Technical Annex: HARITA IRI Report to Oxfam America

Interim Report deliverable for GLO 002/10: General IRI Planning and Technical Support for Harita Micro-Insurance Pilot.

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Project PI: Daniel Osgood (deo@iri.columbia.edu) vspace0.5in
Contributors: Jiehua Chen, Tufa Dinku, Eric Holthaus, Bradfield Lyon, Malgosia Madajewicz, Connor Mullaly, Michael Norton, Daniel Osgood, Angelica Pascualini, Saurabh Pant, Nicole Peterson, Ricardo Saavedra, Jessica Sharoff, Kenneth E. Shirley, Christopher Small, Sarah Stiffel, Tse-Ling Teh

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Contents

List of Figures

List of Tables

1 Introduction

This is the technical annex to HARITA IRI Report to Oxfam America. It is the interim Report deliverable for GLO 002/10: General IRI Planning and Technical Support for Harita Micro-Insurance Pilot and contains background material useful for the main report.

1.1 Statistical modeling of rainfall

1.1.1 Introduction

To design a rainfall-based index insurance contract to protect farmers against drought-related crop losses, it is important to understand the properties of the daily rainfall process in the region that will be covered by the contract. In this section we provide preliminary results from a new model model daily rainfall we are working on. This model extends our previous efforts as a first step towards comparing and integrating information from multiple rainfall data sources. The end goal is to arrive at a formal statistical methodology that will systematically compare and integrate information on remote sensing of rainfall, ground-based data measurements, and other data sets. The goal is to allow data sets to provide information on the existence of potential droughts that were observed in multiple data sets, including those that extend further back in time. In addition, the modeling is intended to allow the level of agreement between data sources to be quantified, which will be important when determining when an index can be transferred from one data source to another. The analysis presented in this section is at a midpoint in this process, and if resources continue to be obtained, we intend to further develop these methods and then package them into tools for contract design and evaluation.

The analysis focuses on Adi Ha, modeling rainfall at five neighboring sites, where daily rainfall amounts have been recorded during different intervals for each site over the course of a 49-year time period from 1961 - 2009. We account for the correlation between the rainfall processes at each site using a hierarchical Bayes structure. We don't, however, explicitly model the spatial correlation as a function of the distance between sites - we simply fit a multilevel model where certain sets of site-specific parameters are drawn from a common distribution. Our main goal is to predict future rainfall at the automated rainfall station at Adi Ha, which is the site that has the least amount of observed data – only 200 days worth of data from 2009. As the analysis continues, we intend to apply these tools to the other sites. In addition, we are working to formally build spatial processes into this analysis.

1.2 The Data

The geographic locations of the five rainfall sites are shown on the map in Figure 1. Figure 1 actually only shows three labeled locations – Adi Ha, Abi Adi, and Hagere Salaam – because the Adi Ha location contains three different rainfall "sites": (1) a remote sensing daily rainfall measurement, (2) a manual rain gauge, and (3) an automatic rain gauge. The differences in daily observed rainfall from these three Adi Ha sites are attributed to the method of rainfall measurement rather than a difference in location. From this point on we will refer to the five separate observed time series as "sites", and we will call them by their names given in Table 1, knowing that three of them consist of measurements from a common location, Adi Ha.

Figure 1: The three unique locations of the five rainfall sites. Adi Ha is the location of three separate sites.

Table 1 contains some background information and summary statistics related to the five sites at which we model daily rainfall.

Figure 2 displays the range of days during the time period from 1961 to 2009 during which daily rainfall observations were made at each of the five sites. The rainfall station at Hagere Salaam is the most complete record, and the automatic rain gauge at Adi Ha is the least complete record. The rainfall station at Abi Adi began collecting data the earliest, in July of 1961, but did not collect any data during the years 1963-1972.

Table 1: Background information about the five sites

	Site	Latitude	Longitude	Elev. (ft.)	Num. Obs
1	Hagere Salaam	13° 38' 25"	39° 10' 13"	8296	8575
2	Abi Adi	13° 33' 20"	38° 58' 27"	5475	7049
3	Adi Ha (Remote Sensing)	13° 43' 47"	39° 05' 59"	5672	5059
4	Adi Ha (Manual)	13° 43' 47"	39° 05' 59"	5672	2769
5	Adi Ha (Automatic)	13° 43' 47"	39° 05' 59"	5672	186

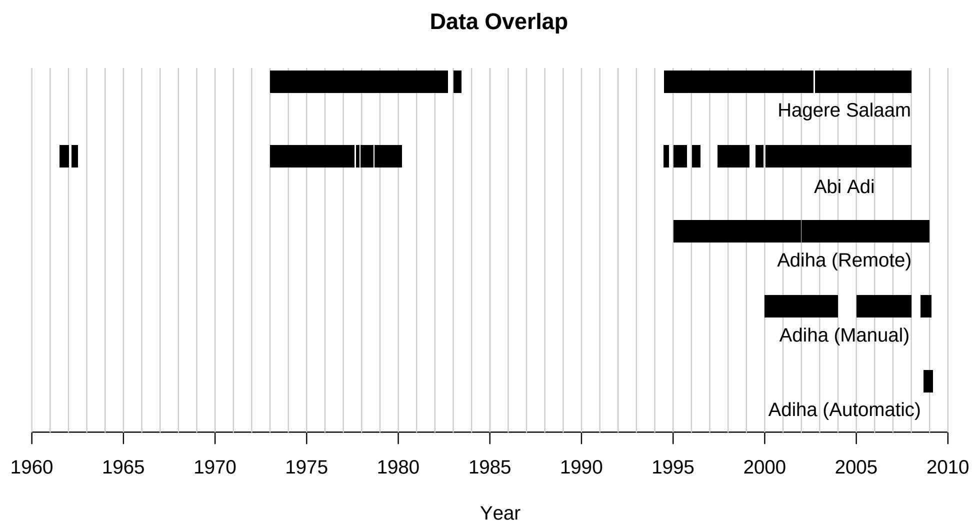


Figure 2: The shaded regions for each of the five sites indicate time spans during which daily rainfall observations were recorded (whether there was rainfall on that day or not); everything else is missing data.

1.3 The Model

The daily rainfall model can be decomposed into two parts: (1) a model for the occurrence of rainfall, which we call the "frequency model", and (2) a model for the amount of rainfall, which we call the "intensity model". Let Y_{it} be the amount of rainfall observed at site i on day t, for sites $i = 1, ..., 5$ as listed in Table 1, and days $t = 1, ..., T$, where day 1 is July 8th, 1961, and day $T = 17,393$ is March 2nd, 2009. (This is the span of days in which there was an observation for at least one of the five sites). Next, let $X_{it} = 1\{Y_{it} > 0\}$, the indicator of whether there was nonzero rainfall at site i on day t. The model consists of a Markov model for $\{X_{it}\}$, and a gamma distribution for the nonzero values of $\{Y_{it}\}$.

1.3.1 The Frequency Model

The "frequency model" is our model for whether it rains at a given site on a given day, denoted by the indicator random variable X_{it}. It is a first order Markov model where the transition probabilities between wet and dry days are modeled using a generalized linear model with a logistic link and a sum of periodic components with varying frequencies:

$$p(X_{it} = 1 \mid X_{(i,t-1)} = j) = p_{itj}, \tag{1}$$

$$\text{logit}(p_{itj}) = \beta_{0ij} + \sum_{m=1}^{M_j} \Big(\beta_{1mij} \cos(2\pi tm/365) + \beta_{2mij} \sin(2\pi tm/365) \Big), \tag{2}$$

for sites $i = 1, .., 5$, days $t = 2, ..., T$, and the indicators of a wet day indexed by $j = 0, 1$. Previous research has shown that setting the number of periodic components (denoted M_0 for transitions from dry days and M_1 for transitions from wet days) somewhere between 2 and 5 provides a good fit for rainfall series in certain parts of the world (Stern and Coe, 1984); we will try different values for M_0 and M_1 bearing this in mind. Note that Equation 2 only allows for frequencies less than or equal to one year in length, ruling out the possibility of modeling El Nino, which is a periodic trend with a multiyear period. Later in the paper we will modify the equation to allow for longer frequencies and test whether they improve the model.

Next, the intercept and sine and cosine coefficients for each of the 5 sites are modeled as coming from a common distribution, such that:

$$\beta_{0ij} \sim \text{N}(\mu_{0j}^{(\beta)}, \sigma_{0j}^2), \tag{3}$$

$$\beta_{pmij} \sim \text{N}(\mu_{pmj}^{(\beta)}, \sigma_{pmj}^2), \tag{4}$$

for sites $i = 1, .., 5$, indicators of a wet day $j = 0, 1$, frequencies $m = 1, ..., M_j$, and periodic components $p = 1, 2$. Fitting this model will "shrink" the estimates for each site toward the global mean, but only to the extent that the data supports. This is especially useful when some rainfall sites have very little observed data, so that instead of estimating model parameters with the MLE, which is highly variable with small sample sizes, the estimates for these sites will be shrunk toward the grand mean across all sites, which tends to give better out-of-sample predictions.

1.3.2 The Intensity Model

The intensity model is our model for the amount of rainfall that occurs on wet days. In other words, it is the model for $p(Y_{it} \mid X_{it} = 1)$.

$$p(Y_{it} \mid X_{it} = 1) \sim \text{Gamma}(\alpha_i, \beta_{it}), \tag{5}$$

where α_i and β_{it} (both of which are positive) are the shape and rate parameters of the gamma distribution, respectively, such that $\mathrm{E}(Y_{it} \mid X_{it} = 1) = \alpha_i/\beta_{it}$. Define this mean as $\mu_{it} = \alpha_i/\beta_{it}$. Note that we model the shape of the gamma distribution for each site as being constant through time (i.e. there is no t subscript on α_i). Next, we use a generalized linear model with a log link for the mean of the gamma distribution:

$$\log(\mu_{it}) = \eta_{0i} + \sum_{m=1}^{M_2} \Big(\eta_{1mi} \cos(2\pi tm/365) + \eta_{2mi} \sin(2\pi tm/365) \Big), \tag{6}$$

for sites $i = 1, ..., 5$, and days $t = 1, ..., T$.

The hierarchical model for the site-specific parameters in the intensity model are as follows:

$$\log(\alpha_i) \sim \mathrm{N}(\mu_\alpha, \tau_\alpha^2), \tag{7}$$

for sites $i = 1, ..., 5$, and

$$\eta_{0i} \sim \mathrm{N}(\mu_0^{(\eta)}, \tau_0^2), \tag{8}$$

$$\eta_{pmi} \sim \mathrm{N}(\mu_{pm}^{(\eta)}, \tau_{pm}^2), \tag{9}$$

for sites $i = 1, ..., 5$, periodic components $p = 1, 2$, and frequencies $m = 1, ..., M_2$.

1.4 The MCMC Algorithm

To fit the model we use a Bayesian approach and use an MCMC algorithm to sample the parameters of interest from their posterior distributions. First, we must define the rest of the necessary prior distributions. For the parameters in Equations 3 and 4, we use the priors

$$\mu_{0j}^{(\beta)} \sim \mathrm{N}(0, 10^2), \tag{10}$$

$$p(\sigma_{0j}) \propto 1, \tag{11}$$

$$\mu_{pmj}^{(\beta)} \sim \mathrm{N}(0, 10^2), \tag{12}$$

$$p(\sigma_{pmj}) \propto 1, \tag{13}$$

for periodic components $p = 1, 2$, frequencies $m = 1, ..., M_j$, and indicators of a wet day $j = 0, 1$.

For the parameters in Equations 7, 8, and 9, we use the priors

$$\mu_\alpha \sim \mathrm{N}(0, 10^2), \tag{14}$$

$$p(\tau_\alpha) \propto 1, \tag{15}$$

$$\mu_0^{(\eta)} \sim \mathrm{N}(0, 10^2), \tag{16}$$

$$p(\tau_0) \propto 1, \tag{17}$$

$$\mu_{pm}^{(\eta)} \sim \mathrm{N}(0, 10^2), \tag{18}$$

$$p(\tau_{pm}) \propto 1, \tag{19}$$

for periodic components $p = 1, 2$ and frequencies $m = 1, ..., M_j$.

We fit the model using the program JAGS ("Just Another Gibbs Sampler"), which implements a Gibbs sampling algorithm that samples from the posterior distribution using either (1) a random draw from the full conditional distribution of a parameter, when the prior and likelihood form a conjugate pair, or (2) slice sampling, when the full conditional distribution of a parameter is not available in closed form.

We ran 3 chains using random starting points for 2,000 iterations, and found that if we set $M_1 = M_2 = M_3 = 4$, and if we discard the first 2000 iterations as burn-in and use iterations 2001 - 4000 as the posterior sample, then all the parameters in the model (there are 196 of them) converge to their stationary distribution, according to the Gelman-Rubin convergence diagnostic, as well as by visual inspection of the trace plots.

1.5 Results

We display the results in a series of three sets of plots to assess the fit of the model. In each set of plots, there are 5 individual plots, one for each site, in which we display the fitted model along with the data. In the first set of plots, in Figure 3, we show the probability of a wet day as a function of the day of the year, given that the previous day was dry. In other words, we display $P(X_{it} = 1 | X_{(i,t-1)} = 0)$ for each of the five sites.

These plots show a few interesting features:

1. During the rainy season, the probability of a wet day following a dry day is reaches a maximum of about 60%, where this probability is slightly higher in Hagere Salaam and Abi Adi, and slightly lower for the Adi Ha manual rain gauge.
2. The multiple periodic components (recall $M_0 = 4$ here) pick up the early rainy season from March through May.
3. The Adi Ha remote rain gauge appears to indicate a slightly later start to the rainy season than the other sites. This is consistent with our information on the Adi Ha microclimate.

Figure 4 is the same type of plot as Figure 3, except that it shows the model fit for the probability of a wet day when the previous day is also wet. In this figure, we see a few more things:

1. As with transitions from dry days, it appears that the probability of a wet day is higher than average in Hagere Salaam and lower than average for the Adi Ha manual rain gauge.

2. There are "bumps" in the probability of a wet day in February and November, where for these months the probability of a wet day is about 10 percent higher than in December and January. These might just be artifacts of the sample, rather than actual rainfall patterns that will repeat themselves in future years.

Next, we display the equivalent plot for the mean rainfall on wet days in Figure 5. Some things to note here:

1. The average rainfall on a wet day ranges from about 5 inches to 12 inches, depending on the time of year.

2. Abi Adi and the Adi Ha manual rain gauge experienced heavier rainfall on wet days than the average, and the Adi Ha remote sensed rainfall received lower than average rainfall on wet days.

Last, the shape parameters for the 5 sites are centered around a mean of about 1.0, with a group sd of about 0.4. Fig 6 shows the trace plots of the shape parameters for each site. The exponential distribution is a gamma distribution with the shape parameter fixed at one.

1.6 Posterior Predictive Checks

To check the fit of the model, we performed a series of posterior predictive checks. A posterior predictive check involves simulating new data from the fitted model, by sampling

$$Y_{\text{new}} \sim p(Y_{\text{new}} \mid Y) = \int p(Y_{\text{new}} \mid \theta) p(\theta \mid Y)$$

some large number of times, such as 500 times, to form a posterior predictive sample $(Y_{\text{new}}^{(1)}, Y_{\text{new}}^{(2)}, ..., Y_{\text{new}}^{(500)})$, where each value of Y_{new} is essentially a simulated version of the entire data set, Y. We then choose a summary statistic of interest, $f(Y)$ (such as the correlation between August total rainfall and September total rainfall, for example), and compare the observed value of $f(Y)$ to the posterior predictive (simulated) values of that statistic, $(f(Y_{\text{new}}^{(1)}), f(Y_{\text{new}}^{(2)}), ..., f(Y_{\text{new}}^{(500)}))$. If the observed value is far away from the simulated values, then the model does not fit well with respect to that particular summary statistic, and should be modified to fit better.

We simulated 500 replications of new data from its posterior predictive distribution, and performed posterior predictive checks for 9 different statistics pertaining to each site and month. The 9 statistics we checked were:

1. The mean number of wet days per month
2. The standard deviation of wet days per month
3. The mean amount of rainfall on wet days
4. The standard deviation of rainfall on wet days
5. The mean total amount of rainfall per month
6. The standard deviation of total rainfall per month
7. The median total amount of rainfall per month
8. The interquartile range of the total amount of rainfall per month
9. The maximum total amount of rainfall per month

We compared the observed values of these statistics for each site and month to the set of 500 simulated values from the posterior predictive distribution of the statistic.

Before we describe the conclusions we draw from these posterior predictive checks, we should describe the procedure for performing them in further detail. First we looked at July rainfall in Abi Adi.; of the 49 years (1961-2009) of Abi Adi daily rainfall in our data set, only 23 of them contained full observations for July (that is, non-missing values for all 31 days of the month). From these 23 years, we computed 9 different summary statistics, such as the mean number of wet days per month. That is, we computed the number of wet days in July of each of the 23 years, and computed their mean (which was about 21). Then, we simulated 23 years of July daily rainfall from Abi Adi 500 separate times, using the posterior samples from the MCMC output. These simulations incorporate not only the noise of the process, but also the extra variability associated with the uncertainty about the parameters in the model. For each of the 500 replications (we use "replications" synonymously with "simulations"), we computed the same 9 summary statistics to estimate each of their respective posterior predictive distributions.

From these posterior predictive checks, we see a few things.

- In the data, there were an average of about 21 wet days per July (31 days total), and the model fits well with respect to this statistic. The model doesn't, however, correctly model the variability of the number of wet days per July - it underestimates the variability. Using a higher-order Markov model for the occurrence of rainfall might fix this lack of fit.
- The model correctly captures the mean intensity of rainfall on wet days in July (about 14.5 mm), but once again underestimates the variability of this statistic (the model simulates wet days with an sd of about 9.5 mm, whereas the observed sd was over 12

mm). To fix this, we might need to condition the intensity model on the occurrence of rain in the past, where a wet day preceded by a wet day would likely have more intense rainfall than one preceded by a dry day. Another idea is to use a mixed exponential distribution to model amounts, rather than a gamma distribution, a la Wilks (1999).

