c and f) is much smaller than that of SWE (Figure 5.4b and e) and is mainly located in the warmer regions with mean seasonal temperature around zero. In other words, SWE is more sensitive to temperature variability than SCDs, and both SWE and SCDs are more sensitive in the region where temperature is close to freezing point. In order to have a visualization of the effect of DTR on the change in SWE and SCDs, the CRU-NCEP/DOE and NCEP/DOE with same daily temperature but different DTR are chosen.

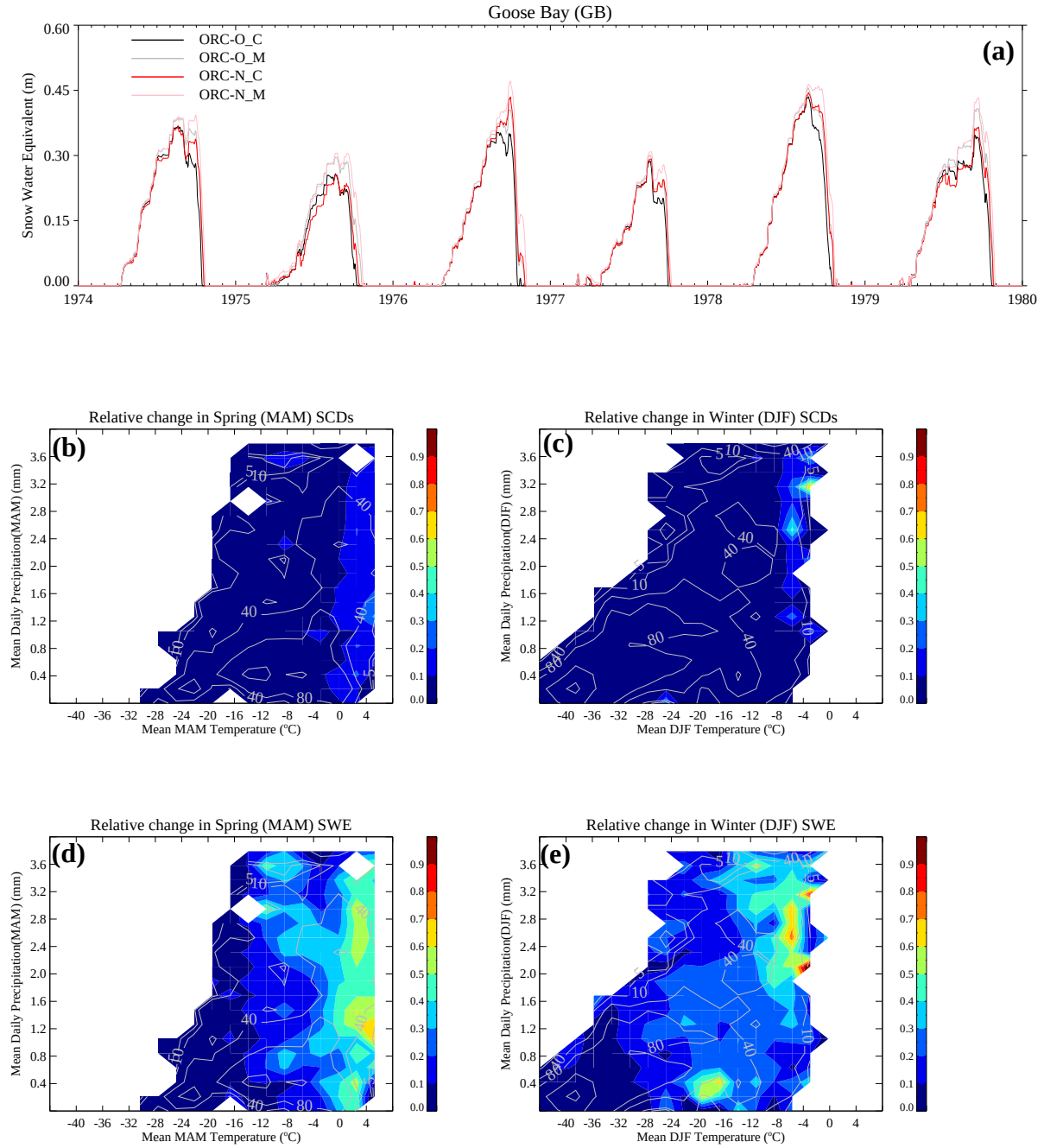


Figure 5.3 (a) The comparison between modeled SWE driven by the meteorological data with (ORC-O_M and ORC-N_M) and without (ORC-O_C and ORC-N_C) sub-daily temperature variability at Goose Bay site during the period 1974-1980. The mean relative change averaged from 1989 to 1995 in (b) spring SCDs, (c) winter SCDs, (d) spring SWE and (e) winter SWE between two modeled values driven by different meteorological forcing datasets (with and without sub-daily temperature variability) in the NH north of 40°N. The relative change is calculated by dividing two modeled values difference (modeled value without temperature variability - modeled value with temperature variability) by their mean values.

Figure 5.5 showed that in both DTR-T and DTR-P domain, positive (negative) relative DTR change is often associated with negative (positive) relative SWE changes in both spring and winter season. This could be explained by the fact that the larger DTR is often associated with the higher exposure of daytime temperature above freezing point, which contributes to the snow melting. As expected, the pattern is not the same in the seasonal SCDs. This analysis implies that the DTR forcing of snow models has a non-negligible effect on the water stored in the seasonal snow pack that would impact the hydrologic budget through spring runoff. However, it should be noted that DTR impacts on snow would break down if daytime air temperature can totally remove the snow on the ground.

The same patterns of the CVs of SWE and SCDs in T-P domain are also found in the second ensemble of forcing (3 forcing datasets with same DTR but different mean daily temperature) (data not shown). As shown in Figure 5.6, impacts of DTR and mean temperature on SWE and SCDs are comparable in both spring and winter season, which was reflected by comparing the frequency distributions of CVs of SWE and SCDs between two different ensemble simulations. The result further emphasized that besides correction of mean daily temperature bias, correctly describing DTR or sub-daily variability in the meteorological forcing dataset used for driving off-line snow models especially for the purpose of hydrologic modeling is also very important. However, cautions should be taken when interpreting the above-mentioned analyses. The snow state (melting or freezing) is more dependent on the hourly or even higher time resolution temperatures than DTR, which could only be an approximate surrogate of sub-daily temperature variability. The number of hours (or even higher time resolution) in a day rising above the freezing point should be a more precise index than DTR in describing sub-daily temperature variability impacts on the snow simulations. The DTR is considered due to its wide availability at most of the meteorological stations on the global scale.

5.5 Evaluation of modeled SWE

5.5.1 Spatially integrated results

The seasonal cycles of monthly mean SWE (1999-2009) over North America (NA) and Eurasia (EA) at different latitudes (40-45°N, 45-50°N, 50-55°N, 55-60°N, 60-65°N, 65-70°N and >70°N) are shown in Figure 5.7. Observation based datasets (GlobSnow and CMC) indicate SWE variations from a minimum value in the early winter (Oct and Nov) to a maximum in Feb or March. Both models (ORC-O and ORC-N) capture this timing of the seasonal cycle well. The difference between the two model versions is smaller during the snow accumulation period than the snow melting period, and decreases with increasing latitude, the date occurring prominent model divergence extends into the late winter or early spring season. The satellite-based GlobSnow SWE using FMI algorithm (Pulliainen, 2006) and CMC SWE based on a snow depth analysis scheme developed by Brasnett (1999) are two independent snow products.

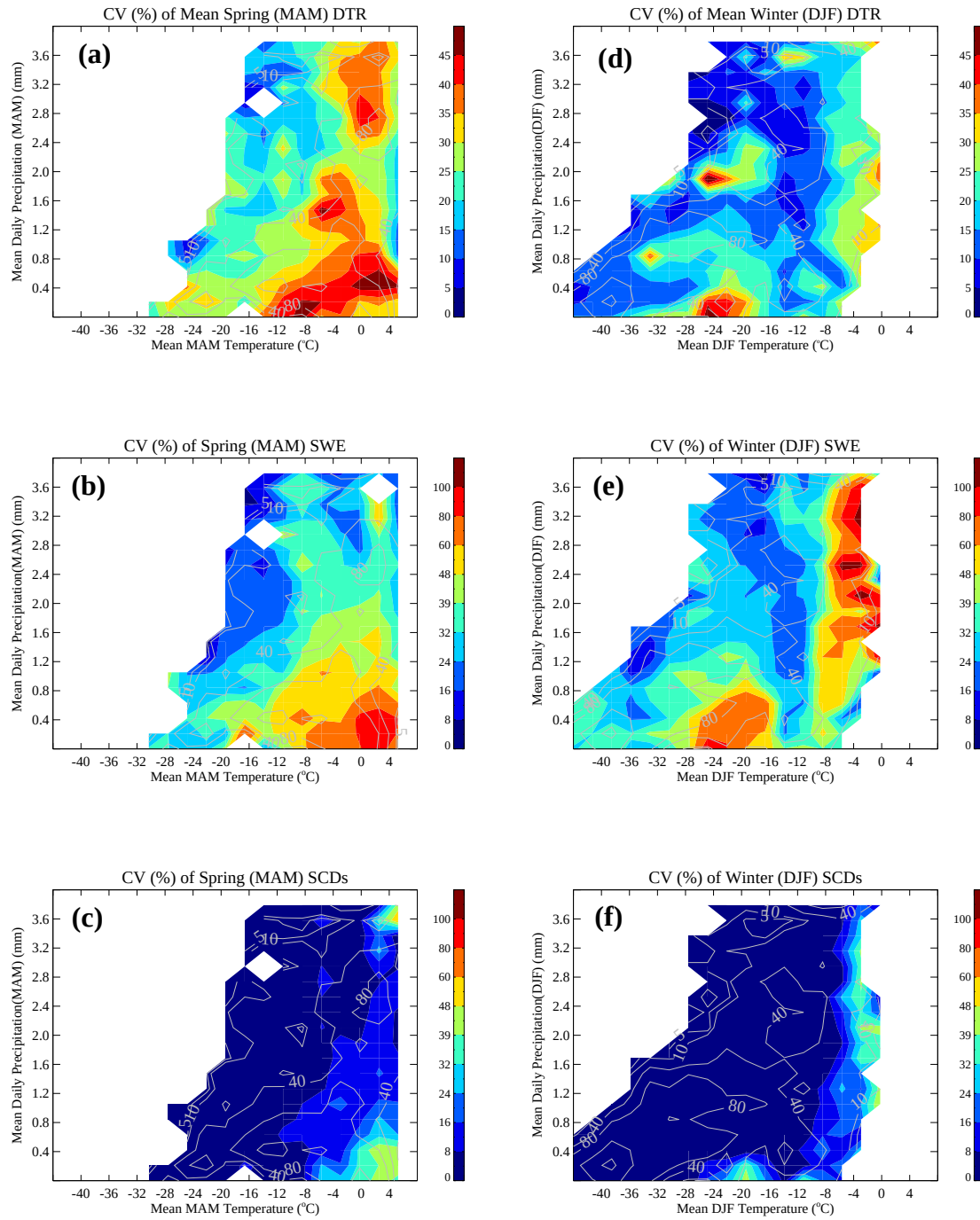


Figure 5.4 The mean CVs of DTR (a: spring and d: winter), simulated SWE (b: spring and e: winter) and SCDs (c: spring and f: winter) averaged from 1989 to 1995 across three different meteorological datasets (with the same mean daily temperature but different DTR) in Temperature-Precipitation (T-P) domain. The T-P domain is divided into 20 x 20 bins, and each bin in T-P has a ‘climate resolution’ of 2.5 °C and 0.4 mm/day.

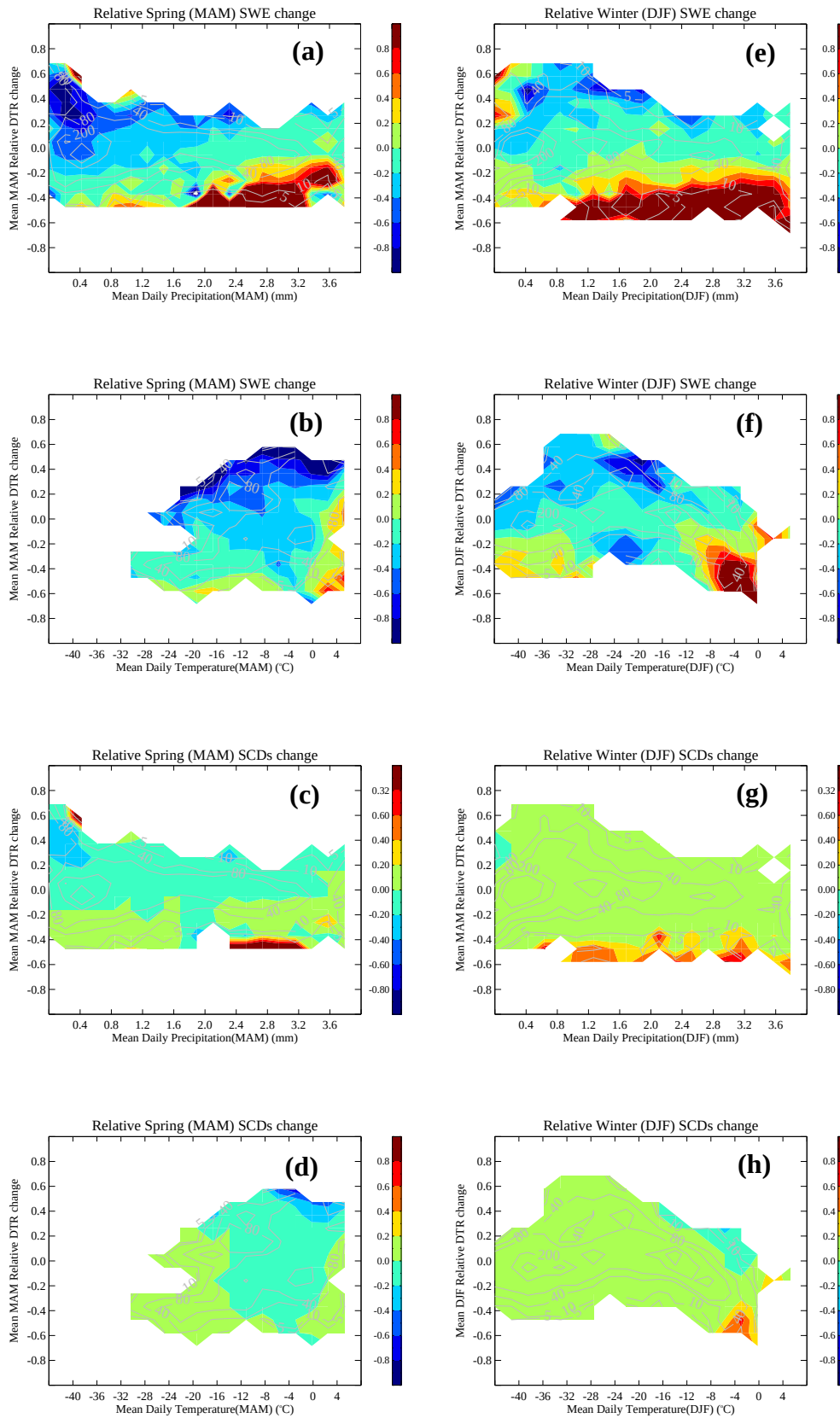


Figure 5.5 The mean relative change in spring SWE (a and b), spring SCDs (c and d), winter SWE (e and f) and winter SCDs (g and h) in both DTR-P and DTR-T domains. The mean relative change of

these variables averaged from 1989 to 1995 is calculated between two modeled values driven by different meteorological forcing datasets (CRU-NCEP/DOE and NCEP/DOE) in the NH north of 40 °N.

