Machine Learning et modèles structure fonction de plantes (FSPM)

Couplages de modèles causaux et modèles neuronaux

De nouvelles approches FSPM ?

M. Jaeger, CIRAD, AMAP-I2P, GreenLab

Deux exemples d’application des systèmes de neurones:

- Reconstruction de la structure
- Identification de paramètres fonctionnels

Un formalisme existant pouvant se décrire selon une architecture NN

- GL stochastique / structure potentielle

Intérêts: de l’application à la théorie

- Identification de paramètres
- Une nouvelle approche de la plasticité
- Une architecture RNN « dédiée à l’exploration spatio-temporelle »

Z. Pan et al. (Eds.): Transactions on Edutainment XII, LNCS 9292, pp. 109–126, 2016.
DOI: 10.1007/978-3-662-50544-1_10

3D Plant Modeling Based on BP Neural Network

Abstract. We propose a fast plant modeling method based on BP neural network.
1 The input is a plant image. Users can sketch the main branches and crown silhouettes on the image. Through branch copying, rotation and adjustment, the 3D main branches are obtained. A BP neural network is built and trained by analyzing the parameters of main branches. This network is used to forecast the parameters of small branches generated based on self-similarity. Finally, leaves are added and a 3D plant model resembling the input image is built.

Keywords: BP neural network · Plant modeling · Image · Sketch

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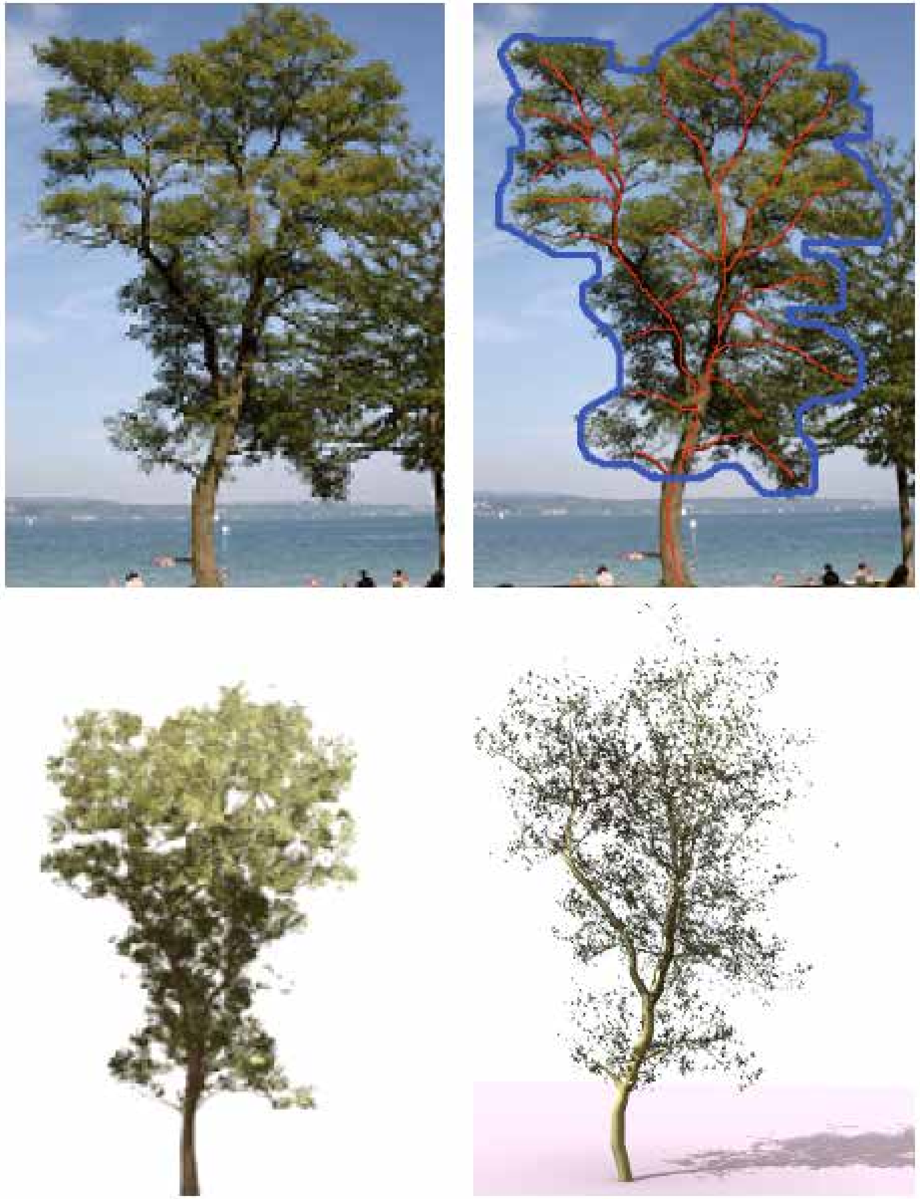

