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SIMULATING LAGOON SLUDGE DRYING IN SOLAR-ASSISTED GREENHOUSE DRYING SYSTEMS

4 Highlights

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• Solar-assisted greenhouse drying is impacted by weather, moisture content and sludge mixing.

• A neural network model successfully simulated ($R^2 > 0.91$) lagoon sludge greenhouse drying.

9 **ABSTRACT.** Greenhouse sludge drying is gaining wider acceptance in agricultural and municipal 10 applications due to the low cost, low energy inputs, and simple operation involved. This approach 11 leverages weather and management practices to facilitate drying. This study evaluated greenhouse sludge 12 drying and the impacts of weather conditions, air exchange rate and material properties on drying rate. Excavated swine lagoon sludge, loaded at 158-177 kg m⁻², was dried in two greenhouses (488.9 m² each) 13 14 near Warsaw, North Carolina. The impact of ventilation rate, ranging between 1.1 and 4.6 m³ m⁻² min⁻¹, 15 was evaluated during the 34 day (d) drying test. A two-phase drying process was observed: average drying rate during the first phase was 4.3 ± 2.0 and 4.5 ± 1.7 kg m⁻² d⁻¹ for GH#1 and GH#2, while the second phase 16 showed rates between 0.6 ± 1.9 and 0.1 ± 2.3 kg m⁻² d⁻¹. The following factors were significant predictors of 17 18 the drving rate: solar radiation, sludge moisture, ambient temperature and relative humidity, time since 19 mixing event, and ventilation rate. Cumulative carbon and nitrogen loss during the process was up to 12 20 and 14%, respectively. Statistical models developed to predict drving using process variables and 21 management decisions performed well ($R^2 > 0.80$), but the absolute penalty neural network model 22 outperformed other models' predictions in both greenhouses ($R^2 > 0.91$, $RASE < 33.5 kg_{H2O} hr^{-1}$). This 23 study is a first of its kind to evaluate feasibility of greenhouse sludge drying in Southeastern US. Findings 24 and models developed in this study will increase process efficiency and incentivize adoption of on-farm 25 greenhouse drying.

26 *Keywords.* Swine Lagoon, Neural Network, Solar greenhouse drying, drying rate,

[•] Average drying rates over 34 days ranged from 2.2 to 2.9 kg m⁻² d⁻¹.

[•] Maximum carbon and nitrogen lost during drying were 12% and 14%, respectively.

27 INTRODUCTION

28 North Carolina is a leading US swine producing state with more than 1,400 permitted farms, majority 29 of which are feed-finish farms, all heavily concentrated in the Southeastern region of the state. The sector 30 produced an average of 18.9 million heads per year from 2000 to 2022 (NASS, 2023). Anaerobic lagoons 31 are the primary method of manure management on these farms where manure is stored and treated for use 32 as two fractions: liquid supernatant and sludge. A median sized feed-finish farm in North Carolina, with 33 3,500 finishing heads (Aghdam, 2022), produces 70.4 Mg of sludge dry matter each year (Bicudo et al., 34 1999; John P. Chastain, 2006) containing ~9.7 Mg of P₂O₅ (Owusu-Twum and Sharara, 2020). Regulatory 35 guidelines stipulate sludge removal if it occupies more than 50% of the designed lagoon treatment volume. 36 Without affordable practices for the management of lagoon sludge nutrients, however, many farms opted 37 to allow sludge accumulation and, if feasible, remove enough sludge to stay in compliance. The NC swine 38 industry, at the current production rate, generates 52,372 Mg of P₂O₅ annually in sludge, which is 39 equivalent to 56% of 2011 NC fertilizer P₂O₅ purchase (Commercial Fertilizer Purchased, EPA). A major 40 hurdle facing recycling this valuable asset, however, is the difficulty of recovering these nutrients in a 41 compact and transportable form. Current sludge management practices recover sludge at a total solid (TS) 42 content between 8% and 12%, which greatly limit transportation. Another challenge in swine sludge use 43 in NC is its high P concentration and elevated soil phosphorus index (P-I) (Johnson, 2004) in areas 44 surrounding animal operations. Export of swine sludge nutrients where they will be valued and could be 45 agronomically utilized will results in its sustainable use. However, transportation costs escalate for longer 46 hauling of wet substrates. Treatment initiatives that reduce weight and volume without losing or diluting 47 nutrients are hence needed for sustainable swine sludge management.

