

Session 2 – Model Evaluation

Comparing Model Predictions With Data

Overview

Data-Driven Approach

Biometric Principles

Techniques

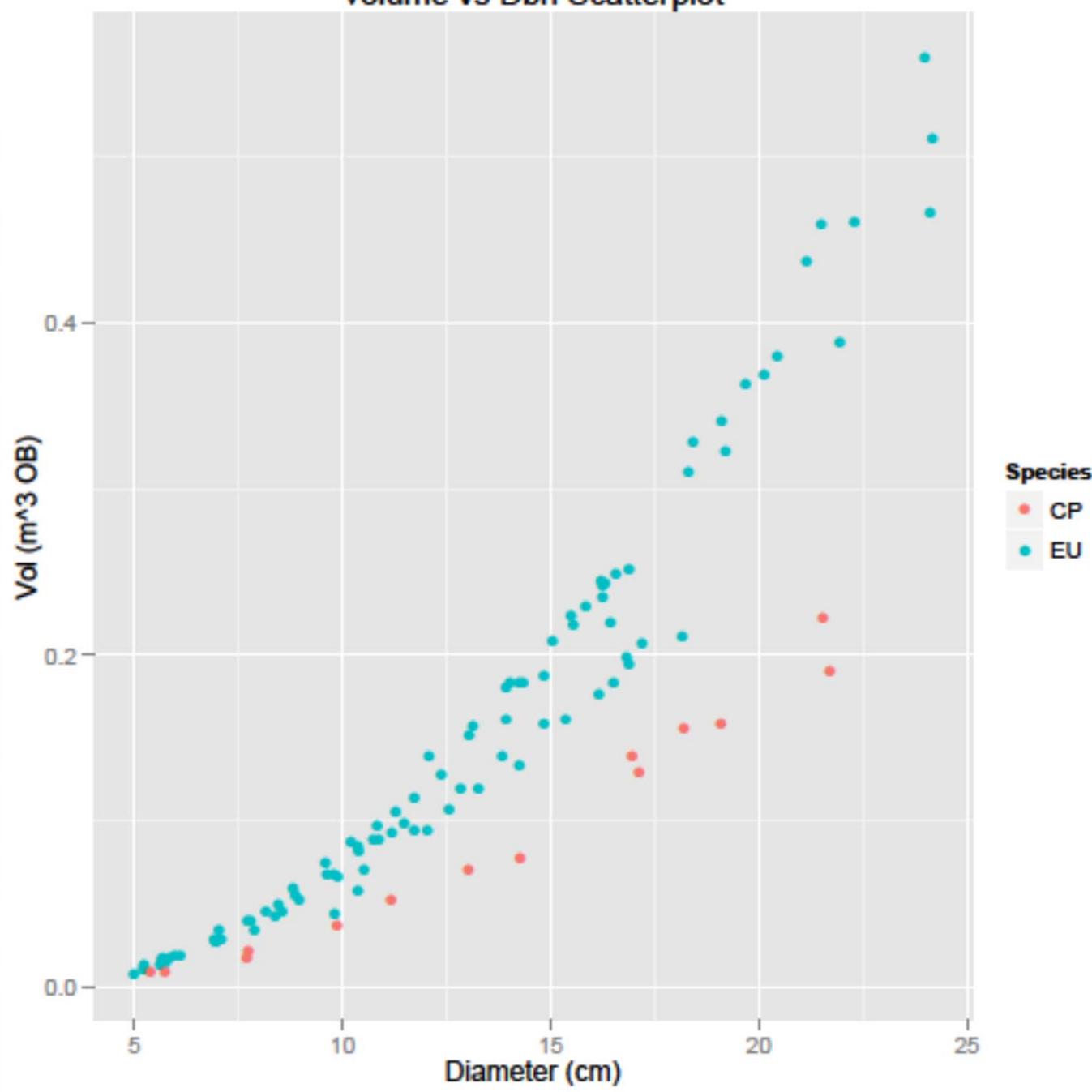
Summary

**Graphical first, then statistical
scatterplots can be quite revealing
new data, old data, yield curves**

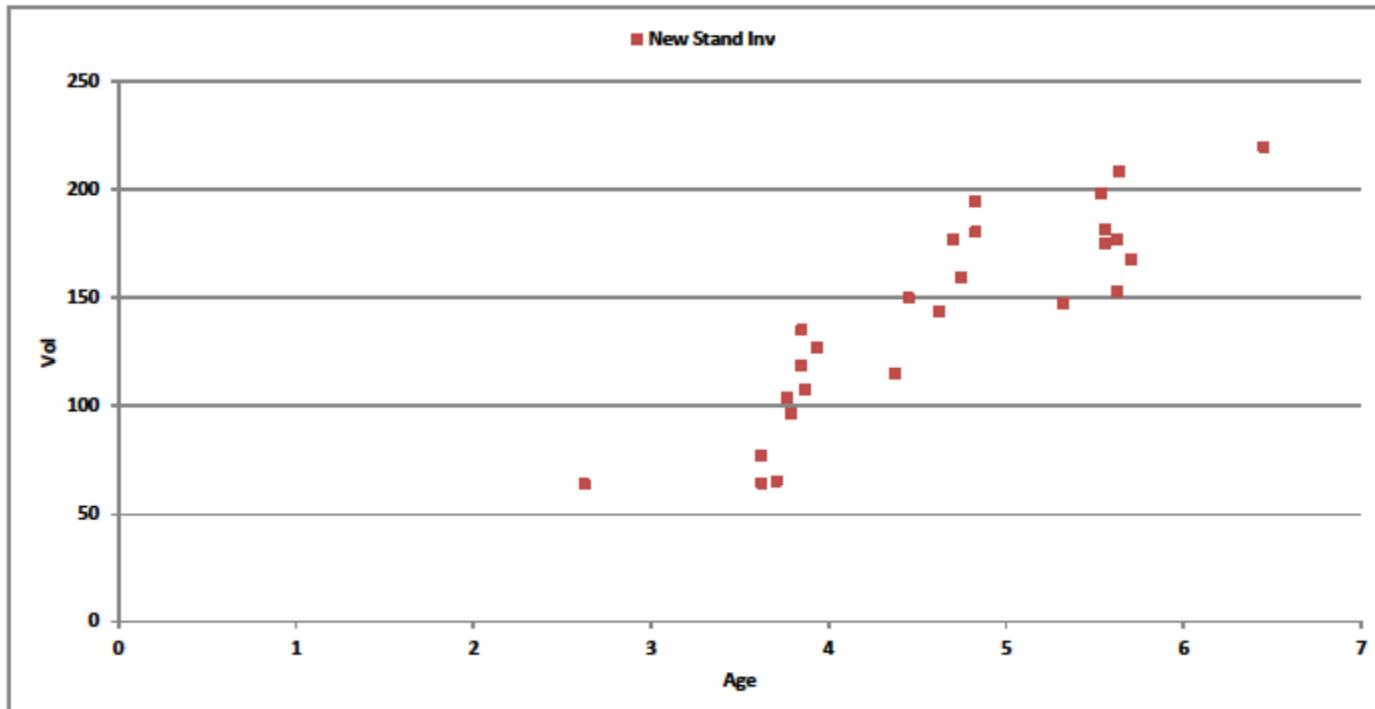
**Re-measured plots
grow to cruise years option in FPS
actual vs projected plots by species and component**

**Statistics
statistical significance? biological relevance?
MAE & RMSE by species and component
hypothesis tests by species and component**

