An analysis of Landsat 7 and Landsat 8 underflight data and the implications for time series investigations

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Abstract

The newly launched Landsat 8 satellite continues the long and extremely important record of Earth observation from the Landsat program. We analyzed differences between Landsat 7 and Landsat 8 surface reflectance and cirrus cloud characterization to address how substitutable Landsat 8 observations are within this long archive. Comparison of surface reflectance estimates acquired near simultaneously during Landsat 8's underflight orbital placement shows that Landsat 8 surface reflectance is consistently darker in the blue, green, and red bands and brighter in the near infrared than in Landsat 7. Vegetation indices that rely on the visible and near infrared bands should be used with caution as individual biases in index components can be amplified to create large biases in vegetation indices. We also analyzed time series datasets from the Landsat Climate Data Record (CDR) surface reflectance product across four scenes that contained only Landsat 7 data, Landsat 7 data and only Landsat 8 data post-launch, and Landsat 7 data and data from both sensors post-launch to investigate how sensor differences propagate in time series analysis. If left uncorrected or unexplained, the difference in reflectance between Landsat 7 and Landsat 8 creates spurious time trends in visible wavelengths and in the Normalized Difference Vegetation Index (NDVI). The introduction of Landsat 8 into time series of Landsat 7 data also biases the mean reflectance or vegeta-

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tion index value as measured by a time series model intercept while increasing the Root Mean Squared Error of such models. We characterized the spectral reflectance of cirrus clouds in the underflight data that were omitted from Landsat 7 cloud masks but were detected in Landsat 8's cloud mask due to the use of the newly added cirrus band. While these cirrus cloud observations missed in Landsat 7's cloud mask are only slightly brighter in the visible bands, a simulation of time series containing Landsat 8 data that does not use the cirrus band shows that omission of cirrus clouds can result in anomalously brighter time series intercepts and positive time trends. Our results indicate that while Landsat 8 has improved on the legacy of previous sensors through increased radiometric resolution, better cloud identification, and better geometric accuracy, difference in reflectance between sensors in the current Landsat CDR product must be corrected or explained within time series analysis to avoid deleterious consequences. Future efforts should identify the contributions of target specific effects versus differences in atmospheric correction methods to better inform approaches to synthesize the two sensors.

Keywords: Landsat 8; time series; change detection; CCDC; cirrus clouds;

1. Introduction

The Landsat program, spanning over 40 years, provides the longest and most informative satellite record of our changing planet (Loveland and Dwyer, 2012; Roy et al., 2014). After spending most of its lifespan operating with a pay for access model, the Landsat archive was finally made freely available in 2008 and methods that take advantage of this data policy quickly proliferated (Wulder et al., 2012). These methods that work on time series of Landsat data have been used extensively to map forest cover change (Kennedy et al., 2007; Asner et al., 2009; Kennedy et al., 2010; Huang et al., 2010; Vogelmann et al., 2012; Zhu et al., 2012; Verbesselt et al., 2012; Zhu and Woodcock, 2014; Brooks et al., 2014; Hansen et al., 2014), including a study that mapped global forest cover change between 2000 and 2012 at Landsat's 30 m resolution (Hansen et al.,

2013). This critical information on the magnitude and spatial patterns of forest change has also been extended to 1990 using Landsat data (Kim et al., 2014). While many recent Landsat time series applications have focused on identification of forest cover change, some methods have attempted to identify changes in all land covers (Zhu and Woodcock, 2014) or classify specific agricultural crops (Yan and Roy, 2014). Landsat time series also provide unique traits suitable for synthesis with lidar data for estimation of forest biomass as disturbance information from Landsat MSS through ETM+ have improved estimates of forest biomass (Pflugmacher et al., 2012). Consistent and continuous Landsat observations enable the transition from static snapshots of ecosystem properties to characterization of processes and dynamics of interest to ecologists (Kennedy et al., 2014), including phenology (Melaas et al., 2013) and insect infestations (Meigs et al., 2011). Refined information about dynamics within human systems is now also a target for Landsat based research because Landsat’s long time record, locally relevant spatial scale (Hansen et al., 2013), and recent advances in mapping frequency enables the analysis of change in land cover within the context of socioeconomic or policy drivers. Such efforts include the monitoring of forest cover change to address policy questions in regions (Kennedy et al., 2012; Griffiths et al., 2012) or nationally using wall to wall maps (Hansen et al., 2014) and within a sampling framework (Masek et al., 2013), and comparing rates of urbanization across rapidly growing cities (Schneider, 2012).

Technological advances since the development of Landsat 7 and the move from a whiskbroom to a pushbroom style sensor have greatly increased the measurement accuracy of Landsat 8 data. The signal to noise ratio (SNR) on Landsat 8’s OLI is much higher than the mission specifications and an order of magnitude higher than the SNR on Landsat 7 (Knight and Kvaran, 2014; Morfitt et al., 2015) while the increase to 12-bit radiometric resolution extends the range of measurable radiances and reduces pixel saturation (Morfitt et al., 2015). The geometric accuracy on Landsat 8 is astounding and meets or exceeds all mission requirements (Storey et al., 2014). The absolute geolocation accuracy of Landsat 8, in particular, improves so much on the mission specifications

that it will be used to improve the geometric accuracy of the entire Landsat archive by improving ground control points in the Global Land Survey (GLS) network. Improvements to onboard storage and ground transmission capacity enable Landsat 8 to acquire 60% more image scenes per day than Landsat 7 as of 2014 (Roy et al., 2014) and approximately 725 scenes are currently acquired per day. This increased image acquisition frequency will help further reduce differences in image availability due to geographic variation in observation conditions and ground receiving station access (Kovalskyy and Roy, 2013). Landsat 8 continues the legacy of the Landsat program by providing much higher quality and quantity Earth observations vital to time series investigations.

Designed to continue this legacy, the spectral band specifications for Landsat 8’s Operational Land Imager (OLI) sensor are, for the most part, very similar to previous sensors (see Table .1). Several spectral bands have been narrowed slightly to provide more precise measurements that are less correlated with other bands. The near infrared band on Landsat 8 (OLI Band 5) changed the most compared to other bands as it was narrowed substantially from $0.77\text{ }\mu\text{m}$ to $0.90\text{ }\mu\text{m}$ on ETM+ to $0.85\text{ }\mu\text{m}$ to $0.88\text{ }\mu\text{m}$ specifically to avoid an atmospheric water absorption feature at $0.85\text{ }\mu\text{m}$. As such, we might expect near infrared measurements from Landsat 8 to be brighter than from previous Landsat sensors. The first shortwave infrared band (ETM+ band 5 and OLI band 6) also narrowed significantly and the second shortwave infrared band (ETM+ band 7 and OLI band 7), while it did not change as much, now excludes wavelengths ($>2.3\text{ }\mu\text{m}$) with the strongest spectral response function in ETM+ band 7 (Flood, 2014).

The changes in spectral bandpasses are an improvement over previous sensors, but one that may affect the comparability with previous sensors. Li et al. (2014) analyzed Landsat 7 and Landsat 8 surface reflectance and vegetation indices in four land cover types. They found differences in spectral bands between the two sensors that contributed to further differences in vegetation indices, especially when using indices calculated using the visible bands. Zhu et al. (2015a) analyzed land cover change and dynamics within the rapidly urbanizing city of

75 Ghuangzhou, China and found the NDVI to be positively biased when adding
 76 Landsat 8 into time series of Landsat 4, 5, and 7. Flood (2014) used 793 cloud
 77 free 8-day pairs of images over 123 Landsat scenes in Australia to assess the
 78 difference between Landsat 8 and Landsat 7 top of atmosphere (TOA) and sur-
 79 face reflectance, including how the differences propagate in biophysical models.
 80 Differences in TOA reflectance were close to 1% for all bands except the near
 81 infrared and second shortwave infrared which were brighter by 6% and 3%,
 82 respectively. Surface reflectance correction using the methods of Flood et al.
 83 (2013) reduced these differences to within 1 to 2% for all bands except the blue
 84 band (ETM+ band 1 and OLI band 2). Unadjusted surface reflectance inputs
 85 to a fractional cover model created biased estimates relative to Landsat 7 with
 86 bare cover underestimated by 5% and vegetated cover overestimated by 7%.
 87 The differences in surface reflectance estimates were systematic and adjustable
 88 using a simple linear regression. Landsat 8 adjusted surface reflectance values
 89 produced fractional cover estimates equal to estimates from Landsat 7. Flood
 90 (2014), however, also noted that there was some variance across the 123 scenes in
 91 the relationship between Landsat 7 and Landsat 8 surface reflectances and that
 92 the corrections performed are not likely to be extendable beyond the study area.
 93 Mishra et al. (2014) used Landsat 7 and Landsat 8 data in combination with
 94 simultaneous or near simultaneous EO-1 Hyperion acquisitions to assess differ-
 95 ences in cross-sensor calibration. EO-1 Hyperion was used to develop Spectral
 96 Band Adjustment Factors (SBAF) that corrected for the measurement differ-
 97 ences due to different spectral bandpasses. Once the SBAF were applied to
 98 Landsat 8 data, TOA reflectance differences in a near simultaneously acquired
 99 Landsat 7 and Landsat 8 image pair were less than 2% for all analogous bands
 100 except for a 4% difference in the near infrared.

