

The World's Largest Open Access Agricultural & Applied Economics Digital Library

This document is discoverable and free to researchers across the globe due to the work of AgEcon Search.

Help ensure our sustainability.

Give to AgEcon Search

AgEcon Search
http://ageconsearch.umn.edu
aesearch@umn.edu

Papers downloaded from **AgEcon Search** may be used for non-commercial purposes and personal study only. No other use, including posting to another Internet site, is permitted without permission from the copyright owner (not AgEcon Search), or as allowed under the provisions of Fair Use, U.S. Copyright Act, Title 17 U.S.C.

"Extreme-Value" Methods Simplified

By Ralph R. Botts

New methods have been devised for fitting skewed statistical distributions that conform to a double exponential model. Such distributions characterize a large class of phenomena of interest to agricultural economists. Distributions of data involving rainfall, temperature, crop yields, crop-hail losses, and others follow this pattern. The new technique, under the name of the theory of extreme values, makes use of graphics and is much less complex and time-consuming than older methods. But most of the available literature is highly mathematical and not easily understood. This paper presents a nonmathematical explanation for the working agricultural economist.

THE THEORY of the statistical distribution of extreme values was developed by E. J. Gumbel.¹ Several others had previously explored the problem.² It is particularly appropriate for measuring flood probabilities. For example, a gage height or mean streamflow is available for each day. The highest such reading for the year is an extreme value. So over a period of, say, 36 years, there are 36 such extreme values. Stated another way, the theory applies to a distribution of independent observations, each of which is an extreme value.³ The control curves (discussed later) are helpful in determining whether or not the theory applies to a particular case.

Such distributions of extreme values tend to be skewed, with the mode or most common value at the left of the mean or average. Probably for that reason, the theory has been applied also to distributions such as those involving rainfall, crop yields, and costs of crop-hail insurance loss, even though the figure for a particular year is a single

observation or an average, and not an extreme value.4

Most statistical theory applies to normal distributions. Heretofore, it has been necessary to fit Pearsonian curves (particularly type III) to small samples in order to derive the probabilities associated with skewed distributions. The fitting procedure is complex and time-consuming and is not generally understood by economists. But extreme-value methods present a much simpler tool for economists, and they will do well to investigate it.

The purpose of this article is not to review the mathematics involved in the theory of extremevalue distributions; but rather to present this relatively new tool in such a way that it can be applied by those not versed in mathematics. Only a few symbols are used, and no formulas are derived. For illustrative purposes, the method is applied to a distribution of annual "loss costs" of a mutual crop-hail insurance company. Then the necessary steps are summarized and the column headings for a spread sheet are given, so that the calculations may be standardized for mass processing of data by clerks.

Application of the method is simplified immensely by the use of double exponential paper (figs. 1 and 2). On this paper, the vertical scale (y) is evenly spaced. It is used for the observed values. The horizontal scale is used as the probability (m/n+1) scale. It never reaches zero on the left nor 1 on the right. Unfortunately, the

¹Gumbel, E. J. Statistical theory of extreme values and some practical applications. National Bureau of Standards, Applied Mathematical Series 33, 1954. For sale by Superintendent of Documents, 40 cents. Also Probability tables for the analysis of extreme-value data. National Bureau of Standards, Applied Mathematical Series 22, 1953. For sale by Superintendent of Documents, 25 cents.

² For example, de Finetti, Fisher, and Tippett. See bibliographies in publications listed in footnote 1.

^{*}A chief difficulty in applying the theory has been a lack of independence of data. For tests of randomness in time series, see F. G. Foster and A. Stuart. Distribution-free tests in time series based on the breaking of records. Jour. Roy. Statis. Soc. Series B, Vol. 16, No. 1 (1954). Pp. 1-22.

⁴Brakensiek, D. L., and Zingg, A. W. Application of THE EXTREME-VALUE STATISTICAL DISTRIBUTION TO ANNUAL PRECIPITATION AND CROP YIELDS. ARS 41–13, in cooperation with 5 State experiment stations.

probability paper is not for sale.⁵ Until it is placed on the market, each person interested in applying the method will have to construct his own paper (a time-consuming job) or obtain it from others.

