Assessment of WRF Model Parameter Sensitivity for High-Intensity Precipitation Events During the Indian Summer Monsoon

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Abstract

Default values for many parameters in Numerical Weather Prediction models are typically adopted based on theoretical or experimental investigations by scheme designers. Short-range forecasts are substantially affected by the specification of parameters in the Weather Research and Forecasting (WRF) model. The presence of a multitude of parameters and several output variables in the WRF model renders appropriate parameter value identification quite challenging. This study aims to identify the parameters that most strongly influence the model output variables using a Global Sensitivity Analysis (GSA) method. Morris One-At-a-Time (MOAT), a GSA method, is used to identify the sensitivities of 23 chosen tunable parameters corresponding to seven physical parameterization schemes of the WRF model. The sensitivity measures (MOAT mean and standard deviation) are evaluated for 11 output variables simulated by the WRF model, corresponding to different parameters. Twelve high-intensity 4-day precipitation events during the Indian summer monsoon during 2015, 2016, and 2017 over India's monsoon core region are considered for the study. Though the parameter sensitivities vary depending on the model output variable, overall results suggest a general trend. The consistency of sensitivity analysis results with different initial and lateral boundary conditions is also assessed.

1. Introduction

Indian summer monsoon (ISM) or the southwest monsoon, is one of the oldest global monsoon phenomena. ISM is irregular and erratic, whose vagaries remarkably affect India both agriculturally and economically (Krishna Kumar et al., 2004). Bursting refers to the quirk increase in mean daily rainfall and is a characteristic of ISM. Quintessentially, ISM bursts at the beginning of June and slowly withdraws toward the start of October. Therefore, the ISM rainfall (ISMR) is more often than not referred to as June-September rainfall. ISMR contributes to more than 80% of the annual rainfall in India (Rajeevan et al., 2013). The monsoon core region (MCR; 69°E to 88°E and 18°N to 28°N) is a critical zone where ISMR plays a crucial role (Rajeevan et al., 2010) corresponding to mean monsoon and intraseasonal variability. Besides being a conspicuous contributor to the food security and water resources of the South Asian region, the ISM rainfall, representing an abundant heat source, has a significant impact on the global climate and general circulation (X. Chen et al., 2018; Rao, 1976). Consequently, accurate predictions of the ISMR over the monsoon core region are critical not only for India's water resource management but also for a superior seasonal forecast across the globe.

An accurate depiction of all the physical processes occurring in the atmosphere is impractical to incorporate in a numerical model, even with state-of-the-art supercomputing technology. Therefore, NWP developers use parameterization schemes. Weather Research and Forecasting (WRF) provides a plethora of advanced physics parameterization schemes (Skamarock et al., 2005) to represent the physical processes (related to the surface layer, cumulus, microphysics, short-wave and long-wave radiation, ocean model, land surface, and planetary boundary layer). Any suitable combination of physics schemes compounds to a different version of the WRF model. To obtain reliable predictions that are close to the truth, correct initial and boundary conditions and the employment of appropriate parameterization schemes alone are not adequate. Each parameterization scheme has a vast number of parameters whose default values are fixed based on experimental or abstract investigations by the scheme designers. These parameters typically are constants and exponents in the model equations. The appropriate specification of parameters within the model physics
plays a pivotal role in the fidelity of WRF model simulations. An accurate estimation of these parameters helps in improving the model forecast.

Some researchers conducted parameter estimation for various regions using trial and error-based techniques (Allen, 1999; Knutti et al., 2002), but the effectiveness of this approach is contingent on the skill of the model observer. Many examined the utility of inverse techniques, a more objective strategy, through parameter adjustment by pruning the objective function to match the simulation results with those of observations. Parameter estimation is a complex procedure due to several issues. As the number of tunable parameters is high (about tens of parameters), the number of model simulations required is very high, leading to the problem of “curse of dimensionality.” Several meteorological variables such as precipitation, wind speed, temperature, humidity, atmospheric pressure need to be considered simultaneously during the parameter tuning. One more issue with parameter tuning is that the NWP model needs to be run a substantial number of times, which is a problem due to limited computational resources. The parameter dimensionality problem can be addressed by performing a sensitivity analysis (SA) to identify the parameters that greatly influence the model output variables of interest. Sensitivity analysis reduces the number of parameters to be tuned to improve the prediction of the model output variables of interest. SA is the most frequently utilized statistical tool to recognize the most critical parameters.

