CHARACTERIZATION OF RAINRATE FIELDS USING A MULTI-DIMENSIONAL PRECIPITATION MODEL

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Abstract: In this study, we characterized the seasonal variation of rainrate fields in the Han river basin using the WGR multi-dimensional precipitation model (Waymire, Gupta, and Rodriguez-Iturbe, 1984) by estimating and comparing the parameters derived for each month and for the plain area, the mountain area and overall basin, respectively. The first- and second-order statistics derived from observed point gauge data were used to estimate the model parameters based on the Davidon-Fletcher-Powell algorithm of optimization. As a result of the study, we can find that the higher rainfall amount during summer is mainly due to the arrival rate of rain bands, mean number of cells per cluster potential center, and raincell intensity. However, other parameters controlling the mean number of rain cells per cluster, the cellular birth rate, and the mean cell age are found invariant to the rainfall amounts. In the application to the downstream plain area and upstream mountain area of the Han river basin, we found that the number of storms in the mountain area was estimated a little higher than that in the plain area, but the cell intensity in the mountain area a little lower than that in the plain area. Thus, in the mountain area more frequent but less intense storms can be expected due to the orographic effect, but the total amount of rainfall in a given period seems to remain the same.

Key Words: rainfall, multi-dimensional precipitation model, parameter estimation

1. Introduction

Rainfall is observed using point gauges, radar, or satellite. Even though the use of radar or satellite is becoming plausible, the raingauge network over a basin is still the most important data provider, especially considering the length of its record. Recent application of radar or satellite to the observation of rainfall field, generally three dimensional considering time and space, requires priori information of rainrate fields, with which accurate and economical design of sampling is possible. This priori information should also be extracted from the data collected by raingauges randomly located over a basin.

Raingauges measure rainfall continuously, but the data available is the time-averaged. Also, the rainfall observed both in time and space is not generally from a single event but the complex one, a combination of several single storm events. Thus, it is difficult to delineate characteristics both statistical and physical from the point gauge records. Even using the spatially distributed data, it is difficult to extract a single storm characteristics including storm arrival rate, number of rain cells per storm, its intensity, size of clusters, storm duartion, etc.

An indirect way to extract the storm characteristics is to use a multi-dimensional model of precipitation, which counts all observed characteristics of physical and statistical point of view. This kind of multi-dimensional model can be helpful to characterize the rainrate field, and also to make applications easy for various purposes such as sampling design, ground validation of remotely sensed data, or realistic rainrate field generation. So far, many multi-dimensional precipitation models have been developed for various purposes, like realistic rainfall simulation, sampling strategy, and calibration of sensors. Examples are the WGR model (Waymire et al., 1984), the noise forced diffusive model (North and Nakamoto, 1989), and recently a model by Yoo et al. (1996). Each model has its own advantages and disadvantages in practical use. A complex model, like the WGR model, can represent the rainfall field more accurately provided the proper estimates of parameters are used. But as shown by Islam et al. (1988) and Valdes et al. (1990), its parameter estimation has been a difficult task.

A relatively simple model, like the noise forced diffusive precipitation model, has advantages of easy parameter estimation and application to the other purposes (mainly due to the simple model structure with a small set of parameters), but it lacks proper description of physical and statistical features of observed rainfall fields (Valdes et al., 1994). The model by Yoo et al. (1996) may be said to be in between the above two. It has relatively simple form with only four parameters. Its parameter estimation is also simple, but it lacks the description of long term storm arrival system and clustering.

In this study, we are to characterize the seasonal variation of rainrate fields of plain area and mountain area in a given basin using the WGR precipitation model. Even though the structure of the WGR model is very complex and non-linear, we believe this model is the best one we can choose for the study purpose. Basically, the characterization of rainrate fields using the WGR model is nothing but the parameter estimation of the model using the first- and second-order statistics derived from observed point gauge data. By comparing the parameters derived for each case, such as rainrate field of summer in plain area or spring in mountain area, etc., we will derive general features of rainrate field both in time and space.

