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SEASONAL AND REGIONAL PATTERNS IN PERFORMANCE FOR A BALTIC SEA DRAINAGE BASIN HYDROLOGIC MODEL[1]

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ABSTRACT: This study evaluates the ability of the Catchment SIMulation (CSIM) hydrologic model to describe seasonal and regional variations in river discharge over the entire Baltic Sea drainage basin (BSDB) based on 31 years of monthly simulation from 1970 through 2000. To date, the model has been successfully applied to simulate annual fluxes of water from the catchments draining into the Baltic Sea. Here, we consider spatiotemporal bias in the distribution of monthly modeling errors across the BSDB since it could potentially reduce the fidelity of predictions and negatively affect the design and implementation of land-management strategies. Within the period considered, the CSIM model accurately reproduced the annual flows across the BSDB; however, it tended to underpredict the proportion of discharge during high-flow periods (i.e., spring months) and overpredict during the summer low flow periods. While the general overpredictions during summer periods are spread across all the subbasins of the BSDB, the underprediction during spring periods is seen largely in the northern regions. By implementing a genetic algorithm calibration procedure and/or seasonal parameterization of subsurface water flows for a subset of the catchments modeled, we demonstrate that it is possible to improve the model performance albeit at the cost of increased parameterization and potential loss of parsimony.

(KEY TERMS: Baltic Sea drainage basin; Baltic NEST; hydrological modeling; generalized watershed loading function (GWLF).)

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INTRODUCTION

The Baltic Sea drainage basin (BSDB) spans a range of watersheds with diverse meteorological, hydrological, and topographic features which permit identification of inconsistencies in both meteorological and hydrological models (Graham and Bergström, 2001). Regions like the BSDB lend themselves naturally to the development of frameworks spanning disciplinary as well as geographical and political boundaries (e.g., the BALTEX project [Bengtsson,

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1995] which investigates the hydrological cycle and the exchange of energy between the atmosphere and the surface of the Earth). Such large regions offer unique challenges of resource management and development of governance (Saaltink *et al.*, 2014). For example, the BSDB intersects 14 countries of different development trajectories: Belarus, Czech Republic, Denmark, Estonia, Finland, Germany, Latvia, Lithuania, Norway, Poland, Russia, Slovakia, Sweden, and Ukraine. Several approaches have been proposed to address the cascading effects of management across scales and political boundaries that influence total ecosystem quality (i.e., eutrophication in the Baltic Sea) and the flows of nutrients from land to sea (e.g., Graham and Bergström, 2001; Arheimer *et al.*, 2012b; Meier *et al.*, 2014). In recent years, these approaches have emphasized decision support systems aimed at facilitating adaptive management of the Baltic Sea environment from the landscape to the sea (e.g., The Baltic NEST approach) (Wulff *et al.*, 2007). Such tools support the whole-ecosystem management approach (Jansson *et al.*, 1999) used to develop the Baltic Sea Action Plan (and signed by Ministers of Environment in 2007) which formulates specific nutrient reduction goals for the Baltic Sea riparian countries (Backer *et al.*, 2010).

Quite naturally, terrestrial hydrologic models form key components of such decision support systems for whole-ecosystem management strategies due to the central role of water in the transport of nutrients and pollutants from terrestrial to aquatic systems. To allow application across such large geographical and geopolitical regions, as well as comparisons between subregions, hydrologic models require consistent data for characterizing model inputs and parameters, as well as for model calibration and validation (Hannerz and Destouni, 2006; Hägg *et al.*, 2014). Inconsistencies between national nutrient load and nutrient source-oriented approaches to estimating loads from catchments to the Baltic Sea may lead to serious misinterpretations and development of inadequate management strategies (Mörth *et al.*, 2007). Consistency between data and modeling frameworks is necessary for moving toward an ecosystem approach to management (van der Velde *et al.*, 2013). Once hydrologic models and/or management tools are established using spatiotemporally consistent data environments, they can help develop better representations of future scenarios and establish reliable model performance over a range of conditions and regions (e.g., Hägg *et al.*, 2014). For example, "hotspots" for improvement (specific periods and locations where more detailed process information is most important) can be identified by explicit testing of modeling assumptions and parameters (i.e., Lyon *et al.*, 2004). This is important to establish critical management zones (Walter *et al.*, 2000) to determine where and when hydrologic responses occur and most influence nutrient transport (Lyon *et al.*, 2006). Such management strategies demonstrate the value of organized spatiotemporal datasets for efficient management of nutrient loads in the landscape.

A related issue is the determination of the appropriate level of hydrologic model complexity given the management issues at hand. Mörth *et al.* (2007) established a BSDB-consistent data and modeling framework with an eye toward a simple and parsimonious approach. To date, this modeling framework has been used to assess annual flows and coupled nutrient loads. Recently, there has been an increased effort to explore smaller spatial and temporal variations in hydrology (and subsequent nutrient transport) within the BSDB to allow improved management and source allocation schemes across the entire drainage basin (e.g., HELCOM, 2011). These efforts typically leverage more dynamic modeling approaches for the BSDB (e.g., Arheimer *et al.*, 2012a, b; Meier *et al.*, 2012, 2014; Donnelly *et al.*, 2014). While these more dynamic modeling approaches (i.e., the recent HYPE modeling developments available at http://balt-hypeweb.smhi.se/) allow representation of seasonal and regional variability in flow using daily time steps, they come at the cost of increased parameterization and move away from the fundamental tenets of parsimonious behavioral modeling approaches (Schaefli *et al.*, 2011). Similar "pseudo-dynamic" effects can be obtained in simple annual models through increased parameterization particularly by moving toward time-variable parameter sets (Hrachowitz *et al.*, 2013). For example, methods based on weighting different parameterizations for low- and high-flow periods (Oudin *et al.*, 2006) or different calibration objectives (Fenicia *et al.*, 2007) allow a balanced representation of the hydrograph. Still, there is much debate about the value of increased parameterization brought about by implementing temporally variable parameters (e.g., Vaze *et al.*, 2010; Romano *et al.*, 2011; Luo *et al.*, 2012) given the effect of increased parameter interactions which reduce parsimony and can complicate causal relationships (Archibald *et al.*, 2014).

Therefore, in this study, we aim to improve the potential of the hydrological model of Mörth *et al.* (2007) to represent monthly variations in river discharge over the entire BSDB (Figure 1a). To this end, we assess seasonal and regional variations in model performance relating to the seasonal timing of flow through the landscape and quantify the potential for improving model performance. Furthermore, as a central experiment, we isolate the potential impact of (1)

