Masters
Program
in **Geospatial**
Technologies

Geospatial Analysis of Extreme Weather Events in Nigeria (1985 -2015) Using Self Organizing Maps

Adeoluwa Stephen Akande

Dissertation submitted in partial fulfilment of the requirements
for the Degree of *Master of Science in Geospatial Technologies*

Masters
Program
in **Geospatial**
Technologies

Geospatial Analysis of Extreme Weather Events in Nigeria (1985 -2015) Using Self Organizing

Adeoluwa Stephen Akande

Dissertation submitted in partial fulfilment of the requirements
for the Degree of *Master of Science in Geospatial Technologies*

NOVA IMS Information Management School

UNIVERSITAT JAUME•I

WESTFÄLISCHE WILHELMS-UNIVERSITÄT MÜNSTER

Geospatial Exploration of Extreme Weather Events

A case study of precipitation in Nigeria between 1979 and 2016

Dissertation supervised by

Professor Roberto Henriques, PhD

Professor Ana Cristina Costa, PhD

Professor Jorge Mateu, PhD

February 2017

ACKNOWLEDGMENTS

I would like to express my profound gratitude to God, the giver and sustainer of life for the privilege of life and a sound mind. I am grateful to the consortium of the master's program in Geospatial Technologies for funding my studies cumulating to this dissertation. My acknowledgement wouldn't be complete without the mention of my wife, Temitayo Ogunjirnrin who patiently stood by me during the course of my study in Europe. I love you baby. Finally, to family, friends and mentors, I appreciate your contribution to my success.

Geospatial analysis of extreme weather events in Nigeria (1985–2015) using Self Organizing Maps

ABSTRACT

The explosion of data in the information age has provided an opportunity to explore the possibility of characterizing the climate patterns using data mining techniques. Nigeria has a unique tropical climate with two precipitation regimes: low precipitation in the north leading to aridity and desertification, and high precipitation in parts of the south west and south east leading to large scale flooding. In this research, four indices have been used to characterize the intensity, frequency and amount of rainfall over Nigeria. A type of Artificial Neural Network called Self Organizing Map has been used to reduce the multiplicity of dimensions and produce four unique zones characterizing extreme precipitation conditions in Nigeria. This approach allowed for the assessment of spatial and temporal patterns in extreme precipitation in the last three decades. Precipitation properties for each cluster are discussed. The cluster spatially closest to the Atlantic has high values of precipitation intensity, frequency and duration, whereas the cluster spatially closest to the Sahara Desert has low values. A significant increasing trend has been observed in the frequency of rainy days in the northern region of Nigeria.

KEYWORDS

Self Organizing Maps
Extreme Climate
Precipitation
Nigeria

SUBMISSION

Submission Resulting from this Thesis

Paper

Akande, A., Costa, A., Mateu, J. & Henriques, R. (2017). Geospatial Analysis of Extreme Weather Events in Nigeria (1985 – 2015) using Self Organizing Maps. *Advances in Meteorology*, *2017*.

ACRONYMS

BMU	Best Matching Unit
CA	Cluster Analysis
CHIRPS	Climate Harzards Group Infrared Precipitation with Stations
ETCCDI	Expert Team on Climate Change Detection and Indices
IDW	Inverse Distance Weighting
ITD	Inter-Tropical Discontinuity
NETCDF	Network Common Data Format
SDII	Simple Daily Intensity Index
SOM	Self Organizing Maps
TFLN	Time Lagged Feedforward Network
R1	Number of Wet Days
Rx1D	Maximum 1-Day Precipitation
Rx5D	Maximum 5-day Precipitation

INDEX OF THE TEXT

INDEX OF FIGURES

INDEX OF TABLES

1 Introduction

One of the visible impacts of climate change and climate variability are extreme weather events that occur from time to time in several parts of the globe. A climate extreme is "the occurrence of a value of a weather or climate variable above (or below) a threshold value near the upper (or lower) ends of the range of observed values of the variable" (IPCC 2012). Climate extremes can result in changes in the frequency, intensity, spatial extent, duration and timing of climatic phenomena. There is a growing global concern that anthropogenic activities are a major cause of the variability in the intensity and frequency of weather and climate extremes (Klein Tank, Zwiers, and Zhang 2009) (IPCC 2007) (Stefan 2005). However, it can also be argued that climate extremes are just a part of decadal global climate cycle and variability (IPCC 2014).

Climate extremes, including the ones related to precipitation, can be analyzed using several approaches (Gorricha, Lobo, and Costa 2013) (Jones et al. 2014) (Thibaud, Mutzner, and Davison 2013). The use of indices to characterize the frequency, intensity and duration of precipitation extremes is one of the ways to assess them (Alexander et al. 2006) (Donat et al. 2013) (Moberg et al. 2006) (Van den Besselaar, Klein Tank, and Buishand 2013). The joint working group CCI/CLIVAR/JCOMM Expert Team on Climate Change Detection and Indices (ETCCDI)[1] has 27 standardized and recommended climate extreme indices (Klein Tank, Zwiers, and Zhang 2009; T. C. Peterson 2005; Karl, Nicholls, and Ghazi 1999; Thomas C Peterson et al. 2001). This set of indices includes both temperature and precipitation indices.

Precipitation is one of the most important climatic parameters responsible for flood and drought in several vulnerable parts of the world. According to (IPCC 2012), there is a high chance that the frequency of heavy precipitation and total precipitation will increase in several parts of the globe in the 21st century. Evidence of climate change in Nigeria has been discussed by (Akpodiogaga- and Odjugo 2009), who reported increasing damages caused by wind and rainstorms, which are projected to increase in southern regions (Abiodun et al. 2013) The northern part of the country has been experiencing a reduction in rainfall, and an increase in the rates of dryness and heat(Obioha 2008; Onyekuru and Marchant 2014), while the rainfall amounts have been increasing in the southern part with an irregular pattern (Onyekuru and Marchant 2014; Ta et al. 2016). Moreover, climate projections for the 21st century show a significant increase of temperature over all the ecological zones (Abiodun et al. 2013) which may have negative impacts on agriculture and food security. (Adejuwon 2006) evaluated how crop yield might respond to climate change in Nigeria, and (Enete and Amusa 2010) discuss the challenges of agricultural adaptation to climate change.

Proper study of climate extremes depends on the quality and quantity of data, as well as on how rigorously they are analyzed (IPCC 2012). When dealing with precipitation extremes, it is important to consider their synoptic aspects and dimensions. The recent increase of data from ground observations, satellites, as well as numerical models, enables the opportunity for exploring the use of data mining techniques in climatic studies (Gorricha, Lobo, and Costa 2013). One of such techniques is Cluster Analysis (CA). The use of CA to gain insight from geographical data had more serious adoption since

[1] *http://etccdi.pacificclimate.org/index.shtml*

the 1990s decade (Xiaofeng Gong and Richman 1995). Several attempts have been made in the past to characterize extreme climate using machine learning methods. Self-Organizing Maps (SOM) have successfully been applied to several climate research including the analysis of atmospheric circulations variability (Res, Hewitson, and Crane 2002), time evolution of seasonal climate (Jr et al. 2004), climate model downscaling (Hewitson and Crane 2005), and to access to access the stationary of global climate models (Hewitson and Crane 2006).

Rodrigues (Rodrigues 2010) did a study on the spatial and temporal variation of extreme weather in the Iberian Peninsula using seven different temperature and precipitation indices. Using geostatistics, these indices were analyzed and Inverse Distance Weighting (IDW) maps were produced to compare the spatial and temporal surface distribution of the indices. Clustering was thereafter done using SOM to study areas with similar climatic characteristics for two time periods, 1951 – 1980 and 1981 – 2010. The SOM analysis were done separately for temperature and precipitation indices as mixing both indices together did not provide consistent conclusions in the Iberian Peninsula. (Gorricha, Lobo, and Costa 2013) also visualized extreme climate conditions using linear models (ordinary kriging and ordinary cokriging) and a non-linear model (a three-dimensional SOM). They made use of indices calculated from precipitation data obtained between 1998 and 2000 from nineteen meteorological station covering Madeira Island in Portugal.

Nigeria has had its fair share of climate extremes in recent times. The floods of July 10, 2011 in Lagos, August 26, 2011 in Ibadan and more recently nationwide floods of 2012 are all pointers to the extreme precipitation being experienced in the country (Okoloye et al. 2013). In Nigeria, making use of nine indices, (Gbode, Akinsanola, and Ajayi 2015) were able to study climate extremes over Kano making use of temperature and precipitation data. Using temperature data, the authors could notice a warming trend characterized by an increase in the number of warm days and warm spell. The rainfall data showed a similar increase in the amount of rainfall over the region. Other studies have attempted to use linear approaches to study temperature and rainfall trends over various parts of the country (Ekpoh and Nsa 2011), (Akinsanola 2014), (Ogungbenro and Morakinyo 2014). However, none of these studies have attempted to study their spatial local patterns. A first attempt to use data mining techniques in climatic studies of Nigeria was carried out by (Olaiya and Adeyemo 2012). Making use of a Time Lagged Feedforward Network (TFLN) and recurrent network, they could predict the future values of 8 climatic parameters.

This study will however be focused on the geoexploration of climate extremes as opposed to its prediction. Based on the framework proposed by (Gorricha, Lobo, and Costa 2013), this research will be making use of a SOM to visualize the phenomenon from a global perspective.

The atmosphere is a continuum and SOM aids the visualization of this continuum by placing very different atmospheric states on distant nodes and similar atmospheric nodes on adjacent nodes.

The objective of this research is to cluster precipitation extreme over Nigeria, characterize regions of similar precipitation patterns and characterize its evolution over a period of 31 years. Our study area is first introduced with emphasis on its climate to give a background on the type of climate we are working with. CHIRPS dataset is subsequently introduced as the precipitation data from which precipitation extreme indices are calculated. The methodology used for this research is explained and results obtained is laid out. We wrap up this paper with a conclusion.

2 Materials and methods

2.1 Study area

Nigeria is a country located in West Africa. It lies between 4^0N and 14^0N latitude and 4^0E and 14^0E longitude and is bordered in the South by the Atlantic Ocean and the North by the Sahara Desert (Figure 1). This gives the country a very wide range of Climatic pattern experienced throughout the year.

Figure 1: Study area in Nigeria

Its weather system is controlled by the Inter-Tropical Discontinuity (ITD). The ITD is the area of lowest pressure over West Africa separating the moist Southwest Monsoon from the Atlantic Ocean and the dry Northeast trade winds from the Sahara Desert. Hence, the ITD can be located with the aid of a change in wind direction as well as the amount of moisture in the atmosphere. This is also given by the dew point temperature. The south of the ITD usually has a dew point temperature greater than 15^0C while the north of the ITD usually has a dew point temperature greater than 15^0C. The atmosphere to the south of the ITD is usually moist aiding the formation of clouds at low altitude including fog while the atmosphere to the north of the ITD is usually dry and dusty preventing the formation of clouds except altocumulus and cirrus at high level.

The movement of the ITD controls the weather systems in Nigeria. It has three unique overlapping movements throughout the year; an annual movement which follows the path of the sun and is responsible for seasons, a diurnal movement consisting of a slight southward shift in the morning and a slight northward shift in the afternoon and intermediate movements observed during the northern hemisphere winter months.

According to the Koppen climate classification (Kottek et al. 2006), Nigeria has four climatic zones; the Warm desert climate in the northeast, the Warm semi-arid climate in the other parts of the north, the Monsoon climate in the Niger Delta and the Tropical savanna climate in the middle belt and parts of the south west. The main ecological zones in Nigeria are the tropical rainforest in the south, savannah in the middle belt and semi-arid zones in the North.

2.2 Data

A set of high resolution reanalysis climatic daily data from the Climate Hazards Group Infrared Precipitation with Stations (CHIRPS) from 1985 to 2015 covering our study area will be used[2]. CHIRPS is a quasi-global (500S – 500N) satellite and observation based precipitation estimates over land. It is a 0.05 degree resolution (about 5.5 kilometres) gridded dataset (C. C. Funk et al. 2014). Reanalysis data, unlike conventional data, provides a more wholesome look at global climatic circulation and can be used as an alternative to ground observation data (Dee et al. 2011). The data comes in the Network Common Data Form (NetCDF) format and will be manipulated using Matlab®, Microsoft Excel® and ArcGIS® software. The Network Common Data Form (NetCDF) is a file format for storing multidimensional scientific data (variables) such as temperature, humidity, rainfall etc. This data was obtained online from the Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS) (ftp://chg-ftpout.geog.ucsb.edu/pub/org/chg/products/CHIRPS-2.0/; accessed: September, 2016). For details, see (C. Funk et al. 2015)

This research utilized four of the precipitation indices as defined by ETCCDI (Table 1). This is because each of the indices, by itself, shows only a part of the problem (Karl, Nicholls, and Ghazi 1999; Thomas C Peterson et al. 2001). We hope the four selected are able to achieve a global characterization of precipitation in its different perspectives (Gorricha, Lobo, and Costa 2013). By global characterization, we are referring to their ability to capture changes in amount, frequency and intensity.

Table 1: Summary of rainfall indices used in the study (a wet day is defined as a day with at least 1 mm of precipitation)

Index	Descriptive name	Definition	Units
R1	Number of wet days	Frequency of rainy days	days
Rx1d	Maximum 1-day precipitation	Maximum 1-day precipitation	mm
SDII	Simple Daily Intensity Index	Ratio between the total rain on wet days and the number of wet days	mm/day
Rx5d	Maximum 5-day precipitation	Highest consecutive 5-day precipitation	mm

2.2.1 Data preparation and pre-processing

The representation and quality of data is very important in determining the quality of clusters that will be seen (Kotsiantis, Kanellopoulos, and Pintelas 2006). Hence, there is a need to do some amount of pre-processing to the data before clustering. Given that we are making use of a gridded reanalysis data,

[2] *ftp://chg-ftpout.geog.ucsb.edu/pub/org/chg/products/CHIRPS-2.0/*

we expect to have a consistent and coherent data without outliers or missing values. For this research, several data preparatory tasks were carried out prior to actual analysis, including:

- **Dimensionality Reduction**: Out of the several temperature and precipitation indices defined by ETCCDI to characterise climate extremes, four precipitation indices (Table 1) were selected based on previous studies by (Gorricha, Lobo, and Costa 2013) and expert opinion to characterise the duration, intensity and frequency of precipitation over our study area.
- **Data Extraction**: Matlab® was used to calculate the four indices and extract them into Microsoft Excel® tables for each year. ArcMap® was further used to clip out our area of interest (Nigeria) from the extracted dataset and export them back to Microsoft Excel® for exploratory data analysis
- **Data Normalization**: This is the scaling down of the values of the selected indices. This step will prevent one variable from dominating over all others (or allow it if that is the aim), thus enabling the data analysis method to treat the data 'fairly' (Bação and Lobo 2011). To achieve this, each index was standardised using its minimum and maximum values. This way, we ensured that the values of each variable range between 0 and 1.

2.3 Methodology

SOM are non-supervised neural networks used for clustering, dimension reduction and visualization. This research aims to achieve these three things by visually showing the areas with similar precipitation extreme characteristics using the indices outlined before. SOM can map high-dimensional data onto one or two dimensions while maintaining the topology of the data structure. (Bação, Lobo, and Painho 2004). SOM works by mapping an n-dimensional data space onto a grid of neurons. These grids of neurons are usually in a two-dimensional data space and rectangular. During training, the Euclidean distance between a neuron and all units in the data space is calculated and the closest is selected. This is called the Best Matching Unit (BMU). This process is iterated and a parameter called the learning rate is used to ensure that the training converges. Although, no preference is given to the spatial property of our climatic data, spatial autocorrelation makes it possible for the BMU attached to each neuron to be geographically close thereby creating clusters that are geographically together (Henriques, Bacao, and Lobo 2012). This algorithm has been implemented in GeoSOM suite based on the SOM toolbox in Matlab® and is used for clustering the climatic data. The dataset is trained and modelled using the SOM algorithm, producing several views and interactively exploring the data, hoping to gain valuable insights. Several parameters were used to initialise the SOM to obtain different models for each year and the final parameters used is given in Table 2. The model with the least quantization error was chosen as the best fit (Spanakis and Weiss 2016).

For this research, SOM was also used to detect outliers, for sensitivity analysis of the parameters of the methods used, for the analysis of the U-matrix, as well as for component planes and for the final clustering. After removing the outliers, a new 4 x 1 SOM was trained using the parameters in Table 2.

Table 2: Values of the parameters used to implement the GeoSOM algorithm

Parameter	Value
X	4
Y	1
Lattice	Hexagonal
Shape	Sheet
Initialization	Random
Map Training	Batch
Neighborhood Function	Gaussian
Rough Iterations	300
Fine-tuning Iterations	400

After clustering, the index values of the centroid of each cluster are calculated and their trend is analyzed through time. The Mann-Kendall test is used to verify if those index values exhibit a monotonic trend. The Mann-Kendall statistic is calculated as follows. Let *S* be the number of positive differences minus the number of negative differences between data values:

$$S = \sum_{j=1}^{n-1} \sum_{k=j+1}^{n} sgn(x_k - x_j)$$

where x_k and x_j are data values, *n* is the number of years under study, and *sgn* is an indicator function that takes on the values 1, 0, or -1 according to the sign of $x_k - x_j$.

A positive (negative) value of S indicates an increasing (decreasing) trend. S is normally distributed (Mann 1945; Kendal 1975) with variance given by:

$$V\ (S) = \frac{1}{18}\left(n(n-1)(2n+5)\right)$$

The test statistic Z_s is given by

$$Z_s = \begin{cases} \dfrac{s-1}{\sqrt{V(S)}}\ for\ S > 0 \\ 0\ for\ S = 0 \\ \dfrac{s+1}{\sqrt{V(S)}}\ for\ S < 0 \end{cases}$$

The significance of the trend can be verified by comparing the observed value of Z_s with the appropriate percentiles of the standard normal distribution (critical values), for a given significance level. We used the 5% significance level to test the null hypothesis that no monotonic trend is present, against the alternative hypothesis that a (upward or downward) monotonic trend is present.

3 Results and discussion

3.1 Exploratory analysis

A total of 30155 equally spaced points spread over Nigeria were analyzed for each year. Descriptive statistics were computed for each of the four indices for each year as well as collectively for the entire period under study (Table 3). Scatter-plots (not shown) of the indices for each year provide evidence of a strong positive linear relationship between all indices. This linear relationship was summarized using the correlation coefficient (Table 4), which allows concluding that all indices are moderately correlated, thus indicating their suitability to characterize the different features of the precipitation regimes in Nigeria (Gorricha, Lobo, and Costa 2013).

The temporal variation of the mean index values was also investigated (Figure 2), and shows that 2006 had both the highest mean consecutive 5-day precipitation (Rx5d index) averaged over our entire study area with a value of 112.2 mm as well as the maximum highest consecutive 5-day precipitation with a value of 502 mm. However, a minimum highest consecutive 5-day precipitation occurred in 1989 with a value of 19.1 mm. 2013 had the highest number of wet days with 244 days having rainfall greater than 1 mm (R1 index), while 1987 had just 23 wet days being the driest in our study period. The highest average intensity of rainfall in a raining day (SDII) was recorded in 1999 as 29.1 mm/day, while the lowest average rainfall intensity was recorded in 1989 as 3.4 mm/day. Furthermore, the highest 1-day precipitation (Rx1d index) of 271.2 mm was observed in 2004, and the minimum was 8.1 mm in 2009.

Table 3: Summary statistics of the precipitation indices for the period 1985 – 2015

Variable	Rx5d (mm)	Rx1d (mm)	R1 (days)	SDII (mm/day)
Minimum	19.1	8.1	23	3.4
Median	88.5	40.5	108	10.2
Maximum	502	271.2	244	29.1
Mean	96	12.1	28	10.6
Standard Deviation	35.8	17.23	35.7	2.4
Skewness	1.96	2.06	0.46	1.03
Kurtosis	6.7	7.43	0.07	2.52

Table 4: Correlation matrix of the precipitation indices for the period 1985 – 2015

	Longitude	*Latitude*	*Rx5d*	*R1*	*Rx1d*	*SDII*
Longitude	1					
Latitude	0.253906	1				
Rx5d	-0.13109	-0.72777	1			
R1	-0.33055	-0.91357	0.749444	1		
Rx1d	-0.27179	-0.58645	0.753508	0.579652	1	
SDII	-0.19219	-0.80291	0.838971	0.736548	0.714564	1

Histograms (not shown) were also plotted for each index by year to check for moderate and heavy extreme values which could be typical values, outliers or perhaps errors. It also helped to graphically perceive the distribution frequency of the indices. Some years exhibit a 'bell-shaped' curve in the histograms, but the majority shows a positively skewed distribution.

