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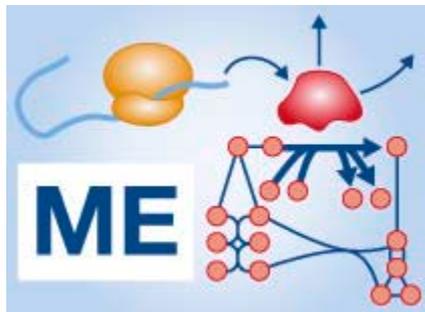
Genome-scale models of metabolism and gene expression extend and refine growth phenotype prediction

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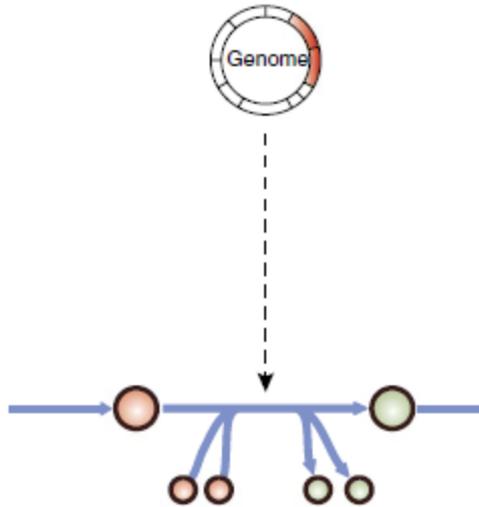


ME-models (Metabolism and Expression): integrate metabolic and gene product expression pathways

- First ME-model for *E.coli*
- Incorporate gene express and proteomic data
- Predict several cellular phenotypes
- Provide a method that can be used to simulate growth and changes in genome scale systems
- Develop into a powerful approach to integrate transcriptomics data with metabolic networks in plant

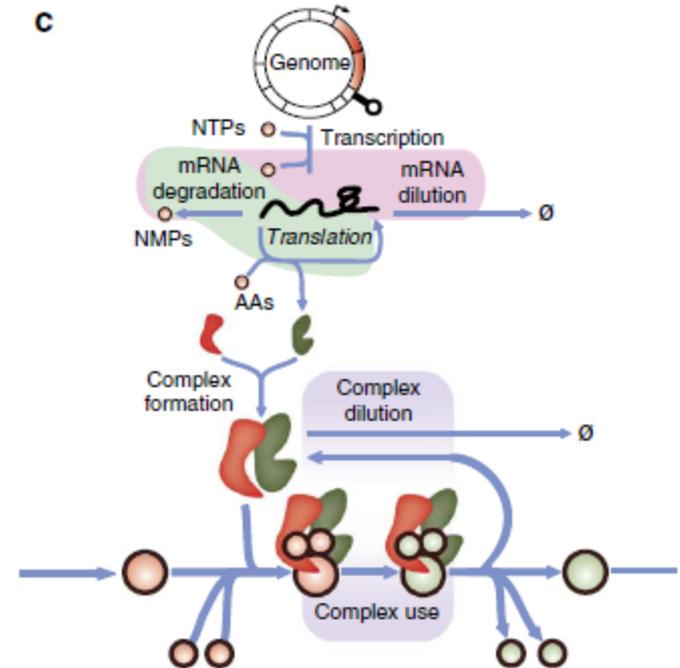
M-models (metabolic) vs. ME-models

a



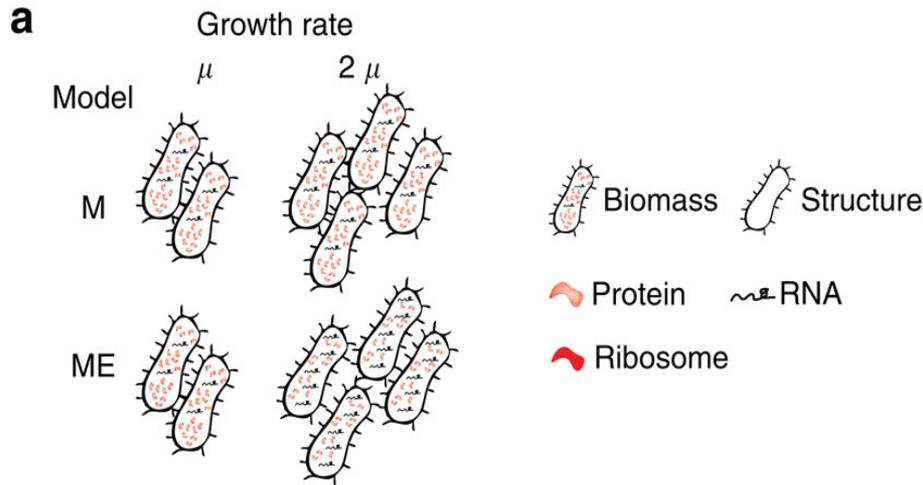
- Predict reaction flux
- Genes are either ON or OFF

c



- Add transcription and translation
- Account for RNA generation and degradation
- Account for peptide creation and degradation
- Gene expression and gene products explicitly modeled and predicted

M-models vs. ME-models (continued)



ME-models

- Account only for “constant” cell structure
 - Cofactors like Coenzyme A
 - DNA like dCTP, dGTP
 - Cell wall lipids
 - Energy necessary to create and maintain them
- Model approximates a cell whose composition is a function of environment and growth rate
- Cellular composition (mRNA, tRNA, ribosomes) taken into account as dynamic reactions
- LP used to identify the minimum ribosome production rate required to support an experimentally determined growth rate

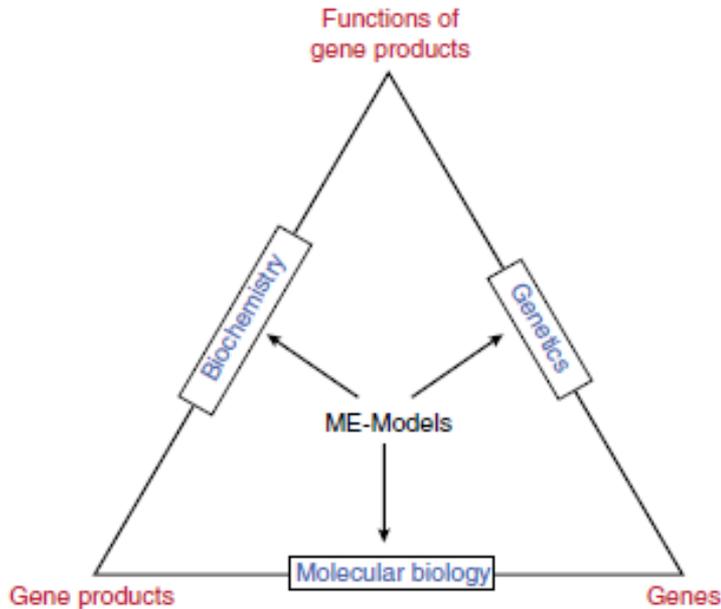
b

Model	Simulation objective	Measurement	Assumption
M	Maximize μ	Subject to $\frac{v_{\text{substrate}}}{v}$	Constant composition
ME	Minimize v_{dilution}	Subject to μ	Constant composition

