

J6.4 A SENSITIVITY STUDY OF AN ENERGY-BUDGET SNOW ACCUMULATION AND ABLATION MODEL

Fan Lei^{1*}, Victor Koren², Michael Smith², and Fekadu Moreda³

¹Riverside Technology, Inc

²Office of Hydrologic Development, National Weather Service, National Oceanic and Atmospheric Administration

³MHW, Inc

1. INTRODUCTION

Research is being conducted at the Office of Hydrologic Development (OHD) of the National Weather Service (NWS), National Oceanic & Atmospheric Administration (NOAA) to evaluate advanced energy-budget snowmelt models for operational hydrologic forecasting. Current NWS river forecasting operations include the use of a degree-day snow model. Historically, this approach has been used primarily because of the lack of reliable observations required by Energy Budget Snow Models (EBSMs). In recent years, products from the Snow Data Assimilation System (SNODAS) of the NWS National Operational Hydrologic Remote Sensing Center (NOHRSC) are being used to update the degree-day snow model (Carrol et al., 2001; Larson et al., 1995). SNODAS is a modeling and data assimilation system developed to provide the best possible estimates of snow cover and other variables to support hydrologic modeling and analysis.

In an early, comprehensive work on snow hydrology, the Corps of Engineers (1956) examined the data then available for energy budget snow modeling. However, sensitivity analyses were not performed. Analysis of the Snow Model Intercomparison Project (SnowMIP) results (Etchevers et al., 2002) showed that energy-budget snowmelt models can generate more accurate simulations of snow variables than conceptual models in certain cases. However, energy-budget models are very sensitive to errors in the input forcing data. More recently, Franz (2006) compared an energy budget model to the NWS operational conceptual model (Snow-17 discussed below). She performed several sensitivity tests in order to compare the two models' performance.

The purpose of our current work is to evaluate the performance of an EBSM driven by meteorological input data with various uncertainty levels, and thus to recommend suitable meteorological forcing data to ensure reliable hydrological forecasting. We perform more comprehensive sensitivity tests than Franz (2006) in an effort to help determine the optimal transition pathway from conceptual to advanced energy-budget snowmelt models for operational hydrologic forecasting.

2. SNOW MODELING BACKGROUND

The energy balance in a snow pack controls snow accumulation and melt processes. The total energy sources, Q , can be expressed as:

$$Q = S + L + H + LE + R + G \quad (1)$$

where S is the short wave radiation; L is the long wave radiation; H is the turbulent exchange of sensible heat with the atmosphere; LE is the turbulent exchange of latent heat with the atmosphere; R is the heat transfer by rain; and G is the conductive exchange of sensible heat with the ground. The sensible heat, and the heat exchange with the ground are determined by the temperature gradients at the snow-air or snow-soil interface. The latent heat is determined by the vapor pressure gradient at the snow-air interface, which is related to the surface humidity.

In an energy budget model, surface incoming short and long wave radiation can be obtained directly from meteorological sources or calculated from bulk formulae. Other components are calculated explicitly according to thermal or dynamic equations governing the corresponding processes. In a temperature index conceptual model, parameters describing snow condition are determined based on empirically derived relationships between air temperature and snow processes from climate events. Due to the empirical nature of the index model, extensive and unbiased calibration is typically necessary in order to get high quality snow modeling results.

EBSMs hold out the promise of more accurate simulation of snow processes since they may better represent non-standard conditions outside the range for which conceptual snow models are calibrated. However, EBSM data requirements are much greater compared to index-based models.

3. EXPERIMENT DESIGN

We select four SNOWpack TELemetry (SNOTEL) sites within the Carson River watershed operated by the Natural Resources Conservation Service (NRCS) of the US Department of Agriculture for sensitivity tests. The sites are Blue Lakes (38.60 N, 119.92 W, Elev. 2438.4m), Ebbetts Pass (38.55N, 119.80W, Elev. 2651.8m), Monitor Pass (38.67N, 119.61W, Elev. 2545.1m), and Poison Flat (38.51N, 119.63W, Elev. 2357.9m). These sites are in a high elevation basin whose hydrology is dominated by snow accumulation and melt. In situ hourly surface temperature and accumulated precipitation data are available. Snow Water Equivalent (SWE) data is also available at a daily frequency. These observed data are necessary to evaluate the meteorological forcing data obtained from other sources and also as a reference to evaluate the performance of energy-budget and index-based models.

We select the NOAA EBSM by Koren et al. (1999) as an example to test energy budget snow model sensitivity to major energy forcing fields. As a reference, a conceptual snowmelt model, SNOW-17

* Corresponding author address: Fan Lei, 10371 Leola Ct, #2, Cupertino, CA 95014; E-mail: toleifan@yahoo.com

(Anderson, 1973, 1976), is tested for sensitivity to temperature. The NOAA EBSM and SNOW-17 are both operational models. In our tests, they are driven by identical air temperature and precipitation data at the same location during the same time period. Additional reasons for selecting these two models are provided in Section 3.1

Considering the physical mechanisms and dominant factors during snow accumulation and ablation processes might be different, we conduct model sensitivity tests for the whole water year period and snowmelt season separately to separate the models' sensitivity for these two periods. The snowmelt season is defined as April 1st to August 31st.

Bias and random errors are applied in the experiments for each meteorological element we consider. SWE simulation is analyzed to show models' relative sensitivity to different variables. Model sensitivity factors are analyzed. The results suggest snow model accuracy requirements for meteorological input fields to achieve reasonable snow simulations.

3.1 Selected model features

3.1.1 NOAA energy-budget snow model

The NOAA EBSM used here (Koren, 1999) was tested in SnowMIP and is a version of the NOAA-Land Surface Model (NOAH-LSM) (Mitchell et al., 2002). The NOAH-LSM is a component of the operational Eta numerical weather prediction model of the National Centers of Environmental Prediction (NCEP). The model neglects heat transferred by the movement of meltwater in the snowpack. However, snowpack properties such as density and thermal conductivity are adjusted depending on snow compaction. To accommodate snow-soil surface interaction, the snow model is linked to a multilayer (four layers in this application) soil model. The NOAA model does not include conceptual-type parameters and no (or very little) calibration is needed. Input energy forcing fields including surface 2-m temperature, relative humidity, surface wind at 10 m, and surface downward short/long wave radiation are derived from meteorological sources. The output variables from the model include: snow depth, snow water equivalent, snow melt rate, liquid water content, bottom runoff, etc. The NOAA EBSM has been enhanced since the version of Koren (1999). However, we believe that the enhancements would not lead to markedly different results than presented here.

3.1.2. SNOW-17 model

The SNOW-17 model (referred to as SN17 in this paper) is one of the models available in the NWS River Forecast System (NWSRFS). SN17 is the baseline operational model to compute snow accumulation and melt. The model is described in detail by Anderson (1973, 1976). Near surface air temperature and precipitation are the only input data required by the model, while air temperature is the sole index for energy exchanges across the snow-air interface. Simple assumptions are applied in the model to mimic the

current meteorological conditions. Some parameters needed in calculating forcing fields or representing the local geography factors are developed via calibration. While it is conceptual, the model represents well the most significant physical processes affecting snow accumulation and melt and is widely used. The output variables of SNOW-17 can be snow depth, snow water equivalent, snow melt rate, etc.

In this experiment, an uncalibrated SN17 is run at a 1-hour time step using identical data as used with the NOAA EBSM. For the purpose of our sensitivity analyses, it is not necessary to calibrate the SN17 parameters to the SNOTEL site conditions. As discussed later, we compare the models' sensitivity using a statistic that is not based on SWE observations. The model control parameters are taken from the calibrated SN17 parameters at the Sleepers River (USA) in SnowMIP (Etchevers et al., 2002). The Sleepers River site is located at 44.5° N, 72.17° W, in the state of Vermont, United States. The elevation of the site is 552 m. The Sleeper River parameters are suitable for this study in that they represent the open conditions at the SNOTEL sites and are within recommended ranges for SN17.

3.2. Data Selection

In the sensitivity tests, constructed data errors are added to each individual driving field. We assume that the test results should not be constrained by specific input data sources since we are focusing on sensitivity to errors and not simulation accuracy. Also, considering the ultimate purpose of this research is to assist operational river forecasting in NWS, we select geophysical and meteorological data from various sources considering real time availability, data quality and easy application. The following is a list of all data sources used.

3.2.1. Background geophysical data

The background geographical data needed for the NOAA EBSM are: vegetation type, soil type, sand/quartz fraction, minimum stomatal resistance, surface roughness height, surface albedo, Leaf Area Index (LAI), Greenness FRACTION (GFRAC), etc.

Most land surface parameters used for the NOAA EBSM in this research are from the North American Land Data Assimilation System (NLDAS) (Mitchell et al., 2004). However, greenness and shade factor parameters are significantly reduced considering the open SNOTEL measurement sites while NLDAS parameters suggested forested area. Parameters used for the same EBSM in the SnowMIP (Etchevers et al., 2002) are applied in this experiment.