- In agreement with the first two posterior predictive checks, the total sum of rainfall in July is well-modeled with respect to its mean, but not in terms of its variability.

- We checked if more robust measures of the total monthly rainfall were better reproduced by the model. The results were mixed. The median and IQR were used as robust measures of center and spread, and the simulated values were generally closer to the observed values (for all sites and months, not just Abi Adi in July). That being said, the model still underestimated the IQR more often than not. Considered in isolation, these posterior predictive checks might not necessarily lead to the conclusion that the model fits poorly, but combined with the knowledge that the dependence structure in both the frequency and the intensity models are very simple, we conclude that the model should be improved to account for this lack of fit (underestimating year-to-year variability). This is a common failing of most rainfall models that we have been able to overcome in our less sophisticated models. Clearly we will need to see if our previous solutions to this problem will be effective in this more sophisticated analysis.

- The maximum monthly sum was also underestimated by the model. It is not clear whether this is important for index insurance purposes, since for index insurance, daily rainfall is usually capped at, say, 60 mm, to account for the fact that rainfall in excess of that threshold usually runs off and doesn't contribute to crop growth.

For next steps in this analysis, we intend to pursue solutions so that the model will better reflect variability, using solutions that have proven successful in previous rainfall models we have worked on as well as additional, new solutions. We will also more explicitly model the relationship between data sets on a daily timescale.

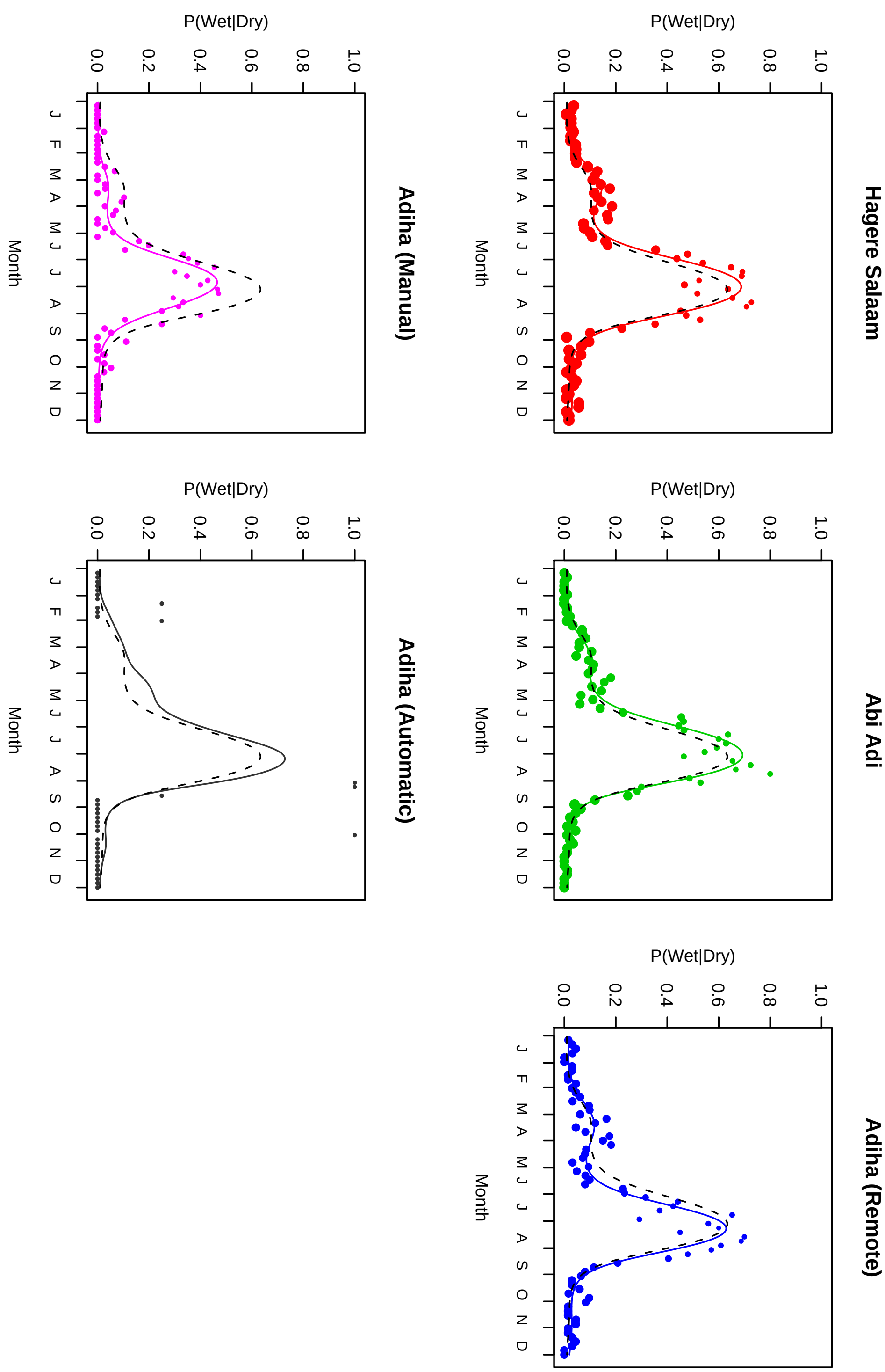


Figure 3: The estimated probability of a wet day given that the previous day was a dry day for all five sites, where the dashed line is the group mean, and the points are the observed percentages binned into 5-day bins, pooled across years, proportional to the sample size.

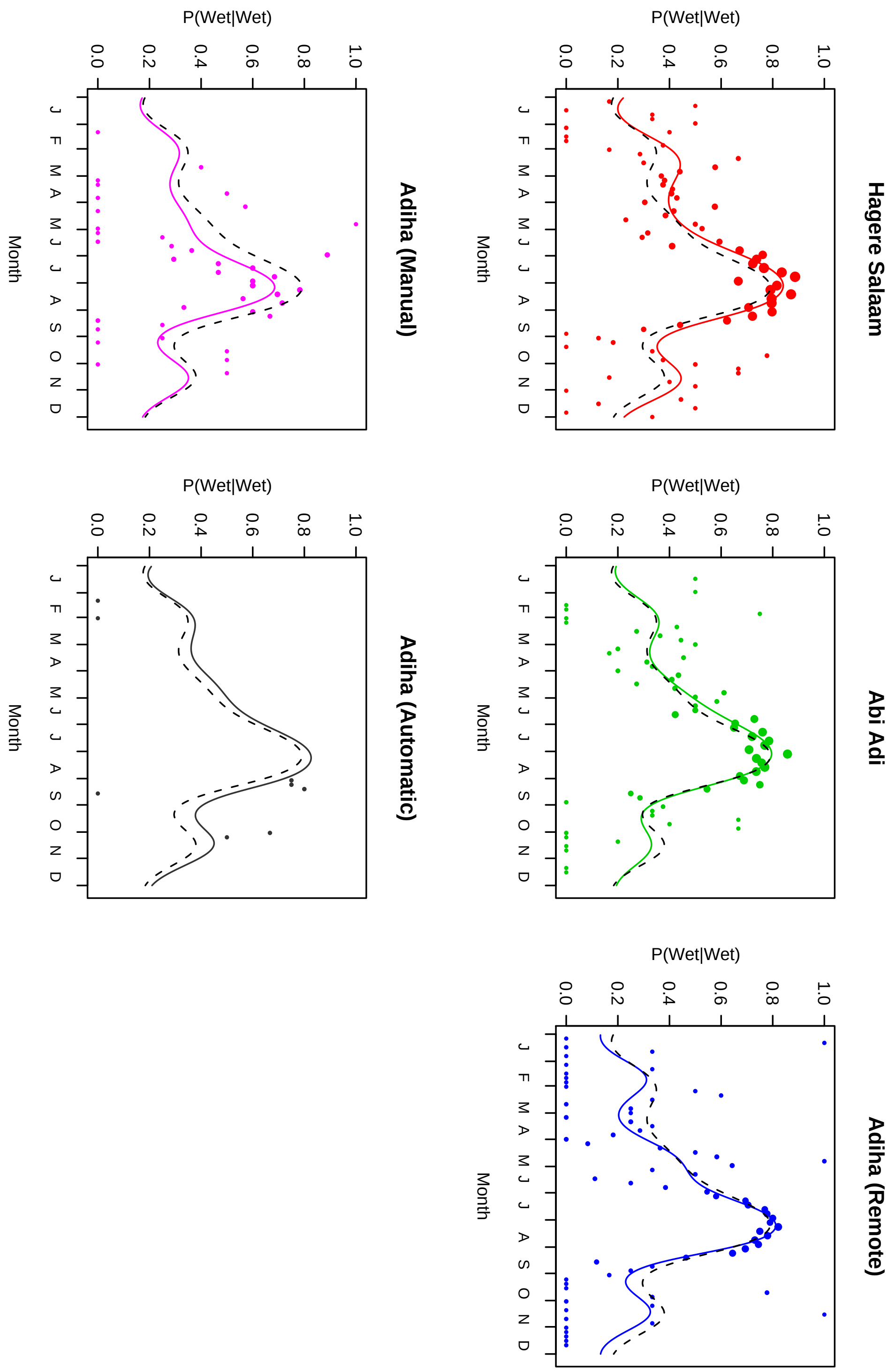


Figure 4: The estimated probability of a wet day given that the previous day was a wet day for all five sites, similar to Figure 3.

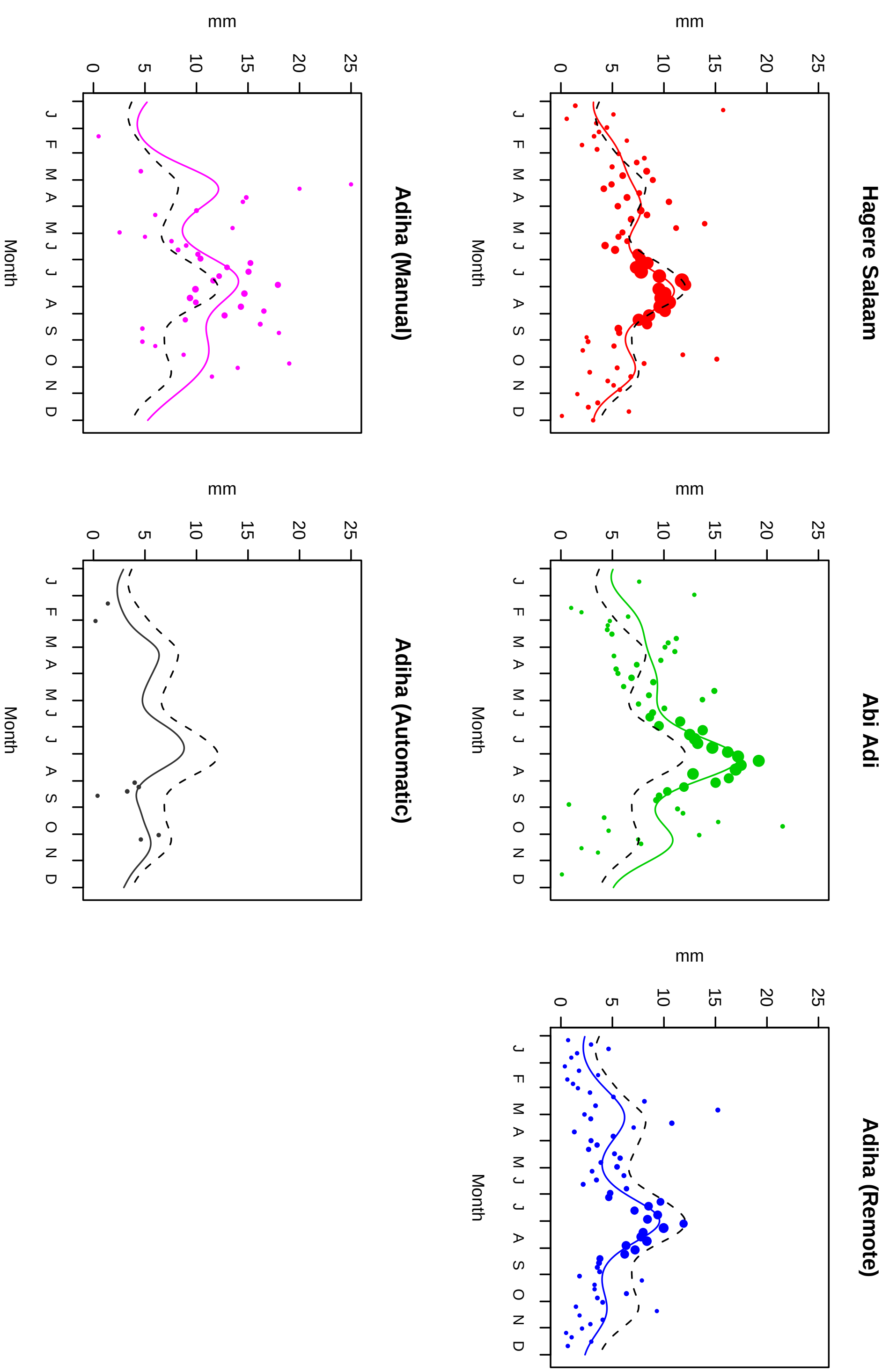


Figure 5: The estimated mean rainfall on wet days for all five sites.

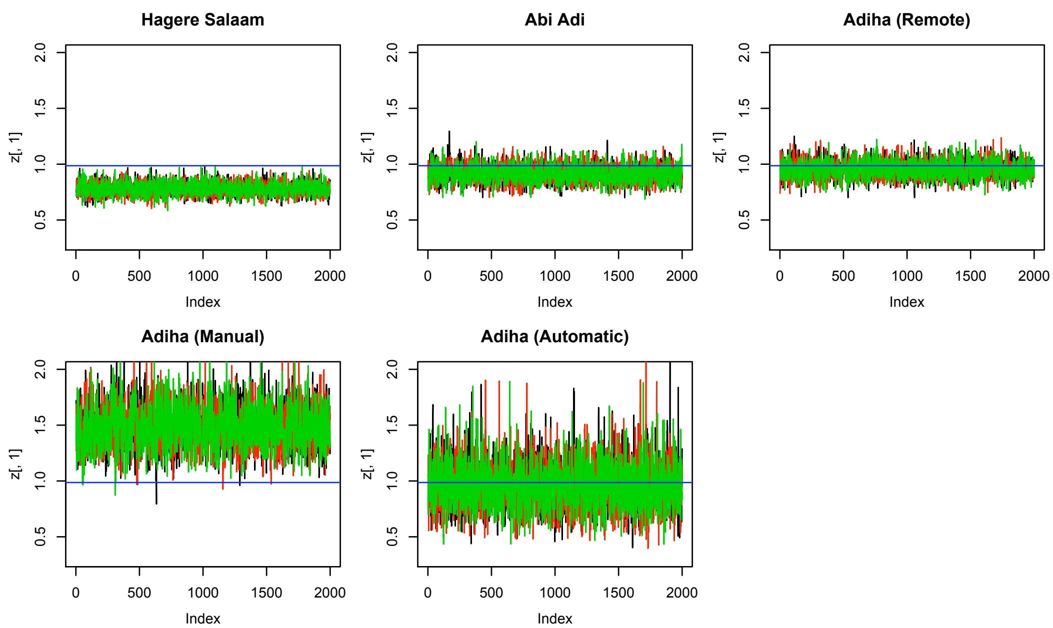


Figure 6: The trace plots of the shape parameters for each site.

Yr	ARC	Mekele	Farmer	WRSI	NDVIg-rg	SPOT-Veg	MODIS	NDWI	EVI
2000	9	6	Bad	10	3	3	1	6	1
2001	2	8	-	5	1	3	7	8	2
2002	3	3	-	7	5	8	10	10	6
2003	1	5	-	1	2	2	2	5	3
2004	10	9	Bad	9	8	8	5	9	10
2005	4	2	-	3	9	6	9	4	5
2006	5	4	-	2	7	7	6	3	8
2007	6	1	-	4	4	1	3	1	9
2008	7	7	Bad	6	10	5	8	7	7
2009	8	#N/A	Bad	8	6	10	4	2	4

Table 2: Adi Ha Maize Ranking.csv

Yr	ARC	Mekele	Farmer	WRSI	NDVIg-rg	SPOT-Veg	MODIS	NDWI	EVI
2000	9	6	Bad	10	3	3	1	6	1
2001	2	8	-	2	1	3	7	8	2
2002	3	3	-	4	5	8	10	10	6
2003	1	5	-	1	2	2	2	5	3
2004	10	9	Bad	8	8	8	5	9	10
2005	4	2	-	6	9	6	9	4	5
2006	5	4	-	3	7	7	6	3	8
2007	6	1	-	5	4	1	3	1	9
2008	7	7	Bad	9	10	5	8	7	7
2009	8	#N/A	Bad	7	6	10	4	2	4

Table 3: Adi Ha Teff Ranking.csv

1.7 Comparisons of off the shelf vegetative sensing products

The full set of tables presenting the ARC contract estimates, the nearby raingauges, and the multiple remote sensing tools is presented in this section. See the main report for discussion.

