An Investigation Into the Effect of Storm Type on Precipitation in a Small Mountain Watershed

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A set of regression equations relating storm rainfall depth to watershed topography and storm type was derived for the high-density precipitation network at Coweeta Hydrologic Laboratory. The most general equation predicted storm amounts for an independent test group of gages with an average error of 0.38 cm (0.15 inches). The dependent variable was the ratio of the rainfall at each gage site to the rainfall at a base gage. Predictive variables were topographic slope, aspect, ground elevation at the gage site, and smoothed elevation. The smoothed elevation, which is the elevation the gage would assume if it were on a smooth plane representing the general topography of the terrain, appeared in more equations than any other variable. One equation was calculated for each of six identified storm types, and one equation was calculated with all storms considered together. Overall, the equations which considered storm type were not better predictors of site rainfall than the equation which did not consider storm type. Predictions of storm amounts were closest to measured amounts for storms where the low-pressure center passed east of Coweeta, while the predictions for the air-mass or thunderstorm type had the greatest errors. The prediction errors of the equations for warm-, cold-, and stationary-front storm types were intermediate. The small number of tropical storms limited development and testing of equations for that type.

INTRODUCTION

Point values of precipitation in mountainous terrain have great spatial variability due to orographic effects. Much of the early research into the effects of orography on precipitation considered annual rainfall and the importance of elevation on the quantity of annual rainfall [*Lee*, 1911; *Henry*, 1919; *Barrows*, 1933; *Price and Evans*, 1937]. Later investigators looked at seasonal aspects of orographic rainfall and the influence of other physiographic variables on rainfall in the mountains [*Donley and Mitchell*, 1939; *Spreen*, 1947; *Burns*, 1953], and the importance of synoptic weather type on determining orographic effects [*Williams and Peck*, 1962]. Today, research into orographic rainfall includes physical modeling [*Struzer*, 1972; *Collier*, 1975; *Colton*, 1976], statistical modeling, and observation of the distribution of storm rainfall in mountainous terrain [*Merva et al.*, 1976; *Storebo*, 1976; *Browning et al.*, 1975].

Dense raingage networks, needed to obtain a representative measure of the areal rainfall distribution in mountainous terrain, are expensive to install and maintain. To estimate rainfall at any point on a watershed given only a single measurement site, we propose to use a rainfall ratio (rainfall at any site on a watershed divided by rainfall at a base measurement station). In application, the ratio would be multiplied by the base station rainfall to obtain a point estimate of rainfall. The primary objective of the study was to develop a method of estimating mean rainfall ratios from independent variables describing the physiography of the ungaged sites. Multiple linear regression techniques were used for this purpose. A secondary objective of the study was to determine the effect upon the rainfall ratio of the type of storm system producing the rainfall.

METHODS AND RESULTS

Study Area and Data Base

In developing the regression model, an extremely dense raingage network was needed. Such a network has been maintained at the Coweeta Hydrologic Laboratory in the mountains of southwest North Carolina since November 1936. Data used in the study were obtained from Coweeta for 60 nonrecording gages with unbroken records between November 1, 1942, and December 31, 1956. The model was developed using data from a random selection of 45 of these gages and was tested using data from the remaining 15 gages. A total of 147 storm events were selected from the 14 years of records. The data set consisted of a random selection of storms supplemented by all storms with durations greater than 18 hours, providing each event was separately measured and data existed for each of the 60 gages.

The study area (Figure 1) is a northeast-facing, 1600-ha watershed with elevations ranging from 670 to 1592 m over a horizontal distance of 4.8 km. Slopes at the high elevations exceed 45 degrees. The climate of the region is marine with cool summers, mild winters, and adequate rainfall in all seasons. Average annual precipitation varies from 170 cm at the lower elevations to 249 cm on the upper slopes.

Storm Typing

After the storms were selected, the study consisted of three steps: (1) storm typing; (2) model development; and (3) model evaluation. Each step is described briefly below. In much the same way that *Mather et al.* [1964] classified storms affecting the coastal southeast United States into eight types, storms in this study were typed on the basis of the predominant surface winds, frontal passages, and overall synoptic weather situation as determined from daily weather maps published in the *New York Times*. Here, six storm types were identified and designated low east (LE), low west (LW), cold front (CF), stationary front (SF), air mass showers (AM), and tropical storms (TS).

