The metabolic demands of cancer cells are coupled to their size and protein synthesis rates

Sonia C. Dolfi¹, Leo Li-Ying Chan², Jean Qiu², Philip M. Tedeschi¹, Joseph R. Bertino¹, Kim M. Hirshfield¹, Zoltán N. Oltvai³, Alexei Vazquez^{4,5,*}

¹Department of Medicine, ⁴Department of Radiation Oncology and ⁵Center for Systems Biology, Rutgers Cancer Institute of New Jersey, Rutgers, The State University of New Jersey, New Brunswick, USA

²Department of Technology R&D, Nexcelom Bioscience LLC, Lawrence, MA, USA

³Department of Pathology, University of Pittsburgh School of Medicine, Pittsburgh, PA, USA

Outline

- **2 Maximum likelihood estimate of the protein synthesis rate**
- **3 Average amino acid molecular weight in the expressed proteome**
- **4 Statistical test for volume dependence**
- **5 Personalized metabolic models**
- **12 Supplementary Figures**
- **16 Supplementary Tables**

Maximum likelihood estimate of the protein synthesis rate

The experimentally measured import rates of an essential amino acid are assumed to be proportional to the protein synthesis rate: $f_a = S_a f_p + \Delta f_a$, where S_a is the relative content of amino acid *a* in proteome (Table S1), *fP* is the rate of protein synthesis and Δ*fa* represents the variability introduced by the experimental procedures. We further assume that the experimental noise Δ*fa* follows a normal distribution with an amino acid dependent variance σ_a . Under these assumptions the probability to observe the reported exchange rates for essential amino acids is

(Eq. 1)
$$
P(f \mid f_p, \sigma) = \prod_{a=1}^n \frac{1}{\sqrt{2\pi\sigma_a^2}} \exp\left(-\frac{\left(f_a - S_a f_p\right)^2}{2\sigma_a^2}\right)
$$

where the product is restricted to essential amino acids and *n* is the number of essential amino acids. Maximizing (Eq. 1) with respect to f_P and σ_a we obtain their maximum likelihood estimates (MLE)

(Eq. 2)
$$
f_{P} = \frac{\sum_{a=1}^{n} \frac{S_{a} f_{a}}{\sigma_{a}^{2}}}{\sum_{a=1}^{n} \frac{S_{a}^{2}}{\sigma_{a}^{2}}}
$$

(Eq. 3)
$$
\sigma_a^2 = \frac{1}{n} \sum_{a=1}^n (f_a - S_a f_p)^2
$$

We solve these equations recursively, starting from the assumption that the measurements of all amino acids exchanges have the same variance

$$
(Eq. 4) \qquad \qquad \sigma_a(0) = \sigma
$$

(Eq. 5)
$$
f_P(0) = \frac{\sum_{a=1}^{n} S_a f_a}{\sum_{a=1}^{n} S_a^2}
$$

Then, recursively, we compute first $\sigma_a(t)$ using as input $f_P(t-1)$ and then $f_P(t)$ using as input $\sigma_a(t)$. We continue this procedure until the relative error: $\varepsilon = \text{abs}(f_P(t) - f_P(t-1))/f_P(t)$ is smaller than 10⁻⁶. The MLE estimates for f_P and σ_a are reported in Tables S5 and S6, respectively.

Average amino acid molecular weight in the expressed proteome

The average amino acid molecular weight in the expressed proteome was calculated as

$$
w_{aa} = \sum_{a} S_a W_a
$$

where S_a is the abundance of amino acid *a* in the expressed proteome and W_a is its molecular weight, as reported in Refs. [9, 21].

