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Effect of rainfall spatial variability and sampling on salinity prediction in an estuarine system

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Summary Reliable and accurate forecasts of salinity changes are essential for the success of current and future management scenarios aimed at restoring and sustaining natural resources of coastal and estuarine ecosystems. Because of the physical complexity of such ecosystems, information on uncertainty associated with salinity forecasts should be assessed and incorporated into management and restoration decisions. This study focuses on the impact of spatial variability and limited sampling of rainfall on salinity prediction in an estuarine system. The analysis is conducted on the Barataria basin, which is a wetland-dominated estuarine system located directly west of the Mississippi Delta complex on the United States coast of south Louisiana. The basin has been experiencing significant losses of wetland at a rate of nearly 23 km^2/year. Radar-rainfall data with high spatial resolution are used to simulate various scenarios of hypothetical rain gauge sampling densities over the basin. A mass-balance hydrologic salinity model is used to assess the effect of reduced rainfall sampling on salinity prediction in the basin. The results indicated that, due to the critical role played by rainfall in determining the overall balance of the basin freshwater budget, a high degree of uncertainty exists in salinity predictions when using typical average rain gauge densities (e.g., 1.3 gauges/1000 km^2 in the US). These uncertainties decline sharply as the number of available gauges is increased beyond the typically available density. Uncertainties in salinity predictions in the Barataria basin are larger in inland locations and smaller near the mouth of the basin, where salinity conditions in the coastal

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waters of the Gulf of Mexico exert a large influence. Rainfall uncertainties also affected parameter estimation during model calibration, where the estimation of some parameters exhibited significant levels of bias and random scatter. The study highlights the necessity of improving rainfall monitoring especially in estuarine systems that are controlled by rainfall as a main source of freshwater and where the management of freshwater supply is a viable option.

Introduction

Salinity forecasting models are expected to play a central role in managing, restoring, and sustaining natural resources in estuarine and coastal ecosystems. Many of the world's ecosystems (e.g., Florida Everglades, Childers, 2006; coastal wetlands along the northern Gulf of Mexico, Day et al., 2005; California estuaries and wetlands, Van Dyke and Wasson, 2005; coastal wetlands in China, Zhang et al., 2006; estuaries and river ecosystems in the Netherlands, de Jonge and de Jong, 2002) have been and continue to be endangered due to the adverse effects of human activities such as conversion to agricultural lands, hydrologic alterations, water quality degradation, erosion, and industrial activities. For example, coastal Louisiana as a part of the Mississippi River Deltaic Plain is experiencing the most critical coastal wetland loss and degradation problems in North America. Long-term reductions in freshwater and sediment inputs are known to be a primary cause for this decline (Boesch et al., 1994). In response to such accelerated wetland loss rates, coastal restoration scenarios have been proposed in the Mississippi River Delta area and along the northern coast of the Gulf of Mexico. The need for such restoration efforts has been further exemplified following the devastating impacts of hurricanes Katrina and Rita that affected coastal areas in the northern Gulf of Mexico in the fall of 2005.

In coastal Louisiana, salinity of surface waters is recognized as a primary factor in the productivity of coastal fisheries, and in controlling the extent and spatial distribution of freshwater, mesohaline and euhaline wetland communities (Visser et al., 2000; Turner, 2006). Therefore, coastal resource managers must be able to predict changes in estuarine salinity that may occur as a result of activities proposed for protecting and restoring coastal resources. In this context, salinity models can provide critical forecast information to assess risks and benefits (i.e., changes in wetland communities, estuarine water quality, and coastal fisheries) under current management activities and for various future alternative management scenarios. However, due to the models inherent approximation of complex ecosystem physical processes, model salinity predictions are inevitably prone to uncertainties. In general, these uncertainties can be attributed to various factors such as limited understanding of the processes involved, inaccuracies in model formulation, and inadequate or inaccurate information needed to apply the models (i.e., input and calibration data, and the lack of direct information on model parameters) (NRC, 2002; Lall et al., 2002; Habib et al., 2007). In the current study, we focus on sources of uncertainties related to inaccurate estimation of rainfall as one of the driving variables of salinity forecasting models.

Summer and Belaineh (2005) highlighted the importance of accounting for temporal rainfall variability in explaining salinity changes especially in flow-restricted estuarine systems. In addition to its pronounced temporal variability, rainfall can be highly variable in space (Crane, 1990; Seed and Austin, 1990), especially with the occurrence of localized convective storms. High spatial variability can translate into large uncertainty in estimating rainfall quantities especially over large areas. Most modeling efforts in estuarine systems are based on operational rainfall monitoring stations, which are usually characterized with low sampling densities. For example, a typical rain gauge average density in the US is about 1.3 rain gauges per 1000 km^2 (Linsley et al., 1992). These sparse measurements provide a poor representation of areal-average rainfall quantities (Bras and Rodriguez-Iturbe, 1993; Morrissey et al., 1995). Therefore, there is a need to analyze the effects of uncertainty imposed by limitations in rainfall measurements on salinity predictions. Rainfall-related uncertainties with respect to salinity forecasting were recently investigated by Habib et al. (2007); however, their analysis was based on synthetically generated rainfall data and therefore was limited to a single case of rainfall sampling density (one gauge in the basin). In the present study, an approach based on actual rainfall data is followed to thoroughly investigate the effect of various rainfall sampling scenarios on the uncertainty of a salinity forecasting mass-balance model when applied to an estuarine system in coastal Louisiana (Barataria basin). We used radar-rainfall data with high spatial resolution to establish a reference state of the Barataria basin in terms of model rainfall input and salinity output. The fully-distributed radar data were sub-sampled to generate rainfall datasets that represent measurements of ''hypothetical rain gauges'' with various degrees of reduced sampling density. A mass-balance model is used with each of these reduced rainfall sampling scenarios to investigate the effect on model calibration (i.e., estimation of model parameters) and subsequent salinity predictions. The paper is organized as follows. First, we present a description of the study basin (Barataria estuarine system) and its representation through a mass-balance model. An exploratory analysis is then introduced on the magnitude of rainfall spatial variability in the basin, followed by a brief description of radar-rainfall data and methodology applied to simulate various scenarios of hypothetical rain gauge densities. We then assess the impact of limited rainfall sampling on model calibration and salinity predictions. Finally we summarize the main conclusions and discuss their practical implications.

