sustainability

MDPI

Article

Unveiling Environmental Influences on Sustainable Fertilizer Production through Insect Farming

Malontema Katchali [1,2], Kennedy Senagi [1,*], Edward Richard [2], Dennis Beesigamukama [1], Chrysantus M. Tanga [1], Gina Athanasiou [3], Theodore Zahariadis [3,4], Domenica Casciano [5], Alexandre Lazarou [5] and Henri E. Z. Tonnang [1,6]

1 Data Management, Modeling and Geo-Information Unit, International Centre of Insect Physiology and Ecology, Nairobi P.O. Box 30772-00100, Kenya; mkatchali@icipe.org (M.K.); dbeesigamukama@icipe.org (D.B.); ctanga@icipe.org (C.M.T.); htonnang@icipe.org (H.E.Z.T.)
2 Department of Applied Mathematics, Pan African University Institute for Basic Sciences, Technology, and Innovation, Nairobi P.O. Box 62000-00200, Kenya; edward.onyango@jkuat.ac.ke
3 Synelixis Solutions S.A., Farmakidou 10, 34100 Chalkida, Greece; athanasiou@synelixis.com (G.A.); zahariad@synelixis.com (T.Z.)
4 Department of Agricultural Development, Agri-Food and Natural Resources, National and Kapodistrian University of Athens, 11528 Athens, Greece
5 Zanasi & Partners, 41124 Modena, Italy; domenica.casciano@zanasi-alessandro.eu (D.C.); alexandre.lazarou@zanasi-alessandro.eu (A.L.)
6 School of Agricultural, Earth, and Environmental Sciences, University of KwaZulu-Natal, Pietermaritzburg 3209, South Africa
* Correspondence: ksenagi@icipe.org

Abstract: Entomocomposting is fast and environmentally friendly, boosts soil quality and crop production, and improves resilience to climate change. The black soldier fly larvae (BSFL) catalyze the composting process, but their efficiency is highly influenced by environmental factors and the quality of the substrate. This study employs response surface methodology to discern physical–chemical factors that influence the nutrient quality of BSF frass fertilizer. Internet of Things (IoT) sensors were deployed to monitor in real-time both independent variables (air temperature, moisture content, humidity, and substrate temperature) and dependent variables (nitrogen, phosphorous, and potassium); the data were relayed to the cloud. A non-linear regression model was used to study the relationship between the dependent and independent variables. Results showed that air humidity and air temperature did not have a significant effect on nitrogen and phosphorus accumulation in frass fertilizer, respectively, but phosphorus was significantly influenced by air humidity. On the other hand, neither air temperature nor moisture content has a significant effect on potassium concentration in frass fertilizer. We found that an air temperature of 30 °C and 41.5 °C, substrate temperature of 32.5 °C and 35 °C, moisture content between 70 and 80%, and relative humidity beyond 38% can be conducive for the production of high-quality BSF frass fertilizer. Model validation results showed better robustness of prediction with R^2 values of 63–77%, and R^2_{adj} values of 62–76% for nitrogen, phosphorous, and potassium. Our findings highlight the potential for the application of digital tools as a fast and cost-effective decision support system to optimize insect farming for the production of high-quality frass fertilizer for use in sustainable agriculture and crop production.

Keywords: waste recycling; black soldier fly; frass fertilizer quality; response surface methodology; Internet of Things; sustainable agriculture

Citation: Katchali, M.; Senagi, K.; Richard, E.; Beesigamukama, D.; Tanga, C.M.; Athanasiou, G.; Zahariadis, T.; Casciano, D.; Lazarou, A.; Tonnang, H.E.Z. Unveiling Environmental Influences on Sustainable Fertilizer Production through Insect Farming. *Sustainability* **2024**, *16*, 3746. https://doi.org/10.3390/su16093746

Academic Editors: Zongguo Wen, Yuan Tao, Fan Fei and Yanyan Tang

Received: 23 March 2024
Revised: 22 April 2024
Accepted: 24 April 2024
Published: 30 April 2024

1. Introduction

Composting is the process of converting organic matter into organic fertilizer [1]. The natural process of organic matter decomposition is mainly driven by microorganisms found in the organic wastes [2]. Besides the microorganisms playing an important role in the decomposition process, their activities are highly influenced by temperature, oxygen content, water, pH, moisture level, and carbon-to-nitrogen (C/N) ratio. The final product (i.e., organic fertilizer) is a dark brown, humus-like substance that can be handled, stored, and utilized as an excellent soil conditioner with ease and safety [3,4]. The long production time and low-quality of organic fertilizer associated with conventional composting [5] have encouraged a major shift to the use of insects in recycling organic waste since insects shorten the composting time from 12–24 weeks to only 5 weeks [6]. For instance, the black soldier fly (BSF) (*Hermetia illucens* (L.) (Diptera: Stratiomydiae) can accelerate the composting of organic wastes into quality organic fertilizer and nutrient-rich insect biomass that can be used as a source of feed for poultry, fish, pigs, and other animals [7–11]. The efficacy of BSF frass fertilizer in boosting soil health, plant defense mechanism, crop productivity, and profit margins has been clearly demonstrated [6,7,12]. Notably, the agronomic effectiveness of frass fertilizer is largely influenced by the quality in terms of nutrients and level of maturity and stability [7]. On the other hand, frass fertilizer quality depends on the type and physical–chemical properties of the insect-rearing substrates and environmental conditions (such as temperature, humidity, and aeration rate) provided during the waste valorization process [9,13]. The provision of sub-optimal conditions and low-quality substrates affects the bioconversion process and the quality of frass fertilizer generated. Therefore, it is critical to optimize the entomocomposting process to improve the efficiency and quality of frass fertilizer. Physical, chemical, and biological strategies have been used to optimize the composting process with varying levels of success [14,15].

Improvements and optimization in the composting process can be further achieved through the application of mathematical models. Petric and Mustafić [16] introduced a mathematical model focused on microbial kinetics offering insights into the complex nature of the composting system. This model considers various parameters such as temperature and oxygen, among others, to better understand the dynamics within the composting environment. Similarly, Vasiliadou et al. [17] established a comprehensive first-order kinetics model for composting olive mill waste. This model incorporates considerations for heat transport, organic substrate degradation, oxygen consumption, carbon dioxide generation, and the presence of biological matter, providing a detailed framework for analyzing and optimizing the composting process.

Composting models can be constructed using either analytical or numerical methods, providing valuable insights into the optimization of the composting process. Courvoisier and Clark [18] employed the finite difference method to create a numerical model of the composting process. The study elucidated complex interactions such as heat transfer, gas exchange, and microbial population dynamics. This model has implications for improving waste management practices and enhancing environmental sustainability. Bongochgetsakul and Ishida [19] presented a novel approach for optimizing large-scale composting facilities by integrating numerical modeling with a 3D finite element system. Their method enabled the calculation of mass/energy distribution influenced by biological activities, leading to cost-effective and efficient facility design without the need for trial tests. Furthermore, mathematical models coupled with real-time data can significantly improve the management of insect-driven waste composting processes. These models take into account environmental parameters such as relative humidity and ambient temperature, which are crucial for insect growth, organic matter decomposition, and nutrient transformation processes [20–23]. Through the use and application of such strategies, composting facility management and design can be revolutionized, leading to improved performance, economic viability, and the advancement of sustainable waste management solutions. Many interconnected factors, such as population expansion, changes in high household consumption habits, economic development, shifts in income, urbanization, and industrialization, have been linked to the increase in waste production and its diversity [24]. The increasing variety of waste categories, including electronic, urban, hospital, and industrial waste, highlights the necessity of accurately classifying garbage and developing efficient management standards [25–27]. As a result, Zafaranlouei et al. [28] addressed the complexities of waste management in Iran by assessing 21 types of waste across economic, social, and environmental criteria.