M-models

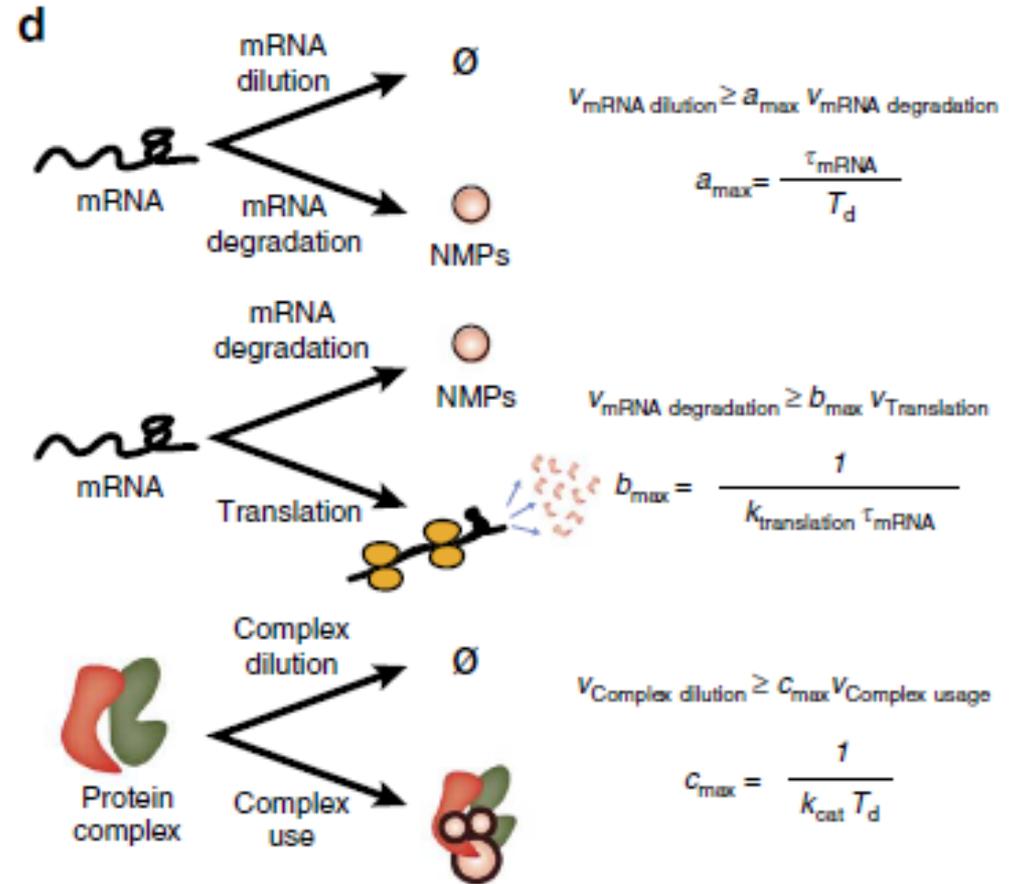
- Account for total biomass reaction
- T_d was integrated to define a biomass reaction
- LP used to find max growth subject to (measured) uptake rate

ME-model: the details



ME-Models provide links between the biological sciences. With an integrated model of metabolism and macromolecular expression, it is possible to explore the relationships between gene products, genetic perturbations and gene functions in the context of cellular physiology.

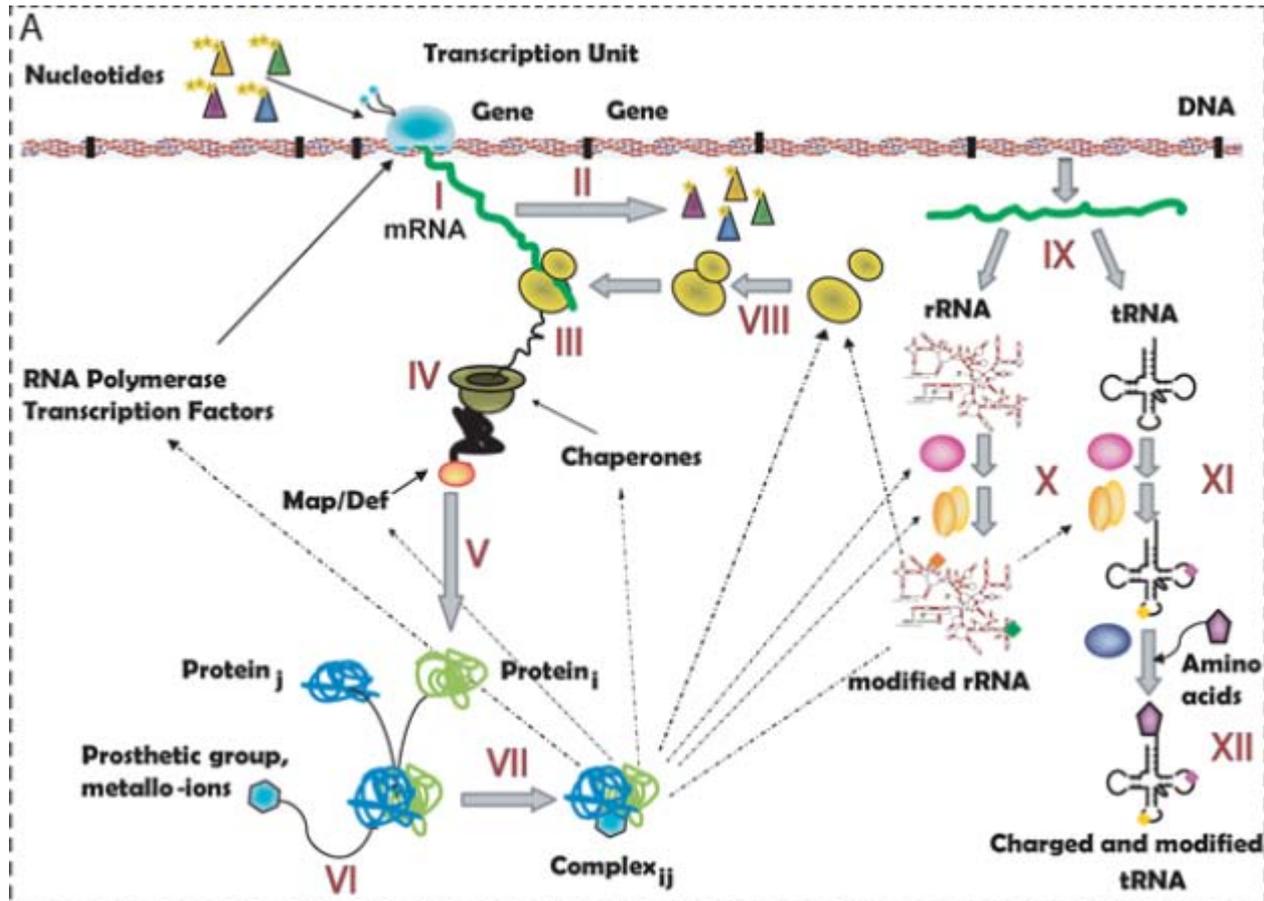
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The transcriptional, translational and enzymatic activities are coupled to doubling time (T_d) using constraints that limit transcription and translation rates as well as enzyme efficiency.