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3D Plant Modeling Based on BP Neural Network

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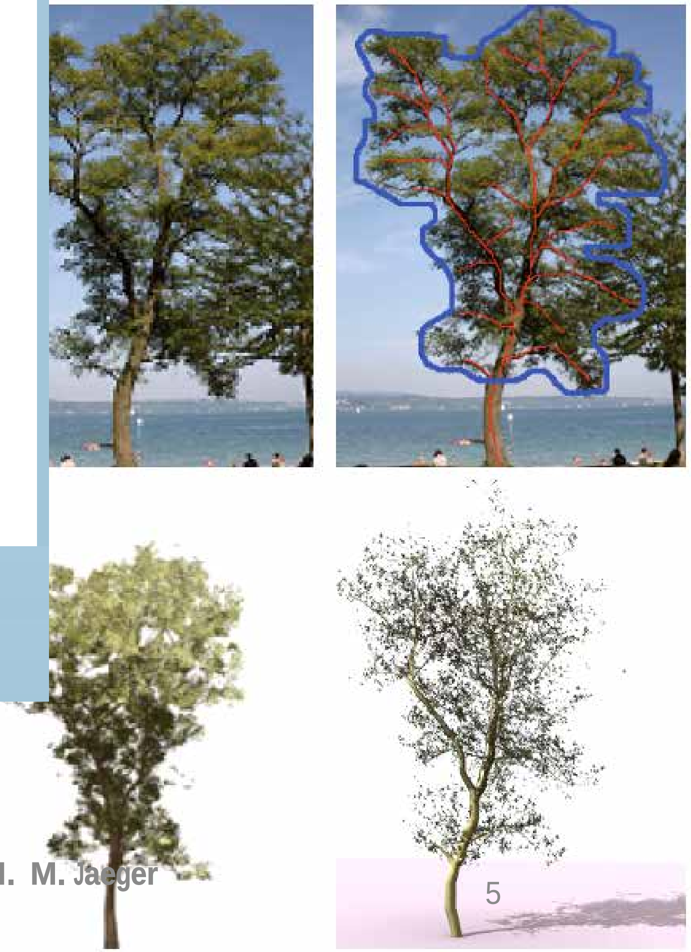

Ecological Modelling 312 (2015) 363–373

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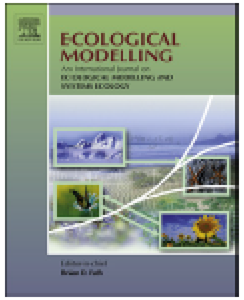

ELSEVIER

A knowledge-and-data-driven modeling approach for simulating plant growth: A case study on tomato growth

CrossMark

A B S T R A C T

This paper proposes a novel knowledge-and-data-driven modeling (KDDM) approach for simulating plant growth that consists of two submodels. One submodel is derived from all available domain knowledge, including all known relationships from physically based or mechanistic models; the other is constructed solely from data without using any domain knowledge.

Tomato growth data sets from twelve greenhouse experiments over five years were used to calibrate and test the model. In comparison with the existing knowledge-driven model (KDM, BIC = 1215.67) and data-driven model (DDM, BIC = 1150.86), the proposed KDDM approach (BIC = 1144.36) presented several benefits in predicting tomato yields. In particular, the KDDM approach is able to provide strong predictions of yields from different types of organs, including leaves, stems, and fruits, even when observational data on the organs are unavailable. The case study confirms that the KDDM approach inherits advantages from both the KDM and DDM approaches.

