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CLASSIFICATION OF PHILIPPINE RAINFALL PATTERNS

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ABSTRACT

Climatic classification is useful to agriculturalists because it aids in determining crop adaptation. Two contrasting types of classifications can be envisioned: in a natural classification, the pattern of differences among climatic classes forms the basis for assigning climatic stations to climatic classes; in a technical classification, class criteria are established at levels critical for crop performance.

Mathematical classification methods can examine patterns among many attributes over numerous rainfall records. This is considered a natural classification. In this study, the primary objective was to compare classifications derived from two mathematical taxonomic algorithms and one technical classification. Another objective was to derive a natural classification system, using differences among rainfall patterns revealed by mathematical classifications. This study used mean monthly rainfall (RR) and standard deviations (LS) determined from long-term records of 100 Philippine rainfall stations.

The comparisons showed little correspondence between technically determined classes and mathematically determined ones. Furthermore, variability within classes determined by technical criteria was greater than within classes determined by either of two mathematical algorithms. This greater variability is undesirable.

In the comparison between two mathematical algorithms, the algorithm that used a minimum increase in the sum of squares to join cluster pairs as the fusion criterion was regarded as superior to the algorithm that used the minimum of the maximum distances between the furthest neighbors in cluster pairs. The superior algorithm formed clusters averaging less within-class variance, left fewer unclassified stations, and produced more multimember classes with more even membership.

Including LS in the mathematical classification had little apparent effect on class differentiation. Factor analysis showed that RR and LS were highly correlated during each of the three seasons: December-April (dry season), May-September (primary wet season), and October-November (secondary wet season).

Analyses showed that the mathematical classes were separated mainly by general rainfall level, seasonal modality, primary wet season (May-September) rainfall levels and peakedness, and dry season severity. A classification system was developed using these characteristics. The system produced a distribution of rainfall classes corresponding to the seasonality of air masses and disturbances, and to major topographic features. This correspondence indicates that the derived classification reflects causal meteorological factors.

Because the natural classes simultaneously carry information on rainfall level and seasonal durations, and exhibit lower within-class variability, such classes should be superior to technical classification for planning agricultural research and development projects.

ERRATA for IRPS 105

Page 9, Table 4.

Column 6, 4th entry: 55 should be 35.
Last column, 4th entry: 29 should be 23.

Page 9, paragraph 1, line 2

"The stem . . ." should read "The item . . ."

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CLASSIFICATION OF PHILIPPINE RAINFALL PATTERNS

Early climatic classifications of the world such as Koeppen's, which was proposed in 1918, were based on differences among seasonal rainfall patterns and thermal regimes, with observations of vegetation and soil distributions aiding interpolation between the sparse number of weather stations with available records. Classifications became more quantitative as records became available from more locations and longer periods, and as science better explained climatic factors and the relations of climatic parameters to biological processes.

For example, after many years of study, Thornthwaite published his seasonal water balance approach to climatic classification in 1948 (26). More recently Papadakis (21) published detailed tables of world climate classes. The system contains more than 500 classes, as Papadakis claims it is not possible to satisfactorily picture the world's climate with less detail. The climatic criteria of Koeppen, Thorthwaite, and Papadakis have been used to classify and map the climate of the world or of an extensive region at a small scale.

In the Philippines, four classifications have been published (3, 5, 6, 16). Whereas Obradovich applied Thornthwaite's water balance method to compute an annual water balance but disregarded seasonal patterns, the classifications of Coronas, Hernandez, and Huke were based on seasonal rainfall distributions. Coronas defined 4 distribution types, Hernandez 6 types, and Huke 7 types. All four climatologists regarded temperature as minor in classifying the Philippine climate. Seasonal temperature variation is slight, and variation with altitude is predictable.

In the remainder of this introduction, we make the distinction between natural and technical climatic classifications, describe two recently published maps of Philippine rainfall patterns, and outline the objectives of this study.

The classifications of Koeppen, Papadakis, Coronas, and Huke are natural in the sense that class limits are based on natural changes in climatic parameters. Technical classifications have recently been developed for agricultural planning and research. Crop planning for agricultural development projects often begins with an agroclimatic classification (25). Such classifications consider the climatic requirements of crop classes as differentiating criteria.

As an example, IRRI (7) published a very small scale map (1:9 million) of Southeast Asia that shows the distribution of rainfall patterns having characteristic numbers of consecutive wet months (total mean monthly rainfall ≥200 mm/mo), secondary rainy seasons, and pronounced dry seasons (mean monthly rainfall <100 mm/mo for 2-3 mo). In this technical classification of rainfall patterns, 200 mm/mo was regarded as adequate to meet the minimum evapotranspiration and percolation requirements of a lowland rice crop. One hundred mm/month was regarded as a lower limit below which common upland crops would not produce economical yields.

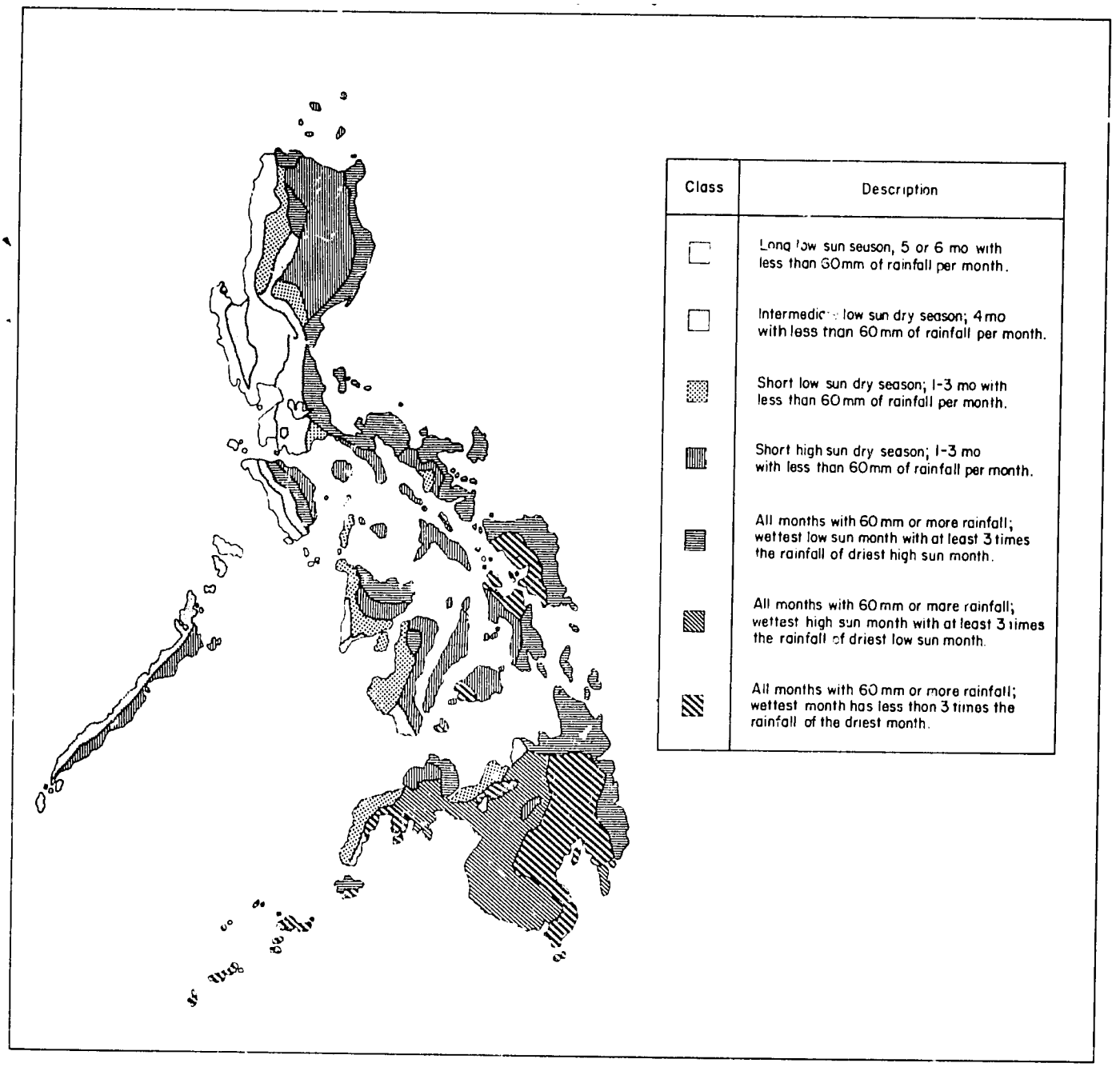
This approach has been used to classify and map rainfall patterns in Bangladesh (14), the Philippines (9), Thailand (15), and Indonesia (17, 18, 19, 20). Technical classifications of rainfall patterns widely appeal to agronomists working on cropping systems research in Southeast Asia; rainfall pattern classes are frequently cited in the environmental description sections of cropping systems research reports

Recently, two maps of the Philippines were published at 1:2,500,000 scale. The maps (and their bases of classification) differ; one conveys primarily rainfall pattern seasonality, and the other conveys wet and dry season durations. The first map, based on Huke's (6) classification system (Fig. 1), was prepared by the URARTIP/IRRI-Philippines Outreach Office (27). The seven classes on this map reflect peak rainfall timing, but also recognize dry season duration. This system allows only limited direct interpretation for rainfall quantity. The second map emphasizes seasonal duration and shows class boundaries differentiated mainly by wet and dry months. Wet and dry months are defined by mean monthly total rainfall. Mean total rainfall of the month of maximum rainfall is a secondary differentiating criterion. The classes on the second map, therefore, carry more information about rainfall level than classes on the first map.

Agricultural research and regional agricultural development planning can well use information on seasonal durations, average monthly rainfall, and expected year-to-year variability. Seasonal durations and mean monthly rainfall and its reliability must be considered in on-farm cropping systems research programs. A classification system that accounts for these rainfall pattern characteristics would help in planning a regional research project, and in extrapolating results to other regions dominated by similar rainfall patterns.