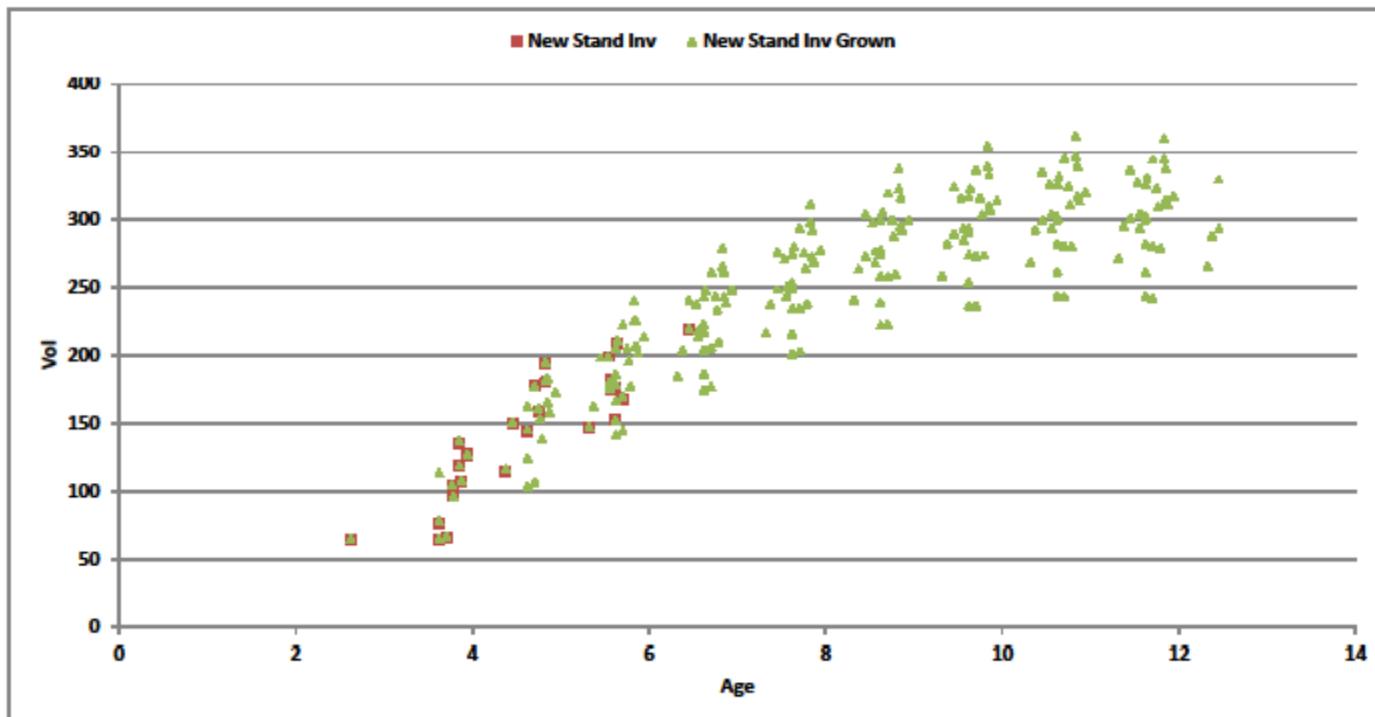
Volume vs Dbh Scatterplot



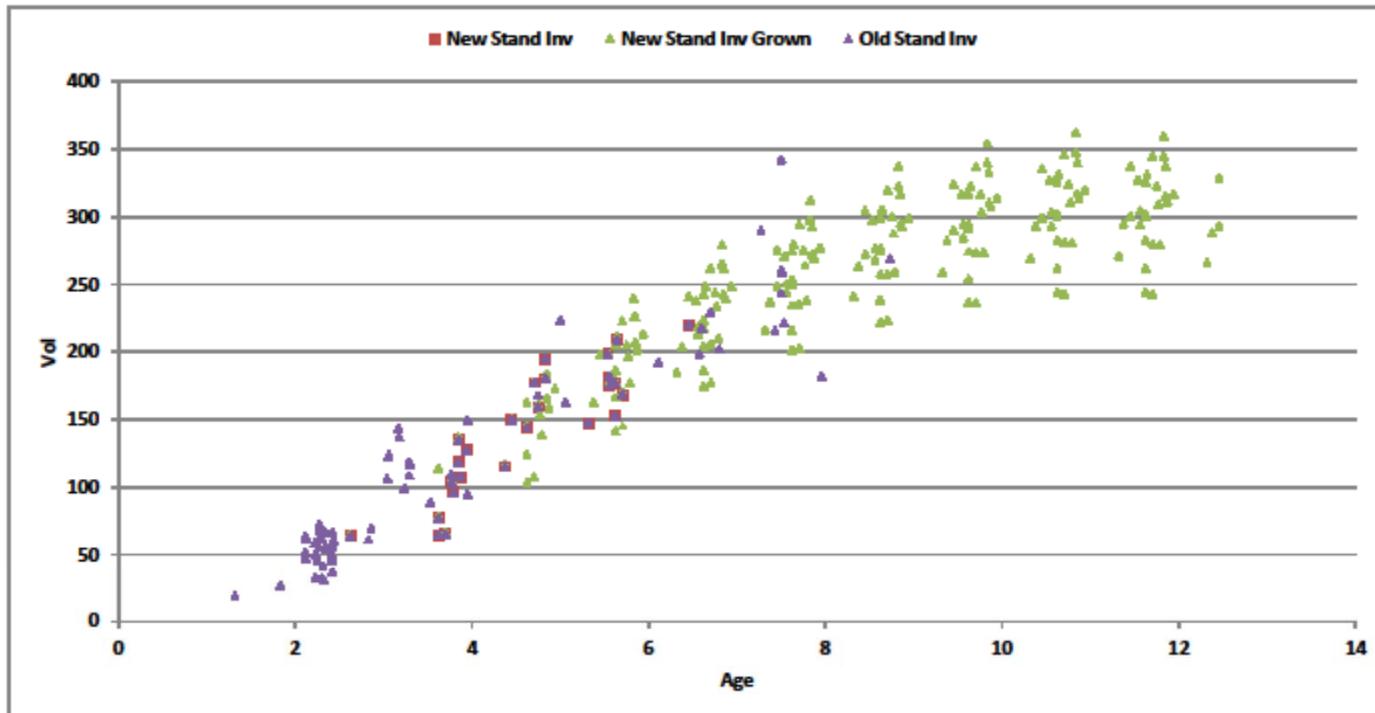
New Stand Inv Vol x Age



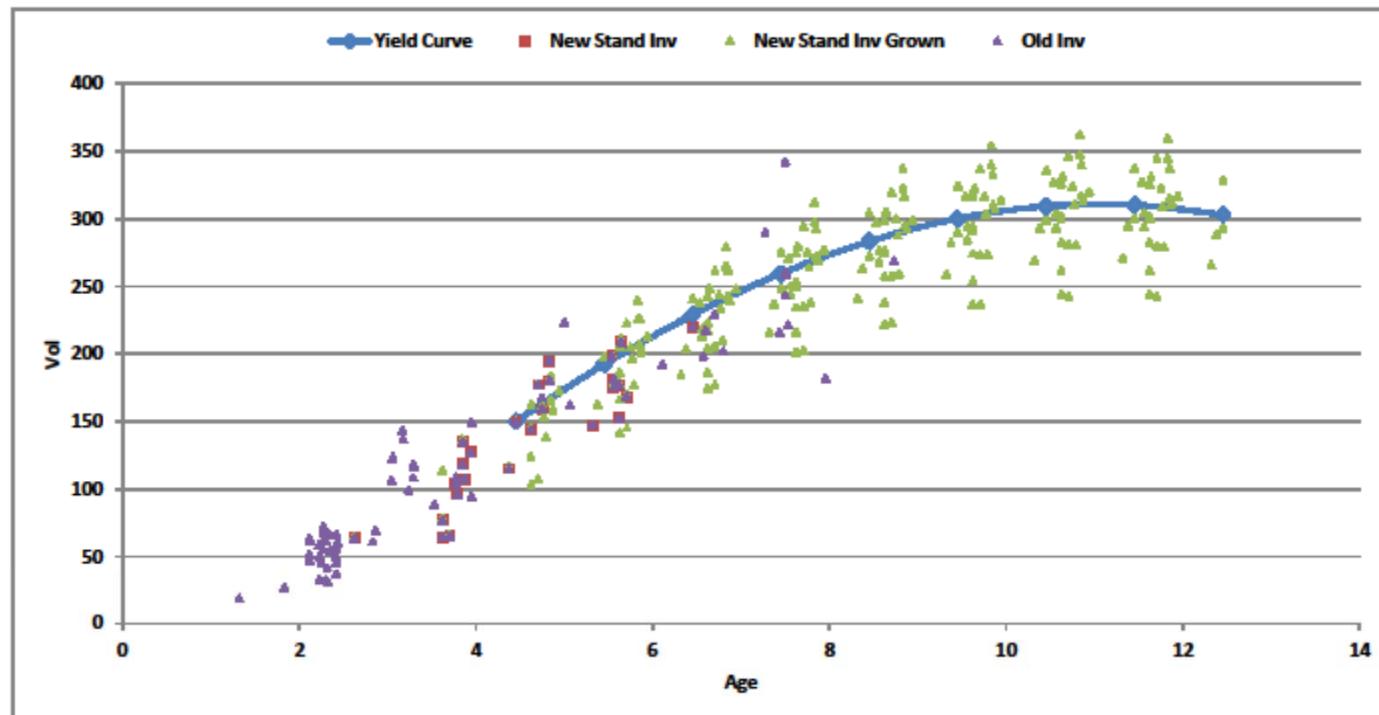
New Stand Inv & Grown Vol x Age



