RAINFALL PREDICTION FOR AGRICULTURE AND WATER RESOURCE MANAGEMENT IN THE UNITED STATES VIRGIN ISLANDS

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ABSTRACT

This paper finds that the gamma model provides a better fit to the rainfall distribution in the United States Virgin Islands, than does the more popular normal distribution model, especially for the dry months. It also shows that in areas of limited longitudinal rainfall data, prediction can be done using shorter rainfall periods than usually the case. Finally, the paper applies the modeling effort to agriculture, crop insurance, and water resource management.

Introduction

This paper is an attempt to use statistical models to predict rainfall patterns in the United States Virgin Islands, a microclimatic region of the Caribbean, as an input into urban water management, agriculture, and crop insurance. The paper describes rainfall variability in the United States Virgin Islands. Statistical models of rainfall prediction are examined, especially with regard to their applicability to data that reflect the pattern of rainfall in the territory. Two statistical models are chosen and used to predict monthly rainfall variability for selected stations in the United States Virgin Islands. For each station, prediction is made of the representative wet and dry months. The models are then evaluated to determine which predictive model can be applied to each of these representative rainfall periods. The applications of this modeling effort to urban water resource management and agriculture are discussed.

Rainfall modeling and prediction are an essential input into agriculture, especially in regions of light, variable, and unreliable rainfall. In such regions, adequate knowledge is needed of the probability of wet and dry periods, because bumper harvests and lean years may depend on rainfall variability. So far, however, there is very little reliable knowledge in this area of study, especially on small subtropical islands, to be used as inputs into effective agricultural planning (Mills, 1984). In the Caribbean, despite the relationship between rainfall variability and production levels in the plantation economies, very little effort has been devoted to the role of rainfall periodicity on food crops. These crops have a growing season generally shorter than those for plantation crops.

For extension officers serving small farmers, especially those growing food crops, understanding rainfall variability will help in making decisions on planting, processing, marketing, and storage activities so as to maximize the farmer's profits. An effective method of rainfall prediction may also be attractive to insurance companies, governments, and other agencies involved in insurance planning for food crops farmers and their properties.

Data Limitations

Unlike the other English-speaking islands of the Caribbean, the U.S. Virgin Islands lacks time series climatic data for periods before 1950. The main sources of rainfall data for the territory are the *Annual reports, Climatological Data for Puerto Rico and the U.S. Virgin Islands,* available at the U.S. Weather Bureau in San Juan and the National Climatic Data Center, Asheville, North Carolina. The available data were found to have a few problems. One was that measurements were made in inches, so we were forced to use inches in our data analysis. A second problem was that no data were collected for the territory in the years 1953 and 1954. We used moving averages to interpolate the missing data. This procedure may underestimate the data for these years. A third was that only Dorothea on St. Thomas, Cruz Bay on St. John, and Anna's Hope on St. Croix have time series rainfall data extending for over 40 years. Therefore, the averages shown in table 1 were computed using 47 years each for Dorothea and Cruz Bay, 40 years each for Cyril King and Hamilton airports, but only 30 years each for Fort Mylner, Annaly, East Hill, Catherineburg, and Lameshur Bay.

A study by Court (1969) in Israel, a semi-arid country with marked rainfall periodicity, showed that shorter periods as little as 15 years can be used successfully in rainfall prediction. However, no such study is known to have been done in the Caribbean. Some stations which were potential sites for selection on the basis of hydrological and spatial variability were eliminated because the time series data were limited, or the stations had periods of missing data that were too long to be useful for analysis. However, the selected stations showed as much climatic and hydrological variability as data availability would permit.

Rainfall Regime of the U.S. Virgin Islands

The U.S. Virgin Islands, located about 18° N and 65° W with a total area of about 343.2 km^2, is composed primarily of three islands: St. Thomas (72.8 km^2), St. Croix (218.4 km^2), and St. John (52 km^2). Tropical easterlies from the predominant trade winds bring maritime tropical air masses from moist high-pressure cells to produce orographic rainfall along the northern coasts. Rainfall shows a marked annual cycle with a peak in the summer when the intertropical convergence zone is dominant in the area. A distinct season of low rainfall distinguishes the winter months.

The small size of these islands limits the formation of large cloud masses from convectional or frontal processes. Consequently, the annual rainfall on these relatively low tropical islands hardly exceeds 1500mm. (Smith,1986). Each island,however, has highland ranges between 300 and

600m in height running from east to west. These ranges induce orographic rainfall from the prevailing northeast trade winds, so that the islands display a rainfall variability beyond what their small size would suggest. For example, on the northern windward slopes, annual rainfall may exceed 60 inches, while on the southern leeward slopes, it may be less than 30 inches (Smith,1986).

This remarkable variability in rainfall is depicted in Table 1, which shows the average monthly and annual rainfalls for nine stations in the U.S. Virgin Islands. These are Dorothea, Fort Mylner, and Cyril King Airport on St. Thomas; Annaly, Hamilton Airport and East Hill on St. Croix; Cruz Bay, Catherineburg, and Lameshur Bay on St. John. These stations were selected to show as much geographic and hydrological variations as data availability would permit. Dorothea on the north side of St. Thomas is on the windward side of Crown Mountain (467 m), Fort Mylner is on

Table1. Mean Monthly Rainfall for selected Stations (inches). Compiled by the authors.

Station	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Total
St. Thomas													
1 Dorothea	2.68	1.74	1.97	2.93	4.83	2.90	2.98	3.68	5.51	5.71	5.12	3.04	43.09
2 C. Airport	2.00	1.47	1.76	2.76	4.28	2.88	3.11	4.18	5.53	5.52	4.70	3.08	41.27
3 Ft. Mylner	2.56	1.73	2.29	3.40	5.64	3.00	3.26	4.35	5.53	6.38	6.41	4.94	49.49
St. Croix													
4 Annaly	3.10	2.15	2.27	3.43	5.70	3.38	3.67	4.78	6.64	6.17	7.45	4.33	53.07
5 C. Airport	2.21	1.95	1.75	2.62	4.06	2.84	3.15	4.06	4.98	5.39	5.17	3.64	41.83
6 East Hill	1.94	1.45	1.44	2.22	3.87	2.47	2.77	4.05	4.30	4.59	5.16	3.60	37.86
St. John													
7 Cruz Bay	2.40	1.89	1.78	2.82	4.93	2.94	3.51	4.13	5.21	5.31	4.90	3.37	43.19
8 Cath'burg	3.13	2.09	2.49	3.62	5.69	2.99	3.81	4.81	5.67	5.93	6.64	4.72	51.59
9 Lameshur	2.60	1.79	2.02	3.10	5.50	2.81	3.20	4.21	5.40	5.21	6.39	4.33	46.56

the east side of the island tangential to the prevailing north-east trade winds, while Cyril King Airport, formerly Truman Field, is on the south leeward side of the island. On the island of St. Croix, Annaly is on the windward side of Mt. Stewart (245 m), Hamilton Airport is on the southern leeward side of the island, while East Hill is on the coast of the dry east end of the island. On the island of St. John, Catherineburg is on the more humid windward side of the island, Cruz Bay is on the leeward west coast, while Lameshur Bay is on the leeward south coast. Therefore, on each island, we have selected stations on the windward and leeward sides, and where data availability permits, stations on the east and west of the island.

