A Review on The Impact of Satellite Imagery in Urban Policy Planning

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Abstract— **This paper reviews some of the works done in the field of satellite image sensing-based policy planning, and how they can be fitted into urban settings for faster and effective decision making. Rapid urbanization due to population growth and migration in the past decades had a consequence on the overall planning of the urban areas. Policy planning schemes are now more developing than the past. Although the demand for new and stable policies regarding in the urban is increasing, proper evidence based on valid studies still needs to keep pace with the policy planning. Satellite remote sensing data can provide enough evidence at a large scale to come to a policy interpretation. Impact analysis of how different researchers in this sector have created a positive impact on different policy planning has been conducted in this research.**

Keywords-satellite image; policy planning; urban; urban development;

I. Introduction

Urbanization has become a major concern in the recent decades. Starting from the 60's, the demographic balance has been shifting towards the urban, and is expected to grow by 80 percent within the next 30 years[1]. This rapid urbanization is causing impact on the habitat, land usage pattern, transportation system, utility consumption on a negative scale, pondering significantly the development of a nation[2].

Therefore, studies on urban planning and policy formation has gained much significance than the past. As the demand for urban livelihood quality increases, new socio-economic issues arise. The problem, however, is neither with the socio-economic issues, nor with the efforts to tackle them, it is the lack of knowledge on new research instruments, similar case studies that can provide insights towards a solution and largest of them all, is the lack of data[3]. Any scientific or social research needs a lot of structured or unstructured information, and in urban case, also recurrent. Research and analysis on new urban changes are the key to decision or policy making which can create pathways to accommodate the change.

Another major issue in the urban areas of developing and under developed countries is that the amount of research and data sources to conduct them is very low. Developed economies has better data availability than their underdeveloped counterparts[4]. Adding to that, the policy makers and governors in the developed countries and cities are already modelling and implementing policy models based on sources like visual satellite data. Since satellite data is open accessible by all, developing and under-developed cities can source on them to conduct action research on their issues and provide policy makers tool for constructing new policy framework.

In this paper, reviews on how an alternative and open data source i.e. Satellite image data, can prove to be an effective solution to the big data problem has been discussed. The paper has been structured in a knowledge-based style, to point out different aspects and practices of the urban policy formation using satellite images and how machine learning can significantly help in the research process. Starting with the discussion on urban policy and planning, discussions on data and its necessity has been discussed. Next discussion of satellite data and machine learning in the context of urban has been discussed, analyzing the works and their impacts in their respective regional policy structure. In the last section different machine learning methodologies which are used on satellite images has been discussed.

II. Urban Policy Planning

A. *Public Policy: Context*

Public policy rationale and benchmarking contributes to the socio-economic development in a nation. Policy implementation process, however, requires a thorough assessment. A combination of survey-based research and insights on different socio-economic context shapes out the structure of a comprehensive framework on which a policy can be shaped properly. The path to making a public policy, therefore, is thorough[5].

In the context of urban, policy planning can be described as a technical and political process of urban development in the right way to preserve sustainability in the future.

B. *Issues making public policy*

One of the major challenges the government and stakeholders face before formulating an urban policy plan is to find acceptable validation of a socio-economic issue that needs to be resolved. The validation may be generated via public identification of a problem, mass analysis, survey-based research etc.

But while these methods may seem enough to prove the necessity to formulate any action plan against an issue, they have a lot of limitations. Such as, time requirement for surveying, conducting field research, inadequate policy instruments, occasional unavailability of similar case studies.

The initiative of developing policy instruments is an appreciative step, although much effort is required in getting into a public policy study, which often prove slow and significantly raises the opportunity cost. Therefore, it is essential to prioritize data-centric approach for preparing urban policies in solving urban socio-economic problems.

C. Data based public policy planning

A common practice by today's government and stakeholders is to evaluate the potential of any public policy based on evidence. Evidence-based approach to policy planning can be lauded as an advancement to one of the three overlapping categories of policy activities, information[6]. Most of the sectors, if not all, can be significantly benefited through data-centric policy making. Such as, land coverage and distribution, water bodies, agriculture and habitat, land transportation, public health, electricity and utilities [7]. Policy planners and makers can refer to the evidence and structure out the suitable policy framework. Although the extent of the policy analytical capacity based on data-centric approach may be questionable, nonetheless it has significantly helped the policy making institutions to become more rigorous and solve major long-term challenges.

