
**E-ISSN:** 2618-0618
**P-ISSN:** 2618-060X

www.agronomyjournals.com
2024; SP-7(9): 873-877
Received: 06-07-2024
Accepted: 12-08-2024

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# Drought coping strategies: An exploration of determinants of adoption by qualitative response model

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**DOI:** https://doi.org/10.33545/2618060X.2024.v7.i9Sl.1624

**Abstract**
Coping mechanisms adopted by the farming community has recently become a subject of increasing importance in climate change research with an objective to reduce the vulnerability of climate sensitive activity. The present study was designed to develop the classificatory statistical model to catalogue the farmers into adopters and non-adopters. Further, the study also aims to identify the determinants of coping mechanisms adopted by the farmers to mitigate the impact of drought on their farming activity in Kolar district of Karnataka. The qualitative response models such as binary logistic regression analysis was carried out by considering the various socio-economic characteristics of farmers as predictors and adoption behavior of the farmers as response variable. The result illustrates that the predictors like age, education, farm size, extension visits, crop diversification, income status, liquid assets and crop insurance were statistically significant at 5% level of significance. The variables such as education (0.54), farm size (0.60), extension visits (1.71), crop diversification (1.96), income status (0.0015), liquid assets (0.0013) and crop insurance (0.0018) are positively influencing on adoption of drought coping mechanisms. Whereas the variable like age (-0.39) negatively influencing on adoption behavior of farmers.

**Keywords:** Logistic regression, drought coping strategies, adoption, hit rate, gamma statistics, accuracy rate, drought

## Introduction
The State of Karnataka has 72 percent of the cultivable area is rainfed and only 28 percent is under irrigation (GOK News, 2023). The State is the second largest in terms of arid region, next only to Rajasthan in India. The State faced consecutive droughts during the years 2001-02, 2002-03 and 2003-04 resulted in a sharp decline in agricultural output (Nagaratna and Sridhar, 2004) [7]. Drought stress is the major limiting factor for rice production and yield stability under the rainfed crop ecosystem (Meenakshi *et al*, 2015) [5]. Karnataka faces a high risk of moisture stress at maximum tillering and reproductive stages of the crop, which may lead to yield loss of 25 to 100 percent (Hanamaratti *et al*., 2008) [4].
Drought is a worst kind of natural disaster that happens slowly and causes huge loss to agriculture and live stock. It develops over a long period of time and covers a wide area. Drought has different dimensions and can be defined or viewed from different perspectives. The severity of drought is expressed in the form of biological degradation and socio-economic distress. Drought is usually understood as a period of dryness due to lack of rainfall. According to the water balance concept, drought is a physical condition in which the amount of water available from precipitation and soil moisture is insufficient to meet the demands of evapotranspiration. The drought-areas are characterized by excess of evaporation over actual rainfall. Kolar district is one of the biggest districts in Karnataka State and experiences recurrent drought conditions.
When drought occurs, the agricultural sector is usually the first to be affected. Even though the meteorological drought is over, the adverse economic impact of drought may persist for several years depending upon the nature of drought. For an instance, rice farmers suffer frequently from drought, they have evolved various strategies to cope with it. Based on the case studies and focus group discussions with farmers, the most commonly used adjustments in rice production practices during drought years are allocating more area to short-duration varieties, switching

from transplanting to direct seeding, switching to traditional varieties which are considered to be more drought-resistant, etc (Serraj, *et al*, 2008; Meenakshi *et al*, 2015) [10, 5]. The objective of the study was to identify the determinants of the adoption of drought coping mechanisms in order to balance and stabilize the farm income of the stakeholders. The study also helps to know how to mitigate the effect of drought on farmers' livelihood.

**Reason for selection of Kolar district as a study area**

Kolar region was one of the drought prone areas in eastern dry zone of Karnataka where most of the farmers were involved in rainfed agriculture. Kolar district was purposively selected based on important parameters like rainfall distribution, Analysis of the rainfall distribution showed that there was a 50 percent probability of occurrence of drought in Kolar district than in any other districts of southern Karnataka. Hence adoption of certain coping strategies against drought in this region is the major solution to stabilize the farm income during the drought period.

The drought occurs in Kolar district is majorly contingent drought, this occurs in climates which have rainfall of an irregular and variable type. Because Kolar district falls in rain shadow region of monsoon flow and located far away from the coastal zone, hence drought is more prevalent there and precipitation occurrence is less. However the district also stands frontline in dairy farming and live-stock rearing which leads to dairy products. Alternative solutions based on scientific assessment of land and water resources are essential to mitigate the losses from recurrent drought (Nagendra M and Ashok Hanjagi, 2019) [8].