Several researchers performed sensitivity studies with respect to different parameterization schemes to improve the prediction of heavy rainfall events during the Indian summer monsoon. For instance, Kumar et al. (2008) observed that the Grell-Dévényi ensemble cumulus scheme performed better for 26 July 2005 heavy rain event over Mumbai whereas, Anil Kumar et al. (2010) observed that the Betts-Miller-Janjić cumulus scheme simulated three heavy rainfall events during 2006 better. Baisya et al. (2017) observed that the Morrison microphysics scheme performed better for a landfalling monsoon depression in October 2013. Chakraborty et al. (2021) observed that the WRF Double-Moment 6-Class (WDM6) microphysics scheme performed better for the heavy rainfall event of Kerala (2018) and Chawla et al. (2018) observed that a combination of Goddard microphysics, Mellor-Yamada-Janjić planetary boundary layer, and Betts-Miller-Janjić cumulus parameterization scheme simulated a heavy rainfall event in June 2013 in the upper Ganga Basin better. However, different combinations of schemes were found to perform better for different heavy rainfall events, and most of these studies considered only a single heavy rainfall event.

Some studies explained various factors responsible for different types of high-intensity precipitation events over the Indian region. Agnihotri and Dimri (2015) observed that the widespread thunderstorm activities over southern peninsular India during the premonsoon season occurred due to a north-south trough, an easterly trough, and low-pressure areas over the surrounding Indian Seas. Srinivas et al. (2018) simulated an extreme rainfall event over Chennai and observed that veering of wind with height is responsible for the development of instability and initiation of convection. Viswanadhapalli et al. (2019), Baisya and Pattnaik (2019), and Chakraborty et al. (2021) simulated the Kerala heavy rainfall event during 2018 and identified strong westerly jet, the transport of mid-tropospheric moisture, and the horizontal moisture flux convergence as the critical drivers of convection. However, in this study, the concentration is on heavy rainfall events in general and on identifying the sensitive model parameters that greatly influence the model output variables for these events.

Various SA studies concentrated on the parameters of a particular parameterization scheme (Hou et al., 2012; Li et al., 2013). Several studies comprehensively considered many parameters across various physics parameterization schemes and performed a SA to identify the sensitive parameters in the WRF model. Di et al. (2015) assessed the sensitivity of 23 chosen tunable parameters corresponding to precipitation prediction in the Greater Beijing area using the WRF model. Quan et al. (2016) evaluated the sensitivity of various model output meteorological variables to the WRF model parameters using the Morris method for various precipitation events in the Greater Beijng region. Wang et al. (2020) implemented three different SA methods to assess the sensitivity of land-atmosphere coupling strength to boundary and surface layer parameters using the WRF model over the Amazon region.

This study aims to identify the model parameters that most significantly influence the different model output meteorological variables in a critical region, such as the MCR for various high-intensity precipitation events during the Indian summer monsoon. The consistency of SA results with different initial and lateral
boundary conditions also needs to be evaluated. The sensitive parameters obtained in this study can be tuned to reduce the model prediction error (Chinta & Balaji, 2020; Duan et al., 2017) using advanced optimization techniques.

This study is organized as follows. Section 2 gives an introduction to the Morris One-At-a-Time (MOAT) SA technique. Section 3 provides a detailed description of the parameters, physics schemes, and events considered for the SA. Section 4 lists out the critical results and inferences related to the sensitivity measures. Section 5 presents the conclusions from this study.

2. Sensitivity Analysis Method

SA is defined as the recalculation of outcomes of the model (numerical or otherwise) under alternative assumptions, owing to the uncertainties in the model inputs, to ascertain the influence of different input variables (i.e., parameters). SA finds its application, among the other things, in robustness evaluation, uncertainty reduction, error search, and model simplification. However, the prime focus of the present study is to identify the model input parameters that cause substantial uncertainty in the model outcome. SA employed in the current study comprises three significant steps: (a) selection of an accurate model to be used and the identification of the adjustable model input variables, (b) quantification of uncertainties (i.e., ranges and probability distributions) in each parameter, and (c) choice of a suitable SA method to evaluate parameter sensitivity.

A set of 23 parameters with uniform distribution corresponding to various physics parameterization schemes are considered for the SA in the present study. The ranges and variations of all the model input variables are presented in the next section. The usage of computationally expensive variance-based methods is not feasible as the number of model input variables is too large. Similarly, the application of group techniques is not required, as the number of parameters considered for the present study is not large enough. The MOAT technique, also known as the Elementary Effects method (Morris, 1991) is an ideal technique for the number of parameters that are considered in this study. Therefore, the MOAT method is used for the SA of the parameters in this study. The sensitivity measures obtained from this method distinguish the parameters based on whether the effect is (a) insignificant, (b) linear and additive, and (c) nonlinear or involves interactions with other model input variables (Saltelli et al., 2008).

