Exploiting a texture framework and high spatial resolution properties of panchromatic images to generate enhanced multi-layer products: Examples of Pleiades and historical CORONA space photographs

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Abstract

Remotely sensed high spatio-temporal resolution panchromatic images have been extensively used globally to visually detect and interpret changes in landscape components, create land cover maps via the on-screen manual digitisation, and to pan-sharpen multi-spectral images among other uses. Despite this attractive array of uses, lack of distinct spectral signatures for panchromatic images from surface elements, e.g., landscape cover types, creates a drawback in their exploitation during any automated classification process, hence limiting their use in the field of remote sensing for land use/land cover change studies. Moreover, the complexities of some panchromatic data (e.g., CORONA) on the one hand, and the traditional texture computation approach on the other hand present additional hurdles in utilising panchromatic images. This contribution looks at the possibility of exploiting panchromatic images (e.g., Pleiades and historical CORONA products) for remote sensing applications by (i), proposing a new approach that optimises and generates new multi-layer datasets from panchromatic images that could be useful e.g., in image classification analysis, (ii), exploiting the combinatorial texture approach to enhance the products generated by the framework in (i) above, and (iii), assessing the capability of the proposed method to handle complex datasets exemplified, e.g., by CORONA. To evaluate the approach, Kurdistan, Iran and Syria regions are selected for study employing the maximum likelihood classification (MLC) scheme. The MLC results indicate an increase in overall accuracy and Kappa coefficient by 32% and 0.42 (compared

to raw CORONA image), and 21% and 0.28 (compared to raw Pleiades image). For Iran and Syria, compared to the raw CORONA image, the MLC results show increase by 35% and 0.47, and 42% and 0.56, respectively. Furthermore, based on the results of the accuracy assessment that show an overall accuracy of 85% and Kappa coefficient of 0.80 for Kurdistan, 94% and 0.92 for Iran, and 96% and 0.95 for Syria, the proposed method can be said to have the potential of handling complex panchromatic datasets such as CORONA.

Keywords: Panchromatic images; CORONA; Texture analysis; Pleiades; Aspect calculation; Optimum direction

1. Introduction

Panchromatic images, e.g., Pleiades, historical CORONA and arial photographs are cost effective single band and high spatio-temporal resolution images traditionally used as input for direct image analysis either for visual interpretations or manual digitisation (e.g., Beck , 2007; Challis , 2002; Fowler , 2004; Gheyle , 2004; Hritz , 2013; Philip et al., 2002; Rgina , 2003; Wilkinson , 2006). Their spatial resolutions are normally two to four times better than most multi-spectral images (Massip et al., 2012), and as such, they are useful for spatial resolution enhancement of multi-spectral images during image data fusion (pan-sharpening). Besides image enhancement, and due to the longevity of some of its products, e.g., the historical CORONA data that stretches back to the 60s, panchromatic images are also useful in providing reference (baseline) datasets used as base maps. Panchromatic images, exemplified by CORONA products, have been used extensively for identification of archaeological sites (e.g., Andersen , 2006; Coskun , 2013; Lorenz , 2004; Ruelland , 2011; Tappan , 2000; Ur , 2003), stereo analysis and digital elevation model (DEM) generation (e.g., Casana , 2008; Goossens et al., 2006; Lamsal , 2011) and extraction of forest areas (Song et al., 2015). On its part, Pleiades images (panchromatic and multi-spectral) have been used in many applications globally, (e.g., Alganci et al., 2018; Bao et al., 2018; Huang et al., 2018; Kalbi et al., 2018; Stewart et al., 2018; Fundisi & Musakwa , 2017; Oikonomidis & Pavlides , 2017).

Even with these exceptional advantages, panchromatic images have limitations for direct use in image spectral classification process leading to poor results due to their inherent single band property (Saleem , 2017). Moreover, the classes that can be distinguished from the panchromatic images do not present unique multispectral properties that can be incorporated into the image classification analysis, (see e.g., Hall-Beyer (2017)). Furthermore, their use in pan-sharpening of multi-spectral images requires closeness of their spatial and spectral resolution properties, a condition that is rarely achieved in practise (Massip et al., 2012). In addition, although the spectral quality is enhanced for multi-spectral images during the pan-sharpening process, the geometrical quality of the fused images still needs some improvement after the pan-sharpening process (e.g., Massip et al. (2012)) due to the fact that geometrical distortions result from the differences in spatial resolutions of the reference (panchromatic) and the targeted (multi-spectral) images. Other than the limitations above, some panchromatic images such as CORONA do not have a uniform spatial resolution with the same pixel size (Hamandawana , 2007), thereby requiring a resampling approach to uniform the pixels size in the images (Saleem , 2017). Exploitation of panchromatic (single band) images, therefore, still remains a challenge and as such, adding some more layers (same source of original input image) to the single band images to construct new enhanced and optimised multi-layer datasets (i.e., texture layers), could simulate the analyst’s eyes to incorporate visual texture information, i.e., descriptive statistics of pixels, into a classification scheme (Hall-Beyer , 2017).

Although procedures for generating enhanced multi-layer products (i.e., texture) from single band panchromatic images are desirable, they have, however, to the best of the authors’ knowledge, never been investigated (Saleem , 2017; Song et al., 2015). To circumvent the lack of texture enhancement procedures, a large number of studies have used panchromatic and other remotely sensed images, i.e., single band or composites such as an index or a principal component, in texture calculation using grey-level co-occurrence matrix (GLCM) with different combinations of parameters (e.g., Franklin et al., 2001; Kayitakire et al., 2006; Pesaresi , 2000; Pesaresi et al., 2008). Most of the time, though, users most of the time depend highly on the set default software parameters (especially

direction of calculation) or use different combinations of parameters to obtain the desired results (Saleem , 2017; Hall-Beyer , 2017; Solórzano et al., 2018). This again, leads to a laborious time-consuming process that imposes extra computations. The influences of some of the required parameters on the final accuracy of the derived texture obtained using GLCM have been largely studied (e.g., Agüera et al., 2008; Marceau et al., 1990; Shaban & Dikshit , 2001; Song et al., 2015), but the use of optimum parameters, e.g., *direction of calculation* during texture calculation has not been considered. For example, Puissant et al. (2005) examined the potential of using the spectral and textural approach for intra-urban land cover types, Zhang et al. (2003) used 10 m spatial resolution Satellite Pour l’Observation de la Terre (SPOT) panchromatic images of Beijing city to capture the spatial patterns of eight textural features from the GLCM, while Wang et al. (2019) used second-order texture indices for exploring the spatial heterogeneity in detecting urban slums at different scales and various directions by using Pleiades, WorldView-2 and Geoeye images. Additional studies that have used texture calculations without optimising the direction in order to enhance its parameters include, e.g., Ma et al. (2018); Sho & Tsatsoulis (1999); Krumm & Shafer (1995); Solórzano et al. (2018); Wang et al. (2018). Majority of the studies above used medium to coarse resolution images, which are less likely to show the directionality (compared to finer resolution imagery such as CORONA and Pleiades) (Hall-Beyer , 2017), hence the reason for not optimising the directions during texture calculation. Besides the computational challenges experienced in texture layer generation using GLCM discussed above, some panchromatic images, e.g., CORONA come with varying degrees of complexity due to the nature of the product resulting from differing spatial resolutions within the images (Hamandawana , 2007; Saleem , 2017; Sohn et al., 2004). Such images, therefore, require extensive pre-processing (Saleem , 2017) due to the severe geometric distortions that are maximum towards the edges of the photographs (Sohn et al., 2004). Based on the literature reviewed, Song et al. (2015) demonstrate the use of CORONA images for texture calculation but does not tackle the problem of the complex nature of CORONA data.