There is marked variability in annual rainfall from island to island (Table 1). St. John, which is the most easterly of the three islands, averages 47.11 inches annually for the three selected stations. St. Thomas and St. Croix, which lie further west, average 2.5 to 3 inches less, with St. Thomas to the north of St. Croix averaging 44.62 inches, and St. Croix to the south of St. Thomas averaging 44.25 inches. There is greater annual variability in rainfall within islands. On St. Thomas, Fort Mylner to the east receives the heaviest fall of 49.49 inches, Dorothea on the northern windward slope receiving 43.09 inches, while Cyril King on the southern leeward coast receives 41.27 inches, giving a range of 6.4 inches for these stations. On the island of St. Croix, the station with the heaviest rainfall is Annaly with 53.07 inches, while the lowest rainfall is at East Hill with 37.86 inches, giving a range of 15.21 inches. On St. John, the heaviest rainfall is 51.59 at Catherineburg, while the lowest is at Cruz Bay with 43.19 inches giving a range of 8.4 inches. Thus, St. John, which is smaller in size than St. Thomas, has more annual rainfall variability as indicated by the range for selected stations. St. Croix, which is about three times the size of St. Thomas, experiences almost three times as much annual rainfall variability as the latter station as indicated by the range.

Monthly rainfall also displays marked variability, though a very consistent seasonal pattern is displayed by all selected stations. The heaviest rainfall months are September, October and November, each of which receives five inches or more of rain. After November, monthly totals tend to decrease gradually until February or March which are the two driest months. Rainfall totals are about 1.79 inches or below for each of these months. The low rainfall of these months reflect the near-northerly presence of the high pressure cells just north of the Equator where surface winds are hot and diverging, and contribute little moisture. After March, the heat equator moves north and the moist northeastern trades begin their slow but increasing dominance of the area. At all stations the month of May is usually wet compared to April or June. It is also marked by extreme variability. In almost all cases, the coefficient of variation exceeds 70 percent.

Rainfall periodicity is evident also from a longitudinal profile (fig.1) of monthly rainfalls for Dorothea on St. Thomas (Mills and Iniama,1990). For the representative dry month of February, only 4 years out of the 47 between 1941 and 1987 have rainfall in excess of 3 inches. Of these, two years (1949 and 1961) precede 1964, while the other two are after 1964. Years having February rainfall of one inch and below are equally spaced also between the two periods. On the other hand, for the wet month of October, all the years with rain in excess of 9 inches occur after 1964. Therefore, October rainfall at Dorothea generally was heavier after 1964 than in the study period preceding 1964.

This periodicity of rainfall raises the question as to whether we could regard the entire rainfall period of the wet months as a single period for statistical analysis, or whether each of these periods is part of a different rainfall cycle. A cursory survey of longitudinal rainfall indicates that, generally, the period after 1964 had heavier rainfalls than the preceding period, especially for the wet months. The apparent cyclical nature of this rainfall regime will have further implications for our modeling procedure.

<u>Modeling Rainfall Variability</u>

The use of stochastic modes to predict seasonal and annual rainfall in tropical areas has engaged the attention of researchers since the pioneering work in East Africa in the 1950's when Manning (1950) fitted normal density functions to monthly rainfall data. As a follow up,

