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Enhanced Environmental Sustainability for the Acoustic Absorption Properties of Cabuya Fiber in Building Construction Using Machine Learning Predictive Model

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Abstract: Sustainability in construction is a growing concern due to the significant polluting waste generated before, during, and after a building's life cycle. The use of natural materials can significantly reduce the environmental footprint in obtaining, manufacturing, transportation, execution, use, maintenance, and demolition of the building, especially when locally sourced. Natural fibers, in particular, can be used in room acoustics, offering good acoustic absorption while meeting sustainability goals. The objectives of this paper are to evaluate cabuya fiber, grown in Ecuador, as an acoustic absorbing material and to introduce a novel approach using machine learning to simulate the material's acoustic properties. Eight samples of cabuya fiber, bound with a solution of water and $Ca(OH)_2$, were prepared with thicknesses between 12 and 30.6 mm. The sound absorption coefficients (SACs) were calculated using an impedance tube, following international standards. A Gaussian regression model was built for the predictions. The results showed that the 30.6 mm sample achieved maximum absorption coefficients of 0.91 at 2 kHz and 0.9 at 5 kHz. The model predictions are very accurate, with a mean square error of just 0.0002. These findings offer valuable insights into using cabuya fiber and advanced predictive models to enhance building acoustic performance and reduce environmental impact.

Keywords: cabuya fiber; environmental sustainability; building construction; sound absorption properties; machine learning simulation model

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1. Introduction

This paper aims to evaluate the acoustic absorption properties of FA fiber grown in Ecuador and to predict the material's acoustic characteristics using a novel machine learning approach. The study examines FA fiber's potential as a sustainable building material for room acoustics through a comprehensive process that includes fiber and sample preparation, acoustic absorption measurements, and predictive modeling with machine learning techniques. By comparing FA fiber with other natural fibers of similar thicknesses, this paper provides valuable insights into its effectiveness as a sound-absorbing material. Additionally, a Gaussian regression model was trained on a dataset comprising experimental data and material characteristics to create a reliable tool for architects, designers, and stakeholders. This tool helps anticipate the acoustic performance of FA fiber in room acoustics configurations. This approach not only integrates cutting-edge technologies into sustainable building practices but also highlights the potential of data-driven decision-making to enhance building performance and ensure user comfort.

Literature Review

In recent years, the building construction industry has faced increasing pressure to adopt sustainable practices and materials to reduce its environmental impact [1–6]. With the challenges of climate change and dwindling natural resources, sustainable building solutions have become urgent [7,8]. Researchers and practitioners are now exploring alternative materials that offer both ecological benefits and good performance [9,10].

Plant fibers have been used as building materials in many cultures worldwide for centuries, valued for their unique properties in constructing homes, infrastructure, and everyday objects [11–17]. The appeal of plant fibers lies in their natural origin and renewable nature. These fibers are obtained from rapidly growing plants like cotton, flax, kenaf, hemp, and cork, which need relatively low water and chemical inputs compared to synthetic materials [18]. This makes them a more sustainable alternative to traditional materials used in the construction industry such as cement, steel, and plastics [19].

In addition, plant fibers have several beneficial properties for the building industry. They are lightweight, flexible, and easy to work with, allowing for the creation of adaptable and customized structures [20]. Many plant fibers also provide excellent thermal and acoustic insulation, enhancing the energy efficiency of buildings and creating comfortable environments [21,22]. They can be used in various construction components, including insulation [20], wall coverings [21,23], roofing sheets [24], bricks [25], pavements [26], and structural elements [27–32]. Another major advantage of plant fibers is their biodegradability [33,34]. Unlike synthetic materials, they decompose naturally over time [34,35], reducing the environmental impact of construction and demolition waste and aligning with the principles of the circular economy [10,34]. Additionally, plant fibers can be combined with natural binders or biodegradable resins to create high-performance composite materials with a minimal environmental footprint [34,35]. The performance results of these fibers can be integrated into digital systems, such as BIM or digital twin, to assess building sustainability during the design phases [36,37].

A plant fiber of particular interest is cabuya fiber, obtained from Furcraea Andina (FA) [35]. FA fiber has been studied for its potential applications in modern construction practices. Its significant weight reduction and lower cost make FA a recommended reinforcement material for automotive purposes [38]. For instance, Pruna et al. [39] studied a polyester matrix composite reinforced with fiberglass and FA fiber for rearview mirrors. In construction, Valdivieso et al. [40] proposed using FA fiber as a structural reinforcement for block masonry walls. They concluded that reinforced mortars showed a 19.71% increase in compressive strength compared to unreinforced mortars. They also tested two block masonry-filled reinforced concrete frames, with a 78.46% increase in resistance to seismic loads and a 32.04% reduction in horizontal displacements at the frame's apex when incorporating electro-welded mesh and FA fiber. Teves et al. [41] studied the elastic properties of FA fibers through unidirectional tensile tests using an elastic model to evaluate their behavior under fatigue and cyclic loads. They calculated the mean micro-fiber angle of the S2 layer [42] and the longitudinal elastic constant using four finite element configurations, achieving an average deviation of 5.5%. Additionally, incorporating geometric and chemical factors like the crystallinity index and MicroFibril Angle (MFA) helped forecast FA's stiffness matrices. Tenazoa et al. [43] explored enhancing FA fibers' physical properties with alkali treatment to remove non-cellulosic components and improve fiber adhesion in composites. The treatment significantly reduced lignin and hemicellulose without affecting the microfibrillar angle, indicating effective surface treatment. Brenes-Acosta et al. assessed the influence of fiber quantity and length on the tensile strength and Young's modulus of FA fiber-reinforced polyester [44]. They found that increasing fiber load reduced the tensile strength of the FA composite. However, increasing fiber load and length enhanced Young's modulus. The Young's modulus and impact resistance of the FA composite were lower than those of the glass fiber composite but higher than those of non-reinforced polyester. These studies suggest that incorporating FA fibers can enhance structural safety while utilizing an environmentally friendly resource. Consequently, FA fiber is a promising sustainable alternative in building construction due to its renewable nature, biodegradability, and low environmental impact.

Many plant fibers are ideal acoustic absorbent materials to be used in room acoustics because they are harmless to human beings, non-toxic, biodegradable, sustainable, abundant, and renewable [15,45,46]. Many studies add artificial binders to the raw fibers, which decreases the biodegradability of the materials [47,48], although they still produce a lower carbon footprint compared to conventional synthetic sound absorbers [49]. However, without the addition of non-biodegradable binders, the sound absorption coefficients (SACs) evaluated in many studies are quite competitive for absorption at a wide frequency range. For example, if the frequency at which the SACs exceed 0.5 is considered a reference, it is approximately 2100 Hz for a 25 mm sample of coir fiber [50], 2740 Hz for a 300 mm sample of tea leaf fiber [51], and 1000 Hz for a 20 mm sample of pineapple fiber [52].

No references were found about the acoustic properties of the FA fibers [15,21,35,45,53,54]. Given its use since prehistoric times in Ecuador [12,13], incorporating it as a room acoustics material would adapt this natural resource to modern societal needs while preserving its connection to Ecuadorian culture. FA belongs to the Asparagaceae family, which comprises more than 20 species [55], some of which are commonly known as "Cabuya" or "Fique". One of them is the Furcraea Agavaceae, whose thermoacoustic properties were studied by Gomez et al. [56]. They evaluated samples of 10.5 mm and 20 mm, achieving outstanding results for the frequency range with a SAC > 0.5 (above 2425 Hz and 875 Hz, respectively). The acoustic absorption of the Furcraea Macrophylla was studied using samples of 0.5 mm, 10 mm, and 15 mm [57], obtaining a SAC above 0.5 for frequencies higher than 2600 Hz, 1415 Hz, and 915 Hz, respectively.