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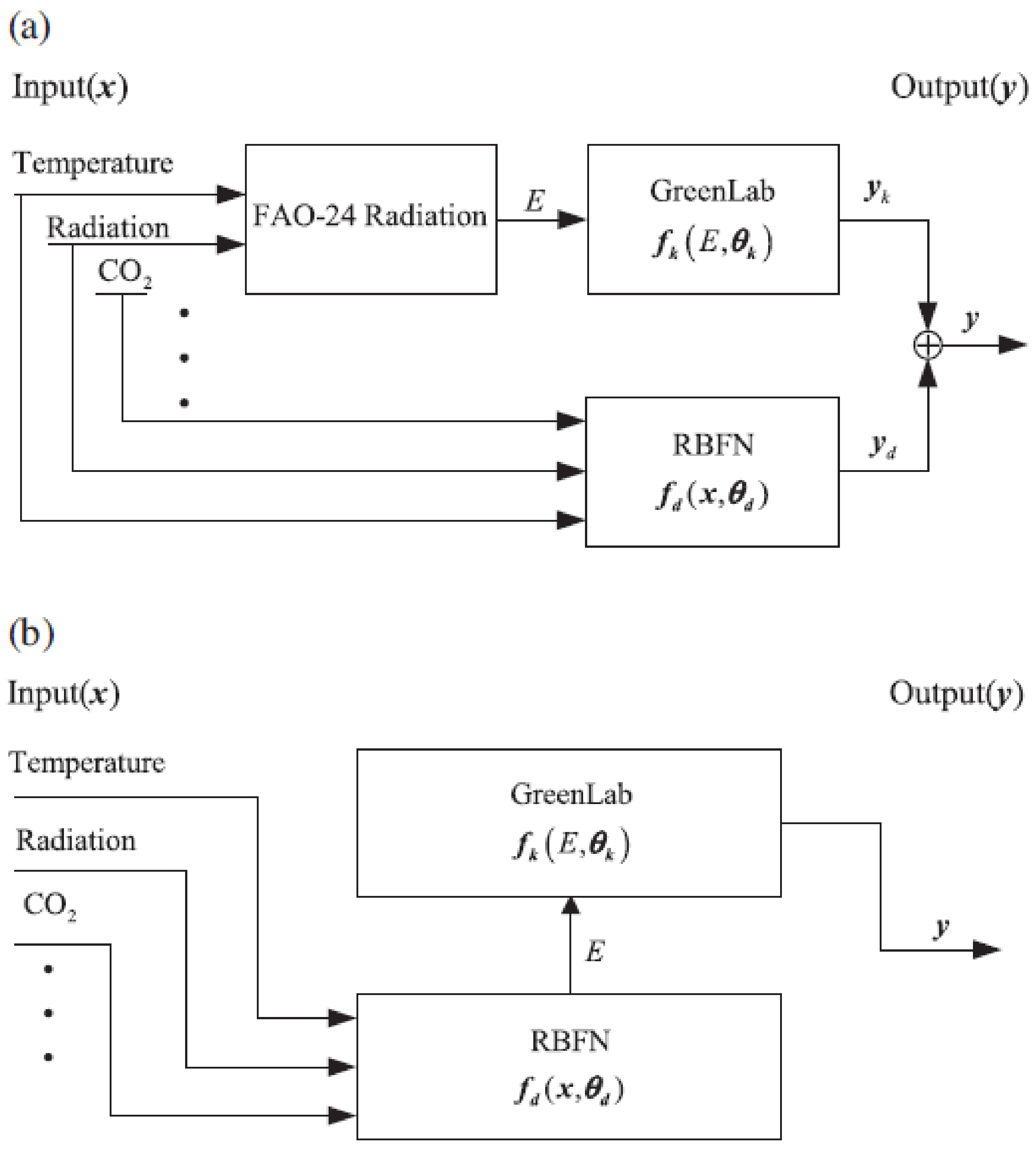

Fig. 2. The knowledge-and-data-driven model (KDDM) with two cases of coupling: (a) superposition coupling operator and (b) composition coupling operator.