A storm was classed LE if it formed and/or passed east of Coweeta. Winds generated by this type storm are generally from the northeast, and rain at the study site is more or less steady. A LW produces a sequence of warm-front and cold-front passages at the site with winds veering from northeast to

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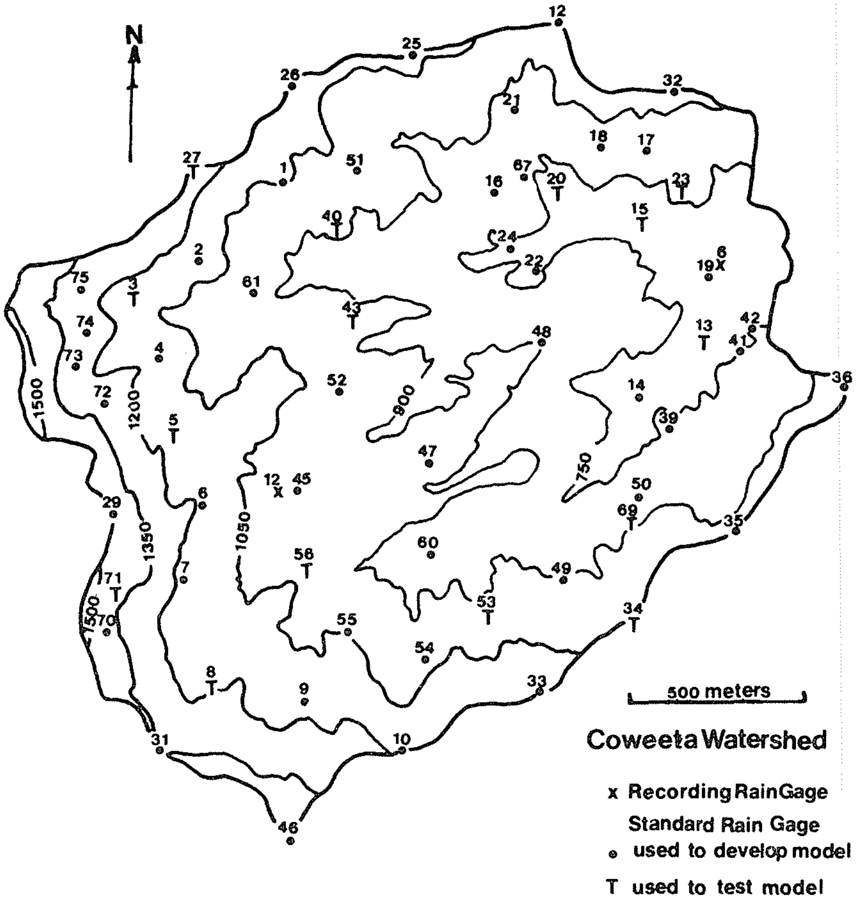

Fig. 1. The Coweeta Hydrologic Laboratory watershed. Numbers next to each symbol are gage numbers for the portion of the Coweeta rain gage network used in this study.

west. Rainfalls include steady, warm-front rains followed by convective, cold-front rains. When the low passed far west or north of Coweeta, only a cold-front passage was observed and the CF classification was made. In this type, winds shift from south to west and rains are convective. A SF classification was made when a stationary front positioned south of Coweeta resulted in surface winds from the east and northeast. Air mass showers were identified as events without significant fronts or lows in the area. Tropical storms were classed TS with no consideration given to storm track. These latter two types were primarily convective rains, but the AM type has substantially greater local spatial variability of rainfall than the TS type.

Model Development

After typing, the 147 events were divided randomly into two groups. Within each storm type except TS, 75% of the events were randomly selected for model development (111 events) and the remainder were placed in the model test group (36 events). All the TS events were used for model development.