Yr	ARC	Maychew	Adisheshu	Alamata	Farmer	WRSI	NDVIg-rg	SPOT-Veg	MODIS	NDWI	EVI
2000	8	1	6	1	-	9	1	1	1	1	1
2001	4	3	1	8	-	7	2	1	2	3	7
2002	3	2	9	3	-	6	7	4	8	5	4
2003	2	6	7	9	-	4	4	5	4	6	5
2004	10	8	8	5	Bad	8	5	6	3	4	8
2005	6	9	4	6	-	3	9	7	7	8	6
2006	7	5	3	4	-	5	3	3	5	2	2
2007	5	7	2	7	Bad	1	6	8	9	7	3
2008	1	4	5	2	Bad	2	8	9	10	10	10
2009	9	#N/A	#N/A	#N/A	Bad	10	10	10	6	9	9

Table 4: Geneti Sorghum Ranking.csv

Yr	ARC	Maychew	Adisheshu	Alamata	Farmer	WRSI	NDVIg-rg	SPOT-Veg	MODIS	NDWI	EVI
2000	8	1	6	1	-	1	1	1	1	1	1
2001	4	3	1	8	-	2	2	1	2	3	7
2002	3	2	9	3	-	7	7	4	8	5	4
2003	2	6	7	9	-	4	4	5	4	6	5
2004	10	8	8	5	Bad	5	5	6	3	4	8
2005	6	9	4	6	-	9	9	7	7	8	6
2006	7	5	3	4	-	3	3	3	5	2	2
2007	5	7	2	7	Bad	6	6	8	9	7	3
2008	1	4	5	2	Bad	8	8	9	10	10	10
2009	9	#N/A	#N/A	#N/A	Bad	10	10	10	6	9	9

Table 5: Geneti Teff Ranking.csv

Yr	ARC	Maychew	Adisheshu	Alamata	Farmer	WRSI	NDVIg-rg	SPOT-Veg	MODIS	NDWI	EVI
2000	8	1	6	1	-	10	1	1	1	1	1
2001	4	3	1	8	-	8	2	1	4	7	3
2002	3	2	9	3	-	6	4	3	2	2	2
2003	2	6	7	9	-	4	5	4	3	8	4
2004	10	8	8	5	Bad	7	7	6	5	9	6
2005	6	9	4	6	-	1	6	8	8	6	8
2006	7	5	3	4	Bad	3	3	7	6	5	7
2007	5	7	2	7	Bad	5	8	5	7	3	5
2008	1	4	5	2	Bad	2	9	9	10	4	10
2009	9	#N/A	#N/A	#N/A	Bad	9	10	10	9	10	9

Table 6: Hade Alga Sorghum Ranking.csv

Yr	ARC	Maychew	Adisheshu	Alamata	Farmer	WRSI	NDVIg-rg	SPOT-Veg	MODIS	NDWI	EVI
2000	8	1	6	1	-	6	1	1	1	1	1
2001	3	3	1	8	-	7	2	1	4	7	3
2002	6	2	9	3	-	5	4	3	2	2	2
2003	1	6	7	9	-	2	5	4	3	8	4
2004	10	8	8	5	Bad	9	7	6	5	9	6
2005	5	9	4	6	-	4	6	8	8	6	8
2006	7	5	3	4	Bad	8	3	7	6	5	7
2007	4	7	2	7	Bad	3	8	5	7	3	5
2008	2	4	5	2	Bad	1	9	9	10	4	10
2009	9	#N/A	#N/A	#N/A	Bad	10	10	10	9	10	9

Table 7: Hade Alga Teff Ranking.csv

Yr	ARC	Adigrat	Frerweni	Farmer	WRSI	NDVIg-rg	SPOT-Veg	MODIS	NDVI MODIS	NDWI
2000	7	#N/A	#N/A	-	9	4	1	3	2	2
2001	3	4	#N/A	-	7	1	1	1	7	1
2002	8	7	5	-	6	2	8	10	9	8
2003	1	2	4	-	4	3	5	6	5	5
2004	10	8	6	Bad	8	9	7	7	8	7
2005	2	5	1	-	3	7	9	9	6	9
2006	5	1	3	-	5	6	4	2	4	6
2007	4	3	2	Bad	1	4	6	5	3	3
2008	6	6	#N/A	Bad	2	9	3	4	1	4
2009	9	#N/A	#N/A	Bad	10	8	10	8	10	10

Table 8: Hadush Adi Wheat Ranking.csv

Title	Adi Ha Maize Dry 1	Adi Ha Maize Dry 2	Adi Ha Maize Dry Index
Start (Dek)	1-May/23-Apr (13)	21-Aug/15-Aug (24)	
End (Dek)	30-Jun/23-Jun (18)	20-Sep/10-Sep (26)	
Trigger (% ave)	17 (0.47)	40 (0.76)	
Exit (% ave)	0 (0)	20 (0.38)	
Cap	25	25	
Expected Payout	9.39	8.41	17.8
Payout Frequency	0.27	0.2	0.33
Maxpay Freq	0	0	0
Freq ¡ E Pay	0.25	0	0.2
1995/1988	0	0	0
1996/1989	0	0	0
1997/1990	0	75	75
1998/1991	0	0	0
1999/1992	0	0	0
2000/1993	58	30	88
2001/1994	0	0	0
2002/1995	0	0	0
2003/1996	0	0	0
2004/1997	26	20	46
2005/1998	0	0	0
2006/1999	0	0	0
2007/2000	7	0	7
2008/2001	0	0	0
2009/2002	50	0	50

Table 9: AdiHaMaizeDryFinal.byphase.csv

2 Contract Tables

For completeness, in this section we present the index tables produced by the analysis software.

Title	Adi Ha Maize Very Dry 1	Adi Ha Maize Very Dry 2	Adi Ha Maize Very Dry Index
Start (Dek)	1-May/23-Apr (13)	21-Aug/15-Aug (24)	
End (Dek)	30-Jun/23-Jun (18)	20-Sep/10-Sep (26)	
Trigger (% ave)	13 (0.36)	30 (0.57)	
Exit (% ave)	7 (0.19)	20 (0.38)	
Cap	25	25	
Expected Payout	11.9	3.39	15.29
Payout Frequency	0.2	0.07	0.27
Maxpay Freq	0	0	0
Freq ¡ E Pay	0.33	0	0.25
1995/1988	0	0	0
1996/1989	0	0	0
1997/1990	0	51	51
1998/1991	0	0	0
1999/1992	0	0	0
2000/1993	97	0	97
2001/1994	0	0	0
2002/1995	0	0	0
2003/1996	0	0	0
2004/1997	8	0	8
2005/1998	0	0	0
2006/1999	0	0	0
2007/2000	0	0	0
2008/2001	0	0	0
2009/2002	74	0	74

Table 10: AdiHaMaizeVeryDryFinal.byphase.csv

Title	Adi Ha Teff Dry 1
Start (Dek)	21-Aug/15-Aug (24)
End (Dek)	30-Sep/20-Sep (27)
Trigger (% ave)	55 (0.97)
Exit (% ave)	40 (0.7)
Cap	25
Expected Payout	22.24
Payout Frequency	0.33
Maxpay Freq	0.2
Freq ¡ E Pay	0.2
1995/1988	0
1996/1989	0
1997/1990	100
1998/1991	0
1999/1992	0
2000/1993	100
2001/1994	0
2002/1995	0
2003/1996	0
2004/1997	100
2005/1998	0
2006/1999	0
2007/2000	0
2008/2001	2
2009/2002	32

Table 11: AdiHaTeffDryFinal.byphase.csv

Title	Adi Ha Very Teff Dry 1
Start (Dek)	21-Aug/15-Aug (24)
End (Dek)	30-Sep/20-Sep (27)
Trigger (% ave)	50 (0.88)
Exit (% ave)	30 (0.53)
Cap	25
Expected Payout	14.96
Payout Frequency	0.2
Maxpay Freq	0.07
Freq ¡ E Pay	0
1995/1988	0
1996/1989	0
1997/1990	100
1998/1991	0
1999/1992	0
2000/1993	54
2001/1994	0
2002/1995	0
2003/1996	0
2004/1997	70
2005/1998	0
2006/1999	0
2007/2000	0
2008/2001	0
2009/2002	0

Table 12: AdiHaTeffVeryDryFinal.byphase.csv

Title	Geneti Sorghum Dry 1	Geneti Sorghum Dry 2	Geneti Sorghum Dry Index
Start (Dek)	11-Apr/3-Apr (11)	11-Jul/4-Jul (20)	
End (Dek)	31-May/23-May (15)	20-Sep/10-Sep (26)	
Trigger (% ave)	17 (0.54)	115 (0.88)	
Exit (% ave)	10 (0.32)	70 (0.54)	
Cap	25	25	
Expected Payout	15.85	9.74	18.92
Payout Frequency	0.27	0.13	0.33
Maxpay Freq	0.13	0.07	0.13
Freq ¡ E Pay	0.25	0	0.2
1995/1988	0	0	0
1996/1989	0	0	0
1997/1990	0	0	0
1998/1991	6	0	6
1999/1992	100	0	100
2000/1993	0	0	0
2001/1994	0	0	0
2002/1995	32	0	32
2003/1996	0	0	0
2004/1997	0	46	46
2005/1998	0	0	0
2006/1999	0	0	0
2007/2000	0	0	0
2008/2001	0	0	0
2009/2002	100	100	100

Table 13: GenetiSorghumDryFinal.byphase.csv

Title	Geneti Sorghum Very Dry 1	Geneti Sorghum Very Dry 2	Geneti Sorghum Very Dry Index
Start (Dek)	11-Apr/3-Apr (11)	11-Jul/4-Jul (20)	
End (Dek)	31-May/23-May (15)	20-Sep/10-Sep (26)	
Trigger (% ave)	6 (0.19)	115 (0.88)	
Exit (% ave)	0 (0)	70 (0.54)	
Cap	25	25	
Expected Payout	9.17	9.74	16.41
Payout Frequency	0.13	0.13	0.2
Maxpay Freq	0.07	0.07	0.13
Freq ¡ E Pay	0	0	0
1995/1988	0	0	0
1996/1989	0	0	0
1997/1990	0	0	0
1998/1991	0	0	0
1999/1992	100	0	100
2000/1993	0	0	0
2001/1994	0	0	0
2002/1995	0	0	0
2003/1996	0	0	0
2004/1997	0	46	46
2005/1998	0	0	0
2006/1999	0	0	0
2007/2000	0	0	0
2008/2001	0	0	0
2009/2002	38	100	100

Table 14: GenetiSorghumVeryDryFinal.byphase.csv

Title	Geneti Teff Dry Kiremt 1
Start (Dek)	21-Aug/15-Aug (24)
End (Dek)	30-Sep/20-Sep (27)
Trigger (% ave)	48 (0.95)
Exit (% ave)	17 (0.34)
Cap	25
Expected Payout	19.71
Payout Frequency	0.33
Maxpay Freq	0.07
Freq ¡ E Pay	0
1995/1988	42
1996/1989	0
1997/1990	58
1998/1991	0
1999/1992	0
2000/1993	21
2001/1994	0
2002/1995	0
2003/1996	0
2004/1997	100
2005/1998	0
2006/1999	0
2007/2000	0
2008/2001	0
2009/2002	74

Table 15: GenetiTeffDryKiremtFinal.byphase.csv

Title	Geneti Teff Very Dry Kiremt 1
Start (Dek)	21-Aug/15-Aug (24)
End (Dek)	30-Sep/20-Sep (27)
Trigger (% ave)	34 (0.67)
Exit (% ave)	17 (0.34)
Cap	25
Expected Payout	11.8
Payout Frequency	0.2
Maxpay Freq	0.07
Freq ¡ E Pay	0
1995/1988	0
1996/1989	0
1997/1990	24
1998/1991	0
1999/1992	0
2000/1993	0
2001/1994	0
2002/1995	0
2003/1996	0
2004/1997	100
2005/1998	0
2006/1999	0
2007/2000	0
2008/2001	0
2009/2002	53

Table 16: GenetiTeffVeryDryKiremtFinal.byphase.csv

Title	Hade Alga Sorghum Dry 1	Hade Alga Sorghum Dry 2	Hade Alga Sorghum Dry Index
Start (Dek)	11-Apr/3-Apr (11)	1-Jul/24-Jun (19)	
End (Dek)	10-Jun/3-Jun (16)	10-Sep/5-Pag (25)	
Trigger (% ave)	17 (0.43)	105 (0.79)	
Exit (% ave)	10 (0.25)	80 (0.6)	
Cap	25	25	
Expected Payout	11.41	8.78	20.19
Payout Frequency	0.2	0.2	0.33
Maxpay Freq	0.07	0	0.07
Freq ¡ E Pay	0	0	0
1995/1988	0	0	0
1996/1989	0	0	0
1997/1990	0	36	36
1998/1991	0	0	0
1999/1992	100	0	100
2000/1993	0	0	0
2001/1994	41	0	41
2002/1995	0	0	0
2003/1996	0	0	0
2004/1997	0	53	53
2005/1998	0	0	0
2006/1999	0	0	0
2007/2000	0	0	0
2008/2001	0	0	0
2009/2002	30	43	73

Table 17: HadeAlgaSorghumDryFinal.byphase.csv

Title	Hade Alga Sorghum Very Dry 1	Hade Alga Sorghum Very Dry 2	Hade Alga Sorghum Very Dry Index
Start (Dek)	11-Apr/3-Apr (11)	1-Jul/24-Jun (19)	
End (Dek)	10-Jun/3-Jun (16)	10-Sep/5-Pag (25)	
Trigger (% ave)	15 (0.38)	95 (0.72)	
Exit (% ave)	10 (0.25)	88 (0.66)	
Cap	25	25	
Expected Payout	7.97	3.78	11.75
Payout Frequency	0.2	0.13	0.27
Maxpay Freq	0.07	0	0.07
Freq ¡ E Pay	0.33	0	0
1995/1988	0	0	0
1996/1989	0	0	0
1997/1990	0	0	0
1998/1991	0	0	0
1999/1992	100	0	100
2000/1993	0	0	0
2001/1994	17	0	17
2002/1995	0	0	0
2003/1996	0	0	0
2004/1997	0	46	46
2005/1998	0	0	0
2006/1999	0	0	0
2007/2000	0	0	0
2008/2001	0	0	0
2009/2002	2	11	13

Table 18: HadeAlgaSorghumVeryDryFinal.byphase.csv

Title	Hade Alga Teff Dry Kiremt 1
Start (Dek)	21-Aug/15-Aug (24)
End (Dek)	30-Sep/20-Sep (27)
Trigger (% ave)	50 (0.95)
Exit (% ave)	20 (0.38)
Cap	25
Expected Payout	17.28
Payout Frequency	0.33
Maxpay Freq	0
Freq ¡ E Pay	0.2
1995/1988	47
1996/1989	0
1997/1990	41
1998/1991	0
1999/1992	0
2000/1993	2
2001/1994	0
2002/1995	0
2003/1996	0
2004/1997	97
2005/1998	0
2006/1999	0
2007/2000	0
2008/2001	0
2009/2002	72

Table 19: HadeAlgaTeffDryFinal.byphase.csv

Title	Hade Alga Teff Very Dry Kiremt 1
Start (Dek)	21-Aug/15-Aug (24)
End (Dek)	30-Sep/20-Sep (27)
Trigger (% ave)	37 (0.71)
Exit (% ave)	25 (0.48)
Cap	25
Expected Payout	12.08
Payout Frequency	0.2
Maxpay Freq	0.07
Freq ¡ E Pay	0.33
1995/1988	10
1996/1989	0
1997/1990	0
1998/1991	0
1999/1992	0
2000/1993	0
2001/1994	0
2002/1995	0
2003/1996	0
2004/1997	100
2005/1998	0
2006/1999	0
2007/2000	0
2008/2001	0
2009/2002	71

Table 20: HadeAlgaTeffVeryDryFinal.byphase.csv

Title	Hadush Adi Wheat 1	Hadush Adi Wheat 2	Hadush Adi Wheat Index
Start (Dek)	21-Jun/14-Jun (18)	21-Aug/15-Aug (24)	
End (Dek)	20-Jul/13-Jul (20)	30-Sep/20-Sep (27)	
Trigger (% ave)	10 (0.34)	48 (0.94)	
Exit (% ave)	0 (0)	15 (0.29)	
Cap	25	25	
Expected Payout	7.32	12.98	20.3
Payout Frequency	0.13	0.27	0.33
Maxpay Freq	0	0	0
Freq ¡ E Pay	0	0.5	0.2
1995/1988	0	0	0
1996/1989	0	0	0
1997/1990	0	98	98
1998/1991	0	0	0
1999/1992	0	0	0
2000/1993	0	0	0
2001/1994	0	0	0
2002/1995	67	2	69
2003/1996	0	0	0
2004/1997	0	85	85
2005/1998	0	0	0
2006/1999	43	0	43
2007/2000	0	0	0
2008/2001	0	0	0
2009/2002	0	10	10

Table 21: HadushAdiWheatDryFinal.byphase.csv

Title	Hadush Adi Wheat Very Dry 1	Hadush Adi Wheat Very Dry 2	Hadush Adi Wheat Very Dry Index
Start (Dek)	21-Jun/14-Jun (18)	21-Aug/15-Aug (24)	
End (Dek)	20-Jul/13-Jul (20)	30-Sep/20-Sep (27)	
Trigger (% ave)	5 (0.17)	25 (0.49)	
Exit (% ave)	4 (0.14)	4 (0.08)	
Cap	25	25	
Expected Payout	6.67	4.54	11.2
Payout Frequency	0.07	0.13	0.2
Maxpay Freq	0.07	0	0.07
Freq ¡ E Pay	0	0	0
1995/1988	0	0	0
1996/1989	0	0	0
1997/1990	0	44	44
1998/1991	0	0	0
1999/1992	0	0	0
2000/1993	0	0	0
2001/1994	0	0	0
2002/1995	100	0	100
2003/1996	0	0	0
2004/1997	0	24	24
2005/1998	0	0	0
2006/1999	0	0	0
2007/2000	0	0	0
2008/2001	0	0	0
2009/2002	0	0	0

Table 22: HadushAdiWheatVeryDryFinal.byphase.csv

3 Histograms

This section presents the histograms generated by the analysis software for design diagnostics. Because the figures are automatically generated and automatically formatted, all features of the figures may not be visible. These histograms present the payouts for the indexes using historical satellite rainfall estimates as well as the rainfall during each phase of each contract. The histograms include automatic labeling of the contract trigger and exit and their associated percentile as well as labeling of the mean, mode (1 in 2 event), as well as the 1 in 3, 1 in 4, and 1 in 5 year events. These labels are inserted to aid with contract design and are not visible in all figures. Note that the software does perform similar analysis using modeled rainfall but those analyses are not included in the graphical results as we work to improve the sophistication of the rainfall model.