While the need for data is obvious, the source of information to build a data driven model to roll different stages of policy cycle is a challenging one. Data driven model gives bottom-up approach to study urban infrastructure, resource and citizen management, and knowledge discovery by using complex unstructured big data[4]. Therefore, to contemplate the need for data we need more mines or sources of information, which in turn gives priority on data acquiring and collection. Advancement in data collecting instruments potentially helps building up data sources.

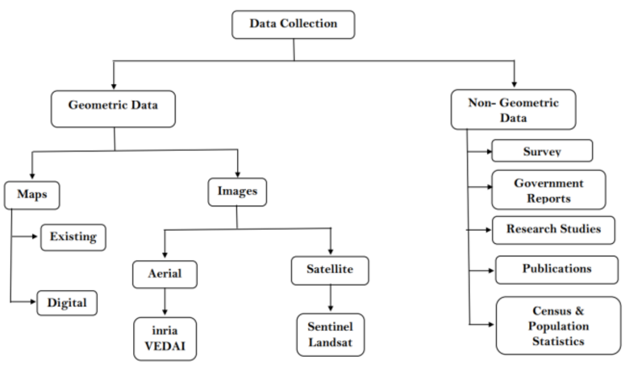

Figure 1 Data collection methodologies in the urban (authors credited)

In fig. 1 we can see different data collection instruments used by scientists, researchers and city planners to collect urban data. Although different institutional bodies use different data collection methodologies, in most cases it is not possible to monitor the effective changes in the data set over a continuous span of time. Also, many of these collected data are questioned with accuracy and precision in terms of collecting body and longevity. Vision based data however, such as aerial and satellite data provides much larger scale data over a larger spatial region. As a result, these data sources are gradually getting popular among the urban policy makers and researchers.

III. Satellite Data

Satellite remote sensing data provides an effective and open source of data for research based on regional setting. The key feature of satellite data is that they provide patterns of social, economic and cultural behavior spatially, which are essential to produce a systematic model for building and testing hypotheses[7]. Wide area coverage and repeat cycles combined with accessibility makes satellite data a suitable sourcing of spatial data.

Satellite sensors which acquire data are of two types: (i) active and (ii) passive. Active sensors, such as Synthetic Aperture Radar (SAR) containing own energy source emits long-wavelength signal with high penetration capability on the Earth's surface and reads the reflected signal based on some certain parameters such time, intensity, geospatial location etc. Optic sensors are passive sensors, which includes photographic and multispectral sensors. They primarily record optical data of reflected radiation of the sun on the Earth's surface. These data are often subjected to resolution, atmospheric noises, cloud density and other factors. As a result, often optic data is combined with active sensors on the satellite to provide enhanced quality on the acquired data.

There are a number of satellite missions which are actively used for urban spatial imagery data collection purposes. Such as Landsat, Sentinel, SPOT, ASTER etc. A detailed description of all the satellites used for urban data sourcing purposes are shown in Table 1. Data access of these satellites have been made public, which provides excellent platforms for the urban researchers in their respective field. The obtained images from these satellites has medium (80m~200m/pixel), high (30m~10m/pixel) or very high (VHR- 5m-0.5m/pixel) spatial resolution. Most of the satellites are multispectral, i.e. they can sense other parts of the electromagnetic spectrum as well as the visible one.

A. Current works by geographers and GIS people using satellite data

Satellite image data had been widely popular among GIS and geography researcher since the 80s[8]. The studies and researches conducted based on satellite imagery has been widely popular among urban policy makers and planners. Remote sensing tools provide tools for biophysical data extraction from urban environment, morphology analysis, vegetation distribution and other natural sectors[7].

The two most recent review of the use of remote sensing imagery in research related to regional science issues in urban settings are Jorge (2013)[7] and Xie (2008)[9]. Jorge (2013) focused on the relationships between socio-economic and land cover to extract information related to urban and suburban infrastructure and socio-economic attributes. They reported that there is not enough analysis of space-time dynamics in urban growth research and local research is a vital step towards urban environments developments. Xie, Sha and Yu (2008) reviewed the potential applications of remote sensing in vegetation mapping, research and policy. They showed that remotely sensed data could be used to study vegetation area, a comparison of advantages and limitations were also provided. They reported about the existing remote sensing sensor and their application was discussed, various image preprocessing and classification techniques were also discussed. Miller and Small (2003)[10] reviewed that remotely sensed data could be used to obtain internally consistent measurements of physical properties at a lower cost than that of in situ measurements.