The modeling objective was to develop an equation to predict rainfall for an individual storm at any site on the Coweeta watershed, given only a base-site observation. The form of the proposed equation to accomplish this objective relates the ratio between storm catch at the gage site and a base gage:

$$\text{RATIO}(i, j) = P_{i,j}/P_{i,45} \qquad (1)$$

to physiographic variables describing the gage location on the watershed, where $P_{i,j}$ is the precipitation from storm i at gage j and $P_{i,45}$ is the storm precipitation at the base gage (gage number 45). No attempt was made to evaluate other model equation forms. *Swift* [1968] successfully used the ratio format based on 6-month total rainfall to obtain mean isohyetal weighting factors for areal precipitation at Coweeta. The use of ratios based on storm totals represents a substantial refinement in time scale to Swift's study. Similarly, *Collinge and Jamieson* [1968] used ratio stations to control inter-catchment variation of storm amount while *Johnston and Holmes* [1960] used ratios to display areal precipitation patterns.

To confirm that the ratios were not a function of storm size, a linear regression

$$\text{RATIO}(i, j) = a + b(P_{i,45}) \qquad (2)$$

was calculated for each gage site relating the ratio to base-gage rainfall for all events in each storm type. In all cases, the slope, b, was very close to zero and the null hypothesis, $b = 0$, was not rejected at the 95% confidence level for any of the 45 stations. Therefore, each ratio was assumed to be unaffected by total storm rainfall, and the characteristic ratio for storms of a particular storm type was assumed to be the average of RATIO(i, j) for that storm type (st),

$$\text{RATIO}(j)_{st} = \sum_{i=1}^{n_{st}} \text{RATIO}(i, j)/n_{st} \qquad (3)$$

where n_{st} is the number of storms of type st. Equation (3) is the defining equation for the dependent variable in the regression analysis. Independent variables selected for study were similar

TABLE 1. Regression Equations for the Storm-Typed Model I and Non-Typed Model II

Storm Type	Equation Coefficients	R^2	MSE
	Storm-Typed Model (Model I)		
Low east	$RATIO(j)_{LE} = 0.852 - 0.023A + 0.387H$	0.71	0.00235
Low west	$RATIO(j)_{LW} = 0.888 + 0.403H$	0.67	0.00291
Cold front	$RATIO(j)_{CF} = 0.794 - 0.024A + 0.531H$	0.79	0.00279
Stationary	$RATIO(j)_{SF} = 0.808 - 0.059A + 0.499H$	0.63	0.00717
Air mass	$RATIO(j)_{AM} = 1.020 + 0.341E - 0.404S + 0.174H$	0.43	0.00448
Tropical	$RATIO(j)_{TS} = 0.792 + 0.522H$	0.79	0.00259
	Non-Typed Model (Model II)		
All storms	$RATIO(j) = 0.834 - 0.024A + 0.473H$	0.78	0.00238

to ones found important by *Spreen* [1947] and *Donley and Mitchell* [1939]. All were determined from a 1:14400 scale topographic map of the watershed. These include land slope at the gage site (S) in m/m; the aspect (A) or direction in radians the slope faces relative to the northeast-facing axis of the watershed (for a northeast-facing site $A = 0$; for a northwest-facing site, $A = \pi/2$; and for a southeast-facing site, $A = -\pi/2$; etc.); elevation (E) of the gage site in thousands of meters above 670 m, the lowest elevation on the watershed; and a smoothed elevation (H) in thousands of meters above 940 m, the lowest smoothed elevation value for the watershed. The smoothed elevation was determined by drawing a line perpendicular to the watershed axis through the gage site to the north and south ridgelines of the watershed. If the gage site was to the north of the watershed axis, the elevation on the north ridge was used; if the gage site was to the south of the watershed axis, the elevation on the south ridge was used. The values for the physiographic variables were coded to a similar order of magnitude to aid in interpreting the relative importance of each variable in the regression equations.

Several equation forms were tried to fit the $RATIO(j)_{st}$ for each storm type to independent variables A, S, E, and H, but none fit the data better than the linear equation:

$$RATIO(j)_{st} = a + bA_j + cE_j + dS_j + eH_j \quad (4)$$

where a, b, c, d, and e are regression coefficients for a storm type. A model was also generated for all sites without consideration of storm type. Only those independent variables significant at the 95% confidence level were included in the final models. The equation coefficients, correlation indices (R^2), and mean squares (MSE) for model I with storm typing, and model II without storm typing are shown in Table 1.

