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EXPLORING THE POTENTIAL OF HYPERSPECTRAL IMAGING TO ESTIMATE THE MOISTURE CONTENT IN NATURAL AND HISTORICAL STONES

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ABSTRACT

The conservation of cultural built heritage is crucial because of its historical, cultural and architectural significance. Water or moisture can cause severe damage, which can lead to deterioration. Therefore, estimating moisture content (MC) using non-destructive techniques is essential to ensure the conservation of these sites. Hyperspectral imaging (HSI) has been widely used in various fields, but its application in estimating MC in cultural built heritage materials has received limited research. This exploratory study investigates the potential of HSI for estimating MC by preparing a comprehensive hyperspectral dataset in the Short-Wave Infrared (SWIR) from six natural and historical stones at five different saturation levels. To estimate MC, a recently developed quantitative approach, the Normalized Relative Arc Length method was applied. The results showed high accuracy (RMSE of less than 5%) in the estimated MC, underscoring the reliability of HSI in this context.

Index Terms— Moisture content, Hyperspectral Imaging, Building Physics, Damage Monitoring

1. INTRODUCTION

Built heritage structures face significant environmental damages, with water being the primary driving force [1]. Among these environmental damages, frost damage [2], salt crystallization [3], and biological growth [4] are the most important [5]. Therefore, it is important to study the effect of moisture on built heritage, for its preservation.

Traditionally, techniques to measure MC in heritage structures have been destructive [6]. The most reliable methods involve collecting samples from sites, measuring their initial weight, and placing them in an oven until all moisture evaporates [7]. The difference between the initial and final weight provides information about the sample's MC [7]. Even though this is the most reliable approach, it is time-consuming and unrealistic in real-life scenarios [8]. Therefore, there is a strong preference for non-destructive sensing techniques to estimate this parameter [9].

Non-destructive techniques are essential for evaluating structural integrity and material properties without causing damage [10]. Point-based methods, such as ultrasonic testing[11] and moisture meters [12] provide localized information by analyzing specific points within the material [13]. Despite their effectiveness in detailed localized analysis, point-based techniques often fail to capture broader patterns of damage or moisture distribution [13]. Imaging-based techniques, including radiography [14], thermography [15], and HSI [16] provide extensive visual data on internal and surface conditions, allowing the identification of defects and moisture variations over large areas. Imaging-based techniques excel for their extensive coverage and extensive material assessment. This is crucial for the estimation of MC, where uniformity and distribution are essential.

HSI captures detailed spectral information over a wide range of wavelengths, providing comprehensive data on the condition of materials. In the field of cultural heritage, HSI has emerged as a powerful non-destructive image-based detection technique for investigating environmental damages in built heritage [16]. Due to the strong absorption capacity of water in the SWIR range, from approximately 1000 nm to 2500 nm, SWIR hyperspectral imagery has been applied to assess water damage in built heritage [17]. Because estimating MC in built heritage structures is crucial for effective conservation strategies [16], HSI offers powerful capabilities for both qualitative and quantitative assessment thereof in historical building materials. While qualitative methods provide visual and comparative data that can highlight areas of moisture presence, quantitative methods provide accurate measurements of moisture levels, allowing for detailed analysis and monitoring. Therefore, quantitative methods that can estimate MC are crucial for the effective conservation of built heritage. However, within the domain of cultural built heritage, the adoption of such techniques remains remarkably limited.

In the field of remote sensing, empirical [18] and physical modeling [19] approaches have been applied to estimate MC of different soil types, and face recurring challenges associated with differences in viewing angles, illumination conditions, and sensor types during data acquisition. In contrast to existing methods, an efficient quantitative method has recently been proposed in [20] that accurately estimates the MC of soil samples with an approach invariant to illumination conditions and sensor type. Therefore, in this work, we will employ this method to estimate the MC of built heritage structures.

To the best of our knowledge, this is the first time that a comprehensive attempt has been made to explore the potential of HSI to estimate the MC in natural stones and historical stones in the field of cultural built heritage. To this end, an extensive laboratory experiment is set up to acquire HSI data from six different stone types under varying moisture conditions. From these data, MC is estimated using the approach of [20]. Validation is performed by comparing to ground truth MC obtained by the gravimetric method. The remainder of this paper is organized as follows: Section 2 covers sample description, preparation, and acquisition. In section 3, we explain the methodology used in this research. The experimental results and discussion are detailed in the section 4. Finally, the conclusions and future work are drawn in the concluding section.