48 Drying is a potential alternative that can be employed to reduce sludge volume and moisture content. It 49 can concentrate and retain sludge nutrients, hence producing a marketable and nutrient-rich product. Other 50 applications for dried swine lagoon sludge include its use as a combustion feedstock, or co-ingredient, for 51 renewable electricity generation, or pyrolysis for biochar and syngas production. Drying, however, is a 52 capital and energy intensive process and is not typically economical for residual materials and agricultural 53 byproducts like lagoon sludge, especially when expenses are borne by producers. A detailed analysis of 54 several commercial drying systems, conducted by Sharara (2022), reported drying costs between \$90 and \$156 Mg⁻¹ dry matter (DM), with additional costs associated with sludge removal and aggregation 55 56 (centralization). Another crucial observation was the high demand of electricity (27 to 170 kWhr Mg⁻¹_{H2O} 57 evaporated) and natural gas (1,550 to 2450 MJ Mg⁻¹H20 evaporated) for conventional drying. Furthermore, 58 farm scale systems may lose the advantage of economies-of-scale and energy use efficiency making 59 conventional drying systems unsuitable for swine lagoon sludge management.

Drying using enclosed, ventilated solar greenhouse systems present a simpler alternative and can 60 61 achieve comparable results with added benefits. These systems use incident solar radiation and ambient 62 weather conditions, coupled with forced ventilation, material mixing, and optional supplemental heating 63 to facilitate drying (Seginer et al., 2007; Seginer and Bux, 2006). Variability in these factors, however, 64 results in slow and variable performance, unlike conventional drying systems (Bennamoun, 2012). While 65 solar systems have lower energy consumption (24-28 kWhr Mg⁻¹_{H2O} evaporated) (Bux et al., 2002), they require a larger footprint. They are typically considered to be economical due to low infrastructure, 66 67 machinery and maintenance costs (Boguniewicz-Zablocka et al., 2021a). While these systems have been studied for managing industrial waste and wastewater treatment sludges, no studies have reported the 68 69 performance of these systems for animal manure or sludge in Southeastern US. In addition, no tools are 70 currently available to help optimize the operation of such systems.

This study aimed to address this knowledge gap through evaluating the drying performance of swine lagoon sludge in a pilot scale ventilated greenhouse system that was newly built in Eastern NC. The main objective is to understand the impact of weather conditions, material mixing and ventilation rates on drying 74 rates. Furthermore, this study developed and evaluated different empirical models to predict drying using 75 process variables and management decisions. The findings in this study provide necessary information 76 and tools to help researchers, producers, and stakeholders evaluate the economic and environmental 77 performance of this technology as an option for animal producers in the state and beyond.

78 MATERIALS AND METHODS

79 SWINE LAGOON SLUDGE REMOVAL AND HANDLING

80 Lagoon sludge was sourced from a farrow-wean swine farm (4,719 allowable heads) in Duplin County, 81 North Carolina, USA. The Sludge was removed using an excavator (313F, Caterpillar, Inc., Peoria, Illinois, 82 USA) equipped with a modified skeleton bucket attachment (Teran Industries, Miami Florida, USA) and 83 mounted on a floating barge. The barge navigated across the lagoon using guided cables and the excavator 84 arm. The excavated sludge was collected in a roll-off dumpster stationed on the barge, the capacity of 85 which was 11.5 m^3 (15 yd³), then emptied into a lorry at the end of each removal cycle. Sludge samples 86 were collected during transfer to characterize as-removed sludge. Subsequently, the excavated sludge was 87 transported to an open, contained storage where it was stored for less than two weeks. The required amount 88 of sludge was transported 25 km to the greenhouses site where it was staged before the commencement 89 of the drying study. The sludge was spread through the greenhouses using a skid steer. The material 90 loading rate was 177.2±9.7 for greenhouse #1 (GH#1) and 158.2±9.7 kg m⁻² for greenhouse #2 (GH#2).

91 GREENHOUSE, VENTILATION AND SLUDGE TILLING SYSTEM

Two greenhouses (pointed-arch design) were employed to study sludge drying. Each greenhouse had a drying area of 444.5 m² (For dimensions refer Figure 1). Each greenhouse had entrances at both ends (garage-style), which were primarily used for material loading, unloading, and handling. Greenhouse ventilation was facilitated through mechanical tunnel ventilation, i.e., flexible louvers to allow air entrance on inlet side (4.5 m² louvered area), and four ventilation fans on exit side (HS9084, Hog Slat, Newton 97 Grove NC, USA), each had 504 m³ min⁻¹ airflow rate and 0.75 kW power rating.



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Figure 1 Picture of sludge excavation, greenhouses, onsite weather station and sludge mixing.

A programmable logic system (PLC) was developed to control fan operation during drying process for 100 101 both greenhouses using air temperature and relative humidity sensors (DOL 104, Aarhus, Denmark), 102 which were used to calculate air psychrometry via a code block in the PLC. The PLC was programmed 103 to control fans in each greenhouse based on the difference in absolute humidity between ambient air and exhaust air. Fan operations ceased when absolute humidity difference was less than 1.6 g m⁻³ (0.1 lbs. 104 105 1,000 ft⁻³). Two fans would operate when absolute humidity difference was greater than 3.2 g m⁻³ (0.2 lbs. 1,000 ft⁻³) and all four fans would be operational when absolute humidity difference rises to 6.4 g m⁻³ (0.4 106 107 lbs. 1,000 ft⁻³). When ambient air relative humidity exceeds 90%, a system override terminates all fan 108 operations to minimize risk of rewetting the sludge.