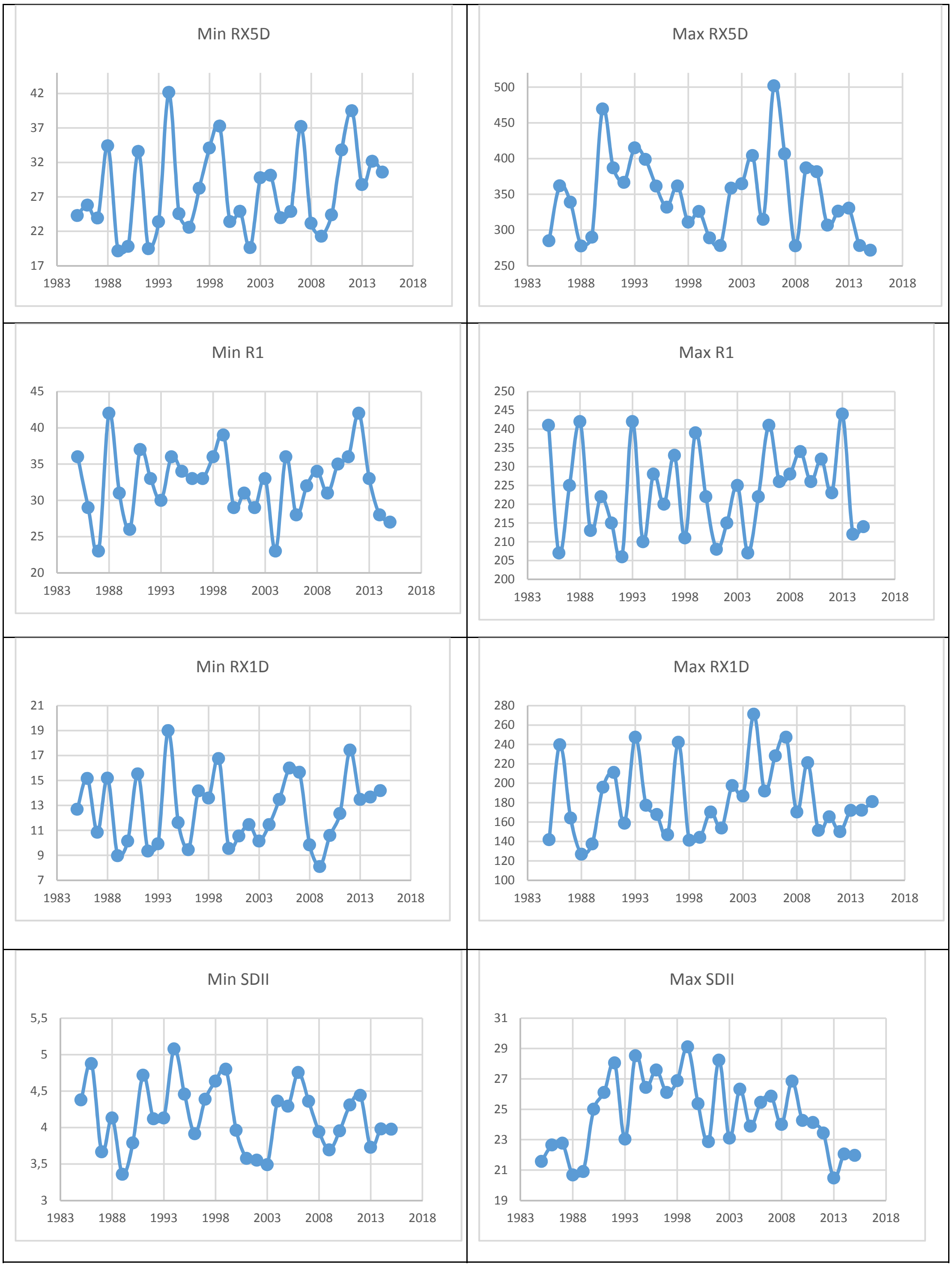


Figure 2: Temporal variation of mean index values over Nigeria from 1985 to 2015

The previous analyses are based on averaged values over the entire study region, thus they are not reflective of the unique precipitation property of specific regions. Nigeria has a broad range of precipitation extremes in various regions. Hence, further analyses were conducted to explore and characterize each region. Exploratory spatial data analysis was used to detect spatial patterns and formulate hypothesis based on the geography of the data. From the posting of the data points (Figure 3) it is clear that the spatial resolution of the dataset is so high (approximately 5.5 km) that maps look like interpolated surfaces. Hence, there is no need to interpolate the data points to a surface using a linear model (e.g., ordinary kriging or cokriging). The overall trend in the study region corresponds to decreasing values from the southern part of Nigeria to the north in all indices. However, each index shows a unique pattern of variation (Figure 3)

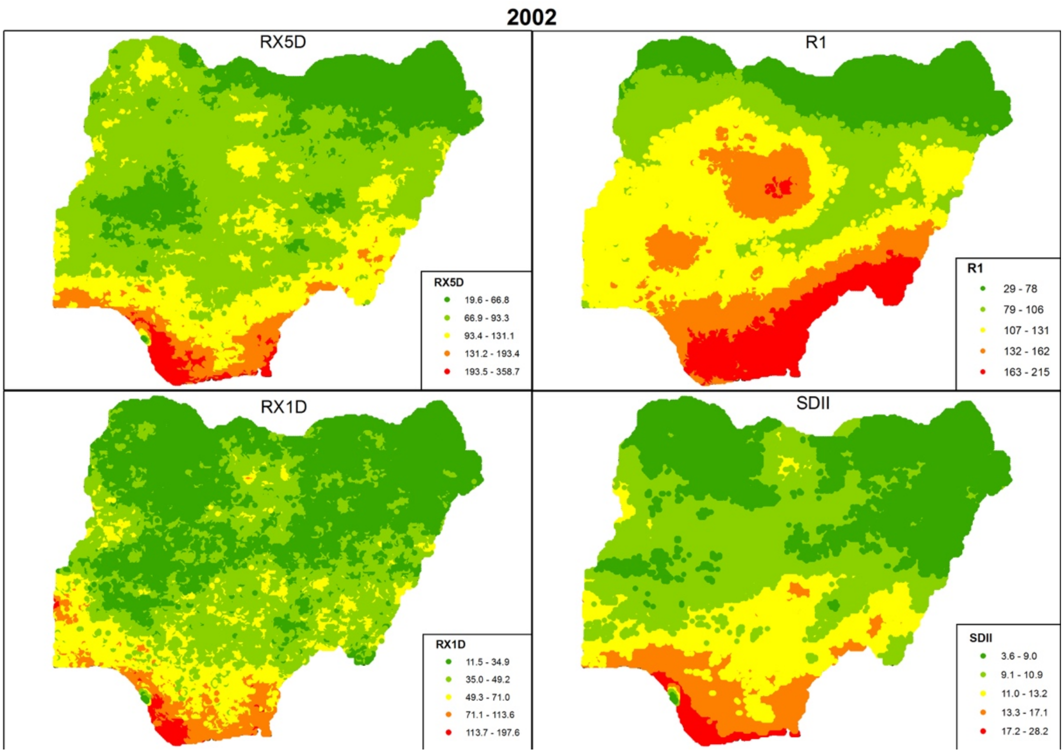


Figure 3: Data posting of indices values from 2002

3.2 GeoSOM results

3.2.1 Outlier analysis

Training was first done using a 20 x 20 hexagonal sheet SOM on all the indices for each year. Outliers were subsequently identified by searching for very high values in a U-matrix. A U-matrix is a visual representation of a self-organizing map (SOM) where the Euclidean distance between neurons are represented in a colour-coded image. If represented as a greyscale image (from white to black), then lighter colours indicate closely spaced neurons while dark colours indicate distant neurons. Therefore, a group of light colours can be regarded as a cluster and the dark colours regarded as boundaries of the cluster. From our analysis, outliers can be clearly identified as bright red spots at the upper left corner of the U-matrix (Figure 4, top graph). Plotting the data on a boxplot confirms them as outliers as they have very large values outside the quantile range of the dataset (Figure 4, middle graph). Further plotting these data (Figure 4, bottom map) shows that they mostly fall in the south eastern and south western region of Nigeria. This region is noted for extremely high precipitation. Hence, it can be argued that these high values are not outliers but simply extreme values which should be of interest for further analysis. However, including them can significantly impact the overall results. Hence, these outliers were removed to better understand and clustering of the indices values.

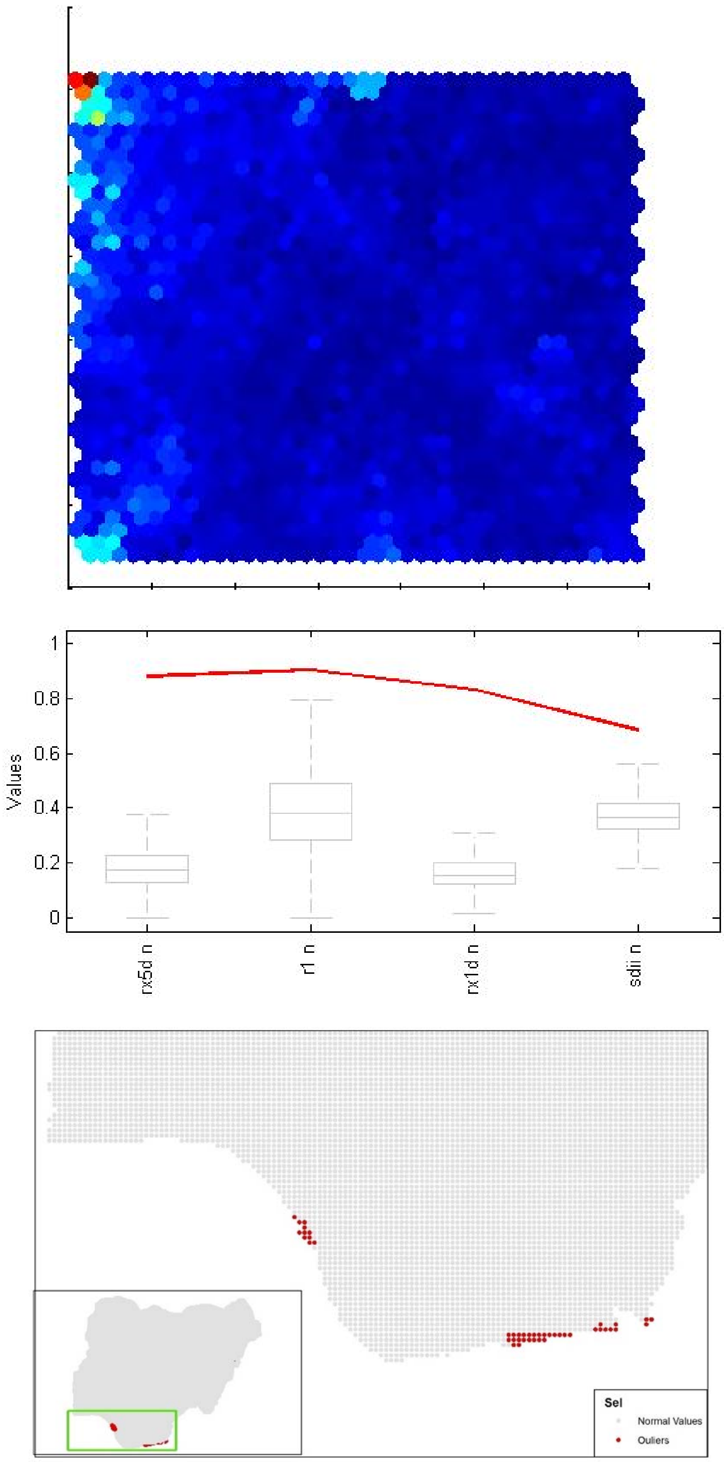


Figure 4: U-matrix (top), boxplot (middle) and map (bottom) of the four precipitation indices showing outliers in red in 2003

3.2.2 Spatial trends

A 4 x 1 SOM was used because we wanted to obtain 4 clusters which is in line with number of Koppen climate classification zones over Nigeria. As expected, there is evidence of spatial autocorrelation in the pattern of the clusters (Figure 5). Four regions with similar precipitation characteristics are evident varying from the south to the north through the middle belt of Nigeria. Although these clusters bare some resemblance with the Koppen climatic zones, there are still several variations in the spatial extent of each zone when both are compared. However, this is not surprising since the Koppen classification characterizes mean climatic characteristics, and the clusters are based on extreme precipitation indices. For better clarity in interpretation, we have applied a color scheme to the value of each precipitation index in a tabular form so that we can easily identify the color's that represent high (red), mean (yellow) and low (green) values of each index. The table in Figure 5 shows the mean value of each index in a cluster.

Cluster 1 covers the Niger-Delta and southeast region of the country. It is characterized by very high precipitation amount, intensity and frequency. This is because of the south-western trade winds that bring a lot of moisture inland from the Atlantic Ocean in the south. Because of the high moisture, this region experiences heavy and abundant monsoonal rainfall and is cloudy all year round. Hence, they have a typical tropical monsoon climate.

Cluster 2 covers the southwest and extends further inland. Although not as high as Cluster 1, it is also characterized by high intensity, frequency and amount of rainfall. This region experiences two peaks of rainfall in a year with a little dry season in August. The first rainfall peak is usually characterized by thunderstorms and occurs in June, while the second rainfall peak is usually monsoonal and occurs around September. A portion of this cluster appears as an island in the middle belt around Jos, Kaduna and Abuja, surrounded by Cluster 3. This might be explained by the terrain of this region, which is a plateau with high elevation. Hence, it has a semi-temperate climate. Therefore, it is interesting to note that it bears similar precipitation characteristics with southwestern Nigeria.

Cluster 3 covers a major part of the middle belt. Unlike Cluster 2, this region exhibits just a single maximum of rainfall during the raining season. Rainfall in this region is primarily associated with thunderstorms and high wind gusts. This is the region where the south-westerlies meet the north-easterlies to create what is known as the Inter Tropical Discontinuity (ITD). The ITD is a region of low pressure and an important factor for Nigeria weather and climate (Odekunle 2010).

Cluster 4 is located predominantly in the northern part of the country. This is a dry and dusty area with the North-Easterly trade winds bringing in dry and dusty air masses from the Sahara Desert. Results show that this region experiences minimal rainfall in terms of amount, duration, frequency and intensity (see table in Figure 5). The raining season in this region is very short lasting just about three months.

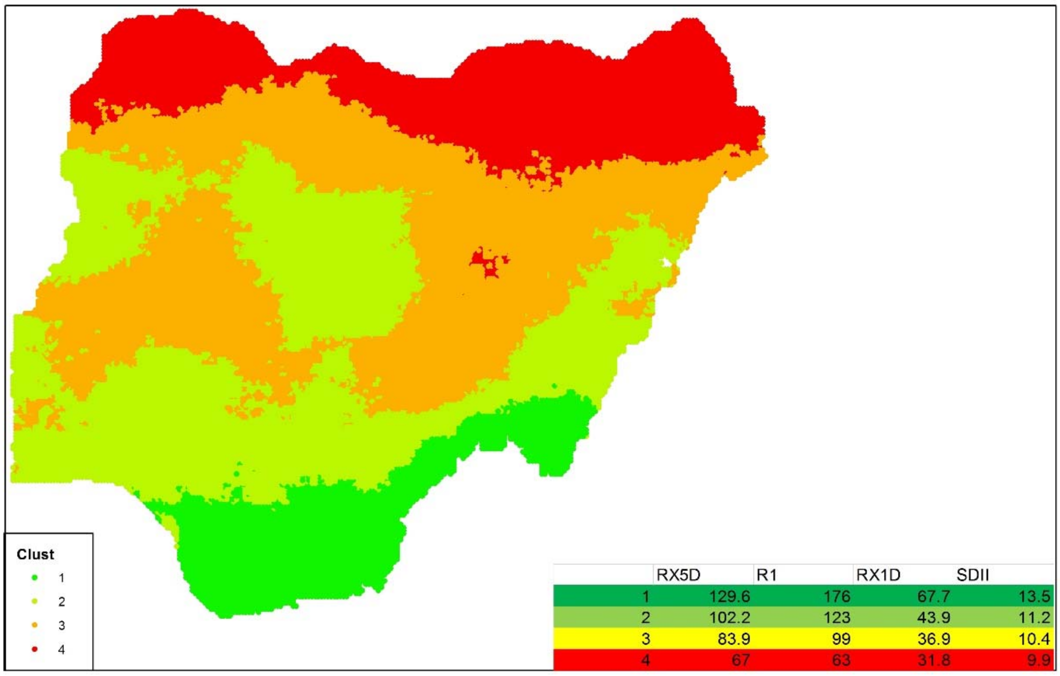


Figure 5: Precipitation indices clustering over Nigeria in 2003

3.2.3 Temporal trends

There was a tendency for the maximum 1-day precipitation, maximum 5-day precipitation and frequency of rainy days to increase with time in clusters 1, 2 and 4. In contrast, the maximum 1-day precipitation decreases with time in cluster 3. The intensity of rainfall was constant in cluster 1 throughout the period under study, while a decreasing trend is noticed in rainfall intensity and maximum 1-day precipitation in cluster 3. However, considering the results of the Mann-Kendall test, those trends were not significant (Figure 6). The only statistically significant upward trend is noticed in the frequency of rainy days in cluster 4.

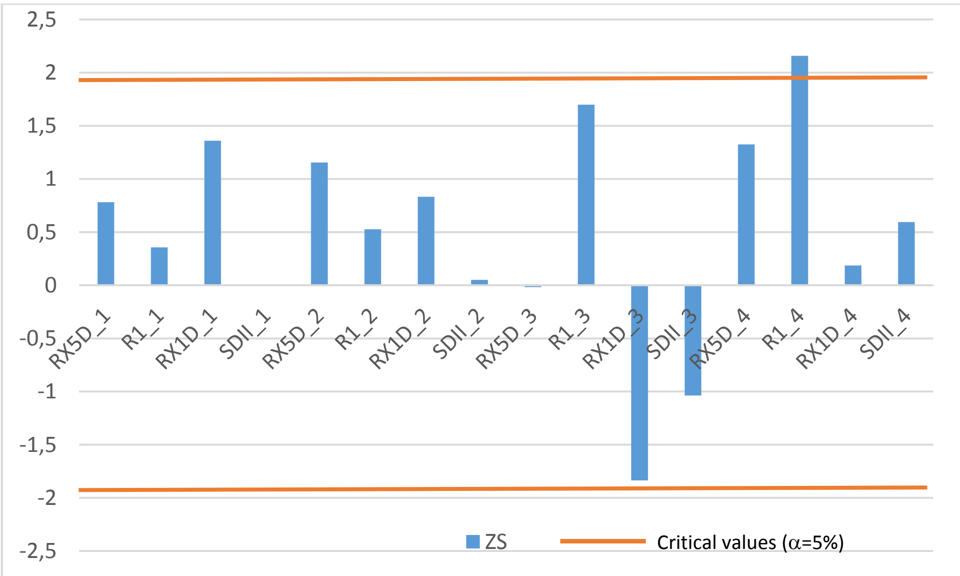


Figure 6:Observed values of the Mann-Kendall's test statistic ZS

4 Conclusion

The main objective of this research was to study the spatial and temporal patterns of precipitation extremes in Nigeria. This was achieved by computing a SOM with four precipitation indices computed from 1985 to 2016. The four clusters created for each year summarize the precipitation dynamics that underline the indices. The spatial extents of the clusters have some resemblances with the Koppen climatic zones, but there are some relevant differences throughout the years. We also identified a significant increasing trend in the frequency of rainy days in cluster 4, which predominantly covers the northern part of the country. It is important to note that this trend was measured at the centroid of the cluster, so that conclusion cannot be extrapolated to the whole cluster.

We have been able to identify the spatial and temporal patterns of extreme precipitation, and thus gain valuable insights into the spatial and temporal dynamics of precipitation in Nigeria. However, the temporal resolution of the dataset is too small to adequately characterize the long-term behavior of extreme precipitation in Nigeria. Further research with a higher temporal resolution dataset should be pursued.

Acknowledgements

The work described in this thesis was supported by the European Commission (EC) Education, Audio-visual and Cultural Executive Agency (EACEA) Erasmus Mundus scholarship. The authors also gratefully appreciate the Information Management School of the Universidade Nova de Lisboa (NOVA IMS), department of Geoinformatics at the university of Munster and Universitat Jaume I.

Conflicts of Interest

The authors declare that there is no conflict of interest regarding the publication of this thesis.

5 References

Abiodun, Babatunde J., Kamoru A. Lawal, Ayobami T. Salami, and Abayomi A. Abatan. 2013. "Potential Influences of Global Warming on Future Climate and Extreme Events in Nigeria." *Regional Environmental Change* 13 (3): 477–91. doi:10.1007/s10113-012-0381-7.

Adejuwon, James O. 2006. "Food Crop Production in Nigeria. II. Potential Effects of Climate Change." *Climate Research* 32 (3): 229–45. doi:10.3354/cr032229.

Akinsanola, Akintomide; Ogunjobi Kehinde. 2014. "Analysis of Rainfall and Temperature Variability Over Nigeria." *Global Journal of Human-Social Science: B Geography, Geo-Sciences, Environmental Disaster Management* 14 (3).

Akpodiogaga-, Peter, and Ovuyovwiroye Odjugo. 2009. "Quantifying the Cost of Climate Change Impact in Nigeria: Emphasis on Wind and Rainstorms." *J Hum Ecol* 28 (2): 93–101.

Alexander, Lisa V., X. Zhang, T. C. Peterson, J. Caesar, B. Gleason, A. M G Klein Tank, M. Haylock, et al. 2006. "Global Observed Changes in Daily Climate Extremes of Temperature and Precipitation." *Journal of Geophysical Research Atmospheres* 111 (5): 1–22. doi:10.1029/2005JD006290.

Bação, Fernando, and Victor Lobo. 2011. "Fundamentals of Data Preparation and Pre-Processing."

Bação, Fernando, Victor Lobo, and Marco Painho. 2004. "Geo-Self-Organizing Map (Geo-SOM) for Building and Exploring Homogeneous Regions." *Geographic Information Science*. http://link.springer.com/chapter/10.1007/978-3-540-30231-5_2.

Dee, D. P., S. M. Uppala, A. J. Simmons, P. Berrisford, P. Poli, S. Kobayashi, U. Andrae, et al. 2011. "The ERA-Interim Reanalysis: Configuration and Performance of the Data Assimilation System." *Quarterly Journal of the Royal Meteorological Society* 137 (656): 553–97. doi:10.1002/qj.828.

Donat, M. G., L. V. Alexander, H. Yang, I. Durre, R. Vose, R. J H Dunn, K. M. Willett, et al. 2013. "Updated Analyses of Temperature and Precipitation Extreme Indices since the Beginning of the Twentieth Century: The HadEX2 Dataset." *Journal of Geophysical Research Atmospheres* 118 (5): 2098–2118. doi:10.1002/jgrd.50150.

Ekpoh, Imo J, and Ekpenyong Nsa. 2011. "Extreme Climatic Variability in North-Western Nigeria: An Analysis of Rainfall Trends and Patterns." *Journal of Geography and Geology* 3 (1): 51–62. doi:10.5539/jgg.v3n1p51.

Enete, Anselm, and Taofeeq Amusa. 2010. "Challenges of Agricultural Adaptation to Climate Change in Nigeria: A Synthesis from the Literature." *Fact Reports* 4 (8): 0–8. http://factsreports.revues.org/678.

Funk, C. C., P. J. Peterson, M. F. Landsfeld, D. H. Pedreros, J. P. Verdin, J. D. Rowland, B. E. Romero, G. J. Husak, J. C. Michaelsen, and A. P. Verdin. 2014. "A Quasi-Global Precipitation Time Series for Drought Monitoring." *U.S. Geological Survey Data Series* 832: 4. doi:http://dx.doi.org/110.3133/ds832.

Funk, Chris, Pete Peterson, Martin Landsfeld, Diego Pedreros, James Verdin, Shraddhanand Shukla, Gregory Husak, et al. 2015. "The Climate Hazards Infrared Precipitation with Stations—a New Environmental Record for Monitoring Extremes." *Scientific Data* 2: 150066. doi:10.1038/sdata.2015.66.

Gbode, Imole Ezekiel, Akintomide Afolayan Akinsanola, and Vincent Olanrewaju Ajayi. 2015. "Recent Changes of Some Observed Climate Extreme Events in Kano" 2015.

Gorricha, J., V. Lobo, and A. C. Costa. 2013. "A Framework for Exploratory Analysis of Extreme Weather Events Using Geostatistical Procedures and 3D Self-Organizing Maps." *International Journal on Advances in Intelligent Systems* 6 (1&2): 16–26. http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.360.5951&rep=rep1&type=pdf#page=30.

Henriques, Roberto, Fernando Bacao, and Victor Lobo. 2012. "Exploratory Geospatial Data Analysis Using the GeoSOM Suite." *Computers, Environment and Urban Systems* 36 (3). Elsevier Ltd: 218–32. doi:10.1016/j.compenvurbsys.2011.11.003.

Hewitson, B. C., and R. G. Crane. 2005. "Gridded Area-Averaged Daily Precipitation via Conditional Interpolation." *Journal of Climate* 18 (1): 41–57. doi:10.1175/JCLI3246.1.

———. 2006. "Consensus between GCM Climate Change Projections with Empirical Downscaling: Precipitation Downscaling over South Africa." *International Journal of Climatology* 26 (10): 1315–37. doi:10.1002/joc.1314.

IPCC. 2007. "Climate Change 2007: The Physical Science Basis. Contribution of Working Group I to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change [Solomon, S., D. Qin, M. Manning, Z. Chen, M. Marquis, K.B. Averyt, M. Tignor and H.L. Miller." *Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA*, 1–4. papers3://publication/uuid/789C871F-F7F3-4AD1-A26B-017707E6A214.

———. 2012. *Managing the Risks of Extreme Events and Disasters to Advance Climate Change Adaptation*. *Ipcc*. doi:10.1596/978-0-8213-8845-7.

———. 2014. "Climate Change 2014 Synthesis Report." *Contribution of Working Groups I, II and III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*, 1–112.

Jones, Mari R., Stephen Blenkinsop, Hayley J. Fowler, and Christopher G. Kilsby. 2014. "Objective Classification of Extreme Rainfall Regions for the UK and Updated Estimates of Trends in Regional Extreme Rainfall." *International Journal of Climatology* 34 (3): 751–65. doi:10.1002/joc.3720.

Jr, William J Gutowski, Francis O Otieno, Raymond W Arritt, and Eugene S Takle. 2004. "Diagnosis and Attribution of a Seasonal Precipitation Deficit in a U . S . Regional Climate Simulation." *Journal of Hydrometeorology* 5: 230–42.

Karl, Thomas, Neville Nicholls, and Anver Ghazi. 1999. "Workshop on Indices and Indicators for Climate Extremes Precipitation.pdf." *Climate Change* 42: 3–7. doi:10.1007/978-94-015-9265-9_2.

Kendal, M.G. 1975. *Rank Correlation Methods*. Fourth ed. London: Charles Griffin.

Klein Tank, Albert M.G., Francis W Zwiers, and Xuebin Zhang. 2009. "Guidelines on Analysis of Extremes in a Changing Climate in Support of Informed Decisions for Adaptation." *Climate Data and Monitoring*, no. WCDMP-No. 72: 52. File Attachment.

Kotsiantis, S B, D Kanellopoulos, and P E Pintelas. 2006. "Data Preprocessing for Supervised Learning." *International Journal of Computer Science* 1 (2): 111–17. doi:10.1080/02331931003692557.