Model Evaluation

Model evaluation was designed to test three questions: (1) Does model I with storm typing give better predictions than lumping all storms as in model II, and what is the accuracy of prediction as determined (2) by the variation between storm types, and (3) by the variation between gage sites? Several statistical and graphical tests were applied to answer these questions.

An analysis of variance (ANOVA) was based upon independent data from 36 previously unused storms at the 15 gage sites not used to construct the models. Scatter diagrams, standard deviations of prediction error, and coefficients of variation were based on measurements of all 147 storms at these 15 gage sites. Basing the tests on the additional gages is equivalent to evaluating the ability of the model to predict rainfall at ungaged sites in the Coweeta Basin.

All three questions were evaluated by carrying out an ANOVA on absolute prediction error,

$$E^k(i, j)_{st} = |P_{i,j} - \hat{P}_{i,j}| \quad (5)$$

where E is the absolute difference between measured and estimated rain for each storm i at site j using model k for storm type st and

$$\hat{P}_{i,j} = RATIO(j)_{st} \cdot P_{i,45} \quad (6)$$

is the estimated rainfall. The ANOVA assumes a mixed model with fixed effects of model and storm type and a random effect

TABLE 2. Analysis of Variance for Evaluating the Effects of Model, Storm Type, and Gage Site on Absolute Prediction Error for 36 Test Storms

Source of Variation	SS	d.f.	MS	F	F_{05}
Main effects					
Model	2.406	1	2.406	17.31*	3.85
Gage	7.810	14	0.558	2.03*	1.70
Storm type	50.374	4	12.593	22.69*	2.38
2-factor interaction					
Model × gage	1.949	14	0.139	0.51	1.70
Model × type	11.331	4	2.833	12.70*	2.38
Gage × type	31.098	56	0.555	2.02*	1.35
3-factor interaction					
Model × gage × type	12.468	56	0.223	0.81	1.35
Residual	255.723	930	0.275		
Total	373.159	1079	0.346		

*Significant at the 0.05 level.

TABLE 3. Average Absolute Prediction Errors for 36 Storms, Grouped by Storm Type, Test Gage, and Model

	Low East		Low West		Cold Front		Stationary Front		Air Mass		
Gage Number	Model I	Model II	Model I	Model II	Model I	Model II	Model I	Model II	Model I	Model II	No Typing (Model II)
3	0.30	0.26	0.59	0.65	0.26	0.25	0.47	0.45	0.63	0.64	0.36
5	0.24	0.33	1.20	1.06	0.38	0.43	0.29	0.29	0.62	0.31	0.47
8	0.42	0.45	0.44	0.46	0.44	0.43	0.12	0.12	0.80	0.43	0.40
13	0.20	0.23	0.62	0.40	0.38	0.33	0.27	0.28	2.59	0.93	0.36
15	0.24	0.25	0.59	0.54	0.31	0.28	0.42	0.31	2.27	0.58	0.34
20	0.25	0.23	0.87	0.54	0.27	0.31	0.54	0.34	2.17	0.68	0.36
23	0.35	0.40	0.77	0.58	0.34	0.30	0.63	0.33	1.87	0.47	0.38
27	0.37	0.40	1.95	1.25	0.43	0.50	0.49	0.43	1.41	0.50	0.57
34	0.20	0.21	0.30	0.21	0.31	0.29	0.26	0.23	0.72	0.99	0.31
40	0.22	0.22	0.82	0.30	0.18	0.18	0.50	0.25	1.27	0.23	0.22
43	0.20	0.20	0.83	0.39	0.20	0.18	0.22	0.13	2.17	0.55	0.24
53	0.14	0.14	0.46	0.40	0.26	0.26	0.40	0.39	0.89	0.38	0.28
56	0.34	0.34	0.51	1.08	0.52	0.39	0.24	0.11	0.68	1.11	0.50
69	0.26	0.25	0.48	0.39	0.34	0.39	0.38	0.37	1.89	1.44	0.44
71	0.37	0.42	1.16	0.74	0.37	0.38	0.24	0.22	0.53	0.14	0.40
15-gage average	0.27	0.29	0.77	0.60	0.33	0.33	0.36	0.28	1.37	0.63	0.38

