

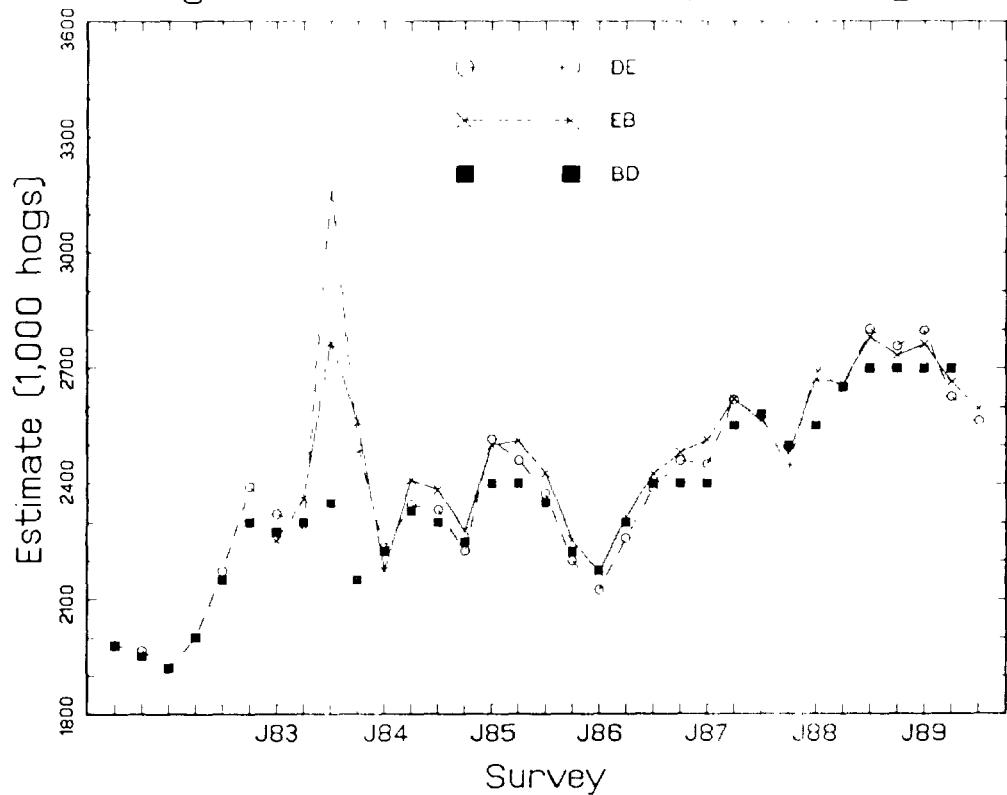
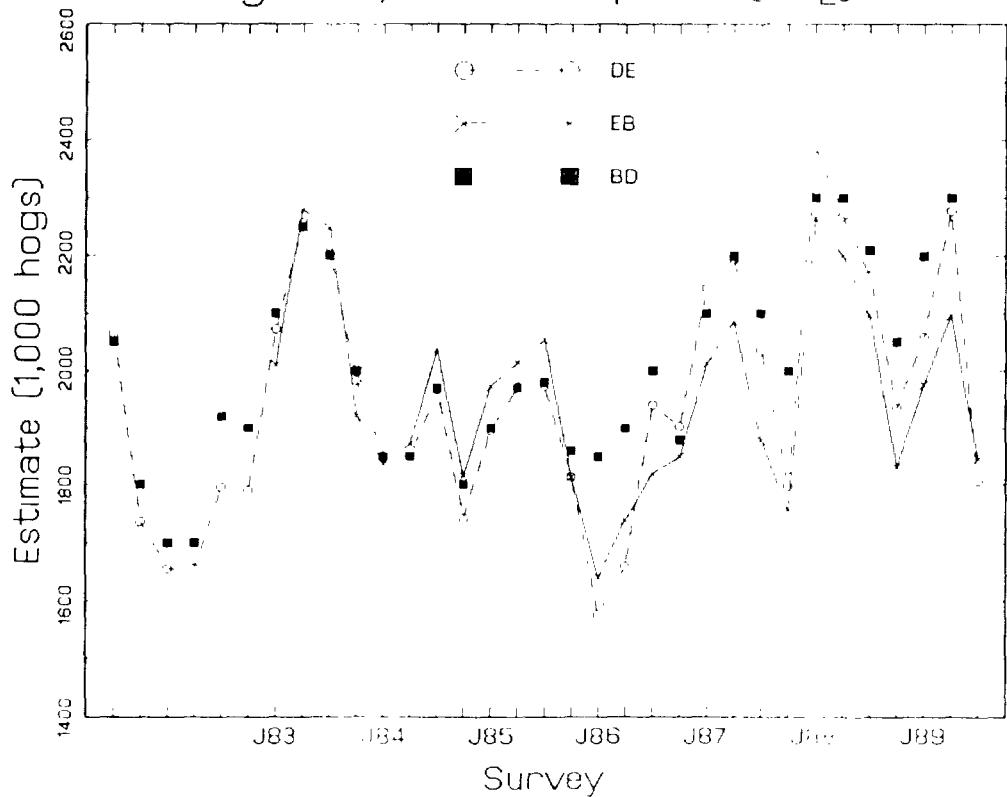
Fig. 6.2.i N Carolina: DE₁ + EB(DE₂)Fig. 6.2.j Ohio: DE₁ + EB(DE₂)

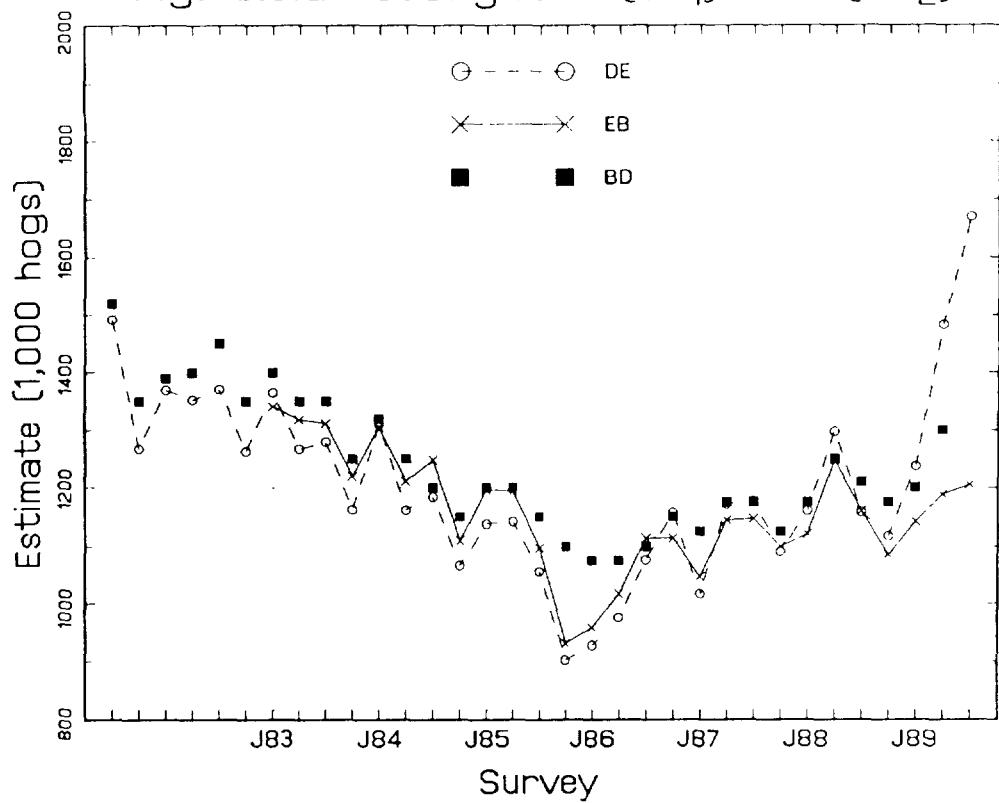
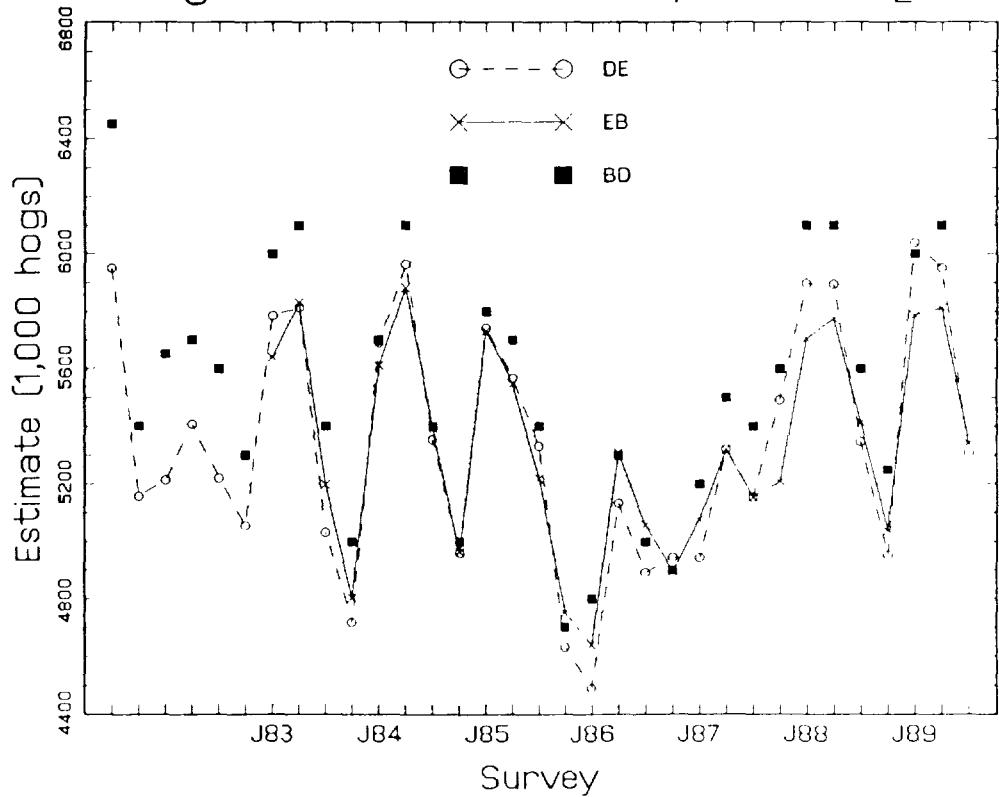
Fig. 6.3.a Georgia: $EB(DE_1) + EB(DE_2)$ Fig. 6.3.b Illinois: $EB(DE_1) + EB(DE_2)$ 

