THE LEVEL OF UNDER REPORTING OF CATCH AND EFFORT DATA IN LOGBOOKS AMONG LARGESCALE FISHERS ON LAKE MALAWI

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Abstract

Accurate fisheries data are fundamental to fisheries management. This ensures accurate stock assessments and equitable allocation of fishing quotas, eventually leading to sustainable fisheries management. In many low- and middle-income countries, such as Malawi, fisheries statistics of commercial or large-scale fisheries rely heavily on secondary reporting systems, such as logbooks maintained by the Government through Department of Fisheries. There have been reports that large-scale fishers underreport catch and effort data in their logbooks submitted to the Department of Fisheries (Government of Malawi). This study was conducted among large-scale fishers to assess the level of underreporting of catch and effort data in logbooks. Data on catch and effort were collected from large-scale fishers in the 2023 fishing season (primary data) and compared with historical data (secondary data) from the same period on catch and effort obtained from logbooks at the Department of Fisheries.

The density plots and Q-Q plot of the secondary and primary catch data were normally distributed. The Shapiro-Wilk p-values of the secondary and primary catch data showed that the datasets were normally distributed, with p-values of 0.2871 and 0.8355, respectively. The boxplot showed that the primary catch data had a higher mean, wider standard error, and range than the secondary catch data. The two-sample t-test showed a p-value of 0.2359, implying that there was no significant difference between the two groups, although physical observation of the two dataset means in the boxplot showed that the primary data was higher than the secondary data. This difference could be a result of variability in the data collection methods.

However, to make the comparison more robust and comprehensive with the Monte Carlo machine-learning approach, nonparametric methods (permutations and bootstraps) that work well even with normally distributed data were employed. The p-value obtained from the permutation test (0.202) indicated that the two datasets were not significantly different, implying that the observed physical differences between the groups could be random.

The original bootstrap statistics were approximately -959.8, with a standard error of approximately 728.28, indicating that, on average, the secondary catch data were lower than the primary catch data by approximately 960 units. The large standard error indicates that there could be substantial sampling variability, which should be studied and improved, especially in the secondary catch data. The CI included zero, suggesting that the observed difference in means was not statistically significant at the 5% level. While the point estimate was negative, the broad CI shows that the effect might be negligible or even in the opposite direction,

depending on how each of the datasets was collected. This implies that the claims that commercial fishers in Malawi underreport the logbooks submitted to the Department of Fisheries may not be true or significant. Primary data verification was performed by comparing the data with what the fish traders reported having bought from individual fishers. It would be ideal to license fish traders to collect data from them, which could be used to validate the logbooks submitted by fishers to the Department of Fisheries.

INTRODUCTION

Accurate fisheries data are fundamental to fisheries management. This ensures accurate stock assessments and equitable allocation of fishing quotas, eventually leading to sustainable fisheries management. In many low- and middle-income countries, such as Malawi, fisheries statistics of commercial or large-scale fisheries rely heavily on secondary reporting systems, such as logbooks maintained by the Government through Department of Fisheries. Although this system is easy to implement and cost-effective, it often does not provide accurate data, as it is based on self-reporting, not regular supervision, with a very limited validation mechanism. Most licence holders do not submit their monthly catch returns, while those who do submit usually under-report their catches. This makes the estimation of the total annual catch and effort for the sector and the computation of catch per unit effort (CPUE) inaccurate (1). Inaccurate data and information can have serious implications, as management may mistake catches by the sector for being within the maximum sustainable yield (MSY) levels when they are not. There is a need to address these challenges in the implementation of commercial fishery strategies in Malawi to support evidence-based policies and guard against the overexploitation of fish stocks.