Statistical test for volume dependence

Given a test quantity Y_i (protein content, DNA content or protein synthesis rate) measured across *i*=1,…,*n* cell lines with cell volumes V_i , we assume that $Y_i = \mu V_i^{\alpha} + \sigma V_i^{\beta} X_i$, where μ and σ are model parameters and $\alpha = \beta = 0$ for the I model, $\alpha = 1$ and $\beta = 0$ for the VDM model, and $\alpha = \beta = 1$ for the VDMV model, and *Xi* are independent random variables with a standard normal distribution. The likelihood to observe the data *Yi* given these models is

$$
P(Y | \mu, \sigma) = \prod_{i=1}^{n} \frac{1}{\sqrt{2\pi\sigma^2 V_i^{\beta}}} \exp\left(-\frac{\left(Y_i - \mu V_i^{\alpha}\right)^2}{2\sigma^2 V_i^{\beta}}\right)
$$

For each model, we assign to μ and σ their maximum log-likelihood $L = \ln P(Y | \mu, \sigma)$, obtaining

$$
\mu_{MLE} = \frac{\sum_{i=1}^{n} Y_i V_i^{\alpha-\beta}}{\sum_{i=1}^{n} V_i^{2\alpha-\beta}}
$$

$$
\sigma_{MLE}^2 = \frac{1}{n} \sum_{i=1}^{n} \frac{\left(Y_i - \mu_{MLE} V_i^{\alpha}\right)^2}{V_i^{\beta}}
$$

The validity of each model is then quantified applying a Shapiro-Wilk normality test to

$$
X_i = \frac{Y_i - \mu_{MLE} V_i^{\alpha}}{\sigma_{MLE} V_i^{\beta/2}}
$$

A model is rejected if the resulting statistical significance falls below 0.05.

Personalized metabolic models

As starting point, we utilize a genome-scale metabolic reconstruction of a generic human cell [1] that includes most biochemical reactions catalyzed by enzymes encoded in the human genome. We add auxiliary reactions to represent nutrient uptake, excretion of metabolic byproducts, basal ATP demand needed for cell maintenance, basal rate of protein degradation, and synthesis of cell biomass components (proteins, lipids, RNA and DNA) (Vazquez et al [2], Table S1). We assume that the cell is in a steady state where the production and consumption of every metabolite and macromolecules balances, known as the flux balance constraint [1]. We use S_{mi} to denote the stoichiometric coefficient of metabolite *m* in reaction *i*. We use F_i to denote the net steady state reaction rate (flux) of the i^{th} reaction per cell, where all reversible reactions are represented by a forward and backward rate, respectively. Reactions are divided into nutrient import reactions (*I*), reactions taking place in the cytosol (*C*) and reactions taking place in the mitochondria (*M*). We use ϕ_c to denote the relative cell volume fraction occupied by the cth cellular compartment. In particular, we denote by N_0 the nonmetabolic protein content per cell and by ϕ_0 its occupied volume fraction. We assume the proliferation rate (μ) and the relative volume fraction occupied by macromolecules and organelles (ϕ_{max}) are known and are given as input parameters of the model. Finally, we estimate the metabolic fluxes and compartment densities as the solution of the following optimization problem:

Find the F_i and ϕ_c that maximize the total content of non-metabolic protein

$$
(1) \qquad N_0
$$

subject to the metabolic constraints: flux balance constraints

$$
(2) \qquad \sum_{i} S_{mi} F_i = 0
$$

minimum/maximum flux constraints

$$
(3) \qquad v_{i,\min} \leq F_i \leq v_{i,\max}
$$

minimum/maximum volume fraction constraints

$$
(4) \qquad 0 \leq \phi_c \leq \phi_{\text{max}}
$$

molecular crowding constraints

(5)
\n
$$
\sum_{i \in C} a_i F_i \le \phi_C V
$$
\n
$$
\sum_{i \in M} a_i F_i \le \phi_M V
$$
\n
$$
a_{M,ATP} \sum_{i \in M \setminus S_{ATP,i} > 0} S_{ATP,i} F_i \le \phi_M V
$$
\n
$$
\phi_0 + \phi_C + \phi_M \le \phi_{\text{max}}
$$