In this study, only one greenhouse (GH#1) was managed using the PLC logic detailed earlier. Fan operations in the second greenhouse (GH#2) were changed manually, with each interval between 48 and 72 hours. The manual fan scheduling started with one fan (1F) in the first interval, followed by two fans (2F), then three (3F) and finally four fans (4F). The same fans sequence was repeated in a cyclic manner until the end of drying. In both greenhouses, the sludge was mixed using a tractor-operated rotary tiller (55 HP, John Deere) at the start of each interval. These fan settings correspond to a nominal air velocity of 1.1. 2.3, 3.4 and 4.6 m s⁻¹

116 **DATA COLLECTION AND ANALYSIS**

Temperature and relative humidity of exhaust air were measured and recorded every 30 seconds using 117 118 HOBO sensors (UX100-003, Onset, Bourne, MA, USA) fitted on each fan in both greenhouses. An 119 additional sensor recorded local ambient temperature and relative humidity conditions. Uptime for each 120 ventilation fan was logged by the PLC system on an hourly basis. A nearby weather station, i.e., 121 Horticultural Crops Research Station, which is part of the state climate monitoring network (18 km from 122 experiment site) was also used to retrieve ambient temperature, relative humidity, and solar radiation 123 observations every minute throughout the experiment duration. Ambient and exhaust air properties and 124 ventilation rate were used to determine vapor loss (VL) on hourly basis as follows:

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$$VL = Q \times \left[\frac{W_{ext}}{V_{ext}} - \frac{W_{amb}}{V_{amb}}\right]$$
(1)

where q = ventilation rate (m³ h⁻¹), W= average humidity ratio (kg H20 kg ⁻¹ dry air), and V = specific volume of air (m³ kg⁻¹dry air), with *ext* and *amb* subscripts represent exhaust air and ambient air properties, respectively. Values for humidity ratio and specific volume were determined from psychrometric air properties using temperature and relative humidity observations. A workflow using MATLAB (R2021a, 9.10), Oracle Crystal Ball (Version 11.1) and Microsoft Excel (Version 16.65) was used to conduct the necessary computations. 132 For sampling purposes, the greenhouse was into gridded into nine grid cells representing front, middle 133 and end of greenhouse (each cell is 3.6m by 15m). One sludge sample was collected from each grid cell at the beginning of each airflow interval. Each of the nine samples were analyzed for moisture and volatile 134 135 solids content. In addition, for each sampling event, homogenous subsamples representing each zone: 'front', 'middle', and 'exit' was composited from corresponding grid cells. Theses samples were analyzed 136 137 to determine elemental composition, i.e., carbon (C), nitrogen (N), phosphorus (P), zinc (Zn) and copper 138 (Cu) concentrations. Four sludge height observations were recorded for each grid cell at the start of every 139 interval. Bulk density was measured in triplicates using grab samples from across the greenhouse during 140 start, end of experiment and at select sampling events. The experiment was terminated when the sludge 141 moisture content on wet basis reached less than 30% in both greenhouses. The total weight of dried sludge 142 removed each greenhouse was determined and recorded.

143 STATISTICAL ANALYSIS

144 Analysis of variance (ANOVA), mean's comparisons, and predictive models' development were carried 145 out using JMP-Pro 16 software (SAS Inc., Cary, NC). The dataset for GH#2 was divided into training 146 (60%), validation (20%) and test (20%) for predictive modeling purposes. Three models predicting the 147 rate of drying were developed, i.e., multiple linear regression, decision tree, and neural network (NN). 148 Multiple linear regression was developed using stepwise analysis to include relevant independent 149 variables. Decision tree analysis partitions data based on response and predictor relationships with 150 decreasing importance. It was chosen considering the ease in result interpretation with findings directly 151 used in PLC algorithm development. The NN model was developed with one hidden layer that had three 152 activation functions: hyperbolic tangent (tanH), linear identity function and Gaussian function. An 153 absolute penalty method with ten tours was used to determine appropriate prediction model. This method 154 avoids overfitting by refitting the model a given number of times (tours) with random starting parameter

estimates to determine best estimates. The observations from GH#1 were used to validate the best modelgenerated and evaluate reliability of predictions.