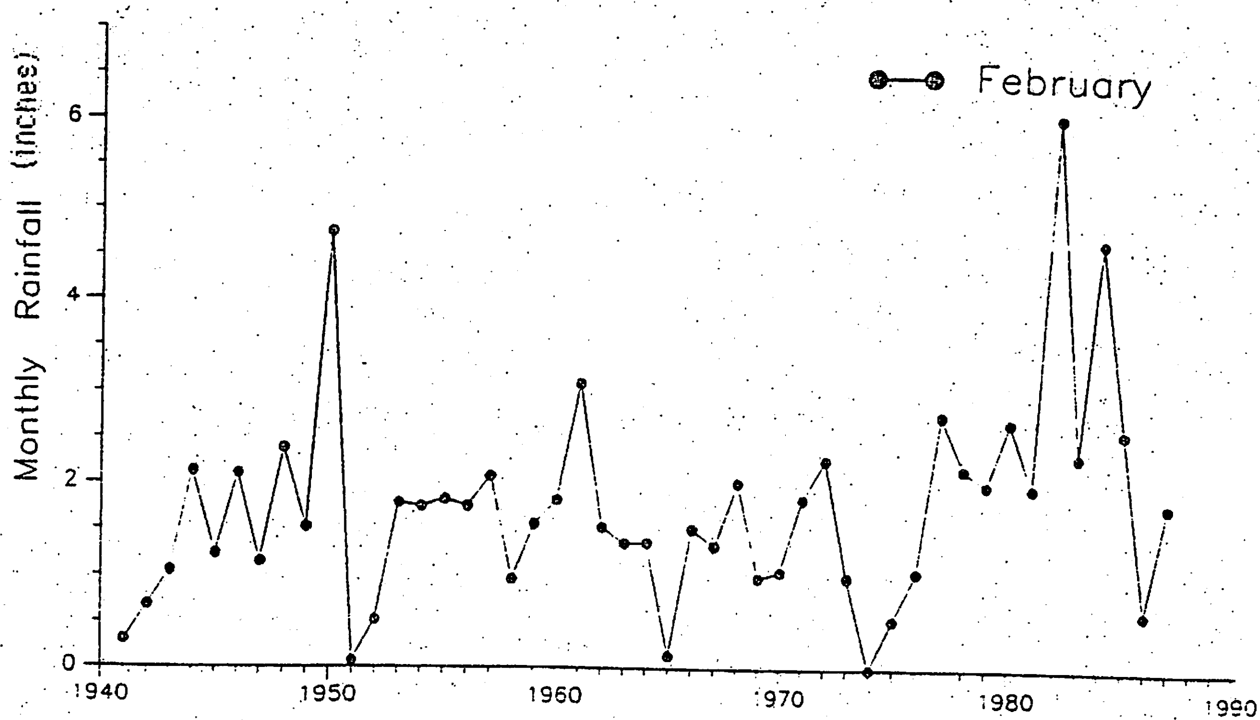

Fig. 1(a) Rainfall Distribution for Dorothea
St. Thomas, February, 1941 – 1987

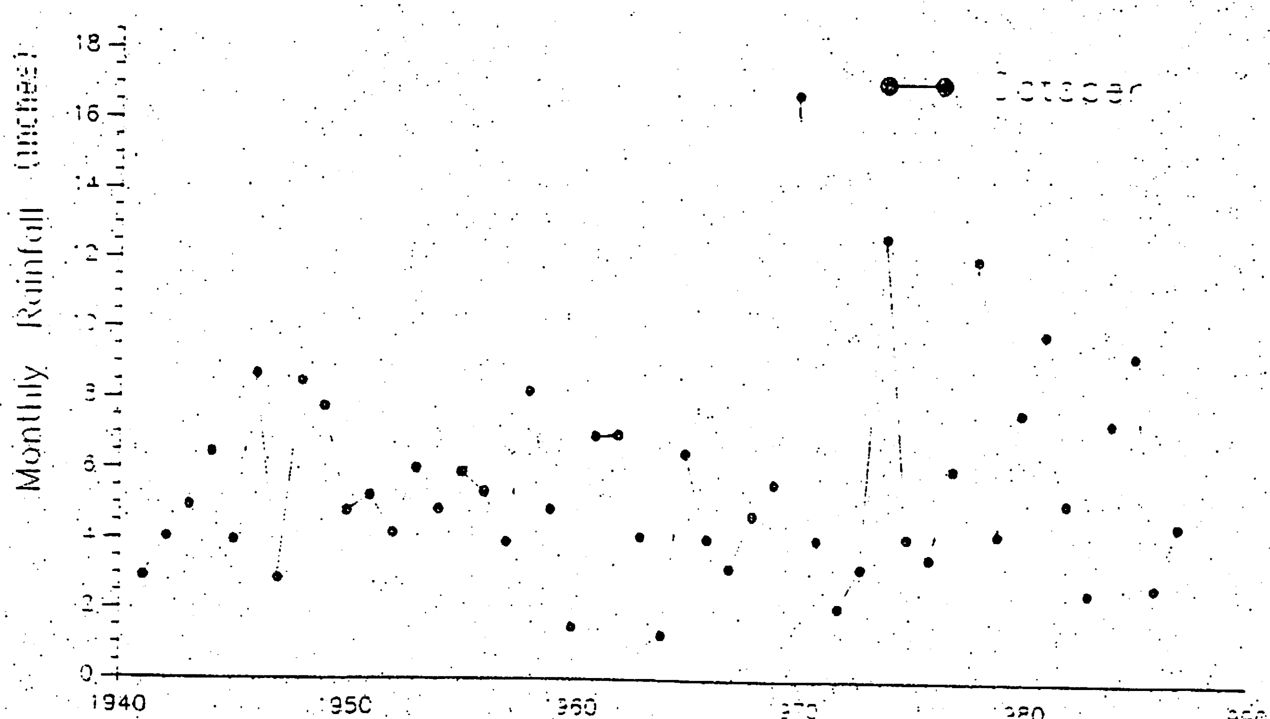

Fig. 1(b) Rainfall Distribution for Dorothea
St. Thomas, October, 1941 – 1987

Friedman (1957) as well as Hartley and Lewis (1959) used the incomplete gamma function to describe rainfall in North America. For the Caribbean, Mills (1976) used the normal and the incomplete gamma density functions to predict rainfall in St. Kitts, and showed later (Mills, 1984) that the incomplete gamma provides a better prediction of the monthly rainfall pattern in that Caribbean island than does the normal distribution.

The methodological approach for this study is as follows: nine rainfall stations, three on each island, are selected for analysis, and the monthly rainfalls for selected stations are tested for normality so as to determine whether the normal density function or some other model should be used to fit these data. The data for the chosen stations are tested for normality using a procedure developed by Snedecor and Cochran (1980). This procedure is used to test the degree of skewness and kurtosis of the distributions to determine whether they are significantly different from those expected in data that are normally distributed.

According to Snedecor and Cochran (1980), the degree of skewness, denoted by the third moment about the mean, is dependent on the scale on which the data are recorded. In order to generate a coefficient of skewness independent of this scale, the authors generated a function denoted by g_1. The sample estimate is given by:

$$g_1 = \{m_3 / (m_2\sqrt{m_2})\}$$

where m_2 is obtained from:

$$m_2 = \Sigma(X - \bar{X})^2$$

and m_3 from:

$$m_3 = \Sigma(X - \bar{X})^3 / n$$

If the sample comes from a normally distributed population, than g_1 is normally distributed with mean equal to zero and standard deviation ($\sqrt{6}/n$) provided $n > 150$. For sample sizes between 25 and 200, the authors provide tabled values of the one-tailed distribution at the $p = 0.05$ and $p = 0.01$ levels as accurate measures of g_1. Therefore, if the coefficient of skewness exceeds the critical levels shown in this table, the distribution is considered significantly different from normal for given values of n at the one-tailed $p = 0.01$ and 0.05 . We shall use this procedure in our test of normality.

We shall test the data also to determine whether the degree of kurtosis in the distribution departs significantly from what would have been expected from a normal distribution. Two procedures are recommended. The first is by Geary (1936) who developed a value *a* which equals the mean deviation divided by the standard deviation. If the population is normally distributed, then *a* has the value 0.7979. Leptokurtic distributions have higher values while platykurtic ones have lower values than 0.7979.

Snedecor and Cochran (1980) have developed another test of kurtosis denoted by g_2 such that:

$$g_2 = (m_4 / m_2^2 - 3)$$

where m_4 is the fourth moment about the mean, and m_2 is defined as above. For large samples exceeding 1000, g_2 is normally distributed with mean 0 and standard deviation $\sqrt{(24/n)} = 0.219$. For smaller sample size (of 50 to 1000), the authors developed tabled values for testing at p-values of 0.05 and 0.01. The authors state that both g_1 and g_2 are similar to that for Geary's measure as described above. Our final step involves fitting observed rainfall frequencies to expected frequencies generated by a selected theoretical model. The Kolmogorov-Smirnov goodness-of-fit test is applied to determine the degree of agreement between the distribution of observed rainfall values for each stationand those generated by the specified theoretical distribution. Mills (1984) applied this method to determine the degree of agreement between the distribution of observed rainfall values for each station in St. Kitts and those generated by the specified theoretical distribution. Next, each rainfall data series is divided into two periods. The expected frequencies of the earlier period are used to predict the observed rainfall in the latter period. Finally, the implications of this study for agriculture and urban water resource management are discussed.

Two Rainfall Prediction Models

From time to time, various theoretical models have been applied to the prediction of rainfall patterns. These include the normal, binomial, truncated normal and incomplete gamma probability distributions, as well as the regression model. Since the pioneering work of Glover and Robinson (1953), the normal distribution model has been the model most commonly used in rainfall prediction, probably because the normal distribution function table is readily available. Another reason may be that the normal distribution tends to model rainfall data in humid climates fairly well. However, its suitability to data in drier climates has not been tested fully. In this study, we compare the normal distribution and the incomplete gamma functions.

Two fundamental assumptions that are made in fitting an observed rainfall frequency distribution to a theoretical one. First, individual annual or monthly totals are considered to be random selections from a set of possible values. A random selection does not necessarily give a good estimate of the population frequencies, but a large number of such selections provides a better fit. However, since data of this kind are limited, a method which provides the most efficient estimate of the population probabilities from a sample must be identified.

Second, since available data limit us to one sample, our task is to use the sample data to estimate the true frequency distribution from which the sample was derived. This approach is based on the assumption that the frequency distribution of the population from which the sample was drawn possesses the characteristics of a defined mathematical model. Even though mathematical models may not exactly replicate the behavior of natural phenomena, the correspondence is often close enough for practical applications.

a) The Normal Distribution Model

One mathematical model which is often used in scientific applications is the normal distribution. Studies of monthly rainfall variability in humid environments tend to show that the normal curve approximates the rainfall distribution pattern. Thus the mean (μ) and standard deviation (σ) of the data present a good fit to the rainfall distribution pattern and confidence limits can be calculated (Manning,1950).

In dry areas, however, the normal distribution has been found inadequate for fitting highly skewed data representative of such areas (Barger and Thom, 1949; Thom, 1958, Friedman, 1957). Mills (1984) showed that this is also the case for monthly rainfalls in St. Kitts. In these cases, average annual monthly rainfall tend to be low, and the natural lower bound of zero inches becomes important. Further, the largest frequencies of rainfall tend to be close to the mean, with a trailing off of frequencies toward the higher values. This characteristic of the data generally suggests a positively skewed distribution. We do not present a formula for the normal distribution since these are commonly found in many fundamental statistical texts.

b) The Incomplete Gamma Model

The incomplete gamma distribution has been applied to precipitation studies under a wide range of conditions because of the relatively good fit that it provides. This mathematical model had been used as a better approximation to the cumulative probability of a variable X, where X represents weekly, monthly, or annual amount of random rainfall (Barger and Thom, 1949; Thom, 1958). Apart from the fact that the incomplete gamma function is suitable for positively skewed distributions, it has the added power of the exponential distribution which has been used for data which show high periodicity. The exponential function distribution has been shown to be a special case of the gamma function with 2 degrees of freedom (Friedman and Jan es, 1957; Clark and Hosking, 1986).

