Forest Hydrology: Lect. 5

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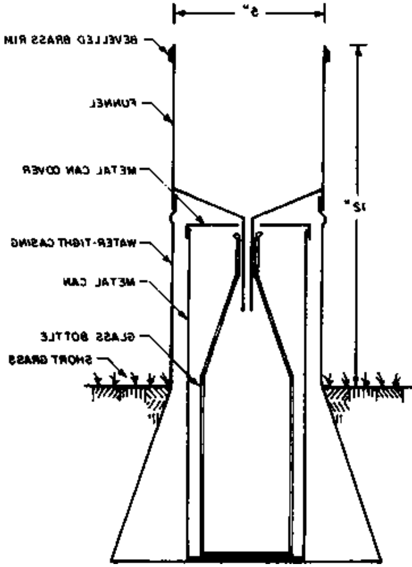
Precipitation measurement: the Raingauge

- Non-Recording Gauges: Manually Observed
  - For 24-hour collection, a standard rain gauge is typically used. This is a hollow metal tube with an open top that collects precipitation. The observer uses a ruler to measure the depth of the water in a small inner tube. In the winter, the small tube is taken out, and snow falls directly into the large tube. Then, snow is melted down and poured into the small tube to be measured.

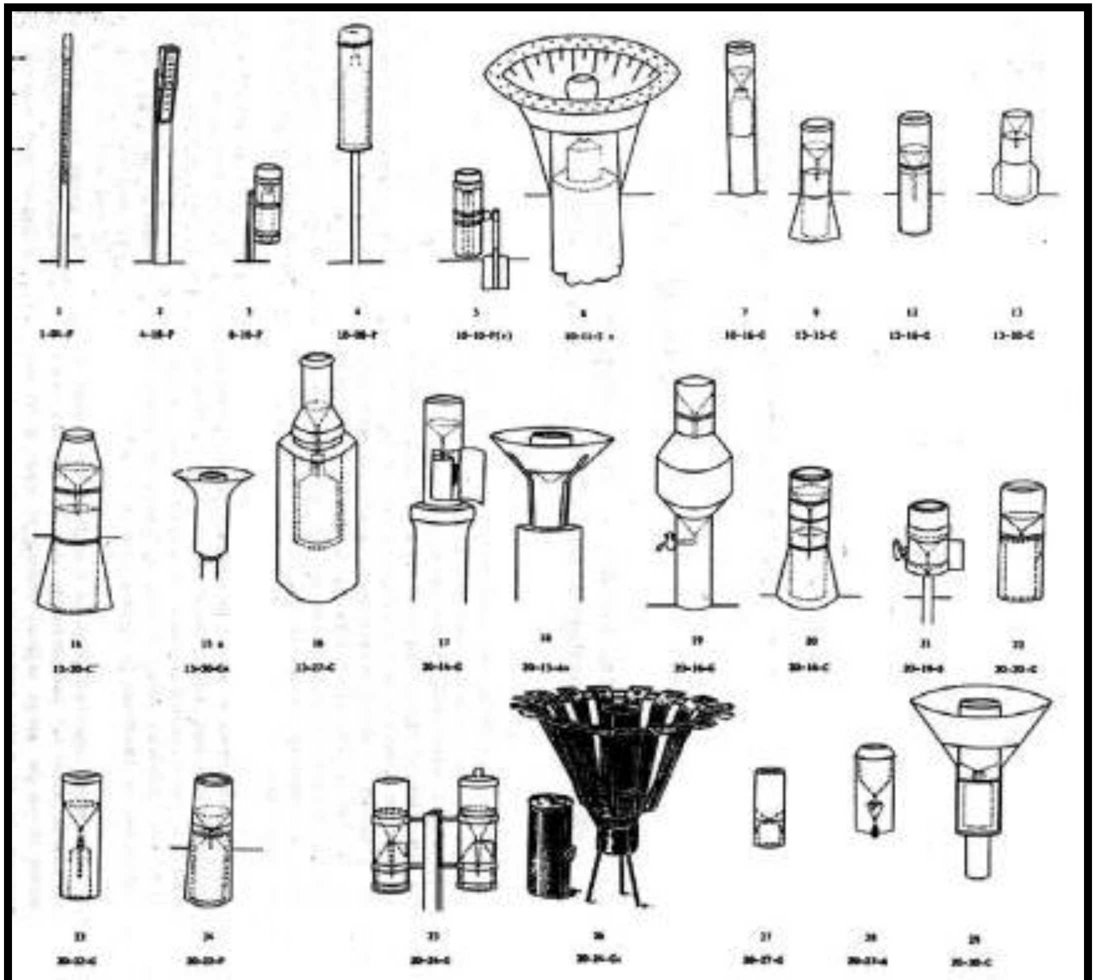


Precipitation measurement: the Raingauge

Tipping Bucket

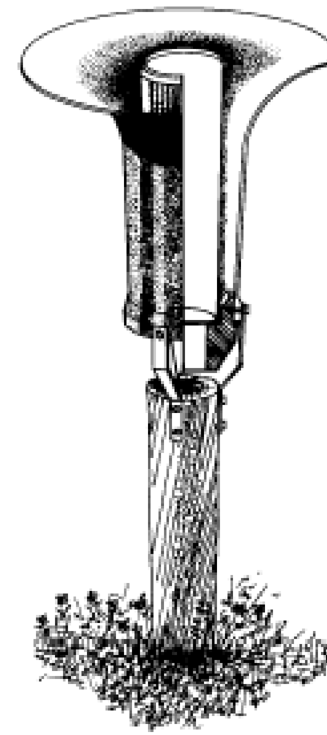
- **Recording Gauges**:
  - Tipping Bucket: Automatically tips when a certain amount of precipitation accumulates inside of it. Total precipitation is determined by the number of tips.
  - Weighing Gauge: Tall and typically cone-shaped. It collects all types of precipitation continuously into a bucket. Its weight presses down on a scale, and every 15 minutes, a hole is punched in a ticker tape or a marking is made on paper by pen to record the bucket's weight. This is useful for hourly collections.
  - Optical Gauge: Measures precipitation rate proportional to a disturbance to a beam between a light-emitting diode and a sensor.