Kottek, Markus, Jürgen Grieser, Christoph Beck, Bruno Rudolf, and Franz Rubel. 2006. "World Map of the Köppen-Geiger

Climate Classification Updated.” *Meteorologische Zeitschrift* 15 (3): 259–63. doi:10.1127/0941-2948/2006/0130.

Mann, H.B. 1945. “Non-Parametric Test Against Trends.” *Econometrica* 13 (3): 245–59.

Moberg, Anders, Philip D. Jones, David Lister, Alexander Walther, Manola Brunet, Jucundus Jacobeit, Lisa V. Alexander, et al. 2006. “Indices for Daily Temperature and Precipitation Extremes in Europe Analyzed for the Period 1901-2000.” *Journal of Geophysical Research Atmospheres* 111 (22). doi:10.1029/2006JD007103.

Obioha, Emeka E. 2008. “Climate Change , Population Drift and Violent Conflict over Land Resources in Northeastern Nigeria.” *Conflict* 23 (4): 311–24.

Odekunle, Theophilus. 2010. “An Assessment of the Influence of the Inter-Tropical Discontinuity on Inter-Annual Rainfall Characteristics in Nigeria.” *Geographical Research* 48 (3): 314–26. doi:10.1111/j.1745-5871.2009.00635.x.

Ogungbenro, Stephen Bunmi, and Tobi Eniolu Morakinyo. 2014. “Rainfall Distribution and Change Detection across Climatic Zones in Nigeria.” *Weather and Climate Extremes* 5 (1). Elsevier: 1–6. doi:10.1016/j.wace.2014.10.002.

Okoloye, CU, NI Aisiokuebo, JE Ukeje, AC Anuforom, and ID Nnodu. 2013. “RAINFALL VARIABILITY AND THE RECENT CLIMATE EXTREMES IN NIGERIA By.” *Journal of Meteorology and Climate Science* 11: 49–57.

Olaiya, Folorunsho, and Adesesan Barnabas Adeyemo. 2012. “Application of Data Mining Techniques in Weather Prediction and Climate Change Studies.” *International Journal of Information Engineering and Electronic Business* 4 (1): 51–59. doi:10.5815/ijieeb.2012.01.07.

Onyekuru, Anthony N, and Rob Marchant. 2014. “Climate Change Impact and Adaptation Pathways for Forest Dependent Livelihood Systems in Nigeria.” *African Journal of Agricultural Research* 9 (24): 1819–32. doi:10.5897/AJAR2013.8315.

Peterson, T. C. 2005. “Climate Change Indices.” *WMO Bulletin* 54 (2): 83–86.

Peterson, Thomas C, Christopher Christoper Folland, George Gruza, William Hogg, Abdallah Mokssit, and Neil Plummer. 2001. “Report on the Activities of the Working Group on Climate Change Detection and Related Rapporteurs 1998–2001.” *Rep. WCDMP-47, WMO-TD 1071*, no. March: 143. doi:WMO, Rep. WCDMP-47,WMO-TD 1071.

Res, Clim, B C Hewitson, and R G Crane. 2002. “Self-Organizing Maps : Applications to Synoptic Climatology.” *Climate Research* 22: 13–26.

Rodrigues, Pedro Marcos Santana. 2010. “An Approach Geo-Data Mining to Climate Regions of the Iberian Peninsula, 1951 - 2010.” New Univerity of Lisbon. https://run.unl.pt/bitstream/10362/18342/1/TSI0111.pdf.

Spanakis, Gerasimos, and Gerhard Weiss. 2016. “AMSOM: Adaptive Moving Self-Organizing Map for Clustering and Visualization.” *Proceedings of the 8th International Conference on Agents and Artificial Intelligence*, 129–40. doi:10.5220/0005704801290140.

Stefan, Rahmstorf. 2005. “Anthropogenic Climate Change: Revisiting the Facts.” *History* 140 (6): 34–53. doi:10.1016/j.cell.2010.01.022.

Ta, S, K Y Kouadio, K E Ali, E Toualy, A Aman, and F Yoroba. 2016. “West Africa Extreme Rainfall Events and Large-Scale Ocean Surface and Atmospheric Conditions in the Tropical Atlantic.” *Advances in Meteorology* 2016: 14. doi:10.1155/2016/1940456.

Thibaud, E., R. Mutzner, and A. C. Davison. 2013. “Threshold Modeling of Extreme Spatial Rainfall.” *Water Resources Research* 49 (8): 4633–44. doi:10.1002/wrcr.20329.

Van den Besselaar, E. J M, A. M G Klein Tank, and T. A. Buishand. 2013. “Trends in European Precipitation Extremes over 1951-2010.” *International Journal of Climatology* 33 (12): 2682–89. doi:10.1002/joc.3619.

Xiaofeng Gong, and M. B. Richman. 1995. “On the Application of Cluster Analysis to Growing Season Precipitation Data in North America East of the Rockies.” *Journal of Climate*. doi:10.1175/1520-0442(1995)008<0897:OTAOCA>2.0.CO;2.

6 Appendix

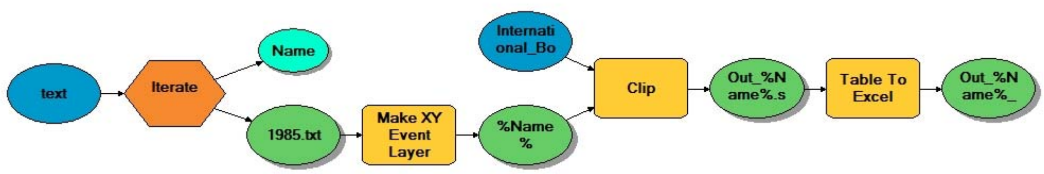
Matlab Script

```
% Clear workspace
clear all;

% Specify netcdf filename
filename='D:\CHIRPS DATA\chirps-v2.0.1999.days_p05.nc';

% displaying the structure of the chirps dataset
ncdisp(filename)

% extracting Nigeria from the global chirps dataset based on
lon/lat
long = ncread(filename,'longitude')'; % Longitudinal coordinates
lat = ncread(filename,'latitude')'; % Latitudinal coordinates


% finding the indices of the latitude within which my grid lies
latstart = find(lat>4.0250,1, 'first');
latend = find(lat<14.0250,1, 'last');

% finding the indices of the longitude within which my grid lies
lonstart = find(long>2.4750,1, 'first');
lonend = find(long<15,1, 'last');

ncid = netcdf.open(filename,'NOWRITE');

%long= netcdf.getVar(ncid,1);
%lat= netcdf.getVar(ncid,0);
time= netcdf.getVar(ncid,3);
%rr= netcdf.getVar(ncid,2,[latstart,lonstart,1],[(latend-
latstart),(lonend-lonstart),355]);
%rr= netcdf.getVar(ncid,2,[10,10,10],[10,10,355]);
rr= netcdf.getVar(ncid,2,[lonstart,latstart,1],[(lonend-
lonstart),(latend-latstart),364]);

[nLong, nLat, nTime]=size(rr);

%[nlong,nlat,ntimes]=size(nigeria1981);
longNigeria=long(lonstart:lonend);
latNigeria=lat(latstart:latend);
nigeria2015=rr(:,:,:);%:lonend,latstart:latend,366:730);

%converting -9999 values to NaN
nigeria2015(nigeria2015 == -9999) = NaN;


rra=zeros(nLong*nLat*nTime,5);
counter=1;
for t=1:nTime % for each year
    ano=floor(t/366)+1;
    for la=1:nLat % for each latitude
        %rra=[rra;
(1:nlong)',ones(nlong,1)*la,ones(nlong,1)*t,ones(nlong,1)*year,
nigeria1981(:,la,t)];
```

```
        rra(counter:counter+nLong-
1,1:5)=[(1:nLong)',ones(nLong,1)*la,ones(nLong,1)*t,ones(nLong,1)
*2015, nigeria2015(:,la,t)];
        counter=counter+nLong;
    end

    disp(t);
end

rra=sortrows(rra,[1,2]);

rrSoma5=zeros(size(rra,1),2);

for ano=2015:2015 % for the year under consideration
    indAno=find(rra(:,4)==ano); %indices do ano
    for i=1:size(indAno,1)-4 % para cada dia de um ano
        valor=rra(indAno(i):indAno(i)+4,5);
        rrSoma5(indAno(i),1)=sum(valor(valor>=1)); %long lat dia
ano rr
        rrSoma5(indAno(i),2)=rra(indAno(i),4);
    end
end

%max por ano do rrSOMA
R5X=zeros(nLat*nLong,5);
counter=1;
for ano=2015:2015 % for the year under consideration
    for lo=1:nLong
        for la=1:nLat
            indAno=find(rra(:,1)==lo & rra(:,2)==la &
rra(:,4)==ano); %indices de uma long uma lat e um ano
            [M, I]=max(rrSoma5(indAno,1));
            %R5X=[R5X; lo,la,ano,I,M];
            R5X(counter,:)=[lo,la,ano,I,M];
            counter=counter+1;
            disp(counter);
        end

    end
    disp(ano)
end

%calculating r1
R1=zeros(nLong*nLat,3);
counter=1;
for lo=1:nLong
    for la=1:nLat

R1(counter,:)=[lo,la,size(find(nigeria2015(lo,la,:)>1),1)];
        counter=counter+1;
    end
end

%calculating rx1d
Rx1d=zeros(nLong*nLat,3);
counter=1;
for lo=1:nLong
    for la=1:nLat
```

```
        Rx1d(counter,:)=[lo,la,max(nigeria2015(lo,la,:))];
        counter=counter+1;
    end
end

%calculating sdii
SDII=zeros(nLong*nLat,3);
counter=1;
%sumPrecBig1=sum(rr>1,3);
for lo=1:nLong
    for la=1:nLat

SDII(counter,:)=[lo,la,sum(nigeria2015(lo,la,nigeria2015(lo,la,:)
>1))./size(find(nigeria2015(lo,la,:)>1),1)];

%SDII(counter,:)=[lo,la,((sum(rr>1,3)./(size(find(rr>1),1))))];
        counter=counter+1;
    end
end



%arranging all calculated values into columns
R5XD=[longNigeria(R5X(:,1))',latNigeria(R5X(:,2))',R5X(:,3),R5X(:
,5),R1(:,3), Rx1d(:,3), SDII(:,3)];
%R1=[longNigeria(R1(:,1)),latNigeria(R1(:,2))',R5X(:,5)];
%need to perfect export to csv/text
```

ArcGIS Model



Descriptive Statistics

1985

	rx5d	*r1*	*rx1d*	*sdii*
Mean	92.51	113.14	43.67	9.84
Standard Error	0.18	0.24	0.07	0.01
Median	87.43	111.00	41.66	9.73
Mode	110.89	96.00	62.79	12.64
Standard Deviation	30.54	41.95	12.67	1.96
Sample Variance	932.42	1760.00	160.59	3.83
Kurtosis	2.63	-0.12	2.78	1.78
Skewness	1.28	0.51	1.11	0.74
Range	260.63	205.00	129.03	17.18
Minimum	24.29	36.00	12.69	4.38
Maximum	284.92	241.00	141.72	21.56
Sum	2789599.82	3411723.00	1316824.45	296735.27
Count	30155.00	30155.00	30155.00	30155.00

1986

	rx5d	*r1*	*rx1d*	*sdii*
Mean	93.12	98.07	46.62	10.80
Standard Error	0.20	0.19	0.11	0.01
Median	86.00	96.00	41.81	10.55
Mode	136.65	95.00	79.64	14.03
Standard Deviation	35.48	32.98	19.81	2.08
Sample Variance	1258.74	1087.54	392.40	4.32
Kurtosis	6.95	0.11	11.12	1.49
Skewness	2.05	0.53	2.40	0.77
Range	335.98	178.00	224.45	17.77
Minimum	25.80	29.00	15.16	4.88
Maximum	361.79	207.00	239.61	22.64
Sum	2808139.40	2957151.00	1405906.95	325731.75
Count	30155.00	30155.00	30155.00	30155.00

1987

	rx5d	*r1*	*rx1d*	*sdii*
Mean	90.98	102.49	43.25	9.79
Standard Error	0.22	0.24	0.10	0.01
Median	86.83	99.00	41.67	9.57
Mode	115.42	85.00	73.27	12.20
Standard Deviation	37.88	40.81	16.90	2.33
Sample Variance	1435.09	1665.50	285.63	5.45
Kurtosis	2.97	-0.56	0.87	1.12
Skewness	1.30	0.38	0.76	0.70
Range	315.05	202.00	153.26	19.10
Minimum	23.92	23.00	10.84	3.67
Maximum	338.97	225.00	164.10	22.77
Sum	2743526.14	3090601.00	1304068.45	295317.59
Count	30155.00	30155.00	30155.00	30155.00

1988

	rx5d	*r1*	*rx1d*	*sdii*
Mean	100.80	113.55	44.49	10.24
Standard Error	0.18	0.22	0.07	0.01
Median	94.29	108.00	42.51	10.15
Mode	133.48	103.00	71.85	13.17
Standard Deviation	30.42	38.34	11.60	1.62
Sample Variance	925.51	1469.74	134.51	2.63
Kurtosis	1.94	0.69	1.78	1.80
Skewness	1.22	0.91	0.96	0.56
Range	243.26	200.00	111.57	16.54
Minimum	34.41	42.00	15.18	4.13
Maximum	277.67	242.00	126.75	20.67
Sum	3039499.66	3424143.00	1341574.74	308639.68
Count	30155.00	30155.00	30155.00	30155.00

1989

	rx5d	*r1*	*rx1d*	*sdii*
Mean	96.17	109.80	45.16	10.60
Standard Error	0.18	0.21	0.10	0.01
Median	91.88	107.00	41.61	10.25
Mode	92.60	95.00	82.90	14.07
Standard Deviation	31.66	36.22	16.63	2.19
Sample Variance	1002.13	1312.20	276.66	4.79
Kurtosis	1.51	-0.29	2.04	0.47
Skewness	0.97	0.38	1.26	0.45
Range	270.82	182.00	128.41	17.54
Minimum	19.15	31.00	8.96	3.36
Maximum	289.97	213.00	137.37	20.89
Sum	2899955.10	3311083.00	1361899.24	319585.62
Count	30155.00	30155.00	30155.00	30155.00

1990

	rx5d	*r1*	*rx1d*	*sdii*
Mean	91.82	106.00	40.14	10.40
Standard Error	0.29	0.22	0.11	0.02
Median	78.62	104.00	35.44	9.71
Mode	80.99	105.00	71.94	14.08
Standard Deviation	50.29	38.33	18.63	2.74
Sample Variance	2529.51	1469.08	346.92	7.51
Kurtosis	9.02	-0.21	9.01	1.07
Skewness	2.73	0.42	2.55	0.98
Range	449.58	196.00	185.68	21.22
Minimum	19.80	26.00	10.14	3.79
Maximum	469.38	222.00	195.81	25.00
Sum	2768857.96	3196501.00	1210395.90	313630.13
Count	30155.00	30155.00	30155.00	30155.00

1991

	rx5d	*r1*	*rx1d*	*sdii*
Mean	101.36	111.44	46.38	10.87
Standard Error	0.22	0.20	0.10	0.01
Median	92.10	112.00	42.13	10.41
Mode	157.12	115.00	92.02	18.43
Standard Deviation	37.45	34.08	16.88	2.55
Sample Variance	1402.75	1161.51	284.84	6.53
Kurtosis	4.19	-0.32	4.70	2.94
Skewness	1.73	0.25	1.68	1.37
Range	353.44	178.00	195.59	21.38
Minimum	33.60	37.00	15.52	4.72
Maximum	387.03	215.00	211.11	26.10
Sum	3056414.50	3360475.00	1398446.83	327715.26
Count	30155.00	30155.00	30155.00	30155.00

1992

	rx5d	*r1*	*rx1d*	*sdii*
Mean	97.27	102.94	44.75	10.77
Standard Error	0.20	0.18	0.09	0.01
Median	92.12	101.00	41.70	10.47
Mode	132.94	99.00	68.50	13.46
Standard Deviation	34.94	31.17	15.81	2.39
Sample Variance	1220.76	971.58	250.04	5.71
Kurtosis	6.97	-0.08	4.44	4.99
Skewness	1.87	0.36	1.52	1.52
Range	347.18	173.00	149.38	23.93
Minimum	19.47	33.00	9.34	4.12
Maximum	366.65	206.00	158.72	28.05
Sum	2933321.98	3104173.00	1349451.72	324657.00
Count	30155.00	30155.00	30155.00	30155.00

1993

	rx5d	*r1*	*rx1d*	*sdii*
Mean	95.49	111.72	48.56	10.17
Standard Error	0.20	0.23	0.10	0.01
Median	88.50	108.00	45.27	9.86
Mode	164.15	98.00	49.37	13.43
Standard Deviation	33.90	40.15	17.83	2.14
Sample Variance	1149.54	1612.16	317.87	4.56
Kurtosis	6.59	-0.16	6.49	1.17
Skewness	1.96	0.49	1.81	0.75
Range	391.55	212.00	237.55	18.91
Minimum	23.40	30.00	9.92	4.13
Maximum	414.94	242.00	247.46	23.04
Sum	2879528.84	3368913.00	1464215.87	306682.61
Count	30155.00	30155.00	30155.00	30155.00

1994

	rx5d	*r1*	*rx1d*	*sdii*
Mean	104.10	110.32	46.91	11.19
Standard Error	0.17	0.18	0.10	0.01
Median	99.15	110.00	42.97	10.71
Mode	100.91	103.00	49.26	10.10
Standard Deviation	29.37	31.74	16.83	2.43
Sample Variance	862.60	1007.70	283.38	5.91
Kurtosis	7.97	-0.07	7.28	5.60
Skewness	2.11	0.22	2.21	1.86
Range	356.80	174.00	158.27	23.45
Minimum	42.16	36.00	19.00	5.08
Maximum	398.96	210.00	177.27	28.52
Sum	3139186.67	3326700.00	1414535.20	337326.00
Count	30155.00	30155.00	30155.00	30155.00

1995

	rx5d	*r1*	*rx1d*	*sdii*
Mean	94.08	113.45	44.26	10.85
Standard Error	0.21	0.22	0.10	0.02
Median	85.91	113.00	40.24	10.26
Mode	117.35	115.00	47.50	16.45
Standard Deviation	36.62	37.93	17.82	2.77
Sample Variance	1341.21	1438.43	317.58	7.65
Kurtosis	7.52	-0.44	4.68	2.44
Skewness	2.33	0.29	1.85	1.32
Range	336.97	194.00	156.07	21.98
Minimum	24.56	34.00	11.63	4.46
Maximum	361.53	228.00	167.69	26.43
Sum	2837048.01	3421046.00	1334767.78	327190.14
Count	30155.00	30155.00	30155.00	30155.00

1996

	rx5d	*r1*	*rx1d*	*sdii*
Mean	99.14	104.88	43.62	11.45
Standard Error	0.23	0.18	0.09	0.02
Median	91.96	103.00	41.09	11.07
Mode	132.93	108.00	64.75	16.89
Standard Deviation	39.13	30.48	14.91	2.93
Sample Variance	1531.34	929.00	222.26	8.60
Kurtosis	4.63	0.52	4.26	1.58
Skewness	1.75	0.62	1.54	0.76
Range	309.28	187.00	137.45	23.67
Minimum	22.57	33.00	9.45	3.91
Maximum	331.85	220.00	146.90	27.58
Sum	2989632.07	3162547.00	1315308.19	345281.58
Count	30155.00	30155.00	30155.00	30155.00

1997

	rx5d	*r1*	*rx1d*	*sdii*
Mean	90.35	119.12	43.10	10.02
Standard Error	0.20	0.20	0.10	0.01
Median	83.49	119.00	38.65	9.55
Mode	104.65	119.00	60.34	14.14
Standard Deviation	35.52	35.58	17.73	2.60
Sample Variance	1261.97	1265.64	314.34	6.74
Kurtosis	5.79	0.05	13.71	2.31
Skewness	1.96	0.21	2.89	1.20
Range	333.53	200.00	227.99	21.72
Minimum	28.23	33.00	14.16	4.39
Maximum	361.76	233.00	242.15	26.10
Sum	2724358.04	3592121.00	1299671.29	302274.29
Count	30155.00	30155.00	30155.00	30155.00

1998

	rx5d	*r1*	*rx1d*	*sdii*
Mean	94.35	105.08	43.22	11.35
Standard Error	0.18	0.18	0.07	0.01
Median	87.24	102.00	40.84	10.95
Mode	94.68	98.00	46.94	14.86
Standard Deviation	30.91	30.69	13.01	2.19
Sample Variance	955.63	941.82	169.29	4.81
Kurtosis	8.32	0.98	3.26	2.65
Skewness	2.39	0.68	1.37	1.15
Range	276.96	175.00	127.57	22.24
Minimum	34.08	36.00	13.59	4.64
Maximum	311.04	211.00	141.16	26.88
Sum	2845069.83	3168827.00	1303425.93	342258.19
Count	30155.00	30155.00	30155.00	30155.00

1999

	rx5d	*r1*	*rx1d*	*sdii*
Mean	102.47	114.68	44.06	11.61
Standard Error	0.20	0.22	0.09	0.01
Median	94.41	113.00	40.38	11.09
Mode	147.53	112.00	72.13	14.55
Standard Deviation	35.43	37.55	15.79	2.26
Sample Variance	1255.10	1410.37	249.43	5.09
Kurtosis	6.50	-0.10	3.71	3.41
Skewness	2.04	0.40	1.63	1.40
Range	288.71	200.00	127.40	24.31
Minimum	37.27	39.00	16.76	4.80
Maximum	325.98	239.00	144.15	29.11
Sum	3089952.86	3458134.00	1328546.62	350210.70
Count	30155.00	30155.00	30155.00	30155.00

2000

	rx5d	*r1*	*rx1d*	*sdii*
Mean	92.68	104.30	43.28	10.89
Standard Error	0.18	0.21	0.10	0.01
Median	85.94	102.00	39.00	10.55
Mode	154.05	103.00	39.96	17.24
Standard Deviation	32.08	35.73	17.05	2.23
Sample Variance	1028.82	1276.29	290.55	4.97
Kurtosis	4.35	0.05	6.18	2.11
Skewness	1.73	0.55	2.09	0.77
Range	265.60	193.00	160.71	21.40
Minimum	23.41	29.00	9.55	3.96
Maximum	289.01	222.00	170.26	25.36
Sum	2794846.39	3145117.00	1305216.73	328299.49
Count	30155.00	30155.00	30155.00	30155.00

2001

	rx5d	*r1*	*rx1d*	*sdii*
Mean	86.01	102.17	41.04	10.37
Standard Error	0.16	0.15	0.08	0.01
Median	81.71	99.00	38.40	10.23
Mode	110.60	96.00	45.82	9.24
Standard Deviation	27.40	26.77	14.75	2.18
Sample Variance	750.71	716.57	217.46	4.74
Kurtosis	2.32	0.34	4.43	1.27
Skewness	1.05	0.54	1.50	0.51
Range	253.29	177.00	143.18	19.29
Minimum	24.90	31.00	10.54	3.58
Maximum	278.19	208.00	153.72	22.87
Sum	2593541.79	3080978.00	1237474.21	312839.22
Count	30155.00	30155.00	30155.00	30155.00

2002

	rx5d	*r1*	*rx1d*	*sdii*
Mean	88.00	111.83	41.56	10.48
Standard Error	0.20	0.20	0.11	0.01
Median	81.55	112.00	37.10	9.89
Mode	110.99	116.00	64.89	14.74
Standard Deviation	34.00	34.75	18.31	2.49
Sample Variance	1156.05	1207.54	335.11	6.22
Kurtosis	7.86	-0.11	11.47	3.97
Skewness	2.21	0.24	2.64	1.46
Range	339.03	186.00	186.11	24.69
Minimum	19.62	29.00	11.45	3.55
Maximum	358.65	215.00	197.57	28.24
Sum	2653572.21	3372224.00	1253124.45	316107.37
Count	30155.00	30155.00	30155.00	30155.00