The methods employed included a novel decision-making approach combining the base criterion method (BCM) and combined compromise solution (CoCoSo) under fuzzy Z-numbers. Sensitivity analysis revealed direct profit and reduced landfill as crucial criteria for sustainable waste management with electronic waste requiring particular attention for recycling and sustainable management. However, the study's focus on a specific urban setting and the complexity of incorporating Z-numbers pose a limitation to its generalizability as suggested by [26].

In the BSF-assisted waste valorization process, previous studies focused on optimizing the quality of larvae for animal feeding purposes [21], while others focused on substrates parameters only [20]. Nonetheless, it is necessary to unravel crucial environmental parameters in the BSF-assisted composting process. This study employs a response surface methodology (RSM) approach to model the prediction of nutrient levels in BSF frass fertilizer assessing how various environmental factors impact the nutrient concentrations within the produced organic fertilizer generated. Through the RSM approach, non-linear regression models are utilized to uncover the complex relationships between nutrient concentrations in frass fertilizer and principal environmental factors that drive the BSF-assisted organic waste valorization process, thereby providing a more comprehensive understanding of how to improve the efficiency and outcome of this sustainable waste management strategy. The following are the key contributions of this research work:

- The integration of the response surface methodology (RSM) and Internet of Things (IoT) technology to optimize black soldier fly larvae (BSFL) entomocomposting process (based on environmental factors) in the production of high-quality frass fertilizer.
- Implementation of a data-driven solution to discern important environmental variables that influence the nutrients generated in the BSFL composting process.
- Proposing a sustainable resilient framework for organic waste valorization and management through BSFL-driven recycling systems toward a circular economy.

The rest of this paper is structured as follows: the experimental setup, data acquisition, and the RSM model's design are described in Section 2; Section 3 outlines the results, which are then discussed in Section 4; and Section 5 concludes this article.

2. Materials and Methods

2.1. Frass Fertilizer Production Experiments

Black solder fly-rearing experiments were conducted at the animal rearing and quarantine unit of the International Center of Insect Physiology and Ecology (*icipe*), Nairobi, Kenya. The purpose of these experiments was to assess the influence of environmental factors on substrate decomposition and nutrient accumulation during BSF-driven composting. The experiments were conducted using potato waste from a local food-processing facility situated in Nairobi Kenya and 5-day-old BSF larvae. Before commencing the experiments, comprehensive laboratory analyses were conducted on the potato waste to evaluate various physical–chemical properties. During the experiments, equal amounts of organic wastes (potato waste) and 14.3 g of 5-day-old BSFL sourced from a colony meticulously maintained at *icipe* were introduced into plastic trays measuring 55 cm × 38 cm × 10 cm. These trays held 10 kg of potato waste: equivalent to 2 kg of dry weight. Following the protocols outlined in [6], the BSFL were reared until they reached the harvesting stage. Thereafter, the FarmShield [29] Internet of Things (IoT) device was placed in the trays to collect the following variables: substrate temperature in °C, air temperature in °C, moisture content of the substrate in percentage (%), relative humidity in percentage (%), and substrate nutrients (that is, nitrogen, potassium, and phosphorus in mg/kg). The IoT transmitted this set of data to the *icipe* cloud database platform in real-time every hour. The experimental environment was set up with an average air temperature of 33.35 °C. BSFL were reared on potato peelings as organic waste (i.e., the substrate). This continuous stream of information served as a foundation for our computational modeling efforts, allowing us to analyze the environmental factors influencing the BSFL ability in their role of substrate decomposition and nutrient accumulation. This dataset played a pivotal role in the validation of our model and in estimating critical parameters. The treatmentswere replicated three times.

2.2. Design of the Response Surface Methodology (RSM)

In this study, the RSM was employed to investigate the nutrient content within decomposing organic waste during the rearing of BSFL. The investigation focused on four independent variables: air and substrate temperatures, moisture content, and relative humidity with nitrogen (N), phosphorus (P), and potassium (K) serving as the dependent variables. A non-linear regression model, a variant of RMS, was developed to establish the relationship between the response (N-P-K) and the independent variables. This relationship was articulated using a second-order polynomial equation [30,31] referred to as Equation (1). The equations tailored to each dependent variable were coded into MINITAB 21.4.1 [32] software for analysis. The collected experimental data were then used to calibrate these equations, enabling a comprehensive understanding of how environmental conditions influence the nutrient concentrations in the resulting frassfertilizer:

$$y = c_o + \sum_{i=1}^{n} c_i x_i + \sum_{i=1}^{n} c_{ii} x_i^2 + \sum_{i=1}^{n-1} \sum_{j=1}^{n} c_{ij} x_i x_j \quad (1)$$

where

y is the predicted response level;

c_o is the constant coefficient;

c_i is the coefficients of linear terms;

c_{ij} is the interaction coefficients;

c_{ii} is the coefficients of quadratic terms;

x_i, x_j are the values of the experimental variables.

2.3. Model Fitting and Evaluation

The analytical process, described in Equation (1), served as the foundation model for analyzing the relationship between independent variables (air and substrate temperatures, moisture content, and relative humidity) and the dependent variables (nutrient concentrations of nitrogen, phosphorus, and potassium) in the context of composting with BSFL. The range of independent variables, derived from experimental data, is incorporated in Table 1 to determine the estimated coefficients for the models. With these coefficients in place, the non-linear (Equation (1)) was evaluated using the coefficient of determination R^2 as in Equation (3) and adjusted-R^2 presented in Equation (4). The model's statistical significance was evaluated using the analysis of variance (ANOVA) components based on the significance level compared to the threshold value 0.05, i.e, Adjusted Sum of Squares (Adj SS) and adjusted mean squares (Adj MS), defined in Equations (5) and (6), respectively. Further statistical evaluation included examining the F-value and p-value, essential ANOVA components for assessing model validity, and the strength of the relationships between variables. To ascertain the statistical significance and identify any biases within the model, plots of the normal probability distribution and the standard residuals were generated. This analytical step was crucial for visually assessing the distribution of residuals and their conformity to normal distribution, essential for validating the model's assumptions. The integration of actual data into the non-linear model, which had been fitted with the estimated coefficients, provides deeper insights into the modeling experiments. The visualization of these patterns, through the lens of normal probability distribution and standardized residual figures, facilitates a comprehensive understanding of the model's performance and its alignment with empirical observations. This approach not only highlights the model's accuracy in capturing the relationships between variables but also aids in identifying potential areas of improvement by revealing systematic deviations or anomalies in the data fit.

Table 1. Levels of experimental independent variables considered during the study.

Variables	SI Units	Annotation	Lower Value	Upper Value
Air humidity	Percentage (%)	x_1	29.1	41.9
Air temperature	Degree Celsius (°C)	x_2	22	46.7
Moisture content	Percentage (%)	x_3	27.0	148.4
Substrate temperature	Degree Celsius (°C)	x_4	30	43

$$RSS = \sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \tag{2}$$

$$R^2 = 1 - \frac{RSS}{TSS} \tag{3}$$

$$R^2_{adj} = 1 - \frac{(1 - R^2)\cdot(n-1)}{n-k-1} \tag{4}$$

$$\text{Adj SS} = SS - \frac{TSS}{k} \tag{5}$$

$$\text{Adj MS} = \frac{\text{Adj SS}}{DF} \tag{6}$$

where,

RSS is the sum of squares of residuals;
TSS is the total sum of squares;
n is the number of observations;
k is the number of independent variables;
SS is the sum of squares;
DF is the degree of freedom.

3. Results

3.1. Nitrogen Accumulation in Frass Fertilizer

The ANOVA results presented in Table 2 show that regression (linear, square, and interaction) relationships within the independent variables were significant (with a $p < 0.05$). Table 3 highlights the estimated regression coefficients for response (N) and other statistical validation values and shows that air humidity was not significant (with a p-value > 0.05) for the generation of nitrogen, while the remaining variables were found significant for the process.