Precipitation gauges in the world



- ~50 types of National Standard gauges
- (Sevruk et al., 1989)

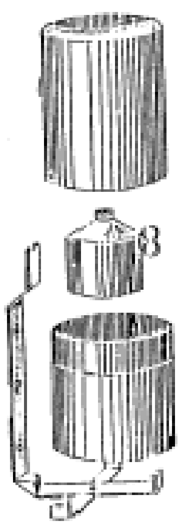
Shilded Nipher Gauge



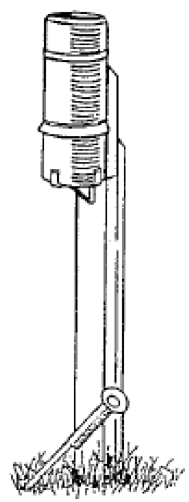
- Used in Canada for Solid Precipitation
- Small errors

Hellmann Gauge

- Various Designs: Italy, German, Polish, Danish, Hungarian
- Standard in 30 countries: used 30,000 locations world-wide



Yugoslav Standard



Danish Standard

German Unshielded

Nipher-Shielded

Undercatch of precipitation using standard gauges

Wind-Induced Undercatch	Snow: 10 to >50% Rain: 2 to 10%
Wetting Losses	2 to 10%
Evaporation Losses	0 to 4%
Treatment of Trace Precipitation as Zero	Significant in Cold Arid Regions
Splash-out and splash-in	1 to 2%
Blowing and Drifting Snow	??

Sevruk, 1982

Estimation of mean areal rainfall (over a basin) - 1

Generally, what is really needed in hydrology is the value of the precipitation over an area (a basin, for instance). So, we frequently need to estimate a mean areal rainfall based on point-values (raingauge measurements).
The various available methods, which provide the value of the mean areal rainfall based on point precipitation values p_i *available at* n stations, can be written down as follows:

$$P_{meanareal} = \sum_{i=1}^{n} \lambda_i p_i$$

$$where:$$

$$n = number\ raingauges;$$

$$p_i = precipitation\ data\ at\ station\ \ i-th$$

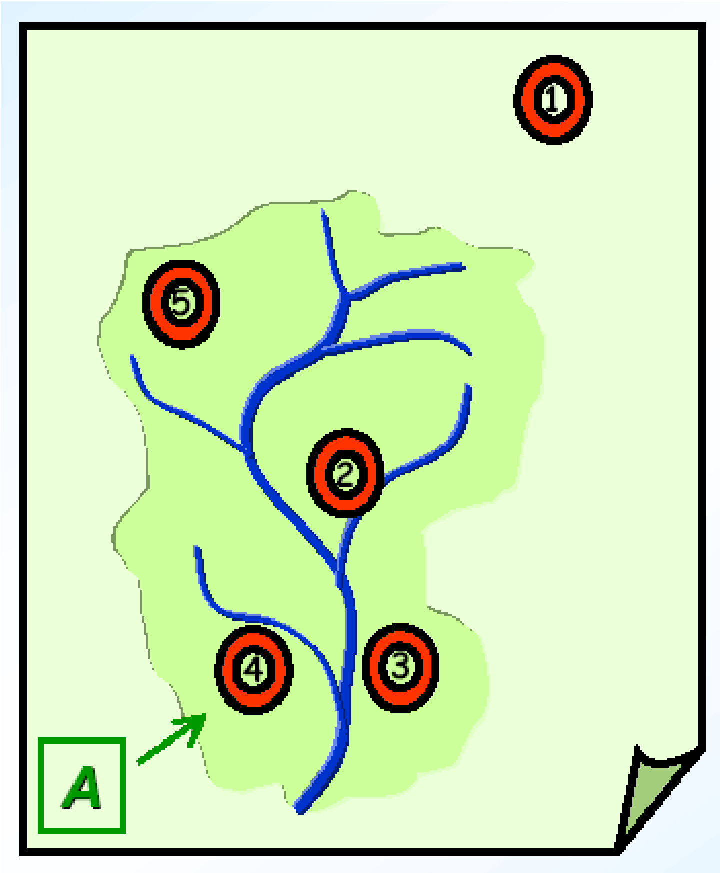
$$\lambda_i = weghting\ \ factor\ for\ station\ \ \ i-th.$$

Estimation of mean areal rainfall - 2

The average

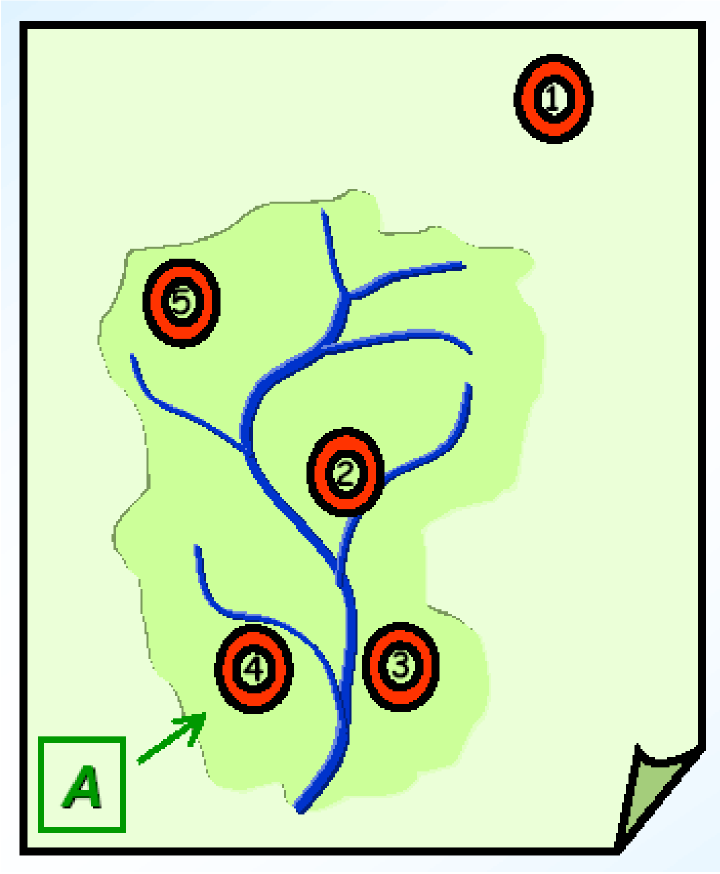
The simplest method is to take the average of the available data. This implies that the weighting factors are all equal to 1/n, when n is the number of available raingauges.

However, this method cannot take really into account the areal representativeness of the various raingauges. A raingauge far from the basin (station 1) is considered the same way as a raingauge in the center of the basin (station 2).
We need to work out a method capable to take geometry of both raingauge net and basin into account.



