AGRI MAGAZINE
(International E-Magazine for Agricultural Articles)
Volume: 02, Issue: 12 (December, 2025)
Available online at http://www.agrimagazine.in
©Agri Magazine, ISSN: 3048-8656

Every Worm Counts: The Science of Predicting Silkworm Health and Cocoon Yield

Sujith Arokia Swamy B[1,2], Naveen Kumar P[3], Raj Shekar M[1,2], *B Samuel Naik[4] and Veershetty[4]

[1]The Graduate School, ICAR-Indian Agricultural Research Institute, New Delhi, India
[2]ICAR-Indian Agricultural Statistics Research Institute, New Delhi, India
[3]University of Agricultural Sciences, Raichur, Karnataka, India
[4]Central Silk Board, Mysore, Karnataka, India
*Corresponding Author's email: banavath.csb@gov.in

A silkworm completes its life cycle in about a month, so a single disease outbreak or hot spell can erase weeks of work. This article describes how routine rearing records can be used to forecast silkworm health and cocoon yield, which statistical and machine learning models are used, and why honest testing of those models matters before a farmer relies on them.

Keywords: silkworm health, cocoon yield prediction, random forest, cross-validation, rearing records

Introduction

In a few weeks a silkworm increases its weight nearly ten-thousand-fold, which makes rearing one of the least forgiving activities in agriculture. Farmers usually learn the damage only when cocoons are harvested. Predicting health and yield while action is still possible is therefore one of the most valuable applications of data in sericulture.

Factors Behind Yield

Performance depends on a web of interacting factors: temperature, humidity, ventilation, leaf quality, rearing density, hygiene and the race of the worm, with ideal conditions changing from one larval stage to the next (Rahmathulla, 2012). Some effects are curved, not straight. A little extra warmth speeds growth, yet beyond a threshold it invites disease. Predictive models are built to learn such curved and interacting relationships from records.

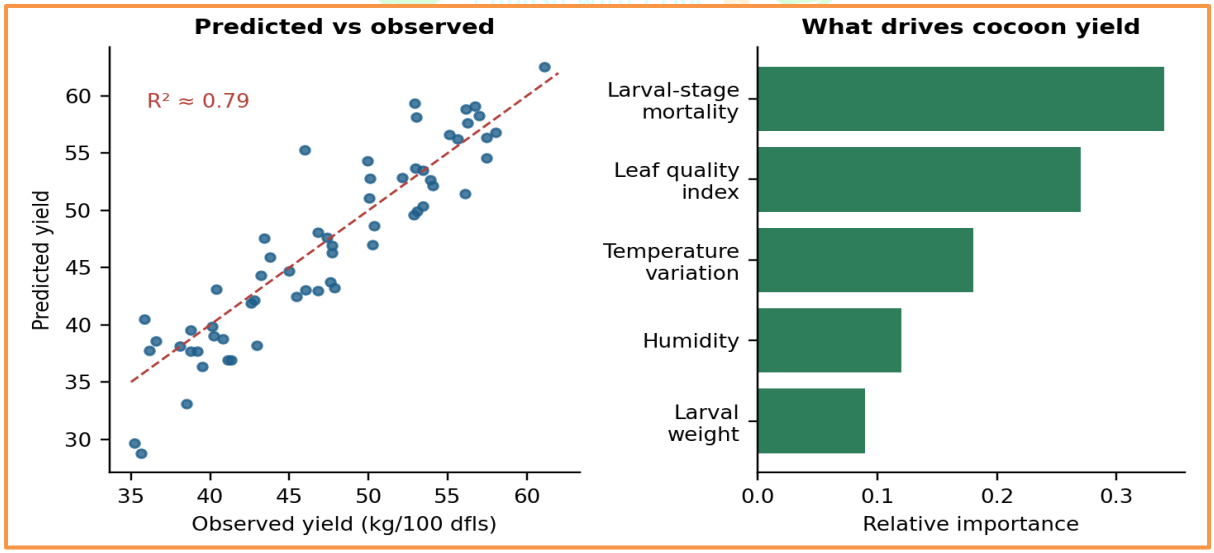

Figure 1: Predicted vs observed cocoon yield and relative importance of rearing factors

Building a Prediction Model

The starting point is good data. A rearer who notes following is quietly building training set:

1. Daily room temperature and humidity.
2. Leaf source and quality at each feeding.
3. Larval weight at each moult and mortality counts by stage.
4. Final cocoon yield per 100 disease-free layings (dfls).

Regression gives an interpretable baseline, while random forests handle thresholds and interactions and report which inputs carry most information (Breiman, 2001). In typical analyses, early larval mortality and leaf quality emerge as strong signals, as sketched in Figure 1.

Testing Honestly

A model judged on the batches it learned from will look excellent and fail in the field. Good practice sets aside unseen batches, or repeats fitting over several data splits (cross-validation), and reports the typical error in kilograms (Hastie *et al*., 2009). The same idea extends to health: instead of a number, the model predicts a class such as healthy or at risk, and image-based deep learning is being tested to spot diseased larvae from photographs (Liakos *et al*., 2018). Pooled across farms, such data also let planners estimate regional cocoon output and let reelers plan supply (Ullal and Narasimhanna, 1981).

Practical Steps for Rearers

A rearer does not need a computer to start. Useful habits that make later prediction possible include:

1. Keeping a notebook or phone sheet for each batch with dates of every moult.
2. Weighing a sample of larvae at each stage and noting mortality.
3. Recording the source and condition of leaf at every feeding.
4. Photographing unhealthy larvae and noting the date and symptoms.
5. Entering the final yield per 100 disease-free layings after harvest.

Shared across a cooperative, even a few hundred such records are enough to build a first useful forecasting model.

Table 1: Key terms at a glance

Term	Meaning
Larval mortality	Share of worms lost by a given stage; an early rise is a warning of disease or poor conditions.
Cross-validation	Repeated testing of a model on batches it has not seen, to check it will work in the field.
Prediction error	Typical gap between forecast and actual yield, expressed in kilograms.
Variable importance	A ranking of rearing factors by how much each improves the forecast.

Conclusion

Prediction does not replace the skilled rearer, but it can act as an early-warning assistant that never tires. The more carefully each batch is recorded, the sooner a model can learn the rhythm of the rearing house and warn in time to save the crop.

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