Using Remote Sensing and Census Data to Estimate the Welfare and Migration Effects of Land Reform in Developing Countries: Evidence from Zimbabwe

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June 2017

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Abstract

Zimbabwe carried out agrarian reform in 2000 to correct colonial land imbalances. Dubbed the Fast Track Land Reform Program (FTLRP), the program is widely considered as the single most important trigger to the country's economic misfortunes. On the back of several other events that preceded FTLRP, we estimate the effects of the program on welfare; and internal migration patterns, following the Harris-Todaro framework since the agrarian redistribution program attracted the urban class into agriculture. The unavailability of nationwide data had confined earlier empirical work to small geographical areas, limiting the extent to which these studies can contribute to the debate. Our work contributes to the literature by using remote sensing data that covers the whole country and estimate the effects on welfare within a natural experiment design. Specifically, we employ Night Lights Data (NLD), Normalised Difference Vegetation Index (NDVI) and land cover changes in crop hectorage and we find a high correlation between these and ward level poverty estimates for the 2012 Population Census. Preliminary findings show that the land reform program negatively affected welfare in Zimbabwe. An important conclusion that we arrive at is that NLD may still be highly viable in the analysis of economic phenomenon in rural areas in developing countries although such areas are largely unlit, and land cover products such as NDVI and Landsat are the next best alternatives. For migration analysis, we use census district level population figures and observe that the program might have had resulted in urban-rural migration, and we find that it altered the intra-rural patterns of migration.

Keywords:

Agrarian Reform, Remote Sensing, Welfare, Urban-Rural Migration, Machine Learning, Night Lights, Landsat images

1.0 Land Reform in Developing Countries

Adams (1995) and Zarin and Bujang (1994) define land reform as the reallocation of property or rights for the benefits of previously disadvantaged groups such as tenants, peasants and farm labourers. Although they are used interchangeably, land reform is a subset of agrarian reform. There are diverse views behind land reform. Zarin and Bujang (1994) offer three motivations for agrarian reform. The political motive is when a government uses land reform either to gain or retain power; the social motive targets a more egalitarian society while the economic one centres around efficiency (Zarin & Bujang, 1994). Adams (1995) and Zarin and Bujang (1994) concur that politics are inseparable from land.

A number of studies acknowledge land reform as a political survival instrument. For example, using a panel of Mexican states for the period 1917-1992, Albertus, Diaz-Cayeros, Magaloni, and Weingast (2012) found empirical evidence that the objective of the country agrarian reform was political survival, leaving peasants much more dependent on the state. Albertus et al. (2012), observe that land redistribution efforts were high during election years in Mexico. Land reform may also be implemented just to break landlord power. In Iraq, for example, Warriner (1969) asserts that land reform did not take the country forward in any significant way, but only achieved to break the power of the Sheikhs. Apart from the political motive, land reform has a very strong political character. The Bolivian and Cuban agrarian reforms in the 1950s attracted economic sanctions (Barraclough, 1999; Seligson, 1984). According to (Barraclough, 1999), land reform in Cuba attracted a trade embargo from the US. Similarly, a number of restrictions were placed on the Zimbabwean economy in the aftermath of FTLRP, notably ZIDERA[1] that prohibited US firms from engaging in any business in Zimbabwe. The political consequences of land reform may thus be an important cause of hesitation by post-independent states to redistribute land.

From an economic standpoint, it is seen a strategy to increase agriculture returns to scale through eliminating the diseconomies of scale associated with larger farms and allowing the agility and innovation of smaller farm holdings (Adams, 1995; Barraclough, 1999; Cotula, Toulmin, & Quan, 2006; Zarin & Bujang, 1994). While larger farms can enjoy economies of scale, Cotula et al. (2006) posit that mechanization returns to scale are evident in crops such as sugarcane, some cereals and soya while crops such as rubber, fruit and vegetables produce

[1] ZIDERA – Zimbabwe Democracy Recovery Act. It was passed by the US in 2000. ZIDERA instructed the director of any US financial institution to block any grants to Zimbabwe or any reduction in debt

better yields under manual labour intensive conditions. Better efficiency under smaller farms may also be due to the outputs gains from the self-employment incentive of family farms; although land reform might just be a response to population growth (De Janvry, Sadoulet, & Wolford, 2001). Warriner (1969), adds that if the costs of land reform are too high, output tends to decline, and land reform cannot contribute to economic growth under such circumstances. Rather, rapid economic growth is a necessary pre-condition for a fruitful land reform program.

Land and poverty are related, thus addressing land imbalances is a strategy towards a more egalitarian society. A number of authors agree that there is a strong positive correlation between rural poverty and landlessness (Adams, 1995; Cotula et al., 2006; Tarisayi, 2013; Zarin & Bujang, 1994). Tarisayi (2013), argues that land reform can influence upward mobility of the previously underprivileged because land ownership increases their asset base. Therefore the question of land redistribution is important in any country where a significant proportion of society is poor although having access to land is only just a beginning (Tarisayi, 2013). Cotula et al. (2006), mentions that the World Bank's Poverty Reduction Strategy Papers (PRSPs) have (to various degrees) linked poverty to landlessness; for example, in Burkina Faso, Mongolia, Honduras, Cambodia, Lao and Southern Africa. Similarly, (Cotula et al., 2006) suggest it will be difficult to lift communities out of poverty unless land reform is implemented on a foundation of commitment and strong political will by the government, as well as effective reorganization, orderliness and the provision of support and incentives. Ciamarra (2004) argues that providing more access to land improves the welfare of the poor, but cautions that this is only possible when both state-led expropriation and market-led polices are simultaneously pursued. Seligson (1984) and Christodoulou (1990) posit that land reform has been viewed as an egalitarian manoeuvre to get the rural poor out of poverty.

1.1 Approaches to Land Reform

Land tenure reform, external inducements, external controls and confirmation of title are the major variants of agrarian reform (Adams, 1995). Land tenure reform involves realignment of reciprocal property rights between owners and conversion of informal tenancy into formal property rights as a way of balancing the tenant-landlord relationship (Adams, 1995; Cotula et al., 2006). In contrast to land tenure reform, external inducements are market based incentives (for example credit to allow land transfers) that are put in place by the state to lead the agrarian property rights structure in a certain way, such as Zimbabwe's willing buyer willing seller model prior to 2000 (Adams, 1995; De Villiers, 2003). External controls describe agrarian reform as a set of legislative controls or prohibitions on property rights including but not limited to nationalization, restitution or land expropriation with or without compensation on the grounds of underutilization, excessive size, landlord absenteeism or just to correct historical imbalances (Adams, 1995). Lastly, land reform may involve the verification and confirming of titles of those already in possession of land holdings (Adams, 1995). In order to secure welfare, the four principal forms of agrarian reform may need to be considered holistically and regarded as a cycle through which the external control version of land reform should pass through.

1.2 Motivation for the study

There is not much debate on the definition for land reform. Tarisayi (2013), suggests that while there appears to be consensus with respect to the definition of land reform, it is the approach and justification that has remained the subject of debate. Therefore, this study attempts to evaluate Zimbabwe's approach to land reform by investigating its short and long-term effects on welfare and migration respectively. The expectation that post-independence states must address colonial land imbalances has always been alive, and it is the aim of this study to provide these countries with useful insights from the case of Zimbabwe. These countries include Namibia, South Africa and many others in the developing world.

Land reform goes beyond the land distribution itself, but can have important long-term effects on the economy, welfare and the politics of a country. It is therefore important to trace the performance of the previously disadvantaged, now newly resettled farmers. Godfrey Huggins (The Prime Minister of Southern Rhodesia) mentioned that those who would ultimately own the land and those who would be able to make the best use of it (Manjengwa, Hanlon, & Smart, 2013). Enhancing understanding on the best approach to land reform is important because land occupies a central place in the economic development of any nation. S. Moyo, Jha, and Yeros (2013) asserts that because no country can absolutely guarantee the food security of its people and that every investment question one way or another falls back to the land – it is important to understand agrarian reform. On the other hand, Branca, McCarthy, Lipper, and Jolejole (2011) asserts that the sustainable management of agricultural areas is indispensable in developing countries given the critical role it plays in the economy. Therefore, attempts at land reform, or any other radical transformation of ownership and/or structure should be subjected to rigorous process of due diligence.

This paper also makes a data contribution. It adds to the debate on the viability of the land reform program by estimating small area welfare effects using remotely sensed data. It uses Night Lights Data (NLD) from The National Oceanic and Atmospheric Administration (NOAA); and Normalised Difference Vegetation Index (NDVI)[2] and Landsat imagery from the U.S. Geological Survey (USGS). The lack of publicly available nationally representative survey data means that it is not possible to track standard welfare measures for the entire economy. To fill this gap, this study contributes by using these unconventional, innovative datasets to estimate changes in welfare for small areas (wards). The paper follows Pinkovskiy and Sala-i-Martin (2014) in the use NLD as a proxy for welfare and adopts the machine learning and Landsat image classification approach by Fernandes (2015). Identification relies on a difference-in-difference econometric approach; that is, we measure differences in economic activity before and after the implementation of Land Reform, but also remove the effects of time changes in regions that were not primarily targeted by the policy.

Lastly, the paper examines whether agrarian reform can influence reverse migration. Williams and Jobes (1990), state that one of the reasons why people may choose to move to rural areas from metropolitan areas is because they would be looking for a new way of living and quality of life. An important gap that this paper fills is that the vast majority of papers look at reverse migration as being motivated by preference for better quality of life, yet for developing countries movement to rural areas might not necessarily be in order to enjoy higher quality of life and fresher air but for much more economic reasons. Urban rural migration is a phenomenon that has been observed in the developed world, *see* (Barcus, 2010); Hugo and Smailes (1985); (Williams & Jobes, 1990). However, from the perspective of developing countries, this phenomenon has largely been rare and this study investigates such a possibility due to land reform.

1.3 The study setting

S. Moyo et al. (2013) state that "the land movement in Zimbabwe may have been the most successful in reclaiming land, but the depth of the political work that has been underway on all continents has set the stage for consideration of 're-peasantization' as a modern, sovereign project in the twenty–first century." This paper considers Zimbabwe not only because it is the

[2] The study uses a historical NDVI from the NOAA vegetation monitoring series that spans the period 1981 to 2016.

most recent 21st Century case study, but also it is the "most successful" from the point of view of acquiring land from European farmers for distribution amongst the landless indigenous population. This is in contrast to its southern neighbour, South Africa, whose land reform program has been a disappointment according to Binswanger-Mkhize (2014), if the number of beneficiaries is considered.