Study site and its rainfall characteristics

The Barataria basin (Fitzgerald et al., 2004) is located in the Mississippi Delta region in southern Louisiana (Fig. 1). The basin is bordered in the east by levees of the Mississippi River and in the west by Bayou Lafourche. A group of barrier islands to the south of the basin separates it from the Gulf of Mexico. Freshwater wetlands and several large lakes comprise the northern portion of the basin while tidally influenced marshes occupy the south. The basin is a wetland-dominated estuarine ecosystem encompassing a total of approximately 6000 km^2 of water bodies and wetlands and has experienced significant losses of wetland at a rate of nearly 23 km^2 per year between 1974 and 1990 (Stone et al., 1997; Coleman et al., 1998). This is attributed to flood control levees and continuous deepening and maintenance of navigation channels, which are starving the wetlands from seasonal inputs of freshwater and sediment from the river (Boesch et al., 1994). Rainfall, averaging approximately 160 cm annually in the region, is currently the dominant source of freshwater to the basin with an annual excess over evaporation. Other freshwater sources include diversions (Fig. 1) introduced to the basin from the Mississippi River at Naomi, West Point á la Hache, and Davis Pond, and from the Gulf Intracoastal Waterway. The Mississippi river, which was a major source of freshwater to the basin before the 20th century, was leveed to control its route and protect against flooding.

Temporal and spatial salinity patterns within the basin are affected by the available amount of freshwater and the effect of the Mississippi River plume on salinity of coastal waters. During times of high river flows, basin salinities are mostly controlled by the influence of the river plume on the salinity levels in the Gulf of Mexico. However, during periods with low river flows, salinities tend to increase and the role of rainfall becomes more significant. In the Barataria basin, as in many other estuarine systems, rainfall measurements are available only at sparse locations (Fig. 1), which can be a source of uncertainty especially if rainfall in the basin area is characterized with high spatial variability. Fig. 2a shows a comparison of monthly rainfall accumulations at two rain gauges within the basin separated by a distance of approximately 30 km. This distance is typical between other gauges in the basin. The comparison shows significant differences between monthly rainfall accumulations at these two gauges. The standard deviation of these differences is about 70 mm (or 55% of monthly average rainfall in the area). Monthly differences as high as 10, 50, and 100 mm are exceeded during approximately 50%, 20%, and 10% of the time, respectively. Further evidence of the significant spatial variability of rainfall in the basin is shown by examining the rainfall monthly spatial correlation function (Bacchi and Kottegoda, 1995; Habib et al., 2001). A fast rate of de-correlation with gauge separation distance will indicate a significant spatial variability in rainfall magnitudes. We computed monthly correlation coefficients for every pair of rain gauges within the basin and plotted them as a function of

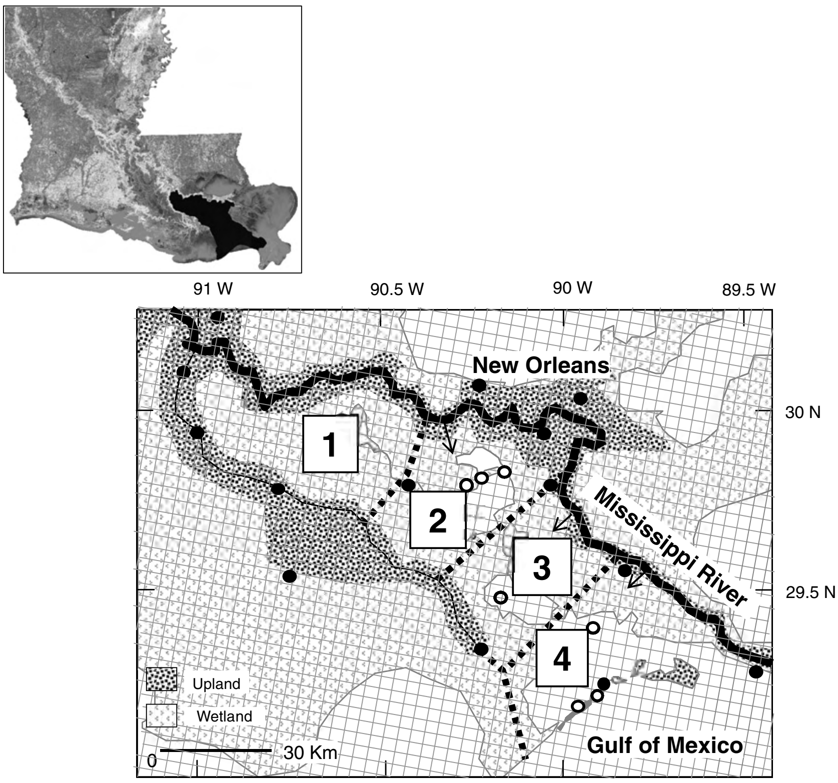

Figure 1 Map of the Barataria Bay estuary in coastal Louisiana showing locations of monitoring sites of salinity (open circles) and rainfall (black circles). Arrows indicate the locations of main river diversions: Davis Pond, Naomi, and Pointe a la Hache (from north to south). The rectangular grid represents 4×4 km^2 radar pixels.

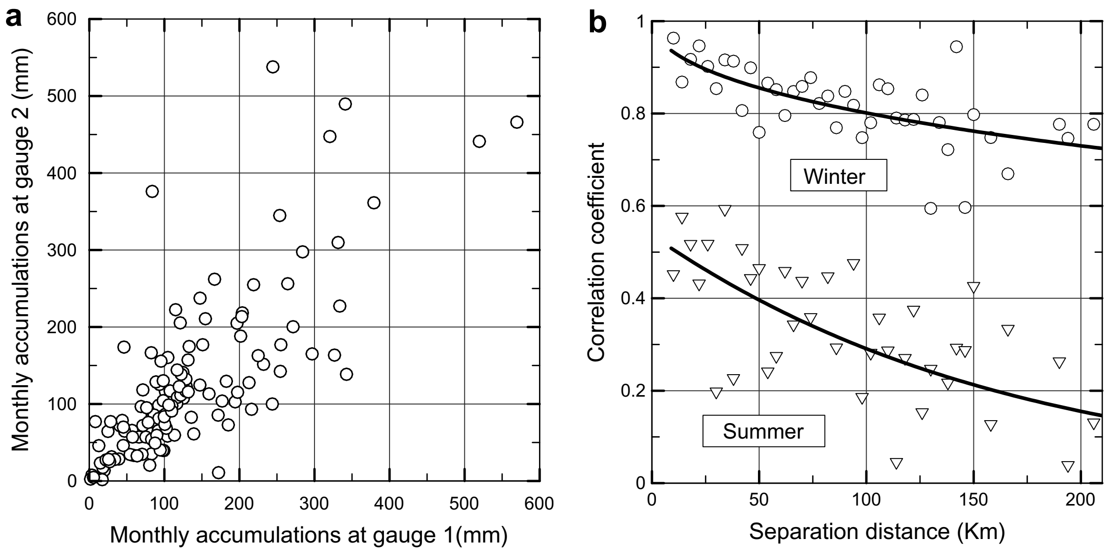

Figure 2 Analysis of rainfall spatial variability: (a) scatter plot of rainfall monthly accumulations at two rain gauge stations separated by 30 km; (b) monthly rainfall correlations for two examples of summer and winter months (July and February).