101 Landsat 8 includes a new band in the mid-infrared centered on $1.375\text{ }\mu\text{m}$
 102 that is designed specifically to find cirrus clouds in Landsat OLI imagery (Love-
 103 land and Dwyer, 2012; Irons et al., 2012; Roy et al., 2014). Successfully used
 104 on the Moderate Resolution Imaging Spectrometer (MODIS) instrument, this
 105 band significantly improves upon alternative methods of detecting cirrus clouds

by at least an order of magnitude (Gao and Kaufman, 1995). Without such a tool, cirrus cloud detection in historical Landsat imagery was significantly more difficult. For example, an analysis of all Landsat images acquired during the first year over the conterminous United States found that 7% of the data were identified as low confidence cloud but high confidence cirrus clouds, suggesting that 7% of historic Landsat data may be contaminated with cirrus clouds (Kovalsky and Roy, 2015). While the percent of undetected cirrus clouds may vary across the globe, this result highlights another difference between Landsat 8 and previous sensors that may be important when combining datasets.

1.1. Objectives

As previous studies have indicated (Li et al., 2014; Flood, 2014; Mishra et al., 2014), the change in Landsat 8’s spectral bandpasses create differences in radiance and reflectance measurements relative to Landsat 7. While these studies have provided excellent evidence on the differences between sensor, they have not assessed sensor-specific differences in the Landsat Climate Data Record (CDR) community product. The Landsat CDR product is designed to improve on the Level 1 Product usability by providing atmospherically corrected Landsat data and uses different algorithms for Landsat TM/ETM+ and Landsat OLI data. Because any potential differences in the correction algorithms might enhance target specific differences due to spectral bandpasses, it is important to assess the relative consistency of the CDR products across sensors. Finally, it is still unclear how differences between Landsat 8 and previous sensors are manifested in time series analyses.

To assess the potential differences between Landsat 7 and Landsat 8 characteristics in the Landsat CDR product, we posed the following questions:

1. Do Landsat 7 and Landsat 8 spectral reflectances from CDR differ significantly? If so, what is the nature of the differences?
2. Are time series of Landsat 7 and Landsat 8 data different? What is the effect of combining data from the two sensors?

- 135 3. What are the spectral characteristics of cloud and cirrus clouds masked
136 by Landsat 8 but omitted in Landsat 7 data?
- 137 4. Are the cloud masking improvements in Landsat 8 apparent in time series?

138 2. Datasets

139 Atmospheric correction of Landsat 7 and Landsat 8 data within the Land-
140 sat CDR is performed using two different algorithms driven by different input
141 ancillary data. Landsat 7 data are corrected using the Landsat Ecosystem Dis-
142 turbance Adaptive Processing System (LEDAPS) algorithm (Masek et al., 2006)
143 while Landsat 8 data are corrected using “L8SR”, a newly developed algorithm
144 that takes advantage of some of Landsat 8’s new sensor characteristics (U.S.
145 Geological Survey, 2015; Vermote, 2016). The LEDAPS algorithm retrieves
146 surface pressure, water vapor, and air temperature inputs from the NOAA Na-
147 tional Centers for Environmental Protection (NCEP) reanalysis dataset while
148 L8SR calculates surface pressure based on the target’s elevation and uses the
149 Moderate Resolution Imaging Spectroradiometer (MODIS) Climate Modeling
150 Grid - Aerosol (CMA) product for water vapor and air temperature estimates.
151 Ozone data are retrieved from the Ozone Monitoring Instrument (OMI) or Total
152 Ozone Mapping Spectrometer (TOMS) for LEDAPS and from the MODIS Cli-
153 mate Modeling Grid (CMG) coarse resolution ozone product in L8SR. Aerosol
154 Optical Thickness (AOT) is estimated in LEDAPS using the dark, dense vegeta-
155 tion (DDV) method (Kaufman et al., 1997) while L8SR uses the MODIS CMA
156 product. LEDAPS uses view zenith angle geometry from the image metadata
157 while L8SR hard codes this angle to 0 degrees. These differences in ancillary
158 data may be another cause for potential disagreement in the surface reflectance
159 estimates, but diagnosing the effect of different ancillary information on the
160 output reflectance estimates is outside of the scope of this effort.

161 The L8SR data products are currently considered “provisional” because the
162 algorithm, the implementation of the algorithm in software, and the subsequent
163 output products have not been completely validated (U.S. Geological Survey,

2015). The algorithm implementation has been corrected to fix artifacts near coastal land and water boundaries, but visual artifacts remain among cloud edges and areas of high topographic variation in some images. The correction of these artifacts should not significantly alter the findings of this work that is based on the analysis of millions of pixels across many scenes. We refer the reader to the product changelog in the Landsat 8 CDR product guide (U.S. Geological Survey, 2015) to monitor changes to the product. In addition, the L8SR algorithm has a few caveats: the algorithm is not run on scenes with a solar zenith angle greater than 76 degrees and surface reflectance retrievals may be uncertain in hyper-arid, snow-covered, coastal regions with small amounts of land relative to water, or high cloud cover environments (U.S. Geological Survey, 2015).

We used two datasets to address the questions posed about the continuity of surface reflectance observations from Landsat 7 to Landsat 8: Landsat “underflight” data that provides near simultaneous observations from both sensors, and time series of Landsat data covering seven years of Landsat 7 and two years of Landsat 8.

2.1. *Landsat 8 Underflight*

On March 29-30, 2013, prior to the establishment of its final orbit, Landsat 8 flew in “underflight” mode in position with Landsat 7 allowing for almost simultaneous image acquisitions. The scene centers for Landsat 8 did not exactly match with Landsat 7 because it had not reached its operational Worldwide Reference System (WRS-2) orbit, but the images acquired provided substantial overlap for comparison. The time delay between the scene center acquisition for Landsat 7 and Landsat 8 was usually between two to five minutes (see Table .2).

The underflight Landsat 8 data were preprocessed to a Level 1 Terrain corrected (L1T) product and processed to surface reflectance using the L8SR algorithm by the USGS EROS Data Center. The data were processed and made available to the Landsat Science Team by the USGS, but can now be downloaded

194 and analyzed as part of the “Pre-WRS-2” Landsat archive (the Landsat Scene
 195 Identifier for each image is available in Table .2). Cloud, cloud shadow, and
 196 snow masks were also provided for Landsat 8 data using CFmask, a C imple-
 197 mentation of the Fmask algorithm (Zhu and Woodcock, 2012; Zhu et al., 2015b).
 198 Two CFmask images were generated for each Landsat 8 image: a mask that in-
 199 corporated information from the new cirrus band on Landsat 8, and a mask that
 200 ignored the cirrus band and used the same algorithm as Fmask uses for Landsat
 201 TM/ETM+ data. The CFmask output used in this evaluation differed from the
 202 standard product because the cloud masks that used the cirrus band identified
 203 cirrus clouds separate from other types of clouds. Landsat 7 data corresponding
 204 to each Landsat 8 underflight acquisition were acquired for comparison. The
 205 Landsat 7 data were preprocessed to L1T products and atmospherically cor-
 206 rected using the Landsat Ecosystem Disturbance Adaptive Processing System
 207 (LEDAPS) algorithm (Masek et al., 2006). Cloud, cloud shadow, and snow
 208 masks were also generated for each Landsat 7 image using CFmask. We created
 209 layer stacked images containing corresponding image bands for each matching
 210 pair of Landsat 7 and Landsat 8 images. The new shorter wavelength blue band
 211 and the cirrus band on Landsat 8 were excluded as they had no direct compari-
 212 son with the Landsat 7 data. To avoid confusion relating to the band numbering
 213 change between Landsat 7 and Landsat 8, we refer to spectral bands on ETM+
 214 and OLI using by the common name of the spectral range they measure. Refer
 215 to Table .1 for the pairing between the spectral wavelength names, the sensor
 216 band numbering, and the spectral wavelengths measured.