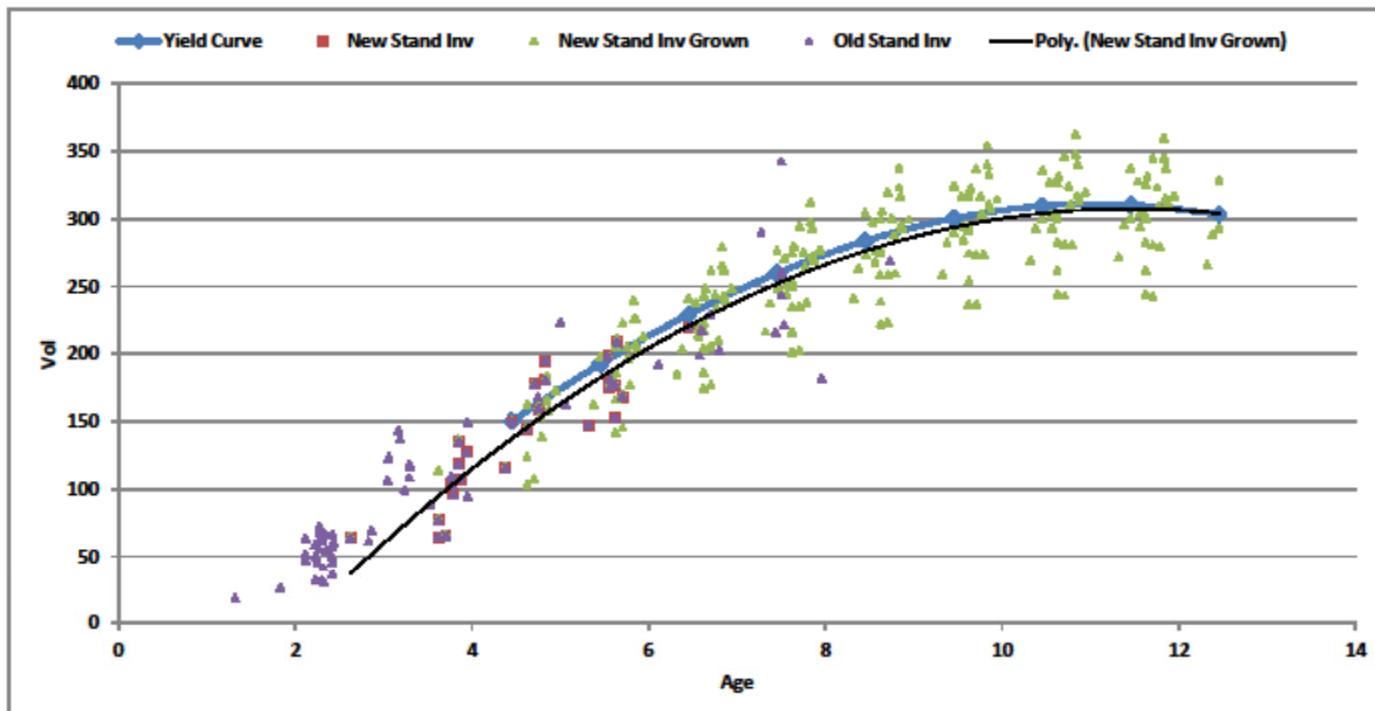
Old Inv Added



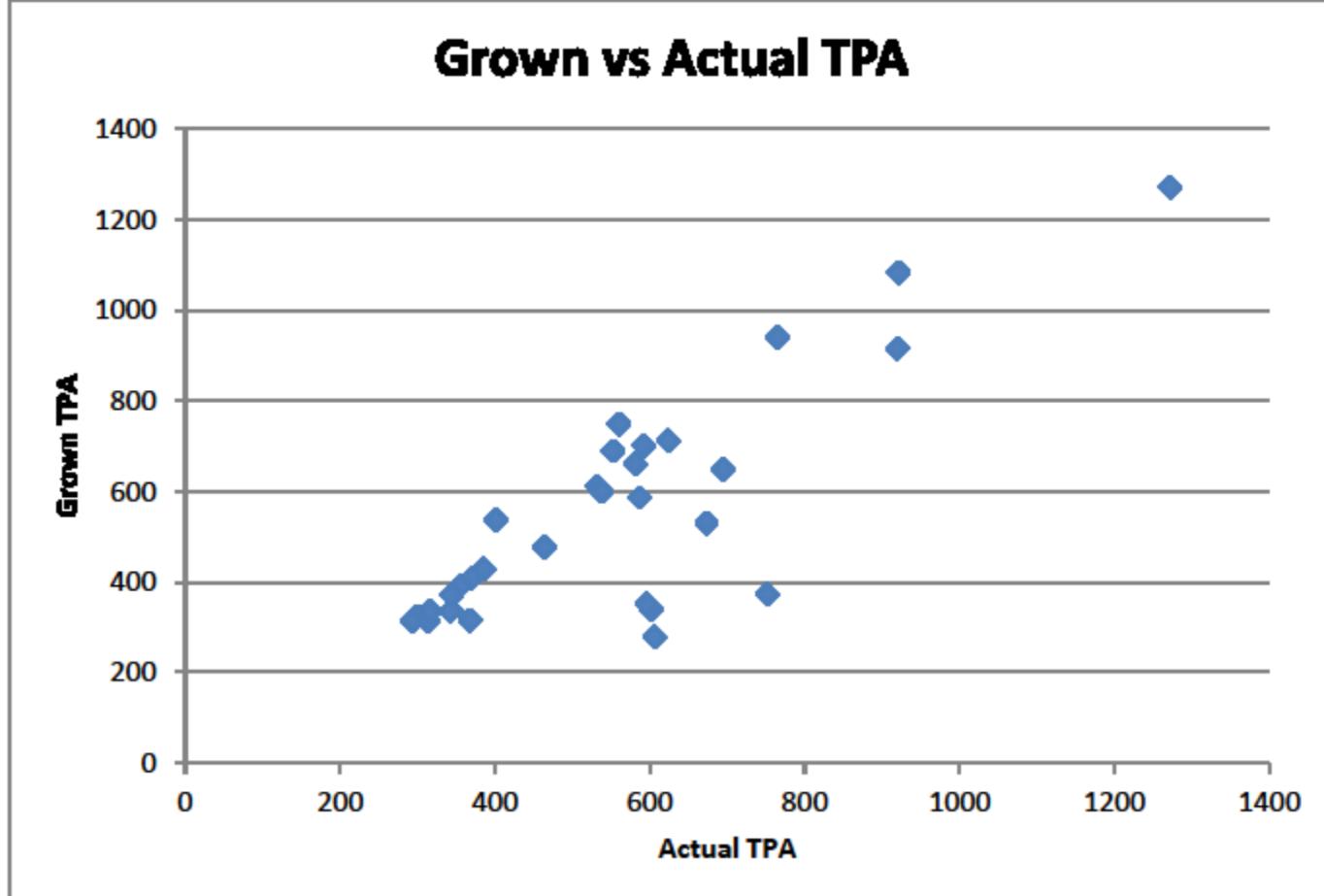
Yield Curve Added



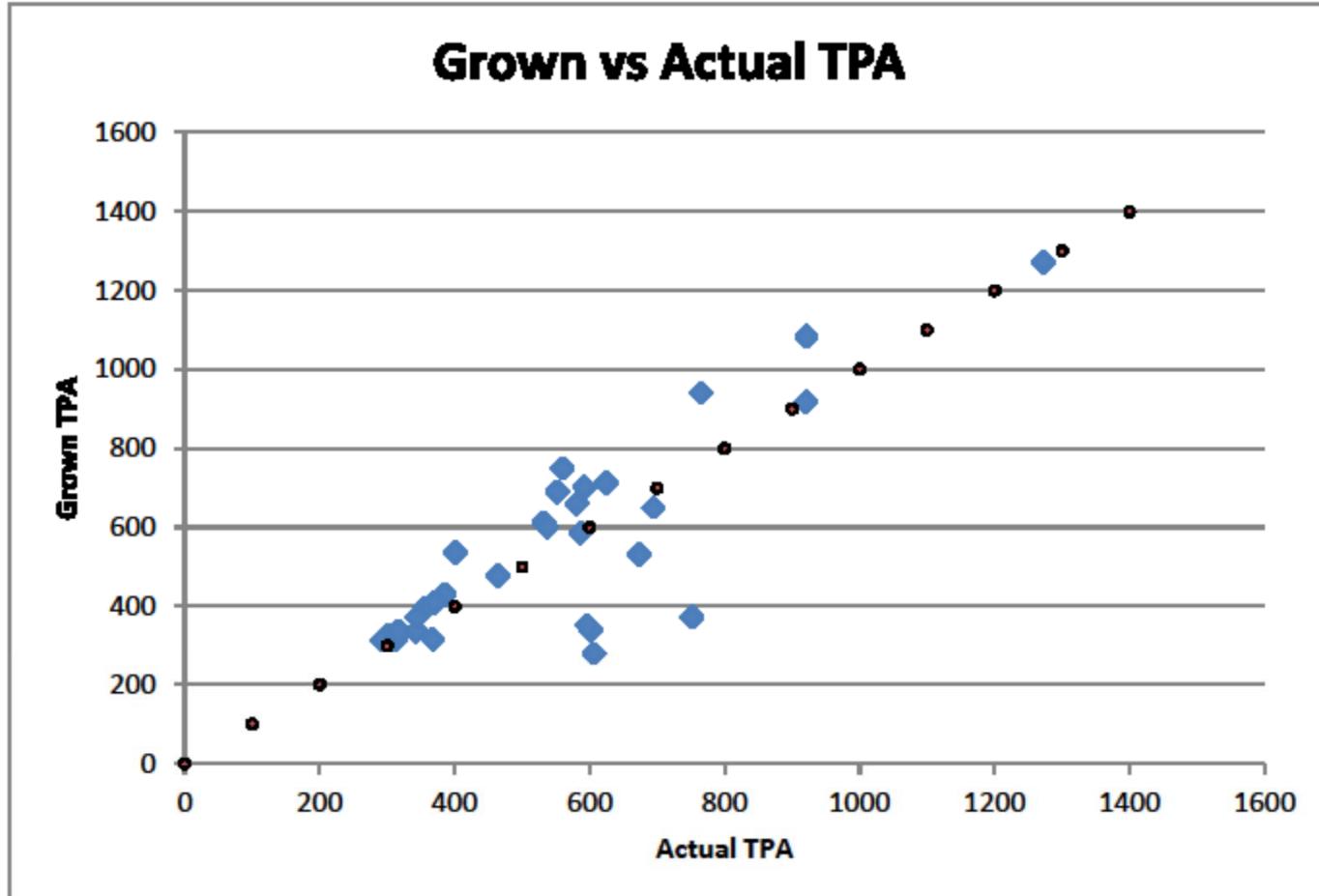
Trend Line of Grown Inv Added