This study evaluated the accuracy of secondary fisheries data reported to the Department of Fisheries in Malawi. This was done by directly comparing these records with primary catch and effort datasets collected in three districts (Mangochi, Salima, and Nkhotakota) over the May–November 2023 fishing season. Well-trained technical assistants from the Department of Fisheries with years of experience in small scall fisheries (Catch Assessment Survey (CAS)) were used to collect this data daily at the designated landing sites of the large-scale fishers. The Government of Malawi, through the Department of Fisheries, allocates large-scale fishers to specific landing sites in fishing licences (2; 3; 4). This was cross-validated by the fishing day activity in the Department's Vessel Monitoring System (VMS), where available. The study applied Inferential statistics (independent-samples t-test), effect size estimation (Cohen's d), and resampling-based approaches (bootstrap and permutation Monte Carlo simulations) were used to quantify the differences between the two data sources. The objective was to identify fisheries data reporting gaps in large-scale data management at the Department of Fisheries. This will strengthen the large-scale fisheries data systems in Malawi by providing evidence-based recommendations.

METHODOLOGY

Data source and collection method

Catch and effort data were collected from fishing vessels in Mangochi, Salima, and Nkhotakota between May and November 2023. These data were compared with those for the same period obtained from the Department of Fisheries to determine their accuracy.

Methods

The catch and effort data on fishing days were collected by technical field assistance for the areas and their BVCs. They were incentivized to commit to data collection. These data were collected daily at each landing site by commercial fishers. Where possible, the data on fishing days were validated by the monthly fishing days observed on the VMS platform at the Department of Fisheries. Later, the collected catch and effort data were compared with the catch and effort data reported by the Department of Fisheries from the fishing logbooks. An independent samples t-test was used to compare the means of the two datasets. The assumptions to be satisfied were the normality of the data; the dependent variable was measured on a continuous scale with homogeneity of variance (5). The data were fitted to the following model to assess any significant differences between the two datasets:

$$t = \frac{\mu_A - \mu_B}{\sqrt{\left[\frac{\left(\Sigma A^2 - \frac{(\Sigma A)^2}{n_A}\right) + \left(\Sigma B^2 - \frac{(\Sigma B)^2}{n_B}\right)}{n_A + n_B - 2}\right] \cdot \left[\frac{1}{n_A} + \frac{1}{n_B}\right]}}$$

Where:

$(\Sigma A)^2$ is the sum of the squared values of dataset A.

$(\Sigma B)^2$ is the sum of the squared values of dataset B.

μA is the mean of dataset A, and

μB is the mean of dataset B.

ΣA^2 is the sum of the squares of data set A

ΣB^2 is the sum of the squares of Dataset B.

nA is the number of items in data set A

nB is the number of items in dataset B.

The Monte Carlo approach was also used. This was done by applying simulations using permutation and bootstrapping to compare the secondary and primary catch data. Cohen's d that the study also used was meant to quantify the standardized difference between group means to understand any practical significance of observed differences between secondary and primary catch data (6).

The bootstrap method involves repeated resampling with replacement from the observed primary and secondary catch datasets. This eventually creates a large number of simulated samples, called bootstrap samples. This allowed estimation of the sampling distribution of a statistic (e.g., mean, median) without making strong parametric assumptions about the underlying population (7).

The nonparametric bootstrap method was used to compare the mean catch of the two groups and involved resampling 10,000 times with replacement from the observed data to approximate the sampling distribution of the estimator. The resampling was repeated several times to build a robust empirical distribution (8). The permutation test employed in this study is a nonparametric method that rearranges the observed secondary and primary catch data points to create a distribution of the test statistics, such as means. This was used to test the null hypothesis that the means of the two datasets were the same. The comparison of the distribution of the observed test statistics assisted in assessing the significance of the observed difference between the secondary and primary catch datasets (9).

RESULTS

The density plots of the two datasets (Secondary and Primary catch data) were normally distributed. However, the primary catch data had larger catch values than the secondary catch data (Fig. 1).