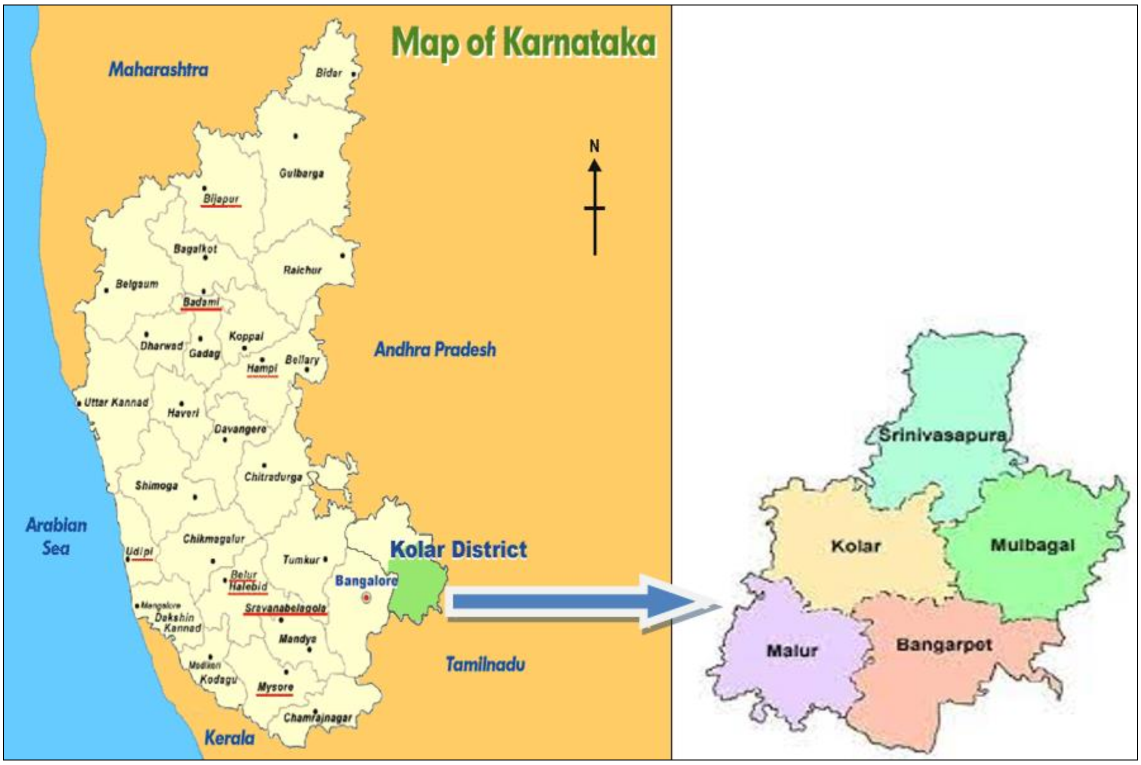


**Fig 1:** Karnataka Map highlighting the Kolar District and the taluk list

**Scope and Objective of the study**

Outcome of the study would be useful to the policy makers to implement drought relief programmes during the drought periods depending upon the intensity of drought and its impact on levels of income and productivity. Identification of factors determining the adoption of drought coping strategies would be helpful to focus more on the factors to speed up the adoption rate. In order to mitigate the effect of drought and stabilize the farm income in Kolar district of Karnataka, the objective of the study has been framed and the study aims to determine and analyze the factors influencing on adoption of drought coping mechanisms.

**The role of fitting logistic regression**

One of the problems of classification lies in the use of appropriate methods to fit the model depending on the nature of the data. It is well known that most of the data related to the adoption of any agriculture technology are ending up with qualitative response variables with two or more categories, which is a problem when using the traditional statistical methods, such as linear regression analysis because of not satisfying the assumptions of quantitative regressand (Halagundegowda *et al*, 2018) [2]. In such a case to measure the farmer's perception towards adoption of particular agriculture technology for evaluating the binary classification problems, logistic regression is a most powerful tool, because it accommodates all kinds of variables (both qualitative and quantitative variables) in the model. In addition to the above advantage, it is robust and void of all kinds of restrictions or assumptions to use.

**Materials and Methods**

The household data were recorded on socio-economic characters of farmers of Kolar district of Karnataka (India). The data is mainly related to coping strategies implemented against drought by the farmers of this region and was collected by employing the multi stage sampling design. The total sample size (farmers) is 150, to develop the model, it is necessary to split the set of data in two different subsets. Therefore, the training data, which consists of 80% of respondents (120 farmers) and test data consists remaining 20% respondents (30 farmers). Before training the model each attributes are normalized to zero mean and unit variances, which will improve performance of the model as well as cut down the learning time. The following table gives the variable of interest and the unit of measurement used in this study.