As an example of application of the method, suppose the cash cost of producing wheat in a Great Plains county is \$10 per acre. Using a support price of, say, \$2 per bushel, the cash cost represents 5 bushels of wheat. In arid regions, crop yields tend to be skewed, and not normally distributed, over time. Applying extreme-value methods to a distribution of appropriate annual yields, one could determine the probability associated with getting a yield equal to or less than cash costs. He might do this for both continuously cropped and fallowed wheat, from which probability comparisons would be possible. The method therefore has application in the fields of risk reduction and crop-insurance ratemaking.

Or, to take another example, suppose you want to evaluate the chances of having annual rainfall of less than 15 inches (or any minimum level deemed necessary for wheat production) at 2 weather stations. From station records, you could get rainfall data, by years, for each station, prepare probability charts, and read the respective probabilities from them.

The method has special value in the field of crop-hail and windstorm insurance. Using this method, the probabilities associated with various loss levels can be ascertained. But in this field of work, one is usually interested in the other end of the distribution—the higher values of y (loss costs) and their associated values of m/n+1 (probabilities of occurrence).

In the example used, there is an 8-percent, or 1 in 12, chance of having an annual loss cost (aggregate annual losses divided by insurance) that exceeds twice the company's average loss cost (of 56.2 cents per \$100). And there is a 3.3 percent, or 1 in 30, chance that annual losses will exceed 250 percent of average. If the company's safety fund or reserve also amounts to $2\frac{1}{2}$ years of average losses, it may want to get aggregate-excess

reinsurance, which goes into effect at \$1.40 per \$100—250 percent of 56.2 cents.

From its own experience, the company can therefore evaluate the chances of having a year of unusually high losses. And, taking the size of its safety fund into consideration, it can arrive at a decision, with respect to the reinsurance protection it needs, that is better than it could otherwise reach.

The basic data for the example used here are shown in table 1. The annual loss costs (losses paid divided by insurance in force) of a crop-hail mutual insurance company are arrayed from lowest to highest, and are ranked in that order. Then, in column 4, the rank for each year is divided by 37, or (n+1) years.

Table 1.—Calculations necessary for plotting data on extreme-value probability paper, based on experience of mutual crop-hail insurance company, 1920–55 ¹

Year	Annual loss cost 2 y	Rank m	$\frac{\mathbf{m}}{\mathbf{n}+\mathbf{l}}$	Z 3
-124 (1)	(2)	(3)	(4)	(5)
-week orner agon	Cents		e) lo Ri Talitivio	GLXCUI est
1926 1938	8	1	0. 027	-1.28424
1932	20 23	2 3	. 054	
1942	26	4	. 108	W. S. 1984
1927	27	5	. 135	
1933	27	6	. 162	
1941	28	7	. 189	 51043
1931	29	8	. 216	
1949 1923	31	9	. 243	
1935	33 37	10	. 270 . 297	
1929	39	12	. 324	or to divi
1951	40	13	. 351	04590
1954	40	14	. 378	+.02751
1924	40	15	. 405	
1936 1945		16	. 432	
$1945_{}$	46 55	17	. 459	
1930	1 1 2 2 1 1			
1925	55 56	19 20	. 514	. 40717
1939	57	21	. 568	
1920	58	22	. 595	
1948	58	23	. 622	
1943	61	24	. 649	
1922	67	25	. 676	. 93761
1952		26	. 703	
1928		27	. 730	
1921 1950	69 74	28 29	. 757	
1940	75	30	. 784	

See footnotes at end of table.

⁵ The author has obtained a limited supply from the Weather Bureau and from the Climatology Unit, Environmental Protection Section, Research and Development Branch, Military Planning Division, Office of Quartermaster General, U. S. Army.