Table 1: Changes in the Distribution Structure of the Land

Land Category	**1980**	**2000**	**2010**
	Area (million ha)	Area (million ha)	Area (million ha)
Communal Areas	16.4	16.4	16.4
Old Settlement	0.0	3.5	3.5
New resettlement: A1	0.0	0.0	4.1
New resettlement: A2	0.0	0.0	3.5
Small-scale commercial farms	1.4	1.4	1.4
Large-scale commercial farms	15.5	11.7	3.4
State farms	0.5	0.7	0.7
Urban land	0.2	0.3	0.3
National parks and forest land	5.1	5.1	5.1
Unallocated land	0.0	0.0	0.7

Source: Scoones et al. (2011)

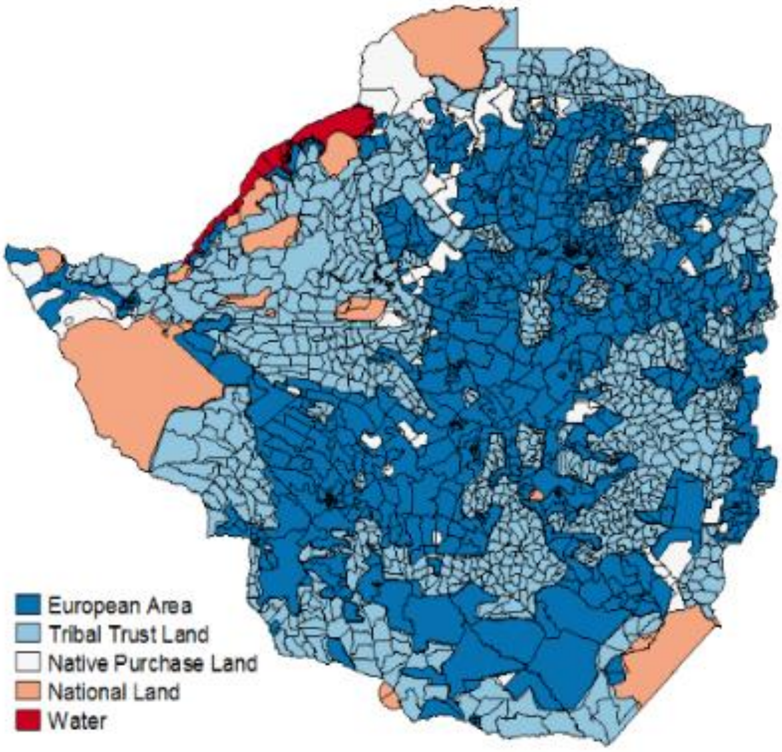
Table 1 shows that 78% of the land that was European large commercial farms in 1980 had been re-allocated to Africans by 2010. This confirms that Zimbabwe land reform program was indeed the most triumphant in as far transferring the land from the privileged class to their less fortunate fellow citizens.

2.0 Zimbabwe Fast Track Land Reform Program (FTLRP)

Land inequality is a colonial legacy that Zimbabwe inherited upon independence in 1980 (Tarisayi, 2013). As at 1980, Europeans farmers owned most of the fertile, rain fed high veld in the middle of the country (about half the size of the country), with Africans occupying mostly the sandy, dry soils of the low veld (*see* Figure 1). However, tenets of the Lancashire House Conference (the treaty that ushered in majority rule) demanded the implementation of land reform on a willing buyer-willing seller basis, with Britain and the USA meeting half the cost.

Partly because these pledges were never really fulfilled (De Villiers, 2003), drastically slowing down the process of agrarian reform between 1980 and 2000; and increased pressure from liberation war veterans and the general masses, the Zimbabwe Government implemented the Fast Track Land Reform (FTLRP) in 2000.

Figure 1: The Land Apportionment Act of 1930



****Notes:**

Figure 1 shows the distribution of land in Zimbabwe (formerly Southern Rhodesia), based on the Land Apportionment Act of 1930 – superimposed on the Zimbabwe Level 3 ward level shape file. The areas in dark blue are the ones designated for Europeans (EAs) while those in light blue were the Tribal Trust Areas (TTLs) (for Africans). Those in white are the Native Purchase Areas (NPAs) (African large-scale farms). Given that land reform only took place in the European Areas, three different sets of regressions (i to ii) are carried out in the difference in difference small area estimation. In (i), EAs is the Treatment Area while TTLs are the Control Area. In (ii) EAs are the Treatment Area while NPAs are the Control. Mutangi (2010) reveals that FTLRP did not affect the Eastern Highlands (the mountainous region bordering Mozambique), thus in (iii) EAs elsewhere in the country are the Treatment Group while EAs in Eastern Highlands are the Control Group.

In 2000, Zimbabweans voted in a constitutional referendum in which the government had proposed that the country compulsorily acquire land from the European farmers without compensation. The government lost this referendum, but would still have its way in FTLRP.

FTLRP commenced soon after the constitutional referendum and in the period leading to elections in 2002 (Tarisayi, 2013) and the initial momentum of the programme was built by disgruntled war veterans who "spontaneously" attacked and occupied white owned commercial farms in 2000 (Marimira, 2010). War veterans led almost the entire program until the government made new constitutional provisions that would seal the expropriation of the land from white commercial farmers. Land reform mainly focused on commercial farms that were involved in crop production, and as a result a number of farms in the Eastern Highlands were left untouched because they consisted mainly of plantations (Mutangi, 2010). Under FTLR program, almost 4000 white-owned Commercial farms were expropriated and re-allocated to the indigenous native population (Richardson, 2007). Chigumira (2010), reveals that by February 2010 the Zimbabwe government had resettled 156,000 households on almost 7 million hectares of land.

There are divergent views regarding the efficacy of agrarian reform and its effect on welfare. In Zimbabwe (Chigumira, 2010; Mutangi, 2010; Zikhali, 2010) argue that the country's land reform program did not improve welfare, while (Mandizadza, 2010; Mbereko, 2010; P. Moyo, 2010a) found that the program resulted in positive gains in productivity and welfare. Each of these studies was localised and did not assess the large-scale effects of the policy. Consequently, this study aims to examine the effects of land reform on welfare and internal migration patterns for *all* of Zimbabwe. This paper makes an important contribution because it offers a first nationwide view of the land reform process and whether it has mitigated the effects of a constrained informal sector by attracting the urban class into agriculture.

The paper also investigates whether reverse migration resulted due to agrarian reform. As expected under Lewis (1954) and Harris and Todaro (1970), the urban areas in Zimbabwe had historically attracted surplus labour from the traditional, rural sector. At the turn of the 21st Century however, Zimbabwe's land reform offered incentives for the urban class to migrate back to the rural areas to take up farming (Marimira, 2010; S. Moyo et al., 2013; Scoones et al., 2011). P. Moyo (2010b) and Murisa (2010) concur, mentioning that FTLRP allocated land plots to the urban working poor as well contrary to embedded belief that land reform only benefited the bourgeoisie and political classes. This paper attempts to test whether the taking up a farm under the land reform program promised a substantial income differential to attract especially the unemployment or underemployment urban class to the rural areas. Formally, we test the occurrence of urban-rural migration after land reform using the same difference in difference identification procedure. The study employs district level population figures for 1992, 2002 and 2012 to trace any changes in internal migration that could have emanated from the land reform.

3.0 Data and Identification

Fernandes (2015) defines remote sensing as the collection of information pertaining to an object without making any physical contact with it. Remotely sensed data has proven to be an important resource in the spatial examination of economic phenomenon, because it is available over time even in parts of the world that would otherwise be lacking in the availability of census and other types of data (Elvidge et al., 2009; Henderson, Storeygard, & Weil, 2012; Li, Ge, & Chen, 2013). Another distinct benefit of these data is that they provide the ability to track welfare for very fine spatial units on an annual basis. Remote sensing data that is obtained by satellites has immense benefits that it provides in the temporal and spatial examination of environmental variables. The data has also been widely used in crop classification and the estimation of yields (Dhumal, YogeshRajendra, & Mehrotra, 2013). Ustuner, Sanli, Abdikan, Esetlili, and Kurucu (2014) mention that due to the expanding need for quick, cost effective data on land cover, many countries have launched several satellites, for example RapidEye, GeoEye-1, WorldView-2, Landsat8, SPOT-7, TerraSAR-X (2007), Sentinel-1A and ALOS-2 (2014).

Estimation of the FTLRP’s effect of welfare in carried out using NLD, NDVI and Landsat images. To test the incidence of migration in Zimbabwe after land reform, the study employs 1992, 2002 and 2012 district population figures from the respective national census waves for those years [obtained from the Zimbabwe Statistical Agency (Zimstat)]. These are used to examine population changes (and by inference migration patterns) within Zimbabwe due to land reform. In this section, NLD and NDVI are discussed briefly, literature on the classification of Landsat Images using machine learning and the techniques used are discussed. The Difference in Difference identification strategy that the study employs is also discussed.

3.1 Night Lights Data

Satellites measure the luminosity of night-lights per pixel at regular time intervals. Pinkovskiy and Sala-i-Martin (2014) define a pixel as 1 square kilometre; each pixel is assigned a Digital

Number (DN) that represents its brightness. The DNs are measured on a scale of 1 to 63 (Pinkovskiy & Sala-i-Martin, 2014). Chen and Nordhaus (2011) indicate that there are three versions of the night lights data, namely raw, stable lights and calibrated. Most researchers use stable lights because it removes veld fires and other noise. Likewise, this research uses stable lights data.

Night Lights Data has been used over the past several years because of its high correlation with economic welfare measures. According to Henderson et al. (2012), light is required for the consumption of any good or service at night so that increases in light intensity may imply increases in consumption; which may in turn increase GDP, economic activity or welfare. Elvidge et al. (2009) and Henderson et al. (2012) concur that satellite sensors address the problem of inconsistency by availing NLD datasets on a yearly basis and thus economic phenomenon can be traced over time.

Chen and Nordhaus (2011) assert that the other advantage of Night Lights data is that there is relative objectivity as well as the ability to take into account geographical variations that would inadvertently affect national income. Literature suggests that several ways have been used by economists to find proxies that can estimate GDP and economic welfare at very fine geographic levels (Henderson et al., 2012). Night light data has been found to be a better alternative amongst a number of proxies for economic activity. Against a backdrop of high rates of informality, night lights data can also be a useful solution to the problem of data unavailability from this poorly sector. To support this argument, Henderson et al. (2012) indicate that in developing countries a significant proportion of economic activity takes place in the informal sector where there is very poor collation of statistics. Thus, NLD is a useful tool to measure spatial economic activity in unmeasured economies such as Zimbabwe over fine geographical areas.

Night lights data can make very effective spatial analysis of economic phenomenon. Henderson et al. (2012) indicate that the data can show light intensity over very fine geographical areas, which makes it a very useful tool for spatial examination of the economic phenomenon, adding that the data is available at higher and more consistent frequency and thus is a good tool to measure the effects of shocks and other events on economic phenomenon. Hentschel (1998) argue that estimates that are available using poverty maps or in another words for the smallest administrative unit of a country are an indispensable avenue to target and refine policy interventions within smaller geographical areas of a country that have different needs. That is why Night Lights Data is used for spatial analysis of almost 2000 wards in Zimbabwe.