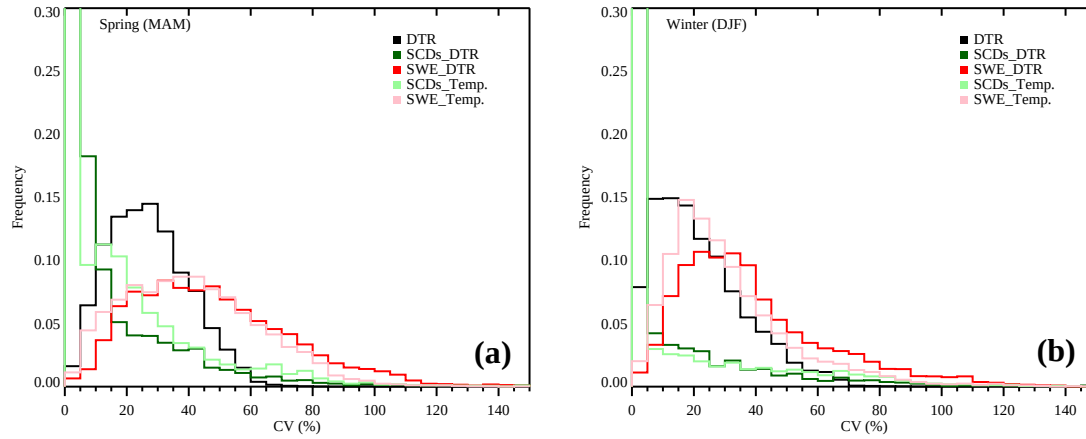


Figure 5.6 The frequency distributions of CVs of spring (a) and winter (b) SWE and SCDs in two ensemble simulations. SWE_Temp and SCDs_Temp are simulated CVs of SWE and SCD across three meteorological datasets with the same DTR but different daily temperature, SWE_DTR and SCDs_DTR are simulated CVs of SWE and SCDs across three meteorological datasets with the same daily temperature but different DTR.

Both datasets were evaluated against in-situ data (Brown et al., 2003; Luoju et al., 2010), and CMC has been regarded as the currently most realistic product over North America (e.g. Niu and Yang, 2007). As shown in Figure 5.7, ORC-N performs better than ORC-O in capturing the seasonal cycle of observed SWE (in km³) at lower latitudes (<65°N) in NA and EA, which are characterized by lower RMSE and higher IOA. However, the improvements are less obvious in the higher latitudes (>65°N). One of the possibilities is that observed SWE could be less accurate in the more northern regions, for example, the monthly averages of CMC SWE in NA are considered most reliable south of about 55°N where the snow depth observing network is relatively dense. However in the data sparse areas, CMC SWE were estimated from an empirically based snowpack model driven with temperature and precipitation fields from CMC Global Environment Multiscale (GEM) model. In addition, a summary of validation results relative to in-situ measurements in Canada showed that GlobSnow SWE exhibits worse performances in tundra (*RMSE*: 50 mm) and northern boreal regions (*RMSE*: 77 mm) than in southern regions (*RMSE*: 24-32 mm) (Luoju et al., 2010).

To examine the model's ability to reproduce interannual anomalies in seasonal SWE, Figure 5.8 summarized the RMSE and IOA calculated between modeled (ORC-O and ORC-N) and observed SWE (CMC and GlobSnow) in Spring (MAM) and Winter (DJF). As shown in Figure 5.8, in general, again not surprisingly, ORC-N performs better than ORC-O in the spring and winter season at lower latitudes (< 55 °N) in both EA and NA.

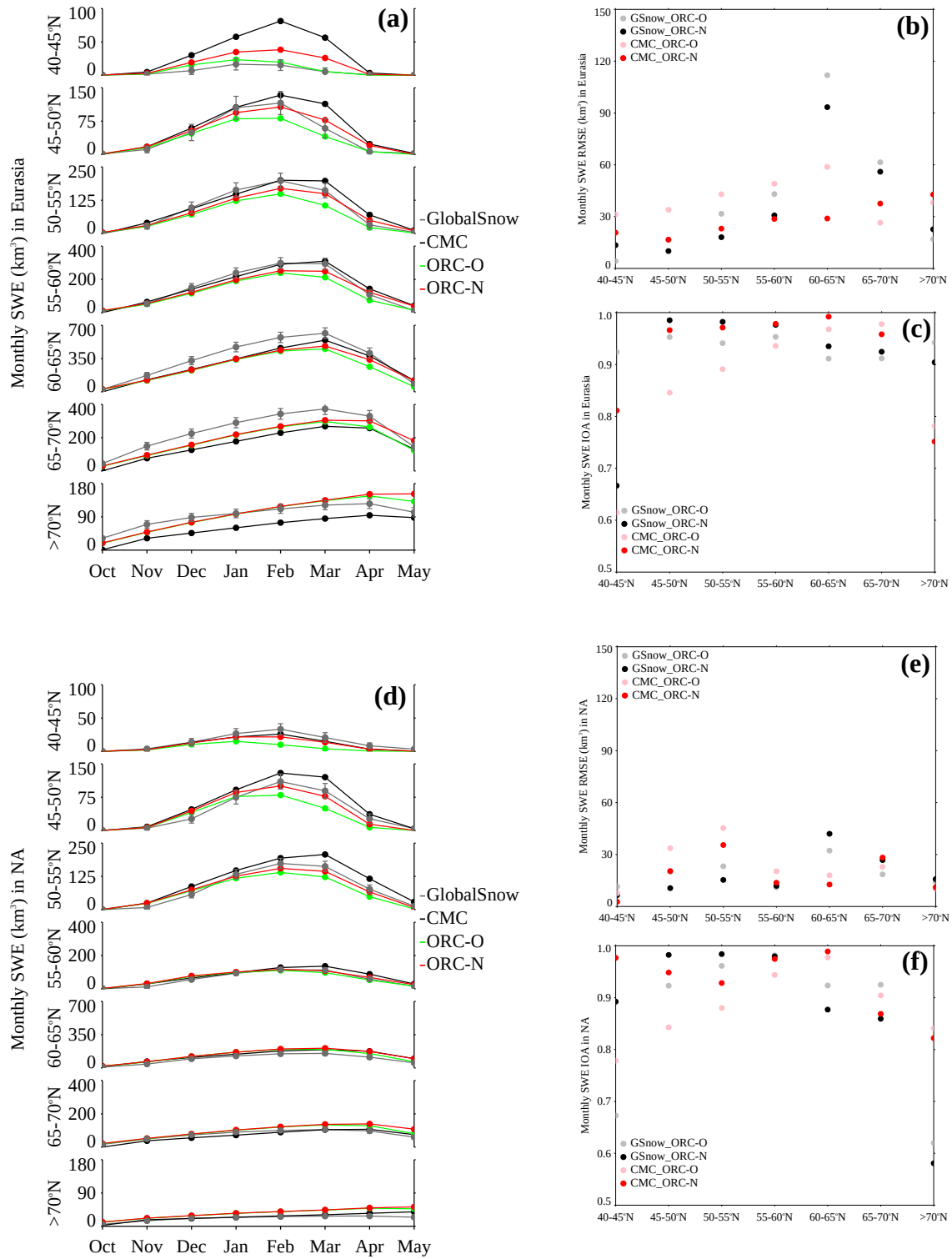


Figure 5.7 Mean monthly SWE (in km³) averaged from 1999 to 2009 at different latitude bands in (a) Eurasia and (b) North America (NA); The RMSE and IOA (index of agreement) between mean (1999-2009) monthly modeled and observed SWE in Eurasia (b and e) and NA (c and f).

The model performances between two time scales shows that both models have a better ability in capturing the seasonal cycle than the interannual time scale (Figure 5.7c vs. Figure 5.8b, Figure 5.7f vs. Figure 5.8d).

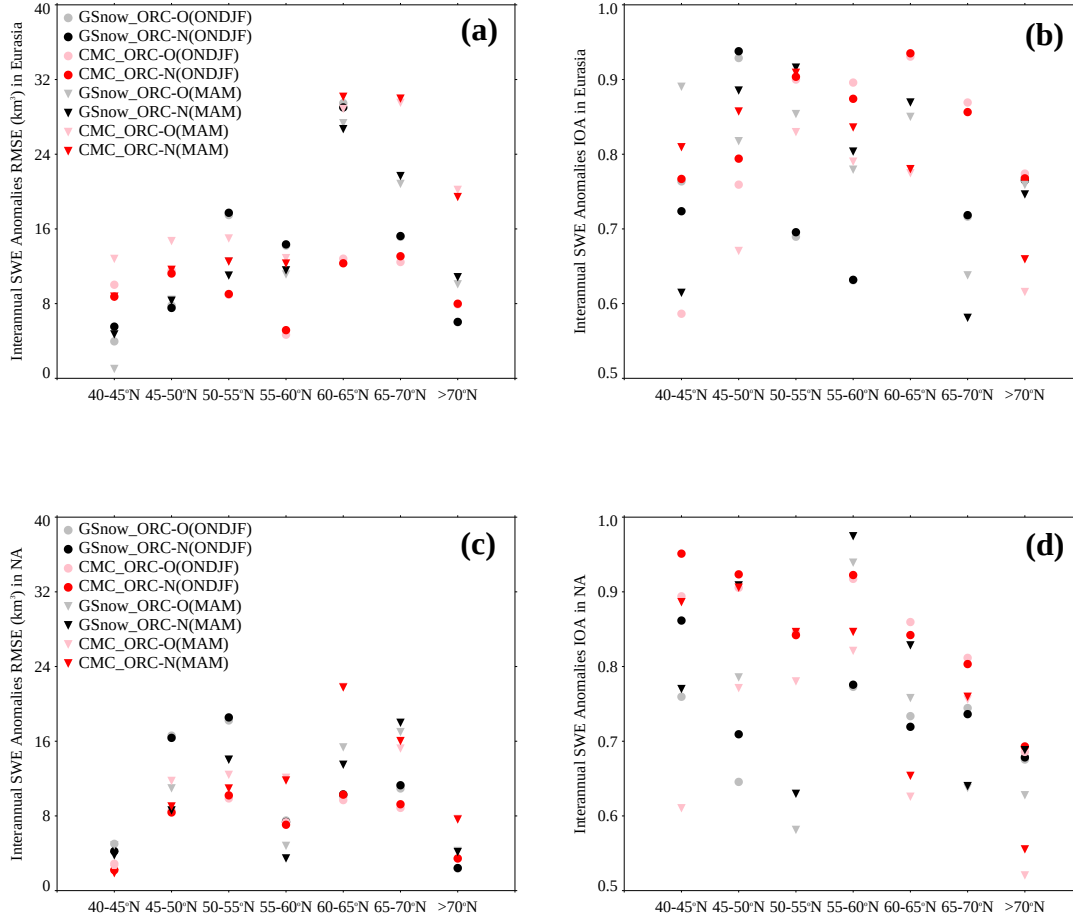


Figure 5.8 The RMSE and IOA (index of agreement) between interannual anomalies of modeled and observed seasonal (spring and winter) SWE during the period 1999-2009 in Eurasia (a and b) and NA (c and d).

5.5.2 Spatial variation in SWE

The spatial distribution of Winter and Spring SWE is shown in Figure 5.9. Both modeled seasonal SWE can capture the distribution of the observed (CMC and GlobSnow) SWE: for example, in the spring season, the spatial R^2 and the slope between modeled and observed SWE is in the range of 0.44-0.51 and 0.76-0.87, respectively. In general, the modeled spring SWE is closer to CMC ($R^2=0.51$) than GlobSnow SWE ($R^2=0.44$) if considering the NH north of 40 °N. Comparison of modeled SWE with CMC in North America reveals similar overall patterns in seasonal SWE with maxima located over the Western Cordillera and Québec-Labrador (e.g. Brown et al., 2003), which are not present in GlobSnow SWE. Another noticeable difference between the two SWE products can be found in Kazakhstan. The reason

for these discrepancies can be related to the fact that the mountainous regions are masked out from the GlobSnow SWE processing system.

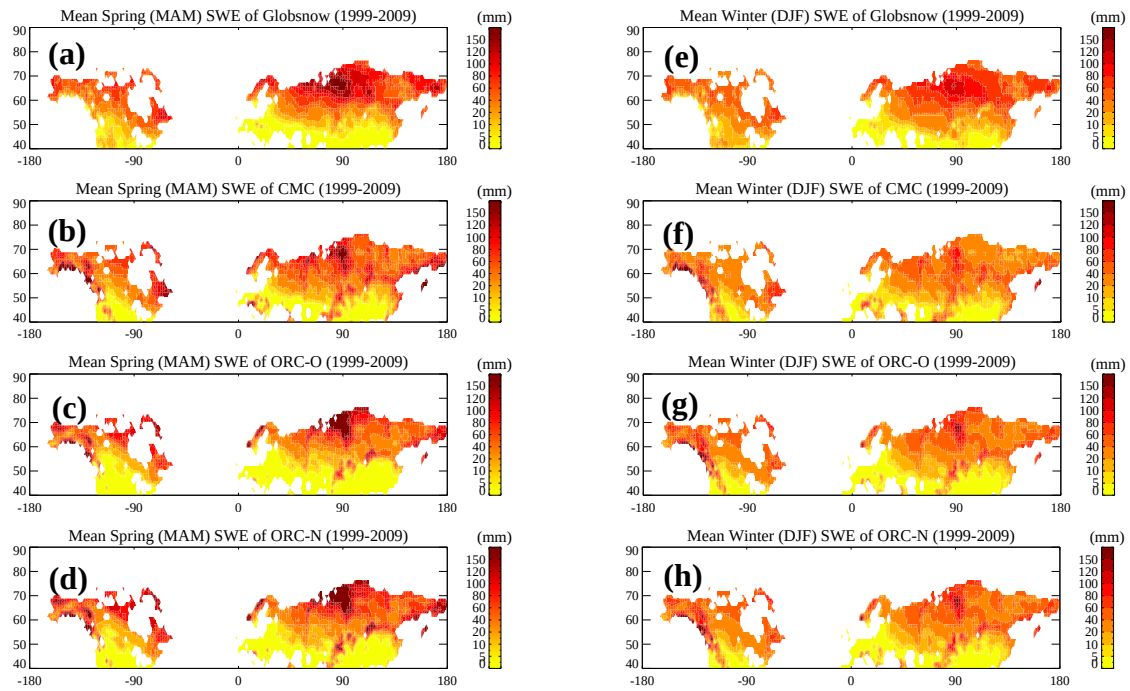


Figure 5.9 The spatial pattern of mean spring and winter SWE (in mm) averaged from 1999 to 2009 for GlobSnow (a and e), CMC (b and f), ORC-O (c and g) and ORC-N (d and h).

Interannual variability of modeled and observed SWE is shown spatially in Figure 5.10. For each type of SWE, at each grid cell, the IQR (interquartile range) of seasonal mean SWE for all simulation years (1999-2009) is calculated, and then the median of IQR values is computed. Observations indicate that interannual variability tends to be highest over the snowiest regions (Figure 5.10). Both models can basically capture the general spatial pattern of variability, for example, in the spring season, the R^2 and the slope between modeled and observed SWE is in the range of 0.28-0.54 and 0.62-0.71, respectively. In general, the modeled spring SWE IQR is closer to CMC ($R^2=0.54$) than GlobSnow SWE ($R^2=0.28$) if considering the NH north of 40 °N. Compared to CMC, GlobSnow has a smaller spring IQR in Yenisei region, however, it should be noted that this region has the largest SWE estimation uncertainty in GlobSnow SWE product. Note that using standard deviation rather than IQR provides the same results (data not shown). The IQR is chosen for this figure because nonparametric statistics are generally more robust than parametric statistics.