2. Materials and Methods

This study investigates the acoustic properties of FA fibers, underlining their environmentally friendly characteristics. This section first describes the methodology used for extracting FA fiber from the plant of origin (Furcraea Andina). The research then moves on to a detailed examination of the sound absorption properties of the fiber, demonstrating its potential to improve acoustic performance in architectural contexts. Furthermore, this paper introduces an innovative approach that uses machine learning techniques to create a simulation model to predict the sound absorption characteristics of FA fiber. Each step, from fiber preparation to simulation model development and validation, is meticulously described, providing a complete understanding of the entire process, as depicted in the flow chart of Figure 1.

2.1. Specimens Preparation Methodology

Furcraea Andina (FA) is a plant native to the mountainous regions of Latin America, particularly the Andes, which cross countries such as Peru, Ecuador, Bolivia, and Colombia [56,58]. This plant has a long history of use by indigenous communities in the Andes, who have exploited its leaves to produce fibers utilized across various applications, from weaving to construction [12,14,55]. FA (Figure 2) has a characteristic rosette of long, narrow leaves, which can reach lengths of several meters [17,59,60]. These leaves are rich in long and resistant fibers, which give the plant a significant commercial value. FA is prized for its strength, flexibility, and durability, making it an ideal material for the production of ropes, baskets, fabrics, and other handcrafted products [13,14,17].

It is important to know some properties of the fibers to evaluate whether they are appropriate for being used in construction [61]. According to Bastidas et al., FA fiber exhibits notable mechanical and thermal properties [35]. Its Young's modulus is quantified at 24.31 GPa (the fiber evaluated had a cross-section of 170 μm approximately), and it remains thermally stable at up to 360 °C in air. These mechanical properties surpass those of similar fibers like jute and sisal, creating new opportunities for using cabuya fiber alone or together with materials such as mortars, concretes, panels, metals, polymers, nanoparticles, and metal–organic frameworks.

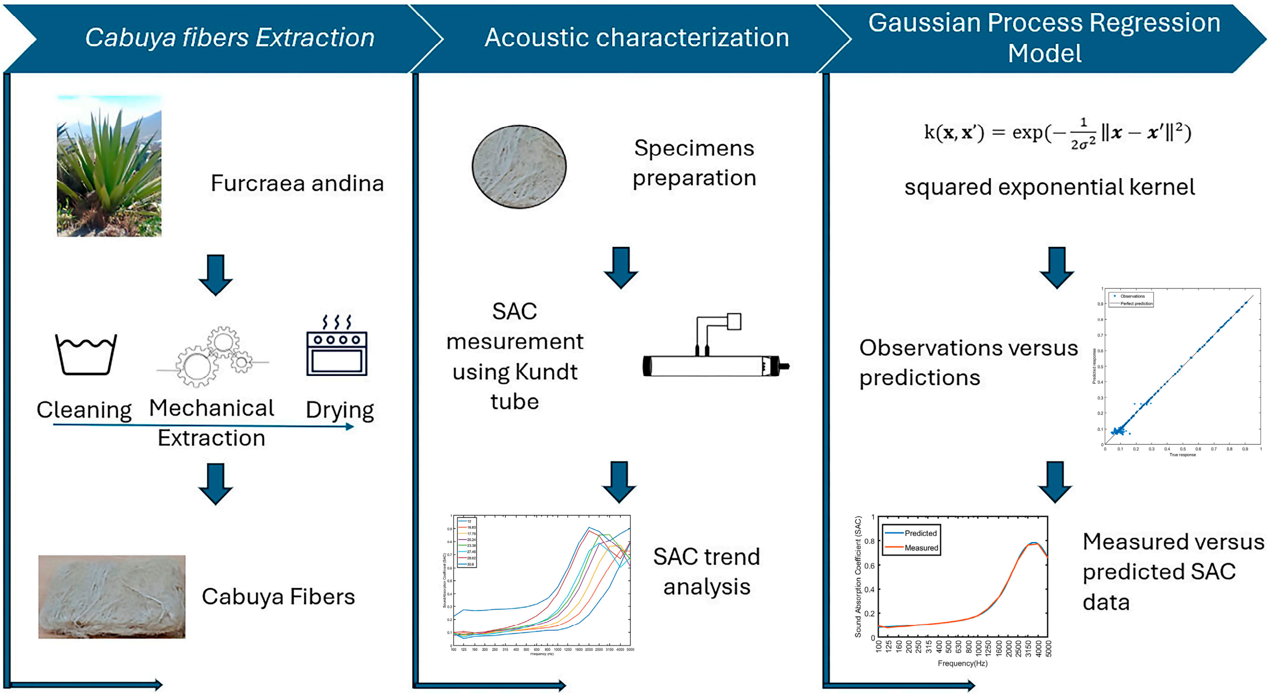

Figure 1. Flow chart of the methodology used in this study.

Figure 2. Furcraea Andina plantation in a typical indigenous environment.

The processing of FA begins with the harvesting of the plant's mature leaves. Once harvested, the leaves undergo a process to extract the fibers. This process may vary slightly depending on local traditional practices but generally involves the mechanical separation of the fibers from the leaf pulp. The fibers are then washed, dried, and sometimes subjected to additional treatments to improve their quality and durability. The fibers extracted from FA, commonly known as FA fibers, are characterized by a natural resistance to weathering and pests, making them suitable for a variety of industrial and handicraft applications. The fibers can be hand-woven or used as reinforcing material in polymer composites, as in the case of the automotive applications mentioned earlier. FA is particularly valued for its versatility and sustainability; in fact, unlike many synthetic materials, FA fibers are completely biodegradable and have a low environmental impact [62]. In addition, the cultivation of FA requires few water resources and does not require the use of pesticides or chemical fertilizers, making it an environmentally friendly choice for natural fiber production. In addition, FA plays an important role in the rural economies of Andean regions, offering an income opportunity for local farming communities. The cultivation and washing of FA contribute to the preservation of artisanal traditions and the sustainable economy of the mountainous regions of Latin America [63].

In this work, the leaves of FA were first subjected to hulling. Hulling is an essential process for extracting the valuable cabuya fibers, which find extensive use across diverse industrial and artisanal applications [64]. Through this process, the outer bark and fibrous parts of the plant's mature leaves are removed to reveal the long, tough fibers within. Hulling can be performed manually or through specialized machinery, depending on local practices and the scale of production; in our case, a manual procedure was performed. Once extracted, the fibers were washed and submitted to a drying process, obtaining 4 to 5 percent of the leaf mass in the form of large fibers. The fibers were cut by hand and mechanically entangled using a spiked rotating drum, creating a nonwoven structure. The fibers were immersed in a binding solution consisting of water (50 percent), glue (35 percent) and calcium hydroxide $Ca(OH)_2$ (15%). This process was performed to remove any chemical or biological constituents, dirt, and other particles adhering to the fibers. Next, the fibers were arranged in wooden frames of 30 × 30 cm dimensions with thicknesses varying between 20 and 60 mm. After being drained, the fibers were completely dried in an oven at 70 degrees Celsius for about 8 h, guaranteeing the formation of homogeneous samples. The FA samples evaluated are shown in Figure 3.

Figure 3. Sample of cabuya fibers that have been prepared according to the specified standards.

The processing of FA obviously has costs. The initial investments for the purchase of machinery and equipment for the extraction and processing of the fiber can be high. The production of FA fiber is considerable. The process of cleaning, drying, and combing the fibers involves additional costs of time and resources. On the other hand, the resulting benefits are important: FA fiber is biodegradable and ecological, reducing the environmental impact compared to synthetic fibers. FA is extremely resistant and long-lasting, making it ideal for producing ropes, fabrics, and other products that require high resistance. FA-derived products, thanks to their quality and sustainability, can command higher market prices. FA fiber production can create jobs and stimulate the local economy in rural regions where the plant grows.