The present study, therefore, proposes a method for obtaining information from raw panchromatic images exemplified through Pleiades and CORONA space photographs to

116 produce enhanced multi-layer products that can be used for further analysis, e.g., in
 117 image classification. Specifically, this contribution (i) proposes a new approach for opti-
 118 mising and generating new enhanced multi-layer datasets from raw panchromatic images,
 119 (ii) exploits the combinatorial framework of texture information to enhance the products
 120 generated in (i), and (iii), evaluates the capability of the proposed method to handle com-
 121 plex datasets exemplified by CORONA. To this end, two high spatio-temporal resolution
 122 panchromatic images (Pleiades 0.5 m and historical CORONA 1.83 m) are employed and
 123 the method evaluated using two subregions of Kurdistan where the enhanced products
 124 generated by the framework are subjected to an image classification scheme to assess
 125 their performance. Kurdistan is selected due to the availability of images, i.e., Pleiades
 126 and CORONA. Furthermore, since CORONA historical photographs are usually very
 127 heterogeneous in radiometric quality from one region to another as the variations of the
 128 data can be extremely large due to the contrast, incidence angle variations, and the na-
 129 ture of various regions, i.e., different topography, the analysis in this study will not be
 130 limited only to Kurdistan, but will include two additional regions: Iran and Syria.

131 The remainder of the study is organised as follows. In section 2, the proposed method
 132 is presented. Section 3 evaluates the method based on Pleiades and CORONA high
 133 spatio-temporal resolution panchromatic images within Kurdistan region. Two examples
 134 are presented and discussed in section 4 to illustrate the method. The first example
 135 employs the method to generate enhanced multi-layer images for Kurdistan, Iran and
 136 Syria when complex panchromatic images are used, e.g., CORONA. The second example
 137 looks at simple panchromatic images, e.g., Pleiades. The strengths and weaknesses of the
 138 proposed method are then discussed in section 5 before concluding the study in section
 139 6.

140 2. Generating enhanced multi-layer image from panchromatic images: The 141 Framework

142 2.1. The Framework and its validation

143 2.1.1. The Framework steps

144 The framework for generating enhanced multi-layer data using the combinatorial tex-
145 ture approach is summarised in Figure 1, where the first two steps are standard pre-
146 processing and texture calculation processing steps that have widely been used. They
147 are, however, necessary processing steps for the input in the main steps (3 and 4) of our
148 framework. All the steps of this framework are processed using Erdas Imagine v.2015,
149 ArcGIS v.10.6, and Environment for Visualizing Images (ENVI) v.5.3 versions. The
150 framework proceeds in five steps as follows:

151 *Step 1 (data pre-processing):* Panchromatic products are single band images (greyscale),
152 which cannot be directly used for analysis. The images require pre-processing, i.e., geo-
153 referencing (Saleem , 2017), ortho-rectification, mosaicking if the study area needs more
154 than one image, brightness balancing and histogram matching to reduce brightness varia-
155 tions in the overlap areas between adjacent scenes (Hamandawana , 2007). In some cases,
156 e.g., for CORONA panchromatic images with 8 bits pixel depth, the spatial resolution
157 differs from one image to another, and even within the same image, the resolution in
158 the middle could be much higher than that of the edges (Hamandawana , 2007; Saleem
159 , 2017), thereby necessitating the resampling of the pixels to generate images with the
160 same pixel sizes (Saleem , 2017). This step of the framework, therefore, addresses these
161 issues with the final output being the *raw (pre-processed) panchromatic images* ready for
162 step 2 (Figure 1).

Figure 1: A flowchart showing the overall process that illustrates both the conventional (B) and the proposed combinatorial enhanced approach (C, gray dashed box). Note that both approaches utilise step 2, where the conventional texture calculation approach uses the traditional multi-layer image as final output, while our proposed method goes via the enhanced combinatorial approach in (C) and employs optimal direction obtained in step 3 to generate the composites in step 4 that are finally combined with the raw panchromatic image (A) in step 5 to generate optimised composite dataset as final output from the proposed framework. These can be used for performance assessment, i.e., in image classification analysis. The first two steps of the framework are standard pre-processing and texture calculation processing steps that have widely been used. However, they are necessary processing steps for the input in the main steps (3 and 4) of our framework.

163 *Step 2 (conventional texture calculation)*: To be able to generate new layers from the
 164 raw panchromatic images and not use them in their raw forms as done traditionally (see
 165 (A) in Figure 1), texture, which forms one of its important characteristics is exploited to
 166 produce many layers (Haralick et al., 1973). Its calculation normally has a set of descrip-
 167 tive properties that can be measured and compared through texture analysis (Figure 1,
 168 step 2) and different positional vectors as shown in Figure 2; usually oriented in the hor-
 169 izontal (0°), diagonal right (45°), vertical (90°), and diagonal left (135°) directions, e.g.,
 170 Haralick et al. (1973); Hudak & Hudak (2001). Different combination of parameters such
 171 as directions of calculation, processing window sizes, and gray scale quantisation levels
 172 can be used during the texture calculation. This process is normally time consuming
 173 since the user needs to use many different parameter combinations (see Figure 1, step 2)
 174 to obtain the desired results. Often, the selection of texture layers for further analysis is
 175 based on intuition, experience, and software defaults (Saleem , 2017) and sometime uses
 176 a selective approach based on correlation among the texture outputs (Hall-Beyer , 2017).
 177 The output from this step is a set of *raw texture layers* (mean, variance, homogeneity,
 178 contrast, dissimilarity, entropy, and correlation) labelled B_2 to B_8 in Figure 1, step 2.
 179 The parameters from this step are used in enhanced combinatorial approach (C in Figure
 180 1) for further analysis in step 3.

Figure 2: Possible texture calculations with different orientations at 0° (horizontal right) refer to $(X,0)$ texture calculation parameter, -0° (horizontal left) refer to $(-X,0)$ texture calculation parameter, 45° (diagonal top right) refer to $(X,-Y)$ texture calculation parameter, -45° (diagonal bottom left) refer to $(-X,Y)$ texture calculation parameter, 90° (vertical up) refer to $(0,-Y)$ texture calculation parameter, -90° (vertical down) refer to $(0,Y)$ texture calculation parameter, 135° (diagonal top left) refer to $(-X,-Y)$ texture calculation parameter, and -135° (diagonal bottom right) refer to (X,Y) texture calculation parameter. This is used in step 2 of the proposed framework in Figure 1.

181 *Step 3 (enhanced combinatorial approach):* Before calculating the texture measures,
182 it is important to check the periodicity of texture in the image as it may give some hints
183 for choosing the direction parameters to obtain better results (Saleem , 2017). This is
184 achieved using Fast Fourier Transform (FFT) as demonstrated in Figure 3. Through FFT
185 analysis, the user would be able to see the texture in the image in three forms: periodic,
186 aperiodic (directional) and random. If the distribution of the Fourier spectral values are
187 not restricted to any particular direction (e.g., Figures 3b and 3d), this indicates that
188 the texture in the image is directionally random (Lee & Chen , 2002). Therefore, the
189 user is required to test the calculation of texture in many directions (see step 2 of the
190 framework or Figure 2) until the desired results are obtained, which is a tedious and time
191 consuming process.

192 Since texture calculation is effected by the direction and orientation of the features
193 in the image (Haralick et al., 1973; Saleem , 2017), from a computational point of view,
194 one of the main elements for accurate texture calculation is the *direction of calculation*
195 (see e.g., Figure 4 for Kurdistan as an example). Most of the time, though, users depend
196 highly on the set default software direction or use different combinations to obtain the
197 desired results. This, again, leads to a laborious time consuming process that imposes
198 extra computations. Given the well known relationship between DEM and Aspect, i.e.,
199 DEM defines the Aspect on the one hand, while Aspect defines orientation and direction
200 in the image on the other hand (see e.g., Bobstad & Stowe (1994)), this study exploits
201 this relationship to obtain the optimized direction. Calculating the Aspect direction of
202 the study area from a digital elevation model (DEM) might be essential since it helps in
203 the selection of optimum direction during texture calculation. The texture calculation
204 uses an arbitrary geometric reference, whereas the analysis of Aspect uses geographical
205 azimuth as a reference; for instance, the geometric zero refers to the horizontal right (0°)
206 with respect to the image, which in geographical terms refers to the eastern aspect (67.5°
207 - 112.5°) in most practical cases. By calculating the percentage of Aspect for the study
208 area, and selecting the largest value among the four directions, which corresponds to the
209 best possible direction of calculation with different combination of processing window
210 size (3, 5, 7, 9, 11 and 13), one may overcome the long process of finding the best possi-

Figure 3: (a) CORONA ortho-image covering Erbil subregion area of Kurdistan, (b) the periodicity of the textures following Fast Fourier Transform (FFT) analysis of CORONA image indicating the texture to be random, (c) Pleiades ortho-image covering Amedy subregion area of Kurdistan, and (d), the periodicity of the textures following Fast Fourier Transform (FFT) analysis of Pleiades image, also indicating the texture to be random. From the Figure, it can be seen in (b) and (d) that the images are non-directional hence the user has to test the calculation in several directions, a time consuming process.