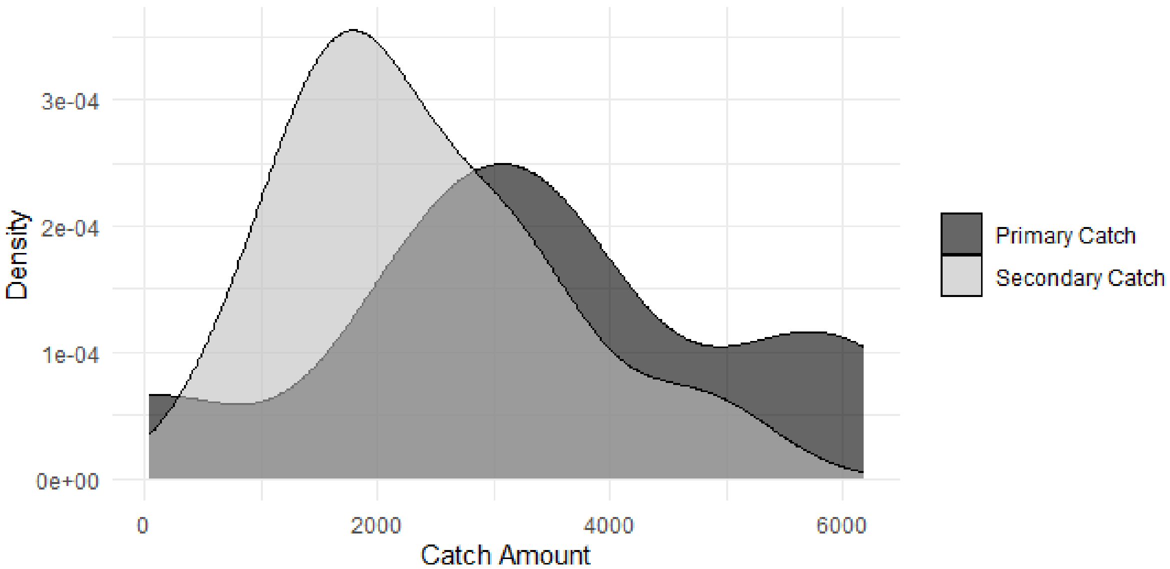

Fig. 1: Density plot of catch from primary and secondary data.

The Q-Q plot also shows that the data points were close to the normality line for both A (secondary catch data) and B (primary catch data), as shown in Fig. 2.

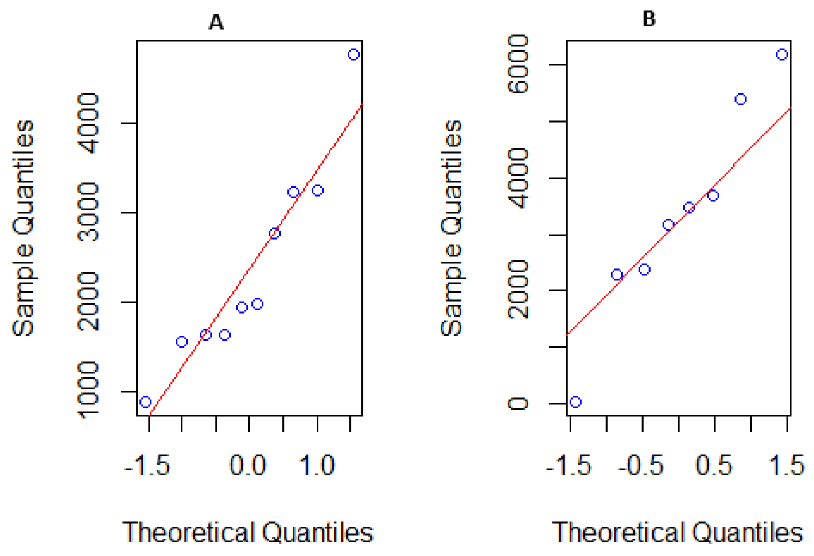

Fig. 2: Q-Q plot of catch from primary and secondary data.

The boxplot in Fig. 3 shows that the primary catch data had a higher mean than the secondary catch data. The primary catch data also showed a wider standard error and range than the secondary catch data.