The frequency distribution of the gamma function is given by:

$$f(x) = \frac{1}{\beta^{\gamma}\,\Gamma(\gamma)}\, x^{\gamma-1}\, \epsilon^{-x/\beta} \qquad (\beta > 0,\ \gamma > 0)$$

given that x denotes the random variable which is the amount of rainfall. ß is the scale parameter, while Y is the shape parameter. The function is positively skewed with the degree of skewness being an inverse function of ß. Since $f(0) = 0$ for X < 0, then the distribution has a lower limit of zero but is unlimited to the right. The cumulative probability function is called the incomplete gamma function and is denoted by:

$$G(x) = \rho + (1-\rho)\int_0^x \left[\frac{x^{\gamma-1}\,\epsilon^{-x/\beta}}{\beta^{\gamma}\,\Gamma(\gamma)}\right] dx.$$

the parameters of which must be estimated from sample data. Friedman and Jan es (1957) stated that efficient estimates of these parameters cannot be made using the method of moments which is used to estimate μ and s. Thom (1958) used the maximum likelihood procedure to estimate these parameters. Following this procedure, the estimate of g is given by:

$$g = \frac{1 + \left[1 + \frac{4}{3} \left[\ln \bar{X} - \frac{1}{n} \sum_{i}^{n} \ln X_i \right] \right]^{0.5}}{4 \left[\ln \bar{X} - \frac{1}{n} \sum_{i}^{n} \ln X_i \right]} \qquad g > 0$$

while the estimate of ß is given by:

$$b = \bar{X} / g \qquad b > 0$$

Since f (X=0) = 0, the model can be estimated only for months with rainfall greater than zero. However, the model has the added power that for $\Upsilon = 1$, the distribution is exponential with ordinate 1/ß at X = 0. It is also a variation of X^2 distribution with 2 degrees of freedom when $\Upsilon = 1/2n$ and ß = 1. It is also different from the normal distribution in that it has a zero lower bound and is highly skewed for low values of Y. It approaches the normal curve as Υ becomes large.

Confidence estimates of these parameters based on their variance estimates can be made on the assumption that the estimators *b* and *g* are normally distributed (Friedman and Jan es, 1957; Thom 1958). However, Mills (1984) found that the method used by Hartley and Lewis (1959, pp. 2-3) is easier to calculate. By this procedure,

$$\text{var}(g) = g^2\{(1.79629 - 1.21163u + 0.77255u^2)/n\}, \qquad u < 0.5772$$

and

$$\text{var}(g) = g^2\{(1.00513 + 0.89538u - 0.3558u^2)/n\}, \qquad u > 0.5772$$

where $u = \ln \overline{X} - (\sum \ln X_i)/n$

Our study uses the normal and incomplete gamma functions to fit the monthly rainfall data for the selected stations, and the Kolmogorov-Smirnov (KS) procedure is used to test the goodness of fit.

Data Analysis

Monthly rainfall data and some parameters for Dorothea, Cruz Bay, and Hamilton Airport underscore the rainfall variability at these representative stations on each island. For Dorothea (Table 2), the month with the greatest coefficient of variability is April, a relatively dry month, while August, a relatively wet month has the lowest. April also has the largest coefficients of skewness and kurtosis. October is the wettest month, with the highest positive kurtosis, while February has the lowest rainfall.

Therefore for Dorothea, October is a very wet and highly variable month, while February is the driest month. Following the same procedure, the same months have been selected for Cruz Bay, except that the driest month for Cruz Bay is March, not February (Table 3). For Hamilton airport (Table 4), the representative months are different from those for the two former stations, probably because it is on the leeward southern shore of

St. Croix(Table 4). February is the most variable dry month with a coefficient of variability of 0.701, and September is the most variable month with a coefficient of variability of 0.663. November is its wettest month, while March is its driest. Thus, spatial and topographical differences produce rainfall variability on these islands far in excess of what would have been expected, given their relatively small sizes. This characteristic should alert planners who use meteorological data to the dangers inherent in extrapolating parameters from one station in an area to other regions, even on relatively small islands.

In order to decide whether the distribution of monthly rainfalls for these stations is significantly different from normal, the procedure developed by Snedecor and Cochran (1980) is used and the skewness and kurtosis are shown in the last two columns of Tables 2, 3, and 4.

Table 2: Rainfall Statistics for Dorothea, St. Thomas, 1941 to 1987 (ins).

Month	Mean	Std. dev.	Coeff. of Variation	Skewness	Kurtosis
January	2.677	1.574	0.588	1.603**	2.959**
February	1.743	1.632	0.667	1.537**	3.478**
March	1.965	1.741	0.886	1.602**	2.565**
April	2.930	2.641	0.901	3.598**	16.021**
May	4.831	3.962	0.820	1.725**	3.741**
June	2.896	2.166	0.748	1.001**	0.073
July	2.966	1.464	0.493	0.773*	1.880**
August	3.680	1.585	0.431	1.170**	1.661
September	5.484	2.880	0.525	0.722*	0.935
October	5.669	2.989	0.527	1.477**	2.859*
November	5.438	4.071	0.749	1.347**	1.794
December	3.020	2.044	0.677	1.272**	1.741

**p-value < 0.01 * p-value < 0.05

Using the procedure, a coefficient of skewness of 0.810 or more is needed to reject the assumption of normality at $p = 0.01$ while a coefficient of 0.548 is needed to reject normality at $p = 0.05$. The information in these tables shows that the monthly rainfall distributions for the selected stations are positively skewed, and that the skewness is significantly different from that which would have been expected from a normal distribution at $p = 0.01$ except July and September at Dorothea, and June to August at Cruz Bay where the p - value is 0.05. Using Snedecor and Cochran's procedure, a value of zero indicates a normal distribution, a negative value suggests a platykurtic curve, while a positive value indicates a leptokurtic curve. Our parameter estimates indicate that the monthly rainfall distributions are significantly different from normal because these estimates are significantly different from zero.

Table 3: Rainfall Statistics for Cruz Bay, St. John 1941 to 1987 (ins).

Month	Mean	Coeff. of Std.dev.	Variation	Skewness	Kurtosis
January	2.400	1.438	0.599	1.735**	4.737**
February	1.885	1.301	0.690	1.695**	4.065**
March	1.776	1.507	0.848	1.870**	3.319**
April	2.824	2.482	0.879	2.458**	7.105**
May	5.013	3.912	0.780	1.358**	0.941
June	2.937	1.655	0.563	0.767*	0.225
July	3.514	1.587	0.451	0.786*	0.543
August	4.147	1.747	0.421	0.557*	-0.702
September	5.209	2.953	0.567	1.509**	3.586**
October	5.310	3.296	0.621	1.896**	5.063**
November	4.903	3.150	0.642	1.214**	1.684
December	3.371	1.842	0.546	1.146**	1.594

**p-value < 0.01　　*p-value < 0.05

A kurtosis coefficient of 1.88 is needed to reject the assumption of normality at p = 0.01, while a coefficient of 1.99 or more is needed to reject this assumption at p = 0.05. Zero implies a normal distribution. Using our results, the coefficient of kurtosis is significantly different from what would have been expected from a normal distribution, except for five months at Dorothea, six at Cruz Bay, and two at Hamilton Airport. This suggests that the wet months tend toward normality while the dry months do not. Our findings are that the skewness is significantly different from what would have been expected from a normal population.

Table 4: Rainfall Statistics for Hamilton Airport, St. Croix, 1948 to 1987 (ins).