2.2. Determining the Sound Absorption Coefficient (SAC)

The sound absorption properties of a material are directly linked to its ability to dissipate incident acoustic energy. This parameter can be accurately measured using standardized methodologies such as the tube impedance test for samples of different sizes, according to ISO 10534-2:1998 [65] and ISO 354:2003 [66]. These methods allow the identification of two types of SAC, one for normal incidence and the other for random incidence. In our work, the SAC was measured via the impedance tube test as indicated by ISO 10534-2:1998 standard. The SACs were measured in 2019. The fiber samples were carefully positioned in the 33 mm sample holder placed at the end of the impedance tube, without any air gap behind the sample. A speaker placed at the other end of the impedance tube reproduced a white noise signal, with a normal incidence on the sample surface. Two ½″ pre-polarized free-field microphones (GRASS 46AO) were placed between the speaker and the sample to record the sound pressure inside the impedance tube.

Data processing was executed utilizing the ACUPRO 4.5 software, which managed the calibration process, data acquisition, and signal recording. The results obtained were considered valid in the interval of frequencies from 100 Hz to 5 kHz, based on the diameter of the impedance tube used [67]. To ensure the accuracy of the measurements, each sample was subjected to three repetitions of the test, with the impedance tube removed and reinserted into the sample holder between each series of measurements. The average of the repeat results was then calculated for each fiber sample. The experimental setup used is illustrated in Figure 4.

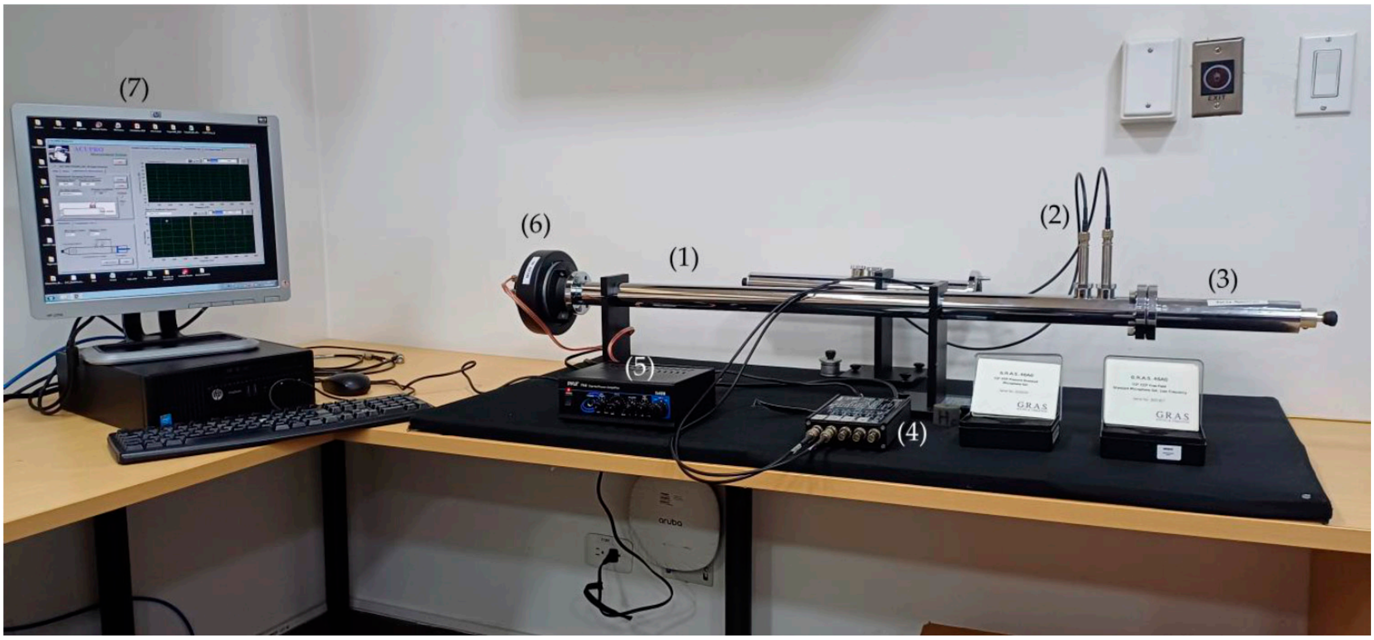

Figure 4. Equipment for the measure of the sound absorption coefficient (SAC) includes: (1) an impedance tube (Spectronics), (2) microphones, (3) a sample holder, (4) a data acquisition system, (5) an amplifier, (6) a speaker, and (7) a PC running ACUPRO 4.5 software.

The materials examined are categorized as porous acoustic materials due to their sample structure facilitating the formation of interconnected pores. This arrangement permits the propagation of acoustic waves and the dissipation of acoustic energy through effects such as viscous boundary layers and thermal conduction from the air to the surrounding milieu. The acoustic absorption of porous materials is affected by various factors, comprising characteristics inherent to the material, like flow resistivity, open porosity, and tortuosity. Additionally, aspects related to production and installation, such as thickness, positioning within the acoustic environment, and the angle of incidence of the acoustic wave, play significant roles [46].

Regarding the effects of non-intrinsic properties, the velocity of the air particles, which reaches its maximum beyond a distance exceeding 1/4 of the wavelength of the incoming sound wave, impacts the dissipative effects of porous absorbers. Therefore, an increase in thickness improves absorption at low frequencies. Finally, the SAC also varies based on the incidence angle of the sound wave, which can be perpendicular or diffuse [68].

2.3. Modeling the SAC Using Gaussian Process Regression (GPR)

Gaussian process regression (GPR) is a powerful and versatile method used in machine learning and statistical modeling to estimate and predict continuous functions [69]. Unlike traditional regression techniques that assume fixed model parameters or distributions, GPR is a non-parametric approach that models the entire functional space as a distribution of functions, allowing for flexible and robust predictions. GPR relies on the principle of Gaussian processes, which consist of sets of random variables, where any finite subset follows a joint Gaussian distribution [70]. In the context of regression, a Gaussian process explains a distribution over functions, where each function can be thought of as an infinite-dimensional vector. These functions are characterized by their mean and covariance, which capture the central tendency and degree of variation, respectively. To perform regression using GPR, we started with a dataset comprising input–output pairs (x, y), where x denotes the input variables and y denotes the related outputs. The objective was to establish a correlation between inputs and outputs, enabling predictions for new and unobserved data points. The key idea behind GPR is to use observed data to infer the underlying function that generated the data. Instead of fitting a single function to the data, GPR estimates a distribution over functions consistent with the observed data. This distribution is thoroughly described by its mean and covariance functions, which are generally chosen based on prior knowledge or assumptions about the data [71].

One of the defining characteristics of GPR is its Bayesian nature, incorporating prior beliefs and updating them with observed data to quantify forecast uncertainty, providing point predictions and confidence intervals. GPR involves two main steps: inference and prediction. During inference, GPR uses observed data to calculate the posterior distribution of functions, updating the results of the underlying function using Bayes' theorem, which involves determining the mean and covariance of the posterior distribution [72]. In the prediction phase, GPR generates forecasts for new data points using the posterior mean and covariance functions. The predictive distribution at an input point is Gaussian, with the mean representing the estimated output value and the variance capturing prediction uncertainty [73].

GPR offers numerous advantages over traditional regression techniques. First, it provides a framework of principles for managing uncertainty in predictions, which is crucial in many real-world applications. Second, GPR naturally handles nonlinear relationships between inputs and outputs without explicitly specifying a parametric model. Furthermore, GPR allows for easy incorporation of prior knowledge and industry expertise via the selection of mean and covariance functions [74].