3.2.2. Energy forcing data-- ground measurement

At the four SNOTEL sites, measured hourly surface temperature and accumulated precipitation data are available since 1997. Snow water equivalent is also available at a daily frequency. These observed data are necessary to evaluate the meteorological forcing data

obtained from other sources and also as a reference to evaluate the performance of the EBSM and SN17. These ground measurements are used as base fields for model sensitivity testing.

3.2.3. Energy forcing data-- North American Regional Reanalysis (NARR)

Another source of meteorological forcing data is the North American Regional Reanalysis (NARR) (Mesinger et al., 2004). The data are available at high spatial and temporal resolution (32-km, 45-layer, 3-hourly) since 1979. The NARR data set is suitable for applications in this project since it is a long-term, consistent, assimilation-based, climate data suite for the North American domain. It is evenly gridded and has high potential for operational availability. NARR data takes advantage of the use of the regional Eta model including the many advances that have been made in the Eta regional modeling and data assimilation systems. Moreover, it is planned for the NARR to run in real time. As such, the NARR data is representative of data that is used operationally

Surface downward long wave flux, surface air temperature, relative humidity at 2-meter height, and wind at 10-meter height are extracted from the NARR data sets and interpolated to SNOTEL stations. Bilinear interpolation and elevation adjustment are performed for NARR temperature data. Simple nearest neighbor method is used for surface downward long wave flux, 2-meter relative humidity and 10-meter wind fields. All data are linearly interpolated to 1-hour from the original 3-hour time interval in the NARR data.

3.2.4. Energy forcing data-- surface incoming short wave flux data

The downward short wave flux in the experiment is taken from GEWEX [Global Energy and Water Cycle Experiment] Continental Scale International Project (GCIP) and GEWEX America Prediction Project (GAPP) Surface Radiation Budget (SRB) data. The data have been reprocessed recently to improve performance over snow-covered areas and are available at 1/8 degree resolution (Pinker et al., 2003). The operational version of the data are stored at and distributed by the University of Maryland, College Park.

3.3. Sensitivity tests

Temperature and precipitation measured at SNOTEL stations are used as base fields in model sensitivity tests. For this study, we introduce a new statistic to judge the impact of input forcing errors. We define the SWE simulation Sensitivity Factor (SF) as the ratio of a root mean square difference, RMSE, between SWE simulated using input data with and without introduced errors, over the standard deviation, STD, of measured SWE, to the root mean square error introduced to the input variable over the standard deviation of the input variable time series:

$$SF = \frac{\left(\frac{RMSE}{STD}\right)_{SWE}}{\left(\frac{RMSE}{STD}\right)_{INPUT}} \quad (2)$$

3.3.1. Selection of meteorology fields for sensitivity test

Temperature, surface incoming solar radiation and surface wind are the forcing fields of primary interest in this project. SnowMIP results showed that EBSMs are sensitive to errors in these forcings as well as to precipitation

Comparison of SWE simulations using extracted NARR precipitation and SNOTEL measurements (Lei et al., 2006) shows that, without appropriate topographic and elevation adjustment, precipitation data from NARR is too coarse to drive either conceptual or EBSMs. According to a comparison of NARR precipitation with SNOTEL in situ measurements in the same reference, the directly extracted NARR precipitation was significantly underestimated, so was the SWE simulation using NARR precipitation compared with SWE simulation using SNOTEL precipitation. Special treatment for NARR precipitation data is necessary or other more reliable data sources need to be explored. For this reason, we decided to forego sensitivity tests on precipitation at this time although we recognize that precipitation is the dominant element controlling snow pack dynamics.

3.3.2. Data perturbations applied in sensitivity tests

To separate the model response to bias and random errors in forcing fields, bias and random errors are applied separately to both EBSM and SN17 forcing data for the entire water year and snow melt periods at each SNOTEL site. Values of bias and random errors as well as the number of error profiles were selected based on many years of experience with snow modeling in Russia and the United States.

3.3.2.1 Bias

Biased profiles used for model sensitivity tests are built by introducing bias with equal intervals to the reference profile, F_0 using accepted procedures. The calculation of the i -th biased profile could be described as:

$$F_i^* = F_0 + E_{max} - (i-1)*d, \quad i=1,2,\dots,N \quad (3)$$

where E_{max} is a bias maximum value, d is a bias interval, and N is a number of profiles that equals 31 for short wave radiation and wind speed tests, and 7 for temperature tests. E_{max} equals 150 W/m², 3 m/s, and 1.5°, and d equals 10 W/m², 0.2 m/s, and 0.5° for short wave radiation, wind (both U and V), and temperature respectively.

In the sensitivity tests for temperature, random errors with 1° STD were included in the bias profiles. This resulted in bias profiles having a Gaussian distribution with the selected bias and 1 degree of random error.

3.3.2.2. Random error

Random errors are constructed according to a Gaussian distribution, $G(0, \sigma^2)$, for the i -th profile of the selected energy forcing field as:

$$F_i^* = F_0 + G\{0, \sigma_i^2 = 0.02i \cdot \text{STD}^2(F_0)\},$$
$$i=1, \dots, 50 \quad (4)$$

In total, 7 bias profiles and 50 random perturbation profiles are applied for temperature sensitivity tests. 31 bias profiles and 50 random perturbation profiles are applied for sensitivity tests on surface incoming short wave radiation and surface wind.

3.4. Experiment design, step by step

The experiment is conducted in the following order:

- 1) Run the NOAH EBSM and SN17 at 4 SNOTEL stations using in situ measurements of temperature and precipitation. The SWE simulation was evaluated against SWE ground measurements. NOAH EBSM background geographical parameters are tested and adjusted based on extracted values from NLDAS to match local site land cover.
- 2) In the second stage, model sensitivity tests of both the NOAH EBSM and SN17 on temperature are conducted. 7 temperature profiles with bias and 50 profiles with Gaussian distributed random errors are applied to both models for the entire water year and the snowmelt periods at each site. The model sensitivity factors are analyzed for each scenario.
- 3) Sensitivity tests of the NOAH EBSM to surface short wave radiation and surface wind are conducted in the third stage of the experiment. 31 bias profiles and 50 random perturbation profiles are applied for tests on each field.
- 4) Sensitivity of the NOAH EBSM on surface maximum albedo is also checked. The reference value of the snow surface maximum albedo is set to 0.8. 7 other maximum albedo values from 0.6 to 0.9 are defined in the sensitivity tests.

4. RESULTS AND DISCUSSION

4.1 NOAH EBSM background geophysical parameters setting

Prior to model sensitivity tests, background geophysical parameters for the NOAH EBSM are evaluated and determined through model SWE simulation tests at SNOTEL stations.

Figure 1 shows simulated and measured snow water equivalent (SWE) at the Blue Lakes site for the 1998-1999 water year. Directly extracted NLDAS geophysical parameters and manual adjusted values are applied. It can be seen that NLDAS-based model parameters lead to significant underestimation of SWE. The discrepancy could be expected since the NLDAS grid resolution (1/8 degree) is too coarse to represent local physical properties, specifically land cover in mountain areas. In the experiment, the NLDAS-based

Fraction of Photosynthetically Active Radiation (FPAR) and Leaf Area Index (LAI) parameters are too high to represent this open site. Reasonable simulations of SWE are obtained after significant reduction of these parameters during the snow accumulation/ablation period. The adjusted parameters are applied to all further tests.

4.2 Model sensitivity to temperature

Here we use SNOTEL in situ temperature measurements as the reference data in the model sensitivity tests.

Simulation results at selected levels of random perturbations for the entire water year and snow melt season are shown in Figure 2. Upper panels, a(1) and b(1) of Figure 2 are plots of SWE ensembles from the NOAH EBSM and SN17 respectively for the 1999 water year. The two plots in the lower panels of Figure 2, a(2) and b(2) show NOAH EBSM and SN17 SWE simulation for the melt season only. In the melt season simulation, temperature perturbations are introduced from the beginning of the melt season, which is April 1, to the end of the melt season, which is August 31. Before April 1, reference temperature is applied for all profiles in the simulations. It can also be seen that at the same levels of random perturbation, SWE simulations by the NOAH EBSM exhibit greater spread than SN17, which indicates that the NOAH EBSM is more sensitive to temperature errors especially in case of the whole year tests.

Sensitivity factor analyses are shown in Figure 3. The x-axis of the plots represents the relative mean square error introduced to temperature profile normalized by standard derivation of temperature measurements at all 4 SNOTEL stations. The y-axis represents the relative root mean square difference between SWE simulated using input data with and without introduced errors normalized by the standard deviation of SWE measurements at all 4 stations. The two plots at the upper panel, a(1) and b(1), are sensitivity factors for the whole year simulations; lower panels, a(2) and b(2) are similar plots for melt season simulations.

Figure 4 and Figure 5 are sensitivity test results for bias errors in temperature. Again, upper panel plots, a(1) and b(1) show results of the whole year simulations and lower panel plots, a(2) and b(2), show results for the melt season simulations only.