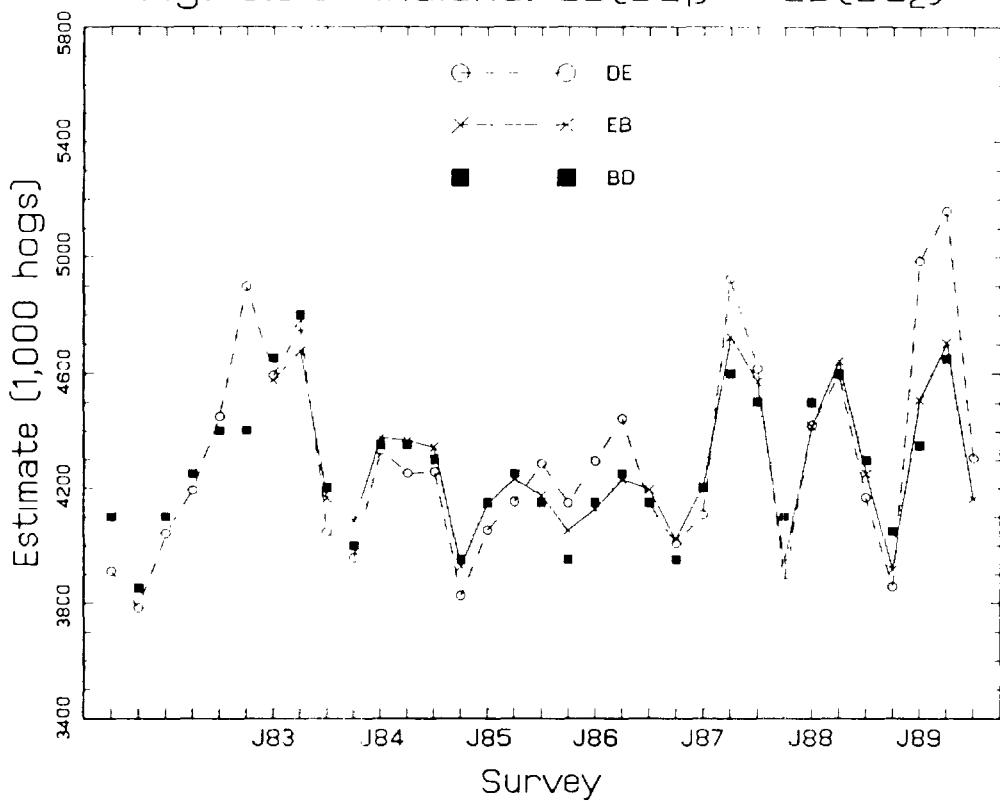
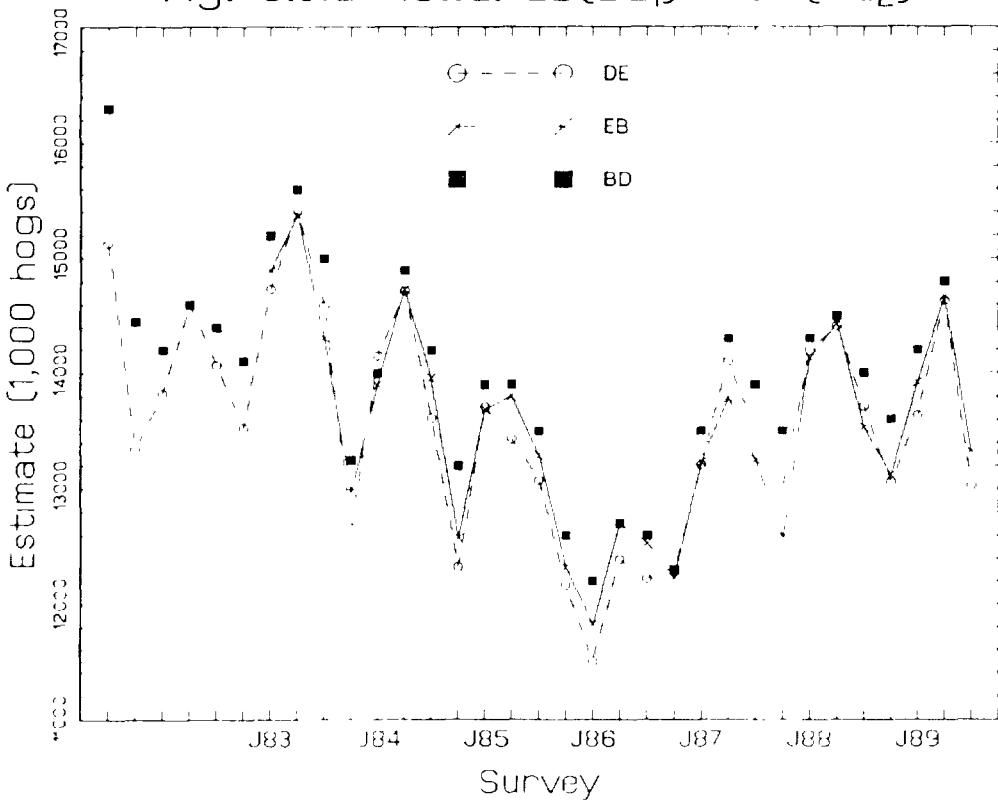
Fig. 6.3.c Indiana: $EB(DE_1) + EB(DE_2)$ Fig. 6.3.d Iowa: $EB(DE_1) + EB(DE_2)$ 

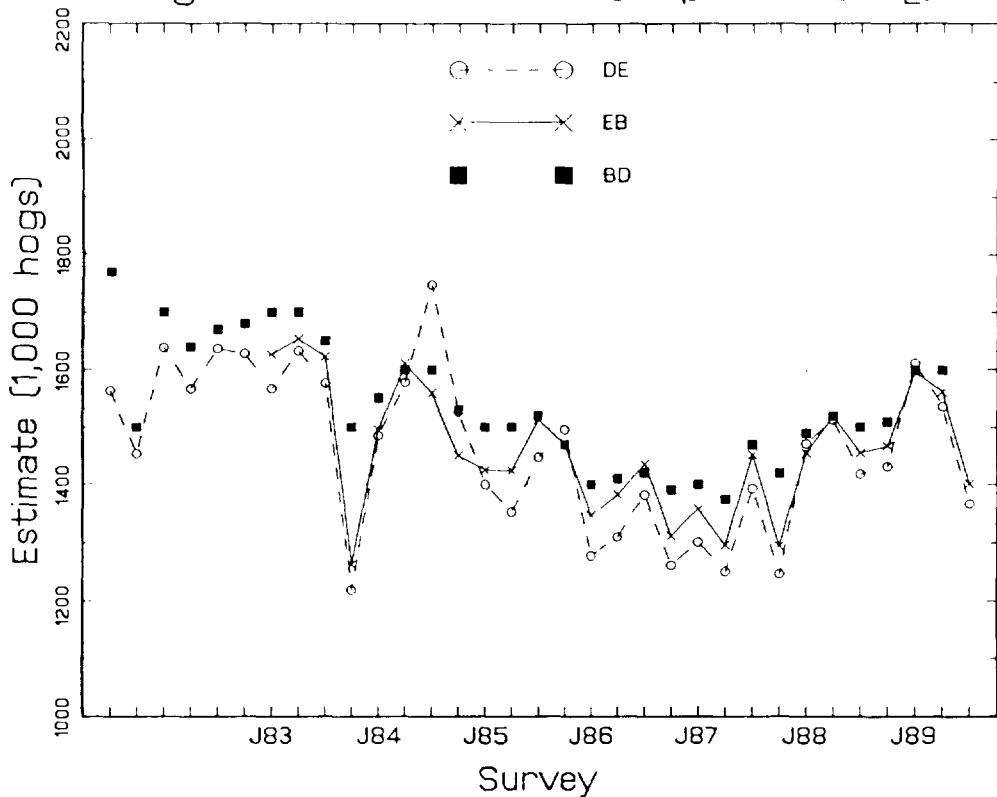
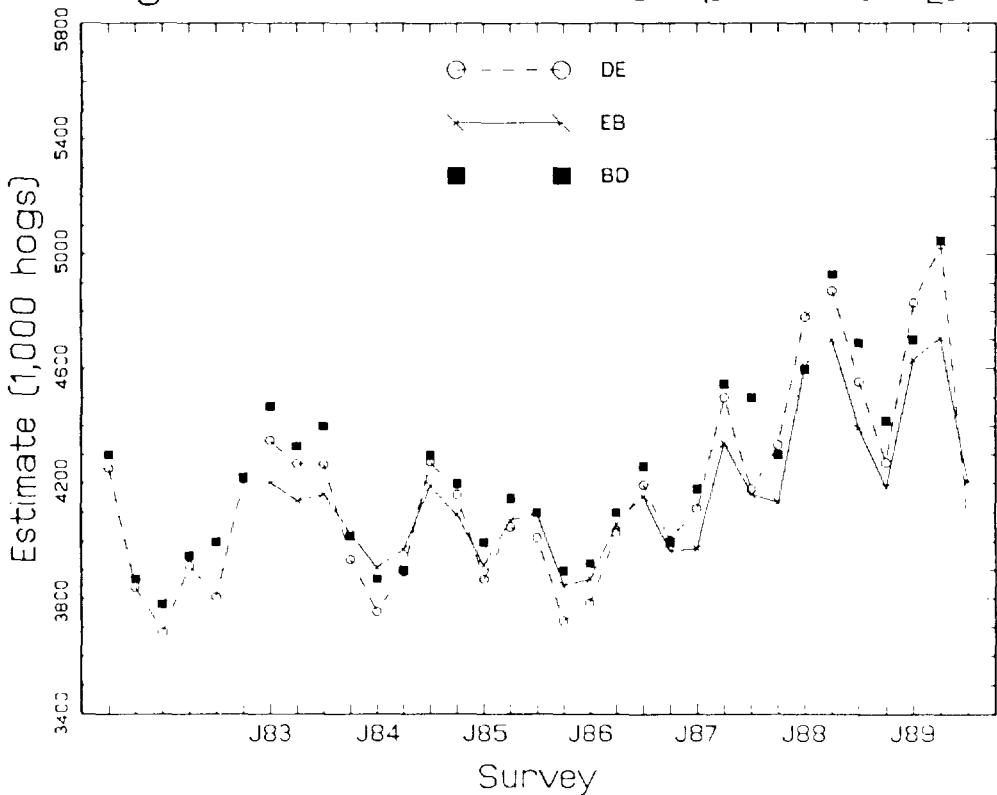