Integration of genome-scale reaction networks of protein synthesis and metabolism

	<i>iJO1366</i> (this study)
Included genes	1366 (32%) ^a
Experimentally based function	1328 (97%)
Computationally predicted function	38 (3%)
Unique functional proteins	1254
Multigene complexes	185
Genes involved in complexes	483
Instances of isozymes ^b	380
Reactions	2251
Metabolic reactions	1473
Unique metabolic reactions ^c	1424
Cytoplasmic	1272
Periplasmic	193
Extracellular	8
Transport reactions	778
Cytoplasm to periplasm	447
Periplasm to extracellular	329
Cytoplasm to extracellular	2
Gene-protein-reaction associations	
Gene associated (metabolic/transport)	1382/706
Spontaneous/diffusion reactions ^d	21/14
Total (gene associated and no association needed)	1403/720 (94%)
No gene association (metabolic/transport)	70/58 (6%)
Exchange reactions	330
Metabolites	
Unique metabolites	1136
Cytoplasmic	1039
Periplasmic	442
Extracellular	324



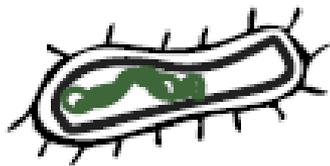
I: Transcription; II: mRNA degradation; III: translation; IV: protein maturation; V: protein folding; VI: metallo-ion binding; VII: protein complex formation; VIII: ribosome assembly; IX: RNA processing; X: rRNA modification; XI: tRNA modification; XII: tRNA charging.

Growth demands and general constraints on molecular catalysis

A

Growth rate-dependent demand functions

1. Cell wall demand (μ)
2. DNA demand (μ)
3. ATP demand (μ)



B

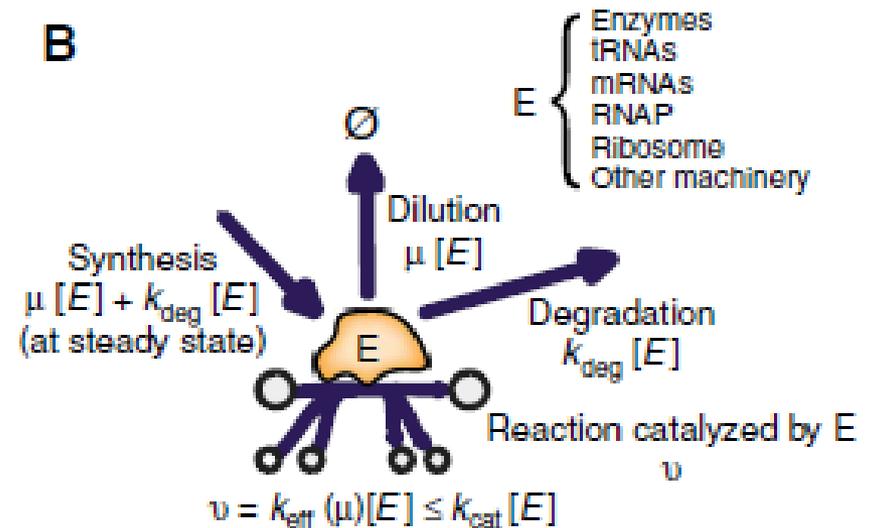
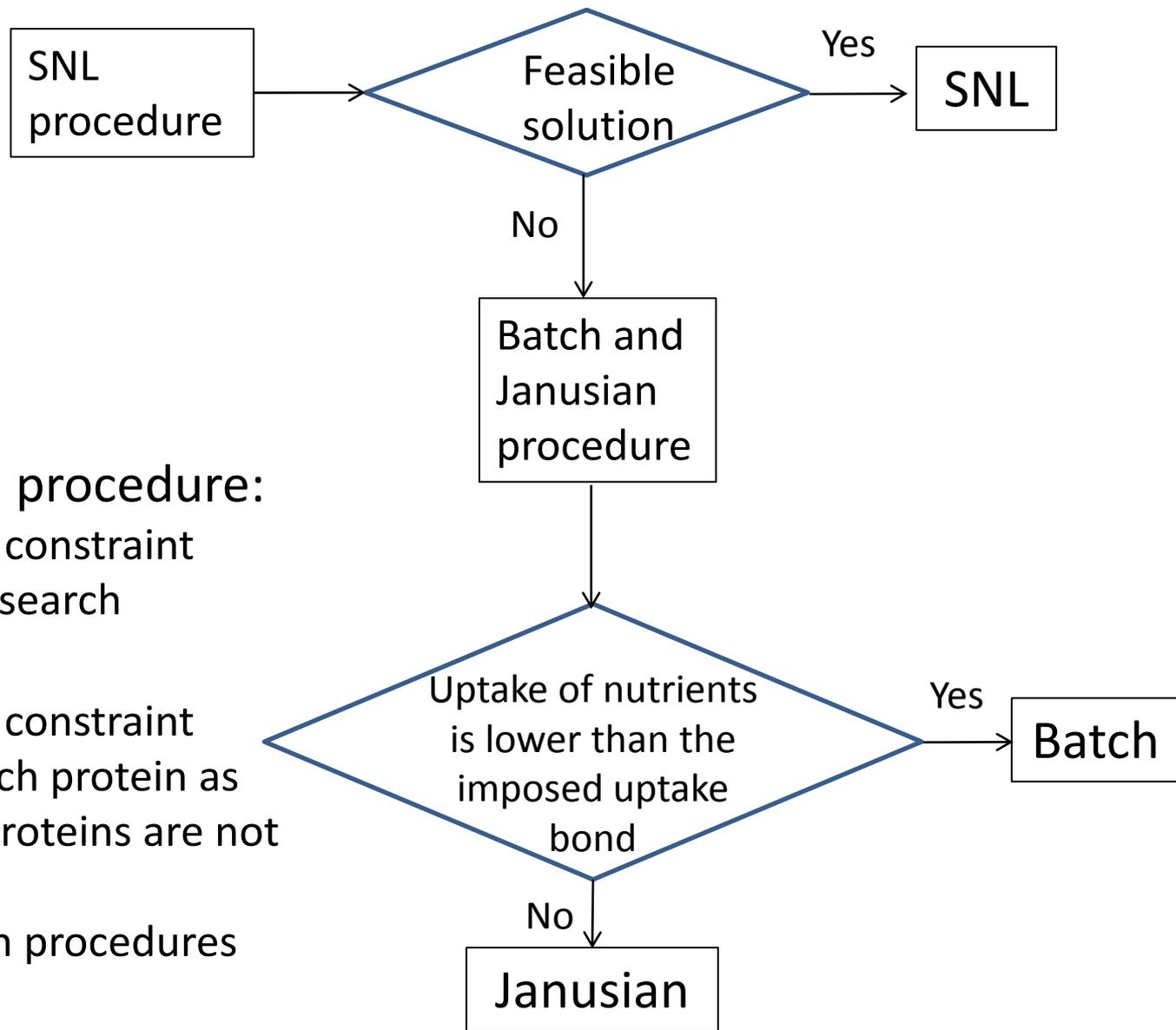
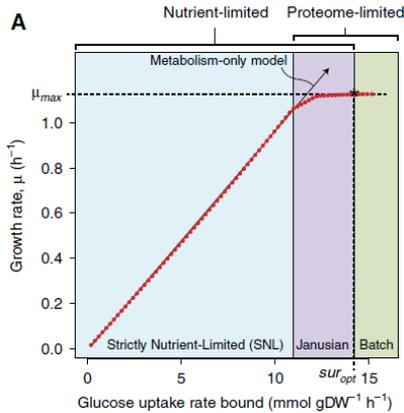


Figure 1. Growth demands and coupling constraints leading to growth rate-dependent changes in enzyme and ribosome efficiency. **(A)** Three growth rate-dependent demand functions derived from empirical observations determine the basic requirements for cell replication. **(B)** Coupling constraints link gene expression to metabolism through the dependence of reaction fluxes on enzyme concentrations.