where *V* is the cell volume, c_i is the nutrient import cost associated with the uptake reaction *i*, $a_i = v_i/k_{\text{eff},i}$ are the crowding coefficients of metabolic enzymes (enzyme molar volume / enzyme effective turnover)[3], and $a_{MATP} = v_{s,M} / r_M$ the crowding coefficient of mitochondria ATP generation (ATP) synthesis rate per mitochondria mass / mitochondria specific volume) [4, 5]. As a difference with our previous work [2], here we express the metabolic fluxes F_i in units of mol/cell/hour. We can recover our previous equations recalling that the metabolic flux per cell volume is given by $f_i = F_i/V$.

Personalized models

The model is tailored for each cell line by specifying the proliferation rate μ , the cell volume V , the DNA conent and the reported exchange fluxes. The model reaction fluxes representing exchange fluxes are fixed to the experimentally measure values, by setting *vi,min*=*vi,max*=*Fi,reported*.

Proliferation rate

The doubling time t_D of each cell line in the NCI60 panel was obtained from the Developmental Therapeutics Program at the NCI (http://dtp.nci.nih.gov/docs/misc/common_files/cell_list.html). Proliferation rates were computed as $\mu = \ln(2)/t_D$.

Nuclear DNA content

The nuclear DNA content of each cell line in the NCI60 panel was estimated using the reported karyotypes for these cell lines [6] and the chromosome lengths reported by Ensembl. Specifically, using the reported copy number for each chromosome band we calculated an average karyotype for each chromosome. Multiplying the average chromosome karyotype by the chromosome length in base pairs and summing over all chromosomes we obtained the DNA content in base pairs (nucleotides/cell). The latter was coverted to mol/cell after dividing by the Avogadro number.

The nuclear DNA content of a normal cell was calculated similarly, using as input the normal chromosomes copy number.

Mitochondrial DNA

The mitochondrial DNA (mtDNA) was assumed proportional to the mitochondrial volume, with a density of 0.3 fmol of mtDNA/pL. The density was calculated based on the reported mitochondrial DNA (\sim 0.75 µg/10⁶ cells) and protein (\sim 2.5 mg/10⁶ cells) content in chick embryo fibroblasts (Table III in Ref. [7]). Dividing the mtDNA mass per cell by the average DNA molecular weight $(\sim 331 \text{ g/mol})$ we obtain a density of 2.3 fmol mtDNA/cell, and dividing by the mitochondrial protein content a density of 0.92 µmol mtDNA/g of mitochondrial protein. Multiplying the latter number by the specific volume of mitochondria (2.6 mL/g protein [8]), we obtain a density of 0.3 fmol mtDNA/pL of mitochondria.

RNA

The RNA composition was estimated by their relative abundance per cell dry weight [9]. The abundance per cell dry weight were converted to abundance per cell volume after dividing by the typical cell specific volume 4.3 mL/g [10]. The abundance per cell volume was finally converted to abundance per cell by multiplying by our measurements of cell volume for each of the cell lines on the NCI60 panel.

Lipids

The lipids composition was estimated by their relative abundance per cell dry weight [9]. The abundance per cell dry weight were converted to abundance per cell volume after dividing by the typical cell specific volume 4.3 mL/g [10]. The abundance per cell volume was finally converted to abundance per cell by multiplying by our measurements of cell volume for each of the cell lines on the NCI60 panel.

Protein content

Proteins are divided into cytosolic and mitochondrial proteins. Within the cytosol, proteins were divided into three pools: ribosomal-, components of metabolic enzyme complexes-, and non-metabolic proteins. Each ribosome contributes to n_{PR} =82 proteins/ribosome (49 in the 60S and 33 in the 40S subunits [11]). The ribosome related protein concentration was computed as $P_{CR} = n_{PR}f_{CP}/k_R$, where f_{CP} is the cytosolic protein synthesis rate and k_R the protein synthesis rate per ribosome. Each enzyme contributes with n_{PF} =2.4 proteins in average, estimated as median enzyme molecular weight (98,750) g/mol, reported above) divided by the median molecular weight of a human protein (40,835 g/mol). The median molecular weight of a human protein was estimated from the median protein length (355 amino acids [12]) and the typical amino acid composition [9]. The enzyme related cytosolic protein concentration was computed as $P_{CF} = \sum_{i} n_{PF} f_i / k_i$. A similar subdivision is carried on for mitochondrial

proteins.