Month	Mean	Std. dev.	Variation	Skewness	Kurtosis
January	2.209	1.250	0.566	1.714**	5.235**
February	1.953	1.369	0.701	2.587**	9.773**
March	1.749	1.218	0.696	1.785**	4.883**
April	2.624	1.847	0.704	1.562**	2.539**
May	4.061	3.647	0.898	1.868**	4.272**
June	2.845	1.952	0.686	1.449**	2.710**
July	3.171	1.729	0.545	0.878**	-0.084
August	4.091	2.037	0.498	1.621**	4.085**
September	4.977	3.300	0.663	3.224**	13.495**
October	5.135	2.941	0.573	1.434**	3.287**
November	5.173	3.482	0.673	1.494**	1.730
December	3.641	2.559	0.702	1.926**	3.556**

**p-value < 0.01 *p-value < 0.05

Even the kurtosis is significantly different from what would have been expected from a normal distribution, except for some of the wetter months, especially on St. Thomas and St. John, which are more humid than St. Croix. This is the first substantive indication that a different theoretical model may be required to describe adequately the distribution of monthly rainfall at these stations especially for drier months and drier stations.

Since one of our purposes is to examine which theoretical model is better suited to rainfall data for selected months for the given stations, a more detailed analysis of these stations follows. In order to test the strength of the models under varying conditions, we selected, in general, the two driest and the two wettest months for each of the three stations, one on each island. The four selected months are February, March, September, and November, the first two months fall in the dry period, and the other two in the wet one. Table 2 indicates that for Dorothea, February and March are the two driest months of the year. Their distributions are significantly skewed with tails to the right, but they are not mesokurtic. September and November are also similarly skewed but appear mesokurtic. Similar characteristics of skewness and kurtosis are evident in the data for Cruz Bay and Hamilton Airport in Tables 3 and 4 respectively.

For Hamilton airport, Table 4 shows that the skewness for the four months selected and the kurtosis for three out of the four are significantly different from what would be expected from a normal distribution. Only the wettest month, November, exhibits a level of kurtosis of 1.730 which is just below the 1.88 which is the critical value for rejecting the assumption of normality. This shows that all months, except the wettest, have degrees of skewness and kurtosis which are significantly different from what would be expected under the assumption of a normal distribution. The wettest month displays a degree of kurtosis significantly different from normal.

In order to determine whether these monthly rainfall data depart significantly from what would have been expected from a normal distribution, the Kolmogorov-Smirnov (K-S) test, a goodness-of-fit test is used. It measures the degree of agreement between the distribution of a set of observed values and those of a specified theoretical distribution. It determines whether the observations in the sample can reasonably be thought to have been derived from a population of values that has the same theoretical distribution (Siegel, 1956).

Table 5: Normal and Incomplete Gamma Distribution Statistics for Three Selected Rain Stations.

	Normal Distribution		Incomplete Gamma		Maximum Difference*	
		Std.	Shape	Scale		
Month	Mean	Dev.	g	b	Normal	Gamma
	(2)	(3)	(4)	(5)	(6)	(7)
(a) Dorothea:						
February	1.743	1.632	2.274	0.783	0.095	0.088
March	1.965	1.741	1.379	1.456	0.131	0.047
September	5.484	2.880	3.252	1.686	0.085	0.086
November	5.438	4.071	1.829	2.972	0.148	0.054
(b) Cruz Bay						
February	1.885	1.301	2.706	0.712	0.090	0.059
March	1.776	1.507	1.845	0.962	0.144	0.081
September	5.209	2.953	3.373	1.544	0.097	0.070
November	4.903	3.150	2.606	1.881	0.124	0.068
(c) Hamilton Airport						
February	1.953	1.369	2.616	0.746	0.138	0.073
March	1.749	1.218	2.521	0.712	0.145	0.067
September	4.977	3.300	3.668	1.357	0.154	0.052
November	5.173	3.482	2.820	1.835	0.171	0.111

*Critical |D| for Dorothea and Cruz Bay at $p = 0.05$ is 0.198.

*Critical |D| for Hamilton at $p = 0.05$ is 0.215.

The parameter estimates for the three stations under study are shown in table 5. The normal distribution is completely described by the mean and standard deviation, while the gamma distribution is described by g (the shape parameter) and b (the scale parameter). February and March have been selected as representative dry months each with under two inches of rainfall, while September and November are used as representative wet months, each with over 5 inches of rainfall. The standard deviations indicate that the wet months have the greatest variability of rainfall, with November having the largest. For the gamma distribution, as *g* (shown in column 4) increases, the distribution tends to normality. An inspection of the shape parameters measured by *g* and the rainfall amount measured by the mean suggest a relationship between them. A small value of g indicates a symmetrical distribution. In general there appears to be an increase in the shape parameter as the average rainfall increases.

Column 6 shows the maximum absolute difference |D| that results from comparing the observed frequencies of each station with expected frequencies generated by the normal distribution function in the Kolmogorov-Smirnov test. All of the maxima in this column are smaller than the critical values of 0.198 for Dorothea and Cruz Bay, and 0.215 for Hamilton Airport. None of the maxima is significant at the 0.05 level. This suggests that the expected frequencies predicted by this model for these months do not depart significantly from the actual rain frequencies. However, the values are not very distant from the critical value. If, shorter time periods are used for prediction, this model may not be as reliable.

Critical |D| values for the differences between the observed values and those predicted by the incomplete gamma distribution demonstrate that this distribution predicts frequencies that are not significantly different from actual frequencies for all months for all the stations

(Table 5, column 7). In addition, the relative smallness of the |D| values in column 7, when compared with those values in column 6, suggests further that the incomplete gamma function predicts more closely than does the normal distribution in months with skewed and/or non-mesokurtic distributions. Graphical representations of these rainfall distributions confirm this to be the case (Mills and Iniama, 1990). Examples are figs. 2 (a) and 2 (b) for Dorothea where the gamma distribution model predicts the most frequent rainfall of 5 inches. while the normal distribution model predicts this as 6 inches. The observed number of years with 5 inches of rainfall was 14 years. The gamma model predicted this as 7 1/2 while the normal distribution predicted it as 6 years. The tail of the gamma model includes more data than does the tail of the normal distribution.

Predicting Future Rainfall

In order to determine how well knowledge of the rainfall pattern in an earlier short period can be used to predict the rainfall pattern in a future period, the rainfall of representative wet and dry months for each station was divided into two periods, each of equal duration. The periods varied from 15 years for Fort Mylner, Annaly, East Hill, Catherineburg and Lameshur Bay to 23 years for Dorothea and Cruz Bay. We decided to use nine rainfall stations, three on each island so as to give more validity to

