

Phenotyping Diverse Bacteria for Metabolic Network Reconstruction



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Introduction

Current bacterial models are built from gene annotations, where gene function is deduced through homology-based algorithms and tools, such as RAST (Rapid Annotation using Subsystem Technology)

Novel functional roles are left undiscovered when they cannot be extrapolated from current annotation software

Using flux-balance analysis (FBA) software, metabolic models can be used for *in silico* prediction of growth rates and biomass yield upon a variety of growth conditions

Recent developments using multi-phenotype assay plates (MAPs) provide a high-throughput technique for profiling bacterial phenotypes upon a variety of growth conditions

Coupling PM experiments with FBA software, metabolic models can be reconciled and optimized to best predict bacteria response and yield

Experimental Design

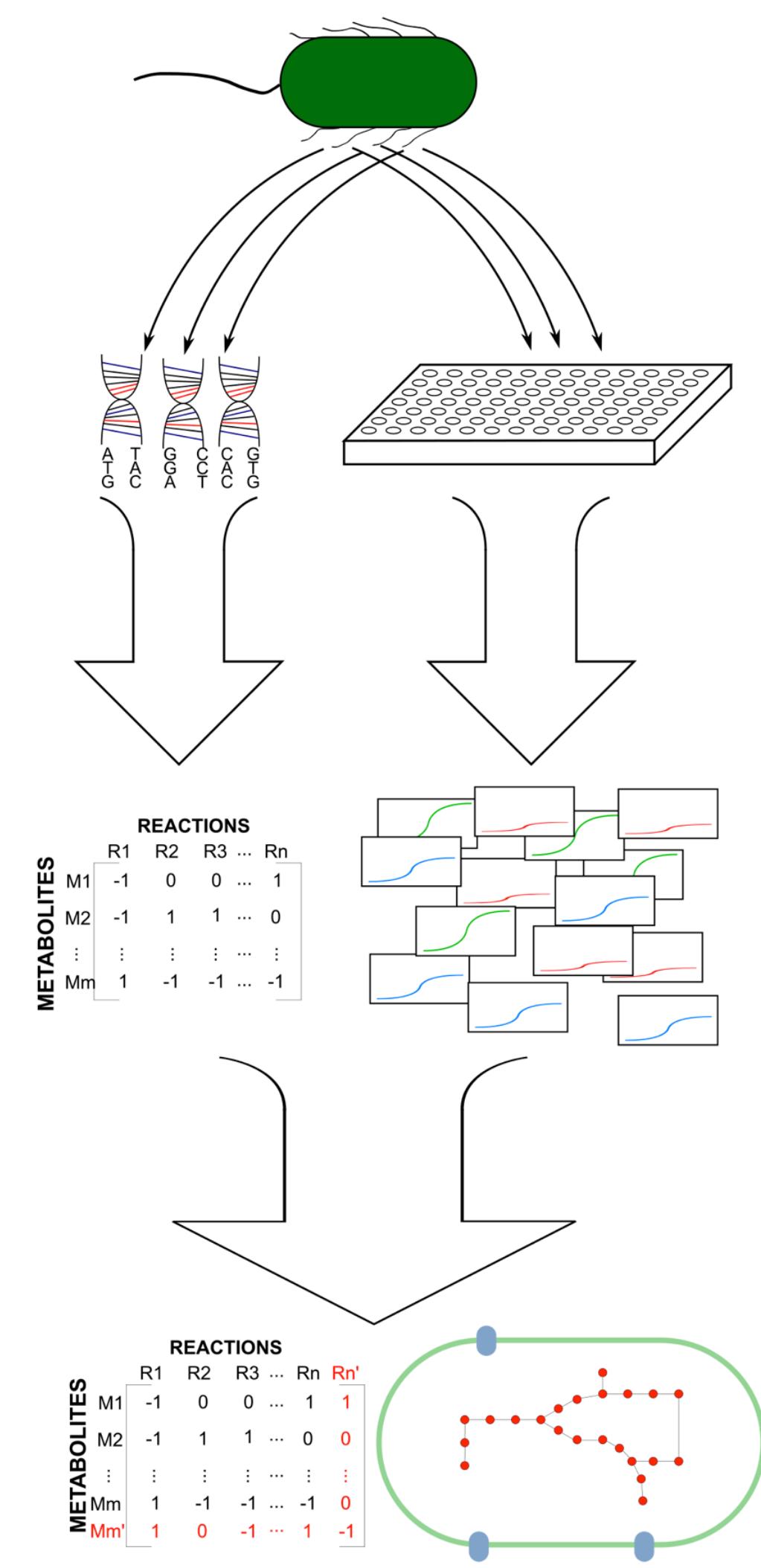


Figure 1. Model reconciliation workflow. Combine genomics and phenomics in order to create, test, and reconcile bacteria metabolic models.