Governmental and private sector data are more easily obtained which makes it feasible for urban planning purposes than urban environmental conditions monitoring and measuring. However, new dataset and techniques are being released into the public domain to study the spatio-temporal dynamics of urbanization. Since Miller and Small (2003), in the areas of nighttime lighting relationships with crime hav been also researched with the advances in remote sensing applications (Weeks, 2003, chap. 16); socio-economic change relationships and urban land cover (Mennis & Liu, 2005)[11]; house value modeling (Yu & Wu, 2006)[12]; population density estimation (Liu, Clarke, & Herold, 2006)[13]; land-cover or land-use changes, and urban morphology, (Lu & Weng, 2004[14]; Rashed, Weeks, Gadalla, & Hill, 2001[15]; Rashed et al., 2005[16]; Taubenböck, Wegmann, Roth, Mehl, & Dech, 2009[17]; Yin, Stewart, Bullard, & MacLachlan, 2005[18]; Griffiths, Hostert, Gruebner, & der Linden, 2010[19];). socio-economic status mapping (Avelar, Zah, & Tavares-Correa, 2009; Stow et al., 2007)[20], [21]; population estimation in informal settlements (Galeon, 2008)[22]; social vulnerability to landslides (Ebert & Kerle, 2008)[23]; land surface temperature relationship with socio-economic parameters (Rajasekar & Weng, 2009)[24]; and spatio-temporal analysis of urban sprawl (Taubenböck, Wurm, et al., 2009)[3]. Experts from various discipline like statisticians, experts in remote sensing, architects, computer scientists, urban planners, sociologists and geographers often worked together to extract useful information from satellite imagery.

B. Current works on satellite based policy planning using machine learning

Machine learning is reshaping the scientific study and researches on urban policy formation using satellite image. Using research data and applying different machine learning approaches in the data processing and interpretation stages, in depth analysis of urban cultural socio-economic characteristics

Table 1 Different Satellites that are used for remote sensing urban imagery data

System	Spectral resolution	Spatial resolution (pixel size – meters)	Temporal resolution (days)	Archive since
Sentinel – 1	2 Bands visible 5 Bands infrared 5 Bands thermal infrared	60	12	2014
Sentinel – 2	1 Bands visible 9 Bands infrared 10 Bands thermal infrared	10	12	2015
Landsat MSS	3 Bands visible 1 Band infrared 1 Band thermal infrared	80	18	1972
Landsat TM	3 Bands visible 3 Bands infrared 1 Band thermal infrared	30 – Visible and infrared 60 – Thermal infrared	16	1986
Landsat ETM+	3 Bands visible 3 Bands infrared 2 Bands thermal infrared 1 Band panchromatic	30 – Visible and infrared 60 – Thermal infrared 15 - Panchromatic	16	1999
SPOT 1 SPOT 2 SPOT 3	2 Bands visible 1 Band infrared 1 Band panchromatic	20 – Visible and infrared 10 - Panchromatic	26	1986
SPOT 4	2 Bands visible 2 Bands infrared 1 Band panchromatic	20 – Visible and infrared 10 - Panchromatic	2-3	1998
SPOT 5	2 Bands visible 2 Bands infrared 1 Band panchromatic	20 – Mid infrared 10 – Visible and near infrared 2.5 – 5 - Panchromatic	2-3	2002
ASTER	3 Bands visible 6 Bands infrared	15 – Visible 30 - Infrared	16	1999

	5 Bands thermal infrared	90 – Thermal infrared		
Ikonos	3 Bands visible 1 Band infrared	4 – Multispectral 1 – Panchromatic	1.5-2.9	1999
Quickbird	3 Bands visible 1 Band infrared 1 Band panchromatic	2.4 – Multispectral 0.6 – Panchromatic	1-3.5	2001
IRS-1C	2 Bands visible 2 Bands infrared 1 Band panchromatic	23.5 – Multispectral 5 – Panchromatic	5-24	1995

can be done at a large scale. The context of learning from training data to generalize hypotheses space helps in prediction, estimation, recognition, decision accuracy by studying different features of spatial data collected from satellites.