Comparison of SWE between the two model versions with observed values shows that ORC-O has a significant underestimation in Spring (cf. Figure 5.9c and d), but not in Winter season (cf. Figure 5.9g and h). The simulated snow line (5 mm SWE isoline) by ORC-N extends into more southern regions and is closer to observed in both CMC and GlobSnow

products. This indicates that ORC-O tends to overestimate the rate of snow ablation in Spring, which is related to the inaccurate albedo parameterization in ORC-O (reference to Chapter 4).

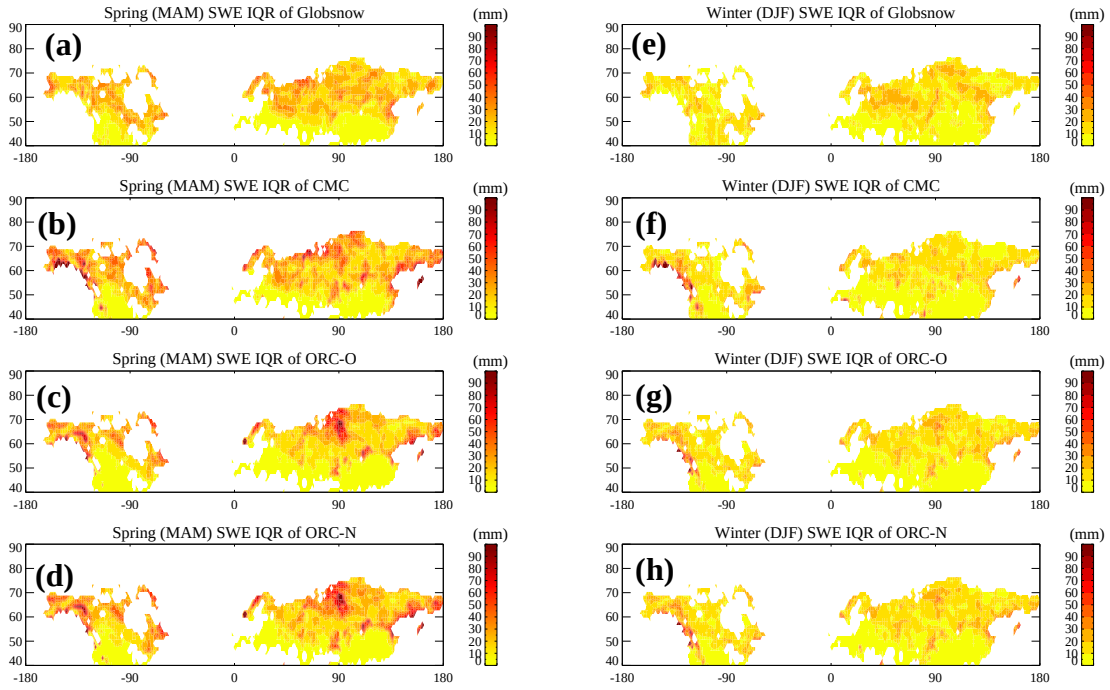


Figure 5.10 The spatial pattern of IQR of spring and winter SWE (in mm) during the period from 1999 to 2009 for Globsnow (a and e), CMC (b and f), ORC-O (c and g) and ORC-N (d and h). IQR (interquartile range) is used to denote the interannual variability of seasonal SWE (in mm).

In addition, as shown in Figure 5.11, the regions where ORC-N shows superior performances (positive RMSE reduction) than ORC-O are mainly located south of 60 °N, consistent with the results found in Sect. 5.5.1. The improvements brought by ORC-N are more significant during spring than during winter. Comparison of RMSE reduction graphs with GlobSnow or CMC reveals that ORC-N is superior to ORC-O in northern regions only if the models are evaluated against GlobSnow SWE. The worse SWE performances of ORC-N at higher latitudes when compared to CMC might be partly related to the inaccuracies of SWE estimates in CMC, since in data sparse areas the SWE of CMC will be entirely simulated from the snowpack model driven with CMC GEM derived temperature and precipitation fields.

5.6 Temperature sensitivity of snow cover days

As shown in Figure 5.12a, based on CMC, in the spring season, s_T (actual temperature sensitivity) is expected to be smaller than s_0 (extreme temperature sensitivity), and their difference becomes smaller in the ‘middle’ latitudes. At the relatively lower latitudes, the current mean seasonal temperature has already reached above the T_0 , and the actual sensitivity in this region (in gray in Figure 5.12a) thus drops off from its extreme sensitivity. In the

higher latitudes, the actual sensitivity is also lower due to the fact that the critical temperature in this region is still much higher than the mean seasonal temperature. However, we should pay much attention to the ‘sensitive’ regions with T_{mean} approaching but below T_0 , as SCDs in these regions may become more sensitive to rising air temperatures in the context of climate warming. For example, 12% and 37% of the pixels with T_{mean} below T_0 would reach their extreme sensitivities for 2 and 4 degree warming in the spring season. The location of this ‘sensitive’ region is seasonal-dependent, for example, in the winter season, this region is mainly distributed in the middle Europe based on CMC (Figure 5.12d). Compared to spring season, most of the pixels at high latitudes (e.g. Siberia region) have zero extreme sensitivity (“full snow” denoted in Figure 5.12d) in winter season. This can be expected due to the fact that the snow pack defined with at least 5 cm usually is already accumulated and stable against the small interannual temperature shifts as the temperature itself is rather cold during the winter months. If the snow cover period is defined using a snow depth threshold of 20 cm, the non-zero extreme temperature sensitivity can be extended into more northern regions (data not shown). In addition, our estimate of extreme sensitivity ($-0.28 \pm 0.07, \%K^{-1}$) in European countries (Austria, France, Germany, Italy, Slovenia and Switzerland) using CMC, is less than $-0.33(0.04) (\%K^{-1})$ by Wielke (2004) based on the meteorological station data extending from 1961 to 2000.

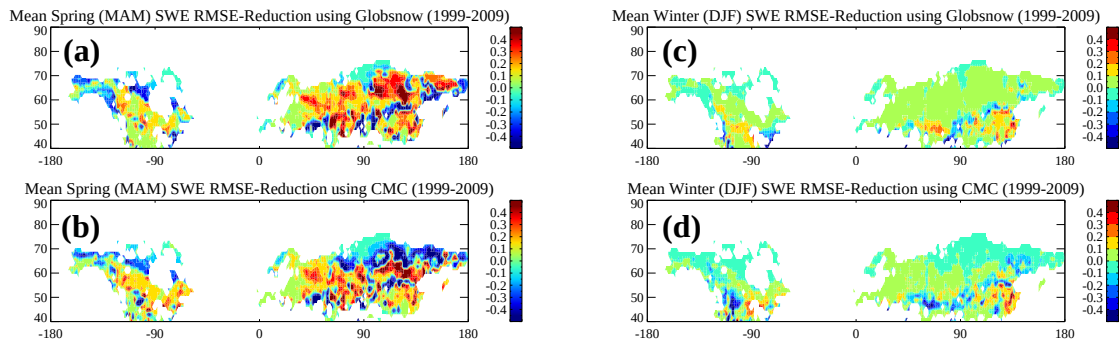


Figure 5.11 The spatial pattern of seasonal SWE RMSE reduction during the period 1999-2009 based on Globsnow (a: spring and c: winter) and CMC (b: spring and d: winter). The RMSE reduction is calculated by dividing two RMSE values difference ($ORC-O_RMSE - ORC-N_RMSE$) by their mean RMSE values.

However, we note some shortcomings in the present analysis. Firstly, the temperature sensitivity of SCDs is actually a combination of temperature and precipitation impacts. That’s to say, we should take cautions to extrapolate SCDs change using s_0 (s_T), which is calculated based on the relation between observed climate shifts and SCDs dynamics. It is possible that increase/decrease in the precipitation could dampen/exacerbate the effect of the future warming, as long as a sufficient fraction of precipitation still falls as snow, which corresponds to damped/amplified temperature sensitivity of SCDs. For example, Howat and Tulaczyk (2005) found that increasing precipitation and temperature from 1950 to 2002 in Sierra Nevada has led to an increase in SWE at high elevations and a decrease at low elevations,

resulting in little or no overall change in SWE volume at the region scale, and the temperature sensitivity of SWE is both highly dependent on concurrent change in precipitation and temperature. Secondly, in order to have more data points to characterize the observed temperature sensitivity, monthly values in spring (winter) season instead of mean seasonal values have been used in nonlinear regression. This would bias the estimation of temperature sensitivity if monthly SCDs dynamics are more responsive to the precipitation change than the temperature change within a season (e.g. winter).

The comparison between modeled and observed values in s_0 , s_T and the difference between T_{mean} and T_0 showed that both models can capture the spatial distributions (Figure 5.12). The ORC-N has a slightly improved ability (lower MAD or RMSE, higher IOA or R^2) than the ORC-O in the spring season. The improvement of ORC-N over ORC-O in temperature sensitivity of SCDs is not as large as the one found in SWE (see Sect. 5.5.1 and 5.5.2), which is related to the fact that SCDs is less sensitive to the temperature than SWE. This is associated with the fact that snow melts earlier in ORC-O than ORC-N, which could enable the parameter T_0 to become larger in Eq. 5.6. In winter season, both models have comparable performances (Table 5.1). Since our main interests are in the regions with T_{mean} below T_0 , the same gray color between ORC-O and ORC-N in the graph of $T_{mean} - T_0$ does not mean that they have the same values.

5.7 Conclusions and perspectives

In this chapter, we concentrated on the evaluation of modeled SWE, and on the temperature sensitivity of SCDs over the NH against two global snow products (CMC and Globsnow). These two snow products are currently best available datasets, although validation of these products showed that CMC is less accurate in regions with fewer in-situ stations, and Globsnow has significant errors over tundra and northern boreal regions. Compared to ORC-O, ORC-N shows significant improvements in capturing the spatial and temporal (intra-annual and inter-annual) variations of spring SWE at relatively lower latitudes ($< 60^\circ\text{N}$) when the modeled SWE is evaluated against both SWE products. This could be also found when comparing CMC-derived SCDs temperature sensitivity to the modeled one. Interestingly, ORC-N did not show significant strengths over ORC-O during the early-to-mid-winter season, which indicates that snow simulation in the accumulation period does not benefit a lot from a more realistic snow parameterization such as in ORC-N.

This is consistent with previous findings that between-model differences are more significant in the spring (or melting period) than during the snow accumulation period (Rutter et al., 2009). There are some questions that need to be further explored in the future. Firstly, by simply accounting for LAI into snow albedo parameterizations, significant improvements could be detected in the forested regions.

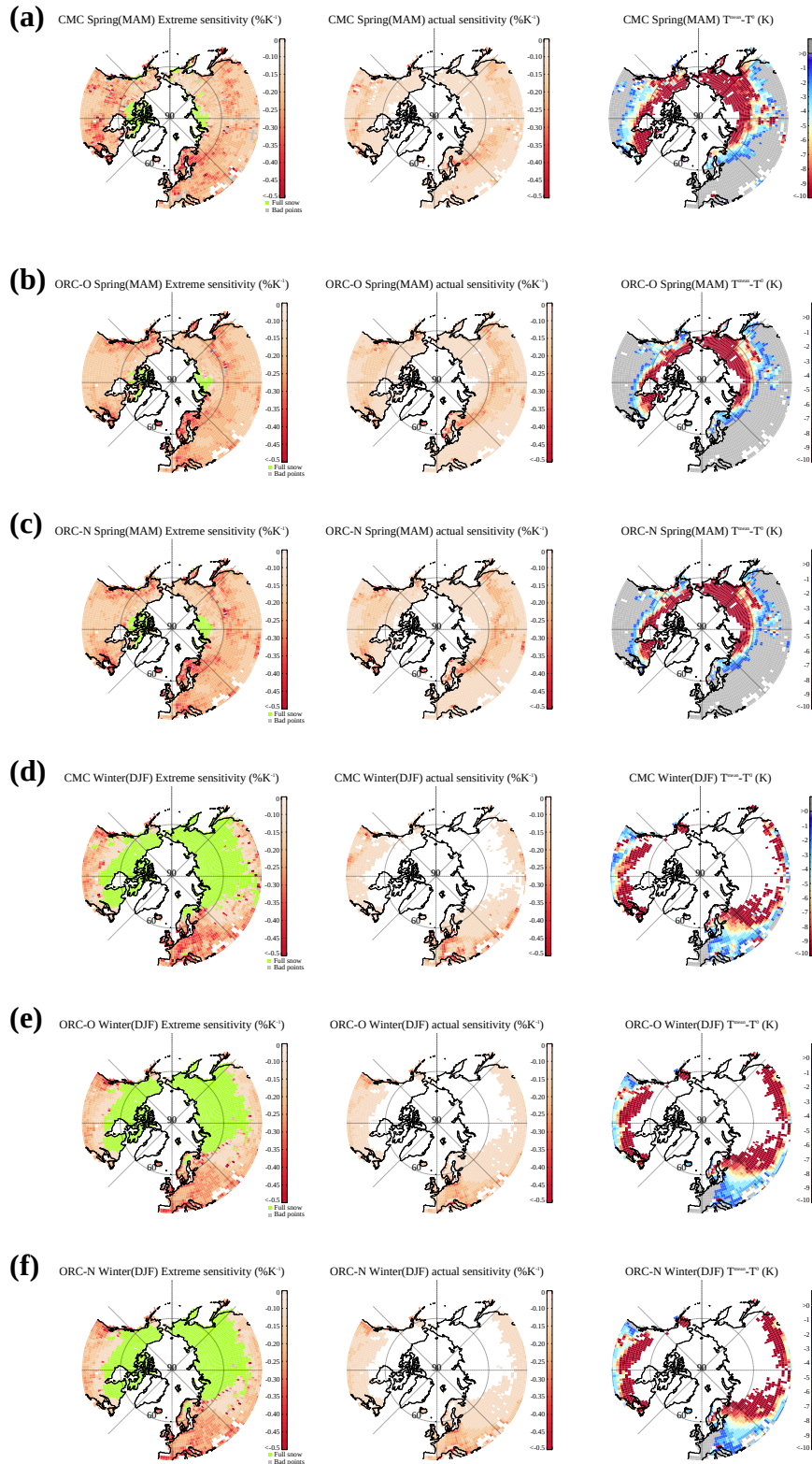


Figure 5.12 The spatial pattern of extreme sensitivity (s_0), actual sensitivity (s_{actual}) and the difference between seasonal Tmean and T0 for CMC (a: spring and d: winter), ORC-O (b: spring and e: winter) and ORC-N (c: spring and f: winter).

		Slope		IOA		R ²		MAD	
		ORC-O	ORC-N	ORC-O	ORC-N	ORC-O	ORC-N	ORC-O	ORC-N
Spring (MAM)	$T_{mean} - T_0$	0.82	0.87	0.93	0.96	0.87	0.88	2.50	2.10
	s_0	0.26	0.30	0.58	0.60	0.11	0.20	0.04	0.03
	s_T	0.50	0.59	0.65	0.70	0.21	0.25	0.01	0.01
Winter (DJF)	$T_{mean} - T_0$	0.78	0.78	0.87	0.87	0.58	0.58	1.70	1.69
	s_0	0.46	0.46	0.72	0.72	0.28	0.28	0.04	0.04
	s_T	0.54	0.54	0.77	0.78	0.39	0.40	0.01	0.01

Table 5.1 The slope, IOA (index of agreement, see details in Chapter 4), R² and MAD comparison between modeled (ORC-O and ORC-N) and observed (CMC) $T_{mean} - T_0$, s_0 , and s_T in both spring and winter season.

However, vegetation-snow processes are still not accounted in ORC-N, and forest canopy can have large effects on under-canopy snow processes through wind sheltering, attenuation of shortwave radiation, snow interception and so on (e.g. Rutter et al., 2009). Secondly, the absence of precipitation partition (rain/snow) and the use of empirical partition scheme (zero temperature threshold in our case) could bias snow simulations, since this partition is more complex and has been found to follow a hyperbolic tangent function of surface air temperature and pressure (Dai, 2008). Thus, in future studies, mapping the parameters of hyperbolic tangent function in different regions (e.g. high/low elevations, forest/non-forested) based on observations could be necessary to get a more realistic precipitation phase.