211 ble direction for texture calculation. Also, if the study area is very large, the proximity
 212 between or among these Aspect percentages or directions can be investigated thus neces-

213 sitating the division of the study area into different zones or sections for accurate results
 214 (Saleem , 2017).

Figure 4: Possible texture calculation taking into consideration the directions (orientations) and the Aspect percentages over Kurdistan region as an example. This figure shows that the Aspect zones are created based on the corresponding geometric zero of the image and used to calculate the percentage of each Aspect or direction, which is calculated from Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) digital elevation model (DEM) data (Table 1). The largest Aspect percentage is then selected and regarded as the optimum direction for texture calculation. This is relevant for step 3 of the proposed framework.

215 Since the calculated texture layers using the traditional approach and even optimum
 216 direction are normally highly correlated (either positively or negatively), see e.g., [Har-](#)
 217 [alick et al. \(1973\)](#); [Cossu \(1988\)](#); [Baraldi & Parmiggiani \(1995\)](#), [Haralick et al. \(1973\)](#)
 218 suggests the use of principle component analysis (PCA) to extract meaningful data. Al-
 219 though PCA is a popular tool used in various data analysis schemes for reducing the
 220 dimensionality of data (e.g., [Awange et al., 2019a,b](#)), especially the multi-spectral re-
 221 motely sensed data, one of its disadvantage is that it transforms the original data into
 222 new orthogonal ones, resulting in changes of the texture information. Using PCA, there-
 223 fore, is not suitable for texture calculation in our proposed method (e.g., [Prasad & Bruce](#)
 224 [, 2008](#)). Often, the selection of the most informative texture layers is based on intuition,
 225 experience, and software defaults. However, calculating correlation matrices makes it
 226 possible to choose the texture layer with the least correlation for use in image composite
 227 generation in step 4. As an example, Figure 5 shows the possibility of any user choosing
 228 the layers with the least correlation, i.e., ≤ 0.3 , with each other. Furthermore, the GLCM
 229 Mean measure was chosen as base texture layer to compare all other texture measures
 230 with the threshold mentioned before. This initial step is taken for this part of the analy-
 231 sis because the GLCM Mean descriptive measure is one of the most informative texture
 232 measures for interior (within a patch of a given class) texture in the image. This step
 233 thus provides the *enhanced least correlated layers* (see step 3, Figure 1 of the proposed
 234 framework).

Figure 5: Calculated correlation matrix for texture layers showing the least correlated measures, i.e., the values circled in black (mean, variance, and contrast), which are used as inputs for the multi-layer generation in step 4.

235 *Step 4 (Enhanced multi-layer image generation):* From the *enhanced least correlated*
236 *layers* obtained in step 3, three least correlated enhanced texture layers are chosen and
237 used as input to generate *different composite images* in this step (see Figure 1, step
238 4), where the combinatorial framework $C = n!/(n - m)!m!$ (e.g., Awange & Grafarend
239 (2005); Awange & Fukuda (2007)) are applied. In this combinatorial framework, n
240 denotes the number of the least correlated layers, i.e., from step 3, $n = 3$ texture layers
241 (mean, variance and contrast), and m the possible number of combinations (i.e., the
242 minimum combination required to generate a composite image). Given that the resulting
243 number of the least composites layers n is 3, and the minimum possible combinations m
244 as 2, the resulting combinations are $C = 3!/(3 - 2)!2!$, i.e., 3. In this step, to generate
245 these different composite images, the image composite tool in ArcGIS is utilised.

246 *Step 5 (Optimising the enhanced multi-layer image):* Finally, out of these 3 compos-
247 ites, the framework selects the least correlated composite, i.e., composite 2 (B_2 and B_4)
248 and combines it with the raw panchromatic image B_1 to generate the *optimised compos-*
249 *ite*. The process of creating this optimised composite can be through using any image
250 processing package that can merge the original panchromatic image with the least corre-
251 lated enhanced composite (see e.g., optimised composite in step 5 of Figure 1, where the
252 raw (pre-processed) panchromatic image B_1 is combined with “mean” B_2 and “contrast”
253 B_4).

254 3. Evaluation of the proposed method

255 3.1. Study area and data

256 3.1.1. Study area

257 To evaluate the newly proposed method, Erbil the capital city of the Kurdistan region
258 and the surrounding area (35°73’-36°43’ N and 44°30’-43°59’ E) located in the middle of
259 Kurdistan region, in the north of the Federal Iraq, with a total area of 2896.3 km² (Figure
260 6d) is selected as a study area for CORONA image. Amedy district in Kurdistan, with a
261 total area of 25 km² is used as a second subregion study area for Pleiades image (Figure
262 6c). Kurdistan region generally consists of the Governorates of Duhok, Erbil, Sulamani,

263 Kirkuk, with parts of Diyala and Nineweh, and shares borders with Syria to the west,
 264 Turkey to the north, Iran to the east, and the middle Governorates of Federal Iraq to
 265 the south. Three Governorates (Duhok, Erbil, and Sulamani) constitute the Kurdistan
 266 Regional Government ([Saleem , 2017](#)) in the northern region of Iraq, which was approved
 267 by the Iraqi Federal Government in the mid 2000s. As stated earlier, these subregions
 268 of Kurdistan are selected for study purely due to the availability of high spatio-temporal
 269 resolution of test panchromatic (Pleiades and CORONA) data. The proposed method
 270 is however applicable to any region as exemplified by the two additional tests based on
 271 Iran and Syria.

Figure 6: (a) Location map for the Kurdistan Region (South Kurdistan) in respect to the Middle Eastern countries, (b) Kurdistan region with three major cities (Duhok, Erbil and Sulamani) as labeled in the figure (Source: Sentinel-2 2016 base map (United State Geological Survey; USGS)). Two sub-regions of Kurdistan region as shown in the figure are here selected for study because of the availability of high spatio-temporal resolution test panchromatic (Pleiades and CORONA) data. (c) Amedy sub-region (Source: Pleiades 2016 base map), and (d), Erbil sub-region (Source: CORONA 1969 base map).

272 3.1.2. Data

273 (a) *CORONA data*: CORONA is one of the United States space programmes that
 274 was operated by the Air Force and the Central Intelligence Agency from August 1960
 275 to May 1972 (Saleem , 2018). CORONA products are single band images with 8 bits
 276 pixel depth that can be downloaded in two forms; either geo-referenced or raw prod-
 277 ucts that require further image pre-processing, i.e., geo-referencing (Saleem , 2017).
 278 Geo-referenced panchromatic products can be downloaded through the “CORONA At-
 279 las for the Middle East” website (<http://corona.cast.uark.edu/>). These products
 280 are prepared (geo-referenced) and provided to end user at no cost from the Centre
 281 for Advanced Spatial Technologies, University of Arkansas and U.S. Geological Survey
 282 (BETA) (Saleem , 2017). On the other hand, the U.S. Geological Survey (USGS) web-
 283 site (<https://earthexplorer.usgs.gov/>) provide raw products at low cost (Kennedy
 284 , 1998), but in some cases the images can be downloaded free of charge directly from
 285 USGS’s website. In both cases, these unique panchromatic products need some pre-
 286 processing before being used for further analysis (Saleem , 2017). The geo-referenced
 287 panchromatic products from BETA are in National Imagery Transmission Format (NITF)
 288 and each NITF file contains an unprocessed geo-referenced CORONA image along with
 289 Rational Polynomial Coefficients (RPC) as a replacement sensor model for the ortho-
 290 rectification process (Adam , 2011). In addition, these panchromatic images require mo-
 291 saicking if the study area needs more than one image, colour balancing, and histogram
 292 matching to reduce the brightness variation in the overlap areas, which is approximately
 293 about 8% between adjacent scenes (Hamandawana , 2007).