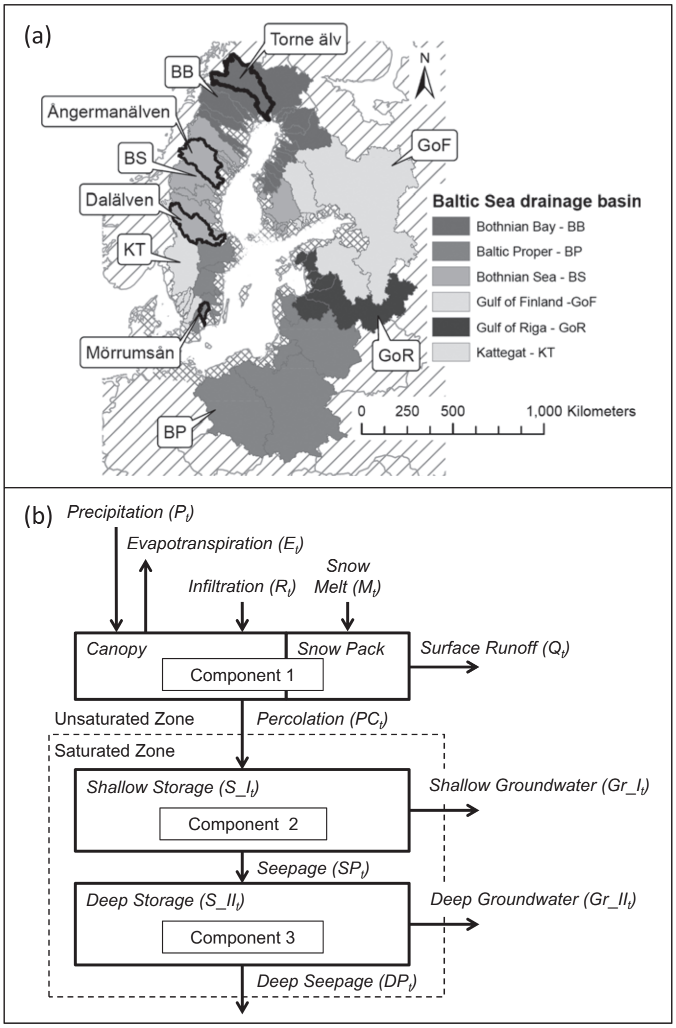

FIGURE 1. The Baltic Sea Drainage Basin (BSDB) with (a) the 81 Catchments Directly Calibrated in the Catchment SIMulation (CSIM) Model and (b) a Schematic Representation of the CSIM Model Conceptualization as It Has Been Applied within Each Catchment. The catchments are grouped here according to their recipient Baltic Sea subbasin and the locations of the four catchments considered in the genetic algorithm calibration are indicated. The cross-hatching indicates small catchments (coastal and all islands) within the BSDB but not considered in the study, while the diagonal hatching indicates the landmasses of Europe and Asia.

an improved calibration procedure and (2) a seasonal parameterization of the movement of water through the landscape for a selection of catchments spanning the region. Together, these analyses provide insight into spatial and temporal bias in the timing of streamflows that should be considered when moving from annual to higher temporal resolution. This is particularly relevant as managers consider models of increasing complexity in which cause-effect relations become increasingly convoluted due to the number and interaction of parameters. Implications of model complexity are of primary concern when considering whether model predictions are sufficiently representative of real processes for governance and management (the estimates of nutrient exports and design of basin-wide land-management strategies in particular).

MODELING APPROACH AND METHODOLOGY

CSIM Hydrologic Model and Application in BSDB

The Baltic NEST (http://nest.su.se/nest/) is a decision support system aimed at facilitating adaptive management of environmental concern in the Baltic Sea. By modeling the entire drainage area, the Baltic NEST is implementing an ecosystem approach for a large marine ecosystem with a main focus on eutrophication and the flows of nutrients from land to sea. At the core of this decision support system sits the Catchment SIMulation (CSIM) hydrologic model framework. The CSIM model framework is an extension of the generalized watershed loading function model (GWLF), a lumped-parameter model, which describes the hydrology and corresponding fluxes of dissolved constituents from a watershed. Whereas the GWLF version considered as the basis for CSIM was initially developed, tested, and described as a model for temperate zone watersheds in North America (Haith and Shoemaker, 1987), CSIM has been developed explicitly to represent the flux of water and nutrients from the BSDB. For a complete description of the GWLF model, we refer the reader to Haith and Shoemaker (1987) for the version behind CSIM and to Haith *et al.* (1992) or Hong and Swaney (2013a) for advances in the GWLF conceptualization. Here, we present a brief overview of specific modifications that make CSIM unique as a hydrologic model framework. In addition, we review its previous application to the BSDB by Mörth *et al.* (2007).

The main difference between GWLF and the CSIM model is the inclusion of an additional compartment of groundwater in an attempt to better represent soil water fluxes. Thus, CSIM has three conceptual components for each catchment that contribute to streamflow (Figure 1b). By dividing a catchment into a number of land use categories (here, deciduous, coniferous, and mixed forest; herbaceous; wetlands; cultivated areas; bare lands; water; snow and ice; and artificial areas) and applying precipitation and evapotranspiration to each land cover type, the streamflow is simulated in CSIM by aggregation of total runoff from each land use (i.e., Component 1) and the two components of groundwater from the saturated zone (i.e., Component 2 and Component 3) representing a common groundwater storage connected to all land use categories. Water from each land cover type is routed to the stream both as direct surface runoff and through subsurface layer compartments as groundwater.

The flux of water across the land surface (e.g., infiltration and evapotranspiration) is determined using the algorithms used in the original GWLF model. The U.S. Soil Conservation Service's curve number method is used to determine the fraction of precipitation (R_t) and snowmelt water (M_t) partitioned directly to surface runoff (Q_t) with the remainder infiltrating into an unsaturated storage from which evapotranspiration (E_t) can occur (Figure 1b). The amount of water in this unsaturated soil storage (the antecedent conditions) is able to feedback and influence infiltration (through curve number conditions) and evapotranspiration rates in the model (Haan, 1972). Excess water from the unsaturated soil storage can percolate (PC_t) into subsurface soil water storages to allow for delayed flows to the stream through the subsurface saturated zone.

The transfer of water between and from the subsurface components is controlled by calibrated seepage and drainage relations (similar to many large-scale conceptually lumped hydrologic models, e.g., VIC) (Wood *et al.*, 1992), respectively. In CSIM, shallow (or more appropriately, relatively short residence time) groundwater flows (Gr_I_t) are modeled as a simple linear reservoir:

$$Gr\_I_t = \alpha \times S\_I_t \tag{1}$$

where the flow coming out of the shallow reservoir is proportional to the amount of water in the storage (S_I_t) by a calibrated recession coefficient (α). Water moves from this shallow storage to the deeper reservoir as seepage (SP_t):

$$SP_t = \beta \times S\_I_t \tag{2}$$

which is proportional to the amount of water in the shallow storage (S_I_t) by a calibrated seepage coefficient (β). From this second storage, deeper (or more appropriately, relatively longer residence time) groundwater flows (Gr_II_t) occur as:

$$Gr\_II_t = \gamma \times S\_II_t \tag{3}$$

where the base flow coming from storage is proportional to the amount of water in the storage (S_II_t) by a calibrated base-flow recession coefficient (γ). Finally, water can be lost from this deeper storage through deep seepage (DP_t) as:

$$DP_t = \delta \times S\_II_t \tag{4}$$

Deep seepage is proportional to the amount of water in the shallow storage (S_II_t) by a calibrated deep seepage coefficient (δ).

Computationally, the original CSIM hydrologic model was modified from GWLFXL (Hong and Swaney, 2004, 2013a) code written in Visual Basic 6.0 and uses an external database (MySQL) to store and retrieve data. The CSIM modeling framework therefore handles input data and results as well as keeping track of the modeling history (files, simulations) to facilitate model analysis and storage of the results. In application to the BSDB (Mörth *et al.*, 2007), the CSIM model framework utilizes daily precipitation and temperature forcing data. Temperature and precipitation data were obtained from the European Observation (E-OBS) database (Haylock *et al.*, 2008) for calibration. E-OBS is a European land-only reanalysis based on interpolation between meteorological stations to a regular grid. Daily mean temperatures and precipitation with the resolution $0.44° \times 0.44°$ (ca. 50 km at Baltic latitudes) were considered. Interpolation of precipitation and temperature was carried out using an external drift kriging technique to account for potential elevation influences. Potential evapotranspiration was estimated using Hamon's method (1961) with actual evapotranspiration scaled under the condition that it cannot exceed available moisture in the unsaturated zone (Haith *et al.*, 1992). Cumulative snow and snowmelt were estimated with a degree-day approach (Haith and Shoemaker, 1987). In addition to the meteorological database, gridded land cover and soils data were derived from satellite images (resolution of about 0.15 km × 0.15 km) and various reference datasets provided through Metria Miljöanalys and by the EU-Joint Research Centre, Ispra, Italy (Mörth *et al.*, 2007).