Table 1.—Calculations necessary for plotting data on extreme-value probability paper, based on experience of mutual crop-hail insurance company, 1920-55 1—Continued

Year	Annual loss cost ²	Rank m	$\frac{\mathrm{m}}{\mathrm{n}+1}$	\mathbb{Z}^3
(1)	(2)	(3)	(4)	(5)
1946	Cents 78 84 93 100 128 182	31 32 33 34 35 36	0. 838 . 865 . 892 . 919 . 946 . 973	1. 73309
TotalAverage	2, 023 56. 2	01 H(6	1444-11- 	19. 47600 . 5410
Standard deviation	33. 2			4 1. 1313

A few values of Z for selected values of m/n+1 are 1 A few values of Z for selected values of m/n+1 are given in column 5 merely to show that the average and standard deviation of the figures in this column depend only on sample size. For a given sample size (36 in example), the average and standard deviation of the reduced (Z) values always remain the same. The value of these constants for various sample sizes is given in table 2.

2 Aggregate loss payments divided by amount of insurance in force.

surance in force.

 3 Z=-1n[-1n(m/n+1)] . . . where 1n stands for natural logarithm.

4 Square root of [sum of squared deviations from average (0.5410) divided by 36 (not 35)].

The average and standard deviation of the Z-values (see table 1, footnote 3) for a sample consisting of 36 years are shown in table 2. Column 5 of table 1 shows how these values were derived for n=36. The average of 0.5410 and the standard deviation of 1.1313, which appear at the bottom of column 5 of table 1, therefore could have been obtained from table 2 opposite n=36.

The next step is to determine the slope of a regression line through the data and the mode of the distribution.

Slope of regression line=33.2/1.1313=29.35 (See standard deviations shown in table 1.) Mode = 56.2 - 29.35 (0.5410) = 56.2 - 15.9 = 40.3(See averages shown in table 1.)

Therefore

y=point on regression line=mode+(slope × Z) and in our problem

(1) ... y=40.3+29.35Z

Three points on the regression line are calculated in table 3, and the coordinates of these points are shown in the first and last columns.

These 3 values or paired observations are then plotted on the extreme-value probability paper (fig. 1). They are joined to form a straight line. Next, the observed values of y and m/n+1 (Cols. 2 and 4 of table 1) are plotted on the probability paper. The 3 coordinates used to fit the line appear as X's while the other coordinates appear as dots on the chart. The latter fall rather close to the line, indicating that the theory applies.

The calculations necessary to fit control curves are shown in table 4.

The vertical distances shown in col. (3) are marked off above and below the respective points on the regression line that are shown in col. (1). Then the points above the line are joined to form the upper boundary or control curve. The points below the regression line are likewise joined to form the lower boundary. Two-thirds of the dots or observations (col. 2 vs. col. 4 in table 1) should fall within the control curves in order for the theory to apply.

Summary of Steps

- 1. Construct a table like table 1. Only columns 2, 3, and 4 are necessary.
 - a. Compute the simple average and the standard deviation of your figures in column 2. In the example, the simple average is 56.9 cents and the standard deviation is 33.2 cents.
- 2. From table 2, find the theoretical average and standard deviation of the "reduced" (Z) values for a sample of the size you have.

In the example, n=36. For a sample of that size, the corresponding average and standard deviation of the Z values (see column 5, table 1) are, respectively, 0.5410 and 1.1313.

3. Compute the slope of your regression line by dividing the actual by the theoretical standard deviation.

> In the example, the slope is 33.2÷1.1313 or 29.35.

4. Multiply the theoretical average (step 2) by the slope (step 3). Then subtract this product from the sample average. The result is the mode of your sample.

> In the example, the mode is 40.3 as $0.5410 \times 29.35 = 15.9$ and 56.2 - 15.9 = 40.3

5. Express your regression line as a straightline equation which has the mode as a constant

Table 1.—Jaloulations necessary for plotting ta on extreme-value probability paper, based on experience of mutual crop-hail insurance company, 1920-55 1-Continued

Year	Annual loss cost ²	Rank m	$\frac{m}{n+1}$	Z ³
(1)	(2)	(3)	(4)	(5)
1946 1947 1944 1934 1937	Cents 78 84 93 100 128 182	31 32 33 34 35 36	0. 838 . 865 . 892 . 919 . 946 . 973	1. 78309
Total Average Standard	2, 023 56. 2			19. 47600 . 5410
deviation	33. 2		- 	1. 1313

A few values of Z for selected values of m/n+1 are given in column 5 merely to show that the average and standard deviation of the figures in this column depend only on sample size. For a given sample size (36 in example), the average and standard deviation of the reduced (Z) values always remain the same. The value of these constants for various sample sizes is given in table 2.