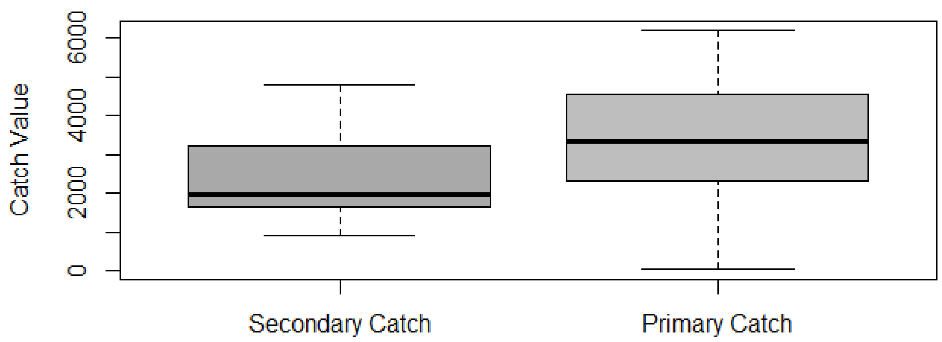

Fig. 3: Box plot of catch data from primary and secondary sources.

The histogram in Fig. 4 shows the bootstrap distributions for the two datasets. The original estimate is represented by a red line. The confidence interval (CI) bounds are indicated by the vertical blue dashed lines.

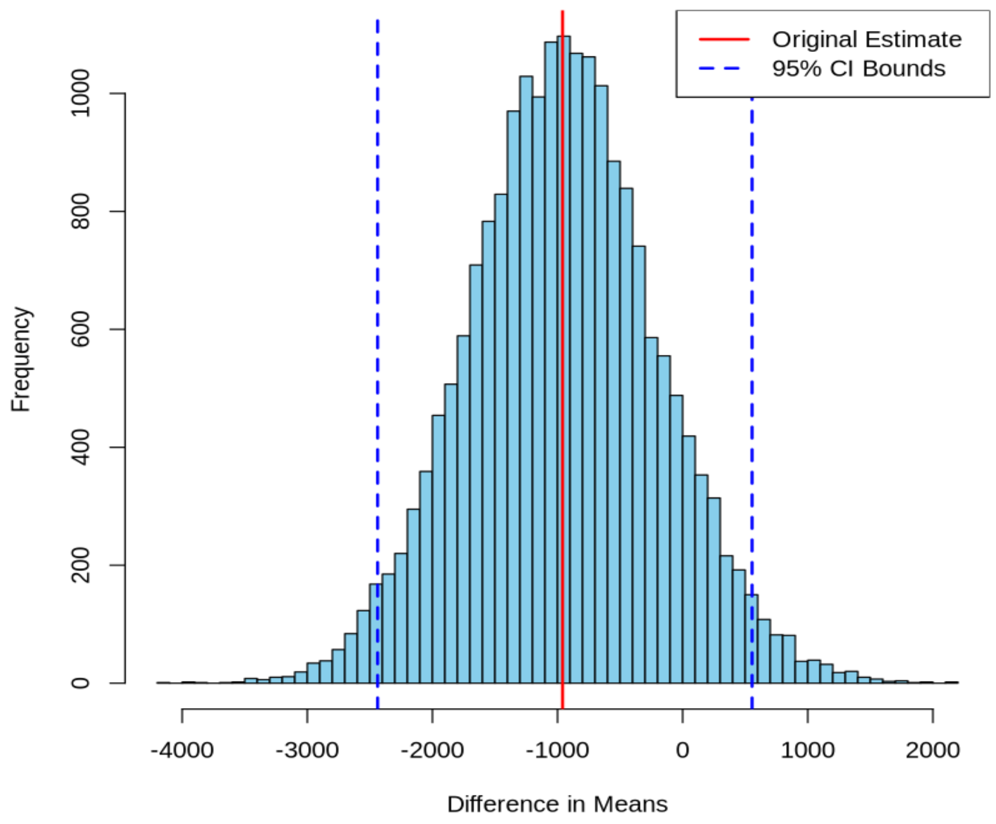

Fig. 4: Bootstrap distribution of mean difference of secondary and primary catch data

This study employed a nonparametric permutation method to compare the two datasets. The bold vertical line represents the value of the observed test statistic, as shown in Fig. 5. The permutation test showed that the difference between the means was not statistically significant ($p = 0.202$), as shown in Table 1.