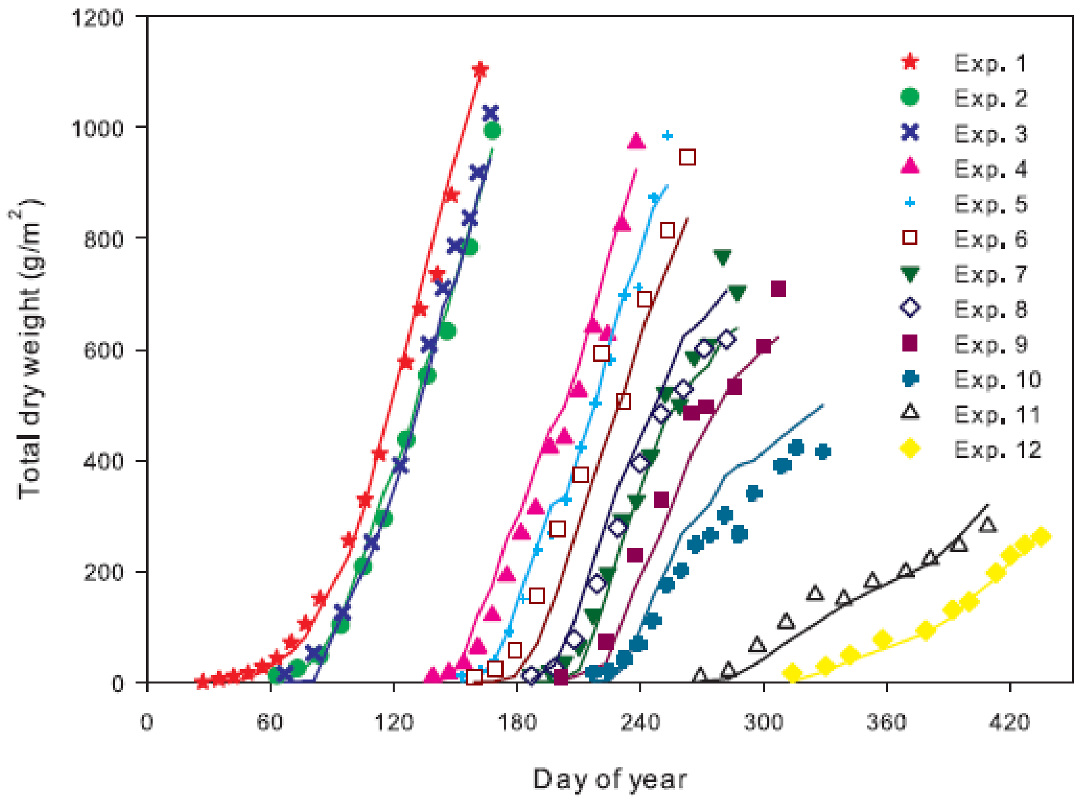

Fig. 3. Regression curves of the total dry weight for the KDDM_Com(A) from twelve greenhouse experiments with different planting dates (January 1 designated day 1). The data points from twelve experiments were taken from Heuvelink (1995).

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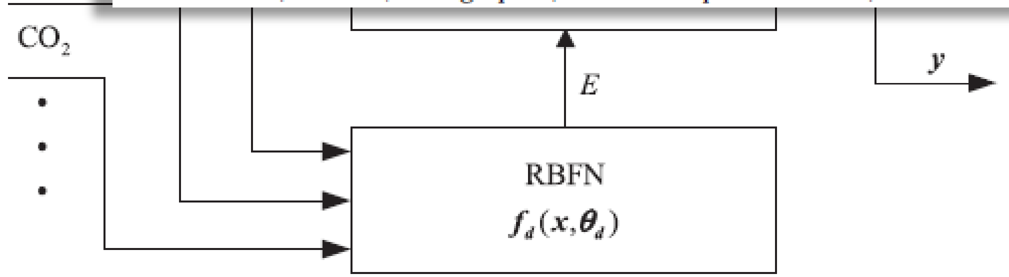
[d] Cirad-Amis, TA 4001, Ave Agropolis, 34398 Montpellier Cedex 5, France



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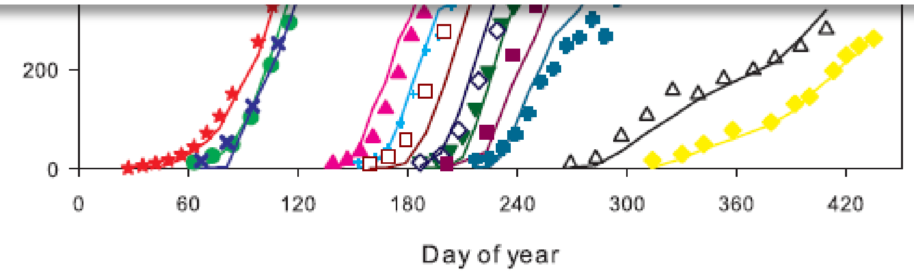

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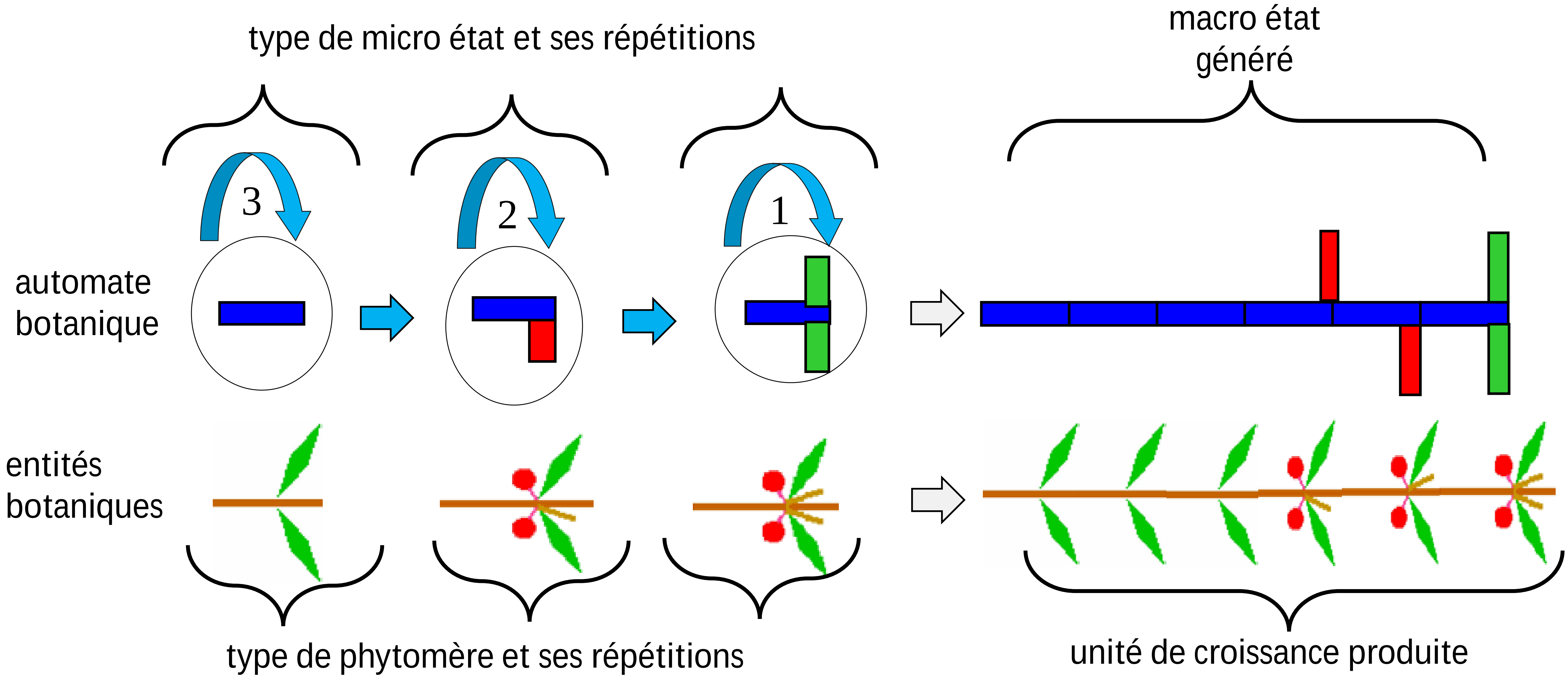
Un formalisme existant pouvant se décrire selon une architecture NN