2 Aggregate loss payments divided by amount of in-

surance in force.

 * Z= $-\ln[-\ln(m/n+1)]$. . . where in stands for natural logarithm.

⁴ Square root of [sum of squared deviations from average (0.5410) divided by 36 (not 35)].

The average and standard deviation of the Z-values (see table 1, footnote 3) for a sample consisting of 36 years are shown in table 2. Column 5 of table 1 shows how these values were derived for n=36. The average of 0.5410 and the standard deviation of 1.1313, which appear at the bottom of column 5 of table 1, therefore could have been obtained from table 2 opposite n=36.

The next step is to determine the slope of a regression line through the data and the mode of the distribution.

Slope of regression line=33.2/1.1313=29.35 (See standard deviations shown in table 1.) Mode=56.2-29.35 (0.5410)=56.2-15.9=40.3 (See averages shown in table 1.)

Therefore

y=point on regression line=mode+(slope \times Z) and in our problem

(1) . . y=40.3+29.35Z

Three points on the regression line are calculated in table 3, and the coordinates of these points are shown in the first and last columns.

These 3 values or paired observations are then plotted on the extreme-value probability paper (fig. 1). They are joined to form a straight line. Next, the observed values of y and m/n+1 (Cols. 2 and 4 of table 1) are plotted on the probability paper. The 3 coordinates used to fit the line appear as X's while the other coordinates appear as dots on the chart. The latter fall rather close to the line, indicating that the theory applies.

The calculations necessary to fit control curves are shown in table 4.

The vertical distances shown in col. (3) are marked off above and below the respective points on the regression line that are shown in col. (1). Then the points above the line are joined to form the upper boundary or control curve. The points below the regression line are likewise joined to form the lower boundary. Two-thirds of the dots or observations (col. 2 vs. col. 4 in table 1) should fall within the control curves in order for the theory to apply.

Summary of Steps

- 1. Construct a table like table 1. Only columns 2, 3, and 4 are necessary.
 - a. Compute the simple average and the standard deviation of your figures in column 2. In the example, the simple average is 56.2. cents and the standard deviation is 33.2 cents.
- 2. From table 2, find the theoretical average and standard deviation of the "reduced" (Z) values for a sample of the size you have.

In the example, n=36. For a sample of that size, the corresponding average and standard deviation of the Z values (see column 5, table 1) are, respectively, 0.5410 and 1.1313.

3. Compute the slope of your regression line by dividing the actual by the theoretical standard deviation.

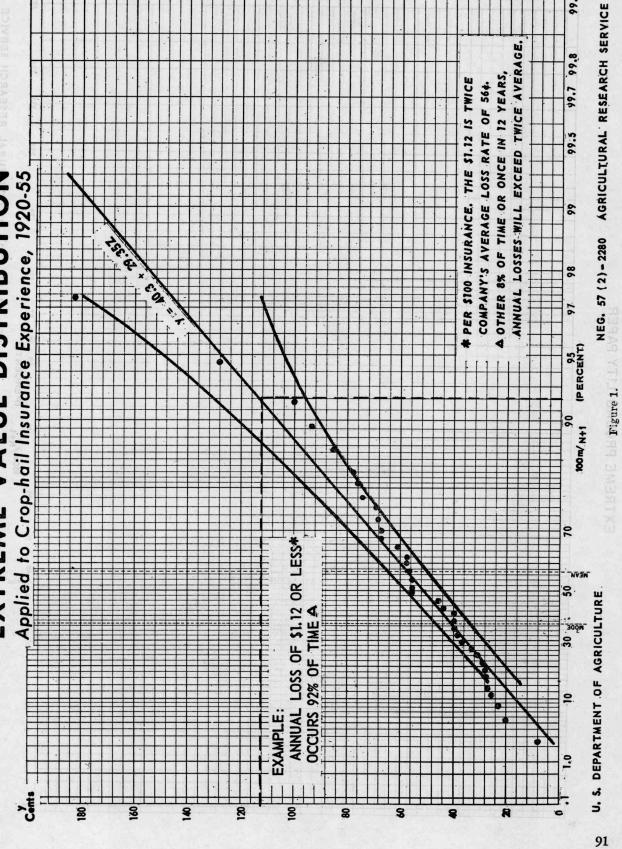
> In the example, the slope is $33.2 \div 1.1313$ or 29.35.