This study's first objective was to determine the correspondence among the classification of 100 Philippine rainfall stations by using technically established criteria and criteria derived from natural differences in the rainfall patterns, particularly emphasizing the heterogeneity among stations within a class.

The second objective was to compare two mathematical



1. Rainfall pattern map based on Huke's classification (6).

classification methods for correspondences of class memberships for the 100 stations. The mathematical classification methods were applied to long-term mean monthly rainfall (RR) and standard deviations (LS) obtained from records of 20 yr or more.

The third objective was to establish, using rainfall pattern differences revealed by the mathematical classifications, differentiating criteria suitable for classifying Philippine stations.

The fourth objective was to examine the spatial distribution of classes relative to the major meteorological factors that determine rainfall patterns.

MATHEMATICAL CLASSIFICATION OF CLIMATE

In recent years, large computers and mathematical classification algorithms have enabled scientists to classify weather stations on the basis of long-term records. However, few scientists have attempted such classifications. Kyuma (11) used mean monthly rainfall and temperature to mathematically classify 125 selected weather stations in South and Southeast Asia, including 15 in the Philippines. In mapping the nine regional climate classes obtained from the numerical method, Kyuma deleted all Philippine stations because he found that climate classes within the Philippines were

distributed too heterogeneously to be mapped at a small scale. Kyuma (12) also used the same numerical approach to place 107 Japanese weather stations into 6 groups.

Russell and Moore (22) sought homoclimates corresponding to 9 northeastern Australian weather stations from among 139 stations between 35°N and S latitudes in Asia, Africa, and North and South America. Russell and Moore (23) also treated data from 94 Australian and 206 southern African stations as a single set, and from their analysis (16 attributes/mo per station) delineated winter, summer, and full year homoclimes common to the two regions. Russell and Moore (24) also used mathematical methods to classify 254 northern Australian stations by monthly rainfall using 5 decile determinations, and to classify a subset of 59 stations by monthly rainfall, humidity, temperature, evaporation, and day length measurements (192 attributes). They obtained encouraging geographical similarities from the two sets of data, but detected some differences.

The remainder of this section briefly discusses mathematical classification methods and describes the two methods used in this study. For more complete discussions of mathematical classification methods, see Williams (28) and books devoted to the subject.

Computer programs, commonly known as clustering algorithms, have been developed for placing entities into groups based on entity attributes. Two distinct steps are required: construction of a matrix of distances between entity pairs, and the fusion of entities into clusters. In this study, rainfall stations were the entities and the 12 RR and 12 LS values were entity attributes. The standard euclidean distance between two entities, i and j, was defined as

$$d^2_{ij} = \sum_{k}^{m} (x_{ik} - x_{jk})^2$$

where x_{ik} and x_{jk} represent m standardized attributes. Standardization is obtained by substracting $\bar{x}_{.k}$ from all x_{ik} and dividing by the standard deviation, s_k, of each attribute. The resultant d^2_{ij} elements form the distance matrix, D^2_{ij}. Entity pairs with low values in D^2_{ij} are in close proximity in the m-dimensional euclidean space.

To combine n entities into clusters, two fusion algorithms were used: furthest neighbor (FN) and Ward's (WD). Fusion starts with the n entities and at each iteration, places an entity (or a group of entities fused into clusters during previous iterations) into a cluster based on distance in D^2_{ij}. This procedure aggregates entities into increasingly large clusters until at the n−1 iteration, all entities are fused.

Each iteration of the FN algorithm fuses those clusters in which the maximum distance among all possible entity pairs from two candidate clusters is minimum. Obviously, during early iterations, many clusters contain only one entity, and therefore only one distance needs to be considered among pairs of entities in two clusters. In the WD method, those clusters fused at each iteration are the two which produce the minimum increase in the total within-group sum of squares. By applying these fusion methods to D^2_{ij}, individuals are fused into clusters which, on average, are increasingly dissimilar following each iteration.

Both the FN and WD fusion strategies are agglomerative because fusion is progressive, beginning with n entities and ending with the complete population (28).

By their nature, the FN and WD fusion strategies are likely to lead to natural classes in which entities are bound to a class from within, not circumscribed from without as with a technical classification. If in fact fusion does suggest a natural classification, it will perform the "important function of organizing and defining the classes used, . . . and organizing the data . . . for discovering relationships within the population"(2). Natural classes separated at a low hierarchical level can be used to place individuals into technical groupings for many applications, including agricultural research and planning.

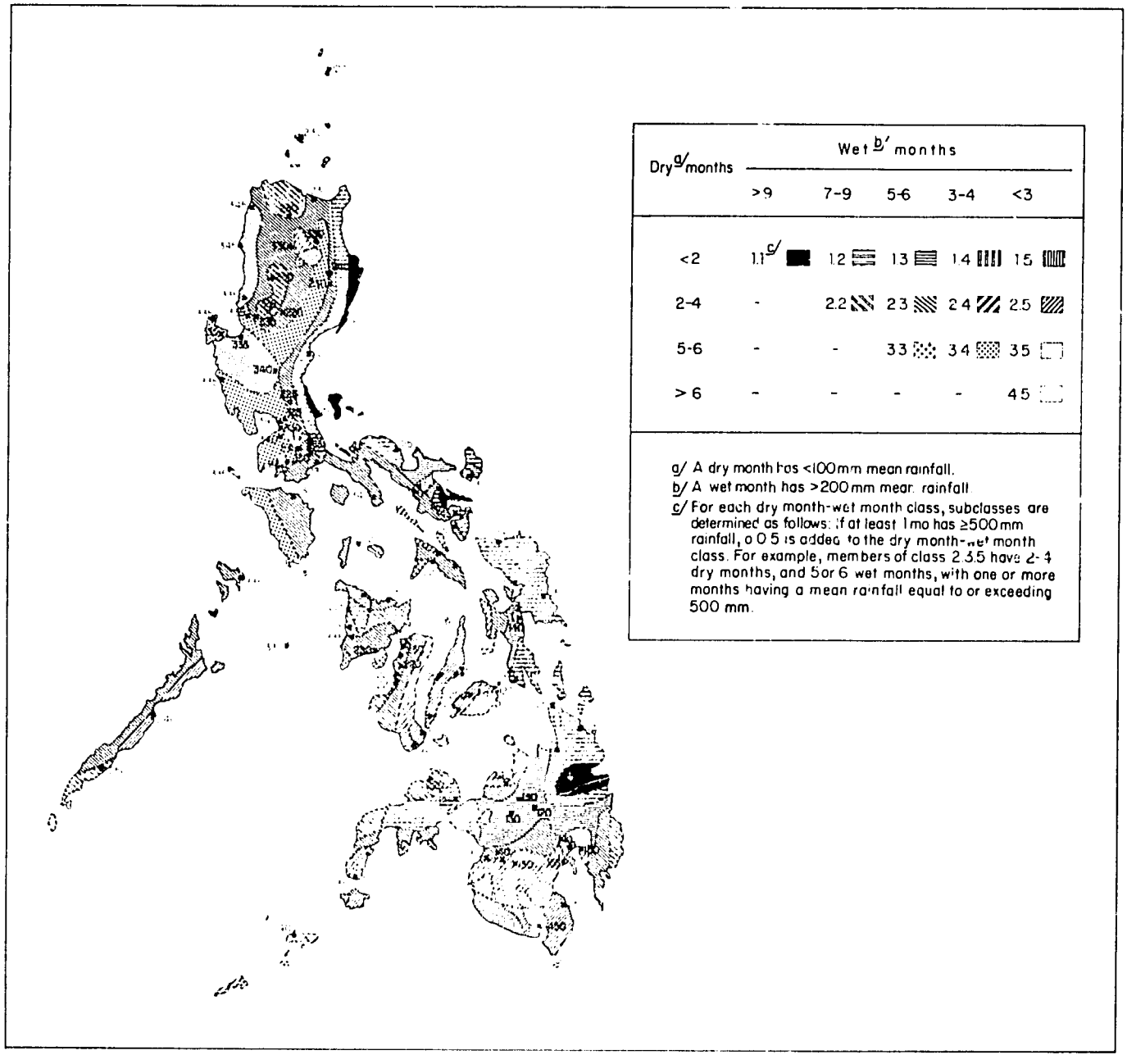
DATA AND METHODS

For this study, daily rainfall records of 20 yr or more from 100 weather stations were used to compute monthly mean rainfall (RR) and standard deviation (LS) of monthly rainfall, creating a set of 24 attributes for each station (entity). In the computations, months with missing data were eliminated unless interpolation from nearby stations could provide reasonable estimates for periods of less than 15 days. For each month, RR was included as a measure of central tendency and LS as a measure of variation in that month. Both measures were used to characterize a station because both the long-term rainfall and the reliability of that rainfall are important natural rainfall pattern attributes.

The 100 stations were classified by applying the technical criteria shown in Figure 2. The technically established criteria were those Manalo used to classify 232 stations in locating map boundaries (8; E. Manalo, pers. comm., 1982). The resultant classification was designated TD. A second technical classification (TM) was obtained by locating station latitude and longitude coordinates on Manalo's map and reading off the map class within which the station fell.

For the mathematical classifications, the 100 stations were clustered using the Ward option of the CLUSTAN package of algorithms (29). PROC CLUSTER of SAS was used to apply the furthest neighbor method (1). The 24 RR and LS values per rainfall station were used to form the 100 × 100 distance matrix, i. e., a matrix of standardized euclidean distances among the 100 rainfall gauging stations (entities).

In summary, 4 classifications of the 100 stations were obtained: the 2 mathematical classifications, WD and FN, corresponding to the Ward's and furthest neighbor groupings, and the 2 technical classifications, TM and TD, corresponding to the map- and data-derived groupings.