Methods

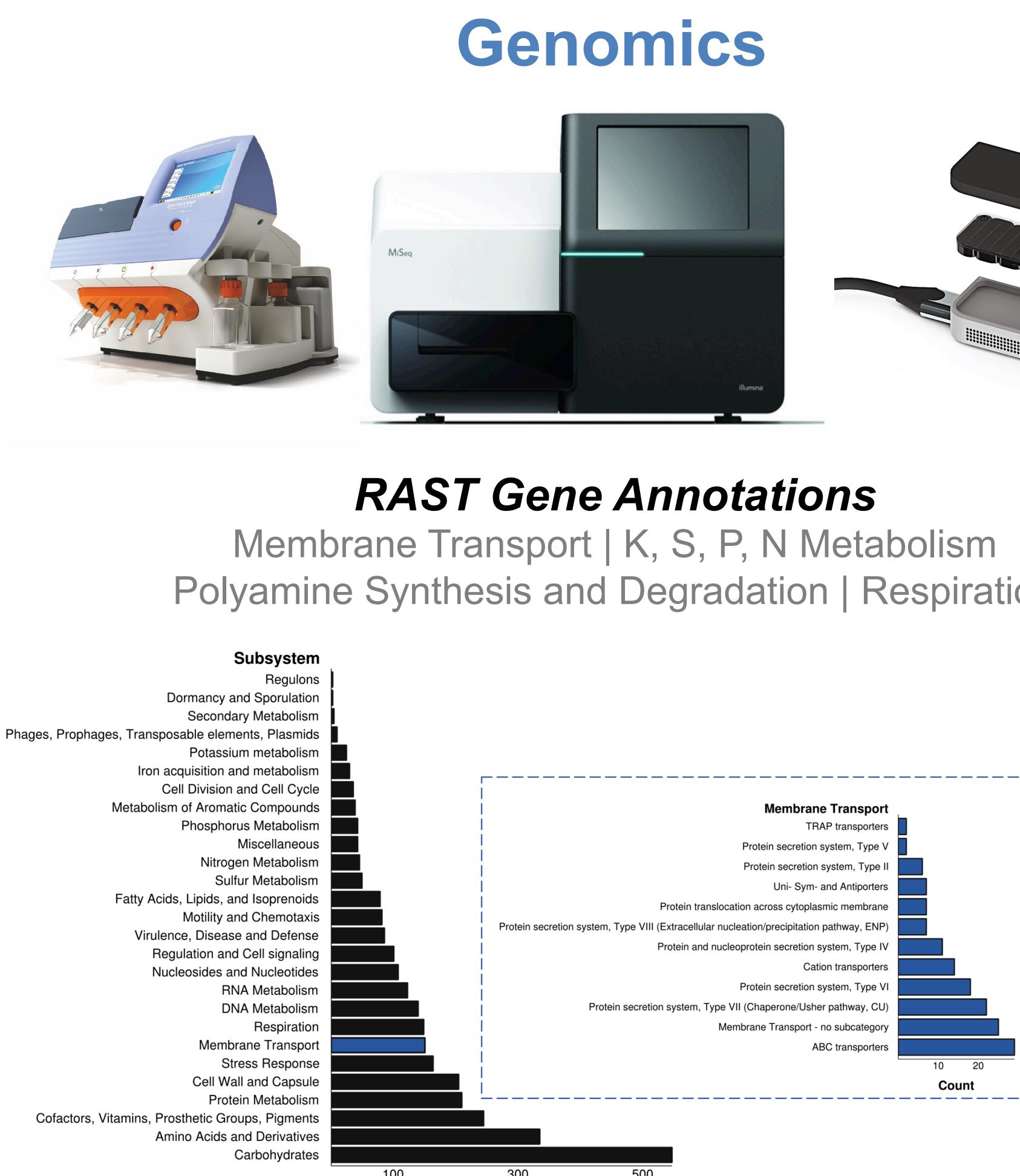


Figure 2. Genomic annotations. Next-generation sequencing platforms are used to sequence the *Citrobacter sedlakii* genome. Sequences are uploaded to RAST to obtain gene function annotations.