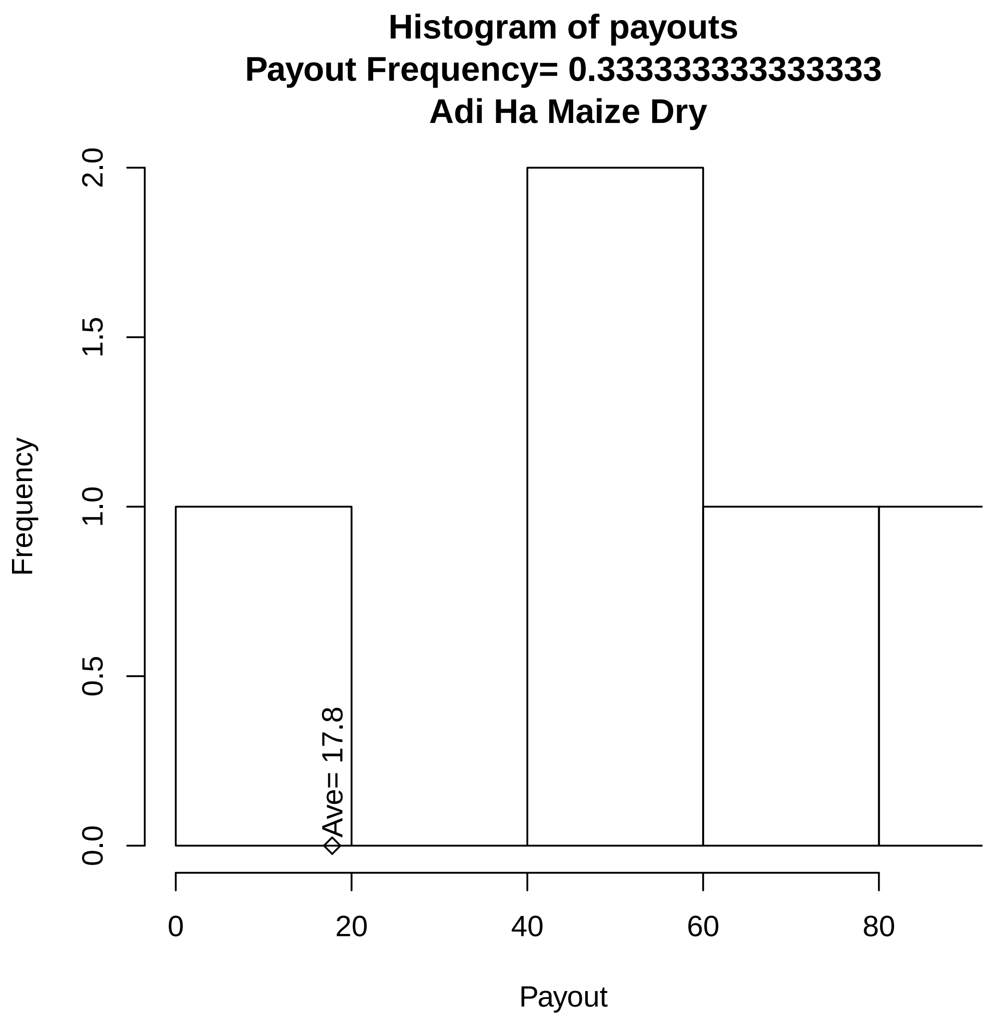


Figure 7: AdiHaMaizeDryFinal-payouthist.pdf

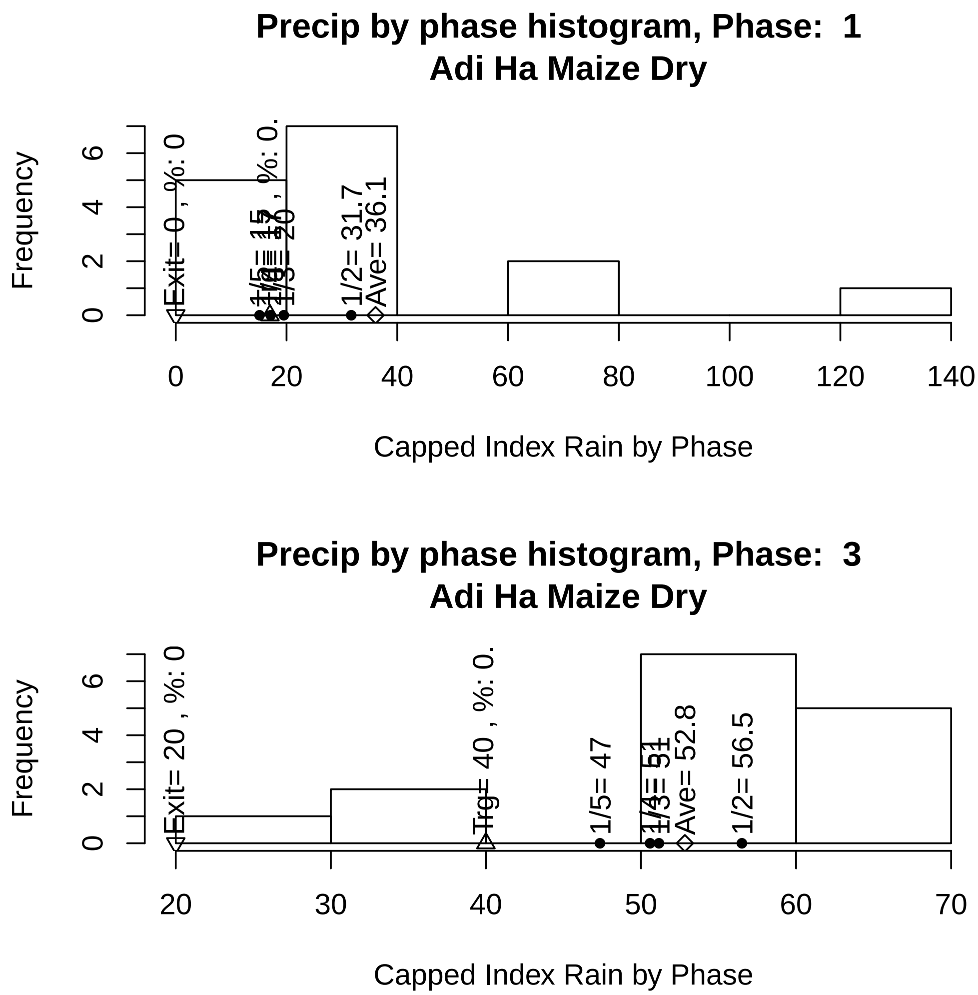


Figure 8: AdiHaMaizeDryFinal-precipbyphase.pdf

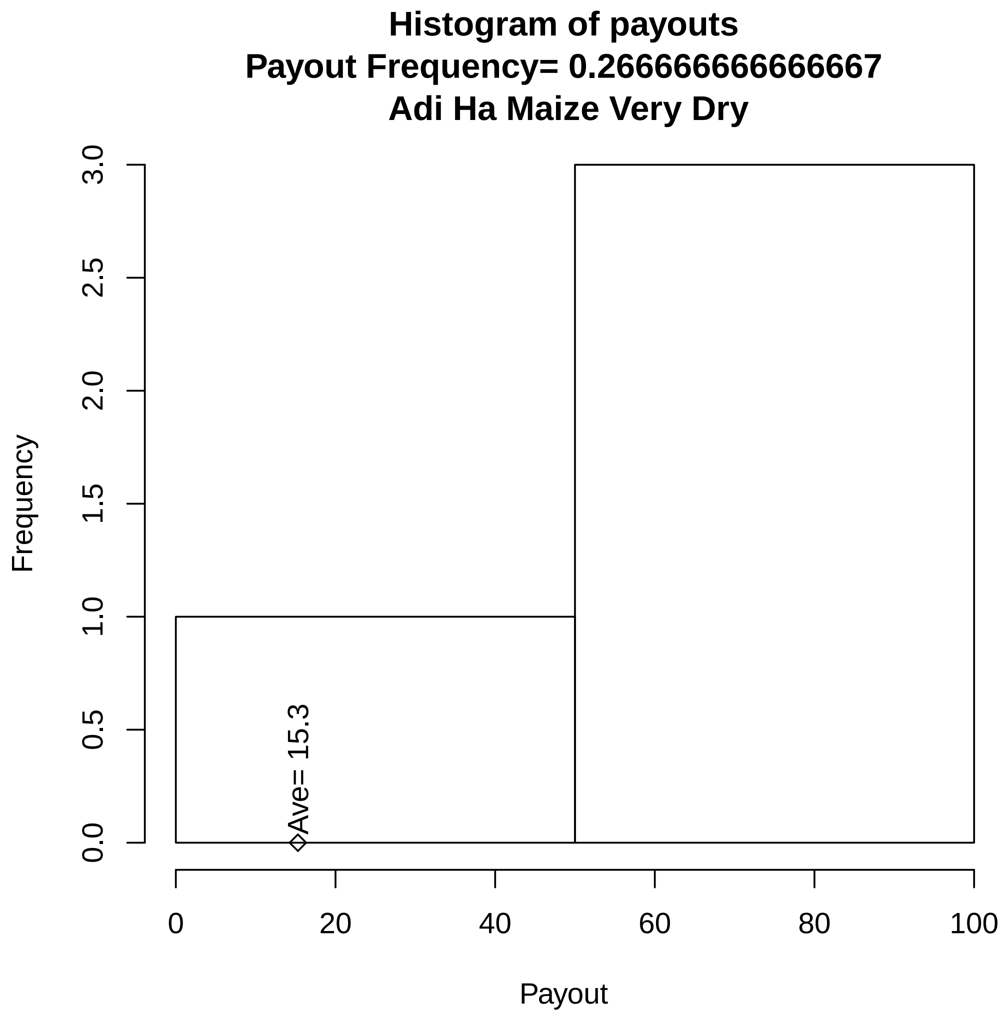


Figure 9: AdiHaMaizeVeryDryFinal-payouthist.pdf

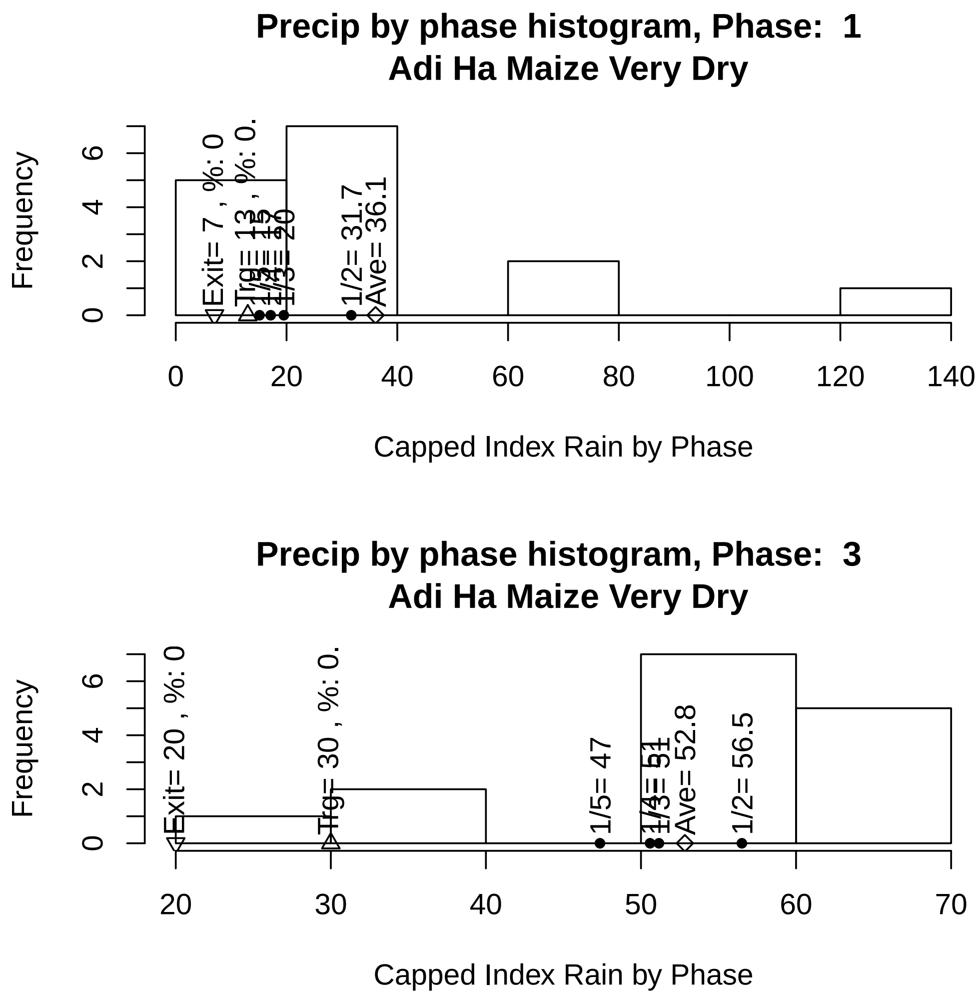


Figure 10: AdiHaMaizeVeryDryFinal-precipbyphase.pdf

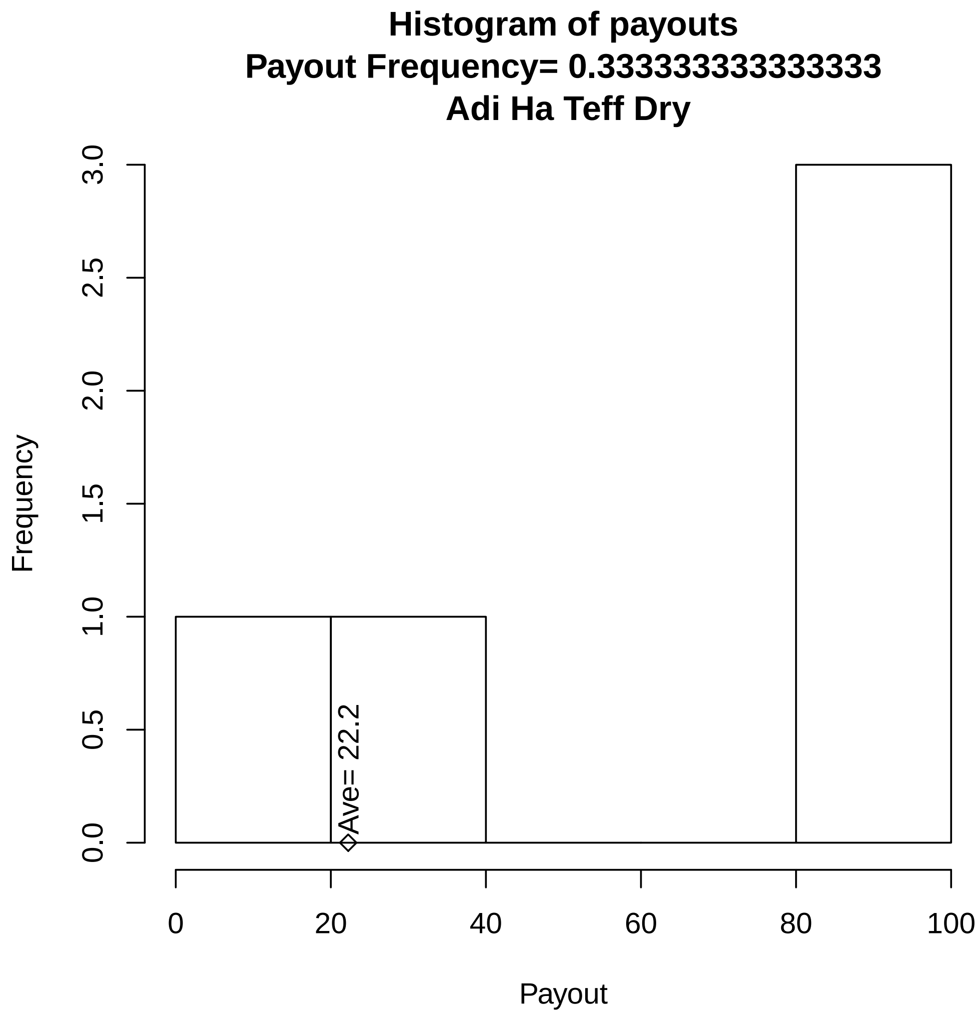


Figure 11: AdiHaTeffDryFinal-payouthist.pdf

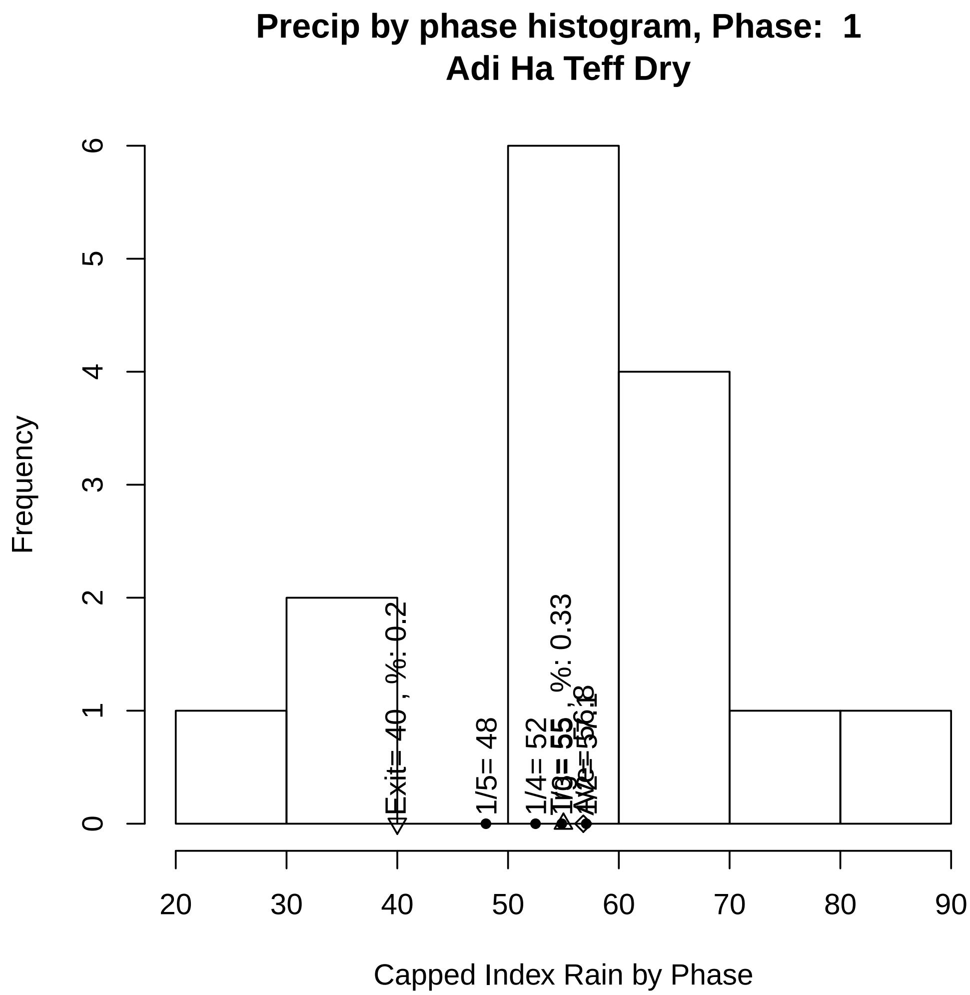


Figure 12: AdiHaTeffDryFinal-precipbyphase.pdf