Before applying the MOAT method, all the ranges of k number of parameters have to be mapped to the parent domain [0,1]. One way of doing this is by obtaining the cumulative distribution function (CDF) for the given parameter distribution, as CDF is bounded by 0 and 1 and is also uniformly distributed over [0,1]. When the parameter distribution itself is uniform, CDF will be a linear mapping from the parameter domain to the parent domain. Let \( X = (x_1, x_2, x_3, \ldots, x_k) \) be the parameter vector containing k parameters with the range of each parameter normalized to \([0,1]\) and divided into p equally spaced intervals (set to 4 in this study). An initial parameter set or a base value \( X^0 = (x_1^0, x_2^0, x_3^0, \ldots, x_k^0) \) is arbitrarily chosen with each parameter taking values from the set \( [0, \frac{1}{(p-1)}, \frac{2}{(p-1)}, \ldots, \frac{p-2}{(p-1)}, 1] \). A parameter, say \( x_i \), is randomly chosen for perturbation, that is, \( X^i = (x_1^0, x_2^0, \ldots, x_i^0 + \Delta x_i, x_{i+1}^0, \ldots, x_k^0) \). \( \Delta x_i \) value is a randomly selected multiple of \( \frac{1}{(p-1)} \) with positive or negative sign.

Determining all the k + 1 points, including the initial parameter set, completes the full MOAT trajectory. The selection of the parameter to which the \( \Delta \) value is added should be such that all the parameters are perturbed at least once when the entire trajectory is completed. This method requires r random replications of MOAT trajectories to obtain reliable sensitivity results. The elementary effect corresponding to the ith parameter, with \( y(X) \) as the model output is formulated as

\[
EE_i = \frac{y(x_1^0, x_2^0, \ldots, x_i^0 + \Delta x_i, \ldots, x_k^0) - y(x_1^0, x_2^0, \ldots, x_k^0)}{\Delta x_i}
\]

The measures used to evaluate the sensitivity (Campolongo et al., 2007) are
μᵢ is the mean of the absolute values of the elementary effects of parameter i, and depicts the overall impact of the ith parameter. A higher mean value of a parameter indicates a greater influence on the model output and that the parameter is sensitive. σᵢ² is the variance (σ being the standard deviation) of elementary effects of parameter i. A higher variance implies that the parameter is more dependent on other parameters to affect the model output.

3. Design of Experiments

The model used in this parameter sensitivity study is the Advanced Research WRF (WRF-ARW) model version 3.7.1 (Skamarock et al., 2005), a nonhydrostatic compressible mesoscale numerical weather prediction system, developed by the National Centre for Atmospheric Research (NCAR). The study area chosen in this study is a two-grid nested model, as shown in Figure 1. The outer domain d01 is enclosing the Indian Subcontinent and the surrounding regions. The inner nested domain is encompassing the Indian monsoon core.
region. As the domain boundaries should not be closer to the interest region, the inner domain is slightly larger than the MCR.

The central point for d01 is 80°N, 23°E. The outer domain (d01) comprises 188 points in the east-west direction and 213 points in the north-south direction with a spatial resolution of 36 km. The inner domain (d02) comprises 262 points in the east-west direction and 181 points in the north-south direction with a spatial resolution of 12 km. The time-step for integration is 120 and 40 s for the domains d01 and d02, respectively. With a higher resolution in the boundary layer, the vertical profile is partitioned into 40 sigma (σ) layers from the land surface to the 50 hPa level in the atmosphere. The initial and lateral boundary conditions for the WRF model are obtained from the Global Forecast System (GFS) model 6-hourly data at 0.5° × 0.5° resolution. To verify the consistency of the SA results with different initial and lateral boundary conditions, another set of experiments are performed with the European Centre for Medium-Range Weather Forecast (ECMWF) Reanalysis 5th Generation data set (ERA5) (Hersbach et al., 2020) at 1° × 1° resolution and 6-h time interval.

This study focuses on the high-intensity rainfall events during the Indian summer monsoon (ISM). Accordingly, twelve 4-day precipitation events over June, July, August, and September are chosen for the SA, as shown in Figure 2. Each event spans over 4 days and contains the day with the highest accumulated rainfall averaged over the monsoon core region in their respective month. This methodology to select the high-intensity precipitation events is adopted from Di et al. (2015). The precipitation data is obtained from the India Meteorological Department (IMD) daily accumulated gridded rainfall data (Pai et al., 2014) at 0.25° × 0.25° resolution.