2003

	rx5d	*r1*	*rx1d*	*sdii*
Mean	92.11	109.04	40.75	10.91
Standard Error	0.16	0.20	0.08	0.01
Median	87.43	106.00	37.34	10.63
Mode	143.15	105.00	71.64	14.21
Standard Deviation	27.81	34.79	13.50	1.64
Sample Variance	773.22	1210.32	182.17	2.68
Kurtosis	3.17	0.09	6.74	3.24
Skewness	1.15	0.51	2.03	1.08
Range	335.03	192.00	176.69	19.61
Minimum	29.78	33.00	10.14	3.49
Maximum	364.81	225.00	186.82	23.10
Sum	2777697.74	3288139.00	1228725.35	328950.28
Count	30155.00	30155.00	30155.00	30155.00

2004

	rx5d	*r1*	*rx1d*	*sdii*
Mean	92.88	107.95	42.13	10.44
Standard Error	0.18	0.19	0.10	0.01
Median	84.56	107.00	37.37	10.18
Mode	87.05	109.00	80.64	14.05
Standard Deviation	31.91	32.96	16.59	2.40
Sample Variance	1018.33	1086.59	275.07	5.78
Kurtosis	5.40	-0.18	8.28	2.15
Skewness	1.91	0.25	2.19	0.94
Range	374.08	184.00	259.71	21.96
Minimum	30.12	23.00	11.46	4.36
Maximum	404.20	207.00	271.16	26.32
Sum	2800663.39	3255092.00	1270506.54	314926.78
Count	30155.00	30155.00	30155.00	30155.00

2005

	rx5d	*r1*	*rx1d*	*sdii*
Mean	94.78	104.10	46.86	10.63
Standard Error	0.21	0.18	0.13	0.01
Median	86.39	103.00	40.99	10.23
Mode	156.39	105.00	122.93	14.38
Standard Deviation	36.27	31.57	21.82	2.15
Sample Variance	1315.61	996.94	476.21	4.64
Kurtosis	3.98	0.17	6.86	2.15
Skewness	1.78	0.56	2.43	1.08
Range	290.87	186.00	178.48	19.59
Minimum	23.97	36.00	13.48	4.29
Maximum	314.84	222.00	191.95	23.89
Sum	2858217.64	3139031.00	1413061.56	320577.26
Count	30155.00	30155.00	30155.00	30155.00

2006

	rx5d	*r1*	*rx1d*	*sdii*
Mean	112.25	113.67	47.56	10.92
Standard Error	0.29	0.21	0.12	0.01
Median	97.30	110.00	41.84	10.55
Mode	165.83	105.00	52.11	14.05
Standard Deviation	50.20	35.74	20.91	2.31
Sample Variance	2519.87	1277.70	437.42	5.34
Kurtosis	6.56	0.27	8.55	2.25
Skewness	2.25	0.55	2.52	1.07
Range	477.08	213.00	212.29	20.70
Minimum	24.88	28.00	15.99	4.75
Maximum	501.97	241.00	228.28	25.45
Sum	3384817.04	3427764.00	1434173.18	329331.68
Count	30155.00	30155.00	30155.00	30155.00

2007

	rx5d	*r1*	*rx1d*	*sdii*
Mean	103.33	110.86	47.88	10.74
Standard Error	0.25	0.21	0.12	0.01
Median	90.40	110.00	42.17	10.22
Mode	212.03	109.00	76.80	13.33
Standard Deviation	42.98	36.44	20.40	2.33
Sample Variance	1847.00	1328.07	416.13	5.44
Kurtosis	5.05	-0.08	7.22	2.01
Skewness	1.96	0.35	2.31	1.18
Range	369.51	194.00	231.81	21.50
Minimum	37.22	32.00	15.65	4.36
Maximum	406.73	226.00	247.46	25.86
Sum	3115899.92	3343044.00	1443942.29	323880.33
Count	30155.00	30155.00	30155.00	30155.00

2008

	rx5d	*r1*	*rx1d*	*sdii*
Mean	100.41	112.20	44.27	10.78
Standard Error	0.15	0.21	0.09	0.01
Median	97.85	109.00	40.81	10.64
Mode	149.41	109.00	58.61	14.47
Standard Deviation	26.51	36.46	15.76	2.17
Sample Variance	703.01	1329.31	248.53	4.72
Kurtosis	1.77	-0.01	3.29	1.77
Skewness	0.74	0.49	1.50	0.61
Range	254.61	194.00	160.52	20.06
Minimum	23.18	34.00	9.83	3.94
Maximum	277.78	228.00	170.35	24.00
Sum	3027761.07	3383506.00	1334993.91	325174.11
Count	30155.00	30155.00	30155.00	30155.00

2009

	rx5d	*r1*	*rx1d*	*sdii*
Mean	97.59	114.28	45.39	10.27
Standard Error	0.27	0.22	0.14	0.02
Median	88.11	113.00	39.13	9.94
Mode	163.39	116.00	144.22	17.34
Standard Deviation	47.65	37.56	24.84	3.05
Sample Variance	2270.18	1410.76	616.80	9.28
Kurtosis	4.76	-0.23	6.27	1.88
Skewness	1.86	0.37	2.25	1.02
Range	365.63	203.00	213.01	23.16
Minimum	21.28	31.00	8.09	3.69
Maximum	386.91	234.00	221.10	26.85
Sum	2942807.95	3446101.00	1368587.38	309801.73
Count	30155.00	30155.00	30155.00	30155.00

2010

	rx5d	*r1*	*rx1d*	*sdii*
Mean	100.82	114.84	46.09	10.64
Standard Error	0.18	0.19	0.10	0.01
Median	95.07	112.00	42.09	10.25
Mode	141.64	107.00	55.73	13.41
Standard Deviation	30.98	33.68	17.34	2.33
Sample Variance	959.83	1134.38	300.84	5.43
Kurtosis	4.44	-0.04	1.20	1.76
Skewness	1.45	0.35	1.06	0.95
Range	357.25	191.00	140.77	20.31
Minimum	24.37	35.00	10.59	3.95
Maximum	381.62	226.00	151.36	24.26
Sum	3040108.71	3463043.00	1389907.36	320855.45
Count	30155.00	30155.00	30155.00	30155.00

2011

	rx5d	*r1*	*rx1d*	*sdii*
Mean	95.54	113.01	44.13	10.15
Standard Error	0.19	0.21	0.10	0.01
Median	89.45	110.00	41.16	9.71
Mode	102.71	107.00	44.47	14.58
Standard Deviation	32.95	36.78	16.66	2.35
Sample Variance	1085.98	1352.47	277.61	5.53
Kurtosis	4.63	0.06	6.76	2.74
Skewness	1.73	0.53	2.01	1.29
Range	272.98	196.00	153.00	19.82
Minimum	33.82	36.00	12.35	4.31
Maximum	306.80	232.00	165.35	24.12
Sum	2881138.01	3407778.00	1330777.51	306026.34
Count	30155.00	30155.00	30155.00	30155.00

2012

	rx5d	*r1*	*rx1d*	*sdii*
Mean	95.79	114.93	45.84	10.90
Standard Error	0.18	0.20	0.09	0.01
Median	86.47	113.00	41.68	10.43
Mode	160.14	106.00	73.25	13.40
Standard Deviation	31.75	34.43	16.07	2.01
Sample Variance	1007.89	1185.50	258.35	4.05
Kurtosis	3.50	-0.08	3.38	2.18
Skewness	1.67	0.35	1.64	1.17
Range	286.86	181.00	132.61	18.99
Minimum	39.50	42.00	17.43	4.44
Maximum	326.36	223.00	150.05	23.43
Sum	2888443.92	3465668.00	1382283.62	328704.07
Count	30155.00	30155.00	30155.00	30155.00

2013

	rx5d	*r1*	*rx1d*	*sdii*
Mean	85.89	115.69	43.26	8.70
Standard Error	0.18	0.23	0.09	0.01
Median	79.46	111.00	39.94	8.40
Mode	111.16	105.00	70.39	11.43
Standard Deviation	30.64	39.38	15.12	1.70
Sample Variance	938.62	1551.06	228.61	2.91
Kurtosis	10.81	0.05	2.63	3.19
Skewness	2.58	0.60	1.28	1.24
Range	301.85	211.00	158.45	16.74
Minimum	28.78	33.00	13.48	3.73
Maximum	330.63	244.00	171.93	20.47
Sum	2590070.87	3488513.00	1304481.69	262239.81
Count	30155.00	30155.00	30155.00	30155.00

2014

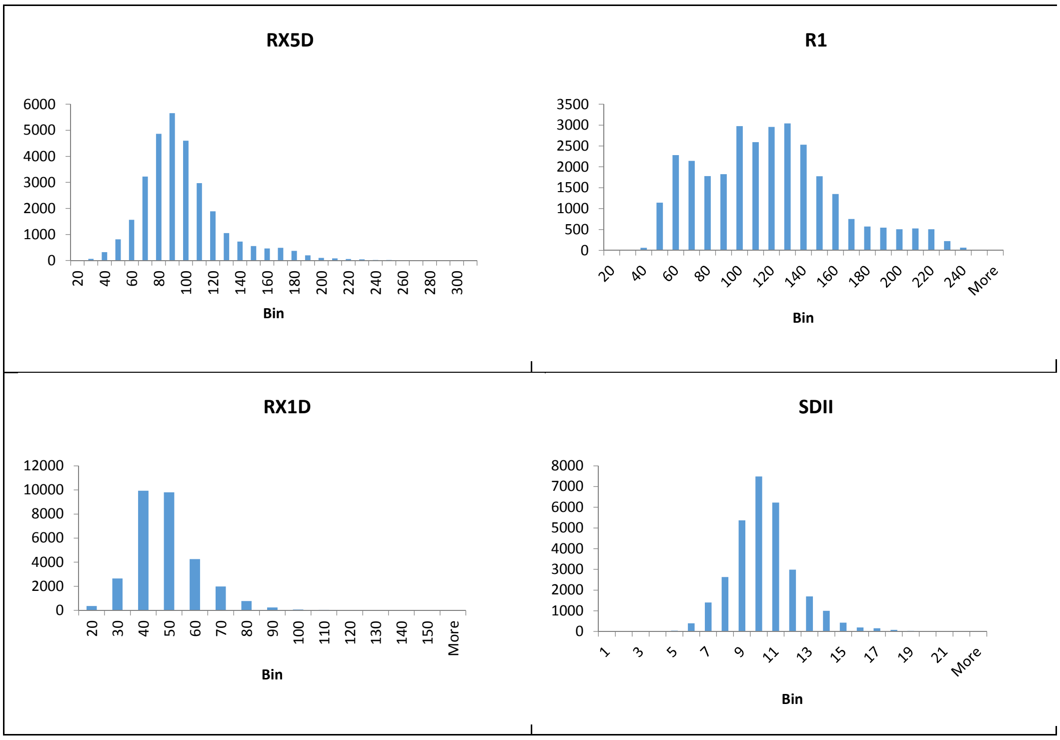
	rx5d	*r1*	*rx1d*	*sdii*
Mean	91.58	113.14	42.46	9.73
Standard Error	0.17	0.20	0.09	0.01
Median	83.50	113.00	39.21	9.45
Mode	136.66	113.00	48.83	14.09
Standard Deviation	30.28	35.37	14.94	2.00
Sample Variance	916.83	1250.73	223.16	4.02
Kurtosis	4.28	-0.27	4.96	1.38
Skewness	1.88	0.08	1.76	0.83
Range	246.03	184.00	158.45	18.07
Minimum	32.16	28.00	13.67	3.98
Maximum	278.19	212.00	172.11	22.05
Sum	2761725.31	3411769.00	1280476.72	293387.46
Count	30155.00	30155.00	30155.00	30155.00

2015

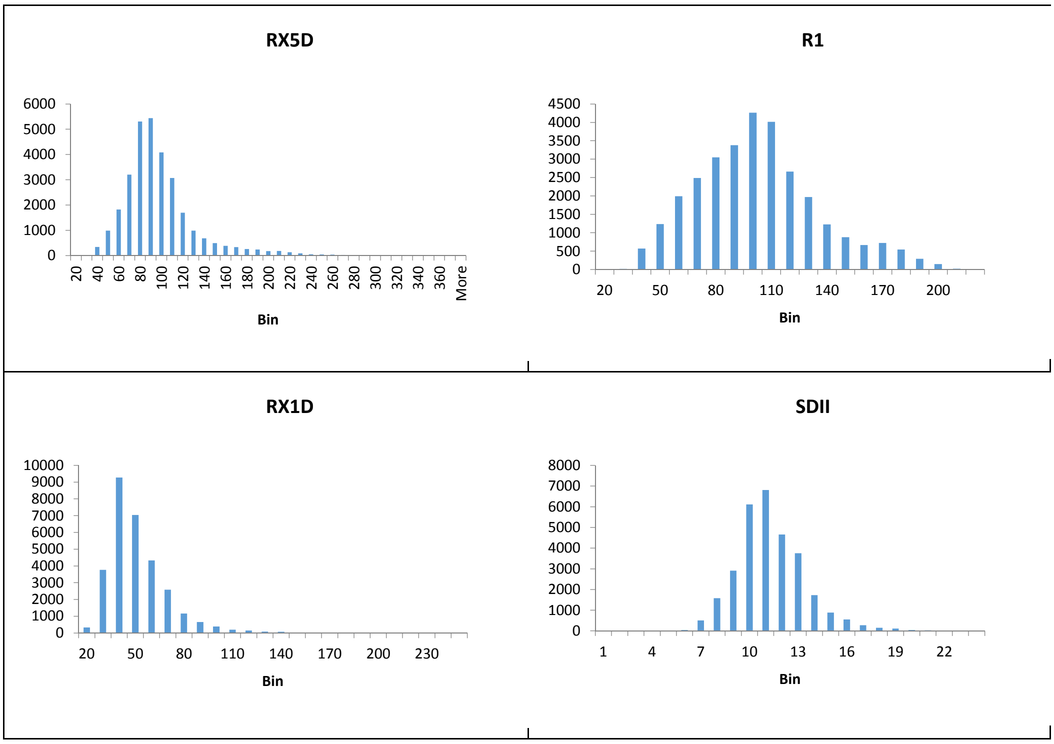
	rx5d	r1	rx1d	sdii
Mean	103.61	99.02	44.34	10.86
Standard Error	0.21	0.17	0.10	0.01
Median	93.33	97.00	39.39	10.44
Mode	93.04	97.00	64.57	13.92
Standard Deviation	36.37	29.41	16.91	1.98
Sample Variance	1322.86	864.86	285.89	3.91
Kurtosis	0.55	0.56	3.36	0.92
Skewness	1.00	0.59	1.63	0.90
Range	241.12	187.00	166.88	17.98
Minimum	30.58	27.00	14.18	3.98
Maximum	271.70	214.00	181.06	21.96
Sum	3124235.25	2985800.00	1337129.57	327412.46
Count	30155.00	30155.00	30155.00	30155.00

Histograms

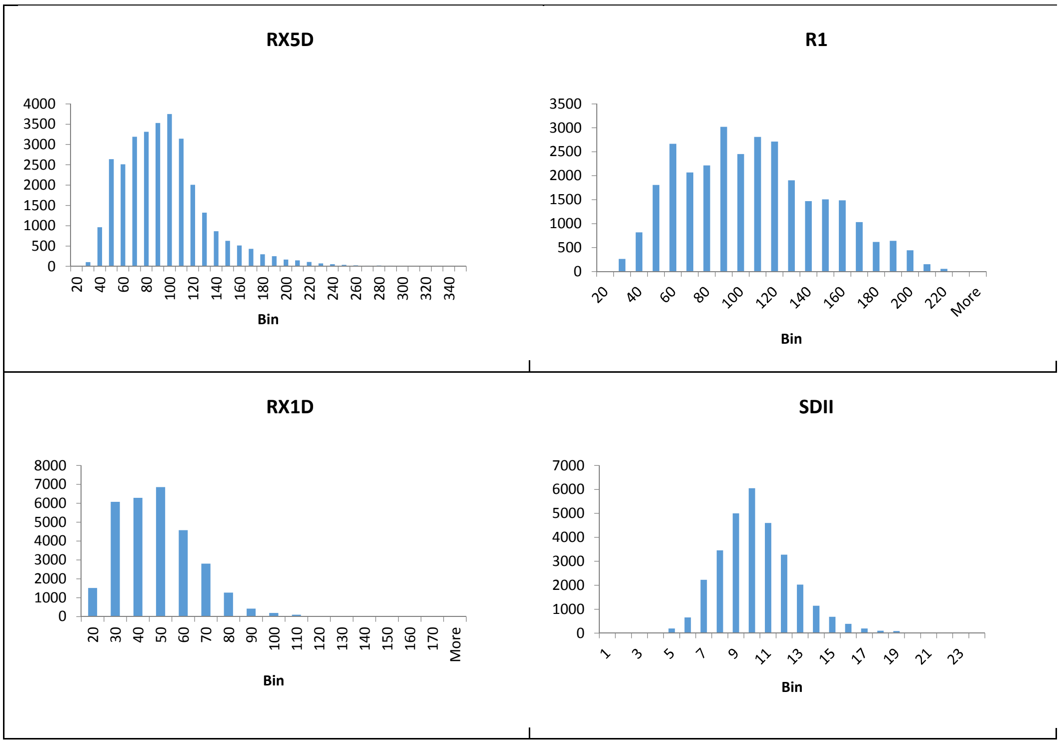
1985



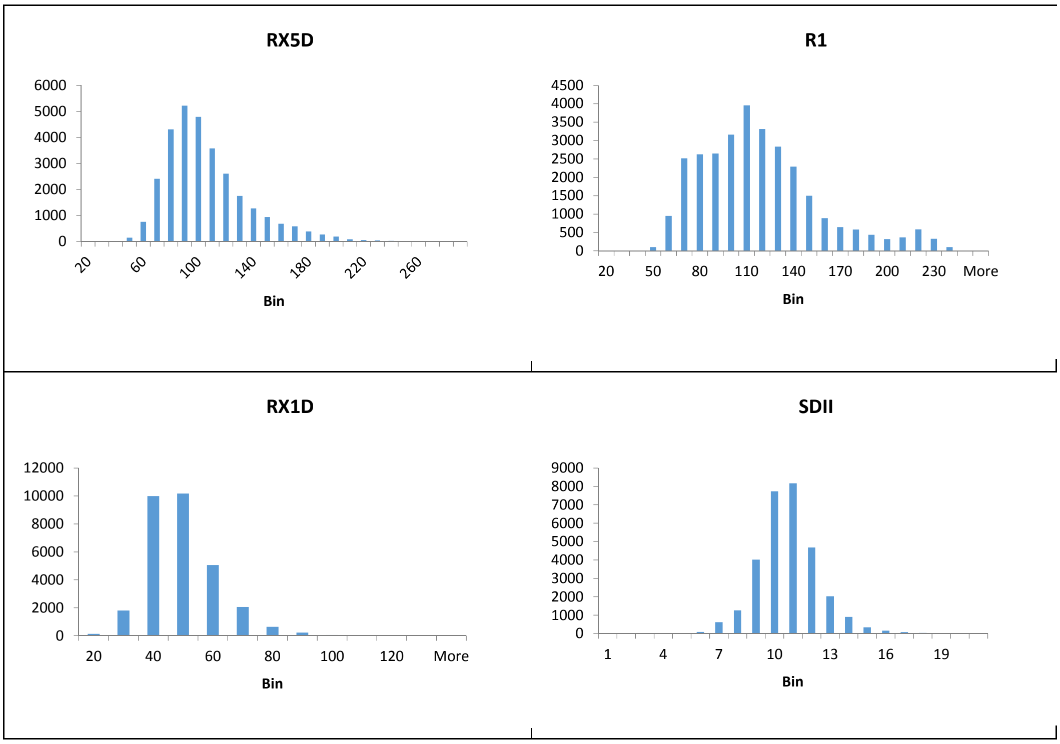
1986


RX5D
Bin
R1
Bin
RX1D
Bin
SDII
Bin

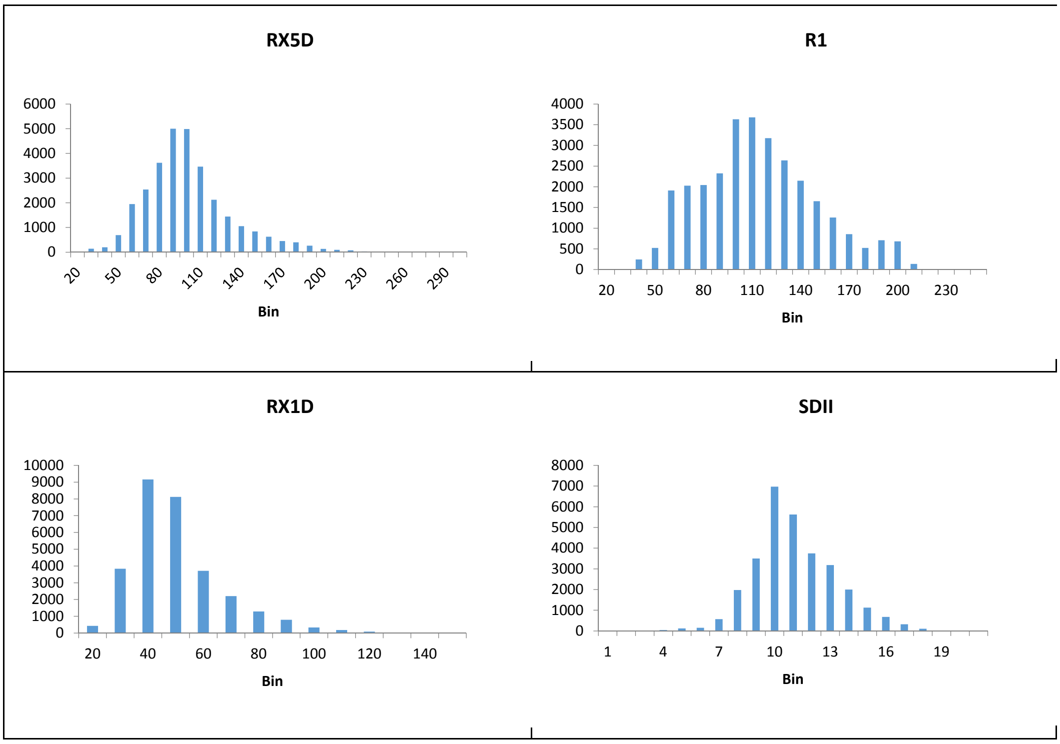
1987


RX5D
Bin
R1
Bin
RX1D
Bin
SDII
Bin

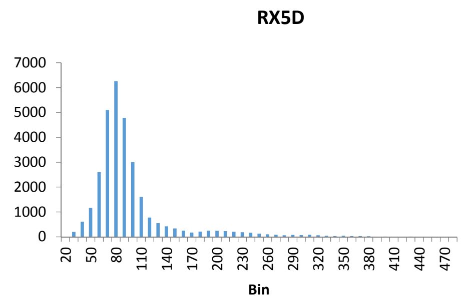
1988

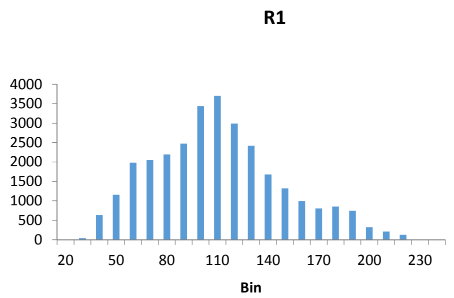

RX5D
6000
5000
4000
3000
2000
1000
0
20
60
100
140
180
220
260
Bin
R1
4500
4000
3500
3000
2500
2000
1500
1000
500
0
20
50
80
110
140
170
200
230
More
Bin
RX1D
12000
10000
8000
6000
4000
2000
0
20
40
60
80
100
120
More
Bin
SDII
9000
8000
7000
6000
5000
4000
3000
2000
1000
0
1
4
7
10
13
16
19
Bin