2. Rainfall pattern map based on a wet month-dry month classification (8). Class codes are shown for the 100 stations used in this study.

In accordance with objectives, these groupings were cross-classified to determine classification similarities. To compare rainfall patterns, mean monthly RR and LS were graphed. To compare the tightness of classes, the standard deviations of RR and LS were computed for TM, TD, FN, or WD classes which had many members in common.

RESULTS AND DISCUSSION

TM vs TD

By using Manalo's map boundaries for the TM classification, entities were placed in 19 of the 34 possible classes. By applying technical classification criteria directly to mean monthly rainfall, entities were also placed in 19 TD classes. The original map and the TD classes appear in Figure 2. The cross-classification of TD and TM appears in Table 1. Forty-seven of the 100 stations were placed in the same technical class by both methods. Cross-classifications of stations using dry, wet, and 500 mm class criteria separately are given in Tables 2, 3, and 4. These cross-classifications show that the 2 methods agreed on 89 stations when differentiating by the 500 mm/mo criterion, on 77 stations by the dry month criterion, and on 67 stations by the wet month criterion. Thus, between TD and TM classifications, the wet month criterion exhibited the most discrepancy.

No general pattern emerged from among the discrepan-

Table 1. Cross-classification of TM and TD classes.

TM class	TD class																			
	110	115	120	125	130	135	140	150	220	225	230	235	240	250	330	335	340	345	350	450
110	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0
115	0	4	2	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
120	0	0	3	1	3	1	0	0	2	0	2	0	0	1	0	0	0	0	0	0
125	0	0	1	4	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0
130	0	0	0	0	2	0	1	0	0	0	1	0	1	0	0	0	0	0	0	0
135	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
140	0	0	0	0	0	0	1	1	0	0	0	0	2	0	0	0	0	0	0	0
150	0	0	0	0	0	0	2	0	0	0	0	0	0	1	0	0	0	0	0	0
220	0	0	1	0	0	0	0	0	7	0	3	0	0	0	0	0	0	0	0	0
225	0	0	0	0	0	0	0	0	0	2	0	1	0	0	0	0	0	0	0	0
230	0	0	0	0	0	0	0	0	1	1	8	0	0	0	1	0	0	0	0	0
235	0	0	0	0	0	0	0	0	0	1	0	1	1	0	0	0	0	0	0	0
240	0	0	0	0	0	0	0	0	0	0	1	0	1	0	0	0	0	0	0	0
250	0	0	0	0	0	0	0	0	0	0	1	0	1	4	0	0	0	0	0	0
330	0	0	0	0	0	0	0	0	1	0	2	0	0	0	0	1	0	0	0	0
335	0	0	0	0	0	0	0	0	0	2	0	1	0	0	0	5	0	3	0	0
340	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	2	1	0	0	0
345	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0
350	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	1	0
450	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1

cies to suggest that particular regions or classes were more prone to differences in classification than others. Thus, whether methodological or data inadequacies or natural heterogeneity were the main cause of the differences, discrepancies were random. The comparison of variability within TM and TD classes will be discussed later.

Reasons for the fairly high discrepancy between the two classifications are many. Because class boundaries were placed on a small scale map (1:2,500,000), boundaries should not be expected to be precisely located. Furthermore, at such a small scale, limited areas of off-classes are likely to be included within a class covering an extensive area. This is especially likely for areas as heterogeneous in rainfall patterns as the Philippines. Inadequate rainfall record length also may have contributed to the discrepancy. Record lengths were 25 yr or shorter for more than half the stations used to draw the original map, and therefore many stations used to locate boundaries may have been misclassified. Even among the 100 stations used in this study, those with short record lengths (20-25 yr) may not have been put in their true classes. Also, stations situated near class boundaries may have been inaccurately located.

For a broad national picture of rainfall pattern classes, however, the map in Figure 2 is probably adequate despite the discrepancies between TM and TD. Table 5 shows that in a cross-classification between TM and TD, using the dry-wet month criteria, 50 stations were in agreement and another 26 differed by no more than 1 criterion increment. The difference between TD and TM classifications suggests, however, that agriculturalists working on research and development plans for regional (subnational) projects should not rely heavily on a rainfall pattern map to determine the number of wet, intermediate, and dry months

Table 2. Cross-classification of TM and TD classes by dry month criterion.

TM dry month class	TD dry month class			
	1	2	3	4
1	27	12	0	0
2	1	34	2	0
3	8	15	0	0
4	0	0	0	1

Table 3. Cross-classification of TM and TD classes by wet month criterion.

TM wet month class	TD wet month class				
	1	2	3	4	5
1	4	3	1	0	0
2	0	21	11	0	1
3	0	6	22	6	0
4	0	0	5	7	1
5	0	0	1	3	8

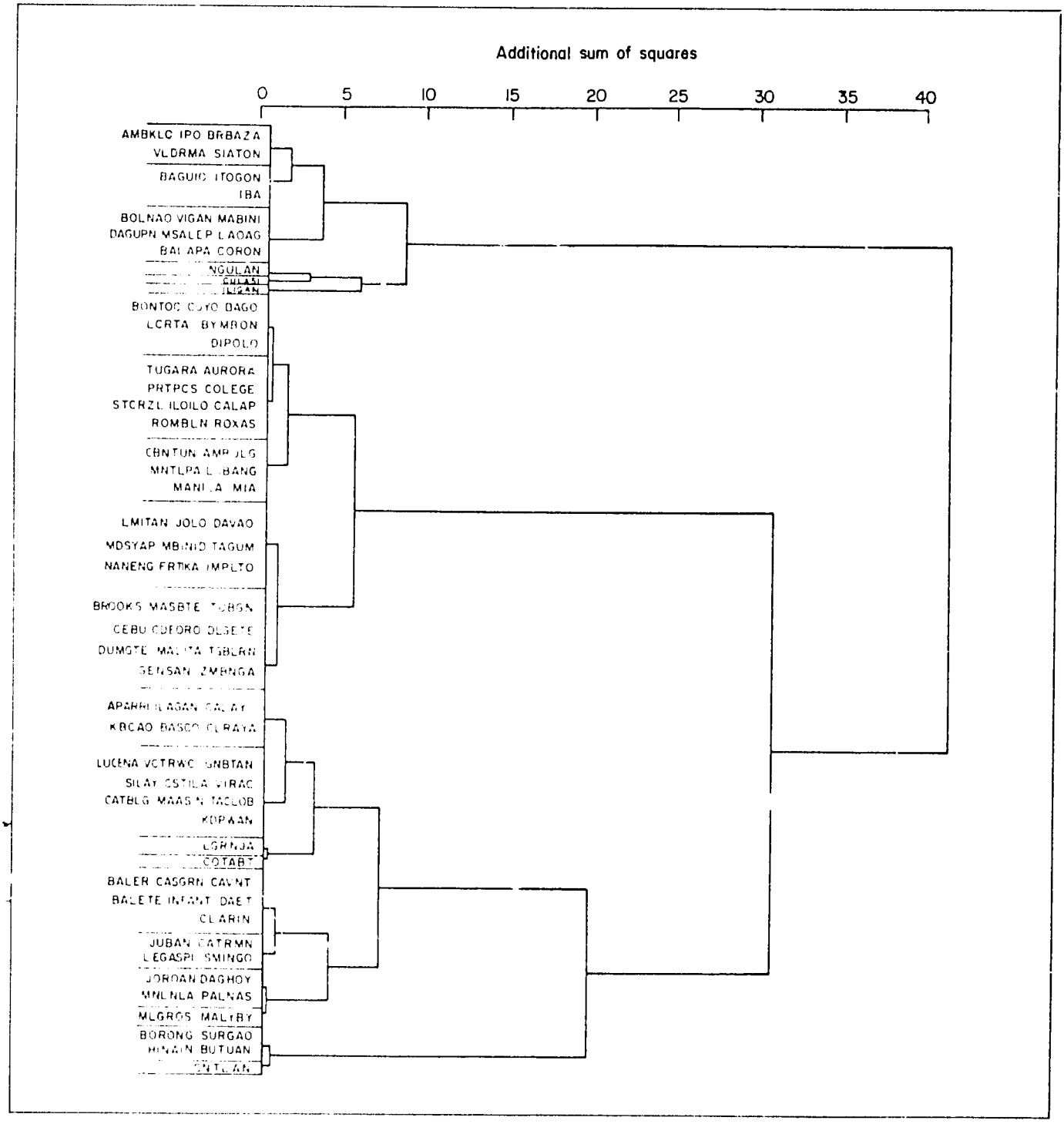
Table 4. Cross-classification of TM and TD classes by 500 mm/month criterion.

TM 500 mm class	TD 500 mm class	
	0[a]	5
0	62	6
5	5	27

[a]0 = mean monthly rainfall <500 mm for all months. 5 = mean monthly rainfall ≥500 for at least one month.

Table 5. Cross-classification of TM and TD classes by dry and wet month criteria.

