Summary Table of Community Metabolic Modelling. Comparison and overview of published metabolic modelling approaches for microbial communities.

Modelling method	Modelling condition	Suitable for large community	Comments	Ref
cFBA	Steady-state, FBA	No, (pairwise analysis)	• Compartmentalised approach • Multi-objective function assuming fixed growth rates • Nonlinear optimisation	[1]
SteadyCom	Steady-state, FBA	Yes	• Compartmentalised approach • Maximises community's specific growth rate • Less computationally demanding than cFBA	[2]
MiCOM	Steady-state, FBA	Yes	• Compartmentalised approach • Maximises weighted sum of biomass fluxes of all species, then minimises sum of the squared biomass fluxes	[3]
OptCom	Steady-state, FBA	No, (2-4 species)	• Bi-level and multi-objective optimisation • Maximises growth of individual species as well as the whole community	[4]
NECom	Steady-state, FBA	No, (2-4 species)	• Bi-level objective optimisation • All feasible solutions are Nash equilibria of microbial community metabolic models	[5]
Koch et al. (OptDeg)	Steady-state, FBA	No, (few species)	• Compartmentalised approach • Maximises the community growth rate, then optimises for optimal substrate usage (biomass yield)	[6]
CASINO	Steady-state, FBA	Yes	• Maximises biomass yield of individual species, then performs iterative multi-level optimisation to maximise biomass production at the community level.	[7]
DMMM	Temporal, FBA	Yes	• Extension of single species dFBA • Iteratively solves linear FBA problem for each time and species (uses Euler forward method)	[8]
μbialSim	Temporal, FBA	Yes	• To prevent negative concentrations, an augmented Euler forward method is adapted to temporarily reduce time steps	[9]
DFBALab	Temporal, FBA	Yes	• Addresses infeasibility and degeneracy for exchange reaction fluxes • Needs user-defined prioritisation of shared metabolites	[10]
ORKA	Temporal, FBA	Yes	• Euler forward method replaced with Runge-Kutta • Assumption of constant reaction rate relaxed over time intervals (trapezoidal rule used)	[11]
dOptCom	Temporal, FBA	No, (2-3 species)	• Bi-level and multi-objective optimisation • Generally the community level objective is to maximise the community biomass concentration.	[12]

Modelling method	Modelling condition	Suitable for large community	Comments	Ref
Brunner et al.	Temporal, FBA	Yes	• Uses prior solutions to inform future time steps, by simulating system forward as an ODE • Reduces the number of FBA problems that are solved	[13]
MCM	Temporal, FBA	Yes	• Tool that unifies model construction, statistical evaluation, sensitivity analysis and parameter calibration • Provides versatility in terms of uptake kinetics	[14]
COMETS	Spatiotemporal, FBA	Yes	• Uses biophysical models to simulate convection and diffusion of metabolites and biomass. • Biophysical models improved in recent update	[15, 16]
BacArena	Spatiotemporal, FBA	No, (few species)	• Agent-based modelling approach • Can give finer resolution of communities, becomes computationally expensive for large communities	[17]
ACBM	Spatiotemporal, FBA	No, (few species)	• Agent-based modelling approach • Can give finer resolution of communities, becomes computationally expensive for large communities	[18]
Taffs et al.	Steady-state, EMA	Yes	• Does not require defined species and community level objective functions • Allows exploration of the entire solution space	[19]
RedCom	Steady-state, EFVA	Yes	• Takes a nested (two-step) approach similar to the one by Taffs et al. but using EFVA instead of EMA • Allows for simulation of compartmentalised models	[20]
CODY	Spatiotemporal, EMA	Yes	• Multiscale framework based on EMA that can be used for spatiotemporal modelling of communities.	[21]

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