Analysis of the simulation results suggests that: 1) both the NOAH EBSM and SN17 are more sensitive to temperature errors during the accumulation season than melt season; 2) both models are more sensitive to bias than random errors; 3) except for the SWE simulation in melt season for temperature bias, the NOAH EBSM is more sensitive to temperature errors than SN17 in all three other scenarios; 4) simulating SWE starting from maximum accumulation (melt period) would greatly reduce simulation errors; 5) for the whole season simulations at four SNOTEL stations, the maximum sensitivity factor can be as large as 6.5 for temperature

bias and 2.7 for random errors, while for the melt period, the corresponding numbers are 2.05 and 0.8.

4.3 Model sensitivity to surface short wave flux

Here we use incoming short wave flux data from the GEWEX GCIP and GAPP Surface Radiation Budget (SRB) projects as the base reference data.

Figures 6 and 7 are sensitivity test results for bias and random perturbations in short wave flux. Similar to the sensitivity tests analysis on temperature perturbation, we can observe that: (1) the NOAH EBSM sensitivity to incoming short wave flux bias varies greatly by station; 2) for the bias error case, there are nearly linear relationships between the relative SWE RMSE and the relative incoming short wave flux RMSE; 3) the NOAH EBSM is much less sensitive to random errors than bias: the maximum sensitivity factor is about 2 for bias, and less than 0.32 for random errors.

4.4. Model sensitivity to surface wind

Surface wind extracted from NARR is the reference data for the NOAH EBSM sensitivity tests on wind.

As shown in Figures 8 and 9, test results indicate that: 1) unlike other input variables, NOAH EBSM sensitivity to the surface wind error is less dependent on the selected period (the whole season vs. melt period) or error type (bias vs. random); 2) the sensitivity factor for random error in wind varies from site to site; 3) unlike with temperature and short wave flux test results, a 'non-sensitive' zone exists for tests on wind before simulation RMSE starts to increase with input error. The sensitivity factor increases dramatically after wind error reaches the threshold.

4.5. Model sensitivity to snow surface maximum albedo

The snow surface maximum albedo values in the range of 0.6-0.9, with increment of 0.05, are applied to test model sensitivity.

Test results shown in Figure 10 suggest that: 1) surface maximum snow albedo has a great influence on the simulation of SWE by the EBSM; 2) maximum albedo has much greater effect in the snow melt season compared to the accumulation season.

5. SUMMARY

The statistics of the NOAH EBSM and SN17 sensitivity tests summarized in Table 1 suggest several conclusions. First, the energy-budget snow model is highly sensitive to meteorological forcing data. Compared to SN17, the NOAH EBSM is more sensitive to temperature perturbations. Among tested input data, the NOAH EBSM sensitivities are ranked as follows: bias in temperature (maximum sensitivity factor = 6.5), solar radiation (sensitivity factor = 2), and wind (sensitivity factor = 0.69). For random errors, the corresponding numbers are 2.7 for temperature, 0.32 for short wave, and 0.5 for wind.

It is critical to have unbiased input data, e.g., a temperature bias of 1 degree can lead to 276 mm error in SWE, while random errors with 1 degree STD will result in two times less SWE error.

Starting simulations from known 'true' maximum accumulation values improves model performance in the melt period.

Based on our sensitivity analyses at these sites, we believe that better estimates of wind, temperature, and solar radiation are needed to run an energy budget snow model for operational river forecasting. We believe that our analysis framework can be used as an initial attempt to define data requirements for EBSM forcing data. For example, suppose we want to achieve a value of the Nash-Sutcliffe Efficiency statistic (Nash and Sutcliffe, 1970) greater than 0.5 for simulated SWE. For this accuracy we would need input data whose errors do not exceed 10% of the variability for temperature, 20-30% for short wave radiation, and 100% for wind speed. Of course, similar studies must be performed in other geographical regions to achieve a comprehensive view of data quality requirements.

The actual sensitivity factors might slightly vary from one EBSM model to another. But considering the test results for both models, it appears that there is fairly good agreement on the snow models' sensitivity to temperature. The maximum sensitivity factors for the EBSM and SN17 are (6.5, 5), (2.7, 2.5), (1.95, 2.05) and (0.8, 0.6), respectively for all experiment scenarios. Based on our experience, we believe It is reasonable to expect that other EBSMs would have similar sensitivity trends.

Model	Perturbed input field	Test setting		Maximum SWE sensitivity factor	Maximum error in input data	Perturbed field reference STD
SN17	Temperature	Whole year	Bias	5	±1.5K	8.64K
			Random	2.5	4.32K	8.64K
		Melt season	Bias	2.05	±1.5K	8.31K
			Random	0.6	8.64K	8.31K
EBSM	Temperature	Whole year	Bias	6.5	±1.5K	8.64K
			Random	2.7	4.32K	8.64K
		Melt season	Bias	1.95	±1.5K	8.31K
			Random	0.8	8.64K	8.31K
	Short wave	Whole year	Bias	1.9	±150W/m ²	291W/m ²
			Random	0.32	291W/m ²	291W/m ²
		Melt season	Bias	2	±150W/m ²	299W/m ²
			Random	0.25	291W/m ²	299W/m ²
	Wind	Whole year	Bias	0.69	±4.24m/s	2.33m/s
			Random	0.50	4.66m/s	2.33m/s
		Melt season	Bias	0.50	±4.24m/s	1.95m/s
			Random	0.50	4.66m/s	1.95m/s

- For whole year simulation, SWE STD is 0.387m; for melt period, the No. is 0.407m.

Table 1. Statistics of the NOAA EBSM and SNOW-17 sensitivity tests

6. FURTHER STUDY

Energy-budget snow modeling is a very important direction in the hydrologic research community. Fundamental and comprehensive studies on model sensitivity tests are the basis of answers to many scientific questions; some of them are directly related to how the research efforts should be used to improve operational forecasts given current meteorological data acquisition techniques. The following research steps should be addressed in future studies.

1) Perform sensitivity tests of the main process components of the EBSM to input data errors. Sensitivity tests show that the EBSM is very sensitive to meteorological forcing fields. But each meteorological field may affect several energy components in a snow model. Evaluation of the overall sensitivity of an EBSM to a single forcing field is not enough to understand the response of each energy element in detail. For example, temperature is related to many energy components in a snow pack. The evaporation rate, heat transfer between soil and snow, air and snow, and even the net long wave radiation depend on temperature. The relative sensitivities of these energy components are also very important for understanding of the overall sensitivity to temperature.

Sensitivity tests of the main energy components of EBSM to input data errors will help determine the relative sensitivity of each energy component to input data uncertainty. At the same time, this kind of test will help check the parameterizations of major physical processes in snow packs and identify the areas of most possible improvement of snow modeling based on availability of meteorology fields;

2) Evaluate the model sensitivity to precipitation during the snow melt period. Since simulation beginning at a known 'true' maximum accumulation improves model performance in the melt period, it might be a more applicable start point for operational application of EBSMs given current model and data availability.

3) Extend sensitivity analysis to a number of typical regions over the USA to understand the effect of climate on model performance.

4) Expand experiments to distributed snow models at basin scales;

5) A unique state in the snow accumulation/ablation processes is the snow melt starting point. In other words, there is an energy threshold for a snow pack when snow begins to melt. Each and every individual energy element interacts with others to achieve this critical melt threshold. Once the total energy in the snow pack approaches this point, the sensitivity of a model to each

input field will increase rapidly. Detailed investigation is needed on this issue.

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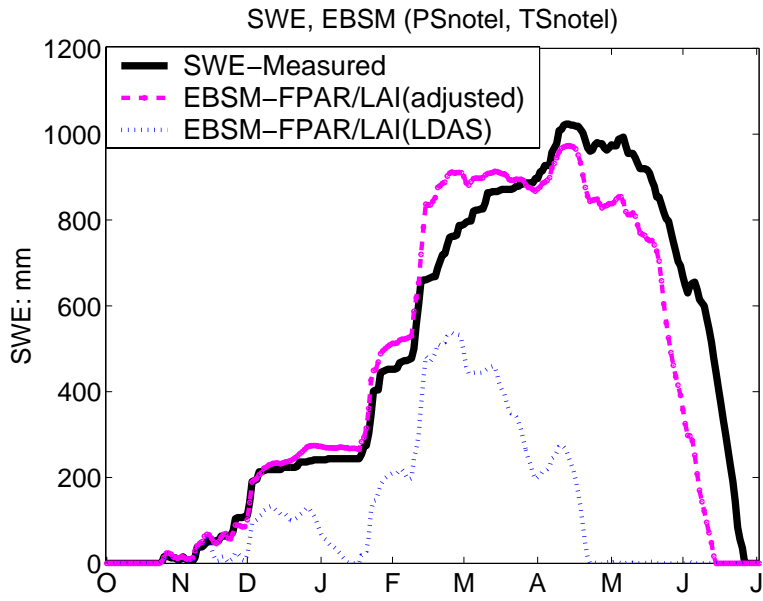


Figure 1. SWE simulated by EBSM using in situ measurements. SNOTEL temperature and precipitation data are used. FPAR/LAI parameters are from NLDAS and/or manual adjustments.