Fig. 6.3.e Kansas: $EB(DE_1) + EB(DE_2)$ Fig. 6.3.f Minnesota: $EB(DE_1) + EB(DE_2)$ 

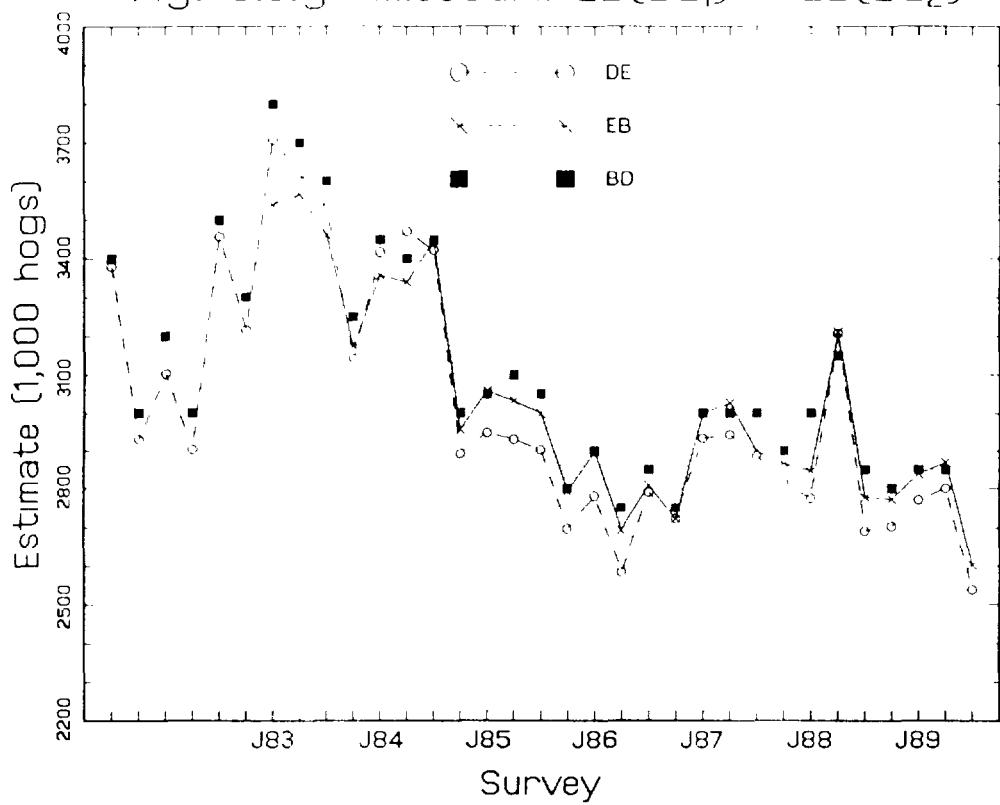
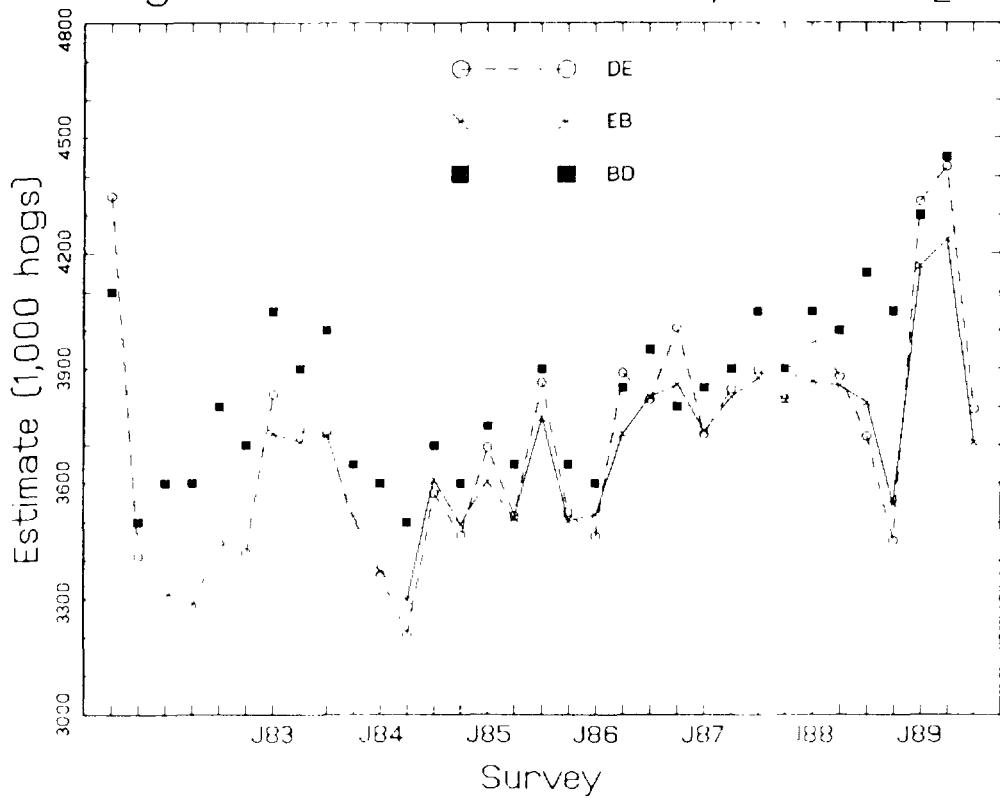
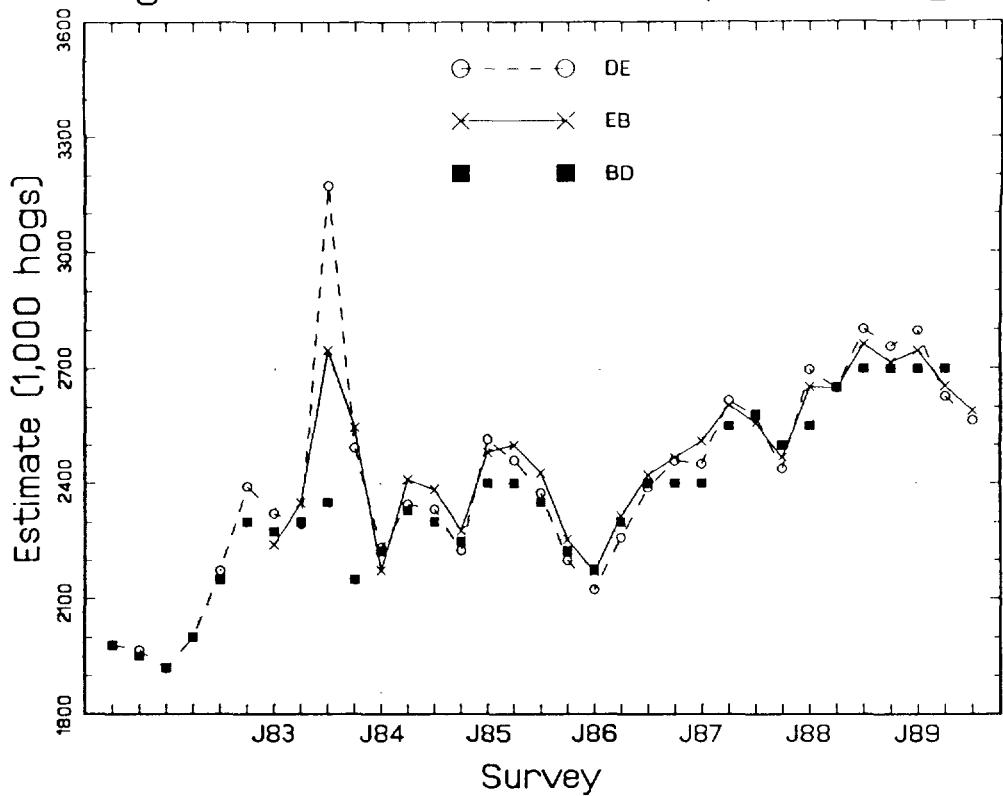
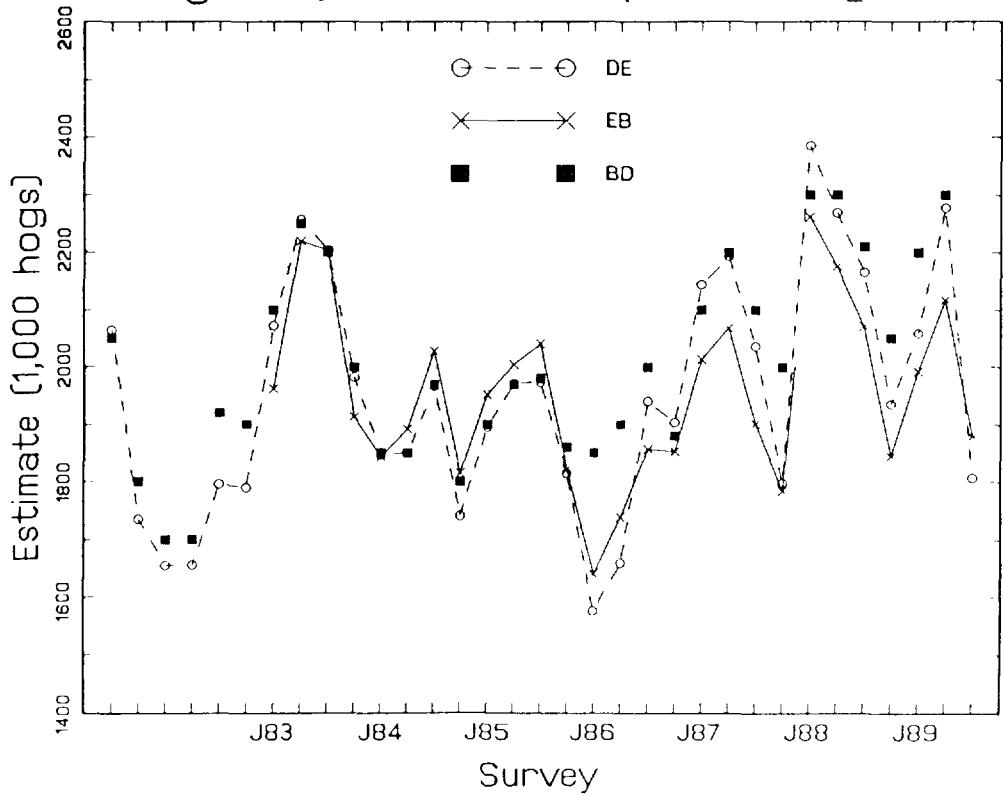