Values are centimeters of rain.

of gage site. Absolute error is used rather than mean error because large positive and negative errors are not cancelled and hidden by the averaging process. Absolute error is also preferred to the squared error where a single large prediction error could dominate the analysis. Consequently, absolute error gives a more representative view of the success or lack of success of a particular model.

Table 2 gives the results of the analysis of the two models, 15 gage sites and 5 storm types for the 36 test storms. The tropical storm type was not included because additional events were not available for testing the tropical storm model. All the main effects are significant at the 5% level for explaining absolute error of prediction. The two-factor interactions, gage × storm type and model × storm type, are also significant at the 5% level.

Table 3 gives values of the average absolute prediction error,

$$AE^k(j)_{st} = \left\{ \sum_{i=1}^{n_{st}} E^k(i,j)_{st} \right\} \Big/ n_{st} \tag{7}$$

for each model k and test gage j. The models were further evaluated by making scatter diagrams of observed versus estimated rainfall and by looking at standard deviations of prediction error and coefficients of variation for all 147 storms used in the study.

Standard deviations of the difference, observed minus predicted rainfall,

$$S(j)_{st} = \left\{ \sum_{i=1}^{n_{st}} (P_{i,j} - \hat{P}_{i,j})^2/(n_{st} - 1) \right\}^{1/2} \tag{8}$$

and coefficients of variation,

$$CV(j)_{st} = S(j)_{st} \Big/ \left(\sum_{i=1}^{n_{st}} P_{i,j}/n_{st} \right) \tag{9}$$

TABLE 4*a*. The Standard Deviation of Prediction Error for All 147 Storms for Models I and II

		Storm Type and Model											
		LE		LW		CF		SF		AM		TS	
Test Gage Number	All Storms II	I	II	I	II	I	II	I	II	I	II	I	II
3	0.84	0.64	0.59	1.15	1.44	0.64	0.67	0.89	0.99	0.62	0.75	0.63	0.75
5	0.95	0.58	0.68	1.08	1.02	1.07	1.15	1.01	1.02	0.55	0.41	0.35	0.36
8	0.84	0.78	0.72	1.15	1.19	0.70	0.71	1.10	1.11	0.76	0.84	1.01	0.83
13	0.67	0.49	0.54	1.04	0.98	0.68	0.58	0.60	0.55	2.19	0.86	0.93	1.02
15	0.69	0.54	0.58	1.05	0.97	0.69	0.62	0.74	0.70	2.11	0.77	0.93	0.95
20	0.74	0.47	0.48	1.04	0.83	0.71	0.79	0.75	0.91	1.98	0.76	0.77	0.79
23	0.89	0.54	0.61	1.20	0.94	1.03	1.05	0.95	0.82	1.69	0.68	1.00	0.95
27	1.27	0.65	0.70	1.92	1.36	1.41	1.52	1.32	1.56	1.25	0.55	0.96	0.95
34	0.69	0.43	0.42	1.04	1.01	0.58	0.53	0.71	0.86	0.96	0.94	1.02	1.17
40	0.57	0.51	0.51	0.85	0.74	0.40	0.45	0.83	0.95	1.11	0.38	0.62	0.62
43	0.53	0.31	0.30	0.85	0.67	0.46	0.53	0.52	0.67	1.81	0.49	0.59	0.66
53	0.75	0.33	0.32	0.89	0.88	0.55	0.51	1.58	1.70	0.99	0.73	0.57	0.44
56	0.77	0.67	0.67	0.86	1.18	0.76	0.58	0.99	0.71	0.65	0.95	1.31	1.10
69	0.78	0.48	0.50	1.08	1.05	0.71	0.67	0.61	0.69	1.58	1.24	1.07	1.28
71	0.69	0.56	0.61	1.14	1.08	0.60	0.62	0.73	0.51	0.66	0.70	0.70	0.58
15-gage average	0.78	0.53	0.55	1.09	1.02	0.73	0.73	0.89	0.92	1.26	0.74	0.83	0.83