217 *2.2. Landsat time series*

218 We acquired all available Level 1 Terrain corrected (L1T) Landsat ETM+
 219 and OLI images with less than 20% cloud cover between 2008 and 2015 for
 220 Worldwide Reference System (WRS-2) path/rows 16/41, 23/37, 34/32, and
 221 43/34 as Landsat CDR products. According to the 2011 National Land Cover
 222 Database (NLCD) (Homer et al., 2015), the land cover in scene in Florida,
 223 United States (P016R041) is primarily comprised of natural or cultivated herba-

224 ceous (36%), wetlands (30%), and developed (12%) categories. The scene in Mis-
 225 sissippi, United States (P023R037) is marked by cultivated herbaceous (53%),
 226 wetlands (17%), and forest cover (16%). Our site in Colorado, United States
 227 (P034R032) intersects the Rocky Mountains and the Denver urban area and
 228 primarily contains forest (40%), natural and cultivated herbaceous (26%), and
 229 shrub (21%) covers. Finally, the site in California, United States (P043R034)
 230 is centered on the Central Valley and is covered by natural or cultivated herba-
 231 ceous vegetation (57%), forest (18%), and shrub (13%) cover.

232 Landsat images were atmospherically corrected using LEDAPS (Masek et al.,
 233 2006) for ETM+ data and L8SR for OLI data (U.S. Geological Survey, 2015).
 234 Atmospheric correction within the Landsat CDR product was performed by
 235 the USGS EROS Science Processing Architecture (ESPA) (LEDAPS version
 236 “LEDAPS.2.2.1” and L8SR version “l8_surface_reflectance_0.2.0”) (Loveland
 237 and Dwyer, 2012). We transformed the surface reflectance values into the NDVI,
 238 EVI, NBR, and NDMI spectral indices. Thermal band data were converted into
 239 top of atmosphere brightness temperature.

240 Clouds, cloud shadows, and snow were identified using the Fmask algorithm
 241 (Zhu and Woodcock, 2012; Zhu et al., 2015b) with a cloud probability threshold
 242 of 12.5 and cloud, cloud shadow, and snow mask dilation of 5 pixels. The cloud
 243 probability threshold and mask dilation parameters were chosen to provide a
 244 conservative cloud mask result intended to limit omission of clouds. Errors of
 245 commission in cloud masks are less harmful than errors of omission in time series
 246 with hundreds of available images, so we used a custom run of Fmask instead of
 247 the available CFmask product. We also generated an additional Fmask image
 248 for Landsat 8 imagery using the same parameters that did not use information
 249 from the new cirrus band (as in Zhu et al. (2015b)) to assess the difference in
 250 noise reduction associated with having a band specifically designed to aid cloud
 251 detection.

252 Images within each path/row were layer stacked and aligned to a uniform
 253 image extent for further analysis. We excluded the new blue and cirrus spectral
 254 bands measured by Landsat 8 and only used one thermal band (Band 10) in

255 Landsat 8 to facilitate comparison with Landsat 7. The number of total images
256 available in each scene location varied between 164 and 183 with Landsat 8
257 contributing between 36 and 39 images (see Table .3).

258 **3. Methods**

259 *3.1. Landsat 8 Underflight*

260 *3.1.1. Spectral comparison*

261 Clouds, cloud shadows, and snow in the Landsat 7 and Landsat 8 image
262 pairs were masked from analysis using the CFmask band. The clouds and cloud
263 shadows shifted position and shape considerably during the short time inter-
264 val between the acquisitions by Landsat 7 and Landsat 8 (see Supplementary
265 Figure 1). Because no solution exists to mask every cloud in a remote sensing
266 image, artifacts remained in the underflight data after masking. This cloud con-
267 tamination problem was amplified when comparing two images because missed
268 clouds or cloud shadows in one image were unlikely to be masked in the other
269 due to the shifts in the cloud and cloud shadow positions. Buffering clouds and
270 cloud shadows in each individual Fmask image by 50 pixels cleaned up most of
271 the noise present in both images and ensured that the remaining area contained
272 only clear observations in both satellite acquisitions. The choice of 50 pixels
273 was a relatively arbitrary decision, but it was the smallest buffer size tested
274 that removed the majority of obvious data contamination.

275 The cloud screened reflectance observations were used to generate several
276 vegetation indices for analysis, including the Normalized Difference Vegetation
277 Index (NDVI Tucker, 1979), Enhanced Vegetation Index (EVI Huete et al.,
278 2002), Normalized Burn Ratio (NBR Key and Benson, 2005), and Normal-
279 ized Difference Moisture Index (NDMI) indices. The Greenness and Wetness
280 components of the Tasseled Cap transforms (Kauth and Thomas, 1976) were
281 also calculated using Landsat TM surface reflectance transform coefficients from
282 Crist (1985). We tested using the tasseled cap coefficients for ETM+ at-satellite
283 reflectance from (Huang et al., 2002), but the outcomes were not meaningfully

different. Linear regressions were constructed to estimate the relationship between Landsat 7 and Landsat 8 reflectance values as a gain and bias. We were concerned with what a corrective equation might look like, so we did not restrict the functional form of the regression to only a gain or a bias. Regression 95% confidence intervals for the slope and intercept estimates were generated using 1,000 bootstrap samples of each dataset. The lower and upper confidence bounds were taken as the 2.5% and 97.5% percentiles of the sorted bootstrap parameter estimates.

3.1.2. *Cirrus cloud characterization*

We also used the underflight data to observe the spectral characteristics of cirrus cloud observations in Landsat data that would not be picked up without the new cirrus band on Landsat 8. We extracted pixels classified as clear land in Landsat 7 and Landsat 8 CFmask results as reference examples for clean observations. Pixels classified as clear land or clear water within the Landsat 7 CFmask image that were classified as cirrus clouds within the Landsat 8 CFmask image were also extracted. To account for errors in the CFmask images and movement of the clouds and cloud shadows between image acquisitions, we eroded the boundaries of CFmask labels by 20 pixels. This erosion helped ensure that the disagreement between the two CFmask images was the result of detection capacity and not random error or spatial mismatches. Not all scenes acquired during the underflight period contained cirrus clouds or contained enough disagreement about cirrus cloud coverage to perform our analysis, so we were limited to two scenes in Mendoza Province, Argentina (P230R084) and Santa Cruz Province, Argentina (P230R094). Visual inspection of these images showed that cloud masks in both scenes shared similar patterns. Areas of dense cirrus cloud cover were identified as cloud cover in Landsat 7 masks and cirrus cloud cover in Landsat 8, but areas of thin cloud cover were misidentified as clear land in Landsat 7 and correctly classified as cirrus cloud in Landsat 8. While the cirrus cloud classification may suffer from false positives over bright targets in dry environments or over high elevation targets (Zhu et al., 2015b),

the mean elevation of the two scenes was relatively low (440m and 675m for P230R084 and P230R094, respectively) and we are confident from visual inspection that the vast majority of pixels identified as clear land and cirrus cloud in Landsat 7 and Landsat 8 masks were omitted in the Landsat 7 cloud masks.

Observations labeled clear in one CFmask image but cirrus cloud in another represent difficult to detect noise within historical Landsat data that may now be routinely filtered using OLI’s cirrus band. These data were analyzed using bivariate plots comparing the spectral reflectance and brightness temperature from Landsat 8 in combinations of spectral bands. Plotted points were colorized according to the classification in Landsat 8’s CFmask image. We added contour lines to describe the overlap of the clear land and cirrus cloud observations by delineating the two dimensional space occupied by 95% of the observations in each population. We used a Gaussian kernel density estimate to approximate the distribution of each population in bivariate space (Silverman, 1986). The 95% percent contour lines were estimated as the 95th percentile of the estimated distribution from the two dimensional kernel density estimate.