Kinetic parameters

The effective turnover numbers, *keff,i*, quantify the reaction rate per enzyme molecule. For example, for an irreversible single substrate reaction satisfying Michaelis-Menten kinetics, $k_{\text{eff}} = kS/(K+S)$, where *k* is the enzyme turnover number, *K* the half-saturation concentration and *S* the substrate concentration. The turnover numbers of some human enzymes are reported in the BRENDA database [13]. They have a typical value of 10 sec^{-1} and a significant variation from 1 to 100 sec^{-1} (Vazquez et al [2], Table S2). However, for most reactions we do not know the turnover number, the kinetic model, or the metabolite concentrations, impeding us to estimate k_{eff} . To cope with this indeterminacy we performed a sampling strategy, whereby the *keff,i* were sampled from a reasonable range of values, and then focused on median and the 90% confidence intervals (see Sensitivity analysis below).

Crowding coefficients

Dividing the mitochondrium specific volume $(3.15 \text{ mL/g in mammalian liver} [14] \text{ and } 2.6 \text{ mL/g in}$ muscle [8]) by the rate of ATP production per mitochondrial mass (0.1-1.0 mmol ATP/min/g [15-17]) we obtain a_M values between 0.0026 to 0.032 min/mM. Except when specified, we use the median 0.017 min/mM. Dividing the ribosome molar volume ($v_R = 4,000$ nm³ \times 6.02 10²³/mol=2.4 L/mmol) by the rate of protein synthesis per ribosome (0.67 proteins/min [18]) we obtain a_R =3.6 min/mM. The enzyme crowding coefficients were estimated as $a_i=v_E/k_i$. Multiplying the median molecular weight of human enzymes (98,750 g/mol, Vazquez et al [2], Table S2) by the enzymes specific volume (approximated by the specific volume of spherical proteins, 0.79 mL/g [19]) we obtain an estimated enzymes molar volume of v_E =0.078 L/mmol.

Maximum macromolecular density

The maximum macromolecular density cannot exceed 100% of the cell volume, therefore ϕ_{max} =1. We have previously used the upper bound of 0.4 based on the typical macromolecular density of cells. However, there may be some variability among cancer cell lines. Furthermore, the constraint over the exchange fluxes of essential amino acids determines the protein content, which is the major component of the cell biomass.

Protein synthesis

The flux balance equation for proteins synthesized in the cytosol is formulated as follows. We account for three major categories, proteins not associated with metabolism, proteins that are components of

enzyme complexes and that are encoded in nuclear genes, and the cytosol ribosomal proteins, with their concentrations (moles/cell volume) denoted by P_0 , P_{NE} , and P_{CR} , respectively. In proliferating cells, these concentrations will decrease at a rate $(\mu + k_D)(P_0 + P_{NE} + P_{CR})$, where μ represents the contribution to cell growth and k_D =0.01/h [20] is the basal protein turnover rate. Putting all these elements together, the balance between protein turnover and synthesis implies f_{CP} - $k_D[P_0 + n_{PE} \Sigma_i(f_i/k_{eff,i}) + n_{PR} f_{CP}/k_R] = 0$, where the index *i* runs over all enzyme catalyzed reactions excluding ATP synthase, NADH dehydroganase, complex III, and complex IV. In a similar manner we formulated the flux balance equation for mitochondrial proteins encoded in the mitochondrial DNA. The mitochondrial protein synthesis reaction accounted for the synthesis of ATP synthase, NADH dehydroganase, complex III, complex IV and the mitochondria ribosomes.