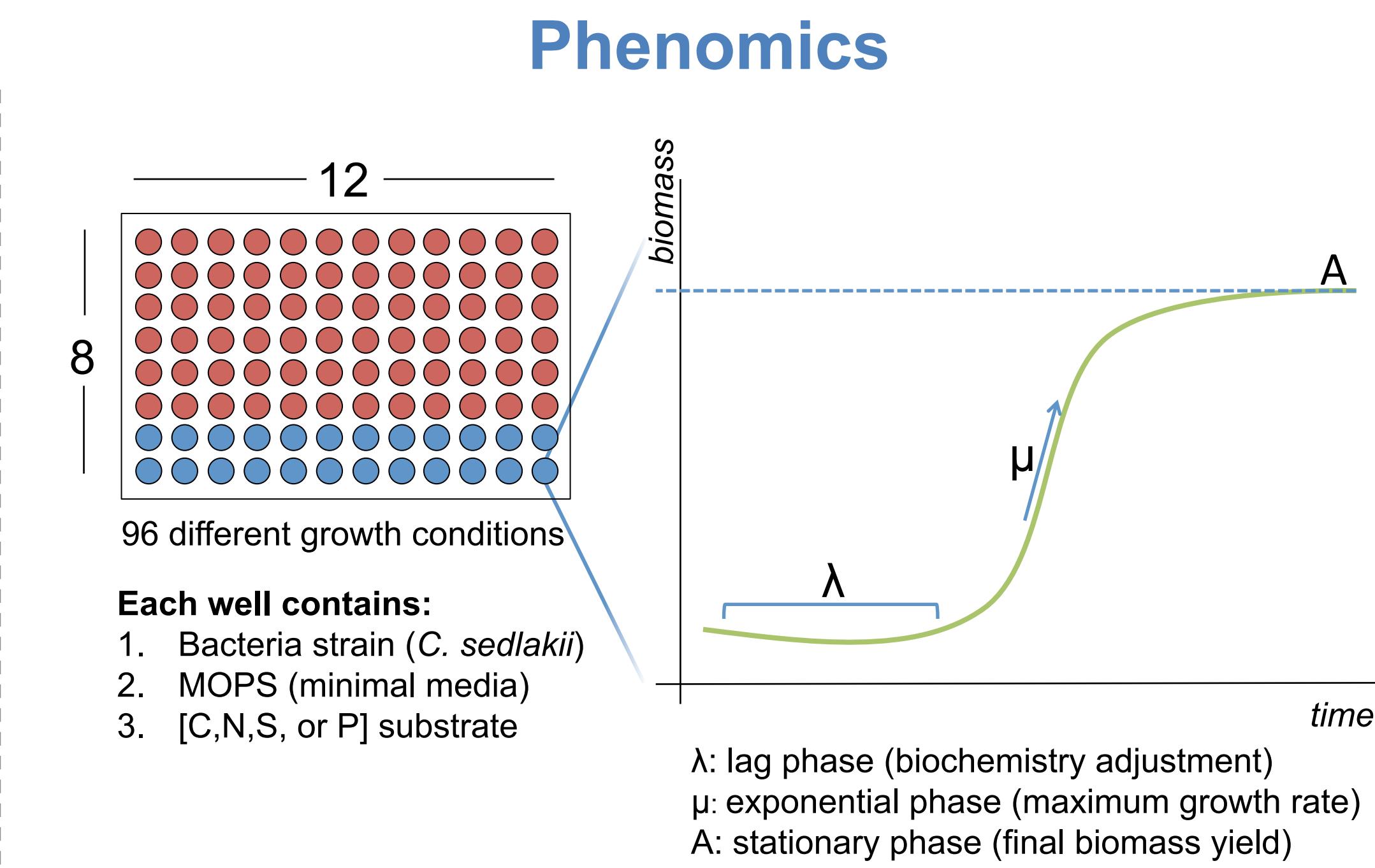


Figure 3. Modeling growth curves. Bacteria are grown on 96-well plates over time. OD 600nm is recorded to produce growth curves. Model parameters are automatically determined using an optimization method to produce a best fit logistic curve. Growth is computed based on model parameters.

$$\text{Growth curve model} \quad \hat{y} = y_1 + \frac{A - y_1}{1 + \exp \left[\left(\frac{\mu_{\max}}{A} \right) (\lambda - t_i) \right] + 2}$$