Optimization procedure



Batch and Janusian procedure:

- Biomass capacity constraint
- Perform a binary search

SNL procedure:

- Biomass capacity constraint
- Cells make as much protein as possible and the proteins are not saturated
- Two binary search procedures

Derivation of constraints on molecular catalytic rates (1)

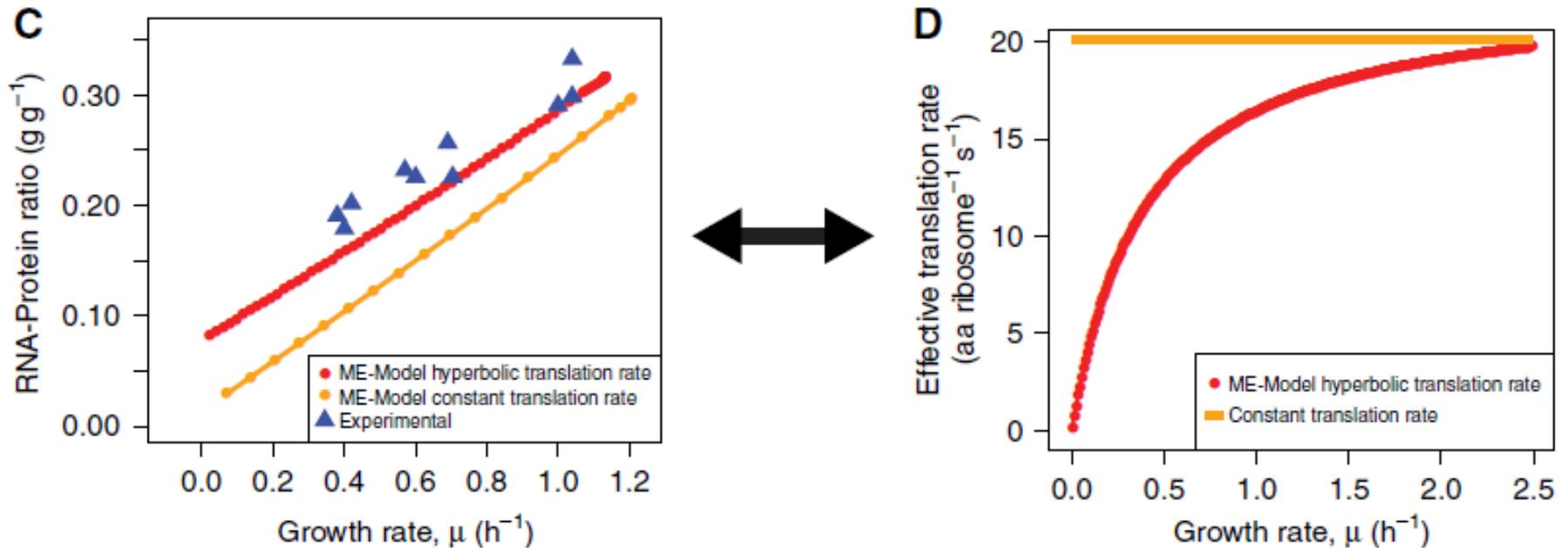


Figure 1. (C, D) RNA:protein ratio predicted by the ME-Model with two different coupling constraint scenarios, one for variable translation rate versus growth rate (red lines) and one for constant translation rate (orange lines). Experimental data in (C) obtained from [Scottet al \(2010\)](#).

Derivation of constraints on molecular catalytic rates (2)

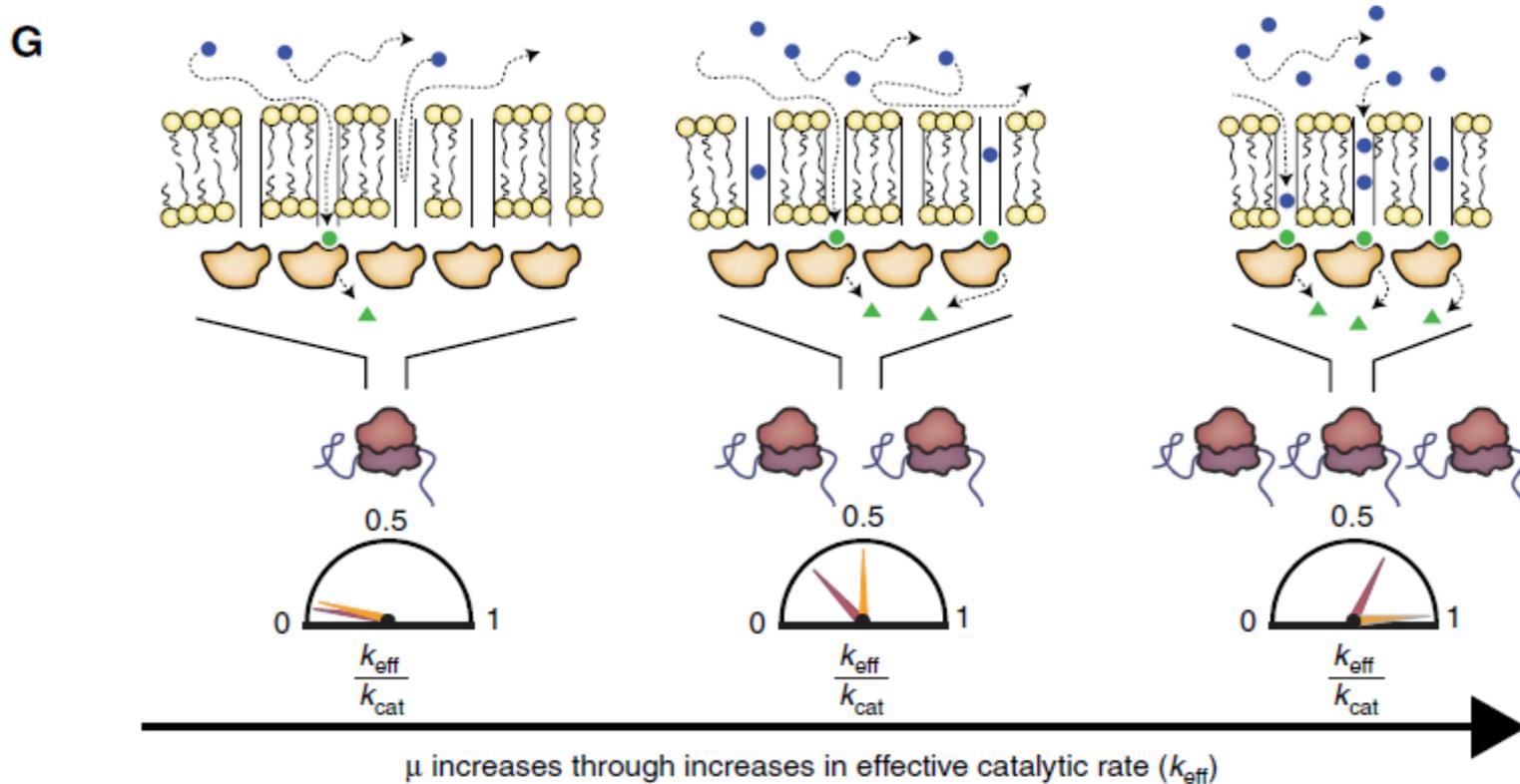


Figure 1. (**G**) The cartoon depicts changes in extra- (blue) and intra- (green) cellular substrate (circle) and product (triangle) concentrations and metabolic enzyme (orange) and ribosome (purple/maroon) levels as the concentration of a growth-limiting nutrient (and growth rate) increases. The dials show $k_{\text{eff}}/k_{\text{cat}}$, the effective catalytic rate over the maximum for metabolic enzymes (orange) and ribosomes (purple/maroon).