Fig. 6.3.g Missouri: $EB(DE_1) + EB(DE_2)$ Fig. 6.3.h Nebraska: $EB(DE_1) + EB(DE_2)$ 

Fig. 6.3.i N Carolina: $EB(DE_1) + EB(DE_2)$ Fig. 6.3.j Ohio: $EB(DE_1) + EB(DE_2)$ 

Chapter 7

Summary and Conclusions

The empirical Bayes approach to smoothing the direct expansion estimates within states was found to improve the overall efficiency of the estimates. In Chapter 4, the bootstrap estimate of the average Root Mean Square Error (RMSE) was found to be about 10% lower for the EB estimators than for the DE estimators. When the large expanded values were modified before application of the empirical Bayes method only a slight additional reduction in the RMSE resulted. Also, only slight improvement resulted from including covariances estimates for the DE estimates from different surveys within a state. This is fortuitous because covariance estimates are not included in the NASS summary files. In Chapter 6, when the empirical Bayes estimates were compared to the most recent revised board estimates for 26 surveys from the ten major hog producing states the Mean Absolute Deviation (MAD) was found to be about 10% smaller than for the corresponding comparison of the DE and board estimates. Multivariate empirical Bayes estimators could also be developed so that information from other states might enhance the smoothing of estimates over surveys within a particular state.

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