294 For this study, a total of 6 geo-referenced CORONA images (see Table 1) are down-
 295 loaded from BETA website (<http://corona.cast.uark.edu/>) and pre-processed using
 296 step 1 of the proposed framework, which includes the method suggested in that website
 297 using ArcGIS, and any digital elevation model (DEM) data, i.e., Advanced Spaceborne
 298 Thermal Emission and Reflection Radiometer (ASTER) DEM data used in this study,
 299 to obtain an ortho-rectified image. All CORONA images are cloud free and resampled
 300 to have a uniform pixel sizes of 2.5 m. The images are then mosaicked using mosaic

seamless in ERDAS Imagine to create *pre-processed ortho-images*. For the additional subregions (Iran and Syria), two images for each are downloaded from the same source and the same pre-processing step 1 of the framework applied to obtain ortho rectified images for further analysis.

(b) *Pleiades data*: Pleiades satellite was first launched in 2011 by Space Agency of France (Centre National D’Etudes Spatiales (CNES)) and its images in both products (panchromatic and multi-spectral) can be purchased from the Apollo mapping website (<https://apollomapping.com/imagery/>). For this study, a high resolution Pleiades A1 image of July 20, 2016 (panchromatic with 16 bits pixel depth (0.5 m) and multi-spectral (2.0 m)) with total areas of 25 km² were purchased and used as input in the proposed method as well as for the validation process of the final classified Pleiades images, respectively (Table 1). Some of the pre-processing techniques in step 1 of the framework are applied to Pleiades image including ortho-rectification using the rational polynomial coefficients (RPC) file, which is supplied by the provider using ERDAS imagine 2015 platform. For Pleiades image, however, mosaicking and color balancing are not required as a single image with limited area is used for this study.

Table 1: A summary of the data employed in this study. These includes; CORONA(KH-4B system captured by the camera afterward looking), Pleiades, and ASTER digital elevation model data (for CORONA ortho-rectification and Aspect calculations).

No. of images	Film type	Mission No.	Acquisition date	Spatial resolution (m)
Erbil, CORONA (6)	70 mm Panoramic	DS1107-2170DA	3 August 1969	1.83
Iran, CORONA (2)	70 mm Panoramic	DS1107-2170DA	3 August 1969	1.83
Syria, CORONA (2)	70 mm Panoramic	DS1105-1009DA	5 November 1968	1.83
Amedy, Pleiades 1A (1)	Panchromatic	NA	20 July 2016	0.50
Amedy, Pleiades 1A (1)	Multi-spectral	NA	20 July 2016	2.00
Kurdistan, ASTER (32)	DEM	NA	17 October 2011	30.00
Iran, ASTER (2)	DEM	NA	17 October 2011	30.00
Syria, ASTER (2)	DEM	NA	17 October 2011	30.00

(c) *ASTER data*: To be able to calculate the Aspect of the study area in order to choose the optimum direction of texture calculation, DEM data are required for this process. ASTER 2011 DEM dataset (36 scenes; 32 for Kurdistan region and two each for Iran and Syria, respectively) were downloaded from the USGS website (<https://earthexplorer.usgs.gov/>) (Table 1) and mosaicked, and then an Aspect calculated

322 using Aspect tool in ArcGIS environment for each study subregion.

323 *(d) Ground reference data:* Due to lack of historical ground reference data to be
324 used for accuracy assessment of CORONA panchromatic dataset, the reference data are
325 collected from the CORONA image itself using visual interpretation. Remote sensing
326 for data collection in most middle East countries including Iraq has been restricted to
327 military use. Many maps and surveys were lost during the invasion of Iraq by the USA
328 in 2003 (Saleem , 2017). In addition, Middle East governments are generally reluctant to
329 supply any type of data (images or ground reference data), which in their opinion may
330 be a threat to the security of their States (Saleem et al., 2018). Since CORONA images
331 are very high in spatial resolution, using them as base maps for collecting this reference
332 dataset, therefore, may be feasible (Saleem , 2017). In the absence of ground reference
333 data, generating large numbers of random points and attributing them using the original
334 image as base layer is one of the acceptable approaches in remote sensing field (see e.g.,
335 Olofsson et al., 2014; Nowak et al., 2006). In contrast to CORONA, Pleiades purchased
336 image packages include both panchromatic (Pan) and multi-spectral (MS), where the MS
337 have been used as reference data collection.

338 Two sets of reference data (points and polygons) are created for both Pleiades and
339 CORONA datasets to be used for accuracy assessment. As already stated, for CORONA
340 image, the pre-processed ortho-image from step 1 of the proposed framework is used
341 as a base map layer. A point dataset is created by using a stratified random sampling
342 approach for each land cover type except for water bodies (details are discussed in the
343 examples section below). A total of 300 random points are generated within the study
344 area (Table 2) for the four land use land cover (LULC) classes namely agriculture, forest,
345 bare land and built up areas. All the random points are overlaid on the pre-processed
346 CORONA ortho-image (Figure 7), and a total of 252 points are attributed (Table 2) to
347 each land cover type and appropriately coded using ArcMap environment. The point
348 reference datasets are converted in to a raster dataset with 2.5 m pixel size to match
349 the pixel size of the classified image for accuracy assessment. For the polygons reference
350 dataset, the reference points are used as an input for the region growth tool. Total areas

of 39.1 km² are produced by the region growth process for the polygons reference dataset (Table 2). For Pleiades image, two sets of reference data (points and polygons) based on the Pleiades multi-spectral image as base map (Table 1) are generated using the same process implemented for CORONA, and a total of 190 points (Figure 7) and 1710 m² for polygons are collected and generated using the region growth tool in the ENVI software v.5.3 environment (Table 2).

Table 2: Reference datasets (points and polygons) for accuracy assessment of CORONA and Pleiades images. The area of CORONA data is in km² as this image covers almost 2896.3 km², meanwhile, Pleiades image area is in m² as only 25 km² was purchased for this study.

		CORONA		Pleiades	
Land use/cover	Code	Number of points	Area (km ²)	Number of points	Area (m ²)
Built-up	2	68	3.6	52	468
Bare land	3	60	15.7	39	351
Forest	4	64	3.3	51	459
Agriculture	5	60	16.5	48	432
Total		252	39.1	190	1710

Figure 7: The locations of the reference points datasets for CORONA and Pleiades that have been used during the accuracy assessment process for both study sites. Figure 7a shows the locations of these points over the entire CORONA image, while Figure 7b shows these reference points in four zoomed figures representing four different LULC classes for reference data. Figure 7c shows the locations of these points over Pleiades multi-spectral image and Figure 7d shows the four zoomed maps of Figures 7c1, 7c2, 7c3, and 7c4 for these LULC classes reference data.

4. Examples: Complex and simple panchromatic images

4.1. Example 1 (Complex panchromatic images, e.g., CORONA)

As already pointed out in Section 1, CORONA images suffer from severe geometric distortions and some other limitations, i.e., spectral signature (Hamandawana , 2007; Saleem , 2017) that limit their usage for supervised image classification (Song et al., 2015). In Example 4.1.1, we demonstrate how our proposed framework overcomes these complexities on the one hand, and enhance the original panchromatic product by generating enhanced multi-layer images that could readily be used as inputs for image classification analysis (see e.g., Example 4.1.2) on the other hand.

4.1.1. Example of CORONA with distortion

In case of the CORONA image (Figure 8), looking at Figure 8a, the red box shows an example of a portion of the image with an overlapping area between images after mosaicking. In Figure 8b, the complexity of the image is illustrated by the differing pixel sizes and geometric distortion, both which combine to distort the image, thus limiting its direct use. In what follows, we show how our framework is used to overcome these complexities. First, the original CORONA images (6 in total to cover the entire study area) are subjected to pre-processing (step 1, Figure 1) using the proposed method, where the images are well aligned using 8% overlap areas and brightness balanced between adjacent images during the image ortho rectification and image mosaicking processes (Saleem , 2017; Hamandawana , 2007). This step of our framework generates a raw (pre-processed) panchromatic image used for further analysis (Figure 8c). Comparing images of Figures 8b and 8c visually, one can see that our framework has successfully handled the complexities by correcting for the pixel size differences, brightness balancing, and the distortion. This is advantageous particularly for CORONA panchromatic datasets that are yet to be used.