Figure 2. Daily precipitation (mm) averaged over the monsoon core region for the months of June to September for the years 2015–2017 from the India Meteorological Department gridded data. Bold faced black boxes show the events that are simulated.
For events (A), (B), (C), and (D) the simulation dates are from 21st June to 24th June, 26th July to 29th July, 14th August to 17th August, and 19th September to 22nd September in the year 2015 respectively. For events (E), (F), (G), and (H) the simulation dates are from 26th June to 29th June, 2nd July to 5th July, 4th August to 7th August, and 23rd September to 26th September in the year 2016 respectively. For events (I), (J), (K), and (L) the simulation dates are from 28th June to 1st July, 22nd July to 25th July, 27th August to 30th August, and 19th September to 22nd September in the year 2017 respectively.

The physical processes represented in WRF are near-surface physics, cumulus convection, microphysics, short-wave and long-wave radiative transfer, land-surface physics, and planetary boundary layer physics. A great variety of parameterization schemes are available for each physical process. Many adjustable parameters are present in each parameterization scheme. The WRF model parameters and the parameterization schemes used for SA are adopted from Di et al. (2015). The parameters that could be sensitive and tunable for high-intensity precipitation events and their corresponding physical range were determined by Di et al. (2015) in discussions with the original scheme developers of each parameterization scheme. Although Di et al. (2015) performed the sensitivity analysis, the parameter sensitivity is generally dependent on local conditions (Quan et al., 2016). Therefore, the same tunable parameters are considered in this study to identify the sensitive parameters in the monsoon core region.

The 23 tunable parameters are spread across seven different parameterization schemes. The Kain-Fritsch Eta scheme (Kain, 2004) is used for cumulus parameterization and the WSM 6 single-class scheme (Hong & Lim, 2006) is used for microphysics parameterization. The Dudhia scheme (Dudhia, 1989) is used for short-wave radiation and RRTM scheme (Mlawer et al., 1997) is used for long-wave radiation. The MM5 Monin-Obukhov scheme (Dudhia, 2005) is used for the surface layer, and the Yonsei University (YSU) scheme (Hong et al., 2006) is used for the planetary boundary layer. The Noah scheme (F. Chen & Dudhia, 2001) is used for land surface parameterization. The comprehensive list of parameters and their allowable physical ranges are presented in Table 1. By no means is this set exhaustive; nonetheless, the present parameter sensitivity study can be considered as a precursor for further investigation of the sensitivity of other potential parameters for the ISM.

MOAT method is used for the SA of the 23 selected parameters. The model with 23 independent inputs varies in the 23-dimensional unit cube across a four-level grid \((k = 23, p = 4)\). For the number of grid levels \(p = 4\), previous studies (Campolongo & Saltelli, 1997; Campolongo et al., 1999; Saltelli et al., 2000) suggested a total of 10 replications \((r)\). So, a total number of 240 \(((23 + 1) \times 10)\) simulations are required. The 240 samples needed for the MOAT method are generated using the Sensitivity Analysis Library (SALib) in python (Herman & Usher, 2017). One complete WRF simulation requires approximately 32 CPU hours. Therefore, considering 12 events, a total of 240 \(32 \times 12 = 92,160\) CPU hours are utilized. The simulations are performed on AADITYA 800 TeraFlops High-Performance Computing system at the Indian Institute of Tropical Meteorology, Pune.

The analysis is carried out over the MCR \((69°E\ to\ 88°E\ and\ 18°N\ to\ 28°N)\). All the required output variables are extracted after each successful run. Once the whole set of 240 simulations are complete, the sensitivity measures, MOAT mean, and standard deviation are evaluated, as explained in the previous section. After the sensitivity results are obtained, to check the consistency of SA results with different initial and lateral boundary conditions, a set of 240 simulations are again performed with ERA5 data for the 12 high-intensity precipitation events.

The output variables from simulations have to be validated with the observed data to verify the accuracy of the simulations. In this study, Tropical Rainfall Measuring Mission (TRMM) Multi-satellite Precipitation Analysis (TMPA) at 0.25° \(\times\) 0.25° resolution (Huffman & Savtchenko, 2017) daily accumulated precipitation data is used to validate the rainfall data and the Indian monsoon data assimilation and analysis (IMDAA) regional reanalysis data (Ashrit et al., 2020; Rani et al., 2021) at 0.12° \(\times\) 0.12° resolution is used to validate surface air temperature, wind speed, and surface pressure. Root Mean Square Error (RMSE) is used as the objective function to verify the closeness of the simulation to the observation for surface air temperature, wind speed, and surface pressure.

\[
RMSE = \sqrt{\frac{\sum_{i=1}^{N} \sum_{t=1}^{T} (sim_i^t - obs_i^t)^2}{N \times T}}
\]  

(4)
where $\text{sim}_i^t$ and $\text{obs}_i^t$ are the simulated and observed values of a variable at grid point $i$ and time $t$, respectively. $N$ is the total number of grid points of domain d02 in MCR and $T$ is the number of days of simulation.