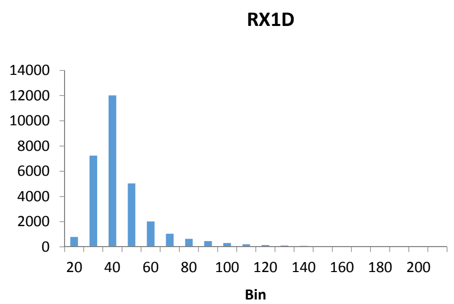
1989

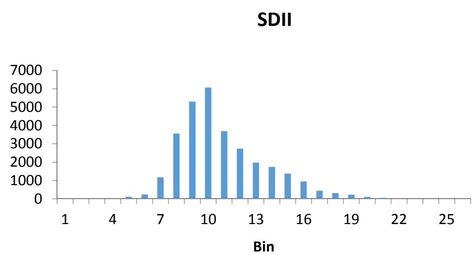

RX5D
6000
5000
4000
3000
2000
1000
0
20
50
80
110
140
170
200
230
260
290
Bin
R1
4000
3500
3000
2500
2000
1500
1000
500
0
20
50
80
110
140
170
200
230
Bin
RX1D
10000
9000
8000
7000
6000
5000
4000
3000
2000
1000
0
20
40
60
80
100
120
140
Bin
SDII
8000
7000
6000
5000
4000
3000
2000
1000
0
1
4
7
10
13
16
19
Bin

1990

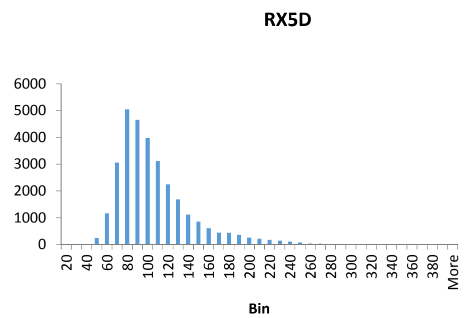

RX5D
7000 6000 5000 4000 3000 2000 1000 0
20 50 80 110 140 170 200 230 260 290 320 350 380 410 440 470
Bin

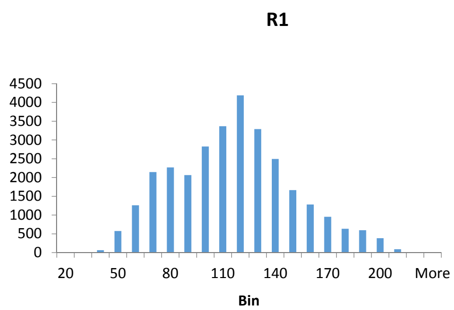

R1
4000 3500 3000 2500 2000 1500 1000 500 0
20 50 80 110 140 170 200 230
Bin

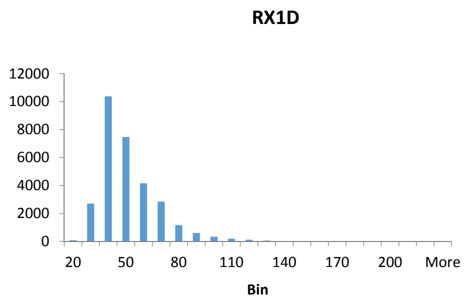

RX1D
14000 12000 10000 8000 6000 4000 2000 0
20 40 60 80 100 120 140 160 180 200
Bin

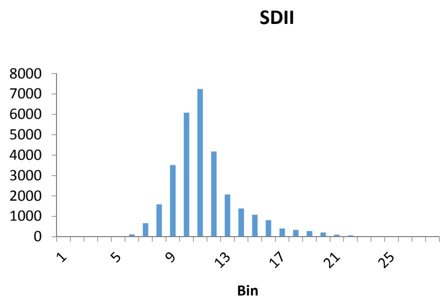

SDII
7000 6000 5000 4000 3000 2000 1000 0
1 4 7 10 13 16 19 22 25
Bin

1991

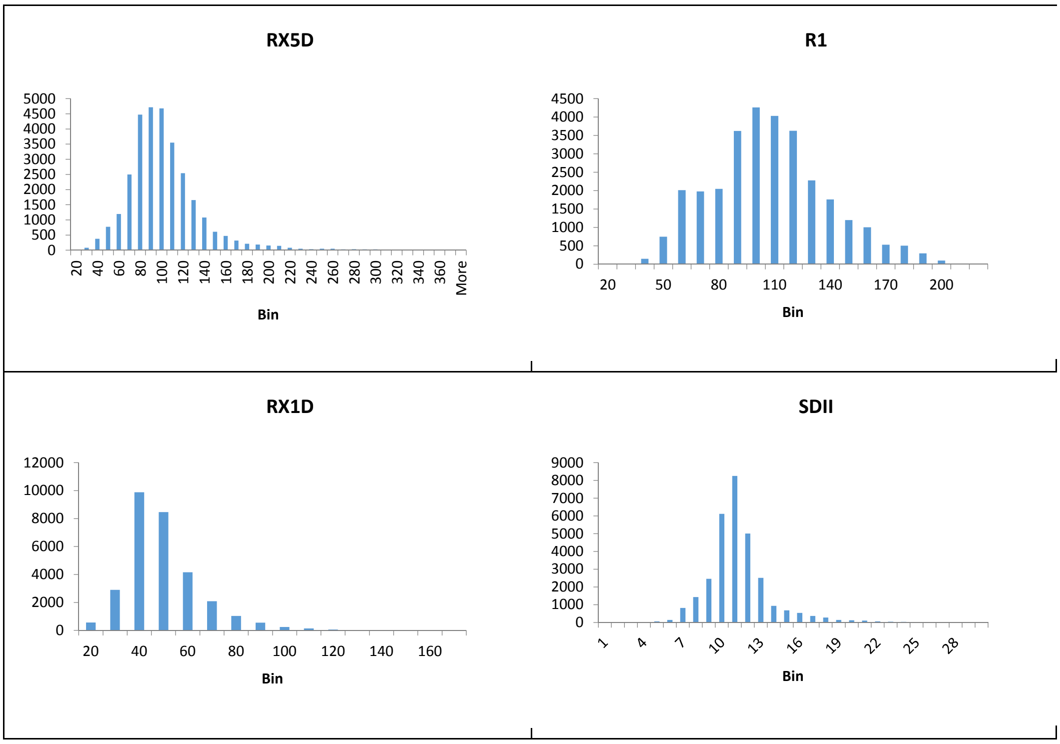

RX5D
6000 5000 4000 3000 2000 1000 0
20 40 60 80 100 120 140 160 180 200 220 240 260 280 300 320 340 360 380 More
Bin


R1
4500 4000 3500 3000 2500 2000 1500 1000 500 0
20 50 80 110 140 170 200 More
Bin

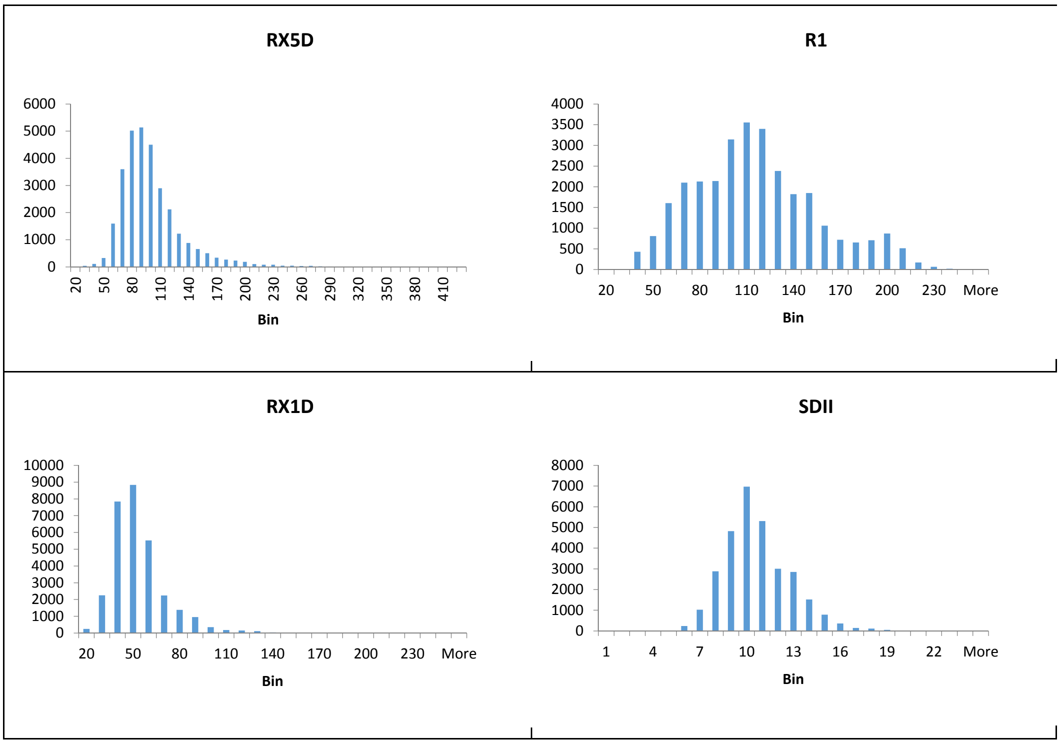

RX1D
12000 10000 8000 6000 4000 2000 0
20 50 80 110 140 170 200 More
Bin


SDII
8000 7000 6000 5000 4000 3000 2000 1000 0
1 5 9 13 17 21 25
Bin

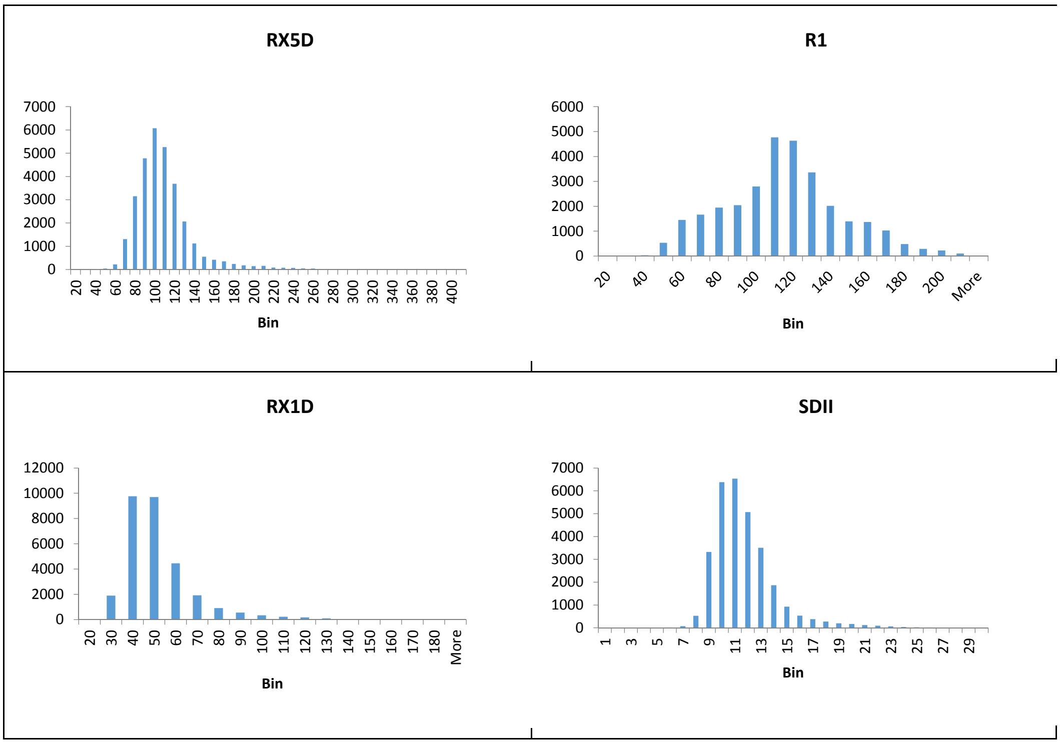
1992


RX5D
5000
4500
4000
3500
3000
2500
2000
1500
1000
500
0
20 40 60 80 100 120 140 160 180 200 220 240 260 280 300 320 340 360 More
Bin
R1
4500
4000
3500
3000
2500
2000
1500
1000
500
0
20 50 80 110 140 170 200
Bin
RX1D
12000
10000
8000
6000
4000
2000
0
20 40 60 80 100 120 140 160
Bin
SDII
9000
8000
7000
6000
5000
4000
3000
2000
1000
0
1 4 7 10 13 16 19 22 25 28
Bin

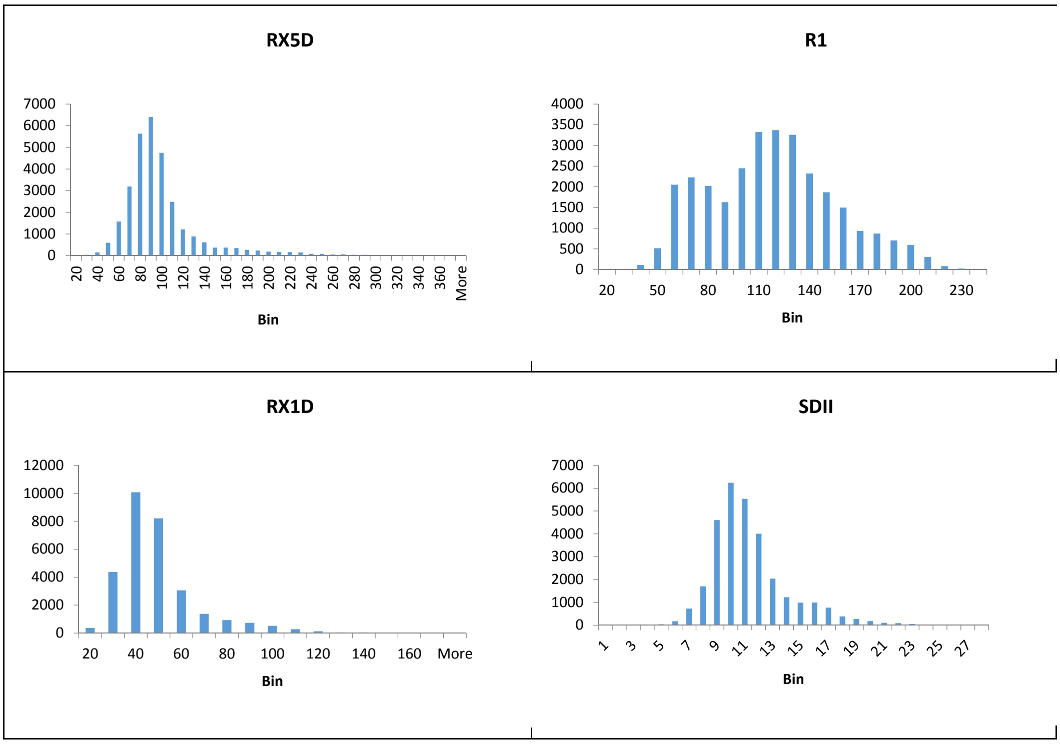
1993


RX5D
6000
5000
4000
3000
2000
1000
0
20 50 80 110 140 170 200 230 260 290 320 350 380 410
Bin
R1
4000
3500
3000
2500
2000
1500
1000
500
0
20 50 80 110 140 170 200 230 More
Bin
RX1D
10000
9000
8000
7000
6000
5000
4000
3000
2000
1000
0
20 50 80 110 140 170 200 230 More
Bin
SDII
8000
7000
6000
5000
4000
3000
2000
1000
0
1 4 7 10 13 16 19 22 More
Bin

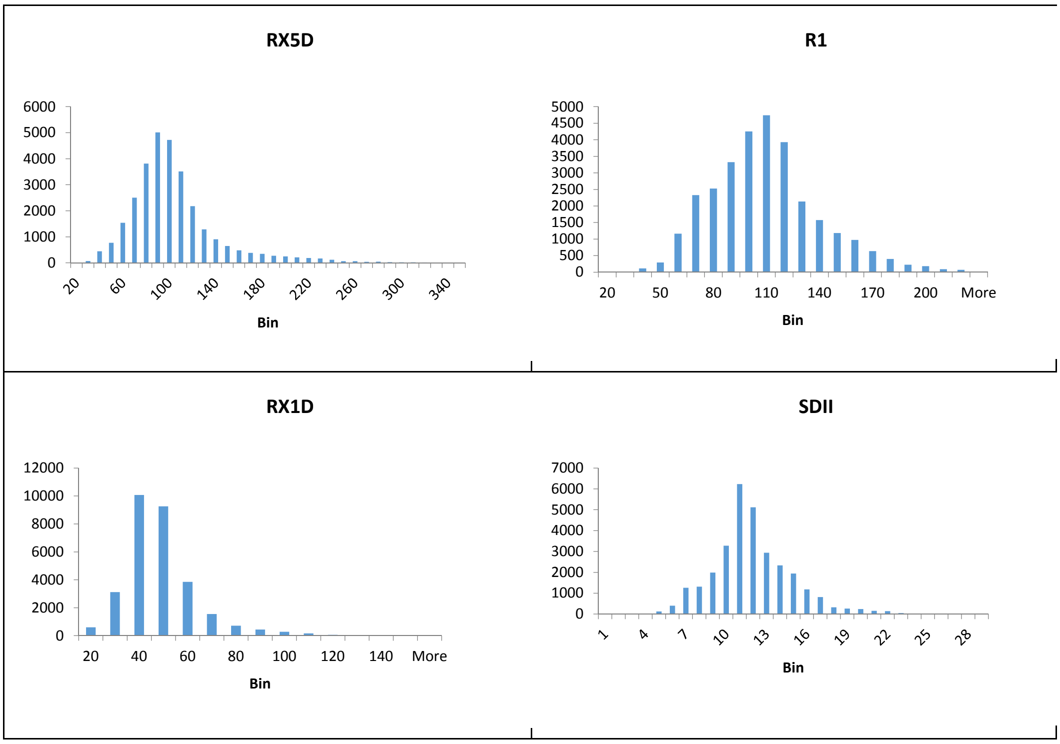
1994


RX5D
Bin
R1
Bin
RX1D
Bin
SDII
Bin

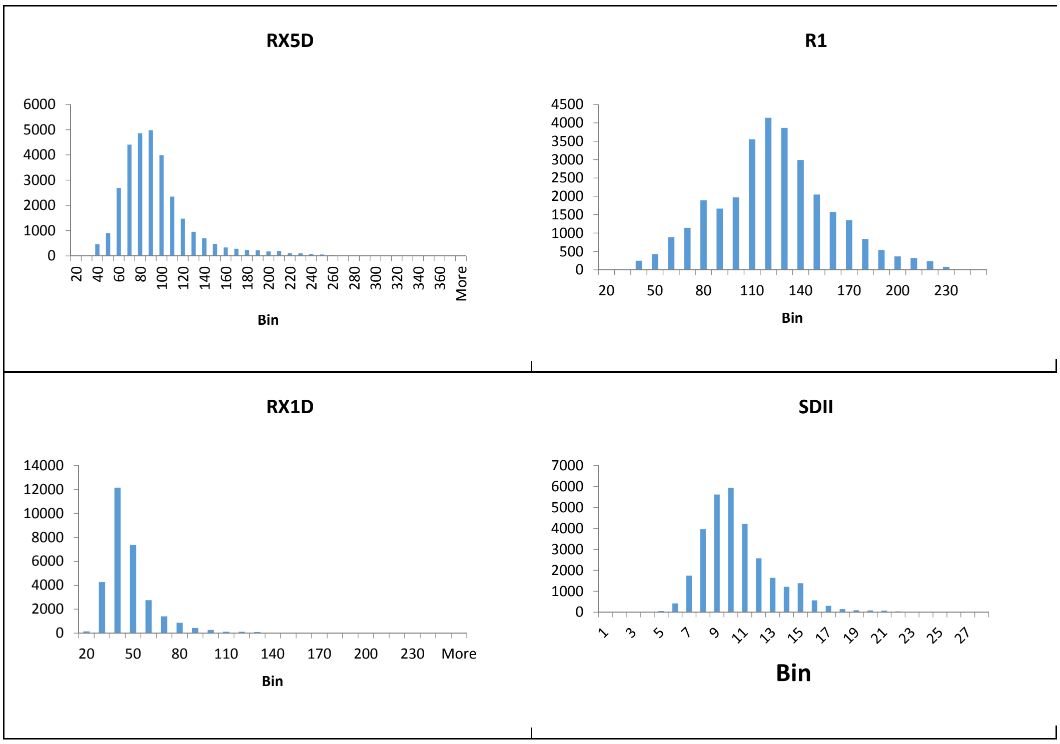
1995


RX5D
Bin
R1
Bin
RX1D
Bin
SDII
Bin

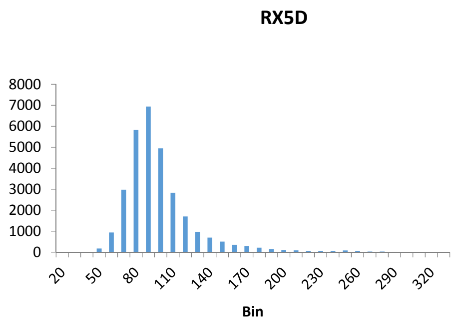
1996

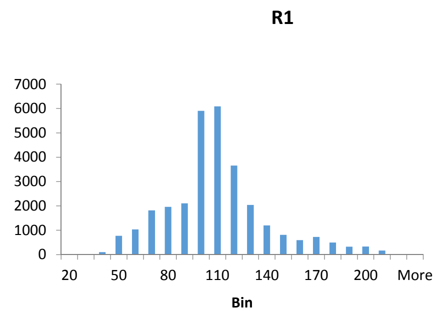

RX5D
Bin
R1
Bin
RX1D
Bin
SDII
Bin

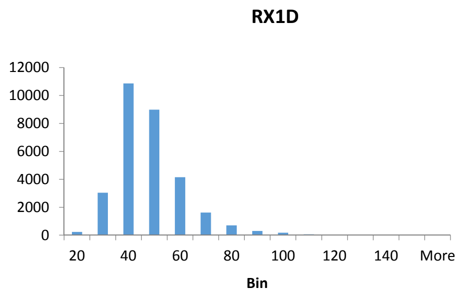
1997

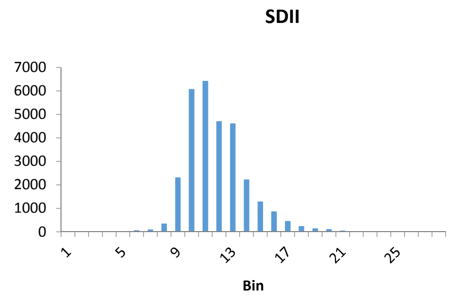

RX5D
Bin
R1
Bin
RX1D
Bin
SDII
Bin

1998

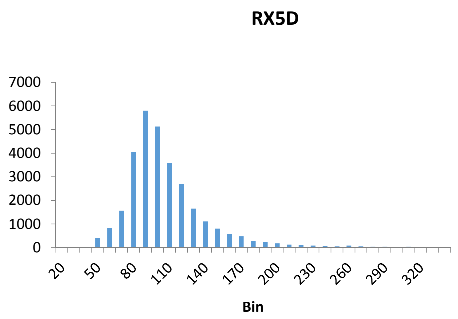

RX5D
8000
7000
6000
5000
4000
3000
2000
1000
0
20
50
80
110
140
170
200
230
260
290
320
Bin