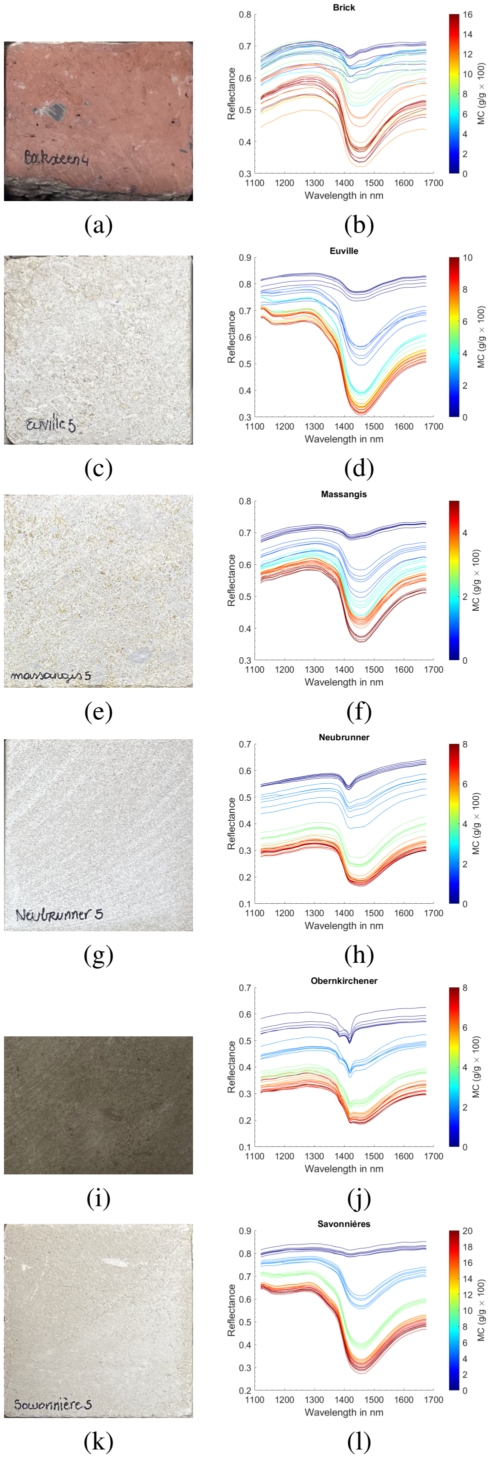
2. MATERIALS

2.1. Material Description

In this exploratory study, we extensively investigated five different stone types and one stone-like material: Savonnières, Massangis, and Euville (French limestones), Neubrunner and Obernkirchener (German sandstones), and a historic red brick sourced from the archaeological Kipdorp site in Antwerp. The RGB images of these materials are shown in Fig.1 (left side). To assess material variability, six samples were made from each material. The stone samples were cubes of 6×6×6 cm^3, while the red brick samples were approximately 3.5×5.5×6.5 cm^3 in size. A total of 36 samples were analyzed, of which 30 were stone samples and 6 were red brick samples.

2.2. Sample preparation

The samples were first fully saturated (100%) under vacuum following the procedure described in the standard NBN EN 1936:2007 for 48 hours to ensure homogeneous moisture distribution. The actual MC (g/g $\times$ 100) of a saturated sample is given by the mass of water over the dry mass of the sample. After fully saturating the samples, the MC of each sample was gradually reduced using an oven at 60°C. Then, samples with different saturation levels (90%, 75%, 50%, and 25%) were produced. For example, to achieve 75% saturation, the samples were oven-dried from their fully saturated state to a mass corresponding to 75% MC. Once the desired saturation level was reached, the samples were wrapped in parafilm for 48 hours to ensure a homogeneous distribution of MC in the



(a) (b)

(c) (d)

(e) (f)

(g) (h)

(i) (j)

(k) (l)

Fig. 1. The RGB image of the stones: (a) Red Brick, (c) Euville, (e) Massangis, (g) Neubrunner, (i) Obernkirchener and (k) Savonnières; their measured reflectance spectra and corresponding MC are shown in (b), (d), (f), (h), (j) and (l) respectively.

samples. This process was carefully repeated for all specified saturation levels.