As a result, since the advent of machine learning in researches at a large scale urban researchers, scientists, analysts and policy makers had been incorporating it with remote imagery data. Schneider et. al[25] studied land usage pattern changes due to urban growth using satellite images of city Chengdu of Western China. They used images from Landsat 3 MSS, 4 TM, 5 TM and 7 ETM for six dates across different seasons to measure fallow farmland to urban conversion. They predicted the map, class confusion and map accuracy using C4.5 decision tree classifier. Their study directly contributed into making policies to improve land management and urban fragmentation reduction. A similar application using land cover change was made from the study of Nemmour et. al [26]. They proposed a combination framework of Fuzzy Integral and Attractor Dynamics over individual SVMs improving efficiency in land cover change detection. Although the above researches show great improvement in methodology, the high temporal and spatial variability of the complex urban settlements proved to be challenging. In that respect, Schneider [27] proposed new approach in urban settlement classification over multi-seasonal information in dense time stacks. Supervised classification to monitor urban expansion was at first compared using three classification algorithms, which resulted decision tree perform better for improving Landsat data stacks combining with band metrics. His study helped in mapping peri-urban villages which scaled over 1800 m^2.

Apart from land cover and pattern study machine learning methodologies have contribution to other satellite data based urban application field. Rajchandar et. al[6] used Random Forest (RF) classifier on Landsat imageries from 1991, 2003 and 2016 within a 10km suburban buffer of Chennai. They observed an expansion of 70.35% in urban area between 1991 and 2016. They also proposed a land change model for 2027. Juan et. al.[28] used spectral, texture and structural feature for slum detection from VHR imagery and compare three different learning algorithms (Logistic Regression, Support Vector Machine and Random Forest) over the data from Buenos Aires, Medellin and Recife and found that SVM performs better with radial basis kernel obtaining more than 81 in F2- scores. Arribas-Bel D et. al.[29] used spectral, texture and structural feature from VHR imagery and compare two learning models (Random Forest and Gradient Boost Regressor) to predict Living Environment Deprivation index in Liverpool. They also compare the results of machine learning models with two econometric models (OLS regression and spatial lag) and reported that Random Forest as the best model.

C. *Impact study of satellite data on urban planning*

Research on urban development using satellite imagery data can create significant impact in terms of data quality, accuracy and research strength to provide platform for construction viable urban policy framework. The culture of building such urban policy framework can be built upon a long-term vision and continuous improvement due to the openness, recurrence and abundance of satellite data on a spatial level of a region.

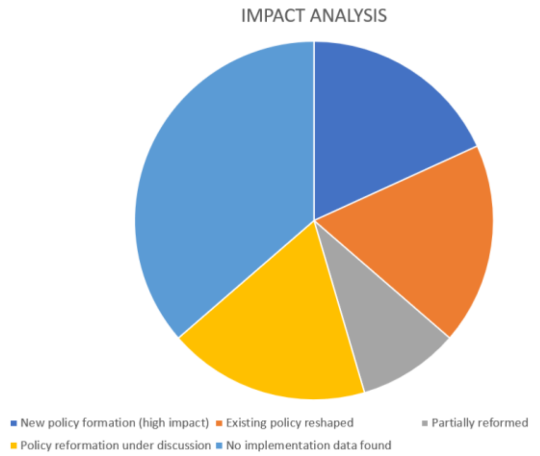

Figure 2 Modelling to implementation impact analysis of satellite image and machine learning in urban policy planning (authors credited)

Numerous action researches on urban using satellite data proved impactful and effective enough to attract policy makers and stakeholders take necessary steps to build a new or construct an existing framework. In this paper we have studied a collection of research works in the urban policy shaping using satellite data and machine learning and tried to analyze their impacts on the urban policy frameworks. The studies have not been taken under bias, they have been studied based on how scientific studies are shaping around this issue.

In the figure 2, a chart has been shown depicting different impact scales of the conducted researches on urban policy. We classified different implementation impacts into a discrete 5-unit scales, with new urban policy formation using machine learning and satellite data as the highest impact factor and no implementation data found as the lowest. We can see here that the result is promising, creating positive impacts in the urban policy sector at different rates. Although the researches proved the burning urban issues of a city with success, in some cases the researches either did not conduct policy level implementation or did not see the limelight of implementation. A historical study may provide convincing information that these researches are attracting more urban policy makers and stakeholders gradually. A detailed analysis of the above chart is give below in Table 2.