Gaussian regression is a statistical method used to model, predict, and understand the relationships between dependent and independent variables if the data follow a Gaussian distribution [75]. In the context of Gaussian regression, it is assumed that the data error follows a normal distribution with a mean of zero and consistent variance [76]. The kernel in a Gaussian regression model is essential as it determines the shape and flexibility of the regression function. From the perspective of Gaussian regression, the kernel is a function that measures the similarity between two points in feature space [77]. This similarity affects the amount of weight that training points have when predicting a test point. A good kernel in a Gaussian regression model should be able to effectively catch the structure of the data and adapt to changes in the relationship between variables. Gaussian kernels, for example, use the Euclidean distance between points in feature space to calculate similarity [78]. This type of kernel is particularly suitable for modeling nonlinear relationships between variables. The importance of the kernel therefore lies in its ability to determine how flexible and adaptable the Gaussian regression model is to the characteristics of the data [79]. A well-chosen kernel can significantly improve model performance, allowing you to capture complex, non-linear relationships between variables, while an inadequate kernel can lead to models that do not fit the data well and produce inaccurate predictions.

In this research, the squared exponential kernel (Gaussian kernel or radial basis function (RBF)) function was applied, which is a fundamental component in machine learning, particularly in Gaussian processes and kernel-based methods [80]. It calculates the similarity or covariance between pairs of data points based on their Euclidean distance in the input space [81].

Mathematically, the squared exponential kernel is defined as:

$$k(x, x') = exp\, exp(-\frac{1}{2\sigma^2}\|x - x'\|^2) \tag{1}$$

In Equation (1):

- x = input vector;
- x' = input vector;
- $\|\ \|$ = Euclidean norm;
- σ = length scale.

The squared exponential kernel assigns high similarity to nearby points, capturing local dependencies and smoothness in the data, making it suitable for modeling smooth variations [82]. However, it assumes stationarity and may struggle with non-stationary patterns, and selecting an appropriate length scale parameter is crucial for model performance. Despite these limitations, it remains popular for its simplicity and effectiveness in various tasks [83].

Hyperparameters are critical in machine learning models, including Gaussian regression, influencing the model's ability to adapt and generalize correctly [84]. High kernel variance can lead to overfitting, while low variance can result in a rigid model [85]. Hyperparameter optimization aims to balance complexity and generalization through methods like grid search, random search, or Bayesian optimization [86]. This study used Bayesian optimization, which efficiently explores the hyperparameter space and leverages past evaluations to guide the search [87]. This method yields better results with fewer evaluations, making it effective for optimizing complex models [88].

- Length scale (σ): this hyperparameter controls the smoothness of the function learned by the Gaussian process [89]. A smaller-length scale leads to a wavier function that can capture fine-grained variations in the data, while a larger-length scale results in a smoother function that better generalizes to unseen data. Adjusting this parameter is essential in adapting the model to the specific characteristics of the data and preventing overfitting or underfitting.
- Noise variance (σ^2): This hyperparameter represents the variance of noise in the data [90]. It considers the uncertainty and measurement errors present in the observed target values. Adjusting the noise variance parameter is critical to balancing the model's fit to the training data and its ability to generalize to new data points. Setting an appropriate noise level is essential for accurate predictions and robustness of the Gaussian process regression model.

Correctly tuning hyperparameters ensures that the Gaussian process regression model effectively captures the underlying patterns in the data and makes reliable predictions.

Once the model was built, the RMSE (root mean square error), MAE (mean absolute error), and MSE (mean squared error) metrics were calculated to evaluate the model's ability to accurately match the measurement outcomes.

2.4. Computational Assumptions, Applicability, and Limitations of the SAC Predictive Model

The GPR-based model assumes that the input data follow a specific distribution, typically a normal distribution. Since FA fibers have a behavior typical of porous materials, this assumption can be justifiably assumed. The model utilizes a squared exponential kernel, which is capable of capturing the underlying data patterns by accounting for smooth variations in the data. The model assumes that the statistical properties of the modeled process do not change over time (stationarity). The SAC predictive model is particularly suitable for scenarios where the relationships between input and output variables are complex and non-linear. The model offers better performance with a significant amount of high-quality data. It is applicable in contexts where sufficient training data are available to learn the underlying models. The model is applicable in situations requiring high predictive accuracy and where uncertainty quantification provided by Gaussian process regression is valuable. The SAC predictive model, based on Gaussian process regression, is computationally intensive, especially for large datasets. This can limit its scalability and applicability to large datasets. Although the model provides accurate predictions, the interpretability of Gaussian process regression can be challenging due to its complexity and the abstract nature of the kernel functions. Model performance is sensitive to the choice of hyperparameters. Incorrect choice of hyperparameters can lead to suboptimal model performance.

3. Results and Discussion

The SAC of a material measures its ability to reduce sound reflections, essential for minimizing reverberation time and maintaining speech intelligibility [91]. This coefficient, determined by the ratio of incident to total acoustic energy, results from a thermal effect caused by air molecule friction within pores [92]. Fibrous materials typically exhibit a maximum absorption peak, influenced by density and thickness. Natural fibers' structures offer varied modes for sound wave energy attenuation. Porous samples with low flow resistivity show minimal attenuation, while higher-density FA samples have lower absorption due to surface reflection and limited acoustic permeation. Tortuosity describes the porous internal structure's effect on sound absorption, correlating with specimen flow resistivity [93].

3.1. Experimental Measurement Results

The samples prepared as outlined in Section 2.1 underwent SAC measurements using an impedance tube [94]. They were positioned into the impedance tube (refer to Figure 3). To assess the material's acoustic properties, various measurements were conducted for each sample. Before each test, the specimens were extracted from the tube and subsequently reinserted to minimize potential errors. The results were analyzed by discarding extreme values and calculating the average of the obtained values. Eight distinct types of specimens were prepared with varying thicknesses to comprehensively assess the material's behavior. Table 1 presents the standard deviation of the measured values.

Table 1. Standard deviation values for the sound absorption coefficient (SAC) measurements of the sample thicknesses of the study.

	Thickness (mm)							
Frequency (Hz)	**12**	**16.83**	**17.76**	**20.24**	**23.38**	**27.46**	**28.62**	**30.6**
100	0.03560	0.00666	0.00420	0.00894	0.05934	0.00963	0.02988	0.02928
125	0.01527	0.01233	0.01909	0.00682	0.02886	0.00517	0.03796	0.01824
160	0.01363	0.00517	0.00198	0.00427	0.00489	0.00971	0.00456	0.00350
200	0.00187	0.00201	0.00183	0.00193	0.00319	0.00193	0.00110	0.00173
250	0.00416	0.00151	0.00446	0.00170	0.00250	0.00657	0.00191	0.00131
315	0.00264	0.00084	0.00119	0.00044	0.00129	0.00069	0.00030	0.00114
400	0.00052	0.00050	0.00021	0.00022	0.00011	0.00030	0.00031	0.00071
500	0.00021	0.00022	0.00019	0.00021	0.00031	0.00017	0.00020	0.00094
630	0.00029	0.00015	0.00015	0.00026	0.00033	0.00023	0.00016	0.00073
800	0.00015	0.00009	0.00015	0.00028	0.00021	0.00006	0.00016	0.00030
1000	0.00014	0.00008	0.00015	0.00003	0.00011	0.00027	0.00024	0.00043
1250	0.00004	0.00014	0.00023	0.00025	0.00052	0.00062	0.00035	0.00093
1600	0.00027	0.00037	0.00023	0.00024	0.00072	0.00045	0.00019	0.00011
2000	0.00027	0.00024	0.00009	0.00009	0.00009	0.00010	0.00046	0.00018
2500	0.00008	0.00032	0.00025	0.00023	0.00026	0.00045	0.00072	0.00066
3150	0.00025	0.00018	0.00025	0.00028	0.00007	0.00016	0.00066	0.00024
4000	0.00038	0.00014	0.00020	0.00015	0.00055	0.00007	0.00030	0.00005
5000	0.00019	0.00043	0.00052	0.00040	0.00020	0.00013	0.00019	0.00095

The standard deviation is an indicator of the dispersion of the data around the mean [95]. Lower standard deviation values mean that the data are more concentrated around the mean, indicating greater precision and consistency of measurements [96]. In the case of Table 1, where the values of the standard deviation are reported for different frequencies, it is observed that the values are generally very low, indicating consistency in the measurements. This suggests that the measurements were taken accurately and reliably. The increase in standard deviation at 100 Hz may be due to greater variability in the data at this specific frequency. However, since the values remain below 0.05, this variation is still relatively small and does not significantly compromise the overall reliability of the measurements. In summary, the low standard deviation in Table 1 provides strong justification for the precision and reliability of the measurements taken, with minimal variations in the data confirming their consistency.