TM dry-wet month class	TD dry-wet month class												
	11	12	13	14	15	22	23	24	25	33	34	35	45
11	4	3	0	0	0	0	1	0	0	0	0	0	0
12	0	9	4	0	0	2	3	0	1	0	0	0	0
13	0	0	2	1	0	0	1	1	0	0	0	0	0
14	0	0	0	1	1	0	0	2	0	0	0	0	0
15	0	0	0	2	0	0	0	0	1	0	0	0	0
22	0	1	0	0	0	9	4	0	0	0	0	0	0
23	0	0	0	0	0	3	9	1	0	1	0	0	0
24	0	0	0	0	0	0	1	1	0	1	0	0	0
25	0	0	0	0	0	0	1	1	4	0	0	0	0
33	0	0	0	0	0	3	5	0	0	6	3	0	0
34	0	0	0	0	0	0	1	0	0	2	3	0	0
35	0	0	0	0	0	0	0	0	1	0	0	1	0
45	0	0	0	0	0	0	0	0	0	0	0	0	1

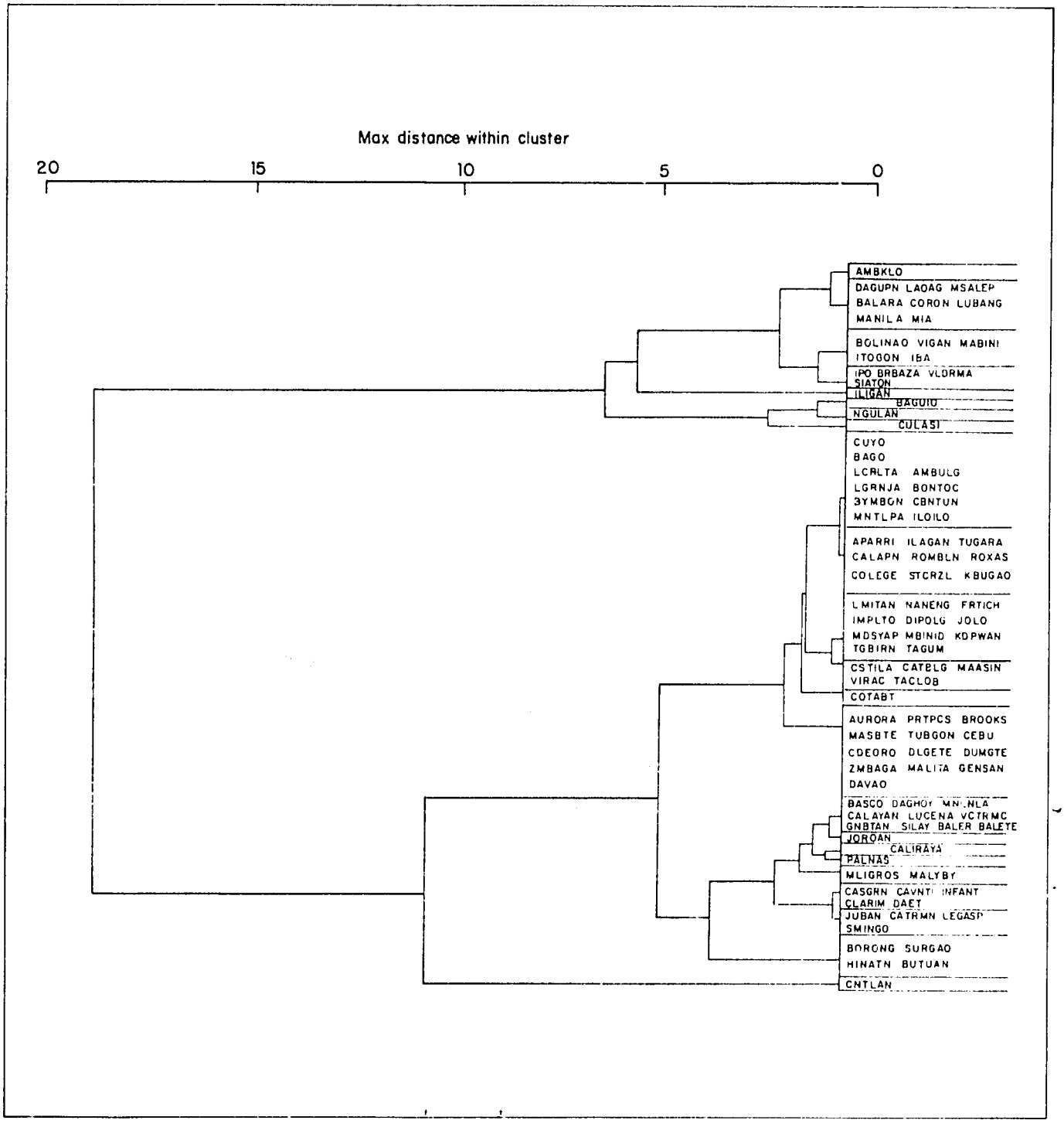


3. Abbreviated dendrogram from Ward's fusion method. The dendrogram was truncated at the fusion level corresponding to 21 clusters, including 6 nonconforming stations. Units are standardized euclidean distances.

they should expect, but should seek rainfall records for as many points as possible within and adjacent to project areas.

FN vs WD

For both clustering algorithms, the fusion level at which classes were separated was based on a combination of selected cluster statistics (maximum within-cluster distance and distance between clusters for FN and additional and within-cluster sum of squares for WD) and judgment as to what groupings constituted meaningfully different classes. Partial dendrograms of the WD and FN classifications are shown in Figures 3 and 4. The cross-classification between FN and WD classes is shown in Table 6. Ignoring the NC label momentarily, the FN and WD algorithms produced 13 and 15 clusters with 2 or more members, respectively. Within each classification, nodes were designated by units



4. Abbreviated dendrogram from the furthest neighbor fusion method. The dendrogram was truncated at the fusion level corresponding to 23 clusters, including 10 nonconforming stations. Units are standardized euclidean distances.

Table 6. Cross-classification between FN and WD classes.

FN class	WD classes															
	11	12	13	21	22	23	31	32	41	42	51	52	53	6	8	NC[a]
11	0	5	0	0	0	3	0	0	0	0	0	0	0	0	0	0
12	0	3	2	0	0	0	0	0	0	0	0	0	0	0	0	0
13	4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
21	0	0	0	5	1	3	0	0	0	0	0	0	0	0	0	1
22	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0
23	0	0	0	0	6	0	0	0	0	3	0	0	0	0	0	0
31	0	0	0	0	0	0	0	0	4	2	2	2	0	0	0	0
32	0	0	0	0	0	0	0	0	0	5	0	0	0	0	0	0
33	0	0	0	0	0	0	0	0	0	0	4	0	0	0	0	0
4	0	0	0	0	2	0	10	1	0	0	0	0	0	0	0	0
7	0	0	0	0	0	0	0	0	0	0	0	0	0	4	0	0
81	0	0	0	0	0	0	0	0	5	0	0	0	0	0	0	0
82	0	0	0	1	0	0	1	8	1	0	0	0	0	0	0	0
NC	1	0	1	0	0	0	0	0	0	1	0	2	0	0	0	5

[a]NC = nonconforming; i.e. clusters containing only a single member.

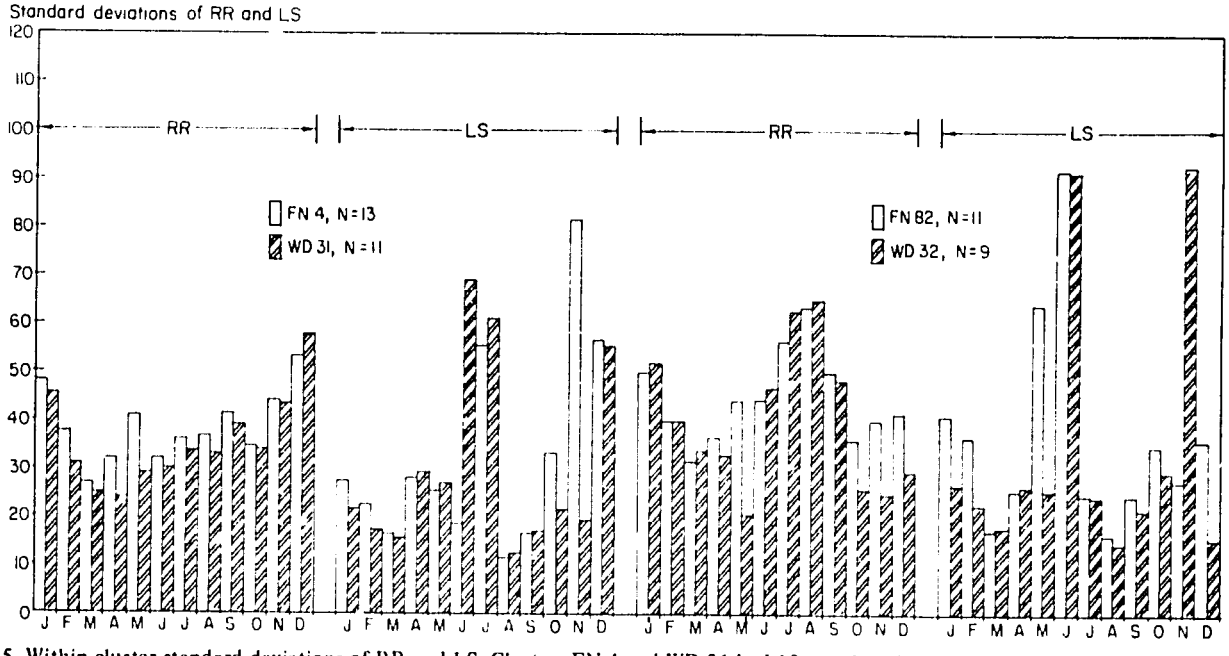
of 10 (e. g., 10, 20, 30) and stations below these nodes designated in series, such that in the WD classification, classes 51, 52, and 53 were below a single higher node. In both classifications, those stations designated NC (nonconforming) (Table 6) were in clusters of single members at the fusion level chosen to separate classes. Several nonconforming entities joined larger classes when the fusion level was slightly higher, i. e., they were clearly more similar to some entities than to others and therefore should not be considered strictly nonconforming. Caliraya and Palanas were representative of this behavior in FN, first joining each other and then Cluster 31. Iligan, however, remained isolated until the fusion level was high. WD isolated fewer nonconforming stations than FN (6 vs 10).

Table 6 shows that only two pairs of clusters – FN 4 and WD 31, and FN 82 and WD 32 – had a high percentage of stations in common at the fusion level used to separate clusters. For the 48 attributes compared in Figure 5, within-cluster variability was lower for WD classes in 32 cases. Given the fusion criteria in the WD algorithm, a generally lower within-cluster variability should be expected at similar aggregation levels.