TABLE 4b. Number of Storms

	All Storms	LE	LW	CF	SF	AM	TS
Development	111	22	17	46	11	10	5
Test	36	8	5	16	4	3	0
Total	147	30	22	62	15	13	5

The values for standard deviation, $S(j)_{st}$ are centimeters of rain.

provide measures of the variations between gage sites and between storm types for model I and between gage sites for model II. Mean storm amounts for each gage, number of storms, standard deviations of prediction error for models I and II, and coefficients of variation for model I are given in Tables 4 and 5.

To further test whether consideration of storm type in model development significantly improves the ability of the model to estimate rainfall at an ungaged site, a paired t-test, comparing prediction errors from the two models, was carried out for storms of each storm type in the sample of 36 test storms. The t-test statistic,

$$t_0 = \frac{\frac{1}{15} \sum_j D(j)}{\left(\frac{1}{15}\right)^{1/2} \left\{\frac{1}{14}\left[\sum_j D(j)^2 - \frac{1}{15}\left(\sum_j D(j)\right)^2\right]\right\}^{1/2}} \quad (10)$$

where

$$D(j) = AE^{I}(j)_{st} - AE^{II}(j)_{st} \quad (11)$$

was compared with the t-statistic at the 0.05 level of significance and 14 degrees of freedom, $t_{0.05,14} = 2.145$, to test the null hypothesis that the prediction errors were not different between the two models. Table 6 gives the number of test storms in each storm type, the t-statistic for the differences between average absolute errors and a count of cases where model I had a lesser, greater, or similar average error to model II. The negative t-value shows that the model I equation for LE storms yielded smaller errors at more gage sites than the model II equation.

DISCUSSION

The various statistical tests indicate that rainfall estimation is not improved by using individual equations derived for each storm type. However, these tests also show that the accuracy of rainfall estimates obtained by means of the ratio approach varies with the type of storm and with the gage site.

Analysis of variance showed that the choice of model and storm type had the greatest effect on absolute error between estimated and measured storm totals. If no difference between model I and model II equation accuracy existed, the model II equation would be selected for use because of its simpler application and the expectation that it would be better for representing rainfall patterns. Model II is based on a large, 111-event sample while the model I equations are based on small sub-samples of that larger sample and are, thus, subject to sampling non-uniformities. The summary of average absolute errors, Table 3, indicates that the general equation, model II, yields similar or smaller errors for all but the LE storm type. The t-tests for the differences between average errors further show that rainfall estimates from the model II equation were closer to measured rainfall for three of the five storm types (LW, SF, and AM) and that both models were equally good for the CF storms. Thus, LE is the only storm type where the Model I equation was clearly better than the general equation.

The scatter diagrams showed relatively good fit between model I and model II predictions and observed rainfall. The mean square error, MSE, for model II was 0.00238. Thus, the standard deviation of RATIO(j) at the mean is $(0.00238/111)^{1/2} = 0.0046$ and the confidence limit for a RATIO is 0.009. The scatter of predicted storm amounts is due to this

TABLE 5. Mean Observed Rainfall for All 147 Storms and the Coefficients of Variation for Model I Predictions at the Test Gage Sites