**Table 1:** Variables Encoding Summary

| Code | Variables | Measurement |
|---|---|---|
| Y | Adoption behavior | Y= 0 for Non-Adopters = 1 for Adopters |
| $X_1$ | Age of the farmer | Number of years |
| $X_2$ | Education of the farmer | Formal Years of Education |
| $X_3$ | Household Size | Number of family members |
| $X_4$ | Farm Size | Number of acre's |
| $X_5$ | Farming Experience | Number of years |
| $X_6$ | Animal Husbandry | Number of farm animals |
| $X_7$ | Media Exposure | Number of sources exposed frequently |
| $X_8$ | Extension Visits | Number of Visits |
| $X_9$ | Crop Diversification | Number of Crops Grown in that year |
| $X_{10}$ | Income Status | In Rupees (Rs.) |
| $X_{11}$ | Worth of Liquid Assets | In Rupees (Rs.) |
| $X_{12}$ | Crop Insurance by Government | In Rupees (Rs.) |

**Logistic Regression Model**

The Logistic response function resembles an S-shape curve where the probability $\pi$ initially increases slowly with increase in X, and then the increase accelerates, finally stabilizes, but does not increase beyond 1. The probability of willingness to adopt drought coping mechanisms approaches zero at slower and slower rate, as Xi becomes small and the probability approaches one at slower and slower rate as Xi becomes large. Since, Pi = E (Yi) = 1 (given Xi) non linearly increases with Xi, let us consider Pi to be a logistic function of Zi, given by

$$P_i = \frac{1}{[1 + e^{(-Z_i)}]}$$

Where $z_i = A + \sum B_i X_i$

Taking logarithm of this odds ratio to the base e, we will get,

$$\text{Log}\,[P_i/(1 - P_i)] = Z = A + \sum B_i X_i + U_i$$

Here, Log [Pi/ (1 – Pi)] is called the logit or the log of odds ratio. It follows logistical distribution. Here to find out the probability of willingness to adopt coping strategies, the mean of all the variables taken and multiplied with their respective co-efficient to get the Zi.

Estimation and testing are two important aspects of regression analysis. The usual method of estimation under logistic regression is maximum likelihood estimation method (MLE). In the present study Wald test and Likelihood Ratio tests have been used for testing the overall significance of the logistic regression model. The Hosmer-Lemeshow test used to assess goodness-of-fit of the final model. Further, once models are fitted and relevant goodness of fit measures are employed, judging the predictive ability of the model can be done. In Classification statistical modeling setup, predictive ability of models can be judged by employing various measures such as Somers'D, Gamma Statistics, Kappa statistics, Accuracy ratios, Kendall's Tau (Tau-a) and c.

**Results and Discussion**

The data recorded on adoption behavior of drought coping strategies across various socio-economic characters of farmers were analyzed using binary logistic regression. The logistic regression works on the principle of computation of probability for each respondent based on the agro economic attributes of farmers. The maximum likelihood model, in which the intercept is included without any predictor variables, such model is called Intercept Model or Null Model. This is basically interesting to calculate the Pseudo $R^2$ that describes the goodness of fit for the logistic model, whereas full model considers all the explanatory variables in the equation along with constant. Here, the analytical framework carried out only for full model.

**Table 2:** Model Summary

| -2 Log likelihood | Cox & Snell R Square | Nagelkerke R Square |
|---|---|---|
| 10.057 | 0.816 | 0.837 |
| **Hosmer and Lemeshow Test** | | |
| **Chi-square** | **DF** | **Sig.** |
| 0.162 | 8 | 0.398 |

Table 2 shows the model summary which provides the -2LL and pseudo-$R^2$ values for the full model. The -2LL value for this model (10.057) which is less compared to the -2LL for the null model (25.623), it depicts that there was a significant decrease in the -2LL from null or Intercept model to full model, that means the full model is significantly better fit than the null model. Lesser the value of -2LL statistics (near to 0) will yields greater fit and vice versa. The current model is good fit and it is potential enough to track the classification accuracy.