	1	2	3	4	5	6	7	8	9	10	11	12
A	Propionate	L-glutamate	D-glucose	Potassium sorbate	Lactulose	Glycerol	Myo inositol	D-serine	Oxalic acid (0.2%)	Malic acid	L-methionine (0.2%)	
B	Glycine	Water	Quinate	Succinate	Dulcitol	Alpha-D-glucoside	L-vylose	L-spartic acid (0.2%)	D-fructose	L-valine	Pyruvate	Lactate
C	Citric acid	D-mannose	L-serine	Salicicole	Cellobiose	Adonitol	D-galactose-6-P	L-sorbose	D-arabinol	D-lysine	D-trehalose	Acetic acid
D	L-alanine	L-arabinose	L-threonine	4-hydroxy phenylacetate	D-ribose	Melibiose	D-alanine	L-fucose	L-asparagine (0.2%)	L-leucine	D-spartic acid (0.2%)	Inosine
E	Thymidine	Sucrose	D-xylene	L-cysteine	Alpha-D-glucoside	Raffinose	D-asparagine	Erythritol	D-cysteine	L-leucine (0.2%)	L-cysteic acid	Adenosine (0.2%)
F	Xylose	L-glutamine	L-threonine	Putrescine	2-deoxy-D-ribose	L-arabinose	D-glucosamine	L-arginine	D-glutamic acid (0.2%)	D-arabinose	L-tryptophan (0.2%)	L-pyro glutamic acid
G	Water	Tyramine (0.2%)	Uridine	Inosine	Histamine	L-pyro glutamic acid	Cysteine	Adenosine (0.2%)	L-arginine (0.2%)	Thiourea	Bluet (0.2%)	Guanine
H	L-histidine	Thymine (0.2%)	L-glutathione	Allantoin	Adenine (0.2%)	Glycine	Beta-phenyl ethylamine	L-proline (0.2%)	D-methionine (0.2%)	Cytosine	D-valine (0.2%)	N-acetyl-D-glucosamine (0.2%)