From Table 3, the positive sign in front of the terms (independent variable) indicates a favorable effect while a negative sign indicates an unfavorable effect. Therefore, the air temperature, the substrate temperature, the rapid fluctuation effect of the moisture content, the interaction of the air humidity and moisture content, the interaction of the air humidity and substrate temperature, the interaction of the air temperature and moisture content, and the interaction of the air temperature and substrate temperature play an important role in increasing the nitrogen yield. Conversely, the accelerated changes in the air humidity and air temperature, the interaction between the air humidity and air temperature, and the interaction between the moisture content and substrate temperature exhibit a negative influence, leading to a decrease in nitrogen yield.

The normal probability plot presented in Figure 1a indicates a normal distribution of residuals obtained from the model. In Figure 1b, the residuals' consistent spread, around (y = 0, which means the error is zero), suggests that the model maintains a steady level of accuracy across a range of projected values. The overall prediction accuracy has an R^2 of 76.9% and R^2_{adj} of 76%.

Considering the most significant variables stated in Table 3, the corresponding three-dimensional response surface plots for nitrogen presented in Figure 2a show that the maximum nitrogen content was obtained at an air temperature of approximately between

41.5 °C and 45 °C and a substrate temperature of 32.5 °C. The maximum nitrogen was generated when the air temperature was 42.5 °C and the moisture content was toward 90% (Figure 2b). It was noted that a combination of substrate temperatures (between 25 °C and 32 °C) and high moisture levels (approximately 80%) would produce fertilizer with the maximum nitrogen levels (Figure 2c).

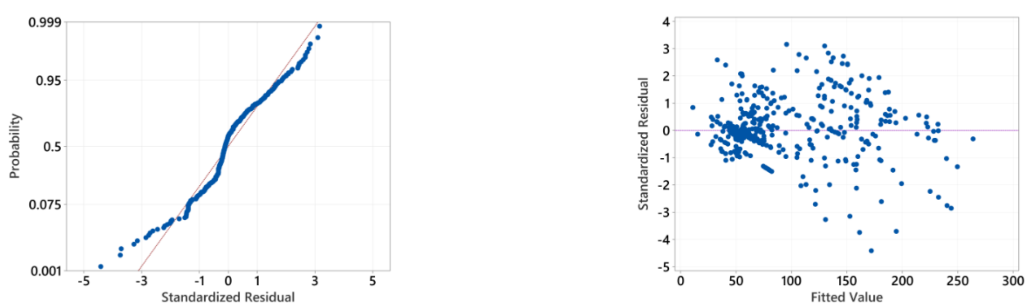
Table 2. ANOVA for the full regression model for nitrogen concentration in frass fertilizer, elucidating the significance of terms within the model analysis.

Source	DF	SS	Adj SS	Adj MS	F-Value	*p*-Value
Regression Model	14	826,514	826,514	59,036.7	86.68	0.000
Linear	4	472,732	171,535	42,883.7	62.96	0.000
Square	4	178,450	74,321	18,580.4	27.28	0.000
Interaction between factors	6	175,332	175,332	29,221.9	42.90	0.000
Residual Error	365	248,607	248,607	681.1		
Lack-of-Fit	338	248,607	248,607	735.5		
Pure Error	27	0	0	0.0		
Total	379	1,075,121				

Table 3. Estimated regression coefficients for nitrogen accumulation in frass fertilizer.

Term	Estimated Coefficient	Standard Error of Coefficient	T-Statistic	*p*-Value	Remarks
Constant (c_o)	121.021	5.336	22.680	0.000	
Air humidity	15.878	9.345	1.699	0.090	Non-significant
Air temperature	39.474	10.944	3.607	0.000	Significant
Moisture content	54.828	15.060	3.641	0.000	Significant
Substrate temperature	85.977	10.569	8.135	0.000	Significant
Air humidity^2	−8.700	16.095	−0.541	0.589	Non-significant
Air temperature^2	−121.940	14.898	−8.185	0.000	Significant
Moisture content^2	38.811	19.309	2.010	0.045	Significant
Substrate temperature^2	23.092	8.814	2.620	0.009	Significant
Air humidity × air temperature	−112.653	24.145	−4.666	0.000	Significant
Air humidity × moisture content	85.410	24.480	3.489	0.001	Significant
Air humidity × substrate temperature	58.580	14.427	4.061	0.000	Significant
Air temperature × moisture content	92.589	37.313	2.481	0.014	Significant
Air temperature × substrate temperature	148.590	15.596	9.527	0.000	Significant
Moisture content × substrate temperature	−84.313	17.982	−4.689	0.000	Significant

Variables (air temperature, moisture content, and substrate temperature) with *p*-value of <0.05 were considered to be the most significant variables.



(**a**) (**b**)

Figure 1. The normal probability and the residual depiction indicating a normal distribution (**a**), the randomness and consistent spread of residuals around zero (**b**), validating the model's unbiased nitrogen predictions and uniform accuracy across predicted values.

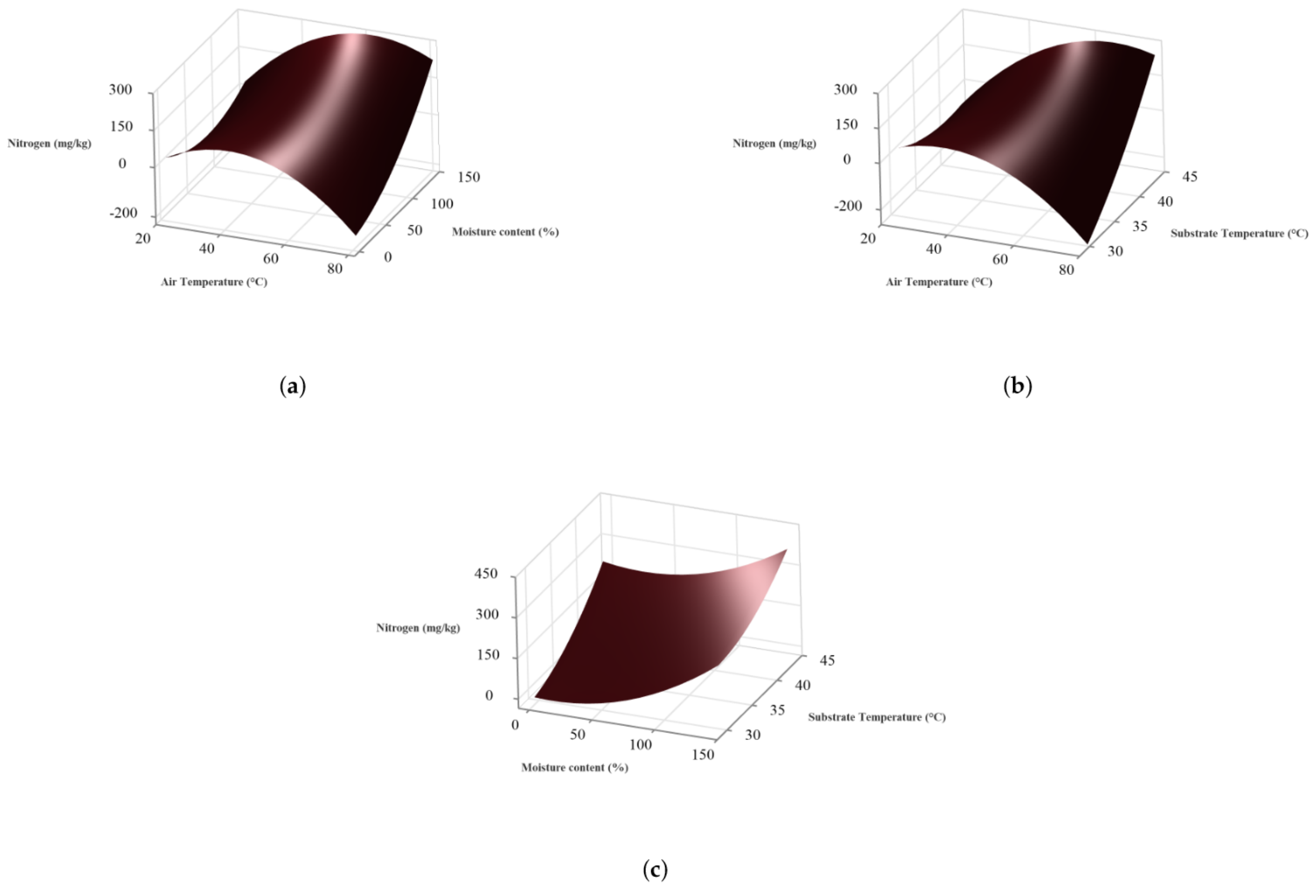


Figure 2. Three-dimensional trends of nitrogen accumulation in frass fertilizer by pairing (**a**) air temperature and moisture content, (**b**) air temperature and substrate temperature and (**c**) moisture content and air temperature.