These gridded data were used to calibrate (and validate) the current generation of the CSIM model for 117 river catchments draining the BSDB as described by Mörth *et al.* (2007). Mörth *et al.* (2007) calibrated the current version of the CSIM model, which forms the starting point for analysis in this study (see following section) using monthly observed discharge data for the time period 1996-2000. Note that the length of the original calibration (and validation) periods from Mörth *et al.* (2007) was necessitated due to computational and data limitations at the time, but retained here to facilitate comparison between the studies. They compared observations with monthly simulated values aggregated from daily discharge estimates obtained from running the model on a daily time step using the daily weather observations from E-OBS (Haylock *et al.*, 2008). Calibration was performed using the Frontline Systems software development kit (SDK) solver platform. The solver module adjusted the CSIM-specific modeling parameters while holding constant the submodel parameters defined by land cover and soils (i.e., curve number values) or hydroclimatological setting (i.e., coefficient related to snowmelt and/or evapotranspiration). In the calibration, the SDK solver optimized parameters to minimize the root mean squared error (RMSE) between modeled and observed streamflows. The solver SDK command option "Problem_type_OptNLP" used here minimizes RMSE, assuming smooth nonlinear responses to parameter changes, using a generalized reduced gradient algorithm (Frontline Systems, 2014). Validation of the model was carried out for the time period 1990-1994. During this period, the model was able to predict the observed annual discharge volume within 8.2% over all the catchments (Mörth *et al.*, 2007). This demonstrates that the CSIM model performs well at this spatiotemporal scale and is appropriate to address large-scale, annual hydrological fluxes into the Baltic Sea. As water residence times within the Baltic Sea can reach up to 30 years, the ability to accurately reproduce observed annual discharge volume is necessary and is reflected in the model setup and design. The question remains as to how well the same model setup performs with regard to the seasonal timing of water fluxes through the BSDB landscape (i.e., hydrology at the monthly time steps). Below, we describe methods used for assessing seasonal flows obtained from CSIM, including alternate methods of calibration and addition of seasonally varying parameters.

Exploring Seasonal and Regional Patterns of Sub-Annual Model Performance

In this study, we consider the sub-annual spatiotemporal performance of the CSIM model within the BSDB. Here, we consider monthly model estimates for a 31-year period from 1970 through 2000 for 81 of the catchments considered in Mörth *et al.* (2007). We excluded catchments with insufficient data for direct calibration in the original study of Mörth *et al.* (2007) and those lacking long-term data availability. We examined the monthly proportional distribution of flow (i.e., the percentage of the total annual flow occurring in each month) to evaluate the ability of CSIM to represent the timing of discharge. This percentage of flow ($\%\text{Flow}_{\text{obs},i}$) was determined via normalization of the observed flows as:

$$\%\text{Flow}_{\text{obs},i} = 100\% \times \frac{Q_{\text{obs},i}}{Q_{\text{total}}} \tag{5}$$

with $Q_{\text{obs},i}$ indicating the observed discharge in a given month, i ($i = 1\ldots12$), and Q_{total} indicating the total annual discharge observed for the year containing the given month. We focus here on individual monthly flows normalized by the annual flow of the year they occur to avoid potential compounding error introduced through any inability to close the annual water balance. Furthermore, we also investigated normalizing by average annual flows over the entire 31-year period to estimate the potential influence of variations between years but this did not influence the results of this current study.

The monthly proportional distribution of flow was also determined for the CSIM model-estimated flows ($\%\text{Flow}_{\text{mod},i}$) by considering the model-estimated monthly discharges ($Q_{\text{mod},i}$) for each month i and the observed annual total discharges (Q_{total}):

$$\%\text{Flow}_{\text{mod},i} = 100\% \times \frac{Q_{\text{mod},i}}{Q_{\text{total}}} \tag{6}$$

Again, we normalized by annual observed discharges to allow for comparison with normalized observed flows from Equation (5). We investigated normalization by model-estimated annual total discharges, but found no significant influence on the main results. Since we are looking at model performance on a monthly interval over 31 years of simulation across 81 catchments, the average percentage of annual flow (both observed and modeled) per month may be considered representative of the variations across the entire time period modeled (i.e., 1970 to 2000).

In addition to looking at the timing of observed and modeled discharge, we also determined the monthly root mean squared error (RMSE_i) between monthly observed and modeled discharges:

$$\text{RMSE}_i = \sqrt{\frac{\sum_1^n (Q_{\text{mod},i} - Q_{\text{obs},i})^2}{n}} \tag{7}$$

where n equals the number of years simulated. Lastly, the monthly model bias (Bias_i) was also estimated as:

$$\%\text{Bias}_i = \frac{\sum_1^n (Q_{\text{mod},i} - Q_{\text{obs},i})^2}{n} \tag{8}$$

to evaluate the distribution of model bias through the time, as well as potential seasonality.

Impacts of Calibration and Seasonal Parameterization

To explore the potential improvement to be made through changing the calibration approach and introducing seasonal parameterization, four catchments (Figure 1a) from across the BSDB were selected as "case studies" for evaluation. The four catchments selected, all from Sweden, span a relevant range of hydroclimatic conditions (e.g., from north to south) (van der Velde *et al.*, 2014) across the BSDB. While we recognize that consideration of only Swedish catchments could potentially bias our findings, it also avoids potential problems related to differences in data standards or reliability across international boundaries. The catchments range in size by an order of magnitude from about 337,000 km^2 for the Mörrumsån catchment in the south to 3,961,300 km^2 for Torne älv catchment in the north (Table 1).

To look at impacts of calibration methodology on the CSIM model, a genetic algorithm (GA) (Holland, 1975) calibration procedure was applied instead of the previously used SDK solver algorithm. Here, we used a modified version of the GA implementation provided by Haupt and Haupt (2004) as presented in Karamouz and Kerachian (2003). The GA was applied to subsurface drainage parameters specific to CSIM. These are, namely, the calibration parameters presented in Equations (1-4) and are the same parameters calibrated with the SDK solver by Mörth *et al.* (2007). All other parameters were kept constant at the values given by Mörth *et al.* (2007). For the GA calibration, as in Mörth *et al.* (2007), the model was optimized by comparing predicted monthly streamflow against observed streamflow using RMSE as an objective function. Furthermore, parameter values were allowed to vary between 0 and a factor of 2 times their previous estimates (i.e., SDK-calibrated values) in Mörth *et al.* (2007) to prevent finding unreasonable parameter values in the GA optimization process (Karamouz and Kerachian, 2003). GA calibration was carried out using the same period (1996-2000) as Mörth *et al.* (2007) to compare model performance from SDK solver calibration to GA calibration. Details with regard to the GA calibration procedure are presented in Meidani (2012).

In addition, the impact of seasonal parameterization of the four subsurface drainage parameters was considered. This was implemented by dividing the years used for the GA calibration into winter (December, January, February), spring (March, April, May), summer (June, July, August), and autumn (September, October, November) seasons. Each of the four drainage parameters from Equations (1-4) was then calibrated separately during each of these four seasons using the GA calibration procedure. Again, this seasonal parameterization does not focus on how water gets into the model's subsurface domain but rather how long it can reside there. Model performance results (measured using both model RMSE and bias) for the GA calibration using both an annual parameterization and using a seasonal parameterization were compared (Equations 7 and 8, respectively) for the entire 31-year period from 1970 through 2000.