Derivation of constraints on molecular catalytic rates (3)

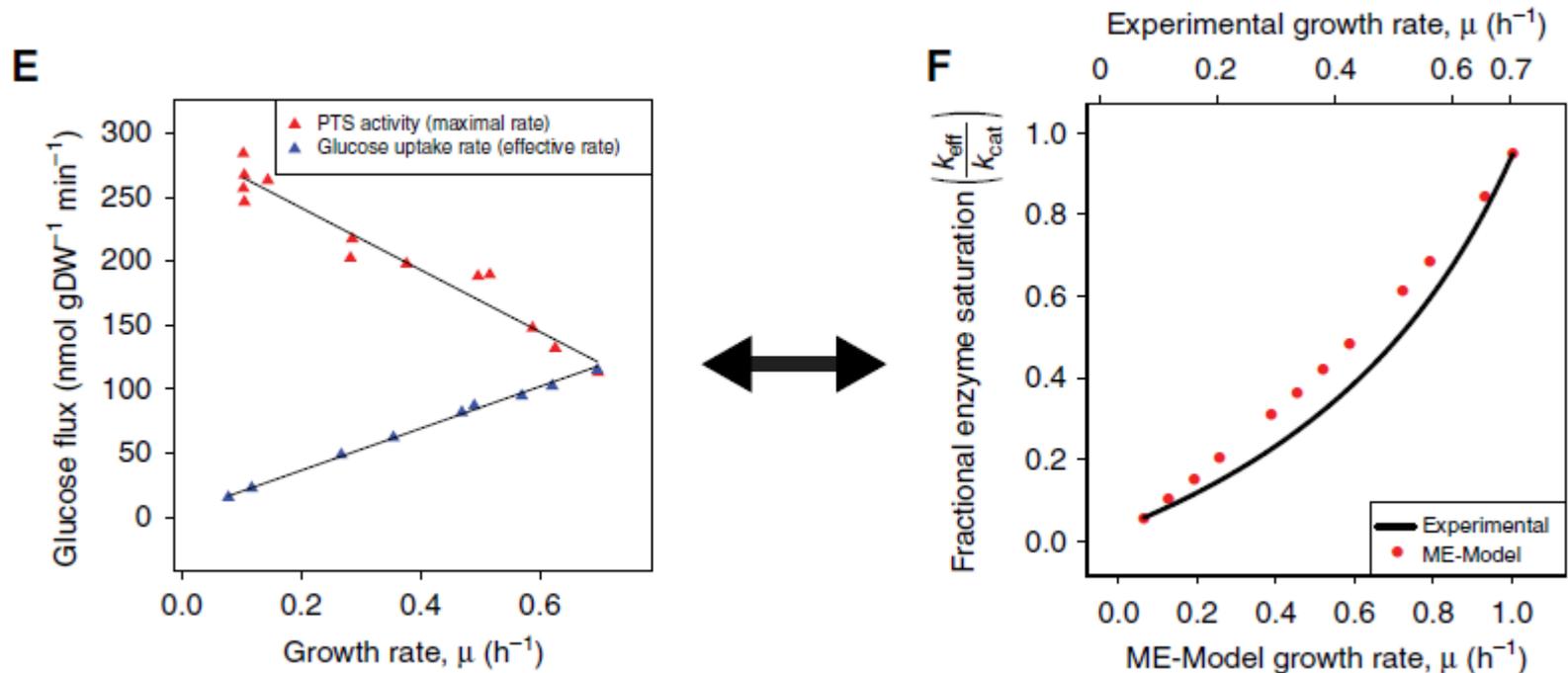


Figure 1. (E) Phosphotransferase system (PTS) transient activity following a glucose pulse in a glucose-limited chemostat culture (red) and glucose uptake before the glucose pulse (blue) is plotted as a function of growth rate. The data shown were obtained from [O'Brien et al \(1980\)](#). (F) Data from (E) are used to plot glucose uptake as a fraction of PTS activity. The resulting value is the fractional enzyme saturation (black line). The fractional enzyme saturation predicted by the ME-Model is plotted as a function of growth rate under carbon limitation (red dots).

Growth regions under varying nutrient availability

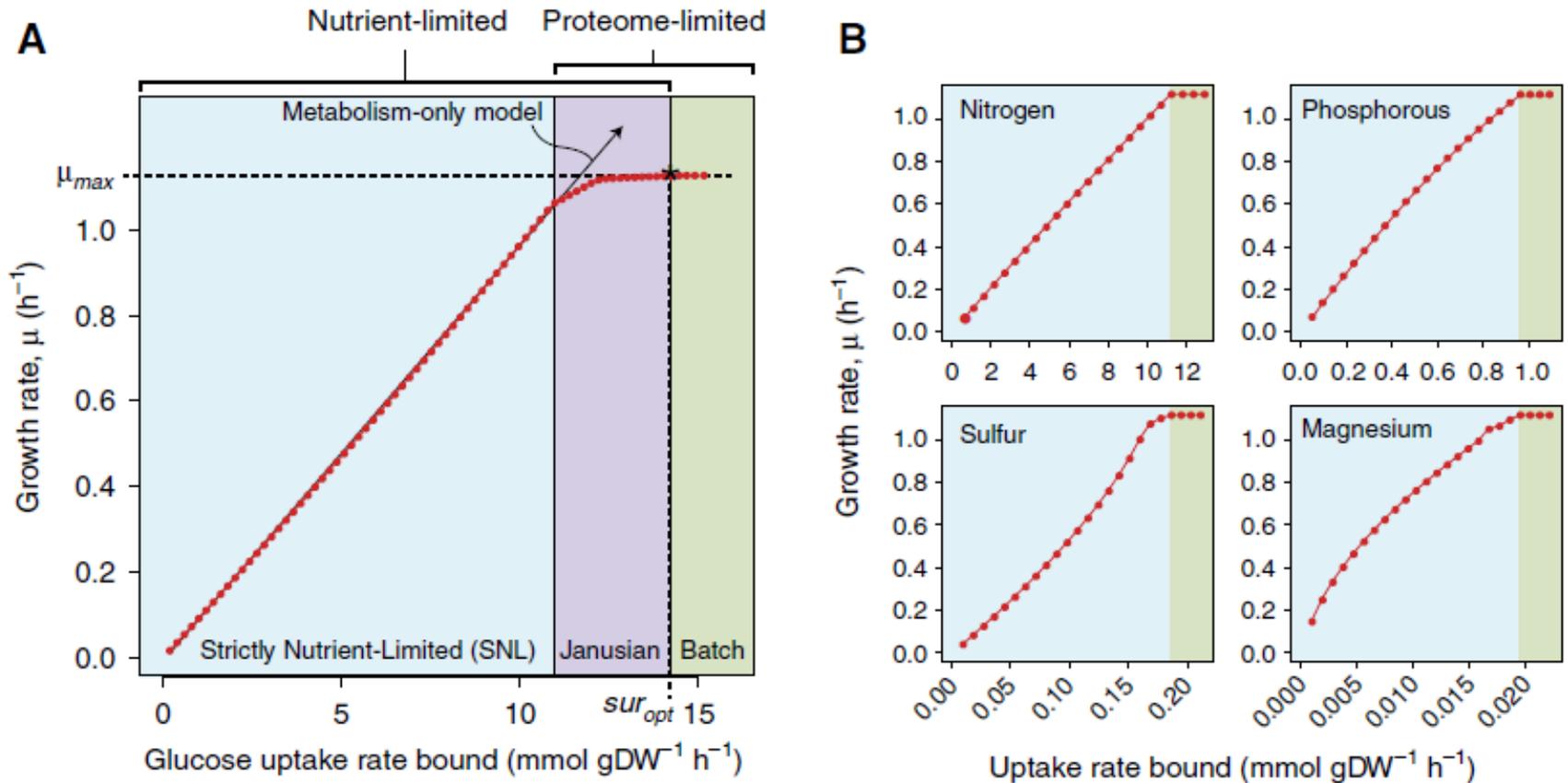


Figure 2. Predicted growth, yield, and secretion. **(A)** Predicted growth rate is plotted as a function of the glucose uptake rate bound imposed in glucose minimal media **(B)** Predicted growth rates as a function of uptake of a limiting nutrient with glucose in excess. The shaded regions correspond to those as labeled in **(A)**.