corresponding separation distance between pairs (two examples of summer and winter months, July and February, are shown in Fig. 2b). A strong spatial variability is evident, especially in summer rainfall which shows significantly weak spatial correlation levels even at small separation distances. Correlation coefficients as low as 0.4–0.6 are obtained at distances of 50 km and less. Overall, the analysis indicates that significant variations exist in monthly rainfall over the basin area. Similar findings, with even stronger spatial decorrelation, were reported by Seed and Austin (1990) for summer rainfall in Florida. To fully analyze the effects of these variations on model salinity predictions, we need a spatially dense field of rainfall measurements that can be used as a ''benchmark'' for assessing limited sampling scenarios; radar-rainfall data provide a potential source of such information.

Experimental data and methods

Radar-rainfall data

Radar-rainfall data concurrent with other input data necessary for driving the mass-balance model (e.g., basin freshwater inflow volumes, evaporation rates, boundary salinities, and sea level changes) were considered for a period of 42 months from January 2003 through June 2006. Radar-rainfall data used in the current study are based on the Stage IV products of the National Center for Environmental Prediction (NCEP). Stage IV radar-rainfall estimates are based on mosaicking of regional multi-sensor precipitation estimates (MPE) which are developed at the National Weather Service River Forecast Centers. Using real-time rain gauge observations, the MPE algorithm applies correction factors to the radar data to reduce mean-field and local biases that are inherent in the radar-only rainfall estimates (Seo and Breidenbach, 2002; Seo et al., 1999). Stage IV data are provided over a 4×4 km^2 national grid system (see Fig. 1) with an hourly resolution, We then accumulate the data into a monthly resolution for use in our mass-balance model.

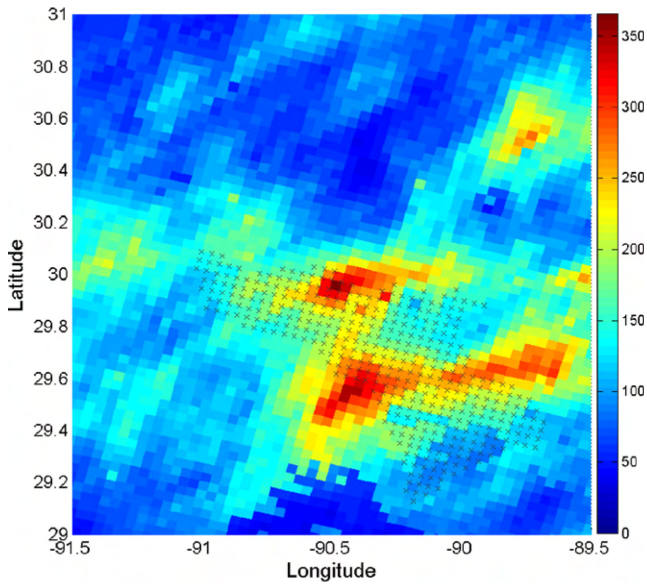

Figure 3 Map of radar-rainfall accumulations (mm) for April 2004. The Barataria basin domain is indicated by cross symbols.

An example of the spatially-distributed radar-rainfall data transposed over the Barataria basin area is shown in Fig. 3 for April of 2004. The plot shows a main advantage of radar data in terms of high spatial detail and resolution. However, since radar data are based on remotely-sensed measurements, the relative accuracy of radar-rainfall estimates must be first assessed and validated before being used in further analysis. This validation can be done by comparing radar estimates against surface rain gauge observations. Such rain gauge data were obtained from a small-scale experimental hydrologic network operated by the University of Louisiana at Lafayette in southern Louisiana. The selection of this particular network was due to the fact that it was not used by the MPE bias-adjustment algorithm, and therefore, can be considered as an independent validation data source. Monthly accumulations from

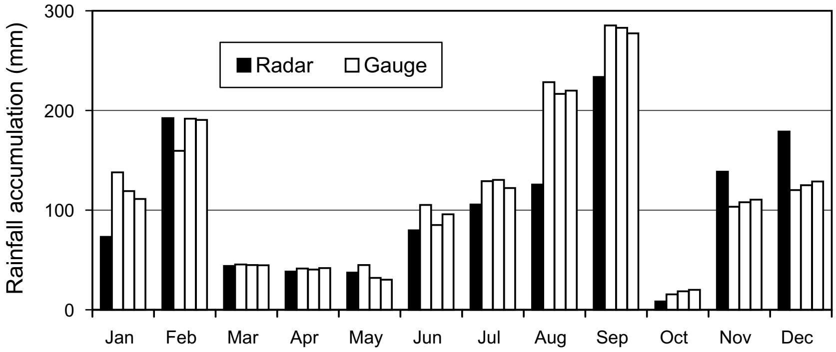

Figure 4 Comparison of radar and gauge monthly rainfall accumulations using data from three rain gauges located within a single radar pixel in an experimental rain gauge network, Lafayette, Louisiana.

three surface gauges, all within proximity of each other and within a single radar pixel, were compared against corresponding radar accumulations (see Fig. 4 for year 2005 comparison). Overall, radar estimates follow a trend similar to that of gauge rainfall accumulations with some overestimations (underestimations) noticed during November and December (August and September) of 2005. Comparisons for other years (2002–2005) and at several other gauge locations in the experimental network (Fig. 5) resulted in a correlation coefficient between radar and gauge estimates of 0.85 for cold months (November–March) and 0.88 for warm (April–October) months. While the degree of scatter between radar and gauge (Fig. 5) is similar to that shown earlier between two gauges separated by a distance of approximately 30 km (Fig. 2a), radar data provide improved estimates of rainfall monthly accumulations over sparsely located gauges especially in summer months. The radar–gauge correlation coefficient of 0.88 in summer months is a clear improvement over those obtained amongst rain gauges in the region (correlation coefficient of less than 0.6; Fig. 2b).

Based on this visual and statistical exploratory analysis of the radar data accuracy, we proceed considering that radar data can provide spatial high-resolution ''true'' representation of surface rainfall to be used for assessing limited rainfall sampling scenarios.