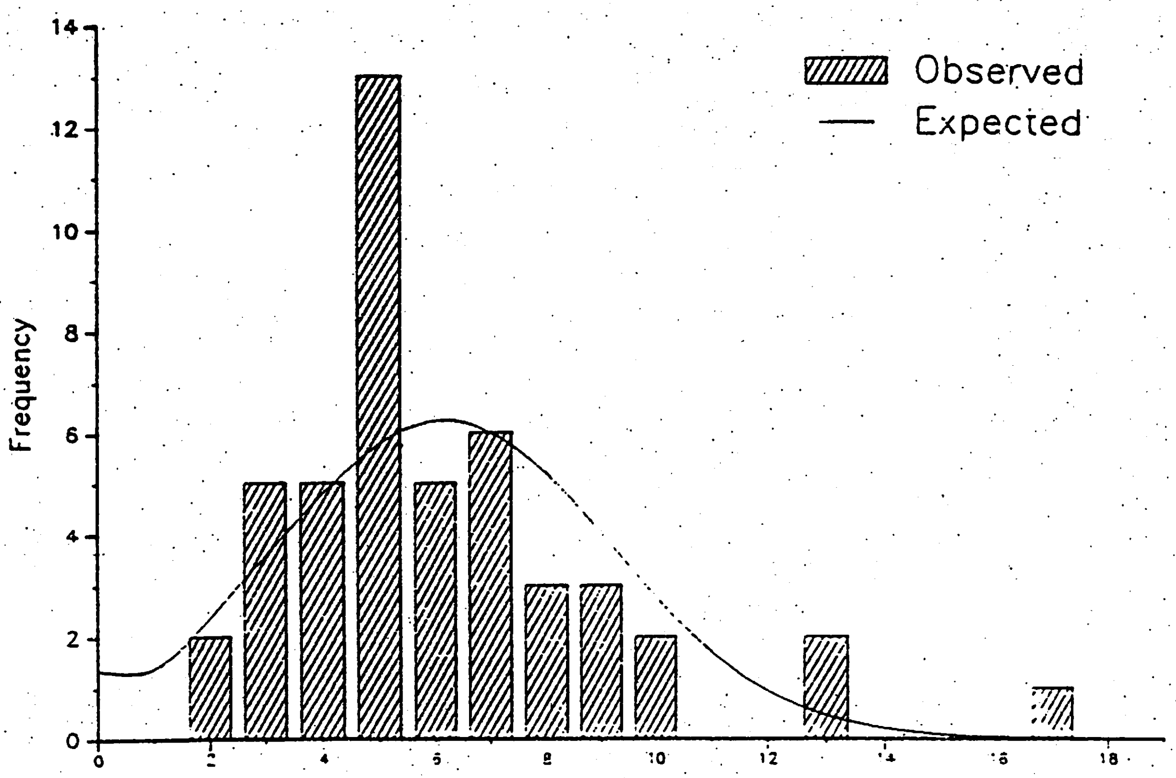

Fig. 2 (a) Rainfall fitted to a normal distribution curve in inches per month for Dorothea St. Thomas (October 1941 - 1967)

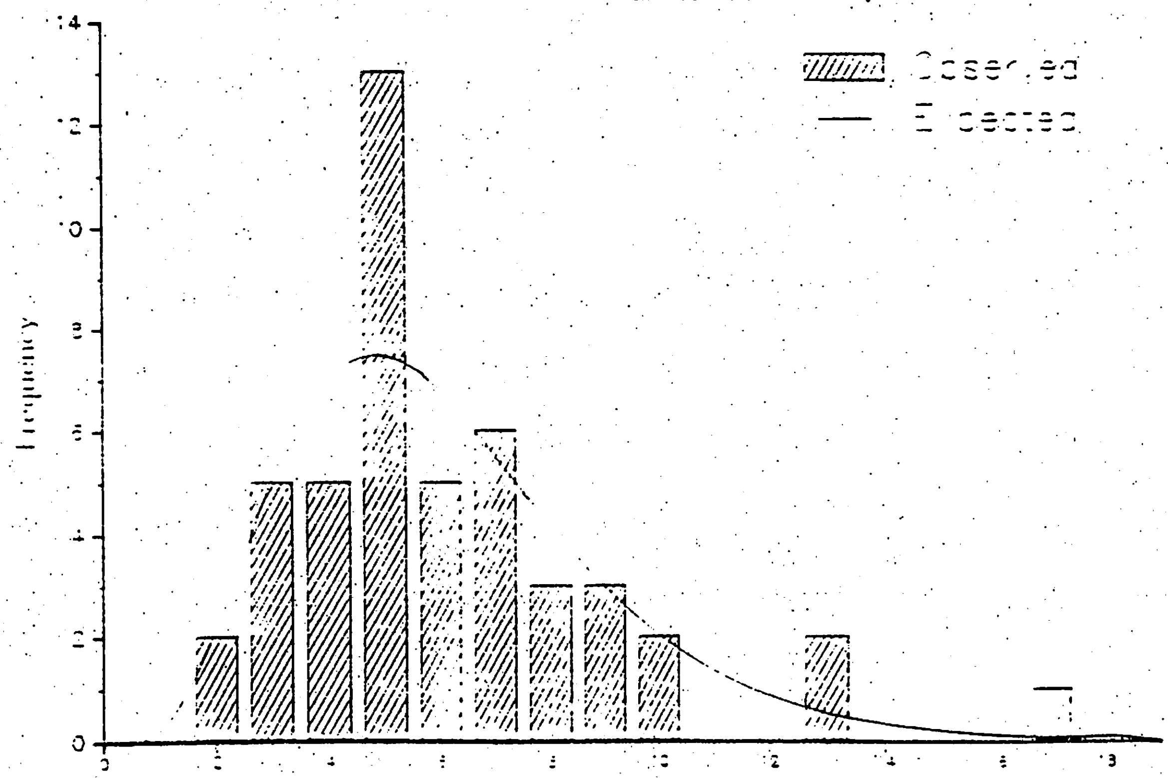

Fig. 2 (b) Rainfall fitted to a gamma distribution curve in inches per month for Dorothea St. Thomas (October 1941 - 1967).

our analysis. The expected frequencies within class limits of one-inch within the earlier period were used to predict the observed frequencies in the latter period, and the Kolmogorov-Smirnov test was used to determine how closely the expected frequencies compared with the observed frequencies in the latter period.

Both the normal and incomplete gamma models predict future rainfall well at the 0.05 level of significance, for all months (Table 6). The critical |D| values for Fort Mylner, Annaly, East Hill, Catherineburg, and Lameshur Bay where the period of prediction was 15 years was 0.338. For Cyril King and Hamilton Airports where the predicted period was 20 years, |D| was 0.294, and for Cruz Bay and Dorothea where the period was 23 years, |D| was 0.275.

A major assumption of our prediction process is that the data from the predictor and predicted periods came from the same population. In other words, there should be no trend or periodicity in the longitudinal data. Where a trend exists in the data, the central tendency and variability parameters are likely to be significantly different, and the predictive ability of the model is diminished. In order to examine the influence of trend on the predictive ability of our model, the month of November for those stations whose predictor period is only 15 years was chosen for further analysis. November was selected because this is a month with notable storm activity in the U.S. Virgin Islands, and our preliminary analysis indicated that both the incomplete gamma and normal models were poor predictors for the month of November at $p = 0.05$.

