

# Mixing Model for Renewable Growing Media: Development, Validation and Application

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**WAGENINGEN**  
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## Referaat

De transitie van niet-hernieuwbare groeimmedia (met name op basis van veen) naar groeimmedia met hernieuwbare materialen is zowel nodig om de milieu-impact van de sector te verlagen als een technische uitdaging. Hernieuwbare materialen zoals kokosvezel, houtvezel, boomschors en compost hebben elk hun eigen beperkingen. Daarom bestaan hernieuwbare groeimmedia vaak uit verschillende componenten, wat betekent dat veel recepturen mogelijk zijn. Mengmodellen kunnen het ontwikkelen van dit soort mengsels versnellen door de behoefte aan proeven en 'trial and error' te verminderen. Dit project heeft een bestaand mengmodel, ontwikkeld door Blok, Eveleens et al. (2019), gevalideerd en toegepast in een praktijkomgeving, en uitgebreid met een module voor volumeverlies om de noodzaak van laboratoriummetingen te verkleinen. Verschillen in bulkdichtheid en het bijhorende volumeverlies werden voorspeld met behulp van een statistisch machinelearningmodel, gebaseerd op de morfologie van de deeltjes in de materialen, verkregen via dynamische beeldanalyse (QICPIC-apparaat). Het model voorspelde nauwkeurig waarden gerelateerd aan porositeit, organische stof en waterretentie voor materialen zoals kokosvezel en boomschors, maar toonde grotere variabiliteit bij compost en fijne houtvezel door batchverschillen en effecten van verwerking. Gewasproeven bevestigden de praktische relevantie van het model voor het sturen van irrigatie en het inschatten van de water-luchtbalans, terwijl ze ook de invloed van variatie, vuldichtheid en materiaalafhankelijke eigenschappen benadrukten. Het voorspellen van volumeverlies met behulp van deeltjesmorfologie bleek haalbaar, waardoor een snellere formulering van hernieuwbare groeimmediarecepturen mogelijk werd, al blijven regelmatige updates met actuele materiaaldata en gerichte laboratoriumvalidatie noodzakelijk voor de betrouwbaarheid.

## Abstract

The transition from non-renewable growing media (mostly based on peat) to renewable growing media presents both an environmental necessity and technical challenge. Renewable materials such as coir, wood fibre, bark and compost each present limitations on their own. Because of this, renewable growing media are often multi-component formulations, leading to many possible recipes. Mixing models can help accelerate the development of renewable growing media by reducing the need for physical trial-and-error. This project validated and applied an existing mixing model developed by Blok, Eveleens, et al. (2019) in a practical setting, and extended it with a volume loss prediction module to reduce the need for prior lab measurements. Lab bulk density difference and associated volume loss were predicted using a two-stage statistical machine-learning model based on particle morphology descriptors, obtained through dynamic image analysis (QICPIC device). The model accurately predicted values related to porosity, organic matter and water retention for materials such as coir and bark, but showed greater variability for compost and fine wood fibre due to batch variation and handling effects. Crop trials confirmed the model's practical relevance for steering irrigation and anticipating water-air balance, while highlighting the influence of batch-to-batch variation, filling density, and material-specific handling characteristics. Predicting volume loss using particle morphology proved feasible, enabling faster formulation of renewable growing media recipes, though regular updates with current material data and targeted laboratory validation remain necessary for reliable performance.

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# Summary

The shift towards renewable growing media requires new approaches to formulating mixtures, as no single alternative material replicates the functional properties of peat. Most renewable raw materials have inherent limitations, meaning mixtures must combine multiple components to achieve suitable physical, chemical, and biological characteristics. The existing mixing model by Blok, Eveleens, et al. (2019) enables prediction of mixture properties, but its reliance on measured volume loss has limited its applicability for rapid development.

This project set out to (1) validate the mixing model in a practical context using renewable materials, (2) refine measurement protocols for model inputs, and (3) develop a method for predicting volume loss based on particle morphology. Component materials from industry partners were characterised through physical, chemical and biological analyses, and their particle size and shape were measured using dynamic image analysis (QICPIC device, Sympatec GmbH, at L'Institut agro in Angers, France). A two-stage statistical model was developed: the first stage predicted the difference between theoretical and measured lab bulk density, and the second stage used this difference to predict volume loss. The mixing model and new volume loss module were incorporated into a webtool, allowing users to manage raw materials, calculate mixture properties, visualise results, and export data.

Validation included three series of crop trials at four commercial propagators, covering 20 renewable peat-free mixtures. In laboratory validation, the model predicted total porosity, organic matter content, and water retention trends well for coir- and bark-based mixtures. Greater variability occurred with compost and fine wood fibre, reflecting batch differences and practical mixing challenges such as fibre tangling. The two-stage volume loss model performed strongly both within its training dataset and for mixtures with multiple components used in crop trials, though further development is needed for mixtures containing clay, which was beyond the scope of this study. Moreover, the model predicted density (but not volume loss, due to its sensitivity to errors in density) as measured in the factory reasonably well, though less accurately than volume loss measured in the lab.

Crop trials confirmed the model's value for anticipating water–air balance and informing irrigation strategy, though practical handling properties and plug integrity also influenced performance. Discrepancies between predictions and measured values were linked to batch variation, differences in packing density between lab and grower conditions, and the structural behaviour of specific materials.

The integration of a volume loss prediction module reduces the need for preliminary lab measurements, offering a faster route to developing renewable growing media formulations. However, regular updates with current material data, inclusion of additional material types in the training dataset, and continued laboratory validation are recommended to ensure robust performance under commercial conditions.



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# 1 Introduction

## 1.1 Background

The transition towards renewable growing media is a considerable challenge, and has involved efforts from suppliers, growers, research, certifiers, and regulators alike. Currently, substrates and potting soils for both professional and consumer markets rely heavily on peat, which is dug up from peatlands (Stichnothe, 2022). This causes environmental impact, though the destruction of peatlands has been increasingly mitigated by the industry through initiatives to source peat more responsibly (Responsibly Produced Peat, 2013). The main concern is the release of carbon into the atmosphere faster than it can be taken up again, since peatlands are a major carbon store (IUCN, 2023; Stichnothe, 2022). The public demand to move away from peat has led to the development of 'peat-free' growing media, with peat even subject to (proposed) bans in some markets (Bundesregierung, 2019; Horticultural Peat (Prohibition of Sale) Bill, 2024; VPN, 2022).

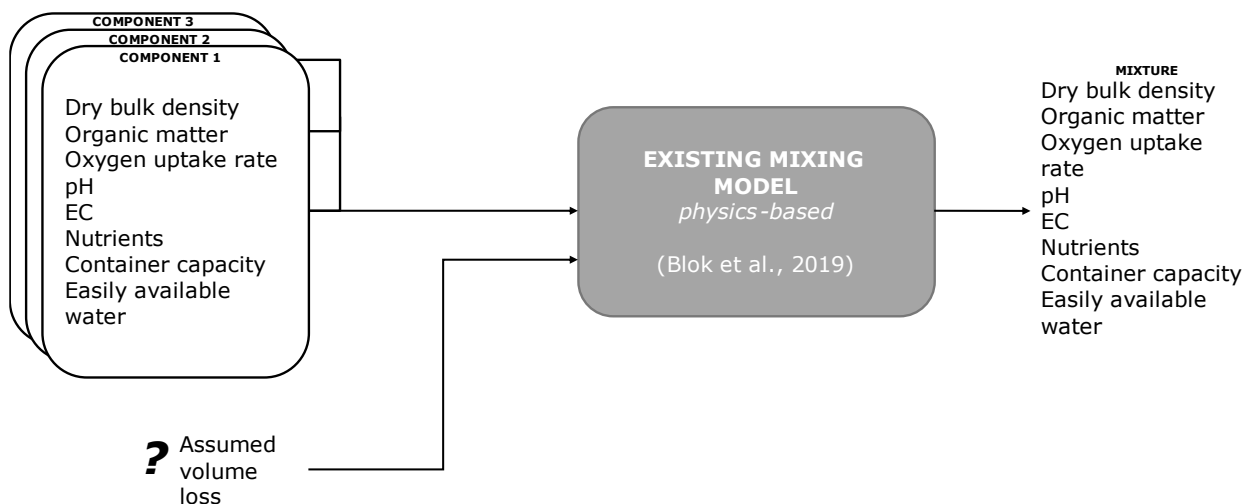
Despite these efforts, peat for the time being remains an important component in growing media due to its unique characteristics. However, this transition is not just about replacing peat: it is about moving towards growing media from sustainable and renewable materials generally. In the Netherlands, this has been highlighted in the 'Convenant Milieu-impact potgrond en substraten' (VPN, 2022). This covenant – signed in late 2022 by the government, private companies, knowledge institutes, certifiers and NGOs – outlines goals for moving towards growing media based on renewable materials.

In the transition towards renewable growing media, there will not just be a single solution. Every product and every crop has its own physical- and chemical requirements. Even peat itself comes in many forms and applications. This makes the transition particularly challenging, with research and development being required for each specific application.

There are other challenges to renewable growing media. Except for coir, which can be used as a stand-alone substrate, other renewable raw materials – such as wood fibres, bark, and compost – have certain performance limitations (e.g., water-holding capacity, pH, and biostability). Therefore, it is common practice to mix several raw material components to compensate for the limitations of each individual component. Typical renewable mixes contain far more components than conventional peat-based mixes, which means finding the optimal mixing ratios would require lots of experiments as there are far more options. Moreover, the quality of component materials can change over time, and new materials or products can become available.

This is where mixing models can play a role. They can reduce trial-and-error by making predictions to guide and accelerate the development of renewable growing media. Mixing models also require a measuring protocol, so that when component materials change quality or new materials come available, adjustments to the recipe can quickly be made by (re-) measuring component materials. Several organisations including RHP have been developing mixing models for this purpose.

Blok et al. (2019) developed such a mixing model too, which could predict the physical- and chemical properties of substrate mixtures (Figure 1). Validation trials, mainly on compost, showed the model to come within 5% of measurements, an acceptable error rate. However, this model had not yet been validated by industry in practice, nor had it been validated on any new materials. Also, whilst the model was shown to work well, it still required one input that had to be measured: the volume loss. Volume loss occurs when two or more materials are mixed and the resulting volume is less than the sum of the components: for example, a litre of marbles mixed with a litre of sand will never make 2 litres of mixture. This type of volume loss is known as 'interstitial filling' in literature. Since nearly all properties depend on the volume loss (which can be up to 20%), this meant predictions could not be made without measurements.



**Figure 1** A graphical representation of the mixing model developed by Blok et al. (2019). Volume loss has to be provided to calculate the properties of the mixture.

## 1.2 Aims

The primary aim of this project was to validate the existing mixing model (Blok, Eveleens, et al., 2019) in a practical setting, applying it to the development of renewable growing media tested in practice. This involved two steps: (1) validating the calculated values of the model with measurements and (2) determining the performance of the mixtures using crop trials.

As previously stated, measuring component materials for such models must be done via a standard protocol. Part of applying the model in a practical setting involved refining the measurement protocol. In doing this, different extraction methods were compared.

Beyond the primary aim of applying and validating the existing mixing model (Blok, Eveleens, et al., 2019) with refined measurement protocols, this project also aimed to investigate the possibility of predicting volume loss. If possible, rather than volume loss needing to be provided by the user, it could be calculated by the model instead, allowing for a faster development of new recipes.

## 1.3 Organisation

This project received 50% co-funding from the Topsector Tuinbouw & Uitgangsmaterialen (horticulture & starting materials). The remaining cash funding came from the Club of 100, with in-kind contributions from the steering committee Club of 100 members. Club of 100 members involved in the steering committee of this project are outlined in Table 1, with specific names in Table 2.

**Table 1** Club of 100 companies in the steering committee of the project and their roles.

Category	Roles	Companies
Propagators	Performing crop trials Providing crop requirements	Beekenkamp Evanthia Florensis Syngenta Flowers
Material suppliers	Supplying substrate materials Providing recipes for crop trials Testing webtool	Jiffy Group Van der Knaap Group
Analysis lab	Measurements on component materials and mixtures	Eurofins Agro



**Table 2** Contacts from steering committee members during the project.

Company	Contact
Beekenkamp	Wilke Goeman Laura Sandifort (2023-24) Mark Smits (2024-25)
Evanthia	Jos van Ernst (2023) Sjoerd van der Plas (2024-25)
Florensis	Alex Leinenga
Syngenta Flowers	Piet van Marrewijk Willem Kögeler (2023) Jan de Winter (2024-25)
Jiffy Group	Paul Poullaidis (2024-25) Bas Voges (2023-24) David van Eersel Bernd van Houten Henri Beekers
Van der Knaap Group	Dirk Zwinkels Jeroen Jansen Peter Quik Kirsty Wu
Eurofins Agro	Jan Hardeman Frank Hoeberichts

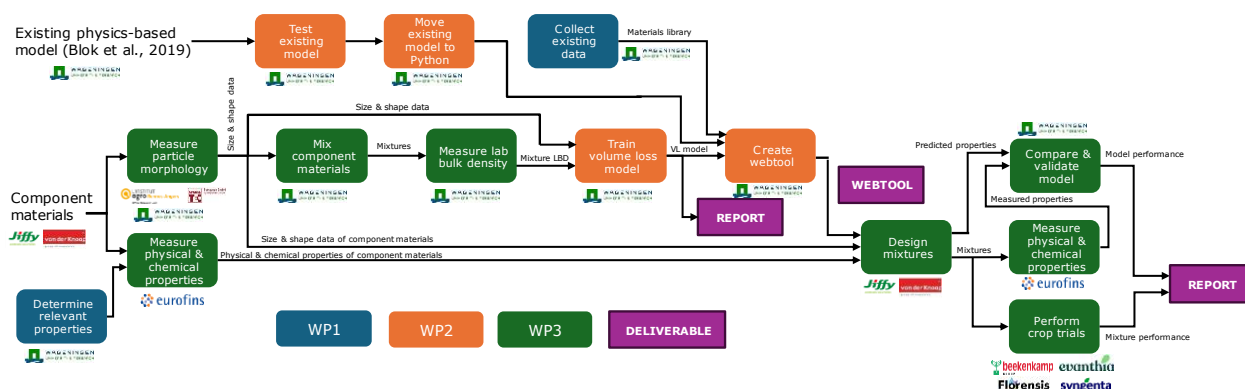
The project was split into three work packages (Table 3):

**Table 3** An overview of the work packages of the project, along with associated activities, deliverables and (work package) leaders from Wageningen Greenhouse Horticulture.

WP	Activities	Deliverables	Leader
Project	Project coordination	(All)	Alexander van Tuyl
1	Collecting existing data	Materials library	Chris Blok
2	Model development and validation Webtool development	Mixing model and webtool	Francisco Mondaca Duarte
3	Crop trial coordination Lab substrate measurements Crop trial model validation	Report	Van Nguyen

### 1.3.1 Approach

The overall approach of the project, explained in more detail in the Materials & Methods section, is visualised in Figure 2:



**Figure 2** A diagram representing the activities of the project and their interrelatedness, with their inputs, outputs, and organisations involved. L’Institut agro Rennes-Angers in France was not a project partner but helped with measurements performed on their QICPIC device (Sympatec GmbH, logo also on the diagram).

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Whilst the work was separated into work packages, the work packages were interdependent. WP1 collected background information on the relevant properties for the model, along with existing data that could be used for testing and demonstrations without using company-specific materials. WP3 provided the data for the volume loss model, which was ultimately included in the new webtool (WP2). This webtool was used in turn in WP3 to design new mixtures. These mixtures were measured, to verify the model's accuracy. They were also applied in crop trials, to see whether mixtures made with a model could perform well in practice.

## 2 Materials & Methods

This section describes the measurements performed on materials and mixtures (2.1), followed by the development of the model and webtool (2.2). The component materials measured and used in the project are then described (2.3). Lastly, an outline is given of the three sets of crop trials used for validation (2.4).

### 2.1 Measurements on component materials and mixtures

Various component materials supplied by substrate producers were used. These materials were characterised in the lab through physical, chemical, and biological analyses (Section 2.1.1) at the Eurofins Agro laboratory in Wageningen. Several mixtures were then prepared for crop trials to validate the mixing model and gain insights into their performance under practical conditions.

To predict the volume loss of mixtures, the particle morphology (size and shape) of component materials was analysed using dynamic image analysis (Section 2.1.2), and raw materials were classified accordingly. This was done using the QICPIC device, developed by Sympatec GmbH. The QICPIC analyses materials by dispersing them into their individual particles and passing these along a camera. This allows for elaborate statistics about the size and shape of particles in component materials. The QICPIC device and dispersion setup in the lab of L'Institut agro (EPHOR research unit) in Angers, France, was used, with the help of Stan Durand, Jean-Charles Michel, and Christine Durand. The research group is active in characterising physical properties of growing media constituents (Durand, 2023; Durand et al., 2023).

To determine the volume loss of mixtures – used to train the volume loss model – selected mixtures from representative morphology groups were chosen for volume loss measurement in the lab using the EN 13040 method (lab bulk density) (CEN, 2007). Additionally, mixtures used in the crop trials were assessed for volume loss at the factory using their in-house measurement tool to establish a connection between lab and factory volume loss measurements.

#### 2.1.1 Physical, chemical and biological analysis

Component materials were analysed at the Eurofins Agro laboratory using the following analysis packages: 410 (Dutch method 1:1.5 water extract), 433 (EN method 1:5 water extract), 434 (EN method 1:5 CAT extract), 920 (water retention), and 976 (oxygen uptake rate). Mixtures for the growth trials were analysed both before and after the addition of base fertilisers using the packages 410, 920 and 976, with the addition of package 421 (Dutch method 1:1.5 water extract and Ca, K, Mg, and Na in a 1:1.5 BaCl<sub>2</sub> extract). Details of the analysis packages are provided in Table 4.

**Table 4** Lists of lab analyses at Eurofins Agro laboratory.

Package	Parameters and description	Method source	Reference
410	pH (H <sub>2</sub> O) after 16 hours stabilisation, EC, NH <sub>4</sub> , K, Na, Ca, Mg, NO <sub>3</sub> , Cl, S, HCO <sub>3</sub> , P, Fe, Mn, Zn, B, Cu, Mo, Si	Potting soil/cocopeat 1:1.5 extract water	(Blok, Baumgarten, et al., 2019)
421	like package 410 + Ca, K, Mg and Na in 1:1.5 extract BaCl <sub>2</sub>	Potting soil/cocopeat 1:1.5 extract water + BaCl <sub>2</sub>	(Blok, Baumgarten, et al., 2019)
433	pH (H <sub>2</sub> O), EC, NH <sub>4</sub> -N, K, Na, Ca, Mg, NO <sub>3</sub> -N, Cl, S, P, Fe, Mn, Zn, B, Cu, Mo, bulk density	EN 13037, EN 13038, EN 13040 and EN 13652	(CEN, 2001b, 2007, 2011a, p. 13037, 2011b)
434	pH (CAT), NH <sub>4</sub> -N, K, Na, Mg, NO <sub>3</sub> -N, S, P, Fe, Mn, Zn, B, Cu, Mo, bulk density	EN 13040 and 13651	(CEN, 2001a, 2007, p. 13040)
920	Moisture, organic matter, bulk density, shrinkage, pores, water, air, water rate of organic matter. Water and air content at -3 cm, -10 cm (pF 1), -32 cm, -50 cm, -100 cm (pF 2)	comparable results like EN 13039 and EN 13041	(CEN, 2011c, 2011d)
976	dry matter, ash, organic matter, mmol oxygen/kg organic matter/hour	OxiTop method	(CEN, 2011e)

While the data from packages 410, 920, and 976 were used as inputs for the mixing model (Table 5), the data from packages 433, 434, and 421 were evaluated as additional information to aid in model validation and potentially support future development.

**Table 5** Lists of inputs for the Mixing Model, measured on each of the component materials.

Name	Symbol (in model)	Definition	Unit	Eurofins package/standard
Dry bulk density	DBD	Dry weight of a known volume of material after the determination of the water holding capacity at -10 cm water head and subsequent drying at 105 °C.	kg/m <sup>3</sup>	920/ EN 13041
Lab bulk density	LBD	A 1-litre cylinder (d=100 mm, h=127 mm), an upper ring, a funnel and a sieve (mesh size 20 mm). A filling, funnel and sieve are removed and a weight (650 g) is placed on top for 180 seconds. LBD = fresh weight of substrate/substrate volume	g/L	433/ EN 13040
Organic matter	OM	Oven-dry sample slowly to a temperature of 550 °C for 24 hours. The loss on weight is reported as the percentage of organic matter in % w/w of the original oven dry sample.	%w/w	920/ EN 13039
Mineral matter	MM	MM = 100 - OM	%w/w	920/EN 13039
Solid filled space	SFS	SFS = OM*DBD/1550 + MM*DBD/2650	%v/v	920/EN 13041
Total pore space	TPS	The total space that is not occupied by solid material, including space where water cannot readily enter. The pores are the column in the substrate that contains air. TPS = 100-SFP	%v/v	920/EN 13041
Water volume		Volumetric water at pressure height -3 cm, -10 cm, -32 cm, -50 cm, and -100 cm	%v/v	920/ EN 13041
Air volume		Air volume at pressure height -3 cm, -10 cm, -32 cm, -50 cm, and -100 cm	%v/v	920/ EN 13041
Easily available water	EAW	Volumetric water between pressure height -10 cm and -50 cm	%v/v	920/ EN 13041
Oxygen uptake rate	OUR	The rate of oxygen consumption under specified conditions setup for OxiTop method.	mmol O <sub>2</sub> /g organic matter/h	976/ EN 16087
pH	pH	pH measured in 1:1.5 water extract	-log[H <sup>+</sup> ]	410
EC	EC	EC measured in 1:1.5 water extract	dS/m	410
Macro-elements	NO <sub>3</sub> , NH <sub>4</sub> , PO <sub>4</sub> , K, Ca, Mg, SO <sub>4</sub> , Na, Cl, HCO <sub>3</sub> , Si	Macro-nutrients measured in 1:1.5 water extract	mmol/L extract	410
Trace elements	Fe, Mn, Zn, B, Cu, Mo	Micro-nutrients measured in 1:1.5 water extract	µmol/L extract	410

### 2.1.2 Particle Morphology of Component Materials

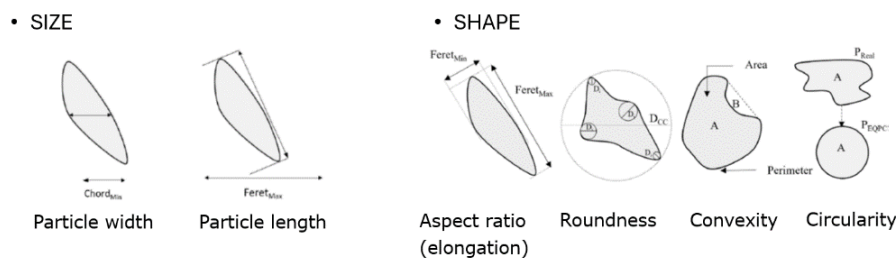
Understanding the physical characteristics of particles, particularly the size and shape, is required when working with mixtures of different materials. These properties, often referred to as particle morphology, play a role in how materials behave when they are combined. In particular, the way particles pack together affects the total volume of the mixture. If the shapes and sizes of particles differ significantly, they may settle in ways that leave gaps or reduce total volume, which affects the prediction of the mixtures when applying the model. This section explains how imaging techniques were used to examine the particles in each component material before mixing. Rather than relying on a single measurement like average size, we used multiple descriptors to consider particle geometry. These included both size (length and width) and shape features that describe how round, elongated or irregular the particles are.

To better understand how materials with different particle shapes and sizes behave when mixed, particularly how much volume may be lost, the individual particles in each material were measured and analysed using a technique called dynamic image analysis (DIA), carried out with a device known as the QICPIC image analyser (Sympatec GmbH, Clausthal-Zellerfeld, Germany) (Figure A1). The measurement protocol outlined below was developed by Durand et al. (2023).

The QICPIC system includes a wet dispersion unit called the Flowcell, which allows particles suspended in water to be analysed. It also has a high-resolution camera that captures detailed images of particles ranging in size from 17  $\mu\text{m}$  to nearly 34 mm.

For each measurement, the test material was mixed with water in a 15 litre tank and continuously stirred using a cone-shape agitator (VJ100 Visco Jet, Küssaberg, Germany). This mixing helped ensure the particles were evenly distributed and not clumped together. The mixture was then circulated through a transparent pipe in front of the camera, allowing the system to capture a continuous stream of images of the particles as they flowed past.

Each material was analysed three times, using 1 to 2 g of sample per run. This sample size was chosen to ensure the number of particles in the images was high enough to be statistically meaningful without overcrowding the images. Each measurement lasted 2 minutes, and the camera captured 80 images per second, about 10 million particles in total per replicate. The images were processed using specialised software (PAQXOS 4.3, Sympatec GmbH), which calculated various size and shape measurements for each particle. These results were averaged based on the area of the particles as seen in the 2D image.



**Figure 3** Example of particle size and shape properties for the component materials measured using the QICPIC image analyser, including both size (width and length) and shape (circularity, elongation, etc.).

To describe particle size, two main measurements were used: width and length (Figure 3). The width (called  $\text{Chord}_{\text{MIN}}$ ) is the shortest straight line that can be drawn across a particle. The length (called  $\text{Feret}_{\text{MAX}}$ ) is the longest straight-line distance between two opposite sides of a particle. These provide more meaningful information for irregularly-shaped particles than using an average diameter.

To describe particle shape, the characteristics measured were: circularity, aspect ratio, elongation, convexity, and roundness (Figure 3). Each of these has a value between 0 and 1, where values closer to 1 indicate a shape that is more smooth, round, or regular. For instance, circularity tells us how closely a particle resembles a perfect circle. Aspect ratio and elongation give an idea of how stretched the particle is compared to its width. Convexity indicates how smooth or jagged the particle's outer edge is. Roundness reflects how sharp or smooth the corners are. These shape characteristics are required to know how particles interact, pack together and settle, factors that indicate how much volume is lost when materials are mixed.

The exact definitions and calculations of particle size and shape descriptors are provided in Table 6 (Durand et al., 2023).



**Table 6** Particle size and shape descriptors analysed with QICPIC image analyser.

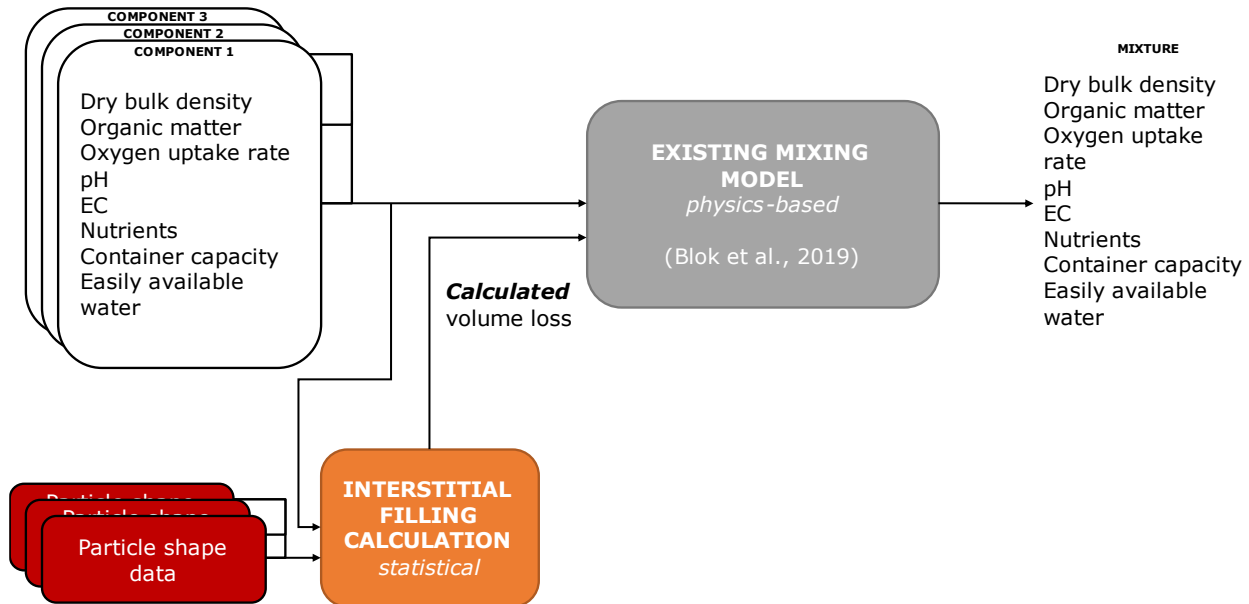
Particle descriptor	Definition
Particle width (Chord <sub>MIN</sub> )	The shortest chord diameter from the measured set of maximum chord lengths of a particle projection.
Particle length (Feret <sub>MAX</sub> )	The longest Feret diameter from the measured set of Feret diameters of a particle projection.
Circularity	An indicator of how much a particle's perimeter deviates from that of a perfect circle with the same area. $\text{Circularity} = 2 \cdot \sqrt{\text{area} \cdot \pi} / \text{perimeter}$ A smaller value indicates a less circular shape.
Aspect ratio	An indicator of the ratio of particle width to particle length. $\text{Aspect ratio} = \text{Feret}_{\text{MIN}} / \text{Feret}_{\text{MAX}}$ A smaller value indicates more elongated particle shape.
Elongation	An indicator of the ratio of particle width to particle length. $\text{Elongation} = D_{\text{Fi}} / L_{\text{Fi}}$ $D_{\text{Fi}}$ : fibre diameter, calculated by dividing the projection area by the total length of all branches in the fibre skeleton. $L_{\text{Fi}}$ : fibre length, defined as the longest direct path from one end to another within the particle contour. A smaller value indicates a more elongated particle shape.
Convexity	An indicator of the compactness of a particle, specifically its edge roughness. $\text{Convexity} = A / (A+B)$ $A$ : projection area of the particle $A+B$ : area of the convex hull, calculated by wrapping an imaginary elastic band around the particle contour. A smaller value indicates more rough surface.
Roundness	An indicator of the relative sharpness of a particle's corners. $\text{Roundness} = ((\sum D_i) / n) / D_{\text{CC}}$ $D_i$ : diameter of the $i^{\text{th}}$ circle at the corner of the particle $N$ : number of corners $D_{\text{CC}}$ : diameter of the circumscribed circle A smaller value indicates more angular shape

## 2.2 Model Development

The web-based mixing model tool incorporated the principles outlined in Blok et al. (2019) to predict the properties of growing media, essentially predicting density-related properties. The model allows users to predict different physical properties, pH, and electroconductivity (EC). However, volume loss through interstitial filling significantly impacts mixing outcomes and therefore the model required a density correction factor, requiring lab measurements.

This research expanded on this to include a predicted volume loss factor for interstitial filling, removing the need for lab measurements. Volume loss was predicted based on statistical ('machine learning') models, iterating several models and finding the best suited for the provided training data. Additionally, the tool features an interactive interface, allowing users to visualise how different substrate compositions influence the resulting properties. This model helps to optimise substrate mixtures and reduce reliance on empirical testing.

Figure 4 provides a visual representation of the WUR Mixing Model's framework, illustrating how the measurements of different component materials contribute to the final mixture. It highlights the approaches described in this section, both physics-based (2.2.1 and 2.2.2) and statistical (2.2.3).



**Figure 4** The WUR Mixing Model, including the statistical interstitial filling calculation for volume loss, an experimental aim of this study, as an input for the model based on Blok et al. (2019) (Figure 1).

## 2.2.1 Mixing Equations

The physics-based mixing equations as used in the WUR Mixing Model based on Blok et al. (2019) are given in this section. Most properties follow the basic mixing equation (2.2.1.1) with a density correction (2.2.1.2), with a few exceptions given at the end.

### 2.2.1.1 Basic mixing equation

$$X_{1,2} = C_1X_1 + C_2X_2$$

This equation calculates the expected property of a mixture  $X$  by applying a weighted sum of its components. Each component's contribution is proportional to its volumetric fraction in the mix  $C$ . This approach is commonly used to estimate bulk properties.

### 2.2.1.2 Density correction

$$X_{1,2} = \frac{(C_1X_1 + C_2X_2) * D_{x1,2}}{(C_1D_{x1} + C_2D_{x2})}$$

This equation adjusts the properties of a mixture  $X_{1,2}$  to account for changes in bulk density when two materials are mixed. The terms  $C_1$  and  $C_2$  represent the mass fractions of the two components, while  $X_1$  and  $X_2$  are the measured values of the property in each individual component. The terms  $D_{x1}$  and  $D_{x2}$  refer to the bulk densities of the unmixed component materials, and  $D_{x1,2}$  is the bulk density of the final mixture. These density values are used to correct the calculated property so that it reflects the changes caused by how the particles of different sizes pack together. For example, smaller particles can fill the voids between larger ones, increasing the mixture's overall density. Without this correction, predictions can be misleading. This is why an important aim of this study was to investigate whether  $D_{x1,2}$  could be predicted.

### 2.2.1.3 Solid-filled Space (SFS)

$$SFS = \frac{OM * DBD}{1550} + \frac{MM * DBD}{2650}$$

Solid-filled space (SFS) determines the proportion of the substrate that is occupied by solid material rather than pores. Based on its Dry Bulk Density  $DBD$ , it is influenced by organic matter  $OM$  and mineral matter  $MM$ , with specific densities assigned to each. The approximate particle density of organic matter in growing media is  $1550 \text{ kg/m}^3$ , and the approximate particle density of mineral matter is  $2650 \text{ kg/m}^3$ .

#### 2.2.1.4 Air at container capacity (CC)

$$\text{Air at CC} = 100\% - \text{SFS} - \text{CC}$$

This equation calculates the amount of air remaining in a substrate at container capacity  $CC$ , as the difference between solid-filled space  $SF$ .

#### 2.2.1.5 Easily Available Water (EAW)

$$\text{EAW} = \text{WC}_{-10 \text{ cm}} - \text{WC}_{-50 \text{ cm}}$$

This equation refers to the portion of water that is readily accessible to plants, hence 'easily available water' ( $EAW$ ). It is measured as the difference in water content between two levels of suction pressure. In this equation at a pressure of -10 cm  $\text{WC}_{-10 \text{ cm}}$  and a pressure of -50 cm  $\text{WC}_{-50 \text{ cm}}$ .

### 2.2.2 Volume loss calculation using density

As described before, volume loss occurs when mixing component materials with diverse particle morphologies. Interstitial filling leads to a reduction in the total volume of the mixture compared to the sum of its individual components.

Volume loss is calculated as the difference between the 'theoretical'- (i.e. without volume loss) and measured volume of the mixture, expressed as a percentage of the theoretical volume. The mixture volume is determined using lab-compacted bulk density (EN13040), which is the weighted sum of the bulk densities of individual components.

$$\begin{aligned} \text{Volume loss (\%)} &= 100 * (\text{V}_{\text{theory}} - \text{V}_{\text{measured}}) / \text{V}_{\text{theory}} \\ &= 100 * (1 - \text{V}_{\text{measured}} / \text{V}_{\text{theory}}) \\ &= 100 * (1 - (\text{m} * \text{LBD}_{\text{theory}}) / (\text{m} * \text{LBD}_{\text{measured}})) \\ &= 100 * (1 - (\text{LBD}_{\text{theory}} / \text{LBD}_{\text{measured}})) \end{aligned}$$

Where theoretical lab bulk density  $\text{LBD}_{\text{theory}}$  is calculated as

$$\text{LBD}_{\text{theory}} = \sum x_i * \text{LBD}_i$$

$x_i$ : proportion of component  $i$  in the mixture  
 $\text{LBD}_i$ : lab bulk density of component  $i$

In this way, volume loss was calculated, for training and validation of the model. If a volume loss occurs, its value is positive. If there is a volume gain (measured volume higher than theoretical volume), the value is negative. Volume gain is uncommon, but where it occurred in the results of this research, its possible causes are explained.