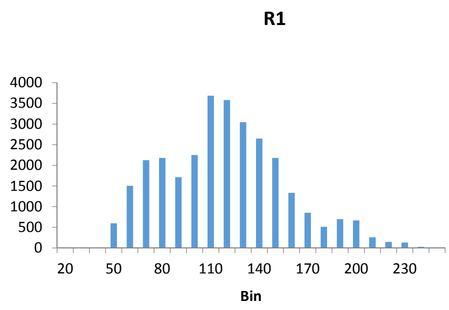

R1
7000
6000
5000
4000
3000
2000
1000
0
20
50
80
110
140
170
200
More
Bin

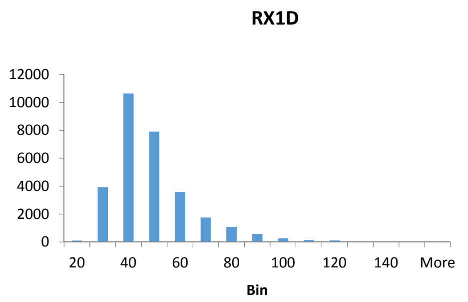

RX1D
12000
10000
8000
6000
4000
2000
0
20
40
60
80
100
120
140
More
Bin

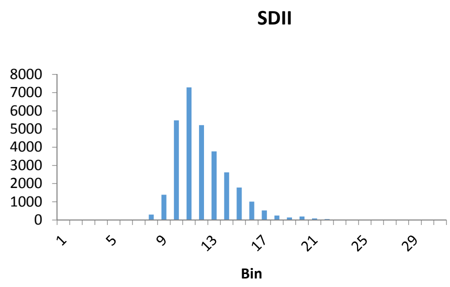

SDII
7000
6000
5000
4000
3000
2000
1000
0
1
5
9
13
17
21
25
Bin

1999

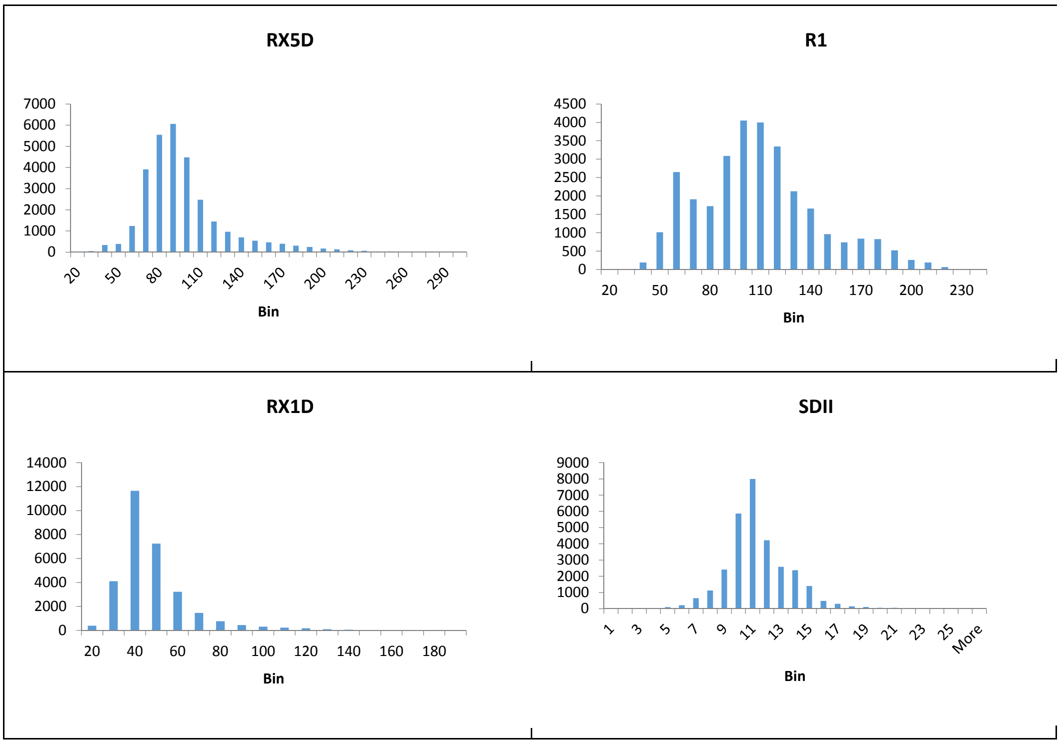

RX5D
7000
6000
5000
4000
3000
2000
1000
0
20
50
80
110
140
170
200
230
260
290
320
Bin


R1
4000
3500
3000
2500
2000
1500
1000
500
0
20
50
80
110
140
170
200
230
Bin

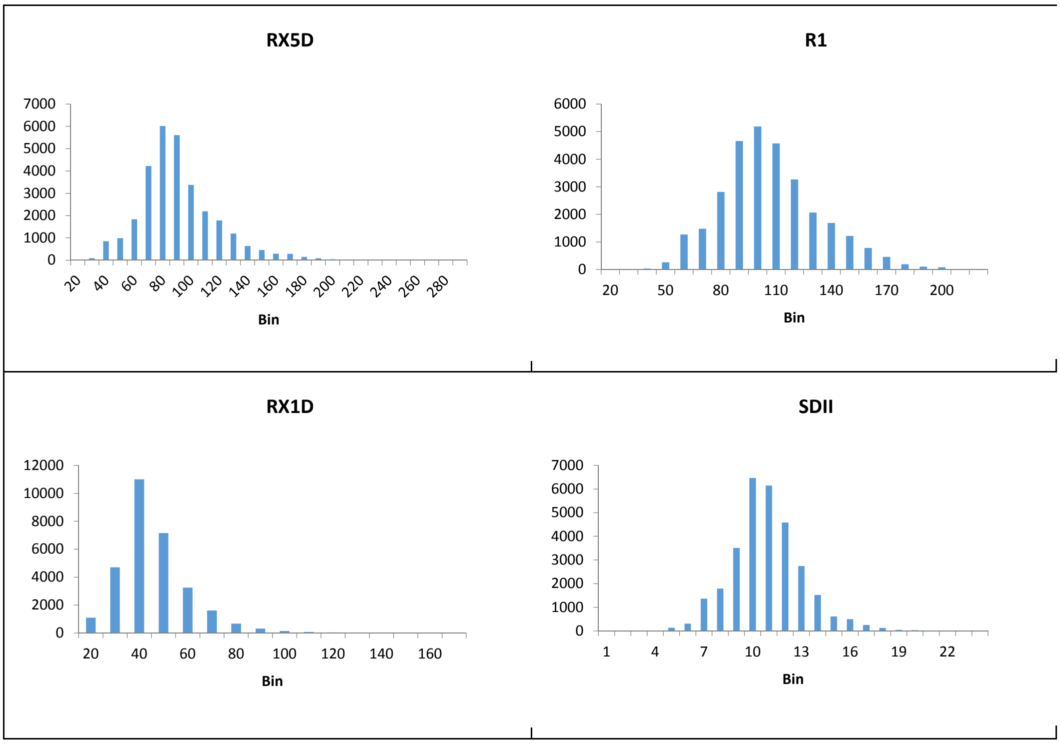

RX1D
12000
10000
8000
6000
4000
2000
0
20
40
60
80
100
120
140
More
Bin


SDII
8000
7000
6000
5000
4000
3000
2000
1000
0
1
5
9
13
17
21
25
29
Bin

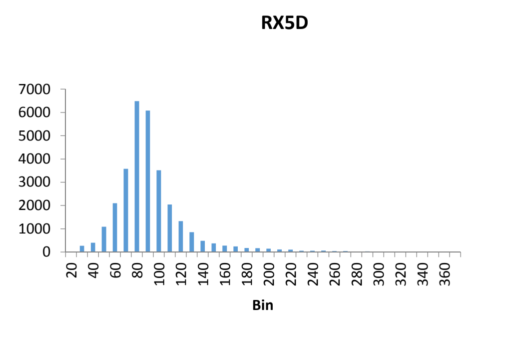
2000

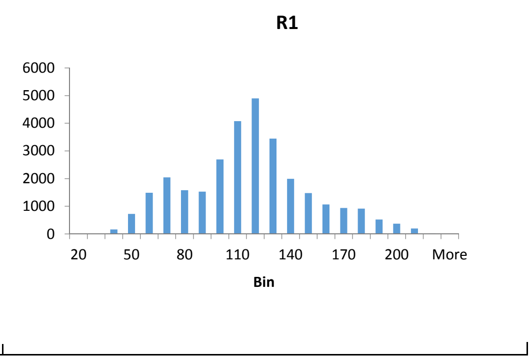

RX5D
7000
6000
5000
4000
3000
2000
1000
0
20 50 80 110 140 170 200 230 260 290
Bin
R1
4500
4000
3500
3000
2500
2000
1500
1000
500
0
20 50 80 110 140 170 200 230
Bin
RX1D
14000
12000
10000
8000
6000
4000
2000
0
20 40 60 80 100 120 140 160 180
Bin
SDII
9000
8000
7000
6000
5000
4000
3000
2000
1000
0
1 3 5 7 9 11 13 15 17 19 21 23 25 More
Bin

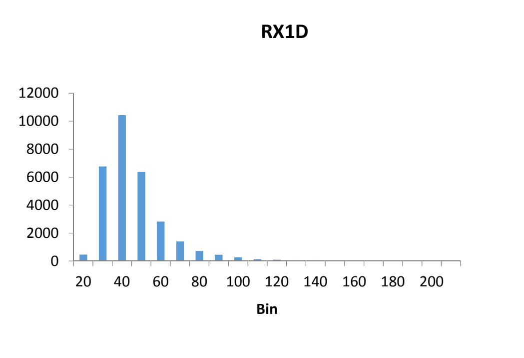
2001

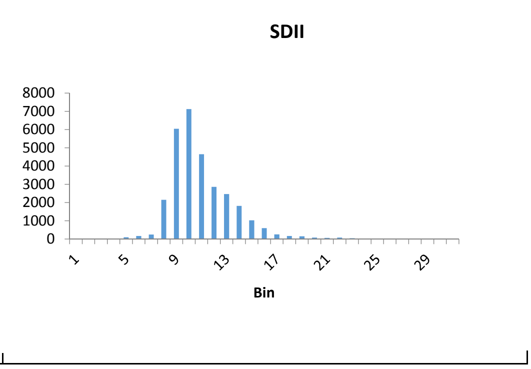

RX5D
7000
6000
5000
4000
3000
2000
1000
0
20 40 60 80 100 120 140 160 180 200 220 240 260 280
Bin
R1
6000
5000
4000
3000
2000
1000
0
20 50 80 110 140 170 200
Bin
RX1D
12000
10000
8000
6000
4000
2000
0
20 40 60 80 100 120 140 160
Bin
SDII
7000
6000
5000
4000
3000
2000
1000
0
1 4 7 10 13 16 19 22
Bin

2002

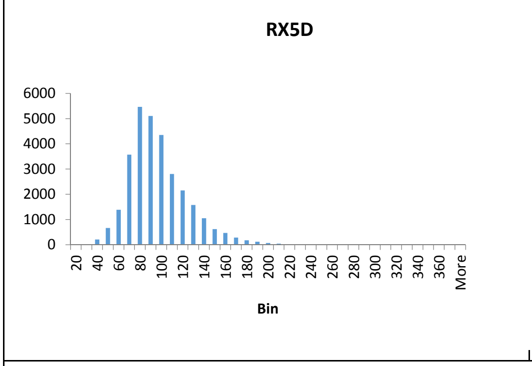

RX5D
7000
6000
5000
4000
3000
2000
1000
0
20 40 60 80 100 120 140 160 180 200 220 240 260 280 300 320 340 360
Bin

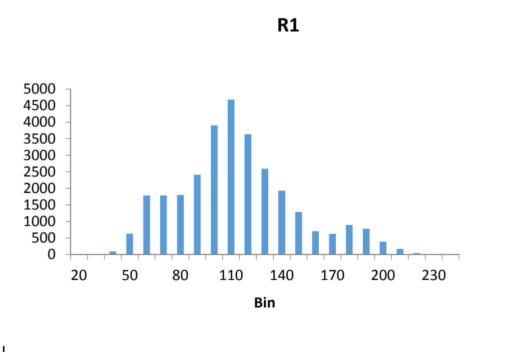

R1
6000
5000
4000
3000
2000
1000
0
20 50 80 110 140 170 200 More
Bin

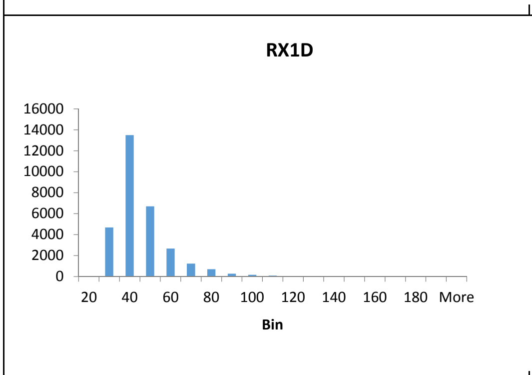

RX1D
12000
10000
8000
6000
4000
2000
0
20 40 60 80 100 120 140 160 180 200
Bin

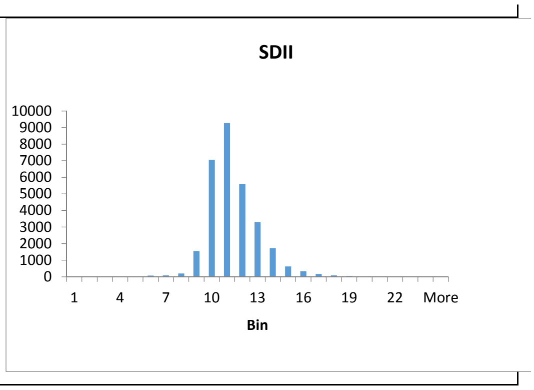

SDII
8000
7000
6000
5000
4000
3000
2000
1000
0
1 5 9 13 17 21 25 29
Bin

2003

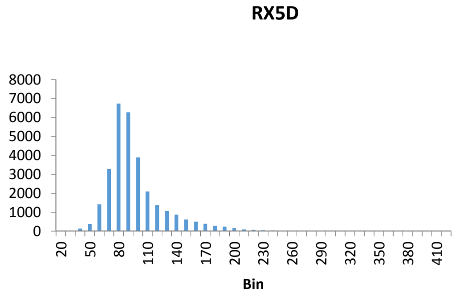

RX5D
6000
5000
4000
3000
2000
1000
0
20 40 60 80 100 120 140 160 180 200 220 240 260 280 300 320 340 360 More
Bin

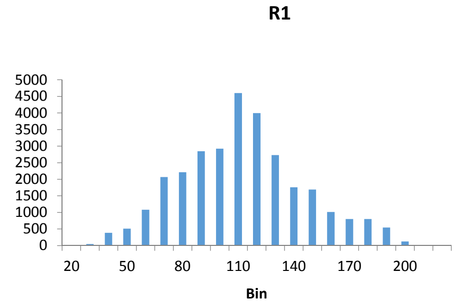

R1
5000
4500
4000
3500
3000
2500
2000
1500
1000
500
0
20 50 80 110 140 170 200 230
Bin

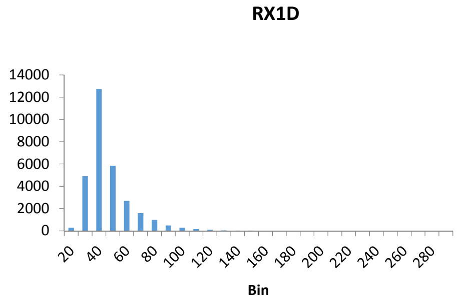

RX1D
16000
14000
12000
10000
8000
6000
4000
2000
0
20 40 60 80 100 120 140 160 180 More
Bin

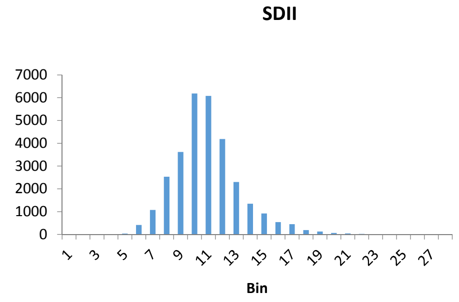

SDII
10000
9000
8000
7000
6000
5000
4000
3000
2000
1000
0
1 4 7 10 13 16 19 22 More
Bin

2004

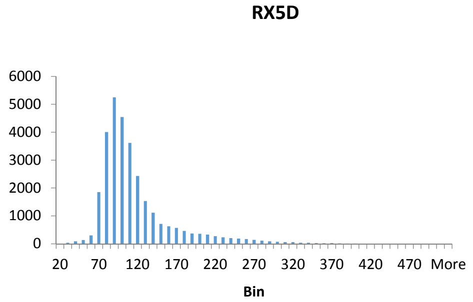

RX5D
Bin

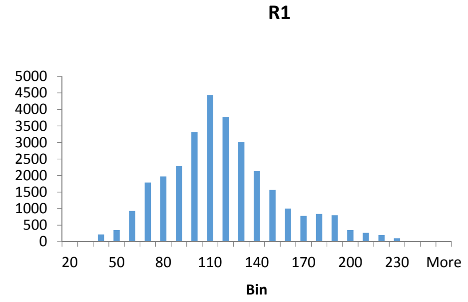

R1
Bin

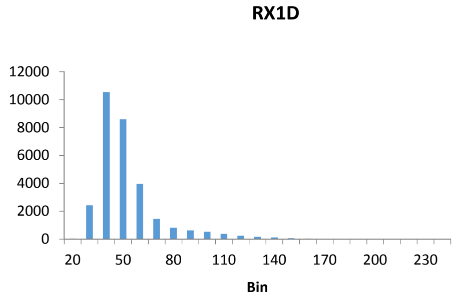

RX1D
Bin

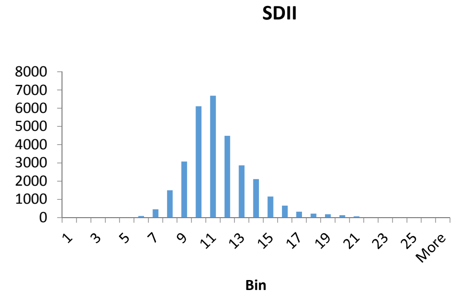

SDII
Bin

2005

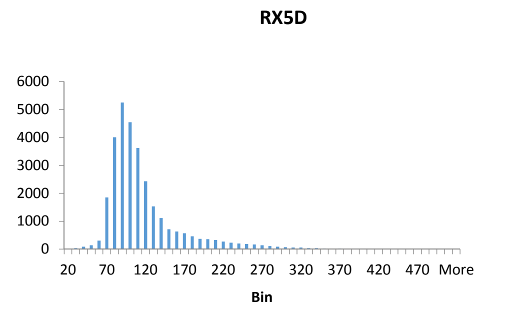

RX5D
Bin

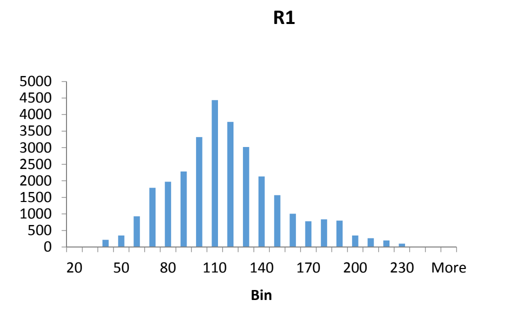

R1
Bin

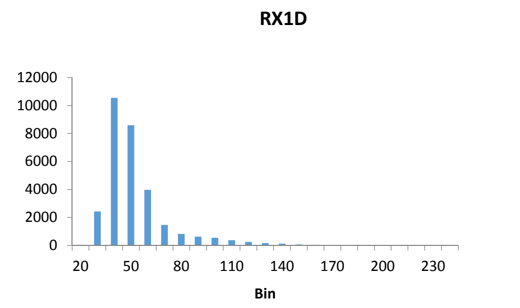

RX1D
Bin

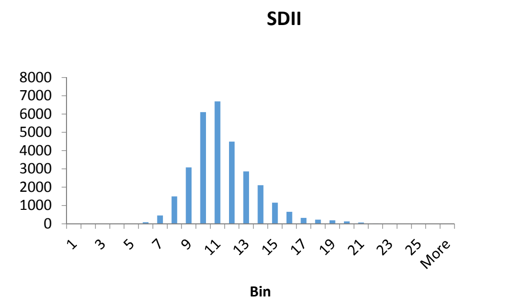

SDII
Bin

2006

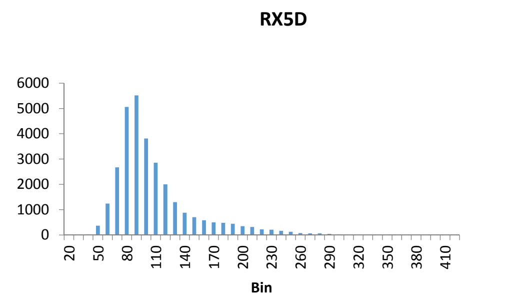

RX5D
6000
5000
4000
3000
2000
1000
0
20 70 120 170 220 270 320 370 420 470 More
Bin

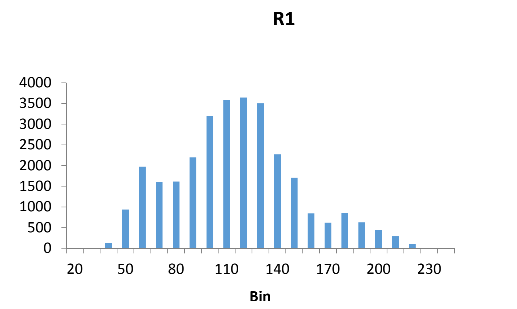

R1
5000
4500
4000
3500
3000
2500
2000
1500
1000
500
0
20 50 80 110 140 170 200 230 More
Bin

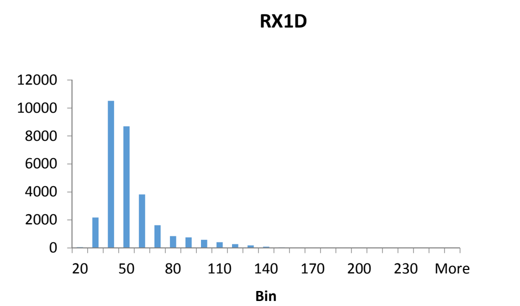

RX1D
12000
10000
8000
6000
4000
2000
0
20 50 80 110 140 170 200 230
Bin

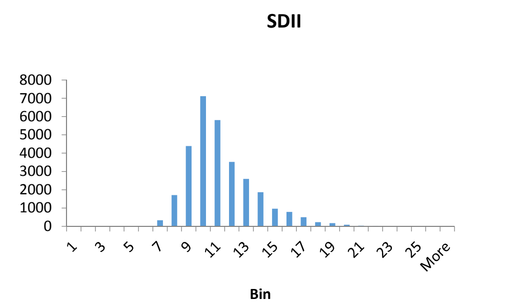

SDII
8000
7000
6000
5000
4000
3000
2000
1000
0
1 3 5 7 9 11 13 15 17 19 21 23 25 More
Bin

2007

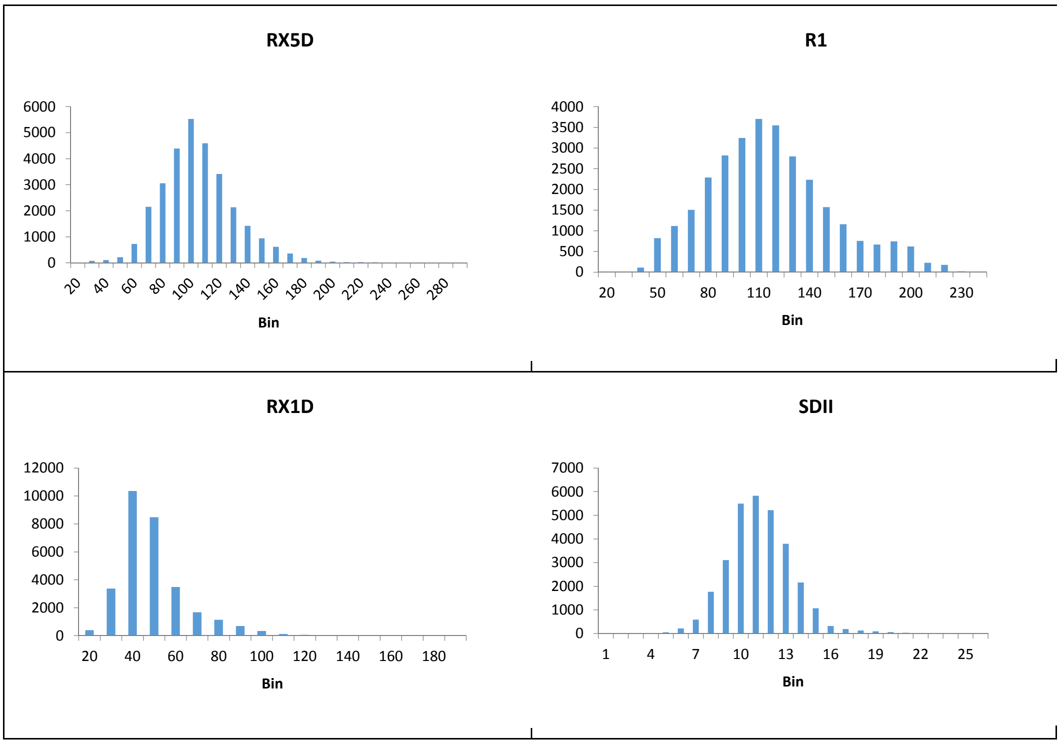

RX5D
6000
5000
4000
3000
2000
1000
0
20 50 80 110 140 170 200 230 260 290 320 350 380 410
Bin