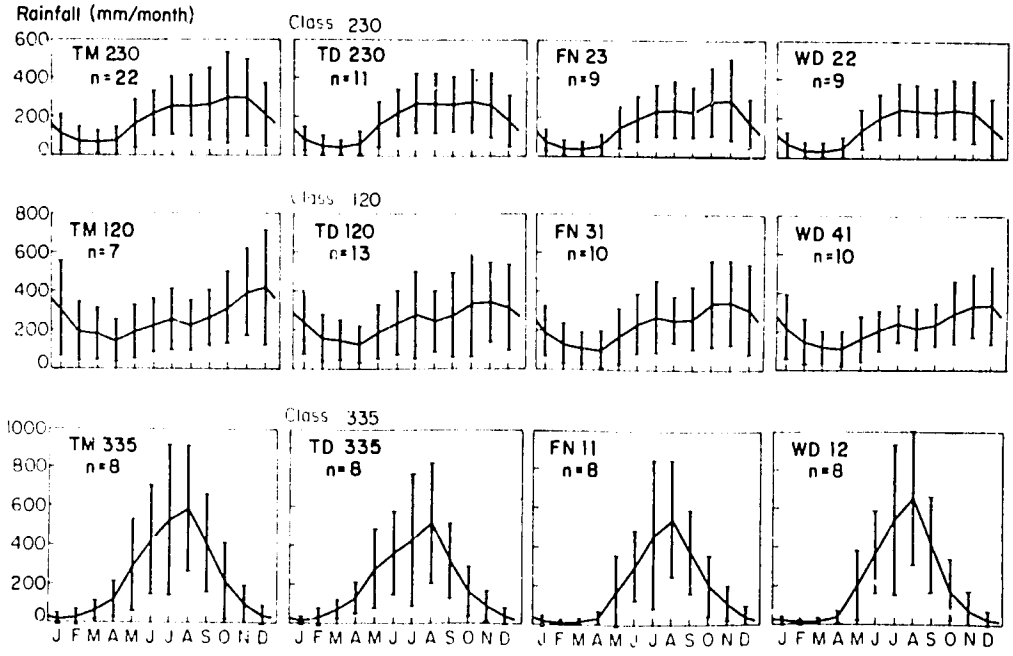
At higher fusion levels, cluster membership was more similar as Table 6 shows. When combined at a higher node, classes FN 11, 12, and 13 had 14 stations in common with WD 11, 12, and 13 classes; FN 21, 22, and 23 had 15 in common with WD 21, 11, and 23; FN 31 and 32 had 11 in common with WD 41 and 42; and FN 4, 81, and 82 had 20 in common with WD 31 and 32.

Comparisons of technical classes

Mean RR and LS for technical rainfall pattern class 230 are



5. Within-cluster standard deviations of RR and LS. Clusters FN 4 and WD 31 had 10 members in common, FN 82 and WD 33 had 8.



6. Mean RR and LS (vertical bars) from technical classes 230, 120, and 335. For the FN and WD means, the technical classes are nominal. FN and WD clusters in which monthly RR patterns showed most agreement to TD class monthly means were used in this comparison.

shown in Figure 6; i. e., monthly rainfall means corresponding to TM, TD, FN, and WD classes that conform to the 230 technical class of 2-4 dry months and 5-6 wet months. FN and WD clusters in which monthly RR patterns showed most agreement to TD class monthly means were used in this figure. Figure 6 also shows mean RR and LS for technical classes 120 and 335 from each classification. Figure 6 shows that mean RR and LS were similar regardless of method used to determine membership. Within-class variability, however, did differ considerably depending on the method used to determine membership. Figure 7 shows that for almost all 24 attributes in the 3 classes, RR and LS variability was greater in the technical classes than in the mathematical classes. The most pronounced difference occurred in the very heterogeneous 335 class. Of the two technical classifications, TD generally, but not consistently, exhibited a lower pattern of variability. Notable exceptions to the generally lower variability of TD are seen in the June-October period of class 335 LS attributes.

Across the mathematically derived classes, WD and FN exhibited approximately equal variability for 75% of the attributes, WD was clearly less variable for 18%, and FN was clearly less variable for 7%. Recalling the within-class variability comparisons in Figure 5 (FN 4 vs WD 31 and FN 82 vs WD 32), we concluded that, even though differences were not pronounced, the WD algorithm formed clusters generally less variable than clusters formed by the FN algorithm. This observation is consistent with the different criteria that the two algorithms use for fusing clusters.

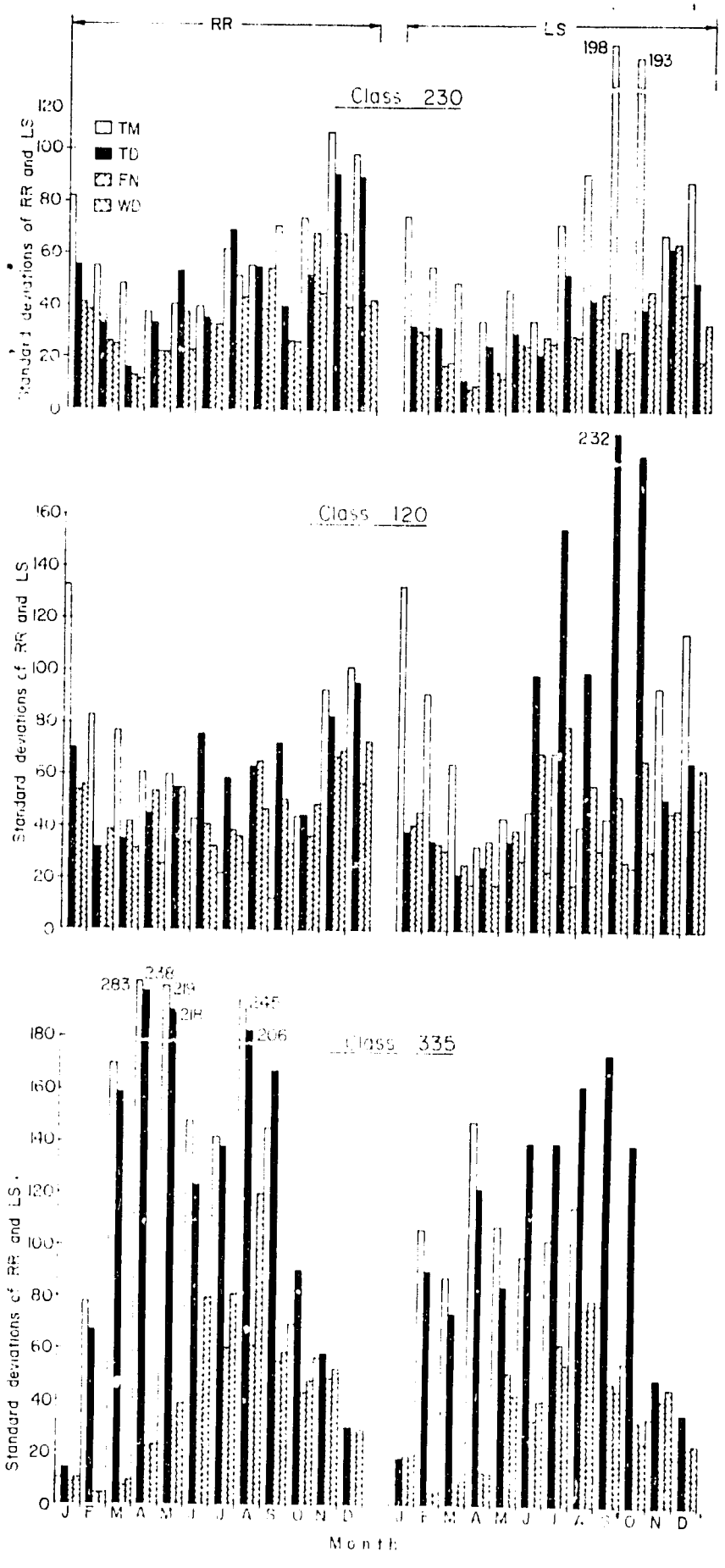
Because the WD-FN comparisons in Figures 5 and 6 showed that WD clusters were less variable over most attributes, this algorithm is preferred. Furthermore, fewer nonconforming individuals were left isolated by the WD algorithm; WD produced more multimember clusters and the numbers of members in WD cluster were more equal. In subsequent sections, WD classes were used to compare technical classes and to develop a derived classification.

TD vs WD

Recognizing that the objectives behind the TD and WD classifications differ, and that the WD method creates inherently less variable classes, a cross-classification between the two was nevertheless of interest. If the two methods would create classes containing common stations, it would imply that latent but similar differentiating criteria were used in both classifications.

The scatter in Table 7 shows very little commonality displayed at the lower levels of the classifications. At higher levels, however, patterns are evident (Table 8). The patterns are perhaps more recognizable by showing where both classifications excluded stations. For example, no stations were observed at the intersections of WD 51, 52, and 53 and the TD dry month divisions of 2, 3, or 4; at the intersections of WD 5 and TD wet month divisions of 3, 4, or 5, and at the intersections of WD 31 to 42 and the TD 500 mm/mo division. It is apparent that WD and TD had latent similarities in their criteria only for a few classes and these similarities were detectable only in the higher categories of the system.

If, as Cline (2) suggests, technical classifications should be organized from natural classes, from the scatter of Table 7, one must conclude that either the mathematical classification has not produced a satisfactory fusion into natural classes despite obvious lower within-class variability, or that a more appropriate technical classification may be formed in which the similarities among entities could be exploited. The exploitation of such similarities should better satisfy the objectives of agriculturalists who rely on similarities of rainfall patterns to identify areas in which new crops or intensified cropping systems are likely to be adapted.



7. Within-class standard deviations of RR and LS by month, from technical classes 230, 120, and 335. These classes correspond to those in Figure 6.

Table 7. Cross-classification between TD classes and WD classes.