	Storm Type											
	LE		LW		CF		SF		AM		TS	
Test Gage	Mean	CV	Mean	CV	Mean	CV	Mean	CV	Mean	CV	Mean	CV
3	5.46	12	8.56	13	5.05	13	5.18	17	3.96	16	10.74	6
5	5.31	11	8.15	13	4.90	22	5.33	19	4.06	13	10.80	3
8	5.89	13	9.04	13	5.61	12	6.27	18	4.50	17	11.51	9
13	4.67	10	6.99	15	4.32	16	4.47	13	3.05	72	8.15	11
15	4.75	11	7.11	15	4.29	16	4.39	17	2.95	71	8.26	11
20	4.70	10	7.11	15	4.19	17	4.37	17	3.10	64	8.56	9
23	4.62	11	6.83	18	4.04	26	4.27	22	2.87	59	8.05	12
27	4.72	14	6.91	28	4.32	33	4.78	28	3.43	37	9.93	10
34	4.93	9	7.19	14	4.67	12	5.23	14	3.63	26	8.76	12
40	5.03	10	7.57	11	4.57	9	4.67	18	3.51	32	9.30	7
43	5.08	6	7.62	11	4.67	10	4.83	11	3.61	50	9.37	6
53	5.36	6	7.77	12	5.03	11	5.61	28	3.68	27	9.70	6
56	5.46	12	8.18	11	5.18	15	5.49	18	4.04	16	10.39	13
69	5.00	10	7.42	15	4.65	15	5.03	12	3.28	48	8.56	12
71	5.59	10	8.59	13	5.46	11	5.77	13	4.32	15	10.77	7
15-gage average	5.10	10	7.67	14	4.73	16	5.05	18	3.60	38	9.52	9
Base-gage 45	5.38		7.98		5.13		5.41		3.84		10.31	

Mean rainfall in centimeters. Coefficient of variation in percent.

TABLE 6. Summary of Paired t-Test for 15 Gages to Determine the Importance of Storm Typing in Model Construction

	Storm Type				
	LE	LW	CF	SF	AM
Number of storms	8	5	16	4	3
t-statistic	−1.841	2.252*	0.472	3.197*	4.015*
Number of gages					
$AE^{I} < AE^{II}$	4	2	4	0	2
$AE^{I} > AE^{II}$	2	12	5	8	12
$AE^{I} \approx AE^{II}$	9	1	6	7	1

Gage count from Table 3.
*Significant at the 0.05 level.

error in estimating the RATIO from physiographic variables and to any inability of the base gage to represent rainfall at some other site. The average absolute error for the test group of gages and storms shows that model II predicted storm amounts within a mean of 0.38 cm.

Each of the four measures of the variation between gages provides an index of the range in error of prediction between locations in the valley. The errors from model I prediction are distinctly greater at several of the gage sites. For example, gage 27 generally had larger absolute errors and higher standard deviations and coefficients of variation than average for the group of 15 test gages. This gage was installed on a prominent and exposed mountain peak, and these results confirm that the gage was subject to wind-induced measurement errors. Some gage sites had large errors for a few storm types, but were near normal for all other types, possibly indicating the need for an additional or different predictive parameter for the CF and SF storms (Table 3).

Predictions for LE storms had the smallest absolute errors, while the AM type had the largest, with LW being intermediate. Similar patterns were shown by standard deivation of prediction error for LE, CF, SF, and TS averaging less than 0.9 cm and for LW and AM averaging greater than 1.0 cm. The coefficient of variation gives a slightly different measure of prediction errors for the various storm-type equations. The larger precipitation amounts in the LW type reduce that coefficient. Contrastingly, the large coefficient for the AM type results from both areal variability and small storm amounts. The use of the ratio approach in estimating rainfall is, thus, seen to be more successful for some storm types than others.

The model I regression equations for LE and SF storms are most easily interpreted. Precipitation in these storms is more uniformly distributed over a watershed than in other storm types. Because the Coweeta watershed axis is directed toward rain-producing winds in LE and SF storms, the regression equations reflect only orographic lifting and are generally free of any blow-over effects due to rain being lifted over ridges and deposited on leeward slopes by local air currents. Regression coefficients (Table 1) are larger for the SF type than the LE type, possibly because winds are generally slower under stationary-front conditions, the boundary layer is shallower, and local topography plays a more significant role in orographic enhancement processes. As reflected by the smaller regression coefficients for aspect and smoothed elevation, the LE storms, with higher wind speeds and a deeper boundary layer, are influenced less by local topographic features than are the SF storms.