3.2. Phosphorus Accumulation in Frass Fertilizer

The results in Table 4 show that regression (linear, square, and interaction) relationships within the independent variables have a significant ($p < 0.05$) impact on P accumulation in frass fertilizer. After fitting the generalized non-linear regression model expressed in Equation (1) with actual data parameters, the resulting empirical model is given in Table 5. While humidity, substrate temperature and moisture emerge as key contributors in phosphorus manufacturing, the air temperature is non-significant, leading to an antagonist effect when combined with other factors (such as moisture content).

In Table 5, the positive coefficients associated with moisture content, substrate temperature, rapid fluctuations in air temperature, substrate temperature and interactions between air humidity–air temperature and moisture content–substrate temperature show their importance in enhancing phosphorus accumulation. An evaluation of the model accuracy revealed R^2 and R^2_{adj} of 63.6% and 62.63%, respectively. The normal probability and standardized residual plot presented in Figure 3a,b highlight the range of occurred errors associated with their occurrence probability within the data.

The substrate moisture content, substrate temperature, rapid fluctuations in air temperature, and substrate temperature, and the interactions between air humidity and air temperature, and moisture content and substrate temperature were positively correlated with phosphorus accumulation.

It was found that air humidity of 34% to 37.5% combined with a substrate moisture content of between 50% and 74% reduced phosphorus accumulation in frass fertilizer (less than 100 mg/kg) (Figure 4a). Similarly, within the same range of air humidity coupled with a substrate temperature of 33.5 °C to 36.5 °C, a plateau concentration of phosphorus, presumably greater than or equal to 100 mg/kg was observed (Figure 4b). On the other hand, phosphorus concentration increased with the rise in substrate temperature up to 36 °C, accompanied by a monotonic increase in moisture content (Figure 4c). However, beyond 36 °C, the phosphorus concentration started to decrease.

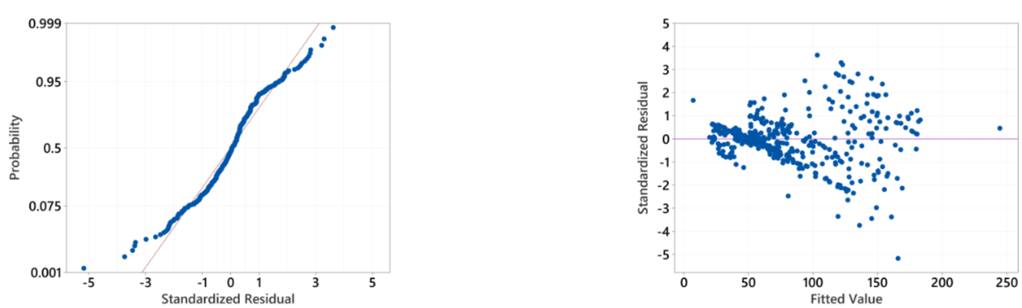
Table 4. ANOVA for the full quadratic model for phosphorus accumulation in frass fertilizer elucidating the significance of terms within the model analysis.

Source	DF	Adj SS	Adj MS	F-Value	*p*-Value
Regression Model	14	1,075,885	76,848.9	64.81	0.000
Linear	4	160,725	40,181.1	33.89	0.000
Square	4	117,409	29,352.2	24.76	0.000
Interaction between factors	6	53,672	8945.4	7.54	0.000
Error	519	615,361	1185.7		
Lack-of-Fit	481	614,881	1278.3		
Pure Error	38	481	12.6		
Total	533	1,691,247			

Table 5. Regression coefficients and level of significance of factors influencing phosphorus accumulation in frass fertilizer.

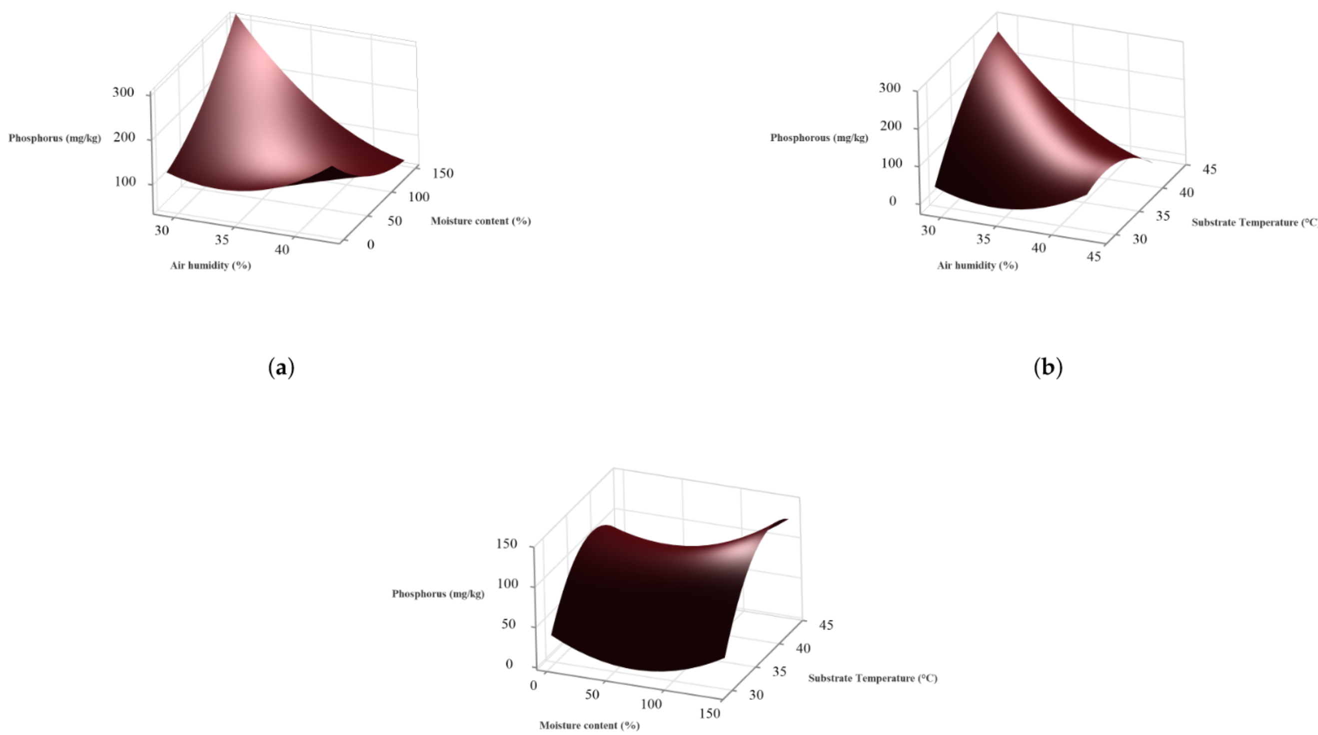
Term	Estimated Coefficient	Standard Error of Coefficient	T-Statistic	*p*-Value	Remarks
Constant (c_o)	−881	4.51	20.21	0.000	Significant
Air humidity	−46.3	9.15	−5.41	0.000	Significant
Air temperature	−17.4	8.58	−1.00	0.316	Non-significant
Moisture content	120.7	8.76	4.49	0.000	Significant
Substrate temperature	2.56	12.2	1.98	0.049	Significant
Air humidity^2	1.03	20.1	2.44	0.015	Significant
Air temperature^2	0.12	16.3	6.80	0.000	Significant
Moisture content^2	−0.65	8.82	2.89	0.004	Significant
Substrate temperature^2	0.05	7.97	−4.02	0.000	Significant
Air humidity × air temperature	0.51	27.9	3.82	0.000	Significant
Air humidity × moisture content	−1.48	20.0	−2.57	0.011	Significant
Air humidity × substrate temperature	−0.1	14.4	−4.93	0.000	Significant
Air temperature × substrate temperature	−0.01	17.5	−4.21	0.000	Significant
Air temperature × moisture content	−0.34	22.9	−1.00	0.316	Non-significant
Moisture content × substrate temperature	0.03	12.9	−2.00	0.031	Significant

The variables (air humidity, moisture content, and substrate temperature) with *p*-value of <0.05 were considered to be the most significant.