Table 6: Kolmogorov-Smirnov Test of Significance of the Normal and Incomplete Gamma Rainfall Prediction for Wettest and Driest Months

Station	Months	|D| Value Normal	Confidence Limits	|D| Value Gamma	Confidence Limits
Dorothea	February	0.8110	p > .20	0.1061	p > .20
n = 23	October	0.1878	p > .20	0.1582	p > .20
C.K. Airport	February	0.1610	p > .20	0.1730	p > .20
n = 20	October	0.1880	p > .20	9.1675	p > .20
Ft. Mylner	February	0.0547	p > .20	0.1120	p > .20
n = 15	October	0.2918	.20>p > .10	0.3156	.10 > p > .05
Annaly	February	0.1673	p > .20	0.1760	p > .20
n = 15	October	0.2453	p > .20	0.1866	p > .20
H. Airport	March	0.1197	p > .20	0.1442	p > .20
n = 20	October	0.1224	p > .20	0.1219	p > .20
East Hill	March	0.0984	p > .20	0.0751	p > .20
n = 15	October	0.1653	p > .20	0.2122	p > .20
Cruz Bay	March	0.2170	p > .20	0.2195	p > .20
n = 23	October	0.1402	p > .20	0.1321	p > .20
Cath'burg	February	0.0660	p > .20	0.0708	p > .20
n = 15	October	0.1847	p > .20	0.0893	p > .20
Lameshur B.	February	0.1476	p > .20	0.0931	p > .20
n = 15	October	0.1376	p > .20	0.1880	p > .20

Conover (1980, pp. 250-259) provided a test for trend in longitudinal data using Spearman's rho, (ρ), or T as the test statistic, given that

$$\text{rho} = \frac{1 - 6T}{n(n^2 - 1)}$$

where

$$T = \Sigma [R(X_i) - R(Y_i)]^2$$

and

$R(X_i)$ = the ranking of longitudinal data X_i
$R(Y_i)$ = the ranking of the time period Y_i

The test procedure using rho is theoretically as robust as that using T, but we present the procedure using T because this requires fewer calculations. By this procedure, a trend exists in the longitudinal data at the stated level if the calculated value for T is less than the critical value for a/2, or greater than the critical value for 1 - a/2, where a is the alpha level. The null hypothesis of no trend is supported if the calculated value of T lies between the values for a/2 and 1 - a/2 (Conover, 1980). Table 7 shows a T test for trend in the longitudinal rainfall data for those stations whose predictor and predicted period is only 15 years. These stations are used because our model predicted stations with n > 20 quite well. This may well be due to the fact that longer periods of prediction tend to smooth out some of the periodicity in the rainfall data, thereby satisfying the assumption that all the data are from the same population. Periodicity may tend to have a greater effect on prediction using shorter rainfall periods.

The longitudinal data for Fort Mylner, Catherineburg, and Lameshur Bay show a significant trend at $p = 0.05$ (Table 7). Consequently, the poor fit of the model for these stations may be explained by the presence of a trend in the longitudinal data which indicated that the data for the two periods do not come from the same population. No trend was found in the data for Annaly and East Hill on St. Croix. Annaly, therefore, represents a station where the model was a good predictor because there was no trend

Table 7: Test of Trend in November Rainfall for Selected Stations

	T-Value[1]	Confidence Limits
Fort Mylner2	2758	$.025 < p < .05$
Annaly	3524	$p < .20$
East Hill	3398	$.10 < p < .20$
Catherineburg	2816	$.025 < p < .05$
Lameshur Bay	2858	$.025 < p < .05$

1. A trend exists if calculated value of T is less than 2868 or greater than 6162 for $n = 15$.
2. $|D|$ critical is 0.338

in the data, while for East Hill the prediction was poor despite the absence of a trend in the longitudinal data. This analysis shows that the presence of a trend in the data may distort the predictive ability of the model over short periods. This is an area for further study.

In summary, this study shows that the gamma density function provides a better fit to the monthly rainfall data for the U.S. Virgin Islands than does the popular normal density function. This is supported by the fact that the gamma curve fits the data more closely than the normal density function, especially for the dry months. In addition, the calculated |D| values from the Kolmogorov-Smirnov distribution are, in general, smaller for the incomplete gamma than for the normal distribution. Where there is no significant trend in the longitudinal data, the gamma model predicts future rainfall equally well for most months. However, for stations in which the study and experimental periods are 15 years each, and where there is a trend in the data, the models are poor predictors especially for very wet months with noticeable storm activity. Where there is no significant trend in the data, as assumed by theory, short periods of predictions as low as 15 years provide as robust a prediction as longer periods of time. This is a crucial finding not only for the Virgin Islands, but also for other Caribbean locations where rainfall records may not be continuous for the standard 50-year period.

Application of the Models

The USDA TR55 study of 1986 stated that for the U.S. Virgin Islands, droughts would have a serious impact on farming and dairying activities, on urban water supply, and the general economy. The islands have no large rivers or reservoirs. Consequently even a few months of drought can be damaging, and especially there is the problem of retaining sufficient soil moisture to produce crops that are otherwise suited to the soil and climate. The study also includes for the nine stations under study, some hydrological characteristics which have implications for agriculture and water resource development in regions surrounding the selected rainfall stations. These characteristics are used to highlight the implications of our modeling efforts for agriculture and municipal water supplies.

Application to Urban Water Supply

In areas where municipal water is in short supply, it is important for water engineers to know how much rain to anticipate over a given period. The findings above suggest that the incomplete gamma model would be a reliable instrument to predict the volume of rain that will fall, and from that it is possible for them to estimate the amount that would collect in the aquifers. This application is particularly significant in island environments, particularly those with dense populations.

Hydrological analysis shows that apart from Aquilisa-Frendensborg-Sion Soil Association in central St. Croix which develops over limestone, most of the islands have very poor aquifers made of volcanic rocks. The steep slopes and poor aquifer development limit permeability of rain in a

24-hour period to maximum of slightly above 6 inches. Using curve number analysis for the stations as presented in USDA TR 55 mentioned above, we find that on average, much of the rainfall escapes as run-off, from a low of 36% for Hamilton Airport to a high of 63% for Annaly on St. Croix. This situation is exacerbated by the fact that since more rain falls by day than by night in the USVI, evapotranspiration exceeds monthly rainfall especially in the dry months (USDA TR 55, 1986). These very poor hydrological conditions indicate that in a territory where 80% of the residents depend on rainwater, primary attention should be paid to mass rainfall collection techniques for urban water resources, especially as potentials for development of wells are generally moderate to low over most sites. Even well water has been shown to contain numerous contaminants from animal and human wastes, septic tanks, sewage, poor sealing of wells, bacteria, and seepage from sea water (Canoy, et al., 1985).

The most popular source of urban water supply for residential use is cisterns. However, cisterns are expensive to construct (Smith, 1986), and may contain serious contaminants (Ruskin and Callender. 1988). Even pipe-borne water from desalinated plants has been found to contain a high amount of bacteria and chemical contaminants. Given these situations, our study would suggest that efforts should be made to reduce runoff and increase the recharge of aquifers by digging infiltration trenches or injection wells. Methods of rooftop collection and storage that are cheaper than cisterns should be explored. But most of all, the most cost-effective way of controlling peak discharge of rainfall is the building of hillside catchments to serve large urban clusters (USDA TR 55, 1986). The volcanic rocks and clayey soils would limit water loss by seepage to the barest minimum, especially since the water table in most locations is within 10 feet of the valley bottoms. USDA TR 55 (1986) and Canoy et al. (1985) showed that this method had not been used widely in Puerto Rico and the Virgin Islands. We recommend that government explores the possibility of constructing large hillside catchments to remedy the already crucial water supply situation in the territory. Hillside catchments have an added advantage that they fit a variety of site conditions and can have multiple outlet spillways. Effective location of hillside catchments may serve hotels and impact tourism by reducing dependence of hotels on hauled water.

Application to Agriculture

Our study has potential for agricultural development in the territory, especially on the island of St. Croix where most agricultural activity is carried on, given that over 70% of St. John is national forest and most of St. Thomas is not cultivable. The average rainwater in a 24-hour period permeates up to less than six inches of the soil, and hence available water capacity in one inch of soil is below 0.20 inches (USDA TR 55, 1986) except in the limestone and marl formation underlying central St. Croix and the Hamilton Airport. Steep slopes and clayey soils limit permeability while potential for wells is largely moderate. Hydrological conditions are generally poor except on flatter land like those around the airport which is not used for cultivation. The high potential for drought and the inadequate rainfall minimum for many crops thereby necessitating irrigation (Navarro, 1987), indicate that alternative water collection systems should be developed for agriculture. We suggest that large water retention basins be built in agricultural areas, because these are the best method for collecting water at periods of peak discharge. Irrigation channels can be led from these basins for cultivation and dairying activities. These retention basins are found to be cheaper than wells and other methods (USDA TR 55, 1986).