- GL stochastique / structure potentielle



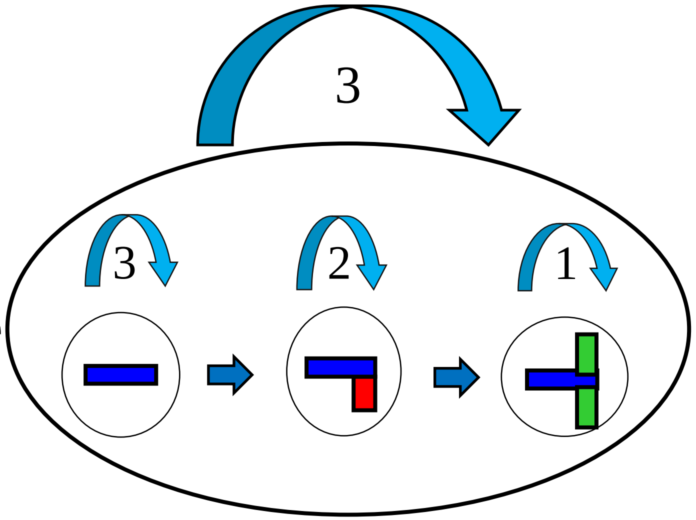
Un formalisme existant pouvant se décrire selon une architecture NN

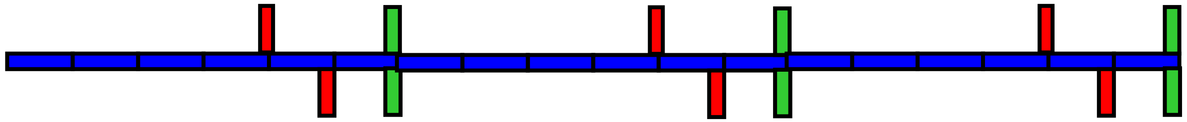
- GL stochastique / structure potentielle