(**a**) (**b**)

Figure 3. The normal probability and the residual depiction indicating a normal distribution (**a**), the randomness and consistent spread of residuals around zero (**b**), validating the model's unbiased phosphorus predictions and uniform accuracy across predicted values.



(**c**)

Figure 4. Three-dimensional trends of phosphorus accumulation in frass fertilizer by pairing (**a**) air humidity and moisture content, (**b**) air humidity and substrate temperature and (**c**) moisture content and substrate temperature.

3.3. Potassium Accumulation in Frass Fertilizer

Table 6 reveals that just like in the case of phosphorus, the interaction between factors, linear combination, and quadratic relationship is pivotal for potassium accumulation in the frass fertilizer. Table 7 shows that potassium concentration significantly relies on air humidity and substrate temperature, whereas air temperature and moisture content are shown to be non-significant. It was observed that air humidity, air temperature, and rapid fluctuations in moisture content lead to a reduction in potassium levels. Moreover, interactions such as air temperature–moisture content and air humidity–substrate temperature do not favor potassium accumulation. Figure 5a,b show that the model was fairly accurate to the data coupled with the overall prediction accuracy of $R^2 = 63.1\%$, $R^2_{adj} = 62.1\%$ signifying the model's ability to effectively capture and explain a significant proportion of the variability in the data, indicating quite good predictive performance for the potassium level.

Considering the two significant independent variables, the corresponding three-dimensional surface plot is illustrated in Figure 6. Results showed that the potassium concentration is predominantly high, ranging from around 100 mg/kg to 200 mg/kg and above, exhibiting a plateau-like pattern. This occurs within the range of air humidity, which varies from 25% to 37.5%, coupled with substrate temperatures between 35 °C and 38 °C. In addition, the combination of favorable factors enhanced the potassium concentration, indicating increased potassium content.

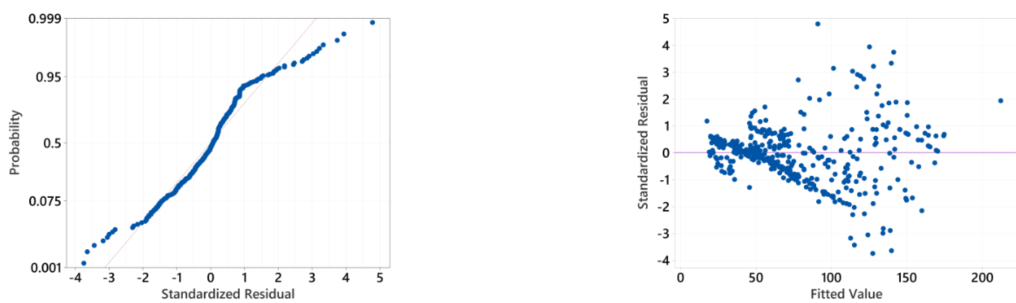
Table 6. ANOVA for the full regression model for potassium accumulation in frass fertilizer elucidating the significance of terms within the model analysis.

Source	DF	Adj SS	Adj MS	F-Value	*p*-Value
Regression Model	14	961,065	68,647.5	63.41	0.000
Linear	4	114,174	28,543.4	26.37	0.000
Square	4	146,978	36,744.4	33.94	0.000
Interaction between factors	6	52,117	8686.2	8.02	0.000
Error	519	561,831	1082.5		
Lack-of-Fit	481	561,350	1167.0		
Pure Error	38	481	12.6		
Total	533	1,522,896			

Table 7. Regression coefficients and statistics regarding potassium accumulation in frass fertilizer.

Term	Estimated Coefficient	Standard Error of Coefficient	T-Statistic	*p*-Value	Remarks
Constant (C_0)	−198	4.31	18.52	0.000	
Air humidity	−76	8.74	−5.08	0.000	Significant
Air temperature	−18.5	8.20	−0.73	0.466	Non-significant
Moisture content	119.2	11.7	1.49	0.137	Non-significant
Substrate temperature	0.25	8.37	3.40	0.001	Significant
Air humidity^2	1.32	19.2	3.28	0.001	Significant
Air temperature^2	0.13	15.6	7.60	0.000	Significant
Moisture content^2	−0.68	8.43	4.42	0.000	Significant
Substrate temperature^2	0.01	7.61	−4.41	0.000	Significant
Air humidity × air temperature	0.54	26.7	4.29	0.000	Significant
Air humidity × substrate temperature	−0.04	13.8	−4.87	0.000	Significant
Air humidity × moisture content	−1.4	19.1	−1.03	0.302	Non-significant
Air temperature × substrate temperature	−0.02	16.7	−4.57	0.000	Significant
Air temperature × moisture content	−0.36	21.9	−1.61	0.109	Non-significant
Substrate temperature × moisture content	0.03	7.93	2.10	0.036	Significant

The variables (air humidity and substrate temperature) with *p*-value of <0.05 were considered to be the most significant.



(**a**) (**b**)

Figure 5. The normal probability and the residual depiction indicating a normal distribution (**a**), the randomness and consistent spread of residuals around zero (**b**), validating the model's unbiased potassium predictions and uniform accuracy across predicted values.

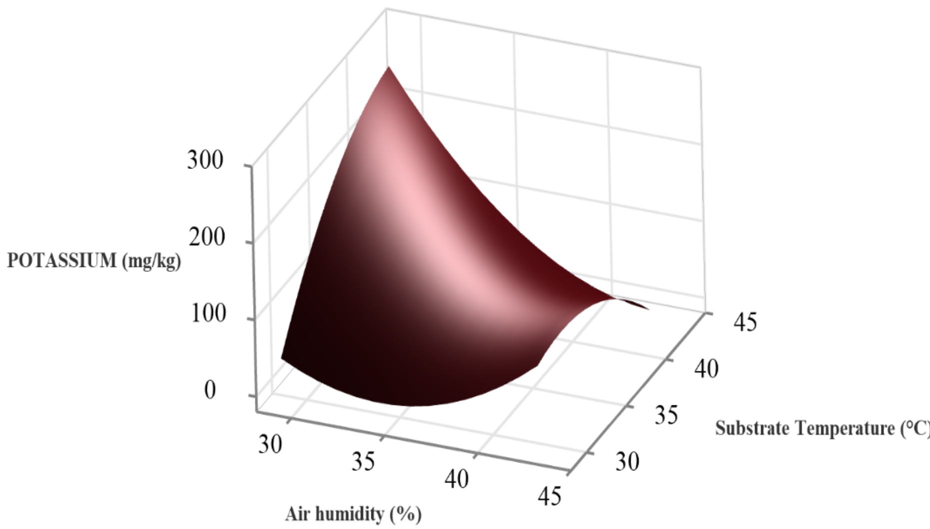


Figure 6. The 3-D trends of the combined effect of air humidity and substrate temperature on the potassium concentration in frass fertilizer.