Effect of proteome limitation on secretion phenotypes

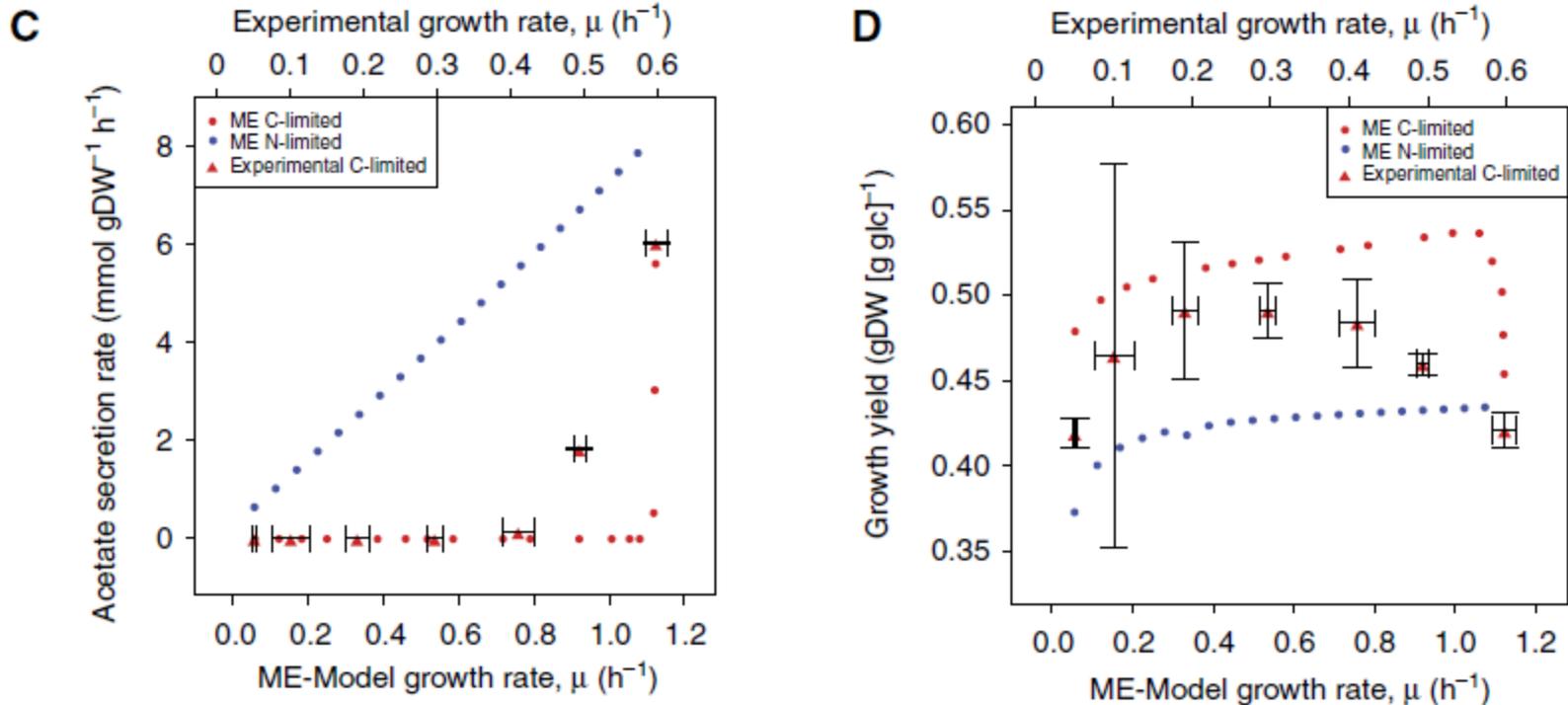


Figure 2. **(C)** Experimental (triangle) and ME-Model-predicted (circle) acetate secretion in Nitrogen- (blue) and Carbon- (red) limited glucose minimal medium are plotted as a function of growth rate. **(D)** Experimental (triangle) and ME-Model-predicted (circle) carbon yield (gDW Biomass/g Glucose) in Carbon- (red) and Nitrogen- (blue) limited glucose minimal medium are plotted as a function of growth rate