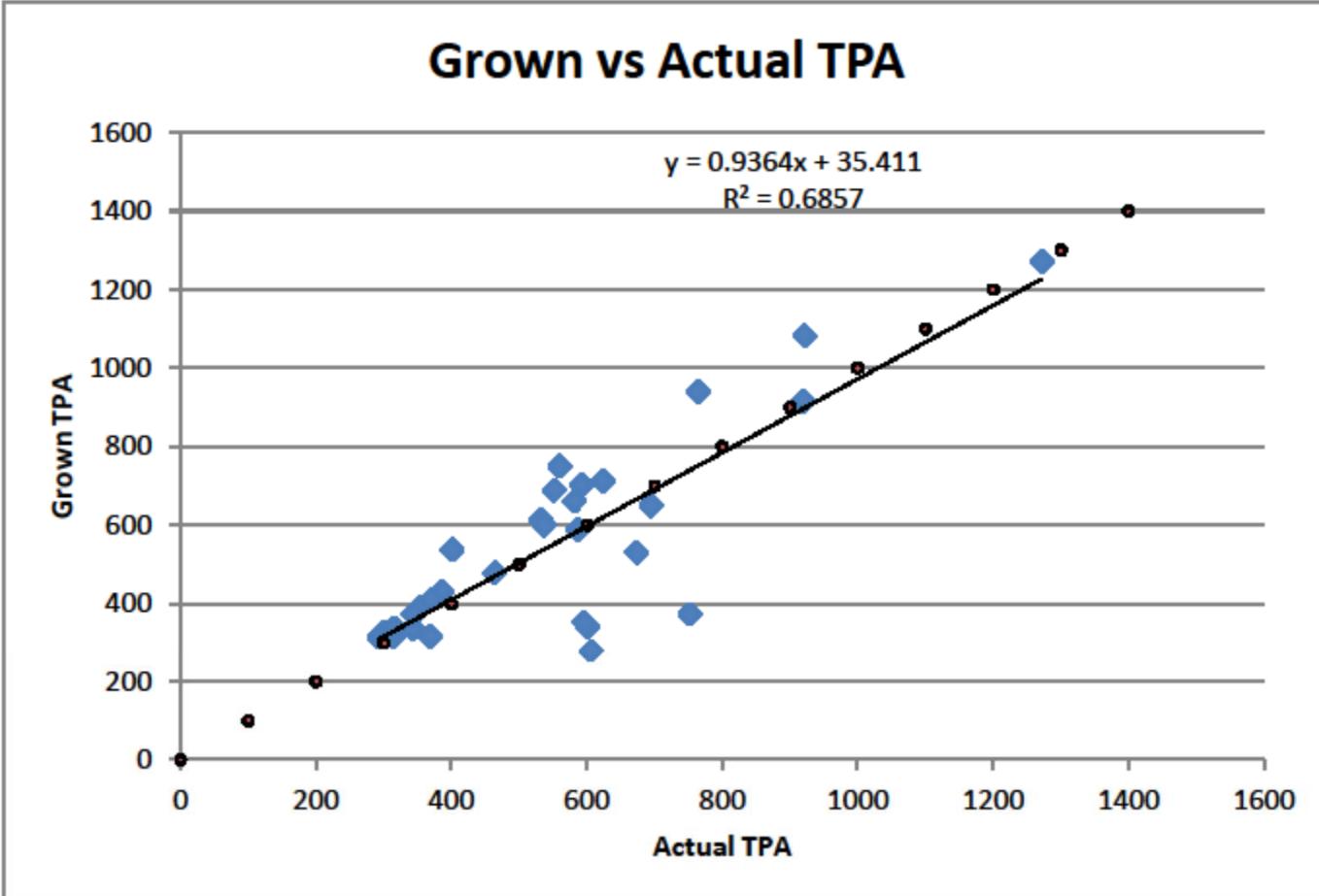
Proj v Act Series



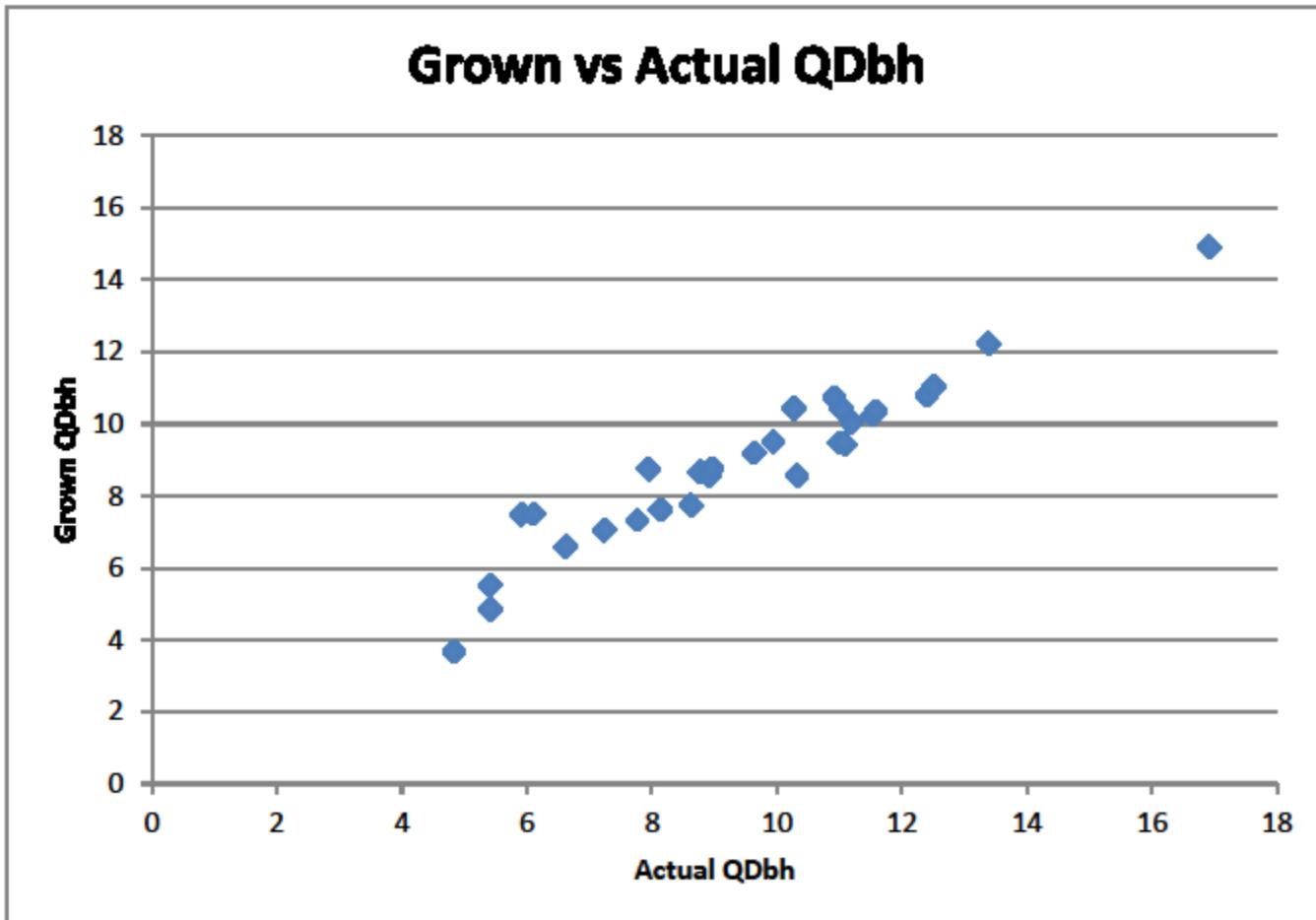
1:1 line added



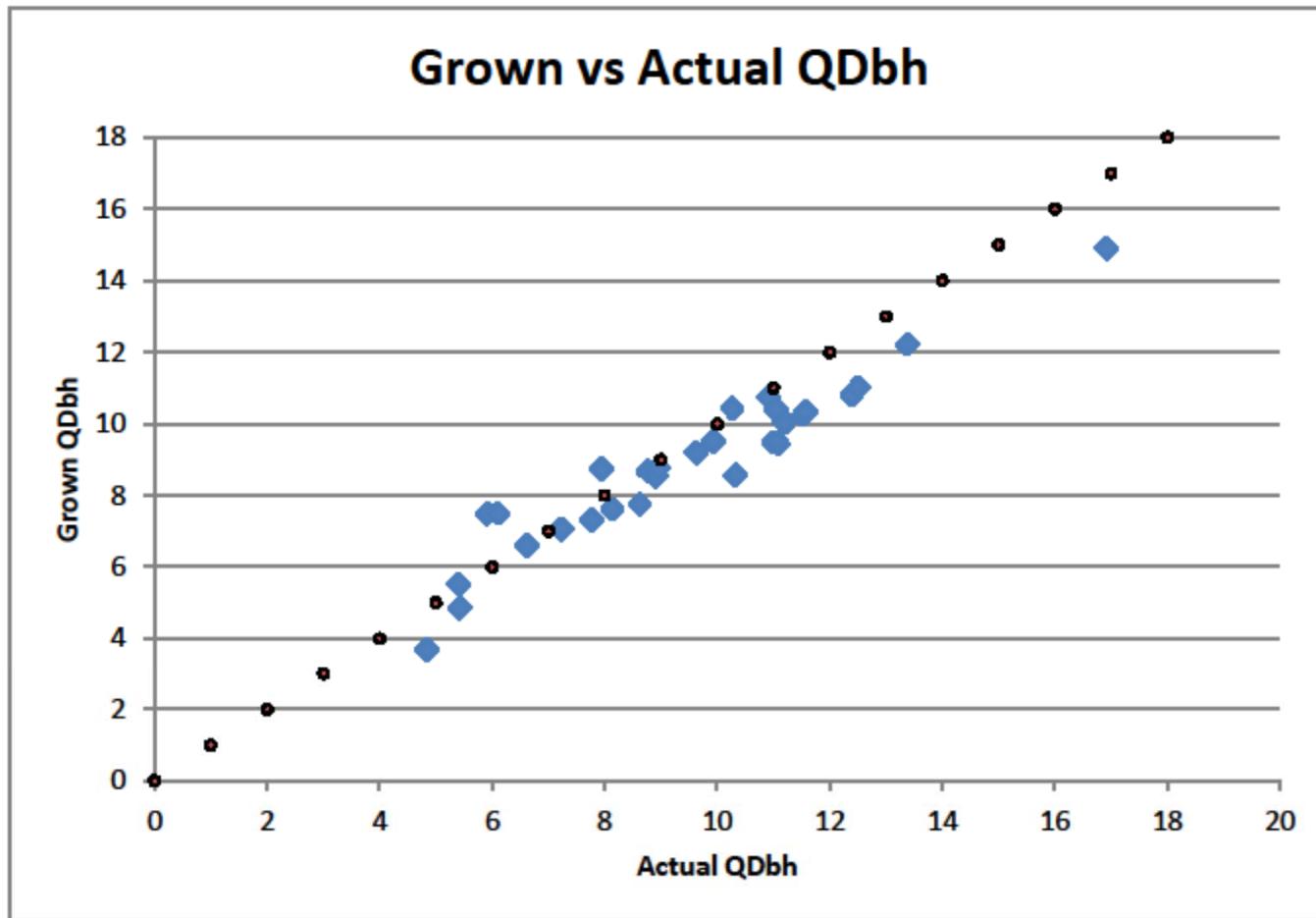
Trend line added