RESULTS

Sub-Annual Performance of Model CSIM Model

Unsurprisingly, and consistent with the previous work by Mörth *et al.* (2007), the CSIM model generally predicts the annual runoff (specific discharge) accurately when considering all catchments in the BSDB together (Figure 2a). The model underestimates discharge in some cases during high-flow peri-

TABLE 1. Summary Characteristics of the Catchments Used to Investigate Impacts of Calibration and Seasonal Parameterization in Catchment SIMulation.

Catchment Name	**Torne älv**	**Ångermanälven**	**Dalälven**	**Mörrumsån**
Baltic subbasin	Bothnian Bay	Bothnian Sea	Bothnian Sea	Baltic Proper
Population	102,000	264,000	52,000	78,000
Area (km^2)	3,961,300	3,182,000	2,864,000	337,000
Deciduous forest (%)	8	7	1	2
Coniferous forest (%)	21	43	59	68
Mixed forest (%)	11	5	3	1
Herbaceous (%)	33	25	19	2
Wetland (%)	15	9	8	1
Cultivated area (%)	1	1	4	12
Bare land (%)	5	1	0	0
Water (%)	5	8	7	13
Snow and ice (%)	0	0	0	0
Artificial area (%)	0	0	1	2

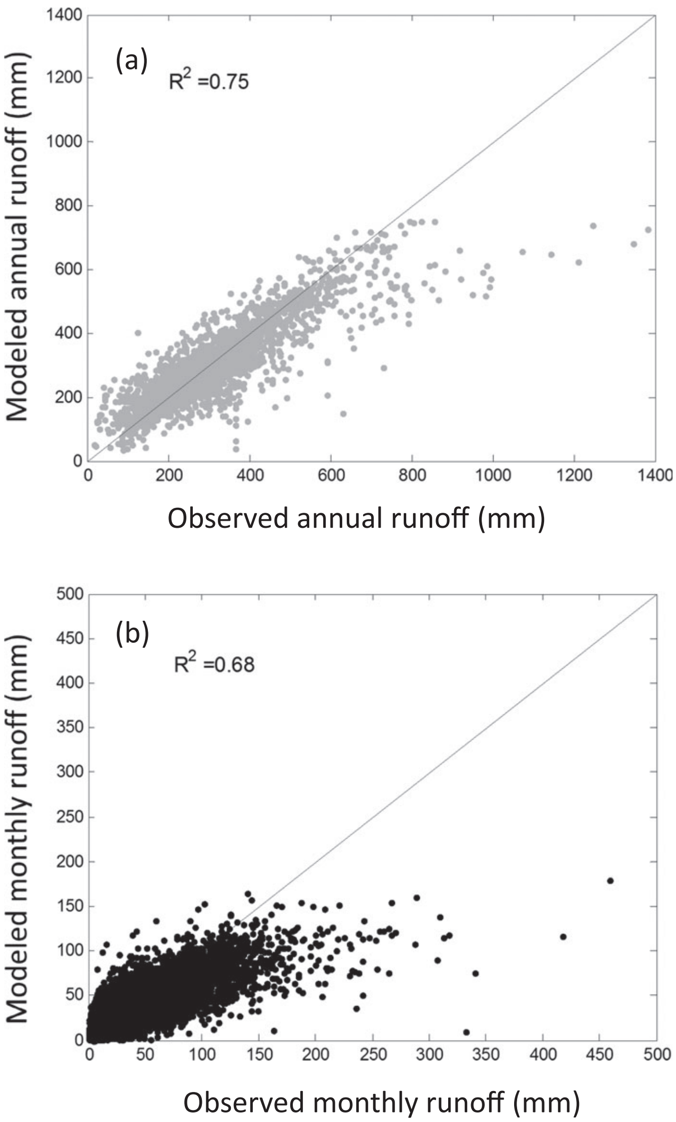

FIGURE 2. Agreement between (a) Modeled and Observed Annual Runoff and (b) Modeled and Observed Monthly Runoff for the Catchment SIMulation Model Applied on the 81 Catchments Considered in This Study.

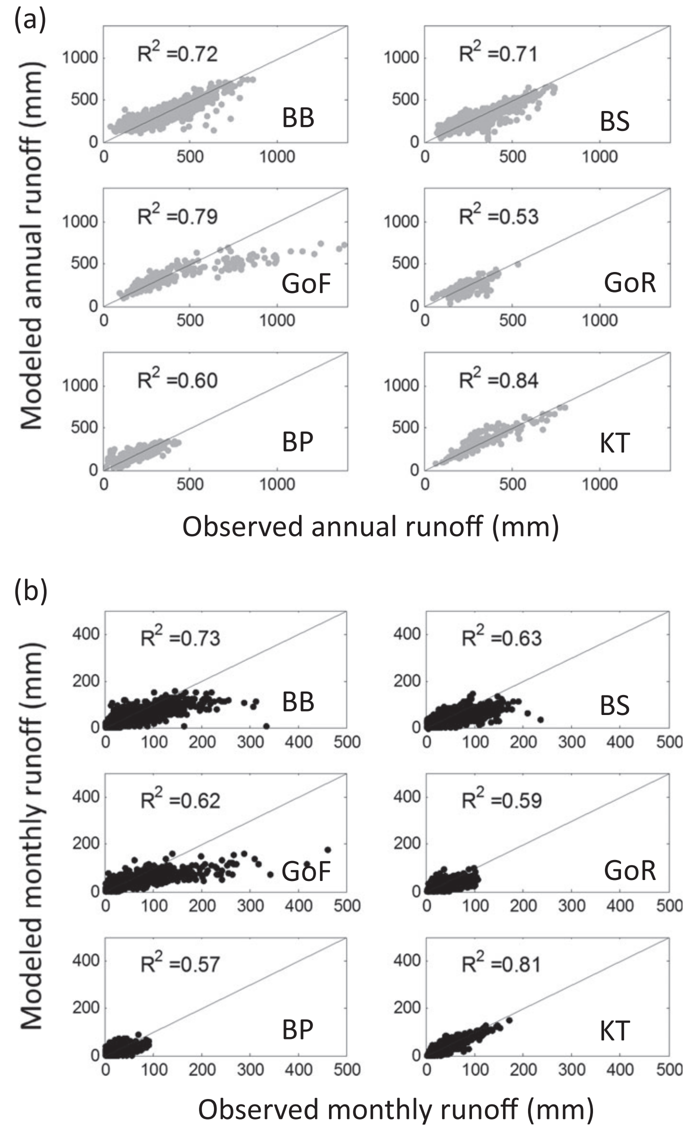

FIGURE 3. Agreement between (a) Modeled and Observed Annual Runoff and (b) Modeled and Observed Monthly Runoff for the Catchment SIMulation Model for Each Catchment within the Six Individual Subbasins Considered in This Study. These are Bothnian Bay (BB), Bothnian Sea (BS), Gulf of Finland (GoF), Gulf of Riga (GoR), Baltic Proper (BP), and Kattegat (KT).

ods. More scatter occurs between model and observation (as expected) when considering the individual monthly estimates across all the catchments (Figure 2b) with model underprediction at higher flows. Examining annual and sub-annual patterns among the six subbasins draining the BSDB (Figure 3), it is clear that this underprediction occurs predominantly in the northern regions. The Gulf of Finland stands out with clear model underprediction at higher annual flows while the rest of the annual subbasin predictions showed better agreement with observations (Figure 3a). Sub-annual, monthly estimates (Figure 3b), show underprediction at higher flows across all northern subbasins.