Mass-balance model

We applied a mass-balance forecasting model to calculate monthly salinity in the basin in response to a pre-specified rainfall input. To implement the model, the Barataria basin was divided into four well-mixed sub-basins linked by water and salt flow exchanges (Fig. 6). The model calculates sub-basin average salinity by keeping track of the water and salt budgets in each sub-basin (see Habib et al., 2007 for further details on model formulation and equations). Model inputs include time series of monthly rainfall accumulations, potential evaporation rates, as well as volume of freshwater diverted from the Mississippi River. Monthly sea level and salinity at the Gulf of Mexico boundary are used to describe model boundary conditions. The model has five parameters that control the exchange of fluxes amongst the four sub-basins and between the Barataria basin and the Gulf of Mexico (X_{1-2}, X_{2-4}, X_{2-3}, X_{3-4}, X_{4-G}). An evaporation coefficient

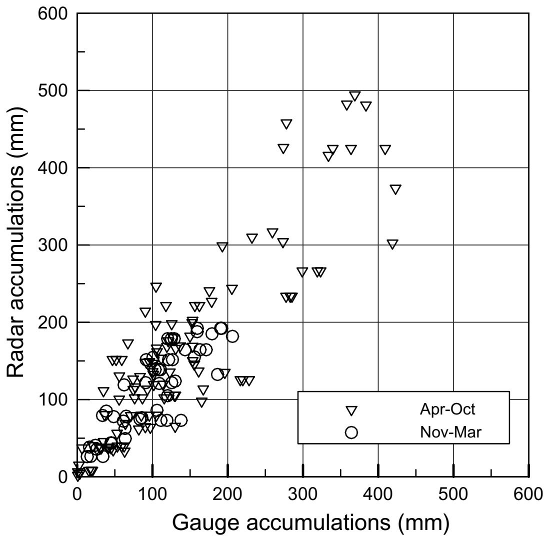

Figure 5 Scatter plot of gauge versus radar-rainfall monthly accumulations during 2002–2005.

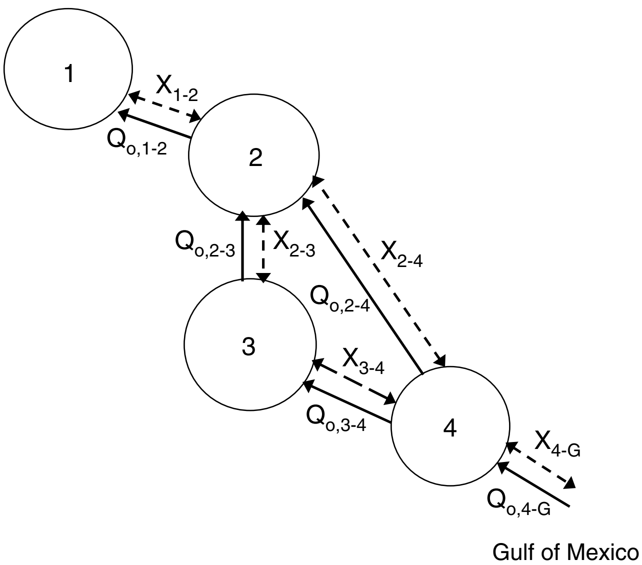

Figure 6 Schematic representation of a four-box mass-balance model for the Barataria basin. Solid and dashed arrows represent advection and mixing flow exchanges, respectively.

(E_C) was also needed to calculate actual evapotranspiration rates over land areas in the basin as a fraction of the rate of potential evaporation. The model output provides predictions of monthly average salinity in each sub-basin. Mass-balance models offer the advantage of computational efficiency and ease of implementation while providing a physically-based description of the relationship between the net supply of fresh water and salinity (Officer, 1980; Hagy et al., 2000; Babson et al., 2006). The spatial and temporal averaging inherent in this representation prevents the mass-balance model from capturing salinity variations that occur at finer scales. However, applications across a number of systems including San Francisco Bay and Chesapeake Bay (Uncles and Peterson, 1996; Gibson and Najjar, 2000) suggest that such aggregated models can capture much of the salinity variation that occurs seasonally and from year to year. This is sufficient to forecast the effects of an altered salinity regime on the distribution of wetland communities within the Barataria basin using the ecological models that are presently available (Visser et al., 2003).

We applied the shuffled complex evolution metropolis (SCEM-UA) optimization algorithm (Vrugt et al., 2003) to calibrate the model and estimate its six parameters based on the specified model input and boundary conditions and a set of salinity observations in each sub-basin. Starting from a set of pre-specified prior parameter distributions (assumed uniform with a wide-enough range), the optimization algorithm performs thousands of model evaluations until convergence is reached and the most likely set of model parameters is identified. This method is based on Markov chain Monte Carlo (MCMC) techniques for Bayesian inference, which have been increasingly applied in analysis of hydro-ecological and environmental systems (Omlin and Reichert, 1999; Engelund et al., 2005; Qian et al., 2003).

Procedure for rainfall sampling and uncertainty analysis

Several sources of uncertainty can affect the accuracy of model salinity predictions (e.g., knowledge uncertainty, errors in input and calibration data, and model structure). In order to isolate the effect of rainfall uncertainty in particular, we established a reference state of the basin in terms of both rainfall input and salinity response. We used radar-rainfall data with their high spatial sampling and resolution to represent a ''true'' reference rainfall field over the area of each of the four sub-basins. The spatially-distributed radar data represent an ideal sampling situation where hypothetical rain gauges are available at all radar pixels within each sub-basin. Sub-sets of surface rain gauges with reduced sampling densities can be readily simulated from the spatially dense radar data (a similar sampling approach was followed by Bradley et al., 2002 to test different rain gauge network design configurations). Similarly, we define a ''true'' reference salinity response as model output when driven by the reference rainfall data. We define the relationship between the reference rainfall input and salinity response through a set of pre-specified ''true'' reference model parameters. These reference parameter values were selected in such a way that model salinity output obtained using reference rainfall input can reproduce the overall spatial gradients and temporal patterns and magnitudes of actual salinity measurements in the basin. The selected values for parameters X_{1-2}, X_{2-4}, X_{2-3}, X_{3-4}, X_{4-G}, and E_C are 1.0, 0.1, 0.5, 4.0, 50.0, and 0.75, respectively. The assumed prior ranges necessary for implementing the SCEM-UA algorithm are from 0 to 300 for all parameters except E_C which was set to have a prior range from 0 to 1. While the model reference state (defined by reference rainfall input, salinity output, and parameters) does not necessarily represent ''actual'' field measurements, it can serve as a benchmark for further assessment of reduced rainfall samplings.