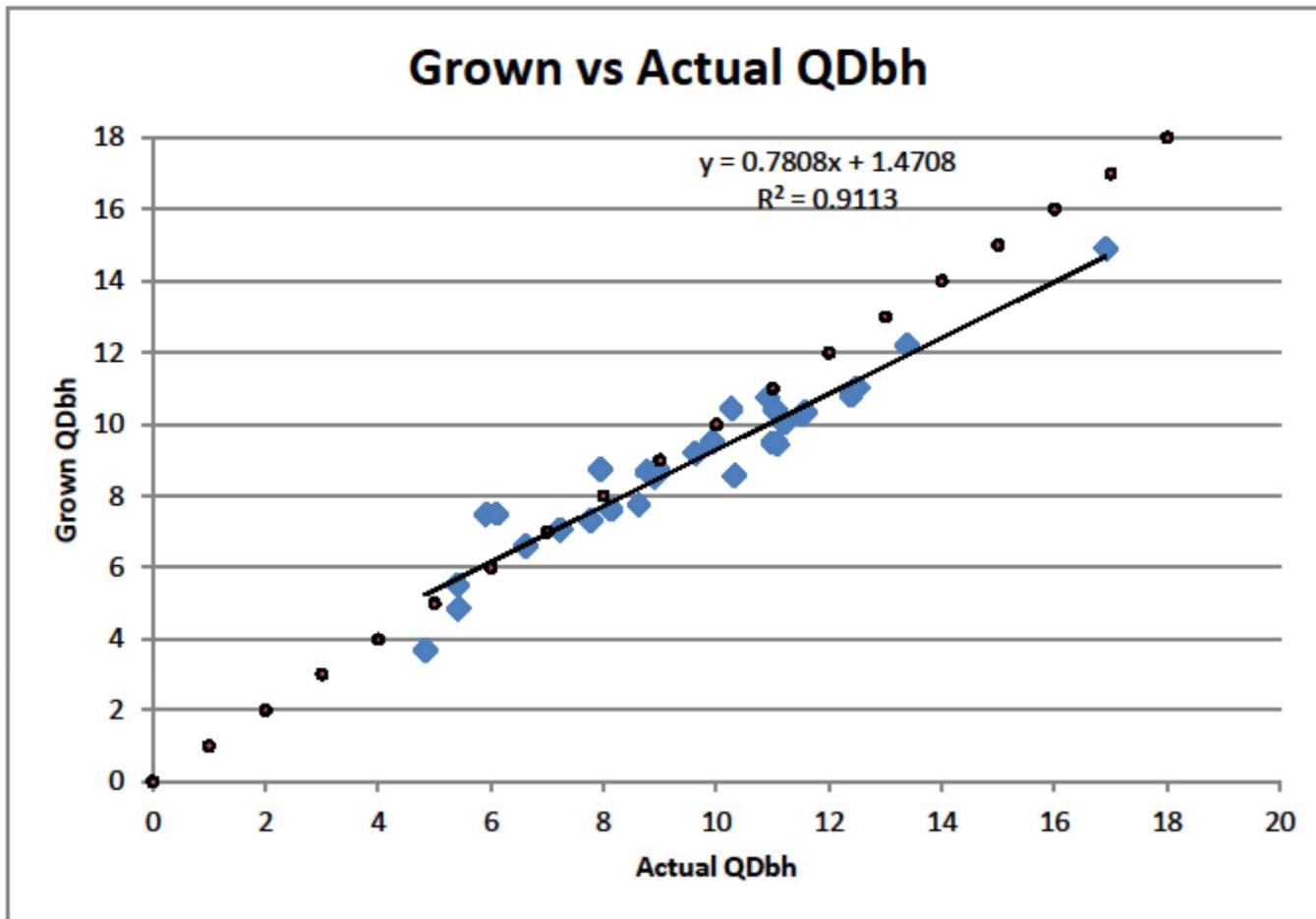
Proj v Act QDbh



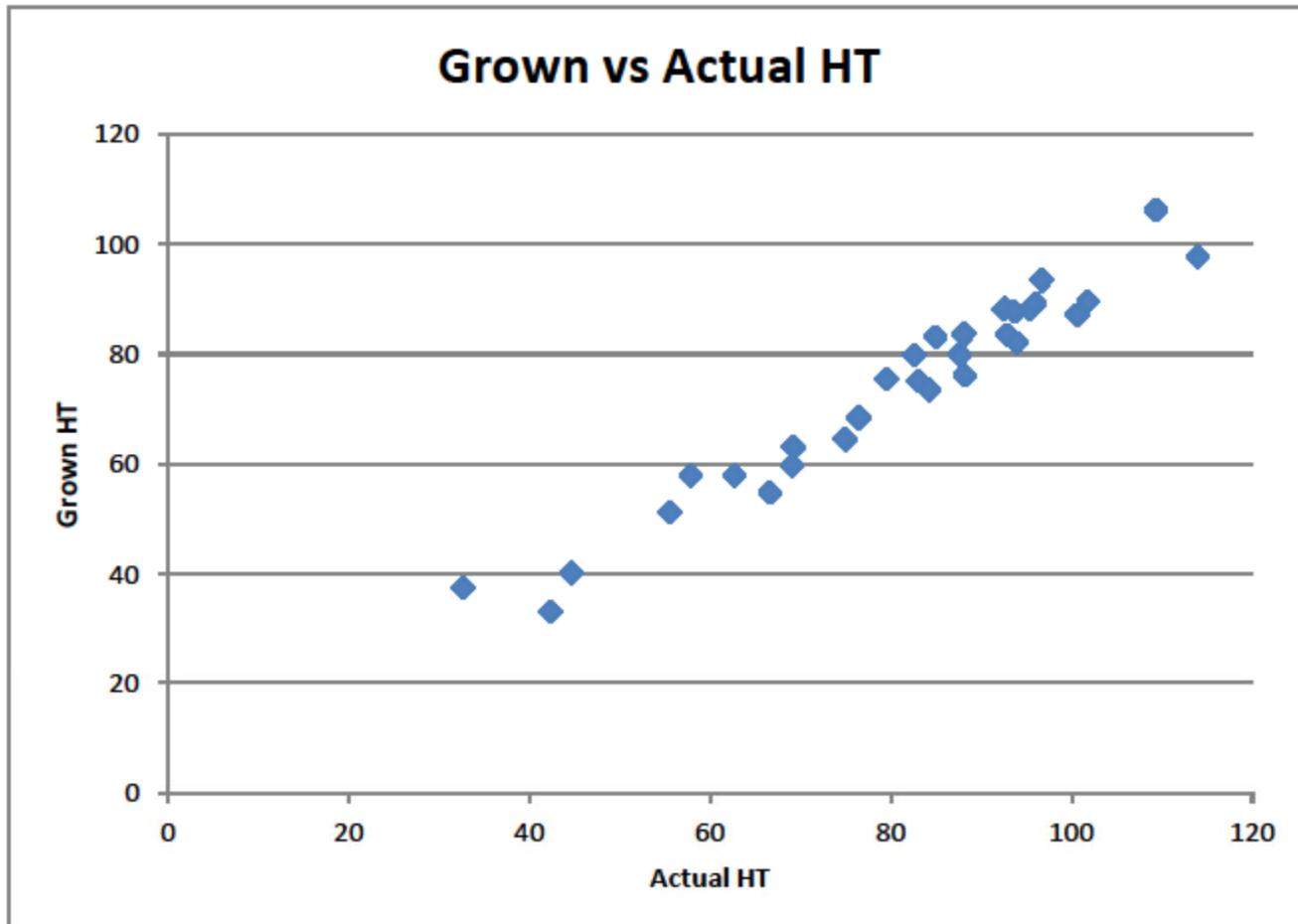
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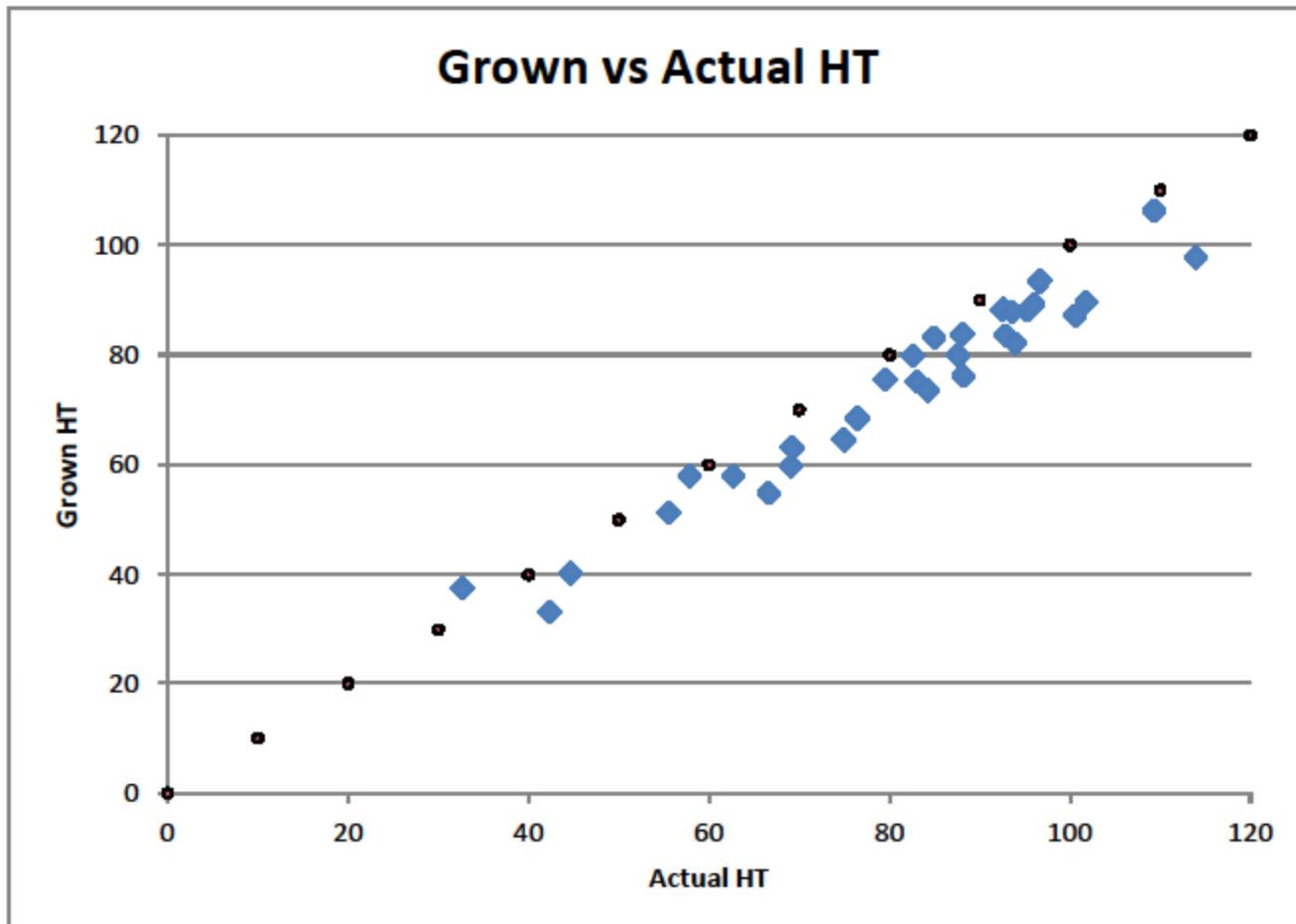
Trend line added