TD class	WD class															
	11	12	13	21	22	23	31	32	41	42	51	52	53	8	6	NC[a]
110	0	0	0	0	0	0	0	0	0	0	6	1	0	0	0	0
115	0	0	0	0	0	0	0	0	0	0	2	0	2	0	3	0
120	0	0	0	0	0	0	0	0	4	1	2	3	1	1	0	1
125	0	0	0	0	0	0	0	0	0	0	3	0	1	0	1	1
230	[illegible]	0	0	0	0	0	0	2	2	0	0	0	0	0	0	1
140	0	0	0	0	0	0	0	3	1	0	0	0	0	0	0	0
150	0	0	0	0	0	0	1	2	0	0	0	0	0	0	0	0
220	0	0	0	4	1	0	0	0	2	2	0	0	0	1	0	1
225	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
230	0	0	0	1	5	1	0	1	1	2	0	0	0	0	0	0
235	1	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0
240	0	0	0	0	1	0	1	0	0	1	0	0	0	0	0	0
250	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
330	0	0	0	1	1	1	0	1	0	0	0	0	0	0	0	0
335	2	6	1	0	0	1	0	0	0	0	0	0	0	0	0	1
340	0	0	0	0	1	3	0	0	0	0	0	0	0	0	0	0
345	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0
350	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0
450	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0

[a]NC = nonconforming.

Table 8. Cross-classification between WD and TD classes by dry month, wet month, and 500 mm/month criteria.

TD month class	WD class														
	11	12	13	21	22	23	31	32	41	42	51	52	53	6	8
						Dry month criterion									
1	0	0	0	0	0	0	1	7	7	1	7	4	4	4	1
2	3	0	2	5	7	1	7	1	3	5	0	0	0	0	1
3	2	8	1	1	2	5	2	1	0	0	0	0	0	0	0
4	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0
						Wet month criterion									
1	0	0	0	0	0	0	0	0	0	0	2	1	2	3	0
2	2	0	0	4	1	0	0	0	6	3	5	2	1	2	0
3	3	6	3	2	6	3	0	4	3	2	0	0	0	0	0
4	0	2	0	0	2	3	1	3	1	1	0	0	0	0	0
5	0	0	0	0	0	0	10	2	0	0	0	0	0	0	0
						500 mm criterion									
0	0	0	0	6	9	5	11	9	10	6	2	4	1	0	2
5	5	8	3	0	0	1	0	0	0	0	5	0	3	4	0

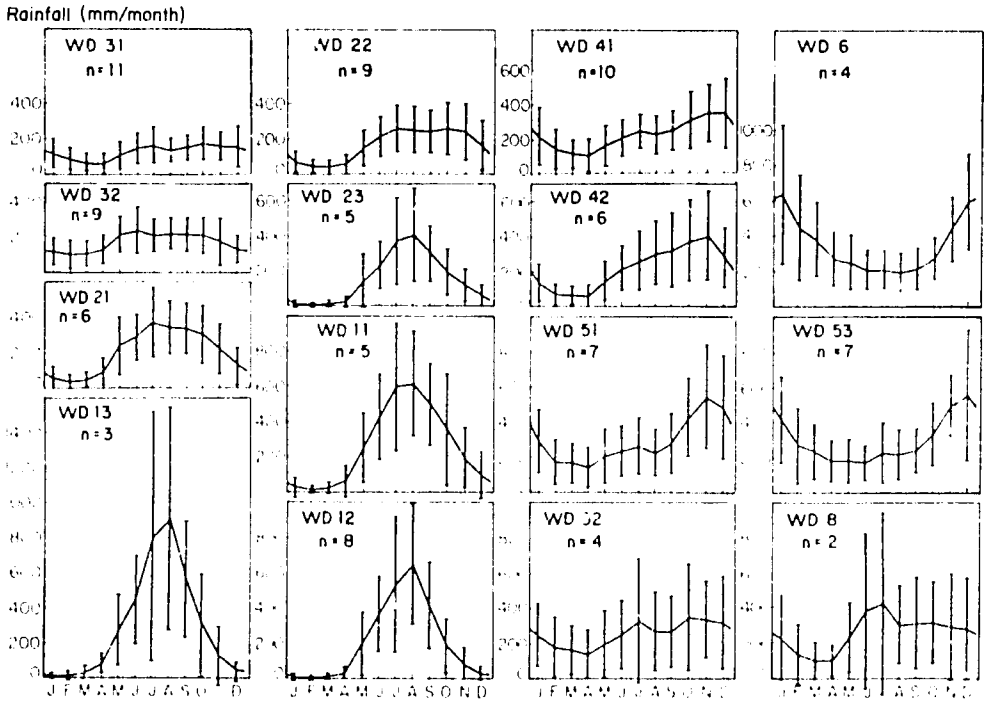
Rainfall patterns of WD classes

Mean RR and LS of the 15 WD classes are shown as a series of frames in Figure 8. The continuity in this series is discernible but we will discuss the association among clusters in a later section where we present a derived-classification system.

Contrary to expectations, we found no clusters that exhibited similar mean monthly rainfall but which differed in rainfall variability as measured by SD. In the process of drawing Figure 8, it became obvious that RR and LS were correlated, both within a cluster and across clusters. Correlations of RR-LS pairs for a given month were significant. Moreover, correlations between RR from adjacent months were very high, as were LS from adjacent months.

By applying factor analysis, 3 factors corresponding to eigenvalues greater than 1 were extracted. These 3 factors explained 80% of the total variance among the 24 attributes. Factor 1 extracted the strong correlation among the December-April attributes, Factor 2 among the May-September attributes, and Factor 3 among the October-November attributes (Table 9). Low communalities were evident during transition periods. The factors accounted poorly for LS in the dry-wet (May-June) and wet-dry (October-November) transition periods and for RR in May.

Because correlations between RR and LS were high and only 3 factors were extracted from the correlations, we concluded that the mathematical classification methods were clustering simultaneously on RR and LS, and that most cluster separation was on rainfall differences within three periods: December-April, May-September, and October-November.



8. Mean RR and LS (vertical bars) for the 15 WD clusters.

A derived classification

Seasonal rainfall patterns are apparent in the 15 WD cluster means shown in Figure 8. Using these seasonal patterns and the general knowledge of meteorological factors contributing to them, a classification was derived for Philippine rainfall stations. Table 10 is a key to the classification, DERIV, in which rainfall level and seasonal modality are used to differentiate stations at the highest category. Dry season severity, level of wet season maxima, and peakedness of the wet season are differentiating criteria used at lower levels in the classification.

Table 9. Factor matrix and communalities of 24 attributes from 100 Philippine raingauging stations.

Attribute	Month	Factor 1	Factor 2	Factor 3	Communality
RR	Jan	0.946	-0.180	0.144	0.949
	Feb	0.963	-0.182	0.037	0.962
	Mar	0.973	-0.143	0.053	0.970
	Apr	0.912	-0.049	0.032	0.835
	May	0.290	0.641	0.004	0.495
	Jun	-0.169	0.921	-0.025	0.878
	Jul	-0.263	0.920	-0.059	0.918
	Aug	-0.230	0.896	-0.099	0.897
	Sep	-0.225	0.906	0.152	0.895
	Oct	0.210	0.259	0.827	0.795
	Nov	0.556	-0.191	0.745	0.900
	Dec	0.803	-0.291	0.452	0.897
LS	Jan	0.874	-0.129	0.255	0.845
	Feb	0.931	-0.133	0.157	0.909
	Mar	0.922	-0.073	0.219	0.903
	Apr	0.753	0.129	0.290	0.668
	May	0.113	0.702	0.102	0.516
	Jun	-0.035	0.758	0.046	0.578
	Jul	-0.176	0.807	-0.049	0.684
	Aug	-0.192	0.870	0.048	0.796
	Sep	-0.095	0.697	0.229	0.547
	Oct	0.020	0.421	0.434	0.366
	Nov	0.194	0.063	0.686	0.512
	Dec	0.598	-0.077	0.590	0.711

Applying the criteria in Table 10, the 100 stations were placed into the 19 classes of DERIV. The means of class members and idealized rainfall patterns for each class are shown in Figure 9. At the higher categories, differences in seasonal patterns and rainfall levels are evident. At the lower categories, differences are smaller and generally appear in only one of the distinct two or three seasons in the pattern. The 19 rainfall stations that most closely typify the idealized patterns are listed in Table 11.

In the lower categories, where class differences are small, technical groupings may be made for some agricultural applications. For example, classes such as 121 and 122, and 131 and 132 may be aggregated. However, the extra 1-2 mo of rainfall exceeding 200 mm/mo that can be expected in robust patterns may be significant if cropping is intensified by planting both early and late crops during the wet season.

In the Philippines, bimodal rainfall patterns do occur, although from differentiating criteria of Table 10 and class means in Figure 9, bimodal expression is weak, and for many technical purposes, classes 232, 321, and 322 could be combined, as could classes 231 and 211. Because inter-peak rainfall minimum is brief and because its timing may vary slightly between years, the minimum between peaks is not strongly expressed in mean monthly data.

Table 10. Key to DERIV rainfall pattern classes.