### 2.2.3 Two-Stage Density & Volume Loss Model

The volume loss prediction model was designed to estimate the expected volume loss in a mixture of materials by integrating substrate particle morphology data from QICPIC results and applying a statistical ('machine learning') regression model. Several approaches were taken to predict density and volume loss. This section describes the method ultimately used after many other attempts, referred to as a 'two-stage' model. Unsuccessful attempts are described in Annex 0.

#### 2.2.3.1 Training data

The first step was to identify which particle shape attributes measured by the QICPIC were most closely associated with the key properties Lab Bulk Density (LBD) and Dry Bulk Density (DBD). These properties were selected due to their strong influence on interstitial filling (Blok, Eveleens, et al., 2019). Correlation analysis was performed using Spearman's rank correlation coefficient. LBD and DBD were correlated with the mean values and aspect ratios from the QICPIC measurements (Table 6).

The analysis was made using Python's Pandas statistical tool, which computes correlation coefficients ranging from -1 (perfect negative correlation) to 1 (perfect positive correlation). A correlation matrix was made to visualise the relationship between QICPIC size and shape measurements and the key properties.

The data used for training consisted of 136 mixtures, each with two component materials, mixed and measured at the RootzoneLab in Bleiswijk. Additionally the component materials themselves were included in the data, as a 100% one-component mixture.

### 2.2.3.2 Two-stage prediction description

The first stage consisted in predicting an LBD difference. Rather than directly predicting LBD measured from a mixture and then using it to calculate volume loss, the first stage predicts the difference between theoretical and measured LBD. The theoretical LBD ( $LBD_{\text{theory}}$ ) is calculated as described in 2.2.2.

Initially, the model was trained to predict measured LBD, however, volume loss was found to be sensitive to small changes in LBD, leading to large errors. This is why ultimately, the goal was to calculate LBD difference, i.e. the difference between LBD measured and theoretical LBD. Compared to the calculation of volume loss, LBD difference is not affected by the absolute LBD of the mixtures. This reflects the real mixture behaviour, which can be influenced by packing behaviour, moisture interaction, and structural properties not captured.

The second stage consisted in predicting volume loss. The predicted LBD difference was used in combination with the  $LBD_{\text{theory}}$  to predict the volume loss of the mixtures. Although volume loss can theoretically be derived from LBD difference, this approach produced high errors in practice. Because of this, a second statistical model was trained to predict volume loss directly, using  $LBD_{\text{theory}}$  and LBD difference as inputs.

This two-step process reflects the physical process happening during mixing, where variation between batches is possible, even accounting for a different  $LBD_{\text{theory}}$ . After all, a difference is first calculated, and based on that difference a volume loss prediction is made.

### 2.2.3.3 Model training and evaluation

Both stages were trained and tested using a 70:30 data split, and evaluated using Root Mean Square error (RMSE) to quantify average prediction error. The coefficient  $R^2$  was used to describe the proportion of variation in the data explained by the model. Additionally we included a cross-validation for reliability. This means that to further validate the model performance, we split the data 70:30 in a different manner 5 times (5-fold), with each of these folds using a different train/test split.

### 2.2.4 Webtool features

These are the key features of the Mixing Model web tool developed (version 1.6, May 2025).



## Mixing Model ver. 1.6

#### Raw material selection and management

- The user can select multiple raw materials to create a mixture.
- The tool provides an interface to add, modify, or remove raw materials.
- Ability to import and export material data via Excel files.
- A drag-and-drop feature to upload Excel files template for material data import.

Calculate Mixture

Add/Modify Material

### Raw materials list

Click on a substrate to view details.

Refresh

Export Material Data

Import Material Data

Drag and Drop or Select an Excel File

No file uploaded yet. Please select a file and click 'Import Material Data'.

X WUR: Perlite

X WUR: Pumice

- List of available raw materials displayed with options to remove.

### Mixture calculation and prediction

- Users can enter a target Electrical Conductivity (EC) value for the final mixture to add fertilisation.
- Volume loss is Predicted in two different types of model, one based on the length mean, and another on the elongation shape mean.
- If the user desires or data is missing, the tool allows specific volume loss (%) to be added manually.
- Calculations of the mixtures based on Blok, Eveleens, et al. (2019) are presented on the right table.

Raw materials list

2

WUR: pumice

0

10

20

30

40

50

60

70

80

90

100

WUR: coir chips

0

10

20

30

40

50

60

70

80

90

100

Volume loss

Choose model for volume loss:

Explanation

Mean Particle Length Model

QICPIC - Shape Elongation Model

Volume loss (length model) is 3.8 %

Volume loss (elongation model) is 3.9 %

Enter measured value manually. If either length or LBD are missing, volume loss cannot be calculated and must be entered.

(%)

%

Volume loss applied is 3.8 %

(model used: length)

Input Target EC

1.6

dS/m

Prepare Excel File

Logout

### Physical and chemical property predictions

- Physical predicted properties of the mixture are shown before adding fertilisation.
- Predicted oxygen uptake rate (OUR) before adding base fertilisers.
- Predicted pH, EC, and nutrient concentrations based on 1:1.5 water extraction before adding fertilisers.

Min/Max variation only due to Volume loss uncertainty

	Units	Min	Mean	Max
Physical Properties of the mix before base fertilizers				
Dry bulk density (DBD)	kg/m³	70	73	77
Organic matter (OM)	%-w/w	94	94	94
Mineral matter (MM)	%-w/w	6	6	6
Solid filled space (SFS)	%-v/v	4	5	5
Total pore space (TPS)	%-v/v	96	95	95
Water volume at -10 cm suction pressure (CC)	%-v/v	73	77	81
Air volume at -10 cm suction pressure	%-v/v	23	18	14
Easily available water (EAW)	%-v/v	21	22	24
Oxygen Uptake Rate of the mixtures before adding base fertilizers				
Oxygen uptake rate (OUR)	mmol O <sub>2</sub> /kg DOM/h	3	3	3
pH, EC and nutrients of the mixtures in 1:1.5 water extraction before adding base fertilizers				
Potential of hydrogen (pH)	-log <sub>10</sub> [H <sup>+</sup> ]	4.9	4.9	4.9

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### Visualisation and data analysis

- The webtool includes a graph representation to visualise relationships between selected variables. This tool calculates not only the selected combination of raw materials and percentages but also iterates from all the possible combinations of selected raw materials.
- Users can select X-axis and Y-axis variables for analysis
- Graph dynamically updates based on selected substrates and mixture percentages.
- The tool can only work with 5 or fewer raw materials due to computational time because it has to iterate all possible combinations.

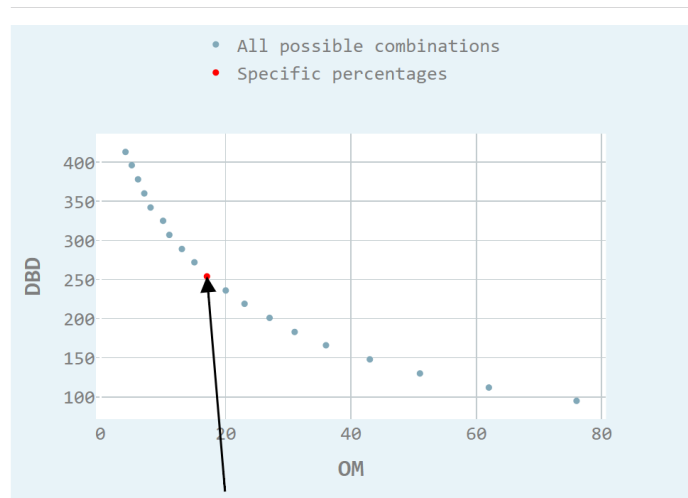
### Select x and y axis variables

X-Axis

Organic matter (OM)

Y-Axis

Dry bulk density (DBD)



### Data export and report generation

- Users can prepare an Excel file with all the possible combinations of the calculated materials.
- It is also possible to export the raw material list as an Excel template. The user can use this template to add new materials to the list.

### Cloud-based storage and Kubernetes deployment

- The tool generates a login function based on unique codes that are provided to the user. Then, the user can create a username and password.
- The tool is deployed on Kubernetes, ensuring scalability, reliability and efficient resource management.
- It uses KubeSeal for securely encrypting secrets, protecting sensitive data such as credentials and own raw material properties.

## 2.3 Component materials

Several component materials, which vary in source and particle size fractions, were supplied for the project by growing media producers Jiffy and Van der Knaap (Table 7). To protect proprietary information, the names and descriptions of these materials have been generalised.

**Table 7** Lists of component materials characterised in this project.

Group	Component materials
acrotelm	2 types
coir	8 types: coir pith, coir husk, coir fibre, and others
wood fibre	6 types: extra fine, fine, medium, coarse, and others
bark	3 types: extra fine, medium, and others
compost	3 types: RHP green waste compost
fibre	1 type
perlite	3 types
vermiculite	1 type

## 2.4 Crop Trials

Beyond validating the model using measurements, crop trials were performed to test the resulting mixtures in practice. Three series of crop trials were conducted: the first- (week 47, 2023 to week 9, 2024), the second- (week 24, 2024 to week 38, 2024), and third series (week 47, 2024 to week 6, 2025). Each series included four trials conducted at four propagators (Beekenkamp, Florensis, Syngenta and Evanthia) (Table 8).

**Table 8** Summary of crop trials, including the type of crop, tray size, timing and propagator involved.

Series	Crop	Propagation material	Tray size	Propagator	Lead time (wk)	Year	Duration (wk)	
							Start	End
1	Viola	seeds	264-plug tray	Syngenta	7	2023	47	1
	Viola	seeds	264-plug tray	Beekenkamp	7	2023	48	1
	Petunia	cuttings	128-plug tray	Florensis	3	2023	47	51
	Petunia	rooted cuttings	12-cm pot	Florensis	8	2023	51	9
	Monstera	seeds	66-plug tray	Evanthia	12	2023	50	9
2	Calocephalus	cuttings	180-plug tray	Florensis	9	2024	25	34
	Strelitzia	seeds	sowing tray 51 x 31 x 4 cm	Evanthia	14	2024	26	38
	Saxifraga arendsii	seeds	264-plug tray	Syngenta	11	2024	27	37
	Lavendula	cuttings	128-plug tray, paperplug	Beekenkamp	5	2024	31	35
3	Dahlia – set 1	cuttings	128-plug tray, paperplug	Beekenkamp	4	2024	47	51
	Dahlia – set 2	cuttings	128-plug tray, paperplug	Beekenkamp	4	2024	50	2
	Calibrachoa	cuttings	84-plug tray	Florensis	6	2024	49	2
	Viola	seeds	264-plug tray	Syngenta	7	2024	51	5
	Asparagus setaceus	seeds	66-plug tray	Evanthia	8	2024	51	6

A total of 20 renewable ('peat-free') mixtures, not counting mixtures with base fertilisers, were tested throughout the project (Table 9). In the first series, one renewable mixture (Mix 3) had the same raw material composition but was adjusted with three different base fertiliser recipes tailored to specific crops.

**Table 9** List of 20 renewable mixtures tested in the crop trials.

Mixture ID	Series of crop trials	Propagator	Crop
Mix 1	1 <sup>st</sup>	Beekenkamp + Syngenta	Viola
Mix 2		Beekenkamp + Syngenta	Viola
Mix 3		Beekenkamp + Syngenta + Florensis + Evanthia	Viola + petunia cuttings + monstera
Mix 4		Florensis	Petunia cuttings
Mix 5		Florensis	Petunia pot
Mix 6		Florensis	Petunia pot
Mix 7		Evanthia	Monstera
Mix 8	2 <sup>nd</sup>	Florensis	Calecephalus
Mix 9		Florensis + Evanthia + Syngenta + Beekenkamp	Calecephalus + Strelitzia + Saxifraga + Lavendula
Mix 10		Evanthia	Strelitzia
Mix 11		Syngenta	Saxifraga
Mix 12		Beekenkamp	Lavendula
Mix 13	3 <sup>rd</sup>	Beekenkamp	Dahlia
Mix 14		Beekenkamp	Dahlia
Mix 15		Florensis	Calibrachoa
Mix 16		Florensis	Calibrachoa
Mix 17		Florensis	Calibrachoa
Mix 18		Syngenta	Viola
Mix 19		Syngenta + Evanthia	Viola + Asparagus
Mix 20		Evanthia	Asparagus

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## 3 Results & Discussion

This section describes and discusses the results, starting with the measurements carried out and their usefulness for the model (3.1). This is followed by results about the statistical model chosen for volume loss (3.2) and overall validation of the new mixing model (3.3). Lastly, the performance of mixtures in crop trials are discussed and, where relevant, compared to model predictions (3.4).

### 3.1 Measurement Methodology

While the specific results cannot be disclosed for confidentiality reasons, general insights into the extraction methods can be discussed. In this section, we compare the results of different extraction methods in light of their relevance for the mixing model.

The 1:5 water extract, due to its higher dilution ratio, resulted in more samples where concentrations of certain elements were below the detection limits of the instruments, compared to the 1:1.5 water extract (Table 10). This was observed for EC, K, Na, Ca, Mg, Cl,  $\text{SO}_4$ , P, Fe, Mn, Zn, and Cu. For EC, only three types of compost and three other components with EC values higher than 1.3 mS/cm in the 1:1.5 water extract were detectable in the 1:5 water extract. Other raw materials that did not show detectable EC in the 1:5 water extract had EC levels in the 1:1.5 water extract ranging from 0.1 to 0.2 mS/cm or below 0.1 mS/cm. For K, Na, Ca, Mg,  $\text{NO}_3$ , and Cl, components with concentrations above 0.5–1 mmol/L in the 1:1.5 water extract could potentially be detected in the more diluted 1:5 water extract. For  $\text{SO}_4^{2-}$ , two components with concentrations greater than 1.2 mmol/L in the 1:1.5 water extract were detectable in the 1:5 extract. For P, components with concentrations above 0.1 mmol/L in the 1:1.5 water extract were possibly detectable in the 1:5 water extract. Phosphorus showed the lowest concentration in the 1:1.5 water extract that could still be detected in the 1:5 extract (0.1 mmol/L), compared to higher thresholds for other elements (0.5–1.2 mmol/L). This can be explained by the lower detection limit for phosphorus using the ICP-AES instrument (0.03 mmol/L), compared to 0.1–0.2 mmol/L for other nutrients. In addition to the dilution ratio, differences in sample packing density between the two extraction methods could also influence the results. Packing density determines how much solid material is included in the analysis for a given volume. A higher density means more sources of nutrients, which could potentially lead to increased nutrient release. In peat-based substrates, the sample packing density in the 1:5 water extract is 15% lower than that in the 1:1.5 water extract (Verhagen, 2011). This observation in peat could be explained by the lower packing pressure applied in the 1:5 extraction method (0.9 kPa for three minutes) compared to that used in the 1:1.5 extract method (10 kPa for ten seconds) (Blok, Baumgarten, et al., 2019). The bulk density of the tested components in the 1:1.5 water extract was not recorded, so no definitive conclusions can be drawn regarding this effect.

When CAT extract was used instead of water, higher concentrations of most elements were detected, increasing their levels to above the detection limits. Exceptions included EC and  $\text{Cl}^-$ , which were not measured in the CAT extract, and P, which was measured but did not exceed the detection limit. The increased concentrations of K and Na in CAT extract can be explained by cation exchange, where these elements are displaced by Ca from the CAT solution (Verhagen, 2011). The increased concentration of micronutrients Fe, Mn and Zn in CAT extract can be explained by increased solubility in acidic solution (CAT solution has pH of 2.6), but mostly by the use of the chelating agent DTPA (Sonneveld & Voogt, 2009).

Among the three extract methods, the 1:1.5 water extract best represents nutrient availability in the substrate solution. The 1:5 water extract, due to its higher dilution, led to more elements falling below detection limits. The 1:5 CAT extract increases the detected concentrations of micronutrients Fe, Mn, and Zn, but its low pH (~2.6) should be carefully considered, as such acidic conditions do not occur in practical growing conditions. Many other extraction protocols exist, some of which may be more appropriate. This however is outside the scope of this study.

**Table 10** Number of samples in which certain parameters reached detection limits across the 1:1.5 water extract, 1:5 water extract, and 1:5 CAT extract.

Parameters	Percentage of samples reach detection limits of the instruments over the total 23 samples (%)		
	1:1.5 water extract (package 410)	1:5 water extract (package 433)	1:5 CAT extract (package 434)
EC	57	26	-
NH <sub>4</sub>	13	13	17
K	91	43	70
Na	78	30	61
Ca	26	9	not measured
Mg	22	4	83
NO <sub>3</sub>	17	13	13
Cl	70	43	not measured
SO <sub>4</sub>	30	9	9
P	87	26	30
Fe	100	52	100
Mn	61	30	100
Zn	61	26	100
B	74	70	74
Cu	48	22	100
Mo	26	4	0

## 3.2 Volume loss

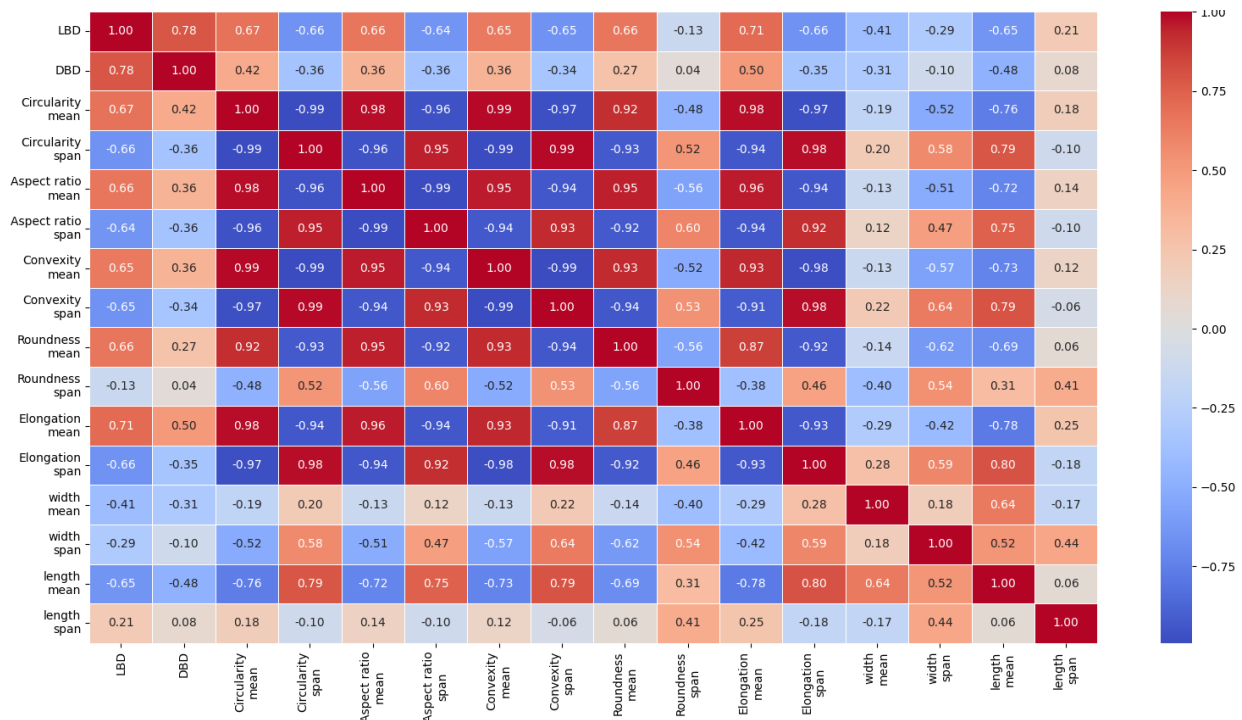
This section starts by presenting the results of the correlations between particle shape metrics and density (3.2.1 and 3.2.2), which were used for model training. Subsequently, results for the two-stage model (3.2.3) are shown. This second approach was found to be more successful. Lastly, volume loss measurements of mixtures from the lab (3.2.2) and factory (3.2.4) are provided.

### 3.2.1 Correlation between particle shape metrics

Figure 5 shows the correlation between different particle shape characteristics, measured by the QICPIC, and selected physical properties of the component materials. This analysis shows that mean elongation displays the strongest positive correlation with the Lab Bulk Density (LBD), with a Pearson correlation coefficient of 0.71. Mean elongation describes the average shape of particles in terms of how stretched or narrow they are relative to their width. It helps identify how streamlined the particles are, which influences how well they can align and settle together in bulk. Within the tested materials, more elongated particles tend to pack more efficiently because their shape allows them to fill the spaces between other particles, reducing voids. This principle applies to soft fibres, which can be compressed and aligned during measurement. In contrast, for rigid materials such as bark, elongated particles could create more empty space between particles. In this study, the bark samples are mostly moderately circular with a low degree of elongation, whereas the more elongated fibres are found in acrotelm, coir, and wood fibres (Table 11).

Another particle characteristic selected was mean length, with a correlation coefficient of -0.65. Mean length measures the average maximum length of the particles, regardless of their shape. As the mean length increases, the LBD decreases, because longer particles tend to overlap. When particles are large in one dimension (irrespective of elongation), tend to lie across each other, stacking in a way that creates more empty space between them. This reduces how tightly the particles can settle, increasing the overall volume and reducing the density of a mixture. This characteristic was not only selected due to having a high correlation but also because it is easier to measure with traditional methods like sieves or image analysis systems that focus on particle boundaries. It offers a reliable way to assess general size across substrate samples and is widely used in both lab and industrial settings. Both mean elongation and mean length were selected because they show two different aspects of the particles' aspects: shape and size.

In the centre of Figure 5 there is a visible 'block' of strong correlations between similar shape parameters. These values were intentionally ignored in the analysis due to autocorrelation: in other words, they describe the same thing indirectly. For example, particles with a higher circularity will mathematically always have a higher roundness. Including both would not meaningfully improve predictions and could lead to redundancy.



**Figure 5** Correlation matrix between QICPIC measurements and selected substrate properties. 'Span' refers to the standard deviation of the metrics.

### 3.2.2 Material characterisation and mixture selection

Volume loss in the lab was measured through lab bulk density, as described in Section 2.2.2. To simplify the approach, volume loss was assessed only for mixtures with two components at a time. The selection of components was based on particle morphology, analysed using the QICPIC device.

To group the components by morphology, we first used Principal Component Analysis (PCA) to reduce the number of variables while keeping the most important features of the components. Then, we applied Hierarchical Cluster Analysis (HCA) to find patterns and form groups based on similarities. HCA was chosen because it does not require us to set the number of groups in advance, and it provides a visual dendrogram that helps us understand how the materials relate.

The result was five morphology-based groups identified, as shown in Table 11. These groups range from particles that are more circular, less elongated, and have smoother surfaces (Group 1) to those that are less circular, more elongated, and angular (Group 5). Group 1 includes one type of bark, four types of coir, and all three types of compost. Group 2 consists of two types of bark and two types of coir. Group 3 contains only perlite. Group 4 includes two types of coir and two other components. Group 5 comprises all wood fibre materials.



**Table 11** Groupings of component materials based on particle morphology measured with the QICPIC.

Group	Description	Raw material	Lab bulk density (kg/m <sup>3</sup> )	Dry bulk density (kg/m <sup>3</sup> )
1	moderate circularity	bark_1	244	197
	slightly elongated	coir_1, 2, 3, 4	150-394	71-114
	high convexity sub-rounded	compost_1, 2, 3	558-603	446-537
2	moderate circularity	bark_2, 3	275-391	191-241
	slightly elongated	coir_5, 6	277-327	104-112
	high convexity sub-rounded highly diversified size			
3	moderate circularity slightly elongated high convexity sub-rounded	perlite	144	114
4	low circularity	acrotelm	164	87
	moderate elongated	coir_7, 8	118-299	97-99
	high convexity sub-rounded	fibre	259	134
5	very low circularity very elongated moderate convexity angular	woodfibre_1, 2, 3, 4, 5, 6	60-130	98-110*

\* Dry bulk density is often lower than lab bulk density. However, dry bulk density of three types of wood fibre (medium and extra fine) was higher than their lab bulk density, with an absolute difference of about approximately 30 kg/m<sup>3</sup>. Numbers assigned after each raw material solely for labelling purposes.

Representative two-component mixtures were chosen for volume loss measurement in the lab, as below:

- Group 1 & 5: coir pith & wood fibre medium
- Group 1 & 5: compost & wood fibre medium
- Group 1 & 5: bark extra fine & wood fibre fine
- Group 2 & 4: bark fraction 1 & acrotelm
- Group 2 & 5: bark fraction 1 & wood fibre medium
- Group 3 & 4: perlite & coir\_8

In general, the volume loss measured in the lab ranged from 0% to 8% (Table 12). However, when mixing bark fraction 1 (Group 2) with wood fibre medium (Group 5), a volume gain of up to 34% v/v was observed. This can be explained by the bark's greater rigidity and weight compared to the wood fibres. During lab measurements, 'demixing' was observed when filling the prepared mixture into the measuring cylinder: bark particles tended to settle first, while wood fibres remained on top. Incrementally filling the cylinder helped reduce layering. Rigidity of bark could create voids leading to an overall volume gain.

Another possible cause of volume gain is that wood fibres falling into the voids created by bark particles were less compressed during the lab bulk density (LBD) measurement than those outside the voids. This observation is supported by the experience that wood fibres tend to compress under the weight applied during LBD measurements in smaller cylinders – a compression not seen when using an 18 L cylinder without added weight.

Compared to mixing the same bark with acrotelm (Group 2 & 4), volume gain also occurred but at much lower levels. Acrotelm compresses less than wood fibre, which may explain the smaller volume gain in this mixture compared to the bark and wood fibre combination (Group 2 & 5).

**Table 12** Volume loss measured in the lab. Negative values mean volume gain after mixing.

Group	Mixtures	Volume loss (%)		
		min	Mean $\pm$ standard deviation	max
1 & 5	20% compost _ 80% wood fibre medium	3	5 $\pm$ 2 (n = 3)	6
1 & 5	80% coir pith _ 20% wood fibre medium	1	3 $\pm$ 1 (n = 10)	5
	60% coir pith _ 40% wood fibre medium	-3	0 $\pm$ 2 (n =10)	3
	40% coir pith _ 60% wood fibre medium	-4	0 $\pm$ 2 (n =10)	3
	20% coir pith _ 80% wood fibre medium	1	4 $\pm$ 2 (n =10)	6
1 & 5	80% bark extra fine_ 20% wood fibre fine	0	3 $\pm$ 2 (n =4)	6
	60% extra fine_ 40% wood fibre fine	-1	2 $\pm$ 2 (n =4)	5
	40% extra fine _ 60% wood fibre fine	-4	-1 $\pm$ 3 (n =4)	2
	20% extra fine _ 80% wood fibre fine	0	3 $\pm$ 3 (n =4)	8
2 & 4	80% bark fraction 1_ 20% acrotelm	-2	1 $\pm$ 2 (n =4)	3
	60% bark fraction 1_ 40% acrotelm	-3	0 $\pm$ 3 (n =4)	4
	40% bark fraction 1_ 60% acrotelm	-4	-2 $\pm$ 2 (n =4)	1
	20% bark fraction 1_ 80% acrotelm	-8	-3 $\pm$ 4 (n =4)	1
2 & 5	80% bark fraction 1_ 20% wood fibre medium	-25	-18 $\pm$ 5 (n =4)	-13
	60% bark fraction 1_ 40% wood fibre medium	-34	-19 $\pm$ 10 (n =4)	-13
	40% bark fraction 1_ 60% wood fibre medium	-13	-11 $\pm$ 2 (n =4)	-8
	20% bark fraction 1_ 80% wood fibre medium	-18	-9 $\pm$ 8 (n =4)	0
3 & 4	80% perlite_20% coir	-2	4 $\pm$ 4 (n =4)	7
	60% perlite_40% coir	-10	-4 $\pm$ 4 (n =4)	-1
	40% perlite_60% coir	-6	-3 $\pm$ 3 (n =4)	2
	20% perlite_80% coir	-6	-4 $\pm$ 2(n =4)	-1

A large standard deviation was observed in the lab measurements of volume loss (Table 12). In contrast, the measured lab bulk density (LBD) of the mixtures showed low relative variability, with a coefficient of variation (*i.e. the standard deviation relative to the mean*) below 10% (data not shown). However, when using these measured LBD values to calculate volume loss, high variability emerged. This increased variability is due to the wide range of volume change values, spanning from volume gain (negative values) to volume loss (positive values) (see minimum and maximum values in Table 12).

### 3.2.3 Two-Stage Density & Volume Loss Model

The two-stage model was evaluated using both interpolated elongation and interpolated length as input features. This means two two-stage models were developed: one for elongation and one for particle length. The performance was measured based on prediction accuracy for LBD difference and volume loss, and results were visualised using actual vs predicted plots. Overall, both features provided strong results, in both cases performing quite similarly. The Random Forest machine learning model (Rigatti, 2017) was found to be most effective in both cases.

#### 3.2.3.1 Model accuracy

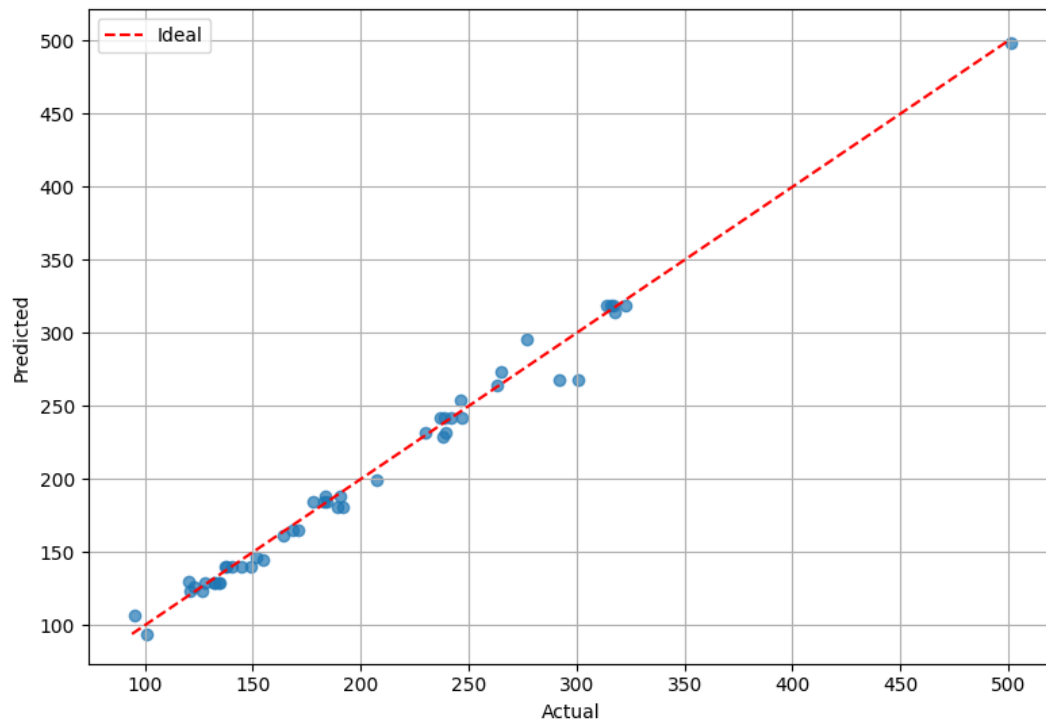
The model accuracy for each stage is summarised in the table below (Table 13).

**Table 13** Model accuracy results.

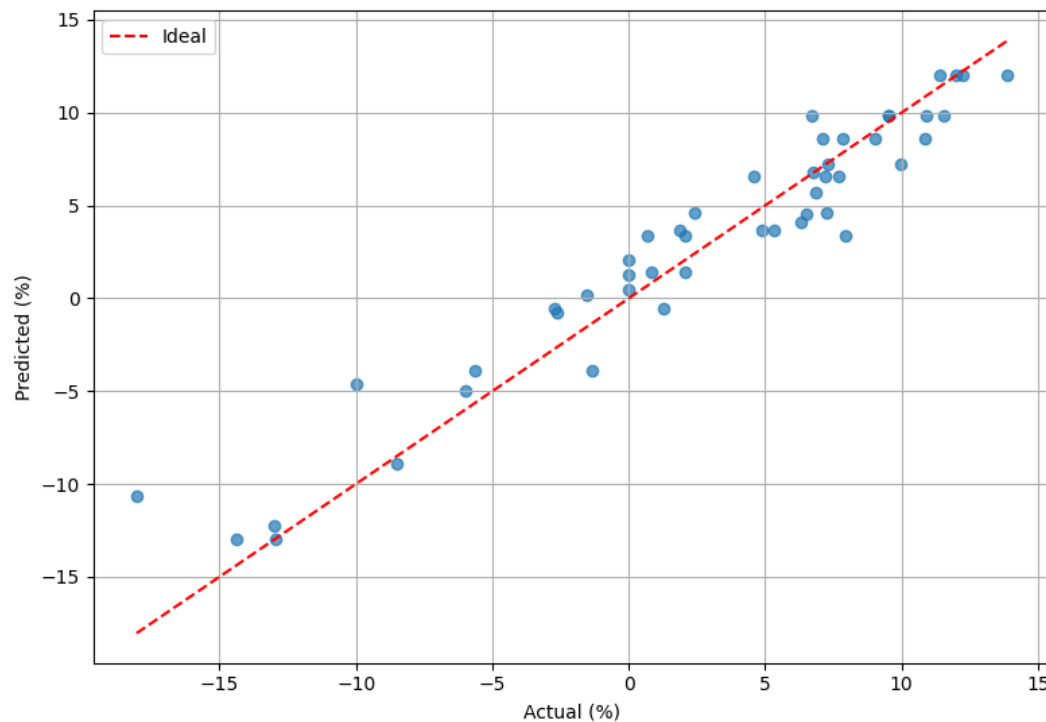
Feature Used	Predicted Target	RMSE	Unit	R <sup>2</sup>
Elongation	LBD difference	7.3	kg m <sup>-3</sup>	0.80
Elongation	Volume loss	2.0	%	0.93
Particle Length	LBD difference	6.8	kg m <sup>-3</sup>	0.82
Particle Length	Volume loss	1.8	%	0.94

### 3.2.3.2 Prediction plots

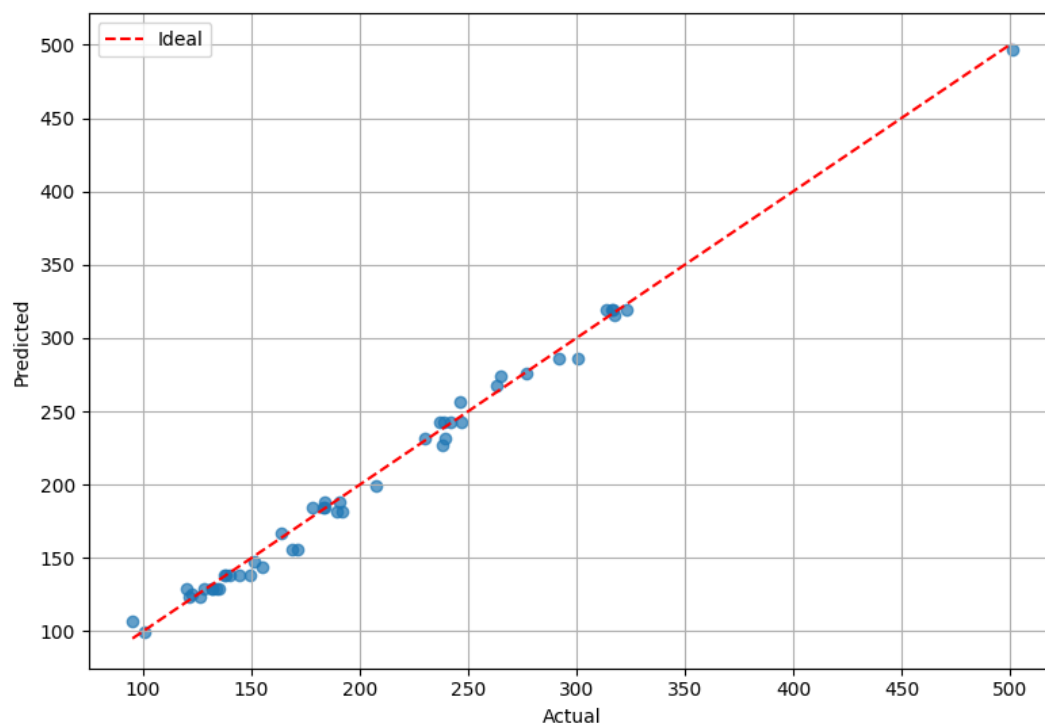
The figures below (Figure 6, Figure 7, Figure 8, Figure 9) illustrate the model performance. These are the results of testing the model using 30% of the measurement data (70% was used for training). These figures are based on the testing part of the data, showing the comparison between the real measurements vs the model predictions for both stages: first for elongation, then for length. The LBD difference prediction was used to calculate the LBD measured, and then compared with real LBD measured.