4. Multiply the theoretical average (step 2) by the slope (step 3). Then subtract this product from the sample average. The result is the mode of your sample.

> In the example, the mode is 40.3 as $0.5410 \times 29.35 = 15.9$ and 56.2 - 15.9 = 40.3

5. Express your regression line as a straightline equation which has the mode as a constant

EXTREME VALUE DISTRIBUTION



EXTREME PROBABILITY PAPER

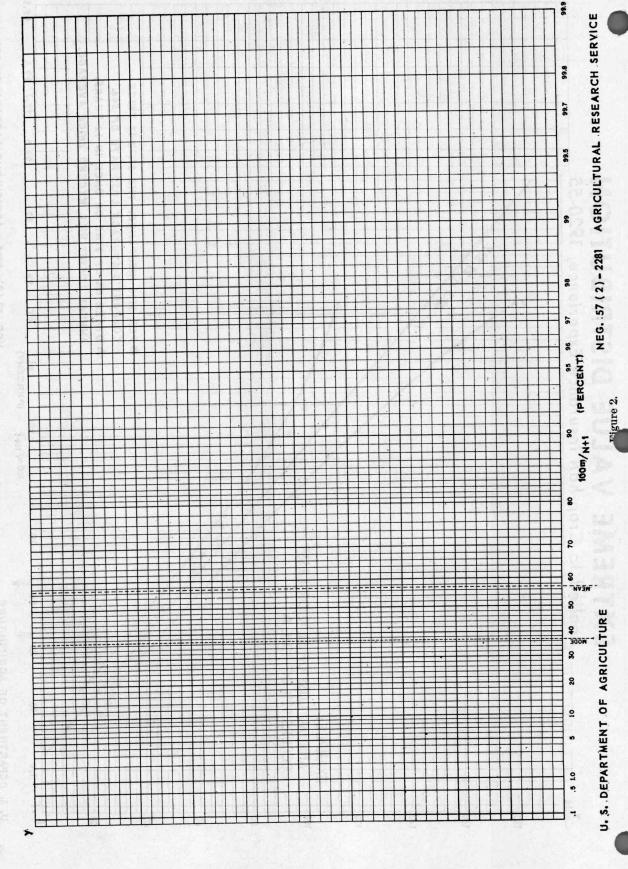


Table 2.—Averages and standard deviations of reduced (Z) values, by sample size 1