Estimation of mean areal rainfall - 3

Station	Precipitation (mm)	Factor
1	10	0
2	20	1/4
3	30	1/4
4	40	1/4
5	50	1/4
Mean rainfall	35 mm	



In this computation, we computed the mean rainfall without taking into account station 1, and applying the average computation over stations 2-5 by using $\frac{1}{4}$ as a weighting factor. Repeat the computation by taking into account Station 1, and repeat again the computation by considering various precipitation data for station 1.

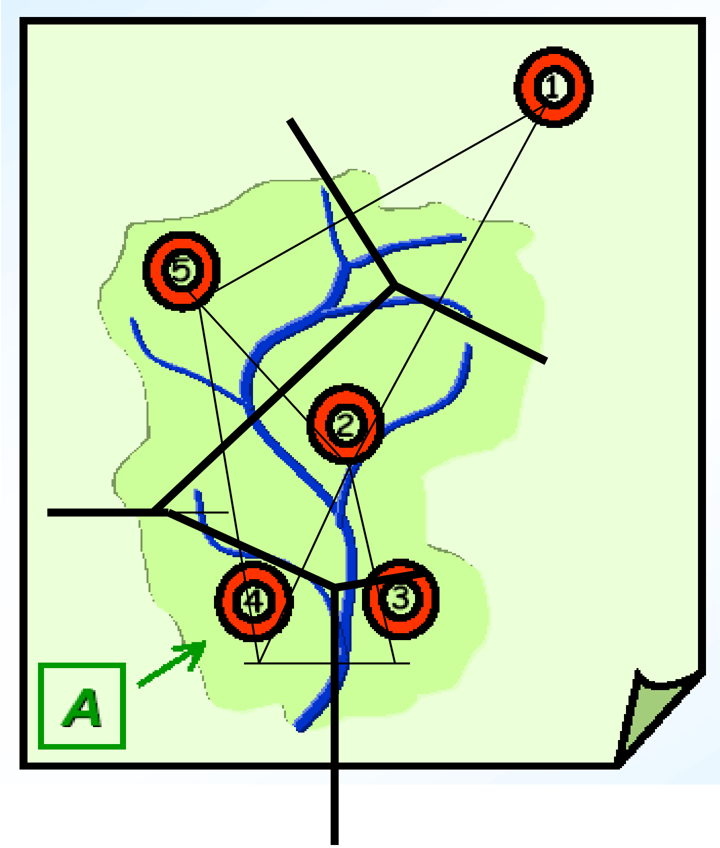
Estimation of mean areal rainfall
Thiessen method - 1

To take geometry into consideration, we can use the Thiessen method.

The Thiessen method takes each point in the watershed and associates it with the nearest weather station, thus a Thiessen polygon of area S_i is formed for each weather station.

The weighting factor λ_i for the i-th station is computed by taking the ratio between basin area S and the Thiessen polygon S_i, as follows:

$$\lambda_{i,s} = \frac{S_i}{S}$$

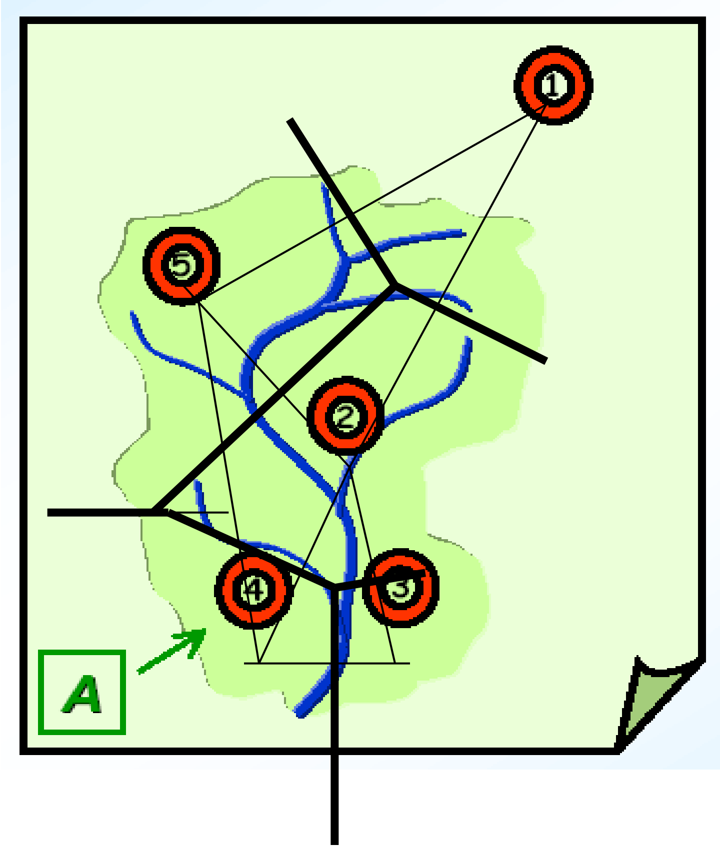


Estimation of mean areal rainfall
Thiessen method - 2

The graphical procedure:

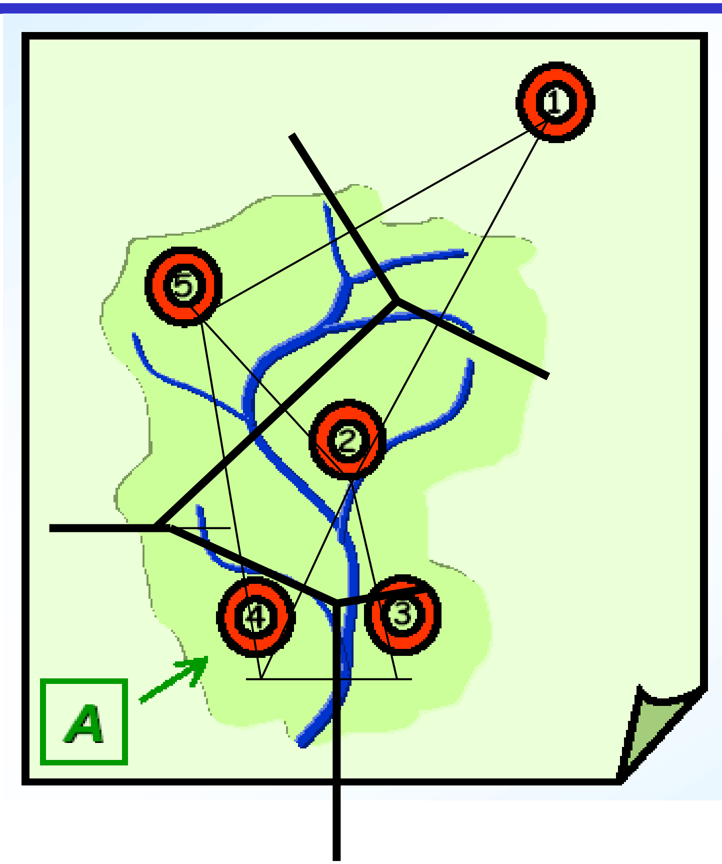
The procedure consists of connecting each precipitation station with straight lines and constructing perpendicular bisectors of the connecting lines to form polygons with these bisectors.

Note that many GIS sw have the capability to compute authomatically Thiessen methods.