2. The WGR Precipitation Model

The WGR model (Waymire et al., 1984) was developed to represent meso-scale (about 20-200km) precipitation. As a conceptual model, this model shows a good link between atmospheric dynamics and a statistical description of meso-scale precipitation. As a space-time representation of the rainfall, this model is characterized by the arrival mechanism of storm events through time. The model represents rainfall in a hierarchical approach with rain cells embedded in cluster potential centers which are, in turn, embedded in rainbands. The Poisson process was introduced for the rainbands arrival scheme and the spatial Poisson process to distribute the cluster potentials within a rainband. The occurrences of rain cells within the cluster potentials and the rainband following are assumed to be a random number of points independently and identically distributed in the space-time cylinder with common probability density function. The representation of the ground-level rainfall intensity (at location x and time t) of the model can be written as follows

$$\xi(t,x) = \int_{-\infty}^{t}\int_{R^d} g[t-s, |x-y-v(t-s)|]\, X(s,y)\,ds\,dy$$
$$= \int_{-\infty}^{t} g_1(t-s) Z[s, x-v(t-s)]\, ds \quad (1)$$

where v is a uniform and steady drift velocity vector and $Z(t,x)$ is given by

$$Z(t,x) = \int_{R^2} g_2(x-y) X(t,y)\,dy \quad (2)$$

where the two-stage point cluster field $X(t,y)$, a random field, governs the instantaneous generation of rain cells in time and space, and the kernel $g_2(r)$ distributes the rainfall intensity in space around each cell. The kernel $g_1(t)$ represents the temporal evolution of the life cycle of a rain cell. Table 1 shows typical parameters and their descriptions. More description of the model can be found in Waymire et al. (1984) and Gupta and Waymire (1987).

For the point rainfall intensity process $\xi(x,t)$, Waymire et al. (1984) derived the expected value $E[\xi(x,t)]$, the variance $Var[\xi(x,t)]$, and the covariance $Cov[\xi(x,t), \xi(x',t')]$ between two points, $x=(x_1, x_2)$ and $x'=(x'_1, x'_2)$. The areal average of the random variable $\xi(x,t)$ over a square area $L\times L$ is defined as

$$\Xi(t) = \frac{1}{L^2}\int_0^L\int_0^L \xi(x, t)\,dx_1\,dx_2 \quad (3)$$

Since the precipitation process was assumed to be weakly ergodic by Waymire et al. (1984), the expected value of $\Xi(t)$ is obtained by performing time averages. Namely, the expected value for $\Xi(t)$ can be computed by

$$E[\xi(L,t)] = \lim_{T\to\infty}\frac{1}{T}\int_0^T \Xi(t)\,dt \quad (4)$$

Since the expected value operator E[ ] commutes with the spatial integral operator in (3), the expected value of the area-averaged rain intensity is not affected by the area-averaging process, i.e., the mean value for the point process is equal to the mean value for

Table 1. A Summary of Typical Parameters of the WGR Model and the Estimates of the Parameters tuned to GATE from Waymire et al. (1984)

Parameter	Description	Order of Magnitude	Estimates(GATE)
λ	rain band arrival rate	bands/hour	0.0128
ρ_L	mean density of cluster potential	clusters/km^2	0.0038
$<\nu>$	mean number of cells per cluster		3.82
β	cellular birth rate	cells/hour	0.355
σ	cell location parameter within a cluster potential region	km	10.0
α^{-1}	mean cell age	hour	0.58
D	spatial range of cell intensity	km	3.0
i_o	raincell intensity at cell center at the time of birth	mm/hour	55.06
$\|U_b\|$	rainband speed relative to the ground	km/hour	10.0
$\|U_c\|$	cell speed relative to the band	km/hour	0.0

the area-averaged rain rate.