Equitable Threat Score (ETS) is used as the measure to evaluate the prediction of rainfall. Three categories of daily accumulated rainfall based on the IMD classification are used in this study. They are light rain (0–
7.5 mm), moderate rain (7.6–35.5 mm), and heavy rain (>35.5 mm). ETS is evaluated for all three categories and is summed to obtain a composite ETS score. Out of the 240 simulations, the simulation with the best composite ETS score is identified as the simulation with optimum parameters. Another measure to validate the quantitative precipitation forecast concerning various aspects is the structure (S), amplitude (A), and location (L) score—SAL score formulated by (Wernli et al., 2008). The amplitude value depicts the domain averaged relative deviation from the observed data. The structure (S) value represents the deviation between simulated and observed values using the ratio of total precipitation to the maximum precipitation. It gives information regarding the shape and size of the precipitation field. If the amplitude (A) value is positive, it indicates an overestimation, whereas if the amplitude value is negative, it indicates an underestimation of the total precipitation. Location (L) value gives the normalized distance from the center of mass of the simulated field corresponding to the observed precipitation field. It also provides the error in the normalized distance of the precipitation fields from the center of mass of the whole field. If the S, A, and L values are closer to zero, it indicates that the simulation is closer to the observations.

4. Results and Discussion

4.1. Parameter Sensitivity of Meteorological and Atmospheric Variables

Several meteorological variables such as daily accumulated precipitation (RAIN), relative humidity (RH), surface air temperature (SAT), wind speed (WS), surface air pressure (SAP), vertical velocity (VVEL), convergence (CNVG), downward short-wave radiative flux (DSWRF), and downward long-wave radiative flux (DLWRF) and also atmospheric variables, such as total precipitable water (TPW), planetary boundary layer height (PBLH), cloud fraction (CF), and outgoing long-wave radiation at the top of the atmosphere (OLR) from the model simulations are used to evaluate the sensitivity of the selected parameters. The mean and standard deviation values obtained form the basis of the analysis of the sensitivity of parameters. A higher value of the MOAT-mean implies that the parameter is more sensitive. A higher MOAT standard deviation value indicates that the parameter is more dependent on other parameters to affect the output.

The sensitivity plots are presented in Figures 3–5. MOAT sensitivity plots for the output variable precipitation for different lead times are shown in Figure 3. Figures 3a–3d correspond to the daily accumulated precipitation for day 1 to day 4 respectively, whereas Figure 3e corresponds to the average daily precipitation (RAIN) for all the days simulated. The x-axis and y-axis in each subplot correspond to the MOAT mean and MOAT standard deviation, respectively. It is observed that P4 has the highest MOAT mean value for all the days, which implies that this parameter influences precipitation the most, and P13 has the least MOAT mean and thus has no influence on the precipitation. Out of all the remaining parameters, P5 and P16 show higher MOAT mean values than the other parameters.

Similar sensitivity plots are generated for other surface meteorological variables represented in Figure 4. Figures 4a–4f correspond to RH, SAP, WS, SAT, VVEL, and CNVG respectively. P4, P5, and P16 show higher MOAT mean values for RH, whereas P13 and P19 show lower MOAT mean values. P12, P4, and P5 show higher MOAT mean values for SAP, whereas P13 and P19 show lower MOAT mean values. P4, P5, P12, and P16 show higher MOAT mean values for WS, whereas P13 and P19 show lower MOAT mean values. P16, P12, and P4 show higher MOAT mean values for SAT, whereas P13 and P19 show lower MOAT mean values. P4 and P16 show higher MOAT mean values for VVEL, whereas P13 and P19 show lower MOAT mean values. P4 and P16 show higher MOAT mean values for CNVG, whereas P13 and P19 show lower MOAT mean values.