Sample size	Average	Standard deviation	Sample size	Average	Standard deviation	Sample size	Average	Standard deviation
15	0. 5128	1. 0206	40	0. 5436	1. 1413	65	. 5535	1. 1803
16	. 5153	1. 0301	41	. 5442	1. 1436	66	. 5538	1. 1814
17	. 5174	1. 0384	42	. 5448	1. 1458	67	. 5540	1. 1824
18	. 5196	1. 0471	43	. 5453	1. 1480	68		1. 1834
9	. 5217	1. 0558	44	. 5458	1. 1499	69	. 5545	1. 1844
			45		1. 1519	00	. 0010	1. 1011
200	. 5236	1. 0628	46	. 5468	1. 1538	70	. 5548	1. 1854
21	. 5252	1. 0696	47	. 5473	1. 1557	71	. 5550	1. 1863
22	. 5268	1. 0754	48	. 5477	1. 1574	72	. 5552	1. 1873
23	. 5283	1. 0811	49	. 5481	1. 1590	73	. 5555	1. 1881
24	. 5296	1. 0864	101111111	.0101	1. 1000	74	. 5557	1. 1890
25	. 5309	1. 0915	50	. 5485	1. 1607	75	. 5559	1. 1898
26	. 5320	1. 0961	51	. 5489	1. 1623	76	. 5561	1. 1906
27	. 5332	1, 1004	52	. 5493	1. 1638	77	. 5565	1. 1915
28	. 5343	1. 1047	53	. 5497	1. 1658	78	. 5565	1. 1923
29	. 5353	1. 1086	54	. 5501	1. 1667	79	. 5567	1. 1930
	. 0000	1. 1000	55	. 5504	1. 1681	10	. 5501	1. 1990
30	. 5362	1. 1124	56	. 5508	1. 1696	80	. 5569	1. 1938
1	. 5371	1. 1159	57	. 5511	1. 1708	90	. 5586	1. 2007
2	. 5380	1. 1193	58	. 5515	1. 1721	100	. 5600	1. 20649
3	. 5388	1. 1226	59	. 5518	1. 1734	150	. 5646	1. 22534
4	. 5396	1. 1255	00	. 0010	1. 1754	200	. 5672	1. 23598
5	. 5403	1. 1285	60	. 5521	1. 1747	Infinity	. 5772	1. 28255
6	. 5410	1, 1313	61	. 5524		Inninty	. 3/12	1. 20200
7	. 5418	1, 1339	62	. 5524	1. 1759 1. 1770		ER PERMIT	
8	. 5424	1. 1363	63					
9	. 5430	1. 1388	64	. 5530 . 5533	1. 1782 1. 1793			

¹ Furnished by Environmental Protection Section, Research and Development Branch, Office of Quartermaster General, U. S. Army (except values for samples of size 16-19).

Table 3.—Determination of 3 points on regression line

Then Z equals ¹	And y equals ²
$ \begin{array}{r} -0.47588 \\ +.36651 \end{array} $	26. 3 51. 1
	equals ¹ -0. 47588

¹ These same values of m/n+1 and Z can be used for all problems, thus eliminating the necessity for computing or looking up values of Z corresponding to various values of m/n+1. Z is defined in footnote 3 of table 1.

² By substitution in formula (1) above.

and Z as the variable (with a coefficient equal to the slope of the line).

In the example . . . y=40.3+29.35Z.

6. Determine 3 points on the regression line. By always using m/n+1 as 0.20, 0.50, and 0.95, respectively, the corresponding values of Z shown in column 2 of table 3 can be used for any example.

a. Fit these values of Z into your equation and solve for corresponding values of y. (See table 3.) Of course, the equation for each problem will include a different mode and slope; but the 3 values of Z need not change.

Table 4.—Computation of control curves

When $m/n+1$ equals ¹	Constant for $\frac{m}{n+1}$ equals 1	Vertical distance from point on line to control curve (4.892×column 2)²
(1)	(2)	(3)
0.15	1, 255 1, 268 1, 443 1, 835 2, 241 2, 585	6. 1 6. 2 7. 1 9. 0 11. 0 12. 6

¹ These values do not need to change from problem to problem.

² (1÷square root of n) ×slope of regression line. In the illustrative problem, n=36 years, so the square of n=6. The slope of the regression line is 29.35. One-sixth of 29.35 = 4.892.

 3 0.7594 \times slope of regression line. For illustrative problem, 0.7594 \times 29.35=22.3 The figure 0.7594 does not change from problem to problem.

 4 1.1407×slope of regression line. For illustrative problem, 1.1407×29.35=33.5. The figure 1.1407 does not change from problem to problem.