The other important application of Night Lights Data is that it can very well show stagnation. Henderson et al. (2012) present an analogy between North and South Korea and light intensity for the South clearly resonates with the over 100%[3] economic growth that the country has gained between 1992 and 2008 yet for the North there is the absolute absence of any change in light intensity that shows may indicate economic stagnation. Thus Night Lights Data may also effectively assess possible stagnation of the economy of Zimbabwe as undertaken by Li et al. (2013). Li et al. (2013) used night lights imagery and found that mining and agricultural towns were worst affected by Zimbabwe's economic decline.

Although Elvidge et al. (2009) and Henderson et al. (2012) commend NLD for its consistency over time, Jian and Weifeng (2013) argue that such consistency may not be achieved if the NLD data is used in their raw state since the satellites lack "inflight calibration". Using the time invariant region approach Jian and Weifeng (2013) calibrated NOAA night lights imagery datasets taken by different satellites in the period 1992 to 2010 and calculated a and b data adjustment coefficients to address (i) satellite sensor differences; (ii) disparity in data acquisition time that could result in spontaneous oscillation in the data taken by satellites in different orbits; and (iii) the saturation of pixels in urban areas. The study therefore uses the calibration model that is shown in below, following Jian and Weifeng (2013).

$$DN_c = a \times (DN_m + 1)^b - 1$$

Where a and b are the adjustment coefficients, DN_c is the NLD after calibration and DN_m is the raw NLD.

3.2 Land Cover Data

The two land cover products that are used in this study are NDVI and Landsat images. The paper assumes that we can measure the welfare of small areas by investigating changes in the quality of crops as measured by NDVI, as well as changes in the acreage of land under crops. Changes in the crop acreage and in the quality of the crops should tell us something about the ability of newly resettled indigenous farmers to match the intensive cropping systems of the

[3] Henderson, Storeyhead and Weil (2012).

dispossessed former European commercial farmers; and the extent to which they have been able to apply expensive fertilisers and chemicals. Therefore, the quality of the cops and the acreage of land under crops should give some fair indication of the welfare of the farmers. By using machine learning techniques to classify Landsat images mainly into cropland and natural forest, this study is thus able to measure the ratio of land under crops to total land hectorage per ward. This ratio is also used to filter out the natural forest that is captured in the "off the shelf" NDVI raster dataset that is employed in the study as a proxy for the quality of crops.

Stojanova, Panov, Gjorgjioski, Kobler, and Džeroski (2010) points out that the conventional approaches for the ground measurement and monitoring of vegetation takes time, aside from the huge financial outlay involved – making the use of land cover data economical. Nagendra, Munroe, and Southworth (2004) posits that land cover data mostly comprises of snapshots or images of different parts of the earth, although the measured pixel value does not for the most part have an obvious correspondence to real economic phenomenon or variables. Therefore, the issue of classification for land cover data assumes a central role.

Several methodologies have been proposed that can be used to classify land cover data to its usable form, *see* (Ahmad, Kalra, & Stephen, 2010; Fernandes, 2015); Gislason, Benediktsson, and Sveinsson (2006); (McIver & Friedl, 2001; Rogan et al., 2008; Shao & Lunetta, 2012; Stojanova et al., 2010). This classification can be supervised on unsupervised. This paper employs supervised classification, following Fernandes (2015).

3.2.1 NDVI

This study uses NDVI, and following Ahmad et al. (2010) postulates that higher agricultural productivity per hectare should reflect in higher vegetation quality and higher NDVI and vice versa. As explained by Ahmad et al. (2010), NDVI has been widely employed as a resource to assess ground vegetation cover. Ahmad et al. (2010), explains that intuition that informs NDVI is that the disparity in the reflectance of red and near red infrared frequencies back to the satellite increase as vegetation becomes denser, and the index is defined as:

$$NDVI = \frac{NIR - RED}{NIR + RED}$$

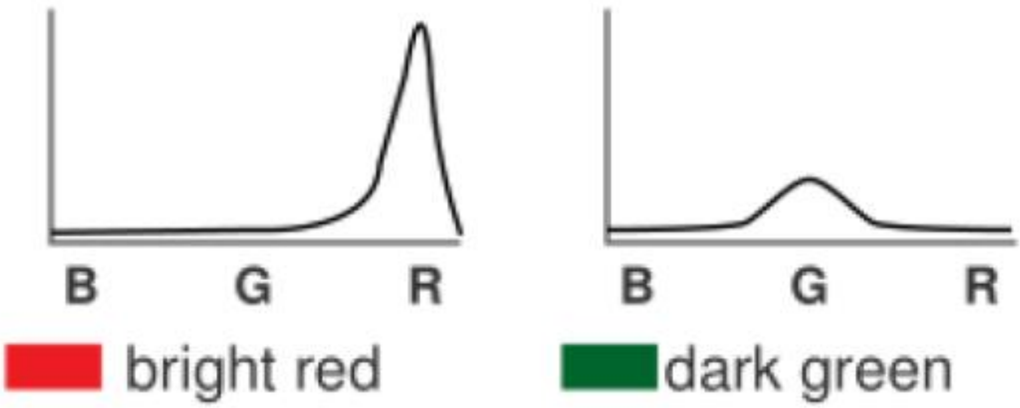
Where NIR and RED are the near red and red frequencies respectively, and normalization of the above expression results in negative NDVI values representing bare to sparse vegetation and positive NDVI values representing dense to very dense vegetation (Ahmad et al., 2010).

3.2.2 Classification of Landsat Images

Classification is defined as the procedure in which an input image that has multi layers in transformed into a single layer thematic map (Dhumal et al., 2013). Dhumal et al. (2013), indicate that satellite multispectral images contain several bands of colour that reveal useful information for classification; adding that the smallest bandwidth contains the finest information about crops. Ustuner et al. (2014), point that classification of remote sensing imagery is the cornerstone of crop monitoring since it gives precise, up to date and less expensive data about crop types and different spatial and temporal resolution.

As mentioned earlier in the paper, classification can broadly be categorised into supervised and unsupervised methods. Dhumal et al. (2013), explain that unsupervised classification is when the researcher groups particular pixels according to similarity and then labels the related land features appropriately. In the unsupervised case, the researcher needs some prior ground knowledge of the area (Dhumal et al., 2013). This usually involves training a sample dataset based on the researcher's knowledge and then predicting the land features for the rest of the images.

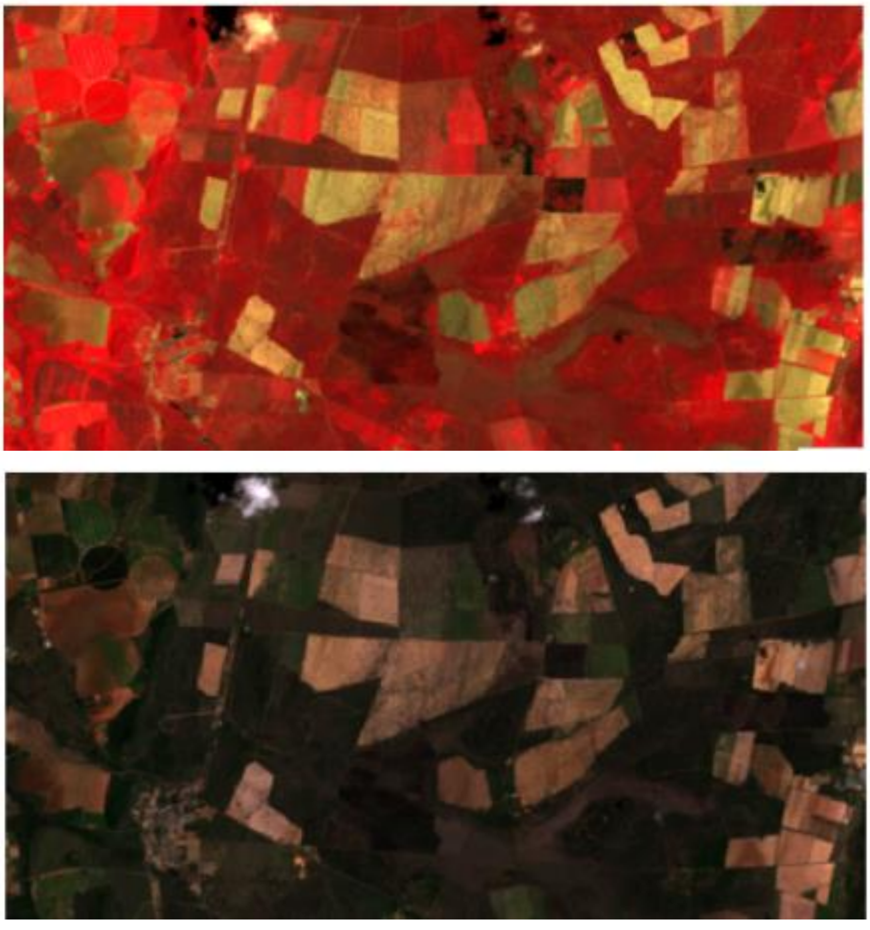
Figure 2 Idealised Spectral Signatures for Selected Colours



Source: Eastman (2003)

Classification of remotely sensed images is made possible by the fact that different objects on the earth's surface have different spectral signatures. Reflection, absorption or transmission are the processes that result when electromagnetic energy reaches a material; and it is the reflection of the sun that is captured by the satellite sensor in remote sensing (Fernandes, 2015). Fernandes (2015), adds that the pattern of spectral response pattern (signature) is a description of the extent to which energy is reflected in various areas of the electromagnetic spectrum. This is normally shown graphically as in Figure 2, following Eastman (2003). Figure 2 shows the signatures for the visual part of the electromagnetic spectrum (Fernandes, 2015). The graph on the left would be a bright red object absorbing the blue (B) and green (G) electromagnetic wavelengths, and then reflecting the red (R) (Fernandes, 2015). The object represented by the graph to the right would be a dark green (as suggested by the low graph value) object would absorbing blue (B) and red (R) bands, and reflecting green (G) back to the satellite sensor (Fernandes, 2015).

Figure 3: Near Infrared and Natural Colour Composites of Agricultural Land



Source: Own composites created from Landsat footprints for Zimbabwe

It has to be noted that the bands that we can visualise (B, G, R) might not be enough to classify land features on their own – there might be need for additional bands such as infrared and near infrared (Fernandes, 2015). Figure 3 shows near infrared (picture on the left) and natural (picture on the right) colour composites created out of Landsat image bands. The images show the corresponding views of fields of farmland in the near infrared or natural (false) colour composites.

Dhumal et al. (2013) explain that crops have different internal structures according to type, and as such, they have different spectral signatures. It follows therefore that different crops with a somewhat similar structure would be much more difficult to distinguish, requiring hyper-spectral imagery that can enable such minute distinction. The focus of this paper is not to distinguish the different kinds of crops, as the interest is just to delineate cropland from natural forest. The paper builds on the observation by Fernandes (2015) that crops emit a lot of the near 'not-visible to the human eye' near-infrared band. This is the centre piece of the classification, although Fernandes (2015) suggests that the best bands for vegetation classification are Blue, Green, Red, near infrared, shortwave infrared 1 and shortwave infrared 2. In both Landsat 4-5 Landsat 7, these bands are 1-5 and 7 as shown in Table 2.