4. Discussion

4.1. Effect of Environmental Factors on Nitrogen Accumulation in Frass Fertilizer

Our findings showed that air temperature, moisture content, and substrate temperature significantly influenced nitrogen accumulation in frass fertilizer. Moreover, the optimal substrate temperature identified aligns with the 30 °C to 35 °C reported by Padmanabha et al. [33] for both nitrogen accumulation and efficient BSF production. The substrate temperature is pivotal for microbial activities [17], enzymatic processes [34], and chemical reactions [35] essential in nitrogen transformation. The identified optimal conditions fall within the mesophilic advantage for mitigating ammonia volatilization prevalent at thermophilic temperatures (>45 °C). Previous studies by MacDonald et al. [36] also found that the rate of microbial respiration and the mineralization of nitrogen waste degradation are temperature-dependent. In Hu et al. [37], it is further highlighted how moisture variation impacts microbial activities, oxygen concentration, and nutrient transport. Excessive moisture potentially leads to nitrogen loss via denitrification and impeding BSF larval growth. Thus, while temperature and moisture content are crucial, their effects might diminish the perceived impact of air humidity on nitrogen accumulation [38]. Nonetheless, both air temperature and relative humidity indirectly influence substrate moisture and temperature, thereby affecting nitrogen transformation during BSF-assisted composting. In essence, the interplay of air humidity, temperature, and moisture content plays a significant role in nitrogen accumulation, waste valorization, and BSF growth dynamics.

4.2. Phosphorus and Potassium Accumulation in Frass Fertilizer as Influenced by Environmental Factors

The observed adverse effect of air humidity on phosphorus accumulation in our study might be attributed to its potential to limit microbial activity essential for nutrient mineralization and organic matter decomposition. Previous studies [39–41] have demonstrated that the optimal air humidity range for BSFL typically falls within 40% to 70%. Thus, deviations from this range can impact the nutrient cycling in the composting system. Suboptimal air humidity conditions may hinder the efficiency of microbial processes, leading to decreased phosphorus mineralization and accumulation in the frass fertilizer. Moreover, Alanna and Cory [42] noted that humidity's impact on reaction kinetics (for instance mineralization), substrate temperature on reaction rates (for instance, phosphatase enzyme activities), and moisture's role in providing a conducive environment are crucial in the composting process. The identified temperature of 33.5 °C to 36.5 °C aligns with the study of Shah et al. [43], which noted that increasing temperature towards the thermophilic range reduces microbial activities, especially bacterial ones. It should be noted that temperatures above 35 °C are not favorable for BSF growth due to the effects on larval feeding and stress that could lead to larval mortality. Furthermore, Eskander and Saleh [44] noted that high temperatures enhance evaporation and reduce water availability in the substrate, which consequently affects BSF feeding, and phosphorus release in the substrate. Therefore, extremely high temperatures lead to thermal stress, and in some cases result in toxicity, which contributes to the decline or denaturation of phosphatase enzyme activities, which leads to poor phosphorus accumulation.

It was also observed that the concentration of potassium is significantly influenced by air humidity and substrate temperature. According to Van Looveren et al. [45], microbial activities involved in composting, especially those driven by BSFL, are sensitive to air humidity and substrate temperature, therefore making these factors critical in regulating potassium accumulation. Furthermore, Van Peer et al. [46] mentioned that these factors affect the bacteria population that supports the digestion and the potassium chloride solution extraction in the composting process. Generally, the substrate temperature within the optimal range for BSFL development likely contributes to increased metabolic activity, which can positively influence the potassium composition [47].

4.3. Implications for Scaling of Frass Fertilizer Production Technologies

The results presented in the previous sections unravel the intricate relationships among environmental variables and their significance in influencing nutrient content in BSF frass fertilizer. The positive coefficients associated with these pivotal variables underscore their direct (proportional relationships) effect on nutrient accumulation in frass fertilizer. This notion aligns with the principles of continuous monitoring and precision farming technologies advocated by Dinnes et al. [48], where sensors (monitoring) and precision farming technologies play a crucial role in optimal frass fertilizer production. Farmers can use enclosed structures greenhouses and insulating techniques to protect against excessive sunlight and control air and substrate temperatures within acceptable limits, as they are factors impacting nutrient yield in BSF production systems. The optimal range of substrate moisture determined is comparable to the moisture content of commonly organic substrates for BSF production and falls within ideal ranges for maximal nutrient output. Therefore, BSF farmers will not incur costs of moisture optimization because the available organic wastes already have optimal moisture levels. To further improve conditions and raise the quality of frass fertilizer production, farmers can place a priority on choosing a variety of nutrient-rich organic waste, optimize ventilation techniques for aeration or oxygen availability, and consider the possibility of integrating intelligence and sensors for real-time monitoring. For example, by prioritizing significant factors (such as air temperature, moisture content, and substrate temperature as stated in this research) that influence nitrogen accumulation, farmers can optimize the investment of the aforementioned resources. This, however, has cost implications on insect farming and frass fertilizer production. For the tropical regions where temperatures range between 25 and 35 °C for most of the year, there is little or no requirement for artificial heating since the determined air temperature falls within the range of tropical region temperatures. This will go a long way in reducing energy requirements for BSF production for farmers in the tropical regions compared to counterparts in other parts of the world where artificial heating is mandatory to maintain optimal temperatures for BSF waste bio-conversion. The availability of favorable weather in the tropics is an incentive for increased adoption of BSF and private sector investment in insect farming in Africa and other regions.

In essence, the results paint a portrait of the intricate relationships within the composting system. This understanding of the impact of individual variables provides a road map for practitioners seeking to harness the full potential of BSF-composted fertilizer. Examining the results, stakeholders can adjust composting conditions to orchestrate an environment conducive to optimal nutrient yield, thereby realizing both the agricultural and environmental advantages of this sustainable waste-to-resource conversion process. Optimizing nutrient content in compost translates to enhanced soil health and increased agricultural productivity. This knowledge empowers agricultural stakeholders to optimize composting processes, resulting in fertilizers enriched with sustenance and essential nutrients for plant growth [49,50].

5. Conclusions

The optimization of organic fertilizer quality is key for sustainable soil health management and crop productivity. We present an information system based on different sensing capabilities, Internet of Things (IoT), and modeling application for insect frass fertilizer production. We conclude that air humidity, air temperature (30–41.5 °C), moisture content (70–80%), and substrate temperature (<35 °C) play a significant role in the accumulation of nitrogen, phosphorous, and potassium in frass fertilizer products during waste recycling using black soldier fly larvae. The development of a digital application to engage end users and facilitate frass fertilizer quality assessment would ensure quality and enhance transparency in the fertilizer supply chain, empowering farmers to make informed decisions about the adoption of novel and sustainable fertilizer inputs for improved food security. The research contributes to IoT-enabled agriculture, demonstrating the potential of digital techniques in improving fertilizer nutrient management and facilitating informed decision-making about soil amendments at the farmer level. This information and communication technologies will enable the creation of low-cost, efficient information systems that can improve resources management, and increase the productivity and sustainability of agri-food systems. However, thorough evaluation of the developed device under large-scale production systems would highlight the capabilities and advantages of the device over existing traditional approaches of composting, demonstrating its potential to revolutionize agricultural practices.

Author Contributions: Conceptualization, M.K., K.S., E.R., D.B., C.M.T., G.A., T.Z., D.C., A.L. and H.E.Z.T.; Methodology, M.K., K.S., E.R., D.B., C.M.T. and H.E.Z.T.; Software, M.K., K.S., E.R., D.B. and C.M.T.; Validation, M.K., K.S., E.R., D.B. and C.M.T.; Formal Analysis, M.K., K.S., E.R., D.B. and C.M.T.; Investigation, M.K., K.S. E.R., D.B. and C.M.T.; Resources, M.K., K.S., E.R., D.B., G.A., D.C., T.Z. and C.M.T.; Writing—Original Draft Preparation, M.K., K.S., E.R., D.B. and C.M.T.; Writing—Review and Editing, M.K., K.S., E.R., D.B., C.M.T., G.A., T.Z., D.C., A.L. and H.E.Z.T.; Visualization, M.K., K.S., E.R., D.B. and C.M.T.; Supervision, K.S., E.R., D.B. and C.M.T.; Project Administration, K.S. D.B. and C.M.T.; Funding Acquisition, C.M.T., G.A., T.Z., D.C. and A.L. All authors have read and agreed to the published version of the manuscript.