157 **Results**

158 SUBSTRATE PROPERTIES

159 The floating barge excavator facilitated sludge removal without significant dilution from lagoon liquid 160 (supernatant) resulting in a higher dry matter content (Table 1). However, the wide range of dry matter 161 observed was attributed to the non-compacted (fluid-like) portion of the recovered sludge. The variability 162 between compacted and fluid-like portions of the sludge was visually observable during sampling. This variability was also reflected in the elemental analysis of the excavated sludge samples. This variability, 163 164 however, was not relevant in the sludge at drying commencement. This can be attributed to the staging 165 period where pooled substrate from multiple excavation tours was combined resulting in a more 166 homogenous mixture. At the start of the experiment, the average dry matter content was $33.0\% \pm 1.1\%$ 167 and $29.4\% \pm 1.7\%$ in GH#1 and GH#2, respectively.

		Initial wet sludge		Dried Sludge			
Parameter	Excavated Sludge	GH#1	GH#2	GH#1	GH#2	Analytical method	
DM (% of wet mass)	29.0 ± 13.2	33.0 ± 1.1	29.4 ± 1.7	68.7 ± 6.7	78.7 ± 1.8	APHA 2015	
VS% (% of DM)	NA	39.7 ± 2.0	$46.4\pm\!\!5.2$	41±2	44±3	APHA 2015	
pH	8.0 ± 0.1	8.1 ± 0.1	8.2 ± 0.0	7.2 ± 0.1	7.3 ± 0.1	EPA 9045D	
EC	3.2 ± 0.1	4.0 ± 0.2	4.2 ± 0.0	4.3 ± 0.5	5.0 ± 0.2	EPA 9045D	
C (g/kg)	227.8 ± 117	185.1 ± 10.1	200.9 ± 3.1	170.3 ± 6.8	175.7 ± 6.2	AOAC 972.43	
N (g/kg)	49.9 ± 26.3	37.4 ± 2.4	41.4 ± 1.1	33.5±1.3	35.7±0.8	AOAC 972.43	
NH ₄ -N (g/kg)	24.6 ± 15.2	14.8 ± 1.4	16.6 ± 3.7	10.5±0.4	11.9±0.3	EPA 350.1	
C/N	4.6 ± 0.0	4.9 ± 0.2	4.9 ± 0.1	5.1 ± 0.0	4.9 ± 0.0	NA	
P (g/kg)	73.8 ± 6.2	67.9 ± 2.3	73.5 ± 1.6	66.4 ± 1.7	72.0 ± 0.4	EPA 200.7	
K (g/kg)	5.6 ± 0.4	5.6 ± 0.3	6.2 ± 0.1	5.7 ± 0.2	6.4 ± 0.1	EPA 200.7	
Zn (g/kg)	3.6 ± 0.8	3.4 ± 0.05	4.9 ± 0.4	3.7 ± 0.6	4.9 ± 0.2	EPA 200.7	
Cu (g/kg)	2.1 ± 0.1	1.6 ± 0.04	1.8 ± 0.2	1.6± 0.1	1.9± 0.1	EPA 200.7	

168 Table 1. Characteristics of freshly excavated and initial sludge used in Greenhouses 1 and 2 (GH#1, GH#2).

NA: Not available, mean ±SD (n= 3), all concentrations are specified on dry basis unless mentioned otherwise.

170 EFFECT OF DRYING ON MOISTURE CONTENT, MATERIAL HEIGHT AND BULK DENSITY

171 The drying progress was tracked through moisture content change (d.b., MC_{db}) as shown in figure 2a. By the 15th day, the dry-basis moisture content decreased to 110.2±24.4% and 103.7±23.6% in GH#1 and 172 173 GH#2, respectively. Additional 19 days were needed to reach 41.4±16.6% and 25.5±7.2% moisture 174 content in GH#1 and GH#2 respectively. The variability in moisture content at each interval, indicated by 175 reported standard deviation values, is attributed to the spatial variability in drying along airflow path from 176 front to exit and, the gap in material loading. The average initial moisture content of samples in the front, 177 middle and end grid cells in GH#2, were $256.0\pm64.8\%$, $192.5\pm9.4\%$, $176.7\pm30.9\%$ respectively, which 178 was primarily due to gap in material loading as the material in the end section was loaded a week before 179 the study commencement while the rest was loaded 24 hours earlier. At the end of the experiment, moisture 180 contents in the GH#1 at the front, middle and end grid cells were 23.8±4.2%, 60.2±5.2% and 40.3±8.3% 181 respectively, although all the material was loaded at the same time i.e., 24 hours before the 182 commencement.

Average daily drying rate estimates show two distinct drying phases that represent the first and second falling rates (figure 3a, 3b). The constant rate drying phase was not observed in this study which could be attributed to the absence of free moisture in the sludge. The average drying rate during the first phase, i.e., $MC_{db} > 100\%$, was 4.3 ± 2.0 and 4.5 ± 1.7 kg m⁻² d⁻¹ for GH#1 and GH#2, respectively. The drying rate dropped to 0.6 ± 0.9 and 0.1 ± 1.1 kg m⁻² d⁻¹ during the second phase. The maximum drying rates observed in the first phase was 7.2 and 6.5 kg m⁻² d⁻¹ in GH#1 and GH#2 respectively, while the maximum drying rates in the second falling phase were 2.1 and 4.3 kg m⁻² d⁻¹ for GH#1 and GH#2 respectively.