Figure 8: The figure illustrates the effectiveness of the pre-processing step 1 of the proposed method applied to the 1969 CORONA original images; (a) Image before pre-processing, (b) different pixel sizes and geometric distortions, and (c), corrected raw panchromatic image using our framework leading to the same pixel sizes, brightness balancing, and free of geometric distortions, which is very important for texture calculation. This capability of our framework is necessary for CORONA products that offer long term baseline data that are yet to be used.

4.1.2. Generation and evaluation of enhanced multi-layer images

To illustrate the effectiveness of our proposed framework, first, we demonstrate how the framework produces enhanced multi-layer images from the raw panchromatic image (Figure 8c), and then evaluate these enhanced multi-layer images through comparison with raw panchromatic (Figure 8c) and traditional multi-layer images (see e.g., the output of step 2 in Figure 1) in a classification framework scheme in Figure 9.

1. *Generation of enhanced multi-layer products:* Here, the optimum parameter, i.e., *direction of calculation* obtained by calculating Aspect percentage from ASTER 2011 DEM dataset downloaded from the USGS website (<https://earthexplorer.usgs.gov/>) is employed during the texture calculation analysis (in step 3 of our framework) with processing window size (3, 5, 7, 9, 11 and 13). This *optimum direction of calculation* parameter is selected based on the largest percentage (36% for the study area), which has easterly and westerly Aspects with respect to azimuth corresponding to the reference geometric orientation of 0° for texture calculation. The texture layers with the lowest correlations (step 3, Figure 1) are then used to generate different enhanced composite images (i.e., step 4 of the framework). Finally, in step 5 of our framework (Figure 1), the optimised enhanced multi-layer images are generated. These are evaluated in (2) below.
2. *Evaluation of the generated enhanced multi-layer products in (1) above:* After generating different enhanced multi-layer images in (1) above, they are subjected to a maximum likelihood classification process (see Figure 9), where a minimum of 10 training samples (texture regions) with large number of pixels (Table 3) are generated for each land cover type (bare land, built up, forest, agriculture, and water) using a region growth method in ENVI environment. The seed pixels for region growth process for each land cover type are identified visually and used to generate “uniform” texture regions for each land cover type. The training texture regions for all the input images are then used as input in the Jeffries-Matusita separability measuring tool (Exelis , 2015; Saleem , 2017). The results of the statistical separability test for CORONA enhanced multi-layers show that all class pairs are

significantly different from each other (within a range of 1.8 to 2) except for the water areas for Erbil, which produced a low value of 0.34. This suggests that the water class cannot be accurately separated during the image classification process as the value is less than 1 (Exelis , 2015). Masking water areas from the images before the classification process could increase the accuracy of the other land cover classes (Saleem , 2017), since they represent less than 2% of the total study area, and as such, can be delineated accurately in the ArcGIS environment using manual digitisation. A desired shapefile for the water areas is created and used as a mask during the image classification process employing Maximum Likelihood Classifier (MLC) to generate the final classified images for the CORONA data. Because MLC is still one of the superior methods (Saleem et al., 2018), and has also been widely used in many studies, e.g., Abdulaziz et al. (2009), Erbek et al. (2004), Frazier & Page (2000), Maselli et al. (1994), Otukey & Blaschke (2010), Paola & Schowengerdt (1995), Paul (2000) and Paul et al. (2002), it is employed in this step to evaluate the performance of the enhanced multi-layer images generated from our proposed framework. It should be pointed out that MLC has limitations for linear feature mapping, i.e, transitional boundary among LULC classes during this process. However, the main focus of our study is to propose a framework that generates enhanced products from panchromatic images. MLC is only employed to demonstrate the effectiveness of these enhanced products compared to the raw panchromatic and traditional multi-layer images (see Figure 9). In this regard, MLC limitations will affect all the products under comparison process equally and using other image classification classifiers such as Random Forest (RF;Awange et al. (2020)) or Support Vector Machine (SVM;Awange et al. (2020)) would give different degrees of advantage to the resulting images, but the comparison of different classifiers is out of the scope of the present study.

Table 3: Number of pixels within training sample for each land use/cover and each study areas, i.e., Amedy Pleiades with 0.5*0.5 m pixel size, Erbil, Iran, and Syria CORONA with 2.5*2.5 m pixel size.

Pleiades		CORONA		
Land use/cover	Amedy	Erbil	Iran	Syria
Built-up	246,437	37,533	78,871	12,338
Bare land	339,586	163,035	373,330	1,191,150
Forest	461,118	143,058	14,676	223,325
Agriculture	47,958	156,268	41,250	556,579
Water	NA	12,105	NA	NA

Figure 9: Evaluating the enhanced multi-layer images from our framework through the comparison of the three pre-processed products; raw panchromatic, traditional multi-layer, and enhanced multi-layer products (images) using MLC classification scheme. The outputs are used to showcase the gains achieved by using our framework to generate enhanced multi-layer products. This figure is a simplified version of our framework, which has been used to generate enhanced multi-layer images for all the study subregions, i.e., CORONA and Pleiades images from original panchromatic images.

From (2) above, the spatial patterns for the complex CORONA data in three forms (raw panchromatic, traditional multi-layer, and enhanced multi-layer images) as classified images can be seen in Figures 10a1, 10b1, and 10c1 for the Erbil subregion. These figures clearly show the effectiveness of our proposed method to produce enhanced multi-layer images that are useful for further analysis, e.g., for mapping of LULC categories. The raw panchromatic image, which is obtained from step 1 of the proposed method (e.g., Figure 8c) is used as a direct input for the image classification (Figure 10a), and also to generate texture layers using the default parameters, i.e., traditional multi-layer images (Figure 10b). The final form (Figure 10c) is the enhanced multi-layer image for CORONA dataset obtained using raw panchromatic image from step 1 and implementing other steps of the newly proposed method. The selected area by black box shows the gain in using the enhanced multi-layer images obtained from our proposed framework. The majority of the areas within this box are forest, but these areas have been misclassified by the other two forms of the CORONA data (i.e., raw panchromatic and traditional multi-layer images in Figures 10a1 and 10b1 to built up and bare land, respectively).

452 Furthermore, the statistical accuracy in Figure 15 supports these results. Other areas that
453 have been misclassified by the first two forms of CORONA data (i.e., raw panchromatic
454 and traditional multi-layer images) are highlighted in Figures 11 and 12, and are described
455 in greater details below.

Figure 10: Evaluation of different forms of CORONA products over Kurdistan subregion of Erbil through the classification scheme in Figure 9: (a) Raw panchromatic image for 1969, and its classified image (a1); (b) traditional multi-layer image, and its classified image (b1); (c) enhanced multi-layer image from our framework in Figure 1, and its classified image (c1). The black rectangles represent different land cover types; bare land, forest, built-up, and agricultural areas. Examining these Figures (10a1, 10b1 and 10c1) visually, one can see that the enhanced multi-layer products from our proposed framework (step 5 in Figure 1) has classified these area accurately in Figure c1 compared to the raw panchromatic (Figure a1) and traditional multi-layer images (Figure b1).29

Figure 11 shows three forms of CORONA data in greater detail (zoomed to the same extend as the Pleiades image), i.e., raw panchromatic and its classified image (Figures 11a and 11a1, respectively), traditional multi-layer image and its classified image (Figures 11b and 11b1, respectively), and, enhanced multi-layer image and its classified image (Figures 11c and 11c1, respectively). These figures further illustrate the effectiveness of our proposed method when employed to produce enhanced multi-layer products that are useful for mapping LULC classes using CORONA data. When the enhanced products from our framework are used within the MLC classification framework in Figure 9, it can visually be seen that the enhanced dataset gives much accurate results for different LULC types (see, e.g., the black rectangles of Figure 11c1). For example, box r1 in Figure 11a represents bare land area, which is very clearly shown as a single class area in Figures 11a, 11b, and 11c. However, when these areas are classified within the framework of Figure 9 (i.e., Figures 11a1, 11b1 and 11c1, respectively), areas of mixed bare land and built-up result from the raw panchromatic (Figures 11a1) and agriculture and built-up from the traditional multi-layer classified images (Figure 11b1) on the one hand. On the other hand, these areas are very accurately classified as a single bare land class when enhanced multi-layer images from our framework are employed in the classification scheme (Figure 11c1).