Funding: The authors gratefully acknowledge the financial support for this research by the following organizations and agencies: Foreign, Commonwealth & Development Office (FCDO) [IMC-Grant 21108]; Australian Centre for International Agricultural Research (ACIAR) (ProteinAfrica—Grant No: LS/2020/154), the Rockefeller Foundation (WAVE-IN—Grant No: 2021 FOD 030); Bill & Melinda Gates Foundation (INV-032416); IKEA Foundation (G-2204-02144), Horizon Europe (NESTLER—Project: 101060762—HORIZON-CL6-2021- FARM2FORK-01), the Curt Bergfors Foundation Food Planet Prize Award; Norwegian Agency for Development Cooperation, the Section for Research, Innovation and Higher Education grant number RAF–3058 KEN–18/0005 (CAP–Africa); the Swedish International Development Cooperation Agency (SIDA); the Swiss Agency for Development and Cooperation (SDC); the Australian Centre for International Agricultural Research (ACIAR); the Norwegian Agency for Development Cooperation (NORAD); the German Federal Ministry for Economic Cooperation and Development (BMZ); the Federal Democratic Republic of Ethiopia; and the Government of the Republic of Kenya. The funders had no role in study design, data collection and analysis, decision to publish, or preparation of the manuscript.

Data Availability Statement: The data is available here [51].

Acknowledgments: The authors wish to thank Pan-African University for co-supervision of this work.

Conflicts of Interest: Authors Gina Athanasiou and Theodore Zahariadis were employed by the company Synelixis Solutions S.A. Authors Domenica Casciano and Alexandre Lazarou were employed by the company Zanasi & Partners. The remaining authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

References

1. Vlyssides, A.; Mai, S.; Barampouti, E. An integrated mathematical model for co-composting of agricultural solid wastes with industrial wastewater. *Bioresour. Technol.* **2009**, *100*, 4797–4806. [CrossRef] [PubMed]
2. Pant, R.; Gupta, A.; Singh, A.; Srivastava, S.; Patrick, N. A Summary of the Role of Microorganisms in Waste Management. In *Microbial Technology for Sustainable E-waste Management*; Springer: Berlin/Heidelberg, Germany, 2023; pp. 337–352. [CrossRef]
3. Oshins, C.; Michel, F.; Louis, P.; Richard, T.L.; Rynk, R. The composting process. In *The Composting Handbook*; Elsevier: Amsterdam, The Netherlands, 2022; pp. 51–101. [CrossRef]
4. Azis, F.A.; Choo, M.; Suhaimi, H.; Abas, P.E. The Effect of Initial Carbon to Nitrogen Ratio on Kitchen Waste Composting Maturity. *Sustainability* **2023**, *15*, 6191. [CrossRef]
5. Tumuhairwe, J.B.; Tenywa, J.S.; Otabbong, E.; Ledin, S. Comparison of four low-technology composting methods for market crop wastes. *Waste Manag.* **2009**, *29*, 2274–2281. [CrossRef] [PubMed]
6. Beesigamukama, D.; Mochoge, B.; Korir, N.K.; Fiaboe, K.K.; Nakimbugwe, D.; Khamis, F.M.; Subramanian, S.; Wangu, M.M.; Dubois, T.; Ekesi, S.; et al. Low-cost technology for recycling agro-industrial waste into nutrient-rich organic fertilizer using black soldier fly. *Waste Manag.* **2021**, *119*, 183–194. [CrossRef] [PubMed]
7. Beesigamukama, D.; Tanga, C.M.; Sevgan, S.; Ekesi, S.; Kelemu, S. Waste to value: Global perspective on the impact of entomocomposting on environmental health, greenhouse gas mitigation and soil bioremediation. *Sci. Total Environ.* **2023**, *902*, 166067. [CrossRef] [PubMed]
8. Tanga, C.M.; Kababu, M.O. New insights into the emerging edible insect industry in Africa. *Anim. Front.* **2023**, *13*, 26–40. [CrossRef] [PubMed]
9. Muinde, J.; Tanga, C.M.; Olukuru, J.; Odhiambo, C.; Tonnang, H.E.Z.; Senagi, K. Application of Machine Learning Techniques to Discern Optimal Rearing Conditions for Improved Black Soldier Fly Farming. *Insects* **2023**, *14*, 479. [CrossRef] [PubMed]
10. Qomi, M.F.; Danaeefard, M.; Farhang, A.; Hosseini, P.; Arast, Y. Effect of Temperature on the Breeding Black Soldier Fly Larvae in Vitro for Basic Health-oriented Research. *Arch. Hyg. Sci.* **2021**, *10*, 67–74.
11. Diener, S.; Zurbrügg, C.; Tockner, K. Conversion of organic material by black soldier fly larvae: Establishing optimal feeding rates. *Waste Manag. Res.* **2009**, *27*, 603–610. [CrossRef] [PubMed]
12. Beesigamukama, D.; Mochoge, B.; Korir, N.K.; Fiaboe, K.K.; Nakimbugwe, D.; Khamis, F.M.; Subramanian, S.; Dubois, T.; Musyoka, M.W.; Ekesi, S.; et al. Exploring black soldier fly frass as novel fertilizer for improved growth, yield, and nitrogen use efficiency of maize under field conditions. *Front. Plant Sci.* **2020**, *11*, 574592. [CrossRef] [PubMed]
13. Oonincx, D.G.; van Broekhoven, S.; van Huis, A.; van Loon, J.J. Correction: Feed conversion, survival and development, and composition of four insect species on diets composed of food by-products. *PLoS ONE* **2019**, *14*, e0222043. [CrossRef] [PubMed]
14. Sánchez, Ó.J.; Ospina, D.A.; Montoya, S. Compost supplementation with nutrients and microorganisms in composting process. *Waste Manag.* **2017**, *69*, 136–153. [CrossRef] [PubMed]
15. Keener, H.; Ekinci, K.; Michel, F. Composting process optimization–using on/off controls. *Compost Sci. Util.* **2005**, *13*, 288–299. [CrossRef]
16. Petric, I.; Mustafić, N. Dynamic modeling the composting process of the mixture of poultry manure and wheat straw. *J. Environ. Manag.* **2015**, *161*, 392–401. [CrossRef] [PubMed]
17. Vasiliadou, I.A.; Chowdhury, A.K.M.M.B.; Akratos, C.S.; Tekerlekopoulou, A.G.; Pavlou, S.; Vayenas, D.V. Mathematical modeling of olive mill waste composting process. *Waste Manag.* **2015**, *43*, 61–71. [CrossRef] [PubMed]
18. Courvoisier, P.; Clark, G. A numerical integrated model of composting processes using finite elements methods. In Proceedings of the XVII World Congress of the International Commission of Agricultural and Biosystems Engineering (CIGR), Québec City, QC, Canada, 6 July 2010; pp. 1–10.
19. Bongochgetsakul, N.; Ishida, T. A new analytical approach to optimizing the design of large-scale composting systems. *Bioresour. Technol.* **2008**, *99*, 1630–1641. [CrossRef] [PubMed]
20. Cheng, J.Y.; Chiu, S.L.; Lo, I.M. Effects of moisture content of food waste on residue separation, larval growth and larval survival in black soldier fly bioconversion. *Waste Manag.* **2017**, *67*, 315–323. [CrossRef] [PubMed]
21. Yang-Jie, D.; Xiang, F.M.; Tao, X.H.; Jiang, C.L.; Zhang, T.Z.; Zhang, Z.J. A full-scale black soldier fly larvae (*Hermetia illucens*) bioconversion system for domestic biodegradable wastes to resource. *Waste Manag. Res.* **2023**, *41*, 143–154. [CrossRef] [PubMed]

