Citizen Science and Mobile Phone Cameras as Tools for Monitoring World Heritage

Gregory Bearman[1]; Eric Doehne[2]; Jon Voss3; Kim Merrill[4]; Rohitashwa Bagaria[4]

[1]ANE Image, Pasadena CA; [2]Conservation Sciences, Pasadena CA; [3]Jon Voss, Strategic Partnerships Director, Historypin; [4]Harvey Mudd College, Claremont Colleges, Claremont CA

Sites and objects of cultural heritage – from modern art to ancient ruins – are under constant attack by time and the environment. They are subject to fading, color loss, material loss, bio-deterioration, soiling and a wide range of other processes. While laboratory-based studies have taught us much about how the material components change, very little is known about the process or rates of change of actual objects and sites in place.

On July 2009 the National Science Foundation 8Arlington, VA, USA) held a workshop titled “Chemistry and Materials Research at the Interface Between Science and Art.” The goal of the workshop was to identify challenges and targets for the application of modern science to the conservation of art and cultural heritage artifacts. The second grand challenge from the workshop reported by Marco [Leona and Van Duyne, 2009] is understanding material degradation and aging: «Effective conservation strategies must be aimed at diagnosing the underlying causes of deterioration, identify early stages of change… ». To tackle this challenge, we propose an imaging approach to detect and monitor early changes in an object.

In collaboration with site managers and conservators, we propose to develop a crowd-sourcing approach by engaging citizen scientists to acquire finely grained, time-sequenced image sets via their mobile phone cameras. These data will serve as the inputs for detecting and measuring change and determining rates and patterns of change caused by biodeterioration, material loss, vandalism and soiling. Additionally, the data can be used to detect color changes which may be proxies for chemical changes such as UV damage, bleaching or pollution-driven chemistry on the surface.

Accurate image calibration is critical to this program, and we suggest and test a calibration method based on on-site calibration kiosks with robust color targets. To determine whether mobile phone cameras can provide colorimetric data quantitative enough to look for changes in scenes, we measured the color errors in images from both Androids and iPhones, using calibrated Colorchecker charts. We report on this key element of our program and also present results from a pilot project on obtaining images via social media.

Our approach is citizen science, in which members of the public become both originator and user of science. While citizen science has gained traction only in recent years [Cohn, 2008; McCaffrey, 2005; Newman et al., 2012], there is a substantial history of research involving a distributed public, particularly in projects that require a large number of observations over time or place. What has changed in recent years is the increased availability of tools with which to engage participants in the research. In our case, smartphone cameras will collect large numbers of images over time, in far-flung locations, at virtually no cost, an activity that would be prohibitive for long-term mounted cameras. Employing social media, we will create an engagement loop that makes it easy and fun for participants to share their contributions, spread the word and draw in additional feedback, engagement and outreach. Our objective in the public engagement strategy is to significantly lower the barriers to contributing to the project, using technologies and apps that smartphone users are already likely to use: Twitter, Instagram or potentially a standalone app.

We propose to work with an existing mobile phone app, Historypin, that provides users with historical images as they visit and view sites worldwide, using online databases and phone GPS. For our purposes, users will take and upload photos to our database for comparison and analysis of change going forward over time.

The project presents technical challenges at both ends of the process. An overlay must be part of the mobile phone app to target the correct field of view. Images uploaded by the users will include an image of the onsite kiosk we will install in collaboration with those responsible for site management and conservation; the kiosk's robust color targets will provide color and white balance standards for image calibration. At the back end, significant computation is required to register, align and calibrate the images to yield data of the quality we need. The resulting, cloud-based image analysis can be accessed by site conservators as well as by the public, enabling our users to see the value of their participation.

We will use the calibration kiosk to transform the cell phone sRGB image into the CIELAB (L*a*b*) color space, in which color is measured by three parameters. L is lightness (similar to luminance or intensity), while a* and b* provide the chromatic information. The red-green axis is described by a* and b* is yellow-blue. These are orthogonal spaces to allow quantitative measurement of color differences and can also be related to human perception of changes.