The 81 monitored catchments draining the BSDB showed considerable seasonal variations in flow over the 31-year period from 1970 through 2000 considered in this study (Figure 4a). This is demonstrated by the higher proportion of discharge occurring in the spring (March, April, May) relative to summer months (June, July, August) which exhibited lower average contribution to annual flows across the entire BSDB. The catchments draining into the northernmost subbasins of the Baltic Sea (e.g., catchments draining into the Bothnian Bay and Bothnian Sea) exhibited the highest proportions of discharge in May, while discharge in more southerly regions of

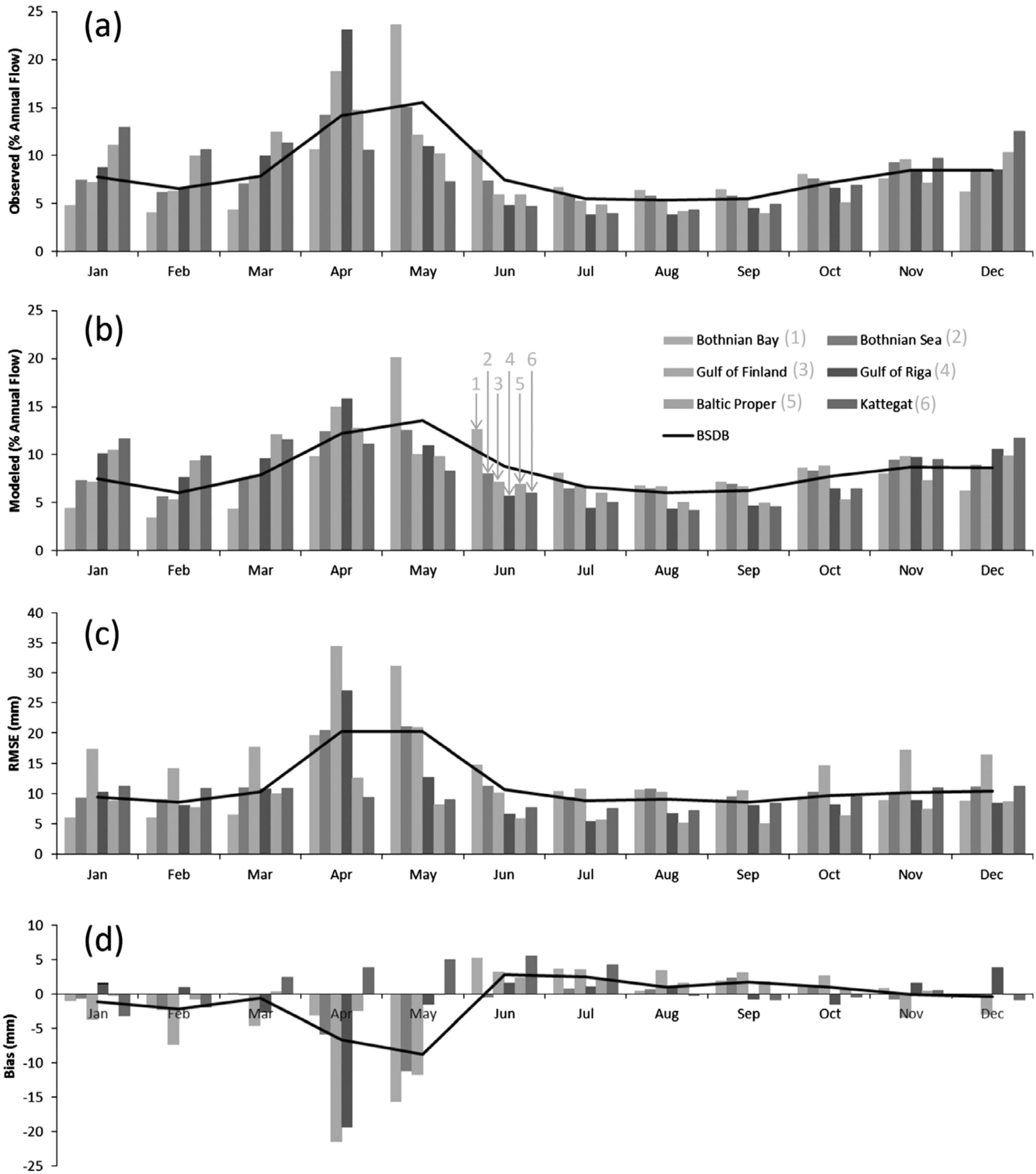

FIGURE 4. Average Monthly Time Series over the Entire 31 Years Considered in This Current Study for the Entire Baltic Sea Drainage Basin (BSDB) and Each of the Six Subbasins of (a) the Percentage of Total Annual Observed Streamflow, (b) the Percentage of Total Annual Modeled Streamflow, (c) the Monthly Model Root Mean Squared Error (RMSE), and (d) the Monthly Model Bias.

the BSDB peaked earlier. The catchments draining into the Gulf of Riga appeared to have a relatively strong seasonality with respect to discharge; about 56% of the observed annual flow occurred in the spring period (March, April, May). This contrasts with the more southern catchments draining into Baltic Proper and Kattegat which exhibited less extreme seasonal variation in flows.

The CSIM model accurately recreates the timing of peak monthly contributions to discharge (Figure 4b), although the model underpredicts discharge contributions during high-flow periods (i.e., spring months) and overpredicts them during low-flow periods (i.e., summer months). Despite these issues, the predictions satisfy the primary goal of development of this relatively simple, lumped model, which is the prediction of annual flows and trends, and associated nutrient loads across the entire BSDB (Mörth *et al.*, 2007). The catchments draining into the Gulf of Riga were estimated to have strong seasonality by the CSIM model in that about 41% of the annual flow occurred in the spring period. The southernmost catchments draining into Baltic Proper and Kattegat exhibited more seasonally consistent flows (Figure 4b) in the model simulations than their northern counterparts.

On average over the entire BSDB, the monthly RMSE shows a seasonal signal with elevated values occurring in April and May corresponding to periods of high flow (Figure 4c). This seasonality is most pronounced in the northern subbasins, where there is a strong pattern in the monthly RMSE relative to the Baltic Proper and Kattegat subbasins. In these northern subbasins, the model mostly underpredicts discharge during high-flow periods (i.e., March, April, and May) and consistently overpredicts it during the remainder of the year. This can be seen through the seasonal signal present in the monthly bias of the model simulations (Figure 4d) particularly in the Gulf of Finland and Gulf of Riga in April and in Bothnian Bay, Bothnian Sea, and Gulf of Finland in May, where the model exhibits negative monthly bias. Counter to this spring seasonal bias in the north, the CSIM model consistently overpredicts streamflow throughout summer (June through August) when the model has relatively large positive bias (and when the flows tend to be lower, on average, across the BSDB — Figure 4a).

Calibration and Seasonal Parameterization Influences

The impact of calibration procedure and seasonal parameterization on CSIM model performance varied across the four catchments considered (Figure 5). The model performance (assessed with RMSE) in only the northernmost catchment (Torne älv) improved when calibration was carried out using a GA approach. The average reduction in RMSE was about 17% (1.2 mm) compared to model performance using the SDK solver calibrated values. The maximum decrease occurred in May where the RMSE was reduced by 35% (6.8 mm). In the remaining three catchments, only slight improvements in model performance were achieved using GA calibration. Adopting a seasonal parameterization of the subsurface drainage parameters in CSIM resulted in improvements in model performance in the two most northern catchments considered (e.g., the 16% [1.2 mm] reduction in the Torne älv and 3% [0.3 mm] in the Ångermanälven catchments) (Figure 5). Again, the largest improvements were seen in May for both catchments with 37% (7.3 mm) and 21% (5.2 mm) reductions in RMSE for the Torne älv and Ångermanälven catchments, respectively. The more southern catchments (Dalälven and Mörrumsån) showed no real change in model performance when adopting either the GA calibration or a seasonal parameterization.