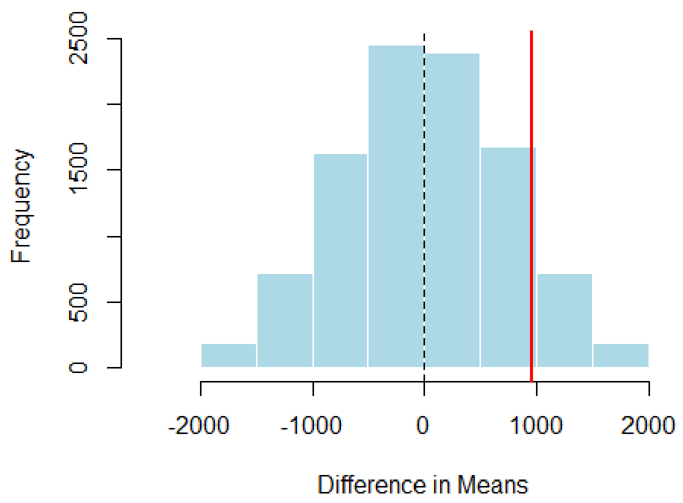

Fig. 5: Histogram of values of test statistic for 1000 permutation with a bold vertical line of value of observed test statistic of secondary and primary catch data

Several test statistics of both parametric and nonparametric methods used to compare secondary and primary catch data are listed in Table 1. These statistics were used to compare the two datasets.

Table 1: Statistics of comparison of secondary and primary catch data of commercial fishery in Malawi

Statistic	Secondary Catch	Primary Catch	Combined
Sample Size (n)	10	8	18
Mean Catch	2372.49	3332.28	NA
Standard Deviation	1140.79	1908.28	NA
Shapiro-Wilk Test (W)	0.91	0.96	NA
Shapiro-Wilk p-value	0.29	0.84	NA
Effect Size (Cohen's d)	NA	NA	0.63
Cohen's d 95% CI Lower	NA	NA	-0.4
Cohen's d 95% CI Upper	NA	NA	1.66
Mean Difference (Primary - Secondary)	NA	NA	959.7956
Mann-Whitney U test: p-value	NA	NA	0.1457
Min	895	38.92	NA
1^{st} Q	1641	2363	NA
Median	1963	3330.42	NA
3^{rd} Q	3127	4115.71	NA
Max	4776	6186.84	NA
Two-sample t-test 95% CI Lower	NA	NA	-2645.92
Two-sample t-test 95% CI Upper	NA	NA	726.32
Two-sample t-test p-value	NA	NA	0.24
Boot strap resampling	20000	20000	NA
Boot strap 95% CI Lower	NA	NA	-2438.1
Boot strap 95% CI Upper	NA	NA	554.7
Permutation sample size	1000	1000	NA
Permutation Test p-value (two sided)	NA	NA	0.202

DISCUSSION

The difference in the means of the secondary and primary catch data was the parameter of interest in this study. The density (Fig. 1) and Q-Q plots (Fig. 2) of each group indicated that they were approximately normally distributed. The Shapiro-Wilk *p*-values of the secondary and primary catch data showed that the datasets were normally distributed, as indicated in Table 1, with *p*-values of 0.2871 and 0.8355, respectively. This scenario necessitated the use of parametric methods to compare the two groups. The two-sample t-test showed a *p*-value of 0.2359, implying that there was no significant difference between the two groups, although physical observation of the two dataset means in the boxplot in Fig. 3 shows that the primary data were higher than the secondary data. This difference could be a result of variability in the data collection methods.

However, to make the comparison more robust and comprehensive with the Monte Carlo machine-learning approach, nonparametric methods that work well even with normally distributed data were employed. These methods were permutations and bootstraps for simulating the two datasets.

In the analysis, the mean difference between the primary and secondary catch data groups was calculated, and a permutation test was performed to determine if the groups were statistically significant, as portrayed by the t-test above. The *p*-value obtained from the permutation test indicated whether the observed differences between the groups were random. The permutation test results showed a *p*-value of approximately 0.202. This suggests that the difference in means between the secondary and primary catch data of the two groups was not statistically significant at the 0.05 level. The distribution of the test statistics of 1000 permutations shows that it is more probable to obtain the observed test statistic or lower values (Fig. 5). As such, there is insufficient evidence to reject the null hypothesis that there is no difference in catch or accuracy between the two groups; hence, reports of underreporting by commercial fishers may not be entirely true.