$$E[\Xi(t)] = E[\xi(x, t)] \equiv \overline{\xi} \tag{5}$$

The variance and covariance of $\Xi(t)$ defined as

$$Var[\Xi(t)] = E[(\Xi(t) - E[\Xi(t)])^2] \tag{6}$$

$$Cov[\Xi(t), \Xi(t')] = E[(\Xi(t) - E[\Xi(t)])(\Xi(t') - E[\Xi(t')])] \tag{7}$$

must be affected by the area averaging, since the expected value operator E[ ] apparently does not commute with the products of the integral operator in the right-hand sides of the above two equations. In practice, smoothing is widely used to filter sequences in order to diminish the effect of measurement errors and other high-frequency disturbances. We expect that the area-averaging process will reduce the variance of the random variables. Resulting mean and variance of the WGR model is as follows.

$$E[\Xi(t)] = \frac{E[\nu]\rho_L \lambda_m, E[i_0] 2\pi D^2}{\alpha} \tag{8}$$

$$Var[\Xi(t)] = \frac{1}{L^4}[\theta_1 P^2(D,0) + (\beta - \alpha)(\theta_2 + \frac{\theta_3}{4\pi(D^2+\sigma^2)})P^2(D,\sigma)] \tag{9}$$

where,

$$P(D,\sigma) = 4(D^2+\sigma^2)[\exp(-\frac{L^2}{(4D^2+\sigma^2)}) - 1] + 2L\sqrt{D^2+\sigma^2}\sqrt{\pi}\,\mathrm{erf}(\frac{L}{2(D^2+\sigma^2)^{1/2}})$$

$$\theta_1 = \frac{\lambda_m E[\nu]\rho_L \pi D^2 E[i_0^2]}{2\alpha}$$

$$\theta_2 = \frac{2\lambda_m \beta E[\nu]^2 \rho_L^2 \pi^2 D^4 E[i_0^2]}{\alpha(\beta^2 - \alpha^2)}$$

$$\theta_3 = \frac{2\lambda_m \beta E[\nu(\nu-1)]\rho_L \pi^2 D^4 E[i_0^2]}{\alpha(\beta^2 - \alpha^2)}$$

and the covariance function of the WGR model is

$$Cov[\Xi(t), \Xi(t')] = \frac{1}{L^4}[\theta_1 e^{-\alpha|\tau|} I_1 I_2 + (\beta e^{-\alpha|\tau|} - \alpha^{-\beta|\tau|})(\theta_2 + \frac{\theta_3}{4\pi(D^2+\sigma^2)}) I_3 I_4] \tag{10}$$

where

$$I_1 = 2D^2[E(L, -u_1, D, 0) - 2E(0, u_1, D, 0)) + E(L, u_1, D, 0)] + D\sqrt{\pi}[(L - u_1\tau)R(L, -u_1, D, 0) - 2R(0, u_1, D, 0) + (L + u_1\tau)R(L, u_1, D, 0)]$$

$$I_2 = 2D^2[E(L, -u_2, D, 0) - 2E(0, u_2, D, 0)) + E(L, u_2, D, 0)] + D\sqrt{\pi}[(L - u_2\tau)R(L, u_2, D, 0) - 2R(0, u_2, D, 0) + (L - u_2\tau)R(L, u_1, D, 0)]$$

$$I_3 = 2(D^2+\sigma^2)[E(L, u_1, D, \sigma) - 2E(0, u_1, D, \sigma)) + E(L, u_1, D, \sigma)] + [(D+\sigma^2)\pi]^{1/2}[(L - u_1\tau)R(L, -u_1, D, \sigma) - 2R(0, u_1, D, \sigma) + (L + u_1\tau)R(L, u_1, D, \sigma)]$$

$$I_4 = 2(D^2+\sigma^2)[E(L, -u_1, D, \sigma) - 2E(0, u_1, D, \sigma)) + E(L, u_1, D, \sigma)] + D\sqrt{\pi}[(L - u_1\tau)R(L, -u_1, D, \sigma) - 2R(0, u_1, D, \sigma) + (L + u_1\tau)R(L, u_1, D, \sigma)]$$

and

$$E(L, u_i, D, \sigma) = \exp\left(-\frac{(L-u_i\tau)^2}{4(D^2+\sigma^2)}\right)$$

$$R(L, u_i, D, \sigma) = \text{erf}\left[\frac{L+u_i\tau}{2(D^2+\sigma^2)^{1/2}}\right]$$