3.2. Landsat time series

Landsat time series were analyzed using a Python implementation of the Continuous Change Detection and Classification (CCDC) algorithm (Zhu and Woodcock, 2014; Zhu et al., 2015c). The CCDC algorithm attempts to detect abrupt changes in a time series using an “online” monitoring approach by sequentially comparing reflectance observations against a prediction. Reflectances are predicted using a simple Fourier style model with independent variables representing the overall reflectance (intercept), the change in reflectance over time (slope), and the intra-annual variation in reflectance due to phenology or sun-sensor geometry (harmonics):

$$\hat{\rho}_i = \beta_0 + \beta_1 x_t + \sum_{j \in N} [\beta_{2j} \cos(\frac{2\pi j}{T} x_t) + \beta_{2j+1} \sin(\frac{2\pi j}{T} x_t)] + \varepsilon_t \quad (1)$$

where $\hat{\rho}_i$ is the predicted reflectance or temperature in each spectral band i ,

341 x_t is the ordinal date of each observation, N is a set of integers specifying the
 342 frequency, j , of the Fourier series harmonics, T is the number of days in a year
 343 (365.25), and ε_t is the residual error term for each observation.

344 This study used a pair of year and half year ($N = \{1, 2\}$) harmonics to be
 345 able to capture most seasonal vegetation patterns while remaining simpler than
 346 the full 8 coefficient model used in Zhu et al. (2015c). The CCDC algorithm
 347 employs the Least Absolute Shrinkage and Selection Operator (LASSO) regu-
 348 larization method to reduce overfitting by estimating coefficients that minimize
 349 the residual sum of squares while also penalizing the absolute magnitude of the
 350 coefficients (Tibshirani, 1996). LASSO can provide coefficient estimates of ex-
 351 actly zero, and this type of model selection helps allow CCDC to use a possibly
 352 overly specified but generic model for all time series.

353 To help provide a stable and robust initial estimate of land surface re-
 354 flectance, the CCDC algorithm screens the training period using a multitem-
 355 poral filtering algorithm designed to remove any cloud and cloud shadows that
 356 might have been missed by Fmask (Zhu and Woodcock, 2014). After the initial
 357 time series model has been fit during this training period, successive observa-
 358 tions are compared against the forecast prediction. A difference between the
 359 observation and prediction is significant if the l^2 -norm, or Euclidean norm, of
 360 forecasted residuals scaled by model RMSE across the set of tested bands is
 361 above a specified threshold:

$$T_{crit} > \sqrt{\sum_{i \in B} (\frac{\hat{\rho}_i - \rho_i}{RMSE_i})^2} \quad (2)$$

362 where T_{crit} is the significance critical threshold, B is a set of spectral bands
 363 used in the change detection, $\hat{\rho}_i$ and ρ_i are the predicted and observed re-
 364 flectances or values in band i , and $RMSE_i$ is the time series model RMSE for
 365 band i .

366 If observed reflectances significantly differ from the forecasted reflectances
 367 for some number of consecutive observations, CCDC places a break in the time
 368 series and begins trying to fit another time series model after the disturbance.

369 The breaks or disturbances in the time series create distinct segments through
370 time that should correspond to a period of stable land cover or land surface
371 condition. These segments in the time series can then be classified into land
372 cover categories using attributes derived from the time series models, including
373 the coefficients and Root Mean Squared Error (RMSE) of the time series models
374 estimated for each Landsat band. The estimated time series model coefficients
375 and RMSE estimates, and not the change detection, are the focus of this study.
376 For further information and detail about the Continuous Change and Classifica-
377 tion Detection algorithm, including how it detects change, the reader is referred
378 to Zhu and Woodcock (2014) and to Zhu et al. (2015c) for algorithm changes
379 and improvements.

380 To address the questions of the effect of spectral differences between Landsat
381 7 and Landsat 8 in time series, we fit time series using CCDC to five different
382 post-launch scenarios. All five time series were initialized between 2008 and
383 2013 using only Landsat 7 data, but were continued after the launch of Landsat
384 8 with different sets of Landsat observations:

- 385 1. Only Landsat 7 data post-launch
- 386 2. Only Landsat 8 data post-launch
- 387 3. Combined Landsat 7 and Landsat 8 data post-launch
- 388 4. Only Landsat 8 data post-launch, excluding information from the cirrus
389 band in the Fmask images for Landsat 8 data
- 390 5. Combined Landsat 7 and Landsat 8 data post-launch, excluding informa-
391 tion from the cirrus band in the Fmask images for Landsat 8 data

392 The first scenario containing only Landsat 7 data was used as a normalizing
393 factor to isolate the influence of including Landsat 8 data within the time series
394 of scenarios two and three. Intercept and RMSE values for scenarios two and
395 three were normalized by dividing these estimates by the corresponding inter-
396 cepts and RMSE values from the Landsat 7 models (scenario one). A value
397 of one for the normalized intercept and RMSE indicate that the inclusion of

398 Landsat 8 data (scenario two and three) did not change the quantity of inter-
 399 est. Values above one indicate the quantity was increased relative to just using
 400 Landsat 7 and values below one signify a decrease in the quantity. The slope
 401 estimates in the CCDC models are usually either zero or very close to zero. To
 402 avoid computational issues of dividing by zero, we normalized the slope values
 403 by subtracting the slopes estimated using Landsat 8 data (scenarios two and
 404 three) by the slope estimated only using Landsat 7 (scenario one). Similarly,
 405 scenarios four and five were compared after being normalized by scenarios two
 406 and three to understand the effect of improved cloud detection possible with
 407 the cirrus band on Landsat 8.

408 We masked and ignored from the analysis any pixels that changed between
 409 2010 and 2015 as found by the CCDC algorithm because time series following
 410 a disturbance can be erratic or noisy. Large variability in the observed target
 411 might have created false differences among the continuation scenarios simply
 412 due to random chance rather than due to a systematic difference. We took a
 413 large random sample of all remaining, stable pixels, and extracted the intercept
 414 and slope coefficients and the Root Mean Squared Error (RMSE) of each time
 415 series model for comparison.

416 **4. Results and Discussion**

417 *4.1. Landsat 8 Underflight*

418 *4.1.1. Spectral Comparison*

419 Spectral comparison results for scenes over Nebraska, United States (WRS-
 420 2 path and row P029R031) and Mendoza Province, Argentina (P230R084) are
 421 shown in Figure 1 and 2, respectively. While only the results for these two
 422 Landsat scenes are shown in the main text of this article, the patterns observed
 423 in these scenes are characteristic of the responses seen in other scenes containing
 424 sufficient clear observations of land. Figures and tables showing the spectral re-
 425 sponses for all other Landsat scenes acquired are available in the supplementary
 426 material (Supplementary Figures 2 - 8).

427 The reflectances in the visible wavelengths (blue, green, and red) of the
 428 Landsat 8 atmospherically corrected product are consistently darker than re-
 429 flectances observed in the Landsat 7 data. The largest bias occurs in the blue
 430 band and decreases with increasing wavelength from green to red. While the
 431 wavelengths measured by the visible bands only changed slightly from Land-
 432 sat 7 to Landsat 8 (Table .1), atmospheric interference is greatest in the blue
 433 band and decreases as wavelength increases. If differences in atmospheric cor-
 434 rection are responsible for some of the difference between sensor measurements,
 435 it makes sense that the greatest difference is visible in the band that requires
 436 the greatest adjustment for scattering and absorption and the LEDAPS and
 437 L8SR algorithms use different inputs to parametrize atmospheric constituents.
 438 Some proportion of this bias is also likely caused by differences calibration or
 439 target specific spectral responses, but estimating the relative contribution of
 440 these three causes is outside the scope of this analysis.

441 The near infrared band, with the largest physical difference in measured
 442 wavelengths, did not show considerable bias in Nebraska, United States (P029R031)
 443 (Figure 1). However, there was a large and consistent positive bias in the near
 444 infrared reflectance in Medoza, Argentina (P230R084) (Figure 2). Summer in
 445 Argentina during the month of March most likely has much higher atmospheric
 446 water vapor content than the United States during winter. The narrower wave-
 447 lengths measured by Landsat 8 avoided an atmospheric water absorption fea-
 448 ture, so it is understandable that the bias in near infrared reflectance is higher
 449 in an environment with more water vapor. The shortwave IR bands may be
 450 slightly brighter in Landsat 8 than in Landsat 7 due to the smaller spectral
 451 band widths, but the measurements have not changed as significantly as the
 452 other bands. The difference in bias across scenes observed in this study is sim-
 453 ilar to the findings of Flood (2014) that there are regional differences in the
 454 sensor bias.