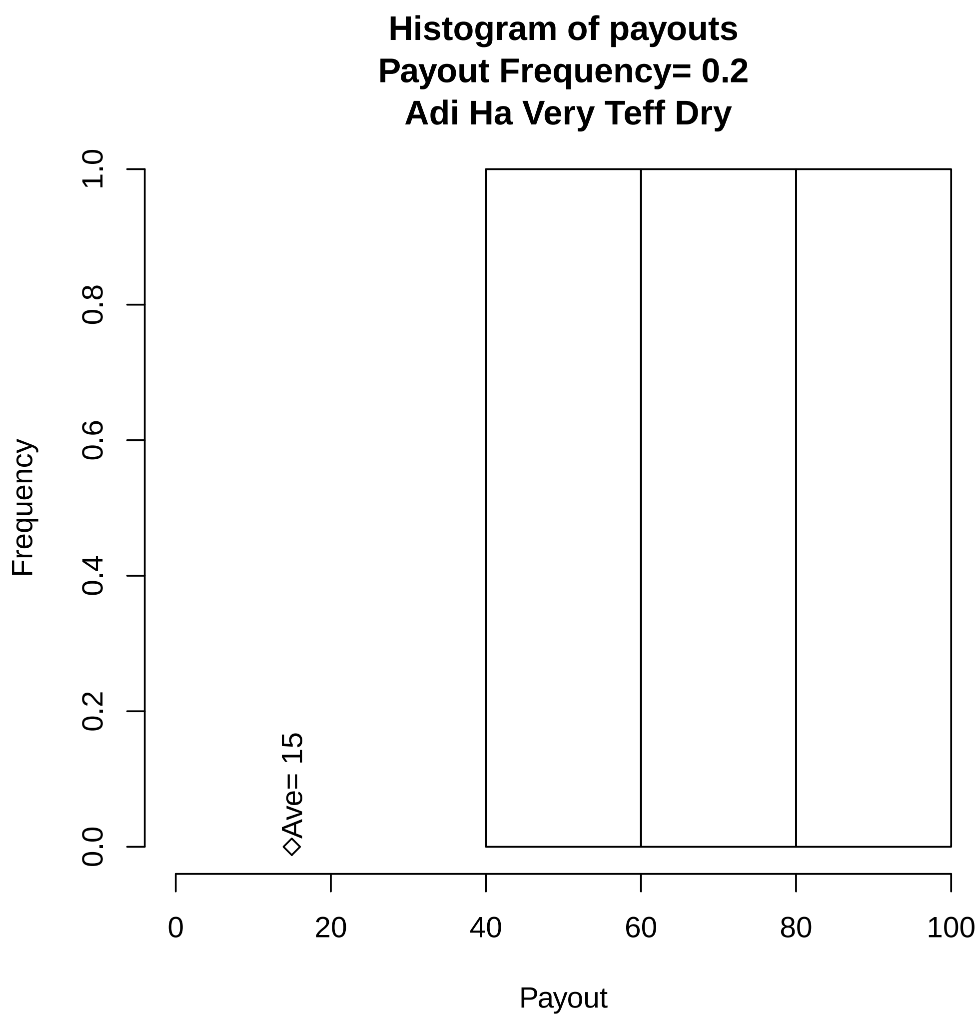


Figure 13: AdiHaTeffVeryDryFinal-payouthist.pdf

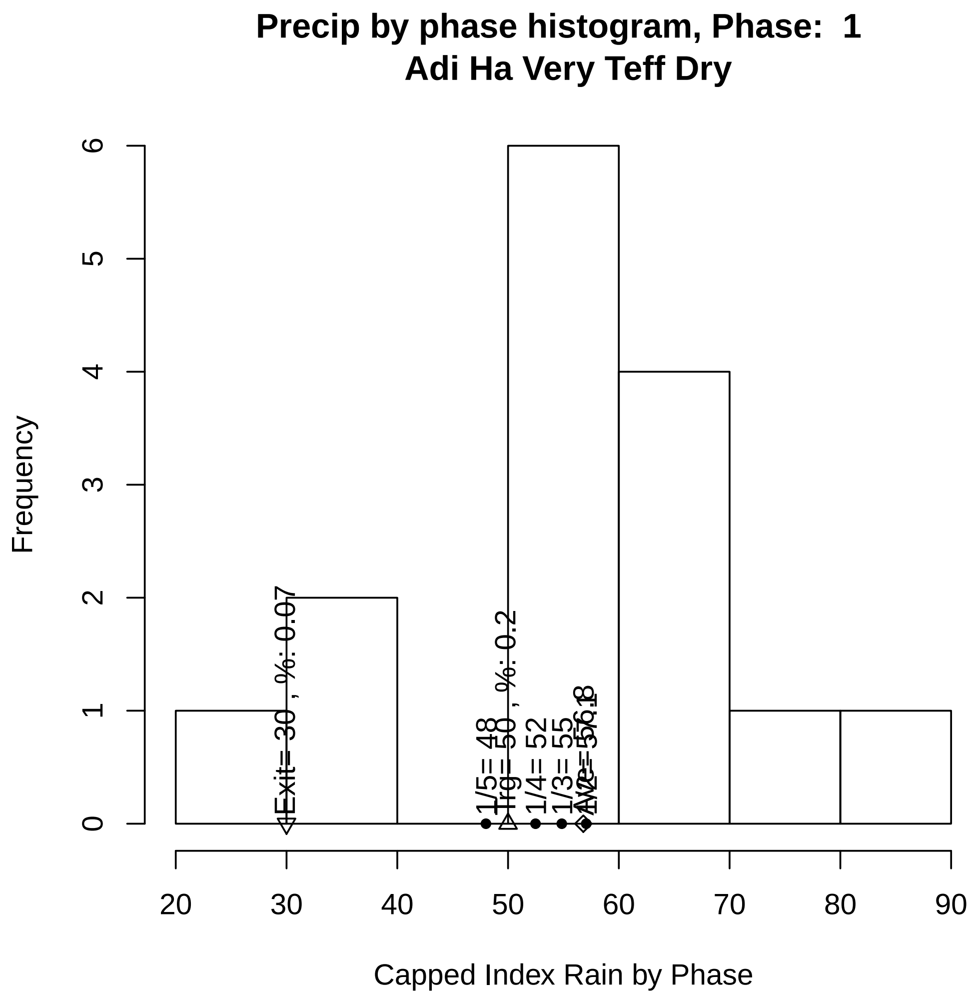


Figure 14: AdiHaTeffVeryDryFinal-precipbyphase.pdf

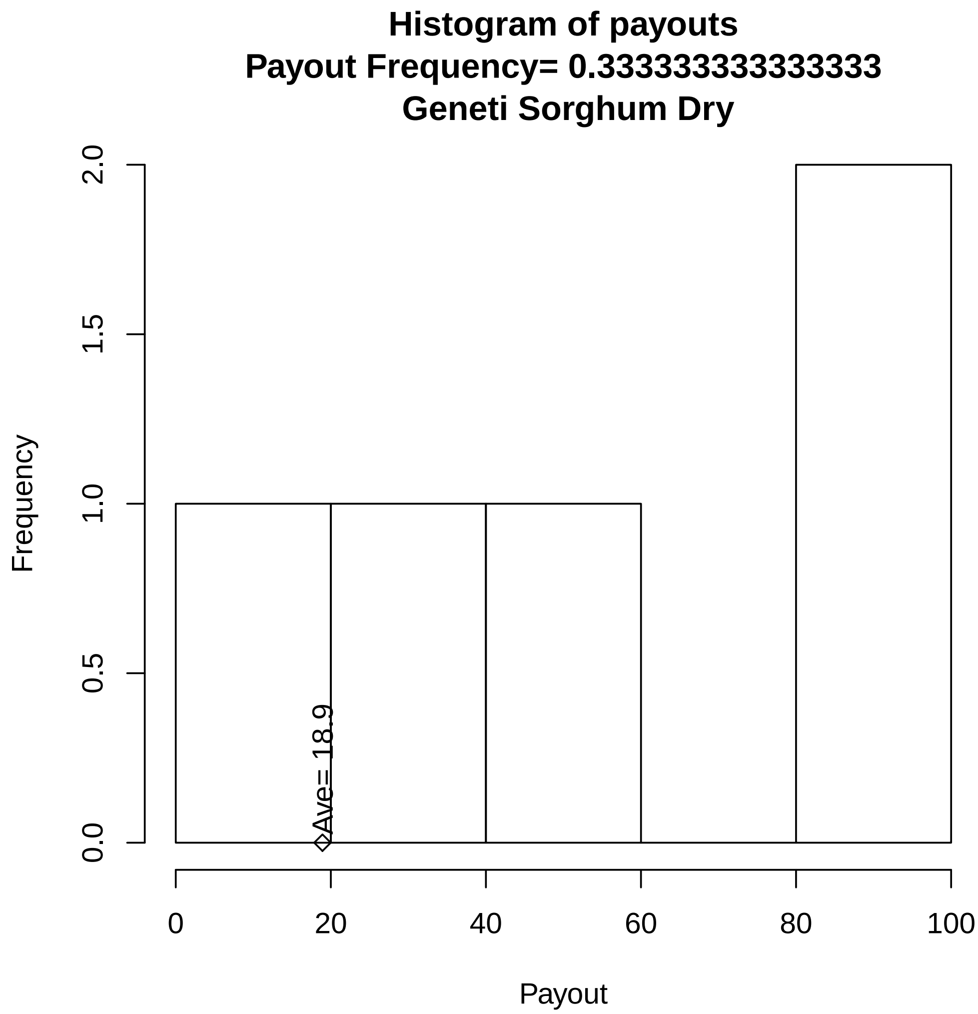
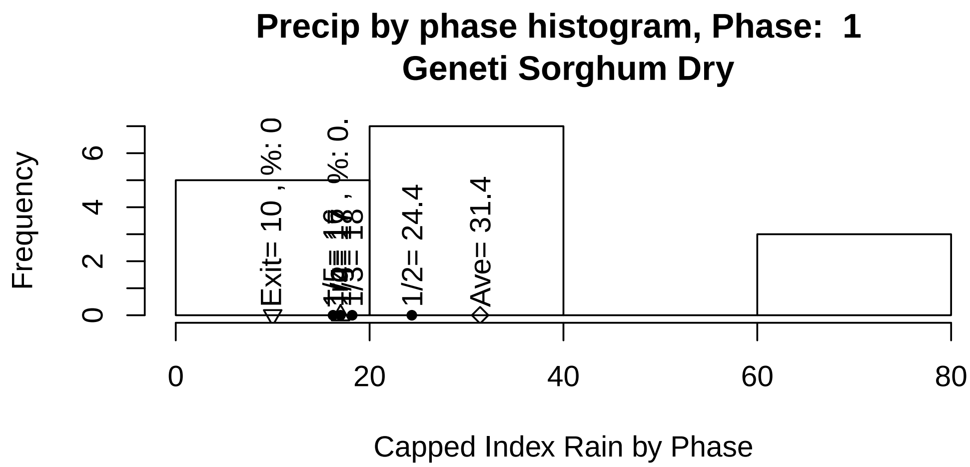


Figure 15: GenetiSorghumDryFinal-payouthist.pdf



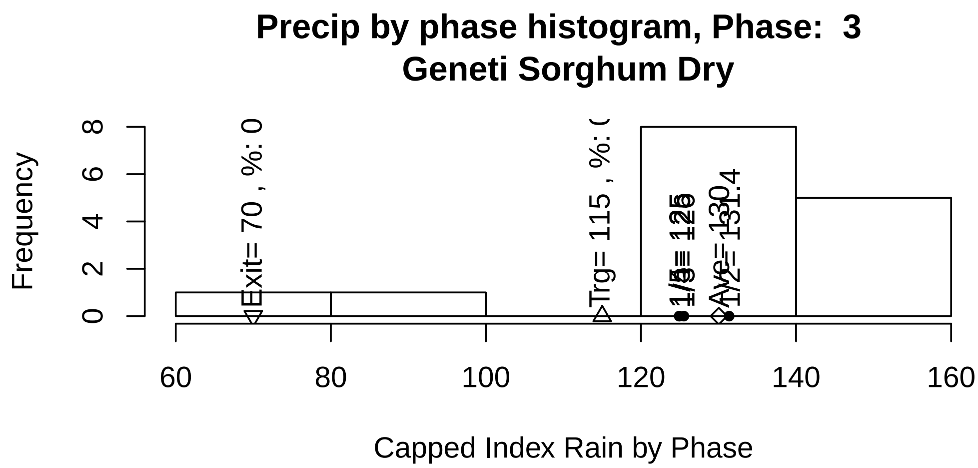


Figure 16: GenetiSorghumDryFinal-precipbyphase.pdf

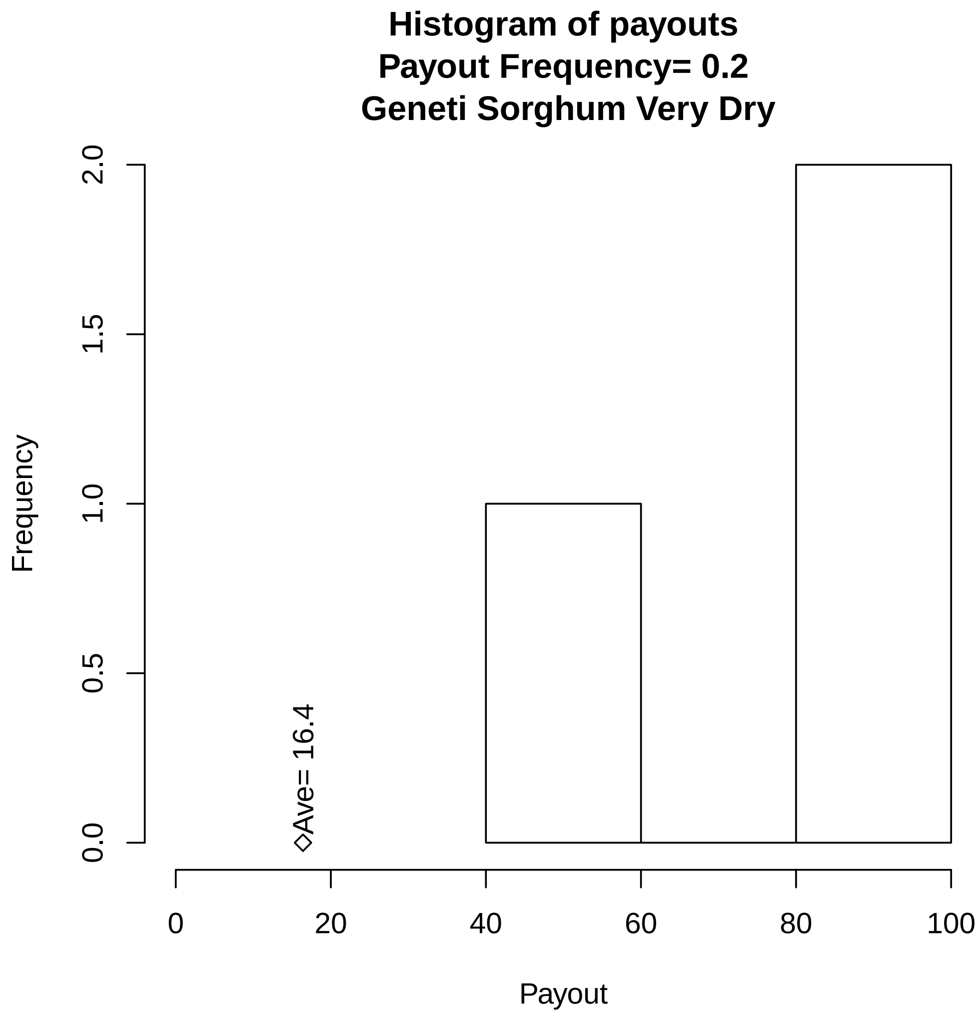
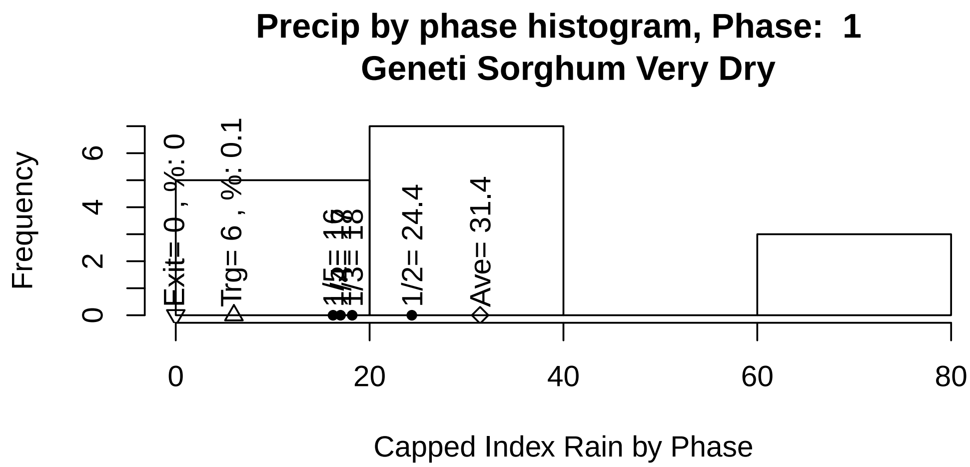