Table 2 Landsat 4-5 Thematic Mapper (TM) satellite Image Bands

Landsat 4-5 Thematic Mapper (TM)	**Bands**	**Wavelength (micrometers)**	**Resolution (meters)**
	Band 1 - Blue	0.45-0.52	30
	Band 2 - Green	0.52-0.60	30
	Band 3 - Red	0.63-0.69	30
	Band 4 – Near Infrared (NIR)	0.76-0.90	30
	Band 5 – Shortwave Infrared (SWIR) 1	1.55-1.75	30
	Band 6 - Thermal	10.40-12.50	120*(30)
	Band 7 – Shortwave Infrared (SWIR) 2	2.08-2.35	30

Source: USGS (2017)

For land classification, the study considers a narrower period 1997 – 2007 as opposed NLD due to the labour and computing power intensive nature of classifying the whole of Zimbabwe into cropland and natural forest using at least 24 image footprints per year downloaded from the USGS website. The study mostly uses data from the Landsat 4 – 5 satellites and Landsat 7 for the periods 1997 – 2000 and 2000 – 2003 respectively. Landsat 7 carried the Enhanced Thematic Mapper Plus (ETM+) sensor that is used to acquire images, the only difference between Landsat 4-5 Thematic Mapper (TM) and Landsat Enhanced Thematic Mapper Plus (ETM+) being that the latter had an additional panchromatic Band 8. The study does not use Band 8 to classify the images.

3.2.2.1 Support Vector Machines (SVM) Classification Algorithm

Ustuner et al. (2014) indicate that the SVM algorithm has proven to be superior to other classification algorithms. SVM is a statistical learning methodology that is premised on fitting the optimal hyperplane separating the two classes, following (Cortes & Vapnik, 1995; Huang, Davis, & Townshend, 2002; Ustuner et al., 2014). The SVM is superior as an approach because it uses kernel functions to create the optimal hyperplane that cannot be accomplished linearly (Huang et al., 2002).

3.2.2.2 Image Correction and Supervised Identification of Training Points in QGIS

The study obtains cloud-free Landsat images from Jan, Feb, Mar, Nov and Dec for the years 1997 – 2003 as these months fall in Zimbabwe's rain fed agricultural season, to enhance the accuracy of classification. Some form of correction and calibration is always required for Landsat Images Fernandes (2015), thus the images are adjusted for Top of the Atmosphere (TOA) correction in QGIS's Semi-Automatic Classification Plugin (SCP) so that image comparison over time and from different satellites is possible following Congedo (2014) and Fernandes (2015). Congedo (2014) and Fernandes (2015), posit that there is need to convert the DNs on the image to Top of Atmosphere (TOA) reflectance values because the electromagnetic energy measured by the satellite sensor is influence the scattering and absorption atmospheric effects; reflectance being the ratio between reflected and incident energy on a surface (Congedo, 2014). More than 20 000 training polygons for all the footprints are identified in QGIS. The study identifies at least 900 training points per Landsat footprint (see appendix 2). For the NLD and NDVI, the images are imported to QGIS, where zonal statistics are computed for every ward, based on the Zimbabwe Level 3 Ward Level shape file.

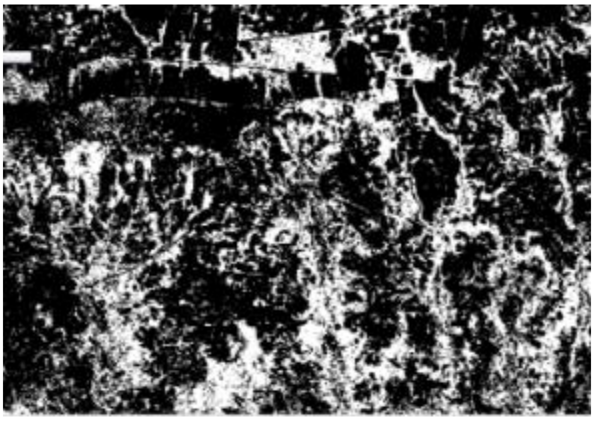
The shape file is exported to STATA for analysis. In STATA, the NDVI is multiplied by the ratio of cropland to total ward area as a way of filtering out natural forest.

3.2.2.3 Classification using the SVM Algorithm in R

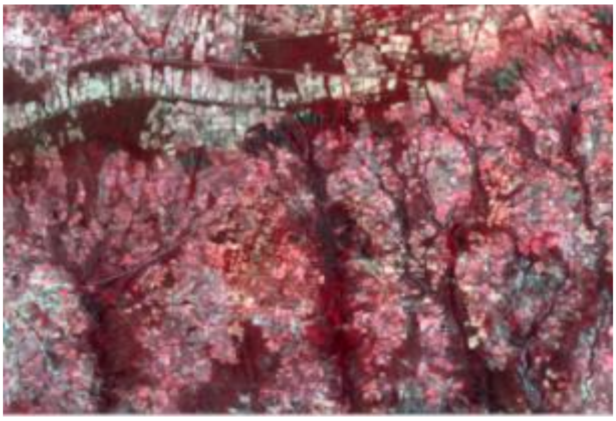
Machine learning classification proceeds in R, following Fernandes (2015). Classification uses the Support Vector Machines (SVM) algorithm (Cortes & Vapnik, 1995; Huang et al., 2002; Ustuner et al., 2014). The two main factors affecting the quality of classification ceteris paribus is the selection of the classification algorithm and the training set (Machová, Barcak, & Bednár, 2006). Therefore, there is need to make sure that the correct algorithm is selected as well as the right training dataset.

Figure 4: Performance of the SVM Algorithm in R

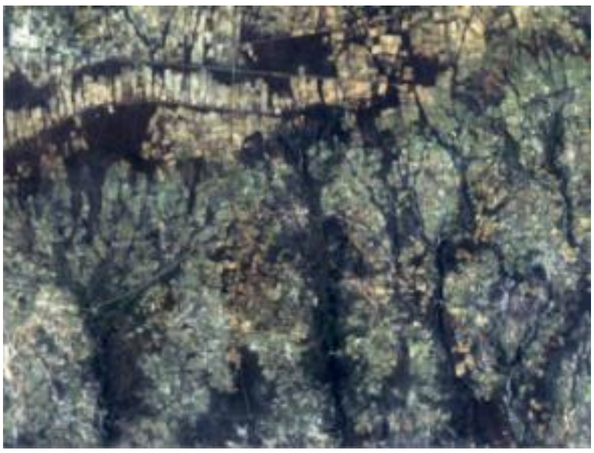
(a) Predicted Image



(b) Near Infrared Red Composite



(c) Natural Colour Composite



In (a) black is assigned a value of 1 (cropland) while white is assigned a value of 0 (natural forest. In (b) pinkish-bright red is cropland while dark red is natural forest. In (c) yellowish-green in cropland while dark green is natural forest. Visual inspection shows that the classification machine learning techniques produce remarkable results.

The training set for this study consists of tens of thousands of training polygons, which gives millions of training pixels. These guarantee the highest classification accuracy, but they sacrifice computing speed. Classification produces predicted raster images, and these are shown side to side with near infrared and natural colour composites for the same area in Figure 4. The zonal (ward) sum is computed in R using the predicted raster images (where cropland pixels=1 and natural forest pixels=0). Natural forest pixels are thus excluded from the total pixels in the ward. In other words, the zonal sum only contains cropland. The data is exported to STATA, where the cropland pixels are then converted to hectares using the following formula (Landsat 4-5 and Landsat 7 images have a resolution of 30 metres):

$$\frac{cropland\ pixels\ \times 0.0009}{ward\ area\ in\ kms^2}$$

3.3 The Difference in Difference Approach

The study proceeds by following a difference-in-difference approach (*see* Bertrand, Duflo, and Mullainathan (2002), Lechner (2010) and Wooldridge (2007)), taking the pre-2000 and post-2000 NLD and NDVI as the 'before' and 'after' land reform periods respectively. Land reform was launched in 2000. Various treatment groups are constructed. Firstly, all wards that are located in European Areas (EAs) (*see* Figure 1) are regarded as the treatment group or area where land reform took place while the Tribal Trust Lands (TTLs) (the areas reserved for indigenous Zimbabweans) are considered to be the control group where reallocation of land did not take place. Secondly, the Tribal Trust Lands (TTLs) are replaced by the Native Purchase Areas (NPAs) as a control group as NPAs were also a black farming areas like the TTLs. Thirdly, European Areas (EAs) in the rest of the country excluding the Eastern Highlands are regarded as the treatment group while those located in the region are taken as the control group; following the assertion by Mutangi (2010) that land reform excluded this region.

The land reform targeted only the European Areas (EAs) while the Tribal Trust Lands (TTLs) and the Native Purchase Areas (NPAs) that were reserved for blacks were not targeted by the land reform program. The Eastern Highlands were targeted for land reform, but it was never pursued in these regions because of the unsuitability for conventional crop farming. Therefore, in the spatial analysis the Tribal Trust Lands (TTLs), Native Purchase Areas (NPAs) and the Eastern Highlands (EHs) are used as the control groups. Placebo effects are also assessed. The difference in difference is used for analysis of both migration and welfare. The model is specified following Ravi, Kapoor, and Ahluwalia (2012) as follows:

$$Y_{it} = \alpha + \beta_1 dT + \beta_2 dY + \delta dT * dY + X_{it\gamma} + \epsilon_{it}$$

where Y_{it} is the outcome of interest in district *i* at time *t* and which welfare as measured by mean night lights of ward population. dT is the treatment group dummy variable which equals 1 for regions targeted by land reform and 0 otherwise. dY is the year dummy, which equals 0 before 2000, and 1 afterwards. X_{it} is a vector of ward characteristics specified after (Garrison, 1982) as:

$$D_r = Ward, Population, Trade\ in\ Crops, Rainfall, Temperature, Calories/hectare$$

Using The Difference on Difference method, the coefficient of interest is δ and its OLS estimates measures the causal effects of Land Reform on the outcomes of interest, which are changes welfare as well as the migration patterns after land reform.

$$\delta = (Y^T_{2002} - Y^C_{2002}) - (Y^T_{1999} - Y^C_{1999})$$

4.0 Results and Discussion

4.1.1 Descriptive Data Analysis

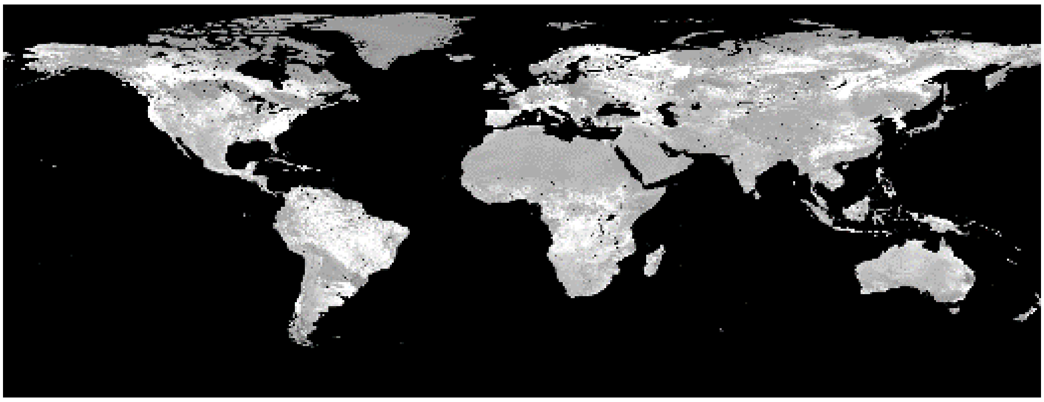
Several studies have used night lights as a proxy for a number of economic variables, including poverty (Chen & Nordhaus, 2011; Ebener, Murray, Tandon, & Elvidge, 2005; Elvidge et al., 2009; Rybnikova & Portnov, 2015; Sutton & Costanza, 2002). The study finds a correlation of -0.5495 between the 2011 poverty estimates (Zimstat, 2015) and mean night lights for the same year (*see* Figure A1 in the appendices). Thus, the average night time lights make a good proxy for local welfare. The inverse relationship means that the lower the night time luminosity the higher the poverty in a particular ward.