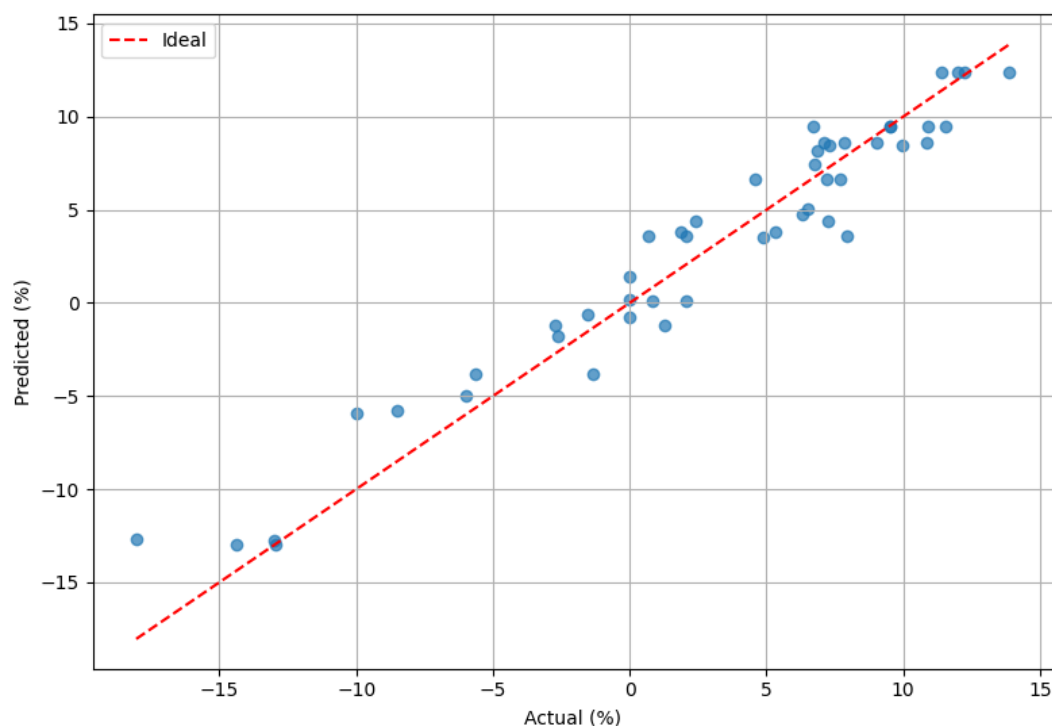
**Figure 6** Comparison of LBD measured ( $\text{kg m}^{-3}$ ) vs LBD predicted ( $\text{kg m}^{-3}$ ) (from LBD difference) using elongation.  $R^2 = 0.99$ ;  $\text{RMSE} = 8.4 \text{ kg m}^{-3}$ .



**Figure 7** Comparison of volume loss measured (%) vs volume loss predicted (%) using elongation.  $R^2 = 0.92$ ;  $\text{RMSE} = 2.1\%$ .



**Figure 8** Comparison of LBD measured ( $\text{kg m}^{-3}$ ) vs LBD predicted ( $\text{kg m}^{-3}$ ) (from LBD difference) using length as a feature.  $R^2 = 0.99$ ;  $\text{RMSE} = 6.6 \text{ kg m}^{-3}$ .



**Figure 9** Comparison of volume loss (%) measured vs volume loss predicted (%) using particle length as a feature.  $R^2 = 0.94$ ;  $\text{RMSE} = 1.9\%$ .

### 3.2.3.3 Cross-validation results

To test the model's robustness, we applied a 5-fold cross-validation. This means the model was retrained and tested on different data splits to evaluate how results vary when input data changes. Table 14 summarises the model performance. It shows how well the model predicted volume loss under cross-validation, which checks how reliable the results are by repeating the test on different parts of the data.

**Table 14** Model performance cross-validation based on particle shape features.

Feature Used	CV RMSE (%) (mean $\pm$ std)	CV R <sup>2</sup> (mean $\pm$ std)
Elongation	4.0 $\pm$ 5.7	0.913 $\pm$ 0.034
Particle Length	4.6 $\pm$ 6.8	0.894 $\pm$ 0.025

### 3.2.4 Volume loss measurement at the factory

For mixtures in the second and third series of crop trials, volume loss was calculated based on the bulk density measured by substrate producers at their factories. The model using elongation as input predicted volume loss with moderate accuracy: for 9 out of 13 mixtures, the absolute difference between predicted and measured values remained within 5%, while the remaining 4 mixtures showed deviations between 5% and 10% (Table 15).

Although the direct correlation between predicted and measured volume loss was limited, the elongation model still captured part of the trend in the prediction errors, as shown in Figure 11. This suggests the model could identify patterns in how predictions deviate from actual measurements, even if not perfectly matching the values themselves. The two-stage model was applied to the 13 mixtures used in the previous crop trials.

These mixtures were not included in the original model training, providing a more realistic assessment of how the model performs on unseen data. In this context, unseen data refers to mixtures that the model never encountered at any point during its creating or testing. Because they were not part of the training or the internal test set, they are considered as independent cases, this helps in understanding how the model behaves when faced with situations similar to what might occur in real practice.

**Table 15** Volume loss measured at the factory for total 13 mixtures used at the 2<sup>nd</sup> and 3<sup>rd</sup> crop trials. Negative values mean volume gain after mixing.

#	Mixture ID*	Volume loss measured at the factory (%)	Predicted volume loss (%)		Absolute difference between predicted and measured volume loss (%)	
			Elongation model	Length model	Elongation model	Length model
1	9	8.2	3.6	12.0	-4.6	3.8
2	8	11.5	2.3	-12.4	-9.2	-23.9
3	10	0.6	0.6	-1.3	0.0	-1.9
4	11	-4.5	1.7	11.8	6.2	16.3
5	12	4.1	-2	7.2	-6.1	3.1
6	14	4.4	-0.1	-0.6	-4.5	-5.0
7	16	7.6	6.2	-0.6	-1.4	-8.2
8	17	11.5	6.5	8.8	-5.0	-2.7
9	19	8.5	6.5	8.8	-2.0	0.3
10	13	10.3	8.6	-0.7	-1.7	-11.0
11	15	3.4	-1.9	8.8	-5.3	5.4
12	18	2.9	6.2	-12.0	3.3	-14.9
13	20	3.6	3.2	12.0	-0.4	8.4

\*similar to Mixture ID used in crop trial.



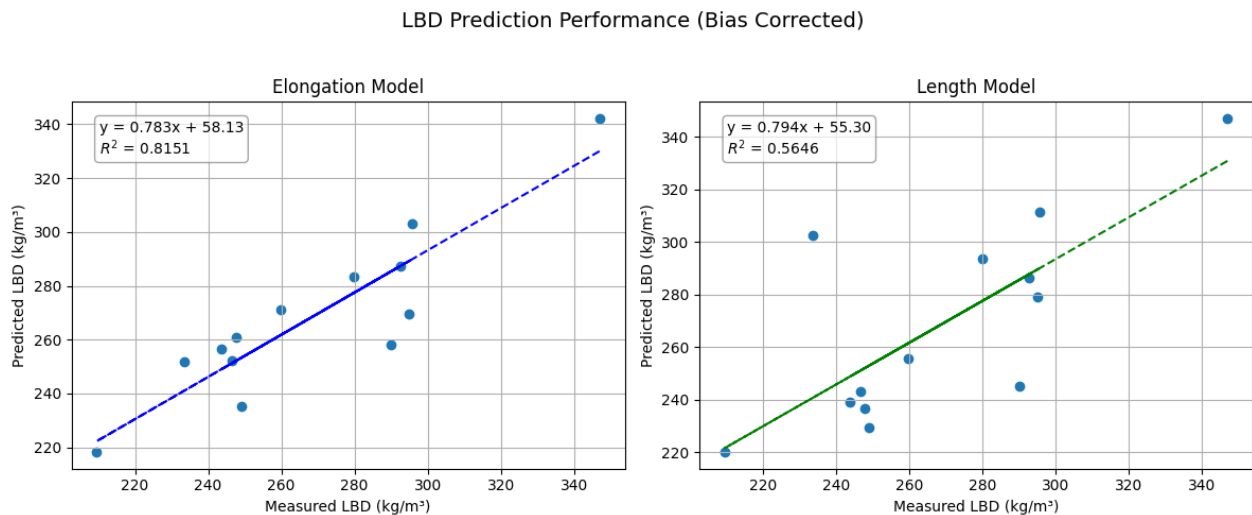
### 3.2.4.1 Lab Bulk Density (LBD) predictions

Before testing on the 13 mixtures, we adjusted both models (elongation and length) to correct a consistent offset between their predictions and the measured LBD differences. This adjustment, known as bias correction, simply shifts the predictions so that, on average, they match the measured values more closely. Making this correction improved accuracy for both models and allowed for a fairer comparison between them. The elongation model again performed better than the length version (Table 16).

**Table 16** Lab Bulk Density (LBD) ( $\text{kg m}^{-3}$ ) result metrics with 13 mixtures. LBD of the 13 mixtures was measured in the factory, unlike model training data, which was measured in the lab.

Feature	RMSE	MAE	R <sup>2</sup>	Min Error	Max Error	Predicted range	True range
Elongation	15.25	12.51	0.815	-33	+18	217 – 343	210 – 347
Length	24.52	16.79	0.564	-44	+67	222 – 344	210 – 347

Figure 10 shows that the elongation model had a good fit ( $R^2 = 0.815$ ), which shows that QICPIC-based elongation is a strong predictor for LBD, even in untrained mixtures. The length model, while still functional, performed considerably worse ( $R^2 = 0.564$ ), suggesting particle length alone may not be sufficient to generalise well in new conditions.



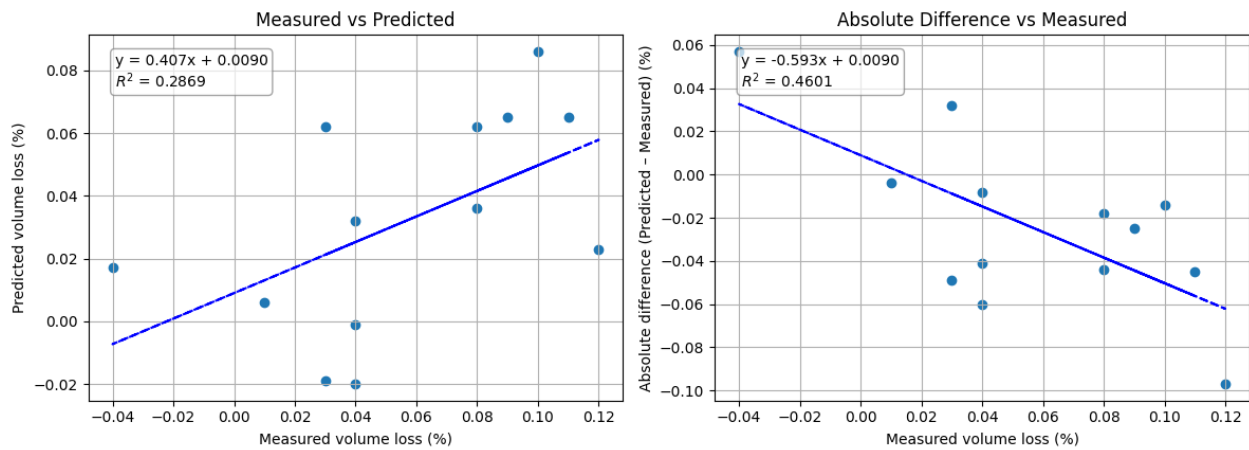
**Figure 10** Visualisation of predicted vs measured LBD for mixtures, with elongation model (left) and length model (right). LBD of the 13 mixtures was measured in the factory, unlike model training data and previous results, which were measured in the lab.

### 3.2.4.2 Volume loss predictions

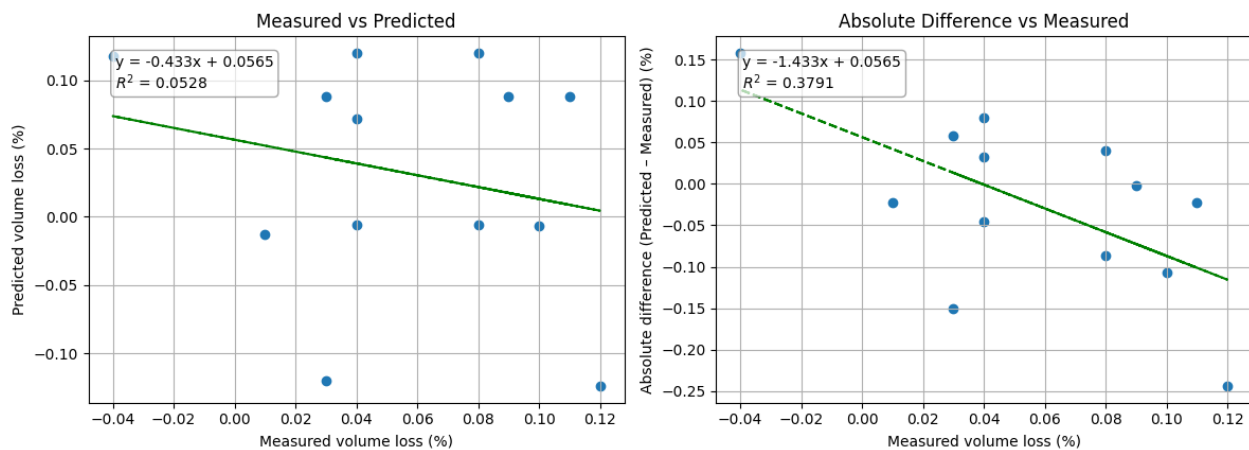
While both models showed positive  $R^2$  values in the regression plots for LBD, the predictive performance for volume loss remains limited. Table 17 shows the elongated model achieved an RMSE of 0.045, MAE of 0.038, and  $R^2$  of 0.29, indicating a small predictive ability. In contrast, the length-based model showed higher error (RMSE = 0.104) and weaker correlation ( $R^2$  = 0.05), suggesting lower reliability for volume loss. Figure 11 and Figure 12 visualise the regression outcomes for the elongation and length models, respectively.

**Table 17** Volume loss result metrics with 13 mixtures. LBD of the 13 mixtures was measured in the factory, unlike model training data, which was measured in the lab.

Feature	RMSE	MAE	$R^2$	Min Error	Max Error	Predicted range	True range
Elongation	0.045	0.038	0.2869	-0.097	+0.057	-0.02 – 0.09	-0.04 – 0.12
Length	0.104	0.081	0.0528	-0.244	+0.158	-0.12 – 0.12	-0.04 – 0.12



**Figure 11** Visualisation of predicted vs measured volume loss for mixtures, using the elongation-based model. LBD of the 13 mixtures was measured in the factory, unlike model training data, which was measured in the lab.



**Figure 12** Visualisation of predicted vs measured volume loss for mixtures, using the length-based model. LBD of the 13 mixtures was measured in the factory, unlike model training data, which was measured in the lab.

## 3.3 Mixing Model Validation

This section describes the validation results of the mixing model, before adding base fertilisers. The model's predicted outputs for the tested mixtures did not include clay as a component. While clay is recognised and used as a component in practice, it falls outside the current scope of the mixing model. For the second and third crop trials, certain mixtures without base fertilisers that were sent to the Eurofins lab contained clay. These mixtures were excluded from the validation of dry bulk density, organic matter, and mineral content due to the strong influence of clay on these parameters. However, they were included in the evaluation of other physical and chemical properties.

### 3.3.1 Effect of volume loss incorporation on prediction

The model's predicted outputs were adjusted by incorporating predicted volume loss. To evaluate whether adding volume loss into the Mixing Model improves the accuracy of predictions compared to laboratory measurements, each mixture was run through the model both with and without volume loss. The results are presented in the Annex 7.4. Where data is not shown in the main section, the key finding is that incorporating volume loss had no effect on predictions of dry bulk density, organic matter content, pH, and OUR. However, it nearly doubled the accuracy of predictions for water retention at –10 cm (Table 18).

**Table 18** Effect of volume loss on predicted water volume at –10 cm suction pressure.

Prediction scenario	Ratio of mixtures with absolute difference of water volume at –10 cm suction pressure*		
	≤5% v/v	>5 & ≤10% v/v	>10% v/v
Without volume loss	6/20	11/20	3/20
With volume loss	11/20	4/20	5/20

\*Absolute difference = predicted water volume – measured water volume.

### 3.3.2 Physical properties

Regarding **dry bulk density, organic matter, and mineral content**, among 20 mixtures, five mixtures containing clays (mixtures 9, 11, 16, 17, and 19) and one mixture containing sand (mixture 10) were excluded from this validation, since clay and sand were not included in the model. The mixing model accurately predicted eight out of the remaining 14 mixtures, with a relative difference not greater than 5% and an absolute difference smaller than 10 kg/m<sup>3</sup> (Table 19). These mixtures were 1, 2, 3, 5, 6, 14, 15, and 20. Four out of 14 mixtures showed a relative difference between 5% and 10%, with an absolute difference smaller than 10 kg/m<sup>3</sup>. Two out of 14 mixtures showed a relative difference of 10–11%, with an absolute difference of 13 kg/m<sup>3</sup>. There was no common pattern in component types among these variation groups; for example, compost and wood fibres appeared in both. One possible explanation is batch-to-batch variation, as the components used for input data and those used to prepare the mixtures came from different batches. This variation might fall within the prediction interval of the model or within the observed variation between predicted and measured values.

Organic matter was well predicted. Seven out of 14 mixtures had a relative difference smaller than 5%. Three out of 14 had a relative difference between 5% and 10%. Three out of 14 showed a relative difference between 10% and 20%. One mixture (mixture 12) had the highest variation at 24%, with an absolute difference of 16% w/w. When deviations occurred, the mixing model tended to overestimate organic matter compared to lab results, with differences up to 10% w/w.

Mineral matter showed the same trend as organic matter because these two parameters are related (i.e., mineral matter is calculated from organic matter). When deviations occurred, the mixing model tended to underestimate mineral matter compared to lab results, with a maximum absolute difference of 16% w/w. The absolute differences for organic matter and mineral matter are comparable (10% and 16%, respectively). However, the higher relative difference in mineral matter (up to 52%) occurs because mineral matter values were lower than organic matter.

**Table 19** Validation of dry bulk density, organic matter and mineral content. The superscript letters 'c' and 's' represent mixtures containing clay and sand respectively, materials on which the model was not trained and which were not included when predicting using the model.

Mixture	DBD (kg/m <sup>3</sup> )		OM (% w)		MM (% w)		Difference in DBD		Difference in OM		Difference in MM	
	predicted	measured	predicted	measured	predicted	measured	absolute (kg/m <sup>3</sup> )	relative (%)	absolute (% w)	relative (%)	absolute (% w)	relative (%)
1	143	145	70	67	30	33	-2	-1	3	4	-3	-9
2	153	162	66	59	34	41	-9	-5	7	11	-7	-16
3	118	120	92	92	8	8	-2	-1	0	0	0	-4
4	102	115	81	79	19	21	-13	-11	2	3	-2	-10
5	171	171	70	69	30	31	0	0	1	2	-1	-4
6	153	161	77	75	23	25	-8	-5	2	3	-2	-9
7	115	107	76	66	24	34	8	7	10	15	-10	-29
8	120	133	78	77	22	23	-13	-10	1	1	-1	-3
9 <sup>c</sup>	109	121	77	65	23	35	-12	-10	12	19	-12	-35
10 <sup>s</sup>	117	184	95	59	5	41	-67	-36	36	61	-36	-88
11 <sup>c</sup>	102	150	95	56	5	44	-48	-32	39	70	-39	-89
12	99	106	85	69	15	31	-7	-7	16	24	-16	-52
13	110	102	85	78	15	22	8	8	7	9	-7	-32
14	98	96	64	71	36	29	2	2	-7	-9	7	23
15	103	102	74	70	26	30	1	1	4	6	-4	-14
16 <sup>c</sup>	126	161	72	58	28	42	-35	-22	14	24	-14	-34
17 <sup>c</sup>	103	131	75	51	25	49	-28	-22	24	48	-24	-50
18	134	125	69	59	31	41	9	7	10	16	-10	-23
19 <sup>c</sup>	112	144	69	53	31	47	-32	-22	16	31	-16	-35
20	129	136	80	80	20	20	-7	-5	0	1	0	-2

DBD: dry bulk density, OM: organic matter, MM: mineral matter. Absolute difference = predicted value – measured value. Relative difference = absolute difference/measured value.

**Total porosity** was accurately predicted in all cases. For the **water retention curve**, the water volume at suction pressures of -32 cm and -50 cm was also well predicted, with a maximum absolute difference of 6% (v/v) occurring in mixture 4; for the other mixtures, the differences were smaller (

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**Table 20).** The greatest deviations occurred at -3 cm and -10 cm, with larger discrepancies at -10 cm than at -3 cm. At -3 cm, the model underestimated water volume by up to 7% v/v in most cases, except for mixture 4, where the underestimation reached 12% v/v. At -10 cm, 12 out of 20 mixtures had an absolute difference not greater than 5% (v/v), four out of 20 had differences between 5% and 10% (v), and four out of 20 had differences between 10% and 15% (v/v). The largest underestimation at -10 cm was 15% v/v (in mixture 4). Overall, the mixing model provided a good prediction of the water retention curve. However, at -3 cm and -10 cm, it tended to slightly underestimate water volume, with maximum absolute deviations of 12–14% (Table 21).

The four mixtures showing the highest variation between predicted and measured values were mixtures 2, 4, 8, and 12. These mixtures contained one type of wood fibre (fine fraction). For propagation mixtures, fine particles are used due to the small size of containers. However, it appears that this type of wood fibre caused the variation. A single effect of this component cannot be conclusively confirmed, but there seems to be a link between the effect of this type of wood fibre – both in its proportion and in its interaction with other components in the mixtures – and the observed variation.

**Table 20** Predicted and measured water content and air content at different suction pressures. The superscript letters 'c' and 's' represent mixtures containing clay and sand respectively, materials on which the model was not trained and which were not included when predicting using the model.

Mix	Predicted values								Measured values							
	Water content (% <sub>v</sub> )				Air content (% <sub>v</sub> )				Water content (% <sub>v</sub> )				Air content (% <sub>v</sub> )			
	3 cm	10 cm	32 cm	50 cm	3 cm	10 cm	32 cm	50 cm	3 cm	10 cm	32 cm	50 cm	3 cm	10 cm	32 cm	50 cm
1	88	70	41	38	4	22	51	54	90	77	43	38	2	15	49	54
2	89	75	45	41	3	17	46	50	91	85	47	43	0	6	44	48
3	90	75	49	45	2	18	44	48	84	75	47	43	8	17	45	50
4	79	69	41	37	15	25	53	57	91	84	47	43	2	9	47	50
5	90	67	42	40	0	23	48	51	90	71	42	38	1	19	49	53
6	84	62	43	39	7	29	49	52	90	70	45	42	1	21	46	49
7	91	71	43	40	2	22	50	53	84	67	40	37	10	27	54	57
8	na	57	na	na	na	37	na	na	84	68	40	36	8	24	52	56
9 <sup>c</sup>	85	70	46	42	8	24	48	51	89	72	46	43	4	21	47	50
10 <sup>s</sup>	82	73	45	42	10	20	47	51	87	76	44	39	3	14	46	51
11 <sup>c</sup>	na	82	na	na	na	13	na	na	91	87	52	49	1	5	40	43
12	na	73	na	na	na	22	na	na	91	86	53	47	3	8	41	47
13	na	84	na	na	na	11	na	na	88	83	51	43	6	11	43	51
14	85	72	48	43	11	24	48	52	89	78	50	45	5	16	45	50
15	na	73	na	na	na	22	na	na	83	77	40	47	12	17	47	54
16 <sup>c</sup>	93	79	52	47	0	14	41	46	89	83	53	48	3	9	39	43
17 <sup>c</sup>	92	80	53	47	2	15	42	48	87	81	53	48	6	12	40	45
18	na	78	na	na	na	16	na	na	89	84	49	44	5	10	44	49
19 <sup>c</sup>	94	83	54	48	0	10	39	45	89	86	56	52	3	7	37	41
20	76	69	46	42	16	23	46	50	82	65	47	44	10	27	45	48

**Table 21** Absolute and relative difference between predicted and measured values of water and air content at different suction pressures. The superscript letters 'c' and 's' represent mixtures containing clay and sand respectively, materials on which the model was not trained and which were not included when predicting using the model.

Mixture	Absolute difference								Relative difference							
	Water content (% <sub>v</sub> )				Air content (% <sub>v</sub> )				Water content (% <sub>v</sub> )				Air content (% <sub>v</sub> )			
	3 cm	10 cm	32 cm	50 cm	3 cm	10 cm	32 cm	50 cm	3 cm	10 cm	32 cm	50 cm	3 cm	10 cm	32 cm	50 cm
1	-2	-7	-2	0	2	7	2	0	-3	-9	-5	-1	117	48	4	0
2	-2	-10	-2	-2	3	11	2	2	-3	-12	-4	-4	na	182	6	4
3	6	0	2	2	-6	1	-1	-2	8	0	3	4	-73	5	-2	-4
4	-12	-15	-6	-6	13	16	6	7	-13	-18	-14	-14	636	182	14	14
5	0	-4	0	2	-1	4	-1	-2	0	-5	1	4	-100	21	-2	-4
6	-6	-8	-2	-3	6	8	3	3	-6	-11	-6	-6	582	37	6	5
7	7	4	3	3	-8	-5	-4	-4	9	6	8	8	-79	-17	-7	-7
8	na	-11	na	na	na	13	na	na	na	-16	na	na	na	54	na	na
9 <sup>c</sup>	-4	-2	0	-1	4	3	1	1	-4	-3	0	-1	111	15	1	3
10 <sup>s</sup>	-5	-3	1	3	7	6	1	0	-5	-4	3	7	241	41	3	0
11 <sup>c</sup>	na	-5	na	na	na	8	na	na	na	-5	na	na	na	152	na	na
12	na	-13	na	na	na	14	na	na	na	-15	na	na	na	175	na	na
13	na	1	na	na	na	0	na	na	na	1	na	na	na	-3	na	na
14	-4	-6	-2	-2	6	8	3	2	-5	-7	-4	-3	122	47	6	5
15	na	-4	na	na	na	5	na	na	na	-5	na	na	na	30	na	na
16 <sup>c</sup>	4	-4	-1	-1	-3	5	2	3	4	-5	-2	-2	-90	51	5	7
17 <sup>c</sup>	5	-1	0	-1	-4	3	2	3	6	-1	-1	-2	-59	23	5	6
18	na	-6	na	na	na	6	na	na	na	-8	na	na	na	62	na	na
19 <sup>c</sup>	5	-3	-2	-4	-3	3	2	4	5	-3	-3	-7	-100	47	6	11
20	-6	4	-1	-2	6	-4	1	2	-7	6	-2	-4	59	-14	3	4

Absolute difference = predicted value – measured value. Relative difference = absolute difference/measured value.

### 3.3.3 pH, EC and nutrients in the 1:1.5 water extract

The mixing model generally tended to slightly underestimate pH, with variation observed across the three series. In the first series, underestimations were typically up to 1 pH unit, although some mixtures containing compost showed larger deviations of 1 to 1.9 (Table 22). In the second and third series, underestimations reached as high as 2.5. These larger deviations were observed in mixtures that included clay, which may explain the greater differences between the model predictions and the measured pH values.

The largest variation in pH prediction, ranging from 2.2 to 2.5, occurred in three mixtures (mixtures 16, 17, and 19). One possible explanation is that these mixtures contained clay while the mixing model did not account for the pH contribution from clay. Clay can influence the pH of the mixtures, but other factors may also be involved, such as the interaction between components and their pH buffering capacities.

The next group, with variations between 1.1 and 1.9, included mixtures 2, 4, 5, 9, 15, 18, and 20. A separate group showing a variation of around 0.9 units included mixtures 1, 10, and 12. Finally, the group with the lowest variation – less than 0.5 – consisted of mixtures 3, 6, 7, 8, 11, 13, and 14.

When comparing the component recipes, it is difficult to draw firm conclusions or identify a clear trend regarding the influence of specific raw materials on pH prediction, as all raw components were distributed across the entire range of variation. In previous study from Blok, Eveleens, et al., (2019), the mixing model similarly underestimated pH in the compost-peat mixtures, especially as the proportion of compost increased in compost-peat mixtures, leading to greater variation.

To better understand the effect of individual components and their buffering capacities, future studies should include a defined series of mixtures with systematically increasing ratios of each component. Additionally, the pH buffering capacity of the raw materials should be evaluated.

EC, macronutrient, and micronutrient levels predicted by the model were generally consistent with laboratory analyses (Annex 7.4). However, in some cases, iron (Fe) concentrations were higher than expected, possibly due to the high variability often associated with Fe measurements.

**Table 22** Difference between lab measured and model predicted values for pH of mixtures without base fertilisers. The superscript letters 'c' and 's' represent mixtures containing clay and sand respectively, materials on which the model was not trained and which were not included when predicting using the model.

Mixture	Series of crop trials	pH of mixture measured in 1:1.5 water extract			
		Predicted value	Measured value	Absolute difference	Relative difference (%)
1	1 <sup>st</sup>	6.3	7.2	-0.9	-13
2		4.6	6.5	-1.9	-30
3		5.6	5.8	-0.2	-4
4		4.4	5.6	-1.2	-21
5		4.7	6.4	-1.7	-27
6		6.3	6.7	-0.4	-5
7		6.9	6.8	0.1	2
8	2 <sup>nd</sup>	5.2	5.7	-0.5	-9
9 <sup>c</sup>		5.8	7	-1.6	-22
10 <sup>s</sup>		4.5	5.4	-0.9	-17
11 <sup>c</sup>		4.3	4.7	-0.4	-9
12		4.4	5.3	-0.9	-18
13	3 <sup>rd</sup>	4.3	4.6	-0.3	-7
14		4.6	5.0	-0.4	-8
15		4.4	6.3	-1.9	-30
16 <sup>c</sup>		4.7	6.9	-2.2	-32
17 <sup>c</sup>		4.5	6.9	-2.4	-35
18		4.5	6.0	-1.5	-25
19 <sup>c</sup>		4.5	7.0	-2.5	-36
20		5.1	6.2	-1.1	-18

Absolute difference = predicted value – measured value. Relative difference = absolute difference/measured value.



### 3.3.4 Oxygen uptake rate (OUR)

The mixing model generally provided good predictions for oxygen uptake rate (OUR) (Table 23). However, in mixtures containing compost, it tended to overestimate OUR by 1.0 to 2.4 units. Underestimation was also observed in some mixtures containing bark, although the maximum deviation in these cases remained within 2.4 mmol O<sub>2</sub>/kg DOM/h.

Out of the 20 mixtures, nine mixtures had a deviation smaller than 1 mmol O<sub>2</sub>/kg DOM/h. The remaining 11 mixtures showed deviations greater than 1, with the largest deviation reaching 2.4 mmol O<sub>2</sub>/kg DOM/h. Mixtures containing compost (mixtures 1, 2, 4, 5, 6, and 18) generally had deviations greater than 1 mmol O<sub>2</sub>/kg DOM/h, except for mixture 4, which showed a deviation of 0.8. Notably, mixture 18 underestimated OUR by -1.2 mmol O<sub>2</sub>/kg DOM/h, while all other compost-containing mixtures overestimated it.

**Table 23** Difference between lab measured and model predicted values for OUR of mixtures without base fertilisers. The superscript letters 'c' and 's' represent mixtures containing clay and sand respectively, materials on which the model was not trained and which were not included when predicting using the model.

Mixture	Oxygen uptake rate of the mixture (mmol O <sub>2</sub> /kg DOM/h)			
	predicted	measured	absolute difference	relative difference (%)
1	5.2	2.8	2.4	85
2	4.8	3.4	1.4	41
3	3.9	4.2	-0.3	-6
4	4.4	3.6	0.8	21
5	5.1	4	1.2	31
6	5.3	4.1	1.2	29
7	4.1	4	-0.1	-3
8	4.7	3.8	0.9	24
9 <sup>c</sup>	3.5	5	-1.5	-31
10 <sup>s</sup>	3.8	4.9	-1.1	-22
11 <sup>c</sup>	3.7	2.4	1.3	54
12	4.3	2.5	1.8	72
13	3.4	3.4	0.0	0
14	2.1	4.0	-1.9	-46
15	3.2	2.3	0.9	37
16 <sup>c</sup>	3.5	2.5	1.0	39
17 <sup>c</sup>	2.2	2	0.2	9
18	3.4	4.6	-1.2	-25
19 <sup>c</sup>	2.2	2.6	-0.4	-16
20	3.7	5.3	-1.6	-30

Absolute difference = predicted value – measured value. Relative difference = absolute difference/measured value.

### 3.3.5 Clay in the mixtures

Although the current mixing model does not account for clay, this project allowed us to test two mixtures that each has two sub-mixtures with one containing clay and one not. These two mixtures were mixture 3 and mixture 6 (Table 9). This allowed for a direct comparison between measured values of mixtures with and without clay to assess its impact on the initial physical and chemical properties. Additionally, we compared the model's predictions to laboratory measurements.

Laboratory results showed that the addition of clay increased dry bulk density (DBD) by 26–61 kg/m<sup>3</sup> (Table 24), with the increase proportional to the amount of clay added. However, clay did not influence moisture retention properties, as laboratory results (Eurofins package 920) showed no difference in water content at -10 cm suction between sub-mixtures (Table 24). Regarding pH, mixture 3 showed an increase of 1 unit (from pH 6 to 7) with clay addition, while mixture 7 showed no change.