Figure 17: GenetiSorghumVeryDryFinal-payouthist.pdf



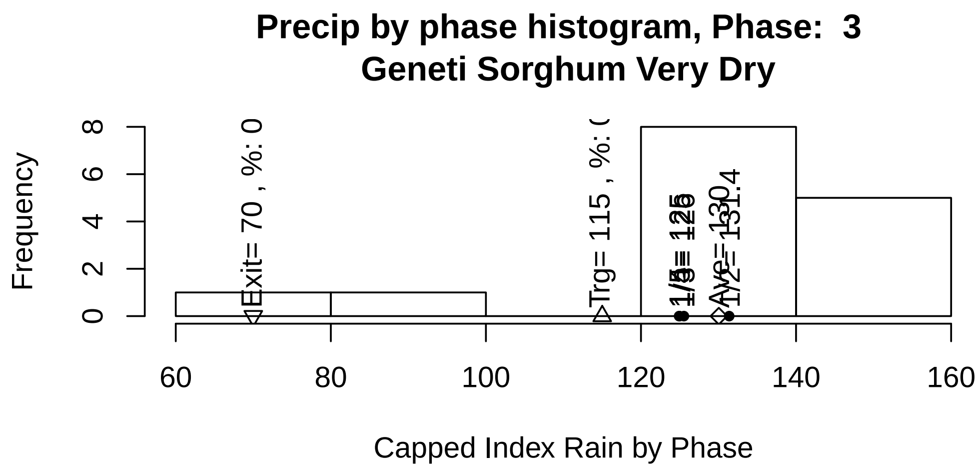


Figure 18: GenetiSorghumVeryDryFinal-precipbyphase.pdf

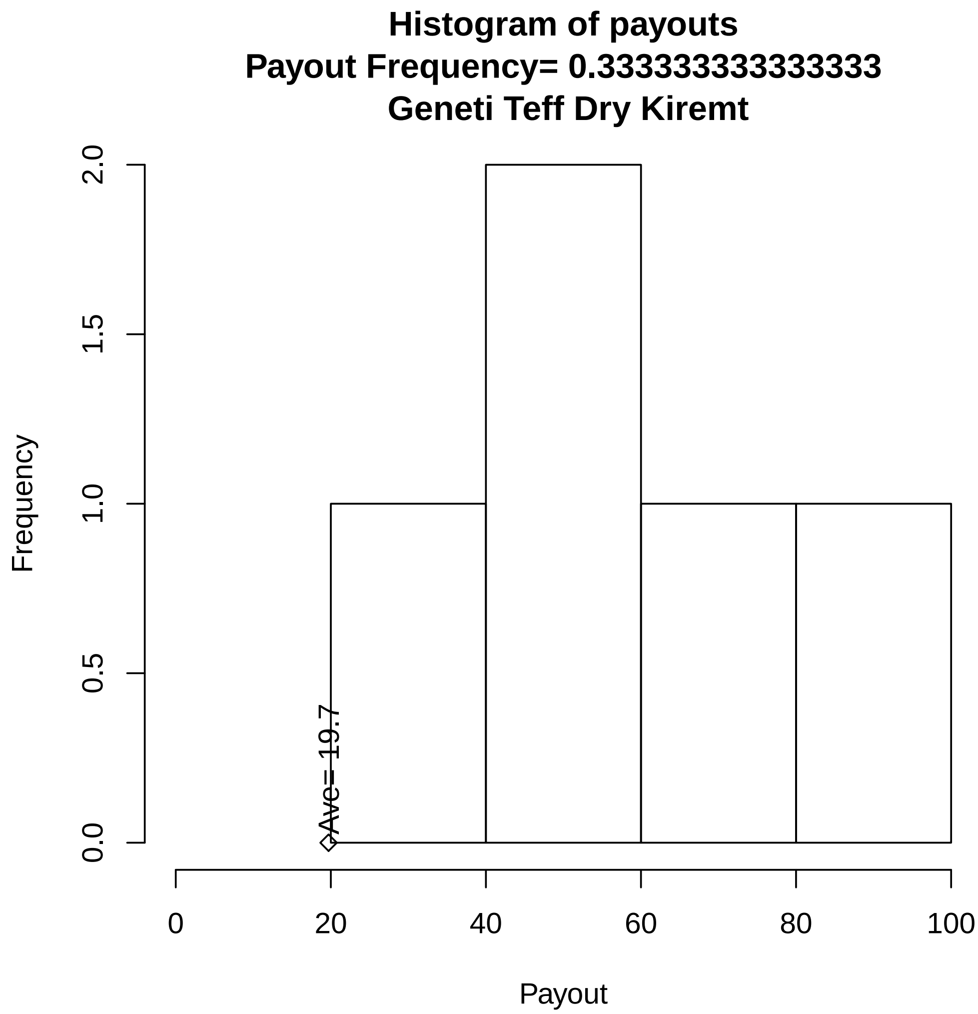


Figure 19: GenetiTeffDryKiremtFinal-payouthist.pdf

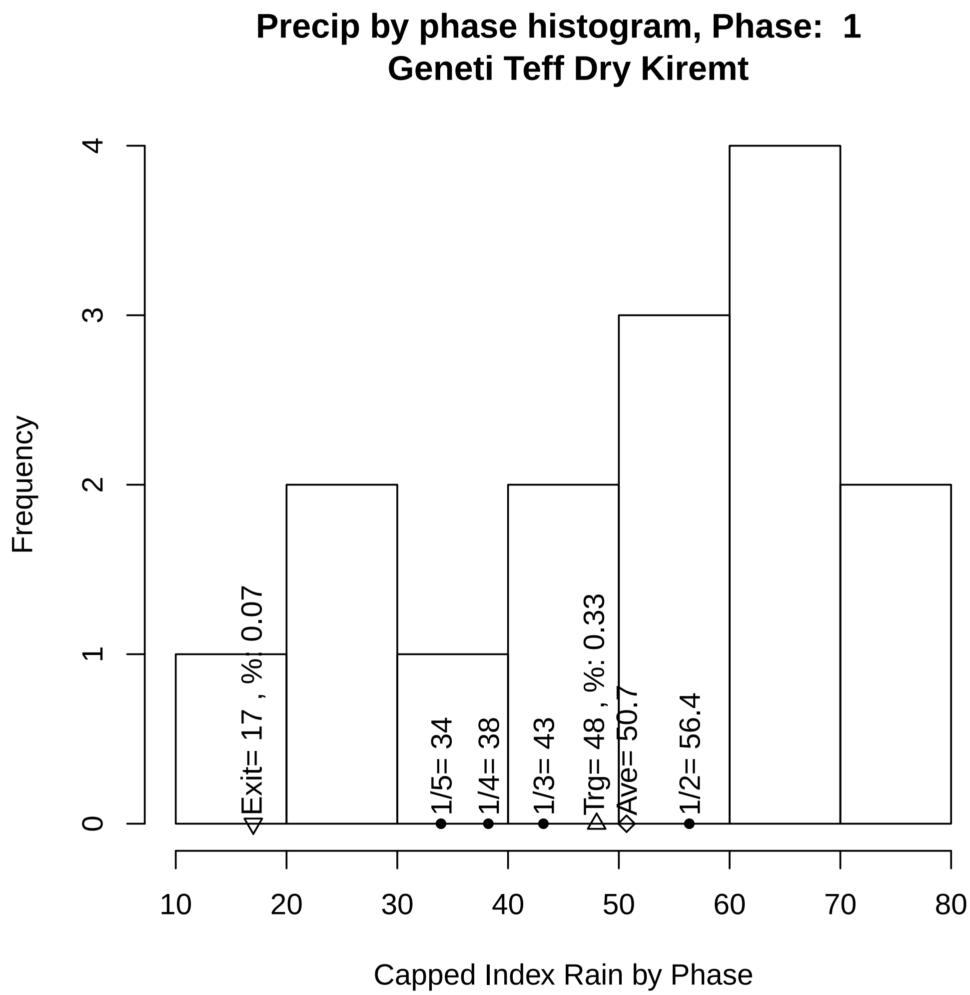


Figure 20: GenetiTeffDryKiremtFinal-precipbyphase.pdf

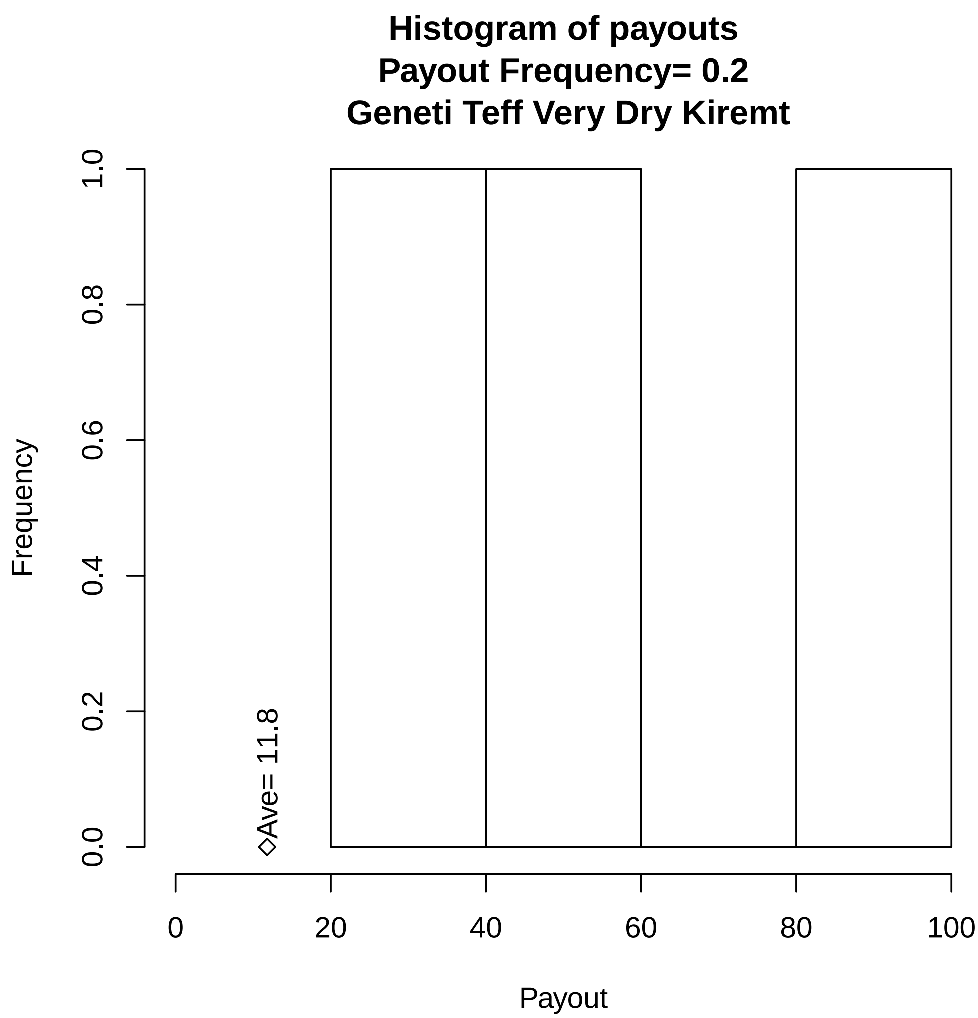


Figure 21: GenetiTeffVeryDryKiremtFinal-payouthist.pdf

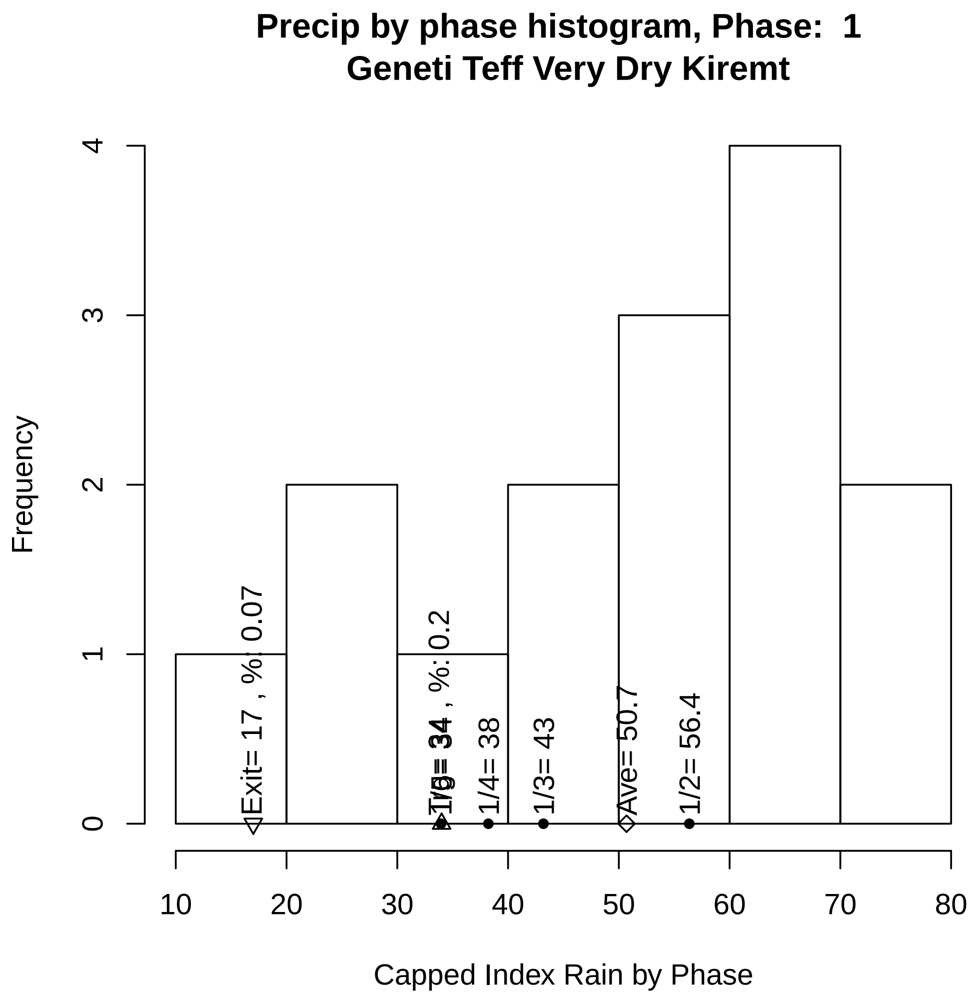


Figure 22: GenetiTeffVeryDryKiremtFinal-precipbyphase.pdf

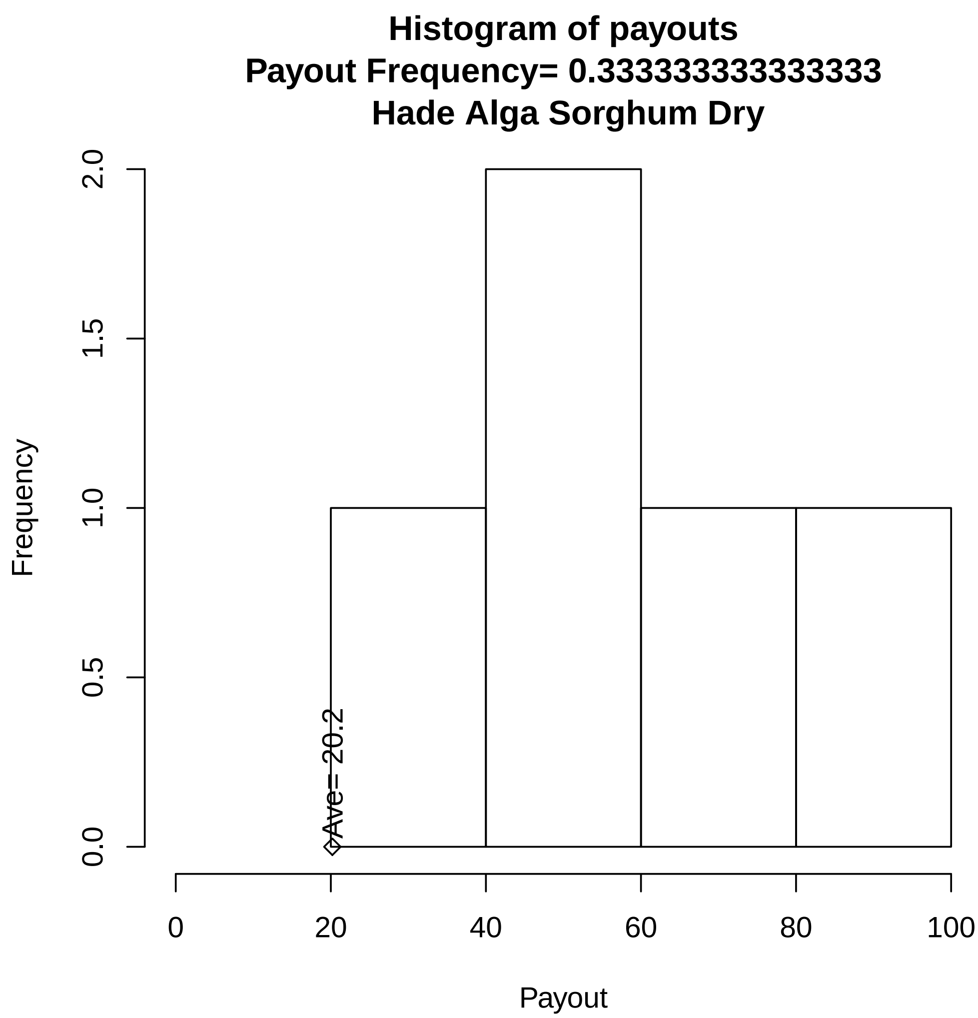
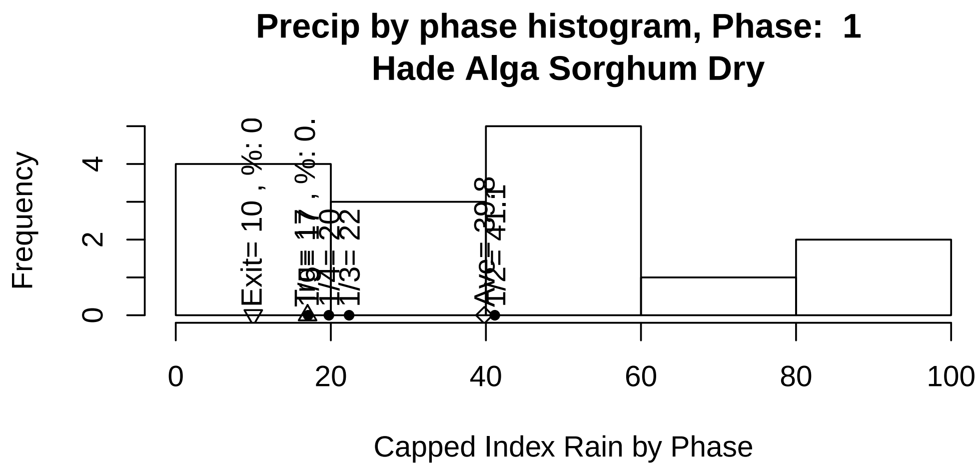