Sludge height and bulk density were monitored during the drying period to correlate weight loss and with volume reduction (shrinkage). Sludge height on the 15^{th} day, 12.8 ± 4.0 cm in GH#1 and 10.8 ± 1.7 cm in GH#2, was 40 to 51% lower than at the start of drying. Correspondingly, a decrease between 21-24% in material bulk density was also observed during this period. Figures 2b and 2c track average material heights and bulk density during the 34-d drying period. Variation in material height primarily indicates the spatial variability in material loading across the greenhouse. Variation in bulk density was attributed to the transition in sludge physical properties from paste-like to granular.





Figure 3. Observed average drying rate in a) GH#1, b) GH#2 as a function of moisture content (dry basis).

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2 ACCOUNTING OF MASS AND VAPOR LOSSES

203 Sludge sampling and analysis were used to track losses of water, organic matter, and nutrients during 204 the drying process. While the final weight of material recovered from GH#1 and GH#2 was recorded, i.e., 205 36.2 and 28.8 Mg respectively, logistical challenges prevented measuring initial total wet weights in both 206 greenhouses. The initial wet weight of sludge was back-calculated using properties of initial and final 207 sludge and assuming no change in ash content. The variability in material properties was incorporated into 208 the initial weight estimates using Monto-Carlo simulation. On the other hand, cumulative water vapor loss 209 was calculated using air properties along with hourly ventilation rates. We observed carbon loss of $12 \pm$ 210 6% and 4±6% during drying from GH#1 and GH#2 respectively. Nitrogen losses were estimated to be 211 14±7% in GH#1 and 5±6% in GH#2. Differences in the carbon and nitrogen losses between GH#1 and 212 GH#2 were observable however, not statistically significant (p > 0.05) indicating no effect of different 213 ventilation techniques employed. Figure 4 illustrates the overall mass balance for both greenhouses, 214 calculated water vapor loss amounted to 104±10% and 79.5±8% of weight loss estimated in GH#1 and 215 GH#2 respectively. These mass balance estimations indicate the methodology used to track water loss on 216 hourly basis via mechanical ventilation was adequate to represent the entire drying process.



217 218 Figure 4. Observed mass loss (vapor and organic matter) and accounted vapor loss in greenhouses (GH#1, GH#2).

219 DRYING PROCESS FACTORS

220 Statistical analysis and model development were conducted using hourly dataset collected from GH#2 221 split into training set (457 observations), validation set (174 observations), and test set (181 observations). 222 Factors observed to be statistically significant in drying rate estimation (p < 0.05) were ambient 223 temperature, relative humidity, solar radiation, sludge moisture content and time elapsed since last tillage 224 (mixing). Seginer and Bux (2006) and Krawczyk, (2016) reported weather conditions and management 225 significantly impacted drying process in solar drying of wastewater sludge. Ventilation rate (0) was not 226 observed to be statistically significant, although at least one fan was operational throughout the entire 227 experiment duration in GH#2. As such, the results indicate that incremental changes in ventilation rate did 228 not significantly affect water vapor loss rate.

229 The multi linear regression model was the simplest model developed to estimate the drying rate (refer

230 to Appendix for model parameters). The decision tree (partition) model resulted in 66 logical data splits 231 with decreasing importance of predictors. To reduce model complexity while maintaining prediction 232 power, the decision tree was pruned resulting in 15 crucial splits. The neural network with learning rate 233 (10%) and 10 trials was the most complex model developed, resulting in 30 individual equations with 10 234 equations for each of the three nodes (i.e., tanH, Linear, Gaussian). The coefficient of regression (R^2) and 235 root averaged square error (RASE) values for the various models are listed in table 2. All models provided 236 a fair prediction ability for training, validation, and test sets with R^2 between 0.80 and 0.92. The absolute 237 penalty NN model was the superior model, outperforming other models across all datasets.