Table 6.—Spread sheet for extreme-value calculations $^{\scriptscriptstyle 1}$

olumn imber	Column heading	Explanation	Example
1	Identification	0.130	Crop-hail mutual
2	n	Number of years	36
3	Sum	From data sheet (table 1)	2, 023
4	Average	(3)÷(2)	56. 2
5	Sum of squared items	From data sheet (table 1)	152, 189
	Sum of squared tems	Square of (3)	4, 092, 529 113, 681
6	Correction	(6) · (2)	113, 681
7	Correction	(6) ÷ (2)	38, 508
8	Sum of squares	$(8) \div (\text{figure in column 2 minus 1})$	1, 100. 23
9	Variance	Covers root of (0)	33. 2
10	Standard deviation	Square root of (9) From table 2	0. 5410
11	Theoretical average	From table 2	1. 1313
12	Theoretical standard deviation	from table 2	29. 35
13	Slope	(10) ÷ (22)	15. 9
14	(11)×(13)	(4) – (14)	40. 3
15	Mode	(4) – (14)	10. 0
First	point on regression line	1006	
051.6	1.1.21 (00 - 5ndn 5ndn		0. 20
16	m/n+1	It can always be 0.20	-0.47588
17	Z	If m/n+1 is 0.20, Z does not change	-0.47588 -14.0
18	Slope×Z	$(13)\times(17)$	26. 3
	y	(15) + (18)	20. 0
Seco	nd point on regression line	1966 - 20	
	0.0222 T	It can always be 0.50 If $m/n+1$ is 0.50 , Z does not change $(13)\times(21)$	0. 50 0. 36651 10. 8 51. 1
Seco 20 21 22 23	nd point on regression line	It can always be 0.50	0. 36651 10. 8
20 21 22 23 Thir	nd point on regression line	It can always be 0.50	0. 36651 10. 8 51. 1
Seco 20 21 22 23 Thir	nd point on regression line	It can always be 0.50	0. 36651 10. 8 51. 1
Seco 20 21 22 23 Thir	nd point on regression line $ \begin{array}{ c c c c c c c c c c c c c c c c c c c$	It can always be 0.50	0. 36651 10. 8 51. 1 0. 95 2. 97020
20 21 22 23 Thir	nd point on regression line $ \begin{array}{ c c c c c c c c c c c c c c c c c c c$	It can always be 0.50	0. 36651 10. 8 51. 1 0. 95 2. 97020 87. 2
Seco 20 21 22 23 Thir	nd point on regression line $ \begin{array}{ c c c c c c c c c c c c c c c c c c c$	It can always be 0.50	0. 36651 10. 8 51. 1 0. 95 2. 97020
20 21 22 23 Thir 24 25 26 27	nd point on regression line $ \begin{array}{ c c c c c c c c c c c c c c c c c c c$	It can always be 0.50	0. 36651 10. 8 51. 1 0. 95 2. 97020 87. 2
20 21 22 23 Thir 24 25 26 27 Con	m/n+1	It can always be 0.50	0. 36651 10. 8 51. 1 0. 95 2. 97020 87. 2 127. 5
Seco 20 21 22 23 Thir 24 25 26 27 Con 28	m/n+1	It can always be 0.50	0. 36651 10. 8 51. 1 0. 95 2. 97020 87. 2 127. 5
20 21 22 23 Thir 24 25 26 27 Con 28 29	m/n+1	It can always be 0.50	0. 36651 10. 8 51. 1 0. 95 2. 97020 87. 2 127. 5
Seco 20 21 22 23 Thir 24 25 26 27 Con 28 29 30	m/n+1	It can always be 0.50	0. 36651 10. 8 51. 1 0. 95 2. 97020 87. 2 127. 5
Seco 20 21 22 23 Thir 24 25 26 27 Con 28 29 30 31	m/n+1	It can always be 0.50	0. 36651 10. 8 51. 1 0. 95 2. 97020 87. 2 127. 5
20 21 22 23 Thir 24 25 26 27 Con 28 29 30 31 32	m/n+1	It can always be 0.50	0. 36651 10. 8 51. 1 0. 95 2. 97020 87. 2 127. 5
20 21 22 23 Thir 24 25 26 27 Con 28 29 30 31 32 33 33 33 33 33 33 33 33 33 33 33 33	m/n+1 Slope×Z Y Slope×Z Slop	It can always be 0.50	0. 36651 10. 8 51. 1 0. 95 2. 97020 87. 2 127. 5 6 0. 16666 4. 892 6. 1 6. 2 7. 1
20 21 22 23 Thir 24 25 26 27 Con 28 29 30 31 32 32 33	nd point on regression line $m/n+1$ Z $Slope \times Z$ Y Z	It can always be 0.50. If m/n+1 is 0.50, Z does not change. (13) × (21). (15) + (22)	0. 36651 10. 8 51. 1 0. 95 2. 97020 87. 2 127. 5 6 0. 16666 4. 892 6. 1 6. 2 7. 1 9. 0
Seco 20 21 22 23 Thir 24 25 26 27 Con 28 29 30 31 32 33 34 34 35	m/n+1	It can always be 0.50. If m/n+1 is 0.50, Z does not change. (13) × (21). (15) + (22)	0. 36651 10. 8 51. 1 0. 95 2. 97020 87. 2 127. 5 6 0. 16666 4. 892 6. 1 6. 2 7. 1 9. 0 11. 0
20 21 22 23 Thir 24 25 26 27 Con 28 29 30 31 32 33 34 35 36 36	nd point on regression line $ \begin{array}{ c c c c c c c }\hline & m/n+1 & & & & \\\hline & z & & & & \\\hline & Slope \times Z_{-} & & & \\\hline & z & & & & \\\hline & z &$	It can always be 0.50	0. 36651 10. 8 51. 1 0. 95 2. 97020 87. 2 127. 5 6 0. 16666 4. 892 6. 1 6. 2 7. 1 9. 0 11. 0 12. 6
Seco 20 21 22 23 Thir 24 25 26 27 Con 28 29 30 31 32 33 34 34 35	m/n+1	It can always be 0.50	0. 36651 10. 8 51. 1 0. 95 2. 97020 87. 2 127. 5 6 0. 16666 4. 892 6. 1 6. 2 7. 1 9. 0 11. 0