The R-Square statistics cannot be computed for logistic regression model or any other qualitative response models, so these approximations are computed instead, pseudo $R^2$ values tell us approximately how much variation in the outcome is explained by the model (like in linear regression analysis). It's prefer to use the Nagelkerke's $R^2$ and Cox and Snell $R^2$ among the family of pseudo $R^2$ and the result indicates that the model explains roughly 83.7% and 81.6% of the variation in the outcome respectively and infer that the model has greater fit. The Hosmer and Lemeshow test result are acceptable $\chi^2$ (8) = 0.162, p = 0.398, which indicates our model predicts events which are not significantly different from observed events, so accept the null hypothesis and which indicates good fit. The stated null hypothesis is "there is association between observed and predicted events".

Table 3 shows the maximum likelihood estimates of logistic regression model, their standard errors and Wald test statistic, the exponential value of coefficient (odds ratio) and their interval estimates. The table provides the influence of each independent variable on dependent variable. The predictors like age, education, farm size, extension visits, crop diversification, income status, liquid assets and crop insurance are statistically significant at 5% level of significance. All predictors are having significant positive relation with dependent variable (adoption behavior) except age variable which is having negative relation.

The interpretation of each coefficient is based on odds is as follows, for predictor like education (Wald= 3.7, P=0.044, Exp (B) = 1.719) having positive significant relation with adoption behaviour of farmers. If one formal year of education increases among farmers then on an average estimated odds of adoption will increases by 1.719 units. Farm Size (Wald= 6.29, P=0.012, Exp (B) = 1.821): if one acre of farm land increases then on an average estimated odds of adoption of drought coping strategies will increased by 1.821 times.

**Table 3:** MLE estimates for variables in the equation

| Variables | B | S.E. | Wald | Sig. | Exp(B) |
|---|---|---|---|---|---|
| Age | -0.39 | 0.16 | 5.45* | 0.020* | 0.673 |
| Education | 0.54 | 0.28 | 3.71* | 0.044* | 1.719 |
| Household Size | 0.002 | 0.28 | 0.00 | 0.993 | 1.002 |
| Farm Size | 0.60 | 0.23 | 6.29* | 0.012* | 1.821 |
| Farming Experience | -0.14 | 0.10 | 1.87 | 0.170 | 0.862 |
| Animal Husbandry | 0.02 | 0.07 | 0.08 | 0.771 | 1.022 |
| Media Exposure | 0.22 | 0.23 | 0.88 | 0.346 | 1.245 |
| Ext Visits | 1.71 | 0.70 | 5.94* | 0.015* | 5.546 |
| Crop Diversification | 1.96 | 1.03 | 3.64* | 0.026* | 7.166 |
| Income Status | 0.001 | 0.00 | 5.84* | 0.016* | 1.000 |
| Liquid Assets | 0.001 | 0.00 | 2.80* | 0.034* | 1.000 |
| Crop Insurance | 0.001 | 0.00 | 2.90* | 0.048* | 1.000 |
| Constant | -27.1 | 13.3 | 4.09* | 0.043* | 0.000 |

The variable Extension visits (Wald= 5.94, P=0.015, Exp (B) = 5.54): if one visit of extension activity increases then on an average estimated odds of adoption of drought coping strategies will significantly increase by 5.54 times. crop diversification (Wald= 3.64, P=0.026, Exp (B) = 7.16): if one extra crop grown in the farm then on an average estimated odds of adoption of drought coping strategies will significantly increase by 5.54 times. Income status (Wald= 5.84, P=0.016, Exp (B) = 1.00): if one rupee increase in the farm income then on an average estimated odds of adoption of drought coping strategies will significantly increase by 1times.

The variable Liquid assets (Wald= 2.80, P=0.034, Exp (B) = 1.00): if one rupee worth increase as a liquid asset then on an average estimated odds of adoption of drought coping strategies will significantly increase by 1times. crop insurance (Wald= 2.90, P=0.048, Exp (B) = 1.00): if one extra rupee got as a crop insurance then on an average estimated odds of adoption of drought coping strategies will significantly increase by1times. The table also provides negatively significant coefficients such as age and intercept, age (Wald= 5.45, P=0.02, Exp (B) = 0.67) if one year increase in the age of farmers then on an average estimated odds of adoption of drought coping strategies will significantly decrease by 0.54 times. The other literature on adoption of drought coping strategies, Francis Ndamani *et al* (2016) [1], Stephen Abugri *et al* (2020) [11] and Mequannt Marie *et al* (2020) [6] are used logistic regression and depicted that education, household size, annual household income, access to information, credit and membership of farmer-based organization are the most important factors that influence farmers' adaptation to drought coping strategies.

Table 4 provides the classification matrix for both training data set and testing data set, the classification matrix helps to assess the performance of the model by cross tabulating the observed response categories with the predicted response categories and shows how well our full model correctly classifies the cases. The rules works for each case such that the predicted response is the category treated as 1, if that category's predicted probability is greater than the user-specified cut-off (0.5), otherwise it's treated as 0.