R1
4000
3500
3000
2500
2000
1500
1000
500
0
20 50 80 110 140 170 200 230
Bin

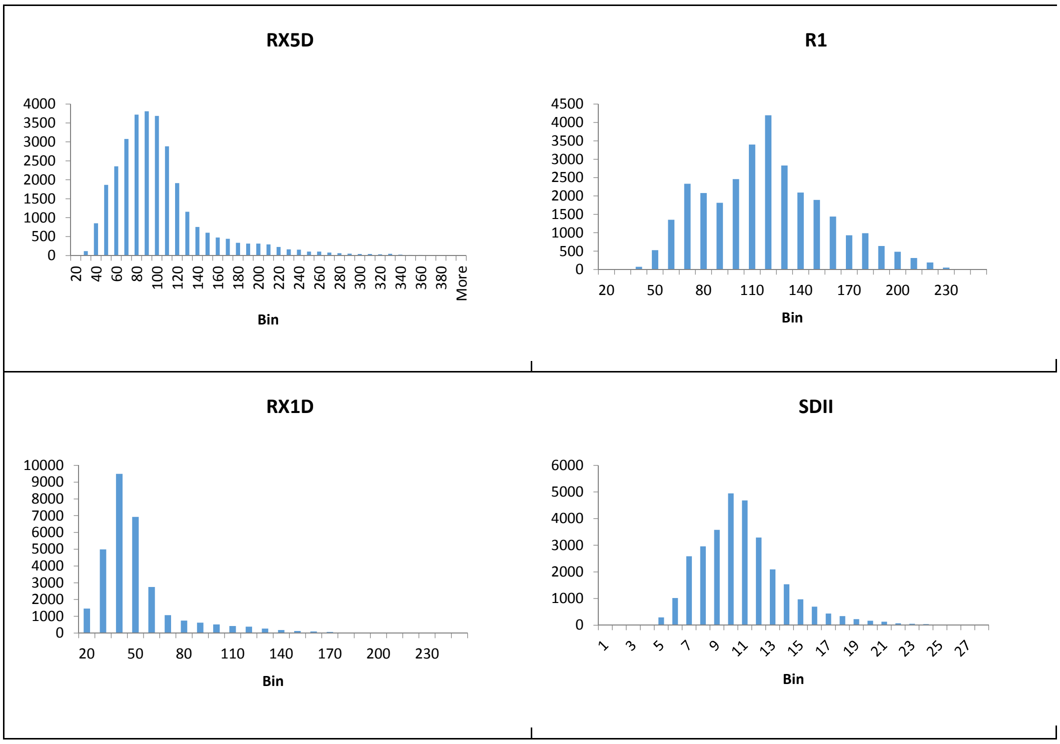

RX1D
12000
10000
8000
6000
4000
2000
0
20 50 80 110 140 170 200 230 More
Bin


SDII
8000
7000
6000
5000
4000
3000
2000
1000
0
1 3 5 7 9 11 13 15 17 19 21 23 25 More
Bin

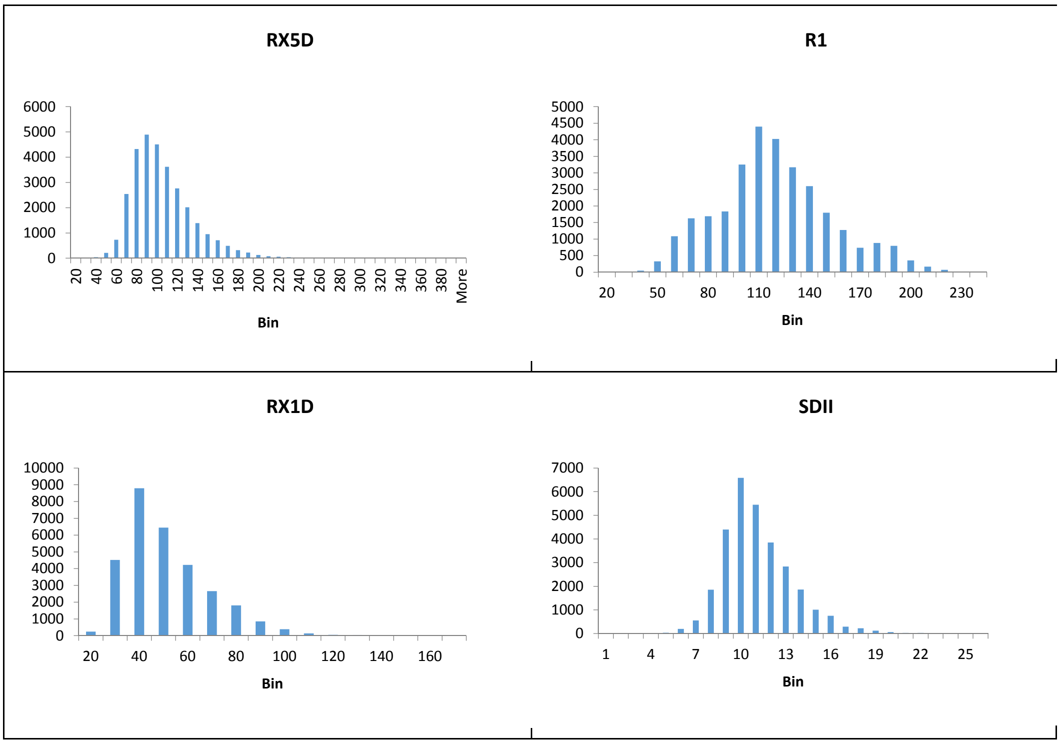
2008


RX5D
6000
5000
4000
3000
2000
1000
0
20 40 60 80 100 120 140 160 180 200 220 240 260 280
Bin
R1
4000
3500
3000
2500
2000
1500
1000
500
0
20 50 80 110 140 170 200 230
Bin
RX1D
12000
10000
8000
6000
4000
2000
0
20 40 60 80 100 120 140 160 180
Bin
SDII
7000
6000
5000
4000
3000
2000
1000
0
1 4 7 10 13 16 19 22 25
Bin

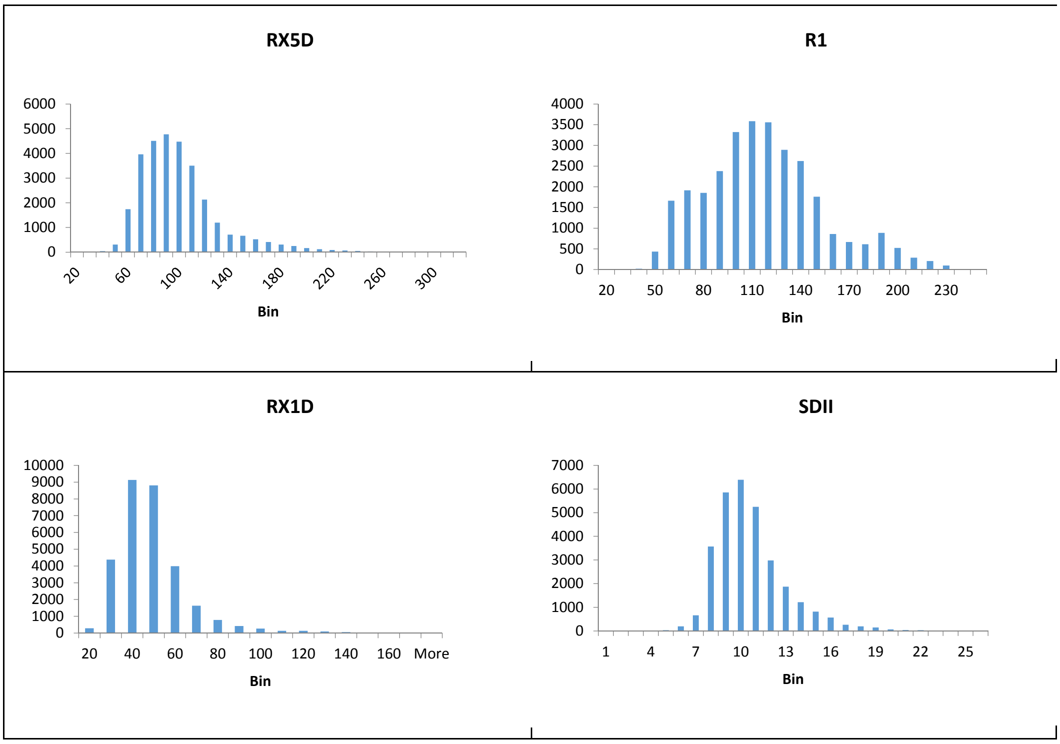
2009


RX5D
4000
3500
3000
2500
2000
1500
1000
500
0
20 40 60 80 100 120 140 160 180 200 220 240 260 280 300 320 340 360 380 More
Bin
R1
4500
4000
3500
3000
2500
2000
1500
1000
500
0
20 50 80 110 140 170 200 230
Bin
RX1D
10000
9000
8000
7000
6000
5000
4000
3000
2000
1000
0
20 50 80 110 140 170 200 230
Bin
SDII
6000
5000
4000
3000
2000
1000
0
1 3 5 7 9 11 13 15 17 19 21 23 25 27
Bin

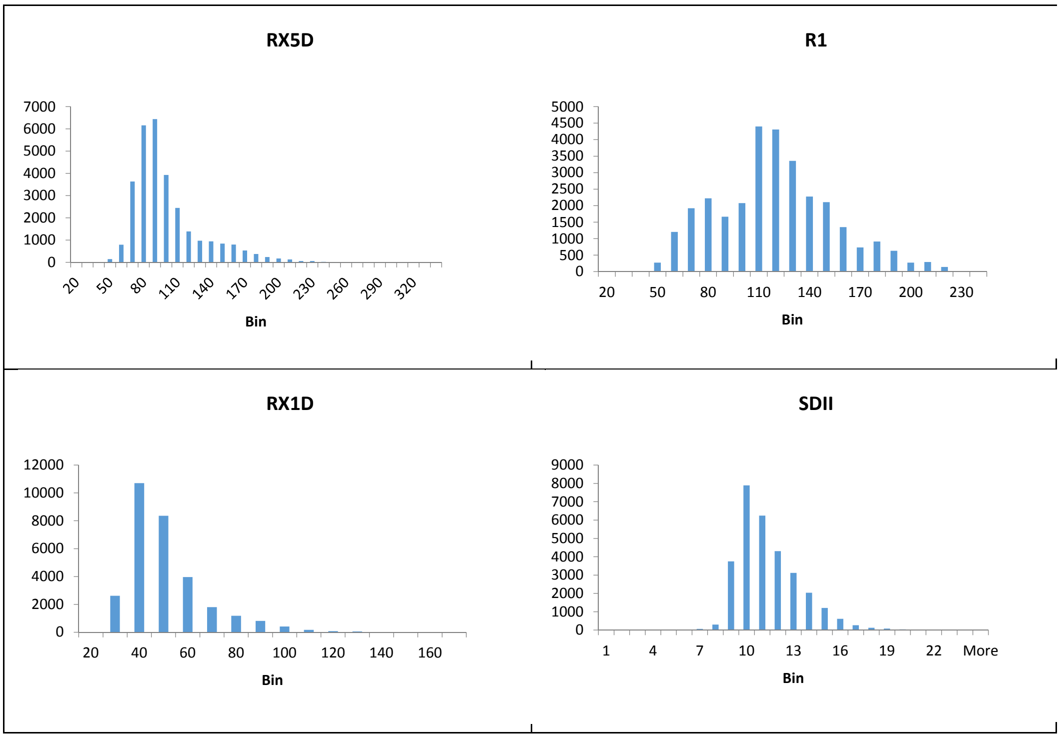
2010


RX5D
R1
RX1D
SDII
Bin
Bin
Bin
Bin

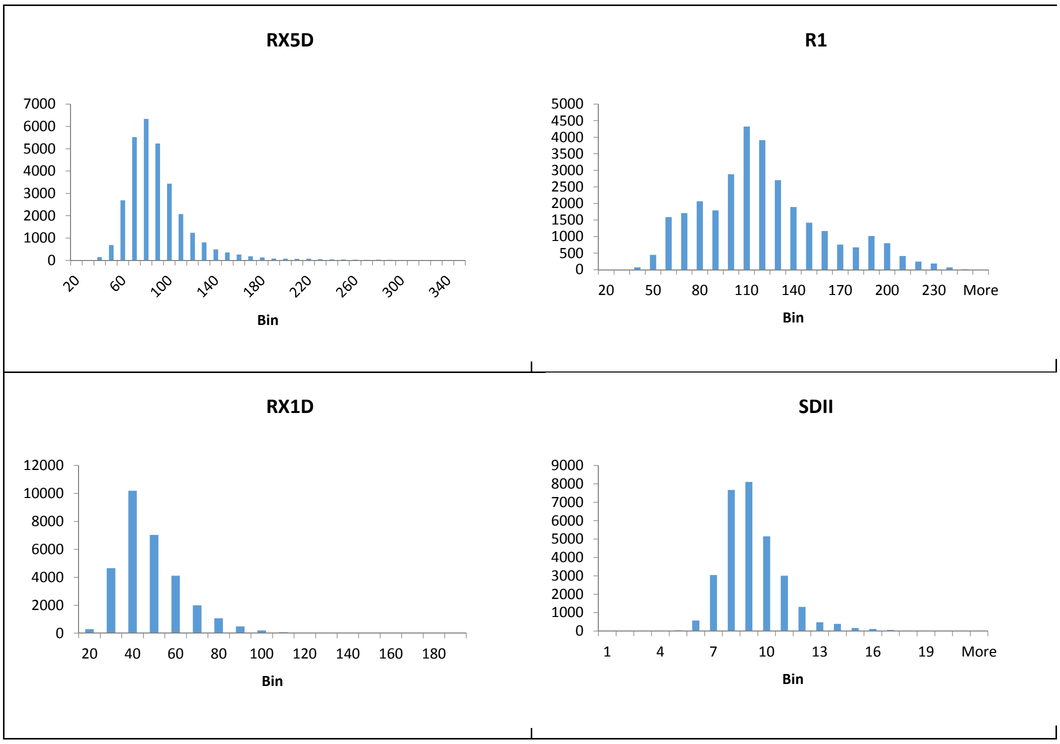
2011


RX5D
R1
RX1D
SDII
Bin
Bin
Bin
Bin

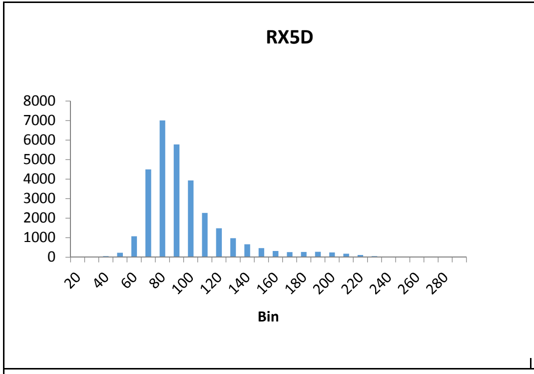
2012

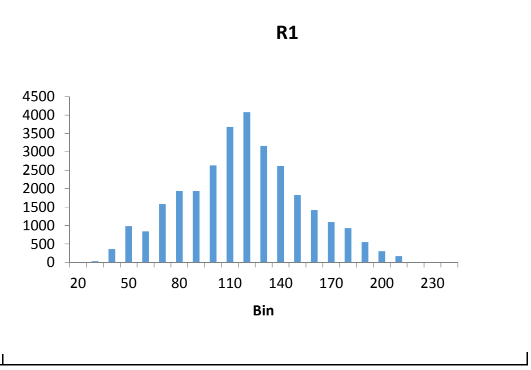

RX5D
7000
6000
5000
4000
3000
2000
1000
0
20 50 80 110 140 170 200 230 260 290 320
Bin
R1
5000
4500
4000
3500
3000
2500
2000
1500
1000
500
0
20 50 80 110 140 170 200 230
Bin
RX1D
12000
10000
8000
6000
4000
2000
0
20 40 60 80 100 120 140 160
Bin
SDII
9000
8000
7000
6000
5000
4000
3000
2000
1000
0
1 4 7 10 13 16 19 22 More
Bin

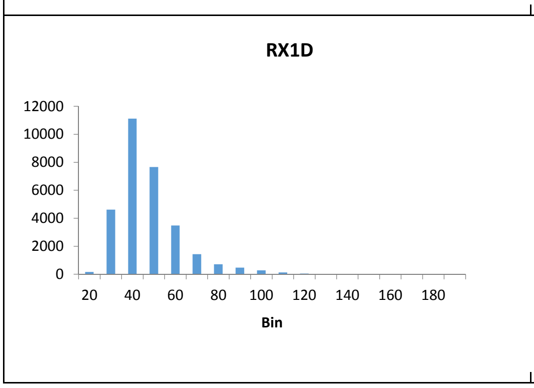
2013

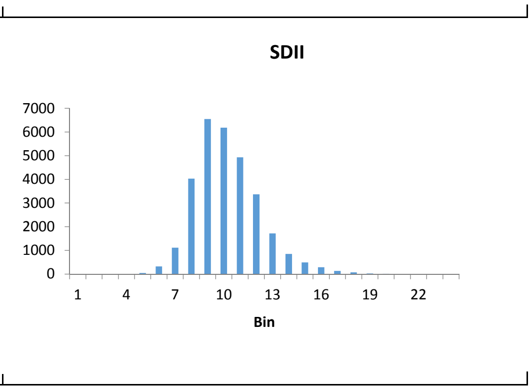

RX5D
7000
6000
5000
4000
3000
2000
1000
0
20 60 100 140 180 220 260 300 340
Bin
R1
5000
4500
4000
3500
3000
2500
2000
1500
1000
500
0
20 50 80 110 140 170 200 230 More
Bin
RX1D
12000
10000
8000
6000
4000
2000
0
20 40 60 80 100 120 140 160 180
Bin
SDII
9000
8000
7000
6000
5000
4000
3000
2000
1000
0
1 4 7 10 13 16 19 More
Bin

2014

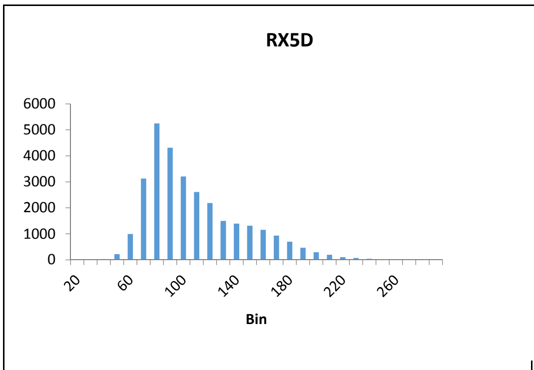

RX5D
8000
7000
6000
5000
4000
3000
2000
1000
0
20 40 60 80 100 120 140 160 180 200 220 240 260 280
Bin

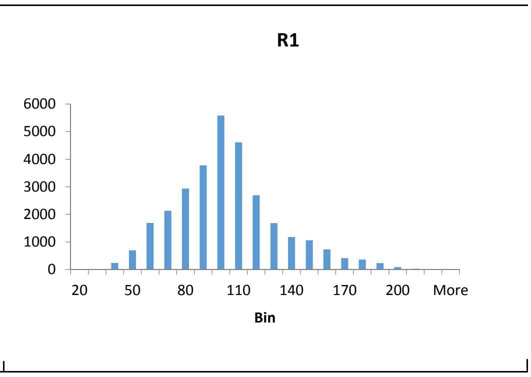

R1
4500
4000
3500
3000
2500
2000
1500
1000
500
0
20 50 80 110 140 170 200 230
Bin

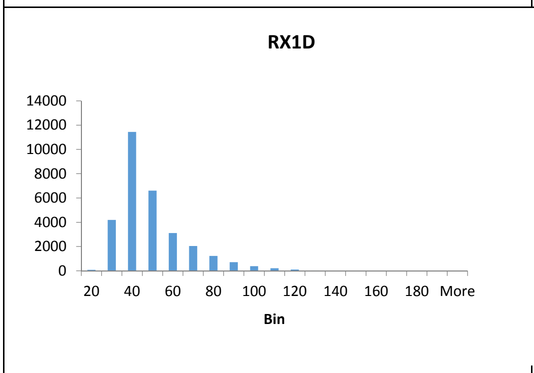

RX1D
12000
10000
8000
6000
4000
2000
0
20 40 60 80 100 120 140 160 180
Bin

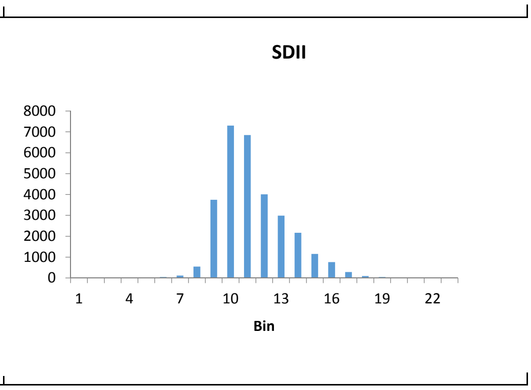

SDII
7000
6000
5000
4000
3000
2000
1000
0
1 4 7 10 13 16 19 22
Bin

2015


RX5D
6000
5000
4000
3000
2000
1000
0
20 60 100 140 180 220 260
Bin

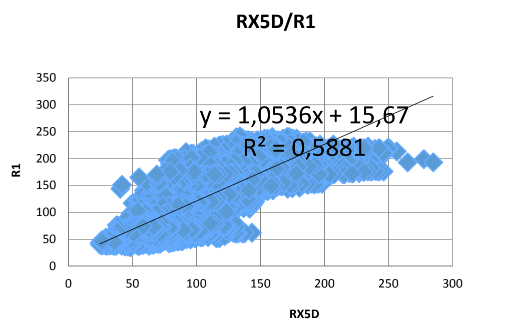

R1
6000
5000
4000
3000
2000
1000
0
20 50 80 110 140 170 200 More
Bin

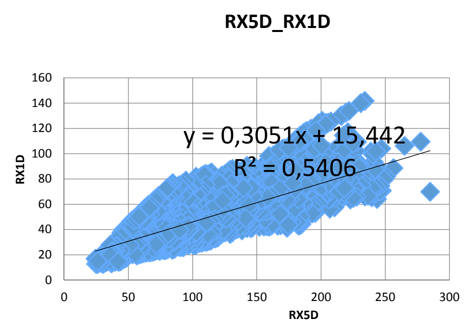

RX1D
14000
12000
10000
8000
6000
4000
2000
0
20 40 60 80 100 120 140 160 180 More
Bin