Repeated imaging of the same site, rephotography, has appeared in the literature but mostly as a means of a one-time visual comparison of then and now, not as an integrated data collection and quantitative analysis method for cultural conservation. There has been some work on the computation challenges faced in registering and aligning images to allow genuine comparison [Bae, Agarwala and Durand, 2010; Hendrick and Copenheaver, 2009; Lee, Luo, and Chen, 2011]. We need to be able to separate 3D translation, rotation, zoom and dolly when comparing two images taken at different times by different people from different viewpoints. In our case, the problem is somewhat easier, as the inclusion of a color and spatial calibration target kiosk in the field of view provides better control over the reimaging.

What can we measure at a site, using just images? Quite a bit, it turns out, that is important to conservators and custodians of sites and objects, including soiling rates, material loss, color changes that are stand-ins for chemical changes and biodeterioration such moss/lichens with photosynthesis pigments detectable in color images There are many processes that can create color changes [Fitzner and Heinrichs, 2001] such as oxidation, reduction, leaching and aeolian deposits. While we may not be able to identify them, we should be able to differentiate between these processes and measure their rate.

Measurement of color changes in stone materials is the primary goal of our mobile phone images. Studies in the literature show that various weathering and soiling processes primarily change lightness, L and b*, rather than a* [Grossi et al., 2007; Lebrun, Toussaint, and Pirard, 2004; Iñigo, Vicente Tavera, and Rives, 2004; García Talegon et al., 1998]. Lightness changes can be due to soiling and darkening from soot, brightening from efflorescence or material loss that exposes a brighter interior. Changes in surface roughness due to weathering can also affect the lightness and chroma [Benavente et al., 2003]. Changes in b* indicate motion along the yellow-blue axis and often indicate yellowing. We will later use data from these studies to evaluate how sensitive mobile phone cameras are to such environmental changes.
In collaboration with the Computer Science Department at Harvey Mudd College (Pomona, CA) we created an independent study course for students. We looked at two components of the project: (1) Citizen science: If we were to put up a target kiosk, how many images would we get? What is the image quality for an untrained but interested and intelligent user? We are concerned about image saturation, focus and field of view (all issues that came up). (2) Color calibration of cell phones off either an outdoor target kiosk and/or standard color charts such as the X-rite Colorchecker or Colorchecker digital SG.

Color Calibration
We used software from Imatest LLC (Imatest.com) to analyze cell phone images of two Xrite color charts. Among its many useful features it uses an optimizer to create a color transform that minimizes the errors for all the tiles. The user can turn tiles off to remove them from the calculation. For the analysis we performed, the software determined the image gamma from grey tiles in the image.
We have data from two popular phones, iPhone 4s and Samsung Galaxy S3. To avoid illumination gradients, we imaged the color checker outdoors so that it was diffusely lit by sunlight and not shadowed by the user.
Some of the calibration color tiles are saturated in hue so it was common for the bright orange/green/yellow tiles to be saturated at a pixel value of 255 in the images. The camera software clips those tiles and fills in the others at lower pixel values to make images appealing to the human eye, rather than being especially color accurate. In building our camera models, we either imaged in outdoor shade or simply excluded the saturated tiles (always with large b*) from the color model. We obtained about the same results either way, but it does point out that we need to choose tiles for a kiosk carefully.
In general, we find that the larger the b, the larger is the Δb, as shown in Figure 1 and the same for L as in Figure 2.This makes sense as larger L and b* imply we are working over a larger gamut, making it more difficult to find an optimized color transform at all values of L and b. The real question here then becomes what is the range of b* values we can expect to be in typical scenes? Grossi et al show values of b* and L ranging from 10-20 and 40-80 respectively. Tanaca et al measures b* ~6 for biocolonized limestone, while Urzi measures b*<30 for biocolonized granite and L ~50-75. This smaller gamut helps with the sensitivity of the camera images and suggests that the