¹ In addition to a spread sheet, for mass production of data, a separate data sheet (like table 1) is needed for each set of annual data.

In the example,

$\frac{m}{n+1}$	Mode	Calculations slope	Z	Y
0.20	40.3+(29	35×47588		26. 3
.50	40.3 + (29)	$0.35 \times + .36651)_{-}$		51. 1
95	$40.3 \pm (29)$	35× 2 97020)		127 5

7. Plot the 3 coordinates (of m/n+1 versus y) on extreme-value probability paper.

a. Find the value for m/n+1 on horizontal scale and, from this point, go up to a point

opposite y on vertical scale, where an x or dot is placed. Locate 3 such coordinate points.

In the example,

Horizontal	scale -	<u>m</u>	ertical scale
0.20	n n	n+1:	y 26. 2
.50			51.1
.95			127.5

- 8. Join these 3 points in a straight line. If they do not fall in a straight line, an error has occurred.
- 9. Now plot your data from table 1 (columns 2 and 4) on the probability paper. The dots should fall quite closely about the line in order for the extreme-value theory to apply.

In the example (from table 1),

Horizontal scale $\frac{m}{n+1}$ (Col. 2):	Vertical scale y (Col. 4)
0.027	8
.054	_ 20
.081	_ 23
etc	- etc.

If control curves are desired,

- 10. Compute vertical distances (above and below) from points on the regression line, as explained in table 4.
- 11. Join these points to form control curves. (See fig. 1.)

ory little can be cultilized for good classes of late.

a. If two-thirds of the dots fall within the control curves, the theory applies.

In the example, 30 of 36 dots, or 83 percent, fall within the control curves.

Table 5.—Probabilities that may be read from regression line in figure 1

Annual los	s cost (y)	Cumulative probability of occurrence $\frac{m}{n+1}$		
Cost per \$100 of insurance	Percentage of average ¹	Equal to or less than y	More than y	
Cents	Percent	Percent	Percent	
56.2	$\begin{array}{c} 72 \\ 100 \end{array}$	37 57	63	
112.4	200	92	8	
140.5	250	96. 7	3. 3	
168.6	300	98. 7	1. 3	

¹ Average loss cost 56.2 cents per \$100 of insurance.

Interpretation of Data

The annual loss costs in the example are distributed fairly well about the regression line.⁶ More than two-thirds of the dots fall within the control curves. The probabilities in table 5 may be read from the regression line in fig. 1:

An extra sheet of the probability paper is included (as fig. 2) in this article for use by those who wish to experiment with the method.

The column headings for a spread sheet, and their explanation, including the data for the example used here, are shown in table 6.

reconcernic as a line to the visite many contribute to the

⁶ Equation: y=40.3+29.35Z.