Figure 5 reports the value of the SAC for every variety of samples prepared with various thicknesses.

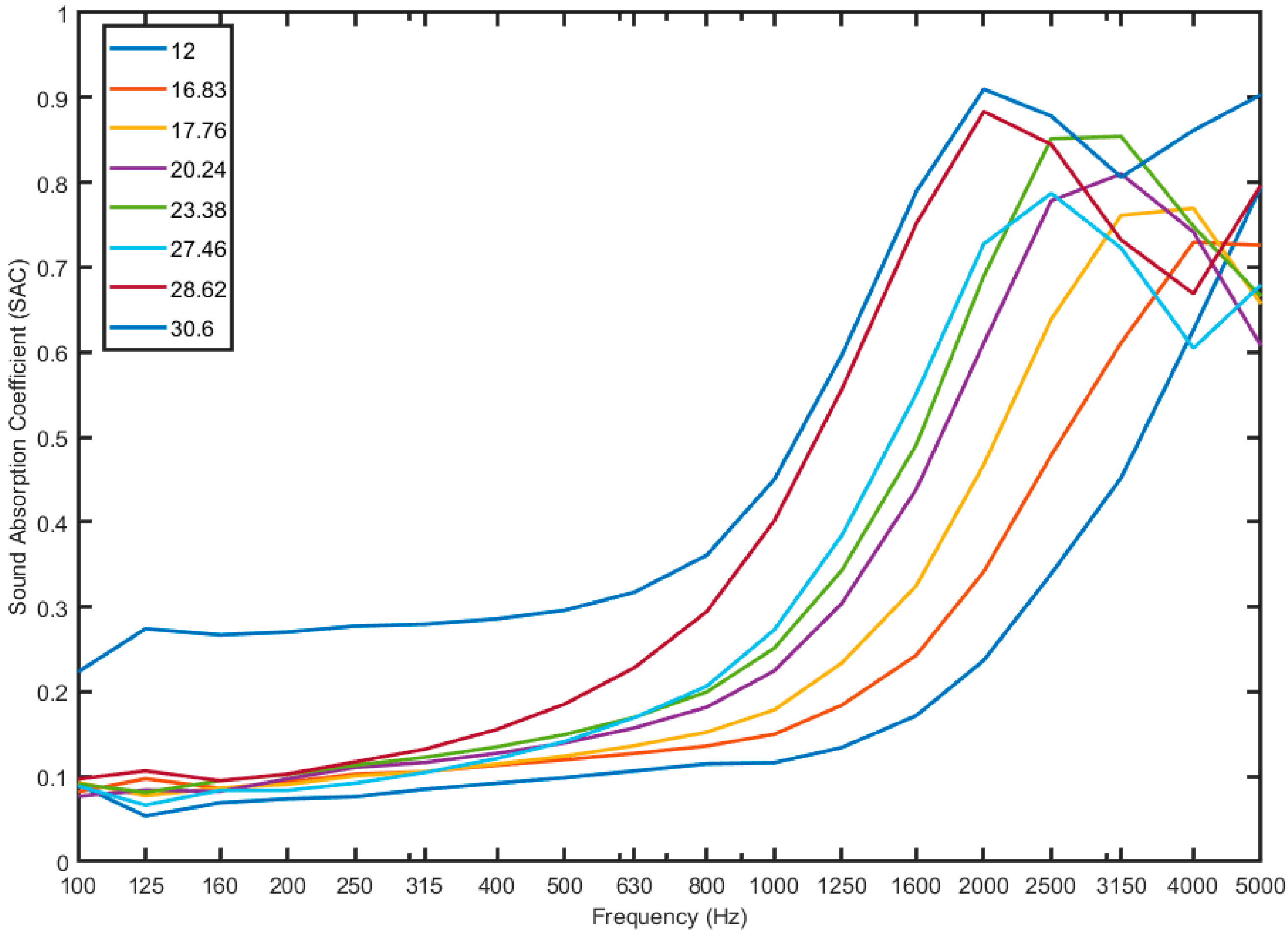

Figure 5. Sound absorption coefficient (SAC) in one-third octave bands, using a log scale for the frequency axes. Eight sample thicknesses as shown in the legend: 12 mm, 16.83 mm, 17.76 mm, 20.24 mm, 23.38 mm, 27.46 mm, 28.62 mm and 30.6 mm.

The SAC trend is shown as a function of frequency, divided into one-third octave bands on a logarithmic scale. The acoustic properties of the material studied reflect the distinctive traits of porous materials, attributable to the characteristics of FA. Cabuya fibers are characterized by a notable roughness, which plays a substantial role in sound absorption. This irregularity generates tiny air pockets on the fiber's surface, resulting from their ridged and irregular surfaces. The effect of this attribute is SAC increase due to the considerable friction generated among the fibers and the incident sound wave. Furthermore, the greater surface area caused by the roughness of the fibers raises the damping capability of the incoming wave, further contributing to the overall sound absorption.

Various factors can justify the acoustic behavior of the samples concerning the thickness. First, samples with greater thickness have greater mass and volume, which can increase sound absorption capacity as more material is available to absorb incident sound energy. This is particularly evident at low frequencies (100–125 Hz), where the greater thickness of the sample allows for greater attenuation of the sound energy. Furthermore, the peak in SAC observed at mid-frequencies is typical of porous materials and can be attributed to acoustic resonance within the porous cavities of the material. Thicker samples tend to have a greater depth of porous cavities, which promotes better resonance and therefore increased SAC. Furthermore, the peak shifting towards lower frequencies with increasing sample thickness could indicate greater sound absorption capacity at lower frequencies. Overall, the increase in SAC with sample thickness and the typical bell-shaped pattern at mid-frequencies are consistent with the characteristics of porous materials and suggest that the efficacy of sound absorption is related to the volume and geometry of the porous cavities in the samples. Sparse SAC values in the high-frequency range (4000–5000 Hz) may be because the structures exhibit multiple vibrational modes, and different modes can cause variations in SAC values.

3.2. Comparison with Other Natural Fibers

Table 2 shows the results frequency at which the SACs exceed 0.5, and the peak values of the SAC of different research studies [50–52,56,57]. Peak absorption occurs at the resonant frequency when the material thickness is an odd multiple of one-quarter of the incident sound's wavelength. Conversely, minimal sound absorption occurs when the thickness is an even multiple of half the wavelength [97,98].

The studies selected for the comparison evaluated samples of similar thicknesses to the ones of our research. Another criterion used for study selection was that the samples were measured by placing the samples directly against the wall of the impedance tube, without an air gap behind the sample. It is worth mentioning that the SACs of other studies were approximated since they were measured directly from the figures of each study using a graphic design program. The studies of Furcraea Agavaceae [54] and Furcraea Macrophylla [57] were included, as both plants belong to the same genus as the FA.

Although the study of pineapple fiber [52] had samples of similar thickness, the appearance of the samples indicates that some kind of binder was used, not stated in the study description, so we do not know whether these binders are bio-degradable or not, or to what extent the binders favor the sound absorption. Similarly, this happened in the study of Furcraea Macrophylla [57], which stated that the samples were composed of "short fique fibers arranged in a "non-textured" way with a superficial covering of polymer", but they do not indicate what kind of polymer was used (there are polymers that may improve the sound absorption coefficient) or whether the polymer was biodegradable or not. For the Furcraea Agavaceae fiber samples [56], natural rubber latex with a concentration of 60% solid content was used.