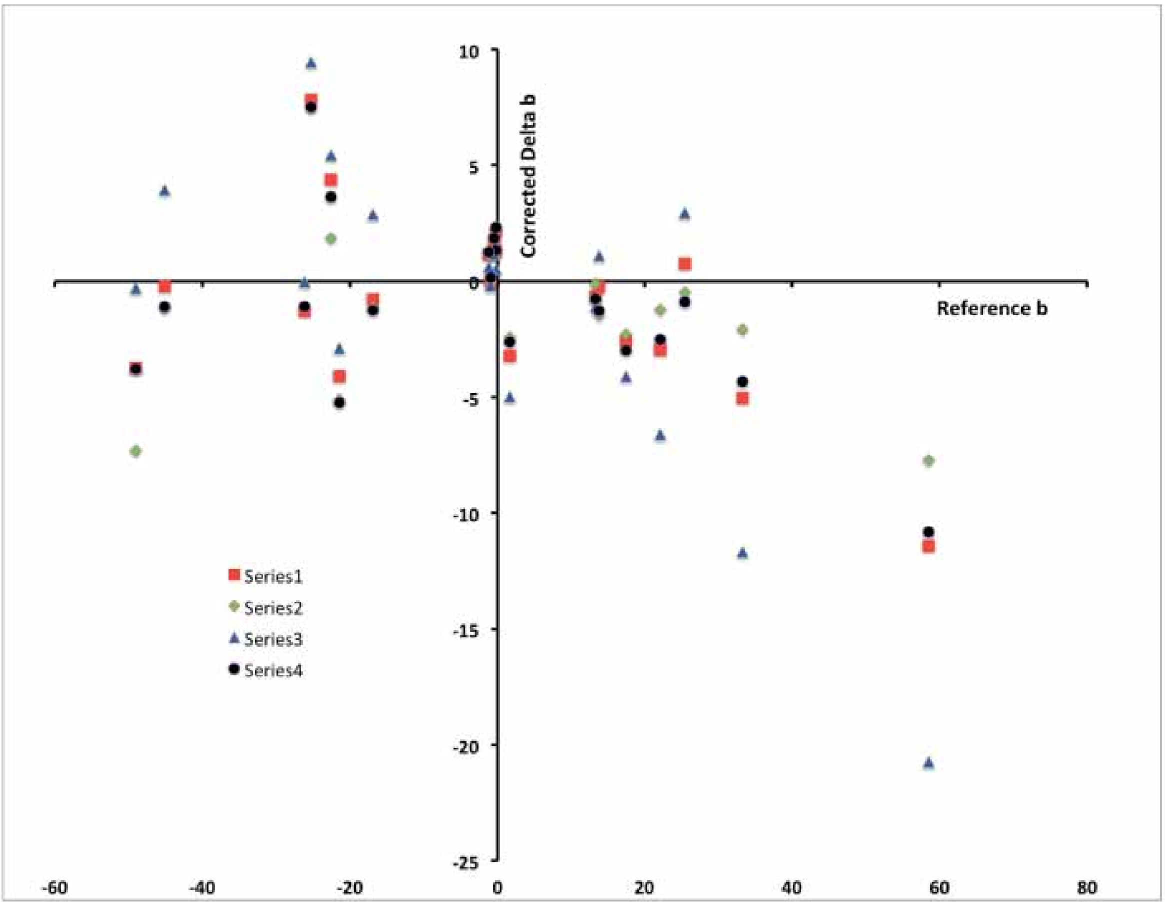

Fig.1 - Measured Δb* for Samsung Galaxy S3. The values are calculated by Imatest software with an optimizer that minimizes color errors for all the tiles. The images were taken sequentially, at single imaging session. The target was an Xrite Passport ColorChecker with three of the color tiles (A2, F2, D3) turned off as well as the brightest white