The original bootstrap statistics were approximately -959.8, with a standard error of approximately 728.28, indicating that, on average, the secondary catch data were lower than the primary catch data by approximately 960 units. The large standard error indicates that there could be substantial sampling variability, which should be studied and improved, especially in the secondary catch data. The confidence interval (CI) on the bootstrap at the 95% percentile confidence interval for the difference in means was estimated to range from -2288.6 to 516.7 (Table 1 and Fig. 4). The CI included zero, suggesting that the observed difference in means was not statistically significant at the 5% level. While the point estimate is negative, the broad CI shows that the effect might be negligible or even in the opposite direction, depending on how each of the compared datasets was collected. This implies that the claims that commercial fishers in Malawi underreport the logbooks submitted to the Department of Fisheries may not be true or significant. Primary data verification was performed by comparing the data with what the fish traders reported to have bought from individual fishers. In some cases, fishers reported that their catch was lower than what the fish trader reported to have bought from the fisher (10). Fish traders seem to have no motivation to underreport the catch (fish bought, figures), unlike commercial fishers, who may under-report catch to hide good fishing grounds and avoid the introduction of taxes by the government on the actual fishing business, which currently does not have a tax on landings. It would be ideal to licence fish traders to collect data from them, which could be used to validate logbooks submitted by fishers to the Department of Fisheries. Licensed fish traders should report the fish they buy from commercial fishers, along with the prices of fish at the material time, among others. Finally, the data collection system used in this study to collect primary catch data produced a higher figure than the method used to collect secondary catch data. Although there was no statistically significant difference in the short term, there could be a difference in the long term. In this regard, the study recommends that fishers embrace information technology (IT) by submitting catch data in real time through an app rather than the conventional monthly manual logbook submission to the Department of Fisheries (Malawi Government) (11).

CONCLUSION

This study compared field-collected catch and effort observations (primary data) with secondary data from the Department of Fisheries collected from the Mangochi, Salima, and Nkhotakota Districts from May to November 2023. The study employed independent-samples t-tests, Cohen's d, and Monte Carlo resampling (bootstrap and permutation) to quantify the differences between datasets and to assess both statistical and practical significance.

While the point estimate is negative, the broad CI shows that the effect might be negligible or even in the opposite direction, depending on how each of the datasets was collected. This implies that the claims that commercial fishers in Malawi underreport the logbooks submitted to the Department of Fisheries may not be true or significant. Primary data verification was performed by comparing the data with what the fish traders reported having bought from individual fishers. Fish traders seem to have no motivation to underreport the catch (fish bought, figures), unlike commercial fishers, who may under-report their catch to hide good fishing grounds and avoid the introduction of taxes by the government on the actual fishing business, which currently does not have a tax on landings. It would be ideal to license fish traders to collect data from them, which could be used to validate the logbooks submitted by fishers to the Department of Fisheries. Finally, the data collection system used in this study to collect primary catch data produced a higher figure than the method used to collect secondary catch data. Although there was no statistically significant difference in the short term, there could be a difference in the long term. In this regard, the study recommends that fishers embrace information technology (IT) by submitting catch data in real time through an app rather than conventional monthly manual (paper-based) logbook submissions to the Department of Fisheries.

RECOMMENDATIONS

To improve the accuracy, reliability, and utility of large-scale fisheries statistics in Malawi, this study recommends the following actionable measures:

1. Paper-based logbooks should be replaced with digital reporting apps for real-time catch and effort recording.
2. Strengthen routine data validation and institute an audit process for large-scale fishery logbooks. This can be implemented by
    a. periodic ground-truthing exercises, where independent field teams sample landing-site catch and effort data and compare them with departmental records. This should be designed to deliberately prioritize high-risk landing sites and seasons that produce the largest discrepancies.
    b. A systematic link of VMS-derived fishing effort activity with logbook and landing site records to automatically flag inconsistencies. At landing sites where VMS coverage is limited, targeted spot-checks and time-of-day matching can be used to infer fishing effort.

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