Along with the model evaluation, we also showed that snow simulations can be significantly affected by sub-daily temperature variability in forcing data. Simulated snow differences due to sub-daily forcing are even comparable to those due to daily mean temperatures. Although in this study we did not show whether the model evaluation could be biased using the forcing datasets with different sub-daily temperature variability, correctly describing this high frequency variability in the forcing dataset seems very necessary and important for the snow simulations especially for the purpose of hydrological forecasting.

6. Conclusion and perspectives

The goal of this thesis was to develop and evaluate the performance of a land surface model – ORCHIDEE (Krinner et al., 2005), which has been widely used and for example, in the studies of plant phenology (e.g. Piao et al., 2008), hydrology (e.g. Ngo-Duc et al., 2007; Piao et al., 2009), permafrost soil carbon (Koven et al., 2011) or impacts of extreme climate events on the terrestrial ecosystem (e.g. Ciais et al., 2005). To date, the ORCHIDEE model evaluation has been still restricted to limited sites or plant function types (e.g. Krinner et al., 2005). Therefore, a characterization of ORCHIDEE capacities to simulate energy and carbon processes has been achieved in this thesis using the available dense eddy covariance network developed in the past two decades, which spans across main vegetation types and main climate regimes on the earth. The model evaluation presented in this thesis is different from the previous ones (e.g. Krinner et al., 2005), which could be contaminated by random errors e.g. from observations due to the fact that simple error metrics were used. Model structural deficiencies (or model systematic errors) in the timescale domain and their characteristics have been investigated based on a combined method using Singular System Analysis (SSA, Mahecha et al., 2010) and Artificial Neural Networks (ANN, Abramowitz et al., 2007). The main results suggested that site simulations could benefit from improving model structural performances at the sites belonging to the same PFT and the same climate regime. In addition, at the site level, the benefits of model simulation on one time scale could be marginal for the model improvement at other time scales. This result is related to the possibility that different processes might impact ecosystem fluxes at different timescales. This new methodology has general implications for LSM community to estimate bounds for the space of model improvement and model uncertainties reduction, and also provides clues on how much benefits could be obtained for the overall model performance from site-based model calibration. From the result of model evaluation, the modeled fluxes have relatively large model bias (or model systematic error) transferability across sites in the boreal region, which suggested that the model structure in higher latitudes characterized by seasonal snow cover should be enhanced. For example, one of the main deficiencies in ORCHIDEE is the neglect of internal snow processes, which could significantly bias the snow simulation and then the water and carbon cycles in this seasonal snow covered regions.

Another motivation of this thesis was the focus on the development and validation of the snow model in ORCHIDEE. Before developing the snow model, we have tried to quantify winter respiration fluxes, based on 55 eddy covariance sites distributed in the mid- and high-latitudes, which are always characterized by seasonal snow cover. The results showed the non-negligible role of winter carbon cycling in the annual carbon balance, and the temperature (air and soil) is found to be the main factor in determining winter ecosystem

respiration across sites. The empirical characterization of temperature controls on winter ecosystem respiration suggested that the temperature sensitivity of winter respiration obtained on spatial and temporal scales should be treated differently, and the temperature sensitivity obtained across sites (spatial temperature sensitivity) is unanimously found to be higher than the temporal sensitivity. Thus, models that estimate the effects of future warming on winter ecosystem respiration based on spatial analyses could over-estimate the impacts of temperature changes on respiration. In addition, soil temperature was found superior to air temperature in explaining anomalies in winter ecosystem respiration, which could suggest the influence of snow cover acting as a thermal insulator controlling soil microbial activity. The snow water equivalent monitored from AMSR-E/Aqua was found to have little influence on winter respiration, however, it should be noted that snow characteristics at the site level might not be truly captured by a remote sensing product at a spatial resolution of 25 km². The direct demonstration of snow effects on winter respiration needs more in-situ data, and was left for future studies.

The existing snow model in ORCHIDEE was a simple bucket model with constant snow density, which adopts a composite snow/top soil structure functioning as a single thermal unit. In this thesis, the internal snow processes parameterizations were revised following a medium complex model (ISBA-ES, Boone et al., 2002) with three snow layers, which has been shown to have a good ability in capturing the snow behaviors in the alpine regions. The main internal snow processes listed as follows have been included in the model: heat consumption/release due to snow melting/refreezing within each snow layer, water infiltration between snow layers and solar radiation absorption within each snow layer. Moreover, a new forest albedo parameterization has been implemented in ORCHIDEE by taking into account the vegetation leaf area index. The new snow model was evaluated at both SNOWMIP sites and at meteorological stations with daily snow records from Canada. At SNOWMIP sites, the new model shows a significant improved ability to simulate the snow pack properties: snow water equivalent (SWE), snow depth (SD), snowmelt runoff and surface albedo. A sensitivity analysis has shown that the failure of the default ORCHIDEE model could be mainly attributed to the ill-adapted previous snow albedo scheme, and its single replacement with the ISBA-ES representation improves significantly the snow simulations especially for SWE. But this default ORCHIDEE with modified albedo scheme still has inferior behaviors in snow depth simulations because of the constant snow density prescribed, which is induced by the neglecting of internal snow processes. However, the new snow model did not show significant improvements at the forest sites compared to default snow model. On the one hand, it suggests that the albedo might play a less important role in the snow simulations in the forests with canopy coverage larger than 70%; on the other hand, it also indicates that one energy budget for snow modeling is not sufficient to represent the evolution of the snow pack in forested areas since the under-canopy microclimate such as sheltered wind speed, reduced solar radiation can be very different than the over-canopy one. Across Canadian meteorological stations, we found that the new snow model could well capture the spatial and temporal patterns of snow depth, and the comparison between the model results driven by

both IERA forcing and the same forcing corrected with temperature and precipitation in-situ data showed the importance of the forcing data and the improvements brought by more accurate analysis. The extent to which the results from IERA driven simulations match observed data is strongly related to the initial accuracy of IERA snowfall. As a matter of fact, it has been shown that the bias in air temperature in IERA could lead to an ill-estimation of snowfall amount. The comparison between the old and new version of the ORCHIDEE snow model also showed the superiority of the new model when the evaluation is done using both IERA and the corrected IERA on the large scale level (Canada region).

Finally, driven by IERA forcing, model evaluation was also performed on the continental scale using two current best available snow products (CMC and GlobSnow). The new snow model shows significant improvement in capturing the spatial and temporal (intra-annual and inter-annual) variations of spring SWE at relatively lower latitudes ($< 60^{\circ}\text{N}$), in agreement with both SWE products. This could be also found when comparing CMC-derived SCDs temperature sensitivity to the modeled one. It is important to note that the two snow products could present biases in higher latitudes since the snow depth observation network is very sparse. The results also showed that the new snow model did not show significant improvements in the early/mid-winter season, which was also found at the site level (chapter 4) and other studies performed with other models (e.g. Rutter et al., 2009). In addition, snow simulations have been significantly affected by the forcing data time resolution (i.e. different sub-daily temperature variability), which is even comparable to the impacts induced by different mean temperatures. Although in this thesis we did not show whether the model evaluation could be biased using the forcing datasets with different sub-daily temperature variability, correctly describing this high frequency variability in the forcing dataset seems very necessary and important for the snow simulation especially for the purpose of hydrological forecasts. Moreover, snow model evaluation presented here is not the whole story: further evaluation will include soil moisture and runoff based on river streamflows (arctic river database), once this snow model is coupled to the newly parameterized hydrological model (Gouttevin et al., 2011), routing river model and permafrost model (Koven et al., 2009, 2011) developed for high latitudes in other works.

In this thesis, due to time constraints, we did not examine other snow related physical and biological processes such as snow-carbon or snow-temperature interactions. For snow-carbon interactions, to what extent and how the snow affect the carbon cycle in both present and future could be investigated through coupled modeling approach e.g. providing different snow boundary conditions for the ORCHIDEE-LMDZ (new snow model coupled with atmospheric model). This coupled model approach could bring new perspectives on the role of snow annual or growing season carbon cycle, question on which conflicting responses have been published (e.g. Aurela et al., 2004; Groendahl et al., 2007; Humphreys and Lafleur, 2011). Snow-temperature feedbacks could also be investigated based on the combined use of models and observations. The investigated snow-temperature feedbacks include not only the

‘conventional’ presence/absence of snow impacts (e.g. S. Peng unpublished) but also snow depth impacts on near-surface air temperature. For ‘observational’ approaches, the temperature-associated changes in ‘observed’ (e.g. CMC, GlobSnow or snow depth network on a global scale) snow characters (SWE, snow depth, snow cover days) would be separated from other covaried factors such as near-surface snowfall, rainfall, initial snow characters and near-surface diurnal temperature amplitude. To this end, an artificial neural network (ANN) such as the one developed in this thesis, could be constructed linking a snow character to its potential impacting factors. Then the separation of near-surface air temperature from other factors can be achieved by calculating the partial derivative of the snow character (e.g. snow depth, snow albedo) relative to near-surface air temperature. For modeling approach, taking snow depth-temperature feedbacks as an example, it would be easy to quantify the snow depth impacts on near surface temperature through providing different initial conditions of snow depth for coupled ORCHIDEE-LMDZ,. In addition, in order to better understand the role of snow on the climate of Arctic regions, this new snow model will be soon combined with the recently developed permafrost soil model (Koven et al., 2011) and hydrological model specific for high latitude frozen soils (Gouttevin et al., 2011). This new version of the ORCHIDEE model will be used in the framework of various projects in the following work.

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Appendix A

ORCHIDEE climate forcing data gap filling algorithms

For off-line simulations ORCHIDEE requires continuous half-hourly incoming shortwave radiation (W m^{-2}), incoming long-wave radiation (W m^{-2}), air temperature (K), specific humidity (kg kg^{-1}), wind speed (m s^{-1}), surface pressure (Pa), and precipitation rate ($\text{kg m}^{-2} \text{s}^{-1}$). Before gap-filling, all half-hourly data in La Thuile FLUXNET synthesis dataset was aggregated to daily values. Each daily gap present in the climate forcing at eddy covariance site was replaced by the corrected daily data from ECMWF ERA-Interim (IERA) 0.7×0.7 degree reanalysis. For all variables except precipitation, the correction applied to daily IERA fields was made by performing a linear regression analysis between daily in-situ and IERA data. For precipitation, we took the daily values directly from IERA without any correction. Since climate forcing in ORCHIDEE is defined at a half-hourly time step, a diurnal cycle for each climate variable should be rebuilt from their daily values. The following algorithm for disaggregating daily field to the half-hourly one only applies to the gap-filled daily values.

For air temperature, half-hourly temperature was generated from daily values of maximum and minimum air temperature by using a sinusoidal function assuming that maximum temperature occurs at 14:00 local time and minimum temperature occurs at sunrise (Campbell and Norman, 1998). Half-hourly specific humidity values were given by half-hourly dew point temperature values. The latter were computed from the interpolated air temperature minus the difference between mean daily dew point temperature and mean daily air temperature. The diurnal cycle of incoming shortwave radiation was assumed to fit a second-order polynomial during daytime with a maximum at noon, and was set to zero before sunrise and after sunset. The incoming longwave radiation was computed at a half-hourly time step from air temperature, air humidity, and incoming shortwave radiation according to Crawford and Duchon (1999). Half-hourly wind speed was obtained by a logarithmic function of both daily value and independent random number generated from the normal distribution (Nicks et al., 1990). For surface pressure, the constant value was assumed throughout the day. Daily precipitation amounts were converted to half-hourly by evenly distributing precipitation throughout the day.

Appendix B

Site ID	Latitude	Longitude	PFT	Climate group	References
AT-Neu	47.12	11.32	GRA	Temperate	(Wohlfahrt et al., 2008)
AU-Tum	-35.66	148.15	TeEBF	Temperate	
AU-Wac	-37.43	145.19	TeEBF	Temperate	
BE-Bra	51.31	4.52	TeDBF	Temperate	(Aubinet et al., 2001)
BE-Lon	50.55	4.74	CRO	Temperate	
BE-Vie	50.31	6	TeDBF	Temperate	
BR-Ban	-9.82	-50.16	TrEBF	Tropical	
BR-Cax	-1.72	-51.46	TrEBF	Tropical	
BR-Ji2	-10.08	-61.93	TrEBF	Tropical	
BR-Ma2	-2.61	-60.21	TrEBF	Tropical	
BR-Sa1	-2.86	-54.96	TrEBF	Tropical	
BR-Sa3	-3.02	-54.97	TrEBF	Tropical	
CA-Ca1	49.87	-125.33	TeENF	Temperate	(Humphreys et al., 2006)
CA-Ca2	49.87	-125.29	TeENF	Temperate	(Humphreys et al., 2006)
CA-Ca3	49.53	-124.9	TeENF	Temperate	
CA-Gro	48.22	-82.16	TeDBF	Temperate-Continental	
CA-Let	49.71	-112.94	GRA	Temperate-Continental	
CA-Man	55.88	-98.48	BoENF	Boreal	(Flanagan et al., 2002; Flanagan and Johnson, 2005)
CA-NS1	55.88	-98.48	BoENF	Boreal	(Dunn et al., 2007)
CA-NS2	55.91	-98.52	BoENF	Boreal	
CA-NS3	55.91	-98.38	BoENF	Boreal	
CA-NS4	55.91	-98.38	BoENF	Boreal	
CA-Obs	53.99	-105.12	BoENF	Boreal	
CA-Ojp	53.92	-104.69	BoENF	Boreal	
CA-Qcu	49.27	-74.04	BoENF	Boreal	
CA-Qfo	49.69	-74.34	BoENF	Boreal	(Kljun et al., 2006)
CA-SF1	54.49	-105.82	BoENF	Boreal	(Giasson et al., 2006)
CA-SF2	54.25	-105.88	BoENF	Boreal	(Bergeron et al., 2007)
CA-SF3	54.09	-106	BoENF	Boreal	(Mkhabela et al., 2009)
CA-SJ1	53.91	-104.66	BoENF	Boreal	(Mkhabela et al., 2009)
CA-SJ2	53.95	-104.65	BoENF	Boreal	(Mkhabela et al., 2009)
CA-TP2	42.77	-80.46	TeENF	Temperate-Continental	(Peichl and Arain, 2007)
CA-TP3	42.71	-80.35	TeENF	Temperate-Continental	(Peichl and Arain, 2007)