455 Differences in individual bands between Landsat 7 and Landsat 8 are espe-
 456 cially important when considering spectral or vegetation indices because these
 457 indices often rely on the contrast between two or more bands. The Normalized

Figure 1: Landsat 7 and Landsat 8 underflight data comparison for Nebraska, United States (P029R031). Regression parameters and R^2 estimates describing the fitted line are provided in the top left of each plot. The 95% confidence interval range around the regression estimate is displayed as a dashed line around the regression line, but it may not be visible for small confidence intervals.

Figure 2: Landsat 7 and Landsat 8 underflight spectral comparison for Mendoza Province, Argentina (P230R084).

458 Differenced Vegetation Index (NDVI) relies on the contrasting relationship be-
 459 tween the near infrared band and the red band. It appears that the near infrared
 460 band and red bands in Landsat 8 are brighter and darker than in Landsat 7, re-
 461 spectively, which enhances the contrast highlighted in NDVI. As such, we see a
 462 strong and consistent positive bias in NDVI with Landsat 8 having much higher
 463 NDVI. The Enhanced Vegetation Index (EVI) differs from NDVI by utilizing
 464 the blue band as an additional normalizing factor that corrects the red band for
 465 atmospheric influences. Either by coincidence or as the intention of Huete et al.
 466 (2002), it appears that the bias in the blue band between Landsat 8 and Landsat
 467 7 nullifies the bias in the red and near infrared band, resulting in a surprisingly
 468 similar EVI across sensors. The Normalized Difference Moisture Index (NDMI)
 469 and the Normalized Burn Ratio (NBR) both compare the shortwave infrared
 470 with the near infrared using either the first or second SWIR bands, respectively.
 471 These vegetation indices show little difference between Landsat 7 and Landsat
 472 8. If there is a difference in the shortwave infrared bands between sensors, it
 473 appears to be in the same positive direction as the bias in the near infrared,
 474 resulting in a cancellation effect. The Tasseled Cap Greenness transform dis-
 475 plays the same strong positive bias as the NDVI while the Wetness Tasseled
 476 Cap transform is darker in Landsat 8 than in Landsat 7. The Wetness trans-
 477 form for Landsat 7 places little weight on the red and near infrared bands in
 478 favor of contrasting the blue and green with the two shortwave infrared bands.
 479 Because the blue and green bands are darker in Landsat 8 than in Landsat 7
 480 and the shortwave infrared bands might be brighter in Landsat 8, this contrast
 481 is enhanced and creates a small bias in the Wetness transform.

482 The effect of increased radiometric resolution is readily apparent when com-
 483 paring reflectance estimates or spectral indices between sensors. Scatter plots
 484 of the data shown using hexbin plots in 1 and 2 both displayed a visual striping
 485 pattern distributed across the X axis that was not simply a visual artifact in
 486 the plot, but a result of the increased quantization possible with Landsat 8's
 487 12-bit radiometric resolution. When the OLI instrument converts the continu-
 488 ous measurement of radiance by its detectors into digital numbers, the 12-bit

radiometric resolution offers sixteen times the digitization detail compared to Landsat 7. The increased detail is carried through when converting from digital numbers back into radiance and the precision remains when converting to surface reflectance. The underflight spectral comparison figures for a Landsat scene over the coast of Greenland (P013R031), included in the supplementary material (Supplementary Figure 3), contains the best example of the effects of increased radiometric resolution as this striping is shown even when using a hexbin plot. Reflectance estimates from Landsat 8 do not display any striping throughout the very low range of reflectance measured (2 - 8%) in the shortwave infrared while Landsat 7's measurements contain distinct discrete gaps representative of the lower quantization. Improvements to the radiometric resolution on OLI thus enhance detection capabilities by allowing the delineation of very similar, previously indistinguishable, targets.

4.1.2. *Cirrus cloud characterization*

We explored the spectral properties of clear land observations and those affected by cirrus clouds by plotting observations of both targets in bivariate combinations of spectral bands available in the Landsat 8 underflight data (Figure 3). Observations affected by cirrus clouds differ most from clear land observations in the visible wavelengths as seen in the high degree of separation within bivariate plots containing only the visible bands. The blue band, specifically, shows the largest difference between the two populations (subfigures A through E). Cirrus clouds, as expected (Gao et al., 1993, 1998; Gao and Li, 2000), increase the reflectance in visible wavelengths, but this increase is not very substantial. The centers of the cirrus cloud and clear land populations differ by approximately 4% reflectance in the blue band, about 3% in the green band, and by even less in the red band. It is interesting to note that even in the visible bands the values of observations affected by cirrus clouds are still within the range of unaffected observations, which helps explain why it is so hard to detect cirrus clouds in any automated fashion in the absence of a cirrus band like the one on Landsat 8. The distinction between clear land and

519 cirrus clouds omitted by Landsat 7 in P230R094 is even smaller, but there is
 520 still a difference in the means of the two populations (Supplementary Figure 9).
 521 The near infrared and shortwave infrared bands provide no separation alone as
 522 the populations completely overlap when only using the infrared bands. The
 523 thermal band shows the largest separation between the two populations of ap-
 524 proximately half a degree Celsius (subfigures F, K, and O). If our objective were
 525 to find cirrus clouds in our dataset without the use of the cirrus band on Land-
 526 sat 8, the shorter and thermal wavelength bands would be most valuable. The
 527 opposite perspective to this conclusion is that if we wish to avoid cirrus cloud
 528 contamination influencing our datasets from all Landsats prior to Landsat 8 we
 529 would exclude the visible bands and thermal bands from our analysis whenever
 530 possible and rely heavily on the NIR and SWIR bands as these appear to be
 531 least affected by cirrus clouds missed without the use of a cirrus band.

532 *4.2. Landsat time series*

533 *4.2.1. Impact of Landsat 8 on time series of Landsat observations*

534 Figure 4 shows an example time series for one pixel in an undisturbed ev-
 535 ergreen forest stand in Colorado (P034R032) in red reflectance and NDVI. The
 536 regression models used are described by equation 1, but some model coefficients,
 537 such as the sinusoidal terms used to model seasonality, may be estimated as 0
 538 due to the regularization performed by the LASSO method. As seen in the
 539 underflight data, the observations from Landsat 8 are darker in the red band,
 540 creating higher NDVI values. The time series models show a small difference in
 541 the intercept estimates and a much larger difference in the slope estimate that
 542 adjusts for the differences between sensors. The unexplained variation due sim-
 543 ply to the sensor differences increases the Root Mean Squared Error (RMSE) in
 544 the models. Only observations in the visible bands and the NDVI were affected
 545 by sensor differences for this specific target. Time series models for the NIR,
 546 SWIR1, SWIR2, and thermal bands and for the EVI, NBR, and NDMI indices
 547 were not different between the Landsat 7 only (scenario one) and combined
 548 sensor (scenario two) datasets. This example is included to demonstrate the

Figure 3: Clear land and cloud cirrus spectral properties for Mendoza Province, Argentina (P230R084). Contour lines contain 95% of the data in the bivariate distribution space for data labeled as clear land (green) and cirrus cloud (magenta) in Landsat 8 CFmask images.

549 influence of observation differences on time series model parameter estimates.
550 Results for millions of pixels across more study sites in all spectral bands and
551 vegetation indices are given in this section.

552 Three time series datasets covering four WRS-2 scenes initialized using Land-
553 sat 7 data and continued after the launch of Landsat 8 with either Landsat 7
554 (scenario one), Landsat 8 (scenario two), or both Landsat 7 and Landsat 8
555 data (scenario three) were analyzed with the Continuous Change Detection and
556 Classification (CCDC) algorithm. Intercept, slope, and RMSE estimates for
557 scenarios two and three containing data from Landsat 8 were normalized rela-
558 tive to Landsat 7 results as described in section 3.2. In essence, we are treating
559 the use of only Landsat 7 as the baseline for comparisons with Landsat 8 or the
560 combination of Landsats 7 and 8. A value of one for the normalized intercepts
561 and RMSE values indicates no difference between scenarios, while values above
562 or below one values indicate the attribute is brighter or darker when including
563 Landsat 8 data. A value of zero in normalized slope estimates indicates no
564 change between scenarios while positive or negative values indicate an increase
565 or decrease in the time series slope relative to only using Landsat 7 data. If
566 the introduction of Landsat 8 data into time series of Landsat 7 data caused
567 no difference, histograms of these normalized parameter estimates from pixels
568 within each scene should approximate a normal distribution centered on one
569 for intercepts and RMSE or zero for slopes. Model parameters greatly affected
570 by the inclusion of Landsat 8 observations should produce histograms that are
571 offset from the “no change” normalized values of one or zero.