Nutrient levels in the 1:1.5 water extract were comparable. OUR values were also similar, with deviations of 0.8–1.3 OUR units. Notably, mixtures containing clay had slightly lower OUR values.

When comparing predicted and measured values, mixture 6 (which contained a higher clay dose than mixture 3) exhibited greater deviations between predicted values and laboratory results for the mixtures without clay. The DBD prediction error ranged from 2 to 8 kg/m<sup>3</sup>. Water content at –10 cm showed absolute differences below 10%, with deviations ranging from 0.2 to 7.8% for mixtures 3 and 6, respectively. Predicted and measured pH values were closely aligned. In terms of OUR, mixture 6 showed an overestimation of 1.2 OUR units.

**Table 24** Predicted and measured properties of two mixtures with and without clay.

Parameter	Unit	Mix 3 without clay		Mix 3 with clay	Mix 6 without clay		Mix 6 with clay
		Predicted	Measured	Measured	Predicted	Measured	Measured
DBD	kg/m <sup>3</sup>	118	120	146	153	161	222
OM	%, w/w	92	92	75	77	75	53
MM	%, w/w	8	8	25	23	25	47
SFS	%, v/v	7	7	8	9	9	12
TPS	%, v/v	93	93	92	91	91	88
Water_3	%, v/v	90	84	85	84	90	87
Water_10	%, v/v	75	75	75	62	70	69
Water_32	%, v/v	49	47	48	43	45	45
Water_50	%, v/v	45	43	45	39	42	43
Air_3	%, v/v	2	8	7	7	1	2
Air_10	%, v/v	18	17	17	29	21	19
Air_32	%, v/v	44	45	43	49	46	43
Air_50	%, v/v	48	50	46	52	49	46
EAW	%, v/v	30	32	30	27	28	26
OUR	mmol O <sub>2</sub> /kg DOM/h	3.9	4.2	3.4	5.3	4.1	2.8
EC	mS/cm	0.1	0.1	0.1	0.2	0.2	0.2
pH	-log[H <sup>+</sup> ]	5.6	5.8	6.9	6.3	6.7	6.6
NH <sub>4</sub>	mmol/L extract	0.1	0.1	0.1	0.1	0.1	0.1
K	mmol/L extract	0.5	0.2	0.4	1.1	1.0	0.8
Na	mmol/L extract	0.2	0.1	0.3	0.3	0.2	0.4
Ca	mmol/L extract	0.1	0.1	0.1	0.1	0.1	0.2
Mg	mmol/L extract	0.1	0.1	0.1	0.1	0.1	0.1
NO <sub>3</sub>	mmol/L extract	0.3	0.2	0.2	0.2	0.2	0.2
Cl	mmol/L extract	0.2	0.2	0.3	0.9	0.8	1.0
SO <sub>4</sub>	mmol/L extract	0.1	0.1	0.1	0.1	0.1	0.2
HCO <sub>3</sub>	mmol/L extract	0.1	0.1	0.1	0.2	0.1	0.1
P	mmol/L extract	0.1	0.1	0.1	0.2	0.3	0.2
Si	mmol/L extract	0.1	0.2	0.4	0.2	0.2	0.3
Fe	μmol/L extract	1.4	3.8	2.8	2.3	4.3	5.1
Mn	μmol/L extract	0.5	0.4	0.4	1.5	1.1	1.1
Zn	μmol/L extract	0.3	0.2	0.3	0.4	0.3	0.5
B	μmol/L extract	5.4	5.7	2.8	4.8	6.5	8.6
Cu	μmol/L extract	0.1	0.1	0.1	0.1	0.1	0.1
Mo	μmol/L extract	0.1	0.1	0.1	0.1	0.1	0.1

DBD: dry bulk density, OM: organic matter, MM: mineral matter; SFS: solid-filled space, TPS: total pore space, Water\_3/Water\_10/Water\_32/Water\_50: water volume measured at -3 cm, -10 cm, -32 cm and -50 cm suction pressure, Air\_3/Air\_10/Air\_32/Air\_50: air volume measured at -3 cm, -10 cm, -32 cm, and -50 cm suction pressure, EAW: easily available water, OUR: oxygen uptake rate.

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## 3.4 Performance of mixtures at crop trials

This section starts with general insights, followed by results of each crop trial. Crop trials are ordered chronologically as in Table 8. A list of mixtures used in each crop trial is provided in the Table 9. Data on mixture properties can be found in the Annex 7.4.

### 3.4.1 General insights

**Ease of tray filling and even distribution:** Fine wood fibre tends to form clumps, making it difficult to fill trays, especially small plug trays. In this study, the proportion of wood fibre (fraction from extra fine to medium) in the mixture seemed to play a role: a mixture containing 15% wood fibre (v) was manageable, but proportions exceeding 20% caused difficulties. In contrast, fine acrotelm did not present the same filling issues as fine wood fibre.

**Water – air content & rooting patterns:** The mixing model was effective in predicting overall trends in water and air content across mixtures. However, when fine wood fibre was used in proportions greater than 20% by volume, clumping caused uneven distribution, which reduced the accuracy of the model predictions—especially in small plug trays (e.g., for *Viola*, *Saxifraga*, and *Petunia* cuttings in 264-plug and 128-plug trays). Differences between the model predictions and laboratory measurements were expected, due to variations between batches of raw materials. The model used input data from a single batch at the beginning of the project, while mixtures for the crop trials were prepared from multiple batches throughout the project.

Despite these variations, the mixing model still showed good predictive trends for mixtures without base fertilisers and clay, even when tested mixtures included clay. Rooting patterns were found to be closely linked to the water–air balance of the mixtures: substrates with higher air content generally supported greater root development.

**Biostability (OUR) and plant growth:** The mixing model's predictions for biostability based on OUR (oxygen uptake rate) were not consistently reflected in the crop trials. In five out of 10 trials, the predicted OUR values aligned with the observed trend of nitrogen immobilisation among the tested mixtures, while in the remaining trials, the model did not predict well. This inconsistency may be due to the influence of base fertilisers on plant growth. In these trials, reduced plant growth tended to correlate more strongly with insufficient air content, as indicated by limited root development.

For crops sensitive to iron deficiency (such as *petunia*, *Calocephalus*, and *calibrachoa*) leaf yellowing was observed in certain mixtures. This may be attributed to a combination of factors: the iron dose in the base fertiliser, an increase in substrate pH during cultivation, and the type of iron chelate used in irrigation water (e.g. EDDHA chelate enhances iron availability at higher pH levels).

### 3.4.2 Viola

The crop trial on *Viola* (seeds) was conducted at the propagator Beekenkamp (first crop trial) and Syngenta (first and third crop trials). The tested mixtures are listed in

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**Table 25.** In the first crop trial, both propagators – Syngenta and Beekenkamp – tested their viola varieties using the same mixtures (Mix 1, 2, and 3) supplied by Jiffy and Van der Knaap. In the third crop trial, viola was tested only at Syngenta. The starting materials were seeds. One variety was tested at Beekenkamp, while two varieties were tested at Syngenta. The reference mixtures were peat-based. Substrates were machine-filled into 264-plug trays. One fertigation treatment was applied across all treatments.

**Table 25** *Mixtures used in the Viola crop trial. A negative value for volume loss indicates a volume gain.*

Trial	Propagator	Mixture	Base fertilisers	Predicted volume loss (%)
1st	Syngenta & Beekenkamp	Mix 1	Slow release N fertiliser, NPK + trace elements	-2.0
1st	Syngenta & Beekenkamp	Mix 2	NPK + trace elements, lime	-1.3
1st	Syngenta & Beekenkamp	Mix 3	Lime, NPK + trace elements	6.1
3 <sup>rd</sup>	Syngenta	Mix 18	Lime, Fe (DTPA), NPK + trace elements	6.2
3 <sup>rd</sup>	Syngenta	Mix 19	Lime, NPK + trace elements, Fe	6.5

Predicted volume loss based on elongation model. All mixtures contained clay.

**Ease of tray filling:** Mix 1 and mix 2, both containing fine wood fibre ( $\geq 30\%$ , v), were reported to cause difficulties in tray filling. Mix 1, with a higher proportion of wood fibre than mix 2, was observed to fall apart more quickly. In contrast, mix 3, which contained no wood fibre, filled trays well. All three mixtures absorbed water effectively from the sowing line. Tray filling at Syngenta was reported to be less difficult than at Beekenkamp, likely due to differences in tray filling machines between the two propagators. Mix 18, which contained 15% fine wood fibre, did not cause any difficulties in tray filling.

**Moisture content:** In the first crop trial, the model prediction indicate that mix 1 hold less 5% (v) than mix 2 and mix 3. However, both lab measurements for mixtures with and without base fertilisers indicated that mix 3 hold less water than mix 1 and mix 2 (2-20% v/v) (Table 26). However, the observed water retention during cultivation did not reflect the predicted trend for mixes 1, 2, and 3. Moisture content, calculated from tray weights during cultivation (Table 27, Table 28), showed that mix 3 actually retained more water than mix 1 and mix 2—by 5–12% in absolute volume. Mix 1 and mix 2 displayed similar moisture content across irrigation events. One possible explanation is that clumping of wood fibres in mix 1 and mix 2 may have introduced more air volume, altering the water-holding characteristics under actual cultivation conditions. This could explain the discrepancy between the predicted values, lab measurements, and in-tray observations.

In the third crop trial, mix 19 held more water than mix 18—around 2–4% by volume (Table 29). This was consistent with the trend observed in both the model's predictions and laboratory measurements, which showed the same range of 2–4% absolute difference (Table 26). It is worth noting that mix 18 contained 15% fine wood fibre but did not show any reported clumping issues. This may suggest a consistent and reliable prediction of moisture content for both mixes 18 and 19, as confirmed by the model, laboratory measurements, and observations during the crop trial.

**Table 26** *Water and air content at -10 cm suction pressure of mixtures used in the Viola trials.*

Mixture	Predicted values from Mixing Model		Lab measurement for mixtures without base fertilisers		Lab measurement for mixtures with base fertilisers	
	Water content - 10 cm (% , v)	Air content at - 10 cm (% , v)	Water content - 10 cm (% , v)	Air content at - 10 cm (% , v)	Water content - 10 cm (% , v)	Air content at - 10 cm (% , v)
Mix 1	70	22	77	15	88	5
Mix 2	75	17	85	6	84	5
Mix 3	75	18	75	17	69	22
Mix 18	78	16	84	10	82	9
Mix 19 <sup>c</sup>	83	10	86	7	84	8

**Table 27** *Moisture content in trays at the Beekenkamp Viola trial (1<sup>st</sup> crop trial).*

Mixture	Moisture content in the trays, calculated from tray weight (% , v)						
	1st irrigation	Week 48	Week 49	Week 50	Week 51	Week 52	Week 1
Mix 1	37	59	60	44	43	50	40
Mix 2	35	60	63	49	42	54	44
Mix 3	62	67	70	55	55	61	48

**Table 28** *Moisture content in trays at the Syngenta Viola trial (1<sup>st</sup> crop trial).*

Mixture	Moisture content in the trays, calculated from tray weight (% v/v)											
	after sowing line	Week 48 before irrigation	Week 48 after irrigation	Week 49 before irrigation	Week 49 after irrigation	Week 50 (14 Dec) no irrigation	Week 50 (15 Dec) no irrigation	Week 50 (16 Dec) before irrigation	Week 50 (17 Dec) no irrigation	Week 50 (18 Dec) no irrigation	Week 50 (19Dec) no irrigation	Week 50 (20 Dec) no irrigation
Mix 1	44	36	44	28	37	51	41	34	61	52	44	37
Mix 2	41	30	37	26	35	54	44	37	63	54	45	37
Mix 3	50	42	50	32	41	57	47	40	67	57	48	41

**Table 29** *Moisture content in trays at the Viola trial at Syngenta (3rd trial)*

Mixture	Moisture content in the tray, calculated from tray weight (% v/v)				
	9 Jan 2025 after 1st irrigation	16 Jan 2025 no irrigation	23 Jan 2025 after irrigation	30 Jan 2025 after irrigation	6 Feb 2025 after irrigation
Reference	57	48	62	62	58
Mix 18	58	49	65	64	62
Mix 19	62	53	68	67	64

**Germination:** In the trial at Beekenkamp, mix 3 had a germination rate similar to the reference (94–98%), while germination in mix 1 and mix 2 was lower (79–82% for mix 1 and 61–76% for mix 2). A similar trend was observed for the percentage of usable seedlings, with mix 3 comparable to the reference, while mix 1 and mix 2 showed a reduction. In the trial at Syngenta, germination rates were comparable across all treatments (97–99%), and the percentage of usable plants was also similar (94–99%). The difference in germination rates between the two trials may be due to differences in crop variety and tray filling methods. In the third crop trial, germination rate and the number of usable plants were highest in mix 19 for one variety (96%), while mix 18 performed comparably to the reference (92–94%).

**Plant biomass:** Viola seedlings were largest in mix 3, comparable to the reference, while plant biomass was reduced in mix 1 and mix 2 (Table 30). Nutrient analysis from a 1:1.5 water extract taken during cultivation did not indicate nitrogen or micronutrient deficiencies (Annex 7.5). In the third crop trial, no differences in plant biomass were observed among the treatments (Table 31). The patterns in OUR values predicted by the mixing model appear to be useful for predicting plant biomass performance among treatments—not because biomass is directly proportional to OUR, but because the trend in OUR may help indicate which treatment is likely to yield higher biomass than others (Table 32).

**Table 30** *Fresh biomass of viola seedling in the 1<sup>st</sup> crop trial.*

Mixture	Fresh biomass of usable plants per tray (g)		
	Beekenkamp	Syngenta	Syngenta
	Petit & Wittrock	Cornuta	Wittrockiana
Reference	60	93	97
Mix 1	48	80	69
Mix 2	47	84	63
Mix 3	59	102	93

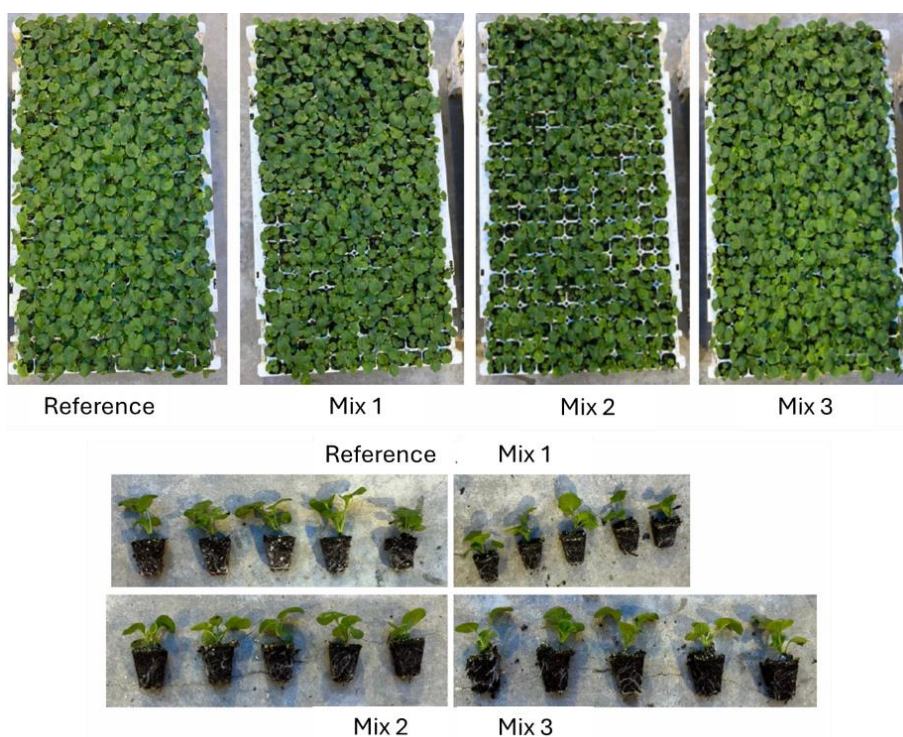
**Table 31** *Fresh biomass of viola seedlings in the 3rd crop trial.*

Mixture	fresh biomass of 100 usable plants (g)	
	Variety VIVF	Variety VICF
Reference	31	28
Mix 18	34	26
Mix 19	33	24

**Table 32** Predicted and measured OUR values of the mixtures used in viola trial.

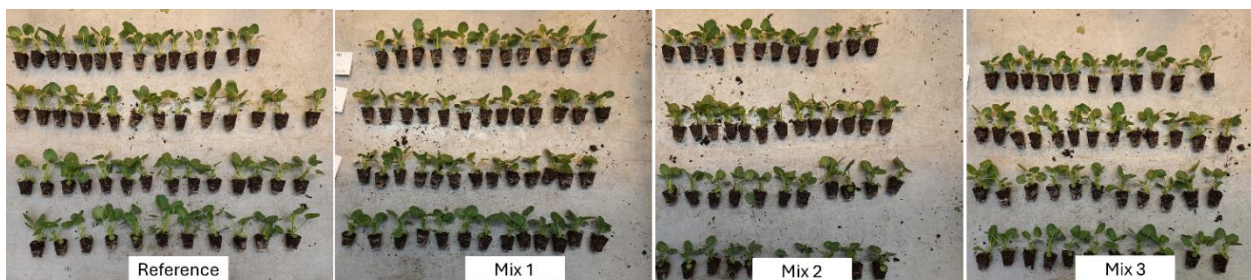
Mixture	Predicted values from Mixing Model	Lab measurement for mixtures without base fertilisers	Lab measurement for mixtures with base fertilisers
1 <sup>st</sup> crop trial			
Mix 1	5.2	2.8	3.0
Mix 2	4.8	3.4	3.2
Mix 3	3.9	4.2	4.9
3 <sup>rd</sup> crop trial			
Reference	4.3	na	na
Mix 18	3.4	4.6	3.7
Mix 19	2.2	2.6	2.4

**Root growth and ease of tray emptying:** In both trials at Beekenkamp and Syngenta, viola seedlings in mix 1 and mix 2 showed root growth similar to those in the reference mixture (Figure 13, Figure 14, Figure 15). The plugs were easy to remove from the trays, with mix 1 and mix 2 performing even better than the reference in terms of tray emptying. Rooting in mix 3 was slightly less than in the reference mixture, and plugs were more difficult to remove from the trays. In the third crop trial, no differences were observed in rooting or ease of tray emptying among the reference, mix 18, and mix 19. The difference in rooting could be explained by variations in moisture content in the trays, as measured during cultivation. Mix 1 and mix 2 retained less water than mix 3, which resulted in increased rooting.

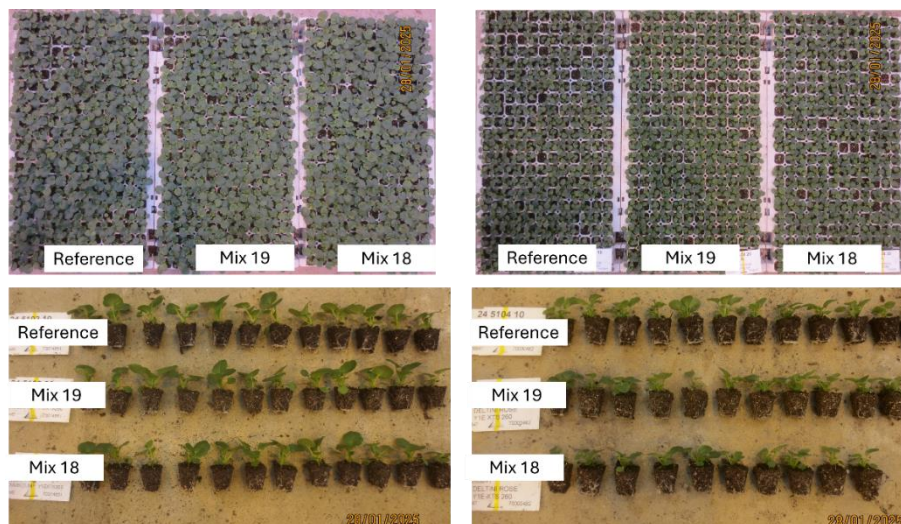


**Figure 13** Viola seedlings at the end of cultivation at Beekenkamp trial (1<sup>st</sup> crop trials).





**Figure 14** Viola seedlings 'Wittrock' at the end of cultivation at Syngenta trial (1<sup>st</sup> crop trials).



**Figure 15** Viola seedling 'VIWF' (left) and 'VICF' (right) at the end of cultivation at Syngenta trial (3<sup>rd</sup> crop trials).

### 3.4.3 Petunia cuttings

The crop trial on Petunia (cuttings) was conducted at the propagator Florensis (first crop trials). The tested mixtures are listed in Table 33. Substrates were hand-filled into 128-plug trays, with 10 trays per mixture. The crop requires a pH of 5.5 and an EC of 0.5–0.8 dS/cm. Petunia is sensitive to iron deficiency. Fertigation was applied by hand.

**Table 33** Mixtures used in the crop trial on Petunia cuttings. A negative value for volume loss indicates a volume gain.

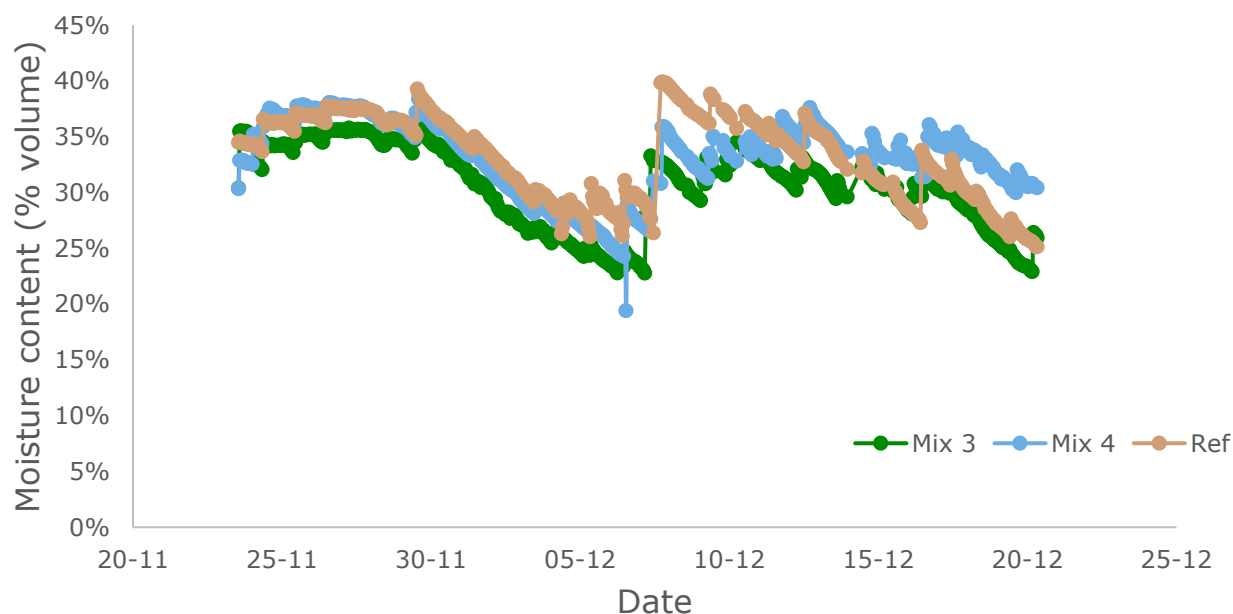
Trial	Propagator	Mixture	Base fertilisers	Volume loss predicted (%)
1st	Florensis	Mix 3	NPK + trace elements, Fe (EDDHA), lime	6.1
1st	Florensis	Mix 4	Lime, NPK + trace elements	-13.5

Predicted volume loss based on elongation model. Mix 3 contained clay.

**Ease of tray filling:** Both mix 3 and mix 4 were more difficult to fill in the tray (hand filling) compared to the reference mix. Mix 3, lacking binding properties, easily fell through the tray. Mix 4, which contained 25% fine wood fibre, was challenging to fill, with woody clumps falling out of the tray.

**Moisture content:** Moisture content, measured from tray weight during cultivation, showed that mix 4 retained more water than mix 3, with a maximum difference of 5% by volume (Figure 16). This trend was also reflected in the laboratory measurements for both mixtures with and without base fertilisers, but not in the mixing model prediction (Table 34). The model predicted the opposite—that mix 4 would hold 6% less water than mix 3.

Similar to what was observed for mix 1 and mix 2 in the Viola trials, mix 4, which contains wood fibre, may have been affected by how the substrate was distributed, influencing the outcome. It is worth noting that a 5–6% difference in moisture content appears to have an impact on cultivation conditions.



**Figure 16** Moisture content in the tray of mix 3, mix 4 and reference mix ('Ref') during cultivation.

**Table 34** Water and air content at -10 cm suction pressure of mixtures used in the Petunia cuttings trial.

Mixture	Predicted values from Mixing Model		Lab measurement for mixtures without base fertilisers		Lab measurement for mixtures with base fertilisers	
	Water content - 10 cm (% , v)	Air content at - 10 cm (% , v)	Water content - 10 cm (% , v)	Air content at - 10 cm (% , v)	Water content - 10 cm (% , v)	Air content at - 10 cm (% , v)
Mix 3	75	18	75	17	70	21
Mix 4	69	25	84	9	87	6

**Rooting:** Overall, the rooting rate (number of cuttings rooted) was good. Mix 4 had a slightly lower rooting rate than mix 3 and the reference (95% vs. 100%) and required two additional days for rooting (13 days vs. 11 days). This difference in rooting pattern might be linked to the moisture–air balance in the plugs. Mix 4 had higher measured moisture content (Figure 16), implying lower air content. Rooting is generally enhanced when sufficient air is available.

**Plant biomass:** Biomass in mix 3 and mix 4 was about 80% of the biomass in the reference (Figure 17). The biomass of marketable plants per tray was 11.1 g, 10.7 g, and 13.2 g for mix 3, mix 4, and the reference, respectively. Plants in mix 3 and mix 4 showed interveinal yellowing in the leaves and were more compact than those in the reference. Substrate analysis showed low Fe levels in mix 3 (3.2 µmol/L extract compared to 10 µmol/L in the reference mix) and low NO<sub>3</sub> levels in mix 4 (0.6 mmol/L extract compared to 2.8 mmol/L in the reference mix) (Annex 7.5, 7.4). While NO<sub>3</sub> concentrations were similar among the three mixtures at the end of the trial (approximately 1–1.3 mmol/L extract), Fe levels in mix 3 remained lower than in the other two mixtures (5.5 µmol/L extract compared to 16–25 µmol/L extract). Plugs in mix 3 shrank and fell apart, while plugs in both the reference and mix 3 had their tops fall off. Plants in mix 4 and mix 3 were more generative, whereas those in the reference remained vegetative.



**Figure 17** *Petunia cuttings in mix 4, reference and mix 3 (left to right).*

Predicted and measured OUR indicated that mix 3 and mix 4 had a similar degree of biostability (modest difference of 0.5 OUR unit) (Table 35). However, the reduced plant growth and low  $\text{NO}_3^-$  levels in mix 4 (0.6 in mix 4 vs 2.8 in reference and 4 in mix 3), as shown in the substrate analysis (Annex 7.5), suggest higher nitrogen immobilisation in mix 4. In this trial, OUR prediction between mix 3 and mix 4 seemed indicate plant performance in cultivation.

Although the difference in OUR was small—only 0.5 OUR unit—it could still indicate nitrogen immobilisation during cultivation. One possible explanation for this is that a small difference in overall OUR can reflect a significant difference in nitrogen immobilisation when one component contributes strongly to the biostability of the mixture, even if the final OUR value appears moderate. Mix 4 contained a component with an OUR of 7.9, whereas the highest OUR value from a component in mix 3 was 6.3.

**Table 35** *Predicted and measured OUR values of the mixtures used in Petunia trial.*

Mixture	Predicted values from Mixing Model	Lab measurement for mixtures without base fertilisers	Lab measurement for mixtures with base fertilisers
Mix 3	3.9	4.2	4.4
Mix 4	4.4	3.6	4.7

**Root growth and ease of tray emptying:** Mix 3 had rooting comparable to the reference, with more root distribution along the plug height (Figure 17). Mix 4 had less root growth than the reference, and rooting was uneven, possibly due to clumps of wood fibre. The differences in rooting between mix 3 and mix 4 could be explained by the higher air content in mix 3 than in mix 4, as indicated by moisture content during cultivation, predicted water-air content, and laboratory measurements.

#### 3.4.4 Petunia (potted)

The crop trial on Petunia (potted) was conducted at the propagator Florensis (first crop trials). The tested mixtures are listed in Table 36.

**Table 36** *Mixtures used in the crop trial on Petunia (potted). A negative value for volume loss indicates a volume gain.*

Trial	Propagator	Mixture	Base fertilisers	Volume loss predicted (%)
1st	Florensis	5	Lime, NPK, slow release N	6.2
1st	Florensis	6	NPK, Fe(EDDHA), lime	3.3

Predicted volume loss based on elongation model. Mix 6 contained clay.

**Ease of pot filling:** Pots were filled by hand, and no difficulties were reported when using the tested mixtures.

**Moisture content:** Both the predicted and measured moisture content during cultivation showed the same trend, indicating that mix 5 retained more water than mix 6 (Table 37, Table 38). The difference was about 5% in absolute moisture content.

**Table 37** *Moisture content of mixtures used in Petunia (potted) trial.*

Mixture	Moisture content in the pot after irrigation, calculated from pot weight (% volume)				
	after 1st irrigation	05 January	31 January	08 February	13 February
Reference	34%	29%	26%	31%	49%
Mix 5	36%	36%	25%	34%	35%
Mix 6	35%	30%	21%	22%	24%

**Table 38** *Water and air content at -10 cm suction pressure of mixtures used in the Petunia potted trial.*

Mixture	Predicted values from Mixing Model		Lab measurement for mixtures without base fertilisers		Lab measurement for mixtures with base fertilisers	
	Water content - 10 cm (% v)	Air content at - 10 cm (% v)	Water content - 10 cm (% v)	Air content at - 10 cm (% v)	Water content - 10 cm (% v)	Air content at - 10 cm (% v)
Mix 5	67	23	71	19	78	11
Mix 6	62	29	70	21	65	24

**Rooting:** Mix 6 have thicker and more roots than in mix 5. This could be linked to the moisture properties that mix 6 hold less water than mix 5 and has more air than mix 5.

**Plant biomass:** Plant growth was assessed qualitatively (Figure 18). Plants in mix 5 showed leaf yellowing at the beginning of the trial, which reduced toward the end. Plants in both mix 5 and mix 6 were more compact compared to the reference. The plants also showed generative growth, with mix 5 having the highest number of flowering plants (17% with flowers), compared to 2% in the reference and 3% in mix 6.

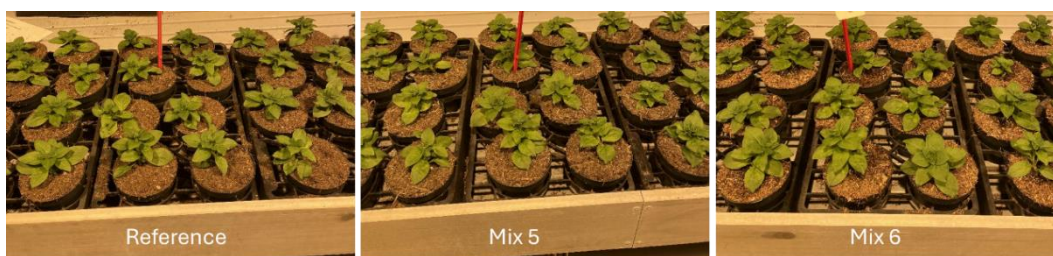
The leaf yellowing could be explained by low Fe concentrations in the substrate solution, which were much lower in mix 5 and mix 6 compared to the reference (6 µmol/L extract vs. 30 µmol/L extract) (Annex 7.5). Nitrate concentrations in mix 5 and mix 6 were higher than in the reference—3.3–3.7 mmol/L in mix 5 and 1.7–1.9 mmol/L in mix 6 around the flowering period, while the reference had low NO<sub>3</sub> levels of 0.2 mmol/L or less. However, iron concentrations in mix 5 and mix 6 (4–7 µmol/L extract) remained much lower than in the reference (30–40 µmol/L extract). The lower iron availability could be caused by the higher pH in mixtures 5 and 6 (pH 6.2–6.5) compared to the reference (pH 5.7–5.9).

Although plant compactness is often a symptom of nitrogen immobilisation, the substrate nitrate concentrations in mix 5 and mix 6 did not indicate nitrogen deficiency compared to the reference. The OUR of the mixtures were comparable between mix 5 and mix 6 (Table 39).

**Table 39** *Predicted and measured OUR values of the mixtures used in Petunia potted trial.*

Mixture	Predicted values from Mixing Model	Lab measurement for mixtures without base fertilisers	Lab measurement for mixtures with base fertilisers
Mix 5	5.1	4	4.8
Mix 6	5.3	4.1	5.0





**Figure 18** *Petunia* in pots in reference mix, mix 5 and mix 6 (left to right).

### 3.4.5 Monstera

The trial on *Monstera deliciosa* was conducted at the propagator Evanthia (1st crop trials). The planting material used was seeds. A large variation in seed size resulted in differences in germination time and rate. Three mixtures were tested, including a reference peat-based mix and two renewable mixtures (Table 40). Substrates were filled by hand into 66-plug trays, with ten trays per mixture. Seeds were sown and then incubated in climate chambers at 25 °C and 99% relative humidity for 2–3 weeks until full germination. Afterward, the trays were transferred to a greenhouse and irrigated using overhead sprinklers, with adjustments made manually. Irrigation was carried out 2–3 times per week based on growers' observations. A single fertilisation recipe was used for all treatments.

**Table 40** *Mixtures used in the crop trial on Monstera. A negative value for volume loss indicates a volume gain.*

Trial	Propagator	Mixture	Base fertilisers	Volume loss predicted (%)
1st	Evanthia	3	Lime, NPK + micronutrients, Fe	6.1
1st	Evanthia	7	Lime, NPK + micronutrients	8.4

Predicted volume loss based on elongation model. Mix 3 contained clay.

**Ease of tray filling:** The trays were filled by hand. Mix 7, which contained 40% wood fibre in two fractions (medium and fine), was reported to be difficult to fill by machine. However, this was not an issue when filled by hand. Mix 3, which contained no wood fibre, did not present any difficulties during tray filling.

**Moisture content:** Predicted and lab measurements of the mixtures before the addition of base fertilisers and clay showed a consistent trend: mix 3 held more water than mix 7, with a 4–8% absolute difference in water volume (v/v) (

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**Table 41).** However, lab measurements of the mixtures with base fertilisers showed higher moisture content in mix 7 compared to the earlier measurements for the same mix. This variation could be due to the fact that the mixture without base fertilisers was prepared by WUR, while the mixture with base fertilisers was prepared by the substrate producer, which may have contributed to the differences observed in the measured moisture content of mix 7. It is worth noting that in the first crop trial, WUR prepared the mixtures without base fertilisers, while the growing media producers prepared mixtures containing base fertilisers. To reduce variation in preparation, all mixtures in the second and third crop trials were prepared by the substrate producers.

Moisture content measured during cultivation showed that after the first irrigation, mix 3 held 14% more water than mix 7 (Table 42). However, towards the end of the cultivation period (week 9/2024), moisture content in mix 3 dropped below that of mix 7. It should be noted that irrigation was applied by hand and reported by the propagator to be inconsistent.