Figure 23: HadeAlgaSorghumDryFinal-payouthist.pdf



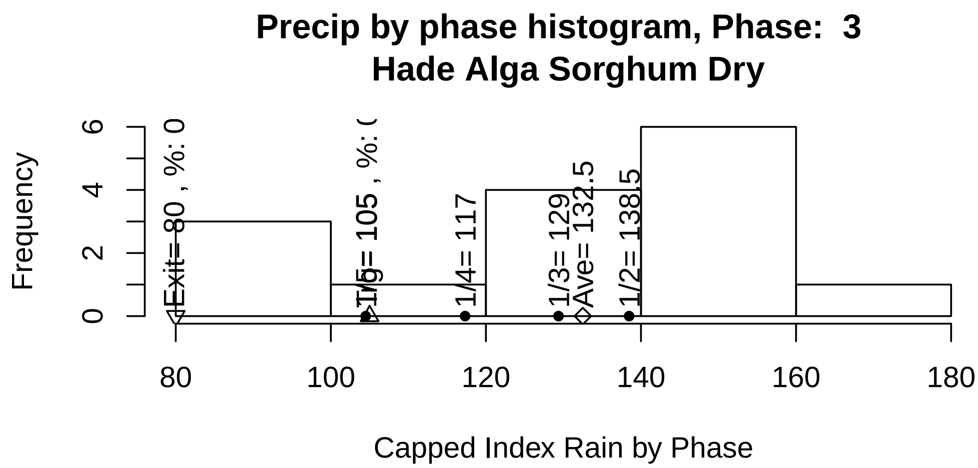


Figure 24: HadeAlgaSorghumDryFinal-precipbyphase.pdf

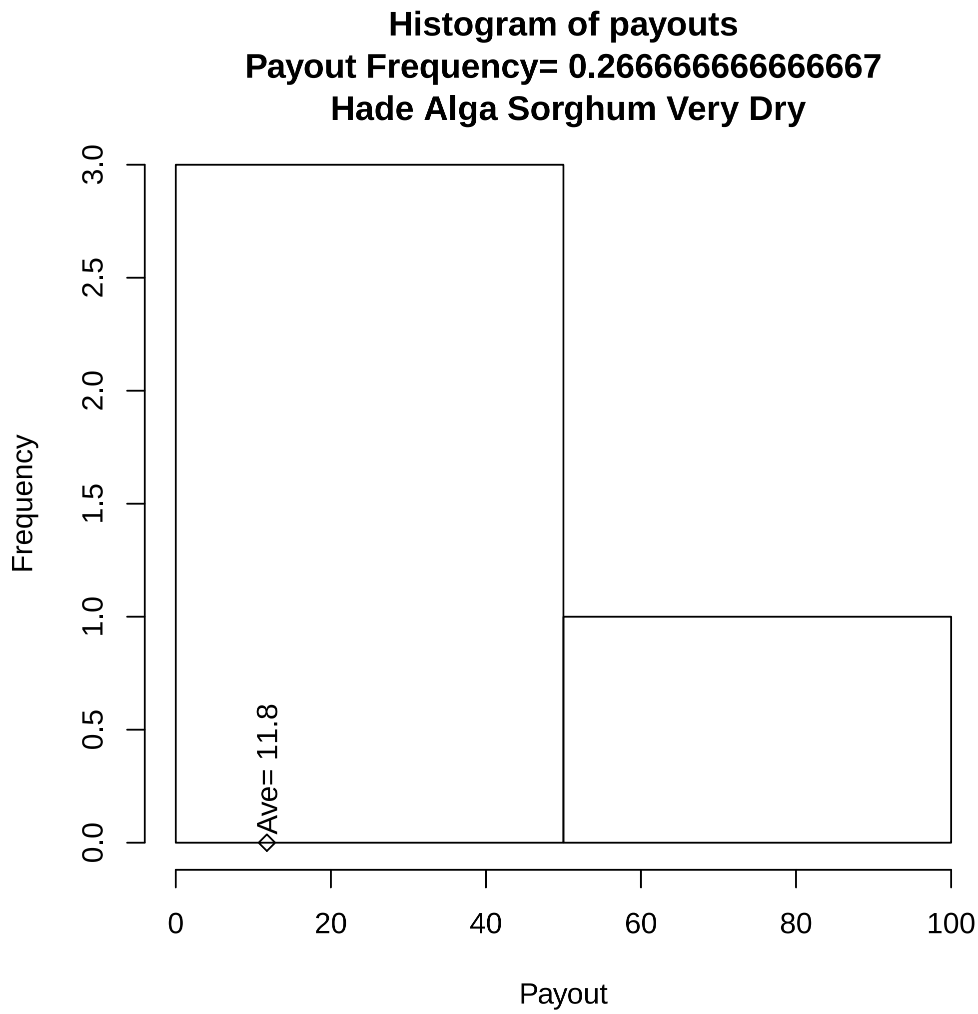
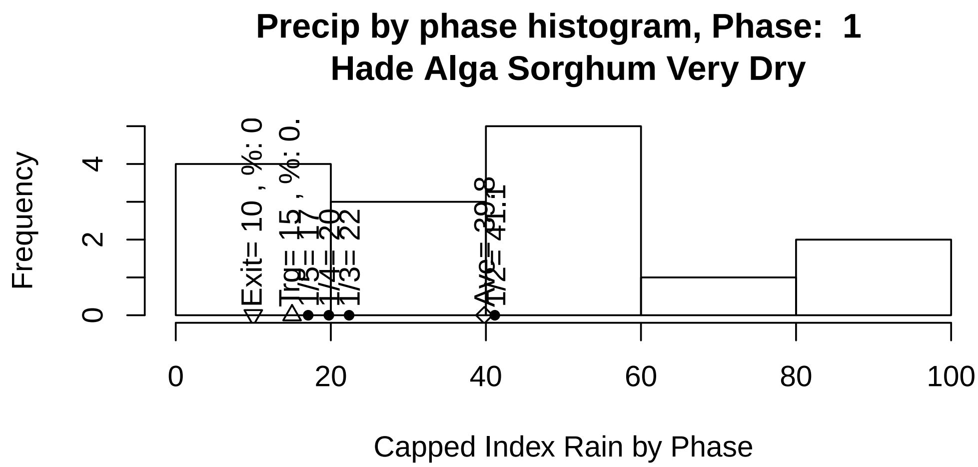