The coir sample of 35 mm has its first peak of the SAC at 2000 Hz and the second one at 5000 Hz, as with the 30 mm samples of FA [50]. The performance of both samples is similar at the 2000 Hz peak, and the FA fiber has slightly higher SAC at the second peak. In this case, the frequency range with SAC > 0.5 is wider for the 30.6 mm FA sample.

The pineapple fiber sample of 20 mm and Furcraea Macrophylla fiber sample of 10 mm have their highest SAC at approximately the same frequency (2000 Hz). Comparisons are challenging due to the different sample sizes, but Furcraea Macrophylla appears to perform better than pineapple samples, with the SAC > 0.5 for the 15 mm sample starting at 915 Hz, and the one of the 20 mm sample starting at 1000 Hz. However, as cited before, the binders were not properly defined in their corresponding studies

The study of Gomez et al. [56] shows that Furcraea Agavaceae fiber samples have a better performance than FA samples at both the maximum SAC and the frequency range with SAC > 0.5. This involves that more research is needed in the use of binders for the FA fibers.

Table 2. Comparison of the maximum sound absorption coefficients, and the frequency range limits above a sound absorption coefficient >0.5 of the samples of coir, tea leaf, pineapple, Furcraea Agavaceae, and Furcraea Macrophylla. The upper limits of the sample coefficient labeled as "max" indicate that the SAC last frequency band evaluated is higher than 0.5.

Material	Thickness (mm)	First Peak		Second Peak		SAC > 0.5	
		Frequency (Hz)	SAC	Frequency (Hz)	SAC	Lower Limit (Hz)	Upper Limit (Hz)
Coir [50]	25	3135	0.95	6350	0.87	2100	max.
	35	2000	0.92	5000	0.74	1245	max.
Tea leaf [51]	10	4373	0.27	-	-	4240	4640
	20	6083	0.63	-	-	4240	max.
	30	5581	0.67	-	-	2740	max.
Pineapple [52]	20	2200	0.97	4280	0.85	1000	max.
	30	1575	0.98	4500	0.80	610	max.
Furcraea Agavaceae [54]	10.5	4275	0.94	-	-	2425	max.
	25	1800	0.99	6292	0.95	875	max.
Furcraea Macrophylla [55]	10	2200	0.98	-	-	1415	max.
	15	3135	0.92	5000	0.90	915	max.
Cabuya (FA) Present study	12	5000	0.79	-	-	3380	max.
	16.83	5000	0.73	-	-	2600	max.
	17.76	4000	0.77	-	-	2095	max.
	20.24	3150	0.81	-	-	1743	max.
	23.38	3150	0.85	-	-	1618	max.
	27.46	2500	0.79	-	-	1493	max.
	28.62	2000	0.88	-	-	1159	max.
	30.6	2000	0.91	5000	0.90	1084	max.

Although FA fiber samples were not the best-performing ones, the results are very competitive, showing that they can work as a sound-absorbing material at a wide range of frequencies. Its thermal resistance makes it an ideal material to reduce reverberation time in room acoustics.

Manufactured artisanal products and the uses associated with traditional construction elements made of FA are being lost due to industrialization. For this reason, it is important to give new uses to this natural product so historically tied to Ecuadorian culture. The materials used in this study are naturally sourced and have the potential to be biodegradable or recyclable, resulting in a lower environmental impact compared to conventional artificial materials used in room acoustic applications. Utilizing these natural materials near their collection and production sites minimizes the environmental footprint and contributes to the sustainability of the building construction sector. This is due to their eco-friendly manufacturing processes and the reduced pollution associated with the transportation and distribution of construction materials. Additionally, the use of these materials can foster the development of small family businesses, thereby enhancing the economic stability of low- or middle-income countries.

3.3. Development of Predictive Models

In recent times, there has been a rise in research employing machine learning techniques to forecast the SAC. In line with this trend, SAC data have been utilized to construct a regression model aimed at predicting material acoustic properties, utilizing a Gaussian model. The SAC prediction model developed for corn FA fibers (refer to Figure 5) integrates two main input factors: frequencies in one-third octave bands ranging from 100 Hz to 5000 Hz, and thickness measurements of specimens ranging from 12 mm to 30.6 mm. This model provides forecasts of SAC values, linking frequency within one-third octave bands to specimen thickness. Given the model's production of continuous numerical outputs, it is apparent that we are addressing a regression issue distinguished by two predictors and one response variable.

The model was carefully trained using data from SAC measurements, obtained through the Kundt tube method. However, ensuring the model's reliability extends beyond the dataset used for training is equally paramount. To achieve this, we turn to the cross-validation technique. Cross-validation is a widely adopted method in machine learning for evaluating model performance and assessing its generalization capabilities [98]. This method entails splitting the dataset into k subsets, or "folds". The model is trained on k − 1 of these folds and evaluated on the remaining one. This procedure is iterated k times, with each iteration holding out a different fold for evaluation. The results from each fold are averaged to provide an overall performance metric. By systematically rotating through different subsets of data for training and testing, cross-validation facilitates a more thorough evaluation of the model's capacity to generalize to new data [99]. This approach helps mitigate the risk of overfitting, where the model remembers the training data instead of capturing underlying patterns, leading to subpar performance on unseen data. The choice of k in cross-validation depends on factors such as dataset size, computational resources, and desired precision. Common values for k include 5-fold and 10-fold cross-validation, although higher values can be used for smaller datasets or when greater precision is required (Figure 6). Conversely, lower values of k may be preferred for larger datasets to reduce computational burden while still providing a reasonable estimate of performance.

Figure 6. K-fold cross-validation process (K = 5).

One advantage of cross-validation is its ability to highlight potential issues with model performance, such as variability in predictions across different subsets of data. This can indicate areas where the model may be struggling to generalize effectively or where additional training data may be beneficial. Moreover, cross-validation allows for the tuning of hyperparameters, such as regularization strength or kernel parameters, in a more robust manner. By evaluating model performance across multiple folds, it becomes clearer which combination of hyperparameters yields the best overall performance, helping to fine-tune the model and optimize its predictive capabilities.

We employed a total of 432 values to train and evaluate the model, ensuring a broad and meaningful representation of the experimental data. The Kundt tube method provides highly accurate and reliable sound absorption coefficient measurements. By focusing on high-quality data, we ensure that our model is trained on precise and consistent inputs, which is crucial for developing a robust predictive model. Our dataset of 432 records was carefully curated to represent a wide range of conditions and variables relevant to the study. This includes different thicknesses and frequencies. Despite the seemingly small size, the dataset captures the essential variability needed for training the model effectively. Collecting a larger dataset with the same level of precision and consistency would require significantly more resources and time. Given the scope of this study, we aimed to balance thoroughness and feasibility. The dataset size was deemed sufficient to demonstrate the model's potential and validity within the constraints of our research. The results obtained from the 432 records provide a solid foundation for our model. However, we acknowledge that expanding the dataset in future studies could further enhance the model's accuracy and generalizability. We plan to include more data points as we continue to refine and validate our approach.

To evaluate the effectiveness of the model in predicting SACs, we used three key metrics:

- RMSE (root mean square error): This metric quantifies the average deviation between the values predicted by the model and those observed in the test data [100]. It measures the square root of the mean of the squares of the differences between forecasts and actual values, providing an estimate of the dispersion of the data around the regression line. A lower RMSE value indicates a better fit of the model to the test data.
- MAE (mean absolute error): This metric calculates the mean absolute deviation between the predicted and observed values [101]. It provides a measure of the average of the absolute discrepancies between model predictions and actual data. MAE is less sensitive to large errors than MSE, providing a more robust estimate of model performance.
- MSE (mean squared error): This metric measures the mean of the squares of the differences between the predicted and observed values [102]. MSE strongly penalizes large errors, producing an estimate of the dispersion of the data around the regression line. However, because MSE is measured in square units of the original measurement units, it can be more difficult to interpret than RMSE and MAE.
- The joint use of these metrics provides a complete evaluation of the model's performance, allowing you to identify any areas for improvement and optimize its predictive capacity on test data.