We investigate the effect of limited rainfall sampling on model salinity calculations according to the following procedure: (1) select a sub-set of radar pixels in each of the four sub-basins to represent a reduced density of hypothetical rain gauges, (2) average observations of the selected sub-set of radar pixels over each sub-basin to provide the required model rainfall input, (3) recalibrate the mass-balance model using the SCEM-UA algorithm to estimate optimal values of its parameters based on the reduced sampling density, (4) generate model salinity predictions that correspond to the reduced rainfall sampling density, and (5) compare the estimated parameters and salinity predictions with their reference values. This procedure is repeated to test several scenarios of hypothetical rain gauge densities. For each sampling scenario, the locations of hypothetical rain gauges were selected randomly without replacement from the full number of radar pixels in each sub-basin. A total of 600 random samples were drawn for each examined scenario. Random sampling without replacement ensured each rain gauge location was unique. A total of 14 rain gauge densities were considered for analysis. Densities ranged from one hypothetical rain gauge per sub-basin (corresponding to an average density of 0.7 gauge/1000 km^2), to the total number of radar pixels in each sub-basin.

Results

Effect on model predictions

For each examined rain gauge density, we analyzed the effect on salinity predictions in each of the four sub-basins. An example of the analysis is given in Fig. 7, which shows 600 monthly rainfall time series sampled from the radar data in sub-basin 3 with a gauge density of 1.5 gauges/1000 km^2 (Fig. 7, top). Also shown are the corresponding salinity predictions obtained after recalibrating the model with each of the 600 rainfall samples (Fig. 7, bottom). Reference rainfall and salinity data are also indicated in the figures. This rather low gauge density (which represents typical average rainfall sampling densities in the US) caused significant uncertainty in quantifying rainfall monthly volumes over the sub-basin, which in turn resulted in the shown variations in predicted salinities. To assess the degree of variation in model salinity predictions as a function of rainfall sampling density, we repeated this analysis for all 14 defined rainfall sampling densities and compared model salinity output against reference values. To gain insight on how rainfall uncertainties propagate into the model, monthly rainfall volumes associated with each sampling scenario were also compared against the reference rainfall.

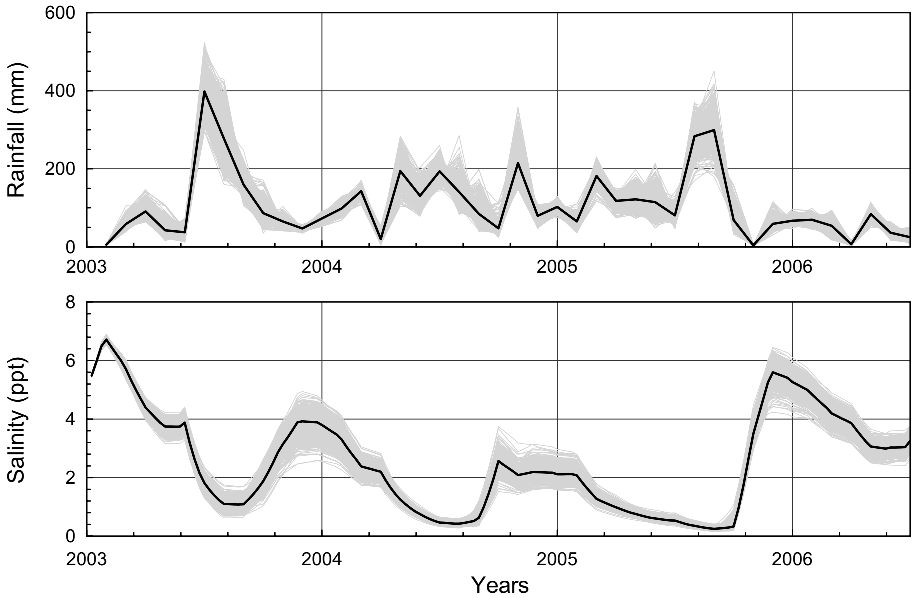

Figure 7 Top panel: rainfall data from 600 random samples (thin lines) obtained with a sampling density of 1.5 gauges/1000 km^2 in sub-basin 3. Lower panel: salinity predictions corresponding to the 600 rainfall samples shown in top panel. Reference rainfall and salinity datasets are shown as thick lines.

Rainfall and salinity uncertainties can be quantified in terms of two statistical measures, relative bias (B) and relative uncertainty range (UR), calculated at each month as follows:

$$B_i = \frac{\frac{1}{n}\sum_{j=1}^{n}(X_{i,j} - \mathrm{REF}_i)}{\overline{\mathrm{REF}}}100 \tag{1}$$

$$\mathrm{UR}_i = \frac{(P_{97.5,i} - P_{2.5,i})}{\overline{\mathrm{REF}}}100 \tag{2}$$

where REF_i is the reference rainfall (or salinity) at month i, $X_{i,j}$ is the rainfall value at a certain sampling density scenario (or the corresponding salinity prediction) for random sample j and month i, n is the number of random samples for each sampling density scenario ($n = 600$), $P_{2.5,i}$ and $P_{97.5,i}$ are the 2.5 and 97.5 percentiles of the n values of X at each month, i. The over-bar symbol represents arithmetic average over all months. Monthly B and UR values are computed for each sub-basin; however, due to large differences in salinity levels amongst the four sub-basins we normalize B and UR by corresponding sub-basin average reference rainfall (or salinity). Therefore, values of UR and B should be interpreted as relative measures of errors.

The results in each sub-basin are presented in terms of B and UR averaged over all 42 months and plotted as a function of sampling density (Fig. 8). To show extreme values of these statistics, maximum UR and maximum B values are also reported. As expected, when rainfall sampling is increased (Fig. 8, left column), biases and uncertainties in estimating sub-basin average rainfall and corresponding predicted salinities decrease (Fig. 8, right column). However, the rate of decrease is much greater at lower sampling densities and becomes increasingly smaller as we approach the full sampling scenario. It is noted that similar results were reported in Bradley et al. (2002) for rainfall analysis at an hourly scale. Rainfall sampling uncertainty is greatly diminished at about 5–10 gauges/1000 km^2, which indicates that a significant portion of the spatial variability in monthly rainfall over the sub-basin scale is probably well captured at such densities. Reduction in rainfall and salinity uncertainty continues but at a much lower rate as densities increase beyond 10–20 gauges/1000 km^2.

Average rainfall bias values were less than 0.30% for all rainfall sampling densities used in this study with extreme bias values remaining below 6%. Such low bias levels resulted from the random sampling procedure followed while selecting locations of hypothetical rain gauges. The corresponding salinity average bias was less than 2%. However, rainfall-to-salinity bias enhancement was evident in the non-negligible maximum positive and negative salinity biases. Note that maximum positive (or maximum negative) salinity biases are related to maximum negative rainfall biases (or maximum positive).