2.3. Acquisition Setup

To acquire hyperspectral images of the prepared samples, in this work we used a Snapscan SWIR hyperspectral camera manufactured by Imec. The Snapscan SWIR camera operates from 1100 to 1670 nm, capturing data over 100 spectral bands with a spectral resolution of approximately 5 nm. The spatial resolution of the image is approximately 0.5 mm. All samples were positioned consistently and scanned from the same side to ensure uniformity in data collection. Four halogen lamps, placed at a 45-degree angle to the hyperspectral camera, provided uniform illumination to reduce shadows and increase brightness. Unlike traditional push broom systems, the Snapscan camera uses an internal sensor motion mechanism to capture a static, full image frame of the sample, improving spatial resolution and simplifying the setup. The measured reflectance spectra of the materials and their corresponding MCs (see colorbar) are shown in Fig.1 (right side). The spectral reflectance for each sample was obtained by taking the average of all pixels of the entire image. It can be observed that the reflectance of the moist samples is predominantly influenced by water, a critical factor in accurately estimating the MC of moist materials. A key aspect of the study was the effort to homogenize the samples, which significantly reduced the variability in spectral reflectance across different regions of the same sample with similar MC. This uniformity in spectral reflectance suggests that the porosity and pore size distribution within the same material were consistent, validating the preparation protocols used to ensure homogeneity. By acquiring hyperspectral images of all 36 samples under six different moisture levels, we were able to prepare a comprehensive hyperspectral dataset to explore the potential of HSI to estimate the MC in natural and historical stones.

3. METHODOLOGY

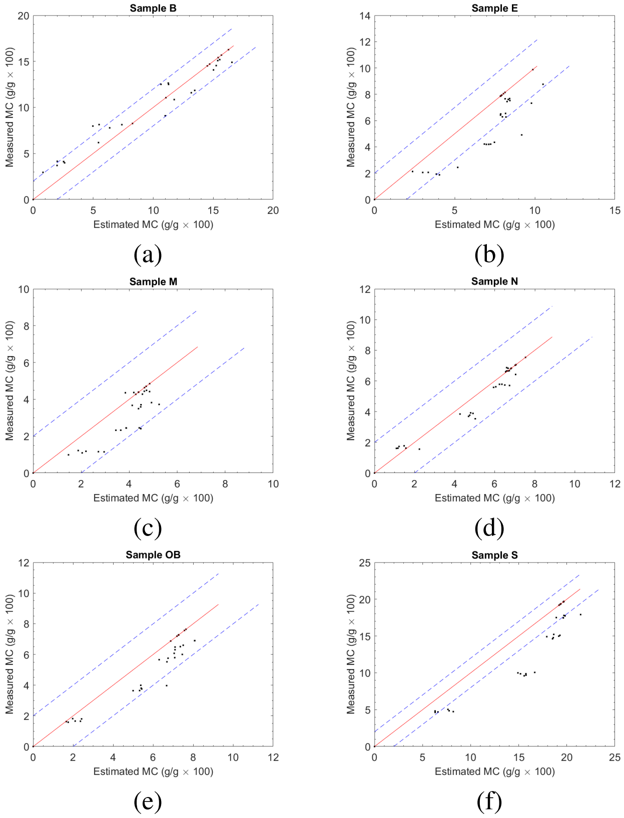
To analyze the reflectance spectra of our dataset samples and estimate their MC, we employ a comprehensive and technically rigorous methodology proposed in [20]. The proposed method i.e., Normalized Relative Arc Length (NRAL) assumes that the spectral reflectance of a moist sample can be described as a binary mixture of two endmembers: the spectra of an oven/air-dried sample and a fully saturated sample. Estimating the moisture content of a moist sample then boils down to determining the relative position of the sample on the curve whose extremes are spanned by two endmembers. A detailed description of the methodology is provided in [20].

4. RESULTS AND DISCUSSION

The error metric used in this work is the Root Mean Square Error (RMSE) between the estimated MC ($\hat{MC}$) and the measured MC (MC):

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(MC_i - \hat{MC}_i)^2} \qquad (1)$$

where n is the number of sample spectra, MC_i is the measured MC and $\hat{MC}_i$ is the estimated MC.