Figure 25: HadeAlgaSorghumVeryDryFinal-payouthist.pdf



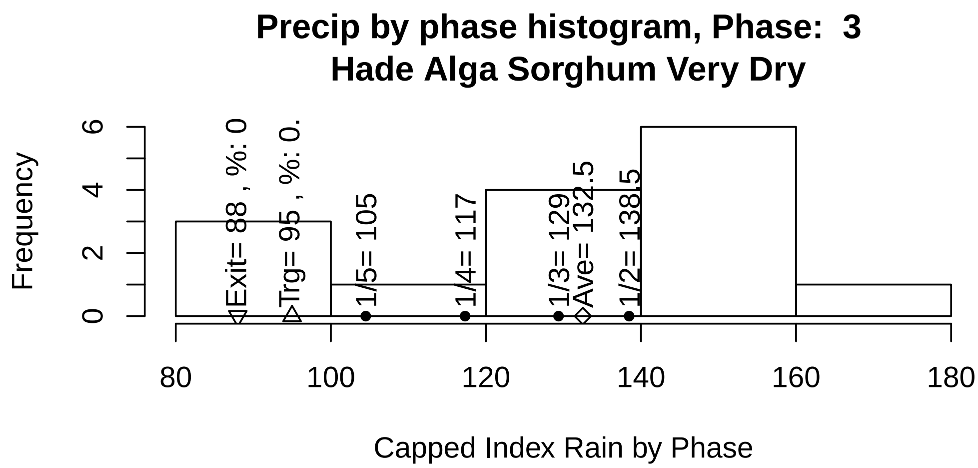


Figure 26: HadeAlgaSorghumVeryDryFinal-precipbyphase.pdf

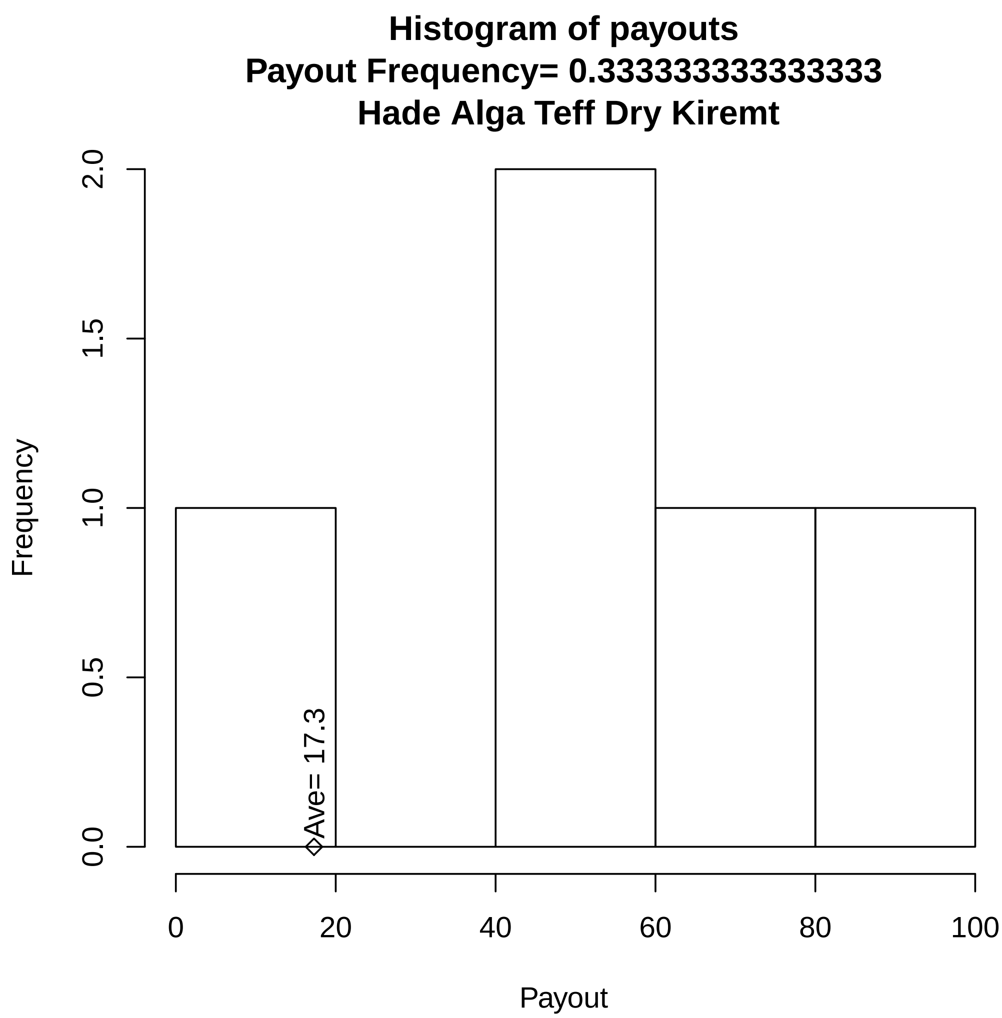


Figure 27: HadeAlgaTeffDryFinal-payouthist.pdf

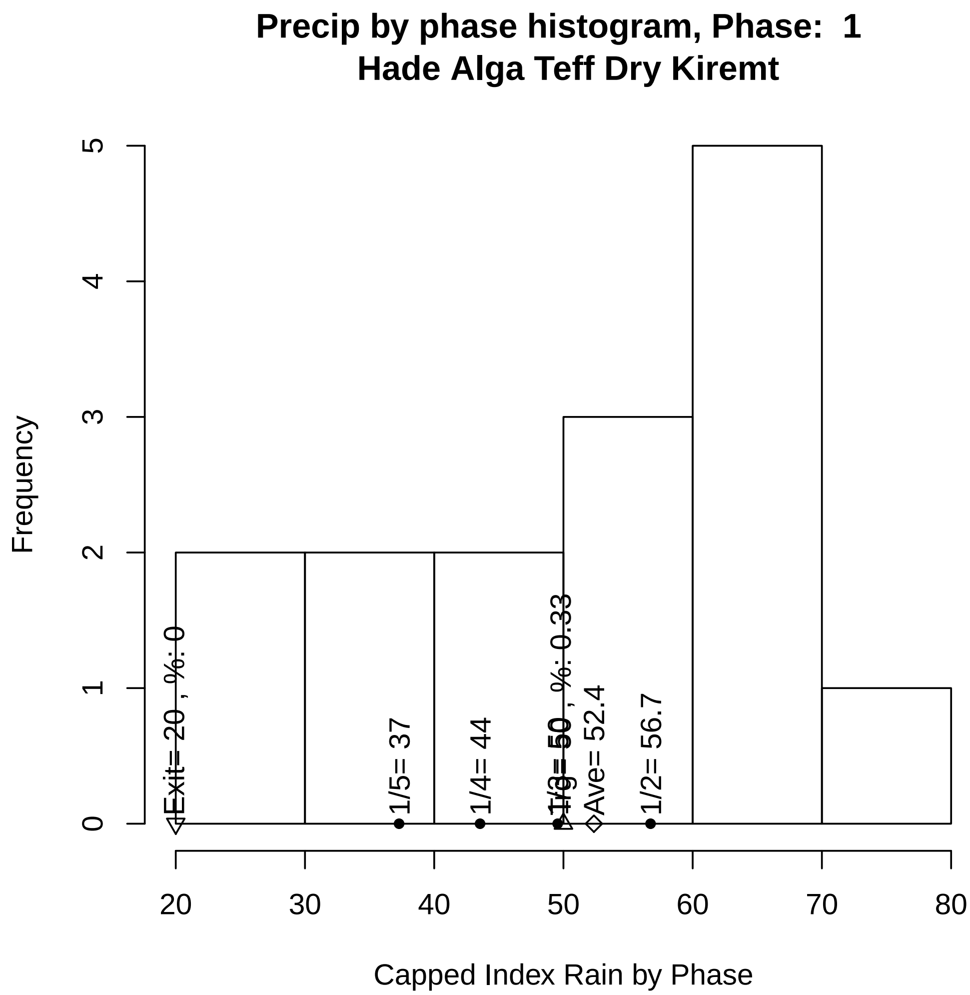


Figure 28: HadeAlgaTeffDryFinal-precipbyphase.pdf

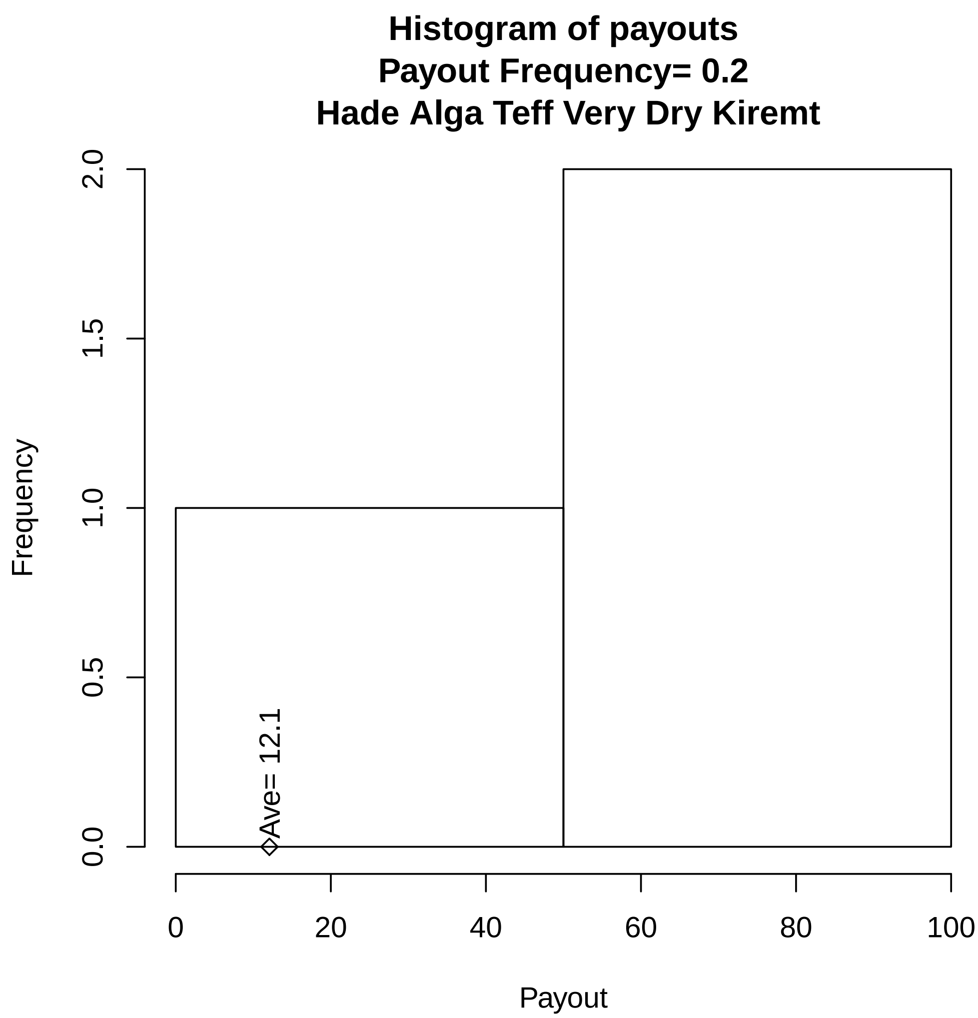


Figure 29: HadeAlgaTeffVeryDryFinal-payouthist.pdf

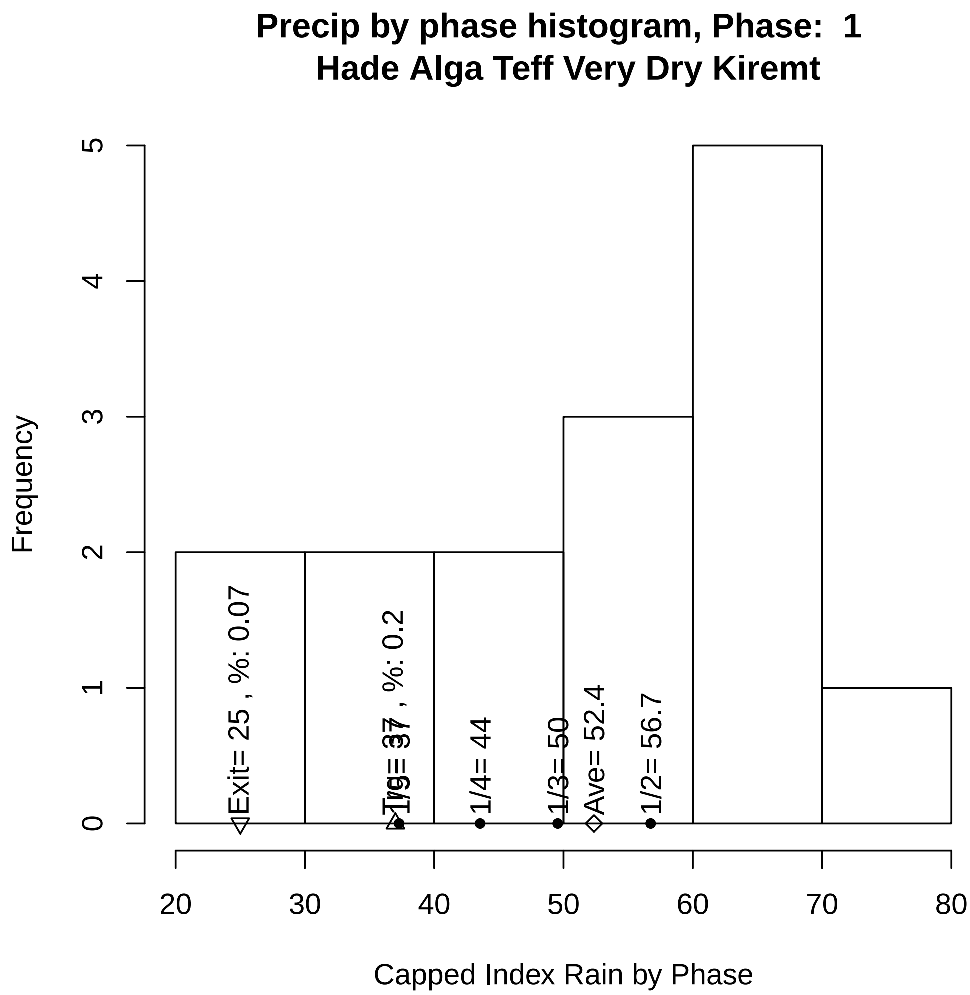


Figure 30: HadeAlgaTeffVeryDryFinal-precipbyphase.pdf

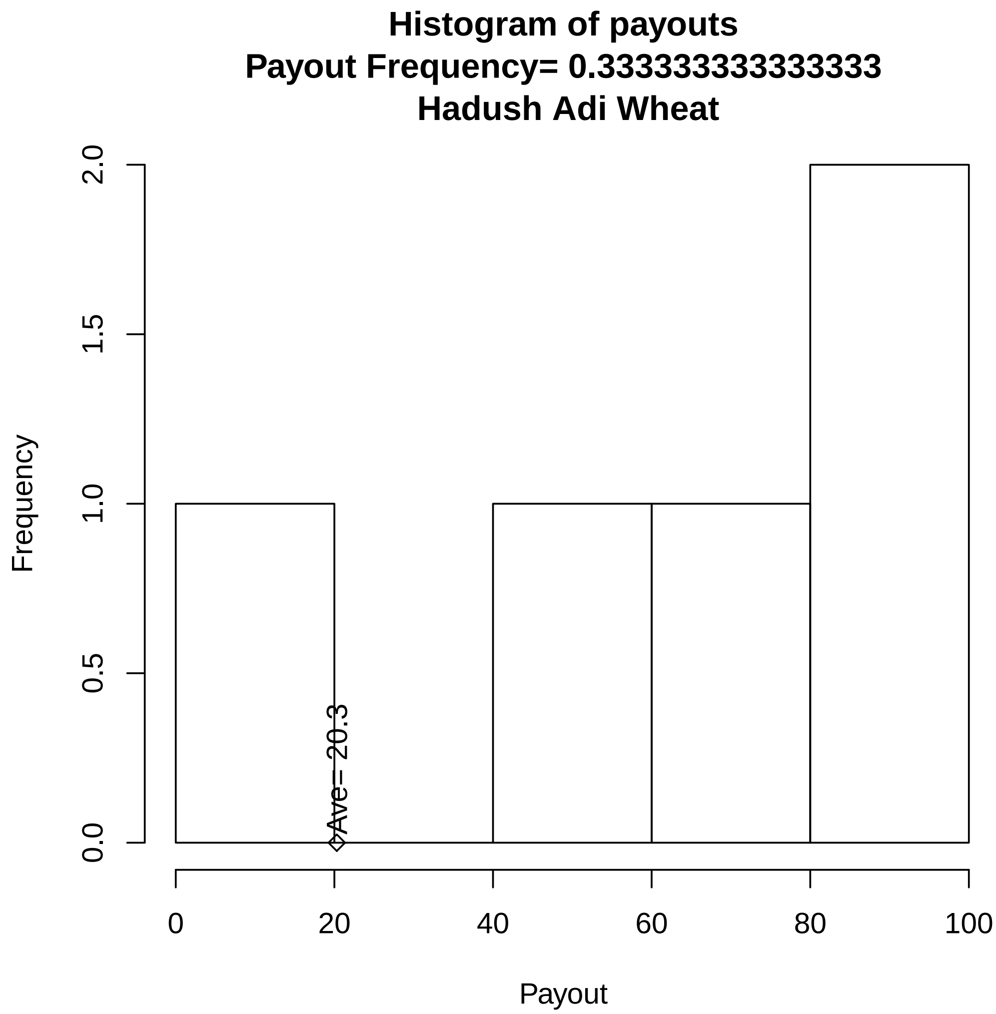
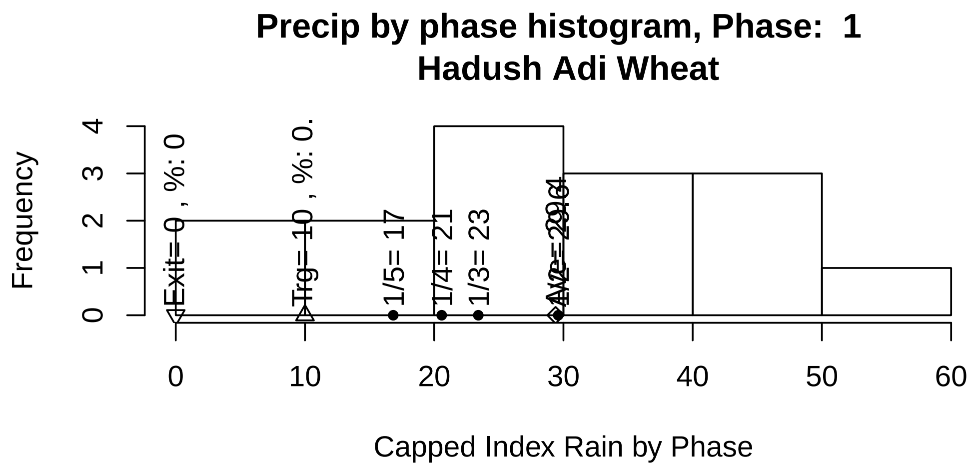


Figure 31: HadushAdiWheatDryFinal-payouthist.pdf



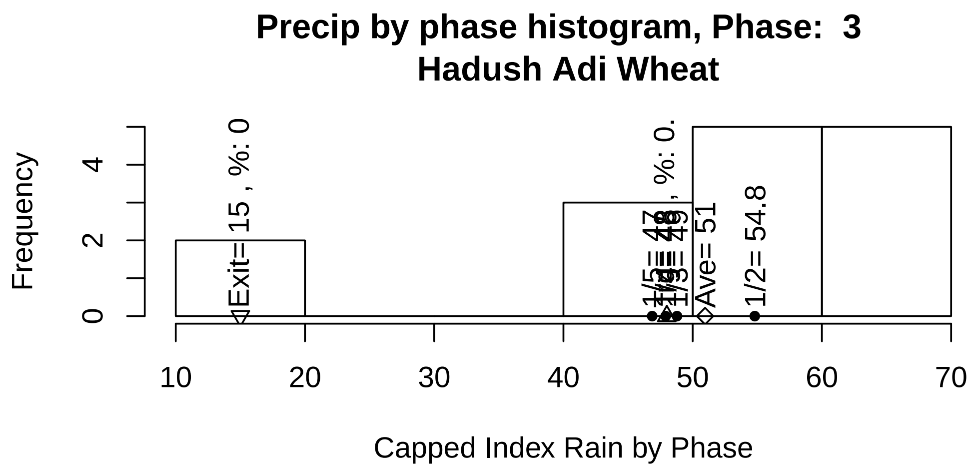


Figure 32: HadushAdiWheatDryFinal-precipbyphase.pdf

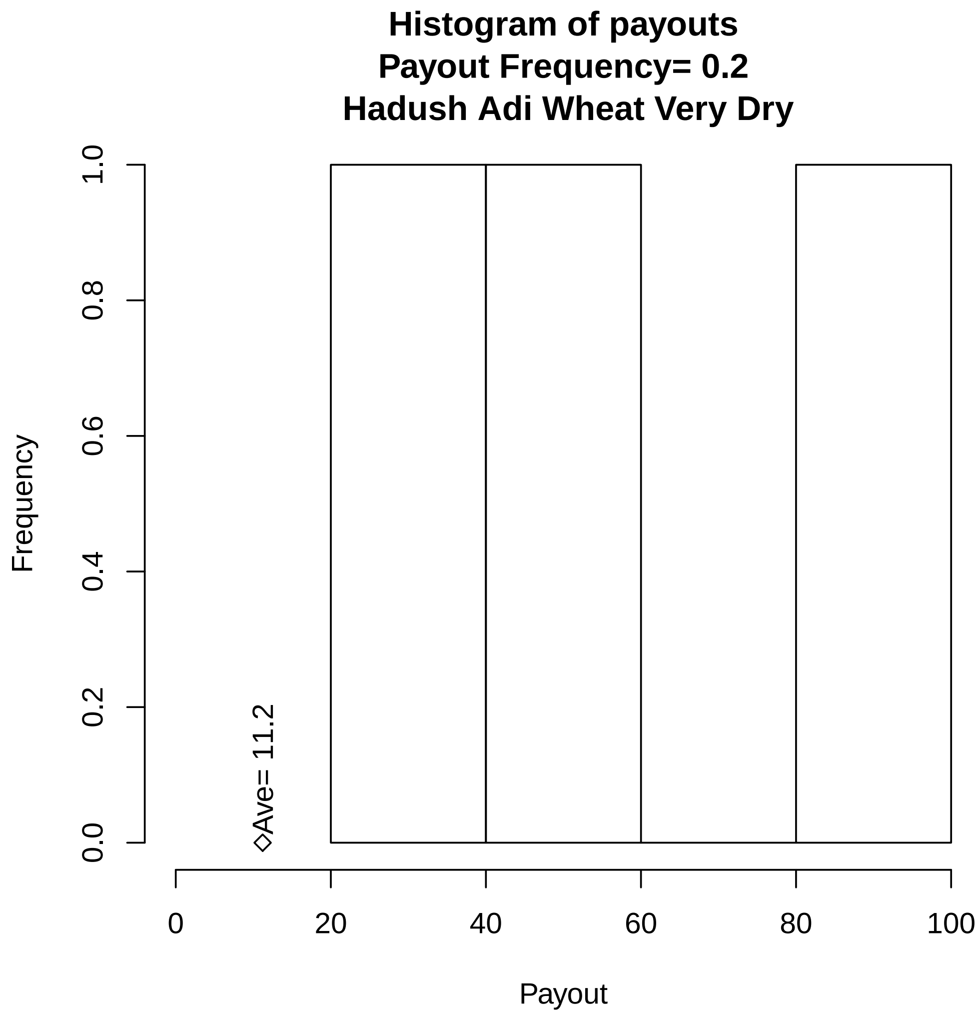
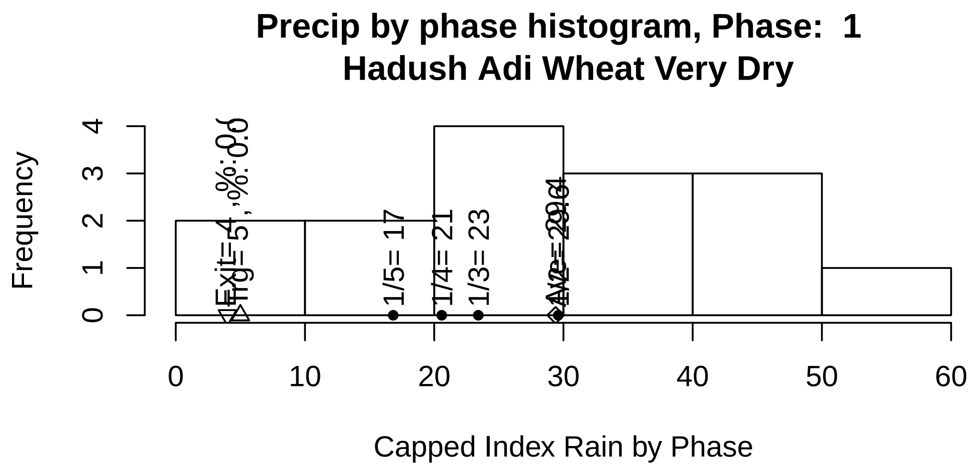


Figure 33: HadushAdiWheatVeryDryFinal-payouthist.pdf



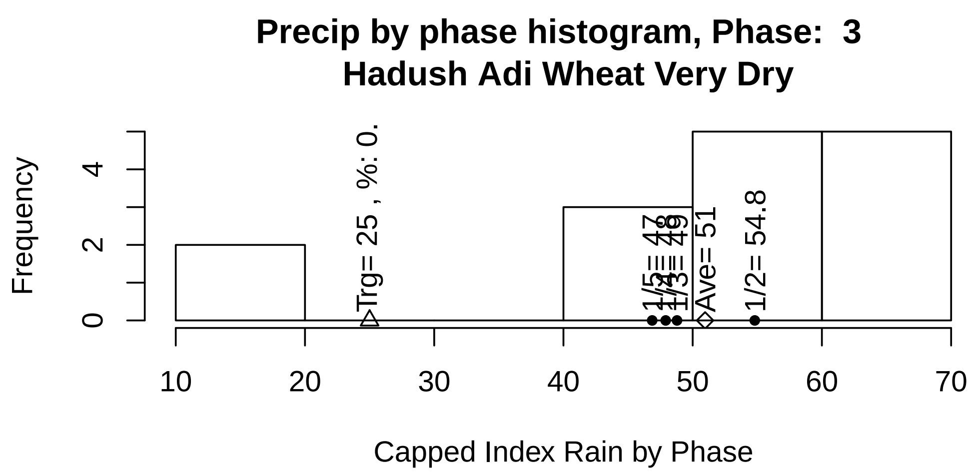


Figure 34: HadushAdiWheatVeryDryFinal-precipbyphase.pdf