Because the four sub-basins are located within close proximity of each other and are affected by the same rainfall climatologic regime, their rainfall uncertainties show similar magnitudes. However, this is not the case for salinity uncertainties. For example, at the lowest examined density, average salinity UR increases up to 110% for sub-basin 1, but reaches only 18% for sub-basin 4. Variations in salinity UR values across the basin can be explained by considering the difference in salinity levels amongst the four sub-basins as a function of the distance from the saline Gulf of Mexico boundary. Uncertainty levels associated with salinity predictions in sub-basin 1 are impacted the most by rainfall uncertainties. Sub-basin 1, which has low salinity levels, is very sensitive to changes in rainfall as a source of freshwater input. In contrast, sub-basin 4 is influenced the least by rainfall uncertainties due to its much higher salinity concentration, which is mostly controlled by the Gulf of Mexico and least affected by rainfall as a source of freshwater input. To examine the dependence of estimated uncertainties on

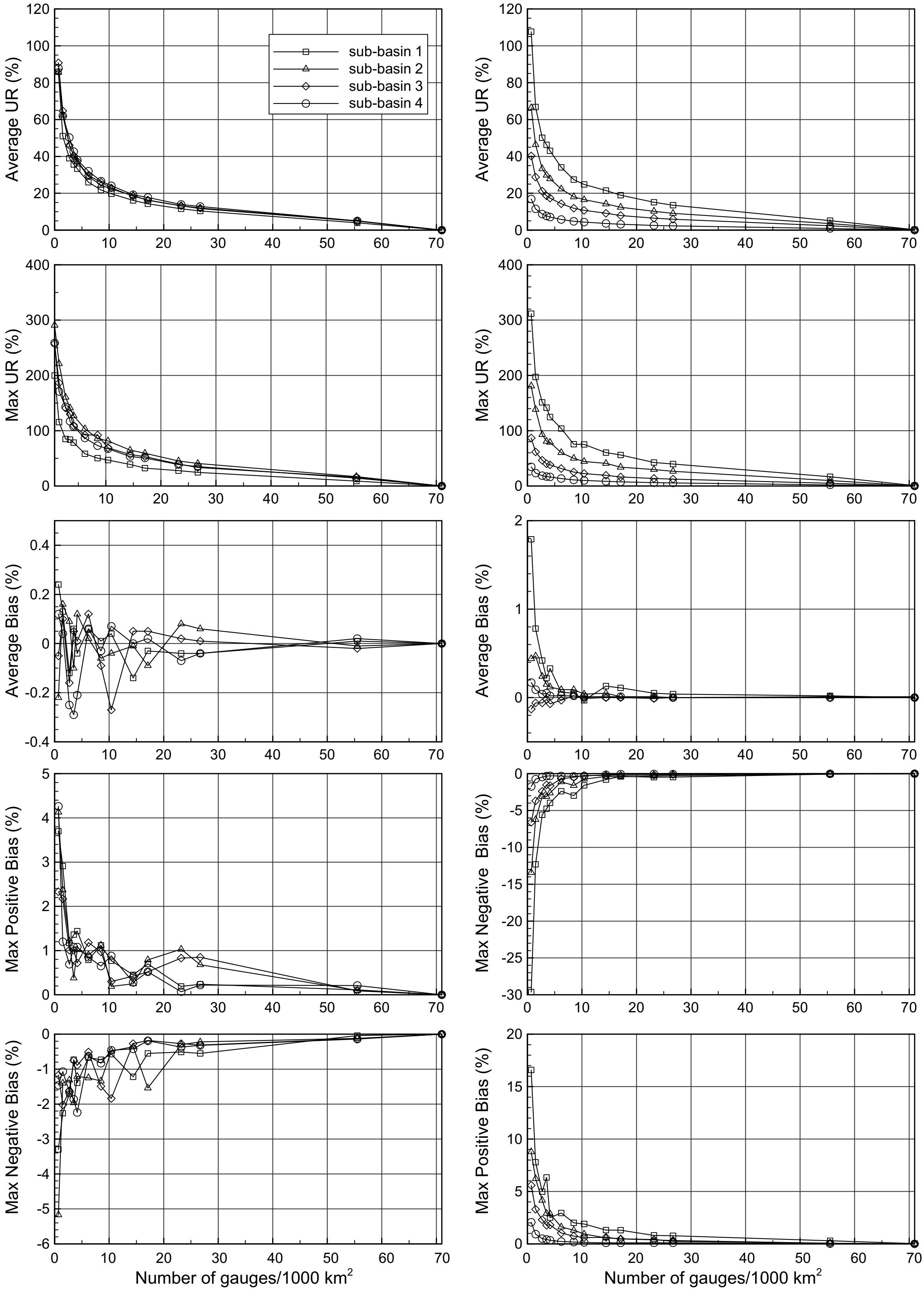

Figure 8 Relative uncertainty ranges and biases of rainfall (left column) and salinity (right column) as a function of rainfall sampling density.

salinity levels, we plotted monthly UR values (computed using Eq. (2)) as a function of corresponding reference salinities in each sub-basin (not shown). We observed that for a certain sub-basin, salinity UR values tended to increase as a function of salinity level.

To further explore the propagation of rainfall uncertainties into model salinity predictions, rainfall average uncertainty ranges were plotted against corresponding salinity uncertainties for the different simulated densities (not shown). It was noticed that errors due to rainfall sampling propagated linearly across the different densities. Enhancement of rainfall uncertainty occurred in sub-basin 1 at a ratio of 1.3. For example, an average rainfall UR of approximately 85% in sub-basin 1 was enhanced to approximately 110% in salinity UR. Sub-basin 2 showed slight reduction in the transformation of rainfall UR to salinity UR while uncertainty of sub-basins 3 and 4 dissipates by approximately 2 and 5 times, respectively. This is not surprising because these two sub-basins are more controlled by the Gulf of Mexico salinity than by rainfall freshwater input.