While the model performances measured by RMSE for the Torne älv catchment are similar irrespective of whether GA calibration or seasonal parameterization is used, the resultant parameter sets from the two methods are quite different (Table 2) indicating potential for equifinality (Beven, 2007). This is particularly true for the spring period during which the most improvement was made. When calibrating the model with a seasonal parameterization, the calibrated seepage coefficient (β) controlling water movement from the upper to lower reservoir decreased by 62% of its original value (obtained with the SDK solver from Mörth *et al.*, 2007), while the base-flow recession coefficient (γ) for the lower reservoir increased by 97% of its original value. Counter to this, using the GA calibration with annual parameterizations, the calibrated seepage coefficient (β) controlling water movement from the upper to lower reservoir increased by 73% of its original value, while the base-flow recession coefficient (γ) for the lower reservoir decreased by 36% of its original value. These variations in the parameter values obtained in Torne älv for the GA calibration and the seasonal parameterization are reflected in the monthly model bias (Figure 6). In general for the catchments, the patterns of monthly model bias were similar among the three different calibration/parameterization approaches considered with small shifts between months. For Torne älv, however, there was change in the seasonal patterns of monthly bias comparing between calibration methods (SDK solver and GA) and also with seasonal parameterization.

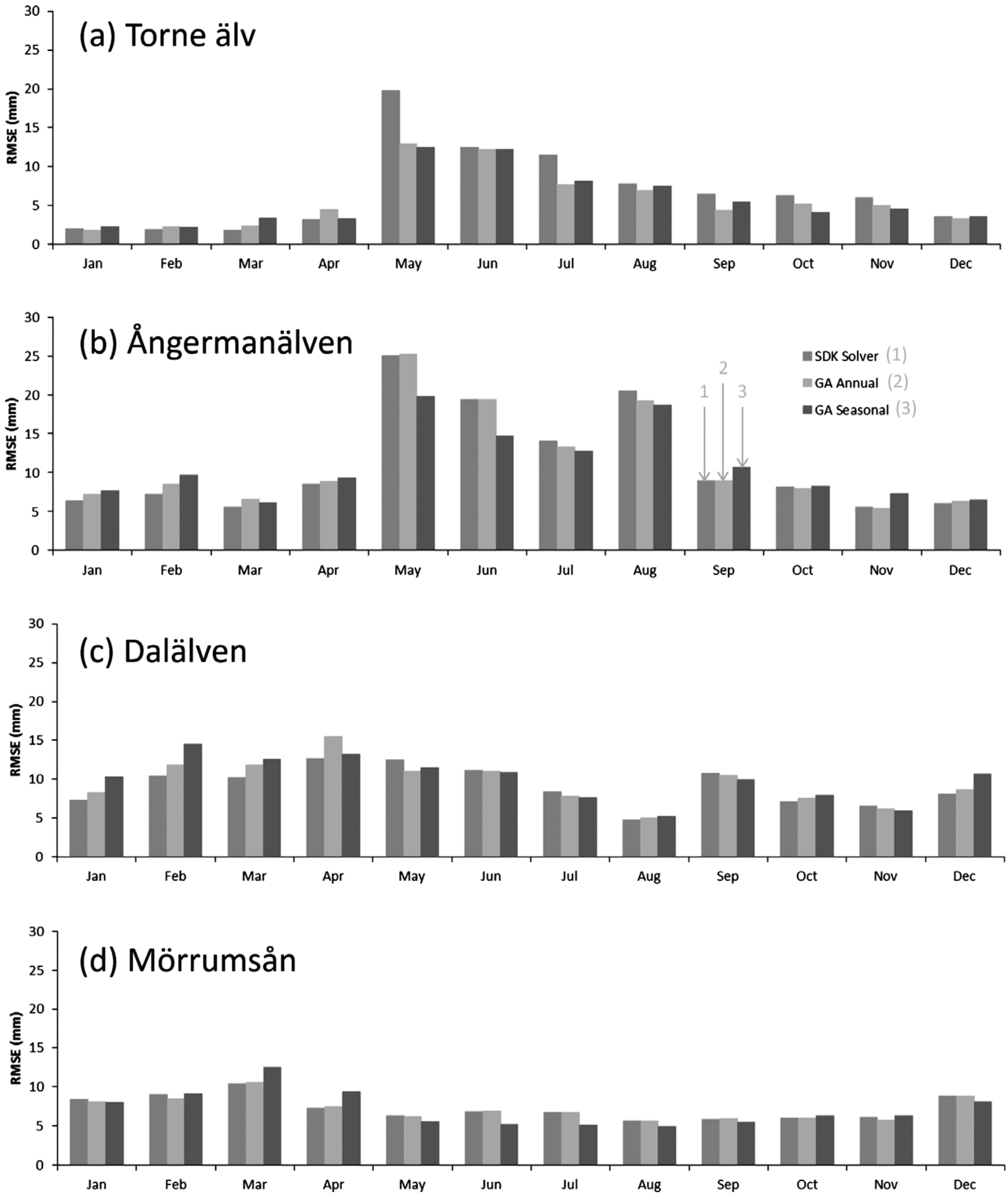

FIGURE 5. Monthly Variations in Root Mean Squared Error (RMSE) for (a) Torne älv, (b) Ångermanälven, (c) Dalälven, and (d) Mörrumsån for the Catchment SIMulation Model When Calibrated Using the SDK Solver as in Mörth *et al.* (2007) or the Genetic Algorithm Procedure with (and without) Seasonal Parameterization of the Subsurface Flow Representation.

TABLE 2. CSIM Calibrated Parameter Sets for the Torne älv Catchment under the Various Calibration and Parameterization Approaches Considered.

Approach	Recession Coefficient (α) (day^{-1})	Seepage Coefficient (β) (day^{-1})	Base-flow Recession Coefficient (γ) (day^{-1})	Deep Seepage Coefficient (δ) (day^{-1})
SDK solver	1.9×10^{-2}	1.1×10^{-2}	4.4×10^{-3}	1.8×10^{-3}
GA annual	2.9×10^{-2}	1.9×10^{-2}	2.8×10^{-3}	1.2×10^{-3}
GA seasonal				
Winter	2.4×10^{-2}	9.2×10^{-3}	3.4×10^{-3}	1.3×10^{-4}
Spring	3.0×10^{-2}	4.2×10^{-3}	8.7×10^{-3}	9.0×10^{-5}
Summer	2.9×10^{-2}	2.1×10^{-2}	1.9×10^{-3}	2.0×10^{-3}
Autumn	1.7×10^{-2}	2.0×10^{-2}	2.5×10^{-3}	1.2×10^{-3}

Note: CSIM, Catchment SIMulation; GA, genetic algorithm; SDK, software development kit.

DISCUSSION

Model Complexity, Parsimony, and Calibration

While CSIM can be considered a simple modeling approach, it allows us to efficiently explore the impact of including seasonal parameterizations and new calibration procedures. As recently highlighted by Hrachowitz *et al.* (2013) in their review of the decade of hydrological Prediction in Ungauged Basins (PUB), it has been recognized early (Beven, 1989; Grayson *et al.*, 1992; Jakeman and Hornberger, 1993; Gupta *et al.*, 1998) and strongly reiterated later (e.g., Gupta *et al.*, 2008) that the predictive capability of hydrological models is limited by high model complexity relative to the typically low number of model constraints used to calibrate the models. Simply put, models calibrated only to the observed hydrographs may be considered overparameterized if they consist of more than five parameters (Jakeman and Hornberger, 1993). Therefore, the increased model performance achieved in this study by introducing seasonality must be considered relative to the increased parameterization. In addition, inclusion of temporally varying parameterizations within modeling efforts (particularly those that target future water fluxes) can be problematic due to potential future shifts in seasonality under climatic changes. Strong climatic shifts, however, have the potential to influence any calibrated set of parameters as they can push models outside their original calibration ranges (Teutschbein and Seibert, 2010).