The outcomes generated by the SAC prediction model, assessed using the selected metrics, are displayed in Table 3.

Table 3. Evaluation of the GPR-based model performance.

	RMSE	**MAE**	**MSE**
Training	0.0101	0.0047	0.0001
Validation	0.0153	0.0053	0.0002
Test	0.0176	0.0062	0.0002

The model's ability to accurately match measurement outcomes can be visually evaluated through scatter plots. These plots display measurement values on the horizontal axis (target) and predicted values on the vertical axis (response). Figure 7 exhibits visual cues demonstrating points near the solid line, indicating the ideal scenario. This depiction serves to showcase the precision of the model's predictions.

In assessing the sound absorption capability of FA fibers, we examine the trend of the SAC in relation to frequency for both measured and simulated data. This comparison is illustrated in Figure 8.

The analysis of Figure 8 reveals a remarkable adaptability of the model to data deriving from SAC measurements via the impedance tube. This observation is particularly evident at high frequencies, where the simulation and reference curves overlap almost perfectly.

This coherence indicates the ability of the model to accurately capture the acoustic behavior of the material in question. However, it is important to note that some deviation is observed at low frequencies. This discrepancy can be attributed to measurement uncertainty, often influenced by the inherent limitations of the impedance tube. Despite this, the model still demonstrates a good ability to simulate the acoustic behavior of the material even in these conditions. These results confirm the effectiveness of the model in predicting SAC and its ability to adapt to variations in sound frequencies. The almost perfect overlap between the curves in the high frequencies underlines the precision of the model, while the ability to correctly simulate even the low frequencies demonstrates its robustness in more challenging conditions.

In summary, the analysis of Figure 8 provides a solid justification of the reliability and accuracy of the model in predicting SAC, highlighting its ability to adapt to variations in measurement conditions and to effectively simulate the acoustic behavior of the material under investigation.

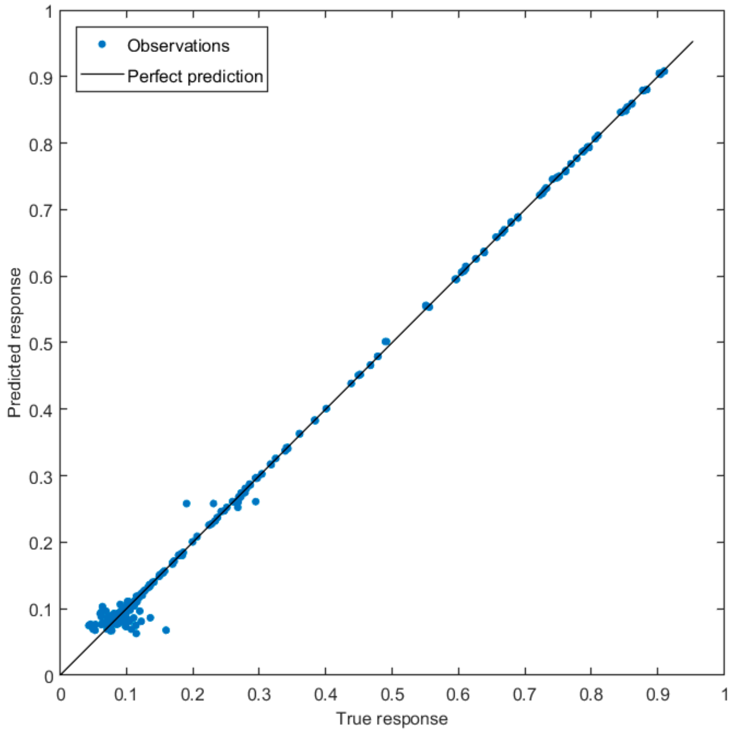

Figure 7. Assessment of the model output versus the target value is conducted across the training, validation, and testing phases.

3.4. Integration of the Research Process in the Construction Sector

Ultimately, the integration of sustainable materials and advanced predictive modeling techniques holds immense promise for achieving greater environmental sustainability and efficiency in the built environment, paving the way for a greener and more sustainable future in architecture and construction. This paper represents a thorough examination of FA fiber as a promising natural and eco-friendly material aimed at bolstering environmental sustainability within the realm of building construction.

The study meticulously outlines a comprehensive methodology for the preparation of FA fiber, accentuating its environmentally friendly characteristics. By placing emphasis on the sustainable sourcing and processing of this material, the research underscores its potential as a viable alternative in the construction industry, aligning with global efforts towards greener and more sustainable practices. Furthermore, the research delves into the measurement and analysis of the sound absorption properties of FA fiber, shedding light on its intrinsic acoustic performance attributes. This exploration underscores the material's capacity to contribute to improved acoustics within built environments, and specifically in room acoustics thus offering potential solutions for noise reduction and enhanced comfort in various architectural settings.