**Table 41** Water and air content at -10 cm suction pressure of mixtures used in the *Monstera* trial.

Mixture	Predicted values from Mixing Model		Lab measurement for mixtures without base fertilisers		Lab measurement for mixtures with base fertilisers	
	Water content - 10 cm (% v)	Air content at - 10 cm (% v)	Water content - 10 cm (% v)	Air content at - 10 cm (% v)	Water content - 10 cm (% v)	Air content at - 10 cm (% v)
Mix 3	75	18	75	17	71	21
Mix 7	71	22	67	27	85	9

**Table 42** Moisture content in the tray calculated by tray weight during the cultivation of *Monstera*.

Mixture	Moisture content in the tray, calculated from tray weight (% volume)			
	After 1st irrigation	Week 5/2024	Week 8/2024	Week 9/2024
Reference	29%	38%	32%	51%
Mix 3	48%	45%	31%	42%
Mix 7	34%	35%	28%	53%

**Root growth:** The propagator rated rooting as best in mix 3, while mix 7 and the reference showed similar performance (Figure 19). The difference in rooting behaviour between mix 3 and mix 7 could not be explained by the water content of the mixtures.

**Plant growth:** Seedlings in mix 7 were slightly more stretched than those in the reference and mix 3. All seedlings per tray were considered marketable. Fresh biomass of the seedlings was comparable across mixtures, with average values of 14.4 g for the reference, 13.7 g for mix 7, and 13.6 g for mix 3. In this trial, the OUR values were comparable between mix 3 and mix 7 and they did not show a trend in biomass difference (Table 43).

**Figure 19** *Monstera* seedlings at the end of cultivation.**Table 43** Predicted and measured OUR values of the mixtures used in *Monstera* trial.

Mixture	Predicted values from Mixing Model	Lab measurement for mixtures without base fertilisers	Lab measurement for mixtures with base fertilisers
Mix 3	3.9	4.2	6.0
Mix 7	4.1	4.0	3.0

### 3.4.6 Calocephalus

The crop trial on *Calocephalus* was conducted at the propagator Florensis (first crop trials). The tested mixtures are listed in Table 44.

**Table 44** Mixtures used in the crop trial on *Calocephalus*. A negative value for volume loss indicates a volume gain.

Trial	Propagator	Mixture	Base fertilisers	Volume loss predicted (%)
2nd	Florensis	8	Lime, NPK	-2.3
2nd	Florensis	9	NPK, Fe(EDDHA), lime	3.6

Predicted volume loss based on elongation model. Mix 9 contained clay.



**Ease of tray filling:** The trays were filled by hand. Mix 8, which contained 20% fine wood fibre, was reported to be more difficult to fill compared to the reference mix, mainly due to clumping of the wood fibres. Additionally, the plugs in mix 8 shrank afterward. In contrast, mix 9, which contained no wood fibre, was reported to be equally easy to fill as the reference mix, with only slight plug shrinkage observed.

**Moisture content:** No moisture content was recorded during cultivation. However, both predicted and laboratory-measured properties indicated that mix 9 retained more water than mix 8 (Table 45). The propagator observed that algae growth was most prominent in the reference mix, followed by mix 9, with the least algae observed in mix 8. This suggests that mix 8 retained less water than mix 9, which is in line with what the model predicted (Table 45). The shrinkage and clumping observed in mix 8 may have influenced its moisture performance during cultivation, leading to differences compared to the measured values in the lab.

**Rooting:** Cuttings in both mixes had similar rooting rates, with 99% rooting achieved 19 days after sticking. Both mixes (mix 8 and mix 9) showed better rooting than the reference mix.

**Plant growth:** Plants in the reference mix were the largest, while plants in mixes 8 and 9 were more compact (Figure 20). Among these, plants in mix 8 were the most compact. OUR values potentially indicated that mix 8 was less biostable than mix 9 (Table 46). As shown in the 1:1.5 water extract (Annex 7.5), nitrate levels were lower in both mix 8 and mix 9, with mix 8 having the lowest values. Both the reference mix and mix 9 showed yellowing of the lower leaves, while plants in mix 8 did not exhibit this symptom and instead had grey-colored leaves. This could be related to the moisture content of the substrate, as Calocephalus does not prefer overly wet conditions.



**Figure 20** Calocephalus plugs at rooting stage and delivery stage.

**Table 45** Water and air content at -10 cm suction pressure of mixtures used in the Calocephalus trial.

Mixture	Predicted values from Mixing Model		Lab measurement for mixtures without base fertilisers		Lab measurement for mixtures with base fertilisers	
	Water content - 10 cm (% , v)	Air content at - 10 cm (% , v)	Water content - 10 cm (% , v)	Air content at - 10 cm (% , v)	Water content - 10 cm (% , v)	Air content at - 10 cm (% , v)
Mix 8	57	37	68	24	67	25
Mix 9	70	24	72	21	67	25

**Table 46** Predicted and measured OUR values of the mixtures used in *Calocephalus* trial.

Mixture	Predicted values from Mixing Model	Lab measurement for mixtures without base fertilisers	Lab measurement for mixtures with base fertilisers
Mix 8	4.7	3.8	4.5
Mix 9	3.5	5	5

### 3.4.7 Strelitzia

The *Strelitzia* trial was conducted at the propagator Evanthia as part of the second crop trials. Seeds were used as the planting material. Three substrates were tested: a reference peat-based mix and two renewable mixtures (**Table 47**). The substrates were filled into sowing trays (51 × 31 × 4 cm), with each tray containing 300 seeds. Four trays were used per treatment. The substrate requirements were a pH of 5.5 and an EC of 0.8 mS/cm. The cultivation period lasted 14 weeks, with germination counts during weeks 6 to 8 being the most critical. A single fertilisation recipe was applied across all treatments.

**Table 47** Mixtures used in the crop trial on *Strelitzia*. A negative value for volume loss indicates a volume gain.

Trial	Propagator	Mixture	Base fertilisers	Volume loss predicted (%)
2nd	Evanthia	9	Lime, NPK + micronutrients, Fe (EDDHA), clay	3.6
2nd	Evanthia	10	Lime, NPK + micronutrients	0.6

Predicted volume loss based on elongation model. Mix 9 contained clay.

Mix 9 showed the highest and fastest germination rate compared to mix 10 and the reference (Table 48). Mix 10 experienced a slight delay during the first week but caught up with the reference by the final week. This suggests that although germination timing differed in mix 10, it did not lead to significant differences in overall plant growth — except for certain variation in plant size, likely due to uneven germination.

Predicted and measured moisture content of the mixtures indicated that mix 9 retained slightly less water than mix 10 (Table 49). OUR values, both predicted and measured, suggested that the biostability of the two mixtures was comparable (Table 50). Substrate analysis during the first week of germination counting showed that mix 9 had slightly lower nitrate levels compared to the reference and mix 10 (3.6 mmol/L vs. 4.7–6 mmol/L), as well as lower iron content (5.3 µmol/L vs. 11–16 µmol/L) (Annex 7.5). This low iron level in mix 9 was also observed at the end of cultivation (3.5 µmol/L vs. 15 µmol/L). Due to the lack of plant biomass data, no conclusions can be drawn about the impact of these nutrient differences. However, visual observations showed no obvious differences in plant growth among the treatments (Figure 21).

**Table 48** Germination rate of *Strelitzia*.

Mixture	Germination rate after 1st week	Germination rate at the end
Reference	27%	32%
Mix 9	32%	37%
Mix 10	22%	33%

**Figure 21** *Strelitzia* seedlings at the end of cultivation.

**Table 49** Water and air content at -10 cm suction pressure of mixtures used in the Strelitzia trial.

Mixture	Predicted values from Mixing Model		Lab measurement for mixtures without base fertilisers		Lab measurement for mixtures with base fertilisers	
	Water content -10 cm (% <sub>v</sub> )	Air content at -10 cm (% <sub>v</sub> )	Water content at -10 cm (% <sub>v</sub> )	Air content at -10 cm (% <sub>v</sub> )	Water content at -10 cm (% <sub>v</sub> )	Air content at -10 cm (% <sub>v</sub> )
Mix 9	70	24	72	21	67	25
Mix 10	73	20	76	14	74	16

**Table 50** Predicted and measured OUR values of the mixtures used in Monstera trial.

Mixture	Predicted values from Mixing Model	Lab measurement for mixtures without base fertilisers	Lab measurement for mixtures with base fertilisers
Mix 9	3.5	5.0	5.2
Mix 10	3.8	4.9	3.8

### 3.4.8 Saxifraga arendisii

The crop trial on Saxifraga (seeds) was conducted at the propagator Syngenta (second crop trials). The tested mixtures are listed in the Table 51.

**Table 51** Mixtures used in the crop trial on Saxifraga. A negative value for volume loss indicates a volume gain.

Trial	Propagator	Mixture	Base fertilisers	Volume loss predicted (%)
2 <sup>nd</sup>	Syngenta	9	Clay, NPK + trace elements, Fe(EDDHA), lime	3.6
2 <sup>nd</sup>	Syngenta	11	Clay, NPK + trace elements, Fe (DPTA), lime	1.7

Predicted volume loss based on elongation model. Both mixtures contained clay.

**Ease of tray filling:** Tray filling was generally comparable to the reference mixture; however, the filling machine required more time to process a given number of trays for mix 11, which contained 10% fine wood fibre.

**Moisture content:** Moisture content, measured by tray weight, showed that mix 9 retained more water than mix 11 (5-6% higher in absolute moisture content) (Table 52). This observation contrasts with the predicted and measured water content at -10 cm suction pressure (Table 53). One possible explanation is that, although mix 11 did not cause difficulties in tray filling, it may have created more air space within the plugs, particularly in the small-volume plugs of the MC264 tray (6 ml plug).

**Table 52** Moisture content of mixtures used in the Saxifraga trial.

Mixture	Moisture content in the tray, calculated from tray weight (% <sub>v</sub> )			
	31/07/2024	07/08/2024	14/08/2024	23/08/2024
Mix 9	72%	70%	72%	71%
Mix 11	66%	64%	66%	66%

**Table 53** Water and air content at -10 cm suction pressure of mixtures used in the Saxifraga trial

Mixture	Predicted values from Mixing Model		Lab measurement for mixtures without base fertilisers		Lab measurement for mixtures with base fertilisers	
	Water content -10 cm (% <sub>v</sub> )	Air content at -10 cm (% <sub>v</sub> )	Water content -10 cm (% <sub>v</sub> )	Air content at -10 cm (% <sub>v</sub> )	Water content -10 cm (% <sub>v</sub> )	Air content at -10 cm (% <sub>v</sub> )
Mix 9	70	24	72	21	67	25
Mix 11	82	13	87	5	86	6



**Germination:** Number of usable plants per tray was comparable among the mixtures (85-89 plants for dark rose, 85-91 plants for Pink shades). This indicates that the moisture and air content in the mixtures were supportive of Saxifraga germination.

**Plant biomass:** The variety Dark Rose reacted more noticeably than Pink Shades. Mix 9 produced less biomass than mix 11 and the reference (Table 54). Plants in mix 9 were more compact and smaller than those in the reference, while mix 11 showed growth comparable to the reference. Leaves in mix 9 were significantly lighter in colour compared to those in mix 11 (Figure 22). This could be linked to nitrogen immobilisation—NO<sub>3</sub> levels during cultivation were 1.9 mmol/L in mix 11 compared to 3.2 mmol/L in mix 9—as well as high pH (6.8) in mix 9 and low iron levels (1.5 µmol/L in mix 9 vs. 4.1 in mix 11 and 14 in the reference) (Annex 7.5). While the predicted OUR did not explain the performance differences between mixtures, the measured OUR values in the lab did show a similar trend, indicating that mix 9 was less biostable than mix 11 (Table 55).



**Figure 22** Saxifraga 'Dark rose' (top) and 'Pink shades' (bottom) at the end of trial.

**Table 54** Plant biomass of Saxifraga at the end of cultivation.

Mixture	Number of marketable plant per tray		Fresh biomass of 100 marketable plants (g)	
	Dark rose	Pink shades	Dark rose	Pink shades
Reference	170	179	91	97
Mix 9	133	152	55	87
Mix 11	139	177	78	94

**Table 55** Predicted and measured OUR values of the mixtures used in *Saxifraga* trial.

Mixture	Predicted values from Mixing Model	Lab measurement for mixtures without base fertilisers	Lab measurement for mixtures with base fertilisers
Mix 9	3.5	5.0	5.2
Mix 11	3.7	2.4	2.9

**Rooting growth and ease of tray emptying:** Rooting in mix 11 was better than in mix 9 and the reference. Mix 9 had more plugs remaining in the tray after emptying. The plugs in mix 9 fell apart and crumbled easily.

### 3.4.9 Lavendula

The crop trial of *Lavandula* (variety Aromance White) was conducted at the propagator Beekenkamp (second crop trials). Paper plugs were prepared by Optiplug. Three mixtures were tested: a reference peat-coir-based mix and two renewable mixes (Table 56). The cuttings were stuck on 29th July 2024 (week 31, day 1) and were covered with an acrylic canvas foil. Irrigation was provided using a low-pressure rain system several times a day, following a phased schedule. After 16 days (14th August 2024, week 33, day 3), the first roots were visible, and the acrylic canvas foil was removed. Sorting took place on 21st August 2024 (week 34, day 3). After sorting, the trays were moved to a hardening climate. The cultivation period ended on 9th September 2024 (week 37, day 1), and the total growing time was 6 weeks (42 days). The plants were kept for an additional week, until 16th September 2024. Only one irrigation regime was applied, and irrigation decisions were based on the standard mix.

**Table 56** Mixtures used in the crop trial on *Lavendula*. A negative value for volume loss indicates a volume gain.

Trial	Propagator	Mixture	Base fertilisers	Volume loss predicted (%)
2nd	Beekenkamp	9	NPK, Fe(EDDHA), lime	3.6
2nd	Beekenkamp	12	Lime, NPK	-2.0

Predicted volume loss based on elongation model. Mixture 9 contained clay.

**Ease of paper plug preparation:** No difficulty in paper plug preparation was reported.

**Moisture content:** No moisture content was recorded during the cultivation. However, both predicted and laboratory-measured properties indicated that mix 12 retained more water than mix 9 (Table 57). The difference between the two mixes was smaller in the predicted values (with an absolute difference of 3% by volume) compared to the measured values (14-17% by volume). Mix 12 was observed to be wetter than mix 9 during cultivation. That is in line with the model prediction. It is important to note that irrigation decisions were based on the reference mix.

**Shoot & root growth:** Plants in mix 12 exhibited the most vigorous shoot growth, while plants in mix 9 developed more root growth, likely due to drier conditions during cultivation. This aligns with the predicted moisture content. The greater shoot growth observed in mix 12 suggests reduced nitrogen immobilisation compared to mix 9. The measured OUR values indicated that mix 12 was more stable than mix 9 (Table 58), which is consistent with the shoot growth results. However, no substrate analysis was conducted to confirm this. Figure 23 showed the plants at the end of cultivation.

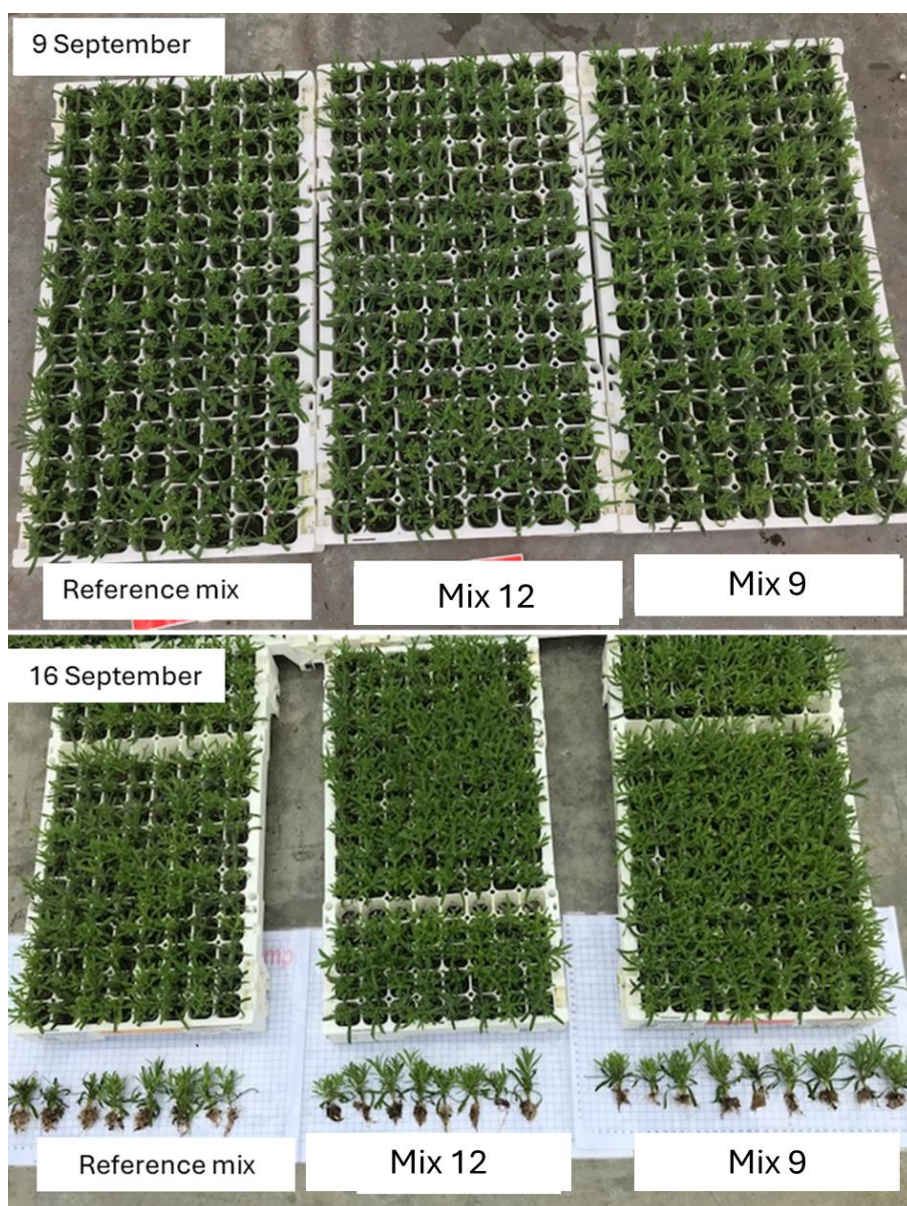
**Table 57** Water and air content at -10 cm suction pressure of mixtures used in the *Lavendula* trial.

Mixture	Predicted values from Mixing Model		Lab measurement for mixtures without base fertilisers		Lab measurement for mixtures with base fertilisers	
	Water content - 10 cm (% v)	Air content at - 10 cm (% v)	Water content - 10 cm (% v)	Air content at - 10 cm (% v)	Water content - 10 cm (% v)	Air content at - 10 cm (% v)
Mix 9	70	24	72	21	67	25
Mix 12	73	22	86	8	84	10



**Table 58** Predicted and measured OUR values of the mixtures used in *Lavendula* trial.

Mixture	Predicted values from Mixing Model	Lab measurement for mixtures without base fertilisers	Lab measurement for mixtures with base fertilisers
Mix 9	3.5	5	5
Mix 12	4.3	2.5	3.2



**Figure 23** *Lavendula* plugs at the end of cultivation.

#### 3.4.10 Dahlia

The crop trial on Dahlia cuttings was conducted at the Beekenkamp propagator as part of the third crop trial series. 128-cell hard plastic plug trays were used. Three substrate mixtures were tested: a reference peat-based mix and two renewable alternatives (Table 59). The substrates were prepared in paper plugs by Optiplug. The target pH was 5.6 and the EC was 0.8 mS/cm. No specific requirements were mentioned for this crop, except that the substrate should support the rooting of Dahlia cuttings, as some varieties can be more difficult to root than others.

There were two trial runs: the first from week 47 to week 51, 2024, using mix 2; the second from week 50, 2024, to week 2, 2025, using both mix 1 and mix 2. In the first trial, only visual observations were recorded. Ten trays per mix were tested, using two Dahlia varieties: orange and pink. During the first two weeks, cuttings were rooted in a warm, high-humidity greenhouse (20 °C, 85% RH). After this period, the trays were moved to the hardening phase, with cooler temperatures, lower humidity, and LED lighting (maximum 150 µmol, with a spectrum ratio of 11:9:80 for blue, green, and red).

**Table 59** *Mixtures used in the crop trial on Dahlia. A negative value for volume loss indicates a volume gain.*

Trial	Propagator	Mixture	Base fertilisers	Volume loss predicted (%)
3rd	Beekenkamp	13	Lime, NPK	8.6
3rd	Beekenkamp	14	Lime, NPK	-0.1

Predicted volume loss based on elongation model.

**Moisture content:** During cultivation, mix 14 was observed to be slightly drier than mix 13, but not in an unusual way (Table 61). Predicted moisture content, lab measurements, and in-cultivation observations all also indicated that mix 14 retained slightly less water than mix 13 (5-10% in values) (Table 60).

**Table 60** *Water and air content at -10 cm suction pressure of mixtures used in the Lavendula trial.*

Mixture	Predicted values from Mixing Model		Lab measurement for mixtures without base fertilisers		Lab measurement for mixtures with base fertilisers	
	Water content - 10 cm (% , v)	Air content at - 10 cm (% , v)	Water content - 10 cm (% , v)	Air content at - 10 cm (% , v)	Water content - 10 cm (% , v)	Air content at - 10 cm (% , v)
Mix 13	84	11	83	11	83	10
Mix 14	72	24	78	16	78	16

**Table 61** *Moisture content in the trays during cultivation.*

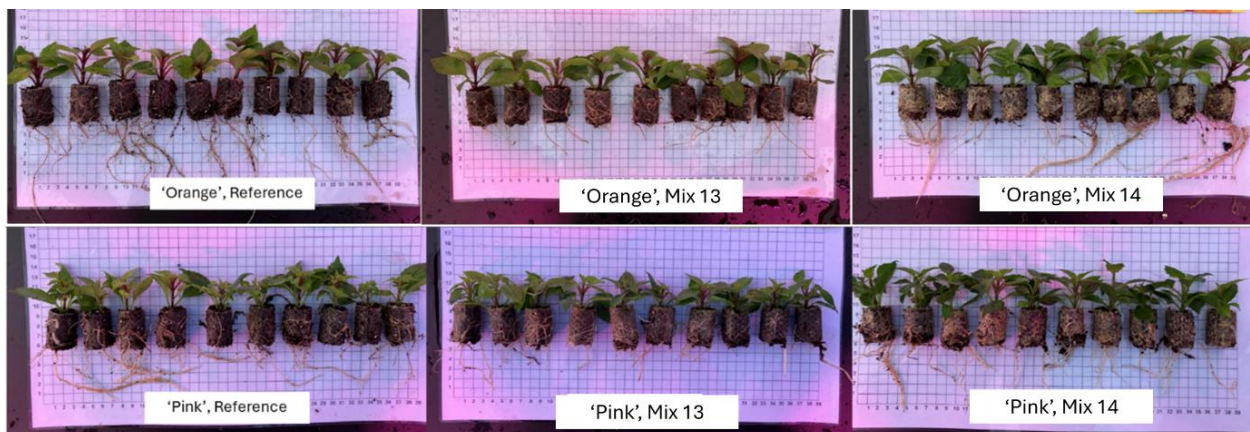
Variety	Mixture	Moisture content in the trays, calculated from tray weight (% , volume)				
		After 1st irrigation	After 2nd irrigation	On 10/01/2025 before irrigation	On 10/01/2025 after irrigation	On 22/01/2025
Orange	Reference	28%	19%	20%	32%	12%
	Mix 13	29%	25%	23%	38%	23%
	Mix 14	22%	21%	19%	36%	15%
Pink	Reference	31%	24%	30%	39%	27%
	Mix 13	29%	30%	31%	43%	23%
	Mix 14	17%	20%	31%	32%	22%

**Rooting:** Cuttings in mix 14 showed a similar rooting percentage to those in the reference mix (Table 62). Mix 13 had a lower rooting rate. Cuttings in mix 14 developed more roots compared to those in the reference mix. Rooting is related to air content in the mixtures.

**Table 62** *Percentage of rooted cuttings in Dahlia.*

Mixture	Percentage of rooted cuttings (%) in variety Orange	Percentage of rooted cuttings (%) in variety Pink
Reference	91.4	89.8
Mix 13	79.3	87.5
Mix 14	91.8	91.0

**Plant growth:** One week after the start, plants in mix 13 had lighter (yellowing) leaves and were more compact (smaller) compared to those in the reference mix. Plants in mix 14 were comparable to the reference. After two weeks, the yellowing in mix 13 had improved; however, the plants remained smaller than those in the reference mix. At that point, differences in plant growth were not very clear until the final week of cultivation. By then, plants in mix 13 were slightly smaller and lagging behind the reference, while plants in mix 214 were larger and greener (Table 63, Figure 24). Mix 14 produced the most marketable plants. OUR values predicted by the mixing model were in line with plant biomass performance, indicating that mix 13 was less stable than mix 14 (Table 64). Substrate analysis showed lower nitrate levels in mix 14 compared to mix 13 (1.3 mmol/L vs. 2.9 mmol/L, with 4.3 mmol/L in the reference) (Annex 7.5).



**Figure 24** Two Dahlia varieties (Orange and Pink) in three mixtures at the harvest date.

**Table 63** The number- and fresh weight of marketable plants of Dahlia varieties.

Mixture	Orange variety		Pink variety	
	Number of marketable plants per tray	Average fresh weight of one marketable plant (g)	Number of marketable plants per tray	Average fresh weight of one marketable plant (g)
Reference	98	1.3	99.5	1.4
Mix 13	84.5	1.5	101	1.4
Mix 14	97	1.6	109	1.4

**Table 64** Predicted and measured OUR values of the mixtures used in Dahlia trial.

Mixture	Predicted values from Mixing Model	Lab measurement for mixtures without base fertilisers	Lab measurement for mixtures with base fertilisers
Mix 13	3.4	3.4	3.5
Mix 14	2.1	4.0	2.4

### 3.4.11 Calibrachoa

The trial on Calibrachoa cuttings was conducted at the propagator Florensis (3<sup>rd</sup> crop trials). Cuttings were inserted into 84-plug trays, with three cuttings per plug. Three mixtures were tested, including a reference peat-based mix and three renewable alternatives (



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**Table 65).** The crop requires a substrate pH of 5.5–5.7, EC of 0.8–1.0 mS/cm, and an adequate iron supply, as it is prone to iron deficiency at higher pH levels. Additionally, Calibrachoa is sensitive to Botrytis. Ten trays were used per mixture treatment.

**Table 65** Mixtures used in the crop trial on *Calibrachoa*. A negative value for volume loss indicates a volume gain.

Trial	Propagator	Mixture	Base fertilisers	Volume loss predicted (%)
3rd	Florensis	15	NPK + micronutrients	-1.9
3rd	Florensis	16	Lime, NPK + micronutrients, Fe	6.2
3rd	Florensis	17	Lime, NPK + micronutrients, Fe	6.5

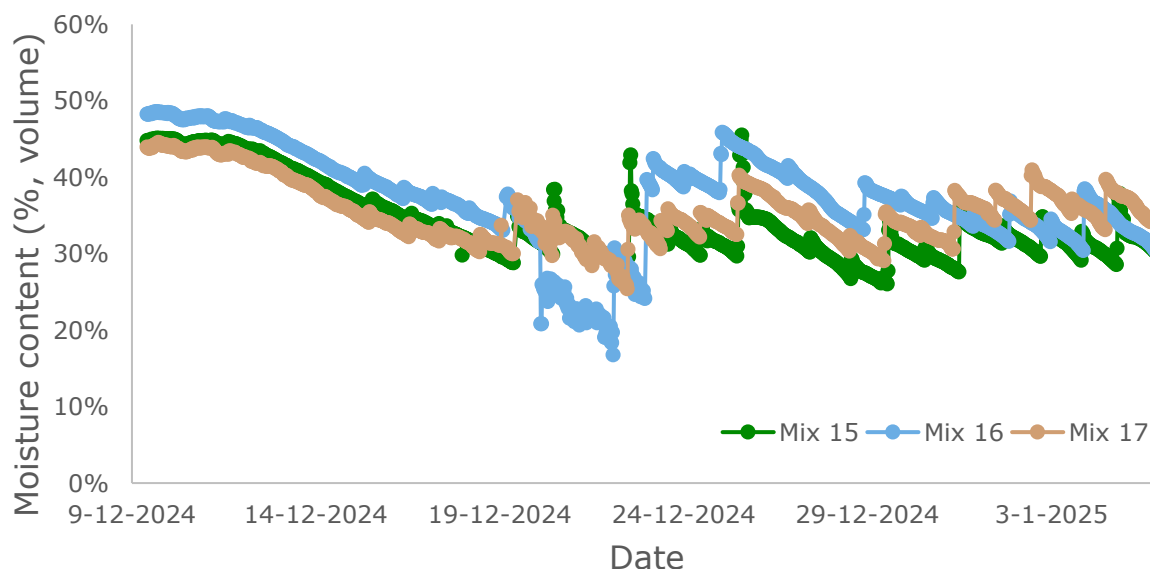
Predicted volume loss based on elongation model. Mix 16 and 17 contained clay.

**Ease of tray filling:** The trays were filled by hand. Mix 15, which contained 30% fine wood fibre, was more difficult to fill due to the presence of wood clumps. Mixes 16 and 17 presented no such difficulties; notably, both contained no wood fibre. All three renewable mixtures were reported to shrink after filling.

**Moisture content:** Predicted and lab-measured values indicated that mix 16 held the most water, followed by mix 17 and then mix 15 (Table 66). However, the difference between mix 16 and mix 17 in the predicted values by the model was less clearly distinguishable than in the lab measurements. During cultivation, moisture content—estimated by tray weight (note: plant biomass was not included in this calculation)—also showed that mix 16 retained the most water, followed by mix 17 and mix 15, which were more or less similar, with mix 17 being slightly higher (Figure 25).

**Table 66** Water and air content at -10 cm suction pressure of mixtures used in the *Calabrachoa* trial.

Mixture	Predicted values from Mixing Model		Lab measurement for mixtures without base fertilisers		Lab measurement for mixtures with base fertilisers	
	Water content - 10 cm (% v)	Air content at - 10 cm (% v)	Water content - 10 cm (% v)	Air content at - 10 cm (% v)	Water content - 10 cm (% v)	Air content at - 10 cm (% v)
Mix 15	69	26	77	17	77	17
Mix 16	74	18	83	9	82	9
Mix 17	75	19	81	12	81	12

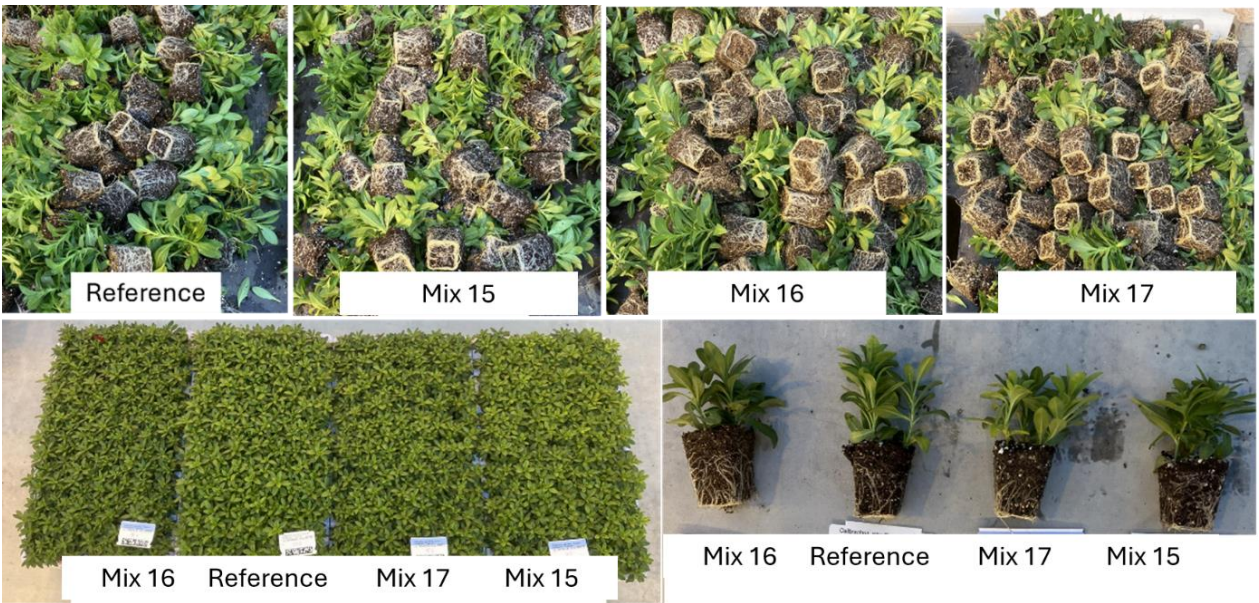


**Figure 25** Moisture content in the tray calculated by tray weight during the cultivation of *Calabrachoa*.

**Rooting:** The percentage of rooted cuttings was similar across all three mixtures (approximately 98%). Root growth in all three renewable mixtures was better than in the reference mix, with the most vigorous root development observed in mix 15 and mix 16, potentially due to slightly higher air content in mix 15 and mix 16 (Table 66). Plug tightness in the renewable mixtures was also better than in the peat-based mix, due to the better rooting in renewable mixtures.

**Shoot growth:** Plants grown in the renewable mixtures were more compact than those in the reference, with the highest compactness observed in mix 16 and mix 17 (Figure 26). Plants in mix 15 appeared lighter in colour than those in the reference, while plants in mix 16 and mix 17 were darker, with mix 16 showing the darkest foliage. Mixture 16 showed the most compact and darkest foliage, which are indicators of nitrogen immobilisation. This is linked to the highest OUR value observed in mix 16 (Table 67).

**Interveinal yellowing** occurred in mix 15 during the middle of the cultivation period. This could be linked to low iron availability in the mixture at the beginning of the trial, possibly related to the base fertiliser used. Iron concentrations at the start of the trial were 14 µmol/L in the reference, and 4.1, 18, and 24 µmol/L in mix 15, mix 16, and mix 17, respectively (Annex 7.5. By the end of the trial, Fe levels in mix 15 remained the lowest at 3.1 µmol/L, compared to 20 µmol/L in the reference, 3.7 µmol/L in mix 16, and 5.5 µmol/L in mix 17.



**Figure 26** Calabrochoa in 128-plug trays at the end of cultivation.

**Table 67** Predicted and measured OUR values of the mixtures used in Calabrochoa trial.

Mixture	Predicted values from Mixing Model	Lab measurement for mixtures without base fertilisers	Lab measurement for mixtures with base fertilisers
Mix 15	3.3	2.3	<2.0
Mix 16	3.5	2.5	2.9
Mix 17	2.2	2	2.1

3.4.12 Asparagus setaceus

The trial on Asparagus setaceus ‘Plumosus Nanus’ was conducted at the propagator Evanthia as part of the third crop trials. Three types of substrates were tested: a peat-based reference and two renewable mixtures (Table 68). The substrates were filled into 66-plug trays, with a target pH of 5.5 and an EC of 0.8 mS/cm. The cultivation period included 2 weeks for germination followed by 6 weeks in the greenhouse.