Estimation of mean areal rainfall
Thiessen method - 3

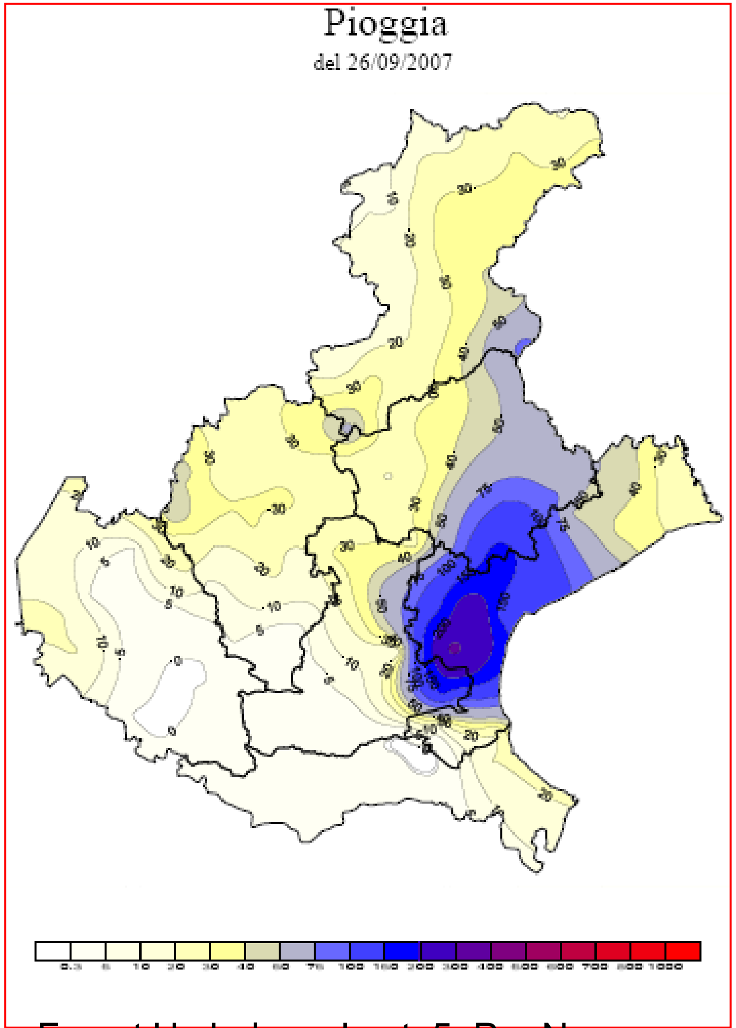
Stat.	Precipitation (mm)	Area (km^2)	Factor	Weighted Precipit. (mm)
1	10	2.2	0.02	0.2
2	20	40.2	0.44	8.8
3	30	13.5	0.15	4.4
4	40	16.0	0.18	7.0
5	50	19.5	0.21	10.7
Mean precip				31.1



Taking geometry into account, the mean areal precipitation is equal to 31.1 mm. Please note the difference between the factors obtained for station 1 and for station 2.

Estimation of the rainfall spatial distribution: Inverse distance, splines, kriging,….

There are several methods which produce rainfall maps. Among these:
Inverse distance,
Splines,
Kringing.



Estimation of the rainfall spatial distribution: Inverse distance - 1

One of the most commonly used techniques for interpolation of scatter points is inverse distance weighted (IDW) interpolation. Inverse distance weighted methods are based on the assumption that the interpolating surface should be influenced most by the nearby points and less by the more distant points.
The required estimate at coordinate t_0, $z^*(t_0)$,is *given* by:

$$z^*(t_0) = \sum_{i=1}^{n} \lambda_i z(t_i)$$

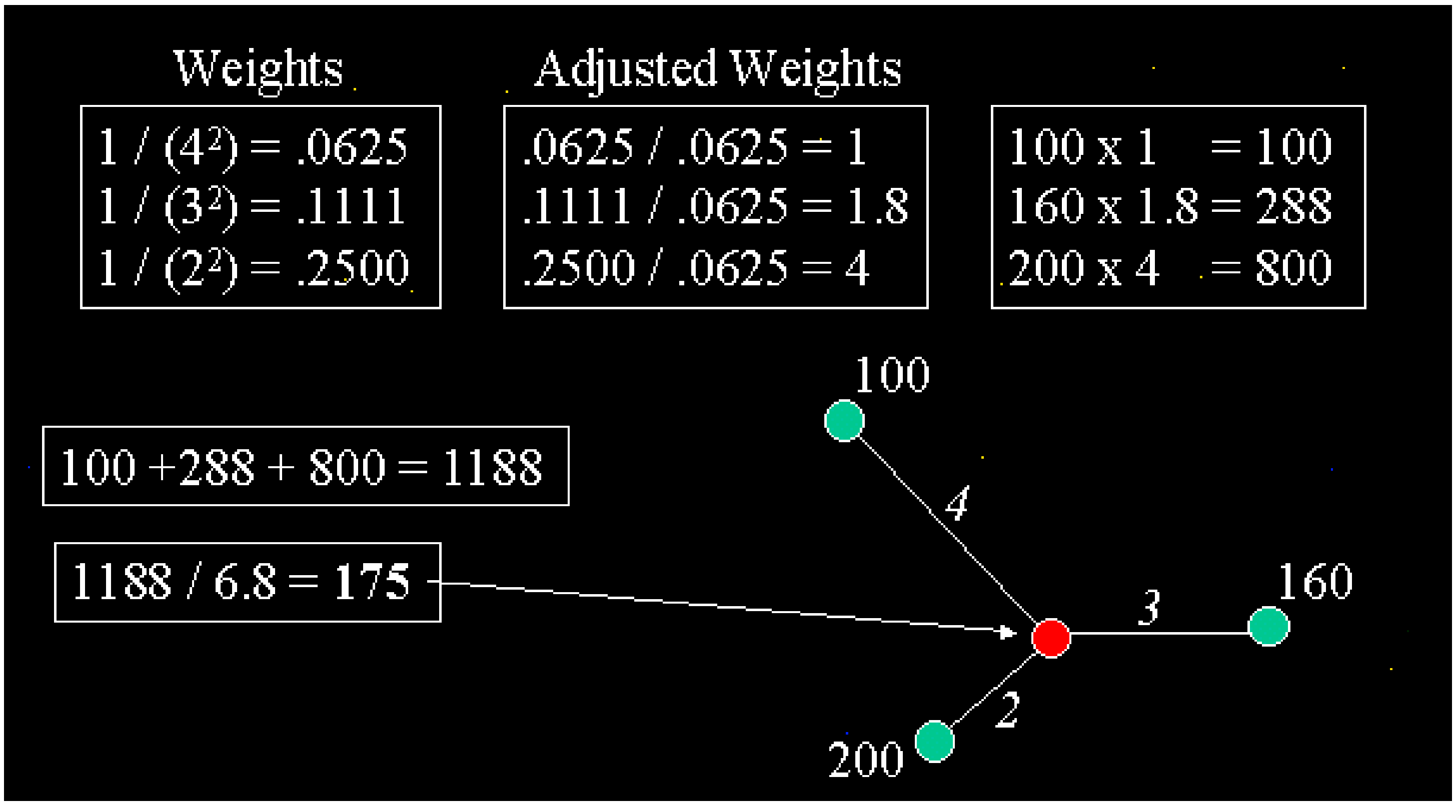
where

$$\lambda_j = \frac{f(d_{oj})}{\sum_{i=1}^{n} f(d_{0i})}$$

and where

$$f(d_{0j}) = \frac{1}{d_{0i}^{\ b}}$$

Estimation of the rainfall spatial distribution: Inverse distance: example



How Inverse Distance Weighted interpolation works

Inverse Distance Weighted interpolation explicitly implements the assumption that things that are close to one another are more alike than those that are farther apart. To predict a value for any unmeasured location, IDW will use the measured values surrounding the prediction location. Those measured values closest to the prediction location will have more influence on the predicted value than those farther away. Thus, IDW assumes that each measured point has a local influence that diminishes with distance. It weights the points closer to the prediction location greater than those farther away, hence the name inverse distance weighted.

The general formula is:

$$\hat{Z}(s_0) = \sum_{i=1}^{N} \lambda_i Z(s_i)$$

where:

$\hat{Z}(s_0)$ is the value we are trying to predict for location s_0.

N is the number of measured sample points surrounding the prediction location that will be used in the prediction.

λ_i are the weights assigned to each measured point that we are going to use. These weights will decrease with distance.

$Z(s_i)$ is the observed value at the location s_i.

The formula to determine the weights is the following:

$$\lambda_i = d_{i0}^{-p} / \sum_{i=1}^{N} d_{i0}^{-p} \qquad \sum_{i=1}^{N} \lambda_i = 1,$$

As the distance becomes larger, the wight is reduced by a factor of p.

The quantity d_{i0} is the distance between the prediction location, s_0, and each of the measured locations, s_i.

The power parameter p influences the weighting of the measured location's value on the prediction location's value; that is, as the distance increases between the measured sample locations and the prediction location, the weight (or influence) that the measured point will have on the prediction will decrease exponentially.

The weights for the measured locations that will be used in the prediction are scaled so that their sum is equal to 1.

The power function

The optimal p value is determined by minimizing the root-mean-square prediction error (RMSPE). The RMSPE is the statistic that is calculated from cross-validation (see Chapter 7, 'Using analytical tools when generating surfaces'). In cross-validation, each measured point is removed and compared to the predicted value for that location. The RMSPE is a summary statistic quantifying the error of the prediction surface. The Geostatistical Analyst tries several different powers for IDW to identify the power that produces the minimum RMSPE. The diagram below shows how the Geostatistical Analyst calculates the optimal power. The RMSPE is plotted for several different powers for the same dataset. A curve is fit to the points (a quadratic local polynomial equation), and from the curve the power that provides the smallest RMSPE is determined as the optimal power.