572 Time series model intercept, slope, and RMSE attributes for a scene in Col-
573 orado, United States (P034R032) are shown in Figures 5, 6, and 7, respectively
574 and confirm the results previously found in the underflight data comparison.
575 The blue, green, and red bands on Landsat 8 were consistently darker than the
576 same measurements in Landsat 7 data in the underflight data, and this consis-
577 tent offset impacts the modeling results in time series scenarios. Time series
578 model intercepts for the blue, green, and red bands shown in figure 5 are un-
579 usually much darker due to the inclusion of Landsat 8 data as shown by the

Figure 4: Example time series of an evergreen forest stand in Colorado, United States (P034R032). Observations from Landsat 7 and Landsat 8 are shown in black and red, respectively. CCDC model regressions for time series including only Landsat 7 data (scenario 1) and both sensors (scenario 2) are plotted in blue and green. Model slope, intercept, and RMSE estimates are included in the figure legend.

580 shift in the median of the histograms from 1.0 to values between approximately
 581 0.90 and 0.96. The median normalized intercept estimated for the blue band
 582 when continuing Landsat 7 time series with only Landsat 8 data (scenario two),
 583 for example, is 10% darker than the intercept that would have been estimated
 584 when using exclusively Landsat 7 data. Time series continued after the launch
 585 of Landsat 8 with both Landsat 7 and Landsat 8 (scenario 3) are less affected
 586 than with Landsat 8 data alone as seen in the reduction in the shift of the
 587 blue colored histogram (scenario three) relative to the red colored histogram
 588 (scenario two). However, the combined scenario still contains a bias in the vis-
 589 ible band intercepts. The histograms of the normalized intercepts in the near
 590 infrared and shortwave infrared bands are centered approximately at one and
 591 are approximately normally distributed. Thus, the NIR and SWIR bands show
 592 little signs of bias relative to Landsat 7 and do not behave difference under the
 593 Landsat 8 or combined sensor scenarios. Among the vegetation indices, only
 594 NDVI is substantially affected and is characteristically brighter in Landsat 8
 595 than in Landsat 7 as the histogram of normalized NDVI values is centered at
 596 approximately 1.03 to 1.04. While the thermal band is slightly darker for the
 597 time series in Colorado, United States, the pattern was not consistent in other
 598 Landsat scenes (Supplementary Figures 10, 13, and 16).

599 While the use of Landsat 8 in regressions might affect the overall mean re-
 600 flectance, measured as the intercept of the regression, any differences between
 601 Landsat 7 and Landsat 8 are best explained using a slope estimate because
 602 the Landsat 8 data are placed at the end of the time series. Figure 6 shows
 603 that the Landsat 8 observations placed at the end of the Landsat 7 time se-
 604 ries create a spurious time trends for many of the bands and indices analyzed.
 605 The darker observations in the visible bands in Landsat 8 create false positive
 606 decreasing time trends in both continuation scenarios, although the influence
 607 in the combined scenario is less pronounced. The median slope response for
 608 the near infrared band is approximately zero indicating no bias in the slope
 609 coefficient. While the shortwave infrared bands appear to have a negative bias
 610 in the results for Colorado, United States (P034R032), this pattern was not

Figure 5: Normalized intercept estimates for time series models in Colorado, United States (P034R032) used to assess spectral differences caused by including Landsat 8 data. The Landsat 8 only and combined Landsat 8 and Landsat 7 intercept estimates were normalized by dividing by the intercepts of time series models using only Landsat 7 data. The Y-axis was truncated at 30% to give better resolution to smaller frequency bins.

611 present in the three other scenes analyzed (Supplementary Figures 11, 14, and
 612 17). Repeating the patterns previously observed, NDVI is highly affected by
 613 differences in Landsat 8's reflectance in the visible bands but the effect does not
 614 carry over to EVI. The NBR and NDMI indices, despite not showing an effect
 615 in the time series intercept coefficient, show a slight positive time trend when
 616 using Landsat 8 data. The positive time trend in NBR and NDMI was also
 617 observed for two scenes over Florida (P016R041) and Mississippi (P023R037),
 618 but not in California (P043R034) (Supplementary Figures 11, 14, and 17). The
 619 distribution of thermal band slope coefficients for Colorado has a long negative
 620 tail, but this phenomenon is not observed in Florida or Mississippi and the slope
 621 distribution for California shows an opposite long positive tail. These results
 622 that show spurious time trends, especially in vegetation indices, can be caused
 623 by differences in reflectance across Landsat 7 and Landsat 8 reinforce the false
 624 positive slopes found in time series analysis over Canadian boreal forest using
 625 Landsat 5 and Landsat 7 (Sulla-Menashe et al., 2015).

626 The change in RMSE of time series models using Landsat 8 (scenarios two
 627 and three) relative to pure Landsat 7 time series models (scenario one) varies de-
 628 pending on how different a particular band or vegetation index looks in Landsat
 629 8 and Landsat 7. For Colorado (P034R032), just as we see the largest difference
 630 in time series model intercepts and slopes in the visible bands and NDVI, we
 631 also see increases in the RMSE of time series models using these data (Figure
 632 7). The other scenes in Florida (P016R041) and Mississippi (P023R037) share
 633 this pattern of increase in the unexplained variance in the visible and NDVI
 634 data (Supplementary Figures 12 and 15). The scene in California (P043R034)
 635 shows weaker evidence for increased noise when using the combined data sce-
 636 nario (scenario three) and no sign of increasing noise when just using Landsat
 637 8 data post-launch (scenario two) (Supplementary Figure 18). The estimated
 638 intercept and slopes for the near infrared and shortwave infrared bands did
 639 not differ among scenarios so we would expect little change in the RMSE of
 640 these models. The EVI, which has consistently shown the smallest smallest dif-
 641 ferences between Landsat 7 and Landsat 8, does not show increases in model

Figure 6: Normalized slope estimates for time series models in Colorado, United States (P034R032) used to assess spectral differences caused by including Landsat 8 data. The Landsat 8 only and combined Landsat 8 and Landsat 7 slope estimates were normalized by subtracting the slopes from time series models using only Landsat 7 data. The Y-axis was truncated at 30% to give better resolution to smaller frequency bins.

642 RMSE relative to Landsat 7. While NBR and NDMI showed a positive time
643 trend in Colorado, Florida, and Mississippi, this bias relative to Landsat 7 has
644 only increased the RMSE of models in Mississippi. The influence of changes
645 in the thermal band may affect the RMSE of models, but the magnitude and
646 direction of this effect is not consistent among scenes analyzed.

647 A systematic difference between Landsat 8 and Landsat 7 observations af-
648 fects time series analysis in three ways. First, a consistently darker or brighter
649 sequence of Landsat 8 observations will eventually affect the mean reflectance
650 of a time series. Variation in reflectance due to the dataset of origin rather than
651 variation in physical attributes hampers inference. For example, if a forest were
652 slightly degraded in 2013, the mean NDVI of a time series after the disturbance
653 might be the same as the time series before the disturbance because the NDVI
654 in Landsat 8 is brighter than the NDVI in Landsat 7. The effect of biases in
655 Landsat 8 relative to Landsat 7 is especially concerning with regard to the time
656 trend or slopes of time series models. Second, consistently darker or brighter
657 observations from Landsat 8 placed at the end of an existing, stable time se-
658 ries of Landsat 7 data are shown to induce a false positive trend in reflectance
659 through time. Time trends in reflectance or vegetation indices have been used as
660 a proxy or indicators of changes in ecosystem function and structure, including
661 vegetation greening, browning, recovery, or degradation. Inference of temporal
662 trends will require relative calibration to ensure trends are not simply due to
663 sensor differences. Lastly, bias in observed reflectance between the two sensors
664 also hinders detection of land cover change in time series analysis. Change de-
665 tection methods that use a regression framework to predict reflectance based on
666 time series models (as in Verbesselt et al. (2012); Zhu and Woodcock (2014))
667 identify a time series break occurs if predictions differ significantly from obser-
668 vations. Bias in reflectance values between sensors adds an unexplained source
669 of variability to the time series that broadens the range of nonsignificant dif-
670 ferences between observed and predicted values. A more familiar comparison is
671 the decreased ability to infer separation between reflectances before and after a
672 land cover change in a paired t-test if each population has larger within-group

Figure 7: Normalized RMSE estimates for time series models in Colorado, United States (P034R032) used to assess spectral differences caused by including Landsat 8 data. The Landsat 8 only and combined Landsat 8 and Landsat 7 RMSE estimates were normalized by dividing by the RMSE from time series models using only Landsat 7 data. The Y-axis was truncated at 30% to give better resolution to smaller frequency bins.