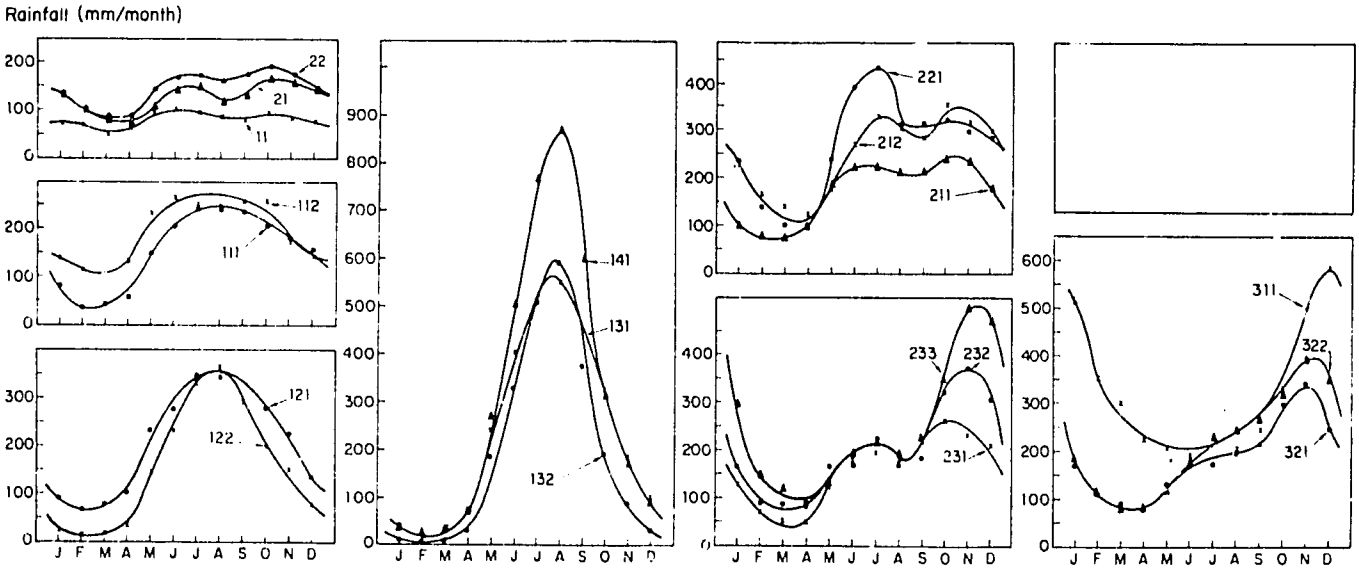
0. Low rainfall, less than 3 mo > 200 mm.
   01 (1). Less than 6 mo > 100 mm.
   02. 6 or more mo > 100 mm.
      021. Less than 6 mo > 150 mm.
      022. 6 or more mo > 150 mm.

1. High rainfall, 3 or more months >200 mm, May-Sep unimodality.
   11. 2 or more consecutive months >200 mm and 0 or 1 > 300 mm.
      111. 2 or more months in the dry period (Jan-Apr) <50 mm.
      112. 0 or 1 mo in the dry period < 50 mm.
   12. 2 or more consecutive months > 300 mm and 0 or 1 > 400 mm.
      121. Robust, 6 or more months > 200 mm.
      122. Peaked, less than 6 mo > 200 mm.
   13. 2 or more consecutive months > 400 mm and 0 or 1 > 650 mm.
      131. Robust, 6 or more months > 200 mm.
      132. Peaked, less than 6 mo > 200 mm.
   14 (1). Two or more consecutive months > 650 mm

2. High rainfall, 3 or more months > 200 mm, May-Sep and Oct-Feb bimodality.[a]
   21. May-Sep maximum about equal to Oct-Feb maximum.[b]
      211. Less than 4 mo > 300 mm.
      212. 4 or more months > 300 mm.
   22 (1). May-Sep maximum greater than Oct-Feb maximum.
   23. May-Sep maximum less than Oct-Feb maximum.
      231. Weak maximum, less than 3 mo > 300 mm, none > 500 mm.
      232. Moderate maximum, 3 or 4 mo > 300mm, none > 500 mm.
      233. Strong maximum, 4 or more months > 300 and 1 or more > 500 mm.

3. High rainfall, 3 or more months > 200 mm, Oct-Feb unimodality.
   31 (1). 2 or more consecutive months > 400 mm.
   32. Less than 2 consecutive months > 400 mm.
      321. 5 or less months > 200 mm.
      322. More than 5 mo > 200 mm.

[a]A pattern is regarded as bimodal if there are differences of at least 25 mm between both months of maximum monthly rainfall in the May-Sep and Oct-Feb peaks and the lowest rainfall of any intervening month and at least 2 mo between the months of maximum rainfall in the peaks.
[b]A pattern is regarded as equal if the months of maximum rainfall in the peaks differ by less than 50 mm.



9. Mean monthly rainfall means from members in the 19 DERIV classes (data points) and idealized rainfall pattern (curves) corresponding to these data points.

A cross-classification between DERIV and WD appears in Table 12. Although most WD classes were distributed over 3 or less closely related DERIV classes, 3 WD clusters (22, 32, and 41) were widely distributed across DERIV classes. The wider distribution of WD 41 members arose from the bimodal criteria, where DERIV 321 and 322, although not bimodal, exhibit a 2-4 mo (June-September) period when mean monthly rainfall is almost uniform. In DERIV 231 and 232, rainfall declines slightly in the August-September period before increasing in the October-December period. The slight decline, to which the mathematical method was only weakly sensitive, probably caused the wide distribution of WD 41 members among DERIV classes.

WD 22 and 32 members were concentrated among the low rainfall, May-September unimodal DERIV classes (111, 112, 121, and 122). Several WD 22 and 32 members, however, did exhibit sufficient bimodality to be placed into DERIV 211. Where 6 or more consecutive months have monthly rainfall means between 200 and 300 mm, bimodality is very weak, often being a depression during

Table 11. Stations and mean monthly rainfall typifying the DERIV classes.

DERIV Class	Station	Mean monthly rainfall											
		Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
11	General Santos	72	73	48	78	93	103	95	89	81	98	87	78
21	Tagbilaran	120	86	90	76	93	183	162	128	148	181	193	145
22	Dalaguete	122	117	101	78	134	167	193	162	160	213	183	153
111	Aurora	56	20	32	23	99	190	214	196	206	211	166	152
112	Kidapawan	185	158	96	156	225	228	227	232	264	271	190	176
121	Basco	50	43	58	104	238	228	317	306	334	252	222	102
122	Ambulong	25	12	20	42	158	215	321	330	294	223	182	102
131	Valderama	47	10	24	48	326	495	627	613	548	358	193	94
132	Masalep	7	3	9	45	202	290	470	609	328	154	49	17
141	Iba	5	4	14	37	230	543	834	940	616	225	90	32
211	Jolo	116	105	101	147	219	244	177	182	193	239	219	169
212	Dagohoy	306	193	155	114	159	270	347	258	287	312	335	265
221	Milagros	302	165	75	72	198	373	460	310	258	308	362	378
231	Dipolog	142	92	84	100	232	267	241	255	252	304	302	234
232	Victoria Mills	197	129	118	106	193	219	254	230	221	365	404	305
233	Clarin	390	188	189	121	196	308	243	266	255	343	549	548
311	Hinatuan	709	511	461	350	290	227	209	205	205	227	361	602
321	Aparri	138	83	56	44	110	178	196	238	286	360	367	208
322	Calayan	192	123	71	42	94	186	273	303	323	346	399	342

Table 12. Cross-classification between DERIV classes and WD class.

DERIV class	WD class													
	11	12	13	21	22	23	31	32	41	42	51	52	53	99
11	0	0	0	0	0	0	4	2	0	0	0	0	0	0
21	0	0	0	0	0	0	5	0	0	0	0	0	0	0
22	0	0	0	0	0	0	1	0	0	0	0	0	0	0
111	0	0	0	0	2	0	1	1	0	0	0	0	0	0
112	0	0	0	0	0	0	0	2	1	0	0	0	0	0
121	0	0	0	3	0	0	0	1	0	1	0	0	0	0
122	0	0	0	0	1	4	0	0	0	0	0	0	0	0
131	4	2	0	2	0	0	0	0	0	0	0	0	0	1
132	0	5	0	0	0	2	0	0	0	0	0	0	0	0
141	1	1	3	0	0	0	0	0	0	0	0	0	0	2
211	0	0	0	0	5	0	0	3	0	0	0	0	0	0
212	0	0	0	0	0	0	0	0	1	0	0	3	0	0
221	0	0	0	0	0	0	0	0	0	0	0	0	0	0
231	0	0	0	1	1	0	0	0	3	0	0	0	0	2
232	0	0	0	0	0	0	0	0	2	1	2	1	0	0
233	0	0	0	0	0	0	0	0	0	0	3	0	1	0
311	0	0	0	0	0	0	0	0	0	1	2	0	3	1
321	0	0	0	0	0	0	0	0	1	2	0	0	0	0
322	0	0	0	0	0	0	0	0	2	1	0	0	0	0