**Table 68** Mixtures used in the crop trial on *Asparagus*. A negative value for volume loss indicates a volume gain.

Trial	Propagator	Mixture	Base fertilisers	Volume loss predicted (%)
3rd	Evanthia	19	Lime, NPK + trace elements, Fe (EDDHA)	6.5
3rd	Evanthia	20	Lime, NPK + trace elements	3.2

Predicted volume loss based on elongation model. Mix 19 contained clay.

Predicted moisture content from the mixing model, along with lab measurements, showed a consistent trend: mix 20 held less water and had more air compared to mix 19 (Table 69). Although no moisture content data were collected from the trays during cultivation, the observed rooting patterns aligned with the moisture-air characteristics of the mixtures—mix 20, with higher air content, showed more root development than mix 19 (Figure 27).

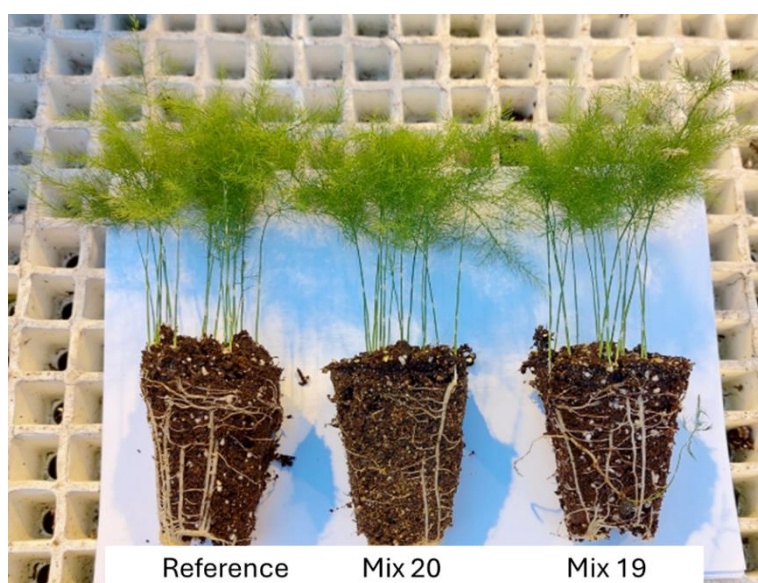
OUR values, both predicted and measured, suggested that mix 20 was less biologically stable than mix 19 (Table 70). However, due to the lack of biomass measurements and limited substrate analysis, no firm conclusions can be drawn regarding the impact on plant performance. Visual observations indicated no obvious differences in overall plant growth between the two mixes.

**Table 69** Water and air content at -10 cm suction pressure of mixtures used in the *Asparagus* trial.

Mixture	Predicted values from Mixing Model		Lab measurement for mixtures without base fertilisers		Lab measurement for mixtures with base fertilisers	
	Water content - 10 cm (% v)	Air content at - 10 cm (% v)	Water content - 10 cm (% v)	Air content at - 10 cm (% v)	Water content - 10 cm (% v)	Air content at - 10 cm (% v)
Mix 19	83	10	86	7	84	8
Mix 20	69	23	65	27	66	27

**Table 70** Predicted and measured OUR values of the mixtures used in *Asparagus* trial.

Mixture	Predicted values from Mixing Model	Lab measurement for mixtures without base fertilisers	Lab measurement for mixtures with base fertilisers
Mix 19	2.2	2.6	2.4
Mix 20	3.7	5.3	4.7



**Figure 27** *Asparagus* seedlings at the end of cultivation.

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## 4 Discussion

### 4.1 Overview

This general discussion synthesises the key findings from model development, validation, and crop trials to provide a general understanding of the project's outcomes. While the Results and Discussion section focused on specific analyses, this section aims to connect the dots, tracing the steps taken to update the model to include the volume loss predictions, confirming the robustness of the mixing model, and highlighting practical insights that inform how the model performs under real conditions.

The project aimed not only to validate an existing mixing model but to enhance it by integrating a volume loss prediction module. This addition has reduced the model's reliance on prior lab-based volume measurements. The general discussion brings together the development of the volume loss model, its validation using lab and in-site measurements, and the practical insight of the crop trials. Together, these parts show how the updated model can support a faster way to integrate new renewable media substrates in development.

### 4.2 Adding volume loss to the previous model

In the original mixing model, volume loss had to be manually measured or estimated, which introduced a limitation, especially when working with new materials. This study introduced a data-driven volume loss prediction using particle morphology, improving the practicality of the model. Although the QICPIC device was used to measure particle size and shape descriptors, in principle, only mean particle length is required to make volume loss predictions using this model. This means that future applications could use more accessible measurement methods, while QICPIC data remains valuable for expanding the model or exploring other future properties.

Despite this, it is worth noting that particle size characterisation differs significantly between the sieving method and dynamic image analysis (DIA), such as with instruments like the QICPIC. Sieving tends to produce a coarser and less detailed particle size distribution compared to DIA, due to its more limited particle separation capability (Durand et al., 2023). Additionally, elongated particles can skew sieving results, as they often remain on a sieve mesh even when their width would allow them to pass through (Bartley et al., 2019). Increasing agitation time during sieving can help reduce this skewness.

Another important aspect is the tangle of particles, especially with materials like wood fibres. While DIA can separate individual wood fibre particles and avoid tangling during measurement, it does not account for the clumping that occurs under practical conditions. These clumps, particularly in fine wood fibres, can significantly affect water retention properties in mixtures, leading to discrepancies between actual performance and mixing model predictions, especially in small plug trays used for propagation. Future work could explore whether particle morphology descriptors generated by DIA (e.g. particle curviness) could help predict the likelihood of particle tangling in real-world applications.

By training a regression model on LBD using particle morphology as inputs, it was possible to make predictions of volume loss without needing to compact and weight mixtures. This reduces time, lab work, and costs when evaluating new combinations. Still, materials with highly irregular shapes and lengths or that are difficult to measure consistently may need further work and confirmation. Moreover, an additional approach or re-training of the model will be necessary to predict volume loss in the factory, as opposed to volume loss measured in the lab, and used for the training/testing of the models (Section 3.2.3), which was used in this project. Factory volume loss, which was measured in the 2<sup>nd</sup> and 3<sup>rd</sup> crop trials, was found to be harder to predict using the developed models.

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## 4.3 Volume loss model performance and limitations

The two-stage volume loss model developed in this study showed strong performance within the main dataset, especially in predicting LBD and volume loss using interpolated features (elongation and length) from QICPIC measurements. The model achieved high  $R^2$  values (above 0.93) and low prediction errors during cross-validation. These results indicate that the approach was correct for mixtures that are similar to those in the training data.

However, when these same models were applied to the 13 mixtures from the crop trials, the performance dropped significantly, particularly for the volume loss. While LBD predictions remained reasonably accurate using elongation ( $R^2 = 0.815$ ), the model failed to capture the variation in volume loss.

There are some reasons why this might be happening. Firstly, the training dataset did not include any mixtures made from more than two materials, whereas the crop trials mixtures likely involved more complex blends. This means the model was never exposed to the interaction effects that can occur when three or more materials are combined, which might significantly influence compaction and interstitial filling and therefore volume loss.

Secondly, some of the materials used in the 13 mixtures were not present in the training data. This is an important factor because the elongation and length features rely on the known properties of the individual materials. If a material's QICPIC base descriptors were not available during the training, an average value was used based on the classification of materials, which introduces uncertainty that the model has not been trained to handle.

Third, volume loss is a compound outcome that depends not just on the particle length or elongation but also on how the particles interact during mixing, moisture retention, compaction behaviour, and even the processing of the material. In training, the model performed quite reliably, but these effects may not be captured fully by elongation or length alone when the model encounters unknown mixtures.

## 4.4 Validation of the mixing model

The mixing model performed well in predicting total porosity and organic matter content. For dry bulk density, the model accurately predicted about half of the cases, while the remaining showed deviations of 7-13 kg/m<sup>3</sup> in absolute difference and 7-11% in relative difference. Regarding the water retention curve, the model accurately predicted water volume at suction pressures of -32 cm and -50 cm, providing a generally good overall prediction. However, at -3 cm and -10 cm, the model tended to slightly underestimate water volume, with maximum absolute deviations of 10-15%, v/v (in absolute difference).

One possible explanation for the deviations in bulk density and water retention is the variation between material batches. The input data for the mixing model were based on a single batch collected at the beginning of the project, while the mixtures used during the trials were prepared from multiple batches over time. To improve the model's accuracy, it is important to regularly update it with data from current material batches.

For chemical properties, the mixing model provided mostly reliable predictions for EC and macronutrients. Regarding pH, the model generally tended to slightly underestimate values – typically up to 1 pH unit, and in some cases (particularly mixtures containing compost) up to 2 pH units. Compost is known to vary significantly between batches. However, due to the project's design constraints, it was not possible to determine whether the observed deviations were primarily due to batch variability or the pH buffering capacity of the components.

An additional factor observed in the second and third crop trials was the inclusion of clay in some mixtures, which coincided with pH deviations of up to 2 units. To improve the model's accuracy, it would be beneficial not only to update it with current data for each component, but also to better understand and incorporate the pH buffering capacity of materials and the effects of clay. For future model development, integrating both clay as a component and the pH buffering capacity of substrates would support more precise pH predictions.

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Material type clearly influenced the performance of the mixing model. Predictions involving coir and bark were generally consistent and reliable, while those with compost and fine wood fibre showed greater variability. Compost often led to deviations in predicted water content and OUR, likely due to its complex composition, high bulk density, and batch-to-batch variability. Fine wood fibre posed handling challenges such as clumping, which impacted the model's accuracy. The model performs best with materials that have well-defined and consistent properties. In contrast, materials that are highly variable, prone to demixing, or difficult to mix homogeneously may require additional verification. The model is a valuable tool for guiding the formulation of new mixtures and component materials, but after an initial exploration phase, it should be used in conjunction with laboratory validation – especially when working with unfamiliar or variable materials.

## 4.5 Practical insights from crop trials

The model was validated using measurements, but also in various crop trials. These were to better understand (1) the model's accuracy, but also (2) to what extent mixtures made using the model would behave as expected and desired in practice. The crop trials confirmed that the model was effective in predicting overall trends in water retention across mixtures. Differences in rooting patterns were closely linked to the water–air balance of the substrates, and the model's output proved useful for steering irrigation during cultivation.

Despite this, there remains a difference of up to 10–15% (in absolute water content by volume) between model predictions and laboratory measurements. This discrepancy may be attributed to batch variability of components and differences in packing density between the lab's density used for water retention measurements and the actual filling density at the grower. The gap becomes even larger in small plug trays when fibre tangling occurs, such as with fine wood fibre. To improve model accuracy, it is recommended to develop a conversion factor between the lab-measured density and the practical filling density used by growers.

The prediction of plant growth based on the biostability indicator OUR was not consistently reflected in the crop trials. This could be due to the influence of base fertilisers on plant growth. In these trials, reduced plant growth tended to correlate more strongly with insufficient air content, as indicated by limited root development.

Moreover, the success of a mixture was not only about chemical and physical properties; handling characteristics like the ease of tray filling and plug integrity also played an important role. Mixtures with high proportions of fine wood fibre or loose structure could fall apart or cause uneven filling, even if the model predicted them well. Successful mixtures generally contained balanced proportions of coarse and fine materials, showed moderate OUR, and retained enough moisture while maintaining good air capacity. The model is currently best suited for crops in plug production, such as the ones tried (*Viola*, *Petunia*, and *Saxifraga*), where quick evaluation of water and air balance is important. Factors like clumping and demixing are not yet included in the model and should be considered when applying it in practice.

Since irrigation was identical across all treatments, predicted moisture properties could inform future irrigation adjustments. Mixtures with low predicted water retention may require more frequent irrigation, which is not accounted for in this study. This is an important observation, as new materials are introduced, the conventional strategies used might require to change to accommodate these new materials. This means that in future work, it will be required to consider the dynamics of water retention based on the used irrigation strategy.

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## 5 Conclusion & Recommendations

The main goal of this project was to validate an existing model using measurements and crop trials, and to explore the possibility of expanding it by predicting volume loss using particle morphology. Overall, the model performed well in predicting total porosity, organic matter, and water retention trends, especially with stable materials like coir and bark. Greater variability was observed with compost and fine wood fibre due to batch differences and handling issues. Crop trials confirmed the model's practical relevance, particularly for predicting water-air balance. Moreover, predicting volume loss using particle morphology was found to be feasible, enabling faster and more focused evaluation of growing media mixtures.

Regarding the volume loss model, to improve generalisation, the model would benefit from a more diverse training dataset. Including mixtures with three or more materials and ensuring a broader range of material types so the model can learn from more combinations. Additionally, increasing the number of samples would help the model recognize patterns in more complex substrates. Finally, for practical use, it may be worthwhile treating the model as a baseline advice for lab bulk density predictions, and then using a simple correction factor based on specific materials used. This way, lab bulk density can be streamlined instead of doing multiple lab analyses in factory conditions.

Growing media manufacturers found the model to be particularly helpful for physical properties and to quantify the amount of lime to be added. For propagators, the model was less directly useful, but was able to help them think along in discussions with manufacturers. Furthermore, the model was helpful for both to give an estimate whilst waiting for lab results, though by no means should it be seen as a substitute for laboratory analysis. To improve accuracy, regular updates with current material data, consideration of pH buffering capacity, and adjustments for practical filling densities are recommended. Complemented with lab validation – especially for new or variable materials – the model can be a valuable tool for determining growing media mixture formulations.



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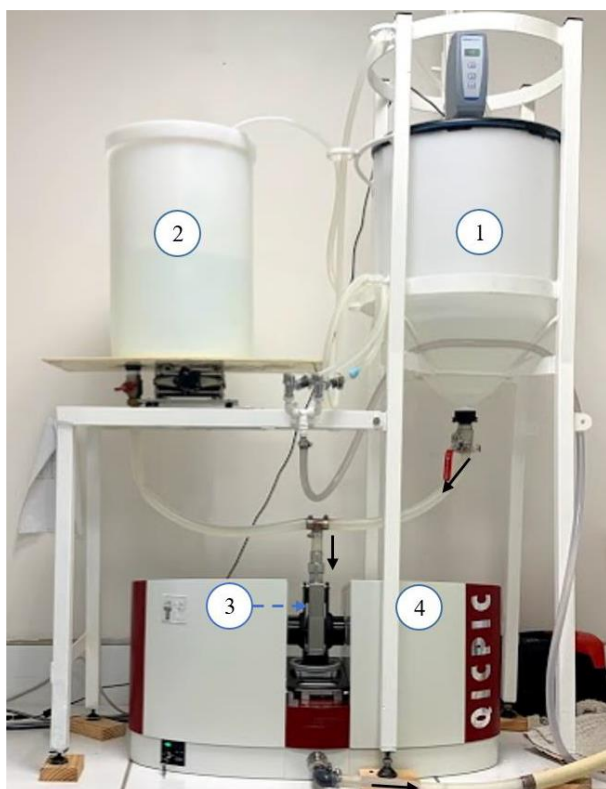
## 7 Annex

### 7.1 QIPIC and its associated set-up

The photo is the QIPIC image analyser and its associated setup at L'Institut agro Rennes-Angers in Angers to capture images of substrate particles in water solution.

1. Water tank (about 15 L) containing measured particles, equipped with an agitator.
2. Water tank to control particle concentration
3. Measurement area
4. High-resolution cameras

Black arrows indicate the particle-water flow, regulated by a peristaltic pump.

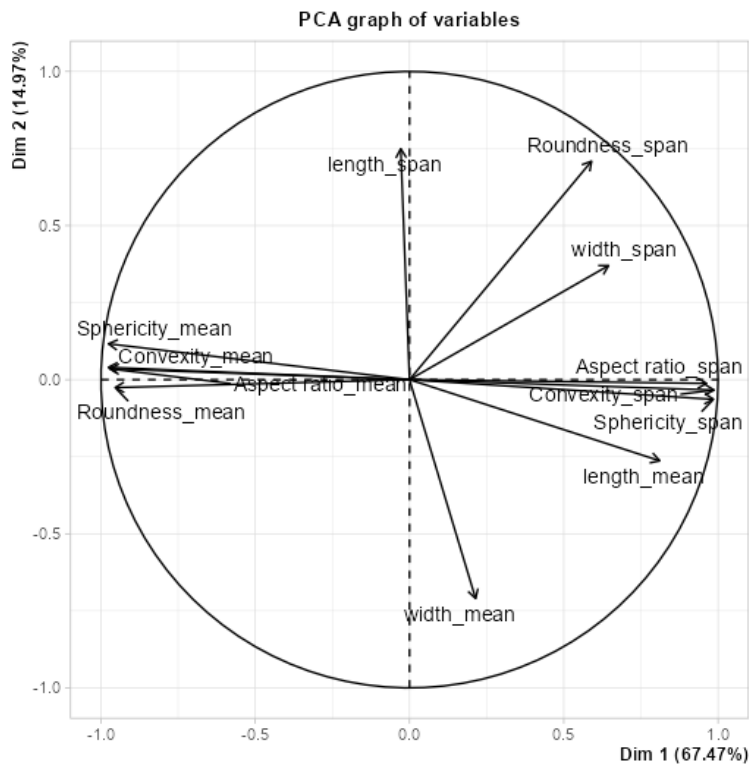


**Figure A1** QIPIC and associated set-up at the substrate lab (L'Institut agro Rennes-Angers).  
Photo credit: Stan Durand.

### 7.2 Principal component analysis for morphology-based groupings

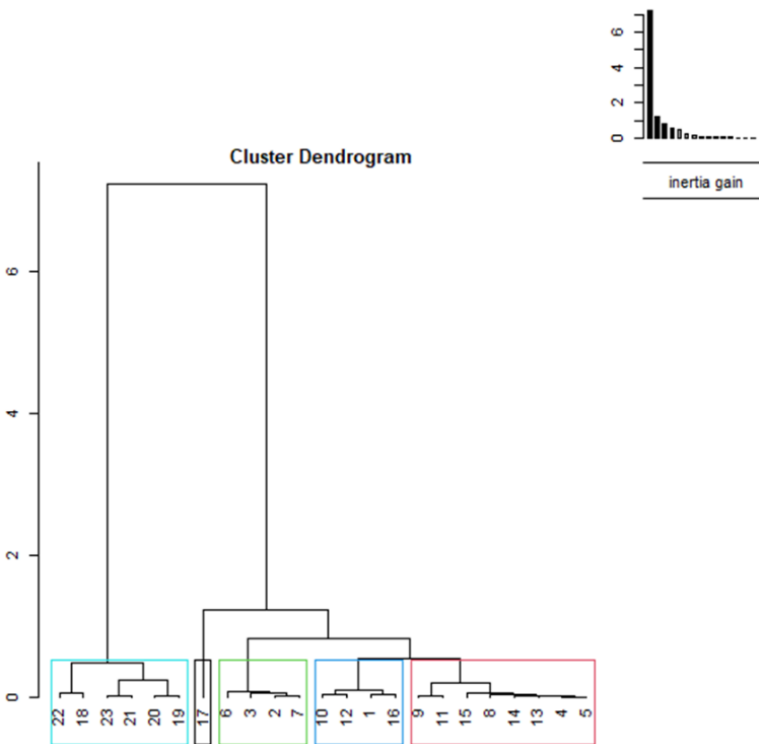
The dataset contains 23 individuals and 12 variables (mean and span values of six shape/size descriptors: aspect ratio, convexity, roundness, sphericity, length, and width). Principal component analysis was analysed using the R package Factorshiny.

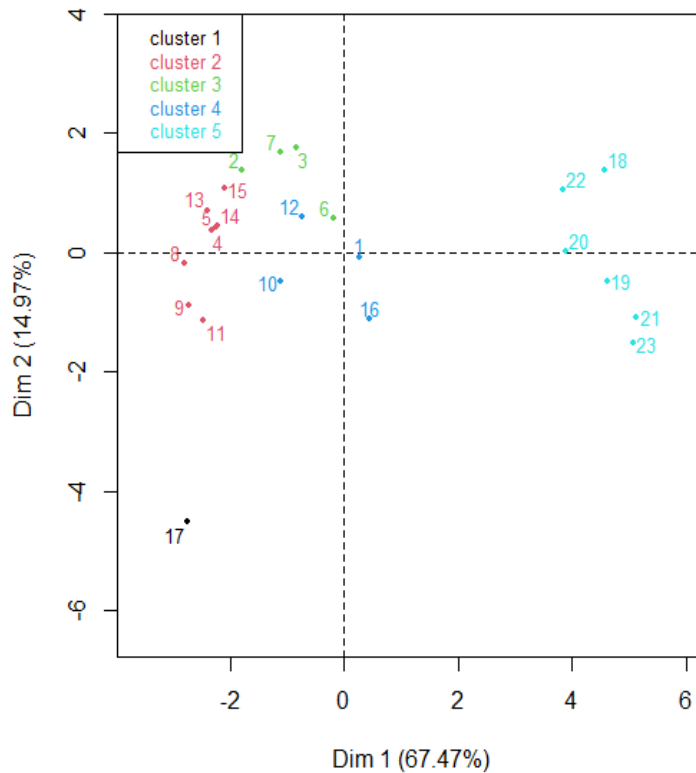
The first component of the PCA is mainly based on particle shape descriptors (mean and span) and the mean of particle length. This component explained 67% of the total variance. The second component based on the mean of particle width and the span of particle length explained only 15% of the variability.



**Figure A2** PCA correlation circle for variables describing arithmetic means and span of particle size and shape descriptors.

The classification made on individuals reveals 5 clusters:





**Figure A3** Identification of five clusters by hierarchical clustering analysis (HCA).

Below is the ascending Hierarchical Classification of the individuals. Note that the order of these five clusters does not match the grouping order listed in the results, although the members within each cluster are the same.

The cluster 1 is made of individual #17. This group is characterised by high values for the variable *width\_mean*; low values for the variable *Roundness\_span*.

The cluster 2 is made of individuals such as 9 and 11. This group is characterised by high values for the variables *Aspect.ratio\_mean*, *Roundness\_mean*, *Sphericity\_mean* and *Convexity\_mean* (variables are sorted from the strongest), and low values for the variables *length\_mean*, *Aspect.ratio\_span*, *Sphericity\_span*, *Convexity\_span*, *width\_mean* and *width\_span* (variables are sorted from the weakest).

The cluster 3 is made of individuals such as 2, 3 and 7. This group is characterised by high values for the variable *length\_span*.

The cluster 4 is made of individuals sharing variables whose values do not differ significantly from the mean.

The cluster 5 is made of individuals such as 18, 19, 20, 21, 22 and 23. This group is characterised by high values for the variables *Convexity\_span*, *Sphericity\_span*, *Aspect.ratio\_span*, *length\_mean*, *width\_span* and *Roundness\_span* (variables are sorted from the strongest), and low values for the variables *Convexity\_mean*, *Sphericity\_mean*, *Roundness\_mean* and *Aspect.ratio\_mean* (variables are sorted from the weakest).

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## 7.3 Unsuccessful Attempts at Predicting Density & Volume Loss

The initial model development process involved running 100 rounds of randomised training and testing using different algorithms. This process, known as Monte Carlo approach, was meant to ensure the results were stable and not overly influenced by one specific data split. To streamline this comparison, we used the LazyPredict tool in Python, which allows multiple models to be tested quickly under the same conditions. Each model's performance was evaluated using two common metrics: Root Mean Square Error (RMSE), which measures how far predictions are from the actual value, and R-Squared ( $R^2$ ), which showed how well the model explains the variation in the data. Ultimately, with new data, this approach was no longer satisfactory. Because of this, a new approach had to be found, described in the rest of the report as the 'two-stage' model.

Lab Bulk Density (LBD) was selected as the target variable instead of Dry Bulk Density (DBD) for two main reasons. First, LBD had a stronger correlation with particle shape measurements from the QICPIC system. Second, LBD better reflects the actual conditions during material handling and mixing, as it is measured with moisture content present, which is more representative of how the substrates are handled in normal practices. In contrast, DBD is measured at -10 cm suction pressure, and then dry weight is measured, which may not represent the structural changes and compaction that occur during the mixing of materials.

The model used QICPIC shape descriptors to predict LBD, because this property showed the strongest correlation with particle morphology. LBD is also closely tied to how much empty space is lost between particles during mixing, making it a useful indicator for volume loss.

The data used for training involves the use of the materials measured with the QICPIC system. However, there is no QICPIC shape descriptors for the mixtures based on the materials. To provide specific shape descriptors without requiring to do extensive measurements, we used an interpolation approach. Since the physical properties of a mixture depend on the relative proportions of each material used, we calculated the overall behaviour of the mixture by interpolating the original QICPIC descriptors as part of the percentage of that material used. For instance, if a mixture contains 70% of material A and 30% of material B, the interpolated value will be closer to that of material A but still reflect the influence of material B. This weighed approach represents more accurately the physical behaviour of the mixture. We avoided using average values for the mixture as this means all components are regarded equally. This can be misleading, because if a mixture of two materials with different shapes might end up with the same average as a mixture of two similar materials, even though their physical characteristics would be quite different. Interpolation helps in maintaining the influence of each material according to the proportion used in the mixture.

To predict volume loss based on particle shape features, several regression models were compared to find one that have a strong and consistent performance. The model selection process can be described in three steps:

### 1. Data splitting for robust testing

To evaluate the models, data has to be split into train and test, this way you can train the model on a set of data, while test the results of the training in the other split. We started evaluating models across 100 different train-test splits using a 70:30 ratio. This helps avoid overfitting and ensures that the results aren't due to chance, this is because the same random state will always generate the same split. Each split is based on a different random seed (or "random state") to introduce variation while still allowing reproducibility.

### 2. Model Comparison LazyPredict implementation

We used the Python library LazyPredict, this library allow us to automatically test a wide range of standard machine learning regression models with minimal setup to quickly identify high-performing models. LazyPredict runs these models all in a single steps and lists and compares multiple regression models. The results are summarised in Table 71, ranked the models based on their performance. This approach made it easy to identify the top performing models, this helped save time and ensure a fair comparison across models using the training and testing data.

3. Performance metric evaluation

We compared model performance using two common measures: mean RMSE (how large the errors are) and  $R^2$  (how well the model fits the data), these measures were calculated for each model, shown in Figure A4. Additionally, the standard deviation of errors was analysed to understand how much these results varied, indicating how stable the models are.

The five best performing models had very similar scores (Figure A5 and Figure A6 in the Annex). When we considered the training data up to August 2024, while several models achieved slightly higher mean  $R^2$  scores (up to 0.73) the ElasticNetCV model was ultimately selected to predict volume loss. Because we were working with a small dataset that had large variability, we chose the ElasticNetCV model. It uses a method called regularisation, which helps prevent the model from fitting too closely to the noise in the data. This makes it more reliable, especially when the amount of data is limited.

When the models were retrained using updated data up to the date of May 2025, LazyPredict showed that the best model to use was RandomForest. This was because more mixtures were added to the training data, which had a larger correlation compared to the previous year data.

Table 71 Complete list of the models evaluated by LazyPredict.

1. AdaBoostRegressor	21. LassoLars
2. BaggingRegressor	22. LassoLarsCV
3. BayesianRidge	23. LassoLarsIC
4. DecisionTreeRegressor	24. LinearRegression
5. DummyRegressor	25. LinearSVR
6. ElasticNet	26. MLPRegressor
7. ElasticNetCV	27. NuSVR
8. ExtraTreeRegressor	28. OrthogonalMatchingPursuit
9. ExtraTreesRegressor	29. OrthogonalMatchingPursuitCV
10. GammaRegressor	30. PassiveAggressiveRegressor
11. GaussianProcessRegressor	31. PoissonRegressor
12. GradientBoostingRegressor	32. RANSACRegressor
13. HistGradientBoostingRegressor	33. RandomForestRegressor
14. HuberRegressor	34. Ridge
15. KNeighborsRegressor	35. RidgeCV
16. KernelRidge	36. SGDRegressor
17. Lars	37. SVR
18. LarsCV	38. TheilSenRegressor
19. Lasso	39. TransformedTargetRegressor
20. LassoCV	40. TweedieRegressor
	41. XGBRegressor

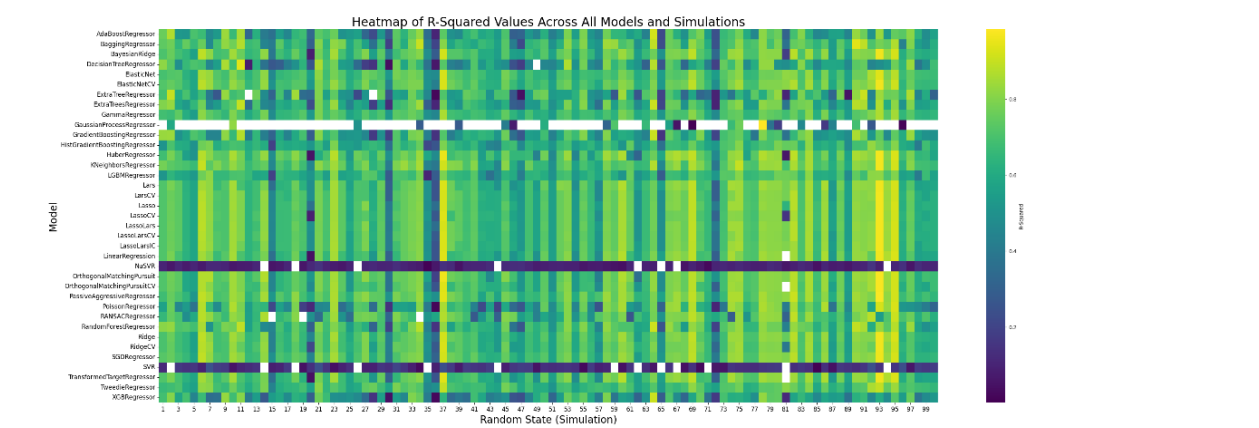
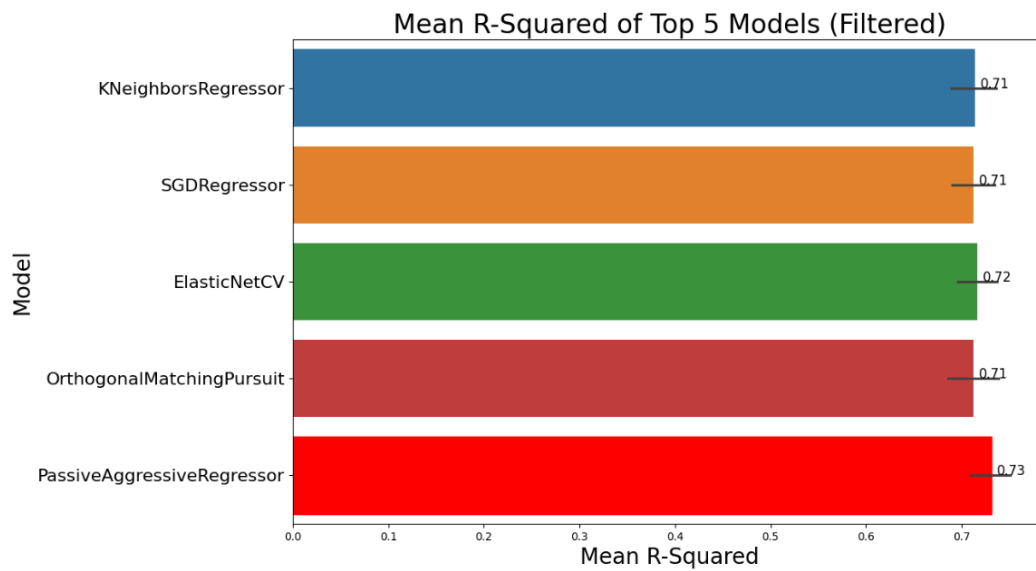
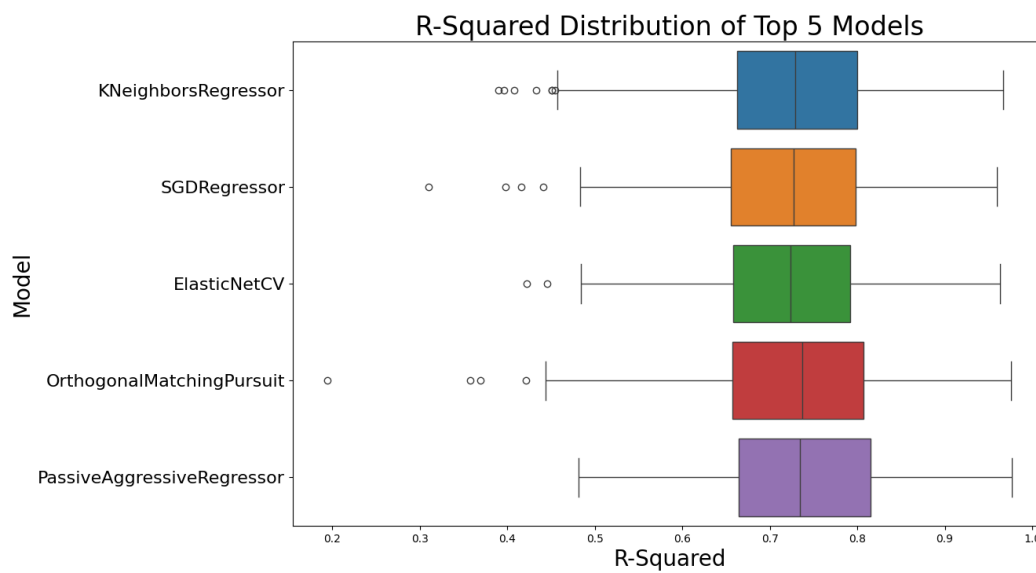


Figure A4 Heatmap of R-squared scores for all models after 100 iterations for August 2024 volume loss model.