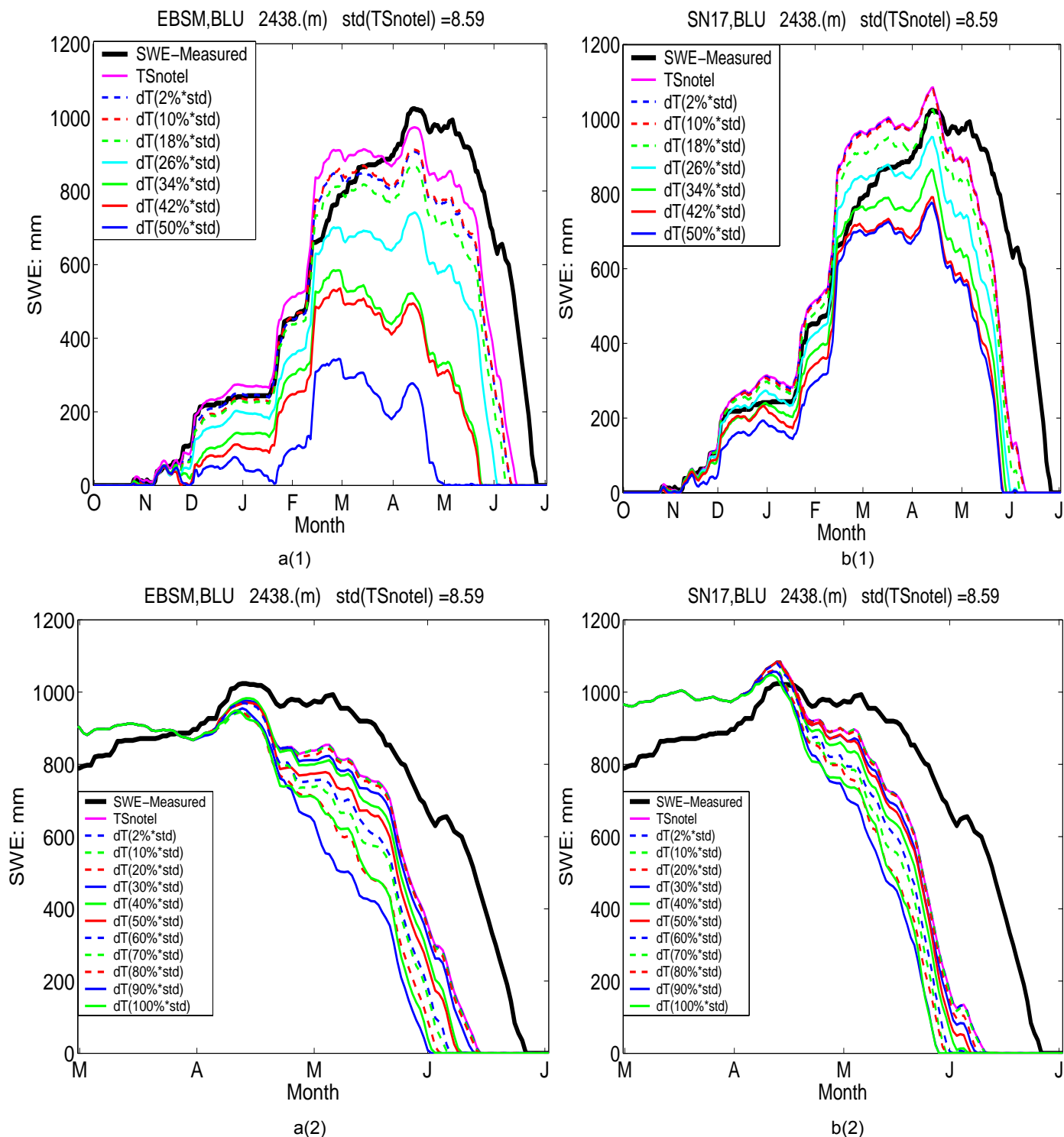


Figure 2. NOAH EBSM and SN17 model simulations with various temperature random errors. The left column shows simulations by NOAH EBSM, the right column shows results from SN17; the upper two rows are simulations for the entire water year (1999) and the lower two rows show results for melt season only (April 1 to August 31, 1999).

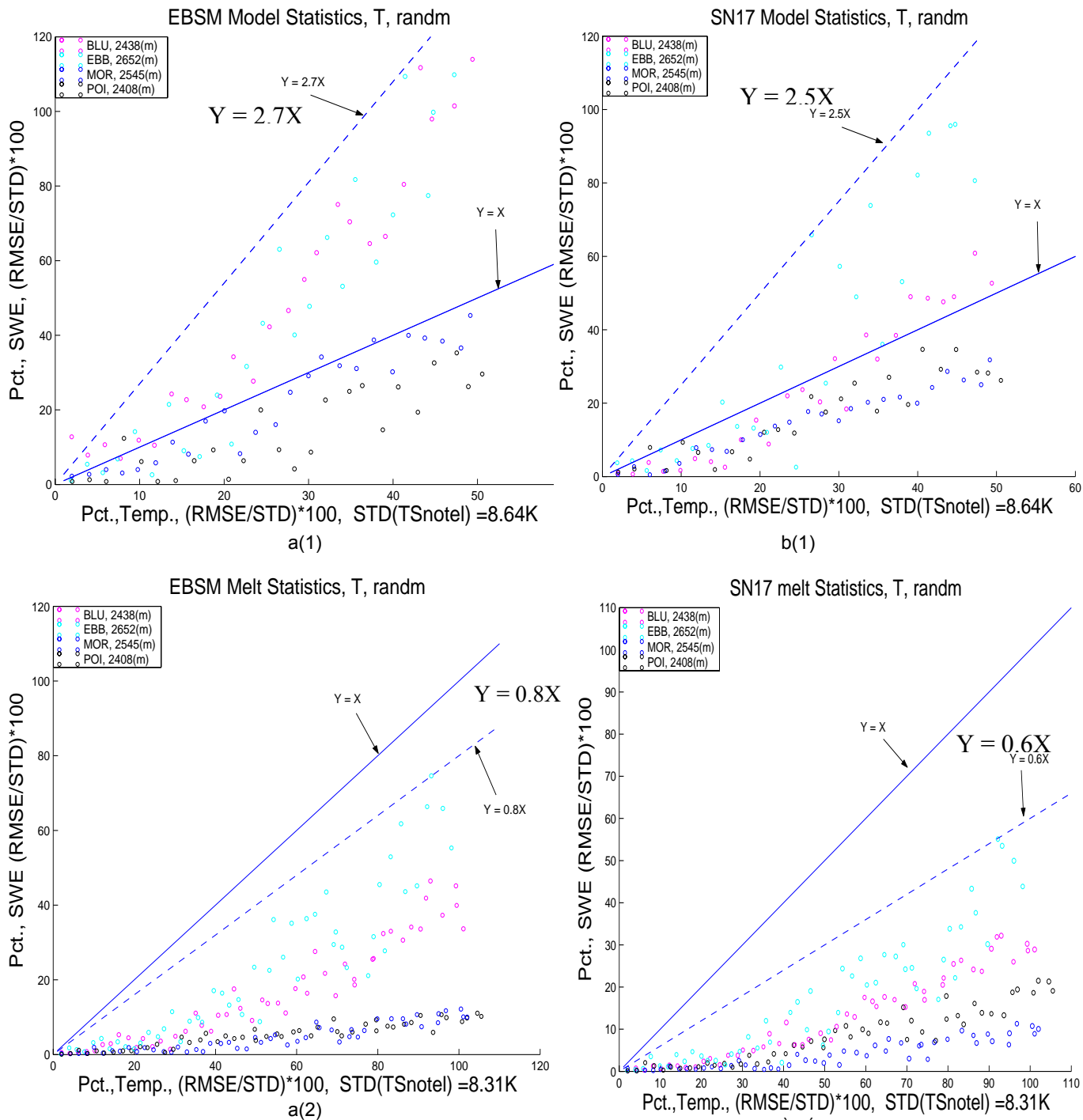


Figure 3. NOAH EBSM and SN17 model sensitivity factor on temperature random error. The left column is for simulations by NOAH EBSM, the right column shows results from SN17; the upper two plots are for simulations for the entire water year (1999) and the lower two plots show results for melt season only (April 1 to August 31, 1999). Sites are in different colors.