The general behavior in the Janusian growth region

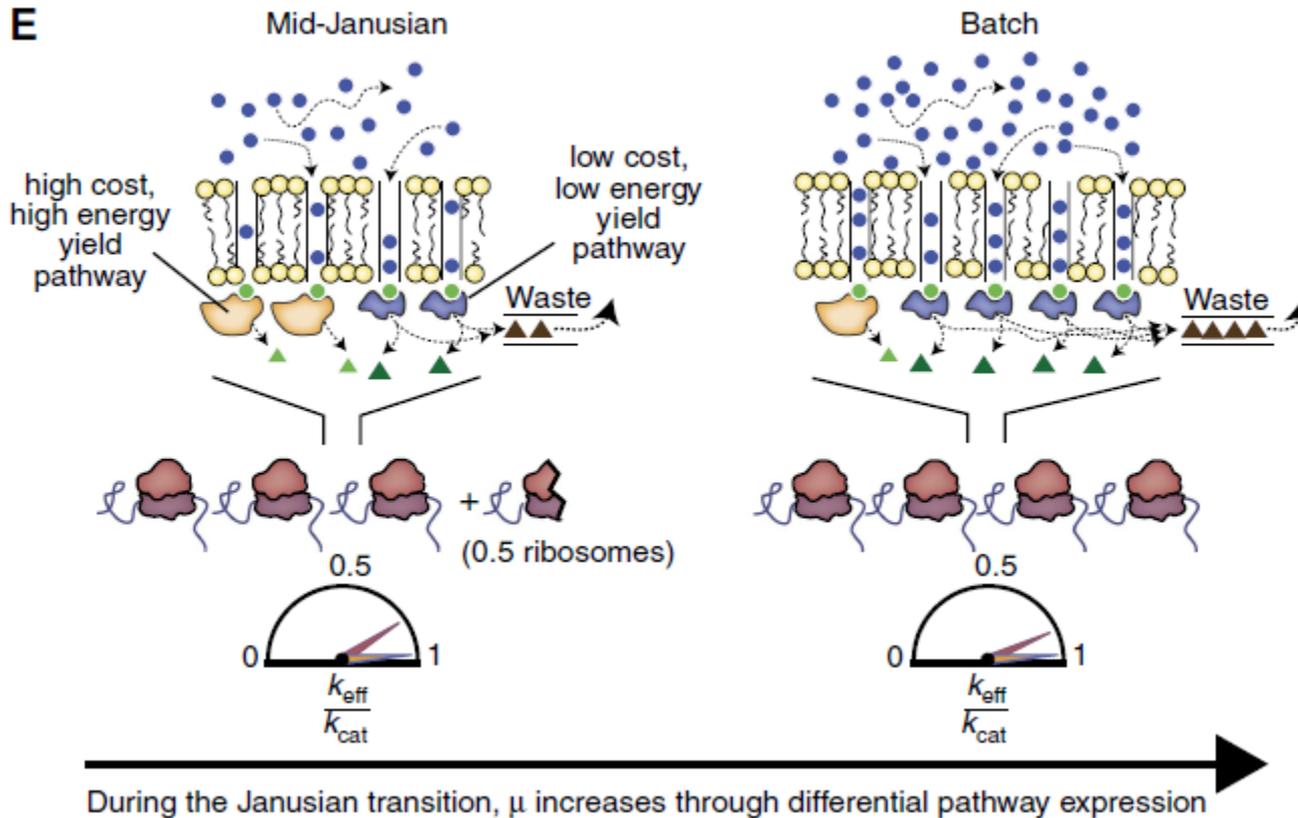


Figure 2. (E) The cartoon depicts changes in extra- (blue) and intra- (green) cellular substrate (circle) and product (triangle) concentrations and metabolic enzyme (blue/orange) and ribosome (purple/maroon) levels during the Janusian region. The dials show k_{eff}/k_{cat} , the effective catalytic rate over the maximum for metabolic enzymes (blue/orange) and ribosomes (purple/maroon).

Metabolic enzymes are saturated throughout the entire Janusian region. To increase the growth rate, the cell expresses metabolic pathways that have lower operating costs. (Pathways with the smaller blue proteins taken to be 0.25 the cost of the pathways with larger orange proteins.) A higher glucose uptake and turnover results, but energy yield is lower and some carbon is 'wasted' and secreted (brown triangles).

Central carbon fluxes reflect growth optimization subject to catalytic constraints

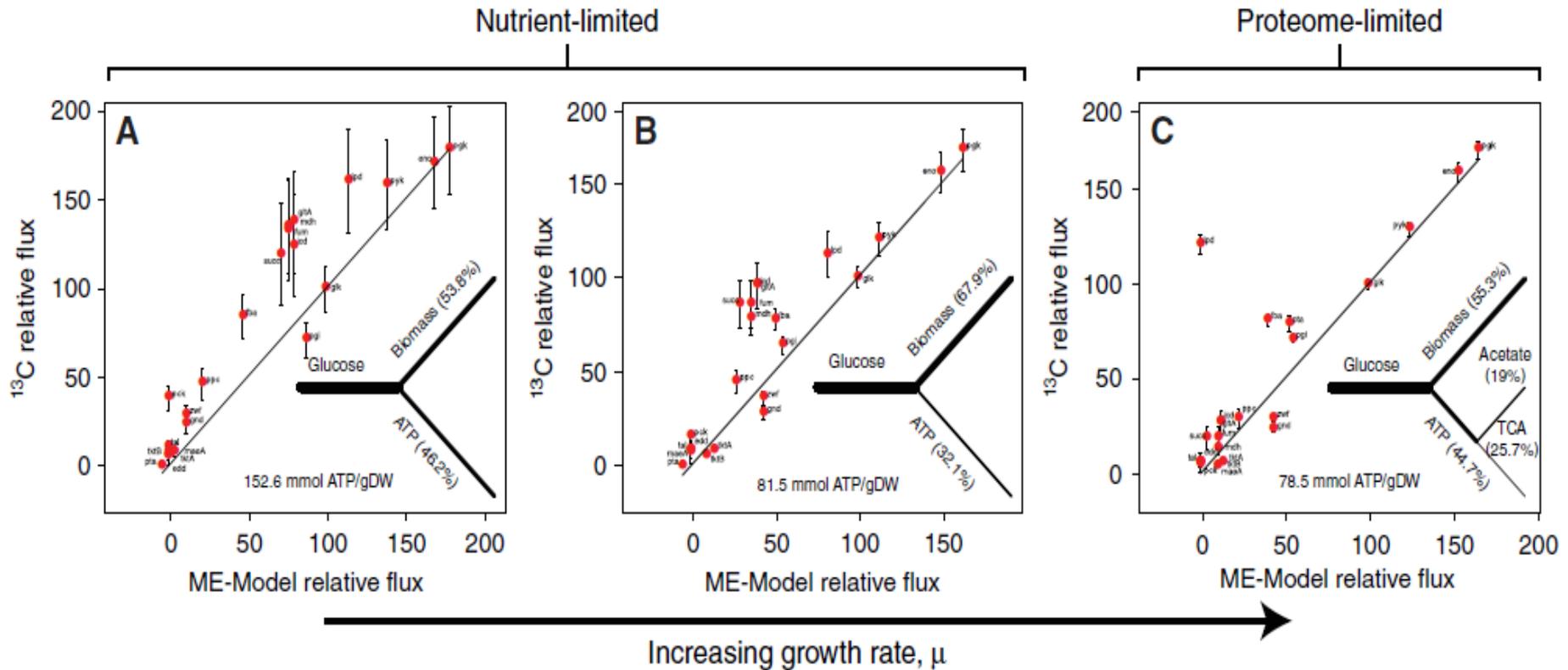


Figure 3. Central carbon metabolic flux patterns under glucose-limited and glucose-excess conditions. **(A–C)** Relative fluxes from ^{13}C experiments are plotted versus the fluxes predicted by the ME-Model. **(A, B)** Comparison of nutrient-limited model solutions with chemostat culture conditions and **(C)** comparison of the batch ME-Model solution with batch culture data.