**Table 4:** Classification matrix

| Sample | Observed | Predicted | | |
|---|---|---|---|---|
| | | Non Adopters | Adopters | Percent Correct |
| Training Set | Non-Adopters | 47 | 3 | 94.00% |
| | Adopters | 1 | 69 | 98.57% |
| | Overall Percent | | | 96.28% |
| Testing Set | Non-Adopters | 10 | 2 | 82.33% |
| | Adopters | 5 | 13 | 71.22% |
| | Overall Percent | | | 76.67% |

A perfect model would only have values in the diagonal correctly classifying all cases. Adding across the rows represents the number of cases in each category in the actual data and adding down the columns represents the number of cases in each category as classified by the full model. In case of training data set out of 50 non-adopters cases 47 cases are correctly categorized as non-adopters and remaining 3 cases are wrongly classified in to adopters section which means 94% accuracy for non-adopters and in the same way out of 70 adopters cases 69 respondents are correctly categorized as adopters and only one respondent is mismatched and grouped in to non-adopters section, which means 98.57% accuracy for adopters.

The key piece of information is the overall percentage in the lower right corner which shows our model (with all predictors & the constant) is 96.28% accurate and which is excellent. One way of assessing the model's fit is to compare the overall percentage in the full model's table (96.28%) to the overall percentage in the null model table (58.3%). The remarkable improvement in full model over null model may due to the effect of potential predictors on responses.

The testing data set, 10 non-adopter cases out of 12 instances are correctly categorized as non-adopters and only 2 cases were wrongly classified in to adopters section which means 82.33% accuracy for non-adopters and in the same way out of 18 adopters cases 13 respondents are correctly categorized as adopters and only 5 respondent is mismatched and grouped in to non-adopters section, which means 71.22% accuracy for adopters. The overall percentage of accuracy is 76.67%. The result of both training and testing classification matrix facilitate to compare the efficiency and classification ability of the model. The comparison made with consideration of the overall percentage of accuracy and the result of training data is quite good. Comparatively the training data shows 96.28% accurate than the testing data set (76.67%). When we take in to consideration of all factors and in broad view there is much difference in the result of training and testing set. When consider the overall performance of the model, which is not good in prediction and classification.

**Table 5:** Assessment of classification and prediction ability of Logistic Regression

| Classification Measures | | | | |
|---|---|---|---|---|
| **Statistics** | **Training Data** | | **Testing Data** | |
| | **Proportion** | **%** | **Proportion** | **%** |
| Hit rate | 0.9628 | 96.28 | 0.7667 | 76.67 |
| **Sensitivity** | 0.9857 | 98.57 | 0.7122 | 71.22 |
| Specificity | 0.9400 | 94.00 | 0.8333 | 83.33 |
| False Positive Rate | 0.0143 | 01.43 | 0.2878 | 28.78 |
| False Negative rate | 0.0600 | 06.00 | 0.1667 | 16.67 |
| **Prediction Measures** | | | | |
| **Statistics** | **Training Data** | | **Testing Data** | |
| Gamma | 0.9384 | | 0.5363 | |
| Somer's D | 0.9372 | | 0.5398 | |
| Kappa Statistics | 0.9394 | | 0.5213 | |
| Accuracy rate | 96.28 (%) | | 76.67 (%) | |

The table 5 provides the classification and prediction ability of the model, where the model with high hit rate, sensitivity, specificity and low false positive rate, low false negative rate considered as best model for classification purpose. Whereas the model with high Gamma statistics or high Kappa or high Somer's D or Accuracy rate were considered as best model for prediction purpose. The result shows good classification measures such as high hit rate, sensitivity, specificity, low false positive rate and low false negative rate. Further, the model poses high Gamma statistics, Kappa, Somer's D and high Accuracy rate (>70%), hence the selected logistic regression model possess good prediction ability.

## Conclusion

Adoption of drought coping strategies is considered as categorical response variable and it's a psychological perception, in which farmers deciding whether to adopt the strategies or not. This process is affected by various socio economic, agro ecological, institutional and resource based factors. Logistic regression was fitted to predict and identify the factors influencing on adoption of drought coping strategies by the farmers in the study area. The result illustrates that the predictors like age, education, farm size, extension visits, crop diversification, income status, liquid assets and crop insurance were significantly contributing for adoption of coping mechanisms. The variables such as education, farm size, extension visits, crop diversification, income status, liquid assets and crop insurance are act as positive drivers and the variable like age is negatively influencing on adoption of drought coping mechanisms by the farmers.

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