The analytical form of the frequency-wavenumber spectrum of the WGR model was derived by Valdes et al. (1990);

$$\begin{aligned} S(f, \nu_x, \nu_y) &= \theta_1 \frac{\alpha E(D,0)}{\alpha^2+\Theta^2} \\ &+ \theta_2 \frac{2\alpha\beta(\beta^2-\alpha^2)}{(\alpha^2+4\pi^2f^2)(\beta^2+4\pi^2f^2)}\delta(\nu_x)\delta(\nu_y) \\ &+ \theta_3 \frac{\alpha\beta(\beta^2-\alpha^2)}{(\alpha^2+\Theta^2)(\beta^2+\Theta^2)} \frac{E(D,\sigma)}{4\pi^2(D^2+\sigma^2)} \end{aligned} \quad (11)$$

where $\delta()$ is a dirac delta function and:

$$E(D, \sigma) = 8\pi(D^2+\sigma^2)\exp[-4\pi^2(D^2+\sigma^2)(\nu_x^2+\nu_y^2)]$$

$$\Theta = 2\pi(\nu_x u_x + \nu_y u_y + f)$$

This spectrum depends on all nine parameters of the reduced version of the model and has the dependencies of order -2 and -4 on both frequency and wavenumber. This dependencies are the consequence of the exponential descriptions of rainfall intensity decay in time and the Gaussian kernel to distribute the rainfall intensity in space.

Islam et al. (1988), Valdes et al. (1990) and Koepsell and Valdes (1991) estimated the parameters for different fields using non-linear optimization techniques by minimizing the sum of the square errors. Because of the large number of the parameters and the large non-linearities, the estimation itself has been a difficult task.

3. Model Non-linearities and Parameter Estimation

The extreme difficulties associated with the estimation of parameters is recognized to be a major impediment to wider use and full utilization of space-time models. Most of the parameters of a space-time rainfall model are not physically measurable. Practical interest often centered in estimating parameters is to use information from rain gage observations.

The WGR model has nine parameters: λ_m, β, α, $E[i_0]$, $E[v]$, ρ_L, D, σ and U. The parameters may be evaluated using the method of moments. Numerical estimates of various combinations of first- and second-order statistics from historical precipitation traces can be equated to their theoretical expressions, resulting in a set of nine highly nonlinear equations with nine unknowns. Although theoretically possible, it appears unrealistic to attempt to solve nine simultaneous equations even when it is possible to determine some of the parameters from the understanding of the physics of the problem. The estimation procedure presented in this paper utilizes a combination of physically determined parameters and parameters estimated from data. Three parameters were determined from physical consideration and kept fixed while other six were estimated using the method of moments.

This results in a set of six equations with six unknown parameters. A minimum least square technique has been employed to obtain estimates of the model parameters. Let $F(X)$ be the set of nonlinear equations in parameter X that must satisfy the observation vector θ:

$$F(\hat{X}) - \theta = 0 \quad (12)$$

where $F(\hat{X})$ is the best estimate of θ. The elements in θ have different order of magnitudes and hence their sum of the squares tend to be biased toward higher values. To circumvent this problem, every $F(X)$ is normalized by the corresponding θ value. Now, the solution of (12) may be derived through a simple unconstrained nonlinear minimization:

$$\min X\left\{\left(\frac{f_1(X)}{\theta_1}-1\right)^2+\left(\frac{f_2(X)}{\theta_2}-1\right)^2+\cdots+\left(\frac{f_i(X)}{\theta_i}-1\right)^2+\cdots\right\} \tag{13}$$