**Figure A5** Best 5 regression models based on Mean R-square for August 2024 volume loss model.



**Figure A6** Distribution of the best 5 regression models after 100 iterations for August 2024 volume loss model.



## 7.4 Predicted and measured properties of the mixtures used in the crop trials

**Table 72** Predicted and measured properties of mixtures used in 1<sup>e</sup> crop trials – Viola at Beekenkamp and Syngenta.

parameter	unit	Mix1_Model onbemest + volume loss	Mix1_Model onbemest	Mix1_ Eurofins onbemest	Mix1_ Eurofins bemest	Mix2_Model onbemest + volume loss	Mix2_Model onbemest	Mix2_ Eurofins onbemest	Mix2_ Eurofins bemest	Mix3_Model onbemest + volume loss	Mix3_Model onbemest	Mix3_ Eurofins onbemest	Mix3_ Eurofins bemest
DBD	kg/m3	143	146	145	220	153	155	162	232	118	112	120	157
OM_920	%, w/w	70	70	67	43	66	66	59	44	92	92	92	76
MM	%, w/w	30	30	33	57	34	34	41	56	8	8	8	24
SFS	%, v/v	8	8	8	11	8	9	9	11	7	7	7	9
TPS	%, v/v	92	92	92	89	92	91	91	89	93	93	93	91
Water_3	%, v/v	88	89	90	88	89	90	91	88	90	85	84	90
Water_10	%, v/v	70	71	77	88	75	76	85	84	75	71	75	69
Water_32	%, v/v	41	42	43	49	45	46	47	50	49	46	47	46
Water_50	%, v/v	38	39	38	44	41	42	43	44	45	42	43	43
Air_3	%, v/v	4	2	2	1	3	2	0	1	2	8	8	1
Air_10	%, v/v	22	21	15	5	17	16	6	5	18	23	17	22
Air_32	%, v/v	51	50	49	40	46	46	44	39	44	47	45	44
Air_50	%, v/v	54	53	54	45	50	49	48	44	48	51	50	47
EAW	%, v/v	32	32.6	39	44	33.2	33.6	42	40	30.2	28.5	32	26
OUR	mmol O2/kg DOM/h	5.2	5.2	2.8	3.0	4.8	4.8	3.4	3.2	3.9	3.9	4.2	4.9
EC	mS/cm	0.3	0.3	0.3	1.1	0.4	0.4	0.4	1.5	0.1	0.1	0.1	1.1
pH	-log[H+]	6.3	6.3	7.2	7.0	4.6	4.6	6.5	6.5	5.6	5.6	5.8	6.0
NH4	mmol/L extract	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.3	0.1	0.1	0.1	0.1
K	mmol/L extract	1.3	1.4	1.7	4.6	1.7	1.7	2.1	5.5	0.5	0.5	0.2	2.1
Na	mmol/L extract	0.3	0.3	0.5	0.9	0.4	0.4	0.5	1.0	0.2	0.2	0.1	0.9
Ca	mmol/L extract	0.2	0.2	0.2	0.9	0.2	0.2	0.3	1.7	0.1	0.1	0.1	1.7
Mg	mmol/L extract	0.1	0.1	0.1	0.4	0.1	0.1	0.1	0.8	0.1	0.1	0.1	1.6
NO3	mmol/L extract	0.6	0.6	0.2	3.1	0.7	0.7	0.2	5.6	0.3	0.3	0.2	6.3
Cl	mmol/L extract	1.0	1.0	1.2	1.5	1.2	1.3	1.6	2.0	0.2	0.2	0.2	0.5
SO4	mmol/L extract	0.1	0.1	0.2	1.3	0.2	0.2	0.3	1.5	0.1	0.1	0.1	0.8
HCO3	mmol/L extract	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1
P	mmol/L extract	0.0	0.0	0.3	0.3	0.1	0.1	0.6	0.5	0.1	0.1	0.1	0.8
Si	mmol/L extract	0.1	0.1	0.2	0.3	0.1	0.1	0.3	0.3	0.1	0.1	0.2	0.3
Fe	µmol/L extract	2.2	2.2	8.3	2.5	2.2	2.2	12.0	9.6	1.4	1.3	3.8	3.3

parameter	unit	Mix1_Model onbemest + volume loss	Mix1_Model onbemest	Mix1_ Eurofins onbemest	Mix1_ Eurofins bemest	Mix2_Model onbemest + volume loss	Mix2_Model onbemest	Mix2_ Eurofins onbemest	Mix2_ Eurofins bemest	Mix3_Model onbemest + volume loss	Mix3_Model onbemest	Mix3_ Eurofins onbemest	Mix3_ Eurofins bemest
Mn	µmol/L extract	0.6	0.6	1.7	1.2	0.6	0.6	2.7	6.7	0.5	0.5	0.4	0.4
Zn	µmol/L extract	0.3	0.3	0.7	6.2	0.3	0.3	0.9	17.0	0.3	0.3	0.2	5.7
B	µmol/L extract	6.5	6.6	7.8	8.4	7.3	7.4	15.0	18.0	5.4	5.1	5.7	4.6
Cu	µmol/L extract	0.1	0.1	0.2	0.3	0.1	0.1	0.3	0.6	0.1	0.1	0.1	1.2
Mo	µmol/L extract	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1

**Table 73** Predicted and measured properties of mixtures used in 1<sup>e</sup> crop trials – Petunia cuttings at Florensis.

parameter	unit	Mix4_Model onbemest + volume loss	Mix4Model onbemest	Mix4_ Eurofins onbemest	Mix4_ Eurofins bemest	Mix3_Model onbemest + volume loss	Mix3_Model onbemest	Mix3_ Eurofins onbemest	Mix3_ Eurofins bemest
DBD	kg/m3	102	118	115	124	118	112	120	153
OM_920	%, w/w	81	81	79	70	92	92	92	77
MM	%, w/w	19	19	21	30	8	8	8	23
SFS	%, v/v	6	7	7	7	7	7	7	9
TPS	%, v/v	94	93	93	93	93	93	93	91
Water_3	%, v/v	79	92	91	93	90	85	84	90
Water_10	%, v/v	69	79	84	87	75	71	75	70
Water_32	%, v/v	41	47	47	48	49	46	47	46
Water_50	%, v/v	37	43	43	43	45	42	43	43
Air_3	%, v/v	15	1	2	0	2	8	8	1
Air_10	%, v/v	25	14	9	6	18	23	17	21
Air_32	%, v/v	53	46	47	45	44	47	45	45
Air_50	%, v/v	57	50.2	50	50	48	51	50	48
EAW	%, v/v	32	36.5	41	44	30	29	32	27
OUR	mmol O2/kg DOM/h	4.4	4.4	3.6	4.7	3.9	3.9	4.2	4.4
EC	mS/cm	0.2	0.2	0.2	0.4	0.1	0.1	0.1	0.8
pH	-log[H+]	4.4	4.4	5.6	6.6	5.6	5.6	5.8	6.2
NH4	mmol/L extract	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1
K	mmol/L extract	0.6	0.7	1.0	2.0	0.5	0.5	0.2	1.8
Na	mmol/L extract	0.2	0.2	0.3	0.5	0.2	0.2	0.1	0.8
Ca	mmol/L extract	0.1	0.1	0.2	0.2	0.1	0.1	0.1	0.9
Mg	mmol/L extract	0.1	0.1	0.1	0.1	0.1	0.1	0.1	1.0

parameter	unit	Mix4_Model onbemest + volume loss	Mix4Model onbemest	Mix4_ Eurofins onbemest	Mix4_ Eurofins bemest	Mix3_Model onbemest + volume loss	Mix3_Model onbemest	Mix3_ Eurofins onbemest	Mix3_ Eurofins bemest
NO3	mmol/L extract	0.2	0.2	0.2	0.2	0.3	0.3	0.2	4.0
Cl	mmol/L extract	0.5	0.6	0.7	0.9	0.2	0.2	0.2	0.4
SO4	mmol/L extract	0.1	0.1	0.2	0.7	0.1	0.1	0.1	0.6
HCO3	mmol/L extract	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1
P	mmol/L extract	0.0	0.0	0.4	0.4	0.1	0.1	0.1	0.6
Si	mmol/L extract	0.1	0.1	0.2	0.3	0.1	0.1	0.2	0.3
Fe	µmol/L extract	1.9	2.2	5.0	16.0	1.4	1.3	3.8	2.0
Mn	µmol/L extract	0.5	0.6	1.9	2.1	0.5	0.5	0.4	0.4
Zn	µmol/L extract	0.3	0.3	0.5	17.0	0.3	0.3	0.2	5.2
B	µmol/L extract	3.3	3.8	14.0	11.0	5.4	5.1	5.7	3.4
Cu	µmol/L extract	0.1	0.1	0.2	0.8	0.1	0.1	0.1	0.8
Mo	µmol/L extract	0.2	0.2	0.1	0.1	0.1	0.1	0.1	0.1

**Table 74** Predicted and measured properties of mixtures used in 1<sup>e</sup> crop trials – *Petunia potted at Florensis*.

parameter	unit	Mix5_Model onbemest + volume loss	Mix5_Model onbemest	Mix5_ Eurofins onbemest	Mix5_ Eurofins bemest	Mix6_Model onbemest + volume loss	Mix6_Model onbemest	Mix6_ Eurofins onbemest	Mix6_ Eurofins bemest
DBD	kg/m3	171	161	171	199	153	148	161	201
OM_920	%, w/w	70	70	69	55	77	77	75	58
MM	%, w/w	30	30	31	45	23	23	25	42
SFS	%, v/v	10	9	10	10	9	9	9	11
TPS	%, v/v	90	91	90	90	91	91	91	89
Water_3	%, v/v	90	85	90	85	84	82	90	89
Water_10	%, v/v	67	63	71	78	62	60	70	65
Water_32	%, v/v	42	40	42	46	43	41	45	45
Water_50	%, v/v	40	37	38	41	39	38	42	43
Air_3	%, v/v	0	6	1	4	7	10	1	0
Air_10	%, v/v	23	27	19	11	29	31	21	24
Air_32	%, v/v	48	51	49	43	49	50	46	44
Air_50	%, v/v	51	54	53	48	52	53	49	46
EAW	%, v/v	22	20.7	33	37	27	26.0	28	22
OUR	mmol O2/kg DOM/h	5.1	5.1	4	4.8	5.3	5.3	4.1	5.0

parameter	unit	Mix5_Model onbemest + volume loss	Mix5_Model onbemest	Mix5_ Eurofins onbemest	Mix5_ Eurofins bemest	Mix6_Model onbemest + volume loss	Mix6_Model onbemest	Mix6_ Eurofins onbemest	Mix6_ Eurofins bemest
EC	mS/cm	0.3	0.3	0.3	1.0	0.2	0.2	0.2	1.1
pH	-log[H+]	4.7	4.68	6.4	6.8	6.3	6.3	6.7	6.1
NH4	mmol/L extract	0.15	0.15	0.1	0.9	0.1	0.1	0.1	0.8
K	mmol/L extract	1.52	1.44	1.6	4.5	1.1	1.1	1.0	2.4
Na	mmol/L extract	0.38	0.36	0.4	0.8	0.3	0.3	0.2	0.8
Ca	mmol/L extract	0.17	0.16	0.2	0.5	0.1	0.1	0.1	1.5
Mg	mmol/L extract	0.12	0.12	0.1	0.3	0.1	0.1	0.1	1.0
NO3	mmol/L extract	0.24	0.23	0.2	2.7	0.2	0.2	0.2	4.8
Cl	mmol/L extract	1.38	1.30	1.2	2.1	0.9	0.9	0.8	1.2
SO4	mmol/L extract	0.14	0.13	0.1	0.7	0.1	0.1	0.1	1.0
HCO3	mmol/L extract	0.17	0.16	0.1	0.1	0.2	0.2	0.1	0.1
P	mmol/L extract	0.06	0.06	0.4	0.5	0.2	0.2	0.3	0.7
Si	mmol/L extract	0.10	0.09	0.2	0.2	0.2	0.2	0.2	0.3
Fe	µmol/L extract	2.15	2.02	9.6	9.9	2.3	2.3	4.3	5.7
Mn	µmol/L extract	0.89	0.84	2.4	5.6	1.5	1.4	1.1	6.4
Zn	µmol/L extract	0.34	0.32	0.7	19.0	0.4	0.4	0.3	12.0
B	µmol/L extract	6.37	6.00	12.0	16.0	4.8	4.6	6.5	9.7
Cu	µmol/L extract	0.18	0.17	0.2	0.8	0.1	0.1	0.1	1.1
Mo	µmol/L extract	0.20	0.19	0.1	0.2	0.1	0.1	0.1	0.1

**Table 75** Predicted and measured properties of mixtures used in 1<sup>e</sup> crop trials – Monstera at Evanthia.

parameter	unit	Mix7_Model onbemest + volume loss	Mix7_Model onbemest	Mix7_ Eurofins onbemest	Mix7_ Eurofins bemest	Mix3_Model onbemest + volume loss	Mix3_Model onbemest	Mix3_ Eurofins onbemest	Mix3_ Eurofins bemest
DBD	kg/m3	115	106	107	106	118	112	120	137
OM	%, w/w	76	76	66	75	92	92	92	79
MM	%, w/w	24	24	34	25	8	8	8	21
SFS	%, v/v	7	6	6	6	7	7	7	8
TPS	%, v/v	93	94	94	94	93	93	93	92
Water_3	%, v/v	91	84	84	91	90	85	84	90
Water_10	%, v/v	71	65	67	85	75	71	75	71
Water_32	%, v/v	43	40	40	48	49	46	47	48
Water_50	%, v/v	40	37	37	43	45	42	43	45

parameter	unit	Mix7_Model onbemest + volume loss	Mix7_Model onbemest	Mix7_ Eurofins onbemest	Mix7_ Eurofins bemest	Mix3_Model onbemest + volume loss	Mix3_Model onbemest	Mix3_ Eurofins onbemest	Mix3_ Eurofins bemest
Air_3	%, v/v	2	10	10	3	2	8	8	2
Air_10	%, v/v	22	28	27	9	18	23	17	21
Air_32	%, v/v	50	54	54	46	44	47	45	44
Air_50	%, v/v	53	57	57	51	48	51	50	47
EAW	%, v/v	31	28.6	30	42	30	29	32	26
OUR	mmol O2/kg DOM/h	4.1	4.1	4	3	4	3.9	4.2	6.0
EC	mS/cm	0.1	0.1	0.1	0.5	0.1	0.1	0.1	0.9
pH	-log[H <sup>+</sup> ]	6.9	6.92	6.8	6.4	5.6	5.6	5.8	6.3
NH4	mmol/L extract	0.11	0.10	0.10	1.00	0.11	0.1	0.1	0.1
K	mmol/L extract	0.18	0.16	0.20	1.00	0.48	0.5	0.2	1.7
Na	mmol/L extract	0.11	0.10	0.20	0.30	0.16	0.2	0.1	0.7
Ca	mmol/L extract	0.11	0.10	0.10	0.20	0.11	0.1	0.1	1.3
Mg	mmol/L extract	0.11	0.10	0.10	0.10	0.11	0.1	0.1	0.9
NO3	mmol/L extract	0.22	0.20	0.20	0.40	0.29	0.3	0.2	4.2
Cl	mmol/L extract	0.16	0.14	0.10	0.10	0.24	0.2	0.2	0.7
SO4	mmol/L extract	0.11	0.10	0.10	0.80	0.11	0.1	0.1	0.6
HCO3	mmol/L extract	0.11	0.10	0.10	0.10	0.11	0.1	0.1	0.1
P	mmol/L extract	0.04	0.03	0.06	0.54	0.08	0.1	0.1	0.7
Si	mmol/L extract	0.11	0.11	0.13	0.14	0.09	0.1	0.2	0.3
Fe	µmol/L extract	1.81	1.67	2.80	23.00	1.35	1.3	3.8	7.0
Mn	µmol/L extract	0.50	0.46	0.40	2.60	0.48	0.5	0.4	5.6
Zn	µmol/L extract	0.22	0.20	0.20	8.20	0.29	0.3	0.2	4.6
B	µmol/L extract	3.21	2.96	4.80	8.60	5.41	5.1	5.7	3.9
Cu	µmol/L extract	0.11	0.10	0.10	2.40	0.11	0.1	0.1	1.2
Mo	µmol/L extract	0.11	0.10	0.10	0.10	0.11	0.1	0.1	0.1

**Table 76** Predicted and measured properties of mixtures used in 2<sup>e</sup> crop trials – *Calocephalus* at *Florensis*.

parameter	unit	Mix8_Model onbemest + volume loss	Mix8_Model onbemest	Mix8_ Eurofins onbemest	Mix8_ Eurofins bemest	Mix9_Model onbemest + volume loss	Mix9_Model onbemest	Mix9_ Eurofins onbemest	Mix9_ Eurofins bemest
DBD	kg/m3	120	123	133	139	109	105	121	134
OM	%, w/w	78	78	77	76	77	77	65	64
MM	%, w/w	22	22	23	24	23	23	35	36
SFS	%, v/v	6	6	8	8	6	6	7	7
TPS	%, v/v	94	94	92	92	94	94	93	93
Water_3	%, v/v	na	na	84	85	85	82	89	89
Water_10	%, v/v	57	59	68	67	70	67	72	67
Water_32	%, v/v	na	na	40	44	46	44	46	46
Water_50	%, v/v	na	na	36	40	42	41	43	42
Air_3	%, v/v	na	na	8	6	8	12	4	4
Air_10	%, v/v	37	35	24	25	24	27	21	25
Air_32	%, v/v	na	na	52	48	48	49	47	47
Air_50	%, v/v	na	na	56	51	51	53	50	50
EAW	%, v/v	21	21.2	32	27	27	26	29	25
OUR	mmol O2/kg DOM/h	4.7	4.7	3.8	4.5	3.5	3.5	5	5
EC	mS/cm	0.2	0.2	0.2	0.9	0.1	0.1	0	1
pH	-log[H+]	5.2	5.2	5.7	5.3	5.8	5.8	7	6
NH4	mmol/L extract	0.12	0.1	0.1	0.5	0.10	0.1	0.1	0.4
K	mmol/L extract	0.16	0.16	0.5	2.3	0.40	0.4	0.4	1.7
Na	mmol/L extract	0.04	0.0	0.4	0.5	0.13	0.1	0.3	0.8
Ca	mmol/L extract	0.12	0.12	0.1	1.0	0.10	0.1	0.1	1
Mg	mmol/L extract	0.04	0.04	0.1	0.5	0.10	0.1	0.1	0.9
NO3	mmol/L extract	0.16	0.16	0.20	3.40	0.28	0.3	0.2	4.6
Cl	mmol/L extract	0.04	0.04	0.7	0.6	0.21	0.2	0.3	0.4
SO4	mmol/L extract	0.12	0.12	0.1	0.8	0.10	0.1	0.1	0.5
HCO3	mmol/L extract	0.04	0.04	0.1	0.1	0.10	0.1	0.1	0.1
P	mmol/L extract	0.04	0.04	0.05	0.78	0.07	0.1	0.03	0.77
Si	mmol/L extract	0.01	0.0	0.2	0.2	0.08	0.1	0.28	0.19
Fe	µmol/L extract	2.11	2.2	3.3	4.6	1.14	1.1	21	20
Mn	µmol/L extract	0.39	0.4	0.4	10.0	0.45	0.4	0.4	3.7
Zn	µmol/L extract	0.20	0.2	0.2	2.5	0.28	0.3	0.2	5.6

parameter	unit	Mix8_Model onbemest + volume loss	Mix8_Model onbemest	Mix8_ Eurofins onbemest	Mix8_ Eurofins bemest	Mix9_Model onbemest + volume loss	Mix9_Model onbemest	Mix9_ Eurofins onbemest	Mix9_ Eurofins bemest
B	µmol/L extract	1.80	1.8	4.3	9.4	4.39	4.2	1.7	4.8
Cu	µmol/L extract	0.12	0.1	0.1	2.2	0.10	0.1	0.1	1.4
Mo	µmol/L extract	0.04	0.0	0.1	0.1	0.10	0.1	0.1	0.1

**Table 77** Predicted and measured properties of mixtures used in 2<sup>e</sup> crop trials – Strelitzia at Evanthia.

parameter	unit	Mix10_Model onbemest + volume loss	Mix10_Model onbemest	Mix1_ Eurofins onbemest	Mix1_ Eurofins bemest	Mix9_Model onbemes + volume loss	Mix9_Model onbemest	Mix9_ Eurofins onbemest	Mix9_ Eurofins bemest
DBD	kg/m3	117	116	184	189	109	105	121	134
OM_920	%, w/w	95	95	59	59	77	77	65	64
MM	%, w/w	5	5	41	41	23	23	35	36
SFS	%, v/v	7	7	10	10	6	6	7	7
TPS	%, v/v	93	93	90	90	94	94	93	93
Water_3	%, v/v	82	82	87	85	85	82	89	89
Water_10	%, v/v	73	72	76	74	70	67	72	67
Water_32	%, v/v	45	45	44	45	46	44	46	46
Water_50	%, v/v	42	41	39	41	42	41	43	42
Air_3	%, v/v	10	11	3	5	8	12	4	4
Air_10	%, v/v	20	20	14	16	24	27	21	25
Air_32	%, v/v	47	48	46	45	48	49	47	47
Air_50	%, v/v	51	51	51	49	51	53	50	50
EAW	%, v/v	31	31	37	33	27	26	29	25
OUR	mmol O2/kg DOM/h	3.8	3.8	4.9	3.8	3.5	3.5	5.0	5.2
EC	mS/cm	0.1	0.12	0.1	0.7	0.1	0.1	0	1
pH	-log[H+]	4.5	4.5	5.4	5.4	5.8	5.8	7	6
NH4	mmol/L extract	0.1	0.1	0.1	0.8	0.10	0.1	0.1	0.4
K	mmol/L extract	0.2	0.2	0.4	1.4	0.40	0.4	0.4	1.7
Na	mmol/L extract	0.1	0.1	0.3	0.5	0.13	0.1	0.3	0.8
Ca	mmol/L extract	0.1	0.1	0.1	0.7	0.10	0.1	0.1	1
Mg	mmol/L extract	0.1	0.1	0.1	0.5	0.10	0.1	0.1	0.9
NO3	mmol/L extract	0.2	0.2	0.20	3.20	0.28	0.3	0.2	4.6
Cl	mmol/L extract	0.1	0.1	0.3	0.3	0.21	0.2	0.3	0.4

parameter	unit	Mix10_Model onbemest + volume loss	Mix10_Model onbemest	Mix1_ Eurofins onbemest	Mix1_ Eurofins bemest	Mix9_Model onbemes + volume loss	Mix9_Model onbemest	Mix9_ Eurofins onbemest	Mix9_ Eurofins bemest
SO4	mmol/L extract	0.1	0.1	0.1	0.6	0.10	0.1	0.1	0.5
HCO3	mmol/L extract	0.1	0.1	0.1	0.1	0.10	0.1	0.1	0.1
P	mmol/L extract	0.038	0.037	0.05	0.38	0.07	0.1	0.03	0.77
Si	mmol/L extract	0.1	0.1	0.3	0.2	0.08	0.1	0.28	0.19
Fe	µmol/L extract	1.7	1.69	2.0	4.3	1.14	1.1	21	20
Mn	µmol/L extract	0.4	0.3	0.4	6.6	0.45	0.4	0.4	3.7
Zn	µmol/L extract	0.2	0.2	0.2	1.0	0.28	0.3	0.2	5.6
B	µmol/L extract	2.6	2.6	6.2	6.6	4.39	4.2	1.7	4.8
Cu	µmol/L extract	0.1	0.1	0.1	0.3	0.10	0.1	0.1	1.4
Mo	µmol/L extract	0.1	0.1	0.1	0.1	0.10	0.1	0.1	0.1

**Table 78** Predicted and measured properties of mixtures used in 2<sup>e</sup> crop trials – *Saxifraga arendisli* at Syngenta.

parameter	unit	Mix11_Model onbemest + volume loss	Mix11_Model onbemest	Mix11_ Eurofins onbemest	Mix11_ Eurofins bemest	Mix9_Model onbemest + volume loss	Mix9_Model onbemest	Mix9_ Eurofins onbemest	Mix9_ Eurofins bemest
DBD	kg/m3	102	101	150	154	109	105	121	134
OM	%, w/w	95	95	56	55	77	77	65	64
MM	%, w/w	5	5	44	45	23	23	35	36
SFS	%, v/v	5	5	8	8	6	6	7	7
TPS	%, v/v	95	95	92	92	94	94	93	93
Water_3	%, v/v	na	na	91	91	85	82	89	89
Water_10	%, v/v	82	81	87	86	70	67	72	67
Water_32	%, v/v	na	na	52	53	46	44	46	46
Water_50	%, v/v	na	na	49	51	42	41	43	42
Air_3	%, v/v	na	na	1	1	8	12	4	4
Air_10	%, v/v	13	14	5	6	24	27	21	25
Air_32	%, v/v	na	na	40	39	48	49	47	47
Air_50	%, v/v	na	na	43	41	51	53	50	50
EAW	%, v/v	35	34.9	38	35	27	26	29	25
OUR	mmol O2/kg DOM/h	3.7	3.7	2.4	2.9	3.5	3.5	5.0	5.2
EC	mS/cm	0.2	0.2	0.1	1.0	0.1	0.1	0	1
pH	-log[H+]	4.3	4.3	4.7	5.1	5.8	5.8	7	6



parameter	unit	Mix11_Model onbemest + volume loss	Mix11_Model onbemest	Mix11_ Eurofins onbemest	Mix11_ Eurofins bemest	Mix9_Model onbemest + volume loss	Mix9_Model onbemest	Mix9_ Eurofins onbemest	Mix9_ Eurofins bemest
NH4	mmol/L extract	0.15	0.2	0.1	1.7	0.10	0.1	0.1	0.4
K	mmol/L extract	0.24	0.2	0.3	1.8	0.40	0.4	0.4	1.7
Na	mmol/L extract	0.05	0.05	0.3	0.6	0.13	0.1	0.3	0.8
Ca	mmol/L extract	0.15	0.2	0.1	1.1	0.10	0.1	0.1	1
Mg	mmol/L extract	0.05	0.1	0.1	0.8	0.10	0.1	0.1	0.9
NO3	mmol/L extract	0.20	0.2	0.2	4.5	0.28	0.3	0.2	4.6
Cl	mmol/L extract	0.05	0.05	0.5	0.6	0.21	0.2	0.3	0.4
SO4	mmol/L extract	0.15	0.2	0.1	1.2	0.10	0.1	0.1	0.5
HCO3	mmol/L extract	0.05	0.1	0.1	0.1	0.10	0.1	0.1	0.1
P	mmol/L extract	0.07	0.07	0.0	0.4	0.07	0.1	0.03	0.77
Si	mmol/L extract	0.04	0.0	0.3	0.3	0.08	0.1	0.28	0.19
Fe	µmol/L extract	3.10	3.1	1.2	29.0	1.14	1.1	21	20
Mn	µmol/L extract	0.48	0.5	0.4	6.0	0.45	0.4	0.4	3.7
Zn	µmol/L extract	0.38	0.4	0.2	1.6	0.28	0.3	0.2	5.6
B	µmol/L extract	2.34	2.3	5.9	17.0	4.39	4.2	1.7	4.8
Cu	µmol/L extract	0.19	0.2	0.1	1.6	0.10	0.1	0.1	1.4
Mo	µmol/L extract	0.13	0.1	0.1	0.1	0.10	0.1	0.1	0.1

**Table 79** Predicted and measured properties of mixtures used in 2<sup>e</sup> crop trials – Lavendula at Beekenkamp.

parameter	unit	Mix12_Model onbemest + volume loss	Mix12_Model onbemest	Mix12_ Eurofins onbemest	Mix12_ Eurofins bemest	Mix9_Model onbemest + volume loss	Mix9_Model onbemest	Mix9_ Eurofins onbemest	Mix9_ Eurofins bemest
DBD	kg/m3	99	102	106	107	109	105	121	134
OM	%, w/w	85	75	69	67	77	77	65	64
MM	%, w/w	15	25	31	33	23	23	35	36
SFS	%, v/v	5	5	6	6	6	6	7	7
TPS	%, v/v	95	95	94	94	94	94	93	93
Water_3	%, v/v	na	na	91	90	85	82	89	89
Water_10	%, v/v	73	73	86	84	70	67	72	67
Water_32	%, v/v	na	na	53	53	46	44	46	46
Water_50	%, v/v	na	na	47	50	42	41	43	42
Air_3	%, v/v	na	na	3	4	8	12	4	4
Air_10	%, v/v	22	22	8	10	24	27	21	25

parameter unit		Mix12_Model onbemest + volume loss	Mix12_Model onbemest	Mix12_ Eurofins onbemest	Mix12_ Eurofins bemest	Mix9_Model onbemest + volume loss	Mix9_Model onbemest	Mix9_ Eurofins onbemest	Mix9_ Eurofins bemest
Air_32	%, v/v	na	na	41	41	48	49	47	47
Air_50	%, v/v	na	na	47	44	51	53	50	50
EAW	%, v/v	31	30.0	39	34	27	26	29	25
OUR	mmol O2/kg DOM/h	4.3	3.8	2.5	3.2	3.5	3.5	5	5
EC	mS/cm	0.1	0.1	0.2	0.9	0.1	0.1	0	1
pH	-log[H+]	4.4	4.4	5.3	5.8	5.8	5.8	7	6
NH4	mmol/L extract	0.13	0.1	0.1	1.2	0.10	0.1	0.1	0.4
K	mmol/L extract	0.20	0.2	0.4	2.4	0.40	0.4	0.4	1.7
Na	mmol/L extract	0.06	0.1	0.4	0.6	0.13	0.1	0.3	0.8
Ca	mmol/L extract	0.13	0.14	0.1	0.7	0.10	0.1	0.1	1
Mg	mmol/L extract	0.06	0.1	0.1	0.8	0.10	0.1	0.1	0.9
NO3	mmol/L extract	0.20	0.2	0.20	3.70	0.28	0.3	0.2	4.6
Cl	mmol/L extract	0.06	0.1	0.3	0.4	0.21	0.2	0.3	0.4
SO4	mmol/L extract	0.13	0.14	0.1	0.9	0.10	0.1	0.1	0.5
HCO3	mmol/L extract	0.06	0.1	0.1	0.1	0.10	0.1	0.1	0.1
P	mmol/L extract	0.06	0.1	0.09	0.83	0.07	0.1	0.03	0.77
Si	mmol/L extract	0.04	0.04	0.4	0.4	0.08	0.1	0.28	0.19
Fe	µmol/L extract	2.36	2.4	2.2	9.7	1.14	1.1	21	20
Mn	µmol/L extract	0.47	0.5	0.4	4.8	0.45	0.4	0.4	3.7
Zn	µmol/L extract	0.33	0.3	0.2	2.8	0.28	0.3	0.2	5.6
B	µmol/L extract	1.87	1.9	5.3	6.7	4.39	4.2	1.7	4.8
Cu	µmol/L extract	0.17	0.2	0.1	1.1	0.10	0.1	0.1	1.4
Mo	µmol/L extract	0.13	0.1	0.1	0.1	0.10	0.1	0.1	0.1

**Table 80** Predicted and measured properties of mixtures used in 3<sup>e</sup> crop trials – Dahlia at Beekenkamp.

parameter unit		Mix13_Model onbemest + volume loss	Mix13_Model onbemest	Mix13_ Eurofins onbemest	Mix13_ Eurofins bemest	Mix14_Model onbemest + volume loss	Mix14_Model onbemest	Mix14_ Eurofins onbemest	Mix14_ Eurofins bemest
DBD	kg/m3	110	101	102	111	98	98	96	97
OM	%, w/w	85	85	78	71	64	64	71	67
MM	%, w/w	15	15	22	29	36	36	29	33
SFS	%, v/v	5	5	6	6	4	4	5	5
TPS	%, v/v	95	95	94	94	96	96	95	95
Water_3	%, v/v	na	na	88	88	85	85	89	89
Water_10	%, v/v	84	77	83	83	72	72	78	78
Water_32	%, v/v	na	na	51	51	48	48	50	50
Water_50	%, v/v	na	na	43	43	43	44	45	45
Air_3	%, v/v	na	na	6	5	11	11	5	6
Air_10	%, v/v	11	18	11	10	24	24	16	16
Air_32	%, v/v	na	na	43	43	48	48	45	45
Air_50	%, v/v	na	na	51	50	52	52	50	49
EAW	%, v/v	36	32.9	40	40	29	28.8	33	33
OUR	mmol O2/kg DOM/h	3.4	3.4	3.4	3.5	2.1	2.1	4.0	2.4
EC	mS/cm	0.1	0.1	0	1	0.1	0.1	0.2	1
pH	-log[H+]	4.3	4.3	4.6	5.7	4.6	4.6	5.0	5.2
NH4	mmol/L extract	0.15	0.1	0.1	0.8	0.10	0.1	0.1	1.2
K	mmol/L extract	0.24	0.2	0.2	3.1	0.32	0.3	0.5	2
Na	mmol/L extract	0.07	0.1	0.3	0.6	0.12	0.1	0.3	0.6
Ca	mmol/L extract	0.15	0.1	0.1	0.8	0.10	0.1	0.1	1.2
Mg	mmol/L extract	0.07	0.07	0.1	0.5	0.10	0.1	0.1	0.8
NO3	mmol/L extract	0.22	0.2	0.20	3.20	0.25	0.3	0.4	5.2
Cl	mmol/L extract	0.07	0.1	0.5	0.5	0.25	0.3	0.2	0.2
SO4	mmol/L extract	0.15	0.1	0.1	1.7	0.10	0.1	0.1	0.8
HCO3	mmol/L extract	0.07	0.07	0.1	0.1	0.10	0.1	0.1	0.1
P	mmol/L extract	0.07	0.1	0.05	0.19	0.05	0.0	0.06	1.1
Si	mmol/L extract	0.05	0.0	0.1	0.4	0.10	0.1	0.1	0.11
Fe	µmol/L extract	2.60	2.4	0.8	10.0	1.35	1.4	3.3	18
Mn	µmol/L extract	0.50	0.5	0.4	4.6	0.42	0.4	0.4	6
Zn	µmol/L extract	0.39	0.4	0.2	3.9	0.25	0.3	0.2	1.4

parameter	unit	Mix13_Model onbemest + volume loss	Mix13_Model onbemest	Mix13_ Eurofins onbemest	Mix13_ Eurofins bemest	Mix14_Model onbemest + volume loss	Mix14_Model onbemest	Mix14_ Eurofins onbemest	Mix14_ Eurofins bemest
B	µmol/L extract	2.60	2.4	9.0	20.0	2.75	2.8	8	15
Cu	µmol/L extract	0.19	0.2	0.1	1.2	0.10	0.1	0.2	0.7
Mo	µmol/L extract	0.16	0.1	0.1	0.1	0.10	0.1	0.1	0.1

**Table 81** Predicted and measured properties of mixtures used in 3<sup>e</sup> crop trials – *Calibrachoa at Florensis*.