(a) (b)

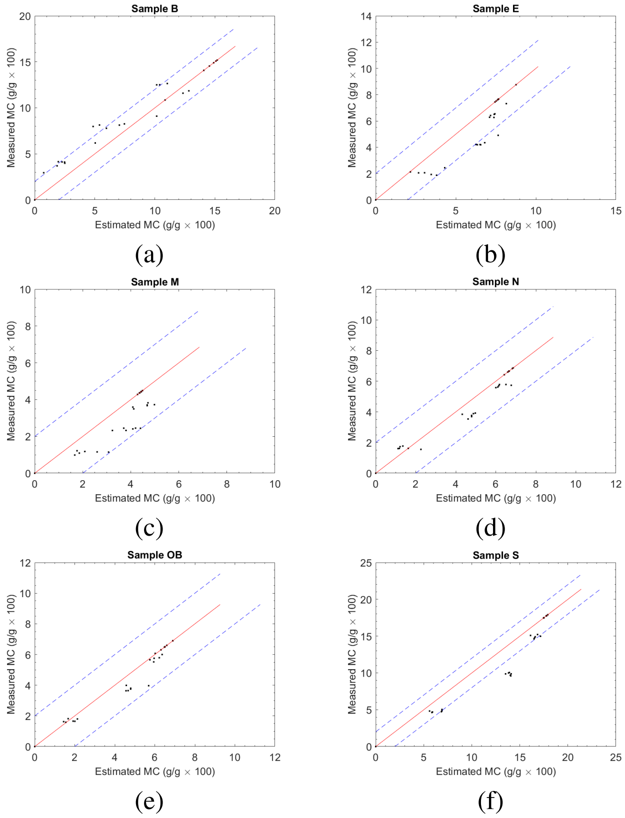
(c) (d)

(e) (f)

Fig. 2. Measured vs Estimated MC of natural and historical stones: (a) Red Brick, (b) Euville, (c) Massangis, (d) Neubrunner, (e) Obernkirchener and (f) Savonnières - sample with 100% saturation level sample as endemember.

We applied NRAL to the prepared dataset. Fig. 2 shows the scatterplots of the estimated versus the measured ground-truth MC. The $(1 : 1)$ line along with the lines denoting a 2 g/g×100 deviation are shown. As can be observed, NRAL accurately estimated MC from the reflectance spectra. The estimated values of the MC demonstrated high precision, with errors that generally ranged between 1-2 g/g × 100. This level of precision highlights the reliability of hyperspectral imaging for estimating MC.

From Fig. 1, it can be observed that the samples of 90% saturation level have lower reflectances compared to the sam-



(a) (b) (c) (d) (e) (f)

Fig. 3. Measured vs Estimated MC of natural and historical stones: (a) Red Brick, (b) Euville, (c) Massangis, (d) Neubrunner, (e) Obernkirchener and (f) Savonnières -sample with 90% saturation level sample as endemember.

ples of 100% saturation level. We have no satisfactory explanation for this non-physical behavior, and it requires further examination. In a follow-up experiment, we replaced the sample of 100% saturation level with the sample of 90% saturation level as endmember. As can be observed from Fig. 3, this replacement improved the performance of NRAL.

It is interesting to observe that the performance of NRAL reduces for samples with lower MC. This can be partially attributed to the inconsistency between the estimated MC from surface reflection and the bulk MC of the samples. The intrinsic limitation of spectral reflectance for MC estimation is that it only contains information from a thin top layer of the samples, typically $100 - 300\mu$m. The information contained in the reflectance spectra matches with the bulk ground truth MC only when the sample is homogeneous and water is homogeneously distributed in the sample. Achieving homogeneity in these samples proved difficult due to the small amount of water available to uniformly fill all pores.

5. CONCLUSION

To conclude, this work presents a comprehensive hyperspectral dataset prepared from 36 cultural heritage samples under varying moisture conditions, aiming to explore the potential of HSI for estimating the MC in natural and historical stones. The data was acquired in the SWIR range due to the high absorption feature of water in that range. The NRAL method was employed to estimate the MC from the spectral reflectance. Validation was done by comparing the results with ground-truth MC from the gravimetric method. The results demonstrated high precision in the estimated MC values, with RMSE values generally ranging between 1-2 g/g × 100, highlighting the reliability of HSI in estimating MC.

Inconsistencies were noted in the spectral reflectance of fully saturated samples compared to other saturation levels, underscored the need for further investigation of the spectral characteristics of fully saturated samples. Despite robust sample preparation protocols, for samples with low MC, achieving homogeneity proved difficult, making MC estimations less reliable.

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6. REFERENCES

[1] C. Sabbioni, M. Cassar, P. Brimblecombe, and R.-A. Lefevre, "Vulnerability of cultural heritage to climate change," *European and Mediterranean Major Hazards Agreement (EUR-OPA)*, pp. 1–24, 2008.