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Category	Model	R ²	RASE ^{\$} (kg _{H20} .h ⁻¹)
	Multiple linear regression	0.80	33.1
Training	Decision tree*	0.87	26.7
	Neural Network (absolute penalty)	0.93	19.3
	Neural Network (10% learning rate)	0.92	21.5
Validation	Multiple linear regression	0.82	33.4
	Decision tree*	0.87	28.1
	Neural Network (absolute penalty)	0.93	21.1
	Neural Network (10% learning rate)	0.92	22.4
Test	Multiple linear regression	0.85	35.0
	Decision tree*	0.86	33.7
	Neural Network (absolute penalty)	0.94	21.5
	Neural Network (10% learning rate)	0.92	24.7

Table 2. Performance summary of Greenhouse drying prediction models

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241 Model validation using GH#1 operation

Drying in GH#1 was automated by using difference in humidity ratio between incoming and exhaust air as feedback to drive mechanical ventilation (using PLC controller). As a result, ventilation settings were changing at a faster rate than the hourly basis used for our data analysis and model development. Nonetheless, we sat out to test the absolute penalty NN model developed using GH#2 dataset to predict

246 the drying rate in GH#1. The model predicted hourly vapor loss using the following inputs: [1] predicted 247 initial wet mass, [2] hourly ventilation records, [3] sludge mixing time records, and [4] weather conditions 248 (temperature, relative humidity, and solar radiation). Predicted vapor loss was used to continuously update 249 sludge moisture content for subsequent model evaluations until the moisture content reached the 250 termination moisture content (experimental observation). Figure 5a illustrates predicted versus measured 251 water vapor loss in GH#1. The coefficient of regression (R^2) indicated a good agreement between 252 predicted and measured hourly water vapor loss rates. The model predictions were consistently below 253 observed values, i.e., on average 17% lower than measured values.





Figure 5. Summary of model predictions, a) vapor loss, b) moisture content for greenhouse drying.

The instantaneous prediction model could better predict drying at peak conditions which are averaged to an hourly basis in the current model. Predicted moisture content (solid line, Figure 5b) were comparable to measurements made at sampling intervals (hollow triangles, Figure 5b). These results demonstrate good prediction ability for the absolute penalty NN model to predict drying performance of a PLC controlled greenhouse system. Such model is a valuable tool to study the impact of PLC set points on drying performance and energy consumption. However, it should be noted that this model was developed based 262 on observations for a part of the year and would need further data to improve performance and prediction263 ability for year-round drying performance.

264 **DISCUSSION**

Changes in sludge physical properties (height and bulk density) were observed to correlate to drying progress and can be potentially employed by operators as indicators of the drying phase. On average the sludge layer lost 50% of its height throughout the drying process. The high variability we observed, primarily due to variable spatial distribution of sludge initially and the implement used for sludge mixing (modified tiller), limited the ability to use these properties to estimate initial sludge mass in the greenhouse.

271 Drying swine lagoon sludge did not significantly change its volatile solids content. Limited information 272 is available on volatile solids loss during greenhouse drying. A few studies that analyzed drying aerobic 273 wastewater treatment sludge (Bux et al., 2002, Sorrenti et al., 2022) have reported reduction of VS from 274 74 to 41% during solar greenhouse drying. Swine lagoon sludge, unlike aerobic primary sludge, is a 275 byproduct of anaerobic digestion after which it was continually stored for years. This results in a heavily 276 degraded residue with marginal potential for further decomposition (Patil and Sharara, 2022), which is a 277 positive attribute in this context as it eliminates concern for volatile organic compounds (VOC) emissions 278 or abatement during drying.

Although, no studies have previously reported reduction in carbon content during greenhouse drying, it is safe to assume that fraction of carbon reduction to be co-related to VS reduction from microbial pathway. The carbon and nitrogen loss estimates in this study were higher in GH#1 compared to GH#2, although not statistically significant. This could be due to differences in ventilation between greenhouses. Intermittent fan operation in GH#1 led to solar thermal energy accumulation and consequently higher internal temperatures boosting aerobic activity and leading to increased C and N losses. The average nitrogen losses observed in this study (4-12%) are comparable to observations in previous studies. O'Shaughnessy et al., (2008), analyzed nitrogen losses from open-bed drying of dewatered sludge from aerobic and aerobic wastewater treatment, and observed 23% N loss from anaerobically tilled sludge, and up to 74% N loss from aerobic tilled sludge. N losses were observed to be impacted by tillage and substrate type. Szypulska et al., (2021) observed ~11% N loss from thermal drying of dewatered wastewater treatment sludge. Due to the agronomic importance of N and concerns over its volatilization as NH₃, additional efforts to estimate and reduce N losses are needed to quantify and mitigate these losses.

Mass balance indicated higher agreement between water vapor loss and estimated weight loss for GH#1 than in GH#2. Differences in ventilation strategy (PLC controlled vs. continuous) is suspected to be the driver for this observation. GH#1 also had an additional override to shut-off ventilation when ambient relative humidity was greater than 90%, unlike GH#2, which limited the risk of moisture addition to the system. Since, the HOBO sensors have a 5% error in relative humidity measurements when operated above 90% compared to 2.5% error below 90%, continued operation at high humidity conditions was a likely cause of the mass balance disagreement.