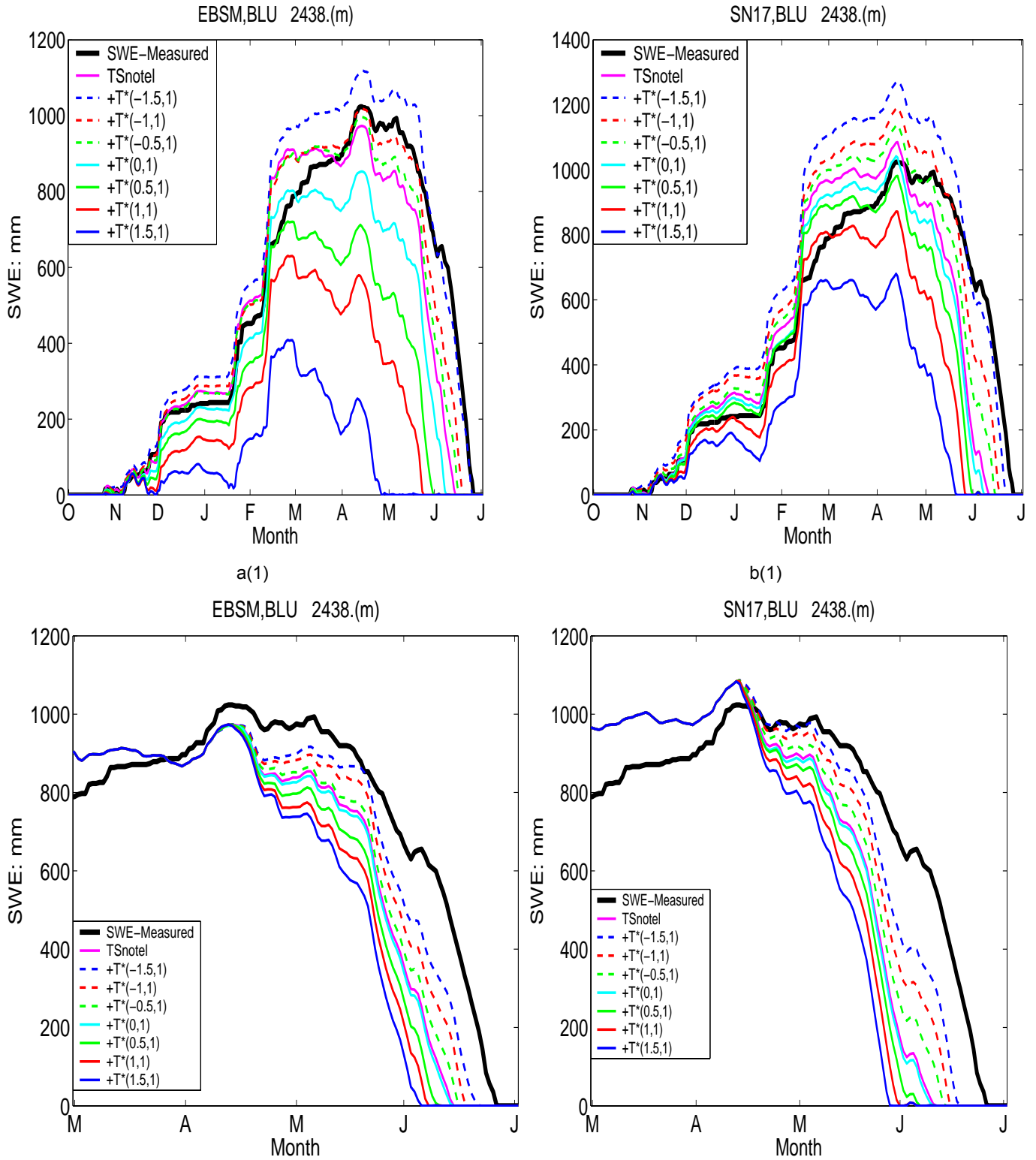


Figure 4. NOAH EBSM and SN17 model simulations with temperature bias (with 1K random error). The left column shows simulations by NOAH EBSM, the right column shows results from SN17; the upper two plots are simulations for the entire water year (1999) and the lower two plots show results for melt season only (April 1 to August 31, 1999).

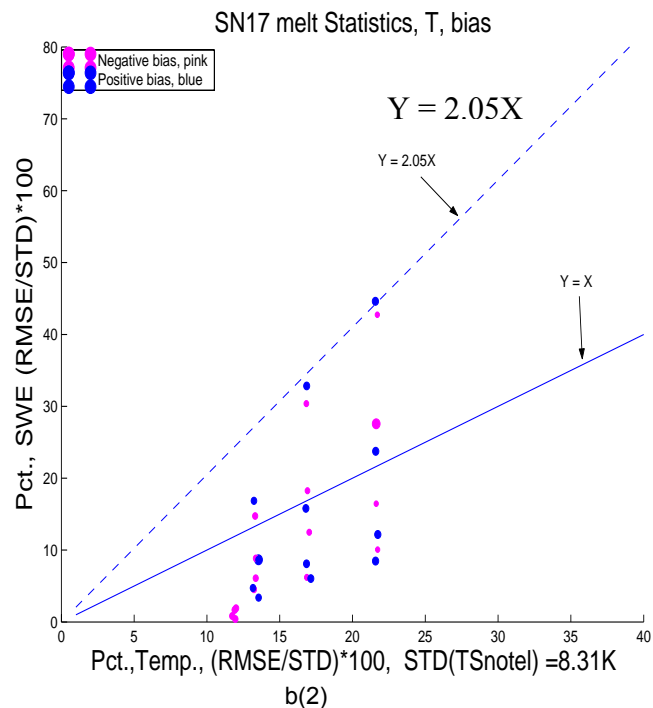
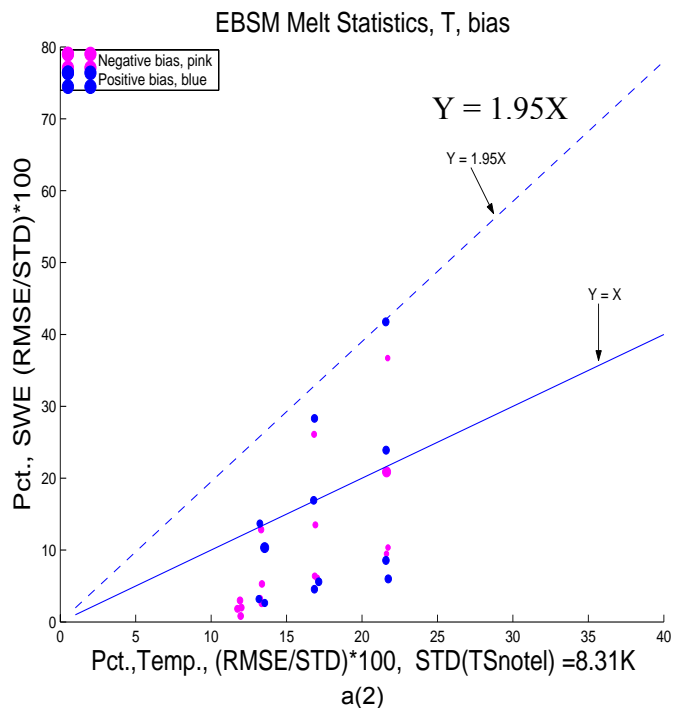
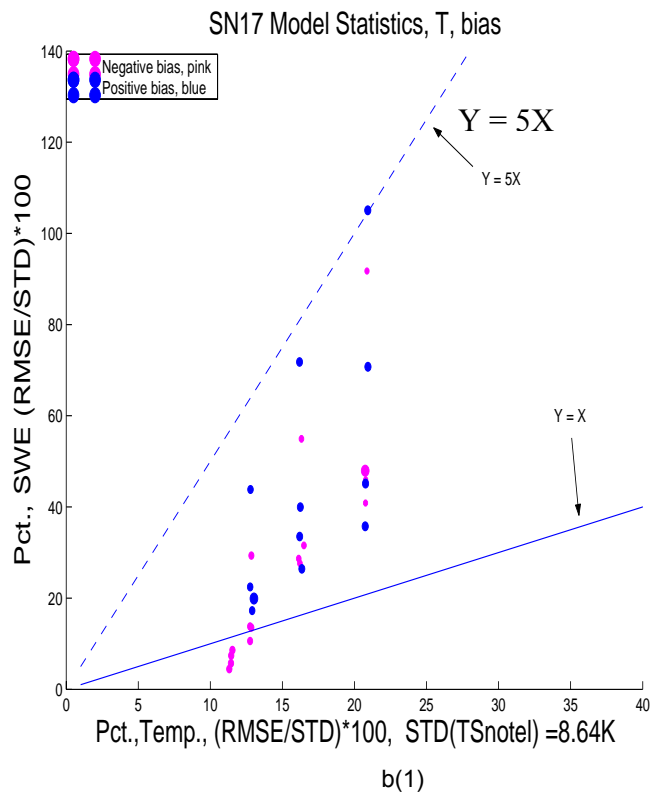
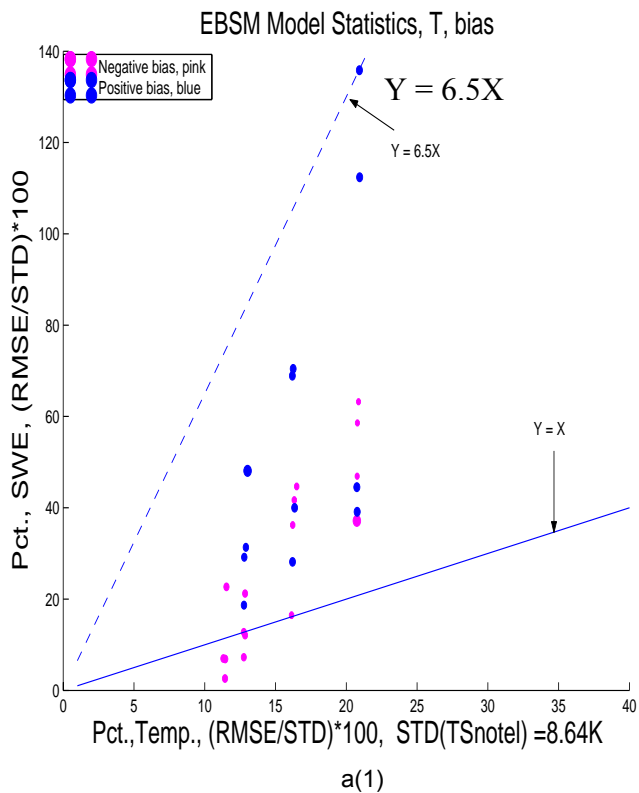