A Basis for Crop Insurance

Farmers run the risk of adverse conditions, some of which are outside their control. One of these risks is associated with climate and weather. Floods or droughts may produce negative impacts on the soil and crops. For example, a study by Schraufnagel and Klemme (1989) in Wisconsin showed that the causes of crop loss to farmers were drought (52%), excessive moisture and floods (29%), and hail (3%). Others were insects, plants disease, hail, wind, and frost. A major way to indemnify farmers against potential crop loss is through crop insurance which in the above Wisconsin study paid an amount equal to 0.73 to 2.6 times the farmer's premium between 1985 and 1987.

To our knowledge, no comparative study has been carried out for the United States Virgin Islands, even though the territory is covered by the same crop insurance programs that cover farmers on the mainland U.S.A. Commercial Hail and Fire Insurance (H/FCI) covers a certain percentage of the farmer's losses, while Minimum Percentage Crop Insurance (MPCI) pays the difference between an estimated minimum yield per acre and the insured quantity. It is customary for farmers to buy crop insurance not in isolation, but along with other insurance for homes, cars, boats, and even life insurance. A reliable prediction of the rainfall on these and other islands will assist agencies interested in providing crop insurance to make decisions regarding policy objectives, goals, and prices.

In the former and current British Caribbean, plantation crops have had, and continue to have, the benefit of crop insurance. This was also the case in the U.S. Virgin Islands before the sugar industry was abandoned in 1966. McDonald (1980) stated that crop insurance is crucial for regional economic growth in the Caribbean. Most of the farmers throughout the region are small-scale producers whose crop production and productivity are subject to the vagaries of the weather, primarily rain. In years when there is little or no rainfall during the growing season, loss of both crop and livestock may reduce the farmer's income. This study provides a basis for some critical information that is necessary in the development of an equitable insurance program for small-scale farmers. It is a relatively easy matter to determine how many years out of 10, say, that a farmer in a particular area can expect to have good crops. If agronomic conditions determine that one inch of rain in three successive months is required for optimum crop growth, then our model can predict the likelihood of receiving that quantity or less of rainfall. Similarly, the method can be extended to predict the likelihood of any combination of rainfall amounts over any number of months.

Studies of monthly rainfall requirements for food crops have been done in the U.S. Virgin Islands only for tomatoes (Navarro, 1987). From this study, we estimate that the Royal Rico variety of tomatoes requires a monthly rainfall of approximately 3.75 inches during the growing season while the Tropic variety requires approximately 4 inches per month for maximum yield.

Given these rainfall requirements to tomatoes, we use our modeling procedure to calculate the probabilities of having three and four inches or more of rainfall at our rainfall stations. Since the Kolmogorov-Smirnov test indicated that both normal and incomplete gamma models performed well in rainfall prediction (Table 6), both models are used to calculate these probabilities.

Table 8: Probability of Three Inches or More of Rain at Selected Stations for Representative Dry and Wet Months

	February (Dry)		October (Wet)	
Rain Station	Normal	Gamma	Normal	Gamma
Dorothea	0.3429	0.2890	0.9421	0.9613
Cyril King Airport	0.2331	0.1931	0.9236	0.9510
Fort Mylner	0.3567	0.2880	0.7853	0.8251
Annaly	0.5017	0.4327	0.9501	0.9229
Hamilton Airport*	0.4158	0.3250	0.8775	0.8784
East Hill*	0.2764	0.2032	0.7752	0.7989
Cruz Bay*	0.2060	0.1723	0.9033	0.9184
Catherineburg	0.6530	0.5105	0.8182	0.9105
Lameshur Bay	0.4142	0.3598	0.8665	0.8965

*The driest month is March, not February.

For the dry month of February, both the normal and gamma models predict that Cruz Bay has the lowest probability and Catherineburg has the highest probability for rainfall in excess of three inches as required by the Royal Chico variety (Table 8). The normal model shows that at Cruz Bay only 2 years out of 10 will have February rain of 3 inches or more, while the gamma model predicts that as 1.7 years in 10. For Catherineburg, the normal distribution model estimates this as 6.5 years in 10 while the gamma model predicts this as about 5 years in 10. For all stations, the predicted probabilities for the incomplete gamma model are lower than those of the normal distribution model. For October, the wet month, these probabilities show that the likelihood of October rain in excess of 3 inches varies from 7.7 years out of 10 at East Hill to about 9.6 in 10 at Dorothea. Though the actual probabilities vary from island to island, we find that stations such as Cyril King Airport, Hamilton Airport, and Lameshur Bay, on the leeward side of the islands, not only have lower rainfall totals, but also have lower rainfall probabilities than Dorothea, Annaly, and Catherineburg on the northern side.

The likelihood of having 4 inches or more of rainfall is much lower than that of having 3 inches or more, especially in the drier months (Tables 8 and 9). For the dry month of February, the normal distribution model predicts that the likelihood of 4 inches or more of rainfall is less than 1 in 10 years at all stations, except Annaly, Hamilton Airport, and Catherineburg. The gamma model, provides a better fit from a low of one in 50 years at Cyril King Airport, to a high of about 1 in 10 years at

Annaly. For October, a representative wet month, the predictions range from 6 out of 10 years at East Hill to about nine out of 10 years at Annaly.

Table 9: Probabilities of Four Inches or More of Rain at Selected Stations for Representative Wet and Dry Months

Rain Station	February (Dry) Normal	February (Dry) Gamma	October (Wet) Normal	October (Wet) Gamma
Dorothea	0.0727	0.1020	0.8597	0.8460
Cyril King Airport	0.0152	0.0223	0.8331	0.8247
Fort Mylner	0.0948	0.1021	0.7077	0.6856
Annaly	0.1658	0.1572	0.8637	0.8841
Hamilton Airport*	0.1858	0.1415	0.7697	0.7855
East Hill*	0.0639	0.0592	0.6370	0.5905
Cruz Bay*	0.0189	0.0324	0.8016	0.7690
Catherineburg	0.4201	0.1524	0.7477	0.7959
Lameshur Bay	0.0730	0.0812	0.7648	0.7428

*The driest month is March, not February.

These findings indicate that irrigation is necessary to supplement rainfall for the growth of tomatoes in the dry months. They also show that, based on these rainfall probabilities, different parts of the islands would have different irrigation requirements for tomatoes. Therefore, a study like that of Navarro (1987) is only location specific, and needs to be repeated for more agricultural areas on the islands so as to derive more realistic irrigation needs. The amount of crop insurance could be weighted by the probability of dry years at each location, so that an equitable crop insurance policy would be one that is spatially differentiated. The probabilities may represent lower and upper limits of weights used to calculate appropriate crop insurance.

In conclusion, this study shows that in areas where municipal water is in short supply, the gamma model is a reliable instrument for predicting the volume of rain which will fall, and from that estimates could be made of the amount of water that could be collected at various points in the territory. The study also provides a useful input into agriculture by providing a methodology for estimating the likelihood of wet and dry months, at specific locations for specific crops. Once the moisture requirements for specific crops during the growing period are known, then this procedure can be used to calculate the probabilities of meeting these minimum moisture requirements during the growing period. Such findings will prove useful for any programs which are designed to provide the much needed crop insurance to food crop farmers in the territory.

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