673 variance.

674 Time series algorithms that do not rely on surface reflectance observations
 675 or perform image normalization prior to analysis may not be as significantly
 676 affected by cross-sensor differences. For example, while the Vegetation Change
 677 Tracker (VCT) (Huang et al., 2010) uses surface reflectance, imagery also under-
 678 goes a normalization using examples of dense and dark forests prior to analysis.
 679 The LandTrendr algorithm (Kennedy et al., 2010) normalized all Landsat im-
 680 agery to a reference image using the Multivariate Alteration Detection and Cal-
 681 ibration (MADCAL) algorithm (Canty et al., 2004). Techniques which rely on
 682 modeled attributes, such as forest cover fraction, derived from Landsat imagery
 683 may also avoid image normalization if separate models are used for each sensor.
 684 Normalization might not be required, however, if the bias associated with a
 685 particular sensor can be modeled as a time series component. One extremely
 686 simple method that could account for the difference in reflectance associated
 687 with a categorical variable is the use of a “dummy” variable within each time
 688 series model. A “dummy”, or treatment, variable acts as an additional inter-
 689 cept estimate specific to one category, or for Landsat 8 in this case. When
 690 the “dummy” variable is incorporated into the CCDC regression model, the
 691 regression model is modified from equation 1 as:

$$\hat{\rho}_i = \beta_0 + \beta_1 x_t + \sum_{j \in N} [\beta_{2j} \cos(\frac{2\pi j}{T} x_t) + \beta_{2j+1} \sin(\frac{2\pi j}{T} x_t)] + \beta_{dummy} D_{sensor,t} + \varepsilon_t \quad (3)$$

692 where:

$$D_{sensor,t} = \begin{cases} 1, & \text{if Landsat 8} \\ 0, & \text{otherwise} \end{cases} \quad (4)$$

693 This “dummy” variable estimate would compensate for sensor specific dif-
 694 ferences allowing for a more efficient estimate of the time series model slope
 695 and intercept, provided that the difference in sensor behavior can be modeled

Figure 8: Example time series of an evergreen forest stand in Colorado, United States (P034R032). Observations from Landsat 7 and Landsat 8 are shown in black and red, respectively. CCDC model regressions for time series including only Landsat 7 data (scenario 1) and both sensors (scenario 2) are plotted in blue and green. The magenta regression line includes a dummy variable that captures the reflectance differences between Landsat 7 and Landsat 8 as an additional intercept. The dummy variable estimates were -94.3409 and 1169.12 for red and NDVI, respectively, which offset the bias in Landsat 8 measurements relative to Landsat 7.

696 as a fixed offset. Figure 8 shows the same time series over an undisturbed ev-
 697 ergreen needleleaf stand as 4, but with an additional regression line estimated
 698 using a Landsat 8 “dummy” variable. “Dummy” variable coefficient estimates
 699 for Landsat 8 are negative in the red band to account for a darker measurement
 700 and positive for NDVI to account for a brighter measurement. The estimated
 701 slope in the red band does not match the slope estimated in the exclusively
 702 Landsat 7 data scenario, but the “dummy” variable accounts for the spurious
 703 time trend in the NDVI time series while greatly reducing the RMSE of both
 704 models. Much more work is required to understand the potential for these sensor
 705 specific intercepts to abate problems in time series due to sensor disagreements,
 706 but such a solution would be an easy and quick way of synthesizing the datasets
 707 without the need for more advanced cross-calibration. This approach also has
 708 the advantage of being estimated per pixel within a period of stable land cover
 709 condition so that target specific effects due to the shifts in the spectral band-
 710 passes should be accounted for.

711 *4.2.2. Impact of cirrus cloud detection*

712 The characterization of cirrus cloud spectral impacts from the Landsat 8
 713 underflight data (section 4.1.2) shows that cirrus clouds increase the reflectance
 714 of the visible bands but have negligible effects in the infrared bands. As a result,
 715 we expect time series containing cirrus clouds to positively bias the estimates
 716 of the intercept and slopes in the visible bands while increasing the RMSE of
 717 these models.

718 Figures 9, 10, and 11 show the time series model intercepts, slopes, and
 719 RMSE estimates for scenarios four and five which did not use cirrus band in-
 720 formation in the Fmask cloud masks for a Landsat scene in Colorado, United
 721 States (P034R032). The intercepts and RMSE estimates were normalized by di-
 722 viding these estimates by the same estimates from time series models using the
 723 cirrus band information (scenarios two and three). The slope coefficients were
 724 scaled by taking the difference between scenarios four and five and scenarios
 725 two and three, respectively.

726 The distribution of the relative intercepts for the visible bands have longer
 727 tails above the value of one, especially for the combined Landsat 7 and Landsat 8
 728 data post-launch scenario (scenario 3). The near infrared and shortwave infrared
 729 bands appear to have less skew toward either side in the distribution. The
 730 intercepts in time series of brightness temperature appear colder without cloud
 731 screening using the cirrus band, demonstrated by the skew toward values less
 732 than one. Pixels affected by cirrus clouds appear to have reduced the intercept
 733 estimate of the NDVI, likely driven by the bias toward brighter values in the red
 734 band. The EVI, NDMI, and NBR vegetation indices do not appear to be have
 735 biased estimates for the time series model intercepts. The slopes of time series
 736 excluding the cirrus band relative to time series including the cirrus band show
 737 the same patterns as the intercept estimates (Figure 10) with large differences
 738 the visible bands and NDVI slope estimates. Eliminating cirrus clouds from
 739 time series images also contributes toward lowering the RMSE of time series
 740 models as shown in Figure 11. The skew in the distribution of relative RMSE
 741 estimates shows that many of the time series contain more noise without the
 742 cirrus band in all bands and indices, but especially in the visible bands and
 743 NDVI.

744 We did not specifically limit our analysis of time series attributes to pixels
 745 containing observations identified as cirrus clouds within the time series. In-
 746 stead, we drew a random sample of pixels within each scene. As such, we do
 747 not expect there to be a systematic shift in slopes, intercepts, and RMSE esti-
 748 mates within the time series models not using cirrus information in the Fmask
 749 images relative to time series models that did mask cirrus clouds. The shifts in
 750 the tails of the relative distributions of these time series variables, positive in
 751 the visible bands and the negative in NDVI, are strong evidence to the benefits
 752 of the cirrus band. Landsat 8 observations will be much less noisy than obser-
 753 vations from previous sensors and this difference might affect future analysis.
 754 Measurements in the visible bands from Landsat 8, integrated over enough time,
 755 are especially likely to be darker than the response in TM and ETM+, all else
 756 equal, simply due to this enhanced screening. The development of methods to

Figure 9: Normalized intercept estimates for time series models in Colorado, United States (P034R032) used to assess the influence of Landsat 8's cirrus band. Intercept estimates from time series not using Landsat 8's cirrus band in cloud masks were scaled by dividing by intercepts from time series using the cirrus band in Fmask. The Y-axis was truncated at 30% to give better resolution to smaller frequency bins.

Figure 10: Normalized slope estimates for time series models in Colorado, United States (P034R032) used to assess the influence of Landsat 8's cirrus band. Slope estimates from time series not using Landsat 8's cirrus band in cloud masks were scaled by subtracting slopes from time series using the cirrus band in Fmask. The Y-axis was truncated at 30% to give better resolution to smaller frequency bins.

Figure 11: Normalized RMSE estimates for time series models in Colorado, United States (P034R032) used to assess the influence of Landsat 8's cirrus band. RMSE estimates from time series not using Landsat 8's cirrus band in cloud masks were scaled by dividing by RMSE from time series using the cirrus band in Fmask. The Y-axis was truncated at 30% to give better resolution to smaller frequency bins.