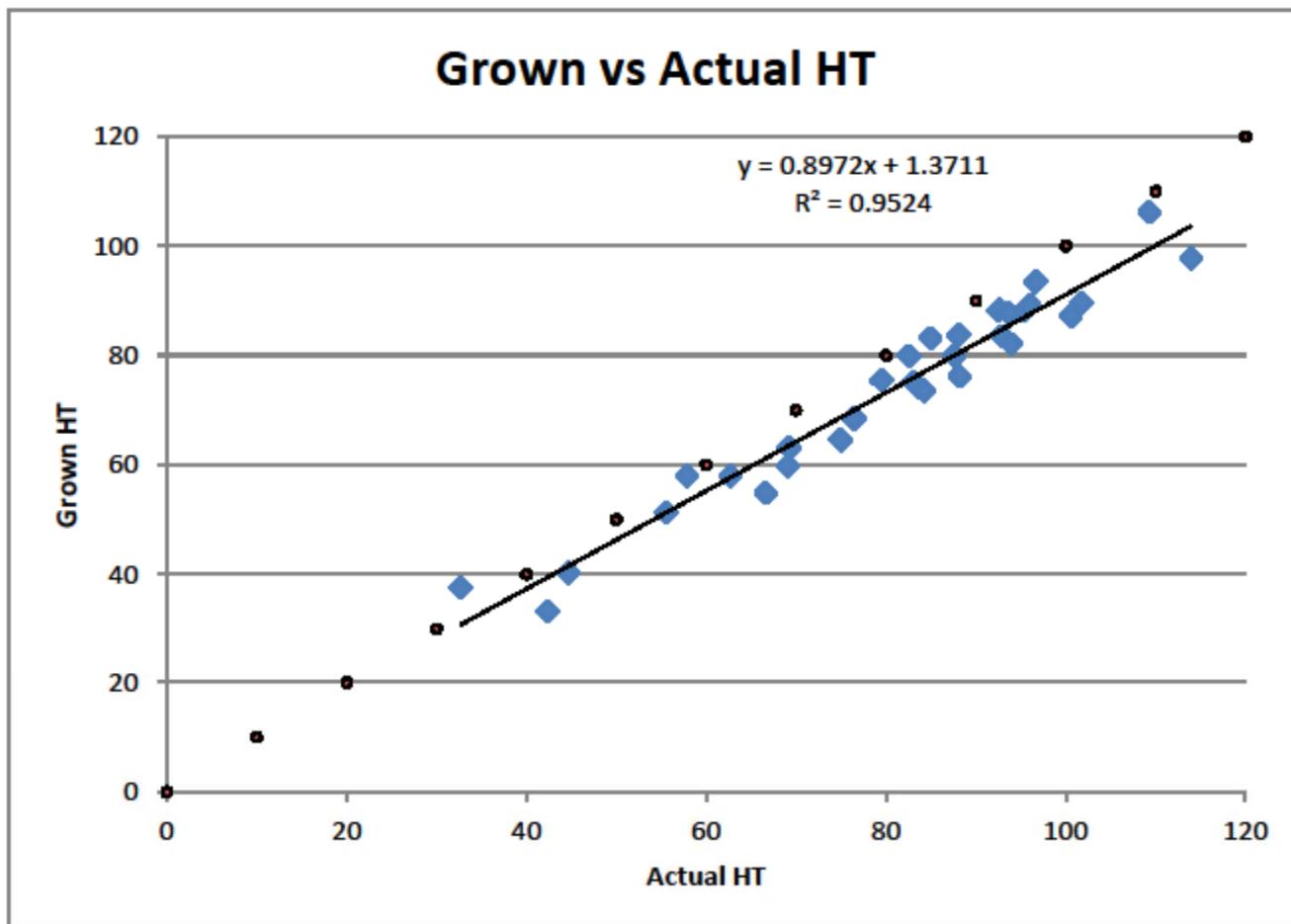
Proj v Act Ht



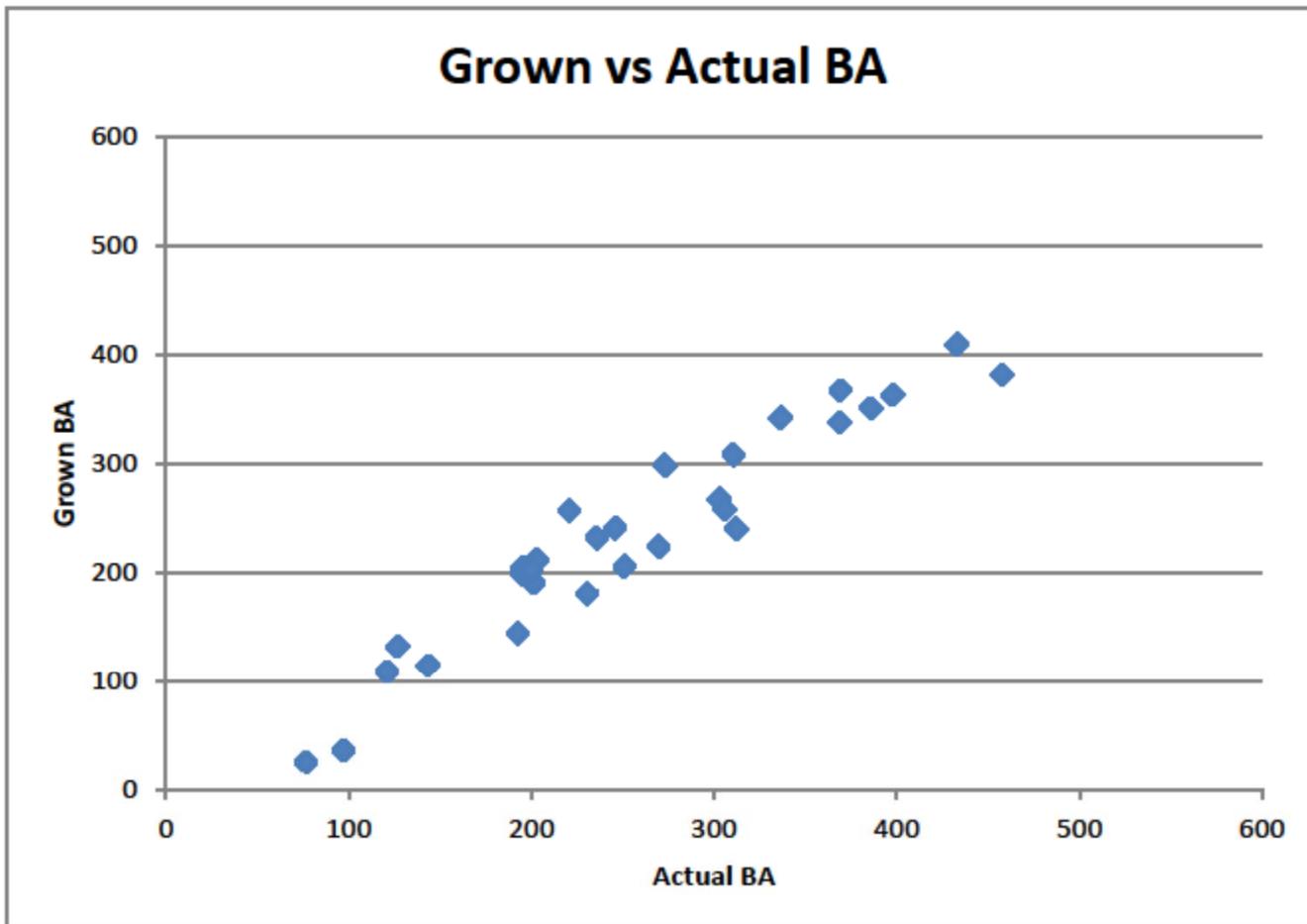
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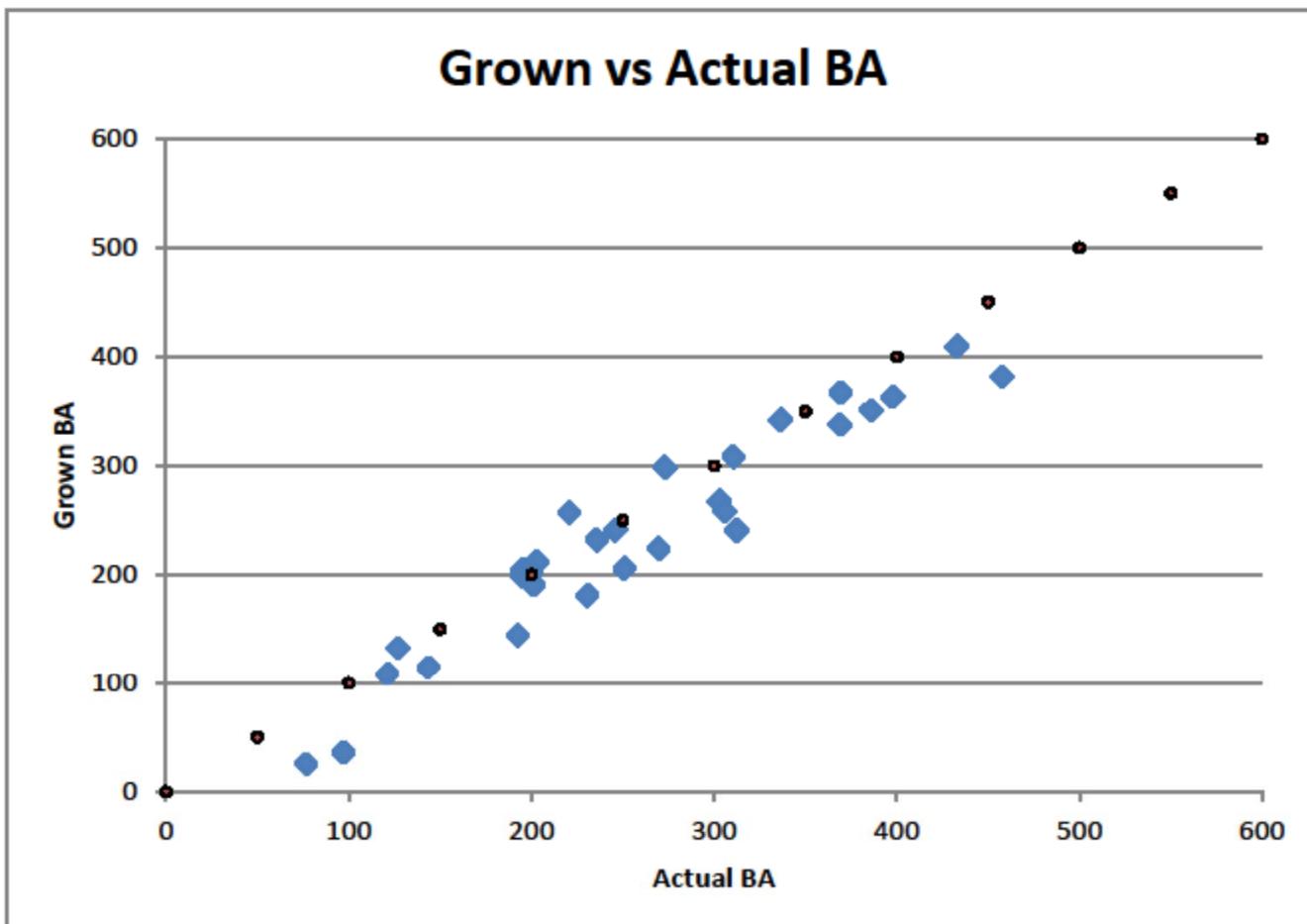
Trend line added