Figure 5. NOAH EBSM and SN17 model sensitivity factors on temperature bias (with 1K random error). Pink line is for negative bias, blue line is for positive bias. The left column is for simulations by NOAH EBSM, the right column shows results from SN17; the upper two plots are simulations for the entire water year (1999) and the lower two plots show results for melt season only (April 1 to August 31, 1999).

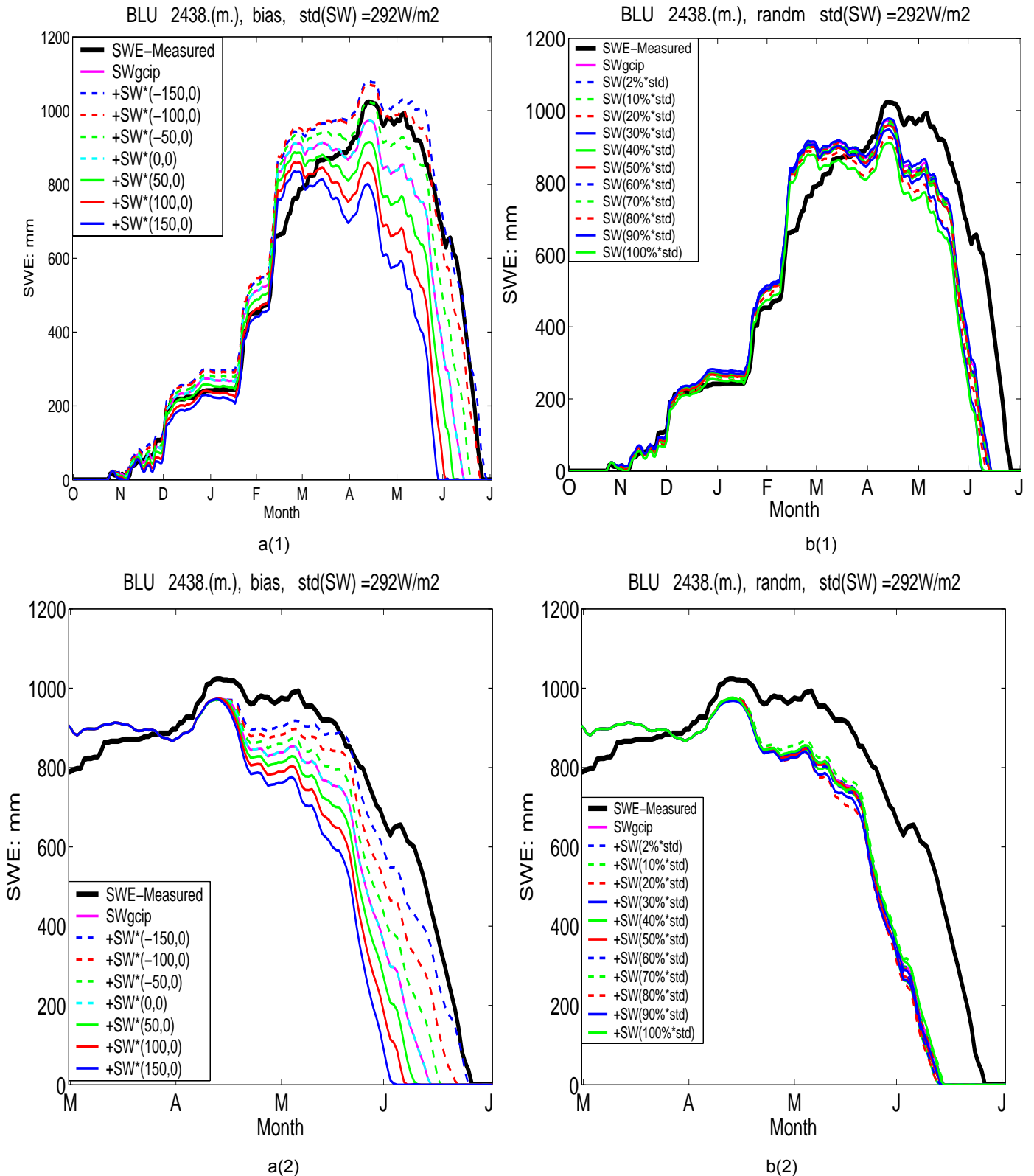
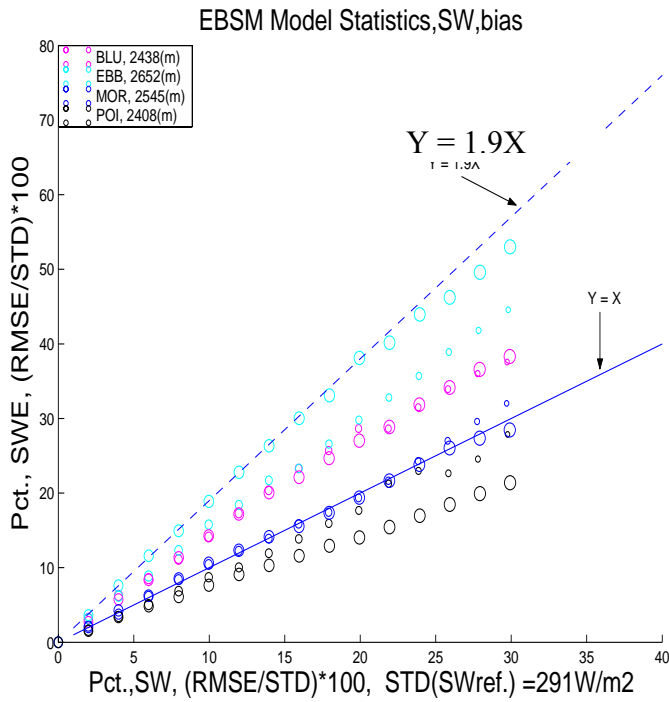
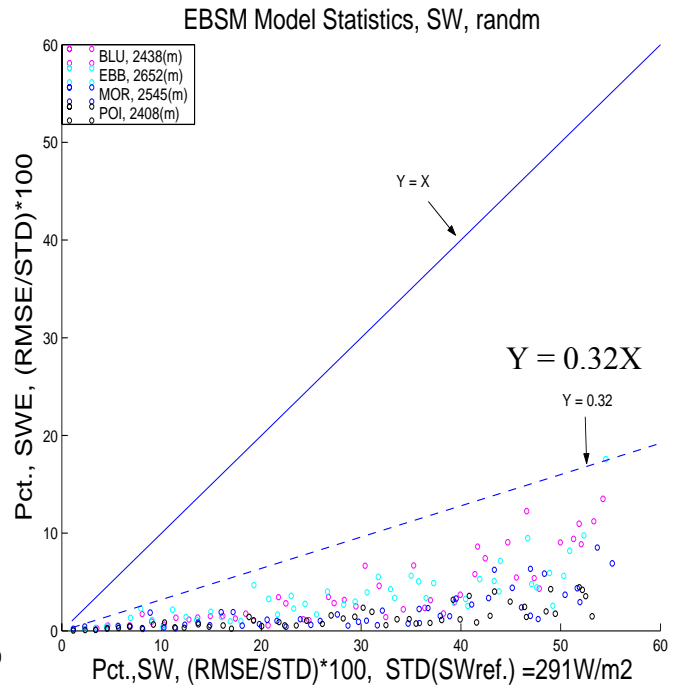


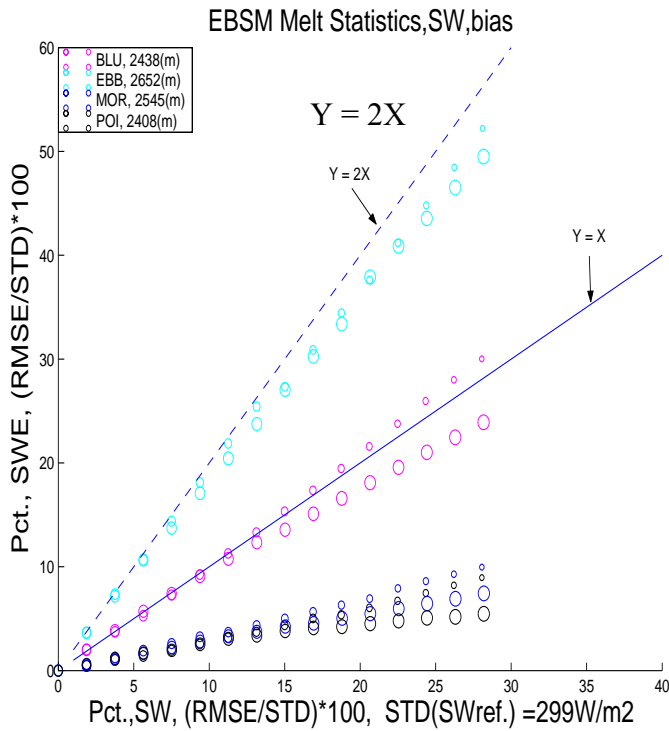
Figure 6. NOAH EBSM model simulations with short wave bias and random error. The left column shows simulations with short wave bias, the right column shows results with random errors; the upper two plots are simulations for the entire water year (1999) and the lower two plots show results for melt season only (April 1 to August 31, 1999).