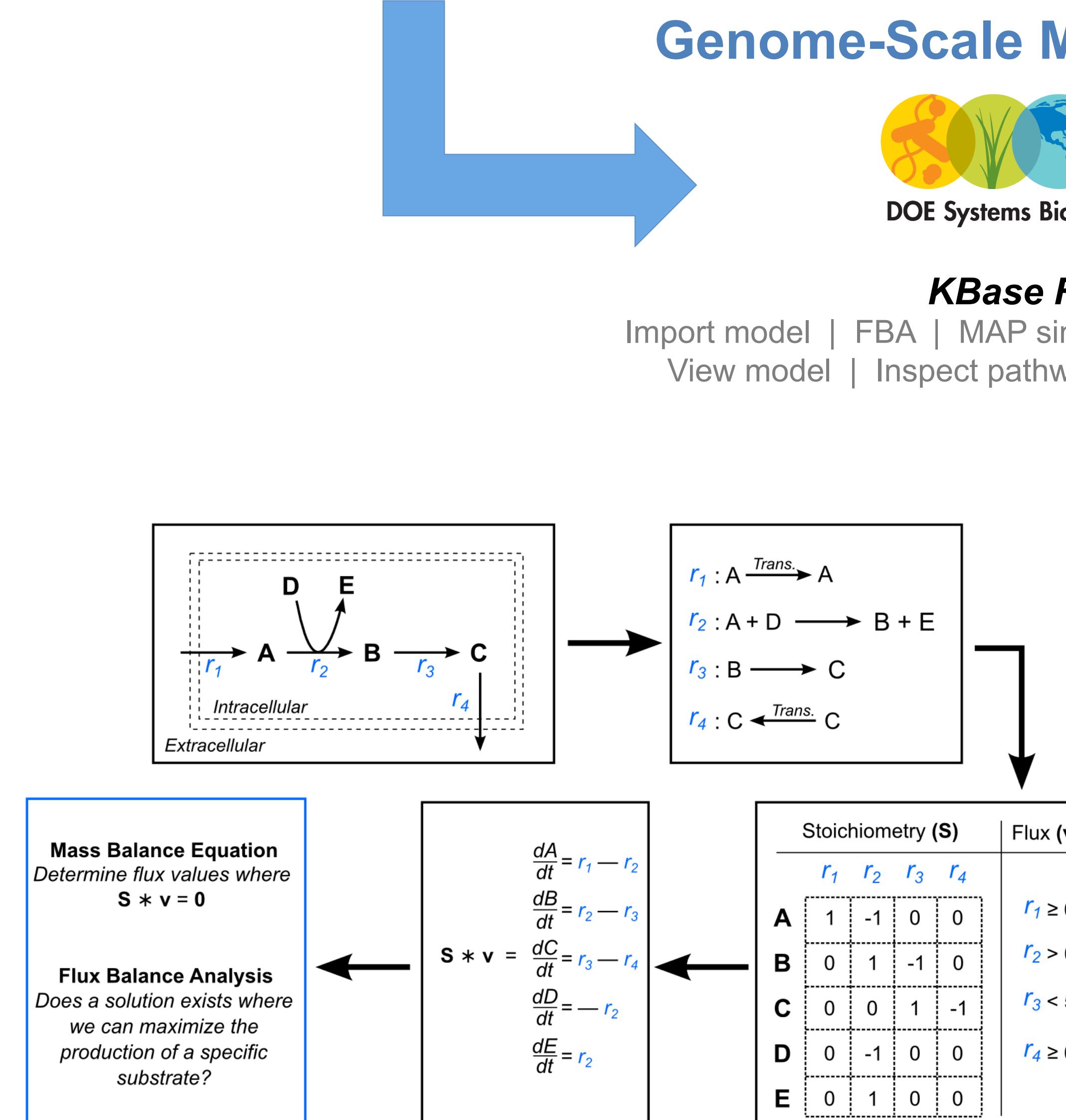


Figure 4. Constraint-based model. KBase supplies the framework where a metabolic model can be imported as a stoichiometric matrix of metabolites and reactions. Included in the model are several constraints including thermodynamics, reaction flux rate, and mass balancing. Linear programming maximizes biomass production to answer the question: does the model predict growth?

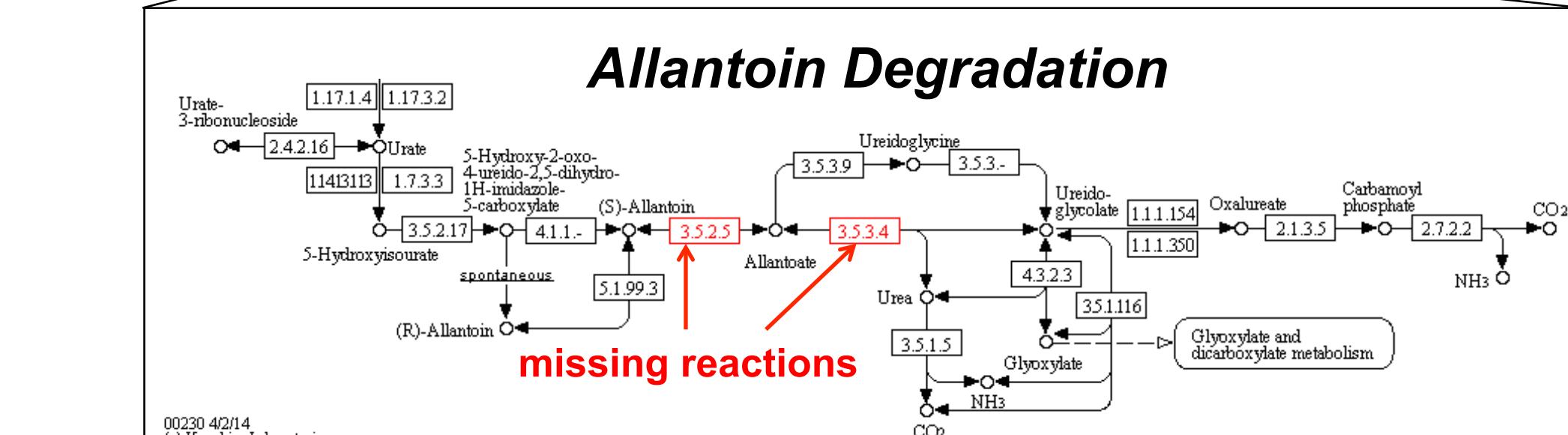


Figure 5. Gap-filling. Given a model that incorrectly predicts no growth, Kbase includes the capability to identify reaction gaps in the model that allow the bacterial model to correctly exhibit growth. Above is an example of two missing reactions in the *C. sedlakii* model involved in the allantoin degradation pathway.