Consider, for example, that the CSIM model (Mörth *et al.*, 2007) was initially calibrated over a relatively small calibration window (1996-2000) and the resulting parameters held constant during the model's application to the entire 31-year period considered in this study. This introduces a potential source of model error by ignoring changes in the timing of water movement and potential shifts in the dominant hydrology across the BSDB over this period. Such changes have been observed through data-driven analysis (e.g., van der Velde *et al.*, 2013, 2014) and modeling work (Jaramillo *et al.*, 2013). A clear potential exists for impact of climatic changes on the timing of snowmelt and the subsequent movement of water through the terrestrial system particularly at the boundaries between northern and southern regions in the BSDB (e.g., Teutschbein and Seibert, 2010). The seasonality in the model errors here could also indicate the role of ongoing hydrologic process shifts (e.g., Dahlke *et al.*, 2012) that should be considered when employing CSIM or other dynamic approaches for future projections of northern regions. This illustrates both the potential strength and weakness of simple, large-scale approaches like the CSIM model within the whole-system Baltic NEST approach. Wagener *et al.* (2010) summed this up nicely, calling for hydrologists to serve as both synthesists, observing systems as a holistic entity, and analysts, understanding the functioning of individual system components, while operating firmly within a well-designed hypothesis-testing framework.

Regardless, it is relevant to examine our findings, i.e., that the method of calibration adopted and degree of parameterization influence model performance, relative to recent dynamic modeling approaches that offer estimates at daily time steps (e.g., Arheimer *et al.*, 2012b). Clearly, the idea of comparing catchment-scale, calibrated model predictions side by side is likely moot as a more complex model (one with more parameters) will typically outperform a simple model (one with fewer parameters) when it comes to representing dynamic hydrologic responses (Beven, 2007). This is, of course, considering all other things (e.g., appropriate model structure, adequate goodness-of-fit measures) are equal. One of the benefits of using a simple model over a more complex one, however, is that some of the difficulties and uncertainties arising from having many parameters to calibrate can be avoided (e.g., Archibald *et al.*, 2014; Klein *et al.*, 2014). This can help shed light on regional differences in hydrological processes by

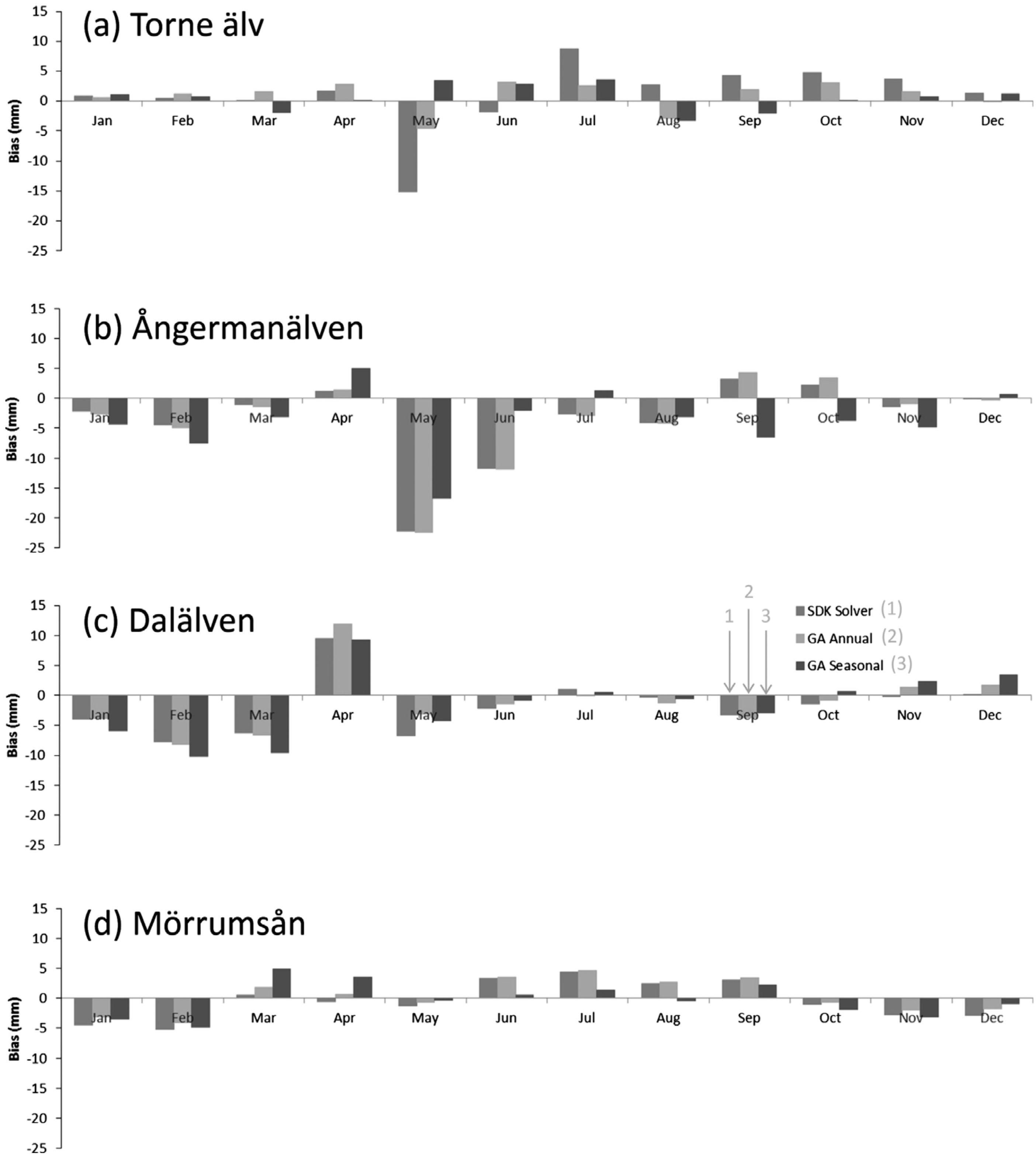

FIGURE 6. Monthly Variations in Model Bias for (a) Torne älv, (b) Ångermanälven, (c) Dalälven, and (d) Mörrumsån for the Catchment SIMulation Model When Calibrated Using the SDK Solver as in Mörth *et al.* (2007) or the Genetic Algorithm Procedure without (and with) Seasonal Parameterization of the Subsurface Flow Representation.

allowing for isolation of various parameter interactions in the modeling environment (see following section). The results of this current study also indicate that care must be taken with calibration and optimization procedures as we increase parameterization and strive for higher spatiotemporal resolution. Other approaches, e.g., Bayesian methods that effectively combine parameter estimation and uncertainty analysis (Sha *et al.*, 2014) may prove useful in future studies. Furthermore, moving forward from the decade of PUB (Hrachowitz *et al.*, 2013), there is increasing acknowledgment of models as potentially useful hypothesis-testing tools and frameworks for improving understanding. With this in mind, models of different levels of complexity are clearly needed to advance the understanding and support different scales of environmental management across the Baltic region.