Raster images for Night Lights Data (NLD) and Normalised Difference Vegetation Index (NDVI) are shown in Figure 5, and the immediate observation is that NLD has fewer data points that NDVI, which makes the latter richer. Due to zero and negative data points for NLD and NDVI respectively, the study does not apply logarithmic transformation, as it would result in loss of data. Instead, the study expresses lights as a proportion of the average 1992 base luminosity for the whole country given that the NLD dataset stretches from 1992 to 2008. On the other hand, the study expressed vegetation NDVI as a proportion of the average 1997 base vegetation cover for the whole country. This particular dataset covers the period 1996 to 2003, but 1997 is used as a base because significant images available for 1996 are damaged and therefore could not be used. For the ward crop hectares, a logarithm transformation is applied.

Figure 5: Raster Images for NLD and NDVI

The World at Night (Night Lights Data)

NDVI image of the World



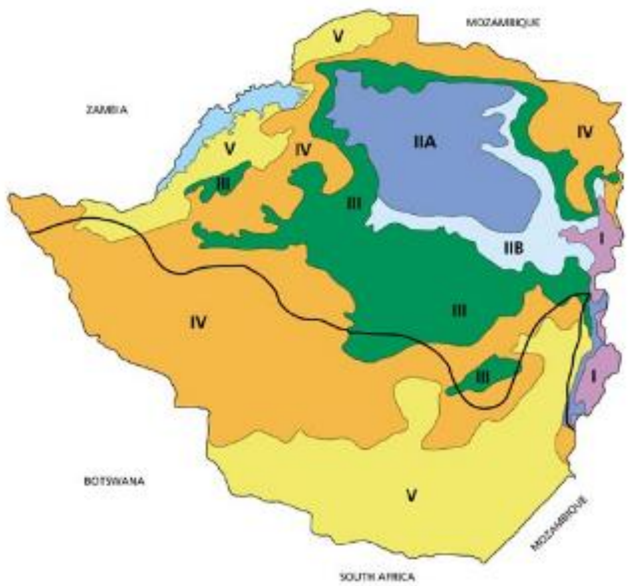
Source: Using NOAA NLD and NDVI NCR

4.1.2 Control Variables

The study controls for several variables namely Caloric Suitability Index, gridded rainfall and temperature time series, ward population figures as well as regional imports and exports. This section briefly discusses the motivation for including these variables in the regression, the sources from which they are obtained and how they are incorporated in the analysis. As has been mentioned before, NLD is a good proxy for economic activity and development patterns, which includes population growth. Therefore, ward level population figures obtained from the 1992, 2002 and 2012 Zimbabwe population censuses are incorporated in the regression to remove the effects of population density.

Apart from that, the study uses the caloric suitability index, following Galor and Özak (2016). Galor and Özak (2016) argue that historic agro-climatic conditions have influenced the pace of economic development, thus we incorporate the Post-1500CE caloric suitability index in order to estimate the extent to which they have affected welfare in Zimbabwe. The caloric index captures the spatial difference in potential agricultural yield in terms of calories per hectare (Galor & Özak, 2016). It is incorporated in our analysis to show that there was no selection effect in the implementation of land reform in Zimbabwe.

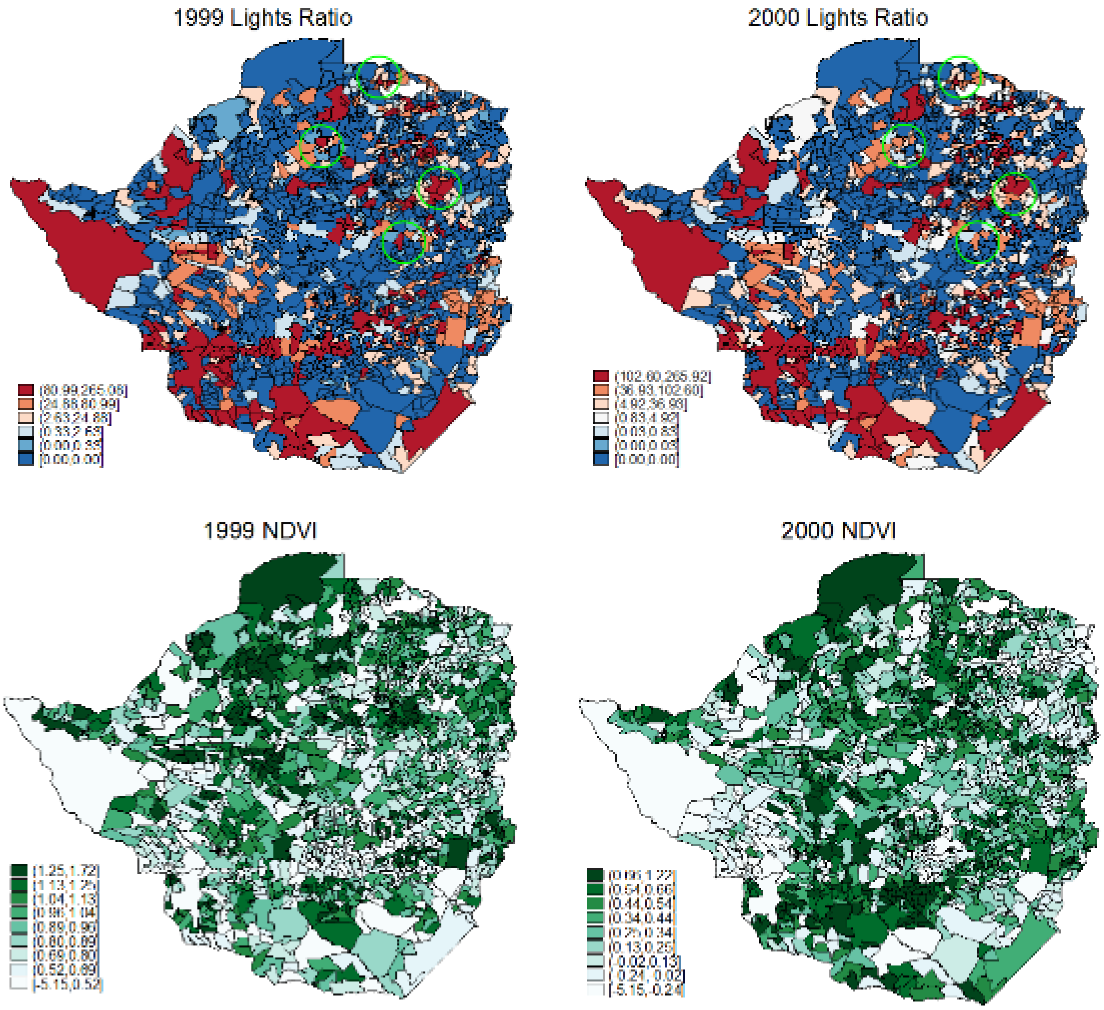
Figure 6: Natural Regions of Zimbabwe



Source: FAO (2016)

The timing of FTLRP coincided with the 2001/2002 drought. In order the separate the effect of drought from that of FTLRP, the study obtained gridded temperature and rainfall data created by Willmott and Matsuura (2015). It also included logged imports and exports data in order to separate the confounding effect of 'Black Friday[4]'. We use the trade in crops as a proxy for the exchange rate, whose downward spiralling was triggered by 'Black Friday'. We obtain a time series dataset of import and export values and quantities from FAOSTAT (2015).

Figure 7: Comparing 1999 versus 2000 (NLD and NDVI)



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[4] In 1997, the Zimbabwe government was under immense pressure to compensate war veterans for liberating the country. As a result, Zimbabwe paid ZW50,000.00 to each and every individual who could prove that they had played an active role during the war at different levels ranging from informer, collaborator to actual combat. On 14 November 1997, the announcement of these unbudgeted payments resulted in the Zimbabwe dollar losing 72% of its value and the Zimbabwe Stock Exchange (ZSE) fell by 46% as foreign investors scurried out (Bond, 1999; Maravanyika, 2007).

To give regional variation to the data, we map different crop exports and imports to different regions using Figure 6. FAO (2016), indicates the different types of crops that are produced in each region. Based on that, we assign different crops to different regions (without overlaps) as shown in Table A1, and then add the different individual crop import or export values per natural region to arrive at the regional figures. The data is then overlaid with the Zimbabwe Level 3 shape file so that the import and export data vary by ward. After 'Black Friday', both imports and exports correlate with the exchange rate (*see* Table A2). Reduced exports signify the negative performance (or welfare) of a particular Natural Region while increased imports also indirectly imply the produce that would otherwise have been produced by a particular region prior to 'Black Friday'.

4.2 Estimating Welfare using Night Time Luminosity

negative performance (or welfare) of a particular Natural Region while increased imports also indirectly

Table 3: Welfare NLD Estimates Excluding Urban Areas

Dep. var *lights ratio*	1	2	3	4
treat#post	-0.58 (0.274)**	0.168 -0.913	0.557 -1.611	-0.641 (0.349)*
Ward Population	0 0	0 (0.000)*	0 0	0 0
Average Calories		0 0	0 -0.001	0 0
Ave. Temperature		0.057 -0.047	0.059 -0.052	0.004 -0.014
Total Precipitation		-0.002 -0.001	-0.002 -0.002	0 0
Imports Value		(0.000)* 0.222	0.219 (0.075)***	0.064 (0.018)***
Exports Value	0.188 (0.017)***	(0.068)*** 0.241	0.306 (0.055)***	0.041 (0.014)***
Constant	-1.015 (0.209)***	-2.448 (1.165)**	-1.326 -1.494	-0.402 -0.335
R-squared N	0.092 5572	0.047 2142	0.05 1840	0.022 3938
p-value	0	0	0	0
Treatment	EAs	EAs	EAs Else	NPAs
Control	TTLs	NPAs	EAs EH	TTLs

NOTES: * p<0.1, ** p<0.05, *** p<0.01. EAs - European Areas, TTLs - Tribal Trust Lands, EAs Else – EAs elsewhere in the country, EAs EH – EAs in Eastern Highlands.