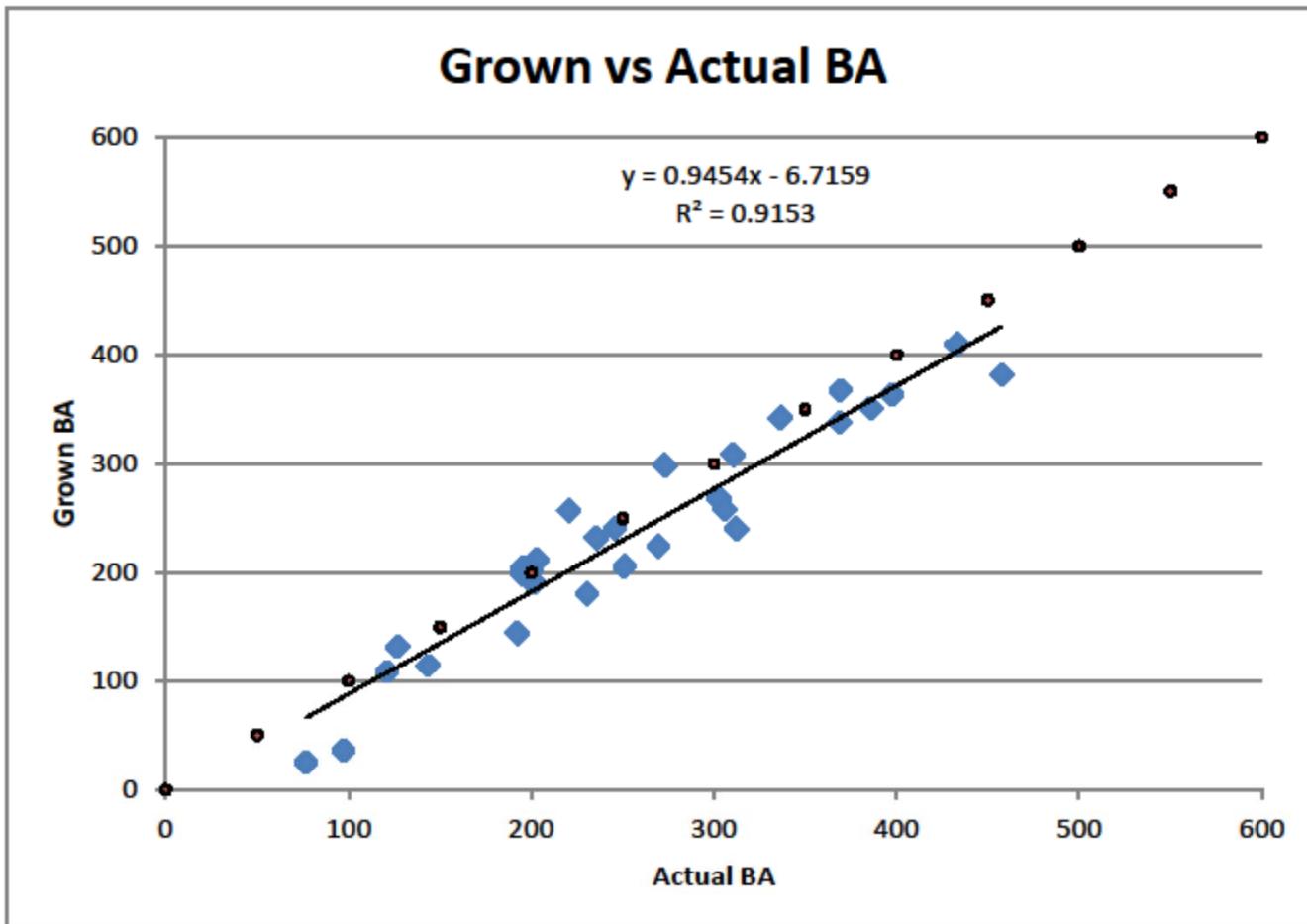
Proj v Act BA



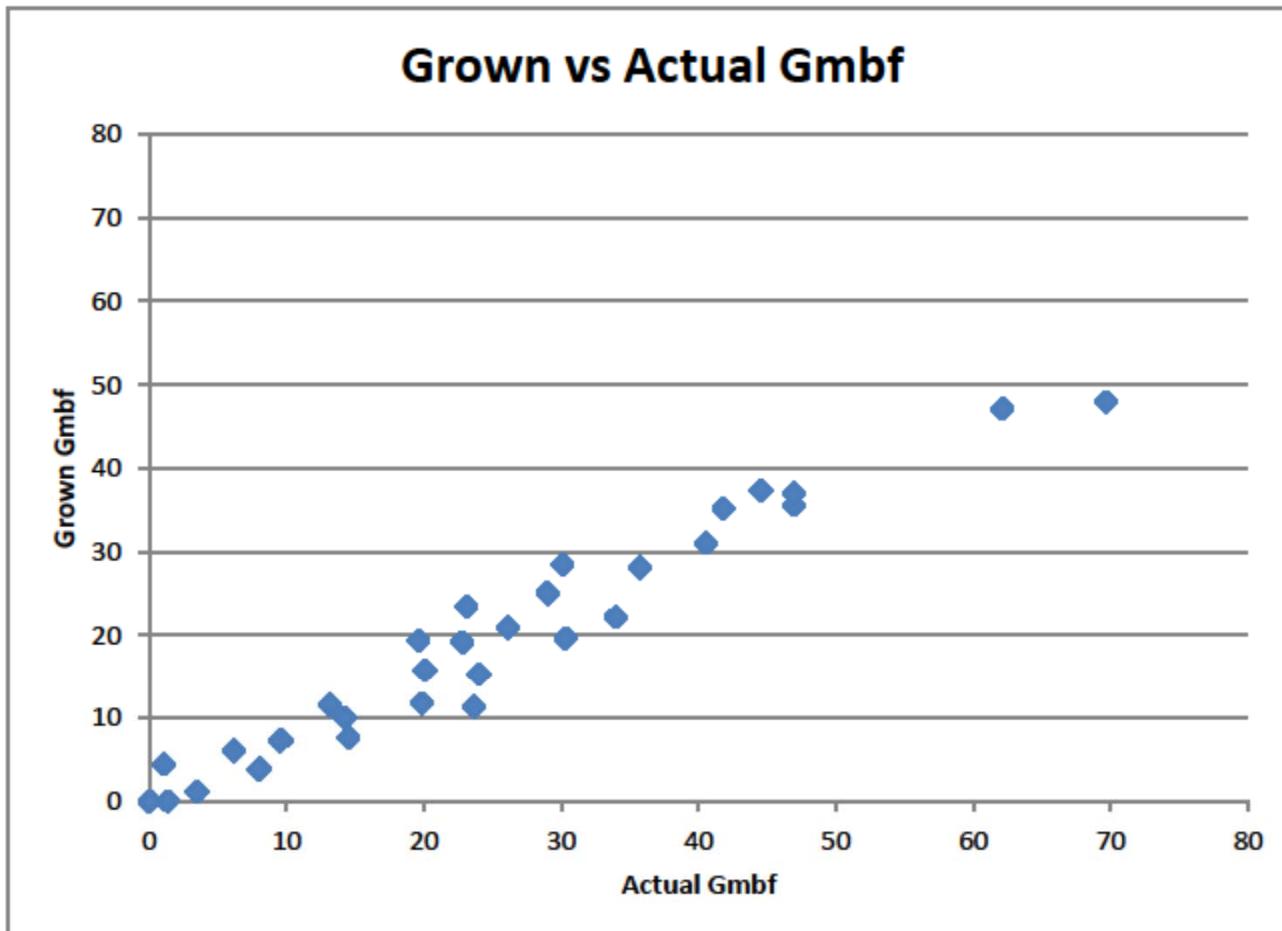
1:1 line added



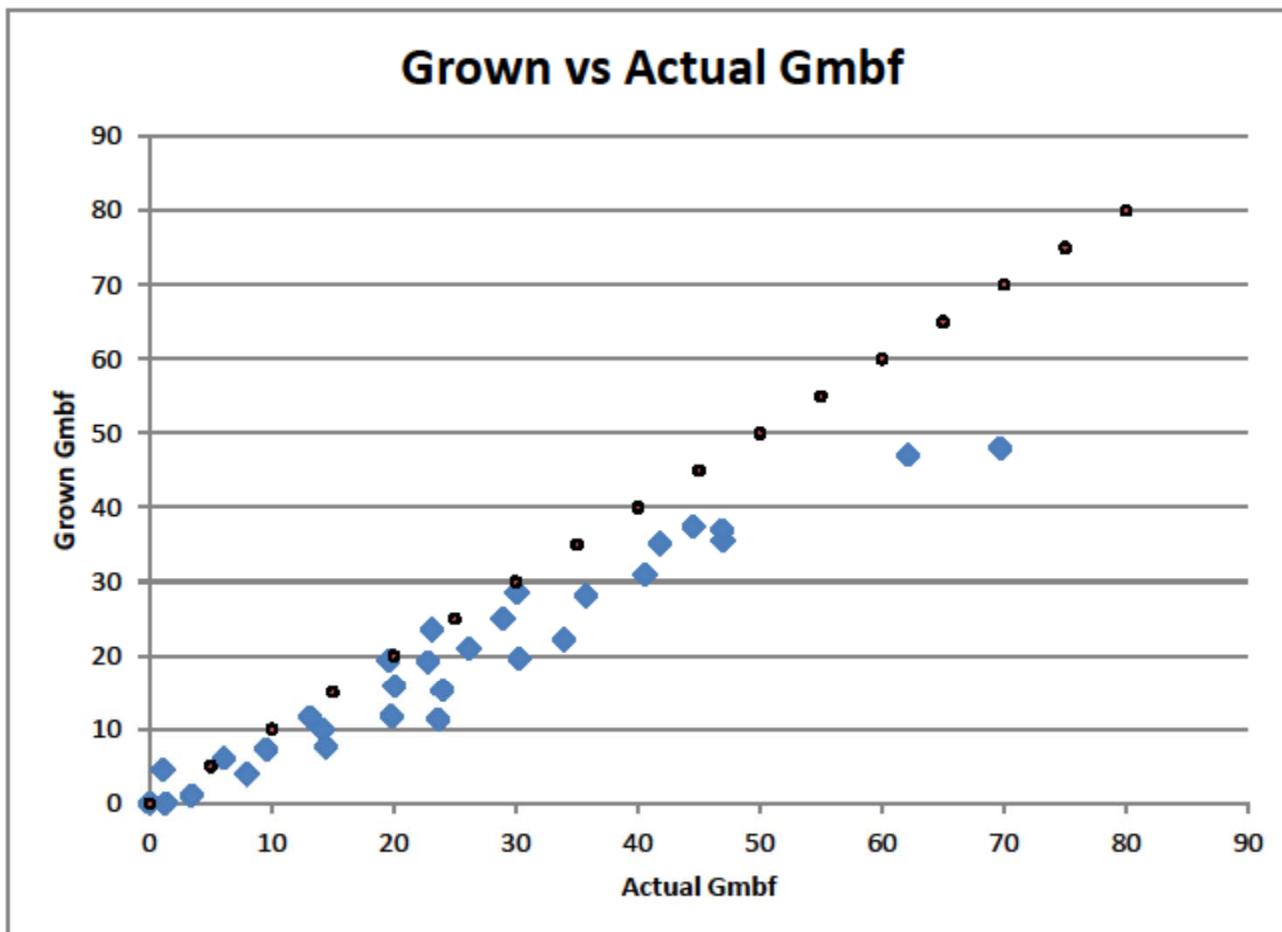
Trend line added



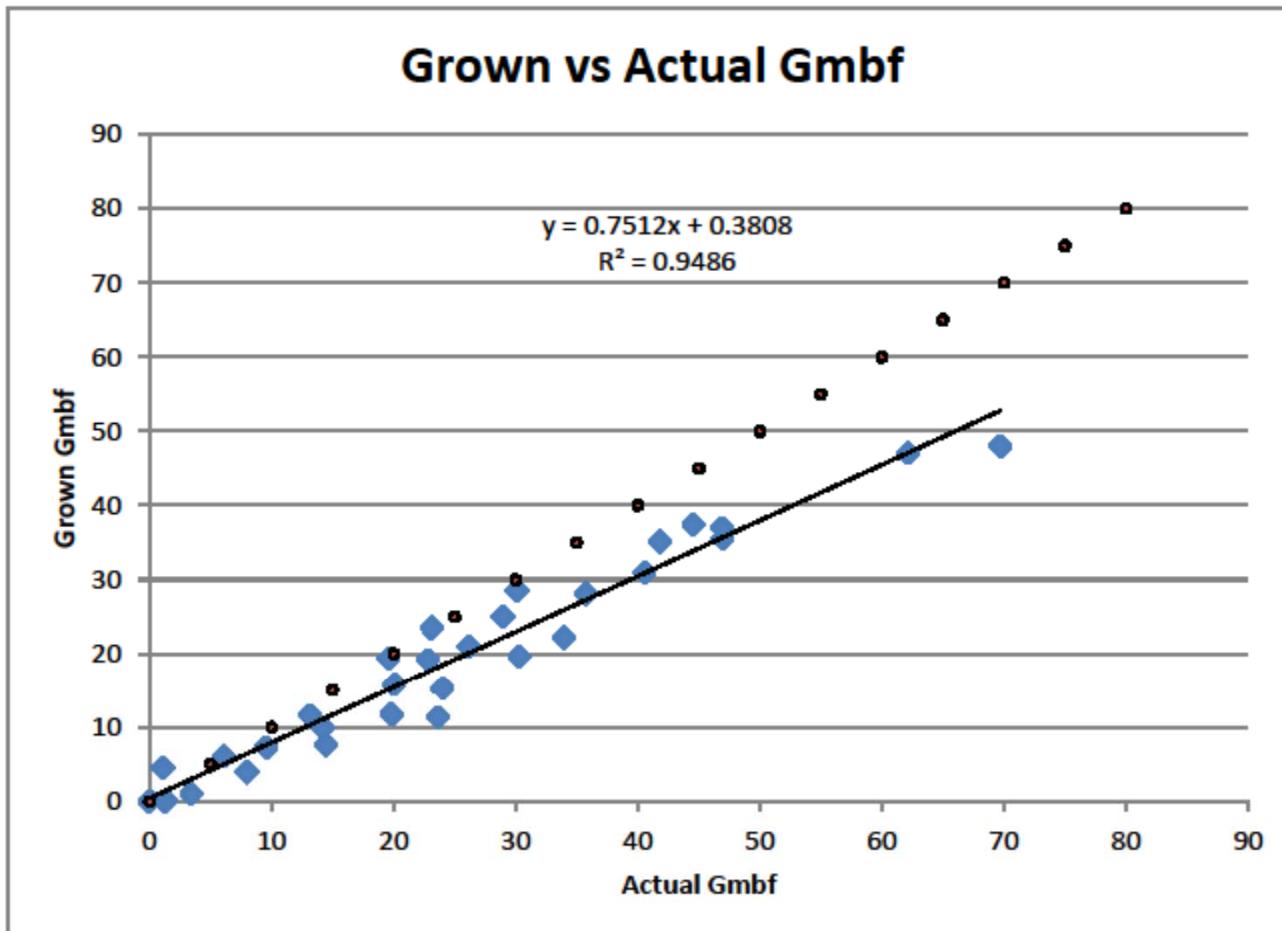
Grown v Actual Gmbf



1:1 line added



Trend line added



Grown v Act Regression Coefficient CIs

TPA	Coefficients	Lower 95%	Upper 95%
Intercept	35.41	-110.67	181.49
X Variable 1	0.94	0.69	1.18

QDbh	Coefficients	Lower 95%	Upper 95%
Intercept	1.47	0.54	2.40
X Variable 1	0.78	0.69	0.88

BA	Coefficients	Lower 95%	Upper 95%
Intercept	-6.72	-37.11	23.68
X Variable 1	0.95	0.83	1.06

HT	Coefficients	Lower 95%	Upper 95%
Intercept	1.37	-5.07	7.81
X Variable 1	0.90	0.82	0.97

Gmbf	Coefficients	Lower 95%	Upper 95%
Intercept	0.38	-1.70	2.46
X Variable 1	0.75	0.68	0.82

Accuracy Stats

*Root Mean Square Error (RMSE)
sensitive to “outliers”*

$$RMSE_{\text{Errors}} = \sqrt{\frac{\sum_{i=1}^n (\hat{y}_i - y_i)^2}{n}}$$

Mean Absolute Error (MAE)

RMSE >= MAE

“Smaller is better”

useful in comparing and refining models

before and after calibration

both estimate “absolute bias”

plots or means indicate bias direction

On Statistical Testing

Yang, Monserud & Huang, 2004:CJFR:34:619-629. An evaluation of diagnostic tests and their roles in validating forest biometric models

- *Compared 5 parametric and 5 non-parametric tests*