Appendix B

CA-TP4	42.71	-80.36	TeENF	Temperate-Continental	(Arain and Restrepo-Coupe, 2005)
CH-Oe1	47.29	7.73	GRA	Temperate	(Ammann et al., 2007)
CZ-BK1	49.5	18.54	TeENF	Temperate-Continental	
CZ-BK2	49.5	18.54	GRA	Temperate-Continental	
DE-Bay	50.14	11.87	TeENF	Temperate	
DE-Geb	51.1	10.91	CRO	Temperate	(Kutsch et al., 2010b)
DE-Hai	51.08	10.45	TeDBF	Temperate	(Knohl et al., 2003; Kutsch et al., 2010a)
DE-Kli	50.89	13.52	CRO	Temperate	
DE-Meh	51.28	10.66	GRA	Temperate	
DE-Tha	50.96	13.57	TeENF	Temperate	(Grunwald and Bernhofer, 2007)
DE-Wet	50.45	11.46	TeENF	Temperate	(Rebmann et al., 2010)
DK-Sor	55.49	11.65	TeDBF	Temperate	(Pilegaard et al., 2003)
ES-ES1	39.35	-0.32	TeENF	SubTropical-Mediterranean	
ES-ES2	39.28	-0.32	CRO	SubTropical-Mediterranean	
ES-VDA	42.15	1.45	GRA	Temperate	
FI-Hyy	61.85	24.29	BoENF	Boreal	(Sun et al., 2003b)
FI-Sod	67.36	26.64	BoENF	Boreal	(Sun et al., 2003a)
FR-Hes	48.67	7.06	TeDBF	Temperate	(Granier et al., 2000)
FR-LBr	44.72	-0.77	TeENF	Temperate	(Berbigier et al., 2001)
FR-Lq1	45.64	2.74	GRA	Temperate	
FR-Lq2	45.64	2.74	GRA	Temperate	
FR-Pue	43.74	3.6	TeEBF	SubTropical-Mediterranean	
GF-Guy	5.28	-52.93	TrEBF	Tropical	(Bonal et al., 2008)
HU-Bug	46.69	19.6	GRA	Temperate	
HU-Mat	47.85	19.73	GRA	Temperate	
IE-Cal	52.86	-6.92	CRO	Temperate	
IE-Dri	51.99	-8.75	GRA	Temperate	
IS-Gun	63.83	-20.22	TeDBF	Temperate	
IT-Amp	41.9	13.61	GRA	SubTropical-Mediterranean	(Gilmanov et al., 2007)
IT-BCi	40.52	14.96	CRO	SubTropical-Mediterranean	
IT-Col	41.85	13.59	TeDBF	SubTropical-Mediterranean	
IT-Cpz	41.71	12.38	TeEBF	SubTropical-Mediterranean	(Garbulsky et al., 2008)
IT-LMa	45.58	7.15	GRA	Temperate	
IT-Lav	45.96	11.28	TeENF	Temperate	
IT-MBo	46.02	11.05	GRA	Temperate	(Marcolla and Cescatti,

Appendix B

					2005; Gianelle et al., 2009)
IT-Mal	46.12	11.7	GRA	Temperate	
IT-Non	44.69	11.09	TeDBF	SubTropical-Mediterranean	
IT-PT1	45.2	9.06	TeDBF	SubTropical-Mediterranean	
IT-Ren	46.59	11.43	TeENF	Temperate	(Montagnani et al., 2009)
IT-Ro1	42.41	11.93	TeDBF	SubTropical-Mediterranean	(Rey et al., 2002)
IT-Ro2	42.39	11.92	TeDBF	SubTropical-Mediterranean	(Tedeschi et al., 2006)
IT-SRo	43.73	10.28	TeENF	SubTropical-Mediterranean	
JP-Tak	36.15	137.42	TeDBF	Temperate-Continental	
JP-Tom	42.74	141.51	TeDBF	Temperate-Continental	
KR-Hnm	34.55	126.57	CRO	SubTropical-Mediterranean	
KR-Kw1	37.75	127.16	TeDBF	Temperate-Continental	
NL-Ca1	51.97	4.93	GRA	Temperate	
NL-Hor	52.03	5.07	GRA	Temperate	
NL-Loo	52.17	5.74	TeENF	Temperate	(Dolman et al., 2002)
PT-Esp	38.64	-8.6	TeEBF	SubTropical-Mediterranean	
PT-Mi1	38.54	-8	TeEBF	SubTropical-Mediterranean	
PT-Mi2	38.48	-8.02	GRA	SubTropical-Mediterranean	
RU-Che	68.61	161.34	TeDBF	Boreal	
RU-Fyo	56.46	32.92	TeENF	Temperate-Continental	(Milyukova et al., 2002)
RU-Ha1	54.73	90	GRA	Boreal	(Marchesini et al., 2007)
RU-Zot	60.8	89.35	BoENF	Boreal	
SE-Fla	64.11	19.46	BoENF	Boreal	
SE-Nor	60.09	17.48	TeENF	Temperate-Continental	
UK-ESa	55.91	-2.86	CRO	Temperate	
US-ARM	36.61	-97.49	CRO	SubTropical-Mediterranean	
US-Bkg	44.35	-96.84	GRA	Temperate-Continental	(Gilmanov et al., 2005)
US-Blo	38.9	-120.63	TeENF	SubTropical-Mediterranean	
US-Bo1	40.01	-88.29	CRO	Temperate-Continental	(Meyers and Hollinger, 2004)

Appendix B

US-Bo2	40.01	-88.29	CRO	Temperate-Continental	(Meyers and Hollinger, 2004)
US-Dk1	35.97	-79.09	GRA	SubTropical-Mediterranean	
US-Dk2	35.97	-79.1	TeDBF	SubTropical-Mediterranean	
US-Dk3	35.98	-79.09	TeENF	SubTropical-Mediterranean	
US-Goo	34.25	-89.97	GRA	SubTropical-Mediterranean	
US-Ha1	42.54	-72.17	TeDBF	Temperate-Continental	(Urbanski et al., 2007)
US-Ho1	45.2	-68.74	TeENF	Temperate-Continental	(Hollinger et al., 2004)
US-Ho2	45.21	-68.75	TeENF	Temperate-Continental	
US-IB1	41.86	-88.22	CRO	Temperate-Continental	
US-IB2	41.84	-88.24	GRA	Temperate-Continental	
US-LPH	42.54	-72.18	TeDBF	Temperate-Continental	(Borken et al., 2006)
US-MMS	39.32	-86.41	TeDBF	SubTropical-Mediterranean	(Schmid et al., 2000)
US-MOz	38.74	-92.2	TeDBF	SubTropical-Mediterranean	
US-Me2	44.45	-121.56	TeENF	SubTropical-Mediterranean	(Thomas et al., 2009)
US-Me4	44.5	-121.62	TeENF	SubTropical-Mediterranean	(Law et al., 2001)
US-Ne1	41.17	-96.48	CRO	Temperate-Continental	(Verma et al., 2005)
US-Ne2	41.16	-96.47	CRO	Temperate-Continental	(Verma et al., 2005)
US-Ne3	41.18	-96.44	CRO	Temperate-Continental	(Verma et al., 2005)
US-PFa	45.95	-90.27	TeDBF	Temperate-Continental	(Ricciuto et al., 2008)
US-SP2	29.76	-82.24	TeENF	SubTropical-Mediterranean	
US-SP3	29.75	-82.16	TeENF	SubTropical-Mediterranean	
US-Syv	46.24	-89.35	TeDBF	Temperate-Continental	(Desai et al., 2005)
US-UMB	45.56	-84.71	TeDBF	Temperate-Continental	(Gough et al., 2008)
US-Var	38.41	-120.95	GRA	SubTropical-Mediterranean	(Ma et al., 2007)
US-WBW	35.96	-84.29	TeDBF	SubTropical-Mediterranean	

Appendix B

US-WCr	45.81	-90.08	TeDBF	Temperate-Continental	(Cook et al., 2004)
US-Wi4	46.74	-91.17	TeENF	Temperate-Continental	
US-Wrc	45.82	-121.95	TeENF	SubTropical-Mediterranean	
VU-Coc	-15.44	167.19	TrEBF	Tropical	

The definitions of different PFTs are: boreal evergreen needleleaf forest (BoENF), temperate evergreen needleleaf forest (TeENF), temperate evergreen broadleaf forest (TeEBF), temperate deciduous broadleaf forest (TeDBF), grasslands (GRA), croplands (CRO), tropical evergreen broadleaf forest (TrEBF).

Table B1. List of site ID, latitude, longitude, PFT and climate of the sites used in the analysis.

Appendix C

What eddy-covariance measurements tell us about prior land flux errors in CO₂-flux inversion schemes¹

Frédéric Chevallier¹, Tao Wang¹, Philippe Ciais¹, Fabienne Maignan¹, Marc Bocquet², Altaf Arain³, Alessandro Cescatti⁴, Jiquan Chen⁵, Han Dolman⁶, Beverly E. Law⁷, Hank A. Margolis⁸, Leonardo Montagnani^{9,10,11}, Eddy J. Moors¹²

¹ Laboratoire des Sciences du Climat et de l'Environnement/IPSL, CEA-CNRS-UVSQ, Gif-sur-Yvette, France

² Université Paris-Est, CERE, École des Ponts ParisTech-EDF R&D, Champs-sur-Marne, France, and INRIA, Paris Rocquencourt Research Centre, France

³ School of Geography and Earth Sciences, and McMaster Centre for Climate Change, McMaster University, Hamilton, Ontario, Canada

⁴ European Commission - DG Joint Research Centre, Ispra, Italy

⁵ Landscape Ecology & Ecosystem Science, Bowman-Oddy Laboratories, University of Toledo, Toledo, OH, USA

⁶ Department of Hydrology and Geo-environmental Sciences, Vrije Universiteit, Amsterdam, Netherlands

⁷ Oregon State University, Corvallis, Oregon, USA

⁸ Centre d'Étude de la Forêt, Faculté de foresterie, de géographie et de géomatique, Université Laval, Québec, Québec, Canada

⁹ Forest Services, Autonomous Province of Bolzano, Bolzano, Italy

¹⁰ Agency for the Environment, Autonomous Province of Bolzano, Bolzano, Italy

¹¹ Faculty of Sciences and Technologies, Free University of Bozen/Bolzano, Bolzano, Italy

¹² Alterra, Wageningen, The Netherlands

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¹ This paper has been accepted by *Global Biogeochemical cycles*. In this paper, I did carbon fluxes simulations at eddy covariance sites from La Thuile dataset using ORCHIDEE model.

Abstract:

To guide the future development of CO₂-atmospheric inversion modeling systems, we analyzed the errors arising from prior information about terrestrial ecosystem fluxes. We compared the surface fluxes calculated by a process-based terrestrial ecosystem model with daily averages of CO₂ flux measurements at 156 sites across the world in the FLUXNET network. At the daily scale, the standard deviation of the model-data fit was 2.5 gC·m⁻²·d⁻¹; temporal autocorrelations were significant at the weekly scale (> 0.3 for lags less than four weeks), while spatial correlations were confined to within the first few hundred kilometers (< 0.2 after 200 km). Separating out the plant functional types did not increase the spatial correlations, except for deciduous broad-leaved forests. Using the statistics of the flux measurements as a proxy for the statistics of the prior flux errors was shown not to be a viable approach. A statistical model allowed us to upscale the site-level flux error statistics to the coarser spatial and temporal resolutions used in regional or global models. This approach allowed us to quantify how aggregation reduces error variances, while increasing correlations. As an example, for a typical inversion of grid-point (300 km x 300 km) monthly fluxes, we found that the prior flux error follows an approximate e-folding correlation length of 500 km only, with correlations from one month to the next as large as 0.6.

Introduction

Carbon dioxide (CO₂) fluxes at the Earth's surface may be recovered (or *inverted*) from the observed spatial and temporal gradients of the CO₂ concentrations in the atmosphere by applying Bayes' theorem (e.g., Enting et al. 1995; Bousquet et al., 2000; Gurney et al., 2002). Atmospheric mixing makes the problem ill-constrained and therefore prior information about the CO₂ flux originating from the land and water surface is also used in the inversion process. In statistical terms, this approach transforms the prior probability density $p(\mathbf{x})$ about the CO₂ fluxes, jointly called *state vector* $\mathbf{x}$ here, into the posterior probability density $p(\mathbf{x}|\mathbf{y})$ conditioned on atmospheric measurements, jointly called $\mathbf{y}$. The statistically-optimal estimator of the fluxes, given the available information, corresponds to the maximum of the function $p(\mathbf{x}|\mathbf{y})$. By design, it critically depends on the assumed prior density function $p(\mathbf{x})$. Under the numerically-convenient assumption of a multivariate Gaussian density, describing $p(\mathbf{x})$ requires assigning means, variances and correlations. The atmospheric inversion studies of CO₂ fluxes published so far have assumed various probability distributions centered on climatology, regional inventory statistics or the output of terrestrial ecosystem, as well as ocean carbon cycle models (Gurney et al., 2002). In practice, some of the key characteristics of the prescribed *a priori* flux error distributions $p(\mathbf{x})$ in use stem from the capacity of the current flux-inversion systems to deal with large state vectors $\mathbf{x}$, rather than from the statistics of the inference problem: the largest correlation patterns in space and time are specified in the case of classical analytical systems (i.e. coarse regions inversions, e.g., Gurney et al., 2002), while the narrowest structures (i.e. pixel size) can be introduced in the variational (i.e. adjoint-based) schemes (Chevallier et al., 2005; Rödenbeck et al., 2005; Baker et al., 2006). Ensemble methods lie in-between (Zupanski et al., 2007; Peters et al., 2007; Feng et al., 2009). This subjective choice of error correlation structures critically influences the way the information from a single atmospheric measurement is spread in space and time for the flux inversion systems.

In the literature, two studies have attempted to shed light on the characteristics of $p(\mathbf{x})$ based on observations. Michalak et al. (2005) used CO₂ concentration measurements within a flux inversion system by introducing some poorly-known characteristics of the prior errors in the state vector $\mathbf{x}$. They highlighted the power of their method but stressed its subjectivity. In the second study, Chevallier et al. (2006) relied on the non-gap-filled, raw CO₂ flux measurements at the eddy-covariance flux sites (total 34) in the northern hemisphere to constrain $p(\mathbf{x})$. They showed a heavy-tail distribution $p(\mathbf{x})$ that contradicts the usual assumption of a multivariate Gaussian distribution. Further, the error correlations appeared to follow a linear temporal dependency after the second lag day without any particular spatial structure.

Following the approach adopted by Chevallier et al. (2006), we examine the characteristics of $p(\mathbf{x})$ for terrestrial ecosystem CO₂ fluxes, when $p(\mathbf{x})$ is centered around the Organizing Carbon and Hydrology In Dynamic Ecosystems (ORCHIDEE) -- a process-based ecosystem model (Krinner et al.; 2005). Our study advances our previous knowledge in two

ways. First, it uses a much-wider archive of eddy-covariance sites (156 in total) with gap-filled records, which provides more detailed information on $p(\mathbf{x})$ for a variety of biomes. Additionally, we explore the influence of temporal and spatial aggregation on the statistics in order to bridge the gap between the local scale of the daily eddy-covariance flux measurements that are used to define $p(\mathbf{x})$ and the typically much larger spatial and temporal scales of the inversion systems.

Methods

Surface CO₂ fluxes were measured at tower sites using the eddy covariance technique, which derives CO₂ flux from the covariance between fluctuations around the mean vertical wind velocity and CO₂ mixing ratio (Aubinet et al., 2000). Eddy covariance fluxes are typically representative of surface areas ranging from a few hectares to a few km², depending on the height of the sensors above the canopy and the roughness of the surface and on the air stability. Flux measurements have been conducted over most major biomes across the world under a global network of flux towers, FLUXNET (Baldocchi et al., 2001; Baldocchi, 2008). A synthesis dataset comprising 253 flux sites, named after the Italian town *La Thuile*, was compiled in 2007. This archive also stores standardized gap-filled measurements of CO₂ fluxes at a 30-minute time step using a common protocol (Papale et al. 2006). The *La Thuile* archive also collects the corresponding meteorological data, which we gap-filled based on the data from the Interim Reanalysis of the European Centre for Medium-Range Weather Forecasts (Berrisford et al., 2009) for use as input to the ORCHIDEE model. The present study focuses on the 156 sites of the *La Thuile* database that encompass at least three consecutive years of measurements between 1991 through 2007. Their locations cover much of the temperature-precipitation climate space across the world and most biomes (Fig. 1). The full site list is given in Appendix 1. Lasslop et al. (2008) estimate the overall uncertainty of the half-hourly gap-filled fluxes to be about 0.07 gC·m⁻² (one sigma uncertainty, cf. Fig. 2e; Lasslop et al., 2008). This relatively large uncertainty does not contain much autocorrelation (i.e., the autocorrelation is <0.2 after only 4 hours; cf. Fig. 5a; Lasslop et al., 2008) so that the uncertainty of the fluxes amounts to only a few tenths of a gC·m⁻²·d⁻¹ for daily totals (Hollinger and Richardson, 2005). Therefore, we will not report results here at scales shorter than a day. Errors are site-specific and therefore have low spatial correlations. Some systematic errors affect the measurements: e.g., the measurements do not show energy balance closure and low night-time wind conditions are not properly treated (Baldocchi et al., 2001). We rely here on the quality control of the database to minimize these biases. In any event, biases should not affect the statistics (standard deviations and correlations) presented in the subsequent analyses.