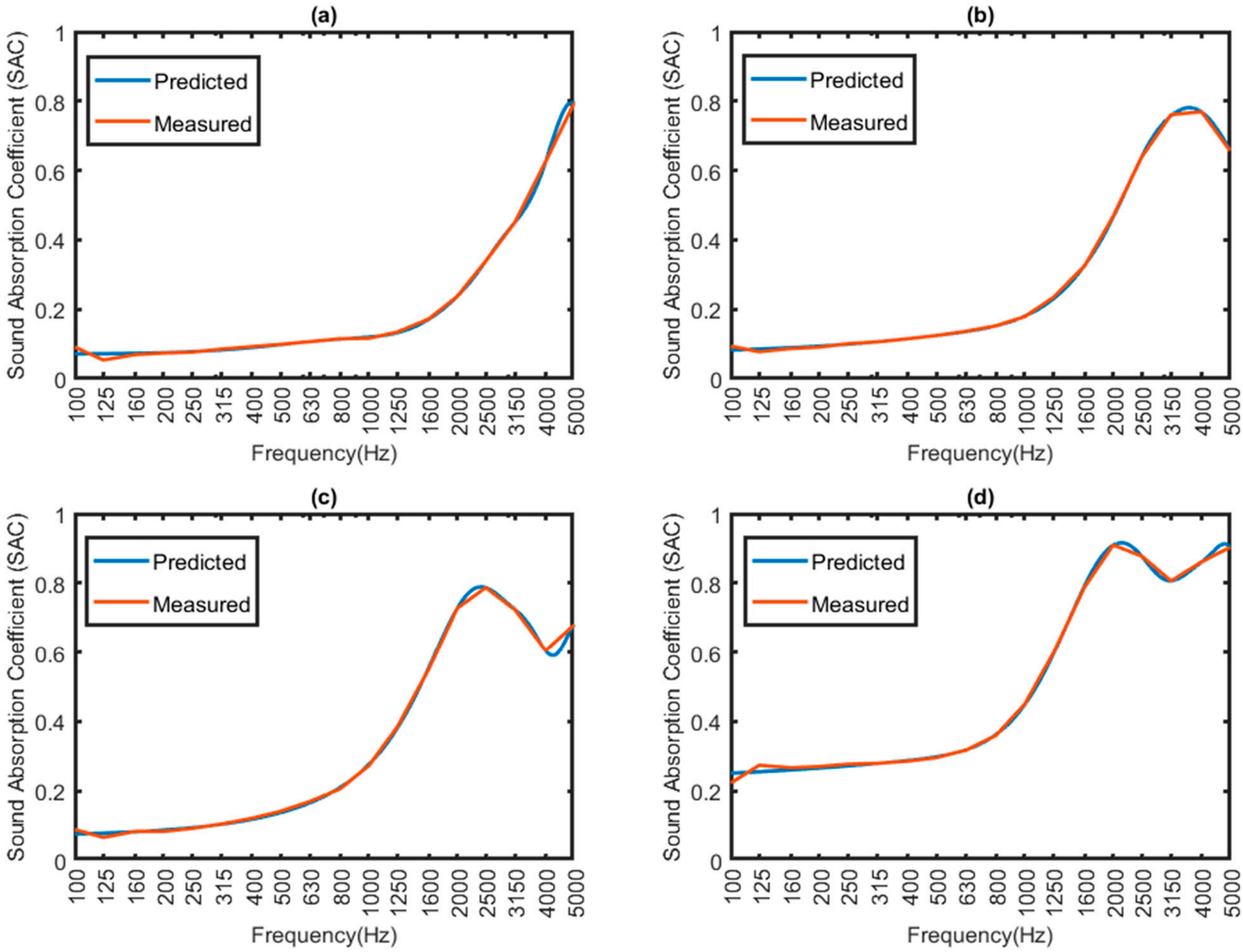

Figure 8. Measured versus predicted sound absorption coefficient (SAC) data: (**a**) 12 mm sample; (**b**) 17.76 mm sample; (**c**) 27.46 mm sample; (**d**) 30.6 mm sample.

By harnessing the power of machine learning, the study not only facilitates more accurate predictions of FA fiber's acoustic performance but also opens avenues for optimizing its utilization in architectural design and construction processes. Machine learning models can be applied to different materials in order to calculate the most appropriate panel thickness according to the specific room requirements. Through this interdisciplinary investigation, intending to bridge the gap between material science, acoustics, and machine learning, the study contributes to the growing body of knowledge aimed at optimizing building performance while mitigating environmental impacts.

The purpose of this procedure is to develop a model for optimizing the thickness of FA-based panels. However, to effectively continue this research line, it is essential to design a specific environment for installing these panels. This involves carefully planning the placement of the panels within the environment and then proceeding with the optimization process. Implementing this procedure as a future development of the study will require a comprehensive approach that includes several critical variables. These variables will encompass not only the physical and acoustic properties of the FA-based material but also practical considerations such as cost and feasibility. By designing an environment tailored to the panels, researchers can accurately assess the material's performance and identify the optimal thickness for various applications using machine learning algorithms. The positioning of the panels within this environment will be crucial, as it will influence their effectiveness in improving acoustic performance. Once the environment is established, the optimization process can begin, leveraging advanced modeling techniques to refine the panel design. The integration of the panel features into integral 3D building design approaches, such as BIM or digital twin, can help to integrate the panel acoustic information in its specific location of the room, to accurately assess sustainability during the design phases of buildings [36,37]. This holistic approach ensures that all relevant factors are considered, leading to a well-rounded and practical solution. The authors propose this comprehensive procedure as a future development, aiming to enhance the study's scope and impact.

3.5. Limitations of the Study and Future Lines of Research

The present research used FA fibers from Ecuador. Different types of terrain, climatic conditions, height above sea level, or water salinity can affect the characteristics of the fibers and, consequently, the results and the repeatability of future studies.

The SACs were measured using an impedance tube with samples extracted from sample panels. However, due to the heterogeneous nature of the material, results may slightly vary if samples are taken from a different part of the panel or from panels built by different researchers even if they use the same process.

SACs can be measured using an impedance tube for small samples, following the ISO 10534-2:1998, and in a reverberation room for larger samples (e.g., sound absorbing panels or furniture), according to the ISO 354:2003. These methods determine two distinct types of metrics, the normal incidence sound absorption coefficient and random incidence coefficient [94]. The random incidence considers the overall absorption performance at various incident angles, not just the normal incidence. This could be considered a limitation of the study; however, this limitation is present in all the plant fiber articles evaluated, as all of them calculate the SAC using an impedance tube.

Although Bastidas et al. report that FA fiber remains thermally stable up to 360 °C [35], its flammability and susceptibility to fungal growth can restrict its widespread use in construction. Therefore, these fibers must be treated prior to installation to ensure adequate resistance to combustion and fungi.

The size of the impedance tube plays a crucial role in the accuracy of the measurements. Different frequency ranges for the same tube size can lead to variations in the identified sound absorption coefficients. Correct mounting of the sample is essential; in fact, the sample must fit perfectly into the sample holder, without protrusions or leaving spaces between its edge and the sample holder. Variations in editing may affect results. Variations in sample cutoff and cell fit can affect the accuracy and repeatability of impedance tube measurements. While extreme accuracy is difficult to achieve, following guidelines can help maintain consistent accuracy and validity. As the frequency of the input signal increases, the effective grid–cathode impedance of the tube decreases due to changes in reactance. This affects the reliability of measurements at different frequencies. The limitations in measuring SAC with the impedance tube can have an impact on the result provided by the prediction model, but we were able to see that in some cases the model was able to overcome these limitations.

Despite the recognized potential of natural fibers in construction, there has been limited research on the integration of FA with building elements. Most studies on FA fiber have focused on its chemical, morphological, and mechanical properties [35,53], without exploring its application in construction materials extensively. The absence of literature on the acoustic properties of FA fiber further underscores the gap in research. This lack of investigation hampers the development of innovative, sustainable building materials that could leverage the unique properties of FA fiber for enhanced performance.

A future line of research could be increasing the dataset with different thicknesses and new input variables to enhance the model's accuracy and generalizability. Another future line of research would be the development and improvement of the product to be introduced in the Ecuadorian market, including a cost–benefit analysis of the different parts of the production process: fiber collection, initial treatments, manufacturing and panels construction, and transportation and distribution. Research on new biodegradable binders to build the FA samples can be conducted to avoid that the binder decreases the sound absorption properties of the fibers.

Future research could aim to explore the integration of FA fiber with other building elements, for example, for the fabrication and manufacturing of materials such as concrete and timber. Investigating how FA fiber can be incorporated into concrete could lead to improved mechanical properties and sustainability of concrete composites. Similarly, combining FA fiber with timber could enhance the durability and acoustic performance of wood-based materials, or allow us to build FA acoustic panels. Such studies would not only fill the existing research gap but also contribute to the advancement of green building technologies, promoting the use of renewable resources in the construction industry.

4. Conclusions

This paper pioneers the adoption of eco-friendly materials like FA fiber in the construction industry. By detailing FA fiber preparation, analyzing its sound absorption properties, and using machine learning predictive modeling, it lays the groundwork for future sustainable building practices.

This research reveals the porous nature of FA fibers, showing that thicker samples increase sound absorption at low frequencies and follow a bell-shaped curve at high frequencies. Compared to other plant fibers, the 30 mm FA sample has a wider frequency range with SAC > 0.5. Furcraea Agavaceae, using natural rubber latex as a binder, outperforms FA fibers, indicating a need for more binder research. FA fibers are excellent sound-absorbing materials, ideal for reducing reverberation time in room acoustics. As the traditional use of FA in Ecuador declines due to industrialization, finding new applications is crucial. FA fibers are naturally sourced, potentially biodegradable or recyclable, and have a lower environmental impact than conventional materials. Using local materials supports sustainable practices and minimizes the environmental footprint.

This study introduces an innovative approach by using a Gaussian regression model to predict FA fiber's sound absorption properties, marking significant progress in combining advanced predictive models with sustainable material science. The model demonstrated excellent predictive capabilities, with low error values (MSE < 0.001), accurately reflecting experimental data. This success supports its use in optimizing building elements for better acoustic performance and environmental sustainability.

Future research aims to develop a model for optimizing FA-based panel thickness by designing specific environments for panel installation. This comprehensive approach will consider various factors, including physical properties and cost, to refine panel design and enhance acoustic performance. The integration of sustainable materials and advanced predictive modeling promises greater efficiency and environmental sustainability in construction.

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