Several algorithms exist to solve this simple unconstrained nonlinear optimization problem. The Davidon-Fletcher-Powell algorithm was used for the numerical search of $\hat{X}$ from (13). Poor initial guess vector to any iterative schemes lead to an obvious divergence. To be as close as possible to $\hat{X}$ at the beginning, an initial search is performed in R^n to find points in the neighborhood of the least square estimate from (13). Though the values for parameter X are not known to any reasonable accuracy, their upper and lower limits are known from the physics of the problem. A window mesh algorithm developed in the work of Entekhabi et al. (1989). uses the fact to zoom into the neighborhood of the minimum. Davidon-Fletcher-Powell method coupled with mesh algorithm has been used in this paper to solve the parameter estimation problem.

4. Application Example

4.1 Data and Summary Statistics

Han river basin is in the middle of Korean peninsula at latitude 36° 30′ ~38° 55′ North and longitude 126° 24′ ~129° 02′ East. As the longest river in Korea, it has its basin area of 26,219 km^2 and main channel length of 467.7 km. The river shows multiple types of dendritic and fan shape (Figure 1).

Han river basin has 145 observation stations

Figure 1. Han river basin and raingauge stations (The basin is also divided into plain, mountain and intermediate areas).

for rainfall, which consist of 85 stations of the ministry of construction, 10 stations of the meteorological office, and 50 stations of KOWACO (Korea Water Resource Corporation). The data used in the research is from 51 raingage stations randomly selected (see Table 2). For the comparison of rainfall characteristics of plain and mountain area, we also arbitrarily divided the Han river basin into three regions, the plain area, the mountain area and the intermediated area. The plain area is located in the downstream part of Han river basin between Paldang Dam and the estuary where the hill slope is about 0.1~0.2 m/km. On the other hand, the mountain area is located in the upstream part of Han river basin where the hill slope is about 0.44~1.33 m/km. The raingauge stations located in the plain area and mountain area are marked in Table 2. As can be seen from the Table 2, each station has different record length, but in the research, the data recorded between 1988 and 1997 were used for the model parameter estimation. Also, the parameter estimation is limited during the wet season from May to October as the data recorded during the dry season is relatively poor.

The estimation of basic statistics is a key part for the analysis of data and also for the model parameter estimation. The mean, variance, and covariance of 1hr- and 6hr-duration data for each month and also for the downstream plain area, upstream mountain area and all the basin, separately, are summarized in Tables 3, 4, and 5. These statistics are those to be used for the model parameter estimation. As can be seen from the tables, the rainfall in the plain area has higher mean values, but lower correlation coefficients than those of mountain area. The variance in the

Table 2. Raingage stations used (Among them, the raingauges in the plain area are marked as ☆, and those in the mountain area are marked as △)

Station	Record year	Station	Record year	Station	Record year
Haenggye	1968~1996	Tanyang	1965~1996	Wontong	1988~1996
Chinbu	1965~1996	Koesan	1965~1996	Changchon	1965~1996
Wangsan	1988~1996	Cheongpung	1981~1996	Hyunlli	1988~1996
Imgye△	1965~1996	Yeongchun	1988~1996	Inje△	1965~1996
Cheongseon△	1981~1996	Puron	1965~1996	Chuyang	1988~1996
Hajang	1988~1996	Chungju Dam	1988~1996	Chuncheon	1965~1996
Sabuk	1988~1996	Chungil	1965~1996	Naechon	1965~1996
Bongpyung	1965~1996	Haengsung	1965~1996	Hongcheon	1967~1996
Daehwa	1988~1996	Ganhyun	1967~1996	Seomyeon	1965~1996
Bangrim	1988~1996	Munmark	1984~1996	Kapyeong☆	1965~1996
Suju	1965~1996	Saenggeuk	1966~1996	Cheongpye-ong☆	1981~1996
Yungwol△	1965~1996	Yongin	1965~1996	Naksaeng	1965~1996
Pyeongchang	1965~1966	Icheon☆	1979~1996	Uijeongbu☆	1965~1996
Mitan△	1965~1996	Yeju	1965~1996	Kuro	1986~1996
Paegun	1965~1996	Yangpyeong☆	1979~1996	Seongnam☆	1986~1996
Checheon	1988~1996	Hwacheon Dam	1981~1996	Anyang☆	1986~1996
Sangdong△	1965~1996	Seohwa	1965~1996	Toegyewon☆	1986~1996