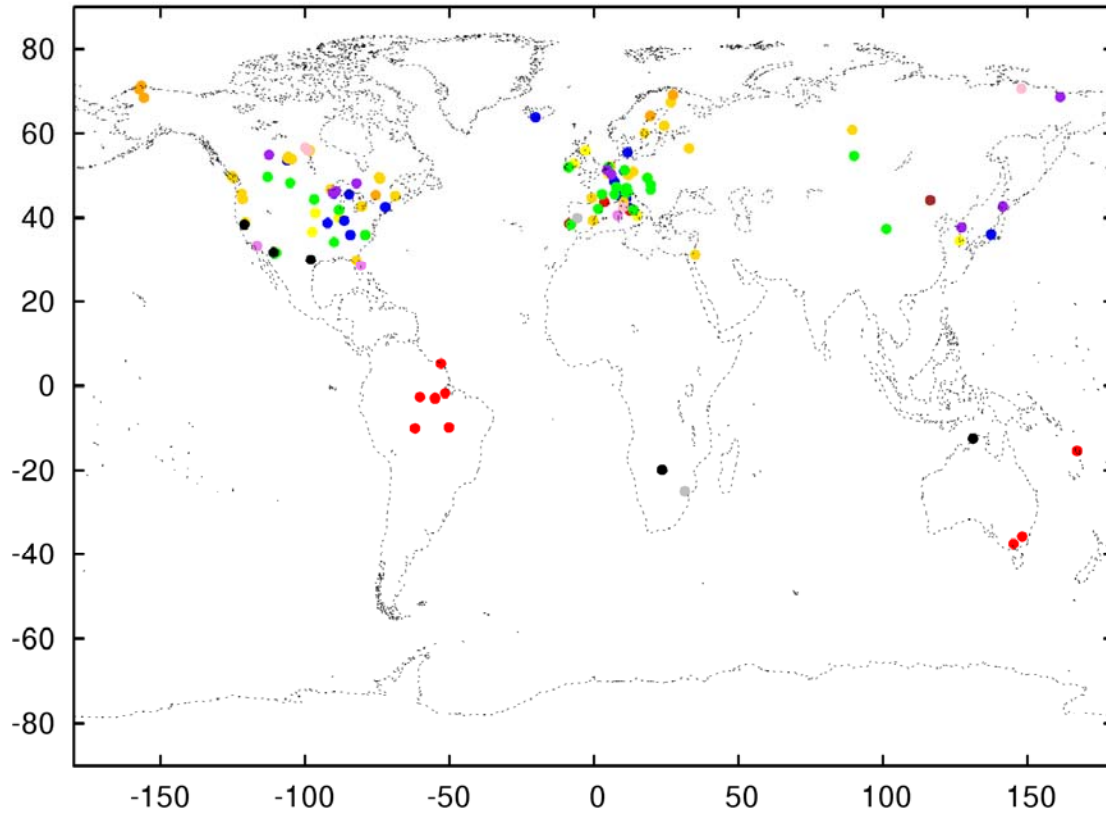


Fig. 1: Location of 156 FLUXNET sites used in this study. A different color is used for each dominant biome type.

The site-level meteorological variables were used as a boundary condition for ORCHIDEE simulations at each site. The plant functional type (PFT) is prescribed in the model using parameters that most closely represent the site vegetation. ORCHIDEE simulates the half-hourly, annual and longer variations of the carbon, water and energy fluxes, as well as soil carbon and water pools (Krinner et al., 2005). This study uses the configuration of the model which was run to set up the prior information for flux inversions at Laboratoire des Sciences du Climat et de l'Environnement (LSCE) as illustrated in Piao et al. (2009) and Chevallier et al. (2010). Each site is often a net sink of CO₂ (and rarely a net source of CO₂) and may be in non-steady state since the last disturbance event. However, the average long-term net ecosystem exchange (NEE) simulated by the ORCHIDEE model is in steady state because the model was spun up for 2000 years until soil and biomass pools reached equilibrium with climate conditions at each site.

Results

3.1. Daily fluxes at site scale

When combining all site-years together, the standard deviation of the differences between simulated and observed daily fluxes is $2.5 \text{ gC} \cdot \text{m}^{-2} \cdot \text{d}^{-1}$. The distribution is biased by $0.7 \text{ gC} \cdot \text{m}^{-2} \cdot \text{d}^{-1}$.

$^2 \cdot d^{-1}$, with the ORCHIDEE model having the smaller annual mean NEE by vegetation. This bias is partially expected because of the equilibrium assumption set for the simulation and the fact that many FLUXNET sites are managed ecosystems with higher NEE than the regional means within the global context. The measurement biases may also explain some of the bias. The differences between model- and observed values vary with the season, with larger values during the growing season. From May to August, the bias rises to $1.2 \text{ gC} \cdot \text{m}^{-2} \cdot \text{d}^{-1}$ with a standard deviation of $3.6 \text{ gC} \cdot \text{m}^{-2} \cdot \text{d}^{-1}$. Interestingly, the observed variability in NEE across the year has a standard deviation of $2.3 \text{ gC} \cdot \text{m}^{-2} \cdot \text{d}^{-1}$ only, suggesting that, at the synoptic scale, the NEE uncertainty for a model like ORCHIDEE is no better than assuming a null flux field.

The spatial structure of the error appears a function of the lag distance between pairs of sites based on the Pearson correlation coefficient of the model-minus-observation differences (Fig. 2). The median reveals spatial structure at short distances (less than 100 km) that did not show up in the 34-site study conducted by Chevallier et al. (2006): the correlation median is 0.33 for distances less than 100 km and 0.26 for distances between 100 and 200 km, and negligible beyond 400 km. Some systematic and spatially coherent errors in the modeling of plant phenology (e.g., Demarty et al., 2007) may contribute to the correlations. As expected, the observed variability of NEE contains larger correlations: the median is 0.55 for distances less than 100 km, 0.44 for distances between 100 and 200 km, and is still larger than 0.1 after 2500 km. Therefore the model errors are at a finer spatial scale than the measured signal itself, which implies that the model captures the main patterns of the true NEE for spatially-averaged quantities.

Chevallier et al. (2006) did not address the possibility that spatial error correlations could be significant within a given vegetation type. If this is the case, inverting surface fluxes directly in eco-regions would be legitimate (e.g., Peters et al., 2007). Figure 3 examines this possibility by restricting the scatter plots to a single dominating PFT, such as cropland, deciduous broad-leaf forest, evergreen broad-leaf forest, evergreen needle-leaf forest, and grassland. Only the deciduous broad-leaf forest type increased the average correlation coefficient, by about 0.4, compared to the all-site statistics. Clearly, assigning biome-dependent correlations does not seem justified, at least given the spatial density of the *La Thuile* flux network data.

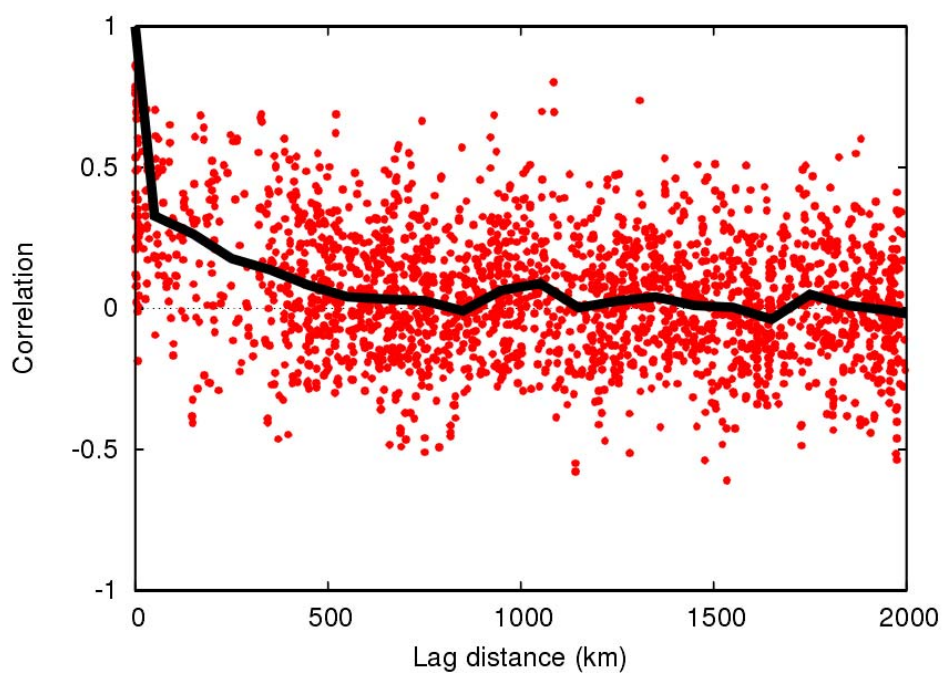


Fig. 2: Distance correlogram, i.e. correlation between the daily net ecosystem exchange (NEE) errors of the ORCHIDEE model at pairs of distant sites for a same time. Each point includes all the common years of one of the site pairs. The black line represents the median of the points per 100-km bin.

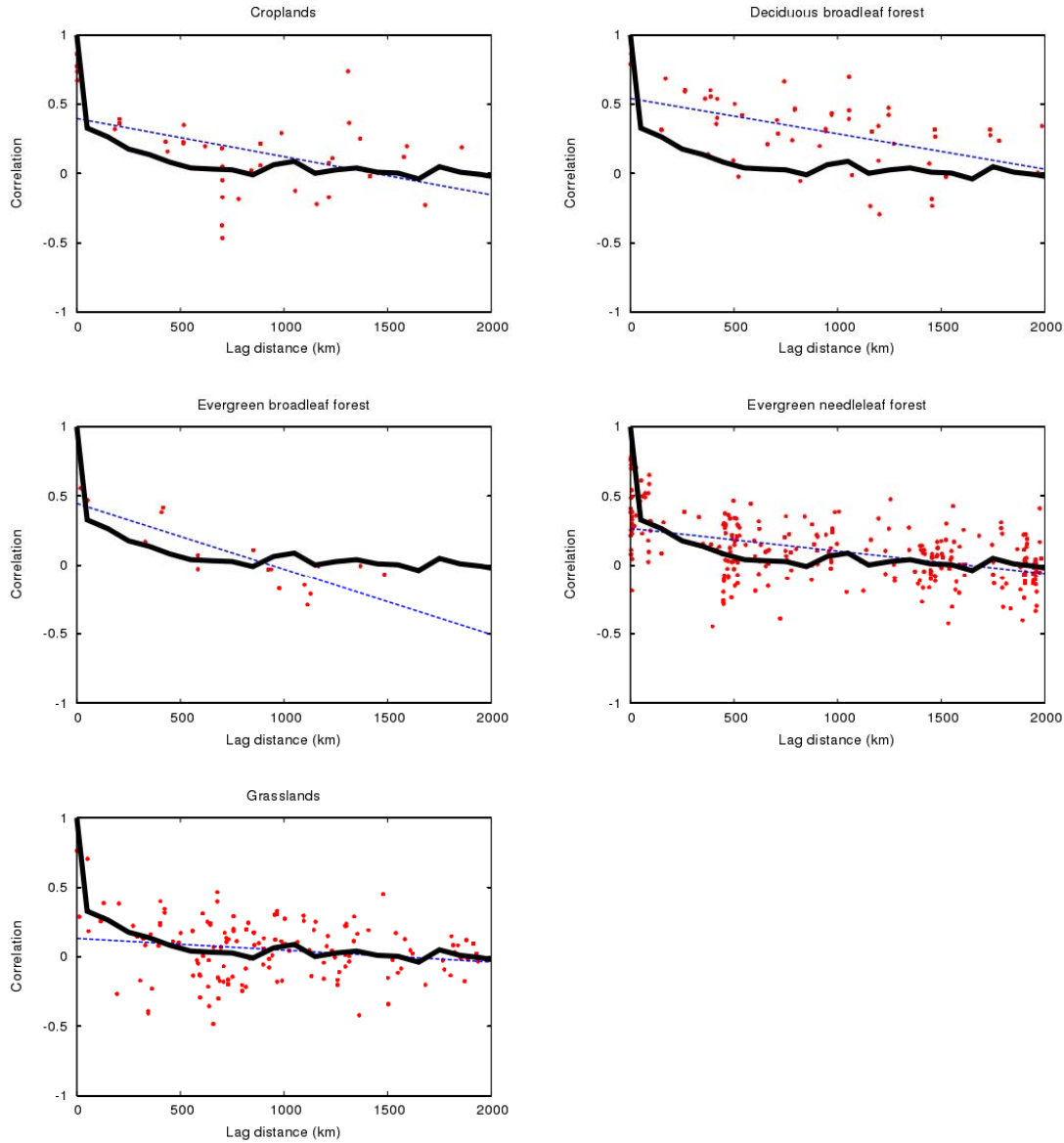


Fig. 3: Distance correlogram for the same dominant PFT. The regression line of the points is shown, for visualization purpose only, in blue. The black line represents the median for all sites, as shown in Fig. 2.

Fig. 4 shows the temporal structure of the error in a manner similar to Fig. 2. To minimize edge effects, we condense the results in an all-site-year correlation, rather than in a binned median correlation. The former quantity gives more weight to the sites with long data records than the latter and yields slightly larger values (Fig. 4). The all-site correlation is positive for lags <85 days and for lags >275 days, which reflects some seasonal pattern of the error. Limited negative correlations (<-0.02) of this quantity exist at lags of 85-275 days. Again, the measurement-only statistics of NEE (not shown) contain larger temporal correlations: the all-site correlation remains positive until day 95 and the negative correlations reach -0.1 around the six-month lag. This highlights some skill of the model at seasonal scale.

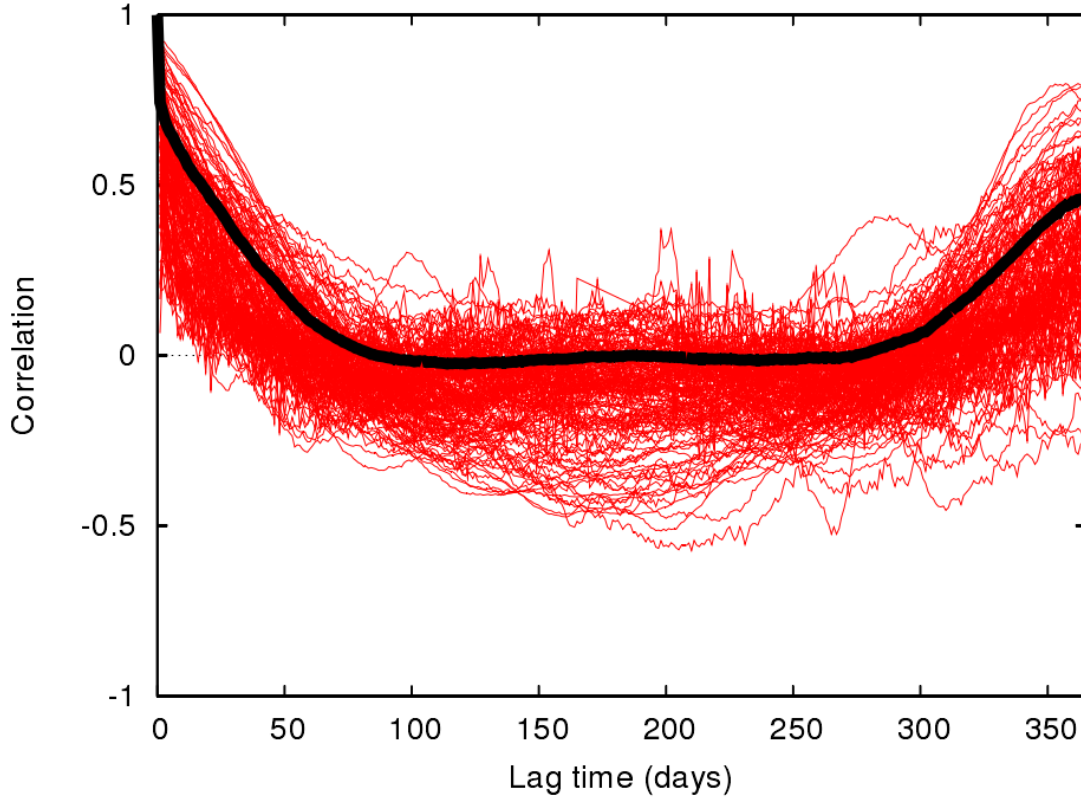


Fig. 4: Time correlogram, i.e. autocorrelation between the errors of the ORCHIDEE model at distant times for a same site. Each red line corresponds to a different site. The black line represents the all-site autocorrelation.