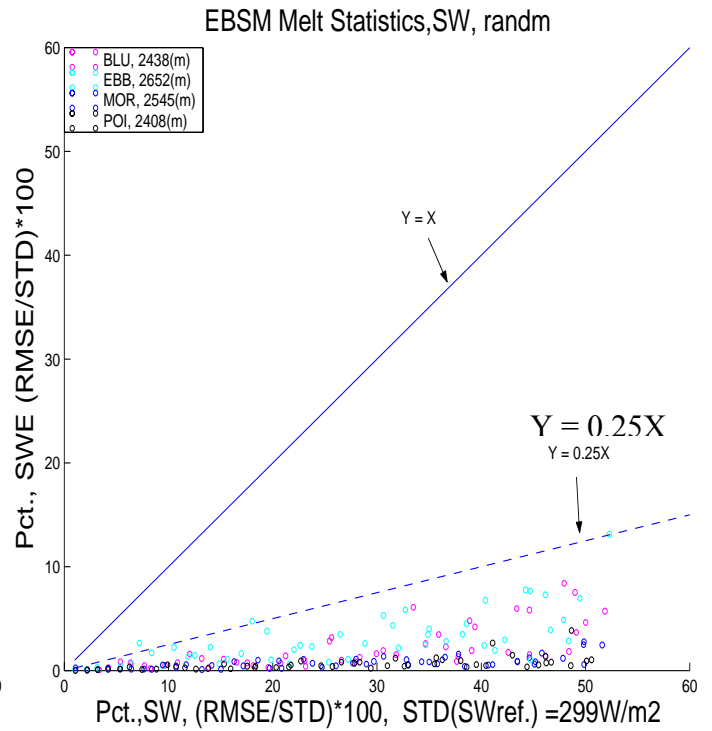
a(1)



b(1)



a(2)



b(2)

Figure 7. NOAH EBSM model sensitivity factors on short wave bias and random error. Sites are in different colors. The left column is for simulations with short wave bias, the right column shows results with random errors; the upper two plots are simulations for the entire water year (1999) and the lower two plots show results for melt season only (April 1 to August 31, 1999).

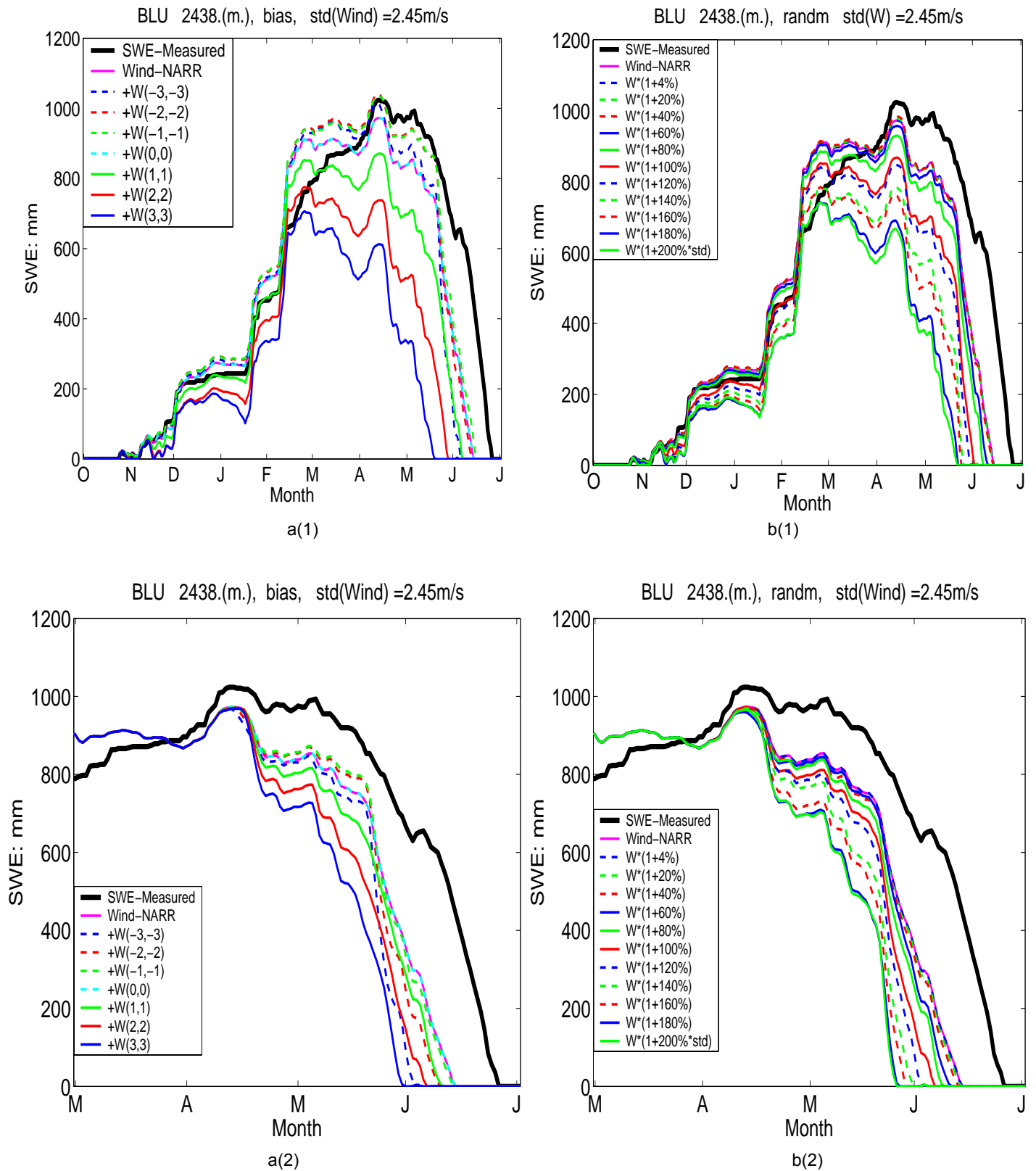


Figure 8. NOAH EBSM model simulations with surface wind bias and random error. The left column shows simulations with wind bias, the right column shows results with random errors; the upper two plots are simulations for the entire water year (1999) and the lower two plots show results for melt season only (April 1 to August 31,