Figure 7 shows a comparison of lights between 1999 and 2000, and it intuitively points out to the possibility of reduction in night-time luminosity after land reform. The analysis commences by estimating the welfare effects for all treatment and control groups, with urban areas excluded from the analysis. The motivation behind this is that land reform took place only in the European farming areas, which are rural. The causal effect of land reform 'treat#post' is significant at the 5% and 10% levels for regressions 1 and 4 only respectively (*see* Table 3). Regressions 2 and 3 are not statistically significant. In regression 1, European Areas are considered as the treatment group while Tribal Trust Areas are considered the control group. The causal effect has a coefficient of -0.58, which means that there was a reduction in light time luminosity as a ratio of 1992 lights after the land reform program. This is after only after controlling for ward population and the external effect/depreciation of the Zimbabwe dollar after 'Black Friday'. Regression 4 yields a negative causal effect of -0.641 after controlling for ward population, soil suitability (caloric index), precipitation, temperature, imports and export values. None of the control variables are statistically significant, with the exception of imports and exports values that capture the external effect of the exchange rate in the model. Although night-lights data has been found not to sufficiently capture economic phenomenon in rural areas, we find contrary evidence for Zimbabwe.

4.3 Estimating Welfare using Ratio of Cropland per ward

Using the SVM machine-learning algorithm, the study classified Landsat 4 - 5 and 7 images that covered the whole of Zimbabwe into cropland and natural forest. Before, the regression results are outlined, Cohen's Kappa classification accuracy coefficients and a brief discussion about the robustness of the classified data are presented.

4.3.0 Kappa Accuracy Coefficients

[PENDING]

4.3.1 Pixel to Square Kilometres Conversion Accuracy

Landsat images have a 30 x 30 metre resolution, and the number of cropland pixels are summed up by ward in R. This sum of cropland per ward is converted into square kilometres by multiplying by 0.009. To obtain the ratio of land under crops per ward this is further divided by the ward area in square kilometres. There were some wards with a ratio above may indicate double counting of pixels due to the fact that some pixels may overlap between different wards. To investigate the distribution of this double counting error we create the variable 'diff' by subtracting the square kilometres under cropland from the ward's total square kilometres. Of the total 9055 observations in the dataset from 1997 to 2003, Figure 8 shows the distribution of the observations with error.

Figure 8 Distribution of Observations with Error

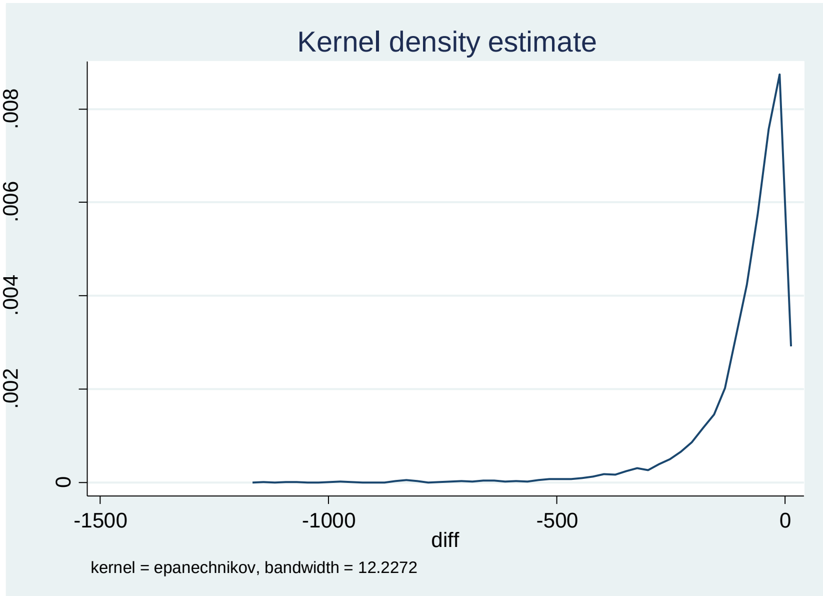


Figure 8 shows that for most of these observations with an error, the bulk of the error is very close to zero. This thus gives credence to the scenario that most of the errors are due to overlapping pixels that are double counted on ward boundaries given the relatively coarse 30m x 30m resolution of the images. As a result of the course resolution, it would also not be too superfluous to imagine wards that are completed sensed as cropland, particularly for smaller wards in more intensive agriculture areas. Table 4 shows the number of observations with error per error margin.

Table 4 Number of Observations with Error per Error Margin

Error Margin	Number of Observations lost
count if diff<0	2774
count if diff<-20	2079
count if diff<-50	1447
count if diff<-100	790
count if diff<-150	461
count if diff<-200	281

Table 4 shows the number of observations that would be lost at each level of error that the study adopts. For all the treatment and control groups, we estimate regressions using three different datasets. Dataset A retains all observations (9055), Dataset B retains observations where diff < 100 (retains 8265 and drops 790) while Dataset C (the clean dataset) excludes all observations whose crop ratio is greater than 1 (hence retains 6281).

4.3.2 Discussion of Crop Hectorage Results

Tables 5A to 5C presents the different results using the three datasets A – C as already indicated. All of the results generally show that FTLRP has a negative effect of welfare. In Table 5A, European Areas and Tribal Trust Areas are considered as the treatment and control groups respectively. The coefficient of the causal effect is negative and remains significant as controls are progressively added. It becomes no longer significant when light lights are added as a control. Using Regression 6, the coefficient of the causal effect is -0.224, significant and the 10% level. It means that the ratio of cropland per ward decreased by 22.4% due to the land reform. We control for population, soil suitability (caloric index), export and import values, temperature and precipitation.

The ward population is significant but has zero effect. There is also no selection effect of land reform as the average calories index is significant but has a very small effect. Temperature is not significant, and rainfall has a small positive effect. Thus, after accounting for several confounding factors, the causal effect of land reform remains robust. The R^2 of the model of

0.132, which means that 13.2% of variation in the cropland ratio is explained by the variables that are exogenous variables that are included in the specification.

Table 5A: Hectorage Estimates considering EAs as treatment and TTLs as:

Dep: Var: Crop Hec	1	2	3	4	5	6	7
treatTT#post	-0.265 (0.136)*	-0.285 (0.142)**	-0.29 (0.137)**	-0.219 -0.136	-0.24 (0.135)*	-0.224 (0.134)*	-0.188 -0.132
ward_pop		0 0	0 (0.000)***	0 (0.000)***	0 (0.000)***	0 (0.000)***	0 (0.000)***
AverageCal			0.001 (0.000)***	0.001 (0.000)***	0.001 (0.000)***	0.001 (0.000)***	0.001 (0.000)***
exvalue			0.083 (0.009)***	0.021 (0.010)**	0.016 (0.010)*	-0.045 (0.020)**	-0.047 (0.020)**
imvalue				0.176 (0.013)***	0.172 (0.013)***	0.082 (0.020)***	0.08 (0.020)***
Average_Temp					-0.02 (0.010)**	-0.011 -0.009	-0.012 -0.009
Total_Precip					0.001 (0.000)***	0.001 (0.000)***	0.001 (0.000)***
lights_ratio							0.092 (0.006)***
Constant	-1.978 (0.052)***	-1.822 (0.081)***	-4.979 (0.171)***	-4.825 (0.171)***	-4.696 (0.224)***	-2.098 (0.422)***	-2.116 (0.414)***
Regional FE	YES	YES	YES	YES	YES	YES	YES
R-squared N	0.003 6416	0.003 5519	0.077 5519	0.109 5425	0.114 5425	0.132 5425	0.165 5425
p-value	0.001	0.001	0	0	0	0	0

* p<0.1, ** p<0.05, *** p<0.01 means significant at the 10%, 5% and 1% levels respectively. The regression considers European Areas (EAs) as the treatment group and Tribal Trust Areas (TTLs) as the control group. Controls are added progressively from regression (1) to (7).

Table 5B uses Dataset B, that excludes all observations whose double counting error on ward boundaries exceeds 100. We obtain a similar result to the case when Dataset A is used. The only difference is that the causal effect remains negative and significant even controlling for population, soil suitability and export value only. The causal effect coefficient of -0.235 is significant at 10%, denoting that FTLRP caused around 24% decline in the amount of land under crops per ward. When additional variables are included such as import value, the causal effect is not significant, which may indicate that the value of goods imported may not capture the exchange rate decline well. The model has a very low R^2 of 0.004, which indicates the model explains very little variation in the endogenous variable.

Table 5B: Hectorage Estimates considering EAs as treatment and TTLs as:

Dep: Var: Crop Hec	1	2	3	4	5	6	7
treatTT#post	-0.24 (0.134)*	-0.235 (0.141)*	-0.244 (0.136)*	-0.169 -0.135	-0.191 -0.135	-0.173 -0.134	-0.153 -0.133
ward_pop		0 0	0 (0.000)**	0 (0.000)**	0 (0.000)***	0 (0.000)***	0 (0.000)***
AverageCal			0.001 (0.000)***	0.001 (0.000)***	0.001 (0.000)***	0.001 (0.000)***	0.001 (0.000)***
exvalue			0.074 (0.009)***	0.014 -0.01	0.01 -0.01	-0.045 (0.020)**	-0.049 (0.020)**
imvalue				0.175 (0.013)***	0.171 (0.013)***	0.094 (0.020)***	0.092 (0.019)***
Average_Temp					-0.01 -0.009	-0.003 -0.009	-0.006 -0.009
Total_Precip					0.001 (0.000)***	0.001 (0.000)***	0.001 (0.000)***
lights_ratio							0.083 (0.008)***
Constant	-2.164 (0.051)***	-2.008 (0.080)***	-4.828 (0.169)***	-4.655 (0.169)***	-4.654 (0.222)***	-2.428 (0.424)***	-2.456 (0.420)***
Regional FE	YES	YES	YES	YES	YES	YES	YES
R-squared N	0.003 6073	0.004 5204	0.068 5204	0.103 5112	0.107 5112	0.121 5112	0.14 5112
p-value	0	0	0	0	0	0	0

* p<0.1, ** p<0.05, *** p<0.01 means significant at the 10%, 5% and 1% levels respectively. The regression considers European Areas (EAs) as the treatment group and Tribal Trust Areas (TTLs) as the control group. Controls are added progressively from regression (1) to (7).