757 screen historical Landsat TM and ETM+ observations of cirrus clouds, already
758 an important task, should be an increased priority to bring these time series
759 closer to parity with Landsat 8.

760 These results are reminders of previously established findings demonstrating
761 how poor cloud and atmospheric contamination screening in time series can lead
762 to spurious temporal trends or anomalies (Samanta et al., 2010, 2012). Improved
763 noise screening will also improve the consistency of surface characterization
764 by removing artificial differences in spectral properties caused by the random
765 chance of cirrus cloud contamination. Reductions in the amount of unexplained
766 variance in reflectance caused by previously undetectable cirrus contamination
767 also aids change detection of surface conditions or land cover because actual
768 changes in surface reflectance will be more distinguishable if the overall variation
769 decreases.

770 5. Conclusions

771 This study of near coincident “underflight” observations and time series anal-
772 ysis finds consistent differences in surface reflectance between Landsat 7 ETM+
773 and Landsat 8 OLI Climate Data Record (CDR) surface reflectance product in
774 the visible wavelengths. While the near infrared and shortwave infrared bands
775 appeared brighter in Landsat 8 within the “underflight” data, differences be-
776 tween sensors for these bands were small and inconsistent in the time series
777 results. Vegetation indices using the visible bands, such as the NDVI and the
778 Tasseled Cap Greenness, tend to be brighter in Landsat 8 and have larger dif-
779 ferences than the individual reflectance bands because the biases in the visible
780 and near infrared bands are in the same direction these indices attempt to con-
781 trast. Despite similarly contrasting the near infrared with the red wavelengths,
782 the Enhanced Vegetation Index (EVI) is not very different between Landsat
783 7 and Landsat 8. The NBR and NDMI spectral indices, which contrast the
784 shortwave infrared bands with the near infrared band, also do not vary across
785 sensors. While these results were generally consistent across the Landsat foot-

prints analyzed, the relationship between Landsat 7 and Landsat 8 varied too substantially to suggest that a global relative correction method could be applied successfully. As was also suggested by Flood (2014), a local, perhaps even per-scene, relative correction should be performed to incorporate the spatial variability of the sensor differences.

Systematic differences in surface reflectance between Landsat 7 and Landsat 8 are shown to have perilous consequences for inference of gradual and abrupt change in land surface conditions. The extension of Landsat 7 time series with Landsat 8 data produces spurious time trends in bands or indices affected by sensor specific differences. Until Landsat 8 surface reflectance can be operationally adjusted to match surface reflectance from Landsat 7, it is recommended to either estimate gradual changes over time using data from only one sensor, to perform relative correction manually, or to avoid affected bands and indices. The sensor specific bias in Landsat 8 data also hampers detection of abrupt changes because time series models are artificially noisier if variation between sensors is left unexplained.

This study did not address the improvements in time series analysis that are due to the resumed 8-day repeat cycle possible with two Landsat spacecraft in operation. Given that much of Landsat 7's acquisition footprint is unobserved due to the failure of the Scan Line Corrector, the launch of Landsat 8 has more than doubled the observation frequency since the failure of Landsat 5. Increasing the sampling frequency of observations helps time series models capture rapid intra-annual transitions, such as the phenological transitions in deciduous forests at the start and end of the growing season or the number of cropping cycles in one year. Near real time monitoring of land cover change is significantly improved with two sensors in orbit because information on change can be retrieved in a more timely manner. Land cover change techniques that use annual image composites can now be more selective when selecting the best available pixel. Even the actual detection of land cover change might be more accurate as higher frequency observations make it more likely to capture the land surface during or immediately after the change event. Increased observa-

tion rates are especially useful in locations with pervasive cloud or snow cover or short growing seasons, including the incredibly important and changing tropical and boreal ecosystems.

Cirrus clouds detected by Fmask using Landsat 8's new cirrus band but not detected in Landsat 7 data are most distinct in the visible and thermal bands. Observations of cirrus clouds differ from clear land in visible wavelengths by less than 3% to 4% and show very little difference in the infrared wavelengths. An experiment comparing Landsat time series that do not use Landsat 8's cirrus band to screen cirrus clouds against time series that do remove cirrus clouds show that residual cirrus clouds create noticeable biases in the intercept, slope, and RMSE estimates of the visible bands and in NDVI. These contamination induced biases mimic vegetation dynamics of interest, including browning or stress events, which highlights the value of Landsat 8's cirrus band. Efforts to enhance existing cloud mask products by improving detection of cirrus clouds within TM and ETM+ data may be aided by the characterization of cirrus clouds possible using Landsat 8 observations and would be a valuable addition.

Inconsistencies in surface reflectance between Landsat 7 and Landsat 8 observed in the Landsat 8 underflight dataset and in four Landsat scenes are due to a combination of three or more factors including physical changes to the spectral characteristics of Landsat 8, differences in relative calibration of sensor detectors, and differences in atmospheric correction ancillary datasets and methodology. This study did not seek to quantify the relative contribution of each factor to the differences observed, but instead focused on quantifying the observed effects and tried to offer practical advice for incorporating Landsat 8 information into existing time series methodologies. Image normalization procedures are recommended to equate the surface reflectance from Landsat 8 to Landsat 7, especially in the visible bands. The difference between sensors might also be modeled as a simple offset in reflectance which could be accomplished as an addition to a time series model specification. It is important to note that the Landsat CDR surface reflectance results described within are subject to change with alterations to sensor calibration or algorithm performance, but

the techniques used and the lessons learned should be applicable when trying to extend the Landsat time series with observations from the upcoming Sentinel-2 satellite.

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Band	Landsat TM (μm)	Landsat ETM+ (μm)	Landsat OLI (μm)
Blue	Band 1: 0.45-0.52	Band 1: 0.45-0.52	Band 2: 0.45-0.51
Green	Band 2: 0.52-0.60	Band 2: 0.52-0.60	Band 3: 0.53-0.59
Red	Band 3: 0.63-0.69	Band 3: 0.63-0.69	Band 4: 0.64-0.67
NIR	Band 4: 0.76-0.90	Band 4: 0.77-0.90	Band 5: 0.85-0.88
SWIR1	Band 5: 1.55-1.75	Band 5: 1.55-1.75	Band 6: 1.57-1.65
SWIR 2	Band 7: 2.08-2.35	Band 7: 2.09-2.35	Band 7: 2.11-2.29
Thermal	Band 6: 10.4-12.5	Band 6: 10.4-12.5	Band 10: 10.6 - 11.19

Table .1: Spectral band specifications for Landsat sensors TM, ETM+, and OLI

WRS-2	Common Name	Landsat 8	Landsat 7
P013R010	Qaasuitsup, Greenland	LC80130102013089LGN01 15:23:37Z	LE70130102013089EDC00 15:20:58Z
P013R029	New Hampshire, United States	LC80130292013089LGN01 15:31:09Z	LE70130292013089EDC00 15:28:32Z
P029R031	Nebraska, United States	LC80290312013089LGN01 17:10:31Z	LE70290312013089EDC00 17:08:13Z
P102R076	Northern Territory, Australia	LC81020762013089LGN01 01:02:39Z	LE71020762013089ASA00 00:57:18Z
P134R042	Arunachal Pradesh, India	LC81340422013089LGN01 04:06:18Z	LE71340422013089EDC00 04:01:31Z
P134R052	Andaman and Nicobar Islands, India	LC81340522013089LGN01 04:10:16Z	LE71340522013089EDC00 04:05:30Z
P150R042	Rajasthan, India	LE71500422013089PFS00 05:44:52Z	LC81500422013089LGN01 05:40:24Z
P198R047	Tombouctou, Mali	LE71980472013089ASN00 10:42:34Z	LC81980472013089LGN01 10:39:03Z
P230R084	Mendoza, Argentina	LE72300842013089CUB00 14:14:24Z	LC82300842013089LGN01 14:11:34Z
P230R094	Santa Cruz, Argentina	LE72300942013089EDC00 14:18:23Z	LC82300942013089LGN01 14:15:34Z

Table .2: Scene center acquisition time for underflight data

WRS-2	Common Name	Landsat 7	Landsat 8	Total
P016R041	Florida, United States	144	39	183
P023R037	Mississippi, United States	128	38	166
P034R032	Colorado, United States	153	36	189
P043R034	California, United States	139	38	177

Table .3: Number of images by sensor in time series datasets