3.2. Effect of temporal and spatial aggregation of the fluxes

The FLUXNET database enables a synthetic estimation of the daily NEE error statistics of the ORCHIDEE model at the site scale, while Bayesian atmospheric CO₂ flux inversion systems usually operate at coarser temporal and spatial scales, typically several 10,000 km² and several days or weeks for global inversions. Therefore, the effect of space-time aggregation on the NEE prior error characterization needs to be investigated.

If the site-level daily error statistics are normally-distributed (i.e., Gaussian) with covariance matrix $\mathbf{B}$, the corresponding low resolution error statistics are also normally-distributed and have a covariance matrix as follows (Bocquet et al. 2011):

$$\mathbf{B}' = \mathbf{U}\mathbf{B}\mathbf{U}^T \quad (1)$$

where $\mathbf{U}$ is the operator that upscales the fluxes from the high-resolution scale to the low resolution one (i.e., coarse-graining operator). Eq. (1) provides a straight forward approach to upscale the error statistics, but its application for global atmospheric inversion systems is hampered by the large dimension of $\mathbf{B}$. We therefore introduce an alternative approach to upscale the error statistics from the relatively high resolution of our previous results to any coarser regular spatial and temporal resolution. The model is described in Appendix 2. It consists of two simple equations (A3) and (A4) that bridge the gap between the scales. They

show that aggregation dampens the higher frequencies of the error and therefore reduces it in relative values (Eq. (A3)), while increasing the low (correlated) frequencies (Eq. (A4)).

Figure 5 shows the effect of temporal and spatial aggregation on the error statistics, as computed from this error model for various lags and aggregation scales. We have assumed that high-resolution pixels of 1 day and 1 km², for time and space, respectively, tile each one of the coarse-resolution NEE fluxes. Correlation lags are defined from a reference point taken as the middle of a coarse-resolution tile of length g . For a given aggregation time or distance g , the correlation behaves like a staircase function: it is constant between lags 0 and $g/2$, between lags $g/2$ and $g+g/2$, between lags $g+g/2$ and $2g+g/2$, etc. We illustrate the variations of the correlations R with two examples: at lag time 30 days (Fig. 5a), R varies between 0.4 (without any aggregation) and 1.0 (with 60-day aggregation or more); at lag distance 500 km, R varies between 0.1 (without any aggregation) and 1.0 (with 1000-km aggregation or more). The standard deviations S decrease from 2.5 gC·m⁻²·d⁻¹ to 1.6 gC·m⁻²·d⁻¹ for 90-day aggregation and to 0.7 gC·m⁻²·d⁻¹ for 1000-km aggregation.

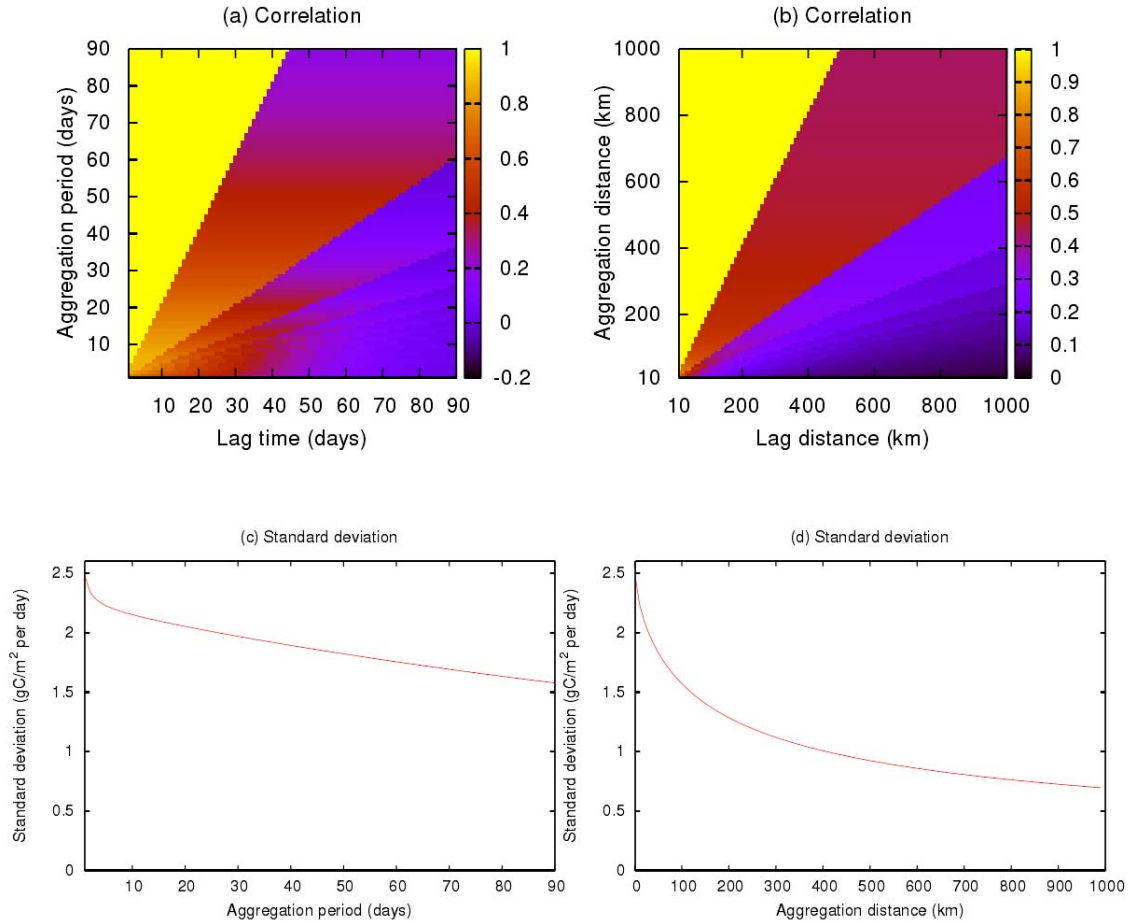


Fig. 5: Effect of temporal (left column, a, c) and spatial (right column, b, d) aggregation of the fluxes on error correlation in the same dimension (upper row, a, b) and on error standard deviation (lower row, c, d). The aggregation distance (b, d) is defined as the length of the side of a square on which the aggregation is performed.

The high temporal density of the flux data allows us to evaluate the model behavior for temporal aggregation. We take here the example of semi-monthly-averaged fluxes, for which we still have a sufficient number of flux pairs to perform the statistics despite the averaging. For the standard deviation S of the semi-monthly flux errors at the site scale, our model yields a value of $2.1 \text{ gC}\cdot\text{m}^{-2}\cdot\text{d}^{-1}$ (Fig. 5c), which is the same value as the actual model-minus-observation statistics (to be compared with $\sigma = 2.5 \text{ gC}\cdot\text{m}^{-2}\cdot\text{d}^{-1}$ for 24-hour site-scale). The correlations in the model and in the data for the semi-monthly fluxes are displayed in Fig. 6. The model reproduces the behavior of the data fairly well, except for lag times longer than 200 days where differences of up to 0.1 are seen. Note for instance the good simulation for lags less than 15 days in Figure 6b, for which the shape of the data all-site correlation significantly differs between high and low temporal resolutions (Fig. 4 vs. Fig. 6b). For longer lags, the 2-week aggregation does not change the correlations much.

We use the statistical model to compute error statistics at the typical space-time resolution of current global atmospheric inversion systems that use ORCHIDEE fluxes as prior information (Piao et al., 2009; Chevallier et al., 2010). For the 8-day fluxes used in Chevallier et al. (2010) that had an e-folding temporal error correlation length of four weeks (the e-folding length being the lag required for the correlation to decrease by a factor of e ; note that these authors separate daytime and night-time, which is not performed here), the coarse-resolution errors (Fig. 5a) are correlated by 0.43 at lag one month (instead of 0.35 in the case of daily fluxes), which is close to an exponentially-decreasing function of e-folding length of 36 days. We note that an exponentially-decreasing function does not capture the positive values at the one-year lag (Fig. 4). The standard deviation of the 8-day flux error at site scale is $2.2 \text{ gC}\cdot\text{m}^{-2}\cdot\text{d}^{-1}$ (Fig. 5c) instead of $2.5 \text{ gC}\cdot\text{m}^{-2}\cdot\text{d}^{-1}$ at daily scale. For monthly fluxes (used in Piao et al., 2009, without any temporal error correlation), the coarse-resolution flux errors are correlated by 0.59 from one month to the next (Fig. 5a). The standard deviation of the monthly error at site scale is $2.0 \text{ gC}\cdot\text{m}^{-2}\cdot\text{d}^{-1}$ (Fig. 5c). For fluxes at the scale of a square grid box of 300 km x 300 km (comparable to Piao et al., 2009, and Chevallier et al., 2010, with, respectively e-folding correlation lengths of 1000 km and 500 km) the between-grid-boxes spatial correlation exponentially decreases with the distance with an approximate e-folding length of 500 km (Fig. 5b). The error standard deviation at the coarse scale reduces to $1.2 \text{ gC}\cdot\text{m}^{-2}\cdot\text{d}^{-1}$ (Fig. 5d). Combining spatial (300 km) and temporal (8-day or monthly) averaging does not change the computed correlations but further reduces the error standard deviation to 1.1 and $1.0 \text{ gC}\cdot\text{m}^{-2}\cdot\text{d}^{-1}$, respectively, for 8-day and monthly fluxes.

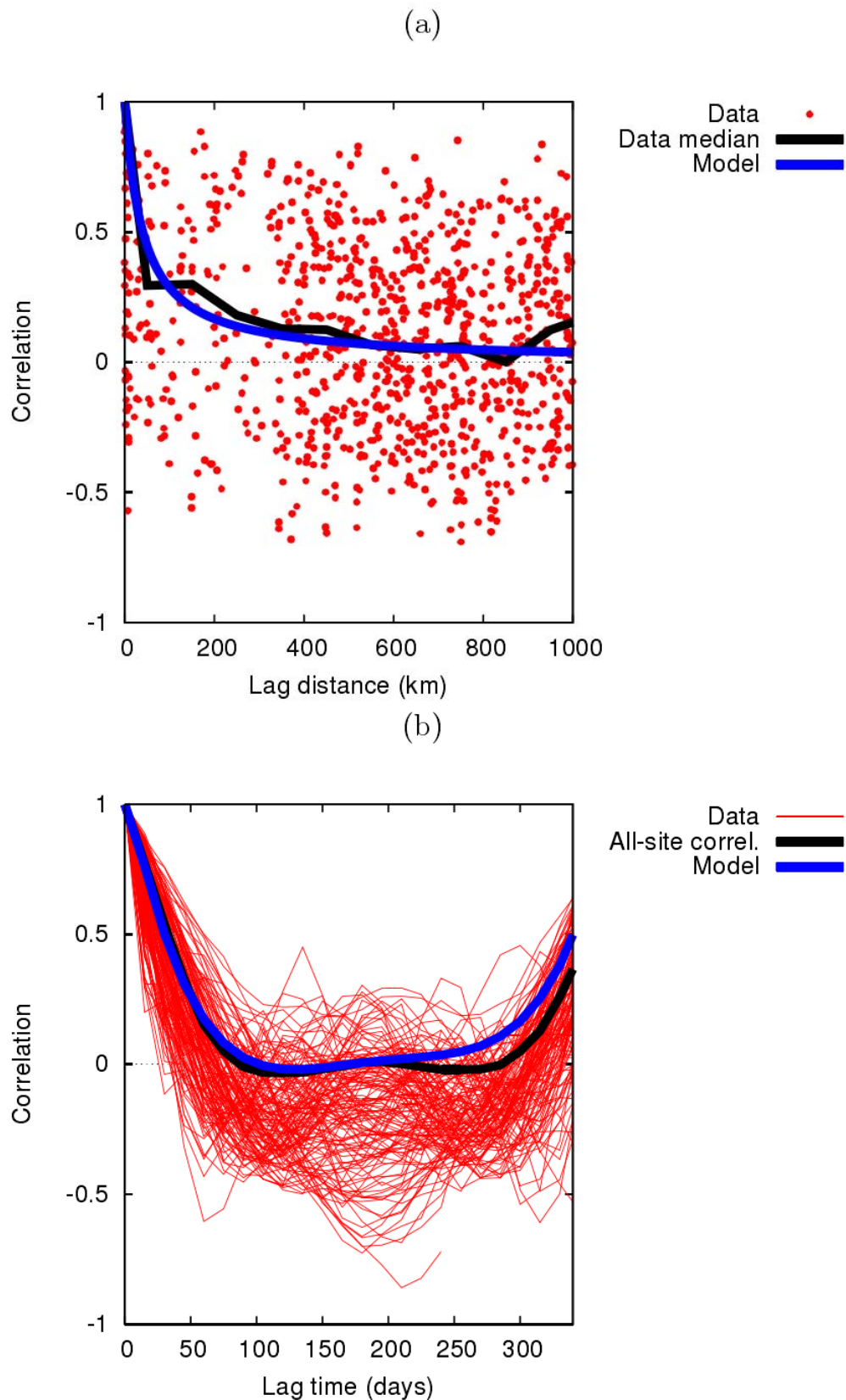


Fig. 6: Distance (a) and time (b) correlograms for semimonthly site-scale fluxes. Each point includes all the common years of a given pair. The black line represents the median of the correlations per 100-

km bin (a) or the all-site correlation (b). The blue lines correspond to the statistical model of the errors. The model curves are extracted from Figs. 5a and 5b with a 2-week smoothing in the case of 5b.

Discussion and Conclusions

We estimated prior NEE errors for CO₂-flux atmospheric inversions. Using the ORCHIDEE simulations as an example of prior information and based on observations made at 156 FLUXNET sites across the world, we described the mean, variances and correlations of the prior errors at the site scale with a 24-hour temporal resolution. The model error statistics differed substantially from those of the fluxes themselves. A model generalized these results to a range of larger temporal and spatial scales.

There are four main limitations to this study. First, it only addresses natural vegetation fluxes and cannot consider the emissions from agricultural crops, fossil fuel, cement manufacturing and fires. Second, the ORCHIDEE simulations at the site scale are based on local meteorological measurements as boundary conditions and rely on accurate description of the vegetation type, but boundary conditions for regional to global simulations can carry large biases. Low accuracy (i.e. large biases) of the coarse resolution boundary conditions (usually provided by weather centers) would tend to increase the spatial correlations of the errors compared to the situation described here. Third, it is not clear if our results apply to models other than ORCHIDEE. We can argue that the correlation lengths would decrease with better model accuracy, and vice versa. Fourth, the results are tied to the *La Thuile* database of the FLUXNET. This spatially-heterogeneous network may represent the error statistics poorly outside North America and Europe, and even there they may not be dense enough to describe fine features of the error statistics.