Effect on model parameters

In actual forecasting applications, the model is usually calibrated based on a single rainfall input available from rain gauges existing in the area of interest. Therefore, it is important to analyze how uncertainties due to limited rainfall sampling affect the calibration of the mass-balance model and the estimation of its parameters. To study this effect, we recorded the set of parameters that resulted from optimizing and calibrating the model for each of the 600 random rainfall samples and analyzed their distribution as a function of rainfall sampling density. An example of this analysis is given in Fig. 9 which shows the distribution of model parameters calibrated using each of the 600 random rainfall samples with a density of 1.5 gauges/1000 km^2. As seen in the wide range of parameter distributions, most parameters (X_{1-2}, X_{2-4}, X_{2-3}, and X_{3-4}) seem to have a rather high degree of spread (random error) with respect to their corresponding reference values. Parameter X_{4-G} and the evaporation coefficient E_C show the lowest spread with most of the distribution lying within approximately 20% of the corresponding reference value. Distributions of some parameters (X_{1-2}, X_{2-4}, and X_{2-3}) are skewed with some occurrences of extreme parameter values compared to reference values. This analysis was repeated for all examined gauge densities and the results are summarized statistically (Figs. 10 and 11). Bias in the estimated parameters (systematic error) is expressed as the average deviation of the 600 optimized parameters from the reference value and normalized with the parameter reference value. Due to their insignificant bias, the evaporation coefficient (E_C) and parameter X_{4-G} are not shown. The 2.5% and 97.5% percentiles (95% confidence interval) of parameter distributions (Fig. 11) provide a characterization of the spread (random error) in each parameter distribution. The effect of rainfall sampling uncertainty is most pronounced in parameters X_{1-2}, X_{2-4}, and X_{2-3}, which control the ex-

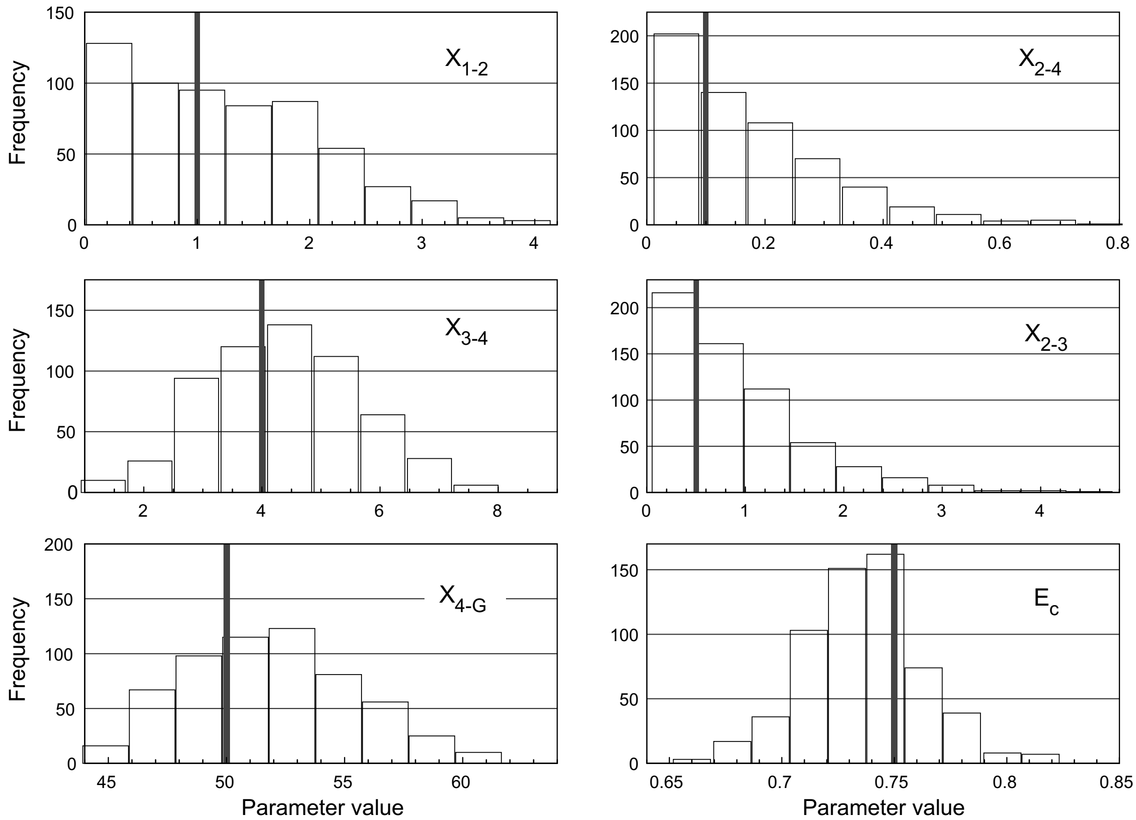

Figure 9 Histograms of calibrated model parameters associated with the 600 rainfall samples at a rain gauge density of 1.5 gauges/1000 km^2. Vertical lines indicate reference parameters values.

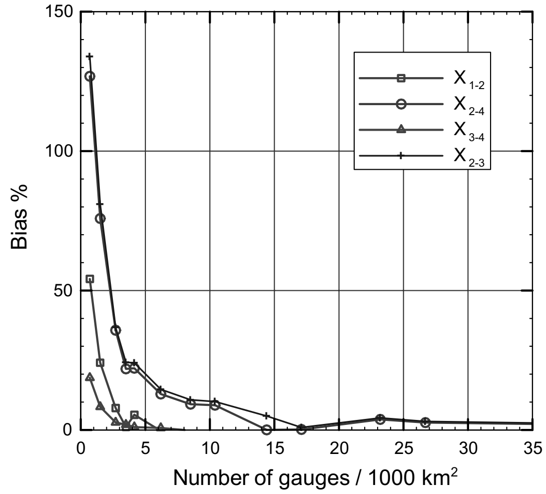

Figure 10 Relative bias in calibrated model parameters as a function of rainfall sampling density. Evaporation coefficient (E_C) and X_{4-G} have negligible bias and are not shown.

change flows amongst the three inland sub-basins 1, 2, and 3. As a result of the significant influence of the Gulf salinity boundary on salinities in sub-basin 4, the effect of rainfall errors on X_{4-G} is not as significant. The impact on estimating the evaporation parameter, E_C, is also minimal since total rainfall volumes were preserved while drawing random samples of the selected gauge densities. Overall, most parameters attain significant convergence towards their reference values by a density of 20 gauges/1000 km^2.

Summary, conclusions and final remarks

This study analyzed effects of rainfall spatial variability and limited sampling on the predictive uncertainty of a salinity mass-balance model when used to simulate salinity changes and patterns in the Barataria estuarine system in south Louisiana. The study used spatially detailed radar-rainfall data with extensive coverage to represent a ''true'' reference rainfall field over the basin area. Sub-sets of rainfall samples were drawn randomly from this reference field to simulate scenarios of rainfall sampling with different hypothetical rain gauge densities. The effect of these limited densities on calibration of model parameters and the subsequent salinity predictions was assessed both visually and statistically. The main conclusions of this analysis and their practical implications are summarized as follows:

- At network densities typical for the US (e.g., ~1.3 gauges/1000 km^2), errors in estimating areal rainfall translate into salinity prediction uncertainty in the range of 15–70% depending on the location within the basin. Rainfall errors and consequent uncertainties in salinity prediction decline sharply as the density of the gauging network increases above the typical value. Similar results can be expected in other estuarine basins where the net supply of freshwater is significantly influenced by rainfall. Given that the density of rain gauges in coastal Louisiana is currently low, this result points to a need to expand the present gauging network to support coastal restoration efforts that will rely on the application of predictive models.