type de macro état et ses répétitions

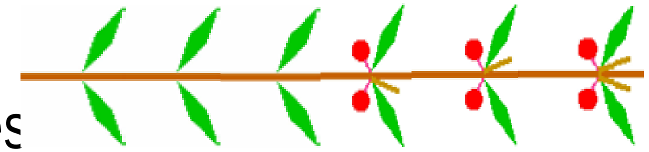
Axe de développement rythmique généré

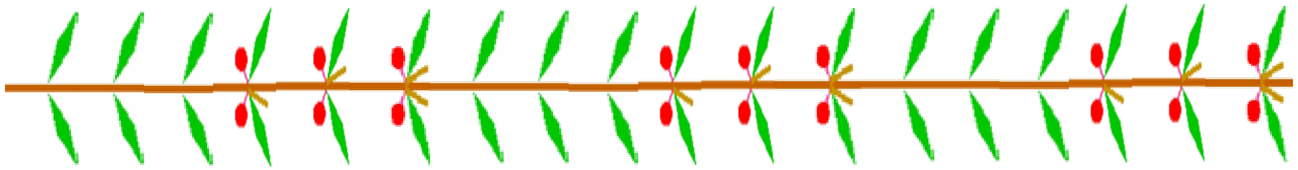
automate botanique





entités botaniques

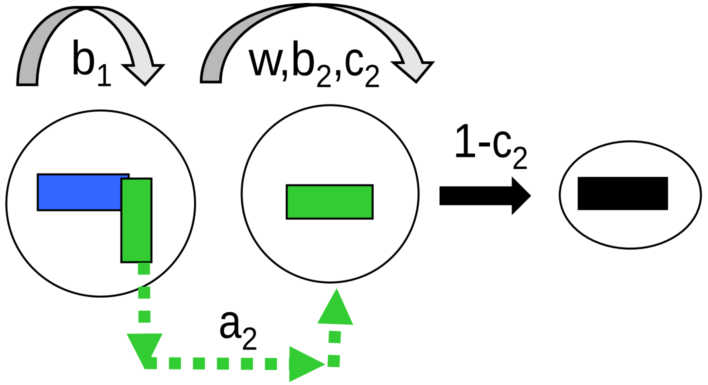