299 The drying was affected by the sludge moisture content, weather conditions, and sludge mixing. Seginer 300 and Bux, (2006) observed ventilation rate was also a critical factor. Other factors that impact drying rate 301 is sludge mixing time. Rates of drying for wastewater treatment sludge in Poland was observed to vary from 0.5 to 2.5 kg m⁻² d⁻¹, depending on weather conditions (Boguniewicz-Zablocka et al., 2021b). Bux 302 303 and Baumann, (2003) analyzed performance of 25 European solar sewage sludge drying plants in Germany, Austria, and Switzerland. They observed an average annual drying rate from 1.6 to 3 kg m⁻² d⁻ 304 ¹. The drying rate increased to 9.6 kg m⁻² d⁻¹ with supplementary heating. The average rate of drying 305 observed in the current study, 2.2 to 2.9 kg m⁻² d⁻¹, exceeds values reported in European systems due to 306 307 favorable conditions for solar drying in Southeastern US. However, the reported rates reflect a short interval in annual operation cycle (Sept 19 - Oct 23, 2022) and continued monitoring is needed for more
 reliable performance estimates.

Our results indicated the drying rate spiked in the first four to eight hours after mixing, followed by a gradual diminishing effect. The mixing was carried out at the start of every interval i.e., once in 48-72 hours. As such, increasing the frequency of mixing can improve drying performance. Internal air circulation system, found to be an important variable in the process (Boguniewicz-Zablocka et al., 2021b), was a missing feature in the current system. Internal mixing increases the vapor gradient resulting in higher mass transfer across the sludge-air interface. Optimal ventilation system operation based on sensors and automation will further increase energy savings.

317 CONCLUSION

318 Swine sludge drying in mechanically ventilated solar greenhouses was evaluated in this study. Weather 319 conditions, mixing events, and material moisture content impacted the drying rate. The height and bulk 320 density served as indicators of drying progress during initial stages but did not provide reliable estimates 321 of total mass in the greenhouse. This study is a first of its kind to investigate solar greenhouse sludge drying in Southeastern US and observed a drying rate of 2.2 to 2.9 kg_{H2O} m⁻² d⁻¹. Continuous drying 322 323 process monitoring using sensors provided fair estimate of water vapor loss (79% to 100% mass balance 324 closure). Absolute penalty neural network model effectively predicted drying performance ($R^2 = 0.92$) 325 based on dominant predictors and was shown to be an effective tool in simulating and optimizing the 326 process when integrated into a programmable logic controller (PLC) system. Ventilated greenhouse sludge 327 drying is a promising alternative for swine lagoon sludge to reduce mass and volume and wider 328 distribution of manure nutrients for sustainable recycling. Further technoeconomic and environmental 329 assessments are needed to benchmark the potential of this technology compared to established and 330 emerging ones.

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REFERENCES

- 337 Aghdam, S. 2022, Environmental Impact Assessment (LCA) and Techno-Economic Assessment (TEA) of Struvite
- 338 Recovery in Swine Manure. MS thesis. Raleigh, North Carolina, North Carolina State University, Biological and
- 339 Agricultural Engineering Department.
- AOAC, Association of Official Analytical Chemists. 1990b. AOAC official method 972.43: microchemical
- determination of carbon, hydrogen, and nitrogen. In: Official methods of analysis. Volume 1. 15th ed. Arlington
- 342 (VA): AOAC International. p 341.
- 343 APHA (2017) Standard Methods for the Examination of Water and Wastewater. 23rd Edition, American Public
- 344 Health Association, American Water Works Association, Water Environment Federation, Denver.
- 345 EPA, United States Environmental Protection Agency. 2001. Method 200.7. Trace elements in water, solids, and
- 346 biosolids by inductively coupled plasma-atomic spectrometry, revision 5.0. Cincinnati (OH): USEPA Office of
- 347 Research and Development. EPA-821-R-01- 010. Available at: nepis.epa.gov/EPA/.
- 348 EPA, United States Environmental Protection Agency. 2015. Method 9045D. Soil and Waste pH. Test Methods for
- 349 Evaluating Solid Wastes, Physical/Chemical Methods. Publication SW-846. National Technical Information
- 350 Service. Springfield, Va.
- Bennamoun, L., 2012. Solar drying of wastewater sludge: A review. Renewable and Sustainable Energy Reviews 16,
 1061–1073. https://doi.org/10.1016/j.rser.2011.10.005
- Bicudo, J.R., Safley Jr, L.M., Westerman, P.W., 1999. Nutrient content and sludge volumes in single-cell recycle
- anaerobic swine lagoons in North Carolina. Transactions of the ASAE 42, 1087.
- 355 Boguniewicz-Zablocka, J., Klosok-Bazan, I., Capodaglio, A.G., 2021a. Sustainable management of biological solids