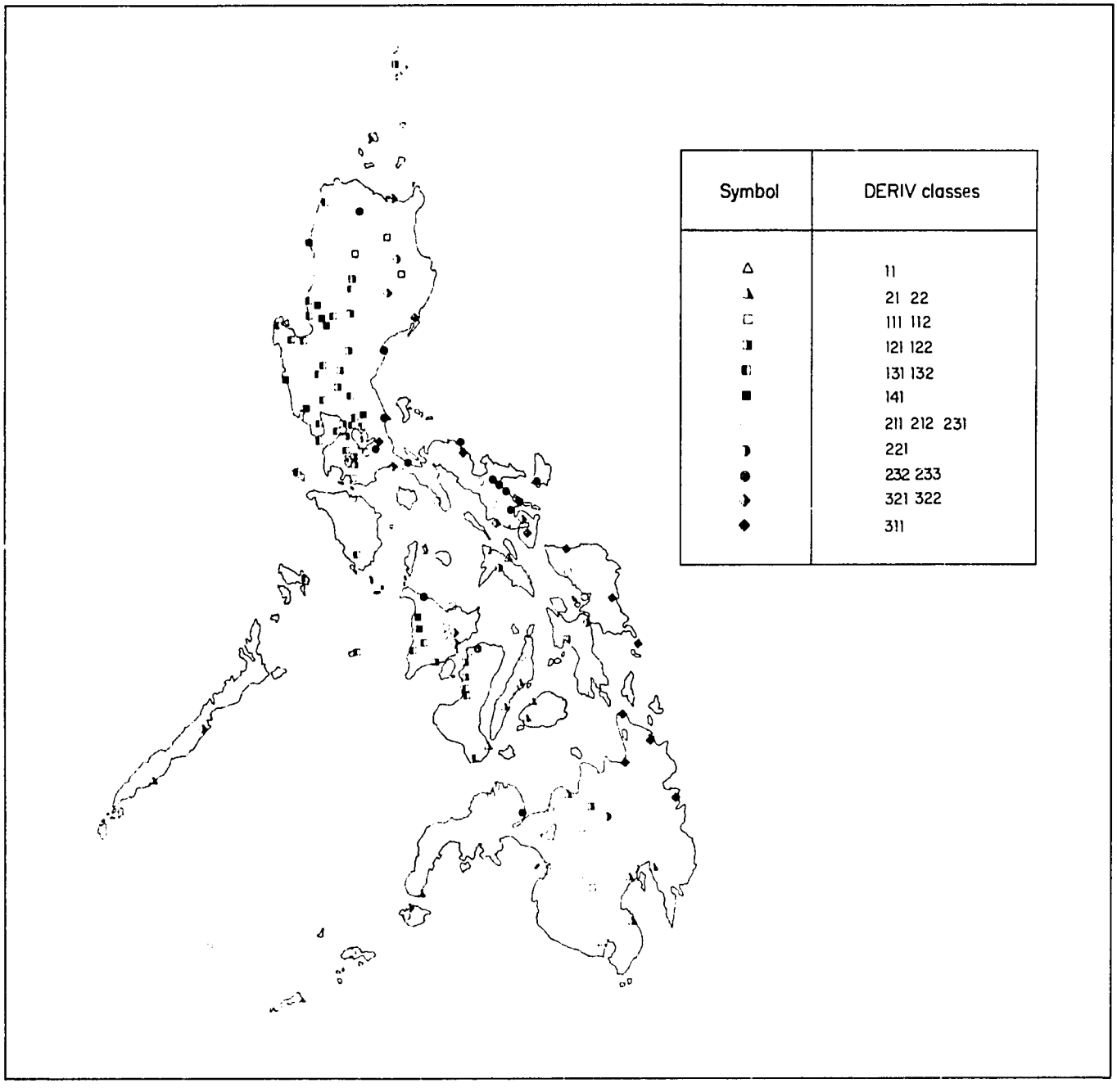
August and September of only 30-50 mm relative to the 2 peaks. The WD method obviously did not discriminate on this nuance, but because the bimodality phenomenon was a dimension in the continuum, DERIV 211 was defined as a class separate from DERIV 111 and 112.

It must be emphasized that we have attempted to illustrate the type of classification possible. The differentiating criteria were applied to the original 100 stations plus 37 additional stations. To reduce complexity in display, classes were combined. Locations of the codes shown in Figure 10 suggest spatial patterns among the classes as well as deviations from those patterns.

Sources of rainfall seasonality

Figure 10 was drawn to facilitate discussion of the meteorological factors contributing to the geographical distribution pattern. Although no attempt was made to map the DERIV classes, similarities clearly appear in the class distribution in Figure 10 and in boundaries on the maps from Huke (Fig. 1), expressing peak rainfall seasonality and in Manalo (Fig. 2), stressing seasonal duration. The symbols in Figure 10 convey information on seasonality, seasonal duration, and mean monthly total rainfall.

Origins of rainfall patterns. Rainfall patterns arise from the seasonality of air masses carrying moisture to the



10. Locations of DERIV class members. Classes were combined to reduce complexity. See Figure 9. Thirty-seven stations were added to the original 100.

country, the seasonality of disturbances causing precipitation, and the distribution of topographic features interacting with the meteorological factors to create spatial variations in precipitation patterns. Manalo (13) and Flores and Balagot (4) discuss major meteorological and topographical factors that create the complex temporal and spatial rainfall patterns seen in Figures 9 and 10. The discussion in this section is based largely on the discussions by Manalo and by Flores and Balagot.

By the directions from which they approach the archipelago and their seasonalities, three maritime tropical air masses – the northeast monsoon, the southwest monsoon, and the North Pacific trades – contribute to rainfall patterns. The northeast monsoon begins in October as a weak stream, strengthens through to January and disappears by April. Most of the moisture in this air mass lies beneath a moderate inversion located at 1500-2000 m. As it crosses the eastern coastline, this air mass produces much of the rainfall released on the windward sides of mountains. Very little rain falls to the lee of the mountains. Unimodal DERIV rainfall patterns with November-January peaks (311, 321, and 322) obtain a moderate to high proportion

of their precipitation from this air mass. The second peaks in bimodal patterns (211, 212, 221, 231, 232, and 233) derive much rainfall from this air mass. The very dry December-March periods of DERIV patterns 122, 131, 132, and 141 are found in the northeast monsoon rain shadows to the lee of high mountain ranges.

Whereas the northeast monsoon is shallow, the southwest monsoon is deep, often attaining an altitude of 10 km. Starting usually in May, this air mass crosses the China and Sulu Seas, peaking in August and disappearing by October. The air mass is unstable, with frequent convective activity. It is the main contributor to June-August peaks in the unimodal and bimodal patterns. The very strong peaks of DERIV patterns 131, 132, and 141 are found along western coastlines and in mountain ranges on the west sides of the islands. These classes are found frequently in central and northern Luzon where air flow across the China Sea is strong, steady, and undisturbed. Because the air mass is deep and unstable from June to September, rainfall is moderate in the western, central, and southern portions of the archipelago.

The North Pacific trades originate in the central Pacific and arrive from the northeast, east, and southeast. These trade winds are the flow of a shallow air mass that dominates over the entire archipelago in April and early May, and over the central and southern areas in October. Convective activity is moderate, but afternoon thunderstorms are common. The air mass also contributes to orographic rainfall. Easterly waves, periodic disturbances moving within the North Pacific trades about twice per week, contribute moderately to precipitation, especially over mountain ranges on the east coast. The North Pacific trades contribute moderately to April and May rainfall along the northwestern coast in DERIV classes 232, 233, and 311, and to October rainfall in all classes found along the east coast of the central and southern islands.

From November to January, weak cold fronts pass across the northern half of the country, creating frontal disturbances that contribute to the moderate-to-high November-December rainfall common to DERIV patterns found in northern locations (DERIV patterns 112, 121, 321, and 322).

The intertropical convergence zone appears in the southwest in May, progresses northward to a limit near the northern boundary of the Philippines by July, and moves south of the country by December. Surface air converges from north and south at this low trough. These convergence zones influence rainfall patterns by contributing precipitation as frequent rain showers, often intense but localized. The weak bimodality common to rainfall patterns of interior central and southern islands is partly attributable to a decline in disturbances when this zone is northward during July, August, and September. In this northward position, this low trough also disrupts flow of the southwest monsoon across the southern half of the archipelago.

Tropical cyclones, although comparatively restricted in area (400-700 km in diameter), short in duration (36 h or less over a point), and irregular in occurrence (within the Philippines, an average of 19 are observed per year), are major contributors to wet season rainfall. Ninety percent of these cyclones occur between June and December, with August the modal month. Only about 10% of them track through the southern one-fourth of the country, whereas 25-40% track through the east central islands of Samar and Masbate. Another 25-40% track through the eastern and northern provinces of Luzon. Ten to 25% track through the western portions of Luzon and through the western Visayas group. Of the tropical cyclones that pass across the Philippines, those in May, June, November, and December tend to track through the Visayan Islands. July, August, and September tropical cyclones generally follow more northerly tracks. Many tropical cyclones track northward, staying east of the archipelago, but traveling parallel to the coastline. The fringes of these depressions contribute directly to rainfall over the east coast (10). By intensifying monsoon flow, they indirectly increase rainfall on areas lying to the southwest of the system.

Topography also affects seasonal rainfall patterns. The influence of the north-south trending mountain ranges on the east coasts of many islands has been mentioned. To their leewards, these mountains also create rain shadows especially from January to April. Minor terrain features and local circulation systems, arising from seasonal and diurnal land-water body temperature differences, also affect seasonal patterns.

CONCLUSIONS

Technical class memberships, using class criteria determined from station wet month-dry month data, did not agree closely with membership determined from mapped classes. When classes were determined from station data, 53% of the stations were in classes different from those indicated by map boundaries. Although the map of technical classes gives an overview of wet and dry season durations at the national level, technical classes determined from data of nearby stations will probably be more accurate than if determined by location on the rainfall pattern map.

Analyses showed very little correspondence between technical and mathematical class memberships. Furthermore, variability was greater within classes determined by technical criteria than those determined by the mathematical algorithms. The greater variability is undesirable. The WD clustering algorithm, with a fusion criterion based on a minimum increase in sum of squares obtained in fusing two clusters, formed clusters that averaged less within-cluster variance than those formed by the FN algorithm. WD left fewer nonconforming stations and produced more multimember classes with a more even frequency of mem-

bership. Therefore, between the two mathematical clustering algorithms, WD was preferred.

High RR-LS correlations were found among the 24 attributes used in the mathematical classifications. Factor analyses showed that 3 factors explained 80% of the variability in these 24 attributes, respectively reflecting seasonality in the rainfall patterns as follows: December-April (dry season), May-September (main wet season), and October-November (wet-dry transition or secondary wet season).

The mathematical classifications revealed seasonal differences in rainfall level and variation. Using the seasonal patterns evident in WD clusters, a natural classification, DERIV, was developed using criteria of rainfall level, seasonal modality, level and peakedness of main wet season maxima, and dry season severity.

Rainfall patterns corresponded to the seasonality of air masses and disturbances, and to major topographic features. This correspondence is regarded as evidence that the derived classification expresses causal meteorological factors. Because these natural classes simultaneously carry information on rainfall level, seasonal distribution and duration, dry season severity, and lower within-cluster variability, DERIV classes should be superior to technical classes for planning agricultural research and development projects and extrapolating results.

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