“It was shown that the usefulness of statistical tests in model validation is very limited. None of the tests seems to be generic enough to work well across a wide range of models and data. Each model passed one or more tests, but not all of them. Because of this, caution should be exercised when choosing a statistical test or several tests together to try to validate a model. It is important to reduce and remove any potential personal bias in selecting a favorite test, which can influence the outcome of the results.”

Hypothesis Testing

Dbh & Height & BA

tempting to use a standard paired-t test
check distribution assumptions first

log ratio of Grown over Actual is better

$\ln(G/A)$: H0: stat = 0, [+]: G>A; [-]:G<A

Tpa (survival and/or mortality)

chi-square or K-S goodness-of-fit test

Equivalence testing

set “practical or acceptable difference”

TOST (two one-sided tests)

Significance level to use?

Technique Summary

Graphical first, then statistical

proj vs actual scatterplots can be quite revealing

add 1:1 line (perfect agreement)

add linear trend line

slope (1)

intercept (0)

Statistics

RMSE and MAE -->smaller is better

distribution assumption for standard paired-t

Dbh, Ht, BA: ln(G/A):

H0: stat = 0; [+]: G>A; [-]:G<A

Tpa: chi-squared or K-S goodness-of-fit test

Equivalence tests --> incorporate “practical est”

Session 2 – Model Evaluation

Slide 2

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Summary

Re-Cap Model Evaluation

- **Evaluation/Validation is relative to Utility and Purpose**
- **Methods parallel the methods used to develop models**
- **Evaluation with Data**
 - Predicted – Actual
- **Evaluation without data**
 - Patterns and principles
- **Techniques**
 - Bias, Precision