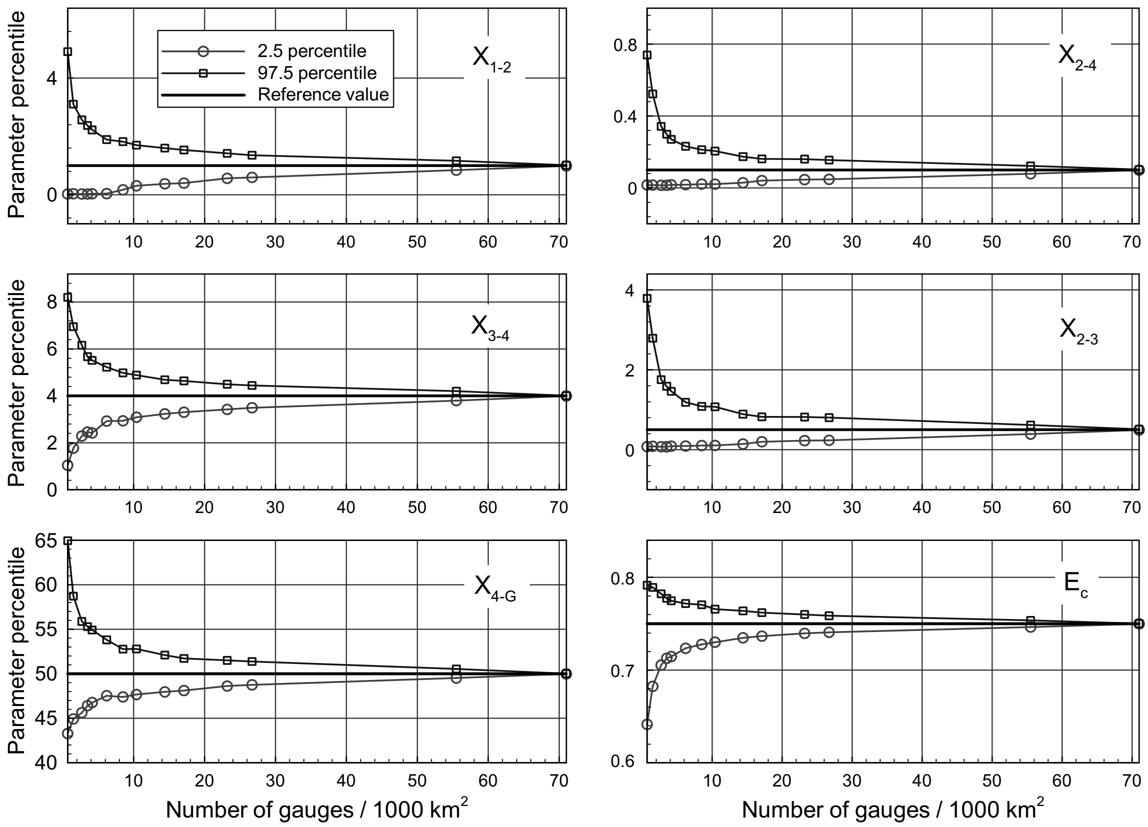

Figure 11 95% (97.5–2.5%) confidence intervals of calibrated model parameters as a function of rainfall sampling density.

- The effect of limited rainfall sampling on estuarine prediction is not uniform. Uncertainties in salinity predictions in the Barataria basin are larger in inland locations and smaller near the mouth of the basin, where salinity conditions in the coastal waters of the Gulf of Mexico exert a large influence. Similarly, the sensitivity of ecological predictions varies greatly across the range of estuarine salinities. Habitat requirements for each of the major ecological communities are defined, in part, by relatively large ranges of salinity values (e.g. freshwater <0.5 ppt; oligohaline 0.5–5 ppt; and mesohaline 5–18 ppt). However, the salinity thresholds that signal a change from one ecological community to another are narrow. Uncertainty in salinity predictions have the greatest influence on predicted extent and composition of ecological communities in an estuarine basin in the vicinity of these thresholds.
- The effect of limited rainfall sampling on salinity predictions might be similarly expected in other basins where rainfall plays a significant role in the overall balance of the freshwater budget and the corresponding salinity response. However, the effect might be of less importance in other climatic regions where rainfall does not necessarily exhibit pronounced levels of spatial variability.
- Rainfall uncertainties also affected parameter estimation during model calibration. The estimation of some parameters exhibited significant bias and random errors. Unless taken into consideration during model applications, parameter uncertainties may impact the reliability of salinity prediction models when used as actual forecasting tools.
- Uncertainties in rainfall propagated through the model calculations and were either enhanced by up to 1.3 times (for inland areas of the basin) or attenuated by up to 2–5 times (for the coastal boundary areas of the basin) in corresponding salinity uncertainties. Interestingly, this propagation was linear for all examined sampling densities. Such linear behavior might not be the case for other types of models that are based on more complex representation of freshwater and salinity transport processes (e.g., hydrodynamic models).
- The results obtained in this study are time scale-dependent. Rainfall sampling-induced uncertainties might actually be higher if salinity predictions are determined at time scales smaller than a month. For models operating at daily or hourly scales (e.g., hydrodynamic models), rainfall spatial variability is much more pronounced than at a monthly scale, which can lead to significantly larger uncertainties in estimating areal-average rainfall from sparse stations. Therefore, we expect that predictions of such models will be sensitive to rainfall variability and sampling. However, since hydrodynamic models are usually based on more complex and refined formulation, the degree and nature of their sensitivity is yet to be investigated.
- Our results indicated that a substantial reduction in salinity prediction uncertainty would require a significant increase in the density of current rainfall monitoring networks, which may not be practically possible. In the current study we used radar data merely as a reference dataset from which reduced rain gauge samplings could be simulated. Given their high-resolution, extensive coverage and continuous availability, the utility of radar data for actual modeling and forecasting purposes should be explored. Uncertainties inherent to radar data should not be a basis for the dismissal of such data as potential rainfall data source. Instead, such uncertainties should be analyzed to assess the extent of their effect on forecasting of hydro-ecological variables. The real value of radar data is mostly appreciated in cases such as estuaries and open water areas with poor monitoring systems, or where enhancing the density of existing operational rain gauge stations, as recommended in this study, might not be possible due to logistic and accessibility problems.

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