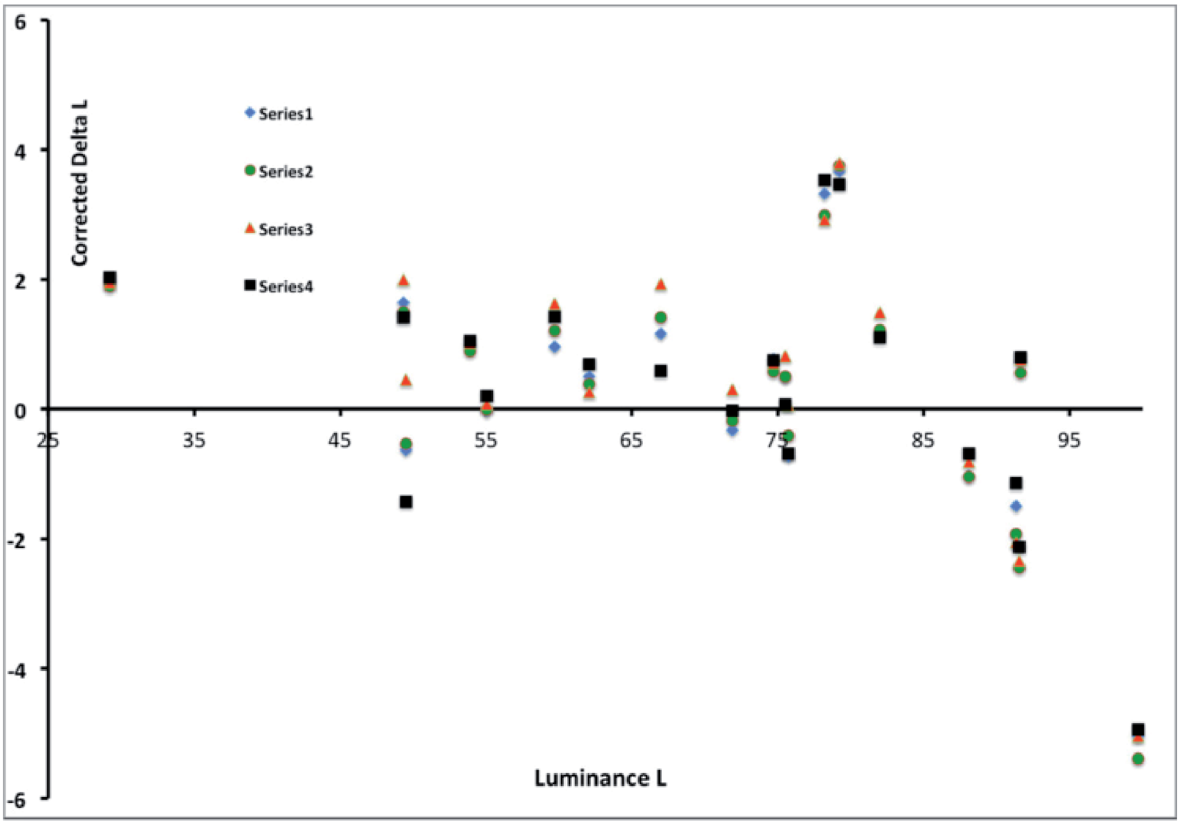

Fig.2 - Measured ΔL for Samsung Galaxy S3. The values are calculated by Imatest software with an optimizer that minimizes color errors for all the tiles. The images were taken sequentially, at single imaging session. The target was an Xrite Passport ColorChecker with three of the color tiles (A2, F2, D3) turned off as well as the brightest white

kiosk tiles can span a small gamut of L and b*. We will not see highly saturated colors with high b* so we can safely exclude them from the color model to obtain better results.
Nominally, sRGB has a gamma of 2.2 and we looked at whether the image data conformed to that, which could make the calibration kiosk simpler to design. However, since both the ColorChecker SG and the ColorChecker Passport have a number of different reflectance greys we checked the gamma using the greys. In most cases, the gamma was not 2.2, but ranged from 2.25 to 2.46. For some of the cameras, the gamma was not even linear, but sigmoidal. We did the gamma analysis separately from the Imatest with the greyscale tiles from the Color Checker SG; these results indicated that the calibration kiosk needs to contain enough greys to recover gamma. There are several blind inverse gamma recovery algorithims (Farid 2001; Asadi, Hassanpour, and Pouyan 2010) that claim a gamma accuracy of ~ 7.5% (Farid 2001). These methods rely on the fact that gamma encoding introduces specific correlations in the image's frequency domain, and minimizing them to determine gamma.
For the Galaxy S3 data displayed, the average |b*| error is 3.05 and average for |L| is 1.45, while for the iPhone 4S we get 3.05 and 1.65 respectively. If we wish to take advantage of the fact that we can span a smaller b* gamut, avoid saturated colors and limit ourselves to b*<33, then we get |b*|=2.15 for the S3 and |b*|=2.5 for the iPhone 4S. For the S3, ΔE76=4.6 and ΔE76=4.7 for the iPhone.
Cell phone cameras are mass produced commodity items that all use the same Bayer filter technology, although each vendor may use different demosaicing algorithms. For this reason we did not think it critical to have a wide range of phone cameras; it is not as if somehow one of them will be 5 times better. How do these results stack up against either DSLR or a mid-level point-and-shoot camera? For that, we have to look at chroma, since that is widely published in camera reviews. A Canon EOS 50D has an average Delta chroma (uncorrected) of 4.55 (http://www.imaging-resource.com/PRODS/E50D/E50DIMATEST.HTM) compared with 7.57 for the S3. As expected, the dedicated cameras are better, but the mobile phone cameras are pretty good and will only improve as they ride the technology wave: there is already one cell phone camera that records RAW images, which contain much less of the pre-processing that at present creates calibration problems. For example, a RAW or DNG image can provide the individual color planes from the Bayer filter pattern, rather than the demosaiced and interpolated ones we get now.
Based on our results, are mobile phones quantitative enough to measure some of the changes over time we are looking for? Since we now have some measured Δb*, ΔL and ΔE, we can apply data from the literature to this question. First, restorations and repairs. Setting the imaging "clock" ticking is easy; it is the date of repair. A study of photo-degradation of acrylic resins used in stone repair [Leona and Van Duyne, 2009; Melo et al. 1999] showed that photo aging at light levels ~1/3 that of sunlight changes b* as much +15 in ~100 hours (the resins yellow). Since we are seeing Δb* ~ 2, we would detect this relatively early.