Table 5C presents the regression results using the 'clean' dataset that excludes all observations with a crop ratio above 1. Like the analysis shown in the previous two tables, the causal effect of FTLRP is negative at -0.269, significant at the 10% level. Although the results show that FTLRP affected agriculture production negatively, the model has a weak R^2 at 0.052.

Table 5C: Hectorage Estimates considering EAs as treatment and TTLs as:

Dep: Var: Crop Hec	1	2	3	4	5	6	7
treatTT#post	-0.263 (0.137)*	-0.248 (0.146)*	-0.269 (0.142)*	-0.187 -0.142	-0.207 -0.142	-0.179 -0.141	-0.175 -0.141
ward_pop		0 (0.000)*	0 0	0 0	0 0	0 (0.000)*	0 (0.000)*
AverageCal			0.001 (0.000)***	0.001 (0.000)***	0 (0.000)***	0 (0.000)***	0 (0.000)***
exvalue			0.071 (0.009)***	0.018 (0.010)*	0.016 -0.01	-0.056 (0.021)***	-0.056 (0.021)***
imvalue				0.155 (0.013)***	0.151 (0.013)***	0.084 (0.020)***	0.084 (0.020)***
Average_Temp					0.002 -0.01	0.008 -0.01	0.007 -0.01
Total_Precip					0.001 (0.000)***	0.001 (0.000)***	0.001 (0.000)***
lights_ratio							0.025 (0.011)**
Constant	-2.632 (0.053)***	-2.516 (0.084)***	-4.726 (0.175)***	-4.546 (0.175)***	-4.703 (0.230)***	-2.617 (0.463)***	-2.637 (0.463)***
Regional FE	YES	YES	YES	YES	YES	YES	YES
R-squared N	0.004 5189	0.005 4380	0.052 4380	0.082 4293	0.085 4293	0.097 4293	0.098 4293
p-value	0	0	0	0	0	0	0

* p<0.1, ** p<0.05, *** p<0.01 means significant at the 10%, 5% and 1% levels respectively. The regression considers European Areas (EAs) as the treatment group and Tribal Trust Areas (TTLs) as the control group. Controls are added progressively from regression (1) to (7).

Another analysis set consisted of European Areas as the control group and Native Purchase Areas as the control group. Using the clean dataset that excludes observations with crop ratio above 1, this analysis yields a negative coefficient of land reform, even as controls are progressively added (except for light lights. In this analysis, we obtain a larger negative effect of land reform at -0.459 (significant at 10%) which means that FTLRP almost halved agricultural production in the European Areas when compared against the Native Purchase Areas that were not affected by the reform exercise. Ward population and average calories or soil suitability index (to control for selection effect) are both significant at 1% but have zero and very small effect respectively. Temperature and rainfall have no significant effects, while exports value, imports value and light ratio are significant at 1%, 5% and 1% respectively. The imports and exports values capture external exchange rate effects while the lights ratio controls for the fact that wards with more lighting might be more developed and are prone to produce more than their counterparts elsewhere ceteris paribus.

Table 6C: Hectorage Estimates considering EAs as treatment and NPAs as:

Dep: Var: Crop Hec	1	2	3	4	5	6	7
treatNP#post	-0.314 -0.266	-0.503 (0.295)*	-0.499 (0.283)*	-0.523 (0.282)*	-0.519 (0.282)*	-0.459 (0.277)*	-0.452 -0.276
ward_pop		0 0	0 (0.000)***	0 (0.000)***	0 (0.000)***	0 (0.000)***	0 (0.000)***
AverageCal			0.001 (0.000)***	0.001 (0.000)***	0.001 (0.000)***	0.001 (0.000)***	0.001 (0.000)***
exvalue			0.073 (0.013)***	0.017 -0.015	0.013 -0.015	-0.086 (0.033)***	-0.089 (0.033)***
imvalue				0.152 (0.020)***	0.15 (0.020)***	0.059 (0.031)*	0.061 (0.030)**
Average_Temp					-0.009 -0.014	0.001 -0.014	-0.002 -0.014
Total_Precip					0.001 (0.000)*	0 0	0 0
lights_ratio							0.044 (0.012)***
Constant	-2.351 (0.157)***	-2.129 (0.194)***	-4.639 (0.282)***	-4.65 (0.281)***	-4.596 (0.351)***	-1.87 (0.657)***	-1.895 (0.654)***
Regional FE	YES	YES	YES	YES	YES	YES	YES
R-squared N	0.012 2038	0.015 1719	0.094 1719	0.126 1695	0.127 1695	0.166 1695	0.172 1695
p-value	0	0	0	0	0	0	0

* p<0.1, ** p<0.05, *** p<0.01 means significant at the 10%, 5% and 1% levels respectively. The regression considers European Areas (EAs) as the treatment group and Native Purchase Areas (NPAs) as the control group. Controls are added progressively from regression (1) to (7).

The R^2 for the model is 0.166 which means that it explains 17% of the variation in the ratio of cropland. It is important to highlight that the negative effect of land reform of agriculture production (welfare) in Zimbabwe has persisted after using datasets with different degrees of 'double counting' accuracy and using different treatment and control groups. It becomes important to learn what happened to welfare, but this time looking at it from the perspective of crop quality. Therefore, the next section discusses results obtained using NDVI as a proxy for crop quality that enables us to infer on the ability of farmers beyond year 2000 to cure their crops with chemicals and also apply fertilisers. This should tell us something about welfare.

4.5 Estimating Welfare using Ward NDVI

The NOAA CDR NDVI is a vegetation monitoring product that is available in the form of daily pictures that are sensed using satellites. Areas without any vegetation such as water bodies as can be seen in the image in Figure 5 are entirely black (represented by an NDVI of -9999) while those areas with dense, highly quality vegetation are represented by higher positive NDVI values. The study selects November, December, January and February daily images as this is Zimbabwe's rain and major agricultural season for the period 1997 to 2003, and averages them. Following Ahmad et al. (2010), we take higher values of NDVI to represent areas with healthier vegetation.

Table 7A: NDVI Estimates considering NPAs as treatment and TTLs as control

	1	2	3	4	5	6	7
treatTTNP#post	-1.931 (0.396)***	-2.399 (0.470)***	-2.426 (0.469)***	-2.378 (0.479)***	-2.409 (0.479)***	-2.381 (0.478)***	-2.04 (0.440)***
ward_pop		0 0	0 0	0 0	0 0	0 0	0 0
AverageCal			0.001 (0.000)***	0 (0.000)**	0 0	0 0	0 0
exvalue			0.034 (0.017)**	0.008 -0.019	0.005 -0.019	0.052 -0.039	0.008 -0.036
imvalue				0.077 (0.024)***	0.073 (0.024)***	0.046 -0.039	0.033 -0.036
Average_Temp					-0.028 -0.019	-0.021 -0.019	-0.022 -0.018
Total_Precip					0.001 (0.001)*	0.001 -0.001	0.001 (0.001)*
lights_ratio							0.539 (0.020)***
Constant	0.681 (0.074)***	0.742 (0.144)***	-0.702 (0.340)**	-0.578 -0.351	-0.3 -0.46	0.862 -0.885	1.12 -0.814
Regional FE	YES	YES	YES	YES	YES	YES	YES
R-squared N	0.014 4711	0.018 4018	0.023 4018	0.026 3937	0.027 3937	0.032 3937	0.182 3937
p-value	0	0	0	0	0	0	0

* p<0.1, ** p<0.05, *** p<0.01 means significant at the 10%, 5% and 1% levels respectively. The regression considers European Areas (EAs) as the treatment group and Native Purchase Areas (NPAs) as the control group. Controls are added progressively from regression (1) to (7).

Figure 7 shows the comparison in NDVI for the years 1999 and 2000. The NDVI regression estimates are shown in Tables 7A - B. The NOAA CDR DVI data is available at a resolution of 1 km by 1km. However it captures both cropland and natural forest so the ward mean NDVI was multiplied by the ward cropland ratio as a way of adjusting or filtering out the NDVI from natural forest, since we are only interested in crop quality. Table 7A shows the results obtained after analysis with the Dataset A that contains all observations, with Native Purchase Areas considered as treatment group and Tribal Trust Areas considered as the control group.

Table 7B: NDVI Estimates considering NPAs as treatment and TTLs as control

	1	2	3	4	5	6	7
treatTTNP#post	-0.575	-0.728 (0.247)**	-0.743 (0.295)**	-0.692 (0.295)**	-0.706 (0.301)**	-0.689 (0.301)**	-0.566 (0.300)**
ward_pop	0	0 0	0 0	0 0	0 0	0 0	0
AverageCal		0	0 (0.000)***	0 0	0 0	0 0	0
exvalue			0.015 -0.011	-0.005 -0.012	-0.007 -0.012	0.018 -0.024	-0.007 -0.023
imvalue				0.059 (0.015)***	0.057 (0.015)***	0.048 (0.025)*	0.039 (0.023)*
Average_Temp				-0.016	-0.011 -0.012	-0.013 -0.012	-0.011
Total_Precip				0	0 0	0 0	0
lights_ratio							0.321 (0.013)***
Constant	0.471 (0.046)***	0.526 (0.091)***	-0.231 -0.214	-0.125 -0.221	0.05 -0.29	1.014 (0.564)*	1.145 (0.524)**
Regional FE	YES	YES	YES	YES	YES	YES	YES
R-squared N	0.008 4470	0.01 3794	0.014 3794	0.018 3714	0.019 3714	0.025 3714	0.158 3714
p-value	0	0	0	0	0	0	0

NOTES: * p<0.1, ** p<0.05, *** p<0.01 means significant at the 10%, 5% and 1% levels respectively. The regression considers European Areas (EAs) as the treatment group and Native Purchase Areas (NPAs) as the control group. Controls are added progressively from regression (1) to (7).

The analysis is repeated in table 7B, using Dataset B, that excludes observations with an error margin of +100. Native Purchase Areas are considered as treatment group because they have may have been indirectly affected via the market mechanism. In the wake of FTLRP, there were a number of restrictions on Zimbabwean merchandise which could have affected the ability of the NPA farmers to enter export markets. This, and the economic decline in the wake of FTLRP may have affected the welfare and ability of NPA farmers to maintain high quality crops as measured by the NDVI.

Tables 7A – B show that FTLRP had a negative effect on welfare, using NPAs and TTLs as treatment and control areas respectively – as shown by the coefficient of negative coefficients of -2.04 and -0.566 respectively for the models computed with Datasets A and B respectively. These coefficients are significant at 1% and 5% respectively. Thus, FTLRP resulted in a decline in the ratio of crop quality to the 1997 base. The ward population control is included in the baseline regression capture the effect of population density given the labour intensive nature of agriculture. To show that there was no selection effect in implementing FTLRP, the soil potential (as measured by average calories) are added, with small or zero significant effects. Imports value has a small, positive effect of 0.039 in the second model (shown in Table 7B), significant at the 10% level. Thus, the effect of "Black Friday" is significant, in increasing the import of crop commodities that would otherwise have been produced in-country. A possible argument is that the dip in the quality of crops is due to the effects of drought, but the temperature and either rainfall variables do not have any significant effects, or the effect is very small for rainfall. The lights ratio (NLD) is added to the specification in order to capture the surrounding economy, and this is positive and significant. Thus, the model is robust, although R^2 is rather low. The conclusion therefore is that FTLRP negatively affected crop quality.