For LE storms, the regression coefficient for the smoothed elevation is 16.8 times larger than the coefficient for aspect, while for SF storms, the smoothed-elevation coefficient is only 8.5 times the coefficient for aspect. The greater importance of the smoothed-elevation term in the LE model may again reflect the fact that the boundary layer is larger under high wind-speed conditions and local topography, thus, plays less of a role in altering rainfall patterns. The SF equation has the largest mean square, suggesting again that the aspect and smoothed elevation are weaker parameters for this storm type.

The AM model predicts air mass rainfall poorly because of spatial non-uniformity of rainfall patterns for this type storm. This equation has the lowest R^2 and a relatively large MSE. Because a rain can occur over a portion of the watershed, yet miss the base station gage, the model could predict zero rainfall while an inch or more might actually have fallen at some sites. The extreme variability in the average absolute errors shown in Table 3 is indicative of this spatial non-uniformity of air mass rainfall, and of the inadequacy of the model for this storm type. The significance of the elevation and slope variables in this model suggests greater rainfall amounts at higher elevations.

The CF model is only slightly less effective than the LE model. The small errors (Table 3) indicate that, although cold-front rainfall is convective in nature and, therefore, somewhat spatially non-uniform, there is a constancy in the effect of the orography on the rainfall distribution. The large coefficient associated with the smoothed-elevation term in the regression model in Table 1 suggests that rain blown over the ridge by the southwest winds of the cold front is deposited primarily on the higher elevations of the watershed.

When coefficients of variation (Table 5) are considered, the LW model is about as successful as the cold-front model, possibly because the low west has a time sequence of rainfall which includes the cold-front storms. Although not completely tested because of the small sample, the TS model showed surprisingly good results.

The model II equation shows that for all storms, regardless of type, the smoothed elevation is more important than fine-scale elevation features in influencing the rainfall ratio. Aspect at the gage site has a small effect.

Considering the simplicity of the model in relation to the complex flow and condensation processes above mountainous watersheds, the good fit between observed and predicted rainfall from individual storms is encouraging. It indicates that the regression approach is valuable in modeling orographic precipitation and that it can be used to fill in missing data in a rainfall record or to gain further insight into the best way to draw isohyetal lines in mountainous terrain.

A problem with this approach is that, in order to construct a model, data from a high-density rain gage network must be available. Development of a general regression model for a region such as the eastern United States, although feasible, would be difficult because of the interaction between storm type (with its varying wind direction and condensation mechanisms) and watershed orientation. For example, for a LE storm type, a southwest-facing watershed is affected by precipitation blowing over a ridge, while a northeast-facing watershed, like the Coweeta watershed, is influenced by a purely orographic lifting effect. If a more general regression model could be developed, it would require data from a large number of watersheds in order to include an orientation variable.

CONCLUSIONS

The goal of this research was to develop a set of regression equations relating precipitation for individual storms to watershed location in much the same way that average annual precipitation has been related to physiography by *Spreen* [1947] and *Burns* [1953] and to determine if storm type is a significant factor in determining rainfall distribution on the Coweeta watershed. At present, an approach like the one reported herein is possible only where there is a high-density raingage network, as the one at Coweeta Hydrologic Laboratory. However, this methodology would be extremely useful when a dense network must be reduced to a fewer number of gages.

Storm types were modeled with varying success. The low-east type with pure orographic lifting was modeled best. Low-west and cold-front types with significant blow-over effects and stationary-front with moderate orographic lifting effects were modeled with intermediate success. The model for air-mass storms was least successful because it was not capable of handling non-uniform and/or time-varying condensation mechanisms. Based on subjective evaluation of plots of observed versus predicted precipitation, the model for the tropical-storm type appeared to be very successful in spite of the small sample size.

The current techniques of physical modeling in reproducing complex flow and condensation patterns for idealized mountain topography [for example, *Colton*, 1976] will be extremely difficult to extend into more rugged terrain. Consequently, the regression model approach will have a prominent role in solving the problem of estimating individual storm rainfall distribution in complex topography. Regression models derived on the basis of storm typing do not appear to be necessary for estimating rainfall distribution over a southern Appalachian Mountain watershed of up to 1600 ha. Regression models are most useful in estimating rainfalls from storms with spatially uniform precipitation-generating mechanisms.

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