Sensitivity plots are also obtained for atmospheric variables represented in Figure 5. Figures 5a–5f correspond to OLR, CF, TPW, PBLH, DLWRF, and DSWRF respectively. P4 and P6 show higher MOAT mean values for OLR, whereas P13 and P11 show lower MOAT mean values. P4, P5, and P8 show higher MOAT mean values for CF, whereas P13, P11, and P19 show lower MOAT mean values. P4, P5, P16, and P12 show higher MOAT mean values for TPW, whereas P13 and P19 show lower MOAT mean values. P20, P4, and P16 show higher MOAT mean values for PBLH, whereas P13, P19, and P6 show lower MOAT mean values. P16, P4, P12, and P21 show higher MOAT mean values for DLWRF, whereas P13 and P19 show lower MOAT mean values. P12, P4, and P5 show higher MOAT mean values for DSWRF, whereas P13 and P19 show lower MOAT mean values.
Figure 3. Morris One-At-a-Time parameter sensitivity plots for precipitation corresponding to different lead times (a–d) lead times of 1 day to 4 days, respectively and (e) for all the days combined.
Figure 4. Morris One-At-a-Time parameter sensitivity plots for surface meteorological variables (a) Relative Humidity, (b) Surface Air Pressure, (c) Wind Speed, (d) Surface Air Temperature, (e) Vertical Velocity, (f) Convergence.
Figure 5. Morris One-At-a-Time parameter sensitivity plots for atmospheric variables (a) Outgoing Long-wave Radiation, (b) Cloud Fraction, (c) Total Precipitable Water, (d) Planetary Boundary Layer Height, (e) Downward long-wave radiative flux, (f) Downward short-wave radiative flux.
4.2. Discussion on Sensitivity Analysis for All Variables

MOAT mean values obtained for all the output variables considered for the 23 parameters are normalized and are plotted on a heat map, as shown in Figure 6. P4 is highly sensitive for almost all the output variables. Apart from P4, other parameters such as P16, P12, P5, P21, P8, and P3 influence the output variables significantly. Four parameters, namely P13, P19, P11, and P6, are least sensitive for all the output variables.

P4 is the multiplier for entrainment mass flux rate, which means that P4 influences the entrainment rate. If the entrainment rate increases, the moist convective core gets diluted, leading to a weak updraft mass flux resulting in lesser convective precipitation (RAIN) (Kain & Fritsch, 1990; Yang et al., 2012). As P4 influences the strength of convection, this means that the formation of clouds also gets impacted. Therefore, atmospheric variables corresponding to clouds such as cloud fraction (CF), OLR at the top of the atmosphere, the DSWRF, and the DLWRF are sensitive to P4. The intensity of convection also affects the total precipitable water (TPW). Precipitation results in a decrease in the surface air temperature, increased relative humidity (RH), and a change in the surface air pressure (SAP). As a result of a change in the atmospheric circulation due to precipitation, wind speed (WS) also gets affected (Quan et al., 2016). P3 is the multiplier for the downdraft mass flux rate, which influences the downdraft. A higher value of P3 results in more downdraft, leading to an increase in condensed water evaporation, resulting in lesser precipitation (Di et al., 2015). P5 is the starting height of the downdraft above the updraft source layer (USL). The downdraft flux starting at higher levels results in tall and narrow downdraft restricting the growth of convective precipitation (Yang et al., 2012). P3 and P5 also influence the strength of convection and, thereby, cloud formation similar to P4, which explains their impact on all the output variables.

The output variables corresponding to cloud formation such as cloud fraction (CF), OLR at the top of the atmosphere, DSWRF, and DLWRF are sensitive to P8, which is the scaling factor applied to icefall velocity. This controls the terminal velocity of the ice crystals that are descending, thereby influencing the cloud formation. Clouds reflect the solar radiation (DSWRF) and absorb and emit long-wave radiation (DLWRF and OLR), which explains the sensitivity of cloud-related variables to P8 (Quan et al., 2016). P12 is a scattering tuning parameter that influences the scattering in the clear sky, thereby affecting the DSWRF that reaches the ground (Di et al., 2015). P16 is the multiplier for the saturated soil water content, which influences the transport of heat and moisture fluxes in the soil resulting in heat exchange and evaporation between the land and atmosphere. Therefore, surface air temperature (SAT) is sensitive to P16 (F. Chen & Dudhia, 2001).
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4.3. Sensitivity Analysis With Different Initial and Lateral Boundary Conditions

The WRF model parameter sensitivity is also assessed using the initial and lateral boundary conditions from the ERA5 data, and the corresponding heat map is presented in Figure 7. The sensitivity results from both GFS and ERA5 data as the initial and boundary conditions are very similar when compared. The parameters are ranked according to their sensitivity and are presented in Figure 8. The parameter sensitivity ranks are the same for both the experiments with different initial and lateral boundary conditions, barring a few exceptions. Therefore, the WRF model sensitivity results are consistent with different initial and lateral boundary conditions.

4.4. Determining the Optimum Parameters and Spatial Pattern Comparison

The above SA depicts the influence of WRF model parameters on the output variables. This SA can act as a foundation to tune the model parameters to minimize the prediction error. The tuning of sensitive parameters is a complex procedure and is beyond the scope of this study. However, the simulation results from the SA can be used to understand how the forecast errors of the output variables for different parameter sets compare to the default parameter values.