Similarity, for the other areas (i.e., r2, r3, and r4), the enhanced multi-layer dataset from our framework (Figures 11c) performed well (see Figure 11c1), with more highly accurate results achieved (see also Figure 15, where accuracy assessment analysis is undertaken to show the gains achieved using the enhanced multi-layer images from our framework compared to raw panchromatic and traditional multi-layer images). Area r2 in Figure 11a is mostly forested areas, however, classification results using both raw panchromatic and traditional multi-layer images show the area as a combination of agriculture, built-up, forest, and bare land. Using enhanced multi-layer image from our framework, however, majority of the features within box r2 are correctly classified as forested, followed by bare land and built-up areas (see Figure 11c1). For box r3 in Figure 11a, its areas are misclassified (i.e., mostly built-up areas followed by bare land), with majority of bare land in Figure 11a1 (raw panchromatic) and agriculture and built-up

486 in Figure 11b1 (traditional multi-layer images). Our framework’s enhanced multi-layer
487 images when used, however, led to the area being properly classified as bare land followed
488 by built-up areas, see e.g., Figure 11c1. As for box r4 (Figure 11a), the areas within it
489 contain a combination of agriculture, bare land and some patches of built-up, but in
490 both cases, using raw panchromatic and traditional multi-layer images, they classified
491 the agriculture as built-up areas (Figures 11a1, and 11b1), respectively. Employing en-
492 hanced multi-layer images from our framework correctly classify the area as agricultural
493 and bare land with some patches of built-up areas (Figure 11c1).

494 In summary, therefore, in this example, the enhanced multi-layer products from our
495 framework when employed within a classification scheme of Figure 9 resulted in more
496 accurate outcomes compared to the use of raw panchromatic or traditional multi-layer
497 images. To clearly visualise the performance of employing the enhanced multi-layer
498 products from our framework for LULC classification (e.g., Figure 9), a zoomed version
499 of Figure 11c1 is presented in Figure 12, which shows the variability of the classification
500 scheme used on the one hand, and on the other hand, the limitation for MLC for linear
501 feature mapping, i.e, transitional boundary among built-up, agriculture, forest, and bare
502 land areas during this process.

Figure 11: Evaluating the gains achieved by employing enhanced multi-layer CORONA images from our framework in a classification scheme (e.g., Figure 9): (a) Raw panchromatic image for 1969, and its classified image (a1); (b) traditional multi-layer image, and its classified image (b1); (c) enhanced multi-layer products from our framework, and its classified image (c1). The black rectangles represents different land cover types; bare land (r1), forest (r2), built-up (r3), and agriculture (r4) areas. Examining Figures 11a1, 11b1 and 11c1 visually, one sees that our proposed framework produces enhanced products that classified these areas accurately (see the zoomed version in Figure 12).

Figure 12: A zoomed version of Figure 11c1 showing the results obtained from the MLC classification scheme (Figure 9) employing the enhanced multi-layer images from our framework. Areas r1 has been correctly classified as bare land, r2 as majority forest followed by built-up, r3 as largely bare land followed by built-up, and 4r as mostly bare land followed by agriculture and patches of built-up. Using raw panchromatic (Figure 11a1) and traditional multi-layer images (Figure 11b1) failed to achieve these levels of classifications. This zoomed version shows the variability and limitations of the MLC for linear feature mapping, i.e., transitional boundary among built-up, agriculture and bare land areas during evaluation through image classification scheme of Figure 9.

503 In addition to the example of Kurdistan subregion (Erbil) using CORONA com-
 504 plex data presented above, two subregions (Iran and Syria) are also tested to further
 505 demonstrate the strengths and feasibility of our proposed new framework (see Figure
 506 13). The required CORONA images for both subregions (see Table 1) are downloaded
 507 from “CORONA Atlas for the Middle East” website (<http://corona.cast.uark.edu/>)
 508 as geo-referenced products. The selection of both sites is purely based on the image avail-
 509 ability although the proposed framework can be applied to any other CORONA images
 510 world wide.

511 The two CORONA images for both subregions are used as inputs in the proposed
 512 framework separately, with the only exception being their direction of texture calcu-
 513 lations, which are undertaken differently from that of Erbil subregion (i.e., east-west
 514 Aspect direction 0° (horizontal)). As perviously mentioned, it is important to check the
 515 periodicity of texture in the image as this process provides some hints on choosing the
 516 optimum direction parameters for texture calculation (Saleem , 2017). By implementing
 517 the Fast Fourier Transform (FFT) for both subregions, the results clearly show that the
 518 texture in both subregions’ images are restricted into two directions, i.e., north to south
 519 (90° (vertical)) and east to west (0° (horizontal)) for Syria (Figure 13a1) and Iran (Figure
 520 13e1).

521 Since the texture is restricted into these two directions, the Aspect for each is cal-
 522 culated from ASTER DEM data (Table 1) in the same way as done for Kurdistan in
 523 order to confirm with FFT analysis result and to be able to select the optimum direction
 524 of texture calculation. The Aspect calculation results for Syria subregion are 29.8% for
 525 north-south (90° (vertical)), 25.0% for east-west (0° (horizontal)), 20.8% (45° (diagonal
 526 right)) northeast-southwest, and 24.3% (135° (diagonal left)) northwest-southeast. For
 527 Iran subregion, the results are 29.0% for north-south (90° (vertical)), 25.0% for east-west
 528 (0° (horizontal)), 21.5% (45° (diagonal right)) northeast-southwest, and 24.3% (135° (di-
 529 agonal left)) northwest-southeast. These Aspect calculation results clearly show that
 530 the direction of 90° (vertical) is more suitable for texture calculations since the largest
 531 percentages of Aspect fall within this direction, i.e., north to south for both subregions.

Once the enhanced multi-layer products for both Iran and Syria have been generated from our framework as discussed above, they are subjected into a classification scheme (Figure 9) similar to the case of Kurdistan. The classification images for both Iran and Syria are presented in Figure 13, where it is once again clearly seen, that our proposed framework generate enhanced multi-layer products that are capable of achieving higher level of accuracy when subjected to image classification (see e.g., areas within white boxes for both subregions in Figure 13). Visually, it can be seen that the enhanced multi-layer images from our framework give more accurate results for different LULC types. For example, the white box in Figure 13b for Syria subregion classified mostly built-up areas using raw panchromatic image (Figure 13b1), but compared to Figures 13c1 for traditional multi-layer and 13d1 for our enhanced multi-layer images, one can clearly see that these areas mixes four classes. These areas, however, are classified very accurately using the enhanced multi-layer images from our proposed framework. Evaluating the areas within the white box in Figure 13f for Iran subregion, the built-up areas are misclassified and over estimated when raw panchromatic (Figure 13f1) and traditional multi-layer images (Figure 13g1), respectively, are used. The enhanced multi-layer images from our framework (Figures 13h), however, classified the classes within this box accurately (e.g., Figure 13h1), where higher accurate results are achieved (e.g., Figures 15 and 16, that compares our framework's outputs to those of raw panchromatic and traditional multi-layer images, using accuracy assessment analysis for both subregions of Iran and Syria).

Figure 13: CORONA LULC maps for two subregions in Syria and Iran: (a) and (e) are the original panchromatic CORONA 1968 images for Syria and Iran, respectively before pre-processing; (a1) and (e1) the periodicity of the textures following Fast Fourier Transform (FFT) analysis for Syria and Iran, respectively; (b) and (f) are the raw panchromatic images for CORONA (pre-processed) covering subregions area for Syria and Iran, respectively; (b1) and (f1) the classified images of (b) and (f) for Syria and Iran, respectively; (c) and (g) traditional multi-layer images for Syria and Iran, respectively; and (c1) and (g1) the classified images of (c) and (g) for Syria and Iran, respectively; (d) and (h) enhanced multi-layer images from our framework for Syria and Iran, respectively; and (d1) and (h1) the classified images of (d) and (h) for Syria and Iran, respectively. The white squares boxes in both sets of maps (left and right) represent different land cover types, i.e., bare land, forest, built-up, and agriculture areas. Visually, examining Figures b1, c1 and d1 for Syria and f1, g1 and h1 for Iran, one can see that our proposed framework, again, has classified these areas accurately.