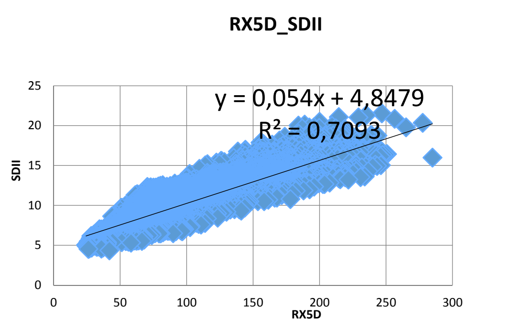

SDII
8000
7000
6000
5000
4000
3000
2000
1000
0
1 4 7 10 13 16 19 22
Bin

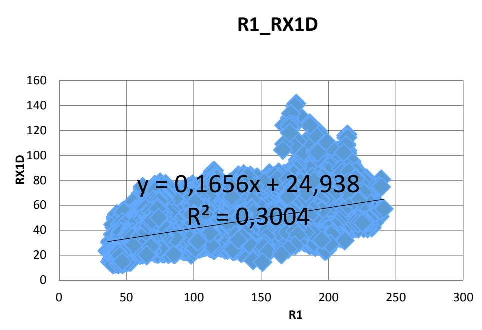
Scatterplots

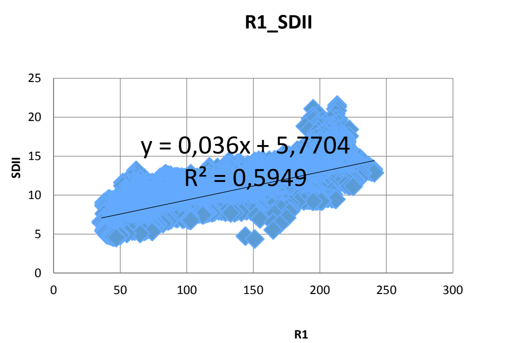
1985

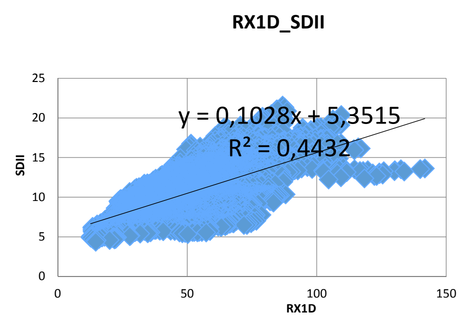




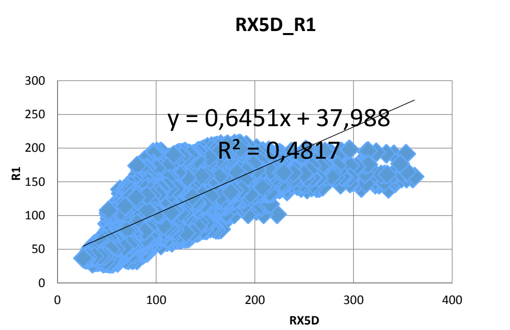


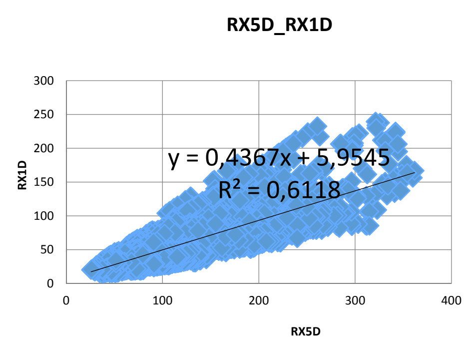


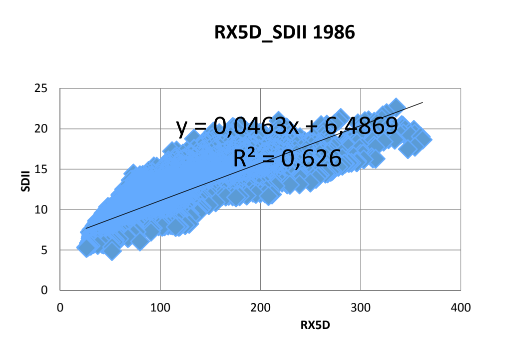


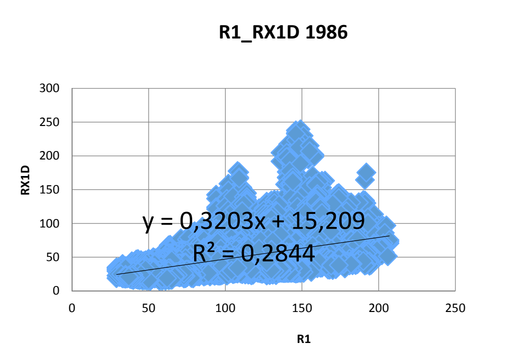


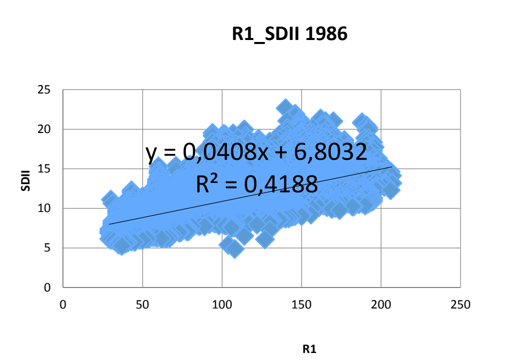
1986

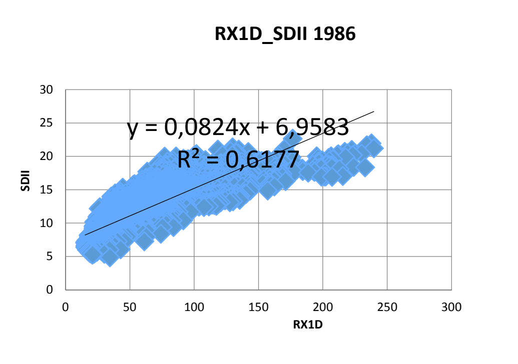




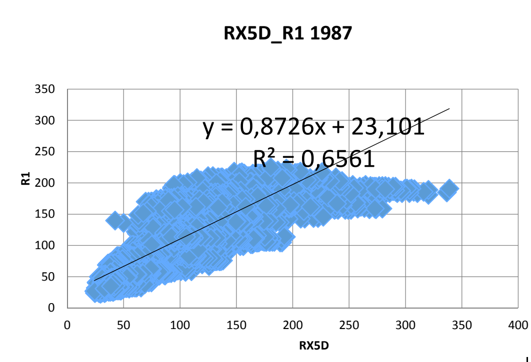

RX5D_SDII 1986
y = 0,0463x + 6,4869
R² = 0,626
SDII
RX5D

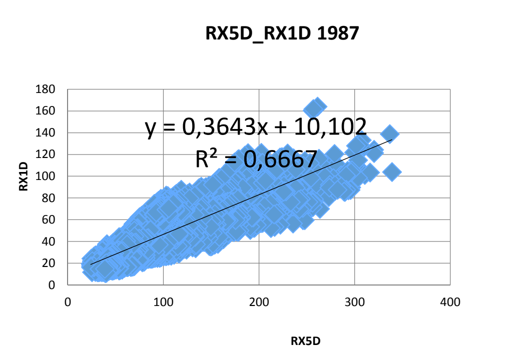

R1_RX1D 1986
y = 0,3203x + 15,209
R² = 0,2844
RX1D
R1

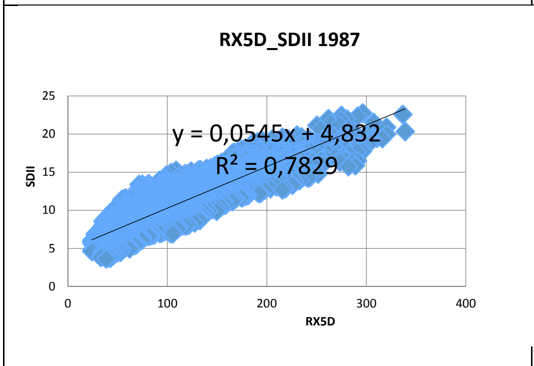

R1_SDII 1986
y = 0,0408x + 6,8032
R² = 0,4188
SDII
R1

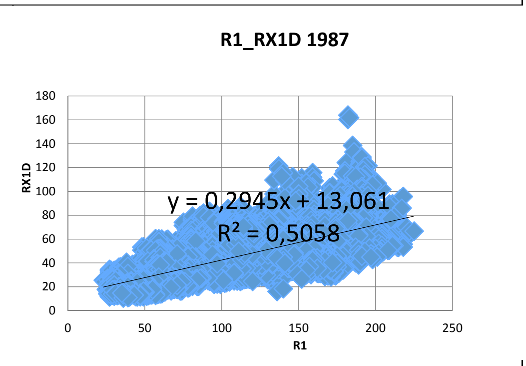

RX1D_SDII 1986
y = 0,0824x + 6,9583
R² = 0,6177
SDII
RX1D

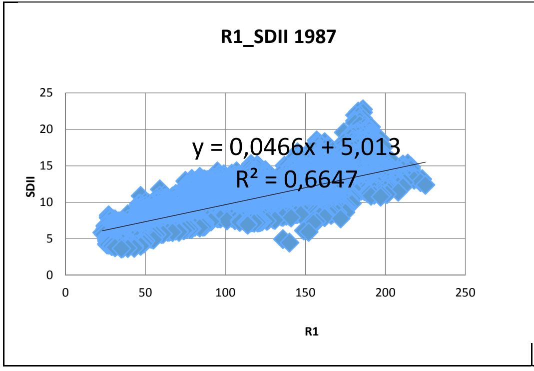
1987

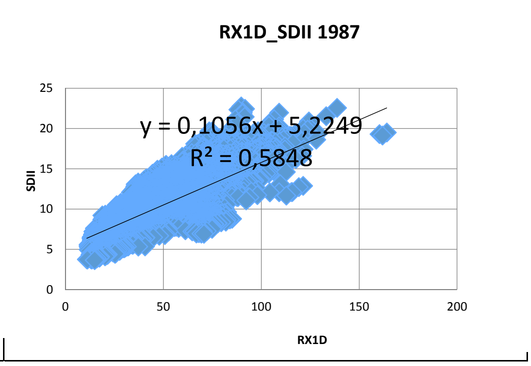

RX5D_R1 1987
y = 0,8726x + 23,101
R² = 0,6561
R1
RX5D


RX5D_RX1D 1987
y = 0,3643x + 10,102
R² = 0,6667
RX1D
RX5D

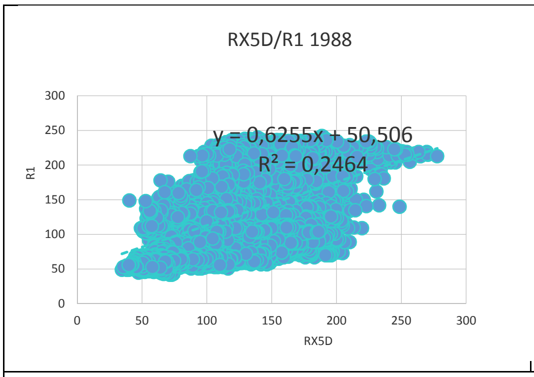

RX5D_SDII 1987
y = 0,0545x + 4,832
R² = 0,7829
SDII
RX5D

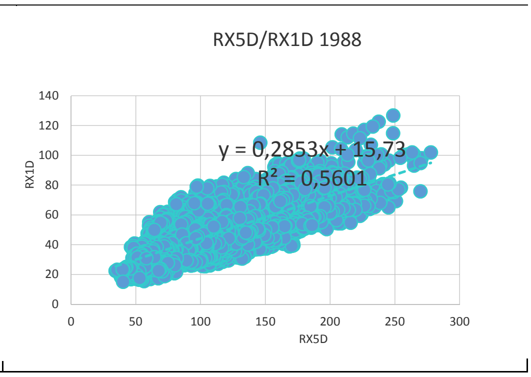

R1_RX1D 1987
y = 0,2945x + 13,061
R² = 0,5058
RX1D
R1

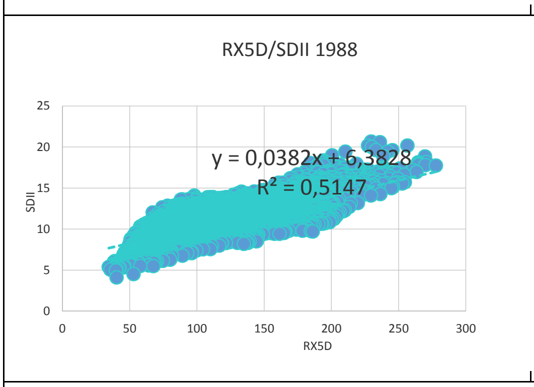

R1_SDII 1987
y = 0,0466x + 5,013
R² = 0,6647
SDII
R1

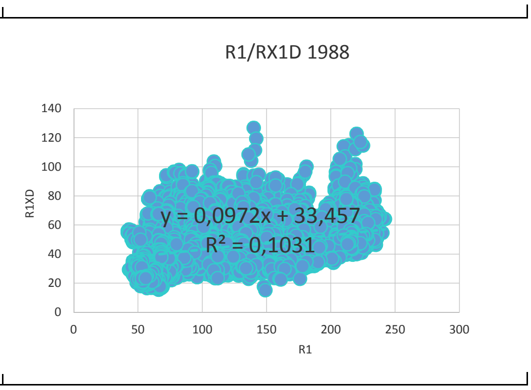

RX1D_SDII 1987
y = 0,1056x + 5,2249
R² = 0,5848
SDII
RX1D

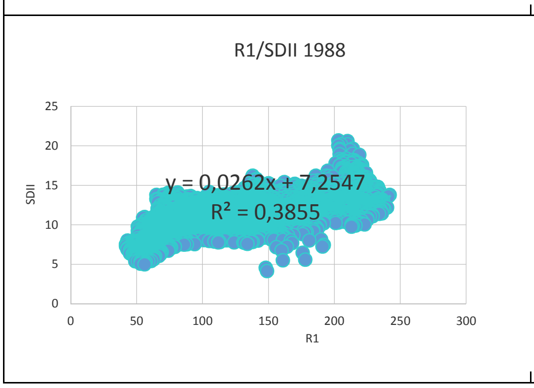
1988

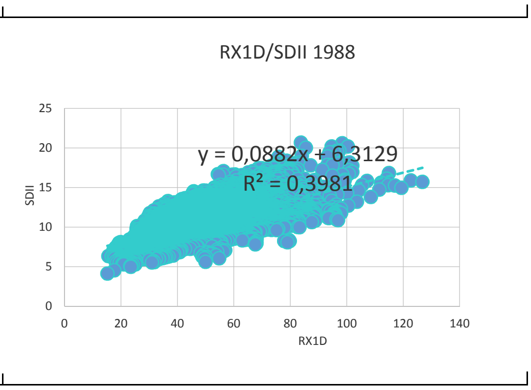

RX5D/R1 1988
y = 0,6255x + 50,506
R² = 0,2464
R1
RX5D


RX5D/RX1D 1988
y = 0,2853x + 15,73
R² = 0,5601
RX1D
RX5D

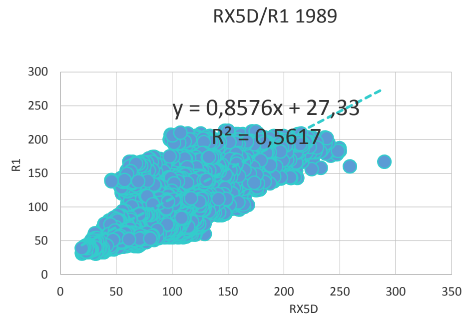

RX5D/SDII 1988
y = 0,0382x + 6,3828
R² = 0,5147
SDII
RX5D

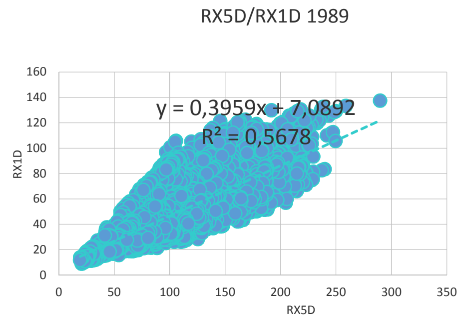

R1/RX1D 1988
y = 0,0972x + 33,457
R² = 0,1031
R1XD
R1

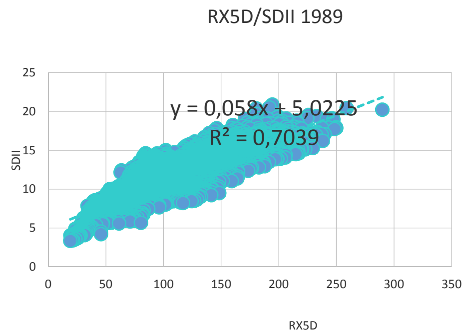

R1/SDII 1988
y = 0,0262x + 7,2547
R² = 0,3855
SDII
R1

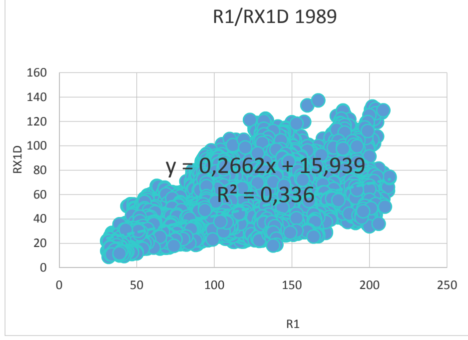

RX1D/SDII 1988
y = 0,0882x + 6,3129
R² = 0,3981
SDII
RX1D

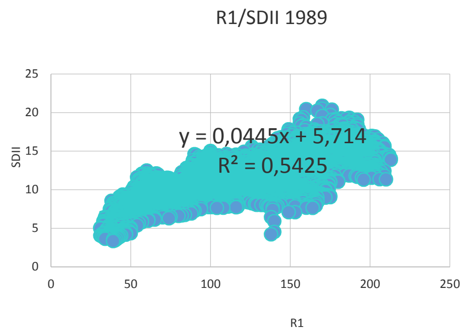
1989

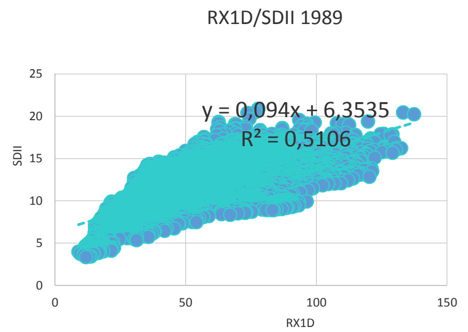

RX5D/R1 1989
y = 0,8576x + 27,33
R² = 0,5617
R1
RX5D


RX5D/RX1D 1989
y = 0,3959x + 7,0892
R² = 0,5678
RX1D
RX5D

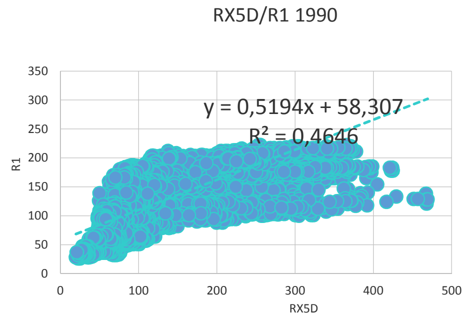

RX5D/SDII 1989
y = 0,058x + 5,0225
R² = 0,7039
SDII
RX5D

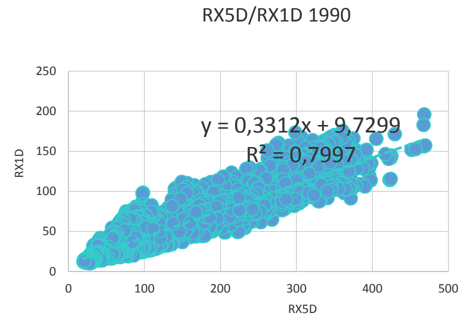

R1/RX1D 1989
y = 0,2662x + 15,939
R² = 0,336
RX1D
R1

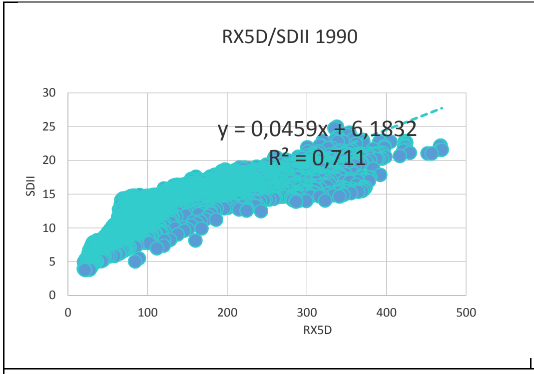

R1/SDII 1989
y = 0,0445x + 5,714
R² = 0,5425
SDII
R1

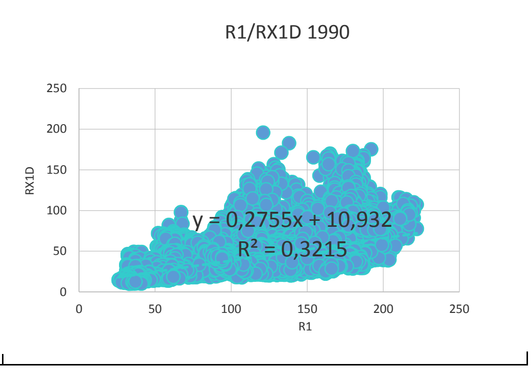

RX1D/SDII 1989
y = 0,094x + 6,3535
R² = 0,5106
SDII
RX1D

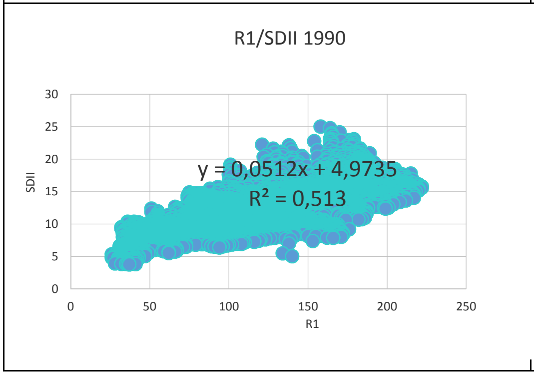
1990

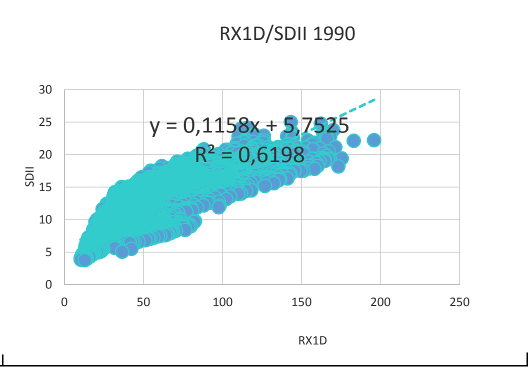

RX5D/R1 1990
y = 0,5194x + 58,307
R² = 0,4646
R1
RX5D


RX5D/RX1D 1990
y = 0,3312x + 9,7299
R² = 0,7997
RX1D
RX5D

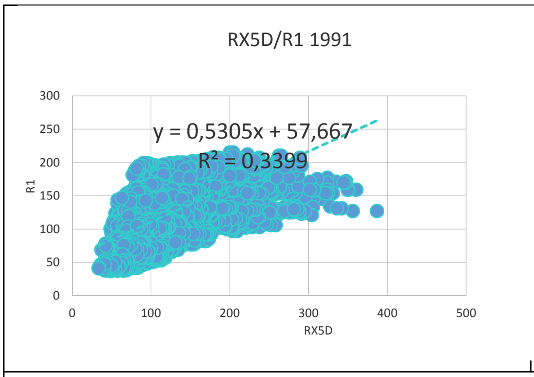

RX5D/SDII 1990
y = 0,0459x + 6,1832
R² = 0,711
SDII
RX5D

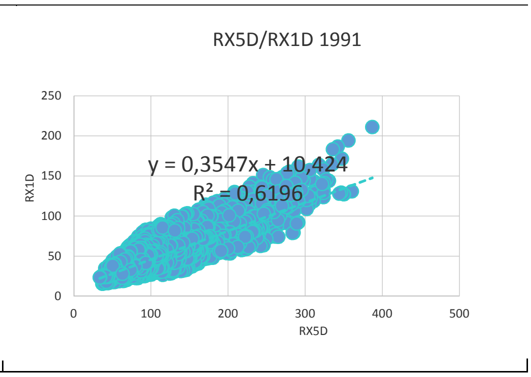

R1/RX1D 1990
y = 0,2755x + 10,932
R² = 0,3215
RX1D
R1

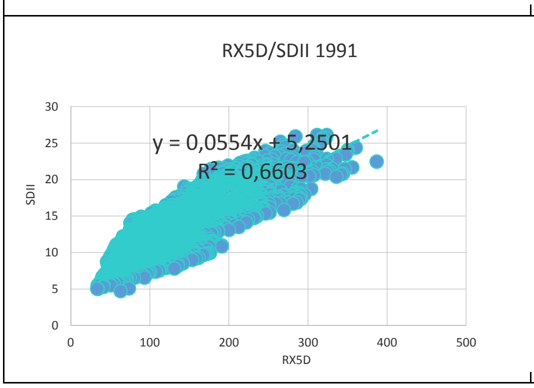

R1/SDII 1990
y = 0,0512x + 4,9735
R² = 0,513
SDII
R1


RX1D/SDII 1990
y = 0,1158x + 5,7525
R² = 0,6198
SDII
RX1D

1991


RX5D/R1 1991
y = 0,5305x + 57,667
R² = 0,3399
R1
RX5D


RX5D/RX1D 1991
y = 0,3547x + 10,424
R² = 0,6196
RX1D
RX5D


RX5D/SDII 1991
y = 0,0554x + 5,2501
R² = 0,6603
SDII
RX5D