[2] C. Bertolin and S. Cavazzani, "Potential of frost damage of off-ground foundation stones in norwegian stave churches since 1950 using land surface temperature," *Heliyon*, vol. 8, no. 11, 2022.

[3] R. J. Flatt, "Salt damage in porous materials: how high supersaturations are generated," *Journal of crystal growth*, vol. 242, no. 3-4, pp. 435–454, 2002.

[4] E. M. Perez-Monserrat, R. Fort, M. Varas-Muriel, M. A. de Buergo, A. de Los Rios, and C. Ascaso, "Physical and aesthetical decay of built heritage from biological films developed on joint mortars," *Science and technology for the conservation of cultural heritage*, p. 93, 2013.

[5] E. Sesana, A. S. Gagnon, C. Ciantelli, J. Cassar, and J. J. Hughes, "Climate change impacts on cultural heritage: A literature review," *Wiley Interdisciplinary Reviews: Climate Change*, vol. 12, no. 4, p. e710, 2021.

[6] A. Rosa, R. Greco, L. Mollo *et al.*, "Moisture measurements in heritage masonries: A review of current methods and techniques," *Materials Evaluation*, vol. 76, no. 11, pp. 1468–1477, 2018.

[7] F. Alfano, B. Palella, and G. Riccio, "Moisture in historical buildings from causes to the application of specific diagnostic methodologies," *Journal of Cultural Heritage*, vol. 61, pp. 150–159, 2023.

[8] V. Flores Sasso and L. Ruiz Valero, "Non-destructive techniques applied to historic building for measuring moisture content in brick vault," *Heritage and Conservation*, vol. 12, no. 4, pp. 455–466, 2020.

[9] L. Valero, V. Sasso, and E. Vicioso, "In situ assessment of superficial moisture condition in façades of historic building using non-destructive techniques," *Case Studies in Construction Materials*, vol. 11, p. e00340, 2019.

[10] M. Solla, M. Maté-González, C. Blázquez *et al.*, "Analysis of structural integrity through the combination of non-destructive testing techniques in heritage inspections: The study case of san segundo's church," *Journal of Building Engineering*, vol. 47, p. 102384, 2024.

[11] C. Rivera-Gomez and C. Galàn-Marin, "In situ assessment of structural timber elements of a historic building by moisture content analyses and ultrasonic velocity tests," *International Journal of Housing Science and its Applications*, vol. 37, no. 1, pp. 33–42, 2013.

[12] M. Martínez-Garrido, R. Fort, M. Gómez-Heras, J. Valles-Iriso, and M. Varas-Muriel, "A comprehensive study for moisture control in cultural heritage using non-destructive techniques," *Journal of Applied Geophysics*, vol. 155, pp. 36–52, 2018.

[13] D. Camuffo and C. Bertolin, "Towards standardisation of moisture content measurement in cultural heritage materials," *E-Preservation Science*, vol. 9, pp. 23–35, 2012.

[14] B. McCarthy, "Examination of processing techniques in cultural heritage objects with radiography," *American Ceramic Society Bulletin*, vol. 99, no. 4, pp. 22–28, 2020.

[15] F. Mercuri, N. Orazi, U. Zammit, S. Paoloni, M. Marinelli, and P. Valentini, "Thermographic analysis of cultural heritage: recent applications and perspectives," *E-Preservation Science*, vol. 9, pp. 84–89, 2012.

[16] Z. Pei, Y. Huang, and T. Zhou, "Review on analysis methods enabled by hyperspectral imaging for cultural relic conservation," *Photonics*, vol. 10, no. 10, p. 1104, 2023.

[17] R. Radpour, "Advanced imaging spectroscopy and chemical sensing in archaeometry and archaeological forensics," PhD thesis, University of California, 2019.

[18] S.-N. Haubrock, S. Chabrillat, C. Lemmnitz, and H. Kaufmann, "Surface soil moisture quantification models from reflectance data under field conditions," *International journal of remote sensing*, vol. 29, no. 1, pp. 3–29, 2008.

[19] H. Bach and W. Mauser, "Modelling and model verification of the spectral reflectance of soils under varying moisture conditions," in *Proceedings of IGARSS'94-1994 IEEE International Geoscience and Remote Sensing Symposium*, vol. 4. IEEE, 1994, pp. 2354–2356.

[20] B. Koirala, Z. Zahiri, and P. Scheunders, "A Robust Supervised Method for Estimating Soil Moisture Content From Spectral Reflectance," *IEEE Transactions on Geoscience and Remote Sensing*, vol. 60, 2022.