DNA synthesis

We explicitly considered a nuclear and a mitochondrial DNA synthesis reaction, each matching the DNA synthesis demands of their respective compartment upon cell proliferation.

Flux bounds

All reversible reactions were represented by an irreversible reaction on each direction with their own effective turnover number $k_{eff,i}$. Flux bounds were set to $v_{i,min}=0$ and $v_{i,max}=\infty$, except for reported exchange fluxes (*vi,min*=*vi,max*=*Fi,reported*) and for the auxiliary reactions representing the basal rate of protein turn over $(v_{i,min}=v_{i,max}=k_D)$ and the biomass production reaction $(v_{i,min}=v_{i,max}= \mu)$.

Simulations

The optimization problem in equations (1)-(5) was solved in Matlab, using the linear programming function linprog.

Sensitivity analysis

The turnover numbers of human enzymes k have significant variations from 1 to 100 sec⁻¹ and the distribution of $log_{10}(k)$ is approximately uniform in this range (Vazquez et al [2], Table S2). Based on this data we sampled the $log_{10}(k_{\text{eff}})$ values from a uniform distribution in the range between $log_{10}(1)$ to $log_{10}(100)$. For each specified condtion we run 100 simulations. On each simulation, for each reaction, a value of *keff,i* is extracted from the distribution described above. With this set of *keff,i* parameters we then solve the optimization problem (1)-(5) and obtain estimates for the reaction rates. Based on the 100 simulations we finally estimate the median and 90% confident intervals for the rate of each reaction. 100 simulations were proven to be sufficient to capture the overall range of behavior, since

running 1,000 simulations did not result in a significant change in the median and 90% confidence intervals.

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Supplementary Figures

Figure S1: Import rate of essential amino acids as a function of the MLE protein synthesis rate. a-h) Each square symbol represents a cell line from the NCI60 panel and the red solid line represents the expected ratio as determined from the relative amino acid abundance.

Figure S2: Validation of the MLE protein synthesis rates. a-d) [4,5-³H]-leucine incorporation into protein as a function of time for four selected cell lines. The red lines are linear fits to the data points. e) The MLE protein synthesis rate as a function of the $[4,5^{-3}H]$ -leucine incorporation rate into protein. Each data point represents a cancer cell line and the solid line represents a linear fit intercepting the origin.

Figure S3: Protein synthesis rate per cell as a function of the proliferation rate. Each square symbol represents a cell line from the NCI60 panel and the dashed red line is a linear fit to the data points**.**

Figure S4: Correlation of measured and estimated protein contents. a) Scatter plot of the model predicted protein synthesis rate vs the MLE protein synthesis rate. b) Scatter plot of the model predicted protein content vs the measured protein content. Each point represents a cell line and the diagonal line represents the case when both values are equal. Although they are not visible due to their small size, there are vertical error bars representing the 90% confidence interval due to variations in the model kinetic parameters. The horizontal error bars in panel b) represent the standard deviation of the protein content measurements.

Supplementary Tables

Table S1: Relative abundance of essential and non-essential amino acids in the expressed proteome [9, 21].

Table S2: Genes whose expression correlates with cell volume. The list of Affymetrix HG-U133 Plus 2.0 array probes whose expression values were highly correlated with the cell volumes (*PCC*>0.5) or highly negatively correlated with the cell volume (*PCC*<-0.5) in the NCI60 cell lines.

Table S3: Correlation between the expression of proteins/phosphoproteins and the cell volume in the NCI60 cell lines.

Table S4: FDA approved drugs included in the *in vitro* **growth inhibition analysis.** NSC stands for National Service Center and it is the identifier utilized by the Department of Therapeutics Program at the National Cancer Institute [22].

Table S5: MLE protein synthesis rates and measured protein content for each NCI60 cell line.

Table S6: Maximum likelihood estimate of the variances (σ_a) . The value for histidine is not shown because its exchange fluxes were not reported.