parameter	unit	Mix15_Model onbemest + volume loss	Mix15_Model onbemest	Mix15_ Eurofins onbemest	Mix15_ Eurofins bemest	Mix16_Model onbemest + volume loss	Mix16_Model onbemest	Mix16_ Eurofins onbemest	Mix16_ Eurofins bemest	Mix17_Model onbemest + volume loss	Mix17_Model onbemest	Mix17_ Eurofins onbemest	Mix17_ Eurofins bemest
DBD	kg/m3	242	109	102	108	126	119	161	167	103	96	131	135
OM_920	%, w/w	107	76	70	57	72	72	58	57	75	75	51	52
MM	%, w/w	76	24	30	43	28	28	42	43	25	25	49	48
SFS	%, v/v	5	5	6	6	7	7	9	9	5	5	7	7
TPS	%, v/v	95	95	94	94	93	93	91	91	95	95	93	93
Water_3	%, v/v	na	na	83	83	93	87	89	87	92	87	87	88
Water_10	%, v/v	65	66	77	77	79	75	83	82	80	75	81	81
Water_32	%, v/v	na	na	40	41	52	49	53	53	53	49	53	54
Water_50	%, v/v	na	na	47	48	47	44	48	49	47	44	48	49
Air_3	%, v/v	na	na	12	12	0	6	3	4	2	8	6	5
Air_10	%, v/v	30	29	17	17	14	19	9	9	15	20	12	12
Air_32	%, v/v	na	na	47	46	41	44	39	38	42	46	40	39
Air_50	%, v/v	na	na	54	53	46	49	43	42	48	51	45	44
EAW	%, v/v	26.1	26.6	30	29	32	30.5	35	33	33	31.1	33	32
OUR	mmol O2/kg DOM/h	3.3	3.3	2.3	<2.0	3.5	3.5	2.5	2.9	2.2	2.2	2	2.1
EC	mS/cm	0.1	0.2	0.1	1.0	0.1	0.1	0.2	1.2	0.1	0.1	0.2	1
pH	-log[H+]	6.61	6.6	6.3	5.7	4.7	4.7	6.9	6.1	4.5	4.5	6.9	6.1
NH4	mmol/L extract	0.15	0.2	0.1	0.6	0.11	0.1	0.1	1.2	0.11	0.1	0.1	1.2
K	mmol/L extract	0.23	0.2	0.3	2.4	0.41	0.4	0.6	2.4	0.38	0.4	0.7	2.5
Na	mmol/L extract	0.05	0.1	0.4	0.6	0.16	0.2	0.5	1	0.14	0.1	0.5	0.9
Ca	mmol/L extract	0.15	0.15	0.1	1.4	0.11	0.1	0.1	1.2	0.11	0.1	0.1	0.9
Mg	mmol/L extract	0.05	0.1	0.1	0.4	0.11	0.1	0.1	1.4	0.11	0.1	0.1	0.9
NO3	mmol/L extract	0.20	0.2	0.20	4.40	0.27	0.3	0.4	6.2	0.27	0.3	0.4	4.6
Cl	mmol/L extract	0.05	0.1	0.5	0.6	0.28	0.3	0.6	0.6	0.31	0.3	0.5	0.5

parameter	unit	Mix15_Model onbemest + volume loss	Mix15_Model onbemest	Mix15_ Eurofins onbemest	Mix15_ Eurofins bemest	Mix16_Model onbemest + volume loss	Mix16_Model onbemest	Mix16_ Eurofins onbemest	Mix16_ Eurofins bemest	Mix17_Model onbemest + volume loss	Mix17_Model onbemest	Mix17_ Eurofins onbemest	Mix17_ Eurofins bemest
SO4	mmol/L extract	0.15	0.15	0.1	1.1	0.11	0.1	0.1	1.1	0.11	0.1	0.2	1.1
HCO3	mmol/L extract	0.05	0.1	0.1	0.1	0.11	0.1	0.1	0.1	0.11	0.1	0.1	0.1
P	mmol/L extract	0.05	0.1	0.03	0.39	0.07	0.1	0.04	0.87	0.05	0.1	0.05	0.82
Si	mmol/L extract	0.01	0.0	0.1	0.1	0.12	0.1	0.29	0.32	0.12	0.1	0.25	0.26
Fe	µmol/L extract	2.59	2.6	0.8	2.4	2.01	1.9	14	29	1.71	1.6	13	33
Mn	µmol/L extract	0.50	0.5	0.4	8.8	0.48	0.5	0.4	7.8	0.46	0.4	0.4	5.1
Zn	µmol/L extract	0.25	0.3	0.4	5.8	0.27	0.3	0.3	9.8	0.27	0.3	0.5	6.3
B	µmol/L extract	3.20	3.3	4.8	12.0	4.01	3.8	1.6	7	3.01	2.8	2.1	11
Cu	µmol/L extract	0.15	0.2	0.1	3.8	0.11	0.1	0.1	6.4	0.11	0.1	0.1	3.2
Mo	µmol/L extract	0.04905	0.1	0.1	0.1	0.11	0.1	0.1	0.1	0.11	0.1	0.1	0.1

**Table 82** Predicted and measured properties of mixtures used in 3<sup>e</sup> crop trials – Viola at Syngenta.

parameter	unit	Mix18_Model onbemest + volume loss	Mix18_Model onbemest	Mix18_ Eurofins onbemest	Mix18_ Eurofins bemest	Mix19_Model onbemest + volume loss	Mix19_Model onbemest	Mix19_ Eurofins onbemest	Mix19_ Eurofins bemest
DBD	kg/m3	134	126	125	187	112	105	144	145
OM	%, w/w	69	69	59	41	69	69	53	53
MM	%, w/w	31	31	41	59	31	31	47	47
SFS	%, v/v	6	6	7	9	6	6	7	8
TPS	%, v/v	94	94	93	91	94	94	93	93
Water_3	%, v/v	na	na	89	87	94	90	89	90
Water_10	%, v/v	78	73	84	82	83	78	86	84
Water_32	%, v/v	na	na	49	52	54	51	56	56
Water_50	%, v/v	na	na	44	49	48	45	52	51
Air_3	%, v/v	na	na	5	4	0	5	3	3
Air_10	%, v/v	16	21	10	9	10	16	7	8
Air_32	%, v/v	na	na	44	39	39	43	37	37
Air_50	%, v/v	na	na	49	42	45	49	41	41
EAW	%, v/v	32	28.9	40	33	35	33.0	34	33
OUR	mmol O2/kg DOM/h	3.4	3.4	4.6	3.7	2.2	2.2	2.6	2.4
EC	mS/cm	0.3	0.2	0.3	0.8	0.1	0.1	0.4	1
pH	-log[H+]	4.5	4.5	6.0	5.9	4.5	4.5	7.0	6.0

parameter unit		Mix18_Model onbemest + volume loss	Mix18_Model onbemest	Mix18_ Eurofins onbemest	Mix18_ Eurofins bemest	Mix19_Model onbemest + volume loss	Mix19_Model onbemest	Mix19_ Eurofins onbemest	Mix19_ Eurofins bemest
NH4	mmol/L extract	0.15	0.1	0.1	0.8	0.11	0.1	0.2	1
K	mmol/L extract	0.85	0.8	1.0	2.1	0.38	0.4	1	2.5
Na	mmol/L extract	0.19	0.18	0.4	0.7	0.14	0.1	0.6	0.9
Ca	mmol/L extract	0.18	0.2	0.1	0.8	0.11	0.1	0.3	0.8
Mg	mmol/L extract	0.07	0.1	0.1	0.4	0.11	0.1	0.3	1.1
NO3	mmol/L extract	0.43	0.4	0.20	2.70	0.27	0.3	1	4.7
Cl	mmol/L extract	0.53	0.50	0.9	0.9	0.31	0.3	0.5	0.6
SO4	mmol/L extract	0.17	0.2	0.2	0.8	0.11	0.1	0.3	1.1
HCO3	mmol/L extract	0.06	0.1	0.1	0.1	0.11	0.1	0.1	0.1
P	mmol/L extract	0.07	0.1	0.35	0.54	0.05	0.1	0.11	0.67
Si	mmol/L extract	0.04	0.0	0.2	0.3	0.14	0.1	0.26	0.32
Fe	μmol/L extract	2.79	2.6	2.2	8.6	2.19	2.1	18	30
Mn	μmol/L extract	0.55	0.5	0.8	7.7	0.46	0.4	1	4.7
Zn	μmol/L extract	0.37	0.3	0.5	8.7	0.27	0.3	2.3	5.1
B	μmol/L extract	4.85	4.6	11.0	15.0	3.01	2.8	1.5	14
Cu	μmol/L extract	0.19	0.2	0.1	1.4	0.11	0.1	1.8	5.5
Mo	μmol/L extract	0.12	0.1	0.1	0.1	0.11	0.1	0.1	0.1

**Table 83** Predicted and measured properties of mixtures used in 3<sup>e</sup> crop trials – Asparagus at Evanthia.

parameter unit		Mix20_Model onbemest + volume loss	Mix20_Model onbemest	Mix20_ Eurofins onbemest	Mix20_ Eurofins bemest	Mix19_Model onbemest + volume loss	Mix19_Model onbemest	Mix2_ Eurofins onbemest	Mix2_ Eurofins bemest
DBD	kg/m3	129	128	136	129	112	105	144	145
OM	%, w/w	80	81	80	80	69	69	53	53
MM	%, w/w	20	19	20	20	31	31	47	47
SFS	%, v/v	8	8	8	8	6	6	7	8
TPS	%, v/v	92	92	92	92	94	94	93	93
Water_3	%, v/v	76	77	82	85	94	90	89	90
Water_10	%, v/v	69	67	65	66	83	78	86	84
Water_32	%, v/v	46	45	47	45	54	51	56	56
Water_50	%, v/v	42	42	44	41	48	45	52	51
Air_3	%, v/v	16	15	10	7	0	5	3	3
Air_10	%, v/v	23	25	27	27	10	16	7	8

parameter	unit	Mix20_Model onbemest + volume loss	Mix20_Model onbemest	Mix20_ Eurofins onbemest	Mix20_ Eurofins bemest	Mix19_Model onbemest + volume loss	Mix19_Model onbemest	Mix2_ Eurofins onbemest	Mix2_ Eurofins bemest
Air_32	%, v/v	46	47	45	47	39	43	37	37
Air_50	%, v/v	50	51	48	51	45	49	41	41
EAW	%, v/v	27	26	21	25	35	33	34	33
OUR	mmol O2/kg DOM/h	3.7	3.8	5.3	4.7	2.2	2.2	2.6	2.4
EC	mS/cm	0.1	0.1	0.2	0.7	0.1	0.1	0.4	1
pH	-log[H+]	5.1	5.3	6.2	5.8	4.5	4.5	7	6
NH4	mmol/L extract	0.08	0.1	0.1	1.0	0.11	0.1	0.2	1
K	mmol/L extract	0.14	0.3	0.5	1.6	0.38	0.4	1	2.5
Na	mmol/L extract	0.08	0.2	0.3	0.4	0.14	0.1	0.6	0.9
Ca	mmol/L extract	0.08	0.1	0.1	0.5	0.11	0.1	0.3	0.8
Mg	mmol/L extract	0.08	0.10	0.1	0.3	0.11	0.1	0.3	1.1
NO3	mmol/L extract	0.15	0.2	0.20	2.50	0.27	0.3	1	4.7
Cl	mmol/L extract	0.14	0.2	0.5	0.5	0.31	0.3	0.5	0.6
SO4	mmol/L extract	0.08	0.1	0.1	0.7	0.11	0.1	0.3	1.1
HCO3	mmol/L extract	0.08	0.10	0.1	0.1	0.11	0.1	0.1	0.1
P	mmol/L extract	0.02	0.0	0.05	0.41	0.05	0.1	0.11	0.67
Si	mmol/L extract	0.13	0.2	0.2	0.2	0.14	0.1	0.26	0.32
Fe	µmol/L extract	1.92	2.2	5.6	3.9	2.19	2.1	18	30
Mn	µmol/L extract	0.31	0.4	0.4	5.2	0.46	0.4	1	4.7
Zn	µmol/L extract	0.15	0.2	0.7	5.0	0.27	0.3	2.3	5.1
B	µmol/L extract	2.69	4.1	6.0	13.0	3.01	2.8	1.5	14
Cu	µmol/L extract	0.08	0.1	0.1	4.8	0.11	0.1	1.8	5.5
Mo	µmol/L extract	0.08	0.1	0.1	0.1	0.11	0.1	0.1	0.1



## 7.5 pH, EC and nutrients in 1:1.5 water extract of substrates during crop cultivation

**Table 84** pH, EC and nutrients in 1:1.5 water extract of mixtures – 1<sup>st</sup> crop trial - Viola at Beekenkamp.

Mixture	EC (mS/cm)	pH	NH4 (mmol)	K (mmol)	Na (mmol)	Ca (mmol)	Mg (mmol)	NO3 (mmol)	Cl (mmol)	SO4 (mmol)	HCO3 (mmol)	P (mmol)	Si (mmol)	Fe (μmol)	Mn (μmol)	Zn (μmol)	B (μmol)	Cu (μmol)	Mo (μmol)
Sampling date: 28/11/2023																			
reference	0.7	5.9	0.1	0.8	0.6	1.1	1.1	3	0.2	1.1	0.1	0.1	0.19	20	5.7	1.6	8.5	0.8	0.1
Mix 1	1.5	6.4	0.9	5	1	1.6	0.9	6.3	1.4	1.7	0.1	0.38	0.17	3.4	11	25	15	2.2	0.1
Mix 2	1.1	5.9	0.6	2	0.9	1.5	1.4	5.8	0.5	0.9	0.1	0.78	0.24	5.7	4	6.1	3.5	1.4	0.1
Mix 3	1.5	6.3	1	5.5	1.1	1.3	0.7	5.3	2.2	1.5	0.1	0.42	0.19	9.5	7.8	21	21	0.9	0.1
Sampling date: 12/12/2023																			
reference	0.5	6.3	0.1	0.8	0.7	0.7	0.7	2.2	0.4	0.7	0.1	0.11	0.16	13	3.6	2.7	9.8	1.1	0.1
Mix 1	1	6.7	0.1	3.8	1	1.1	0.7	4.4	1.4	1	0.1	0.26	0.2	2.3	1	6.8	16	0.6	0.1
Mix 2	1	6.5	0.6	3.5	0.9	1.1	0.7	4.2	1.5	1	0.1	0.31	0.22	5.1	1.8	17	17	0.9	0.1
Mix 3	0.9	6.2	0.1	1.7	0.9	1.1	1.3	4.6	0.6	0.7	0.1	0.54	0.3	1.4	0.4	3.4	4	1.2	0.1
Sampling day: 03/01/2024																			
reference	0.6	6.6	0.1	0.9	0.9	0.8	0.8	0.3	1.6	1.3	0.1	0.05	0.14	6.7	2	1	11	1.5	0.3
Mix 1	0.8	7.4	0.1	3.2	1	0.6	0.4	0.2	2	1.3	1	0.12	0.21	12	0.4	3.5	9	0.8	0.1
Mix 2	0.6	7.2	0.1	2.4	0.8	0.6	0.3	0.3	1.7	1	0.3	0.16	0.12	8.4	0.4	2.7	10	0.7	0.1
Mix 3	0.6	7	0.1	1.5	0.9	0.5	0.6	0.5	1.6	1	0.1	0.12	0.16	1	0.4	2	2	1.3	0.1

**Table 85** pH, EC and nutrients in 1:1.5 water extract of mixtures – 1<sup>st</sup> crop trial - Viola at Syngenta.

Mixture	EC (mS/cm)	pH	NH4 (mmol)	K (mmol)	Na (mmol)	Ca (mmol)	Mg (mmol)	NO3 (mmol)	Cl (mmol)	SO4 (mmol)	HCO3 (mmol)	P (mmol)	Si (mmol)	Fe (μmol)	Mn (μmol)	Zn (μmol)	B (μmol)	Cu (μmol)	Mo (μmol)
Sampling date: 23/11/2023 before use																			
reference	0.8	6	0.2	1.3	0.5	1.3	1	4.1	0.2	0.8	<0.1	0.37	0.16	8	3.8	1	2.6	0.2	<0.1
Mix 1	1.5	6.2	0.2	5.1	1	2.4	1	7.3	1.4	1.6	<0.1	0.37	0.2	7.9	19	31	19	3.7	<0.1
Mix 2	1.3	6.1	0.8	4.6	1	1.8	0.8	6	1.5	1.4	<0.1	0.41	0.2	23	16	22	19	1.7	<0.1
Mix 3	0.9	5.9	0.7	1.7	0.7	1.2	1.1	4.7	0.4	0.8	<0.1	0.7	0.17	6.5	8	4.3	5.5	1.2	<0.1
Sampling date: 14/12/2023 - Variety Wittrickiana																			
reference	1.2	6.1	0.2	3.5	0.8	1.3	1	6.8	0.5	0.7	<0.1	0.39	0.07	7.7	3.4	1.1	3.7	0.5	<0.1
Mix 1	1.5	6.5	0.1	6.4	1.1	1.4	0.7	8.3	1.4	0.9	<0.1	0.42	0.13	4.9	1.3	4.3	13	1.2	<0.1
Mix 2	1.8	6.2	0.3	7.2	1.3	2.1	1.1	10.2	1.7	1.3	<0.1	0.59	0.15	10	12	8.1	19	0.8	<0.1
Mix 3	1.3	6.2	0.2	4.1	1.1	1.5	1.4	8.2	0.6	0.8	<0.1	0.64	0.17	3.3	0.4	2.5	4.7	1.3	<0.1

Mixture	EC (mS/cm)	pH	NH4 (mmol)	K (mmol)	Na (mmol)	Ca (mmol)	Mg (mmol)	NO3 (mmol)	Cl (mmol)	SO4 (mmol)	HCO3 (mmol)	P (mmol)	Si (mmol)	Fe (μmol)	Mn (μmol)	Zn (μmol)	B (μmol)	Cu (μmol)	Mo (μmol)
Sampling day: 14/12/2024 - Variety Cornuta																			
reference	1.1	6.2	0.3	3.7	0.7	1	0.8	6.1	0.4	0.6	<0.1	0.38	0.06	9.6	2.9	1.4	4.2	0.6	<0.1
Mix 1	1.4	6.5	0.1	6	1	1.3	0.7	7.8	1.2	0.8	<0.1	0.42	0.11	5.5	1.5	5.6	12	1.4	<0.1
Mix 2	1.3	6.3	0.2	5.5	1	1.1	0.5	6.8	1.2	0.7	<0.1	0.42	0.09	8.4	7	3.5	15	0.6	<0.1
Mix 3	1.1	6.2	0.2	3.8	0.9	1.1	1	7	0.5	0.6	<0.1	0.51	0.12	4	0.4	1.6	4.5	1.4	<0.1

**Table 86** pH, EC and nutrients in 1:1.5 water extract of mixtures – 1<sup>st</sup> crop trial - Petunia cuttings at Florensis.

Mixture	EC (mS/cm)	pH	NH4 (mmol)	K (mmol)	Na (mmol)	Ca (mmol)	Mg (mmol)	NO3 (mmol)	Cl (mmol)	SO4 (mmol)	HCO3 (mmol)	P (mmol)	Si (mmol)	Fe (μmol)	Mn (μmol)	Zn (μmol)	B (μmol)	Cu (μmol)	Mo (μmol)
Before the start of the trial																			
Reference	0.8	5.9	2	1.5	0.4	0.7	0.6	2.8	0.2	1.1	<0.1	0.78	0.15	10	1.9	0.7	5.7	0.3	<0.1
Mix 4	0.4	6.3	<0.1	1.7	0.4	0.3	0.2	0.6	0.6	0.7	<0.1	0.29	0.17	17	3.5	13	14	0.9	<0.1
Mix 3	0.8	6.1	<0.1	1.8	0.8	1	1	4	0.5	0.7	<0.1	0.55	0.22	3.2	<0.4	5.4	4.3	0.7	<0.1
At the end of the trial																			
Reference	0.7	6.1	<0.1	1.6	0.4	0.9	0.8	1.1	0.5	1.6	<0.1	0.27	0.12	25	3.4	2.9	11	0.7	<0.1
Mix 4	0.7	6.4	<0.1	2.9	0.3	0.9	0.5	1.3	0.9	1.5	<0.1	0.42	0.09	16	8.1	13	14	1.7	<0.1
Mix 3	0.7	6.7	0.2	2.2	0.4	0.6	0.6	1	0.6	1.4	<0.1	0.31	0.16	5.5	<0.4	3	5.9	2.3	<0.1

**Table 87** pH, EC and nutrients in 1:1.5 water extract of mixtures – 1<sup>st</sup> crop trial - Petunia potted at Florensis.

Mixture	EC (mS/cm)	pH	NH4 (mmol)	K (mmol)	Na (mmol)	Ca (mmol)	Mg (mmol)	NO3 (mmol)	Cl (mmol)	SO4 (mmol)	HCO3 (mmol)	P (mmol)	Si (mmol)	Fe (μmol)	Mn (μmol)	Zn (μmol)	B (μmol)	Cu (μmol)	Mo (μmol)
Before the start of the trial																			
Reference	0.6	5.9	0.2	0.9	0.3	1.1	0.7	1.9	0.2	1.2	<0.1	0.32	0.25	30	0.5	1.4	8.5	0.2	<0.1
Mix 5	0.9	6.5	0.5	3.2	0.7	0.7	0.4	3.7	1.3	0.5	<0.1	0.31	0.14	6.4	6.7	11	15	0.6	<0.1
Mix 6	1.1	6.2	1	2.8	0.8	1.5	1	4.6	1.3	1.3	<0.1	0.69	0.23	6.1	7.5	12	12	1.2	<0.1
Before flowering																			
Reference	0.3	5.8	<0.1	0.3	0.3	0.6	0.4	0.2	0.1	1.2	<0.1	0.04	0.12	42	0.4	1.1	7.5	0.3	<0.1
Mix 5	0.8	6.4	<0.1	3	0.7	0.9	0.5	3.3	1.3	0.8	<0.1	0.27	0.09	5.1	2.3	4.8	16	0.3	<0.1
Mix 6	0.5	6.3	<0.1	1.3	0.5	0.6	0.4	1.7	0.6	0.7	<0.1	0.19	0.09	4.7	0.8	5.5	7.4	0.4	<0.1
At flowering																			
Reference	0.4	5.7	<0.1	0.2	0.3	1	0.6	<0.1	<0.1	1.8	<0.1	0.05	0.08	40	<0.4	1.3	7.3	0.2	<0.1
Mix 5	0.9	6.5	0.3	2.3	0.7	1.5	0.8	3.7	1.1	1.3	<0.1	0.21	0.06	7.6	3.2	9.6	13	0.5	<0.1
Mix 6	0.8	6.3	<0.1	1.6	1	1.5	1	1.9	0.7	2	<0.1	0.25	0.2	7.1	1.8	10	11	0.8	<0.1

**Table 88** pH, EC and nutrients in 1:1.5 water extract of mixtures – 1<sup>st</sup> crop trial - *Monstera* at *Evanthia*.

Mixture	EC (mS/cm)	pH	NH4 (mmol)	K (mmol)	Na (mmol)	Ca (mmol)	Mg (mmol)	NO3 (mmol)	Cl (mmol)	SO4 (mmol)	HCO3 (mmol)	P (mmol)	Si (mmol)	Fe (μmol)	Mn (μmol)	Zn (μmol)	B (μmol)	Cu (μmol)	Mo (μmol)
reference	1.4	5.40	<0.1	3.9	1.1	2.7	1.4	7	1.2	1.8	<0.1	1.3	0.2	12.3	1	1.7	5.2	0.4	<0.1
Mix 7	1	5.7	<0.1	3.4	1	1.3	0.9	3.1	1.1	1.8	0.2	1	0.2	3.3	0.3	0.8	12.7	0.5	<0.1
Mix 3	1.3	6.2	<0.1	3.3	1.2	2.2	1.6	6.6	1.3	1.5	0.3	1.3	0.4	3.8	0.5	0.7	5.8	0.5	<0.1

**Table 89** pH, EC and nutrients in 1:1.5 water extract of mixtures – 2<sup>nd</sup> crop trial - *Calocephalus* at *Florensis*.

Mixture	EC (mS/cm)	pH	NH4 (mmol)	K (mmol)	Na (mmol)	Ca (mmol)	Mg (mmol)	NO3 (mmol)	Cl (mmol)	SO4 (mmol)	HCO3 (mmol)	P (mmol)	Si (mmol)	Fe (μmol)	Mn (μmol)	Zn (μmol)	B (μmol)	Cu (μmol)	Mo (μmol)
Before cultivation																			
Reference	0.9	6.1	1.8	1.7	0.7	0.8	0.8	3.7	0.4	1.1	<0.1	0.68	0.13	13	2.7	1.8	3.1	0.5	<0.1
Mix 8	0.9	5.5	0.7	2.4	0.5	1.1	0.5	3.6	0.6	0.9	<0.1	0.78	0.13	5.3	8.6	2.4	10	2	<0.1
Mix 9	0.6	6.4	0.2	1.5	0.7	0.6	0.6	3.1	0.3	0.4	<0.1	0.51	0.18	10	<0,4	6.2	3.5	0.7	<0.1
Half way of cultivation																			
Reference	0.7	6.2	<0,1	1.9	0.5	0.6	0.7	1.3	0.8	1.1	<0,1	0.36	0.08	13	1.8	1.9	6.4	0.9	<0,1
Mix 8	0.4	6.8	<0,1	2	0.4	0.2	0.1	<0,2	0.7	0.9	<0,1	0.24	0.11	3.6	<0,4	2.8	5.7	2.5	<0,1
Mix 9	0.6	7	<0,1	2.4	0.5	0.4	0.4	0.5	0.8	1.3	<0,1	0.3	0.17	8	6.3	3.6	3.9	3.1	<0,1
End of cultivation																			
Reference	1.6	6.4	0.2	5.6	0.8	1.9	2.1	4.5	1.9	3.3	<0,1	0.71	0.08	18	2.8	4.6	16	2.8	<0,1
Mix 8	1.3	6.7	0.3	5.4	0.7	1.2	1.1	2.9	1.7	2.5	<0,1	0.54	0.1	7.9	4.9	5.1	12	4.6	<0,1
Mix 9	1.5	6.9	0.2	5.8	0.9	1.5	1.5	3.7	1.9	3.1	<0,1	0.41	0.11	11	21	5.9	11	5	<0,1

**Table 90** pH, EC and nutrients in 1:1.5 water extract of mixtures – 2<sup>nd</sup> crop trial - *Strelitzia* at *Evanthia*.

Mixture	EC (mS/cm)	pH	NH4 (mmol)	K (mmol)	Na (mmol)	Ca (mmol)	Mg (mmol)	NO3 (mmol)	Cl (mmol)	SO4 (mmol)	HCO3 (mmol)	P (mmol)	Si (mmol)	Fe (μmol)	Mn (μmol)	Zn (μmol)	B (μmol)	Cu (μmol)	Mo (μmol)
30/07/2024																			
Reference	1	5.7	1.5	2.6	0.8	1.3	0.7	4.7	0.7	1	0.2	0.8	0.2	16.7	1.9	2.8	5.3	0.4	<0.1
Mix 10	1.1	5.2	0.9	2.8	0.9	1.7	1	6.1	0.7	0.9	<0.1	0.7	0.3	11.7	6.6	2.3	10.6	0.5	<0.1
Mix 9	0.7	6.1	<0.1	2	1	0.8	0.7	3.6	0.5	0.6	0.4	0.6	0.3	5.3	0.2	4	4.8	0.6	<0.1
05/09/2024																			
Reference	1.7	4.7	<0.1	2.4	1	3.6	1.8	10.4	1	1.5	<0.1	0.7	0.1	15.2	3.4	0.8	6.5	0.2	<0.1
Mix 10	1.4	4.6	<0.1	1.6	0.9	2.9	1.5	8.7	0.8	1.1	<0.1	0.3	0.2	14	5.4	1	9.9	0.2	<0.1
Mix 9	1.2	5.5	<0.1	1.9	1	1.9	1.5	8.1	0.8	0.9	0.2	0.5	0.2	3.5	0.9	1.1	5.7	0.2	<0.1

**Table 91**    *pH, EC and nutrients in 1:1.5 water extract of mixtures –2<sup>nd</sup> crop trial- Saxifrage at Syngenta.*

Mixture	EC (mS/cm)	pH	NH4 (mmol)	K (mmol)	Na (mmol)	Ca (mmol)	Mg (mmol)	NO3 (mmol)	Cl (mmol)	SO4 (mmol)	HCO3 (mmol)	P (mmol)	Si (mmol)	Fe (μmol)	Mn (μmol)	Zn (μmol)	B (μmol)	Cu (μmol)	Mo (μmol)
Sampling date: before filling the trays (27 June 2024)																			
Reference	1	6.1	1.5	1.4	0.4	1.6	0.5	4.5	0.4	0.8	0.1	0.43	0.12	15	4.5	0.4	4.4	0.2	0.1
Mix 11	0.9	5.4	1.3	1.5	0.6	1.1	0.7	4	0.6	1	< 0,1	0.31	0.25	26	5.2	1.4	13	1.5	< 0,1
Mix 9	0.7	6.4	< 0,1	1.6	0.8	0.6	0.7	3.3	0.4	0.4	< 0,1	0.52	0.2	9.8	0.6	5.6	2.2	0.6	< 0,1
Sampling date: filled trays were stored at 15 oC in a cool room (29 August 2024)																			
Reference	0.9	5.8	1.4	2.1	0.5	1.1	0.5	4.1	0.2	0.9	< 0,1	0.54	0.09	15	3.9	0.8	6	0.1	0.3
Mix 11	0.8	5.2	0.2	2	0.7	1.3	0.9	3.9	0.6	0.9	< 0,1	0.29	0.3	37	7	1.8	11	1	0.2
Mix 9	0.5	6.8	0.1	2	1	0.4	0.4	2	0.4	0.4	< 0,1	0.45	0.25	6.9	< 0,4	4	3.2	0.1	0.3
Sampling date: during cultivation (05 September 2024)																			
Reference	0.8	7.6	0.1	3.8	1.3	0.4	0.2	2.1	0.8	0.8	1.2	0.21	0.05	14	1.6	4.8	3.4	2.9	0.6
Mix 11	0.8	7.5	0.1	3.8	1.3	0.3	0.1	1.9	0.9	0.9	0.5	0.36	0.13	4.1	< 0,4	4.7	3.2	2.7	0.2
Mix 9	0.8	7.5	< 0,1	3.8	0.9	0.5	0.3	3.2	0.4	0.6	0.8	0.38	0.13	1.5	0.9	3.5	3.4	5	< 0,1
Sampling date: at the end of the trial (20 September 2024)																			
Reference	1.1	7.4	0.3	3.1	1	1.7	0.7	5.6	0.7	1.2	< 0,1	0.37	0.04	15	2.6	0.6	7	0.6	< 0,1
Mix 11	0.8	7.2	< 0,1	3.2	1.4	0.4	0.2	2	0.7	1	0.4	0.3	0.12	5.1	0.6	5.6	3.9	4.4	< 0,1
Mix 9	0.9	7.3	< 0,1	3.8	1.3	0.6	0.4	3.4	0.7	0.9	0.6	0.33	0.12	2.4	3.2	3.5	3.9	5.9	< 0,1

**Table 92**    *pH, EC and nutrients in 1:1.5 water extract of mixtures – 3<sup>rd</sup> crop trial - Dahlia at Beekenkamp.*

Mixture	EC (mS/cm)	pH	NH4 (mmol)	K (mmol)	Na (mmol)	Ca (mmol)	Mg (mmol)	NO3 (mmol)	Cl (mmol)	SO4 (mmol)	HCO3 (mmol)	P (mmol)	Si (mmol)	Fe (μmol)	Mn (μmol)	Zn (μmol)	B (μmol)	Cu (μmol)	Mo (μmol)
Reference	0.9	5.9	0.5	1.8	0.7	1.1	0.9	4.3	0.3	0.7	0.1	0.87	0.15	13	4.6	3.4	10	0.8	0.1
Mix 13	0.9	5.7	0.9	2.9	0.7	0.7	0.4	2.9	0.5	1.6	0.1	0.22	0.37	15	4.7	1.2	26	0.9	0.1
Mix 14	0.4	6.3	0.1	1	0.7	0.4	0.3	1.3	0.3	0.6	0.1	0.16	0.31	16	0.4	7.5	5	0.9	0.1

**Table 93** pH, EC and nutrients in 1:1.5 water extract of mixtures – 3<sup>rd</sup> crop trial - Calibrachoa at Florensis.

Mixture	EC (mS/cm)	pH	NH4	K	Na	Ca	Mg	NO3	Cl	SO4	HCO3	P	Si	Fe	Mn	Zn	B	Cu	Mo
Start of cultivation																			
Reference	0.7	5.5	1.6	1.2	0.5	0.4	0.6	2.3	0.2	1	<0,1	0.8	0.1	14	1.6	0.5	5.8	0.4	<0,1
Mix 15	0.9	6.1	0.6	2.3	0.6	1.4	0.4	4.3	0.6	1.1	<0,1	0.35	0.12	4.1	7.8	5.8	12	3.1	<0,1
Mix 16	1	6.5	1.1	1.9	0.9	1	1.1	5.4	0.5	0.8	<0,1	0.51	0.22	18	4.1	6.7	4.8	3.5	<0,1
Mix 17	1.1	6.4	1.8	2.5	0.9	0.8	0.8	4.8	0.4	1.1	<0,1	0.79	0.2	24	6.2	6.8	10	2.5	<0,1
End of cultivation																			
Reference	1.1	5.8	<0,1	2.7	0.7	1.4	0.9	3.4	1.1	1.5	<0,1	0.32	0.15	20	1.2	2.2	11	0.5	<0,1
Mix 15	0.7	6.7	<0,1	3	0.5	0.5	0.3	1.1	1.1	1.3	0.1	0.2	0.18	3.1	1.9	2.5	11	2.5	<0,1
Mix 16	1	6.9	0.1	2.7	0.9	1	1.3	3.9	1.3	1.2	0.1	0.4	0.23	3.7	<0,4	1.4	5	1.9	<0,1
Mix 17	1.2	6.8	<0,1	3.7	0.8	1.2	1.1	3.9	1.4	1.6	<0,1	0.42	0.21	5.5	<0,4	1.7	11	1.4	<0,1
One week extra																			
Reference HIA EDDHA	1	6	0.1	2.8	0.7	1	0.7	2.6	1.1	1.6	<0,1	0.25	0.07	22	1.2	2.8	13	0.7	<0,1
Mix 1 HIA EDDHA	0.9	6.9	0.1	3.8	0.6	0.6	0.3	0.7	1.3	2	<0,1	0.15	0.18	1.2	1.5	3.4	12	3.5	<0,1
Reference DIN Dinteloord	1.2	6.1	<0,1	4.4	0.6	1.4	0.9	3.1	1.4	2.3	<0,1	0.29	0.08	21	1.4	3.8	17	1.1	<0,1
Mix 1 DIN Dinteloord	1	7	<0,1	4.2	0.6	0.9	0.5	1.6	1.4	1.9	0.1	0.29	0.15	1.8	3.8	3.9	12	3.4	<0,1

**Table 94** pH, EC and nutrients in 1:1.5 water extract of mixtures – 3<sup>rd</sup> crop trial - Viola at Syngenta.

Mixture	EC (mS/cm)	pH	NH4 (mmol)	K (mmol)	Na (mmol)	Ca (mmol)	Mg (mmol)	NO3 (mmol)	Cl (mmol)	SO4 (mmol)	HCO3 (mmol)	P (mmol)	Si (mmol)	Fe (μmol)	Mn (μmol)	Zn (μmol)	B (μmol)	Cu (μmol)	Mo (μmol)
Before the start of the trial																			
Reference	1.2	5.9	1.9	1.6	0.5	1.8	0.6	5.9	0.4	1.1	< 0,1	0.44	0.16	16	3.8	0.6	4.7	< 0,1	< 0,1
Mix 18	1.1	6.5	1.1	2.4	0.9	0.9	1.1	5.2	0.6	1.1	< 0,1	0.54	0.26	20	4.6	6.9	8	4.4	< 0,1
Mix 19	0.9	6.1	1.2	2.4	0.9	0.9	0.4	2.7	0.9	1	< 0,1	0.59	0.18	27	8.2	9.6	16	3.9	< 0,1
At the end of the trial - variety VIWF																			
Reference	0.9	6.4	0.1	2.2	0.9	1.3	0.6	3.4	0.9	1.1	< 0,1	0.36	0.03	11	2.1	1.2	6	0.4	< 0,1
Mix 18	0.8	6.9	0.1	2.8	0.9	0.8	0.6	2.4	0.9	1	0.2	0.48	0.1	5.1	1.6	4.5	7	2.6	< 0,1
Mix 19	0.7	6.1	0.2	2.2	0.8	0.6	0.3	2	0.9	0.9	< 0,1	0.42	0.1	14	2	3.7	10	1.2	< 0,1
At the end of the trial - variety VICF																			
Reference	1	6.3	< 0,1	2.9	0.9	1.2	0.6	4.1	1.1	1	< 0,1	0.38	0.04	10	2	0.9	5	0.4	< 0,1
Mix 18	1.1	7	< 0,1	3.7	1	1	1.1	4.3	1.1	1.1	0.5	0.52	0.09	6.1	1.9	3.5	6	4.6	< 0,1
Mix 19	1.2	6.6	0.1	4.2	1.2	1.4	0.7	5	1.4	1.2	0.1	0.68	0.08	5.3	4.7	4	10	1.5	< 0,1







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