There has been work on using colorimetry to measure stone discoloration after exposure to the environment and time [Cohn, 2008; Sanmartín et al., 2012; McCaffrey, 2005; Grossi and Brimblecombe, 2008; Newman et al., 2012; Bae, Agarwala and Durand, 2010; Tanaca et al., 2011; Hendrick and Copenheaver, 2009; Lee, Luo and Chen, 2011], and we can use this data to set a detection level. A wide range of laboratory and natural experiments examine color changes from environmental insults. These studies range from granite to limestone and include natural weathering and soiling (Fitzner and Heinrichs, 2001; Thornbush, 2010] [Grossi et al., 2007; Grossi et al., 2003; Lebrun, Toussaint Pirard, 2004; Iñigo, Vicente Tavera Rives, 2004; García Talegon et al., 1998] as well as laboratory SO2 and acid aging.
Biofilm growth creates color changes through the photosynthetic pigments. While the studies report on a number of color difference measurements, we can usually match with one calculated from our data. For example, Tanaca et al measure color changes from fungal growth on concrete over 5 years at 3 locations: $\Delta E76$ ranges from 5.5-17.28, all three of which are within our color uncertainty and would allow building a timeline to monitor the rate of growth. A study of biofilms on exposed granite [Benavente et al., 2003; Sanmartín et al., 2012] reported a range Δb^* of ~ 4 after 194 days and a concurrent ΔL ~8. These changes slowly increased to about 10 and 10 respectively after 276 days of exposure. Outdoor monitoring of sandstone with ongoing biofilm colonization [Farid, 2001; Urzì and Realini, 1998; Asadi, Hassanpour and Pouyan, 2010] measured $\Delta E76$ ranging from ~1-5. These changes are easily detectable with mobile cameras. Several studies have demonstrated that color change can be correlated with the amount of cyanobacteria [Farid, 2001; Sanmartín et al., 2010; Prieto, Rivas and Silva, 2002], so we may be able to develop a quantitative assay for bacterial growth.
Can we learn anything in detail about biofilm growth based just on color? Bacteria growth, in general, changes b*, typically moving towards orange [Urzì and Realini, 1998] while fungi lead to blackening or greying. Various lichens/algae/bacteria have different enough reflectance spectra to allow a segmented image but are not sufficient for identification. As an example, we obtained reflectance spectra of some cyanobacteria from the literature [Bechtel, Rivard and Sánchez-Azofeifa, 2002; Van Der Veen and Csatho, 2005] and then computed the L*a*b* values for a few examples; c. nivalis has (L*a*b*)=(79.58,0.86, 3.51) while c.uncialis has (39.21,3.39,12.97).
Another example is using our approach to evaluate soiling rates. A study of soiling rates of exposed untreated limestone over a decade [Moreau et al., 2008] measured a L* change of ~2.2/year, while we see a detectable ΔL about the same. Another study of soiling [Grossi et al., 2007] shows a ΔL ~5-10, depending on the material, for an urban exposure of 4 months and concurrent Δb^* ~2-3. Both parameters are within the measured errors for mobile phone cameras.
Harvey Mudd College, Claremont, CA, has a student population of ~800 and the kiosk was up for ~ 48 days. Over the course of the study, we received 75 images, Common problems were bad lighting, i.e., self shadow, out of focus or zoomed way out. We even got a few taken with a flash at night! Only a few