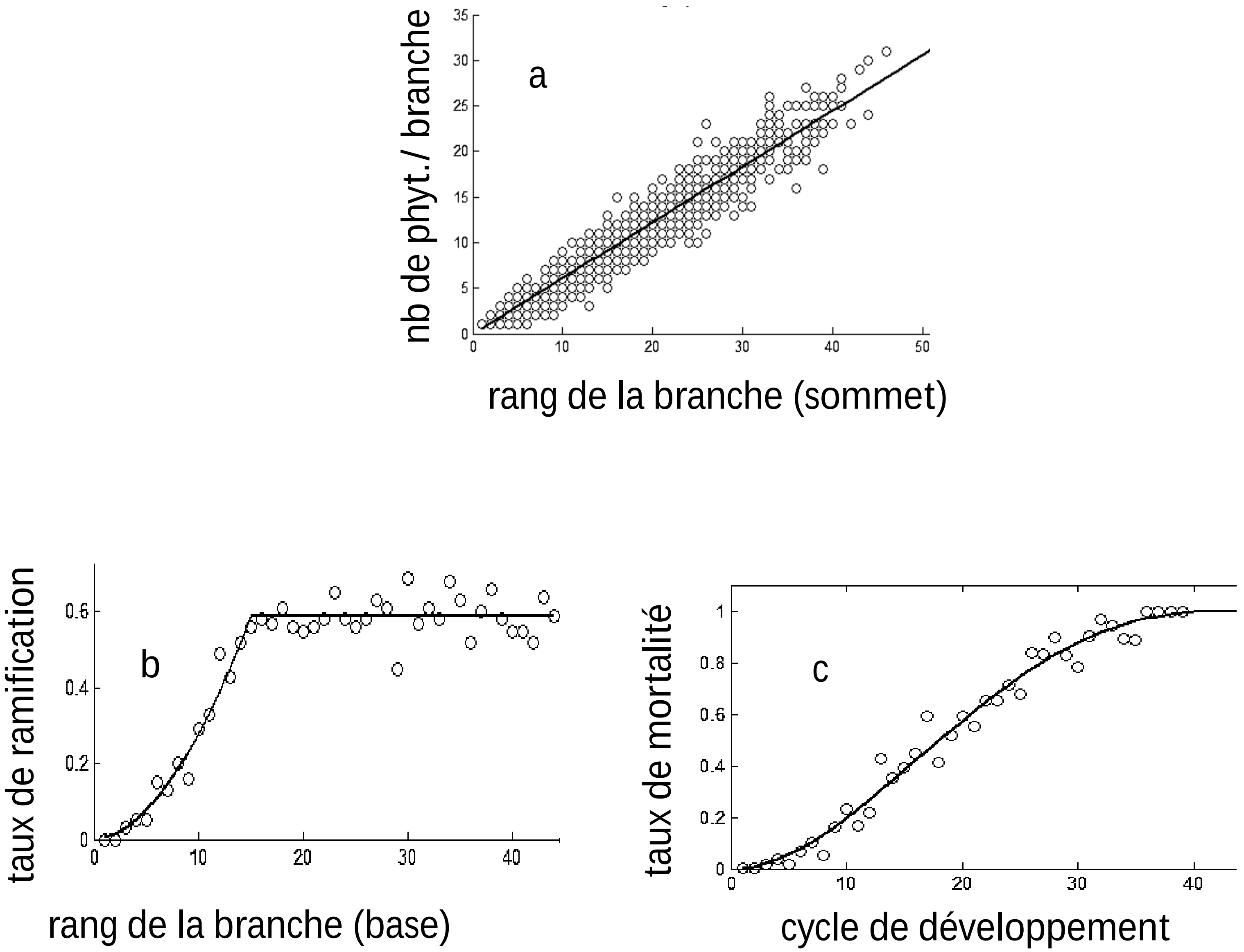


type d’unité de croissance

axe végétatif produit

automate botanique stochastique





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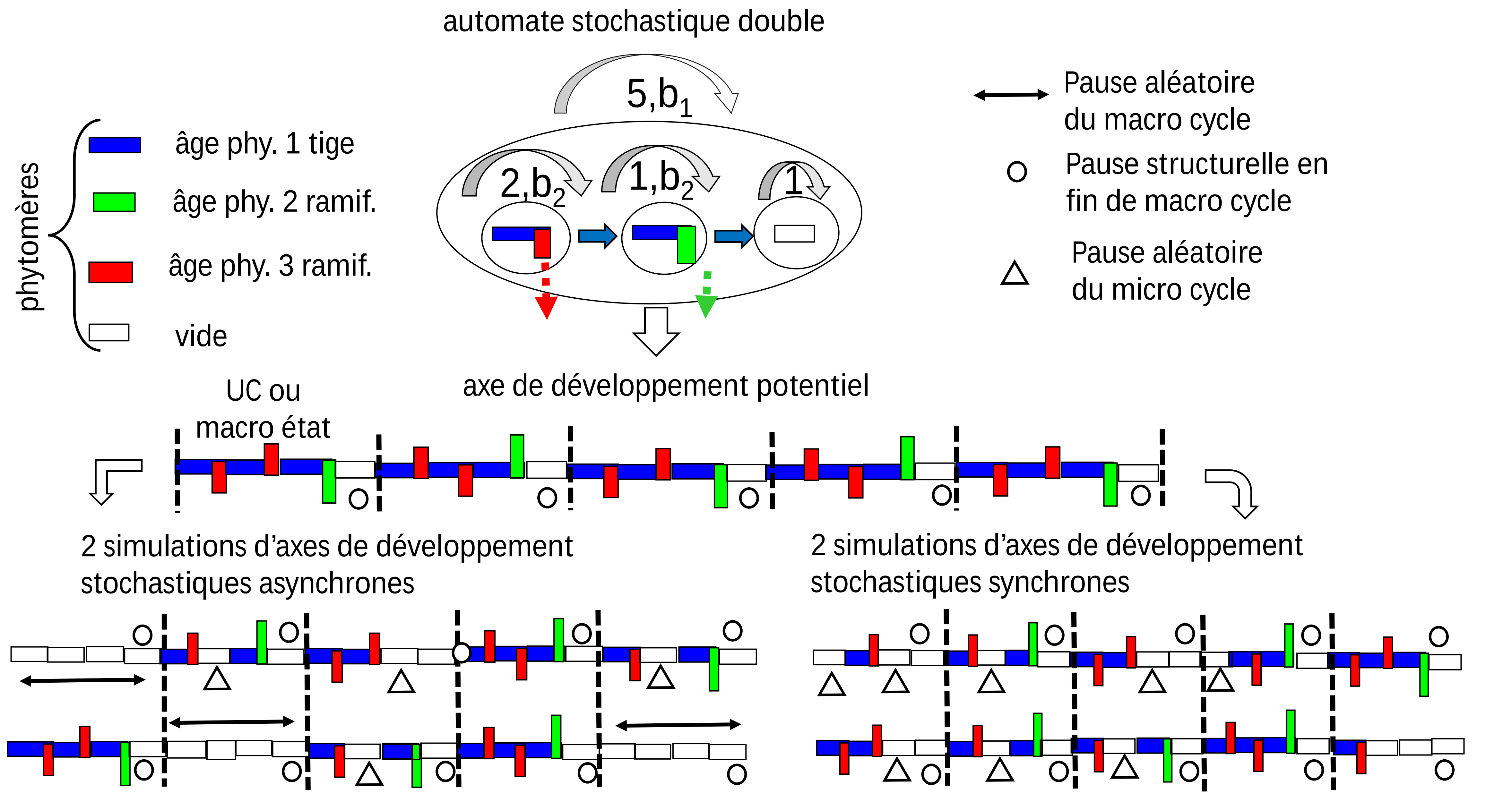
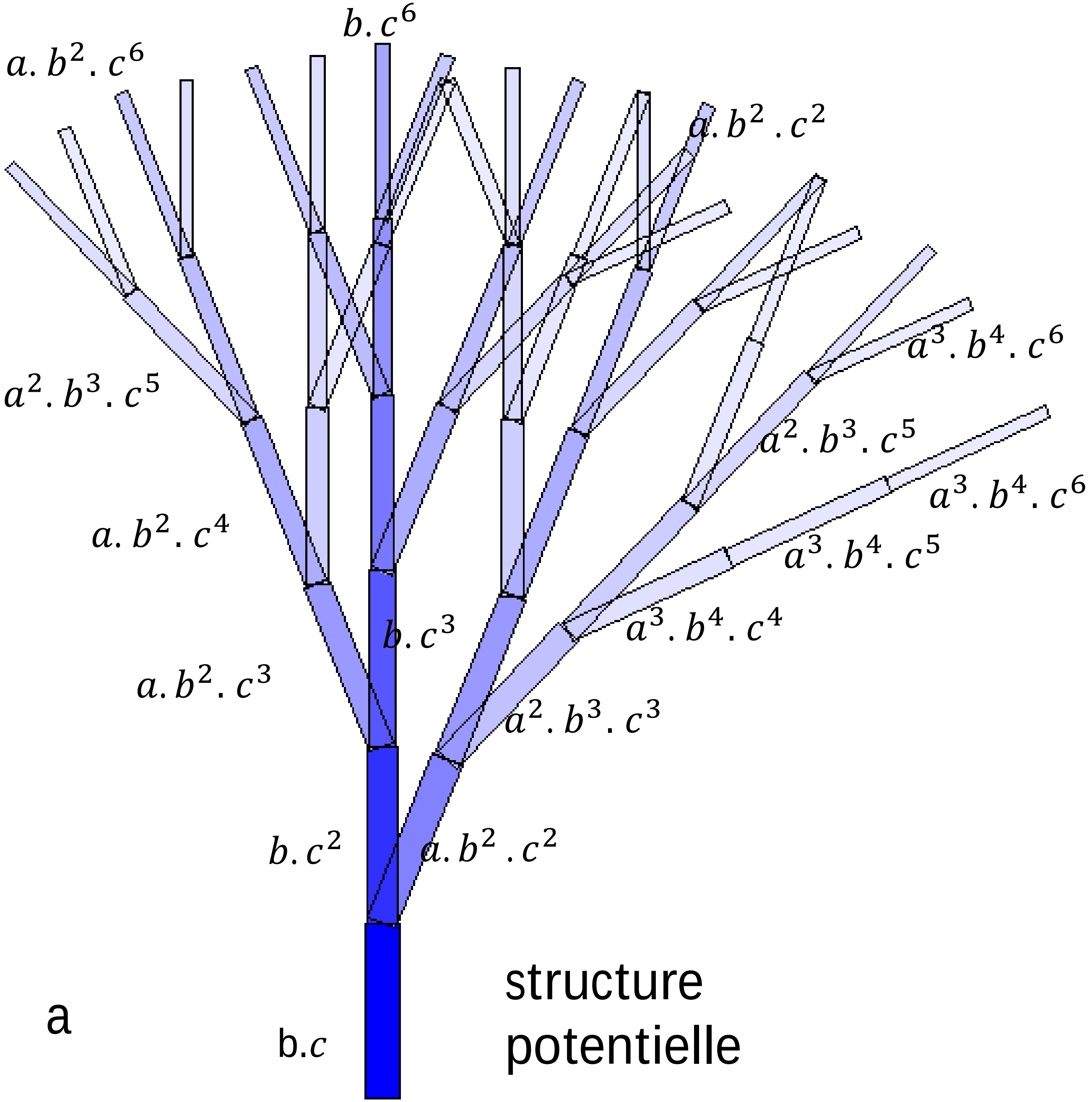