A composite Equitable Threat Score (ETS), the sum of ETS for light rain (LR), moderate rain (MR), and heavy rain (HR), is used as the measure to evaluate the prediction of rainfall. The simulation with the default parameters has a composite ETS score of 0.1410 (LR-0.0112, MR-0.0648, and 0.0650) assessed across the 12 precipitation events. Out of the 240 parameter sets, the parameter set with the highest composite ETS score is identified as the optimum parameter set for predicting precipitation (RAIN). The optimum parameter set has a composite ETS value of 0.1542 (LR-0.0165, MR-0.0704, and 0.0674), which is about 9.36% better than the score for the default parameters. Figure 9 presents the comparison of event-wise ETS values.
of the three rainfall categories for different precipitation simulations using the default and optimum parameters. The ETS for the light rain category is higher for almost all the events for the optimum parameters compared to the default parameters. The ETS is less than zero for one event each in the light rain category and moderate rain category. Overall, there is an improvement of about 47.62% for the optimum parameters compared to the default parameters for the light rain category. The ETS improvement of optimum parameters compared to the default parameters are 8.63% and 6.02% for moderate rain and heavy rain categories. Although there are a few events where the optimum parameters had lower ETS than the default parameters, the performance of optimum parameters is better overall. In the composite ETS considered in this study, equal weightage is given to the three rainfall categories. If more weightage is assigned in the composite ETS to the heavy rain category, a different set of optimum parameters could be obtained that further improves the heavy rainfall category's prediction compared with the default parameters. But, this could result in a decrease in the ETS values for the other two categories.

The performance of default and optimum parameters for rainfall is further investigated by evaluating the SAL scores. Figure 10 presents the comparison of structure (S), amplitude (A), and location (L) scores for the default and optimum parameters. The negative value of S indicates that the simulated precipitation objects are small compared to those of the observed precipitation. The structure (S) score for the optimum parameters (−1.04) is closer to zero compared to the default parameters (−1.194), which implies that the optimum parameters have captured the structure of precipitation better than the default parameters. The positive value of amplitude (A) score indicates the domain averaged simulated precipitation is more than

**Figure 8.** Parameters ranked according to their sensitivity from simulations with initial and lateral boundary conditions from (a) Global Forecast System data, and (b) ERA5 data.
that of the observed precipitation. The optimum parameters ($A = 0.0034$) captured the amplitude of precipitation better than the default parameters ($A = 0.0773$). Location ($L$) scores for the optimum (0.52) and default parameters (0.54) show that the optimum parameters captured the location of precipitation slightly better compared to the default parameters. All the $S$, $A$, and $L$ scores for optimum parameters are closer to zero compared to the default case, which indicates the superiority of the optimum parameters over the default parameters.

The RMSE values for the output variables surface air temperature (SAT), surface air pressure (SAP), and wind speed at 10 m (WS10) are also evaluated for all the 240 parameter sets and compared with the default parameter set. The parameter set from which the minimum value of RMSE from the 240 parameter sets is identified as the optimum parameter set for that particular output variable. The RMSE values for the optimum (default) parameters for SAT, WS10, and SAP are 3.29 (3.42) K, 2.33 (2.84) m/s, and 8.62 (9.00) hPa respectively. A reduction in the RMSE is observed for the optimum parameters compared to the default parameters for SAT (3.52%), WS10 (18.13%), and SAP (4.25%). The optimum parameters obtained in this

Figure 9. Comparison of Equitable Threat score values using default parameters and optimum parameter values for different precipitation events over the monsoon core region: (a) Light Rain, (b) Moderate Rain, (c) Heavy Rain. The percentage value above the bars indicate the improvement in Equitable Threat Score values compared to the default parameters.
study for all the variables considered are only from the 240 MOAT parameter sample set only. Also, the obtained optimum parameters are different for different variables. An advanced optimization technique such as the multi-objective adaptive surrogate model-based optimization method (Chinta & Balaji, 2020) can be used to tune the parameters and obtain a single optimum parameter set that improves the prediction of multiple variables simultaneously.

Figure 11 presents the spatial pattern comparison of bias (simulated—observed) for default and optimum parameters for RAIN, SAT, WS10, and SAP, averaged over 48 days (twelve 4-day events). The bias for RAIN by the optimum parameter set is significantly lower in the eastern part of MCR and slightly lower in the other parts compared to the default parameters. The bias of the optimum parameter set for SAT is lower than the default parameters in the northern and central parts, whereas the bias remains almost the same in other areas. The bias for WS10 by the optimum parameter set is much lower than that from the default parameters throughout the MCR, which also justifies the high percentage of reduction in RMSE. A negative bias is observed for the default parameters in the case of SAP, whereas the optimum parameters generated a positive bias. The overall trend suggests that the bias from the optimum parameter set is less than that from the default parameter set for all the variables.