Growth rate-dependent gene expression under glucose limitation

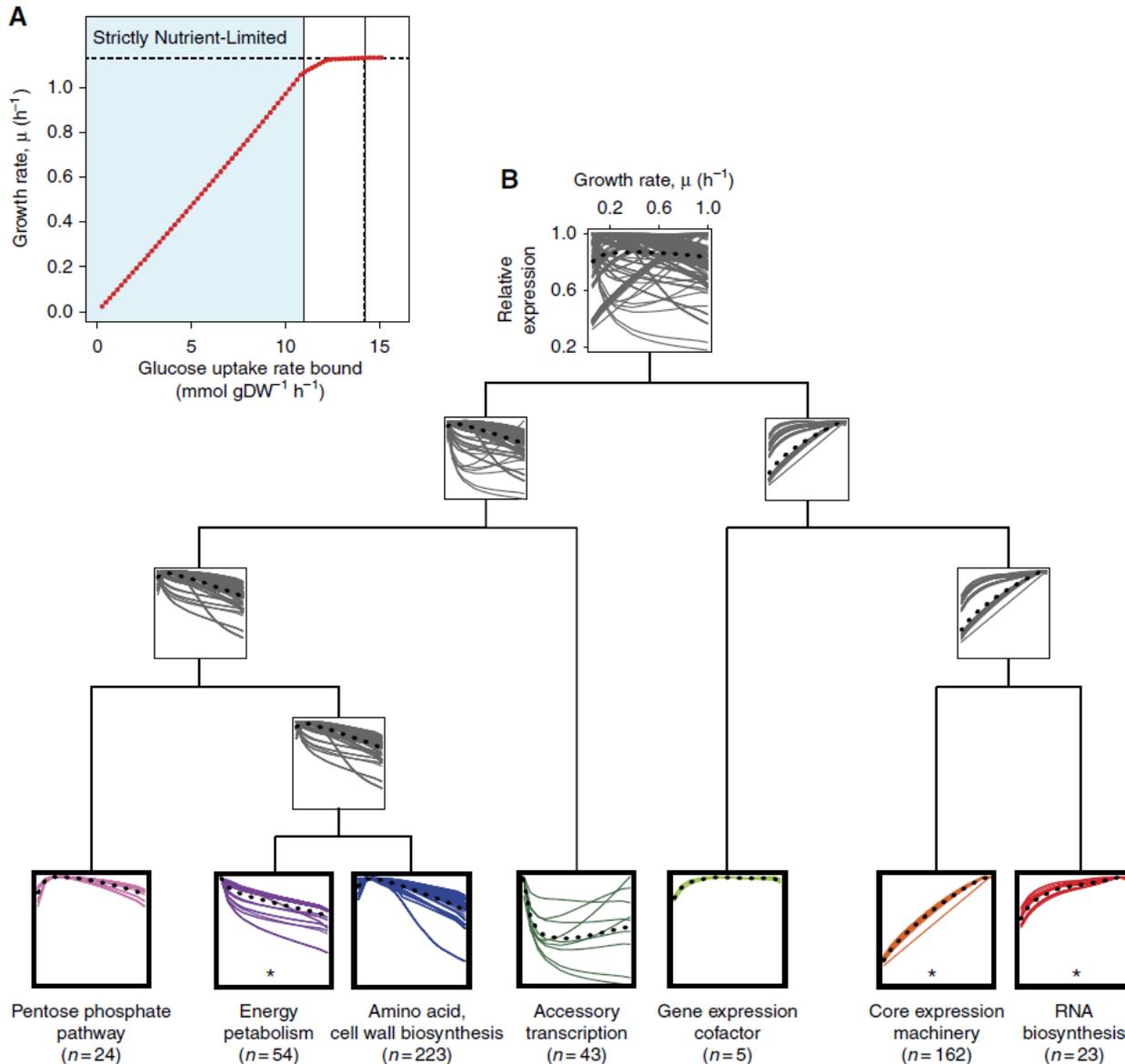


Figure 4. (A) Gene expression changes predicted by the ME-Model to occur in the Strictly Nutrient-Limited (SNL) growth region indicated in light blue under glucose limitation in minimal media are analyzed. (B) ME-Model-computed relative gene-enzyme pair expression is plotted as a function of growth rate; the normalized *in silico* expression profiles are clustered hierarchically.

Gene expression during the Janusian region

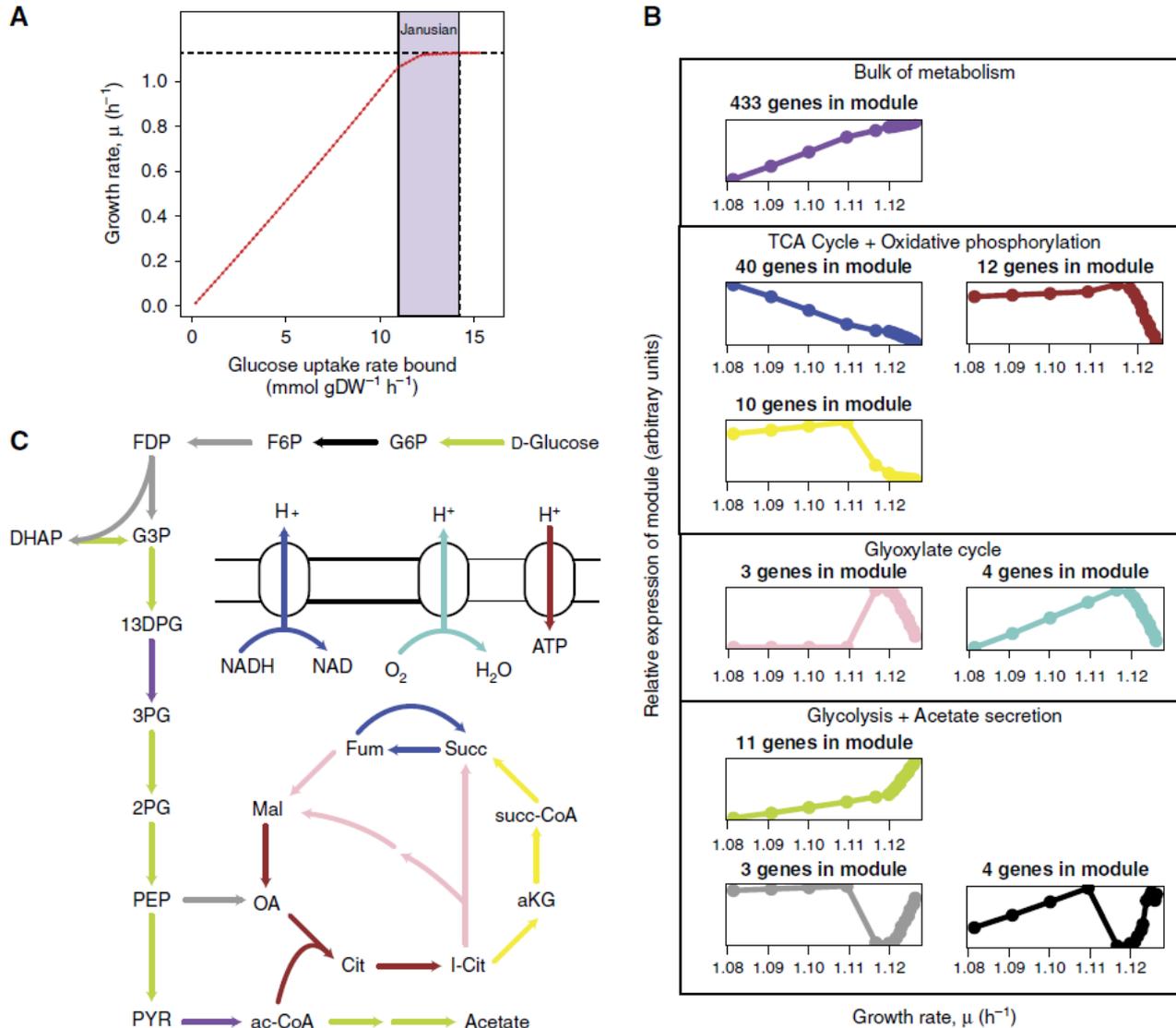


Figure 5. **(A)** Gene expression changes predicted by the ME-Model to occur in the Janusian growth region indicated in purple under glucose limitation in minimal media are analyzed. **(B)** Simulated expression profiles are clustered using signed power ($\beta=25$) correlation similarity and average agglomeration **(C)** Many of the expression modules correspond to genes of central carbon energy metabolism. Reactions are colored according to the module color in **(B)**.

Conclusion

- An integrated network of metabolic and gene expression pathways is built for *E. coli*.
- A growth model is developed by adding demands and constraints on molecular catalysis.
- Model yields accurate predictions of growth phenotypes from molecules to whole cell:
 1. the cell's maximum growth rate (μ^*) in the specified environment
 2. substrate uptake/by-product secretion rates at μ^*
 3. metabolic fluxes at μ^*
 4. gene product expression levels at μ^*
- A few basic principles underlie growth rate optimization at the systems level.
 - The model predicts three distinct regions of microbial growth, defined by the factors (nutrient and/or proteome) limiting growth.
 - A growth rate-dependent Michaelis–Menten-type model for polymerization speed
 - Proteomic constraints improve predictions of metabolism itself
 - Gene expression changes as the cell transitions through and between the different growth regions

Take-Home Message

- Because ME-Models explicitly represent gene expression, directly investigating omics data in the context of the whole is now feasible
- ME-model is more intricate than M-model, more room for unknown/incomplete knowledge
 - Lack of specific translation efficacy for each protein
 - Lack of specific degradation rates for each mRNA
 - lack of signaling
 - Lack of regulatory circuitry
- A big challenge for Plant system