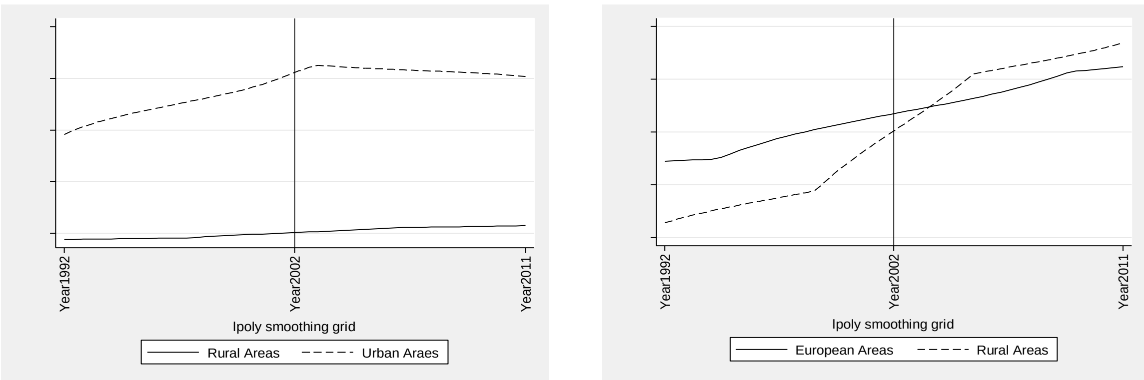
4.6 Estimating Reverse Migration using Census Data

Households in urban areas were also targeted as beneficiaries of the land reform program. The study, therefore sought to answer the question whether there was significant urban-rural migration, which is an important extension after Harris and Todaro (1970). Figure 8 presents the linear polynomials of the (i) urban-rural and (ii) Tribal Trust-European farming areas. The linear polynomials in Figure 8 are illustrated using the population figures for 1992, 2002 and 2012 census. Figure 8(a), seems to indicate that the population levels in the urban areas where negatively affected by the land reform program (the growth trajectory flattens off). In the Difference in Difference analysis, the urban areas are treated as the treatment group and the rural areas are treated as the control group. An important argument here is that from a migration point of view, it is people in urban areas that were ‘affected’ or attracted to leave the urban sector and enter the rural sector and take up farming under FTLRP. The rural sector, as a control remained unaffected because the former peasants simply moved to the EAs within the same rural sector and there is thus a zero net effect.

In comparison with TTLs, EAs (rural European Areas) would have been expected to record higher population levels after FTLRP, but Figure 8(b) shows the opposite. After FTLRP, TTLs overtake EAs in terms of population. These findings may be indicative of a “dis-employment” effect that resulted in farm workers relocating to the Tribal Trust Lands (TTLs) after losing employment and also having failed to obtain an allocation of a piece of land in the EAs farms – the former agricultural work lands for the farm workers. Table 6 presents the regression results.

Figure 8: Internal Migration Effects of Land Reform

a) Urban-Rural Comparison **b) Tribal Trust-European Areas**



Source: Own Illustration using 1992, 2002 and 2012 Zimstat Census data

Although, Figure 8(a) shows that there was a decline in the urban population post the year 2000, the regression results do not confirm that. The migration causal effect has a positive coefficient of 0.507, significant and 1%. This may suggest that reverse migration to take up farming in rural areas may not be the main cause of the flattening off of the urban population. It could actually be the result of emigration to foreign countries such as South Africa, which is however not the focus of this study. On the other hand, the analysis of the intra-rural migration patterns shows that after FTLRP, there was a significant growth in population in the TTLs. This may suggest that as some people from the TTLs and urban areas benefitted from new, fertile land; farms workers were largely at a disadvantage and probably had migration back to the TTLs as the only option available to them.

Table 6: Migration Regression Results

	Urban-Rural Areas 1	**Rural EAs-TTLs** 2
Treatment	-0.757*** (0.047)	-0.122*** (0.030)
Post	0.086*** (0.026)	0.056** (0.027)
Treat##Post	0.507*** (0.058)	0.096*** (0.036)
Constant	11.769	11.755
R-squared N	0.064 5490	0.013 4444
p-value	0	0
Treatment	Urban Areas	Tribal Trust Lands
Control	Rural Areas	European Farms

NOTES: * p<0.1, ** p<0.05, *** p<0.01 means significant at the 10%, 5% and 1% levels respectively.

5.0 Conclusion

The study contributes to the debate around the efficacy of land reform in developing countries, given its importance and strong link to poverty reduction efforts. The study finds agrarian reform may have a negative effect on welfare as measured by the amount of land under crops and the quality of the crops – using evidence from Zimbabwe. Previous studies focusing on the effects of land reform in Zimbabwe have not examined the issue within a robust quasi-experimental design. This study used the Difference in Difference methodology to correctly measure the effect of land reform on welfare by constructing various treatment and control groups in order to ensure that there is effective selection.

The availability of data to fully comprehend the effects of land reform in Zimbabwe, as in any other developing country is an important constraint that would inadvertently have affected the extent to which more empirical work could be done on Zimbabwe regarding the efficacy of FTLRP. The study exploits the advantages of remote sensing data as a proxy for welfare and estimates the effect of FTLRP on welfare using Nights Lights Data (NLD) and Normalised

Difference Vegetation Index (NDVI) and data derived from the classification of Landsat images using machine-learning techniques. It has been asserted that NLD suffers viability problems because it has low explanatory power when it comes to the analysis of economic phenomenon in a rural developing country context due to the low electricity proliferation rates in these areas, however our findings point to the contrary. We introduce NDVI and Landsat images, using the former to estimate changes in crop quality and the latter to approximate changes in land under crop production. This is an important data contribution that the study makes.

We observe the possibilities that there was urban-rural migration as a result of land reform, although the empirical strategy fails to support this, and we speculate that the slow down of the population growth in urban centres vis a vis rural areas in outmigration to other countries, although we are unable to test this. What the empirical strategy does confirm however is that there was significant migration to the Tribal Trust Lands (TTLs) from the European farming areas after land reform. We suggest that this is the 'dis-employment' effect of displaced farm workers having to relocate to the TTLs after suffering unemployment as their white commercial farmer employers where dispossessed of the land. This new dimension of internal migration patterns could also have been another indicator of the effect of FTLRP on the welfare of farm workers.

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Appendices 1 Tables

Table A1: Assignment of Crops to Different Natural Regions

Natural region	Crops Types
I	Dairy farming Tea Coffee Bananas Apples
II	Wheat Maize Tobacco Cotton Citrus
III	Barley Soya beans
IV	Millet Sorghum
V	Cattle ranching Oranges

Based on FAO (2016)

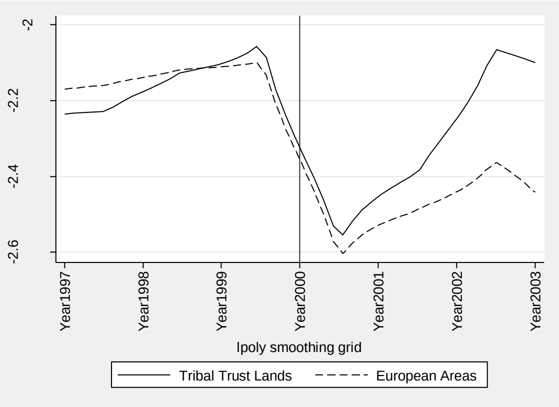
Table A2: Correlation between Trade in Agriculture and the Exchange Rate

	Exports		Imports	
Crop	**r (quantity)**	**r (value)**	**r (quantity)**	**r (value)**
Apples	-0.0858	-0.0938	-0.1082	-0.1082
Bananas	-0.3781	-0.3159	0.2617	0.2617
Barley			0.3108	0.2707
Catte_and_beef	0.6005	0.4448	-0.3881	-0.3676
CitrusJuice	0.4283	0.5721	-0.3574	-0.2358
Coffee	0.6319	0.4672	-0.4446	-0.4141
Cotton	-0.6413	-0.5550	-0.3083	-0.2569
Dairy		0.1063		-0.5111
Maize	0.4424	0.4851	0.2969	0.1646
Millet	0.4326	0.5665	0.3311	0.3737
Oranges	-0.8194	-0.6381	-0.0253	-0.0562
Sorghum	0.2776	0.4726	-0.0572	-0.0572
Soyabeans	0.0182	0.0858	0.5414	0.5506
Tea	-0.3841	-0.3841	-0.3391	-0.3761
Tobacco	0.4603	0.4285	-0.4964	-0.4964
Wheat	0.2522	0.1740	0.3101	0.3101

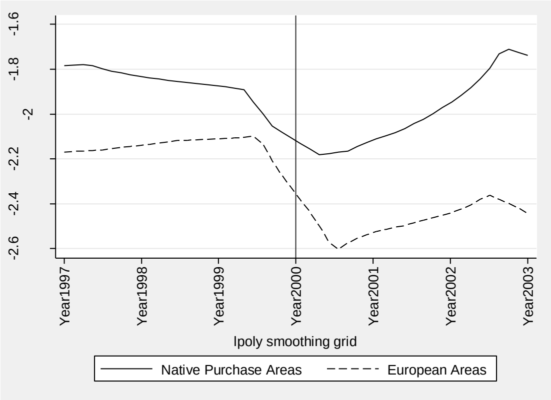
Appendix 2

L-Polynomials

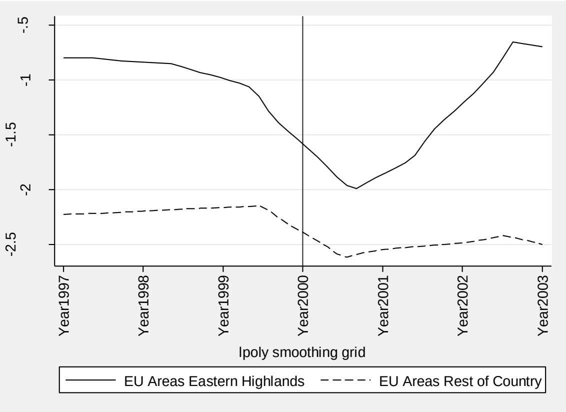
Treatment: European Areas
Control: Tribal Trust Areas



Treatment: European Areas
Control: Native Purchase Areas



Treatment: European Areas Rest of Country
Control: European Areas Eastern Highlands



Treatment: Native Purchase Areas
Control: Tribal Trust Areas