Results

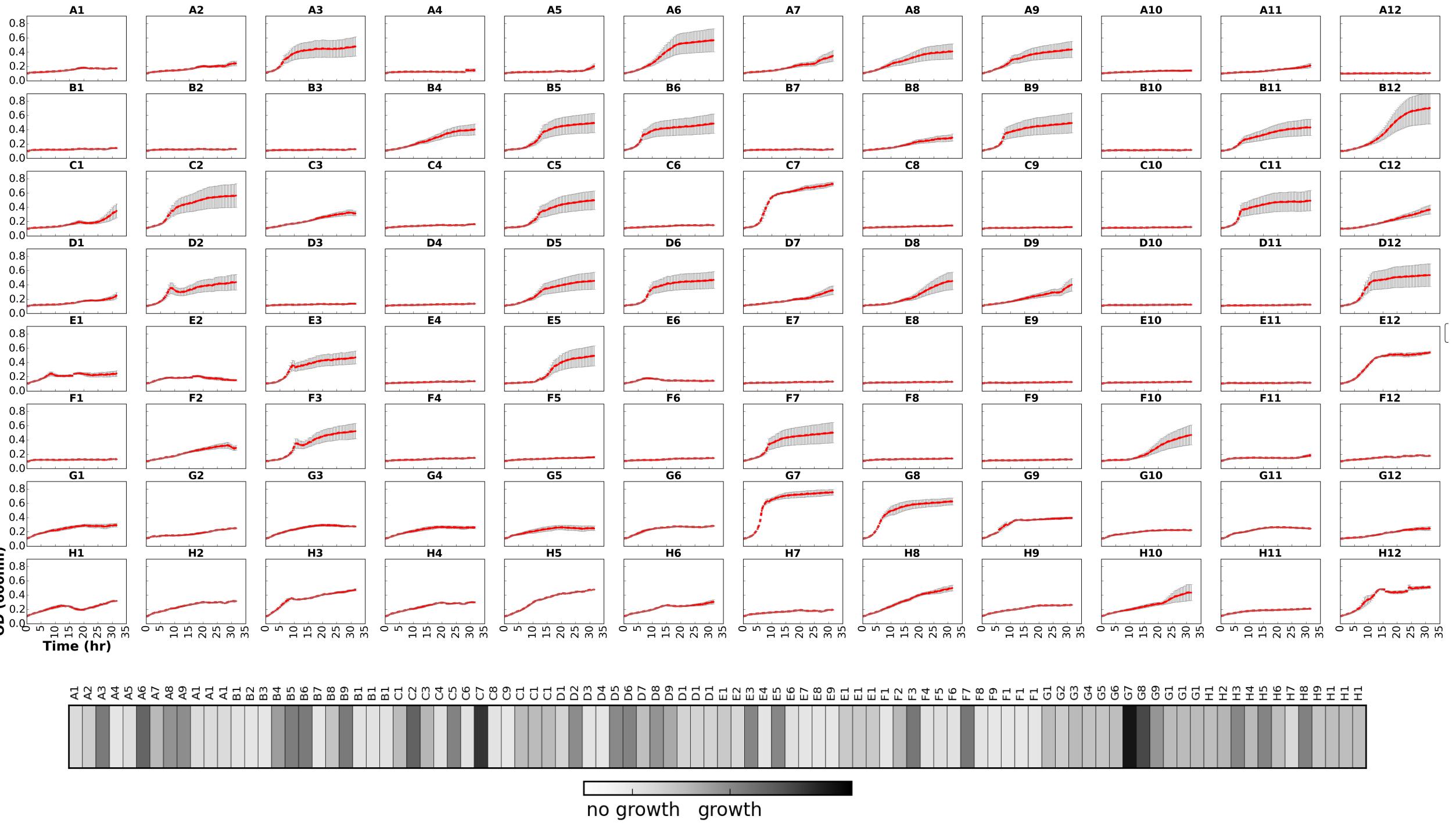


Figure 6. *C. sedlakii* growth curves. The automated analysis pipeline creates growth curve plots with standard error bars. Growth levels are quickly assessed in the grey-scale bar.

FBA Prediction		
Phenotypic Result	G	NG
NG	48	0
G	6	36

Table 1. A comparison between experimental results and FBA prediction. After using gap-filling on KBase, 84 cases (93%) were in agreement with the MAPs results. 6 cases did not match the MAPs experiments.

# of Bacteria	Sequenced	22
MAPs	49	

Table 2. Current data collection.

Questions

Why were these reactions missing from model?

Continue to model, sequence, and assay a broad and diverse set of bacteria – can we improve annotations?

Additional Information

<https://vdm.sdsu.edu/pmanalyzer>
<https://edwards.sdsu.edu/dbbp>

PMAnalyzer

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