were out of focus. As long as the targets covered a more than a few dozen pixels, we could get data from them. However, it would appear that users will need more direction to take better images. The advantage of the Historypin mobile app is that the overlay guides the participant to the correct image. For a real project, we would simply exclude bad images; and we anticipate getting a lot of images from which to cull them. The iconic sites we are looking at get thousands of visitors - some many more. The very advantage of crowd sourcing and big data is that you can throw away bad data. Our study had, in effect, the same visitors every day, thus limiting the number of images we could get, since the typical student did not upload more than one image. Still, it is noteworthy that about 10% of "visitors" took and uploaded an image.
We find that cell phone cameras can measure Δb^* with an uncertainty of ~2.1 and ΔL with an uncertainty of ~1.5. Literature values for weathering and biofilm changes in $\Delta b^*$and ΔL range from 2-8 and 1.5-10, respectively, well within the capability of mobile phone cameras. The color errors show that the calibration kiosk should use a smaller than normal color gamut to match the expected values in the scene and avoid bright saturated colors as these only make it harder to obtain a minimized error color transform.

References

Asadi, Sekineh, Hamid Hassanpour and Ali Akbar Pouyan, 2010, *Texture Based Image Enhancment Using Gamma Correction*, «Middle East Journal of Scientific Research», (December 27): 569–574.

Bae, Soonmin, Aseem Agarwala, and Frédo Durand, 2010, *Computational Rephotography*, «ACM Transactions on Graphics 29» (3) (June 1): 1–15. doi:10.1145/1805964.1805968.

Bechtel, Robert, Benoit Rivard and Arturo Sánchez-Azofeifa, 2002, *Spectral Properties of Foliose and Crustose Lichens Based on Laboratory Experiments*, Remote Sensing of Environment 82 (2): 389–396.

Benavente, D., F Mart nez-Verd, Bernabeu A., Viqueira V., Fort R., Garc a del Cura M. A., Illueca C. and Ord S. ez., 2003, *Influence of Surface Roughness on Color Changes in Building Stones*, «Color Research and Application», 28 (5) (August 1): 343–351. doi:10.1002/col.10178.

Cohn J. P., 2008, *Citizen Science: Can Volunteers Do Real Research?*, BioScience.

Farid H., 2001, *Blind Inverse Gamma Correction,* «IEEE Transactions on Image Processing», 10 (10): 1428–1433.

Fitzner, Bernd and Kurt Heinrichs, 2001, *Damage Diagnosis on Stone Monuments - Weathering Forms, Damage Categories and Damage Indices*, Acta-Universitatas Carlinae Gerologica (January 29).

García Talegon J., Vicente M. A., Vicente Tavera S. and Molina Ballesteros E., 1998, *Assessment of Chromatic Changes Due to Artificial Ageing and/or Conservation Treatments of Sandstones*, «Color Research and Application», 23 (1): 46–51.

Grossi C. M. and Brimblecombe P., 2008, *Past and Future Colouring Patterns of Historic Stone Buildings*, «Materiales De Construccion» 58 (289/290): 143.

Grossi C. M., Esbert R. M., Dıaz-Pache F. and Alonso F. J., 2003, *Soiling of Building Stones in Urban Environments*, «Building and Environment», 38 (1): 147–159.

Grossi, Carlotta M., Peter Brimblecombe, Rosa M. Esbert and Francisco Javier Alonso, 2007, *Color Changes in Architectural Limestones From Pollution and Cleaning*, «Color Research and Application», 32 (4): 320–331. doi:10.1002/col.20322.