Interpreting Seasonal Model Performance

Implementing different calibration methodologies and seasonal parameterization to increase model performance (Figure 5) came at the price of greater model bias during part of the year to compensate for other parts of the year (Figure 6). Increase in model bias is especially manifest in the underprediction of flows in the northern region which may be due to the differences in the dominant hydrologic processes between the northern and southern regions of the BSDB. This likely indicates that certain process characterizations in the CSIM model are missing or inadequate, or that different regional parameterizations are required in CSIM to influence the timing of water flows to predict them accurately at a sub-annual scale. Furthermore, this redistribution of monthly model bias incurred with improved model performance (specifically in the northernmost catchments considered Figures 6a and 6b) may also be related to the various submodels adopted in the model setup such as the degree-day snow model or the U.S. Soil Conservation Service's curve number method. Even though we are not explicitly considering these submodels in this exploratory study, the improvements in model performance achieved through seasonal parameterization of subsurface flows could be due, in part, to compensation for errors in the timing of infiltration (e.g., Fuka *et al.*, 2012). This can be seen, for example, by the different resultant parameter sets controlling the timing of subsurface water movement obtained by changing the calibration procedure or by implementing seasonal parameterization in the Torne älv catchment indicating that issues of timing of water flows are not purely dependent on the CSIM model's subsurface characterization. Identification of different resultant "optimal" parameter sets can also be indicative of equifinality (i.e., Beven, 2007). Still, variations of model performance across the BSDB can help us in identifying potential avenues for improving our ability to model the region's hydrology through balancing parsimony with representative parameterization.

The regional (subbasin) variation in patterns of seasonal performance (with southernmost catchments exhibiting different seasonal variations than their northern counterparts, Figure 4c) helps indicate where the CSIM modeling approach could benefit from inclusion of explicit process representation or more regionalization of model parameters. In the southern regions, for example, the consistent overprediction of streamflow evenly distributed across the entire year might indicate underrepresentation of anthropogenic influences along river courses and larger abstractions such that the model estimates more streamflow than actually is observed. This is consistent with previous work (e.g., Hägg *et al.*, 2010) indicating the potential impacts of the larger populations in southern BSDB on discharge (and subsequent nutrient transport). In the northern regions of the BSDB, there is clear misrepresentation of the timing of water flows associated with spring flood periods. In these catchments, the significance for model performance of representing snowmelt timing and the movement of the meltwater pulse through the landscape is larger (particularly when considering sub-annual time steps) than in the southern region (e.g., Lyon *et al.*, 2010).

Arguably, these seasonal and regional differences in the monthly model error are to be expected since, in the current generation of model development, the CSIM model is not fully process based and has not been calibrated explicitly to control the timing of snowmelt or the partitioning of surface runoff and infiltration. These aspects potentially can be handled better in more parameterized and dynamic approaches (e.g., Arheimer *et al.*, 2012b). Such hydrologic processes have been shown to be important at smaller catchment scales in similar hydroclimatic settings when applying models with similar structure to CSIM (e.g., Dahlke *et al.*, 2009). However, Woodbury *et al.* (2013) demonstrated that including more process representation in large-scale, semidistributed models (e.g., SWAT) may not be significant in the estimation of flow volumes but more important with regard to spatial distributions of hydrologically active regions. Also, to account for such spatial distributions, it is likely that additional information pertaining, for example, to flow pathway distributions within the landscape (e.g., Lyon *et al.*, 2010) will be required. Our results appear to support this conclusion for the relatively large catchments of the BSDB (Figure 1) in that CSIM performs well at simulation of annual flow amounts (Figure 2) but has difficulty in predicting flow timing at sub-annual scales (Figure 4). Furthermore, the seasonality of the hydrological regime within a catchment plays a role in the importance of process representation (Figure 4) making the case for a regionalization of the models as we move from large-scale annual applications (CSIM application in Mörth *et al.* (2007)) to individual catchment performance at sub-annual scales (results in this current study).

Implications for Management of Nutrients in the BSDB

In addition to its usefulness in identification of regional patterns and trends in model performance, a consistent and rather parsimonious modeling framework across the entire BSDB permits development of coherent management strategies across the region and facilitates coupling to other large-scale models or global climate scenarios. This is a clear necessity when applying an ecosystem approach to management of the Baltic Sea to reduce nutrient fluxes (Jansson *et al.*, 1999). By maintaining a parsimonious representation of the hydrology, the CSIM modeling framework provides a basis to employ nutrient transport modeling consistently across the BSDB such that alternative scenarios of management linked to potential climatic shifts can be considered. For example, the net anthropogenic nitrogen input (NANI) approach, first introduced by Howarth *et al.* (1996), provides estimates of the human-induced nitrogen inputs to a watershed and has been shown to be a good predictor of riverine nitrogen export on a large scale, multiyear average basis (Howarth *et al.*, 2012). Recent work by Hong *et al.* (2012) extended the NANI approach to also consider phosphorus (creating a Net Anthropogenic Phosphorus Input or NAPI approach) with application to the BSDB. That work showed a clear north-to-south gradient across the monitored Baltic Sea catchments with regional-scale nutrient inputs strongly related to regional-scale nutrient fluxes, and that the regional variations in the spatial distribution of driving variables (e.g., fertilizer use, population, livestock numbers, and atmospheric deposition) were the first-order controls on riverine exports.

This level of representation of regional patterns of nutrient loading matches well with the spatial pattern of model error and performance seen for the CSIM modeling framework. Such scale consistency is important if our goals are to improve the ability to develop and test future management strategies. This is primarily because the flux of nutrients from a landscape depends on both the pattern of activities in the landscape and the pattern of water discharge (Temnerud *et al.*, 2007; Lyon *et al.*, 2012). In fact, the fraction of NANI and NAPI exported to the Baltic Sea is positively related to the specific discharge, i.e., watersheds receiving high precipitation and having a low lake area (lakes retain nutrients efficiently) are potential hot spots of nutrient exports (Hong *et al.*, 2012). In addition, currently planned modifications to the CSIM model due to the findings of this study, combining the NANI approach to address spatial variation of major nutrient loads over the region with further consideration of watershed-scale hydrological processes (as has been done in the ReNuMa model: Hong and Swaney, 2013b; Sha *et al.*, 2013, 2014; or potentially the VWLF model from Schneiderman *et al.*, 2007) should address some of the existing spatial and temporal patterns of model error that exist when targeting smaller spatiotemporal scales.

While other techniques for riverine nutrient export estimation exist (e.g., Alexander *et al.*, 2002; Preston *et al.*, 2009) and other approaches to model water fluxes in the BSDB have been developed (e.g., Graham and Bergström, 2001; Reckermann *et al.*, 2011; Arheimer *et al.*, 2012b; Meier *et al.*, 2014), the NANI methodology coupled with the CSIM framework (with some further consideration of the results presented here) could offer a straightforward coherent approach for application at the sub-annual and subbasin scale. The consistent database embedded within the CSIM framework paired with a general, parsimonious modeling approach makes for a good testing ground to explore various management strategies and development scenarios, and to isolate clear cause-effect relationships. Such consistency and transparency are necessary as we refine our models for prediction at smaller spatiotemporal scales over longer management horizons.

CONCLUDING REMARKS

The CSIM hydrologic model was developed within the Baltic NEST specifically with the goal to utilize a consistent data handling approach and framework to address the large-scale and whole-system management of the BSDB. To date, calibration and application have guided model development to improved estimation of annual flows and coupled annual nutrient loads. A full range of hydrological process representation was not the focal point of the modeling approach. Rather, the approach seeks to provide a consistent basis for addressing nutrient transport and landscape management. The results of this study indicate that the implementation of GA calibration (which potentially explores the full model parameter space more thoroughly than the original SDK solver considered) and seasonal parameterization can both lead to improved CSIM model performance.

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