Keeping these limitations in mind, the main characteristics of the prior errors can be listed as: (i) the simulated site-scale daily (24-hour) flux is biased by a few tenths of a $\text{gC}\cdot\text{m}^{-2}\cdot\text{d}^{-1}$, with random errors of standard deviations of $2.5 \text{ gC}\cdot\text{m}^{-2}\cdot\text{d}^{-1}$ (by comparison, Chevallier et al., 2006, obtained $2.0 \text{ gC}\cdot\text{m}^{-2}\cdot\text{d}^{-1}$ as the standard deviation for their 34 study sites without gap-filling); (ii) some small positive spatial correlations of the error (unnoticed in Chevallier et al., 2006) are seen within the first few hundred kilometres only; (iii) correlations between areas dominated by a same vegetation type are not larger than the others, except in the case of deciduous broad-leaf forests; (iv) positive temporal correlations exist within the first few weeks and after a year; and (v) negative correlations are negligible. Aggregating the fluxes in space or time makes the covariance matrix of the error a bit denser and significantly reduces the variances. It should be highlighted that a side effect of aggregation is the increase of the observation errors and of their complexity (see discussed by Kaminski et al., 2001).

The unknown but certainly non-zero mean distribution of the NEE of the terrestrial biosphere violates the assumption of unbiased prior error statistics in the Bayesian CO₂-flux inversions. One may therefore wonder if assigned variances and correlations could empirically be tuned to account for biases. To meet the requirement of optimal estimation, any bias on the prior is reduced by the inversion anyway, by the same amount as the prior error variances. However, it is common practice to inflate the prior variances in order to allow

the inversion system to yield larger reductions of the bias, at the expense of increased random errors. As long as the biases of the prior fluxes are much smaller than their error standard deviations, there is no advantage to tune the prior correlations as well and biases can be neglected in the inversion design.

Acknowledgments

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Appendix 1: list of the selected FLUXNET sites

The identification codes of the FLUXNET sites used in this study are: AT-Neu (Wohlfahrt et al., 2008), AU-How, AU-Tum, AU-Wac, BE-Bra, BE-Lon, BE-Vie, BR-Ban, BR-Cax, BR-Ji2, BR-Ma2, BR-Sa1, BR-Sa3, BW-Ma1, CA-Ca1, CA-Ca2, CA-Ca3, CA-Gro, CA-Let (Flanagan and Johnson, 2005), CA-Man (Dun et al., 2007), CA-Mer (Lafleur et al., 2003), CA-NS1, CA-NS2, CA-NS3, CA-NS4, CA-NS5, CA-NS6, CA-NS7, CA-Oas, CA-Obs, CA-Ojp, CA-Qcu (Giasson et al., 2006), CA-Qfo (Bergeron et al., 2007), CA-SF1 (Mkhabela et al. 2009), CA-SF2 (Mkhabela et al. 2009), CA-SF3 (Mkhabela et al. 2009), CA-SJ1, CA-SJ2, CA-TP2 (Peichl and Arain, 2007), CA-TP3 (Peichl and Arain, 2007), CA-TP4 (Peichl and Arain, 2007), CA-WP1 (Cai et al., 2010), CH-Oe1, CN-HaM, CN-Xfs, CZ-BK1, CZ-BK2, DE-Bay, DE-Geb, DE-Hai, DE-Kli, DE-Meh, DE-Tha, DE-Wet, DK-Sor, ES-ES1, ES-ES2, ES-LMa, ES-VDA, FI-Hyy, FI-Kaa, FI-Sod, FR-Hes, FR-LBr (Berbigier et al. 2001), FR-Lq1, FR-Lq2, FR-Pue, GF-Guy, HU-Bug, HU-Mat, IE-Ca1, IE-Dri, IL-Yat, IS-Gun, IT-Amp, IT-BCi, IT-Col, IT-Cpz (Garbulsy et al., 2008), IT-Lav, IT-LMa, IT-Mal, IT-MBo, IT-Noe, IT-Non, IT-Pia, IT-PT1, IT-Ren, IT-Ro1 (Rey et al. 2002), IT-Ro2 (Tedeschi et al. 2006), IT-SRo, JP-Tak, JP-Tom, KR-Hnm, KR-Kw1, NL-Ca1, NL-Hor, NL-Loo, PT-Esp, PT-Mi1, PT-Mi2, RU-Che, RU-Cok, RU-Fyo, RU-Ha1 (Belleli Marchesini et al. 2007), RU-Zot, SE-Deg, SE-Fla, SE-Nor, UK-ESa, US-ARM, US-Atq, US-Aud, US-Bkg, US-Blo, US-Bo1, US-Bo2, US-Brw, US-Dk1, US-Dk2, US-Dk3, US-FPe, US-FR2, US-Goo, US-Ha1 (Urbanski et al. 2007), US-Ho1, US-Ho2, US-IB1, US-IB2, US-Ivo, US-KS2, US-Los, US-LPH, US-Me2 (Thomas et al. 2009), US-Me4 (Law et al., 2001), US-MMS, US-MOz, US-Ne1, US-Ne2, US-Ne3, US-PFa, US-SO2, US-SO4, US-SP2, US-SP3, US-SRM, US-Syv, US-Ton (Ma et al., 2007), US-UMB, US-Var (Ma et al., 2007), US-WBW, US-WCr, US-Wi4, US-Wkg, US-Wrc, VU-Coc, ZA-Kru.

The site citations above are those given at <http://www.fluxdata.org/> (access 5 October 2010), as requested by the *La Thuile* data policy. A description of each site can be found at <http://www.fluxdata.org:8080/SitePages/> (access 16 July 2010).

Appendix 2: Aggregation model

In the following, the high-resolution (in space or time) error statistics are symbolized by lowercase letters (σ for a standard deviation and r for a correlation), while capital letters (S for a standard deviation and R for a correlation) represent the coarse resolution (in space or time) error statistics. We represent the high-resolution errors as a stationary field of normally- and identically-distributed random variables, all with zero mean and the same standard deviation σ . The stationarity property implies that the correlations depend on the time-space distance between the pairs of random variables but not on their absolute position in time and space. The high-resolution standard deviation σ is set to $2.5 \text{ gC} \cdot \text{m}^{-2} \cdot \text{d}^{-1}$ (i.e. the standard deviation of the model-minus-observation differences for daily fluxes at site scale). The high resolution correlations are represented (i) by a continuous parameterization of the all-site autocorrelation as a function of the lag time (Eq. A1, Fig. 4) and (ii) by a continuous parameterization of the median correlation as a function of the lag distance between pairs of sites (Eq. A2, Fig. 2):

$$r_\tau(\tau) = 0.767 - 0.018 \cdot \tau + (0.01222 \cdot \tau)^2 - (0.00809 \cdot \tau)^3 + (0.00513 \cdot \tau)^4 - (0.0012 \cdot \tau)^5 + 0.216 / (1 + 10 \cdot \tau) \quad (\text{A1})$$

$$r_\delta(\delta) = 1 / (0.032 \cdot \delta + 1) \quad (\text{A2})$$

with r_τ the dependency of the correlation as a function of lag time τ , in days, and r_δ the correlation as a function of the lag distance δ , in km. The parameterization of r_τ (Eq. A1) is only valid for lag times less than 365 days. Eqns. (A1) and (A2) have been obtained by regression on the data. They fit the thick lines of Figs. 2 and 4 with a root mean square of 0.01 and 0.06, respectively.

By developing the variance estimator (i.e. $\sum x_i^2 / n$, with x_i the n random samples of a random variable with zero mean) for the errors of the coarse-resolution NEE fluxes (i.e. time- and space-normalized), one can show that:

$$S^2 = \sigma^2 \cdot \bar{r}_{intra} \quad (\text{A3})$$

with $\bar{r}_{intra}$ being the arithmetic mean of the correlations r between all possible pairs of high-resolution-fluxes within the coarse-resolution fluxes. The definition of $\bar{r}_{intra}$ is illustrated in Fig. A1a.

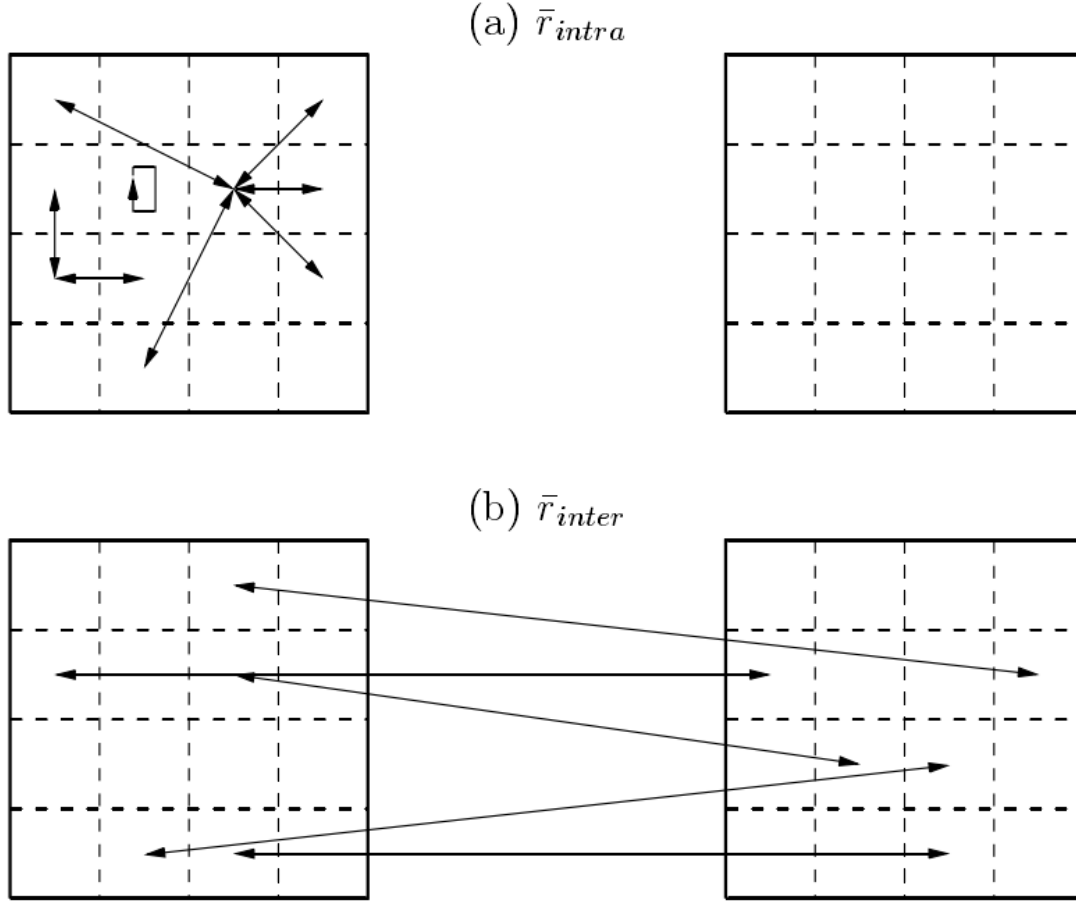


Fig. A1: illustration of the definition of the mean correlations $\bar{r}_{intra}$ (a) and $\bar{r}_{inter}$ (b). Dotted lines represent the boundaries of high-resolution fluxes and continuous lines correspond to two low resolution fluxes. The arrows illustrate the pairs over which the average correlations are computed.

Similarly, the Pearson correlation between the errors of a pair of coarse-resolution NEE fluxes f_1 and f_2 can be expressed as:

$$R(f_1, f_2) = \bar{r}_{inter}(f_1, f_2) / \bar{r}_{intra} \quad (\text{A4})$$

where $\bar{r}_{inter}(f_1, f_2)$ is the arithmetic mean of the distant correlations between all the different possible pairs of fine-resolution NEE fluxes that it is possible to construct from those inside coarse flux regions f_1 and f_2 . The definition of $\bar{r}_{inter}$ is illustrated in Fig. A1b.

The computation of $\bar{r}_{inter}(f_1, f_2)$ and $\bar{r}_{intra}$ stems from the above-described high-resolution statistics (σ and the correlations r) and the geometry of the fluxes. Eqns (A3) and (A4) quantify how aggregation dampens the higher frequencies of the error (Eq. (A3)), while increasing the low (correlated) frequencies (Eq. (A4)).

The last hypothesis of our error model is that spatial upscaling is independent from temporal upscaling. In this case, the coarse-scale standard deviation after aggregation in both space and time can be simply simulated by applying Eq. (A3) in each dimension successively, while coarse-scale correlations follow Eq. (A4) in each dimension separately.

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UNIVERSITÉ DE VERSAILLES SAINT-QUENTIN-EN-YVELINES

«Développement et évaluation du modèle de surface ORCHIDEE : apport pour la simulation des cycles de l'eau et du carbone aux hautes latitudes»

Présentée par : **Monsieur Tao WANG**

Résumé :

L'objectif de cette thèse est d'évaluer et de développer le modèle de surface ORCHIDEE (Organizing Carbon and Hydrology In Dynamic Ecosystems). Dans la première partie, l'évaluation du modèle à différentes échelles est présentée à l'aide d'une nouvelle méthodologie basée sur une analyse spectrale et des réseaux de neurones. Cette analyse nous a permis de mettre en évidence les erreurs systématiques du modèle, et d'ouvrir de nouvelles perspectives pour les développements futurs ORCHIDEE. Dans une seconde étape, afin de mieux comprendre les effets de la neige sur les flux de carbone présents et futurs, différentes études ont été menées. Une analyse de la respiration des écosystèmes d'hiver a été effectuée, à l'aide de mesures de station de flux « eddy covariance ». Les résultats démontrent le rôle de la respiration d'hiver dans le bilan annuel de carbone, ainsi que les effets de la neige sur la respiration. L'objectif d'une troisième étape a été de développer un nouveau module de neige dans ORCHIDEE. Dans ce nouveau modèle, les processus internes de la neige (neige fondante par exemple / regel, infiltration de l'eau entre les couches de neige) sont pris en compte. Par ailleurs, une nouvelle paramétrisation de l'albédo des forêts a été testée. Ces développements ont été validés à l'échelle locale sur quelques sites instrumentés puis à l'aide de produits spatialisés sur les régions des hautes latitudes Nord. Des améliorations significatives ont été mises en évidence en termes de propriétés du couvert nival. Ce nouveau modèle va maintenant permettre de mieux comprendre et modéliser les cycles de l'eau et du carbone aux hautes latitudes dans de prochaines études.

Abstract :

This thesis is to evaluate and develop a land surface model ORCHIDEE (Organizing Carbon and Hydrology In Dynamic Ecosystems). In the first part, ORCHIDEE on multiple timescales is evaluated by a novel methodology linking Artificial Neural Networks to Singular System Analysis. The joint analysis of observations and simulations uncovers the characteristics of model bias at and across timescales in different plant function types and climate groups, which provide references for future ORCHIDEE developments. To have a throughout understanding of snow effects on present and future carbon fluxes, ORCHIDEE with a decent snow model should be developed. In the second part, a site-synthesis analysis of winter ecosystem respiration and its controls across eddy covariance sites in mid- and high-latitude regions has been conducted. The result corroborates the role of winter respiration in annual carbon budget, and snow effects on winter respiration could be indirectly observed by its insulating effect on soil. The standard ORCHIDEE snow model is a simple bucket model and has been shown to bias snow simulations. In the third part, internal snow processes (e.g. snow melting/refreezing; water infiltration between snow layers) were thus developed in ORCHIDEE. Moreover, a new forest albedo parameterization was also implemented. In the third and final parts, this newly developed snow model has been validated based on both site and continental levels, and a significant improvement has been seen in terms of snow pack properties examined. This new snow model coupled with permafrost will be used to explore high-latitude water and carbon dynamics in the future.