Hendrick Laura E., and Carolyn A. Copenheaver, 2009, *Using Repeat Landscape Photography to Assess Vegetation Changes in Rural Communities of the Southern Appalachian Mountains in Virginia, USA*, Http://Dx.Doi.org/10.1659/Mrd.1028 29 (1) (February): 21–29. doi:10.1659/mrd.1028.
Iñigo A .C., Vicente Tavera S. and Rives V., 2004, “MANOVA□Biplot Statistical Analysis of the Effect of Artificial Ageing (Freezing/Thawing) on the Colour of Treated Granite Stones.” Color Research and Application 29 (2): 115–120. doi:10.1002/col.
Lebrun V., Toussaint C. and Pirard E., 2004, *Monitoring Color Alteration of Ornamental Flagstones Using Digital Image Analysis*, in, edited by R Prikryl, 139–144. Prague: Taylor & Francis.
Lee, Kun-Ting, Sheng-Jie Luo, and Bing-Yu Chen, 2011, *Rephotography Using Image Collections*, «Computer Graphics Forum» 30 (7) (November 4): 1895–1901. doi:10.1111/j.1467-8659.2011.02042.x.
Leona Marco and Richard Van Duyne, 2009, *Chemistry and Materials Research at the Interface Between Science and Art*, Arlington VA: NSF Workshop.
McCaffrey R. E., 2005, *Using Citizen Science in Urban Bird Studies*, Urban Habitats.
Melo M. J., Bracci S., Camaiti M., Chiantore O. and Piacenti F., 1999, *Photodegradation of Acrylic Resins Used in the Conservation of Stone*, «Polymer Degradation and Stability», 66 (1) (January 28): 23–30.
Moreau C., Verges-Belmin V., Leroux L., KIsselinskia A., Orial G. and Barbin V., 2008, *The Influence of Protective Treatments on Limestone Soiling, Sulphation and Cleaning: Results After Ten Years of Outdoor Exposure*, 9th international Conference on stone deterioration and conservation (Torun) 2008.
Newman G., Wiggins A., Crall A., Graham E., Newman S. and Crowston K., 2012, *The Future of Citizen Science: Emerging Technologies and Shifting Paradigms*, «Frontiers in Ecology and the Environment», 10 (6): 298–304. doi:10.1890/110294.
Prieto B., Rivas T. and Silva B., 2002, *Rapid Quantification of Phototrophic Microorganisms and Their Physiological State Through Their Colour*, «Biofouling» 18 (3) (January): 237–245. doi:10.1080/08927010290014917.
Sanmartín P., Vázquez-Nion D., Silva B. and Prieto B., 2012, *Spectrophotometric Color Measurement for Early Detection and Monitoring of Greening on Granite Buildings*, «Biofouling», 28 (3) (March): 329–338. doi:10.1080/08927014.2012.673220.
Sanmartín P., Villa F., Silva B., Cappitelli F. and Prieto B., 2010, *Color Measurements as a Reliable Method for Estimating Chlorophyll Degradation to Phaeopigments*, «Biodegradation», 22 (4) (August 17): 763–771. doi:10.1007/s10532-010-9402-8.
Tanaca H. K., Dias C. M. R., Gaylarde C. C., John V. M. and Shirakawa M. A., 2011, *Discoloration and Fungal Growth on Three Fiber Cement Formulations Exposed in Urban, Rural and Coastal Zones*, «Building and Environment», 46 (2) (February 1): 324–330. doi:10.1016/j.buildenv.2010.07.025.
Thornbush M. J., 2010, *Measurements of Soiling and Colour Change Using Outdoor Rephotography and Image Processing in Adobe Photoshop Along the Southern Facade of the Ashmolean Museum, Oxford*, Geological Society, London, Special Publications 331 (1) (March 29): 231–236. doi:10.1144/SP331.21.
Urzì C. and Realini M., 1998, *Colour Changes of Notos Calcareous Sandstone as Related to Its Colonisation by Microorganisms*, «International Biodeterioration & Biodegradation», 42 (1): 45–54.
Van Der Veen, Cornelis J. and Bea M. Csatho, 2005, *Spectral Characteristics of Greenland Lichens*, «Géographie Physique Et Quaternaire», 59 (1): 63–73. doi:10.7202/013737ar.