Table 3. Basic statistics for downstream plain area, Han river basin

Month	Mean(1hr)	Variance(1hr)	Corr.(1hr)	Variance(6hr)	Corr.(6hr)
5	0.121	0.890	0.493	11.864	0.409
6	0.190	1.664	0.500	27.130	0.312
7	0.446	5.830	0.451	86.877	0.328
8	0.376	4.799	0.471	81.736	0.323
9	0.224	2.541	0.548	53.222	0.405
10	0.038	0.382	0.318	3.003	0.165

Table 4. Basic statistics for upstream mountain area, Han river basin

Month	Mean(1hr)	Variance(1hr)	Corr.(1hr)	Variance(6hr)	Corr.(6hr)
5	0.111	0.820	0.416	12.075	0.337
6	0.200	3.266	0.367	35.424	0.265
7	0.397	4.208	0.482	74.355	0.354
8	0.326	4.693	0.395	58.756	0.291
9	0.232	2.207	0.510	42.687	0.392
10	0.025	0.078	0.334	0.977	0.185

Table 5. Basic statistics for overall Han river basin

Month	Mean(1hr)	Variance(1hr)	Corr.(1hr)	Variance(6hr)	Corr.(6hr)
5	0.116	0.860	0.460	11.954	0.378
6	0.195	2.351	0.443	30.684	0.292
7	0.425	5.135	0.464	81.510	0.339
8	0.355	4.754	0.439	71.887	0.309
9	0.227	2.398	0.532	48.707	0.399
10	0.032	0.252	0.325	2.135	0.173

plain area seems more or less the same as in the mountain area. We can also find obvious monthly differences of each statistics as already well known in the monsoon area.

4.2 Parameter Estimation

The estimation procedure presented in this paper utilizes a combination of physically determined parameters and parameters estimated from data. Three parameters, D, σ and U, were determined from physical consideration and kept fixed while other six were estimated using the method of moments.

Islam et al. (1988) recommended that D and σ of nine parameters should be estimated from meteorological data. Ideally, the parameters describing the physical structure of the rainfall field should be measured and recorded through time at the area of interest and then used as constants. Unfortunately, while the parameters describe the physical structure of the rainfall field, they are not normally observed features in the atmosphere. The works of Austin and Houze (1972) and Sorman (1972) provide fairly reasonable ranges within which the parameter values will be found but specific values of the parameters are generally not known. Islam et al. (1988) conducted a sensitivity analysis of each of the parameters on the autocorrelation function as defined by the WGR model and concluded that the D and σ could be held constant

Table 6. Parameter estimated for downstream plain area, Han river basin

Month	λ_m (storms/min)	β (cells/min)	$E(v)$ (cells/CPC)	α (min^{-1})	ρ ($CPCs/km^2$)	$E(i_0)$ (mm/min)
5	0.0170	1.1562	6.2188	3.1891	0.0015	71.0938
6	0.0245	1.0313	5.6563	3.1891	0.0014	71.0938
7	0.0231	1.0117	9.8398	1.0117	0.0020	82.5195
8	0.0214	1.2477	4.2493	3.3366	0.0022	218.7500
9	0.0153	1.0391	9.6641	3.1074	0.0015	83.3984
10	0.0109	1.0625	4.8125	3.2780	0.0015	92.1875