4.2. Example 2 (Simple panchromatic images, e.g., Pleiades):

In contrast to Example 1 in Section 4.1 that employed complex CORONA images over Kurdistan, Iran and Syria, one Pleiades panchromatic image covering 25 km² has been used as input into the proposed framework (Figure 1) for Kurdistan to showcase and validate the effectiveness of the proposed method for utilising high spatial resolution panchromatic image for new generation of satellites. Ortho rectification is the only pre-process applied to the Pleiades panchromatic image from step 1 (Figure 1) of the proposed framework, as other pre-processing approaches are not required. Similar to Example 1 in section 4.1, the Pleiades image:

1. Is subjected to the proposed framework in order to generate enhanced multi-layer images for further analysis, i.e., image classification, and
2. the enhanced multi-layer images from (1) above, together with raw panchromatic and traditional multi-layer images are compared in a classification scheme (e.g., Figure 9) to assess the gains achieved by using the enhanced multi-layer products generated by our framework.

Evaluating the areas in the centre of the black box in Figure 14a, the proposed framework generated enhanced multi-layer images that performed well, with higher accurate results achieved (e.g., Figure 15 that compares our framework's output, i.e., enhanced multi-layer image, to other forms (raw panchromatic and traditional multi-layer images) by performing assessment test and accuracy assessment analysis). The area in Figure 14a is mostly built-up but both raw panchromatic and traditional multi-layer images classify it as a combination of built-up, agriculture and bare lands. Enhanced multi-layer image produced from our framework, however, classify a majority of the areas in the centre of this selected black box as built-up (see Figure 14c1). The result for this evaluation, once again, consolidate the effectiveness of our proposed framework for handling panchromatic images (either complex or simple) to generate enhanced multi-layer images that perform superbly when used, e.g., for image classification.

Figure 14: Pleiades LULC images for the second study area subregion in Kurdistan (Amedy): (a) Pleiades raw panchromatic image for 2016, and its classified image (a1); (b) Pleiades traditional multi-layer image; and its classified image (b1); (c) Pleiades enhanced multi-layer image, and its classified image (c1). Examining Figures 14a1, 14b1 and 14c1 visually, one can see that using enhanced multi-layer images from our proposed framework, once again, has classified these areas accurately.

580 4.3. Validation of the framework and its enhanced products

581 The proposed framework has been employed to process panchromatic images (CORONA
582 and Pleiades) to produce enhanced multi-layer images for different study regions: Erbil
583 and Amedy in Kurdistan, Iran and Syria. When the products of the framework are
584 used for a classification scheme in Figure 9, the results achieved by using CORONA
585 and Pleiades enhanced multi-layer images compared to raw panchromatic and tradi-
586 tional multi-layer images clearly show the superiority of the products from our proposed
587 framework. Furthermore, the validation process includes the accuracy assessment of the
588 classified images in three forms (see Figure 9). The accuracy of the final classification
589 results obtained for both panchromatic images, i.e., CORONA and Pleiades in the three
590 forms for Kurdistan's two subregions (Erbil and Amedy) are validated using two sets of
591 ground reference data (points and polygons; see Table 2), with the classified images using
592 confusion matrix in ENVI environment.

593 For Iran and Syria subregions, the reference points' data are collected from the same
594 CORONA images as done for Erbil subregion. For Iran, a total of 136 reference points
595 are collected (i.e., 33 for built-up, bare land, and forest, and 37 for agriculture), while
596 for Syria, a total of 122 points (i.e., 30 for built-up and bare land; and 31 for forest and
597 agriculture) are collected and used (in a similar way to Kurdistan subregions) during
598 the accuracy assessment process using error metrics in ENVI environment. During the
599 accuracy assessment process, the overall accuracy, Kappa coefficient, producer and user
600 accuracy measurements are calculated for all the classified images. Figures 15 and 16
601 show the accuracy assessment results for all study regions for CORONA (Kurdistan,
602 Iran, and Syria) and Pleiades (Kurdistan) images in three forms, e.g., raw panchromatic,
603 traditional multi-layer, and enhanced multi-layer classified images. In what follows, the
604 overall accuracies and Kappa coefficients are presented in Section 4.3.1 and the producer
605 and user accuracies in Section 4.3.2.

4.3.1. Overall accuracy and Kappa coefficient

From Figure 15 that includes all the study regions, it is clear that the use of enhanced multi-layer images from our framework performed better, and achieved higher accuracies compared to classified images from the other two forms (i.e., raw panchromatic and traditional multi-layer images). The overall accuracy gained in using point dataset with enhance multi-layer images from our framework for CORONA and Pleiades for Kurdistan subregions (Erbil and Amedy; (Figure 15a)) are 85% and 81%, and the Kappa coefficients are 0.80 and 0.74 (Figure 15b), respectively. Using the enhanced multi-layer products from our framework are the main factors contributing to the increase in the overall accuracy and Kappa coefficients using point reference dataset (by 32% and 0.42; for CORONA, and 21% and 0.28; for Pleiades) compared to the results of the raw panchromatic classified images of CORONA and Pleiades, respectively (Figures 15a and 15b). Also, the overall accuracy and Kappa coefficients are increased using point reference dataset (by 14% and 0.24; for CORONA, and 3% and 0.11; for Pleiades) compared to the results of traditional multi-layer classified images.

As shown in Figure 15a, the overall accuracies for the raw panchromatic classified images are not high, possibly due to the fact that these images are single band in nature (Song et al., 2015). The accuracies of the traditional multi-layer classified images are much higher than those of the raw panchromatic classified images probably due to the use of more informative texture layers during image classification scheme in Figure 9. In addition, the lower accuracies obtained by the traditional multi-layer classified images compared to those of the enhanced multi-layer classified images from our framework might be related to their use of default parameters, i.e., direction of calculation of 135° , window size of 3×3 during the texture calculation (Saleem , 2017), and the features in the images requiring higher window size to be captured and classified accurately (Song et al., 2015).

For Kurdistan's two subregions (Erbil and Amedy), the overall accuracies and Kappa coefficients using the polygons reference dataset are still high (Figures 15a and 15b) in comparison to the raw panchromatic and the traditional multi-layer classified images.

635 The accuracies for the CORONA and Pleiades images from enhanced multi-layer images
636 obtained from our framework compared with raw panchromatic classified images using
637 regions reference dataset indicate a gain in the overall accuracy by 39% and Kappa
638 coefficient of 0.52 for CORONA dataset, and 20% and 0.27 for Pleiades image (Figures
639 15a and 15b). Compared with the traditional multi-layer classified images, gains in the
640 overall accuracy by 17% and Kappa coefficient of 0.25 for CORONA dataset, and 5%
641 and 0.13 for Pleiades image, are recorded (Figures 15a and 15b).

642 In regards to the accuracy measurements of Iran and Syria subregions (for CORONA
643 data), the overall accuracy and Kappa coefficients using point reference dataset increased
644 by 35% and 0.47 for Iran, and 42% and 0.56 for Syria when using the enhanced multi-layer
645 images compared to the raw panchromatic image (see Figure 15c). The accuracy values
646 for the enhanced multi-layer classified images are still higher than traditional multi-layer
647 classified images with overall accuracy and Kappa coefficient of 8% and 0.10 for Iran and
648 15% and 0.18 for (Figures 15c and 15d).

649 All the accuracy results above indicate the capability of the developed framework to
650 produce enhanced products that distinguish these particular common different land cover
651 types (Song et al., 2015; Puissant et al., 2005) with high level of accuracy when used in
652 supervised classification schemes (e.g., Figure 9). These gains in accuracy are attributed
653 to the use of the optimum direction of calculation obtained from the Aspect calculation
654 in conjunction with the DEM for the study area (Saleem , 2017). The results from the
655 accuracy assessment for all classified images from enhanced multi-layer classified images
656 are compatible with standard accuracy recommended by Anderson (1976).

Figure 15: Accuracy assessment for CORONA and Pleiades data for raw panchromatic, traditional multi-layer, and enhanced multi-layer classified images for all the study subregions; (a and c) overall accuracies and (b and d) Kappa coefficients. From the results, it can be seen that all enhanced multi-layer classified images in red outperform the raw panchromatic and traditional multi-layer classified images, with the enhancement comprising (optimised composite 4) of raw panchromatic image (B_1), mean (B_2) and contrast (B_4) (i.e., red bar) emerging the best combination. Also, the record with * refers to the maximum values of the accuracy among all traditional multi-layer classified images.