Table 2 Study comparison based on impact analysis of urban policy planning using satellite image and machine learning

Authors	Identified problem	Proposed solution	Implementation/Interpretation and impact
Kumarb *et. al*[1]	Urban expansion control due to migration in Vellore, Tamilnadu	Landuse classification using GLCF satellite image and Elshayal GIS	Study conducted only at a scientific level. No impact analysis conducted
Agapiou *et. al.*[2]	Impact on Archaeological sites due to rapid urbanization near Paphos, Cyprus	Predicting urban expansion applying Markov equation on Landsat ETM+ and TM satellite image from 1980-2013.	Proposed to the Govt. of the Republic of Cyprus. Study assisted Cultural Resource Management (CRM) authorities in formulating cultural heritage management policy
Khare *et. al.*[8]	Urban sprawl in Ajmer, Rajasthan	Shanon's entropy and landscape metric obtained over 25 years using Landsat MSS, TM, ETM+ and IRS LISS-III image.	Proposed to PHED, Ajmer for redesigning urban drainage infrastructure and optimal planning of natural resources.
Schneider *et. al.*[25]	Impact of rapid urbanization due to westernization in the coastal areas of Western China	Finding out urban land usage pattern based on Landsat MSS, TM, ETM from 1978-2002.	Collaborative study jointly conducted with EARIO, World bank. Initiatives to reexamine policy plans on urban land use has been taken.
Schneider[27]	Land classification at a high temporal and spatial variability	Classification algorithms analyzed patterns of development and expansion of peri-urban areas using Landsat time series data	Study conducted only at a scientific level. No impact analysis conducted
Padmanaban *et. al.*[30]	Affect on the urban ecosystem due to extensive migration in Chennai, Tamilnadu	Finding out urban fragments formation from suburban agricultural and forests using RF classification Landsat imagery	Scientific study and implementation into policy shaping conducted.
Duque *et al.*[31]	Expensive and time-consuming slum detection methodologies for pro-poor policy formulation	Proposed algorithm for automated slum detection based on urban characteristics using a unified classification model	Scientific study and implementation into policy shaping conducted.
Duque *et al.*[28]	Scientific development of geospatial extraction of socioeconomic information in urban settlements	Algorithmic analysis at different model settings based on efficiency	Scientific study and implementation into policy shaping conducted.
Davis *et al.*[9]	Combining satellite imagery and machine learning to predict poverty	Implemented transfer learning in estimating average household expense using nightlights recorded by satellite imagery	Proposed effective methodology for far reaching implementation. Impact analysis conducted.
Koukolas *et al.*[32]	Post-Competition effect on the metropolitan growth of Athens, Greece	Study using satellite image showed that unordered expansion and unobserved instrastructural construction led to erratic sprawl	Study was presented with effective implementation plan. New policy framework implemented
Erna *et al.*[33]	Quantifying relationship between urban growth to landscape change and population growth in Morelia, Mexico	Regression analysis and Markov chain to predict land cover and land use change 2o years ahead	Effective methodology application and implementation, with impact analysis for future policy planning

IV. COMPARISON OF METHODOLOGY

To extract relevant information from different satellite images different researchers implemented various types of algorithms. Authors reported that, decision tree and support vector machine perform better compared to other methods. They are computationally fast, and distribution of data is of no concern.

Table 3 Comparison of different machine learning algorithms for acquiring data from satellite image

Authors	Method	Advantages	Limitations
Arya *et. al.*[34]	Multi Wavelet Transform	Reduces noise, artifacts, distortion.	Used only for low resolution images, Does not effective in edge enhancement.
Brindha *et. al.*[35]	2D Discrete wavelet Transform	Noise removal and edge enhancement.	Weak color information is often a problem.
Huang *et. al.*[36]	Support Vector Machines	High classification accuracy.	Weak color information is often a problem
Jiang *et. al.*[37]	Decision trees, Support Vector Machine,	Computationally fast	

	Artificial Neural Networks		
Otukei *et. al.*[38]	Decision trees, Support Vector Machine, Maximum Likelihood	Computationally fast	
Li *et. al.*[30]	Decision trees, Support Vector Machine, Random Forest	Multi-temporal classification	

V. CONCLUSION

This paper reviewed some of the notable studies in the context of urban policy and planning, satellite imagery and impact of machine learning in the relevant studies. Our main objectives were to find methods to analyze these urban studies and create a common knowledge platform for enthusiasts and to call for further researches in this field. We tried to follow a knowledge-based style of representing our reviews and studied to find qualitative and quantitative measures among the researches. Discussions were made to provide research-based knowledge on urban policy, satellite visual remote data and machine learning and how different researches approaches to different solutions. We proposed measurement mechanisms and tried to analyze how the researches are impacting in the urban community. Although we opined on the analysis on a set of studies, we do not claim the impact measurements as conclusive remarks, rather they can be thought as "initial data" to a classification in the language of machine learning. We also tried to compare some popularly used machine learning methodologies on satellite data in the urban context. The research field of urban policy shaping using data and machine learning is far from saturation yet, especially in the developing and under-developed cities across the world.

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