automate stochastique double
5,b1
2,b2
1,b2
1
phytomères
âge phy. 1 tige
âge phy. 2 ramif.
âge phy. 3 ramif.
vide
Pause aléatoire du macro cycle
Pause structurelle en fin de macro cycle
Pause aléatoire du micro cycle
axe de développement potentiel
UC ou macro état
2 simulations d'axes de développement stochastiques asynchrones
2 simulations d'axes de développement stochastiques synchrones



Un formalisme existant pouvant se décrire selon une architecture NN

- GL stochastique / structure potentielle

Intérêts: de l’application à la théorie

- Identification/Estimation de paramètres de modèles FSPM existants

- Une nouvelle approche de la plasticité
  - Par la simulation et par les données

- Une architecture NN « dédiée à l’exploration spatio-temporelle »
  - Peux t on définir une architecture RNN générique au végétal ?

Intérêts: de l'application à la théorie

Deux exemples d'application des systèmes de neurones:

actuel:
- Reconstruction de la structure
- Paramètres fonctionnels

avec du deep learning:
analyse des cimes à partir d'images
effet environnementaux

Un formalisme existant pouvant se décrire selon une architecture NN

actuel:
- feedback sur plantes simples

avec du deep learning: feedback sur arbres, réitération automatique

Une nouvelle approche de l'architecture des plantes par des architecture NN

« dédiée à l'exploration spatio-temporelle »
- Aspects multiéchelles –phytomère, unité de croissance, axe, complexe réitéré
- Rétro actions temporelles => rétroaction de fonctionnement
- De l'individu à la communauté: est ce une problématique de généricité du RNN ?