- in small treatment plants: overview of strategies and reuse options for a solar drying facility in Poland. Environ
- 357 Sci Pollut Res 28, 24680–24693. https://doi.org/10.1007/s11356-020-10200-9
- 358 Boguniewicz-Zablocka, J., Klosok-Bazan, I., Capodaglio, A.G., 2021b. Sustainable management of biological solids
- in small treatment plants: overview of strategies and reuse options for a solar drying facility in Poland. Environ
- 360 Sci Pollut Res 28, 24680–24693. https://doi.org/10.1007/s11356-020-10200-9
- 361 Bux, M., Baumann, R., 2003. Performance, Energy Consumption and Energetic Efficiency Analysis of 25 Solar
- 362 Sludge Dryers. Presented at the WEFTEC 2003, Water Environment Federation, pp. 522–534.
- Bux, M., Baumann, R., Quadt, S., Pinnekamp, J., Mühlbauer, W., 2002. Volume Reduction and Biological
- 364 Stabilization of Sludge in Small Sewage Plants by Solar Drying. Drying Technology 20, 829–837.
- 365 https://doi.org/10.1081/DRT-120003765
- 366 Chastain, J. P., 2006. Estimation of Sludge Accumulation in Lagoons, in: 2006 Portland, Oregon, July 9-12, 2006.
- 367 Presented at the 2006 Portland, Oregon, July 9-12, 2006, American Society of Agricultural and Biological
- 368 Engineers. https://doi.org/10.13031/2013.21753
- 369 Commercial Fertilizer Purchased, EPA, <u>https://www.epa.gov/nutrient-policy-data/commercial-fertilizer-purchased</u>,
 370 March 10th, 2023.
- Johnson A. 2004, Phosphorus Loss assessment in North Carolina, Ph.D. Thesis, North Carolina, North Carolina
 State University, Crop and Soil Science Department.
- 373 Krawczyk, P., 2016. Numerical Modeling of Simultaneous Heat and Moisture Transfer During Sewage Sludge
- Drying in Solar Dryer. Procedia Engineering 157, 230–237. https://doi.org/10.1016/j.proeng.2016.08.361
- 375 NASS, USDA, Annual Swine Crop Production in North Carolina,
- <u>https://quickstats.nass.usda.gov/results/2E4302E5-F1B1-30B1-BF9C-63B75FC3D8D0</u>, last viewed March 10th,
 2023.
- 378 O'Shaughnessy, S.A., Song, I., Artiola, J.F., Choi, C.Y., 2008. Nitrogen Loss During Solar Drying of Biosolids.
- 379 Environmental Technology 29, 55–65. https://doi.org/10.1080/09593330802008818
- 380 Owusu-Twum, M.Y., Sharara, M.A., 2020. Sludge management in anaerobic swine lagoons: A review. Journal of
- 381 Environmental Management 271, 110949.

- 382 Patil, P.S., Sharara, M.A., 2022. Impacts of sonication on biomethane potential (BMP) and degradation kinetics of
- jig lagoon sludge. Biosystems Engineering 223, 129–137. https://doi.org/10.1016/j.biosystemseng.2022.08.008
- Seginer, I., Bux, M., 2006. Modeling Solar Drying Rate of Wastewater Sludge. Drying Technology 24, 1353–1363.
 https://doi.org/10.1080/07373930600952362
- Seginer, I., Ioslovich, I., Bux, M., 2007. Optimal Control of Solar Sludge Dryers. Drying Technology 25, 401–415.
 https://doi.org/10.1080/07373930601184577
- Sorrenti, A., Corsino, S.F., Traina, F., Viviani, G., Torregrossa, M., 2022. Enhanced Sewage Sludge Drying with a
 Modified Solar Greenhouse. Clean Technologies 4, 407–419. https://doi.org/10.3390/cleantechnol4020025
- 390 Spiegal, S., Kleinman, P.J.A., Endale, D.M., Bryant, R.B., Dell, C., Goslee, S., Meinen, R.J., Flynn, K.C., Baker,
- J.M., Browning, D.M., McCarty, G., Bittman, S., Carter, J., Cavigelli, M., Duncan, E., Gowda, P., Li, X., Ponce-
- 392 Campos, G.E., Cibin, R., Silveira, M.L., Smith, D.R., Arthur, D.K., Yang, Q., 2020. Manuresheds: Advancing
- nutrient recycling in US agriculture. Agricultural Systems 182, 102813.
- 394 https://doi.org/10.1016/j.agsy.2020.102813
- 395 Szypulska, D., Kokurewicz, Ł., Zięba, B., Miodoński, S., Muszyński-Huhajło, M., Jurga, A., Janiak, K., 2021.
- 396 Impact of the thermal drying of sludge on the nitrogen mass balance of a WWTP, and GHG emissions with
- 397 classical and novel treatment approach A full-scale case study. Journal of Environmental Management 294,
- 398 113049. https://doi.org/10.1016/j.jenvman.2021.113049