A straightforward relationship connecting the parameter values and the simulated model variables is difficult to establish because of the highly nonlinear interactions involving numerous physical processes such as transport of water vapor, turbulent interactions of water and heat fluxes between the atmosphere and land surface, and horizontal advection of mass, momentum, and energy.

5. Conclusions
The current study evaluated the sensitivity of WRF model parameters and identified those parameters that caused a more significant influence on the model output variables. Those parameters which cause a very minimal effect on the model outcome are also vetted out in this process. The SA study considered 23 parameters corresponding to seven different physics schemes for the SA. MOAT method, a global SA method, is utilized for the present parametric study. The SA is conducted over the monsoon core region during the Indian summer monsoon, which immensely affects India’s agricultural economy. The study was conducted for 12 high-intensity rainfall events during June, July, August, and September over 2015, 2016, and 2017.

The multiplier for downdraft mass flux rate (P4) is identified as the most sensitive parameter, and the aerosol scattering tuning parameter (P13) is specified as the least sensitive parameter. The study identified seven parameters, namely the multiplier for entrainment mass flux rate (P4), the multiplier for the saturated soil water content (P16), scattering tuning parameter (P12), starting height of downdraft over updraft source layer (P5), profile shape exponent for calculating the momentum diffusivity coefficient (P21), scaling factor applied to icefall velocity (P8), and the multiplier for downdraft mass flux rate (P3) that show a significant impact on the output variables. Four of the 23 parameters, namely aerosol scattering tuning parameter (P13), critical Richardson number for boundary layer of water (P19), mean consumption time of CAPE (P6), and collection efficiency from cloud to rain auto conversion (P11), show a negligible effect on the model output. The SA results were consistent with different initial and lateral boundary conditions.

The sensitivity study also helps the scheme developers to focus more on conducting relevant experiments and more accurately formulating the physics around the sensitive parameters. The parameters analyzed in this study are only a selective few parameters in the WRF model. There may be other parameters to which the output variables may be more sensitive than the selected parameters. Furthermore, the sensitivity to the parameters in this study is obtained over the monsoon core region. The sensitivity of the output variables to the parameters may not remain the same for other areas of interest. The present study can be considered as a precursor for more investigation of the sensitivities of other potential parameters for the Indian summer...
Further, tuning the sensitive parameters using advanced optimization techniques can be implemented to improve prediction accuracy.

**Data Availability Statement**

The authors thank NCEP for providing the GFS model data at [https://www.ncei.noaa.gov/has/HAS.File-AppRouter?datasetname=GFSGRB24&subqueryby=STATION&apppname=&outdest=FILE](https://www.ncei.noaa.gov/has/HAS.File-AppRouter?datasetname=GFSGRB24&subqueryby=STATION&apppname=&outdest=FILE). The authors also thank ECMWF for making available the ERA5 reanalysis pressure level data from [https://cds.climate.copernicus.eu/cdsapp#!/dataset/reanalysis-era5-pressure-levels?tab=overview](https://cds.climate.copernicus.eu/cdsapp#!/dataset/reanalysis-era5-pressure-levels?tab=overview) and single-level data from [https://cds.climate.copernicus.eu/cdsapp#!/dataset/reanalysis-era5-single-levels?tab=overview](https://cds.climate.copernicus.eu/cdsapp#!/dataset/reanalysis-era5-single-levels?tab=overview). Authors gratefully acknowledge NCMRWF, Ministry of Earth Sciences, Government of India, for the IMDAA reanalysis data [https://rds.ncmrwf.gov.in/dashboard/download](https://rds.ncmrwf.gov.in/dashboard/download). IMDAA reanalysis was produced under the collaboration between the UK Met Office, NCMRWF, and IMD with financial support from the Ministry of Earth Sciences, under the National Monsoon Mission program. The authors thank IMD for providing the

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**Figure 11.** Spatial pattern comparison of bias for default and optimum parameters for RAIN (a–b), surface air temperature (c–d), WS10 (e–f), surface air pressure (g–h) respectively, averaged over 48 days (Twelve 4-day events).
gridded rainfall data from the Indian Institute of Tropical Meteorology (IITM), Pune, India. The sample processed WRF model output files, plot scripts, and other data files are accessible at the Mendeley Data Repository https://data.mendeley.com/datasets/3bf779wx9/draft?r=8a33136-871b-46fe-9d33-e4b498d302f2.

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