Table 7. Parameter estimated for upstream mountain area, Han river basin

Month	λ_m (storms/min)	β (cells/min)	$E(v)$ (cells/CPC)	α (min^{-1})	ρ ($CPCs/km^2$)	$E(i_0)$ (mm/min)
5	0.0240	1.0020	5.9199	3.1130	0.0015	65.3809
6	0.0146	1.0211	9.3131	3.1724	0.0021	92.1872
7	0.0367	1.0313	10.7188	3.1297	0.0019	85.1563
8	0.0330	1.0938	9.5938	3.3672	0.0017	141.4063
9	0.0237	1.0020	9.2949	4.0519	0.0015	82.9590
10	0.0170	1.0312	3.4063	4.6734	0.0013	71.0938

Table 8. Parameter estimated for overall Han river basin

Month	λ_m (storms/min)	β (cells/min)	$E(v)$ (cells/CPC)	α (min^{-1})	ρ ($CPCs/km^2$)	$E(i_0)$ (mm/min)
5	0.0165	1.0020	10.9824	3.5843	0.0013	67.1387
6	0.0147	1.0584	9.3123	3.1603	0.0021	92.1875
7	0.0244	1.0234	9.5234	3.1520	0.0017	86.9141
8	0.0350	1.0020	8.6973	3.1390	0.0020	116.3574
9	0.0234	1.1113	9.8574	3.1019	0.0015	80.3223
10	0.0105	1.4063	5.6563	3.6641	0.0011	71.0938

without adversely affection the estimation. In this research D and σ are chosen to be 7~9 km and 1.6~2.6 km, respectively, from the observation of radar snapshots. The cell velocity U was determined from the climatological conditions for each month, which was set to be 7 to 11 km/hr (Korea Meteorological Administration, 1995). Other parameters estimated are summarized in Tables 6, 7 and 8.

4.3 Comment on the Parameters estimated

Tables 6, 7 and 8 summarize the parameters estimated for each month and for downstream plain area, upstream mountain area and overall Han river basin. As can be seen from the tables, the high rainfall amount during summer is mainly due to the arrival rate of rain bands, mean number of cells per cluster potential center, and raincell intensity. Considering the slight increase of the arrival rate of rain bands and the mean number of cells per cluster potential center during summer, exceptionally very high values of rain cell intensity in August is worth noting. Other parameters controlling the mean number of rain cells per cluster, the cellular birth rate, and the mean cell age are found invariant to the rainfall amounts.

In the application to the downstream plain area and upstream mountain area of the Han river basin, no obvious difference in the parameter estimates could be found. However, the number of storms in the mountain area was estimated a little higher than that in the plain area and the cell intensity in the mountain area a little lower than that in the plain area. Thus, due to the orographic effect, more frequent but less intense storms can be expected in the mountain area, but the total amount of rainfall in a given period seems to remain the same.

5. Conclusions

In this study, we characterized the seasonal variation of rainrate fields in the Han river basin using the WGR multi-dimensional precipitation model. The characterization of rainrate fields was done by estimating and comparing the parameters derived for each month and for the plain area, the mountain area and overall basin, separately. The first- and second-order statistics derived from observed point gauge data were used to estimate the model parameters based on the Davidon-Fletcher-Powell algorithm of optimization.

As a result of the study, we can find that the higher rainfall amount during summer is mainly due to the arrival rate of rain bands, mean number of cells per cluster potential center, and raincell intensity. However, other parameters controlling the mean number of rain cells per cluster, the cellular birth rate, and the mean cell age are found invariant to the rainfall amounts.

In the application to the downstream plain area and upstream mountain area of the Han river basin, no obvious difference in the parameter estimates could be found. However, the number of storms in the mountain area was estimated a little higher than that in the plain area and the cell intensity in the mountain area a little lower than that in the plain area. Thus, due to the orographic effect, more frequent but less intense storms can be expected in the mountain area, but the total amount of rainfall in a given period seems to remain the same.

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