657 4.3.2. *Producer and user accuracies*

658 The accuracy of the enhanced multi-layer classified images for both images (CORONA
659 and Pleiades) in greater details (other measures, i.e., producer and user accuracies) are
660 shown in Figure 16. The minimum producer accuracy value for both reference datasets
661 achieved for Kurdistan subregions (Figures 16a, 16b, 16c, and 16d) is for built up areas
662 (from CORONA enhanced multi-layer image), i.e., 62% (Figure 16c) and the highest is for
663 agricultural areas (i.e., 99%; Figure 16c). As for the user accuracy, the lowest value is for
664 forested areas (62%; Figure 16c) and the highest is for built-up areas (100%; Figures 16b
665 and 16d), which again, showcase the effectiveness of the enhanced multi-layer products
666 of the proposed method for LULC mapping studies. In regards to Iran and Syria, the
667 minimum producer accuracy value for subregions (Figures 16e, and 16f) is 87% for built-
668 up areas and maximum is again for built-up areas with 100%. Finally, for user accuracy
669 in both subregions, the minimum value is for bare land 88% and the maximum is for
670 agriculture and forest areas with 100% (see Figure 16f). The results from the accuracy
671 assessment for all classified images from enhanced multi-layer classified images for both
672 subregions, again, are compatible with standard accuracy mentioned before in Section
673 4.3.1.

Figure 16: Detailed accuracy assessment for CORONA and Pleiades data for the enhanced multi-layer images (optimised composite 4 in Figure 15) employed in MLC scheme in Figure 9 for all subregions used in this study; (a) Points reference data for CORONA, Erbil subregion, (b) points reference data for Pleiades, Amedy subregion, (c) regions reference data for CORONA, Erbil subregion, (d) regions reference data for Pleiades, Amedy subregion, (e) points reference data for CORONA, Iran subregion, and (f) points reference data for CORONA, Syria subregion. For the overall accuracy and Kappa Coefficient for these enhanced multi-layer images, i.e., optimised composite 4 generated from raw panchromatic image (B_1), mean (B_2) and contrast (B_4)) refer to the Figure 15.

5. Discussion: Strengths and Weaknesses of the framework

This study proposed a new framework that can be used to produce enhanced multi-layer images from remotely sensed panchromatic data useful for further analysis, e.g., image classification. The above examples have shown the effectiveness and advantages of the newly proposed framework for generating enhanced multi-layer images compared to the traditional methods that use raw panchromatic images for direct analysis (e.g., [Challis , 2002](#); [Ur , 2003](#); [Beck , 2007](#); [Hritz , 2013](#)), and those that use default parameters for texture calculation to generate traditional multi-layer images (e.g., [Franklin et al., 2001](#); [Song et al., 2015](#)). It is noteworthy that the highly accurate classification results achieved by the use of the enhanced multi-layer images produced by our framework during this analysis are related directly to multiple key factors below. The framework:

1. *Offers pre-processing capabilities for complex images:* In step 1 of our proposed framework, its capability to correct the severe distortions of the original panchromatic images that limited their usage in the field of remote sensing is shown. Due to the nature of these panchromatic images, some of them require more image pre-processing (e.g., complex panchromatic CORONA images). Our proposed framework provided many important technical approaches for the image pre-processing step that needs to be performed, i.e., image rectification (alignment in the overlap areas), image resampling and color balancing, especially when the study area requires more than one image as they have direct impacts on the texture calculation process ([Saleem , 2017](#); [Hamandawana , 2007](#)). Our developed framework could handle and solve all these issues, especially for complex data, e.g., CORONA. This is advantageous given that CORONA products date back to the 60s, and as such, have the potential to extend baseline products back to that period. Given that CORONA products are yet to be fully exploited by the remote sensing community, this capability of our framework is timely.
2. *Optimises direction of texture calculation:* As mentioned before, texture in any image is normally affected by the direction of the feature in the image (e.g., [Haralick et al., 1973](#); [Saleem , 2017](#)). Our framework realises this by utilising a new ap-

proach (Aspect calculation), that helps to select an optimum direction for texture calculation based on the Aspect percentage obtained from DEM dataset.

3. *Provides enhanced multi-layer products:* Texture (measures) layers can be regarded as additional informative layers that can supplement panchromatic images (lacking in spectral bands) helping to better distinguish between land cover types in order to produce final accurate outcomes (i.e., LULC maps) (Saleem , 2017; Song et al., 2015; Hu et al., 2008; Puissant et al., 2005). The proposed framework is capable of generating new enhanced multi-layer images by using the additional texture layers from the texture calculation. The selection of these layers is based on correlation matrix calculation (not random selection) provided by our framework. The increase in the classification accuracy when using the enhanced multi-layer images for CORONA and Pleiades panchromatic data produced by our framework are related directly to the additional combination of the co-occurrence texture layers, i.e., different spatial patterns during the texture calculation (Puissant et al., 2005; Song et al., 2015), that generated these enhanced multi-layer images in step 4 of our framework.
4. *Offers computational simplicity and efficiency:* Our proposed framework reduced the computation time of texture calculation significantly by implementing enhanced combinatorial framework that generates enhanced multi-layer products efficiently from raw panchromatic images through steps 3 to 4. As mentioned before, different combination of parameters is traditionally used for texture calculation (Franklin et al., 2001; Song et al., 2015) significantly leading to increase in texture calculation time. Also, our proposed framework provides a simple and enhanced combinatorial framework that users can follow to generate these enhanced multi-layer products from raw panchromatic images through steps 3 to 4 of our framework (see Figures 1 and 9).

Apart from the advantages mentioned above, there are some drawbacks in that the generated enhanced multi-layer images from our framework are not able to classify a water-scarce area (as it was the case for the CORONA images used) accurately from the

732 remotely sensed CORONA data. These were masked out from the CORONA images
733 during the image classification for all the three subregions in Figure 9. For Pleiades,
734 however, this was not the case as the water class was originally not present in the image.
735 Furthermore, the proximity among the Aspect percentages need to be investigated in
736 future studies.

737 6. Conclusions

738 This study proposed a new framework for generating enhanced multi-layer products
739 from raw panchromatic images, i.e., CORONA and Pleiades. The evaluation of these
740 enhanced multi-layer images produced by the framework through a classification scheme
741 showcased the credibility of the proposed approach, where high level of accuracies were
742 achieved. Although there are some limitations in directly using raw panchromatic im-
743 ages in the image classification process, the method described and used by this research
744 might overcome, to some extent, these limitations by producing enhanced products. In
745 addition, the developed framework was capable of enhancing CORONA complex data,
746 thereby making them useable for further analysis, e.g., supervised image classification.
747 In summary, the results indicated that:

- 748 1. The new proposed framework showed its applicability when similar high accurate
749 results were achieved for both CORONA and Pleiades images over four study re-
750 gions (Erbil, Amedy, Iran, and Syria). The accuracy results showed an increase
751 in overall accuracy and Kappa coefficients by 32% and 0.42 (CORONA) and 21%
752 and 0.28 (Pleiades). Also, the overall accuracies and Kappa coefficients for Iran
753 showed an increase by 35% and 0.47; and 42% and 0.56 for Syria when enhanced
754 multi-layer images generated from our proposed framework were used during image
755 classification scheme. The proposed framework can be tested to validate further its
756 applicability in other ecosystems and with common classes.
- 757 2. The proposed framework is capable of handling complex datasets exemplified by
758 CORONA as high level of accuracies were achieved. In return, CORONA datasets
759 could extend the time-line of change detection analysis studies globally since they

760 go back to the 60s. This can be achieved through cross-referencing with other
761 satellite imagery, i.e., Landsat data. This is vital since a significant amount of
762 modern land development started in the early 1960s onward.

763 3. The only drawback of the enhanced products from the proposed framework was
764 unable to accurately separate the water surface areas from other land cover classes,
765 therefore, the water surface delineation and the proximity among the Aspect cal-
766 culation (percentages) would be the subject of future investigation.

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