22. Stloukal, P.; Pekařová, S.; Kalendova, A.; Mattausch, H.; Laske, S.; Holzer, C.; Chitu, L.; Bodner, S.; Maier, G.; Slouf, M.; et al. Kinetics and mechanism of the biodegradation of PLA/clay nanocomposites during thermophilic phase of composting process. *Waste Manag.* **2015**, *42*, 31–40. [CrossRef] [PubMed]
23. Oudart, D.; Robin, P.; Paillat, J.; Paul, E. Modelling nitrogen and carbon interactions in composting of animal manure in naturally aerated piles. *Waste Manag.* **2015**, *46*, 588–598. [CrossRef] [PubMed]
24. Dickson, E.M.; Hastings, A.; Smith, J. Energy production from municipal solid waste in low to middle income countries: A case study of how to build a circular economy in Abuja, Nigeria. *Front. Sustain.* **2023**, *4*, 1173474. [CrossRef]
25. Vishwakarma, A.; Kanaujia, K.; Hait, S. Global scenario of E-waste generation: Trends and future predictions. In *Global E-Waste Management Strategies and Future Implications*; Elsevier: Amsterdam, The Netherlands, 2023; pp. 13–30. [CrossRef]
26. Haseli, G.; Torkayesh, A.E.; Hajiaghaei-Keshteli, M.; Venghaus, S. Sustainable resilient recycling partner selection for urban waste management: Consolidating perspectives of decision-makers and experts. *Appl. Soft Comput.* **2023**, *137*, 110120. [CrossRef]
27. Waqas, M.; Hashim, S.; Humphries, U.W.; Ahmad, S.; Noor, R.; Shoaib, M.; Naseem, A.; Hlaing, P.T.; Lin, H.A. Composting processes for agricultural waste management: A comprehensive review. *Processes* **2023**, *11*, 731. [CrossRef]
28. Zafaranlouei, N.; Ghoushchi, S.J.; Haseli, G. Assessment of sustainable waste management alternatives using the extensions of the base criterion method and combined compromise solution based on the fuzzy Z-numbers. *Environ. Sci. Pollut. Res.* **2023**, *30*, 62121–62136. [CrossRef] [PubMed]
29. Synnefa. 2023. Available online: https://www.synnefa.io/farmshield (accessed on 1 December 2023).
30. Perry, L.A.; Montgomery, D.C.; Fowler, J.W. Partition experimental designs for sequential processes: Part I—First-order models. *Qual. Reliab. Eng. Int.* **2001**, *17*, 429–438. [CrossRef]
31. Bosque-Sendra, J.M.; Pescarolo, S.; Cuadros-Rodríguez, L.; García-Campaña, A.M.; Almansa-López, E.M. Optimizing analytical methods using sequential response surface methodology. Application to the pararosaniline determination of formaldehyde. *Fresenius' J. Anal. Chem.* **2001**, *369*, 715–718. [CrossRef] [PubMed]
32. Alin, A. Minitab. *Wiley Interdiscip. Rev. Comput. Stat.* **2010**, *2*, 723–727. [CrossRef]
33. Padmanabha, M.; Kobelski, A.; Hempel, A.J.; Streif, S. A comprehensive dynamic growth and development model of *Hermetia illucens* larvae. *PLoS ONE* **2020**, *15*, e0239084. [CrossRef] [PubMed]
34. Vargas-García, M.; Suárez-Estrella, F.; López, M.; Moreno, J. Microbial population dynamics and enzyme activities in composting processes with different starting materials. *Waste Manag.* **2010**, *30*, 771–778. [CrossRef] [PubMed]
35. Mathur, S.P. Composting processes. In *Bioconversion of Waste Materials to Industrial Products*; Springer: Boston, MA, USA, 1998; pp. 154–193. [CrossRef]
36. MacDonald, N.W.; Zak, D.R.; Pregitzer, K.S. Temperature Effects on Kinetics of Microbial Respiration and Net Nitrogen and Sulfur Mineralization. *Soil Sci. Soc. Am. J.* **1995**, *59*, 233–240. [CrossRef]
37. Hu, X.; Zhang, Y.; Wang, D.; Ma, J.; Xue, K.; An, Z.; Luo, W.; Sheng, Y. Effects of Temperature and Humidity on Soil Gross Nitrogen Transformation in a Typical Shrub Ecosystem in Yanshan Mountain and Hilly Region. *Life* **2023**, *13*, 643. [CrossRef] [PubMed]
38. Mosavian, S.N.; Eisvand, H.R.; Akbari, N.; Moshatati, A.; Ismaili, A. Do nitrogen and zinc application alleviate the adverse effect of heat stress on wheat (*Triticum aestivum* L.)? *Not. Bot. Horti Agrobot. Cluj-Napoca* **2021**, *49*, 12252–12252. [CrossRef]
39. Shumo, M.; Osuga, I.M.; Khamis, F.M.; Tanga, C.M.; Fiaboe, K.K.; Subramanian, S.; Ekesi, S.; van Huis, A.; Borgemeister, C. The nutritive value of black soldier fly larvae reared on common organic waste streams in Kenya. *Sci. Rep.* **2019**, *9*, 10110. [CrossRef]
40. Singh, A.; Marathe, D.; Kumari, K. Black Soldier Fly *Hermetia illucens* (L.): Ideal environmental conditions and rearing strategies. *Indian J. Entomol.* **2022**, *84*, 743–753. [CrossRef]
41. Mahmood, S.; Ali, A.; Zurbrügg, C.; Dortmans, B.; Asmara, D.R. Rearing performance of black soldier fly (*Hermetia illucens*) on municipal biowaste in the outdoor ambient weather conditions of Pakistan and Indonesia. *Waste Manag. Res.* **2023**, *41*, 644–652. [CrossRef] [PubMed]
42. Alanna, N., S.; Cory, C., C. The effects of temperature on soil phosphorus availability and phosphatase enzyme activities: A cross-ecosystem study from the tropics to the Arctic. *Biogeochemistry* **2020**, *151*, 113–125. [CrossRef]
43. Shah, P.N.; Ruan, X.; van Loon, J.J.; Dicke, M. Temperature-modulated host-pathogen interactions between *Hermetia illucens* L.(Diptera: Stratiomyidae) and *Pseudomonas protegens* Pf-5. *J. Invertebr. Pathol.* **2023**, *198*, 107934. [CrossRef] [PubMed]
44. Eskander, S.; Saleh, H. Biodegradation: Process mechanism. *Environ. Sci. Eng.* **2017**, *8*, 1–31.
45. Van Looveren, N.; Vandeweyer, D.; Van Campenhout, L. Impact of Heat Treatment on the Microbiological Quality of Frass Originating from Black Soldier Fly Larvae (*Hermetia illucens*). *Insects* **2022**, *13*, 22. [CrossRef] [PubMed]
46. Van Peer, M.; Coudron, C.; Alvarez, C.; Kingston-Smith, J.A.A.; Van Miert, S. *Literature Review to Define Knowledge Gaps on the Sustainable Production of Insects for Feed*; European Union: Maastricht, The Netherlands, 2022.
47. Mulu, D.; Yimer, F.; Opande, G. Characterizing quality of frass produced by black soldier fly (*Hermetia illucens*) larvae after treating water hyacinth and fruit wastes in various proportions. *Biomass Convers. Biorefinery* **2023**, *13*, 15185–15196. [CrossRef]
48. Dinnes, D.L.; Karlen, D.L.; Jaynes, D.B.; Kaspar, T.C.; Hatfield, J.L.; Colvin, T.S.; Cambardella, C.A. Nitrogen management strategies to reduce nitrate leaching in tile-drained Midwestern soils. *Agron. J.* **2002**, *94*, 153–171. [CrossRef]
49. Sanginga, N.; Woomer, P.L. *Integrated Soil Fertility Management in Africa: Principles, Practices, and Developmental Process*; CIAT: Palmira, Colombia, 2009.

50. Gebbers, R.; Adamchuk, V.I. Precision agriculture and food security. *Science* **2010**, *327*, 828–831. [CrossRef]
51. Katchali, M.; Senagi, K. Frass Fertilizer Production. Available online: https://dmmg.icipe.org/dataportal/dataset/unveiling-environmental-influences-on-sustainable-fertilizer-production-through-insect-farming (accessed on 1 January 2024).