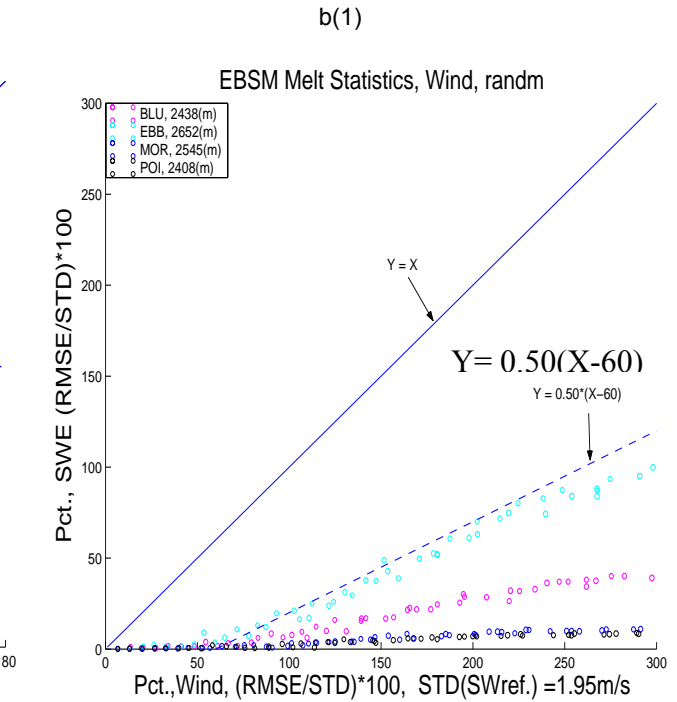
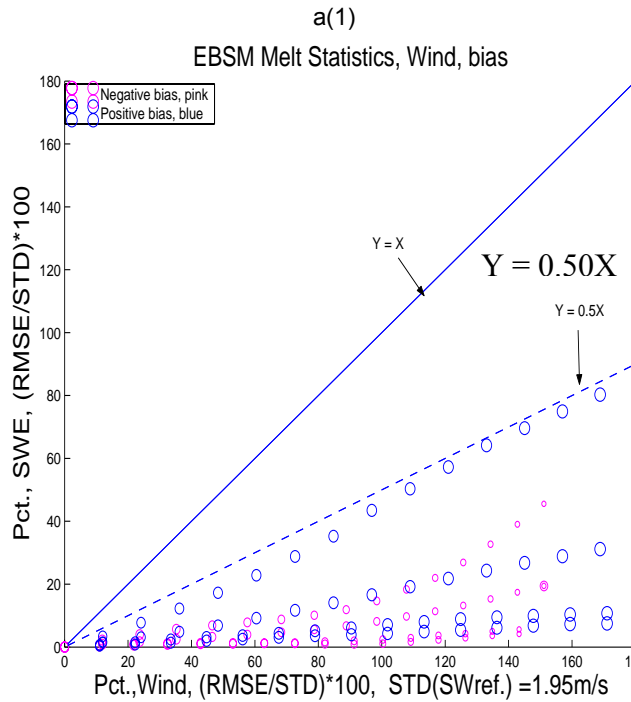
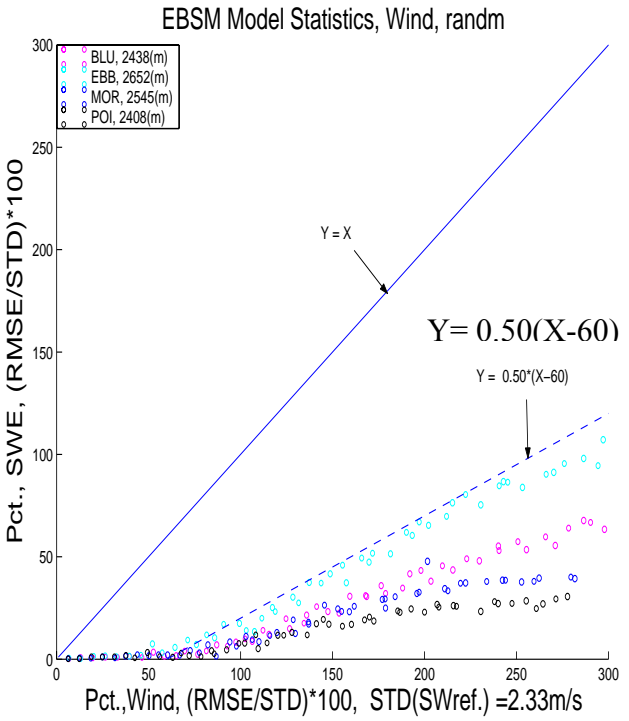
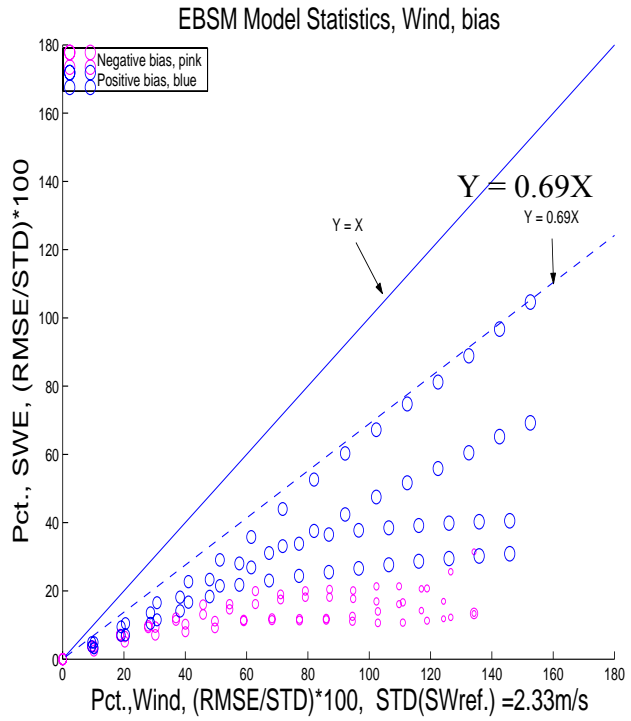


Fig. 9 NOAH EBSM model sensitivity factors on surface wind bias and random error. The left column is for simulations with wind bias (pink line is for negative bias, blue line is for positive bias); the right column shows results with random errors (sites are in different colors); the upper two plots are simulations for the entire water year (1999) and the lower two plots show results for melt season only (April 1 to August 31, 1999).

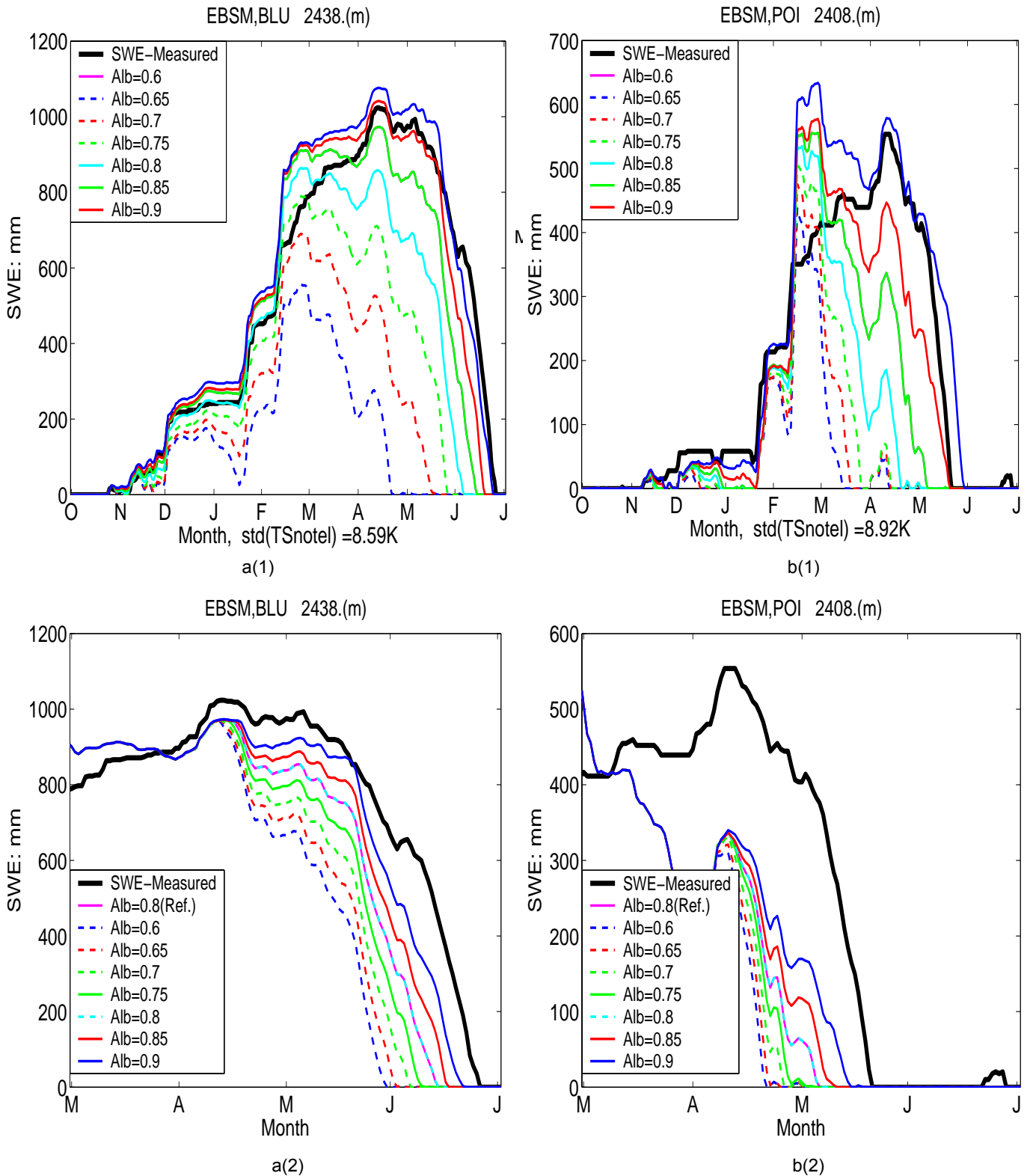


Figure 10. NOAH EBSM model simulations with various maximum snow albedo values. The upper two plots are simulations for the entire water year (1999) and the lower two plots show results for melt season only (April 1 to August 31, 1999).